Estimation of the Production Potential of Ukraine's Regions using Kohonen Neural Network

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Abstract. The problem of estimating the level of production potential for different time periods is investigated. It is proposed to apply an integrated approach to the analysis of the regional indicators complex that characterize the level of production potential. At the first stage, the normalization of indicators is carried out taking into account their economic content. The next stage is the calculation of integral indicators in three different approaches. At the last stage, the clustering of the regions by the level of production potential is carried out using Kohonen neural network. Application the Kohonen map with the database clustering simultaneously allows to project multidimensional data into two-dimensional space and analyze the resulting cluster system. The choice of the clusters number is based on the cluster indicator calculation, in contrast to the traditional statistical approach, based on the Störges formula using. It allows to improve the clustering results by selecting the optimal number of partition groups. The convenient form of visualization of the clustering results enables to localize the features and make appropriate adjustments to the rating list, based on expert judgements.

Keywords: production potential, Kohonen neural network, level of region development, integral estimation, competitiveness of regions.

1 Introduction

The current development of Ukraine is characterized by interregional socio-economy disparity, an increased level of disproportion in the development of individual regions and the emergence of differences in the sectoral structure of economic systems of different regions. The difference in the economic development of the country as a whole leads to the domination of some regional systems over others. Therefore, an important stage in the analysis of the development of the country as a whole, is the assessment of each of the regions.

This topic is relevant and open to new research because it is difficult to identify a single set of indicators that characterize the state of regional development fully. There is a problem of calculating the integral indicator the estimation and ranking of regions by level of development.

The purpose of the paper is application of integrated approach to assessing the level of development of regions of Ukraine in terms of production potential based on the construction of integral indicators and clustering by methods of neural networks.

2 Analysis of Recent Research

The problem of disproportionate regional development is one of the most important and actual that must be solved not in Ukraine only but also in the whole world. For effective public administration it is necessary to assess the level of development of regions, to identify regions with different levels of development. Therefore, a large number of scientific papers are devoted to this sphere. A lot of scientific works are devoted to the development and research of the problem of assessing the level of development of regions, their competitiveness. The theoretical basis for estimation the development of regions is considered in [1-5]. Different approaches and methods of diagnostics of regional development are presented in works [6-18]. Depending on the goals and objectives of the study, both statistical indicators and expert assessments are used, methods of integrated indicators construction are used [7, 10, 14], and develop scenario models for the development of regions [16].

Thus, (Pike, Rodriguez-Pose, Tomaney) [1] consider purposes, principles and values of regional development, and integrated approaches to local and regional development throughout the world. The approach provides a theoretically informed, critical analysis of contemporary local and regional development in an international and multi-disciplinary context, grounded in concrete empirical analysis.

Rivza, Azena, Sunina [2] study the impact of regional development on the development of enterprise environment. In order to implement the aim the authors investigated theories of regional development and studied the indicators of environment development in two cities in Latvia.

Ciobanu [3] considers regional development that is currently being discussed at national or European level, the effects of reorganization, the greatest achievement concerning economic and social cohesion, mitigating intra- and inter regional differences.

Korent, Vukovic, Brcic [8] apply correlation and dynamic panel data analysis on the set of data from Croatian counties with levels and relative changes of the selected regional growth indicators.

Meyer, De Johng, Meyer [11] construct a composite regional development index that successfully measures all the dimensions of development in a quantitative manner. The index was designed to be able to assess regions on a national, regional and local level. The hypothesised index consisted of four dimensions (demographic, social, labour and economic) that were constructed using 17 indicators.

Di Pietro et al. [12] study the influence of regional institutional environment, measured as regional development, on capital structure of small and medium-sized enterprises (SMEs).

Bachtler and Begg [13] highlights innovation, human capital and effective institutions as three crucial dimensions of future regional policy.

Li and Xu [15] use multi-index comprehensive measurement to calculate the composite index of the level of economic development of each evaluation unit for counties in Taiwan.

Kohonen neural networks are used for solving research problems in different fields of knowledge [19-36]. Lototskiy [19] considered the method of images fractal compression. The algorithm of clustering by means of artificial Kohonen neural networks was constructed.

Bacao, Lobo, Painho [20] review different initialization procedures, and propose Kohonen's Self-Organizing Maps as the most convenient method, given the proper training parameters.

Mingoti and Lima [21] present a comparison among some nonhierarchical and hierarchical clustering algorithms including SOM (Self-Organization Map) neural network and Fuzzy c-means methods.

Fayos and Fayos [22] consider time series of Circulation Weather Type, including daily averaged wind direction and vorticity, that are self-classified by similarity using Kohonen Neural Networks.

Dekker [23] presents a self-organizing Kohonen neural network for quantizing colour graphics images. The network is compared with existing algorithmic methods for colour quantization. It is shown experimentally that, by adjusting a quality factor, the network can produce images of much greater quality with longer running times, or slightly better quality with shorter running times than the existing methods

Nizam [24] presents a new cluster bus technique using Kohonen neural network for the purpose of forming bus clusters in power systems from the voltage stability viewpoint. This cluster formation will simplify voltage control in power system.

Singh et al. [25] propose and analyze Kohonen neural network tracking control of nonlinear system. Proposed adaptive Kohonen neural network are used to recognize class of nonlinear discrete-time systems.

3 Research Methods

The economic situation of any country is largely determined by the level of development of industry and agriculture. So, one of the most important groups of indicators of socio-economic development of the regions is exactly the production potential.

Production potential is the maximum possible volume of output that the economy is able to produce with the full involvement of all available resources in the process of social production [6]. The assessment of the production potential of the region is based on the analysis of its components: industrial, agricultural and investment potential. In turn, the characteristic of the industrial potential of the region is based on the research of the following indicators: the volume of industrial products sold (works, services), the share of the region; volume of sold industrial products (works, services) and volume of sold industrial products (works, services) per person. Regarding agricultural potential, its analysis is carried out on such indicators as gross crop production and gross livestock production. The investment potential in this research is characterized by an indicator of capital investment.

The construction of the integral index for assessing the production potential of the regions is carried out according to the following three approaches.

The first methodology is an integrated assessment of the competitiveness of regions, proposed in [7]. It has a hierarchical structure, which consists of three types of indices:

1) general integral index of the benefits of the region;
2) group integral indices of various aspects of the region's life;
3) partial integral indices characterizing the advantages of the region.

The proposed technology for calculating the regional benefits index implies the formation of databases, that is, the formation of a matrix of output data (X), determination of indicators of stimulant and distimulant, as well as their normalization.

Indicators-stimulant are calculated by the formula:

$$k = \frac{X_{ij}}{X_{ij\max}}. \tag{1}$$

Indicators-distimulant:

$$k = \frac{X_{ij\min}}{X_{ij}}, \tag{2}$$

where $X_{ij\max}$ - the maximum value of the indicator j in the region i; - the minimum value of indicator j in the region i.

Calculation of the consolidated integral index of investment advantages of the region is carried out on the basis of the formula of the average geometric group integral indexes, which characterize its main aspects:

$$K_w = \sqrt[r]{K_{part.1} \cdot K_{part.2} \cdot \ldots \cdot K_{part.r}}, \tag{3}$$

where $K_{part} = \sqrt[n]{k_1 \cdot k_2 \cdot \ldots \cdot k_n}$, n is the number of indicators included in a certain group indicator.

The second technique [14] also uses a hierarchical analysis scheme. At the stage of calculation of the group indicator from the obtained normalized indicators it is suggested to use the formula:

$$K_{part} = \sqrt[n]{\prod(1+k_n)} - 1. \tag{4}$$

Next, the radial diagram of regional competitiveness is being constructed according to the group indicators. The total area of the sectors of the chart will determine the integral index of the region's competitiveness and will be calculated according to the following formula:

$$I_i = \frac{1}{2}\sin\frac{360}{r}\sum_{r=1} K_{part_{ir}} K_{part_{ir+1}}, \tag{5}$$

where I_i - the integral index of the region i; r - the number of groups of indicators or the number of calculated integral indicators for each of the groups of indicators.

The third method [37] for the valuation of indicators offers the following formulas: for indicator-stimulants:

$$k_{ij} = \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}}, \tag{6}$$

for indicators-distimulants:

$$k_{ij} = \frac{X_{\max} - X_{ij}}{X_{\max} - X_{\min}}, \tag{7}$$

where X_{ij} - the value of the indicator in the region i; $X_{\max}$ - the maximum value of the indicator j for all regions; $X_{\min}$ - the minimum value of indicator j for all regions.

Then the value of the factor weight is calculated. This procedure consists of three consecutive steps: calculation of the product of the factor load $|f|_k$ and the share of the total dispersion d_k that it explains; calculation of the sum of the received products of all factors and calculation of each factor contribution to the specified amount, that is, the actual weight of the factor in the general model:

$$W_k = \frac{q_k}{\sum_{k=1} q_k}. \tag{8}$$

The next stage is the calculation of aggregate indicators I_{jl}, characterizing certain aspects of economic development and the calculation of the integral index of economic development by the following formulas:

$$I_{jl} = \sum_{i=1}^{n} k_{ij} W_i, \tag{9}$$

$$I_{ej} = \sum_{l=1}^{r} I_{jl} W_l, \tag{10}$$

where k_{ij} is the normalized indicator i of the economic development block l in the region j; W_i is the weight of indicator i in the aggregate indicator of the block l; n is the number of indicators for economic development estimation; W_l is the weight of the block l in the integral index of economic development.

In [7, 10, 14] for clusterization of regions by integral indicators, it is proposed to determine the number of groups by the Störges formula:

$$N = 1 + 3{,}322 \lg m, \tag{11}$$

where m is the number of regions under consideration.

At the same time grouping is calculated by the formula:

$$h = \frac{I_{\max} - I_{\min}}{N}, \tag{12}$$

where $I_{\max}$ is the maximum of integral indicators; $I_{\min}$ is the minimum of integral indicators.

A powerful alternative clustering method is the use of Kohonen's neural networks (Kohonen self-organizing maps – SOM) [20-36]. It is the most well-known unsupervised neural network approach to clustering [26]. Its advantage over traditional clustering technique is improved visualization capabilities. SOMs find a mapping from high dimensional input space into the feature space of reduced dimension and make possible visualization in reduced dimensionality.

On the initial stage of SOM learning algorithm we should set the weights to small random values, the initial neighborhood size $N_m(0)$ and the values of parameter function $\alpha(t)$ and $\sigma^2(t)$ (between 0 and 1). The steps of algorithms are as follows [26].

STEP 1: Randomly select an input pattern x to present to the SOM through the input layer.

STEP 2: Calculate the similarity (distance) between this input and the weights of each neuron j:

$$d_j = \left\| x - w_j \right\| = \sqrt{\sum_{i=1}^{n} \left(x_i - w_{ji} \right)^2}. \tag{13}$$

STEP 3: Select the neuron with minimum distance as the winner m

STEP 4: Update the weights connecting the input layer to the winning neuron and its neighboring neurons according to the learning rule:

$$w_{ji}(t+1) = w_{ji}(t) + c\left[x_i - w_{ji}(t) \right], \tag{14}$$

where $c = \alpha(t) \exp\left(-\left\| r_i - r_m \right\| / \sigma^2(t) \right)$ for all neuron j in $N_m(t)$

STEP 5: Continue from STEP1 for Ω epochs; the decreased neighborhood size, $\alpha(t)$ and $\sigma^2(t)$: Repeat until weights have stabilized.

The Ward clustering in general is hierarchical agglomerative clustering algorithm [27, 28]. On the initial stage of clustering each node is defined as a cluster itself. At each next stage two clusters with minimum distance between them are combined in one new cluster. This distance is called Ward distance and defined as follows:

$$d_{rs} = \frac{n_r n_s}{(n_r + n_s)} \left\| \overline{x}_r - \overline{x}_s \right\|^2 , \tag{15}$$

where r and s denote two specific clusters, n_r and n_s are the number of data points in the two clusters, and $\overline{x}_r$ and $\overline{x}_s$ denote the centers of gravity of the clusters; $\|.\|$ is the Euclidean norm. Starting from the full distance matrix (lower triangle matrix as the distance measure is commutative), at every step a row and a column is stripped (and a different row and column is updated) until the matrix is completely cleared and only one cluster remains. The mean and cardinality of the new cluster built as product of the combining step is as follows:

$$x_r^{(new)} = \frac{n_r \overline{x}_r + n_s \overline{x}_s}{n_r + n_s}, \tag{16}$$

$$n_r^{(new)} = n_r + n_s . \tag{17}$$

The SOM-Ward clustering approach is a two-level clustering approach which combines the standard Ward's algorithm to determine the SOM and clustering results. Ward clustering algorithm as agglomerative hierarchical algorithm have the following steps [29]:

1. Initialize: assign each vector to its own cluster.
2. Compute distances between all clusters.
3. Merge the two clusters that are the closest to each other.
4. Return to step (2) until there is only one cluster left.

As a specialty, the distance matrix is initialized in a manner that takes into account the number of data records matching to the nodes of the map. Nodes with many matching data records are weighted stronger than nodes with fewer matching records. As distance measure we have to use a modified Ward distance

$$d_{rs} = \begin{cases} 0 \quad if \quad n_r = n_s = 0, \\ \dfrac{n_r n_s}{n_r + n_s} \left\| \overline{x}_r - \overline{x}_s \right\|^2 \quad otherwise. \end{cases} \tag{18}$$

While determining the distance, both the Ward distance and the topological properties of SOM are taken into account. In other words, the distance between two nonassociated clusters is considered as infinite and only the associated clusters are combined. Low SOM-Ward distance value represents a more natural clustering for the map, and high value represents an artificial clustering for the map. By this means, users can select the optimal cluster number in a flexible manner [30].

For the SOM-Ward clustering the distance is redefined as

$$d'_{rs} = \begin{cases} d_{rs} \quad if \ clusters\ r\ and\ s\ are\ adjacent\ in\ the\ SOM, \\ \infty \quad otherwise. \end{cases} \tag{19}$$

The modified SOM-Ward clustering algorithm combines a method of displaying data using self-organizing maps with a classical hierarchical Ward clustering algorithm [31, 32]. This method offers its own clustered indicator, which defines the reasonable number of clusters into which the input sample is broken [33].

4 Research results

The statistical data of 24 regions (excluding Kyiv) for the period 2010-2016 [37] is used for estimation of the productive potential of the regions. Results of ranking of regions by integral indicator of production potential are presented in Table 1. The calculations were carried out according to three methods mentioned above. Method 1 is described by formulas (1) – (3), method 2 – formulas (1), (2), (4), (5) and method 3 – formulas (8) – (10). For the convenience of the user, the methods were implemented in the EXCEL environment. The clustering algorithm and the variance analysis are implemented in EXCEL and SOMine. The ratings that adduced for comparison are based on the results of the regions in 2010, 2013 and 2016.

Table 1. Places of regions of Ukraine in the ranking on the level of production potential

Regions	The first method			The second method			The third method		
	2010	2013	2016	2010	2013	2016	2010	2013	2016
Vinnytsia	11	9	7	10	8	8	12	11	9
Volyn	21	20	18	22	19	18	21	20	18
Dnipropetrovsk	1	1	1	1	2	1	2	2	1
Donetsk	2	2	5	2	1	6	1	1	2
Zhytomyr	17	17	15	18	18	17	18	17	15
Zakarpattia	23	23	23	23	23	23	22	23	23
Zaporizhia	5	7	6	4	10	7	3	4	4
Ivano-Frankivsk	13	14	16	13	14	15	13	14	14
Kiev	3	3	2	3	3	2	6	5	5
Kirovohrad	19	16	14	15	15	13	19	16	16
Luhansk	7	6	22	9	6	22	4	6	21
Lviv	9	8	8	8	9	5	9	8	7
Mykolaiv	12	12	11	12	12	11	11	12	10
Odessa	8	10	10	7	7	9	8	10	11
Poltava	4	4	4	5	4	4	5	3	3
Rivne	18	19	20	21	21	21	17	19	17
Sumy	15	15	13	16	16	14	14	13	13
Ternopil	22	22	21	20	20	20	23	22	22
Kharkiv	6	5	3	6	5	3	7	7	6
Kherson	20	21	19	19	22	19	20	21	20
Khmelnytskyi	14	13	12	14	13	12	15	15	12
Cherkasy	10	11	9	11	11	10	10	9	8

Chernivtsi	24	24	24	24	24	24	24	24	24
Chernihiv	16	18	17	17	17	16	16	18	19

From Table 1 it follows that the use of different techniques gives close results for leaders and outsiders ranking. Donetsk and Dnipropetrovsk regions occupied the first and second places in the level of production potential in 2010 and 2013, and Dnipropetrovsk region is also the leader in 2016. As for the Donetsk region, it dropped to 5-6 places by the results of the use of the first and second methodology. Donetsk region remained in second place for the third method. But according to all approaches, the value of productive potential level of this region has significantly decreased compared with 2013 and 2010. This is not surprising given the situation in the east of the country. The worst indicators for all years showed the Chernivtsi region (24th place) and the Zakarpattia region (23). Over the researched period, the following regions improved their results: Vinnytsia, Kiev, Lviv, Poltava, Mykolaiv, Kharkiv, Cherkasy. As well as minor but positive changes have taken place in the Volyn, Zhytomyr, Kirovohrad, Sumy and Khmelnytskyi regions.

There were 5 clusters allocated for 24 regions using the Störges formula. In Table 2 shows the clustering of regions of Ukraine by the level of production potential in 2016 for each of the three methods.

It should be noted that for regions with average values of integral indicators, calculated according to different approaches, there are significant differences in the distribution of regions by clusters and their mutual ordering. The Kohonen neural network was used to verify the results and identify stable homogeneous groups of regions.

Table 2. Clusterization of the regions of Ukraine by the level of production potential in 2016

Level of competitive	The first method	The second method	The third method
MAXIMUM	Dnipropetrovsk (1)	Dnipropetrovsk (1)	Dnipropetrovsk (1)
HIGH	Kiev (2)	Kiev (2)	-
MODERATE	Kharkiv (3) Poltava (4) Donetsk (5)	-	Donetsk (2) Poltava (3) Zaporizhia (4) Kiev (5) Kharkiv (6)
MEDIUM	Zaporizhia (6) Vinnytsia (7) Lviv (8) Cherkasy (9) Odessa (10) Mykolaiv (11) Khmelnytskyi (12)	Kharkiv (3) Poltava (4) Lviv (5)	Lviv (7) Cherkasy (8) Vinnytsia (9) Mykolaiv (10)

LOW	Sumy (13) Kirovohrad (14) Zhytomyr (15) Ivano-Frankivsk (16) Chernihiv (17) Volyn (18) Kherson (19) Rivne (20) Ternopil (21) Luhansk (22) Zakarpattia (23) Chernivtsi (24)	Donetsk (6) Zaporizhia (7) Vinnytsia (8) Odessa (9) Cherkasy (10) Mykolaiv (11) Khmelnytskyi (12) Kirovohrad (13) Sumy (14) Ivano-Frankivsk (15) Chernihiv (16) Zhytomyr (17) Volyn (18) Kherson (19) Ternopil (20) Rivne (21) Luhansk (22) Zakarpattia (23) Chernivtsi (24)	Odessa (11) Khmelnytskyi (12) Sumy (13) Ivano-Frankivsk (14) Zhytomyr (15) Kirovohrad (16) Rivne (17) Volyn (18) Chernihiv (19) Kherson (20) Luhansk (21) Ternopil (22) Zakarpattia (23) Chernivtsi (24)

Calculations were made according to the statistics of 2016. The same indicators as in previous methods were considered. The SOM-Ward method performed clustering of input data and calculated the clustered indicator [34] for each of the possible cluster numbers (see Fig. 1).

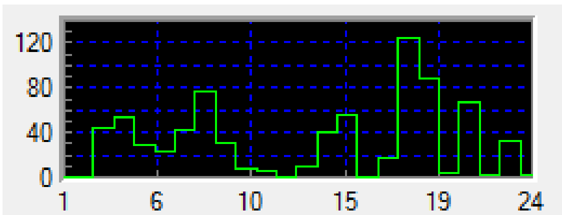

Fig. 1. Cluster indicator diagram

The horizontal axis of the diagram indicates the number of clusters, the vertical axis shows the indicator value for each cluster system. The diagram can be interpreted as follows: if the indicator value is high for a particular cluster system, then clustering can be considered as "natural" for the constructed map. Accordingly, when the indicator value is low for some cluster system, clustering is "artificial." Consequently, the peaks of the clustered indicator graph represent true clustering.

According to calculations, the largest indicator corresponds to 18 clusters, the next maximum is 8 clusters. But, given that the number of investigated objects is 24, it is expedient to group the regions into the 8 clusters. Fig. 2 shows the division of regions into 8 groups by the level of production potential in 2016. In brackets, under the name of the region, the average place in the ranking is indicated by the results of previous calculations. Note that the regions-leaders tend to the left side of the map, and outsiders tend to the right side of the map. The division of regions into five groups (Fig. 3), which was proposed earlier, is considered in parallel, in order to compare the results. It should be noted that the indicator for such a number of clusters was very low, clustering in five groups is artificial and not entirely correct.

The adequacy of the constructed clusterization models was verified using a dispersion analysis. For each investigated indicator, the intergroup and intragroup components of the variance were calculated and the hypothesis of their significant difference was checked. The results of the calculations confirmed the quality of clustering at the level of significance of 5% (Table 3).

Table 3. Results of the dispersion analysis

Indicator	Intergroup variance	Dispersion inside the cluster	F	p
Gross crop production	1,65	0,21	66,44	0,00009
Gross livestock production	0,74	0,04	151,75	0,00001
Volume of sold industrial products (works, services)	0,53	0,04	107,08	0,00003
Volume of sold industrial products (works, services), share of the region	0,50	0,04	101,75	0,00003
Volume of sold industrial products (works, services) per person	0,15	0,18	7,29	0,01728
Capital investments	0,16	0,22	6,11	0,02551

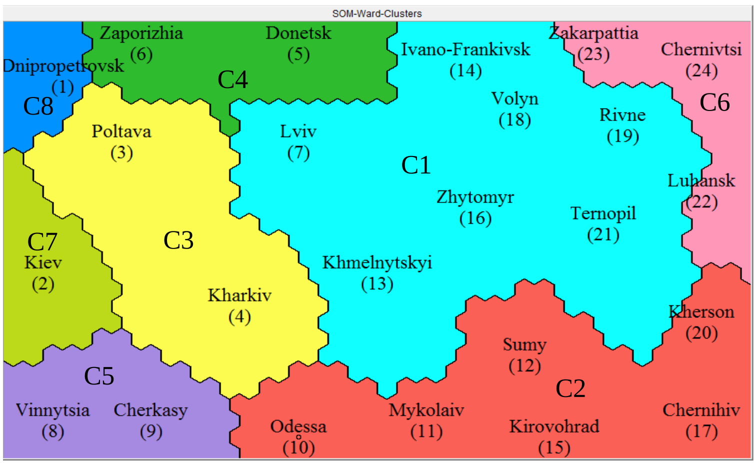

Fig. 2. Distribution of regions into 8 groups by level of productive potential (year 2016).

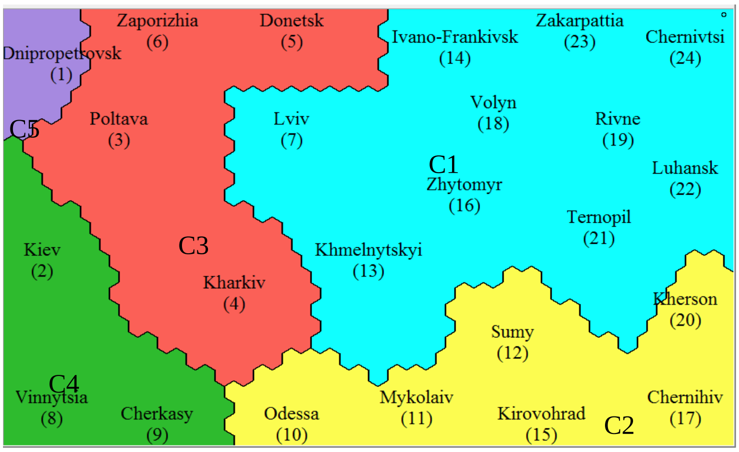

Fig. 3. Distribution of regions into 5 groups by level of productive potential (year 2016).

Fig. 4 presents a profile of contributions of indicators in the formation of 8 clusters (the contributions of indicators are arranged from the bottom up according to their ordering in the performed calculations out and marked with different colors).

The Dnipropetrovsk region is in the first place with the highest value of the integral indicator and is isolated in the C8 cluster. All cluster metrics are at levels above the average significantly. The next cluster (C7) consists of the Kiev region, which has somewhat lower levels of indicators.

Vinnytsia (8) and Cherkasy (9) are in the same cluster (C5), which is characterized by a very high level of gross livestock production and gross crop production. One can note that on Fig. 3 Kiev, Vinnytsia and Cherkasy regions form one of the 5 clusters. However, Kiev region is significantly different from the other two regions by the level of capital investment, therefore, its allocation to a separate cluster is justified.

Poltava (3) and Kharkiv (4) regions from the C3 cluster have the values of indicators that are higher significantly than the average level. Also, the following cluster C4 consists of two regions: Zaporizhia (6) and Donetsk (5) regions. In Fig. 3 all four regions form one cluster. However, the C4 cluster, unlike C3, includes regions whose agricultural production indicators are lower significantly than the average level. Odessa (10), Mykolaiv (11), Sumy (12), Kirovohrad (15), Chernihiv (17) and Kherson (20) form the C2 cluster (Fig. 2) and the C3 cluster (Fig. 3). All indicators of these regions are lower than the average level, except of gross crop production indicator.

The C1 cluster includes Lviv (7), Ivano-Frankivsk (14), Khmelnytskyi (13), Zhytomyr (16), Volyn (18), Rivne (19), Ternopil (21) regions. All indicators of this group of regions are at a level that is significantly lower than the average. The C6 cluster is characterized by the largest deviation in the negative side of all studied indicators and includes the following areas: Luhansk (22), Zakarpattia (23), Chernivtsi (24). Note that in Fig. 3 clusters C1 and C6 have been united into one cluster. Separating the last three regions into a separate group is logical and reasonable.

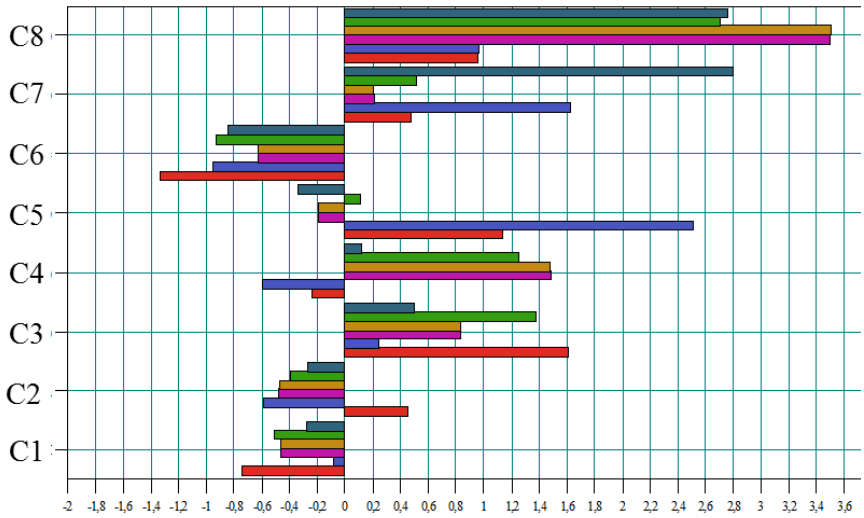

Fig. 4. Profile of contributions to the formation of 8 clusters.

At the next step Kohonen maps are built without taking into account the six regions that have ranked as the leaders. That is done in order to improve the results of conducted clustering and the allocation of stable homogeneous groups. This approach allows to reveal structural features of the aggregate of regions with average values of integral indicators.

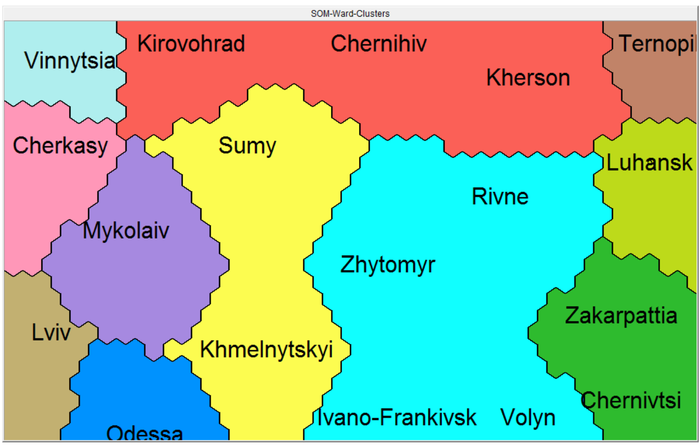

Fig. 5. Distribution of regions into 11 groups by level of productive potential (year 2016)

In Fig. 5 the distribution of regions into 11 clusters is presented and new groups are allocated. The proximity of following regions is detected: Sumy and Khmelnytskyi; Zhytomyr, Rivne, Ivano-Frankivsk, Volyn; Kirovohrad, Chernihiv, Kherson. It should take into account the location of the region on the map, compared with its neighbors, proximity to the leaders or outsiders of the rating.

During clustering using the Kohonen network, it was discovered that distribution into five clusters does not allow to make qualitative grouping and ranking of regions. Note that the rating estimation of the region did not always coincide with the location of the region itself on the map in terms of ratings of the closest neighbors by cluster. Therefore, there are grounds for improvement and modification of the proposed algorithms for determining the competitiveness of regions, taking into account the possibility of the Kohonen neural networks.

Also, it should be noted that the city of Kiev was not included in the list of studied regions. If we take into account the indicators of the city of Kiev, this will greatly complicate the processes of ranking and clustering, because most regions have low rates compared to the city of Kiev. Therefore it is expedient to compare the indicators of the city of Kiev with the indicators of areas with the highest level of production potential.

5 Conclusion

By means of various methodological approaches, the level of Ukraine's regions production potential was assessed by taking into account the industrial, agricultural and investment potential of the regions in different time moments. Further clustering of the studied regions was accomplished with the Kohonen neural maps. Using Kohonen maps with simultaneous database clustering made it possible to design multidimensional data in two-dimensional space, visually analyze the obtained cluster system and improve the results of clustering by choosing the optimal number of distribution groups. The number of clusters calculated according to the statistical approach was artificial. The construction of the Kohonen map allowed to improve the situation and select a reasonable number of clusters.

Note that the rating estimation of the region did not always coincide with the location of the region itself on the map in terms of ratings of the closest neighbors by cluster. This is due to the fact that the whole database and the nonlinear model of clustering were used in constructing the map and conducting clustering, in contrast to the methods for calculating total integral indicators and even grouping. A convenient form of visualization of the results of clustering allows to localize the features and make appropriate adjustments to the rating lists based on expert considerations.

During the research period, the growth of all indicators in most areas was observed, and therefore the value of the integral index of production potential improved year after year. But this tendency is not typical for all regions of Ukraine. The presence of significant regional differences in development requires the introduction of an effective arrangement for implementing the regional policy of Ukraine.

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