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Multivariate analysis of CO^2 emissions by energy generation in IEA member countries

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Abstract. The concentration of carbon dioxide (CO^2), the main catalyst for global warming, reached an average of 414.7 parts per million in 2021 and 2.3 ppm more than in 2020. This theme is significant and has gained space in global discussions. This research aimed to deal with and analyze essential points in this discussion. With the study, it was possible to point out evidence that Brazil is a country that has been significantly reducing its CO^2 emissions, being in the cluster along with IEA member countries that least issue CO^2. With this article, it was possible to point out similar characteristics between the CO2 emissions of the countries, making it possible to highlight three latent variables: countries that have a constant tall or low trend in CO^2 emissions, Grouping of countries that showed an upward trend at the beginning of the analyzed period, but with a significant reduction CO^2 over time, and countries that have had more discrepant behavior from the others, these being the countries that have a structural breakdown in their time series of CO^2 emissions by power generation.

Key words. Cluster; Factor Analysis; CO2 emissions, Renewable Energy; Multivariate Statistics

1. Introduction

High concentration of carbon dioxide is responsible for the greenhouse effect and increased global temperature. Excessive CO2 in the atmosphere is responsible for overheating the planet, which generates severe environmental imbalances. The high concentration of this gas results in air pollution and acid rain, among other negative points. One of the main sources of CO2 in Brazil and worldwide is the burning of fossil fuels. Investing in renewable energy can help prevent greenhouse gas emissions and protect communities from climate change effects.

There is great concern about changes in atmospheric gas concentrations due to anthropogenic activities. This was observed more intensely from 1750 onwards, with the advent of the first Industrial Revolution. Electric power generation, improvement, transportation system expansion, and indoor heating, among others. It is based essentially on the consumption of energy obtained by burning fossil fuels, the leading energy resource used until today. This is the most significant anthropogenic source of greenhouse gases, such as carbon dioxide [1].

To enable energy cooperation focusing on energy security, The International Energy Agency (IEA) was conceived after the oil crisis of 1973-1974, focusing on energy security. The Agency operates within the financial framework of the OECD, and the OECD Council appoints the Supreme Audit Institution of a member country, which performs an audit externally independent of the accounts and financial management of the IEA. It is at the center of the global energy dialogue. It has become a key player in environmental discussions, providing reliable statistics and analysis on energy production, transmission, and consumption worldwide.

IEA analysis shapes policy to enable the world to meet climate, energy access, and air quality goals while maintaining a strong focus on the reliability and affordability of energy for all.

In 2017, Brazil joined the International Energy Agency (IEA). In 2022 Brazil and the International Energy Agency signed a technical cooperation agreement. The plan provides for Brazilian participation in reviewing the organization's reports on matters related to the energy transition for the 2022-2023 biennium.

Large emitters of greenhouse gases greenhouse effect, like Brazil and the other G20 countries, have the most significant responsibility for the substantial reduction of emissions required to comply with the Paris Agreement's goal of stabilizing Earth's warming at 1.5°C this century. The IEA (International Energy Agency), in its World

Energy Outlook 2021[1], estimated 14 billion tons of CO^2 equivalent to the total emissions they need to be shot down by 2030 to get the world on track of 1.5°C. Currently, the national targets on the table are at 2.7°C [2].

This article aims to carry out an exploratory analysis, which highlights the importance of investments in renewable energy generation to reduce CO2 per energy generation. In this work, we seek to apply multivariate statistical methods, which allow the grouping by similarity of the variables of interest (CO2 emissions of the IEA member countries and the associated country Brazil), with this, the objective is to find latent variables that significantly characterize the groups.

The intended article is divided into 4 sections. The first addresses a brief introduction on the subject, section 2 presents the implemented methodology. Section 3 brings the analysis and results, followed by section 4 where the results achieved in the study are concluded.

2. Methodology

According to [3], multivariate statistical analysis refers to a set of methods implemented simultaneously, enabling the analysis of multiple measures on the variable of interest.

Vicinni (2005) [4], points out that multivariate statistics is more than treating a larger number of variables. Still, in multiple analyses of the data, the variables considered in the research must be random and interrelated, in which the effect of each one is interpreted simultaneously, that is, jointly. To develop an efficient multivariate analysis, an exploratory study of the observed data must be carried out in the first instance to examine and adequately treat them.

2.1. Principal Components

The main component technique used in this article seeks to extract the most relevant information from the set of variables that have been selected. Once this is done, it can be represented as a set of new orthogonal variables nominated from the main components. This way, the data is reduced, and the features that reduce it are interpreted.

The database is first verified to be adequate to use the main component technique, i.e., if the variables in question are correlated. Bartlett's sphericity test is implemented to verify this suitability. The test is based on the correlation matrix (σ) of the variables under study, with the following hypotheses.

$$\begin{cases} H_0: \Sigma \text{ is a diagonal matrix} \\ H_1: \Sigma \text{ not a diagonal matrix} \end{cases}$$

If H_0 is not rejected, applying the main component technique becomes inadequate, as the variables under study are decorated.

This method is sample-based, so obtaining the actual correlation matrix from the data is impossible. Therefore, it is necessary to get the estimate of Σ, which can be obtained through the equation:

$$S_x = \frac{1}{n-1} X^T H X \qquad (1)$$

To determine the principal components, we need to calculate the eigenvalues (λ) and eigenvectors (γ) of matrix (S). An array is defined $Y = P^T X_i$, being $i = 1, \dots, p$, in which p it is an orthogonal matrix whose components are the p eigenvectors of S. With this, the i-th principal component is given by:

$$Y_i = a_{i1} X_1 + \cdots + a_{ip} X_p \qquad (2)$$

Where, a_{ip} represents the i-th element of the eigenvector of characteristic p.

Therefore, the loadings (loads) of each variable in each principal component are calculated, that is, the weight that each variable has in each component is equal to the i-th element of the eigenvector. The score of each principal component is given by the linear combination of the loading of each variable multiplied by its value. An efficient way to verify the quantity of components to be used is by observing the Scree Plot, which is the graph that contains the eigenvalues of each element.

2.2. Factor analysis

According to [5], factor analysis consists of a statistical technique, where it is possible to represent a multivariate process through the creation of new variables, which are derived from the original variables and, generally, in smaller numbers, which represent the commonalities of the process.
Factor analysis provides the description of the variability of correlated variables observed in a smaller number of unobserved variables, which are linearly related to the original variables. The observed variables are modelled as a linear combination of common factors plus a random error.

Factor Analysis assumes the existence of a statistical model that uses regression techniques to test hypotheses and is related to principal component [6]. In short, the factor analysis is considered as an extension of the aforementioned principal component analysis, both seek to approximate the covariance matrix $\mathbf{\Sigma}$;

The suitability of data for factor analysis can be analyzed using the Kaiser-Meyer-Olkin (KMO) and Barlett's Sphericity tests. The KMO test provides a value in the range [0,1] and the closer to 1 means that the factor analysis will be adequate. Value 0 indicates inadequate for factorial analysis, acceptable if greater than 0.5, recommended above 0.8.

To start interpreting the results of a factor analysis, it is necessary to verify the loading matrix. It is essential to point out that if this matrix presents similar numerical magnitude values, the difficulty of interpreting the original factors increases, that is, when the original variable is

[1] IEA, World Energy Outlook 2021. Available in https://www.iea.org/reports/world-energy-outlook-2021/executive-summary

highly correlated with more than one factor, its interpretation becomes difficult. There are numerous possible criteria to apply factor rotation, allowing a better interpretation. In this work, the VARIMAX criterion will be used, which consists of trying to find, for a fixed factor, a group of variables highly correlated with it and another group of variables that have little or moderate correlation with the element.

Once the axes have been rotated, the next step is to analyze the new load matrix, and thereby obtain which variables are part of each factor, interpreting them in order to highlight their main characteristics.

2.3. Cluster Analysis

Cluster analysis consists of multivariate techniques that allow the separation of objects into groups. This analysis is a statistical procedure that aims to partition the elements into two or more groups called clusters, considering their similarity according to pre-established criteria. According to [7], these criteria are usually based on a dissimilarity function that receives two objects and returns the distance between them.

After the implementation of a quality metric, the groups must present a high internal homogeneity and external heterogeneity, that is, the elements of a set must be mutually similar and different from the elements of other locations [8].

Clustering can be said as an auxiliary tool, it can be used as a set of procedures to organize time series based on similarity or dissimilarity data. The dissimilarity between objects is measured by a distance matrix whose components resemble the distance between two points. The technique above can be described as a two-step process: (i) the choice of a distance measure and (ii) the choice of the clustering algorithm. These two steps together define the complete clustering result.

Cluster analysis is divided into two methods for grouping variables, hierarchical and non-hierarchical. In this work, the non-hierarchical K-means method will be used. K-means is a non-hierarchical clustering heuristic that aims to minimize the distance of objects to a set of $\boldsymbol{k}$ centers. The distance between a point $\boldsymbol{p_i}$ and a group of clusters is g iven by $\boldsymbol{d(p_i, \chi)}$, defined as the distance from the point to the center closest to it. The function to be minimized is then given by:

$$\boldsymbol{d(P, \chi) = \frac{1}{n}\sum_{i=1}^{n} d(p_i, \chi)^2} \qquad (4)$$

There are two clustering techniques for building clusters, known as the hierarchical method, which consists of identifying clusters and the probable number $\boldsymbol{g}$ of groups, by a series of successive mergers, or a series of consecutive divisions, with the results observed in the dendrogram, which illustrates mergers or divisions made at successive levels. The other method is kon-hierarchical, where the number $\boldsymbol{g}$ of groups is pre-established,; this technique consists of directly finding a partition of $\boldsymbol{n}$ items in $\boldsymbol{k}$clusters by two requirements, such as, internal similarity and isolation of the formed clusters.

According to [6], defining the optimal number of clusters for se is subjective, but criteria make it possible to determine this number of clusters more efficiently. These criteria are the behavior of the level of fusion, the behavior of the level of similarity, the $\boldsymbol{R^2}$ coefficient, the Pseudo $\boldsymbol{F}$ statistic, the semipartial correlation and the Pseudo $\boldsymbol{T^2}$ statistic. That said, there is an adequate number of clusters for a more accurate and efficient analysis.

3. Analysis and Results

To carry out the analysis, carbon dioxide emission data by power generation and population of the 30 member countries of the International Energy Agency (IEA) [10] were used, namely: Austria, Czech Republic, France, Ireland, Lithuania, Norway, Spain , Turkey, Belgium, Estonia, Greece, Japan, Mexico, Portugal, Switzerland, Australia, Denmark, Germany, Italy, Luxembourg, Poland, Sweden, United Kingdom, Canada, Finland, Hungary, Korea, New Zealand, Slovak Republic and Netherlands and the associated country Brazil. Population data from these countries were also used, and the period selected for the analysis was from 1990 to 2021. It should be noted that data regarding $\boldsymbol{CO^2}$ emissions were collected through the British Petroleum (bp) [11] database, and data on country populations in each reference year are taken from the Research Federal Reserve Bank of st: Louis [12].

Seeking to start an exploratory analysis of the data, in table 1, it is possible to observe the descriptive statistics of $\boldsymbol{CO^2}$ emission by energy generation and population of the 30 member countries of the IEA, and of the associated country Brazil, figure 1 presents the minimum, median, average, maximum and standard deviation of the variable of interest in this study.

Countries	Min	Median	Average	Max	SD
Australia	14.31	17.43	17.48	19.57	0.62
Austria	0.1	7.64	7.1	9.17	0.66
Belgium	9.1	12.68	12.01	13.66	1.37
Brazil	1.31	1.77	1.84	2.49	0.29
Canada	13.7	15.96	16.14	17.71	1,008
Switzerland	10.16	16.68	15.85	23.5	3.21
Czech Republi	2.5	5.43	5.02	7.64	1.31
Germany	0.18	0.26	0.27	0.51	0.06
Denmark	6.34	10.92	10.4	13.9	1.93
South Korea	4.9	7.77	7.32	9.07	1.04
Spain	12.84	18.82	19.05	25.7	3.37
Estonia	41.3	64.8	64.29	83.87	12.21
Finland	7.56	10.69	10.13	14.19	1.68
France	0.48	0.59	0.62	0.75	0.08
Hungary	1.06	1.26	1.44	3.76	0.59
Ireland	1.81	2.5	2.54	3.13	0.37
Italy	4.69	6.61	6.57	7.91	1.06
Japan	1.38	1.67	1.66	1.81	0.1
Lithuania	7	10.92	10.43	13.94	1.97
Luxembourg	52.18	74.73	72.78	85.68	9.77
Mexico	2.2	2.89	3.05	4.44	0.61
Netherlands	2.31	3.2	3.26	3.94	0.43
Norway	5.13	8.04	7.9	12.91	1.82
New Zealand	69.28	119.93	117.13	138.93	18.79
Poland	5.65	7.64	7.58	9.92	1.22
Portugal	3.94	4.61	5.45	6.8	0.82
Slovakia	5.98	7.99	7.73	8.56	0.63
Sweden	15.9	26.07	27.01	40.09	7.87
Turkey	3.74	8.94	7.78	11.04	2.08

Fig. 1. Descriptive statistics
Source: Elaborated by the authors.

Figure 2 presents the correlation matrix between the countries; the blue color represents the positive correlation, and the stronger the positive correlation between the countries, the more intense the shade of blue; in this way, the countries that present a positive correlation walk together in periods reduction and more $\boldsymbol{CO^2}$ emissions, that is when a country reduces emissions the other also presents a reduction. The same goes for the increase in emissions. The red color represents the negative correlation between the countries, that is, when a country is in the $\boldsymbol{CO^2}$ emission reduction period, the other is emitting more emission reduction period, the other is emitting more.

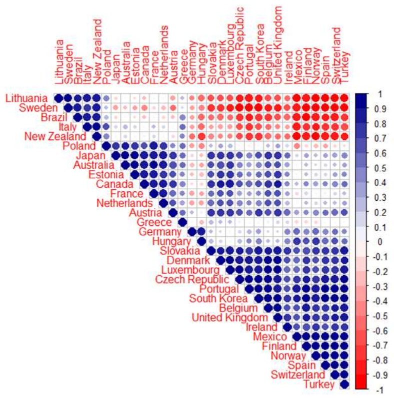

Fig. 2. Correlation Matrix
Source: Elaborated by the authors.

After the initial analyses, Bartlet's Sphericity Test was performed to check the correlations between the variables. The test result showed a significantly small p-value, less than 5% (chosen significance level), so we have evidence to reject the null hypothesis. With that, there are some relationships between the variables. The component analysis main will be valid.

After estimating the S matrix, according to the methodology above, the eigenvalues and eigenvectors are calculated to obtain the components, the explained variation per component, and the accumulated explained variation, which can be seen in figure 3.

Components	Eigenvalue	Explained Variation	Accumulated Explained Variation
1	4.27	0.58	0.58
2	2.86	0.26	0.85
3	1.32	0.05	0.91
4	0.94	0.02	0.93
5	0.65	0.01	0.95
6	0.54	0.009	0.96
7	0.52	0.008	0.971
8	0.46	0.006	0.978
9	0.37	0.004	0.97

Fig. 3. Components
Source: Elaborated by the authors.

As seen in Table 2, two components will be necessary to follow the criterion of using the components that explain at least 70% of the total variation. Still, considering the standard of selecting all the details with an eigenvalue greater than 1, it would result in 3 three components. To decide efficiently and more accurately, the Scree Plot is used, Figure 4, where it is noted that after the 4th component, the distance between the components remains constant. This result corroborates the second criterion that three components are sufficient, thus explaining 91% of the total variance.

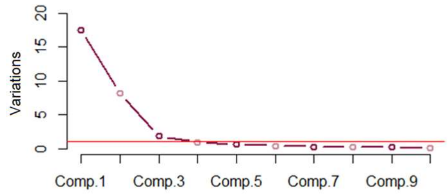

Fig. 4. Scree Plot
Source: Elaborated by the authors.

It is important to emphasize that the commonalities were analysed, and no country had a commonality below 0.72, so none of the countries needed to be removed from the sample. That said, the KMO test (Kaiser-Meyer-Olkin) was applied to assess the adequacy of the sample size, the result of this test varies between 0 and 1, with results above 0.5 being acceptable for factor analysis. In this test, KMO = 0.61 was obtained, so the sample is suitable for factor analysis. Considering the analysis already carried out in Principal Components, three factors will be used, explaining 91% of the total variance.

As previously mentioned, there are numerous criteria to apply factor rotation; in this work, the orthogonal factor rotation method used was VARIMAX, proposed by Kaiser in 1958, which makes it possible to find the rotation matrix that maximizes the variance of the loadings of each factor on all variables (FIGURE 5).

Countries	Factor 1	Factor 2	Factor 3	Countries	Factor 1	Factor 2	Factor 3
Australia		0.971		Hungary	0.603		
Austria		0.739		Ireland	0.574		
Belgium	0.756			Italy	-0.921		
Brazil	-0.937			Japan		0.951	
Canada		0.907		Lithuania	-0.959		
Switzerland	0.924			Luxembourg		0.719	
Czech Republic	0.826			Mexico	0.944		
Germany			-0.840	Netherlands		0.897	
Denmark		0.702		Norway	0.945		
South Korea	0.849			New Zealand	-0.942		
Spain	0.935			Poland		0.840	
Estonia		0.937		Portugal	0.901		
Finland	0.944			Slovakia	0.625		
France		0.939		Sweden	-0.946		
United Kingdom	0.705			Turkey	0.905		
Greece			0.598				

Fig. 5. Factor loadings with rotation
Source: Elaborated by the authors.

From the correlation matrix between the variables and the latent factors, after the rotation, given in figure 6, one can observe the presence of three latent factors, which, due to their form of association with the original variables, can be interpreted in the same way. Following way:

Factor 1: O factor 1 represents the countries that show downward or upward trends in the analysed period; that is, in this factor are the countries that have significantly and constantly reduced their $\boldsymbol{CO^2}$ emissions by the generation of energy and population in the observed period, in it too this is the country that only showed an upward trend over the years, that is, the one that at no time reduced its $\boldsymbol{CO^2}$ emissions, with Lithuania being the only country in this factor that did not present a reduction in the period studied (Figure 6).

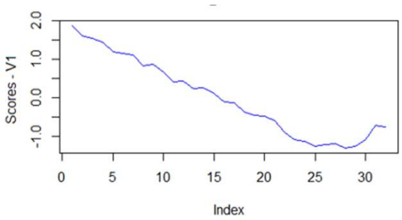

Fig. 6. Factor 1 and its belonging series.
Source: Elaborated by the authors.

Factor 2: Factor 2 comprises countries that show an upward trend in the first years analysed, but with a significant drop in CO^2 emissions per energy generation and population over time. The striking characteristic of this factor is that all the countries that comprise it reached the year 2021 with a reduction in CO^2. It is noteworthy that the countries that invested in renewable energy over the period separated for analysis reduced the emission of polluting gases (FIGURE 7).

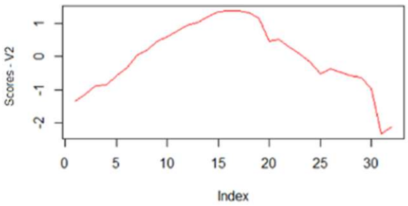

Fig. 7. Factor 2 and its belonging series.
Source: Elaborated by the authors.

Factor 3: Factor 3 is composed of only two countries, that is, those that have different characteristics from the countries that are contained in Factor 1 and 2. In this Factor, the striking characteristic is that the two countries do not show an upward or downward trend, but a structural break. Germany presents a significant drop in the year 1993, emphasizing that the analysis deals with the emission of CO^2 by energy generation, this result corroborates the data presented by Bicalho (2015), since the beginning of the 90s, Germany has been making significant changes to its energy matrix, which justifies the reduction in CO^2 emissions during this period. In summary, the two countries in this Factor 3 achieved their greatest CO^2 reduction in the period between 2019 and 2020 (Figure 8).

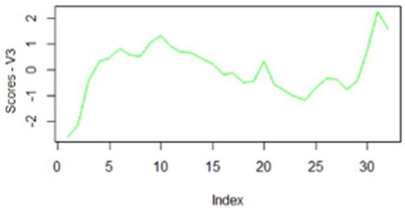

Fig. 8. Factor 3 and its belonging series.
Source:Elaborated by the authors.

To start the cluster analysis, hierarchical methods with Euclidean distance were used. To analyse the optimal number of clusters, it is not feasible to use the dendrogram, as there are many observations, so the Scree Plot will be used again, which can be seen in Figure 9, so it is noted that the distances between objects become constant, defining thus choosing 4 clusters for analysis.

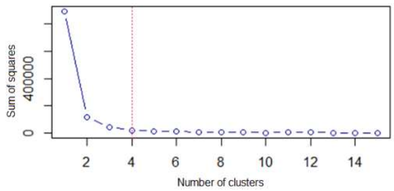

Fig. 9. Scree Plot – Clusters
Source: Elaborated by the authors.

Through the analyses previously presented, it was defined that the ideal number of clusters is K=4. After determining the number of sets to be used, the non-hierarchical K-means method is applied. The k-means method is a partition method that measures the proximity between groups using the Euclidean distance between the centroids of the groups, which is the case of this study.

Figure 10 illustrates the clusters grouped using the K-means method. The green lines represent the positive correlation between the observed variables, and the red ones show a negative correlation.

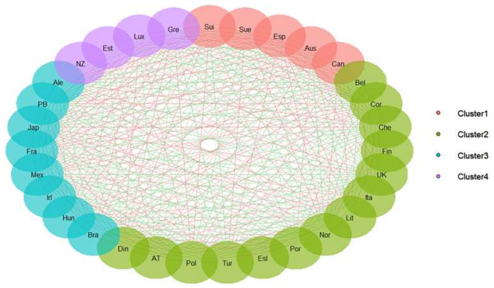

Fig. 10. Clusters - K-means method
Source: Elaborated by the authors.

Figures 11 and 12 presents the result of the 4 clusters. It can be noted that cluster 4 contains the countries that emit the most CO^2 per generation of energy in the period analyzed, with an average of 91,185 emissions, these countries showed little decrease over the years compared to the others. In Cluster 3, there are the countries that emit the least CO^2 per generation of energy and population, which emit an average of around 1,839 CO^2. It should be noted that Brazil is in this cluster, and that the country has been investing heavily in renewable energy over the period analyzed, an important point that can be seen in figure 12, is that Brazil has been showing a downward trend throughout the analyzed period, with the exception of the year 2015, when the country went through a period of drought, reducing the production of energy by hydroelectric plants, making it necessary to activate the thermoelectric plants, which significantly increased the emission of CO^2 in the country. With this fact, there is strong evidence that investment in renewable energy is of paramount importance for CO^2 reduction, countries that invest in sustainable sources are able to significantly reduce CO^2 emissions.

Cluster 1		Cluster 2	
Countries	Average	Countries	Average
Switzerland (Sui)	15.854	Belgium (Bel)	12.011
Sweden (Sue)	27.007	Korea (Cor)	7.322
Spain (Esp)	19.049	Czech Republic (Che)	5.028
Australia (Aus)	7.800	Finland (Fin)	10.139
Canada (Can)	16.143	Kingdom United (UK)	6.445
		Italy (Ita)	6.578
		Lithuania (Lit)	10.438
		Norway (Nor)	7.908
		Portugal (Por)	5.455
		Slovakia (Esl)	7.733
		Turkey (Tur)	7.783
		Poland (Pol)	7.581
		Austria (AT)	7.759
		Denmark (Din)	10.401
Total Average	**17.171**		**8.042**
variance	**55.031**		**5.749**
SD	**7.418**		**2.398**

Fig. 11. Principal Components(Cluster 1 and 2)
Source: Elaborated by the authors.

Cluster 3		Cluster 4	
Countries	Average	Countries	Average
Brazil (Bra)	1.846	New Zealand (NZ)	117.131
Hungary (Hun)	1.442	Estonia (Est)	64.287
Ireland (Irl)	2.542	Luxembourg (Lux)	72.782
Mexico (Mex)	3.057	Greece (Gre)	110.539
France (Fra)	0.628		
Japan (Jap)	1.661		
Netherlands (PB)	3.260		
Germany (Ale)	0.274		
	1.839		91.185
	1.159		683.268
	1.077		26.139

Fig. 12. Principal Components (Cluster 3 and 4)
Source: Elaborated by the authors.

4. Conclusion

The high concentration of carbon dioxide is responsible for the greenhouse effect and increased global temperatures. Excess CO^2 in the atmosphere is responsible for overheating the planet. One of the main sources of CO^2 is the burning of fossil fuels. Investing in renewable energy has become a priority for many countries. Given the global pollution problem, IEA has taken on an essential proportion worldwide.

The agency has become essential in environmental discussions, providing reliable statistics and analysis of energy production, transmission, and consumption worldwide. IEA analysis shapes policy to allow the world to achieve climate, access to energy, and air quality, maintaining a strong focus on the reliability and accessibility of energy for all.

This article aimed at the multivariate analysis of CO^2 emissions by power generation in IEA member countries and verifying standards in the redemptions and the existence of clusters. Additionally, the verification of Brazil fits the agency member countries in this regard.

The research achieved its main objective, which was to verify and validate the importance of investments in renewable energy generation, in order to reduce CO^2 emissions. With the research it was possible to point out evidence that Brazil is a country that has been significantly reducing its CO^2 emissions, being in the cluster together with the IEA member countries that emit lessCO^2.

Another relevant result in the research is the analysis of the Factors, where it was possible to point out characteristics of similarity between the CO^2 emissions of the countries, making it possible to highlight 3 latent variables, being factor 1 composed of countries that present a constant tendency of high or low in the emission of CO^2, whereas Factor 2 allowed the grouping of countries that showed an upward trend at the beginning of the analysed period, but with a significant reduction over time, with this, all countries that make up this factor arrived in 2021 with a reduction in their CO^2 emissions CO^2. Factor 3, on the other hand, grouped the two countries that presented the most discrepant behavior from the others, these being the

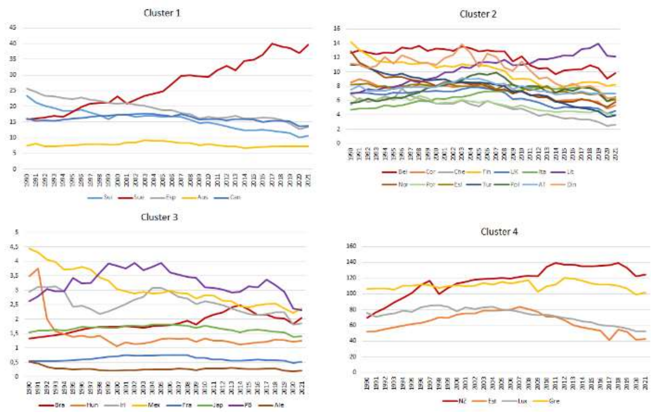

Fig. 12. Clusters by countries
Source: Elaborated by the authors.

countries that have a structural break in their time series of CO^2 emissions per energy generation, Germany presents this drop at the beginning of the period and has been remaining constant over the years, but the two countries Germany and Greece had their lowest CO^2 emissions in the year 2020.

With the study it was possible to delve deeper into the importance of renewable energy generation and the behavior of countries over the years regarding CO^2 emissions caused by energy generation. For future works it is intended to analyse the CO^2 emission by type of energy.

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