



Looking ahead - from fossil fuel to a circular bioeconomy in Europe. Evolution and behaviour

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Abstract. *Giving due consideration to sustainability, the new concept of bioeconomy has faced strong support from international policymakers, changing the way the economy is currently working. And it does not involve only the replacement of fossil feedstock with bio-based fuels, but also acquiring value from waste and bringing to light the resource efficiency that can lead to a smooth transition from a linear to a circular economy. This paper aims to track the EU states movement in implementing the bioeconomy best practices by building clusters based on their progress in adapting their industries to the new requirements. To make this possible, we created two scenarios for recording the evolution of the energy industry in 27 countries: the first one that groups them according to the fossil-fuel sources, and the second one based on renewable resources. Our results revealed that the biomass tends to be used as a complementary source and not a substitute, in comparison to the traditional fuels. Same actors keep the leading positions in both scenarios, making us believe that they may face strong challenges in reaching the European Commission goals. Thus, the present study emphasizes the need to develop highly efficient policies for all EU members to keep the same path.*

Keywords: bioeconomy, circular economy, biomass, fossil fuels, cluster analysis, Horizon 2020, bioenergy.

Introduction

The transition from a linear to a circular economy has never seen huge support from the global organisations as of today. Targets are being set all around the world for the governments to increase their involvement in assuring a smooth and efficient integration of sustainable tools and techniques. In accordance with this, bioeconomy plays an important role through its drivers in meeting the climate requirements agreed by the international institutions and helping the states proceed in their sustainable change (Stegmann et al., 2020). And one of these drivers is represented by the biomass and its potential in replacing the fossil feedstock, thereby reducing the GHG emissions. Brought to light as an option for

sustainability, it stands as a renewable resource that can be efficiently used in the chemical industry, road transportation, the marine sector, aviation as a solution for fossil fuels reduction and for its properties, being a replenishable carbon source (Cheng et al., 2020).

Furthermore, there is evidence to suggest that humanity is becoming more and more aware of the increasing level of solid waste, coupled with limitations in terms of natural resources. As an effect, the fossil-based industries started rethinking their strategies by including renewable resources as environmental-friendly alternatives. This is the point where the traditional bioeconomy gained a new definition and additional value for a sustainable future. According to the European Commission (2012), bioeconomy was set to be defined as the *“production of renewable biological resources and the conversion of these resources and waste streams into value-added products, such as food, feed, bio-based products and bioenergy”*. In other words, it replaces the old linear economy with a circular and sustainable one, by pointing out its long-term benefits: permanently sustainable, it is intended to tackle the challenges for food and energy by approaching biological innovation through collaboration with researchers, stakeholders and policymakers. Many other organisations have seen, so far, the benefits of implementing the concept globally. The Organization for Economic Co-operation and Development (OECD) mentioned the advanced knowledge of genes and bioprocesses (OECD, 2009), while the Government of India stressed out its importance also in terms of human resources (Mohan et al., 2019).

Going more into details, at the basis of bioeconomy lies the usage of biomass in an efficient and targeted way to progressively replace the fossil fuels, as globally we will find more than 170 billion tonnes being produced annually (Cheng et al., 2020). In comparison, only 6 billion tonnes find a place in the industrial processes, while less than 1 billion tonnes are thrown away (Bhatia et al. 2018). While many authors make different assumptions regarding the classification of biomass by source, this paper will concentrate on analysing the potential of the reusable waste from agricultural processes, forestry, fishery, municipal residuals, as well as solid biofuels, biogases, geothermal and solar energy drivers.

As a result of the new sustainable goals and dimensions being defined, the policymakers at a European level and not only, have seen the strengths of the new economy and the weaknesses of the linear one, pushing for an environmental-friendly way of providing wellbeing. For instance, the huge potential for the energy sector can be seen in diversifying the supply, increasing the internal market, decarbonising the economy, and boosting competitiveness. Therefore, several programs started being implemented, some of them already giving their first good results. Horizon 2020 is the most important key framework for setting ideas and implementing them for clever use of resources and support for supply and demand in the region.

The aim of the study is to deep dive into the potential of the bioeconomy and its drivers in the context of a green-based economy in the European Union, as well as tracking the changes in EU countries' behaviour in terms of the transition from a fossil fuel industry to a bio-based one. Specifically, we will focus on determining the main clusters in both scenarios at different points in time for an overview of evolution and changes in behaviour.

Literature review

The bioeconomy developed during these years a high interest from the international organisations as well as individual researches, strategies and action plans being fulfilled with key aspects like bio-agricultural development, life quality increase or research and

innovation for the bioeconomy progress (Socaciu, 2014). Furthermore, in terms of quantitative analysis, current trends highlight the use of data mining techniques and high-rated statistical tools. Another key thing to remember is the evidence of sustainability that challenges authors all over the world to add value through it in all the related topics. Thus, the criticality of bioeconomy itself in a holistic approach, as well as its pillars and sectors, combined with modern statistical instruments were set to high priority (Opia et al, 2020).

The 2015 Joint Research Centre Science for Policy Report states the bioenergy potentials for EU based on three cornerstones in the future. According to it, biomass will play a key role in diversifying the energy supply, increasing the energy internal market and self-sufficiency, as well as boosting competitiveness and fair prices. Their study revealed a high potential of biogas usage across the European Union. Likewise, the woody biomass, the crops biofuel and the municipal waste will follow a comparable usage in all the EU states by 2050. The valorisation of biowaste as a hot topic was deeply monitored by many individual researchers as well. Cheng et al. (2020) acknowledged the need for the economic environment to integrate biowaste into multiple aspects and to evidence the advantages of each bioeconomy pillar for producing value-added products.

Davis et al. (2017), Lange (2014), Luzardoa and Venselaar (2012), Stegman et al. (2020), developed the bio-based value pyramid by placing the energy, heat and fuels at the base level. They are low-value components in terms of profitability, but at the same time they produce high volumes of biomass for this sector. Stegman et al. (2020) used the cluster analysis for tracking the evolution of bioeconomy to a circular economy by considering wastes and residues as resources and putting more focus on biomass applications. Daioglou et al. (2015) revealed the biomass potential in the electricity sector as it showed the highest GHG-mitigation when replacing coal.

A similar approach to our research we can find in Parobek et al. (2016). With an accent put on the primary production of energy from renewable resources at the European level, the authors also took into consideration some economic variables. As a result, it was confirmed that the most important producers of energy from renewable resources - Germany and France - determined a cluster, as well as the Nordic states, Italy and Spain. Moreover, based on the economic approach, the availability and the use of biofuels, all the 27 EU countries have shown relatively high values. Thus, the research confirmed the existence of above-average primary energy production from renewable resources in the developed states. In accordance with this study, one of our purposes is to find the biomass clusters for the member states to see their performance on every pillar, by taking into consideration mainly the energy sector, as well as the biofuel types.

Methodology

This study uses the latest available data from the World Input-Output Database (WIOD), release 2016, for the bioeconomic analysis in terms of agricultural output for the industry usage. Specifically, values for barley, maize, oats, potatoes, rapeseed, rye, wheat, oilseeds, and other agricultural dry residuals were included in the dataset from this source. Besides, data for the renewable sources of biofuel used in the energy sector were taken from EUROSTAT, and the sectors of fishery and forestry were represented by estimations made by the Joint Research Centre (JRC) of the European Commission. Likewise, the analysis of fossil fuels was possible by using data related to inland consumption from the EUROSTAT database.

The paper's core analysis was focused on the 27 member states of the European Union, excluding the United Kingdom, and their evolution throughout the years, with three milestones: 1992 (the year that sets the borders of each of the current EU states), 2000 (as a starting point for the third millennium) and 2014 (the latest available data for all the variables to be assessed together). As a tool, RStudio was used for the entire analysis as the R language provides fully documented packages and functions for building clusters.

Using the `na.omit` and `scale` functions for missing data omission and values standardisation, the datasets were prepared for applying the cluster analysis. No missing values were found, as the null value was replaced with 0 because of the missing resource production and usage in some countries' industries.

The next step was to assess the clustering tendency of each dataset used for the analysis by testing the spatial randomness of the data or, in other terms, the probability that a data set is driven by a uniform data distribution through the Hopskin statistic. As mentioned by Lawson and Jurs (1990), the statistic bases its results on the distance between two reference points: y , as a real point, x , as a randomly chosen one. The formula is described as follow:

$$H = \frac{\sum U_i}{\sum U_i + \sum W_i} \quad (1)$$

where:

U_i - the distance of y_i from its nearest neighbour;

W_i - the distance of several randomly chosen x_i from its nearest neighbour.

Based on this information, the two hypotheses were defined, a value higher than a set threshold of 0.7 for a 90% confidence level showing that the dataset contains meaningful clusters (alternative hypothesis), and a lower value indicating a uniformly distributed dataset. The test is implemented in R using the `get_clust_tendency` function from the `factoextra` package. It returns the statistic as defined by the formula above and a heat map representing the dissimilarity matrix.

The optimal number of clusters was determined using three methods given by the R function `fviz_nbclust`, included in the `NbClust` package. The Elbow method takes each number of clusters k and applies the clustering algorithm and calculates the total within-cluster sum of squares. Hadi et al. (1992) came with an alternative approach to the previous method to solve the ambiguity that may appear. For that, they computed a new measure that determines the average silhouette of observations for different values of k . Another method used for setting the optimal number of clusters is the gap statistic (Tibshirani et al., 2001), which compares the total within intra-cluster variation with their expected values, for each value of k . This is a more sophisticated statistic which reduces the heuristic tendency for clustering characteristic.

K-means and Ward methods were considered for partitioning as, in our case, may offer the best results. For enhanced clustering analysis, we used the `eclust` function in both cases. K-means uses a given number of centroids k , then allocates each data point to the centre of the cluster by reducing the in-cluster sum of squares, thus, keeping the centroids as small as possible. In contrast, the minimum variance method starts with n clusters and combines them to obtain a single cluster, based on the distance between the objects in a cluster and the cluster's mean. Between the two mentioned above we were choosing the best partitioning method using `clValid` package.

Results and discussions

Giving the fact that a stable cluster analysis method on panel data was not fully developed yet, three moments in time were chosen for showing the evolution of clusters: the years 1992, 2000 and 2014. By choosing this approach, we will be able to track the changes made by EU countries in their policies and behaviour, and to see if their goal was to reduce the usage of fossil fuels in industry, specifically energy, or to develop in parallel both a linear and a circular sides of the economy.

By starting with the inland consumption of fossil fuels at a macroeconomic level, four variables were included in the first dataset, as being represented by the natural and derived types of fuels: natural gas, oil and petroleum, coal and derived heat. The data was recommended to be used for cluster analysis, as proven by the statistically significant values of Hopskin test (Lawson and Jurs, 1990) in all three cases and by the low and moderate correlation between them. The affirmation is strongly supported by the dissimilarity matrix that shows cluster structures in the datasets.

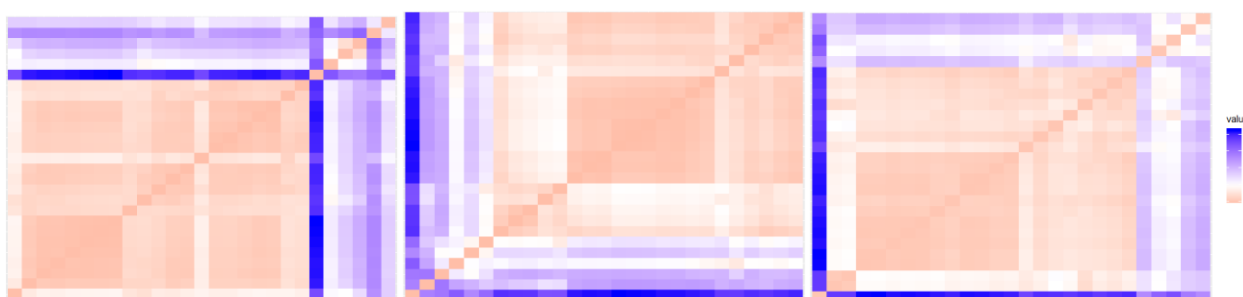


Figure no. 1. Heatmaps representing dissimilarity matrixes for the first scenario (1992 left, 2000 center, 2014 right)

Source: Authors' computation using R plot function

As shown above, the ordered dissimilarity images detect the clustering tendency for each considered variable. In this case, we can validate the existence of such a tendency by counting the blocks alongside the diagonals, based on the colour intensity. Thus, it is fully confirmed that the values will give relevant outputs regarding the evolution of countries in terms of fossil fuel usage in the energy sector.

To proceed with the cluster analysis, three methods were used to determine the number of clusters after the data was cleaned and standardised. The Elbow test estimated 4 clusters in all three cases as being the optimal number, while silhouette and gap statistic methods provided different numbers.

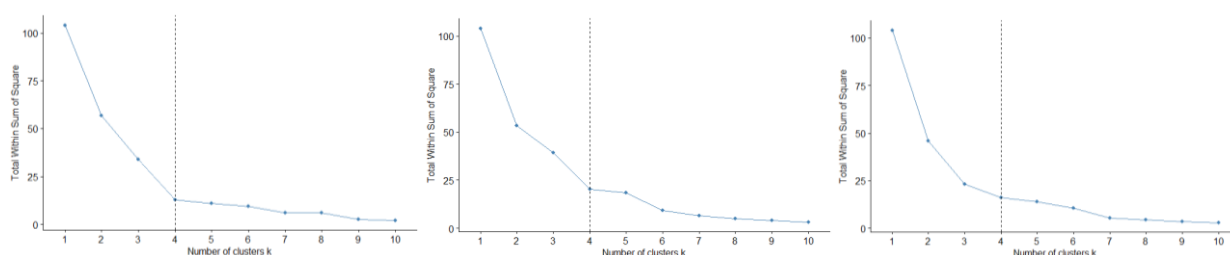


Figure no. 2. The optimal number of clusters using Elbow method for the first scenario (1992 left, 2000 center, 2014 right)

Source: Authors' computation using R plot function

That said, to better compare the outputs for each year, 4 clusters were chosen to group the countries included in the analysis.

Using the first method of clustering, the countries were grouped according to their performance in fossil fuels used in energy production. Even if the figures show the existence of outliers, the decision was to keep them, having in mind that every country is required to be part of the analysis to track its performance through the time.

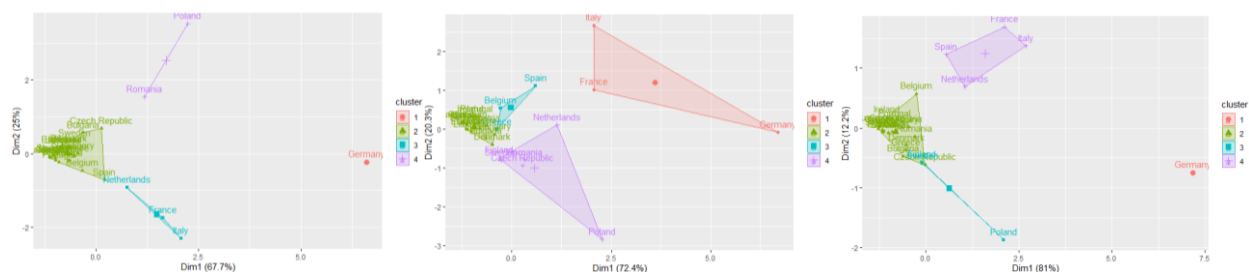


Figure no. 3. The resulted clusters using K-means method for the first scenario (1992 left, 2000 center, 2014 right)

Source: Authors' computation using R fviz function

As shown in the figure above, the biggest outlier is Germany in all monitored years. Biggest changes throughout the time were seen at Romania, surprisingly decreasing its fossil fuels usage from 1992 to 2014, moving to a similar performance with most of the European countries nowadays. France and Italy reached different stages by trying to reach the German performance and being caught up by Poland, the Netherlands and Spain. From an initial image dominated by France, Germany, Italy, Poland, Romania and the Netherlands in 1992, we are facing a small change at this time with Spain increasing its fossil fuels usage on one hand, and Romania reducing it, on the other hand.

Another way of explaining the resulted clusters is by finding similarities in the inland consumption based on fuel's type. According to this, Romania and Poland formed a cluster back in 1992 due to their high levels of oil and derived head used in the industry sector. Germany holds the leading position in all the cases, while France, Italy and the Netherlands registered biggest values for gas and oil, medium ones for coal and low records for derived heat used for the energy sector. Close to nowadays we find Romania's fossil fuel usage at half of the value in each case, while Germany reported higher values for 2 out of 4.

Following the second method, similar outputs were shown for the three years included in the analysis.

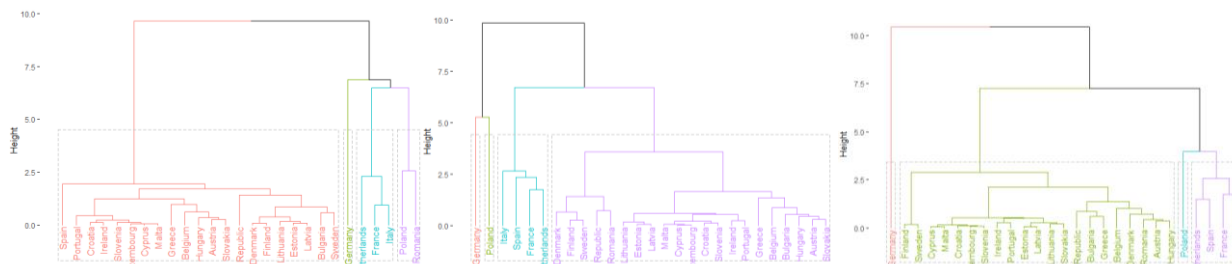


Figure no. 4. The resulted clusters in dendrograms using Ward method for the first scenario (1992 left, 2000 center, 2014 right)

Source: Authors' computation using R fviz function

Important to mention is the similarity among clusters of the two methods for the year 1992, where Germany holds the record, followed by Poland and Romania. Interesting to follow is the evolution of Romania, from high usage of fossil fuels together with Poland, to a decreased value in 2000, forming a cluster with the Czech Republic, and then with Austria and Hungary.

After using `clValid` function to choose the best partitioning method, the optimal scores validated the results in a 4 clusters scenario as in the table below. The method uses 4 stability measures: APN as the average proportion of non-overlap, AD which stands for the average distance, ADM as the average distance between means, and the figure of merit (FOM).

Table no 1. Validation measures for the partitioning methods in a 4-clusters scenario

Stability measure	No. of clusters	1992	2000	2014
APN	4	Kmeans (0.0185)	Hierarchical (0.0424)	Kmeans (0.0474)
AD	4	Kmeans (0.8825)	Hierarchical (1.0256)	Kmeans (0.8819)
ADM	4	Kmeans (0.2316)	Hierarchical (0.1462)	Kmeans (0.1310)
FOM	4	Kmeans (0.5484)	Hierarchical (0.5093)	Kmeans (0.4707)

Source: Authors' computation using RStudio.

Therefore, the optimal way to explain the change through the years is by taking the snapshots of 1992 and 2014 from the first method, and 2000 from the hierarchical clustering.

Based on these results, we can mention that the common regional and energetic patterns are being fully represented in this analysis: Germany in the lead; Poland forming a cluster alone or together with Romania or the Nordics; France, Spain, Italy and the Netherlands with similar approaches; and Hungary, Austria, the Baltics, Bulgaria and Greece.

On the other way around, it is highly important to observe the patterns in the EU countries behaviour based on their new sustainable approach. With an eye on the main purpose of this study, we want to find out if the trend resulted previously is being replicated in this second scenario or there is an overall tendency of reducing the fossil fuel usage while adopting new paths, dominated by a circular and sustainable economy. The same years (1992, 2000 and 2014) and the same countries were taken into consideration, while the number of variables increased significantly, due to a bigger number of biomass sources.

According to Hopskin statistic, the resulted values bigger than 0.7 allow us to reject the null hypothesis and conclude that the values in datasets are significantly clusterable.

Table no 2. Hopskin statistic for data clusterability estimation

Test	1992	2000	2014
Hopskin	0.7487	0.7857	0.7873

Source: Authors' computation using RStudio.

The decision is strongly supported by the dissimilarity matrix for each of the years that shows cluster structures in the datasets.

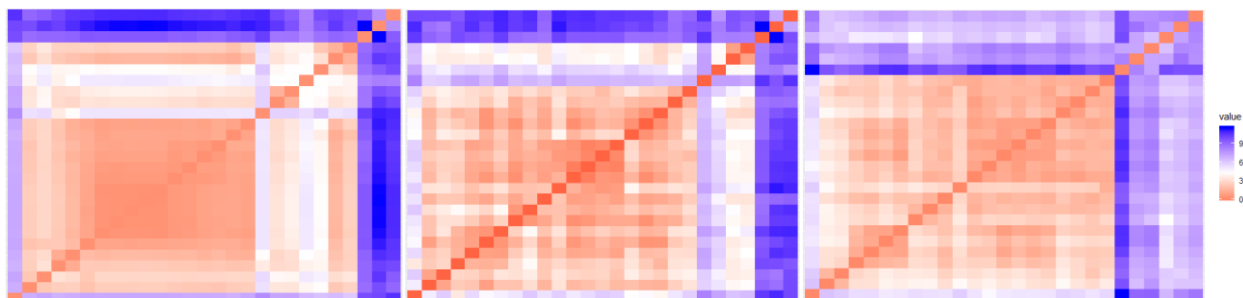


Figure no. 5. Heatmaps representing dissimilarity matrixes for the second scenario (1992 left, 2000 center, 2014 right)

Source: Authors' computation using R plot function

Using K-means clustering method and lowering the number of clusters to 4 to have a comparable output, we will observe that the majority of EU countries are being grouped into one cluster, with France and Germany setting the second one, Italy the third one, and Poland the fourth one. In this case, by examining the data, the Central European country reported very high values for agricultural dry residual used as fuel in the energy sector mainly, but very low values other sustainable sources like biogases, geothermal and solar. On the other hand, there is Germany and France with high values for agricultural residuals, biogases, solar and municipal waste used in energy. Visible changes were being recorded at the beginning of the new millennium as Poland started investing in new sustainable sources, as well as Spain, Italy, Scandinavia, and the Baltic states.

Likewise, Romania registered high performance over the past years, forming a cluster in 2014 with France and Poland, due to its renewable resources, as well as new investments in dealing with municipal waste.

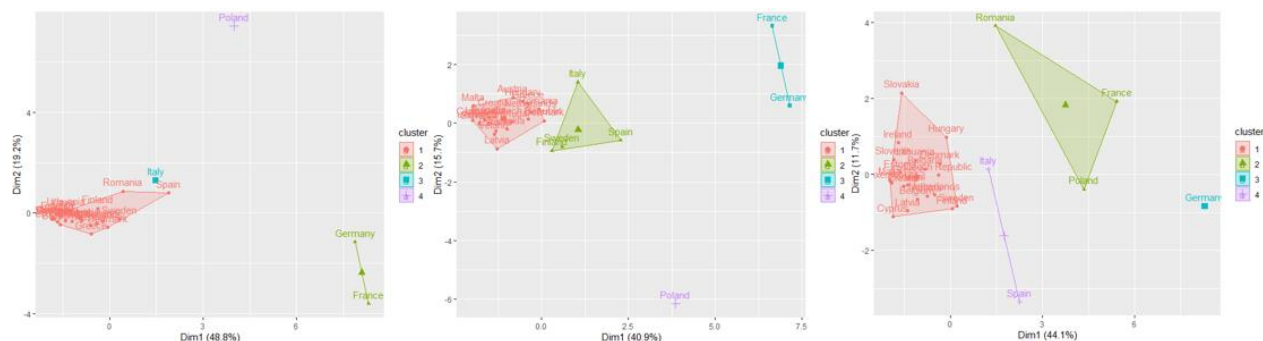


Figure no. 6. The resulted clusters using K-means method for the second scenario (1992 left, 2000 center, 2014 right)

Source: Authors' computation using R fviz function

The same scenario is also applied when analysing the dendrogram, based on hierarchical clustering. In this case, there can be seen some slight differences among clusters for the year 2014.

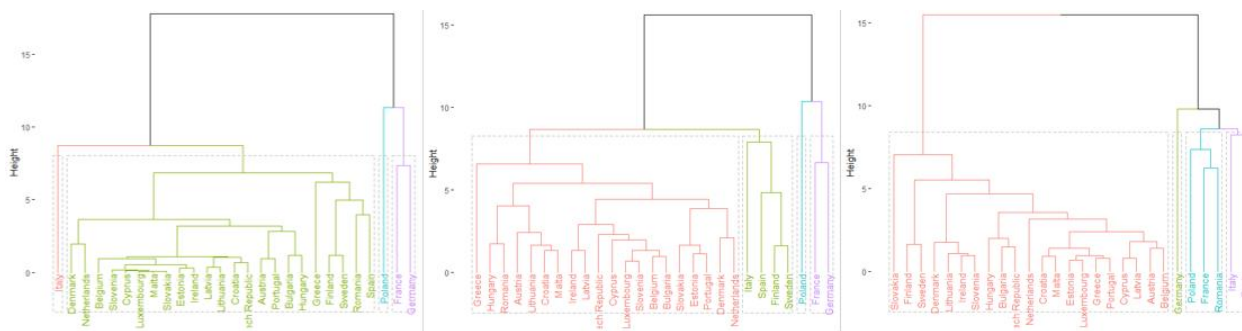


Figure no. 7. The resulted clusters in dendrograms using Ward method for the first scenario (1992 left, 2000 center, 2014 right)

Source: Authors' computation using R fviz function

In this scenario, the results of the two methods are identical in all the cases, which means that a comparison between them may be redundant. However, the output of the validation considers the hierarchical partitioning as optimal in all the cases, with an exception for 2014 when the average distance is being chosen as a stability measure.

Table no 3. Validation measures for the partitioning methods in a 4-clusters scenario

Stability measure	No. of clusters	1992	2000	2014
APN	4	Hierarchical (0.0051)	Hierarchical (0.0266)	Hierarchical (0.0177)
AD	4	Hierarchical (2.2948)	Hierarchical (3.1452)	Kmeans (2.9416)
ADM	4	Hierarchical (0.0511)	Hierarchical (0.2669)	Hierarchical (0.1874)
FOM	4	Hierarchical (0.5716)	Hierarchical (0.6693)	Hierarchical (0.7225)

Source: Authors' computation using RStudio.

According to the results, the actors in this scenario are the same as the ones in the fossil-based industry. The reason may stand in their strategy to find sustainable sources that can be used in addition to the existing ones and not as a substitute. Thus, the leading countries may reach their supply and demand capabilities in the energy sector and not only by adopting both traditional and renewable fuels approach in their economy.

Conclusion

The long-term replacement of the fossil-driven economy with a more sustainable alternative has become highly debated in the last period. As for that, the European Commission through its policies (Institute for Energy and Transport, 2015) considered the bioeconomy's potential as high priority for the development of all member states and paved the ground for an efficient transition to a circular economy, by planning and fostering effective programs like Horizon 2020, and later on, Horizon Europe. Some of their advantages are being reflected in the present paper's results. Starting in 1992, a milestone in Europe's biggest political changes, we can observe the fossil-based industry trendsetters like France, Germany, Italy, Poland and Romania forming clusters. Finishing with 2014, where some of the mentioned states keep their constancy while others regress (Romania) or progress (Spain, the Netherlands), the governments and EU policymakers still have to work in setting boundaries or guiding the countries to a downtrend, otherwise, it can slow the change to an

environmental-friendly way. By performing the same analysis on biofuels, we can conclude that most of the previous actors are also setting the trend in this case, as previously determined by Parobek et al. (2016). Therefore, they use biomass as a complementary source and not a substitute. Important to point out is the behaviour of the countries in the green cluster as they might become the biggest game-changers and the EU's "favourite children" because of their effective policy implementation.

Limitations in the analysis have been determined by the lack of variables that were included in clusters computation due to the small number of fossil-fuel types, the correlation among the variables that has been reduced in most of the cases by taking them out from the analysis or combining the most correlated ones. In some of the cases, none of the previously mentioned options could have been applied due to the importance of keeping both variables in the analysis.

Further developments of the current research can be made by including other dimensions to the cluster analysis like economic and social indicators, but also by widening the time horizon. Moreover, other substantial improvements of the analysis are being found in strong connection with future progress made in developing the cluster analysis on panel data.

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