UDC 338.2

O. A. Romanova, D. V. Sirotin
Institute of Economics of the Ural Branch of RAS (Ekaterinburg, Russian Federation; e-mail: econ@uran.ru)

A DESIRED FUTURE IMAGE FOR THE ECONOMY OF INDUSTRIAL REGION: DEVELOPMENT TRENDS AND ASSESSMENT METHODOLOGY

The article highlights the essential role belonging to the industrial regions in addressing the task of increasing the technological independence of Russia. It demonstrates that the declining share of manufacturing industries in the structure of GRP cannot be interpreted as a negative de-industrialization of the economy. The article substantiated the observation that increasingly rapid changes, growing instability of socio-economic systems, and multiple risks predetermine the need to develop new methodological approaches to predictive studies. It emphasizes the high importance of research related to the development of technology for designing the desired future image and the methodology to assess it. As the initial stage of these studies, the authors proposed the methodological approach to assessing the desired future image of metallurgy, one of the most important specialization sectors in the industrial region. They proposed the concept of "technological image of the metallurgical complex of the region." The article shows that the process of repositioning the image of the regional metallurgical complex from the present to the desired future is fairly long, which predetermined the need to identify the repositioning stages. The proposed methodology for assessing the desired future image includes methodological provisions developed for quantifying the goals achieved at the relevant stages of repositioning the metallurgical complex. The methodological approach to the formation of desired future image is based on the sequential implementation of the following stages: using bibliometric and patent analysis to identify the priority areas of technological development of the metallurgical complex of the region; using the comparative analysis and relevant analytical methods to assess the dynamics and prepare the forecast on the development of the structure in the domestic consumer sector of metal products; using principal component method to build the factor model allowing to identify the parameters for quantitative description of technological image of the regional metallurgical complex; systematizing the forecast values of parameters defining the stages of repositioning and formation of the new technological image of regional metallurgical complex; using the methods of neural network modeling to build a mathematical model for recognizing the technological image of regional metallurgical complex.

Keywords: industrial region, deindustrialization, future image, repositioning, technological image of regional metallurgical complex, assessment methodology, forecasting, principal component method, regression analysis, neural network modeling

Introduction

The ambitious goal of achieving the technological parity with the most developed countries by 2035 is increasingly shifting towards achieving the technological independence of the Russian economy. This not only involves ensuring a qualitative renewal for the technological basis of material production, but also makes relevant the task of creating a qualitatively new technological base for the manufacturing industry. In Russia, it is impossible to address this task without the active participation of industrial regions, where the industry is the basic component of the economy, and its competitiveness depends not only on the development and application of high technology, but also on the quality of human capital capable of implementing such technology.

A correct assessment of the industrial capacity of the regions requires to consider both internal and external factors that determine the potential dynamics of industrial development. Currently, there are three technological systems that exist side by side in the industrialized regions. One of them was established as early as at the time of the Soviet Union, but it underwent serious modernization in the current period and continues to cover a significant share of demand for industrial products. The second was created on the basis of numerous foreign technologies imported to Russia back in the 2000s. This system is successfully operating today, and its manufactured products are quite competitive not only on the Russian market, but also on the global market. The third technological system is based on a few completely Russian-made designs, developed primarily in the defense industry sector, but their high level meets the requirements of the Sixth Techno-Economic Paradigm. In 2014–2016, the development of the scientific and technological capacity of Russia and its industrial regions begins to become systemic. The forced development of import substitution projects contributed to the implementation of effective projects that trigger the emergence of not only new production chains, but also research chains embedded into them.

Typology of Industrial Regions

There are numerous studies on the typology of industrial regions of Russia, which assess their industrial, production, scientific, and technological capacity. For example, the industrial capacity of the region is viewed as the possibility, capability, and real conditions of a certain output as a result of using the interconnected limited resources [1, P. 107]. The model of industrial potential of a country's regions implies the ranking of its factors in the descending order of their importance—the average annual number of employees in the economy, average monthly nominal accrued wages of workers, average annual residual value of annual funds, costs of technological innovation of economic entities [1].

The production capacity is viewed as "the potential output at fixed volumes of the main production factors amid the random input of concurrent production factors, as well as uncertainty factors" [2]. The models of production capacity of Russian regions take into account the assessments of intellectual capital. The use of these models demonstrated that the characteristics of well-being and quality of life of the population have a significant impact on the efficiency of regional production.

There are various typologies of industrial regions, for example, those based on GRP and labor productivity criteria [3]. Another known typology is based on such criteria as the share of manufacturing industries in the GRP of the relevant subjects of the Russian Federation. This share should be no less than 25 % [4]. This approach appears to be quite convincing for establishing the fact of the industrial profile of the territory. However, the use of this criterion to describe not just the processes of industrial development, but the processes that characterize the new industrialization or deindustrialization of the Russian economy, seems to be incorrect. In accordance with the above typology, the authors analyzed the development of industrial regions of Russia for the period of 2004–2012. The growing share of manufacturing industries in the GRP of the regions was a factor for referring them to the regions where are developing the processes of new industrialization.

One can also note the emergence of new industrial regions in Russia, that is, the subjects of the Russian Federation, where the share of manufacturing industries in GRP exceeded 25 % in the reviewed period. There are traditionally industrial regions which, during this period, lost their industrial status, that is, the share of manufacturing industries in the GRP of the subject of the Russian Federation dropped to less than 25 %. The authors have particularly noted a group of traditionally highly developed industrial regions which, during this period, have experienced a serious decline in the share of processing industries in their GRP. These regions include, for example, Lipetsk Region, Krasnoyarsk Krai, Omsk Region, Chelyabinsk Region, Vologda Region, Samara Region, Sverdlovsk Region, and other regions. In these regions, the share of manufacturing in the GRP of the relevant subjects of the Russian Federation has not dropped below 25 %. However, this group of regions is defined as regions with the development of negative deindustrialization processes. This conclusion seems rather controversial. We ranked the subjects of the Russian Federation where, in the period of 2004–2012, the share of manufacturing industries in the GRP exceeded 25 %, under the same criterion but according to the data for 2015 (Table 1).

It should be noted that, in many regions of the Russian Federation, there is a sharp change in the ranking by the share of manufacturing industries in GRP. For example, the rank of Kaluga Region decreased from the 1st in 2012 to 9th in 2015; for the Republic of Bashkortostan, respectively, from the 3rd to the 15th. But, for example, Lipetsk Region, referred to the areas with negative deindustrialization, not only increased its ranking, but also became the leader by the above-mentioned criterion (8th rank in 2012; 1st rank in 2015). The absence of a vector pointing in one direction is shown in Fig. 1.

However, even if this share dropped below 25 % limit, we believe that it would be incorrect to claim that negative deindustrialization processes are developing in these regions. Processes of deindustrialization cannot be described only by one indicator, such as the share of industry or even the share of manufacturing industries in the GRP of the region. To describe the phenomenon of deindustrialization, it is important to analyze a wider range of indicators. We share the position of S.D. Bodrunov, E. B. Lenchuk, and other researchers who are considering the processes of deindustrialization from a broader perspective [5–7]. In our view, the processes of deindustrialization can be identified only on the basis of a comprehensive assessment which, in addition to the share of processing industries in

Table 1

Ranking of Industrial Regions of Russia by Share of Manufacturing Industries in their GRP in 2004, 2012, 2015*

Subject of the Russian Federation	2004		2012		2015	
	%	ranking	%	ranking	%	ranking
Lipetsk Region	63.34	1	32.30	8	40.58	1
Tula Region	33.77	8	33.32	7	39.96	2
Vologda Region	45.48	4	36.24	4	38.90	3
Novgorod Region	33.03	10	36.13	5	36.43	4
Omsk Region	52.94	2	37.72	2	36.06	5
Chelyabinsk Region	45.15	5	35.83	6	35.75	6
Krasnoyarsk Krai	47.77	3	29.70	13	33.46	7
Vladimir Region	33.37	9	30.49	10	32.48	8
Kaluga Region	28.46	15	39.90	1	32.04	9
Nizhny Novgorod Region	31.81	13	30.08	11	30.66	10
Sverdlovsk Region	35.01	7	27.09	14	30.43	11
Perm Krai	24.88	17	31.05	9	29.52	12
Leningrad Region	31.89	12	22.89	20	29.45	13
Kirov Region	22.28	19	25.55	18	29.36	14
Republic of Bashkortostan	29.47	14	37.26	3	28.87	15
Ryazan Region	23.57	18	25.69	17	28.70	16
Republic of Mari El	20.79	20	29.72	12	28.21	17
Ulyanovsk Region	25.67	16	22.10	21	26.02	18
Yaroslavl Region	36.62	6	26.47	16	26.00	19
Samara Region	32.26	11	25.31	19	23.94	20
Volgograd Region	20.69	21	26.69	15	23.51	21

* Prepared by the authors in accordance with the data of Rosstat.

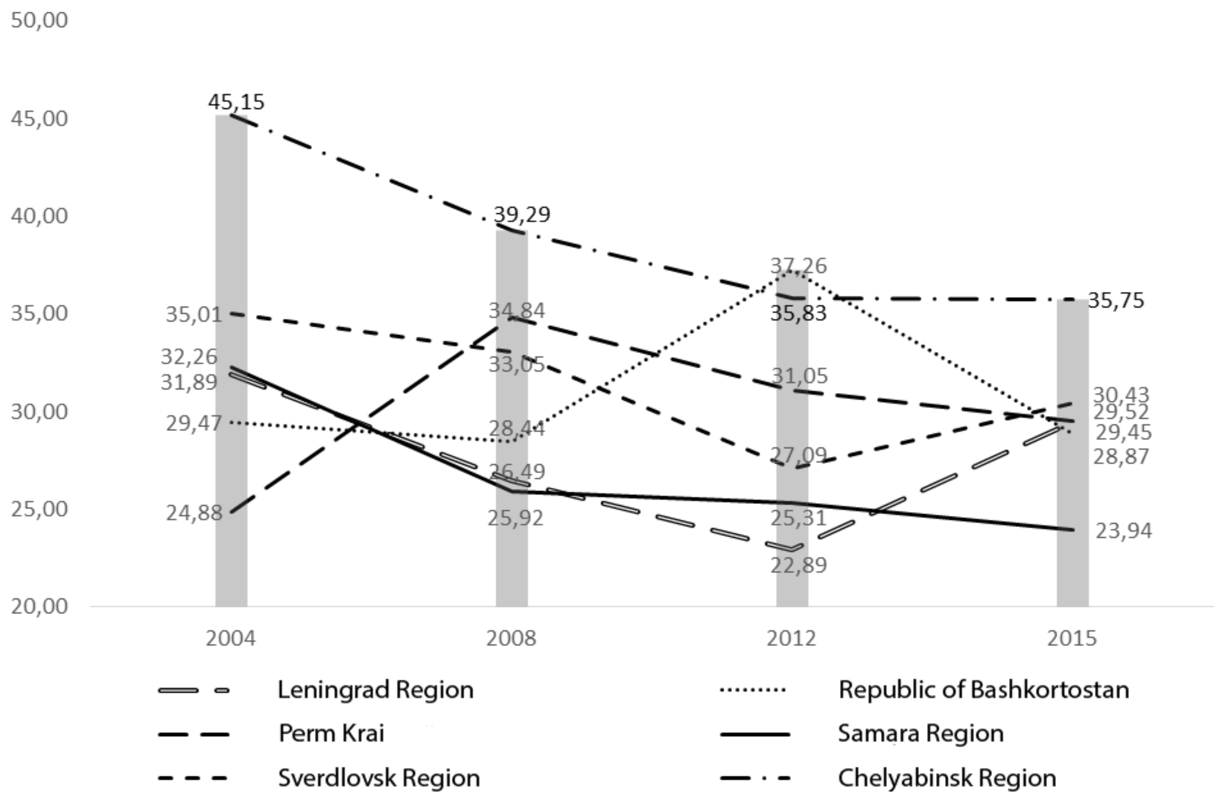

Fig. 1. *The change in the share of manufacturing activities in the GRP of some industrial regions of Russia, %*

the GRP of the region, should include changes in the organization of production, quality and nature of labor, technological characteristics of production, and changing quality parameters of the output.

From this standpoint, it would be inappropriate to identify the process of deindustrialization, for example, in such industrialized area as Sverdlovsk Region, although the share of manufacturing industries in the GRP of the region has declined from 35.1 % in 2004 to 27.1 % in 2012. Simultaneously with the change in the dynamics of the above indicator, it is necessary to find out what processes accompanied this change. For example, there were significant progressive changes in the technological development of the metallurgy, the leading industry in the Middle Urals. The industry completely eliminated the production facilities that are typical for the Third Techno-Economic Paradigm (for example, open-hearth steelmaking); the output of electric furnace steel was growing at the highest pace, which describes the development of production facilities in the Fifth Techno-Economic Paradigm; there is further development of the so-called “white metallurgy,” which ensures not only the environmentally friendly manufacturing, but also the uses highly skilled human resources. These processes are directly opposite to processes which, in our opinion, describe the de-industrialization of production. Its significant negative effects include the simplification of labor and used technologies, reduction in the science intensity of production, destruction of production teams, i.e., it causes significant negative effects in the social sphere [8–11]. Therefore, the current situation in Sverdlovsk Region and, in particular, in metallurgy, its leading industry, cannot be described as deindustrialization, because the technological level of production, quality of manufactured metal products, qualitative and qualification structure of the labor force, trends in improving the environmental situation—all this indicates the improvement in the scientific and technological level of production and improvement in the quality of the labor force. We can also be noted that as early as in 2015, the share of manufacturing industries in the GRP structure in the Middle Urals has increased to 30.43 % compared to 27.1 % in 2012.

Methodological Approach to Assessing the Desired Future Image

The unstable vector orientation of regional development is a specific characteristic of the modern economy at all its hierarchical levels. A high degree of uncertainty, increase in the pace of change, growing instability of socio-economic systems, multiple risks, not only economic but also political ones, allow to describe the contemporary period as “the era of weak ties,” “risk society,” and “liquid modernity” [12, 13, P. 44].

The multiple challenges of current times predetermine the need to develop new methodological approaches to predictive studies. The problems of forecasting methodology are largely concentrated in the procedures for identifying the most substantial processes and establishing links between them. At this point, the problem of interpreting past processes that have determined the present results, remains unresolved. But today’s knowledge is always incomplete in relation to the processes of the future. There is a well-known statement by N. Taleb that mankind is not capable of successfully predicting its future, since its inherent confidence in its knowledge is ahead of the knowledge itself[1]. Yet the problem of foreseeing the future on the basis of often alternative methodological approaches requires to actively develop the research in this field.

A promising solution to address the above difficulties is provided by the use of interdisciplinary approach as the basis of forecasting methodology. It is known that the same process can be interpreted differently under different methodological approaches. But a simple mechanical combination of results obtained on the basis of different approaches is unproductive. It is obvious that the future in forecasting is associated with the transition to the multilateral interaction of various methodological solutions that facilitate the emergence of synergy [13, P. 47, 50]. At the same time, the successful development of interdisciplinary approach as the basis for economic forecasting is associated not only with the interdependence of socio-economic processes, but also with the development of a dialog between the experts of different disciplines.

Such dialog is especially necessary in the process of elaborating the desired future image of the regional economy. Unfortunately, the contemporary documents of strategic nature do not include any technology for designing the future. It is this technology that should become one of the defining spheres of strategic analysis and conceptual and strategic planning, as it was emphasized in the

[1] Taleb, N. N. (2007, April 22). The Black Swan: The Impact of the Highly Improbable. The New York Times, 401.

National Technology Initiative. It mentioned the need to plan the work based on the future outcome by going from the so-called “preferred reality” to the present. Some publications also emphasize the need for not only generating the agreed long-term goals for the development of the Russian economy, but also for building its “future image” [14, P. 18].

When building a sequence of actions to design the criteria for preferred future image, which in our case is the image of the future of industrial region’s economy, the existing documents of strategic nature, as well as the models for the development of production or industrial capacity of the regions, do not allow to use the toolkit that has been already developed.

Within the framework of this technology, it is necessary to design the defining criteria for the image of the future of the regional economy, which appears to be the most desirable. It should be in line with the global trends of technological development and take into account the characteristics of national and regional development. The trends that we identified earlier in the global technological development, and trends in the development of industrial region based on the case of economy in the Sverdlovsk region, were presented in a number of publications [15–17].

However, the problem of developing the methodological approach to the assessment of technological image of the economy in the industrial region so far remains unresolved. As the initial stage, the authors built the methodological approach to assessing the desired future image of metallurgy, one of the most important specialization sectors in the Middle Urals.

Methodology for Assessing the Stage-By-Stage Change in the Technological Image of Regional Metallurgical Complex

When building a methodology for assessing the technological image of the desired future, it is necessary to define the concept of “technological image of the metallurgical complex of the region.” We consider the desired technological image of the regional metallurgical complex (RMC) as an intricate mental image of metallurgy as it is perceived by the society and characterized by the progressiveness of its technological structure, high level of efficiency, science intensity, environmental friendliness, and organization of production, continuously developing key personnel competencies and a developed consumer market for high-tech metal products.

Today, the technological image of metallurgy in Sverdlovsk Region is characterized by the existence of large-tonnage, environmentally burdensome production facilities with a predominance of metal products manufactured at the low processing stage. The process of distinctive repositioning of the image of the regional metallurgical complex from the present to desired future is fairly long. It can be viewed as a stage-by-stage process of interdependent technological, economic, social, institutional, ecological, and organizational transformations made on an innovative basis which, after meeting the criteria for the best available technologies and implementing the principles of green economy, build the image of the desired future of the regional metallurgical complex [16, P. 31].

It is practical to consider this process by individual stages of its development. We formulated a hypothesis in accordance with which the stages of RMC repositioning can be described by forecast assessments that correspond to the growth vector and do not contradict the condition for accumulating the experience, that is, having the experience of the previous stage in order to make the transition to a higher level. The best practices in the development of metallurgical production facilities, individual indicators of development strategies for Russian and foreign metallurgy, strategic documents for the development of metallurgy in the Ural Federal District and Sverdlovsk Region can serve as the forecast base.

When building the methodology for assessing the desired future image, it is practical to consider the possibilities of solving the image recognition problems. They are built, primarily, on the basis of classification methods, the application of which requires preliminary data processing, identifying a set of characteristics, and compressing the analysis data. One of the hardest tasks in developing the recognition systems is to ensure a high-quality classification by a set of characteristics [18]. In this regard, the optimal recognition system should be built based on a clear description of characteristics, the possible values of the assessment of which should be achievable by the subject matter of the study.

Overall, the methodology for assessing the change in the technological image of RMC is based on the system analysis, system of principles and methods for organizing scientific and technological activities in the area of development of metallurgical production. Building such methodology predetermined the need to develop a number of methodological provisions for quantitative characterization of the goals to be achieved at the relevant stages of repositioning of the metallurgical complex.

The preliminary stage of study included the analysis of results obtained during Foresight conducted by the Institute of Economics of the Ural Branch of the Russian Academy of Sciences together with the Institute of Metallurgy (IMET) of the Ural Branch of the Russian Academy of Sciences with the participation of authorities and representatives of entities of the metallurgical industry in the region. The analysis allowed to assess the accumulated potential of the regional metallurgical complex, its strengths and weaknesses, as well as possible threats and advantages of its development amid the new industrialization vector [19].

The developed methodology involves the consistent implementation of six stages:

— Using bibliometric and patent analysis to identify the priority areas of technological development of the metallurgical complex of the region;

— Using the comparative analysis and relevant analytical methods to assess the dynamics and prepare the forecast on the development of the structure in the domestic consumer sector of metal products;

— Using principal component method to build the factor model allowing to identify the parameters for quantitative description of technological image of the regional metallurgical complex;

— Using the methods of correlation and regression analysis to bring the function of principal components to non-linear form in order to improve the quality of the forecast models describing the technological image of the regional metallurgical complex;

— Using the methods of system and comparative analysis to systematize the forecast values of parameters defining the stages of repositioning and formation of the new technological image of regional metallurgical complex; and

— Using the methods of neural network modeling to build a mathematical model for recognizing the technological image of regional metallurgical complex and stages of its formation.

Goals and Methods for Assessing the Stages of Changes in Technological Image of Regional Metallurgy

Stage 1. In accordance with the developed methodology, it provides for the identification of key areas in the technological development of basic industries. This task involves the bibliometric modeling with the further study of regional patent activity.

The use of bibliometric methods in the course of the study is intended to identify the areas of knowledge that form the scientific basis of metallurgy in the structure of the Sixth Techno-Economic Paradigm, and assess the contribution of Russian science to their development. The case of bibliometric analysis in the metallurgical industry allowed to identify the materials and methods of manufacturing that are jointly used in the nanoindustry (as the defining discipline at the core of the Sixth Techno-Economic Paradigm) and metallurgy, and establish the speed of development in the identified areas.

In order to clarify the structural characteristics for identified prospective areas, the authors determined the relevant sections of International Patent Classification, which allowed to distribute them in accordance with the regulatory framework. The patent analysis established the points of intersection in the scientific base of studied activities. The authors identified secondary and main perspective areas for the development of metallurgy that have found support from the scientific disciplines which form the core of the Sixth Techno-Economic Paradigm. The proposed approach allowed to build a technological map for the global development of a scientific base of the metallurgical processes in the contemporary techno-economic paradigm, and also to establish a vector of scientific and technological development for Russian metallurgy.

Further research on the previously identified promising areas for the development of metallurgy was aimed at clarifying the regional affiliation of the patentee, year of granting the patent and the status of patent validity. Therefore, it was a complete analysis of scientific and technological potential of metallurgy in Sverdlovsk Region. The basis of the study was made by the patents for inventions, including materials, technical equipment and ways to improve the quality of steel. The analysis identified the prospective directions of technological development of metallurgy in the region, such as ladle treatment of molten steel; metal treatment under pressure, including in combination with heat treatment; application of various coating in the molten and solid state onto the metal surface; as well as the production of rare earth metals (Table 2).

Table 2

Patents granted for inventions in the perspective areas of metallurgy development, units*

Federal District	Year of Patent Publication										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Central	23	24	29	36	57	27	58	55	62	74	58
North-Western	8	8	5	4	12	4	13	13	6	16	17
Southern	1	1	3	2	2	3	3	3	2	1	6
North Caucasus	0	1	0	2	3	1	1	1	1	0	0
Volga	16	9	12	6	12	11	10	16	6	7	8
Ural including:	9	9	6	13	17	15	3	18	16	3	7
Sverdlovsk Region	2	5	4	3	6	3	1	6	7	3	5
Siberian	3	3	6	4	5	9	7	8	5	8	8
Far Eastern	2	1	0	0	1	0	0	1	2	0	1
Total for Russia	62	56	61	67	109	70	95	115	100	109	105

* Prepared by the authors based on the data from open registers of the Federal Institute of Industrial Property. [Electronic resource]. Available at: http://www1.fips.ru/wps/portal/Registers/.

The selected areas determine the boundaries of the technological base for the development of metallurgy that takes into account the requirements of the best available technologies. The dynamics of patents granted in the Russian Federation in the perspective areas of metallurgy development are in line with the global level. In recent years, the share of the Middle Urals has been growing in the structure of metallurgy of the Ural Federal District.

The results of the study allowed to identify and systematize the list of promising areas for the technological development of metallurgy in the Middle Urals.

Stage 2. It included the harmonization of identified areas of technological development of metallurgy with the data of the state program of the Russian Federation "Developing the Industry and Improving its Competitiveness for the Period until 2020"; "The Strategy for the Development of the Ferrous Metallurgy of Russia for 2014–2020 and for the Long-Term Period until 2030;" and the "Strategy for the Development of Mining and Metallurgical complex of Sverdlovsk Region for the Planning Period until 2020 and for the Long-Term Period until 2030." The systematization of the data included in the above materials, and analysis of investment projects in the relevant industries allowed to determine the structure of the domestic consumer market of high-tech metal products of RMC for the period until 2050. [20]

The results of studies allowed to build a vector for the development of metal product manufacturing, the direction of which is associated with the changes in the consumer market for high-tech metal products of RMC (Fig. 2).

To define the parameters describing the technological image of RMC, the authors built economic and mathematical models based on the methods of factor analysis.

Stage 3. The factor model is based on the principal component method. This method allows to reduce the scale of data, identify the relationship between the analyzed variables, and use them as the basis to build generalized integrated factors [21]. The conducted analysis allowed to build a list of indicators that have a substantial impact on the development of metallurgy [22–26] (Table 3).

The prepared parameters describing the technological image of the regional metallurgical complex meet the standard requirements for quantitative and qualitative analysis. To prepare the initial data, the authors normalized the variables by comparing their mean values and variance, and identified and eliminated the outliers. The correlation analysis revealed a close relationship between individual variables, and in some cases the correlation coefficients are negative. The computer processing of initial data by using Statistica application allowed to build a factor matrix, set the values of principal components, and define their utility. It is established that the first four principal components with a total variance greater than 85 % are significant in accordance with the Cattell criterion. The total variance following the factor matrix rotation by varimax method was distributed among the first four principal components in descending order as 39.9, 16.3, 15 % and 13.3 % (Table 4). All four principal

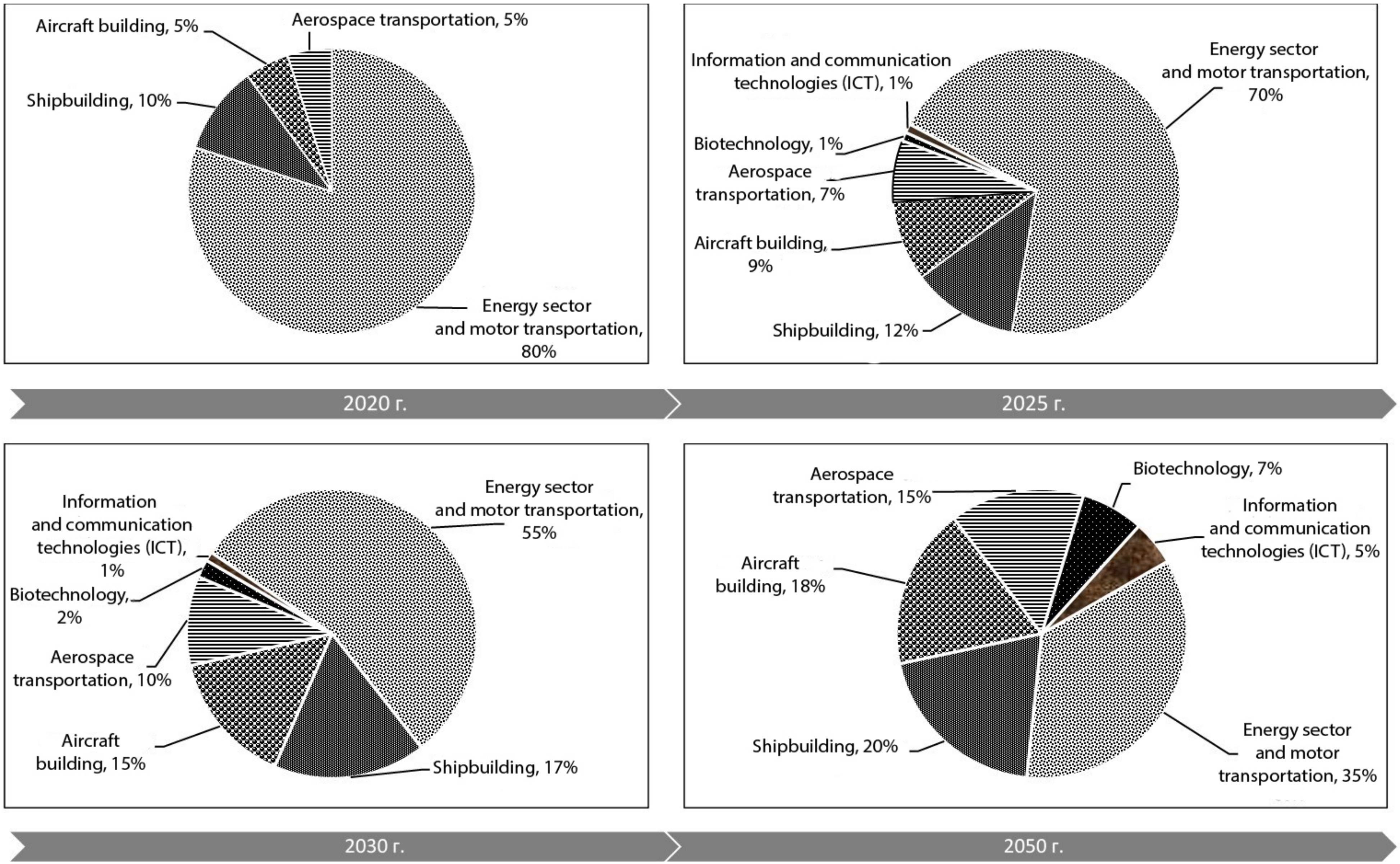

Fig. 2. *The structure of consumers of high-tech metal products in the Middle Urals*

Table 3

The system of indicators affecting the development of metallurgical complex in Sverdlovsk Region*

Indicator	Unit of Measurement	Symbol
Investments in fixed capital of enterprises of metallurgical complex	billion rubles	x_1
Internal consumption of metal products	million tons	x_2
Publication of previously granted patents for inventions related to promising areas	units	x_3
Costs of metallurgical enterprises on technological innovation	million rubles	x_4
USD exchange rate against the ruble	rubles	x_5
Average annual prices for Brent crude oil in the world market	dollars	x_6
Exports of metals and metal products by enterprises	thousand tons	x_7
Average number of employees in metallurgical manufacturing and manufacturing of finished metal products	thousand people	x_8
Finished products manufactured by the metallurgical complex	million tons	x_9
Labor productivity in metallurgical industry	million rubles/person	x_{10}
Share of steel smelting in electric furnaces	%	x_{11}
Share of high-level processing metal products manufactured by enterprises	%	x_{12}
Air emissions of pollutants by metallurgical enterprises	thousand tons	x_{13}
Wastewater contaminated by metallurgy	million m^3	x_{14}
Share of innovative products manufactured by metallurgical enterprises	%	x_{15}
Rolled steel resource intensity	kg/tons	x_{16}
Share of high-tech metal products in the structure of exports	%	x_{17}
Share of skilled employees in the number of employees of metallurgical complex	%	x_{18}
Depreciation rate of fixed assets at the end of the year	%	x_{19}

* Prepared by the authors. The information base was prepared analytically and it is based on the data of the space-time sample from the statistical database of the Federal State Statistics Service in Sverdlovsk Region, bulletins of scientific, technical, and economic information "Ferrous Metallurgy" issued by JSC Central Research Institute for Information and Technical and Economic Studies of Ferrous Metallurgy for 2006–2015, and a series of State Reports on the condition and protection of the environment of the Sverdlovsk region for 2006–2015. The values of indicators were selected within a single time interval (2005–2014).

components have the values greater than one. The remainder of the undistributed variance, by definition, is a noise that does not contain the desired information.

The reduction of the number of variables that are insignificant for the desired model and the grouping of significant variables allowed to lower the scale of these models. The principal components obtained as a result of the calculations were interpreted by using the set of dependent variables. In this case, the first principal component turned out to be cumbersome and poorly interpretable; as a result, we conducted an additional factor analysis for the aggregate of factors that are forming it. This approach allowed to break the first principal component into three clearly interpretable components: $F_{1.1}$, $F_{1.2}$, $F_{1.3}$.

The obtained principal components are the mathematical functions of measured variables. Based on obtained data, we can identify the component of innovative capacity implementation; improvement of competitiveness; component of lower emissions and resource consumption in manufacturing; dependence of high-quality metallurgy on the global market environment; component of production activities of regional metallurgy and component of stimulating the innovative activity and higher qualifications of the labor force.

Stage 4. In order to improve the quality of obtained models, we used the methods of correlation/regression analysis to approximate the functions describing the change in the parameters of the technological image of RMC. We conducted a check for multicollinearity and, based on its results, eliminated the indicator of internal consumption of metal products in the region (x_2). The graphic analysis of the distribution in the plane of scores of obtained principal components (Factor Scores) showed that, for all functions, the distribution of points was in a polynomial form. The obtained data allowed to build a complex of nonlinear regression models reflecting the dependence of principal

Table 4

The formation of principal components and interpretation of solutions*

Component	Indicators of metallurgical manufacturing in Sverdlovsk Region that form the principal component	Share of total variance, %	Interpretation
$F_{1.1}$	Exports of metals and metal products by enterprises, thousand tons (x_7)	39.90	Implementation of innovative capacity
	Share of innovative products manufactured by metallurgical enterprises, % (x_{15})		
$F_{1.2}$	Average annual number of employees in metallurgy, thousand people (x_8)		Improving the competitiveness of metal products
	Labor productivity in metallurgical industry, million rubles/person (x_{10})		
	Share of steel smelting in electric furnaces, % (x_{11})		
$F_{1.3}$	Air emissions of pollutants by metallurgical enterprises, thousand tons (x_{13})		Reducing emissions and resource consumption in manufacturing process
	Wastewater contaminated by metallurgy, million m^3 (x_{14})		
	Rolled steel resource intensity, kg/tons (x_{16})		
F_2	USD exchange rate against the ruble (x_5)	15.80	Dependence of high-quality metallurgy on global market environment
	Share of high-level processing metal products manufactured by enterprises, % (x_{12})		
F_3	Internal consumption of metal products, million tons (x_2)	13.30	Component of production activity of RMC
	Finished products manufactured by the metallurgical complex, million tons (x_9)		
F_4	Investments in fixed capital of enterprises of metallurgical complex, million rubles (x_1)	16.30	Stimulating the innovative activity and higher qualifications of the labor force
	Costs of metallurgical enterprises on technological innovation, thousand rubles (x_4)		
	Share of skilled employees in the number of employees of metallurgical complex, % (x_{18})		

* Prepared by the authors.

components on the input variables in a form of a second-order polynomial for the principal components $F_{1.2}$; $F_{1.3}$; F_2; F_4 and a third-order polynomial for $F_{1.1}$ (Table 5).

The analysis confirmed the high reliability of the approximation (R2) in obtained models. The hypothesis that all regression coefficients are equal to zero was discarded for each obtained dependency. The regression analysis of the third principal component revealed that this component is influenced by only one factor. In this regard, it would be practical to consider the factor of metal product manufacturing in the region (x9) for assessing the change in the production parameter of RMC technological image. The complex of non-linear economic and mathematical models obtained by using the principal component method and refined as a result of regression analysis allows to forecast the change in the parameters of RMC technological image with a high degree of reliability.

Stage 5. The stage allowed to substantiate and systematize the forecast values describing the parameters and conditions for the formation of a new RMC technological image. In order to substantiate the forecast parameters, the authors formulated a hypothesis that the correct distribution of the forecast values for describing the change in the RMC technological image must meet the following conditions: 1) all forecast values of variables should belong to the range of allowed values of the new technological image, or the stages of its achievement; 2) the range of allowed values must be filled from its lower boundary set on the basis of retrospective analysis data to the upper boundaries that form the desired image; 3) retrospective data of the last 11 years form the boundaries of traditional RMC technological image; next, we extrapolate the functions of obtained regression models by taking into account the global trends, these programs and indicated strategies for the development of the

Table 5

The econometric dependencies for assessing the parameters of RMC technological image*

No.	Principal Component	Obtained Econometric Dependencies	Hypothesis Test
1	$F_{1.1}$ — Implementation of innovative capacity	$F_{1.1} = -1.68 + 0.052x_{73} + 0.00072x_{153}$ Innovations in the process of manufacturing the finished products stimulates the growth of exports	$R = 0.99255692$ $RI = 0.98516924$ $F(2.8) = 265.71$ $p < .00000$
2	$F_{1.2}$ — Improving the competitiveness	$F_{1.2} = 1.078 - 0.00012x_{82} + 0.0097x_{102} + 0.000386x_{112}$ Increased volumes of steel smelting in electric furnaces allow to improve its quality, labor productivity, and reduce the environmental load	$R = 0.99933170$ $RI = 0.99866385$ $F(3,7) = 1744.0$ $p < .00000$
3	$F_{1.3}$ — Reducing emissions and resource consumption in manufacturing process	$F_{1.3} = -8.092 + 0.000003x_{132} + 0.00004x_{142} + 0.00001x_{162}$ Lower resource intensity of finished products, reduced air emissions and wastewater decreases the environmental load	$R = 0.99979743$ $RI = 0.99959489$ $F(3.7) = 5757.5$ $p < .00000$
4	F_2 — Factor of dependence of high-quality metallurgy on global market environment	$F_3 = -2.9 - 0.00064x_{52} + 0.0114x_{122}$ The volumes of production and exports of high-level processing metal products are largely determined by the global market environment	$R = 0.98121266$ $RI = 0.96277828$ $F(2.8) = 103.46$ $p < .00000$
5	$F_3 = x_9$ — Finished products manufactured by the metallurgical complex of Sverdlovsk Region, million tons		
6	F_4 — Factor of stimulating the innovative activity and higher qualifications of the labor force	$F_2 = -4.83 + 0.00084x_{12} + 0.00212x_{42} + 0.00065x_{182}$ More investments in the industry allow to finance the development of technological innovations, and stimulate the attraction of qualified human resources and training of employees	$R = 0.99134236$ $RI = 0.98275967$ $F(3.7) = 133.01$ $p < .00000$

* Prepared by the authors.

industry and metallurgy in Russia, Sverdlovsk Region, published materials of leading industry research and academic institutions [23, 26, 27]; 4) the ranges of allowed values limited by the forecast values of relevant strategic documents are filled in accordance with the principle of uniform distribution of random variables.

The values of the parameters of the changing RMC technological image systematized in the table of forecast values correspond to the conditions set for the implementation of innovative scenario of the Strategy for the Development of the Ferrous Metallurgy of Russia for 2014–2020 and for the Long-Term Period until 2030, and also take into account the expected changes in the qualitative structure of consumer markets for metal products. Therefore, all conditions of the hypothesis on the correct distribution of forecast values were met, and their values can be taken for further analysis.

Stage 6. The stage allowed to prepare the algorithm for building a mathematical model for recognizing the images and stages of RMC repositioning developed on the basis of a neural network classification model [28]. A characteristic of the neural network approach is the ability of the model to correctly respond to new data that are not provided in the learning process (learning principle) and the ability to memorize changes in the functioning of the modeling object when obtaining new data (adaptivity principle). A great contribution to the development of neural network forecasting was made by such scientists as B. Widrow, M. Minsky, S. Papert, J. Hopfield, M. Hoff et al. [29–31].

Neural networks are built on the basis Statistica, an application software product. The approximated mathematical functions of principal components served as a basis to assess the change in the parameters of RMC technological image by using the table of forecast values of the input variables. The obtained values of principal components in combination with the variables, that determine the specific weight of the five main segments of the consumer market of metal products, formed the information base for the construction of neural networks. In order to improve the learning ability of networks, the database was divided into training, control and test subsamples.

Following the training, we selected the most appropriate networks that can be used both as an ensemble and separately (Table 6).

Table 6

The results of training the neural networks*

No.	Architecture	Training Performance	Control Performance	Test Performance	Learning Algorithm	Error Function	Activation Function of Hidden Neurons	Activation Function of Output Neurons
1	MLP 11–20–5	98.984	96.634	98.454	BFGS 12	Entropy	Tanh	Softmax
2	MLP 11–14–5	96.457	95.568	96.356	BFGS 10	Entropy	Logistic	Softmax
3	RBF 11–5-5	89.607	95.347	94.809	RBFT	SOS	Gaussian	Identity

* Prepared by the authors.

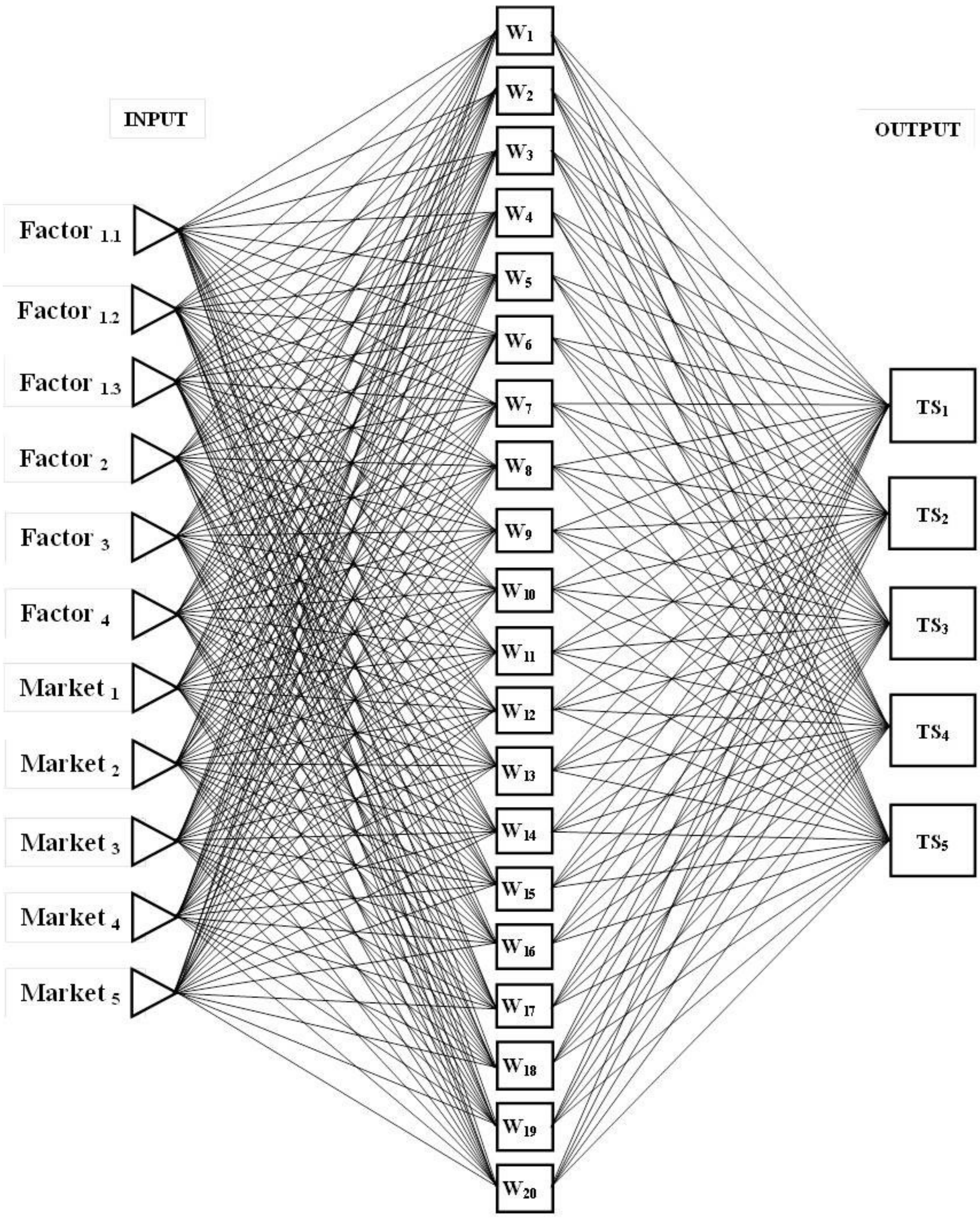

Fig. 3. *The diagram of neural network MLP 11–20–5*

Translation

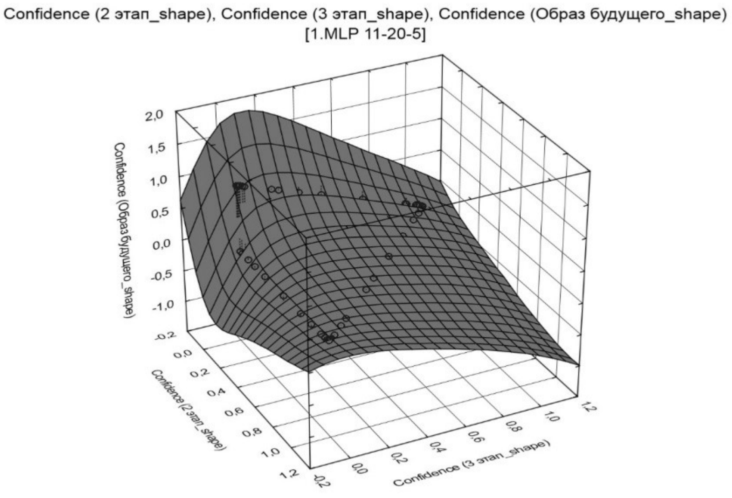

Fig. 4. *X-Y-Z chart referring the observations to different stages of RMC repositioning by confidence levels of selected network*

The presented Table shows that the network No. 1. MLP 11–20–5 has the best performance. To confirm the selection of the optimal network, we built the error matrices, analyzed the data of descriptive statistics, and conducted the analysis of confidence level distribution in terms of its adequacy. The performance was taken into account on all three subsamples. The results of comparative analysis confirmed that the network was selected correctly.

The selected neural network comes as a multi-layer perceptron with eleven neurons on the input layer, twenty neurons on the hidden layer (w_i), and five output neurons. The network has a direct propagation structure (Fig. 3).

The input neurons of the network include the parameters described by the principal components ($Factor_{1.1, \ldots, 4}$) and the specific weight of principal metal-intensive sectors that form the domestic consumer market of metal products ($market_{1, \ldots, 5}$). The function of neuron activation on the hidden layer ($w_i = 1, \ldots, 20$) has the form of a hyperbolic tangent, while the Softmax function was used on the output layer (*Technological Shape*). In this case, the summing is made across all neurons in the output layer ($TS_{1, \ldots, 5}$), and the sum of all outputs of the layer is equal to one for any values of the signal. This defines the stages of RMC repositioning with a specific probability.

During the data processing, the initial values of the image or repositioning stage and the values predicted by the network are compared through the trained network by confidence levels. Next, we determine the probability of whether RMC belongs, by the specified observations, to one of the repositioning stages or expected image in general (Fig. 4).

The points on the surface of the chart (Fig. 4) represent the values of the output signal of the network, while the surface itself is the approximation created by the network. The absolute majority of points are distributed over the surface, which confirms with a high level of confidence that forecast value provided by the network belongs to specific stages of repositioning.

The high accuracy of the obtained model allows to assess, with a high degree of probability, the technological image of the metallurgical complex of the region in terms of specified conditions.

Conclusion

The testing of developed methodological approach confirms the appropriateness of using the indicators describing the parameters of the technological image of the metallurgy in the Urals and the changing structure of promising markets for metal products. The consideration of interactions between various parameters creates a synergy that allows to reflect the qualitative change in the functioning of the regional metallurgical complex. The proposed methodology served as a basis for creating an algorithm to assess the possibility of repositioning the RMC, which meets the criteria of being promising in terms of technology, socio-economic efficiency and environmental attractiveness.

The calculations showed that there is a real possibility of stage-by-stage repositioning of the regional metallurgical complex and achieving a new technological image by 2050. Its characteristics will include network interaction of competitive, structurally balanced production facilities, the metal products of which correspond to the global level in terms of their set of consumer properties or, in some cases, exceed it; capability to meet the growing qualitative needs of traditional economic sectors; ensuring the individualized needs of the high-tech sector in science-intensive goods and services.

Acknowledgments

The article has been prepared with the support of the grant from the Russian Foundation for Basic Research No. 16–36–00097 "Economic and Mathematical Modeling of the Repositioning of Regional Metallurgical Complex in the Context of New Industrialization of the Economy."

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Translation