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METHODOLOGICAL FOUNDATIONS OF COUNTRIES' GREEN ECONOMY POLICY IMPLEMENTATION BASED ON CLUSTER ANALYSIS

Background. *In the context of global climate policy, it is necessary to systematize the countries by CO_2 emissions, energy consumption structure and economic development to identify typical patterns of trajectories of transition to a low-carbon economy. For this purpose, the authors perform country clustering by decarbonization potential using Kohonen self-organizing maps (SOMs). To achieve this goal, the study focuses on the following tasks: generating a dataset of economic, energy, and environmental indicators to study decarbonization processes across countries over time; processing data (filling gaps, normalization), and eliminating multicollinearity; algorithmizing the SOM construction, taking into account the stages of training and hyperparameter tuning; determining a method for optimizing the number and validating the composition of clusters based on quantitative metrics, taking into account their semantic consistency and economic content; identifying country clusters based on decarbonization profiles and key factors for achieving renewable energy development targets and emission reductions; and analyzing the dynamic trajectories of countries on the map over time to formulate practical recommendations for decarbonization policy.*

Methods. *Self-organizing maps were used to cluster countries by decarbonization potential. This tool allows modeling nonlinear relationships and taking into account high data dimensionality, providing flexible and accurate segmentation and a more effective means for analytical research compared to other clustering methods. The article included hyperparameter tuning, preparation and normalization of the input dataset (which consists of 14 indicators of a country's socio-economic, energy, and environmental sectors, which collectively contribute to its decarbonization potential, covering the period 2013–2022 for 40 countries), and cluster validation using series of quantitative metrics (the Silhouette coefficient, the Davies-Bouldin and Calinski-Harabasz indices).*

Results. *The six clusters of countries with different decarbonization profiles (leaders-decarbonization hubs, followers, resource-intensive economies, producing countries, hydrocarbon-oriented countries, and large industrial countries) have been identified in the study. Based on the clustering results, the authors assessed the dynamic trajectories of countries over time and identified key indicators that influence the achievement of renewable energy targets and emission reductions. In addition, the original approach based on using Kohonen maps in scenario modelling, which shows how simple clustering turns into practical scenario analysis and reveals which structural changes are most critical for achieving a country's target profile has been proposed. Within the framework, the analysis indicates that for Ukraine, improving global positioning by increasing the share of renewable energy sources in the energy sector can ensure a transition to follower or leader clusters.*

Conclusions. *The use of SOM provides an effective tool for formulating strategic recommendations for the development of a low-carbon economy and the optimization of national energy policy.*

Keywords: *decarbonization, CO_2 emissions, clustering, self-organizing map, machine learning, energy policy.*

Background

The problem of climate change and the associated emissions of greenhouse gases, in particular carbon dioxide, has become one of the most discussed issues for states. Increasing intensity of extreme weather events, rising average annual temperatures, and devastating impacts on the biosphere are pushing governments, scientists and businesses to search for optimal decarbonization strategies. International initiatives, in particular United Nations Framework Convention on Climate Change (2015) have created framework obligations for countries to reduce emissions, but national decarbonization trajectories differ significantly complicating the problem.

In Ukraine, the situation is exacerbated by russia's full-scale military invasion, which increases the risks of achieving sustainable development goals and leads to the need to transform approaches to sustainable development (Sereda, Nahachevska, & Hryhorova, 2024). As a consequence of the war, a significant portion of Ukraine's energy infrastructure has been damaged, making it urgent not only to restore what was lost but also to introduce innovations in the fields of energy efficiency and renewable energy sources (Soboliev, & Zatonatska, 2024). However, the destruction of Ukraine's energy infrastructure caused by the russian invasion presents both a significant challenge and an opportunity to rebuild the sector in accordance with the principles of sustainable development (Zatonatska et al., 2025). In this regard, there is an urgent need to identify strategies for the most effective and efficient implementation of green economy policy for the restoration and accelerated development of the energy sector of Ukraine, focusing on the examples of developed countries.

The purpose of the paper is to develop the methodological foundations for green economy policymaking based on the building a model of clustering countries according to their decarbonization potential.

Literature Review. The authors conducted a systematic literature review focused on assessing the decarbonization levels of different countries using various modeling methods, identifying their strengths and weaknesses to select the most suitable approach. For instance, in the author's article (Matviychuk, Zhytkevych, & Osadcha, 2024), after a thorough analysis of the literature and a wide range of databases, a well-founded conclusion was reached about the feasibility of modeling decarbonization processes only on an annual basis, taking into account the specifics of the process being studied and the frequency of data in the relevant information resources. However, in this case, we

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obtain very short time series for each country – only a couple dozen observations (and even shorter if we include information on renewable energy sources). This precludes the use of cutting edge modeling techniques designed to identify complex patterns in large data sets.

Therefore, it makes sense to analyze CO_2 emission data for many countries at once to expand the sample for model building and identify existing patterns. However, given that countries vary greatly in both emission volumes and the energy, economic, demographic, and other determinants, using a single forecast model for all countries would be ineffective due to the extreme heterogeneity of the data. Therefore, it makes sense to identify more homogeneous groups of countries for subsequent analysis of the dependence of carbon dioxide emissions on a variety of different factors. To separate such groups of countries and to identify key factors in data sets, such data mining tool as cluster analysis is used. In scientific literature, the commonly applied methods for clustering economic and environmental indicators are K-means (MacQueen, 1967), hierarchical clustering (Johnson, 1967) and the principal component analysis (PCA) method (Jolliffe, 2002).

In the paper (Jiménez-Preciado, Cruz-Aké, & Venegas-Martínez, 2024), patterns were identified using K-means clustering combined with PCA and non-Linear t-SNE dimensional reduction techniques, in total and per capita CO_2 emissions among 208 countries considering different emission sources. Despite popularity of clustering methods, they are limited by assumptions about data linearity and low resistance to multicollinearity (Poznyak, & Kolyada, 2023). An experimental comparison of K-means, GMM, and self-organizing maps on a dataset for assessing the decarbonization potential of countries demonstrated the superiority of SOM in solving the clustering problem for this dataset (Zhytkevych, 2025).

Vlaović et al. (2023) built a 28-dimensional model with indicators like CO_2 per capita, the share of electricity from wind, etc., applying SOM clustering to obtain a map of country clusters by energy sustainability. Bucur et al. (2021) analyzed several energy indicators calculated for a 12-year time span with statistical methods and SOM to understand dynamics towards a green energy transition of the European Union State Members. The results show that some countries are leaders in the use of renewable energy and pollution reduction, while others face high levels of environmental pollution due to low share of renewable energy.

Criado-Ramón, Ruiz and Pegalajar (2023) presented a new pattern sequence-based algorithm that uses a genetic algorithm to optimize the number of clusters alongside all other hyperparameters of the forecasting model that combines SOM and multilayer artificial neural network. A similar approach to forecasting based on multilayer perceptrons on the data of objects of each individual cluster obtained as a result of using self-organizing maps was applied in the work (Osadchuk, Yatsenko, & Iatsenko, 2024).

These studies confirm the effectiveness of SOM clustering in identifying patterns among countries with different levels of development. The analysis of literature review identified that SOM is a powerful tool for analyzing and clustering countries according to their decarbonization potential, taking into account a wide range of economic, energy and environmental indicators. Therefore, it was decided to utilize this tool for our study. At the same time, the conducted analysis revealed that there is a wide range of models for segmenting countries by the level of energy sustainability and green energy development, forecasting the energy sector, including in war conditions, but there is a gap in research devoted to scenario forecasting of energy development and planning based on target indicators. Therefore, our research will focus on developing such an approach based on self-organizing maps that facilitates effective green economy policymaking.

Methods

The SOM is an artificial neural network consisting of an input layer and an output layer (a two-dimensional lattice of neurons). Its training algorithm includes initialization of weight coefficients and determination of the best matching unit (BMU), updating the BMU and neighbor weights, iterations until convergence. The main quality metrics are quantization error and topographic error (Kohonen, 2001).

SOM allows to take into account the nonlinearity of economic and environmental processes, to combine clustering with data visualization, provides high interpretive value and is robust to noise and outliers in the data. In particular, in addition to efficient object segmentation, Kohonen self-organizing maps, unlike all other clustering algorithms, clearly indicates to the analyst the level of development of a particular object, since the best and worst ones in terms of the characteristic under study will be placed in opposite corners of the map. This makes SOM an optimal tool for analysis and policymaking compared to other clustering approaches. However, it should be noted that despite its advantages, there are certain limitations. For example, the complexity of choosing hyperparameters (map size, learning rate), the risk of overfitting on small samples and the need for careful data preprocessing are one of the main limitations of the method (Matviychuk, Zhytkevych, & Osadcha, 2024). In our study, we applied the Kohonen self-organizing maps method to cluster countries, which allows to reduce the dimensionality of multidimensional data and identify natural groups (clusters) among countries. The classical formula (Krejcie, & Morgan, 1970) was used to estimate the sample size:

$$n_0 = \left(Z^2 \times p \times (1 - p)\right) \div E^2, \qquad (1)$$

where $Z = 1.96$ (for a confidence level of 95%), $p = 0.5$, $E = 0.05$. Substituting the values: $n_0 = (1.96^2 \times 0.5 \times 0.5) \div 0.05^2 = 384.16$.

Results

In article (Matviychuk, Zhytkevych, & Osadcha, 2024), we conducted a comprehensive review of a wide range of databases and information resources from international organizations. Taking into account the relevance of the available data for the task at hand and their completeness across indicators, years, and countries, World Bank (2023) database and EnerData (2023) reports were selected as the primary sources. Based on these, a sample of 14 indicators for the period 2013–2022 was compiled for 40 countries. The dataset integrates indicators from the country's socio-economic, energy and environmental sectors that together contribute to its decarbonization potential. The selection and development of indicators followed the principles of comprehensiveness and avoidance of redundant indicators, as outlined in previous studies (Zhytkevych, & Brochado, 2022).

Thus, the sample size used for our study is 400 (40 countries × 10 years), which is grater than 384.16 (1), hence statistically justified for cluster analysis, reflecting the main trends and structural characteristics while maintaining a balance between the reliability of estimates (confidence level 95% and $E = 0.05$) and data availability.

Using verified independent databases (The World Bank, 2023; EnerData, 2023) minimizes subjectivity in the selection of indicators and ensures comprehensive coverage of the economic and energy characteristics of countries. The selected

data from the World Bank (2023) include GDP per capita growth, urbanization level, total energy consumption and energy intensity of the economy, etc. The EnerData (2023) database provides information on the trade balance of key energy resources (coal, oil, natural gas, electricity), their domestic consumption, the share of renewable sources in electricity production and the average CO_2 emission factor. It is important that we did not use raw data for the clustering but an aggregated set of parameters that allows us to more accurately describe the structure of energy consumption and the economic context of each country. As a result, an integrated database was created that simultaneously reflects economic and energy characteristics and serves as the basis for further cluster analysis.

However, the values of different indicators in the dataset had significantly different orders of magnitude and units of measurement. For example, GDP growth rates were measured in percentages, energy consumption in terajoules, and the average CO_2 emission factor in tons per megawatt-hour. In quantitative terms, some metrics are measured in units, while others can be measured in billions. Using such a dataset without preprocessing to train a SOM map would be incorrect, since the selection of BMU will focus mainly on those parameters that have the largest absolute values, due to the fact that the optimization is based on calculating the Euclidean distance between the input data vectors and the neuron parameters.

Taking this into account, the critically important stages of data preparation are scaling and normalizing selected parameters, creating new significant predictors and ensuring the absence of multicollinearity among the input indicators. To scale and normalize each parameter, Min-Max normalization was applied in the range [0, 1], which allows to ensure the sensitivity of SOM to all parameters without the advantage of one over the other and to preserve the relative proportions of the values of each indicator (Zhytkevych, Matviychuk, & Kmytiuk, 2023).

The correlation matrix analysis was performed to eliminate multicollinearity and redundant parameters. Indicators with a correlation exceeding 0.95 were combined or replaced with aggregated factors, which allows to increase the informativeness of the model and ensure stable SOM training. Some highly correlated parameters (e.g., total energy consumption and energy intensity) were kept since they reflect the impact on the energy profile and decarbonization processes differently.

The last stage of database preparation was feature selection. Only the most important indicators were selected that provide informativeness to the model and at the same time do not overload it. As a result, a final database of 14 indicators was formed (e.g., GDP per capita growth (annual %); Urban population (% of total population); Total energy consumption; Energy intensity of GDP; Average CO_2 emission factor (tons of CO_2 per MWh); Trade balance for: coal and lignite, oil products, natural gas, electricity; Share of renewables in electricity; Domestic consumption by coal and lignite, oil products, natural gas, electricity).

Thus, the final dataset was formed as a two-dimensional matrix with 400 rows (*Nr*), composed of records for 40 countries over 10 years, and 14 columns containing normalized indicators. This database provides a balanced, normalized and statistically correct basis for further training the Kohonen self-organizing map and building country clusters by decarbonization potentials (Zhytkevych, & Brochado, 2022).

After preparing the normalized dataset, the main stage began – training the Kohonen self-organizing map. This allows us to detect hidden patterns in multidimensional data and visualize them as a two-dimensional map, where objects with similar characteristics (in our case, countries) are located nearby. To implement the described method, we have utilized Scikit-learn (2024), Python MiniSom – a lightweight but powerful library for building Kohonen maps, Python Matplotlib and Seaborn – for visualization of the results, as well as Deductor Studio Academic for creating interactive U-Matrix heat maps (Matviychuk, Zhytkevych, & Osadcha, 2024).

To visualize results and configure the self-organizing map, authors determined optimal size of the map, applying the empirical rule for calculating the number of neurons (Heaton, 2008):

$$M \approx 5 \times \sqrt{Nr}, \quad (2)$$

where *M* is the number of neurons and *Nr* is the number of records in the dataset. As it was mentioned, *Nr* = 400, so the optimal number of neurons should be around 100 or slightly higher. As a result of a series of experiments, the map size was chosen to be 16 × 12 neurons, which is a total of 192 neurons. The hexagonal topology of neuron placement was chosen to ensure better local connectivity and a more natural distribution of objects on the map. This contributes to a more organic formation of neighborhoods and clusters on the SOM. As a result of map optimization on the formed dataset, a topological structure was obtained, the heatmaps of which for each of 14 indicators are presented in Fig. 1.

The heat maps in Fig. 1 show the distribution of each indicator, with its values colored from blue (minimum) to red (maximum). The scale of the normalized values for the corresponding indicator is shown on the ruler below each heatmap. For example, the first indicator, Total Energy Consumption, is highest for China, which is in the upper left corner of the map. The USA is also visible nearby. Against the backdrop of its high energy consumption, almost the entire rest of the map turns blue.

Here, the cluster boundaries are not visible on the heatmaps. In this regard, it is worth noting that, in general, a self-organizing map is a dimensionality reduction method. Clustering itself is implemented using another clustering method, such as K-means (but for the parameter vectors of the map's neurons, not for the data vectors) (Vesanto, & Alhoniemi, 2000).

During the segmentation, its quality was assessed using three standard criteria: the Silhouette coefficient, the Davies-Bouldin and Calinski-Harabasz indices, and an integrated indicator based on them (Poznyak, & Kolyada, 2023), as well as semantic analysis, which confirmed the logic and relevance of the resulting clusters for studying decarbonization processes. As a result, it was revealed that the optimal clustering is obtained by dividing the dataset into six groups, which allowed to distinguish leaders, followers, resource-intensive economies, producing, hydrocarbon-oriented and large industrial countries.

Since our study is based on an unsupervised learning approach, semantic validation is an important stage, as it involves assessing the logic and content of the resulting groups. In this regard, authors checked how well the clusters correspond to the real economic and energy profiles of the countries. The average values of each indicator for each cluster were calculated for assessing semantic validity, which allowed us to form a generalized portrait of a typical country within the cluster. Comparing the profiles of different clusters allows us to identify countries with a high share of renewable energy and low energy intensity, etc.

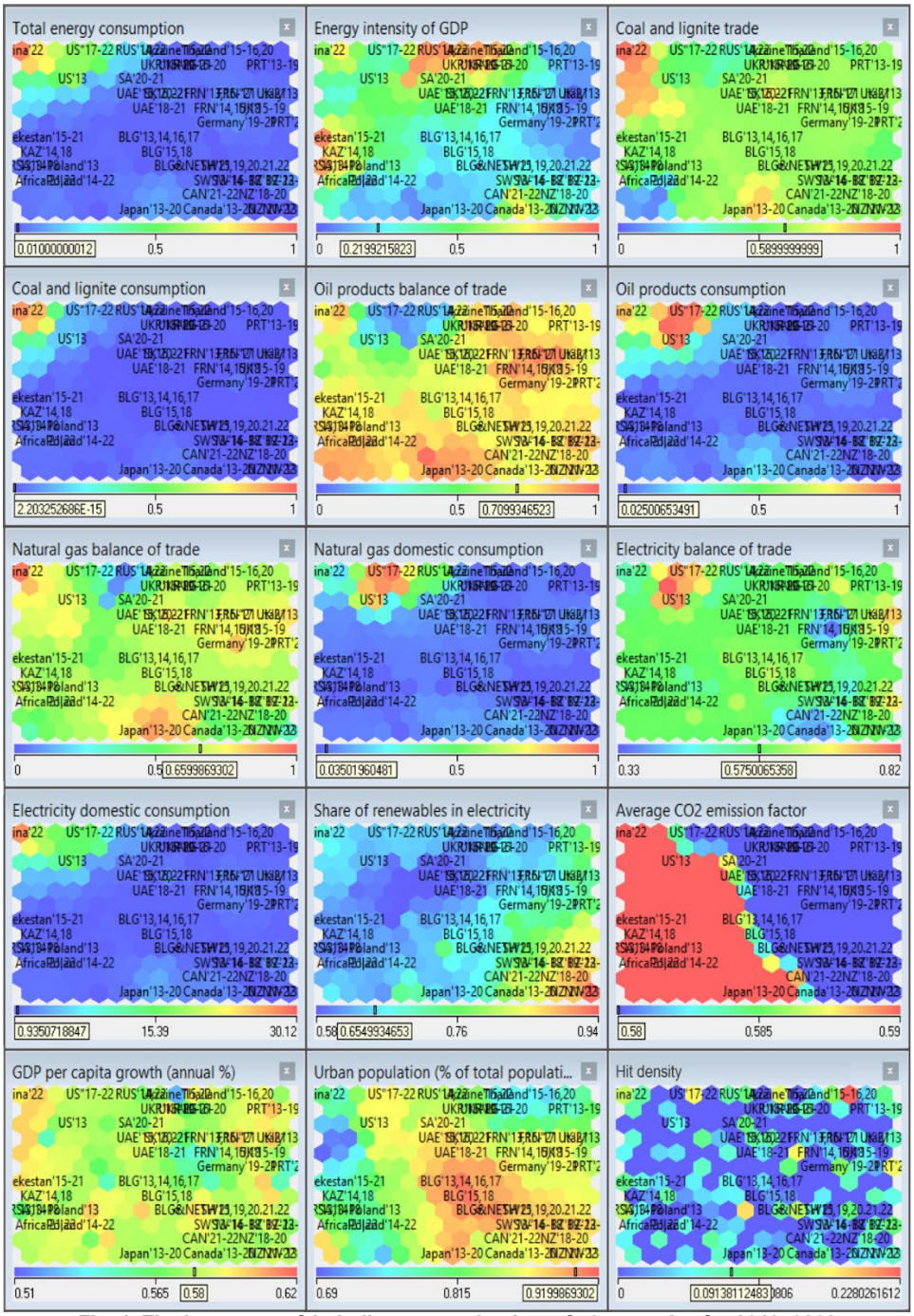


Fig. 1. The heatmaps of 14 indicators on the data of 40 countries for 2013–2022

Table 1

Six-cluster structure of division of countries

Cluster name	Cluster number	Description of the cluster composition
Leaders – decarbonization hubs	1	Countries with a high share of renewable energy and low energy intensity (Canada, New Zealand, Norway, Sweden, etc.)
Followers	0	Demonstrate progress in decarbonization, but remain partially dependent on traditional energy sources (Great Britain, EU countries, developed countries of Latin America)
Resource-intensive economies	3	Countries with high energy intensity of GDP and dependence on fossil fuels (Nigeria, Saudi Arabia, UAE, Ukraine, etc.)
Producing countries	4	Countries which are characterized by high energy intensity and CO_2 emissions with a relatively low share of renewables in electricity (Australia, Germany, India, Japan, Poland, Turkey, etc.)
Hydrocarbon-oriented countries	2	Countries with large volumes of oil and gas production and consumption (russia, USA)
Large industrial countries	5	The largest energy and coal consumption countries with high CO_2 emissions, but at the same time investing in renewable energy (China, USA)

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This approach not only checks the adequacy of the clustering, but also provides a meaningful economic interpretation of the groups, which is essential for the practical application of the model. By dividing the countries into six clusters, the most balanced and interpretable structure was obtained, presented in Table 1. The cluster boundaries can be seen in Fig. 2, and their numbers are indicated by the corresponding color on the ruler below the figure. The average levels of each indicator can be estimated from the corresponding heatmaps in Fig. 1.

Since each country is represented by ten entries (one for each year), individual countries could change their location in the clusters during the studied period, reflecting the dynamics of the energy profile (Fig. 2).

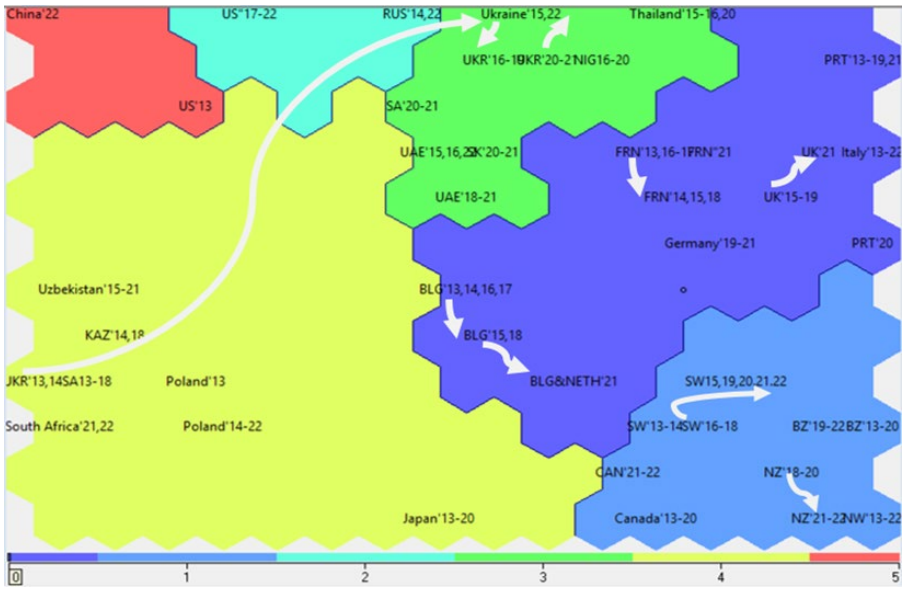


Fig. 2. The SOM of 6 clusters for 40 countries based on 14 indicators and trajectories of movement of some countries between clusters (Matviychuk, Zhytkevych, & Osadcha, 2024)

Note, that increasing the number of clusters beyond six led to excessive fragmentation of groups and loss of analytical value, and decreasing below six led to artificial merging of fundamentally different profiles, which complicated interpretation. Hence, the six identified clusters became the basis for building development scenarios and analyzing the dynamics of countries' movement between groups, which made it possible to assess progress or stagnation in efforts to decarbonize national economies.

Taking the advantages of one of the unique capabilities of SOM (visualization of object movement trajectories in a multidimensional feature space over time), authors recorded how countries (in particular, Ukraine) changed their decarbonization profile over a 10-year period (Fig. 2).

To do this, for each annual dataset of each country, a winning neuron was determined that best matched the country's profile for that year. Next, the country's trajectory was plotted on the Kohonen map, allowing for a visual tracking of the dynamics of its changes – whether the country was approaching the leaders, remaining stable, or moving away from the target decarbonization profiles. Thus, this approach allows for the analysis of not only the static states, but also the temporal evolution of the countries' energy profiles.

Discussion and conclusions

The conducted study found three characteristic patterns in countries' decarbonization development:

1. Leaders that have traditionally been active in implementing decarbonization policies have remained in their cluster (lower right corner of the SOM) throughout the entire period. Meanwhile, followers have shown a gradual shift towards the leaders, indicating real progress in transforming energy infrastructure and reducing emissions. However, they did not move into the leader cluster.

2. High energy consumption countries also generally remained relatively stable. The United States is an exception, which has moved from the top-left cluster (along with China) to the neighboring "hydrocarbon-oriented countries" cluster. But this is explained not so much by any actions of the USA, but by the accelerated industrial development of China, due to which the United States has shifted to a different cluster against this background.

3. Although most of the countries in the clusters in the central part of the Kohonen map also did not leave their clusters, however, if there were any noticeable changes, they have occurred precisely in this area. For example, the UK and some Latin American countries changed their cluster from producing to followers, improving their positions in the context of decarbonization. Ukraine made a sharp transition from producing to the "resource-intensive" economies in 2015 and has remained in this cluster, moving between different neurons within the group.

Thus, visualization of trajectories on a self-organizing map allows not only to reflect the state of each country in a specific year, but also to assess the dynamics of changes in energy profiles over time, revealing trends of progress or stagnation in the decarbonization processes of national economies.

SOM as a tool for decision makers can be used to trace the distribution of countries by decarbonization potential and to determine priority areas of policy in the field of emission reduction. Thus, countries with a significant share of renewable energy demonstrate a high potential for emission reductions. SOM visualization allows to identify patterns that are not obvious through simple statistical analysis.

To enhance the practical importance of the study in terms of creating an effective tool for developing decarbonization strategies, we proposed an original approach to the use of Kohonen maps in scenario modeling (for the "what-if" analysis). Authors conducted series of simulations to model the impact of changes in individual indicators on the position of the country on the cluster map.

The scenario modeling methodology can be described by the following three steps:

1. The current country profile, represented by a vector of characteristic indicator values, is manually modified – for example, the indicators "Share of renewables in electricity" (increase by 10%) and "Energy intensity of GDP" (decrease by 20%) are changed.

2. Passing the modified profile through the SOM.winner() function, which determined the BMU. This step helped to identify whether the country's placement on the SOM would change.

3. Entering results into an interactive change matrix, reflecting which parameters of the energy structure needed to be adjusted to move the country to the desired cluster, for example, into the group of decarbonization leaders. The average values of the indicators of the leader cluster served as a guideline for such recommendations.

This approach allowed us to move from simple clustering to practical scenario analysis, revealing which structural changes are most critical for achieving the country's target profile. For example, for resource-intensive economies such as Ukraine, a key factor in improving global positioning is increasing the share of renewables in electricity, which can ensure a transition to follower or leader clusters. However, taking into account the current economic situation of country and its difficult geopolitical situation caused by war, decarbonization processes should be implemented taking into account the risk of deindustrialization. Strict and unsynchronized climate policy measures can limit Ukraine's production potential, while in the middle and long run it needs to build economic capabilities for post-war recovery. In this context, innovation and investment, in particular foreign direct investment in the "green" economy, will play crucial role in the modernization of the power sector and overall economic recovery.

In the context of the large industrial countries (USA, China), an increase in the share of renewable energy without a simultaneous decrease in energy intensity does not guarantee a transition to more "green" clusters. This emphasizes the need for a comprehensive energy-saving policy.

Thus, scenario modeling allows to identify key "influence points" for improving positions in global decarbonization. The modeling results form a practical basis for developing targeted energy sector development strategies for individual countries and provide specific recommendations for governments, businesses, and think tanks on priority areas of decarbonization policy.

The implemented study, devoted to the analysis of the decarbonization potential of countries around the world, demonstrated that Self-Organizing Maps is an effective tool not only for clustering and visualization of multidimensional data, but also for forming profiles of research objects (in this case, country energy profiles), conducting scenario modeling, and identifying key influence points for achieving targets, in particular, reducing CO_2 emissions. Using SOM allowed authors to identify hidden patterns in the structure of characteristic indicators, and visualization of Ukrainian's movement trajectory provides an analysis of the dynamics of implementation of policies and an assessment of their effectiveness in the long term.

The identified six clusters became the basis for building development scenarios and analyzing the dynamics of countries' movements over time, which made it possible to assess the progress or stagnation of national economies in decarbonization efforts and to propose a methodology for formulating national policies in the field of green energy based on the results of scenario modelling. In particular, the conducted scenario modeling allowed us to determine that for a cluster of resource-intensive economies, which includes Ukraine, the key factor in improving global positions is an increase in the share of renewable energy sources in the electric power industry, which can ensure a transition to clusters of followers or leaders.

At the same time, the SOM method has certain limitations. It is not a classic forecasting model and does not allow for accurate forecasts of CO_2 emissions for several years ahead. Further development of the study involves developing a hierarchical multi-level model. In particular, after segmenting countries into separate clusters, their own forecasting models (regressions, neural networks, etc.) will be built for each of them. This approach will ensure greater accuracy and stability of the models due to training on homogeneous datasets, which increases the relevance of the training sample for each cluster.

Additionally, it is planned to use fuzzy clustering, which will allow determining the degree of country belonging to each cluster. This will open the possibility of using an ensemble of models in forecasting, where the influence of each cluster will be determined by the degree of membership of the forecasted object, which will increase the adaptability and efficiency of forecasting decisions.

Authors' contribution: Olena Zhytkevych – conceptualization; methodology; analysis of sources, preparation of literature review, theoretical foundations of the study; collection of empirical data and their validation and empirical research; Andriy Matviychuk – conceptualization; methodology; revision and editing.

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МЕТОДОЛОГІЧНІ ОСНОВИ РЕАЛІЗАЦІЇ ПОЛІТИКИ ЗЕЛЕНОЇ ЕКОНОМІКИ КРАЇН НА ОСНОВІ КЛАСТЕРНОГО АНАЛІЗУ

В с т у п . ***У контексті глобальної кліматичної політики виникає необхідність систематизувати країни за рівнем викидів CO_2, структурою енергоспоживання й економічним розвитком для виявлення типових патернів траєкторій переходу до низьковуглецевої економіки. Із цією метою в статті здійснено кластеризацію країн за потенціалом декарбонізації із застосуванням самоорганізаційних карт Кохонена. Цей інструментарій дозволяє моделювати нелінійні взаємозв'язки та враховувати високу розмірність даних, забезпечуючи гнучку та точну сегментацію та ефективніший засіб аналітичного дослідження порівняно з іншими методами кластеризації. У роботі проведено підбір гіперпараметрів, підготовку та нормалізацію вхідного набору даних, процедури валідації кластерів на основі ряду кількісних метрик та з урахуванням семантичної відповідності.***

М е т о д и . ***Для кластеризації країн за потенціалом декарбонізації застосовано самоорганізаційні карти Кохонена. Цей інструментарій дає змогу моделювати нелінійні зв'язки та враховувати високу розмірність даних, забезпечуючи гнучку й точну сегментацію, та є ефективнішим засобом для аналітичних досліджень порівняно з іншими методами кластеризації. Стаття містить налаштування гіперпараметрів, підготовку та нормалізацію вхідного набору даних, а також валідацію кластерів за допомогою ряду кількісних метрик (коефіцієнта силуету, індексів Девіса – Болдіна та Калінскі – Харабаша).***

Р е з у л ь т а т и . ***Отримані результати дозволили виокремити шість кластерів країн із різними профілями декарбонізації (лідери – декарбонізаційні хаби, послідовники, ресурсомісткі економіки, країни-виробники, вуглеводневі країни й основні промислово розвинені країни). На основі отриманих результатів кластеризації автори оцінили динамічні траєкторії країн у часі й визначили ключові показники, що впливають на досягнення цілей відновлюваної енергетики та скорочення викидів. Крім того, запропоновано оригінальний підхід, заснований на використанні карт Кохонена у сценарному моделюванні, який показує, як стандартна кластеризація трансформується у практичний сценарний аналіз і дає змогу виявляти, які структурні зміни є найкритичнішими для досягнення цільового профілю країни. В межах цього аналізу зазначено, що для України покращення глобального позиціонування шляхом збільшення частки відновлюваних джерел енергії в енергетичному секторі може забезпечити перехід до кластерів послідовників або лідерів.***

В и с н о в к и . ***Використання самоорганізаційних карт надає ефективний інструмент для формування стратегічних рекомендацій щодо розвитку низьковуглецевих економік та оптимізації національних енергетичних політик.***

К л ю ч о в і с л о в а : ***декарбонізація, викиди CO_2, кластеризація, самоорганізаційна карта, машинне навчання, енергетична політика.***

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