

*Research Article*

Assessment of The Potential of Russian Regions for The Introduction of Industrial Microgrid

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Abstract: Industrial microgrids are independent energy systems that provide stable power supply to production facilities. In this study, the potential of Russian regions to implement this technology was assessed using cluster analysis. The study used 15 indicators to characterize the level of industrial development, electricity consumption volumes, innovation climate, energy resource availability, and the possible economic effect of using the technology. Two promising clusters were identified. The first cluster includes 7 regions: Rostov, Nizhny Novgorod, Samara, Sverdlovsk, and Chelyabinsk, as well as the Republics of Tatarstan and Bashkortostan. The second cluster includes 14 regions: Belgorod, Kursk, Lipetsk, Arkhangelsk, Vologda, Leningrad, Orenburg, Tyumen, Kemerovo, and Amur, the Republics of Komi, Karelia, and Yakutsk, as well as Perm Krai. If the potential for implementation in the first cluster is explained by the high level of industrial development and a favorable innovation climate, then the second cluster is characterized by the highest tariffs for network maintenance. Therefore, the implementation of the industrial microgrid concept in this cluster can result in the greatest savings, which makes it especially attractive.

Keywords: Cluster analysis; Energy efficiency; Industrial microgrid; Power system development

1. Introduction

In recent years, several key factors have led to global changes in the field of electric power development in economic science (Nurulin et al., 2023; Farghali et al., 2023; Kyzym et al., 2020). First, monitoring the ecological state of the environment, which is associated with climate change, is an important aspect. Second, the popularity of new breakthrough technologies based on digital solutions and artificial intelligence has grown rapidly (Zagloel et al., 2023). The third important factor is the rapid urbanization growth, which also affects the energy sector. Finally, the structural changes taking place in the global economy, which affect trade and production, cannot be ignored.

The requirements for ensuring global sustainable development include solving problems related to improving energy efficiency, energy production environmental friendliness, and energy availability. The existing centralized power supply system has exhausted its capacity to increase the efficiency of power systems (Çolak and Irmak, 2023; Byk et al., 2019). Centralized energy supply is being replaced by decentralized (distributed) generation, which includes not only low-power generators but also programs for price-dependent reduction of energy consumption, smart grids, and energy acquisition systems (Ahlqvist et al., 2022; Burger et al., 2019). In recent years, microgrids have become very popular.

Microgrids are electrical structures with small, decentralized generation sources located near local loads (Peyghami et al., 2019; Wang et al., 2013). According to Russian authors, a microgrid is an electric distribution network that includes a group of consumers, distributed generators (for example, renewable energy sources such as solar panels and wind turbines), and

energy transmission and storage systems (Karanina and Bortnikov, 2020).

A microgrid combines power generation and consumption (Zhou et al., 2015). Unlike a utility network that generates electricity from a centralized power plant and then distributes it along power lines for hundreds of kilometers, a microgrid generates electricity locally. Electricity generation typically involves a combination of backup diesel generators and renewable energy sources, such as solar panels. Microgrids can include battery systems for storing and deploying electricity during outages or during peak network loads.

As a result, such a system provides more environmentally friendly energy production and reduces costs by optimizing demand, storing energy, and allowing the surplus to be sold to the general grid during peak demand (Azimian et al., 2020; Adefarati and Bansal, 2019). Additionally, the presence of intelligent control increases the overall reliability and uninterrupted power supply (Onibonoje et al., 2023; Bie et al., 2012; Bae and Kim, 2008).

Thus, a microgrid is a tool of the digital economy that allows the creation of energy systems that are maximally focused on the needs and requirements of specific consumers. A microgrid aggregates all the considered distributed energy technologies and is a local intelligent power system (Uddin et al., 2023). Modern scientific research in this field is devoted to the issues of design (Strasser et al., 2015; Fang et al., 2012), optimization and planning (Mina-Casaran et al., 2021; Liang and Zhuang, 2014), operation (Cagnano et al., 2020; Parhizi et al., 2015), and incentives (Suryad et al., 2017; Sanz et al., 2014).

Interest in the development of industrial microgrids worldwide is largely due to the desire to ensure constant power within the enterprise's network and to insure against a drop in incoming power from external sources. On the other hand, the ever-increasing cost of electricity in the backbone networks also contributes to increased interest in the development of own-generation power generation (Dzyuba et al., 2022).

The main advantages of using industrial microgrids are energy resource savings and increased energy efficiency, which are achieved by increasing the efficiency of using green energy and eliminating traditional energy sources (Parag and Ainspan, 2019). In addition, industrial microgrids provide reliable and safe electrical system operation that can withstand loads in emergency situations, such as software failures or cyber-attacks.

The development of industrial microgrids in Russia began with the approval of the NTI «Energinet» Roadmap by Decree of the Government of the Russian Federation, which set out the conditions for implementing a pilot project for the creation and development of an Active energy complex (AEC). The project under consideration can be identified as an infrastructure project involving new markets. The main goal of the project is to create conditions for the effective development of distributed generation by establishing a transparent and cost-effective system of relations in the electricity market. Simultaneously, ensuring the integration of local industrial clusters into the Unified Energy System of Russia while maintaining the reliability and operational safety level is necessary (Dzyuba and Semikolenov, 2024).

Despite the wide range of research areas in the field of distributed generation, few modern scientific studies have focused on the selection of a promising site for the implementation of an industrial microgrid. The implementation of microgrids requires not only the fulfillment of technological requirements but also the consideration of the specific characteristics of the regions. The effectiveness of microgrids is associated with the volume and nature of the electrical load schedule and industry affiliation of consumers. The economic effect of the implementation of the industrial microgrid concept in each region primarily depends on the network maintenance tariff (Dzyuba et al., 2022). It is also important to consider the climate of innovation (Bolsunovskaya et al., 2023; Zaytsev et al., 2021). To increase the generation efficiency and reduce the payback period of microgrid projects, it is necessary to competently approach each specific territory's analysis. In this regard, it is necessary to determine the regions for which it is advisable to implement such a system (Glukhov et al., 2023). This study aims to assess the attractiveness of regions for the implementation of an industrial microgrid using the example of the Russian Federation. The cluster analysis method was considered as a basis for deciding on the choice of a

site for the implementation of microgrid projects. Cluster analysis allows simultaneous splitting by several features. The quantitative indicator similarities are calculated in each way based on the selected data characterizing the regions (Brazovskaia and Gutman, 2021).

2. Methods

2.1 Research Methodology

Each region of Russia is a complex management system that depends on both internal and external factors. Despite the peculiarities of each subject, many similar characteristics of various factors are characteristic of a few regions.

Cluster analysis is widely used in tasks of socio-economic significance (Balasankar et al., 2021), in the analysis of regions, for example, to determine the level of economic or innovative development (Pelau and Chinie, 2018), the characteristics and specifics of individual regions; to plan and effectively manage development processes and improve the quality of life of the population (Žmuk, 2015). Thus, the method under consideration allows identifying regional problems, determining the development vector, and concentrating resources on the most important areas.

The task of cluster analysis is to divide the set G of objects G into m (m – integer) clusters (subsets) $Q_1, \dots, Q_m$, based on the data contained in the set X , so that each object G_j belongs to one and only one subset of the partition. Moreover, objects belonging to the same cluster were similar, whereas objects belonging to different clusters were heterogeneous (Landau and Chis-Ster, 2010).

The study consists of the following consecutive stages (Nasledov, 2013):

1. Selection of a set of attributes that will be used for comparison
2. Calculation of descriptive statistics for selected variables.
3. Selection of objects (regions) for cluster analysis.
4. Grouping objects into clusters.
5. Analysis of the results obtained.

2.2 Size of the dataset

Data were collected and analyzed for 84 subjects of the Russian Federation for 2021 to identify the most promising regions of Russia for the development of industrial microgrids based on the concept of active energy complexes. For the cluster analysis, 15 variables were selected that characterize the potential attractiveness of regions in terms of the development of industrial microgrids. The rationale for selecting these specific indicators is explained by a literature review and data availability. Data on the indicators are published in the Federal State Statistics Service of the Russian Federation's annual reports. Table 1 lists the grouped variables.

It is necessary to identify the regions with the largest share of industrial energy consumption to assess the potential of regions in the development of industrial microgrids. To do this, we will form the first group of variables that characterize the industry's energy consumption. These groups include the following:

- electricity consumption for mining, manufacturing, provision of electric energy, gas and steam, and air conditioning;
- Industrial production index;
- energy intensity of the gross regional product (GRP);
- Electric power availability per person.

Table 1 Grouping of variables

No	Data group	Variables
1	Industrial energy consumption	– electricity consumption for mining, manufacturing etc. (X1)
		– GRP energy intensity (X2)
		– industrial production index (X4)
		– electric power availability per man (X5)
2	Economic	– average network charges (X3)
3	Innovation climate	– innovation activity (X6)
		– depreciation of fixed assets (X7)
		– number of employees in research and development activities (X8)
		– share of investment in modernization (X9)
4	Energy supply	– average annual wind speed (X10)
		– solar potential (X11)
		– wholesale gas prices (X12)
5	Nature of industry	– volume of goods shipped "mining" (X13)
		– volume of goods shipped "manufacturing" (X14)
		– labour productivity index (X15)

The first indicator in this group is the absolute value of electricity consumed to produce goods, extract minerals, and provide energy resources (gas, steam, etc.). The index of industrial production is measured as a percentage of the previous year and reflects the aggregate changes in the production of all types of goods, works, and services. It is a macroeconomic indicator of the industry development of the region. Based on the index value, we can conclude that production in the region is expanding, new enterprises are appearing, or the volume of products produced is decreasing. The GRP energy intensity indicator can be used to assess the energy efficiency of the production process, which reflects the ratio of energy resources spent to the value of the domestic regional product. Key factors influencing this indicator include changes in capacity utilization, energy prices, energy characteristics of production equipment, and GRP. The last variable related to this group is the availability of electric power per person. This is an indicator that characterizes the labor security of employees of industrial companies with electric energy, that is, it is the ratio of the amount of energy consumed in production to the number of man-hours worked. Thus, based on this indicator, we can draw a conclusion about enterprises' level of electrification in the region under consideration.

The second group of indicators characterizes the regions' innovative climate. To characterize this group, indicators of the level of innovation activity, depreciation of fixed assets, the share of investment in modernization, and the number of personnel engaged in R&D will be used. The innovation activity level reflects the share of organizations engaged in innovation activities in the total number of organizations.

Innovation activity is aimed at transforming, improving, or introducing processes, products, services, etc. that have new qualities. Innovation activity has several areas, for example, in material and technical, social, or economic terms, as well as in organizational, managerial, and legal aspects. Thus, this type of activity includes a set of scientific, financial, and technical activities aimed at the practical use of scientific research results and various developments. The second indicator—the degree of depreciation of electric power enterprises' fixed assets—may indicate the level of need for capacity modernization. The next variable shows the share of investments aimed at modernization and reconstruction in the total fixed asset investment volume. Based on regional indicators on the share of investment in the modernization of fixed assets, the level of readiness and capabilities of the region to carry out such activities, as well as the specifics of

the investment climate in the region, can be judged.

In addition to analyzing the economic components, assessing the human capital (potential) for implementing innovative solutions in the region is necessary. To do this, we select the number of employees engaged in R&D as a variable. As mentioned earlier, the implementation of innovative activity is the implementation of the results of scientific research in the form of a specific product, service, or approach in an organization, i.e., the implementation of the result of scientific activity in a practically significant component of any process. Thus, the more staff involved in research activities, the better the region's innovation climate.

The next group of data is the type of energy source received from the generating equipment as part of an active power complex. The sources selected for analysis are renewable (wind and solar) and nonrenewable (gas) sources. We use the average annual wind speed in the region to determine the possible level of wind generation development, and we use the number of clear days per year to analyze the solar potential. The data for analysis were taken from meteorological sites on the Internet. Hybrid installations can be used due to the spontaneity of renewable energy sources, complementing the generation of green sources with efficient gas-fired co-generation plants. In addition, industrial enterprises can use gas in their production process; thus, in most cases, a gas pipeline can already be installed in the enterprise, which facilitates the installation of their own gas turbine or gas piston power plant. To assess the gas potential, wholesale gas prices will be analyzed. The data are current as of the end of 2022 and are taken from Federal Antimonopoly Service orders.

The choice of AEC generation sources can significantly influence the deployment and subsequent development of renewable energy in the regions, which contributes to reducing the carbon footprint, improving environmental performance, developing responsible consumption, and achieving sustainable development goals related to production decarbonization. Thus, the introduction of industrial microgrids can have an environmental impact. To identify the greatest economic effect of implementing the AEC concept, analyzing the average network charges in each region is necessary. For this study, tariffs were taken as an average value for all voltage levels as of the end of 2022. Information on tariffs is published on the Tariff Committee website of a particular region in the Regulations on setting Tariffs for Electric Power Transmission Services over Electric Networks.

The last group of data allows us to draw conclusions about the nature of industry in the region. To do this, we will take analysis data on the volume of goods shipped by economic activity: extractive industry and manufacturing, as well as on the labor productivity index, which reflects the ratio of the GRP physical volume index to changes in total labor costs. Simultaneously, the GRP physical volume index is determined based on the absolute values of GRP in constant prices, and the change in labor costs is determined based on the labor costs of all types of work.

2.3 Descriptive statistics indicator calculation for selected variables.

In this analysis, we examine the descriptive statistics for each of the previously selected indicators. First, we check the data distribution, which should be close to normal according to the conditions of cluster analysis. The normality of the distribution was determined by evaluating the following indicators (Bera et al., 2016): the average value and median, standard deviation, kurtosis coefficient, and skewness coefficient.

A small deviation of the average value of a random variable from the standard deviation and median is one of the signs of a normal distribution. The standard deviation is a measure of the dispersion of a random variable's values relative to its mathematical expectation. The next metric to analyze is the kurtosis coefficient. For a normal distribution of a random variable, this coefficient should approach 0. In addition, one of the significant criteria for normality is the ratio of kurtosis to its standard error: if this ratio is modulo > 2 , then the distribution is far from normal. The skewness coefficient is the last indicator for analysis, which should approach 0 for a normal distribution. The rule for determining normality can be described as follows:

skewness coefficient values that are more than 2 times higher than its standard error indicate that the distribution is abnormal.

The analysis was performed using the STATISTICA software product, which implements the functions of data analysis, data management, and visualization using statistical methods. The descriptive statistics of the variables are presented in Table 2. All variables are characterized by a large sample size due to the different nature of regional development, and the normality criteria are not met for most variables.

Table 2 Results of calculating descriptive statistics of variables

variable			Descriptive statistics					
			number	mean	median	st.dev	asimmetry	kurtosis
Industry electricity consumption, mln. kWh			84	7074	3694	9945	2.927	10.258
GRP energy intensity, kg/1000rubles			84	104	99	42	0.832	0.767
Average network charges, rubles/MWh per month			84	1316159	1348557	491782	-0.613	1.107
Industrial production index, %			84	106	105	8	1.814	7.431
Electric power availability in industry, kWh per employee			84	70038	44663	84963	5.136	33.96
Innovation activity, %			84	10	9	5	1.005	1.6333
Depreciation of fixed assets, %			84	48	50	12	-0.864	1.6333
Share of investment in modernization, %			84	18	17	8	0.743	1.417
Number of employees in research and development activities, per			84	7888	1439	25309	6.455	47.144
Average annual wind speed, m/s			84	3	3	1	0.348	-0.945
Solar potential, days per year			84	113	100	42	0.938	0.099
Wholesale gas price, rubles/1000m ³			84	4830	5392	1690	-2.194	3.946
Volume of goods shipped "mining", mln rubles			84	280020	21013	701051	4.451	22.597
Volume of goods shipped "manufacturing", mln rubles			84	749739	534899	1279851	4.893	30.997
Labour productivity index, %			84	103	103	4	1.149	3.802

In addition to normality, the correlations between the selected variables must be checked. The correlation coefficient is measured in the range from -1 to +1. The coefficient's sign indicates the positive or negative influence of variables. The closer the coefficient value modulo 1 is, the stronger the relationship exists between the data. Figure 1 presents the results of the correlation analysis. Considering the matrix of correlation coefficients, it should be noted that the relationships between variables are not practically valid; therefore, the selected variables can be used for cluster analysis.

Variables	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15
X1	1														
X2	0.2	1													
X3	-0.06	0.23	1												
X4	-0.05	-0.14	0.15	1											
X5	0.51	0.39	-0.15	-0.14	1										
X6	0.08	-0.12	0.01	0.09	-0.17	1									
X7	0.05	0.07	-0.1	-0.15	-0.02	0.08	1								
X8	-0.04	0.3	0.27	-0.17	0.08	0.03	0.09	1							
X9	0.15	-0.31	-0.08	0.44	-0.07	0.18	0.05	-0.13	1						
X10	-0.06	-0.28	-0.2	-0.01	-0.13	0.07	0.2	0.15	-0.04	1					
X11	-0.17	0.01	0.03	0.13	-0.18	-0.21	-0.31	0.09	-0.12	-0.15	1				
X12	-0.19	-0.15	0.19	0.22	-0.5	0.24	-0.19	-0.06	0.11	0.21	0.14	1			
X13	0.63	-0.12	-0.03	0.1	0.27	-0.04	0.09	-0.23	0.17	-0.04	-0.28	-0.17	1		
X14	0.35	-0.21	-0.05	0.37	0.01	0.31	0.06	-0.23	0.93	0	-0.17	0.12	0.24	1	
X15	0.06	-0.3	-0.02	0.36	-0.1	0.07	0.08	-0.11	0.36	0	-0.24	0.01	0.2	0.35	1

Figure 1 Results of calculating paired correlation coefficients between selected variables

2.4 Selection of objects (regions) for the cluster analysis

To conduct qualitative analysis, it is essential to perform data processing, commonly referred to as data cleaning. In this context, we employ a graphical approach to assess the distribution's normality, specifically using the box-and-whisker plot.

Initially, we will exclude from our study regions where the implementation of industrial microgrids in accordance with the Autonomous Energy Complex (AEC) concept is unfeasible due to the absence of a two-part tariff structure for electricity transmission. Given that the use of a single-rate tariff for transmission services lacks legislative regulation within the AEC's operational guidelines, the following regions will be omitted from our analysis: Kamchatka Krai, Magadan Region, Sakhalin Region, and Chukotka Autonomous Okrug.

In addition, not all regions of Russia have completed the construction of the main gas pipelines: there is no possibility for wholesale gas supplies. In addition to missing data, anomalous values (outliers) affect the distribution of variables. Critical outliers were also recorded for variable X1 in the Khanty-Mansi Autonomous Okrug, Krasnoyarsk Krai, and Irkutsk Region. A clear outlier of the X2 variable was observed in the RCK. Emissions from variables X14 and X15 were also excluded. Cities of federal significance (St. Petersburg and Moscow) also exhibit abnormal values in several variables. Owing to the significant differences and complexity of the organization of energy supply systems of such large cities, they are excluded from further analysis, and the issues of the attractiveness of their territory for the implementation of microgrids should be considered separately. Because of data cleaning, the number of observations for analysis decreased from 84 to 66.

Because of data processing, Table 3 presents descriptive statistics of variables for the remaining regions.

Table 3 Results of calculating descriptive statistics of variables after data cleanup

variable	Descriptive statistics					
	number	mean	median	st.dev	asimmetry	kurtosis
Industry electricity consumption, mln. kWh	66	5643	3694	6406.5	2.101	4.794
GRP energy intensity, kg/1000rubles	66	108	102	36.6	0.985	0.913
Average network charges, rubles/MWh per month	66	1425645	1426397	384807.2	0.236	0.463
Industrial production index, %	66	106	105	7.0	2.628	13.499
Electric power availability in industry, kWh per employee	66	53411	42572	33326.3	1.118	0.803
Innovation activity, %	66	11	11	5.5	0.898	1.373
Depreciation of fixed assets, %	66	48	50	11.3	-1.272	2.335
Share of investment in modernization, %	66	19	19	6.8	0.789	1.263
Number of employees in research and development activities, per	66	4280	1613	6519	3.530	16.423
Average annual wind speed, m/s	66	3	3	1.1	0.318	-1.082
Solar potential, days per year	66	116	100	42.8	0.913	-0.257
Wholesale gas price, rubles/1000m ³	66	5377	5469	485.7	-0.383	0.289
Volume of goods shipped "mining", mln rubles	66	151108	9706	299961.8	2.829	8.510
Volume of goods shipped "manufacturing", mln rubles	66	597280	373998	615237.9	1.678	3.094
Labour productivity index, %	66	102	102	3.8	0.782	3.311

The picture for descriptive statistics of variables has become much better: there is a slight deviation of the standard deviation, the average value, and the median for almost all variables. Abnormal values of the variables were eliminated, and the data distribution became normal. Based on the data cleaning results, you can perform clustering.

2.5 Group objects into clusters.

After preparing the data for cluster analysis, we will use the STATISTICA program's built-in function - standardization of variables. In this program, the normalization of indicators is performed according to the following formula:

$$Z = \frac{x - \bar{x}}{\sigma} \quad (1)$$

Where Z is the normalized value, x is the initial value; $\bar{x}$ is the average value; σ is the standard deviation.

Next, we use the hierarchical method of cluster analysis to construct a dendrogram (Fig. 2) to determine the optimal number of clusters. As metrics, we use the Euclidean distance, and we choose the Ward method to determine the distance between clusters (the union rule) (Ferreira and Hitchcock, 2009). The Ward method differs from other methods in using variance analysis to estimate distances. The method function minimizes the sum of squares for any two clusters.

When a variety of methods were tested, Ward's method appeared to be the most effective. The number of clusters is chosen based on a visual analysis of the dendrogram. The greatest difference among the distance axes between adjacent levels indicates the preferred number of classes (corresponding to the level from which the transition to the next one is made). However, this approach is not formalized and can therefore be easily criticized. The procedure is useful but only as a preliminary analysis of the partitioning result. The optimal number of clusters is assumed to be five.

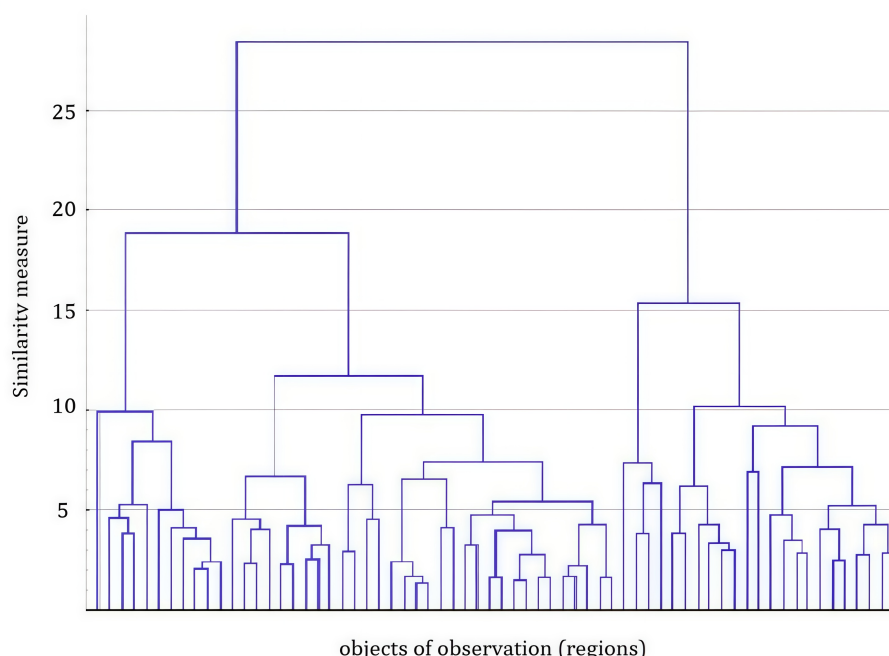


Figure 2 Dendrogram of 66 observations

For the next clustering step, the k-means method will be used (Ahmed et al., 2020). To do this, we set the number of clusters to 5. The rule for forming initial cluster centers is to maximize the initial distances between clusters. Clusters were somewhat unequal in size. The smallest cluster includes only 7 observations, and the largest included 26 observations.

3. Results and Discussion

3.1 Clustering results

To visualize the results of regional clustering, we created a map of the regions of Russia indicating the resulting clusters and the regions that they include, as well as marked areas with abnormal values or no data (Figure 3).

3.1.1 The first cluster

The first cluster includes 7 regions: Rostov, Nizhny Novgorod, Samara, Sverdlovsk, and Chelyabinsk, as well as the Republic of Tatarstan and Bashkortostan. Among the resulting clusters, these regions are characterized by the largest volumes of electricity consumption for mining and processing industries, as well as for providing electric energy, gas and steam, and air conditioning. The average value of this indicator is 17,524 million kWh. The energy intensity of GRP is slightly higher than the national average of approximately 115 kg CU/10 thousand rubles, indicating a low degree of energy efficiency of production. The industry index in the regions under review is equal to the average for Russia—an increase of approximately 6% over the year.

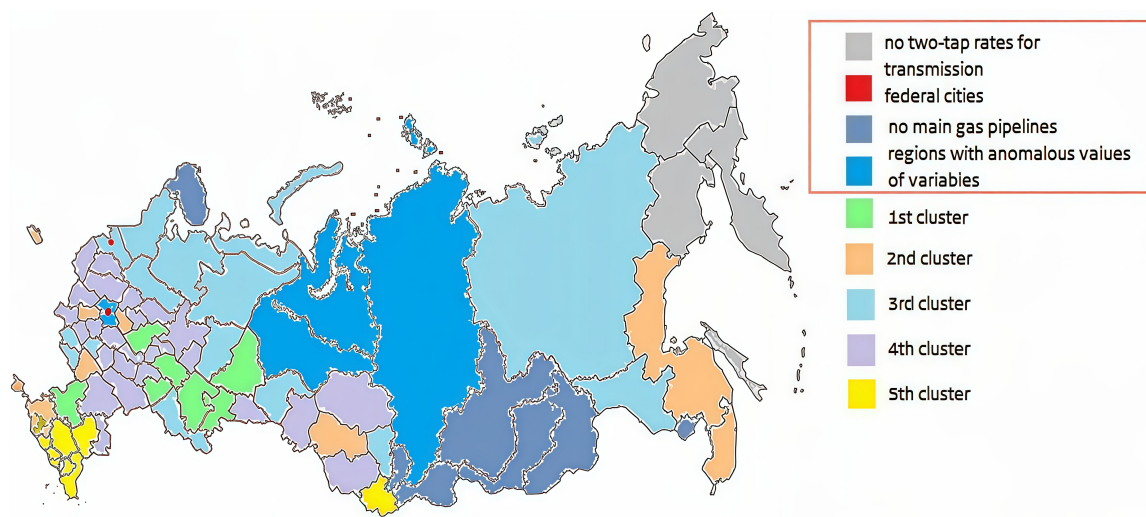


Figure 3 Map of Russian regions based on clustering results

The indicator of electric power supply for industrial workers is slightly different from the average for Russia, amounting to 63,258 million kWh. All these indicators indicate a high degree of industrial production development and scaling, indicating the relevance of the AEC concept in these regions.

It should be noted that manufacturing industries predominate in these regions—the average value of the volume of goods shipped is 2.5 times higher than the average value in Russia. Extractive industries are developed with a slight deviation from the national average: the excess is about 14%. At the same time, labor productivity is one of the lowest among the considered clusters, with growth compared to the previous year being only 2%.

Considering the potential energy sources for generating equipment, the rather low prices for wholesale gas (the average for the cluster is 5,161 rubles/thousand cubic meters, which is 3% lower than the average price for the entire sample of melons) should be noted. This indicates the promising use of GTU or GPU. When choosing between renewable energy sources, solar energy should be preferred: the wind potential is quite low—the average wind speed in the first cluster is 2.6 m / s, while the average number of clear days per year is 125 days, which is 10% higher than the value for the whole of Russia.

Assessing the innovation potential, the level of innovation activity is the highest among all the clusters under consideration, at 19%, while the average level among all observations is only 10%. The Republic of Tatarstan is the leader in this indicator. The cluster also has a low level of fixed asset depreciation (43%), and the share of investments in modernization exceeds the sample's average of about 21%. This cluster also has the largest number of personnel in the field of scientific development, with an average number of approximately 17 thousand, which is 2 times higher than the average value for all observations. Thus, we can discuss a favorable investment climate in the first cluster. The average network maintenance rate for the first cluster is 1,328,415.67 rubles/MWh per month, which is 4% lower than the national average.

3.1.2 The first cluster

The second cluster was formed by such regions as: Vladimir, Voronezh, Kaluga, Novosibirsk, Krasnodar, Primorsky, and Khabarovsk, as well as the Republic of Crimea. Consider the first data group for the second cluster. We primarily distinguish the regions from the rest by the low energy intensity of GRP, which is 30% lower than the national average. Notably, the industry index grew by an average of 9% for the cluster, but industrial consumption and electric equipment of industrial workers are still lower by 45% than in other clusters for both indicators. This cluster can thus be characterized as a poorly developed industry.

In terms of the nature of production, we should note the highest labor productivity index

compared with other clusters is 106%. Manufacturing industries are the most common; the volume of goods shipped is 15% higher than the sample average. The performance of the extractive industry is significantly worse, with 20% below the national average.

This cluster is characterized by low values of variables in this group when assessing the innovation climate: the level of innovation activity reaches only 9%, when the average for the sample is 11%, and depreciation of fixed assets is 50%, with the lowest share of investment in modernization among all clusters at 17%. However, over time, the situation may become much better due to sufficient personnel engaged in scientific development, the value of which exceeds the sample's average by 1.5 times.

When choosing an energy source for new generating equipment in the AEC, it should be noted that this cluster has the highest wholesale gas prices-8% higher than the national average. Therefore, it is better to choose renewable energy sources, namely wind generation. The average wind speed of the cluster is 4.4 m/s, which is almost 1.5 times higher than the national average. The solar potential is at the level of 1 cluster. In addition, this cluster has the lowest transmission rates, with an average of only 1,207,117.65 rubles/MWh per month, which is 13% lower than the Russian average. Thus, the lowest economic effect among all clusters can be assumed.

3.1.3 The third cluster

The third cluster includes 14 regions: Belgorod, Kursk, Lipetsk, Arkhangelsk, Vologda, Leningrad, Orenburg, Tyumen, Kemerovo, and Amur regions, the Komi Republic, Karelia, and Yakutsk, as well as the Perm region. These regions have a well-developed industrial sector: industrial consumption is 1.6 times higher than the sample average, the average industrial index is 105%, and industrial employees have a fairly high electric power supply. Considering the nature of the industry, it is worth noting that these are the regions with the most developed extractive industry. The volume of goods shipped is 3 times higher than the sample's average, and we can also note a good indicator of the labor productivity index, which is 104%.

Simultaneously, the cluster's innovativeness is below average: a high depreciation of fixed assets is typical, the share of investments in modernization is low (about 17%), the number of research employees is 40% lower than the sample's average value, and enterprises' innovative activity is only 9.5%. This cluster is characterized by the lowest potential for deploying renewable energy based on solar generation, but wind installations and gas sources are possible: the average wind speed is 3.4 m / s, the gas price is almost equal to the average in Russia and is 5039.61 rubles/thousand cubic meters. Along with the considered variables, these regions have the highest tariffs for network maintenance, with an average of 1,572,889.10 rubles/MW per month, which is 10% higher than the national average. Thus, the largest savings from implementing the AEC concept are possible in this cluster.

3.1.4 The fourth cluster

Most extensive cluster No. 4 consists of 26 regions, namely: Bryansk, Ivanovo, Kostroma, Orel, Ryazan, Smolensk, Tambov, Tver, Tula, Yaroslavl, Novgorod, Pskov, Astrakhan, Volgograd, Kirov, Penza, Saratov, Ulyanovsk, Kurgan, Omsk, and Tomsk, as well as the Mari El Republic, The Republic of Mordovia, Udmurtia, and Chuvashia, as well as the Altai Territory.

In these regions, the industry is poorly developed: consumption is more than 2 times lower than the sample's average, the energy intensity of GRP is equal to the average for all observations (109 kg cu/10 thousand rubles), the industry index is 2 percentage points lower, and the indicator of electric equipment is 25% lower than the national average. Considering the nature of production, manufacturing industries are more developed, but for both industries, the indicators are lower than the average for Russia: by 72% for the extractive industry and by 38% for manufacturing production. There is also a low value of labor productivity, only 100.06%. Thus, this cluster has a poorly developed industrial sphere, which may indicate that AEC implementation is irrelevant. Whether enterprises have the funds to implement their own

generation is also doubtful.

The investment climate is almost identical to cluster 3, but the level of innovation activity of organizations is slightly higher and amounts to almost 13%. Despite the low level of industrial development in the region, there is a good wind potential (the average annual wind speed in the cluster is 3.5 m/s), solar generation is possible (103 clear days a year), and the wholesale gas price is close to the average in Russia and amounts to 5329.69 rubles/thousand cubic meters. In this cluster, the network maintenance rates are at the Russian average level: they amount to 1,427,068.76 rubles/MWh per month.

3.1.5 The fifth cluster

Finally, the last cluster includes 10 regions: the Republics of Adygea, Kalmykia, Dagestan, Ingushetia, Kabardino-Balkaria, Karachay-Cherkessia, North Ossetia, and Chechnya, as well as the Stavropol Territory and the Altai Republic. The fifth cluster is the least promising for developing industrial microgrids because practically no industrial production occurs in these regions. All values of variables in the data groups "Consumption industry" and "Nature of industry" are much lower than the average for Russia. The least favorable innovation climate is also observed. High gas prices characterize this cluster. Gas prices in this cluster are 8 percent higher than the national average. Here is the lowest potential for the use of wind turbines, but this cluster is the most promising for introducing solar generation.

4. Conclusions

The main direction of microgrid development is to ensure integration into the main network to balance the energy system, stability, and power supply quality. The cluster analysis identified the most promising regions in terms of implementing microgrid technology. The two most promising clusters for the introduction of IMGs were identified. The first cluster includes the regions of Rostov, Nizhny Novgorod, Samara, Sverdlovsk, and Chelyabinsk, as well as the Republics of Tatarstan and Bashkortostan. The second cluster consists of 14 regions: Belgorod, Kursk, Lipetsk, Arkhangelsk, Vologda, Leningrad, Orenburg, Tyumen, Kemerovo, and Amur, the Republics of Komi, Sakha and Karelia, and Perm Krai. These regions have a favorable innovative climate and a high level of industrial development. There is also potential for the development of renewable energy sources based on wind and solar generation. Despite the identified advantages of the AEC, the most acute issue remains the issue of legal risks due to the lack of specific requirements for the form of ownership and conditions for concluding contracts. These issues require further study. Because of the implementation of the AEC concept, the cost of production, energy intensity of GRP, and environmental indicators can be reduced by introducing renewable energy generation.

Acknowledgements

The research is financed as part of the project "Development of a methodology for instrumental base formation for analysis and modeling of the spatial socio-economic development of systems based on internal reserves in the context of digitalization" (FSEG-2023-0008).

Conflict of Interest

The authors declare no conflicts of interest.

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