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Analysis of Sector Based Energy Consumption Rates of OECD Countries with Louvain Clustering

OECD Ülkelerinin Sektör Bazlı Enerji Tüketim Oranlarının Louvain Kümeleme ile Analizi

ABSTRACT

This study examines the shares of sectors (agriculture, services, industry, transportation and other sectors) in total energy consumption in OECD countries for the period 2011-2020 using Louvain cluster analysis. Energy consumption is an important development indicator and provides important information about the development of countries. In particular, the analysis of the shares of energy consumption of main sectors such as agriculture, services, industry and transport sectors can provide important information about a country's economic diversity, level of industrialization and economic focus. Cluster analysis can provide important insights by identifying countries with similar energy consumption patterns. Louvain cluster analysis was preferred in this study. Louvain clustering has the advantage of being fast and dealing with noise compared to K-means and Hierarchical clustering methods. The results of the study are evaluated from two perspectives. The first one is the inferences obtained from the descriptive statistics of the data set and the second one is the inferences obtained from the clustering analysis. The results of the cluster analysis emphasize the insights offered by the cluster changes in the temporal dimension and the formation of year-based clusters. In addition, the insights provided by the clustering results for Türkiye are evaluated.

Keywords: Energy Consumption, Sectoral Analysis, Louvain Cluster Analysis, OECD Countries, Türkiye.

ÖZ

Bu çalışma, OECD ülkelerindeki sektörlerin (tarım, hizmetler, endüstri, taşımacılık ve diğer sektörler) toplam enerji tüketimindeki paylarını 2011-2020 döneminde Louvain kümeleme analizi ile incelemektedir. Enerji tüketimi önemli bir kalkınma göstergesidir ve ülkelerin gelişimi hakkında önemli bilgiler sunar. Özellikle tarım, hizmetler, endüstri ve ulaştırma sektörleri gibi ana sektörlerin enerji tüketimindeki paylarının analizi, bir ülkenin ekonomik çeşitliliği, sanayileşme düzeyi ve ekonomik odakları hakkında önemli bilgiler sunabilir. Kümeleme analizi ile benzer enerji tüketim desenlerine sahip ülkeleri belirleyerek önemli çıkarımlar elde edilebilir. Çalışmada Louvain kümeleme analizi tercih edilmiştir. Louvain K-ortalama ve Hiyerarşik kümeleme yöntemlerine göre hızlı ve gürültü ile başaçıkabilme avantajına sahiptir. Çalışmanın sonuçları iki perspektiften değerlendirilmektedir. İlki veri setinin tanımlayıcı istatistiklerinden elde edilen çıkarımlar, ikincisi kümeleme analizinden elde edilen çıkarımlardır. Kümeleme analizi sonuçları zamansal boyuttaki küme değişimleri ve yıl bazlı kümelerin oluşumuna göre sunduğu içgörüler vurgulanmıştır. Ayrıca Türkiye özelinde kümeleme sonuçlarının sağladığı içgörüler değerlendirilmiştir.

Anahtar Kelimeler: Enerji Tüketimi, Sektörel Analiz, Louvain Kümeleme Analizi, OECD Ülkeleri, Türkiye

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Introduction

Energy is the driving force of economic development (Lloyd, 2017). Energy consumption is recognised as one of the main indicators reflecting the status of a sector (Komarnicka & Murawska, 2021). In this respect, the shares of sectors in total energy consumption can also depict the economic profile of a country. For example, the high share of the agricultural sector in total energy consumption can form the basis for inferences about the intensive use of mechanisation and modern agricultural practices in the country, while the high share of the service sector can form the basis for inferences about the country's economic diversity and the level of service-based activities. Any information that can be obtained by analysing the shares of sectors in total energy consumption sheds light on the formulation of energy policies, determination of sustainable development strategies and guidance of energy efficiency studies.

The different shares of sectors in total energy consumption among countries reflect each country's economic structure, industrial development and energy use strategies, and point to economic and industrial diversity (Xueyao, 2022). These differences provide information about countries' economic development focuses. For example, in an agriculture-focused country, the agricultural sector is expected to account for a larger share of energy consumption than other countries, while in a highly industrialized country, the industrial sector is expected to account for a larger share of total energy. consumption is higher than other countries. On the other hand, the large share of agriculture in energy consumption may indicate that the country has an economy based on agriculture or that agriculture is economically decisive. High energy consumption rates in the service sector may indicate that a country is transitioning to a more service-oriented or technology-based economy.

Member countries of the Organization for Economic Cooperation and Development (OECD) play an important role in the world economy and differ in their energy demands and policy preferences. In these countries, the shares of sectors in overall energy consumption are similar. However, differences in the energy consumption of sectors indicate which sectors countries invest more in and in which sectors they innovate more. Examining the shares of sectors in total energy consumption across OECD countries and assessing Türkiye's position can provide a meaningful perspective full of important information and recommendations.

This study examines the share of sectors (agriculture, services, industry, transportation and other sectors) in total energy consumption in OECD countries through cluster analysis. The objectives of the study can be listed as follows: i) Identifying Energy Consumption Patterns: Cluster analysis aims to reveal similar trends by identifying countries with similar energy consumption patterns. ii) Assessing the Impact of Energy Policies: The study allows similar countries to analyse each other and identify successful practices and weak points. This enables countries to identify policy approaches that can be taken as an example. In this framework, the sectors in OECD countries were analysed with Louvain cluster analysis based on their shares in total energy consumption in the 10-year period between 2011-2020. In the year-based clustering analysis, for each year, which countries Türkiye is similar to and Türkiye's performance change over the years are analysed.

In the literature, hierarchical or k-means methods are frequently used in cluster analysis. The main reason motivating the choice of Louvain cluster analysis method in this study is the flexibility of the method and its capacity to produce more effective results in large data sets. Louvain clustering has the advantage of obtaining fast and precise solutions, especially on large and complex data sets. It is known to work faster than other clustering methods and is resistant to noise in the data set. This feature provides the advantage of obtaining reliable solutions that are more resistant to potential anomalies in the data.

The remainder of the study is organized as follows. The literature review related to the study is presented in Section 2. Section 3 explains the dataset used in the study and the clustering methodology. Section 4 discusses the findings and Section 5 presents the conclusions.

1. Literature Review

The background of this study has two branches. The first one consists of studies focusing on sector-based energy consumption. The second one consists of studies adopting the Louvain clustering. In the subheadings of this section, studies related to these branches are mentioned.

1.1. Sector-Based Energy Consumption

Numerous studies have focused on providing insight into countries' energy profiles by analysing energy use patterns in various sectors. Some of them can be summarized as follows. Apergis & Payne (2009) examined the relationship between CO2 emissions, energy usage, and output in Central America, emphasizing the variations in carbon dioxide emissions across countries even after adjusting for economic size or population. Odhiambo (2009) investigated the energy consumption and economic growth nexus in Tanzania, indicating a unidirectional causality from electricity consumption to economic growth. Lean & Smyth (2010) explored CO2 emissions, electricity consumption, and output in ASEAN countries, showing conflicting results for OPEC nations like Algeria, Indonesia, Nigeria, Saudi Arabia, and Venezuela. Apergis & Payne (2010) conducted a panel study on nuclear energy consumption and economic growth, revealing a long-run equilibrium relationship between real GDP, nuclear energy consumption, and other factors. Shahbaz et al. (2012) studied the effectiveness of energy consumption in promoting economic growth in Pakistan, contributing to the literature on the energy consumption and economic growth nexus. Furthermore, Ke et al. (2012) analysed China's industrial energy consumption trends and the impacts of energy-saving programs, emphasizing the importance of energy efficiency improvements in reducing industrial energy intensity. Öztürk et al. (2013) focused on the causal relationship between energy consumption and GDP in Türkiye, highlighting the bidirectional relationship between energy consumption and economic growth. By examining patterns of energy consumption in Beijing, Zhang et al. (2014) have provided valuable insights into the changing nature of urban energy use. Their analysis specifically focuses on the shift from production-oriented to consumption-oriented economies. Bozkurt and Yanardağ (2017) offered evidence for the relationship between economic growth and energy consumption using the panel analysis. Hanifi and Özen (2018) studied that energy consumption from different sectors played a crucial role in the economic growth of Türkiye also. Marinescu (2019) performed a statistical analysis for the development of renewable energy sector within the European Union. Cansız et al. (2020) designed a model that makes it possible to assess the usage of energy in the transportation area, which, in turn, increases the comprehension of how much energy is used in that field. Akyol (2020) depicted the different directions of energy consumption in the agrarian sector by disclosing the effect of energy on agriculture value added. Demir and Görür (2021) conducted a set of analyses to investigate the relationship between the use of energy and economic growth for OECD countries by performing cross section analyses of energy consumption and economic growth. Komarnicka and Murawska (2021) employed the energy consumption and the based on the renewable resources' utilization comparing in European Union countries to focus on the sectoral distribution of energy consumption. Bednarczyk et al. (2021) state that renewable energy sources are vital for any attempt to affect sectors' energy consumption. Güngör (2023) had detailed research of the allocation of energy usage across the sectors. These studies collectively contribute to the understanding of the complex relationship between energy consumption and economic growth by emphasising the importance of energy efficiency, renewable energy sources and bidirectional causality between energy consumption and economic growth in various countries and regions. Moreover, these studies emphasise the continuing interest and relevance of researchers in the sectoral distribution of energy consumption and its effects on economic growth.

1.2. Louvain Clustering

The Louvain clustering algorithm which was named after the University of Louvain where it was first developed, is a way of recognizing communities within the networks of complexity (You et al., 2022). This implies matching with maximization of modularity, which is the way cluster partition efficiency is being gauged (Matta et al. 2023). One of the favoured clustering algorithms, which is proposed by Blondel et al. (2008) is Louvain, is particularly suitable for community detection in different fields and disciplines because of its fast and effective identification of communities Some of these studies can be summarized as follows. Wang and Koopman (2017) used the Louvain algorithm to categorize articles based on semantic similarity. Williams et al. (2019) compared different methods to identify modules in noisy or incomplete brain networks and advocated the use of the Louvain algorithm. Pradana et al (2020) highlighted the robust performance of the Louvain algorithm in clustering and highlighted its adaptability and flexibility for practical clustering purposes, especially in cases where the number of clusters is not predetermined. Moreover, Dekker et al. (2021) investigated the application of the Louvain clustering algorithm in different sectors which included railway traffic network, diversions air transport, diplomatic systems and atmospheric conditions. These studies offer a deep dive into the various applications of the Louvain algorithm, showcasing its effectiveness in clustering, community detection, and hybrid clustering strategies.

To the best of our knowledge, there is no study in the literature that examines energy consumption with the Louvain clustering algorithm, while there are two studies that use it to cluster countries as in this research. Formoso et al. (2018) focused on clustering countries based on delay-defined distances using the Louvain algorithm after computing a weighted undirected graph. Erandathi et al. (2022) applied the Louvain clustering to group countries according to their financial strength and health facilities in the context of measuring the status of Covid-19. In this respect, this study contributes to the related researchers and practitioners by using Louvain clustering for the first time in the energy consumption analysis of countries.

2. Method

This section introduces the dataset used in the study, Louvain clustering analysis, Orange data mining tool. The study uses publicly available data obtained through OECD. Stat. Therefore, there is no need for ethics committee approval.

2.1. Data

In this study, data from 38 OECD member countries, whose data were obtained from the OECD. Stat database were analysed. The data set includes the indicators shown in Table 1. Indicators show the share of sectoral energy consumption in total energy consumption. The data set covers 10 years from 2011 to 2020. More recent data has not yet been published. The data set for 2020 is shown in Table 2, and descriptive statistics for all years are shown in Table 3.

Table 1. Indicators

K1	Energy consumption in agriculture, % total energy consumption
K2	Energy consumption in services, % total energy consumption
K3	Energy consumption in industry, % total energy consumption
K4	Energy consumption in transport, % total energy consumption
K5	Energy consumption in other sectors, % total energy consumption

Table 2. Dataset of 2020

Countries	K1	K2	K3	K4	K5	Countries	K1	K2	K3	K4	K5
Australia	2.45	9.86	28.39	39.13	20.17	Japan	1.78	17.69	28.58	23.76	28.20
Austria	1.93	8.90	27.60	29.49	32.08	Korea	1.63	11.74	26.11	19.59	40.92
Belgium	2.11	11.68	26.98	20.18	39.04	Latvia	5.43	14.11	22.35	26.89	31.22
Canada	3.47	14.44	23.62	29.72	28.74	Lithuania	1.79	9.00	16.03	33.14	40.04
Chile	2.40	6.00	38.17	31.60	21.83	Luxembourg	0.72	14.95	17.72	50.83	15.79
Colombia	1.46	5.85	26.51	34.35	31.82	Mexico	3.04	4.21	31.91	37.60	23.24
Costa Rica	1.96	9.93	23.56	47.68	16.86	Netherlands	7.22	11.43	24.28	16.87	40.20
Czechia	2.46	11.47	25.29	24.45	36.34	New Zealand	5.81	9.43	28.59	34.33	21.83
Denmark	5.19	13.99	17.24	30.12	33.46	Norway	2.93	13.42	30.58	21.83	31.23
Estonia	3.79	16.21	14.05	27.38	38.56	Poland	5.08	9.86	21.11	28.69	35.26
Finland	2.87	11.40	42.74	16.04	26.94	Portugal	3.22	10.88	28.87	31.94	25.10
France	3.26	14.46	18.69	27.71	35.87	Slovak Republic	1.22	10.09	29.55	23.11	36.04
Germany	1.71	12.46	25.34	24.01	36.48	Slovenia	1.59	9.16	27.80	34.94	26.51
Greece	1.94	10.73	16.92	34.47	35.95	Spain	3.87	11.55	24.41	33.68	26.50
Hungary	3.54	10.03	22.35	22.32	41.76	Sweden	1.90	12.62	36.60	20.87	28.01
Iceland	8.51	16.33	43.25	10.14	21.77	Switzerland	0.60	17.54	19.35	30.38	32.12
Ireland	2.17	16.54	19.80	31.37	30.11	Türkiye	4.61	12.90	30.57	24.52	27.40
Israel	2.13	10.13	18.05	36.09	33.60	United Kingdom	1.22	13.68	17.61	29.00	38.49
Italy	2.76	13.20	22.29	26.97	34.79	United States	1.38	13.74	18.13	37.56	29.19

Table 3. Descriptive Statistics of Datasets of the Years 2011-2020

		K1	K2	K3	K4	K5				K1	K2	K3	K4	K5
2011	Average	2.78	11.58	25.73	29.27	30.64		2016	Average	2.64	11.87	25.14	30.30	30.05
	St. Dev.	1.80	2.92	7.77	8.44	6.79			St. Dev.	1.55	3.01	6.87	8.21	6.15
	Coe. Var.	0.65	0.25	0.30	0.29	0.22			Coe. Var.	0.59	0.25	0.27	0.27	0.20
	Min	0.54	3.01	9.45	10.45	13.03			Min	0.55	3.26	15.39	10.83	14.57
	Max	9.41	17.22	50.32	58.94	45.85			Max	8.68	17.85	44.35	53.59	42.21
2012	Average	2.72	11.75	25.52	29.10	30.91		2017	Average	2.65	11.79	25.17	30.40	29.99
	St. Dev.	1.77	2.87	7.56	8.57	6.83			St. Dev.	1.54	2.87	6.87	8.22	6.40
	Coe. Var.	0.65	0.24	0.30	0.29	0.22			Coe. Var.	0.58	0.24	0.27	0.27	0.21
	Min	0.54	3.10	10.94	10.06	13.76			Min	0.56	3.20	15.77	11.28	15.00
	Max	9.05	17.64	50.80	57.63	45.36			Max	8.56	17.71	45.10	54.15	42.61
2013	Average	2.65	11.85	25.75	28.96	30.79		2018	Average	2.67	11.77	25.24	30.69	29.62
	St. Dev.	1.70	3.02	7.23	8.41	6.61			St. Dev.	1.52	2.93	6.75	8.41	6.21
	Coe. Var.	0.64	0.25	0.28	0.29	0.21			Coe. Var.	0.57	0.25	0.27	0.27	0.21
	Min	0.53	3.26	15.79	9.96	14.06			Min	0.59	3.80	16.20	11.12	14.19
	Max	9.89	17.79	51.39	57.31	43.43			Max	8.32	17.68	43.13	55.80	40.46
2014	Average	2.66	11.62	26.14	29.67	29.91		2019	Average	2.69	11.79	24.96	30.90	29.67
	St. Dev.	1.67	2.96	7.29	8.28	6.21			St. Dev.	1.50	2.98	6.73	8.40	6.14
	Coe. Var.	0.63	0.25	0.28	0.28	0.21			Coe. Var.	0.56	0.25	0.27	0.27	0.21
	Min	0.55	3.29	16.01	9.81	13.79			Min	0.59	3.69	15.59	11.37	12.96
	Max	9.34	17.61	50.84	57.61	41.79			Max	8.09	17.65	43.21	56.41	40.96
2015	Average	2.65	11.80	25.56	30.05	29.94		2020	Average	2.81	11.76	25.59	28.66	31.19
	St. Dev.	1.68	2.95	7.29	8.14	6.30			St. Dev.	1.57	3.06	6.90	7.54	6.10
	Coe. Var.	0.63	0.25	0.29	0.27	0.21			Coe. Var.	0.56	0.26	0.27	0.26	0.20
	Min	0.56	3.33	15.31	10.02	15.11			Min	0.60	4.21	14.05	10.14	15.79
	Max	9.66	17.63	49.08	55.04	42.23			Max	8.51	17.69	43.25	50.83	41.76

Note. St. Dev.: Standard deviation Coe. Var.: Coefficient of Variation

2.2. Louvain Clustering and Orange Data Mining Tool

Louvain algorithm which is presented by Blondel et al. (2008) is a community detection network clustering algorithm. The compared results suggest that the Louvain algorithm is dominant in many conditions compared to K-means and hierarchical methods, in terms of accuracy of clustering (Liu et al. 2021; Pradana et al. 2020; S. Wang and Koopman 2017). Similarly, the application of the Louvain algorithm with the genetic algorithms along with particle swarm optimization resulted in the emergence of diverse hybrid strategies thereof (Rezaeipanah and Ghanat, 2021).

Blondel et al. provide the following details about the Louvain clustering algorithm. The basic steps of the algorithm are as follows:

Step 1 Initialisation: Each node creates its own cluster.

Step 2 Local Optimisation: For each node, it is checked whether modularity (Q) (Q is the measure of the number of edges of a cluster compared to the number of edges within a cluster) is increased by moving it to one of the neighbouring clusters. The move that provides the largest modularity increase is performed.

$$Q = \frac{1}{2m}\sum_{i,j}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j)$$

Where A_{ij} represents the weight of the edge between i and j, $k_i = \sum_j A_{ij}$ is the sum of the weights of the edges attached to vertex i, c_i is the community to which vertex i is assigned, the δ-function $\delta(u, v)$ is 1 if $u = v$ and 0 otherwise and $m = \frac{1}{2}\sum_{ij} A_{ij}$.

Step 3 Repetition: Step 2 is repeated until all nodes are stable.

Step 4 Cluster Merge: Clusters that are connected to each other are merged.

Repeat steps 3 and 4: Repeat steps 3 and 4 until the number of clusters reaches the desired level.

The Louvain clustering algorithm has some assumptions. Firstly, the network must be connected, i.e. all nodes must be connected to each other in at least one way. Also, the algorithm does not take edge weights into account and there is likely to be a hierarchical structure in the network.

There are several ways to determine the number of clusters. One way is to visualise the resulting clusters and adjust the number of clusters until the desired level of detail is reached. Another method is to monitor the value of the modularity metric (Q) and stop clustering when it reaches the maximum value. It is also possible to determine the optimal number of clusters using a criterion such as the information criterion.

The orange data mining software stands apart from other data mining software with its intuitive UI that makes it a favourite among the users. This has facilitated the implementation of various data visualization, preprocessing, and modelling functions (Manimannan et al., 2019). Thanks to its multifunctionality, it is preferred in various fields, including marine data analysis (Maximov et al., 2021), agricultural productivity index performance, and even Bitcoin price prediction (Indriyanti et al., 2022). Besides, it is used as a tool for data mining and its importance is highlighted with comparisons to other tools such as Weka, KNIME, and RapidMiner (Rohit Ranjan et al., 2017). In the literature, several open-source and commercial data mining tools are mentioned, and Orange is one of the most notable (Verma et al., 2019). In this study, Orange data mining software was used to implement the Louvain clustering algorithm.

3. Findings

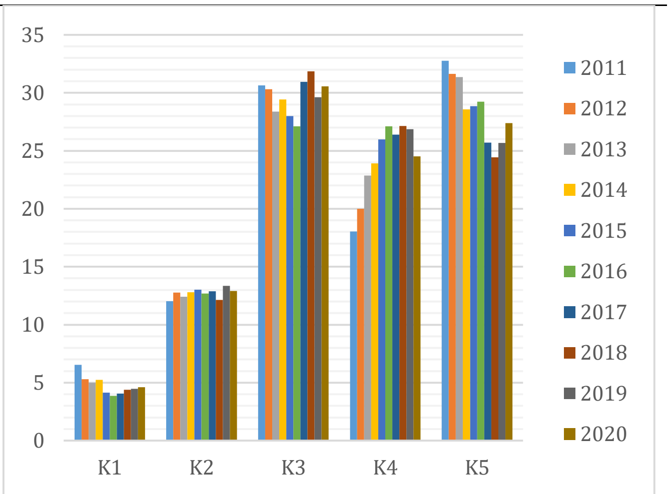
3.1. Findings From Descriptive Statistics

The data analysis summarised in Table 3 provides valuable insights into the energy consumption patterns observed in different sectors over the years. In contrast to the stable energy consumption levels in categories K1, K2, K3 and K5, K4 shows a 1.1% decrease between 2011-2013, a 6.7% increase between 2013-2019, and a 7.2% decrease between 2019-2020. The significant decline in energy use in 2020 can be attributed to the repercussions of the COVID-19 pandemic, such as changes in travelling habits and temporary shutdown in industrial activities. Except for 2020, the energy consumption of the transportation sector shows an overall upward trend. Energy demand in the transportation sector is influenced by various factors, such as sectoral growth, population growth, economic progress and increasing transport requirements. However, it is also noteworthy that the coefficient of variation of the share of energy consumption in the agriculture sector (K1) shows an overall decreasing trend from 2011 to 2020. This suggests that energy use in the agricultural sector tends to be more evenly and consistently distributed across countries over time. This can be interpreted as an indication of increasing stability and predictability in the energy consumption of the agricultural sector globally. These findings raise the possibility of a shift towards more sustainable energy practices in agriculture.

The ranking of the indicators according to the average of the annual standard deviation values is K4 > K3 > K5 > K2 > K1. This ranking gives an idea about inter-sectoral differences in energy consumption. The transport sector (K4) shows the highest volatility across countries, followed by the industrial sector (K3) and other sectors (K5), while services (K2) and agriculture (K1) exhibit relatively stable energy consumption patterns. This ranking serves to emphasise the relative stability of the agricultural sector despite significant fluctuations in the transport sector. It provides valuable information for energy policy formulation and the implementation of sector-specific strategies. In particular, the international emphasis on energy efficiency and sustainability becomes critical in sectors with high standard deviations.

Table 4. Türkiye Data and Graph

Türkiye	K1	K2	K3	K4	K5
2011	6.54	12.03	30.64	18.03	32.76
2012	5.29	12.77	30.30	19.99	31.64
2013	4.99	12.40	28.39	22.86	31.36
2014	5.25	12.81	29.43	23.92	28.58
2015	4.15	13.02	27.99	25.99	28.85
2016	3.87	12.68	27.10	27.11	29.24
2017	4.06	12.89	30.95	26.40	25.70
2018	4.40	12.15	31.85	27.15	24.45
2019	4.46	13.36	29.63	26.87	25.68
2020	4.61	12.90	30.57	24.52	27.40



As observed in Table 4, significant changes are detected when comparing the sectoral shares of Türkiye's energy consumption from 2011 to 2020. The energy consumption of the agriculture sector (K1) declines steadily, reaching 4.61 % in 2020. This decrease is likely due to the increasing adoption of energy efficient practices and sustainable methods in agriculture. In contrast, the energy consumption of the services sector (K2) has remained relatively stable over the years. The share of the industrial sector (K3) exhibited a bell-shaped curve, initially decreasing and then recovering. This trend indicates that Türkiye is undergoing an industrial transformation and energy intensive sectors are experiencing growth. Energy consumption in the transport sector (K4) has generally increased, reflecting increased mobility and transport demands in a growing industry. Fluctuations also characterised the share of other sectors (K5), which recorded a significant increase in 2020, possibly due to diversification in energy consumption or evolving sectoral activities. These changes underline Türkiye's changing economic and industrial environment and provide valuable insights for shaping energy policies and sustainability targets.

3.2. Findings From Clustering

Year-based clustering results are shown in Table 5. It should be noted that the clusters cover similar countries in terms of the shares of sectors in total energy consumption and there is no relationship of importance between clusters. The similarity of the countries and the change in the clusters over time allows us to comment on the change in the overall development strategy of the country.

Table 5. Clustering Results in 2011-2020

Countries	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Australia	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2
Austria	C3	C4	C1	C1	C1	C1	C1	C1	C1	C2
Belgium	C1	C2	C2	C4	C3	C4	C4	C4	C4	C3
Canada	C2	C1	C1	C2	C5	C5	C1	C5	C2	C1
Chile	C4	C4	C1	C3	C1	C1	C1	C1	C1	C2
Colombia	C3	C1	C1	C2	C5	C5	C1	C1	C1	C2
Costa Rica	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2
Czechia	C1	C2	C2	C4	C3	C4	C4	C4	C4	C3
Denmark	C2	C3	C4	C5	C2	C2	C2	C2	C2	C1
Estonia	C1	C3	C4	C5	C2	C2	C2	C2	C2	C1
Finland	C4	C4	C3	C3	C4	C3	C3	C3	C3	C4
France	C2	C3	C4	C5	C2	C2	C2	C2	C2	C1
Germany	C1	C2	C2	C4	C3	C4	C4	C4	C4	C3
Greece	C2	C3	C5	C2	C2	C5	C2	C5	C5	C1
Hungary	C1	C2	C2	C4	C3	C4	C4	C4	C4	C3
Iceland	C4	C4	C3	C3	C4	C3	C3	C3	C3	C4
Ireland	C2	C3	C5	C2	C5	C5	C1	C5	C5	C1
Israel	C2	C3	C1	C2	C5	C5	C1	C5	C5	C1
Italy	C2	C3	C4	C2	C2	C2	C2	C2	C2	C1
Japan	C4	C4	C3	C3	C4	C3	C3	C3	C3	C4
Korea	C1	C2	C2	C4	C3	C4	C4	C4	C4	C3
Latvia	C1	C2	C4	C5	C2	C2	C2	C2	C2	C1
Lithuania	C1	C2	C2	C5	C2	C2	C2	C2	C2	C1
Luxembourg	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2
Mexico	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2
Netherlands	C1	C2	C2	C4	C3	C4	C4	C4	C4	C3
New Zealand	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2
Norway	C4	C4	C3	C3	C4	C3	C3	C3	C3	C4
Poland	C1	C2	C2	C4	C3	C2	C2	C2	C2	C1
Portugal	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2
Slovak Republic	C4	C4	C3	C3	C4	C3	C3	C3	C3	C3
Slovenia	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2
Spain	C3	C1	C1	C1	C1	C1	C1	C1	C1	C2

Countries	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Sweden	C4	C4	C3	C3	C4	C3	C3	C3	C3	C4
Switzerland	C2	C3	C4	C2	C2	C2	C2	C2	C2	C1
Türkiye	C1	C4	C3	C3	C4	C3	C3	C3	C3	C4
United Kingdom	C2	C3	C4	C5	C2	C2	C2	C2	C2	C1
United States	C2	C1	C5	C2	C5	C5	C1	C5	C5	C1
# of clusters	4	4	5	5	5	5	4	5	5	4

When the clustering results are analysed on the horizontal axis, basically two country profiles emerge. The first is countries that are similar to different countries over time, and the other is countries that are similar to the same countries in all years. For example, while Canada was similar to developed countries such as United Kingdom, France, Italy in 2011, it was in the same cluster with Greece and Colombia in 2015, and in 2020 it was again in the same cluster with developed countries. This reflects the diversity in the economic dynamics of countries and their flexibility over time. These shifts in similarities across countries therefore allow us to understand flexibility, adaptation and diversity in overall development strategies. On the other hand, Sweden was in the same cluster as Iceland, Japan, Norway, Finland for 10 years. This example can show that countries are able to sustain policies and energy strategies in a long-term and stable manner. This may imply that a specific development path has been adopted and that these strategies reflect a sustainable energy consumption pattern in the long run.

Analysing clustering results on the vertical axis allows countries to identify similar counterparts, facilitating the examination of policies and the pursuit of improvement. In 2020, countries within the same cluster encompassed European nations (Lithuania, Latvia, Estonia, Poland, Italy, Switzerland, Denmark, France, United Kingdom, Ireland, Greece), North American counterparts (Canada, United States), and Israel from the Middle East. Such clustering suggests shared characteristics in energy consumption and policies among these nations. For instance, Poland's inclusion hints at parallels in energy profiles and problem-solving approaches with other cluster members. Consequently, Poland can glean valuable insights into energy strategies from its cluster peers, fostering the refinement and development of its own policies.

Türkiye consistently exhibits similarities with countries like Finland, Iceland, Japan, Norway, Slovak Republic, and Sweden from 2011 to 2020 (Table 6). These coincidences indicate shared characteristics in areas such as energy consumption, economic structure, and environmental policies. Learning from and exchanging experiences with these nations on energy policies or economic strategies could be advantageous for Türkiye. Such similarities imply potential benefits for Türkiye in refining its energy strategies or enhancing existing policies through insights gleaned from these countries' experiences.

Table 6. Countries in the Same Cluster with Türkiye by Year

2011	Belgium	Czechia	Estonia	Germany	Hungary	Korea	Latvia	Lithuania	Netherlands	Poland	Türkiye
2012	Austria	Chile	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye		
2013	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye				
2014	Chile	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye			
2015	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye				
2016	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye				
2017	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye				
2018	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye				
2019	Finland	Iceland	Japan	Norway	Slovak Rep.	Sweden	Türkiye				
2020	Finland	Iceland	Japan	Norway	Sweden	Türkiye					

The energy consumption of these countries, including Türkiye, is concentrated in the industry and service sectors. The industrial sector is an important sector that supports Türkiye's exports and is the driving force of economic growth. The service sector is growing rapidly with the rapid urbanization of Türkiye's population and rising living standards. There are some points where Türkiye's energy consumption structure differs from these countries. For example, Türkiye's share of energy consumption in the transportation sector is higher than these countries. This situation is related to Türkiye's young population and increasing vehicle ownership.

Conclusion

This study examines sectoral energy consumption patterns in OECD countries using Louvain Cluster Analysis. In this context, it is aimed to provide insight about the countries and Türkiye by taking into account the shares of the sectors in total energy consumption between 2011-2020. First of all, the trend over the 10-year period was evaluated through the descriptive statistics of the data set. Then, the change in the cluster analysis results and Türkiye's position were evaluated.

According to the clustering results, countries with similar shares of sectors in total energy consumption are grouped into clusters. Cluster changes over time allow us to interpret changes in the overall development strategies of countries. The analysis reveals essentially two country profiles: those that are similar to different countries over time and those that are similar to the same countries in all years. For example, while Canada was similar to developed countries in 2011, in 2015 it was in the same cluster as Greece and Colombia, and in 2020 it was again in the same cluster as developed countries. This reflects the diversity in the economic dynamics of countries and their flexibility over time. On the other hand, Sweden was in the same cluster with Iceland, Japan, Norway and Finland for 10 years. This example can show that countries are able to sustain their policies and energy strategies in a long-term and stable manner. When analysed on the vertical axis, countries can identify similar counterparts and examine their policies to find opportunities for improvement. In 2020, the clusters incorporated Europe countries, Canada and the United States from North America and Israel from the Middle Even. It indicates that they share the same features of the energy use and policy.

The most critical implication for Türkiye is the large share of the transport sector in total energy consumption. It is clear that Türkiye, as an energy dependent country, needs to make special efforts to reduce this ratio. This emphasises the need for energy policies and sustainable development strategies specifically designed for this sector.

The results can serve as a guide for countries to revise their energy policies and identify the sectors that should be the focus of energy efficiency programmes. Countries with similar energy consumption patterns can be guided in determining feasible policies. In conclusion, understanding changes in sectoral energy consumption is an important cornerstone for shaping energy policies, designing sustainable development strategies and guiding energy efficiency initiatives.

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