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[1] Akhundov V.J

[2] Rustamov İ.S

Application of The Aggregation and Multicriteria Optimization Method in Assessing the Level of the Knowledge Economy of World Regions in Industry 4.0

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Abstract: - The article proposes a new methodology for determining the level of the knowledge economy of countries in terms of the possibilities of using Industry 4.0 technologies. The relevance of the study is due to the transition to a new technological structure – "Industry 4.0" in the world. The aim of the study is to analyze data on the main sub-indices of the knowledge economy associated with Industry 4.0 for countries around the world based on the author's methodology. As a tool for this analysis, the k-means++ clustering method was used to classify countries according to their characteristics. The assessment of the potential of Industry 4.0 is determined on the basis of 5 criteria characterizing various aspects of the development of countries at the level of economic knowledge. In the calculation process, determining the extent to which the indicators used describe the level of the knowledge economy, and the use of the aggregation formula and multi-criteria optimization, constitutes the scientific novelty of the study. It was concluded that as a result of clustering the countries of the world using the formula Aggregation and Multicriteria Optimization, the number of clusters decreased and the distribution of countries between clusters began to more adequately reflect reality. The results of the study can be used in the process of assessing the competitiveness of countries during the transition to the Industry 4.0 economy, as well as in developing strategies and concepts for countries.

Keywords: k-means++, Industry 4.0, knowledge economy index, метод Elbow и F-ratio.

INTRODUCTION

The main goal of our research is to rank world regions according to the level of development of the knowledge economy in Industry 4.0 based on the author's methodology. To achieve the research goal, it is necessary to solve the following set of scientific problems.

Firstly, it is necessary to analyze the factors and conditions that determine the prospects for the formation of regional clusters of the knowledge economy in the modern world, including: an analysis of global experience in the formation of clusters of the knowledge economy.

Secondly, it is necessary to develop a model of a regional cluster of the knowledge economy, including: a description of the elements of the model of a regional cluster of the knowledge economy in Industry 4.0.

Today, the introduction of Industry 4.0 into the professional activities of workers has contributed to a change in the business models of companies. In the IT industry and heavy industry, new production process technologies are gradually beginning to be used, such as analytics, modeling, cybersecurity, cloud technologies, and 3D printing. Thanks to smart technologies, it is possible to create business models for entire factories, as well as specific industries.

The implementation of the Industry 4.0 concept demonstrates a responsible attitude towards issues of production optimization and industry competitiveness. The transition to Industry 4.0 is determined, first of all, by the active implementation of innovative technologies.

LITERATURE REVIEW

Well-known scientists such as F. Machlup [1], D. Bell [2], M. Porat [3] were engaged in methodological approaches to measuring the knowledge economy.

They formed the concept of a post-industrial society based on free access to scientific knowledge and scientific and technological progress. This concept gave rise to the widely used term "information society". These issues were addressed by researchers such as V.L. Makarov [4], V.A. Logachev [5], D.G. Kochergin [5] and others.

According to Bratian and Bolisani (2015), there are four main strategies for creating knowledge based on a matrix: exploitation strategy, acquisition strategy, sharing strategy and search (knowledge creation) strategy [6].

Most authors identify three groups of criteria characterizing the development of the knowledge economy:

1,2 Economics and Management, Azerbaijan State Oil and Industry Universityline, Baku, Azerbaijan

1https://orcid.org/0000-0001-7529-7142, 2https://orcid.org/0000-0002-7300-9458

1. Economic criteria that include taking into account the economic manifestations of the process of development of the knowledge economy -D. Bell [2]

2. Technological criteria that record the progress of the technological sphere during the transition to a new stage of economic development. K. Perez [7] notes the pattern of mass replacement of one set of technology with another or the modernization of existing equipment, processes, solutions, or the production of radically new techniques.

3. Social criteria that determine the impact of the development of the knowledge economy on the driving force of this economy - people, whose main ability generates the main factor of production of the new period - knowledge Alvin and Handy Toffler [8].

Much work on the classification of the knowledge economy was done by the American economist of Austrian origin Fritz Machlup[1], who divided knowledge into areas of application in economic activity. Some authors considered knowledge as an economic category, focusing on the costs of searching for information. However, the real role of knowledge in the process of creating added value was revealed in the works of Peter Drucker[9]. P. Drucker who revealed the importance of knowledge as the main economic resource of the new society.

An analysis of modern literature has shown that the methodological problems of forming regional clusters of the knowledge economy as an inducing factor in the development of the regional economy, and, ultimately, the national economy, have not yet been resolved. In this regard, there is a need to develop the theory of regional economics in the interests of solving problems of regional economic measurements based on the development of theoretical, methodological and applied aspects of the formation of regional clusters of the knowledge economy.

SUBINDEXES OF THE KNOWLEDGE ECONOMY OF REGIONS IN INDUSTRY 4.0

Technological modernization associated with the improvement of the production process is becoming a key factor in the growth of production efficiency, ensuring the transition of the economy to a qualitatively new level of development. They show the path to a gradual search for opportunities for innovation and the introduction of modern approaches, experience in networking with customers and customizing products. Based on this, we can determine the following key statistical indicators that characterize this aspect of the region's development: the share of technological innovations carried out; the share of innovative goods, works, services in the total volume of goods shipped, works performed, services; indicators of production optimization and competitiveness.

The article proposes a new methodology for determining the level of the knowledge economy in the regions in the conditions of Industry 4.0. The calculations use 5 main indicators, which more accurately reflect the level of implementation of Industry 4 in the regions:

1. Competitive Industrial Performance Index;
2. Growth rate of gross regional product (GRP);
3. Telecommunication Infrastructure Index;
4. Communications, computer, etc, (of service exports BoP)) is an indicator of the digital economy.
5. High-technology exports ($);

During the research process, a data set was generated based on World Bank data (Table 1). The data was taken for 2019. It should be noted that some countries did not provide data on these indicators. For this reason, clustering was carried out for 120 countries.

Table 1. Indicators characterizing the level of implementation of the Industry 4.0 concept by country**.**

№	Country	Competitive Industrial Performance Index (CIP score)	Growth rate of gross regional product (GRP);	Telecommunication Infrastructure Index	Communications, computer, etc, (of service exports BoP)	High-technology exports ($)
1	Algeria	0.01	3.5	0.3889	0.7	9027.4

2	Angola	0.01	1.1	0.0972	0.61	77770.74
3	United Arab Emirates	0.10	3.9	0.8564	0.76	2904969
...	…	…	…	…	…	…
…	…	…	…	…	…	…
118	Yemen, Rep,	0.00	0.8	0.1454	0.6	1030.32
119	Zambia	0.01	4.6	0.1853	0.08	10697.41
120	Zimbabwe	0.01	8.5	0.2144	0.28	8275.26

METHODOLOGY

Mahalanobis Distance (MD) is an effective distance metric that finds the distance between the point and distribution. It works quite effectively on multivariate data because it uses a covariance matrix of variables to find the distance between data points and the center [10]. This means that MD detects outliers based on the distribution pattern of data points, unlike the Euclidean distance. The main reason for this difference is the covariance matrix becausecovariance indicates how variables variate together. Using covariance while calculating distance between center and points in n-dimensional space provides finding true threshold border based on the variation

$$D^2 = (X_{P_1} - X_{P_2})^T \cdot C^{-1} \cdot (X_{P_1} - X_{P_2}) \qquad (1)$$

Where, D^2 = squared mahalanobis distance between points X_1 and X_2, $X_{P_1}$and X_{P_2}-coordinates of X_1 and X_2 observations in n-dimensional space, T - transpose matrix,

C^{-1} – negative first power of covariance matrix.

K-means clustering is a simple unsupervised learning algorithm that is used to solve clustering problems. It follows a simple procedure of classifying a given data set into a number of clusters, defined by the letter “k,” which is fixed beforehand. The clusters are then positioned as points and all observations or data points are associated with the nearest cluster, computed, adjusted and then the process starts over using the new adjustments until a desired result is reached. ‘k-means++’ which is modified type of k-means selects initial cluster centroids using sampling based on an empirical probability distribution of the points’ contribution to the overall inertia[11]. This technique speeds up convergence. Randomly select a new centroid by choosing a point with probability proportional to

$$\frac{\min_j d2(Cj, xi)}{\sum_i \min_j d2(Cj, xi)} \qquad (2)$$

Where, d^2 – square deuclidean distance from a point to centroid, C_1 - initial centroid coordinates, C_j – the next centroid coordinates.

F-Ratio is a statistical ratio which is used to analyze if the expected values of a variable within predefined groups differ from one another. In other words, it shows how the differences between groups compares to the differences within one group. It is calculated by dividing the MSB (Mean Square of Between groups) by the MSW (Mean Square of Within groups)

$$F = MSB / MSW \qquad (3).$$

In the future, it is proposed to use fuzzy clustering for a more accurate and adequate classification of countries according to the knowledge index[12].

ANALYS AND RESULTS ANALYSIS

Data consist of 120 countries evaluated on 5 economical indicators related to knowledge index[13]. As software, Jupyter Notebook online programming platform was used which is based on Python programming language. Before starting clustering, data was standardized by using Standard Scaler. During standardization, 23 countries turned out to be outsiders. Of these, 18 countries (USA, Japan, China, Germany, Great Britain, France, Canada, Austria, etc.) turned out to be outsiders with high rates, and 5 countries - Afghanistan, Fiji, Kuwait, Lebanon, Myanmar - turned out to be outsiders with high rates. low performance.

To classify countries according to their characteristics, the k-means++ clustering method was used. To find the most optimal number of clusters, the F-ratio number was used for each number of clusters.

However, the elbow method may not be sufficient to find the optimal number of clusters. In this case, calculating the F-ratio number will indicate the quality of clustering. According to the rule, a smaller number of F-ratio emphasizes the most optimal number of clusters.

To find the optimal number of clusters, both methods were used: Elbow and F-ratio. In addition, the second derivative method was used to find the optimal number of clusters. The largest second derivative of both the elbow and the F-ratio showed that the optimal number of clusters is 5. Table 2 shows the results of calculations for 5 clusters.

Table 2. Cluster indicators

Clusters	Indicators	Competitive Industrial Performance Index (CIP score)	Growth rate of gross regional product (GRP);	Telecommunication Infrastructure Index	Communications, computer, etc, (of service exports BoP)	High-technology exports ($)
Cluster 1	country	23				
	mean	0.664572	0.258918	1.206578	-0.16656	0.100248
	std	0.745518	0.762096	0.41248	0.69934	0.479379
	min	-0.70454	-0.89466	0.606834	-1.46874	-0.43652
	max	2.477566	1.862298	1.952549	1.179784	1.105416
Cluster 2	count	20				
	mean	-0.80896	-0.96017	-0.86242	1.016965	-0.43427
	std	0.175488	0.613537	0.525274	0.595302	0.011962
	min	-0.96972	-2.06842	-1.55225	0.050906	-0.44082
	max	-0.40622	-0.13036	0.286651	2.438917	-0.39603
Cluster 3	count	24				
	mean	-0.4518	1.005866	-0.52493	0.063027	-0.37071
	std	0.336591	0.661801	0.584402	0.816485	0.108586
	min	-0.96972	-0.02117	-1.69082	-1.27336	-0.44081
	max	0.25672	2.299043	0.634376	1.744223	-0.07179
Cluster 4	count	9				
	mean	2.223439	0.075886	1.118237	0.861382	2.604402
	std	0.643598	0.806419	0.800978	0.675083	1.61434
	min	1.350569	-0.73088	-0.30423	-0.12277	0.82043
	max	3.273093	1.780408	1.994724	1.744223	6.54496
Cluster 5	count	22				
	mean	-0.37609	-0.52616	-0.36223	-1.17152	-0.37104
	std	0.409291	0.768091	0.57379	0.392706	0.145657
	min	-0.90342	-2.39597	-1.24498	-1.72925	-0.44083
	max	0.521896	0.688543	0.777254	-0.4267	0.116466

Table 3 shows the distribution of countries by clusters according to the clustering performed (excluding outsider countries).

Table 3. Clusters of countries before applying the formula Aggregation and Multicriteria Optimization

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Algeria	Algeria	Azerbaijan	Un.ArabEmirates	Armenia
Bulgaria	Angola	BurkinaFaso	Australia	Bolivia
Bahrain	Burundi	Bangladesh	Brazil	Ecuador
Belarus	CAR	Bosn.andHerzeg.	Finland	Cameroon
Chile	Congo, Rep,	Botswana	Indonesia	Egypt, Arab Rep,
Cyprus	Iraq	Colombia	Israel	Haiti
Estonia	Lesotho	Djibouti	Norway	Iran, IslamicRep,

Ghana	Madagascar	Domin. Repub.	Romania	Jamaica
Greece	Mali	Eritrea	Turkiye	Jordan
Iceland	Mauritania	Georgia		Liberia
Kazakhstan	Malawi	Honduras		Sri Lanka
Lithuania	Liberia	Kenya		Mongolia
Luxembourg	Nepal	Morocco		Mozambique
Latvia	Pap.NewGuinea	Nicaragua		Nigeria
Malta	Paraguay	Pakistan		Sudan
New Zealand	Solomon Islands	Peru		Trinidad and Tobago
Oman	Suriname	Rwanda		Tunisia
Portugal	Chad	Senegal		Uganda
Qatar	Tonga	Eswatini		Ukraine
Serbia	Yemen, Rep,	Togo		Uzbekistan
Slovenia		Tajikistan		Venezuela, RB
Uruguay		Turkmenistan		Zambia
		Zimbabwe		

The main goal is to carry out clustering by countries of the world using the the formula Aggregation and Multicriteria Optimization[14]. This formulation reflects that in most real-world situations, aggregation occurs under conditions of inaccuracy, uncertainty, and incomplete information. The FA indicator in the formula corresponds to the spirit of approximate thinking in fuzzy logic; under such conditions, traditional logical systems become non-functional.

To apply the aggregation and multicriteria optimization formula, it is first necessary to determine to what extent these indicators describe the level of the knowledge economy. The extent to which indicators describe the level of the knowledge economy is determined based on their classification into subelements and probability assessments. The results are shown in Table 4.

Table 4. The degree to which the indicators describe the level of the knowledge economy

Competitive Industrial Performance Index (CIP score)	Growth rate of gross regional product (GRP)	Telecommunication Infrastructure Index	Communications, computer, etc, (of service exports BoP)	High-technology exports ($)
0.487	0.3	0.74		1

Let us explain the essence of the formula for Aggregation and Multicriteria Optimization. Granulated/Categorized courses fall into 3 importance-based categories: high importance (H), medium importance (M), low importance (L). Categorization is a coarse way of associatinga degree of importance with each datum.

For Aggregation and Multicriteria Optimization we find the average score each category countries: aver (H), aver (M), aver (L). Then we form a convex combination of these averages with coefficients $\lambda_1 = 0.6$, $\lambda_2 = 0.3$, $\lambda_3 = 0.1$. Form a convex combination of these averages with coefficients $\lambda_1= 0.6$, $\lambda_2=0.3$, $\lambda_3=0.1$.The convex combinationis the aggregated grade.

FA=Weighted graded performance aggregation formula

FA=0.6 aver (H) + 0.3 aver (M) + 0.1 aver (L)

After applying the formula Aggregation and Multicriteria Optimization, as a result of clustering the number of clusters decreased to 4 (without taking into account outsider countries) carried out according to the same rule. The results are shown in Table 5.

Table 5. Cluster indicators after applying the formula Aggregation and Multicriteria Optimization.

Clusters	Data	Competitive Industrial Performance Index (CIP score)	Growth rate ofgross regional product (GRP);	Telecommunication Infrastructure Index (TII)	Communications, computer, etc. (of service exports BoP)	High-technology exports ($)
Cluster 1	country	33				
	mean	-0,083381	-0,012033	-0,215164	0,221345	-0,107268
	std	0,042286	0,045765	0,119097	0,168371	0,019318
	min	-0,126485	-0,089931	-0,404935	-0,043353	-0,114997
	max	0,033485	0,090464	0,074778	0,636239	-0,018726
Cluster 2	country	28				
	mean	0,088301	0,008701	0,303697	-0,026768	0,034981
	std	0,108194	0,035969	0,123403	0,184259	0,146144
	min	-0,091897	-0,069755	0,054234	-0,383149	-0,114406
	max	0,323161	0,080969	0,520363	0,364402	0,422596
Cluster 3	country	7				
	mean	0,297837	0,007557	0,249368	0,241429	0,78258
	std	0,091219	0,039293	0,21597	0,163671	0,420669
	min	0,176161	-0,031777	-0,079363	0,001953	0,506776
	max	0,426925	0,077409	0,512729	0,455015	1,707381
Cluster 4	country	30				
	mean	-0,060191	0,003352	-0,104956	-0,274829	-0,097256
	std	0,047961	0,047851	0,149512	0,113535	0,034263
	min	-0,126485	-0,104173	-0,441085	-0,451108	-0,114998
	max	0,068073	0,099958	0,165489	-0,077332	0,030382

Based on the average number of indices, the fourth cluster, consisting of 30 countries, has the lowest values among the rest, which practically shows that this is a cluster of countries with underdeveloped economies. Looking at the average values (-0.53388) of the features of this cluster, we see that almost all indices have negative values. Compared to the fourth cluster, the first cluster, consisting of 33 countries, has the most positive feature. However, the average value of the indicators still remains negative (-0.1965). The second cluster, consisting of 28 countries, has 4 positive means and 1 negative mean (Communications, computer, etc.). The average value of all indices is positive (0.408912), but practically equal to zero, which means that countries within this cluster have average economic performance. Finally, the third cluster, consisting of 7 countries, is the strongest among all clusters in terms of average indicators (1.57877).

Table 6. Clusters of countries after applying the formula Aggregation and Multicriteria Optimization

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Algeria	Un. Arab Emirates	Australia	Bolivia
Angola	Argentina	Brazil	Bosnia and Herzegovina
Burundi	Azerbaijan	Finland	Armenia
Burkina Faso	Bulgaria	Indonesia	Botswana
Bangladesh	Bahrain	Israel	Cameroon
CentralAfricanRepublic	Belarus	Romania	DominicanRepublic
Congo, Rep,	Chile	Turkiye	Ecuador
Djibouti	Colombia		Egypt, ArabRep,
Guatemala	Cyprus		Eritrea
Honduras	Estonia		Georgia
Iraq	Ghana		Haiti
Lesotho	Greece		Iran, IslamicRep,
Morocco	Iceland		Jamaica
Madagascar	Kazakhstan		Jordan
Mali	Lithuania		Liberia
Namibia	Luxembourg		SriLanka
Nicaragua	Latvia		Kenya
Pakistan	Malta		Mongolia
PapuaNewGuinea	Norway		Mozambique
Paraguay	Oman		Nigeria
Rwanda	Pakistan		Peru
Senegal	Portugal		Sudan
SolomonIslands	Qatar		Tajikistan
Suriname	SaudiArabia		Tunisia
Chad	Serbia		Uruguay
Togo	Slovenia		Ukraine
Turkmenistan	TrinidadandTobago		Uzbekistan
Tonga	Uruguay		Venezuela, RB
Yemen, Rep,			Zambia
			Zimbabwe

As can be seen from the table, the number of clusters decreased as a result of clustering carried out by countries around the world using an aggregation formula and multi-criteria optimization. At the same time, the division of countries into clusters more adequately reflected reality.

CONCLUSIONS

The use of the proposed methodology provides a comprehensive analysis of the possibilities of using Industry 4.0 technologies. The advantage of the methodology is that the analysis algorithm takes into account the inaccuracy of aggregation, uncertainty and incompleteness of information. As a result of clustering the countries of the world using the formula Aggregation and Multicriteria Optimization, the number of clusters was reduced and the distribution of countries between clusters began to more adequately reflect reality.

An analysis of the assessment of the knowledge economy of regions and their clustering in terms of the possibilities of using Industry 4.0 technologies showed that there are large differences in the level of the knowledge economy both between countries and between regions of the world. This can serve as a basis for indicative planning and setting priorities for regional economic policy.

The results obtained can be used in the process of assessing the competitiveness of countries during the transition to the Industry 4.0 economy, as well as in developing strategies and concepts for countries.

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