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NEURAL NETWORK MODELING OF THE ECONOMIC AND SOCIAL DEVELOPMENT TRAJECTORY TRANSFORMATION DUE TO QUARANTINE RESTRICTIONS DURING COVID-19

Tetyana Vasilyeva
Department of Finance and Entrepreneurship,
Sumy State University,
Ukraine
tavasilyeva@fem.sumdu.edu.ua
ORCID 0000-0003-0635-7978

Olha Kuzmenko
Department of Economic Cybernetics,
Sumy State University,
Ukraine
o.kuzmenko@uabs.sumdu.edu.ua
ORCID 0000-0001-8520-2266

Mariusz Kuryłowicz
Institute of Security Sciences, Higher School of Criminology and Penitentiary Science in Warsaw,
Warsaw, Poland
mariusz.kurylowicz@wskip.edu.pl
ORCID 0000-0001-8995-6516

Nataliia Letunovska
Department of Marketing,
Sumy State University,
Ukraine
n.letunovska@kmm.sumdu.edu.ua
ORCID 0000-0001-8207-9178

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ABSTRACT. The article uses neural networks to model the effects of quarantine restrictions on the most important indicators of the country's socio-economic development. The authors selected the most relevant indicators and formed a specific sequence of its calculation to study the direction of transforming the trajectory of socio-economic development of a particular country due to quarantine restrictions. They used a multilayer MLP perceptron and networks based on radial basis functions. They chose BFGS and RBFT algorithms in neural network modeling. Collinearity study was the basis for data mining in terms of key factors of change. The author's approach is unique due to an iterative procedure of numerical optimization and quasi-Newton methods ("self-learning" and step-by-step "improvement" of neural networks). The model projected gross domestic product and the number of unemployed in the country affected by the COVID-19 pandemic over the three years.

JEL Classification: C45, O18, R13

Keywords: impact of COVID-19, forecast of quarantine measures impact, socio-economic development of Ukraine, economic-mathematical model, neural network.

Introduction

Since the first cases of the SARS-CoV-2 virus, the COVID-19 pandemic has caused a number of negative effects on society and the economic development of entire regions. There is an urgent need to analyze the impact of COVID-19 as a threat to health and sustainable development on the current vector of world society transformations with a clear answer to the question of what this impact will be in retrospect on a national and regional scale. The trajectory of the strength and direction of the impact made by coronavirus and quarantine measures on socio-economic development can provide opportunities to develop accurate and sound forecasts of the consequences of the events 2020 for the coming years' global economy.

The pandemic lockdown affects almost all areas on a national scale - public health (direct effect), economic, social, environmental development (indirect effect). The downside of lockdown includes the collisions in the economic, social, and ecological spheres (Smiianov et al., 2020b). Experts in various fields of knowledge confirm that this global pandemic is an element of tension, primarily for global supply chains, causing catastrophic negative consequences due to the world economy's interconnectedness (Cek & Eyupoglu, 2020). Didenko et al. (2020), through bibliographic analysis, prove that migration parameters as a key economic indicator, environment, and security often meet each other. When writing the article, the coronavirus has killed nearly 2 million people worldwide (Worldometers, 2021), created problems for many people, and caused trillion economic losses. Most countries worldwide take strict measures, particularly national blockades and border closures, to contain the growing number of COVID-19 cases and limit the transmission of the dangerous virus. It is essential to provide calculations and realistic models to answer what changes are appropriate to implement in the countries to reduce the negative impact of the pandemic on most aspects of public life.

The purpose of this study is to forecast the impact of quarantine measures aimed at preventing the spread of coronavirus, at changing trends in social and economic development in different scenarios of future epidemiological threats. It considers the most important indicators of socio-economic development with forecasts for three years. The authors apply an approach that is fundamentally different from those already existing in the scientific literature, using an iterative procedure of numerical optimization and quasi-Newton methods that provide the "self-learning" and step-by-step "improvement" of neural networks. The approach considers possible dynamic changes of input parameters and parallel processing of information by many neurons.

1. Literature review

The articles of scientists from different countries deal with the impact of various crises, mainly of economic nature, and its quantitative and parametric analysis, in their works. The comparison of socio-economic development of individual regions, which are differently susceptible to such crises and form different resulting actions on the directed influence, is of particular importance (Bazyliuk et al., 2019; Kryshtanovych et al., 2020; Haller, 2020; Mikhaylova et al., 2019; Afanasyev et al., 2020; Dinu et al., 2020; Iacobuta et al., 2019; Semenenko et al., 2019; Harust et al., 2019; Vysochyna et al., 2020; Mikhnevych et al., 2020;

Deyneka et al., 2019; Medani, 2020; Balas and Kaya, 2019; Yelnikova and Miskiewicz, 2020; Dave, 2019; Marcel, 2019; Hashim et al., 2018; Kuzmenko et al., 2020; Djalilov et al., 2015). Attention is paid to the calculation of these impact limits in different activities (Mach, 2019; Moyo, 2020; Sawangchai, 2020; Przytuła et al., 2020; Raychev et al., 2020; Kowo et al., 2020; Jafarzadeh and He, 2019; Greco, 2018; Yiu et al., 2020; Dutta et al., 2020; Lopez and Alcaide, 2020; Kouassi, 2018) or in different countries and in the world as a whole (Sułkowski, 2020; Nagy and Kiss, 2018; Zolkover and Renkas, 2020). In particular, Kuc-Czarnecka (2020) examines specific aspects of the COVID-19 pandemic impact through the example of Poland, identifying particularly vulnerable areas due to infrastructural deficiencies. Censolo and Morelli (2020) view COVID-19 as a factor of unexpected and unpredictable social stability changes. According to them, it is urgent to consolidate the government and society's actions to achieve pre-pandemic stability. They separately study the incubator of conflict and repression caused by a pandemic. Leach et al. (2021) justify the need to forecast future uncertain shocks, which include pandemics. Such events form a challenge to the structural conditions in some countries, their social relations and economic order (Rui et al., 2019). Long-term transformations in the socio-economic sphere aim to solve fundamental issues of stimulating reliable and innovative alternatives to post-pandemic economic recovery. Vo (2020) views the COVID-19 pandemic from two perspectives - as an economic crisis and a crisis in the public health system. The author argues that it is essential to study changes in the agricultural market and the energy market during the crisis. The research in this article is based on the example of the United States. There are interesting practical studies, mainly (Cepel et al., 2020), that analyze the COVID-19 crisis impact on the entrepreneurs' attitude to risk. The study is conducted on the example of the small and medium enterprises segment in the Czech Republic and Slovakia, outlining the pandemic impact on these European countries' business sector.

Mofijur et al. (2021) present a comprehensive study regarding the COVID-19 impact on public life, including the economy, social sphere, environment and energy sector. It is essential to comprehensively analyze governments' measures to prevent the epidemic and their effectiveness in achieving a sustainable socio-economic environment. Smiianov V.A. et al. (2020a) thoroughly investigate the labor market analysis methods in a pandemic, forming their approach with a system of calculated parameters-indicators of the market situation. Many authors offer their economic and mathematical models to forecast the COVID-19 dynamics in the world, which differ in approach to construction, the accuracy of presented results, validity, etc. (Kufel, 2020), as well as valuable results of marketing research on mechanisms to improve the medical service quality, which is an essential aspect in preventing the epidemics spread (Smiianov et al., 2017). The scientists' achievements in the sustainable development of territorial units are relevant in current conditions because there is an essential strategic task of society to balance the development of different regions to overcome the crisis is (Petrushenko et al., 2017, Petrushenko et al., 2020, Stukalo et al., 2020). The appropriateness of applying modern mathematical methods to forecast economic phenomena is substantiated in many scientific studies (Teletov et al., 2019; Rosokhata et al., 2020; Vasilyeva et al., 2020; Yarovenko et al., 2021). Such scientists as Hruschka (1993), Luxhoy et al. (1996), Morozov et al. (2020), Vrbka (2020) are working to develop certain specific issues regarding the neural networks in the socio-economic sphere to define the drivers for further development of individual economic entities and countries as a whole.

2. Methodology

The most relevant indicators and calculations are used (Sumiyana, 2020; Malyarets et al., 2019; Vasilyeva et al., 2019) to study the economic and social development trajectory transformation in the country due to the quarantine restriction introduction. The study's time range is: the first alternative (excluding quarantine restrictions: quarterly data from the first quarter of 2015 to the fourth quarter of 2019); the second alternative (including quarantine restrictions: quarterly data from the first quarter of 2015 to the second quarter of 2020).

Two indicators are regressors: Gross domestic product (excluding Crimea) in actual prices, million UAH and Unemployed population (according to the methodology of the International Labor Organization), thousand people. The unemployment index is an important parameter of the country's long-term development success (Okuneviciute Neverauskiene & Rakauskiene, 2018). Twenty-one indicators are regressors.

4 social indicators (Need for workers, thousand people, Employed population aged 15-70 years, thousand people, Natural population growth (reduction), Migratory population growth (decline), persons);

12 indicators of capital investment (Rights to commercial designations, industrial property, copyright and related rights, patents, licenses, concessions, etc; Funds from foreign investors; Funds of the population for individual housing; Fisheries; Water transport; Postal and courier activities; Telecommunications; Production of coke and refined petroleum products; Production of computers, electronic and optical products; Production of electrical equipment; Production of motor vehicles, trailers, semi-trailers and other vehicles; Production of furniture and other products, repair and repair installation of machines and equipment);

2 trade indicators (Turnover of retail trade, estimated data; Wholesale and retail motor gasoline, sale of light oil products and gas through gas stations, thousand UAH);

3 indicators of enterprises' expectations (Estimation of changes in sales (turnover) for the previous three months, balance %; Expected changes in sales (turnover) in the next three months, balance%; Estimation of current inventories, balance %).

Eighteen indicators from the above are selected to study the economic and social development transformation direction due to quarantine restrictions. In terms of specific indicators, there are no statistics for the first and second quarters of 2020. The authors collected primary data for further calculations from open sources (State, 2021).

The collinearity study (Table 1) and the correlation analysis on regressand's dependence on each of regressors' indicators (Figure 2) substantiate reasonability to include the specified indicators. One proposes using the program Statistica, Analysis package, Advanced tab methods, tab General linear models of GLM to conduct the key factor identification method.

Table 1 (beta coefficients – column Gross domestic product, excluding Crimea, actual prices million UAH) shows the feasibility to range predictors by their impact degree on the regressor as follows: 1) Wholesale and retail motor gasoline, sale of light petroleum products and gas through gas stations UAH; 2) Production of coke and refined petroleum products; 3) Natural increase (reduction); 4) Estimation of changes in sales volume (turnover) for the previous three months, balance %; 5) Production of computers, electronic and optical products; 6) Rights to commercial designations, industrial property objects rights, copyrights and related rights, patents, licenses, concessions, etc; 7) Water transport; 8) Fisheries; 9) funds from foreign investors; 10) Production of motor vehicles, trailers, semi-trailers and other vehicles; 11) Postal and courier activities; 12) funds of the population for individual housing construction; 13) migratory increase (decrease), axis; 14) Retail trade turnover; 15) The need for employees, thousand people; 16) Telecommunications; 17) Employed population aged 15-70 years, thousand people; 18) Production of electrical equipment; 19) Production of furniture, other products, repair and installation of machinery and equipment; 20) Expected changes in sales (turnover) in the next three months, balance%; 21) Estimation of the current volume of goods stocks balance, %.

Table 1. Statistics for the indicator collinearity of the statistical base in the research

Effect	Tolernce	Variance	R square	GDP, without Crimea at actual prices, million UAH Beta in	GDP, without Crimea at actual prices, million UAH Partial	GDP, without Crimea at actual prices, million UAH Semi-par	Unemployed population, thousand people Beta in	Unemployed population, thousand people Partial	Unemployed population, thousand people Semi-par
The need for workers, thousand people	0,012	82,454	0,988	0,081	1,000	0,009	0,067	1,000	0,007
Employed population aged 15-70 years, thousand people	0,04	25,171	0,96	0,029	1,000	0,006	-0,87	-1,000	-0,168
Natural increase (reduction), people	0,007	142,505	0,993	-0,528	-1,000	-0,044	0,684	1,000	0,057
Migration increase (decrease), people	0,004	241,128	0,996	-0,126	-1,000	-0,008	0,242	1,000	0,016
Rights to commercial designations, industrial property objects, copyrights and related rights, patents, licenses, concessions, etc.	0,045	22,013	0,955	-0,356	-1,000	-0,076	0,004	1,000	0,001
Funds from foreign investors	0,025	40,48	0,975	-0,224	-1,000	-0,035	0,238	1,000	0,037
Population funds for individual housing consumption	0,063	15,995	0,937	-0,142	-1,000	-0,036	0,087	1,000	0,022
Fisheries	0,017	59,416	0,983	-0,262	-1,000	-0,034	0,235	1,000	0,03
Water transport	0,088	11,366	0,912	-0,321	-1,000	-0,095	0,129	1,000	0,038
Postal and courier activities	0,035	28,418	0,965	0,144	1,000	0,027	-0,118	-1,000	-0,022
Telecommunications	0,013	75,987	0,987	0,03	1,000	0,004	0,231	1,000	0,027
Production of coke and refined petroleum products	0,009	106,962	0,991	0,549	1,000	0,053	0,14	1,000	0,014
Production of computers, electronic and optical products	0,01	97,041	0,99	-0,368	-1,000	-0,037	0,04	1,000	0,004
Production of electrical equipment	0,013	74,196	0,987	0,012	1,000	0,002	0,146	1,000	0,017
Production of motor vehicles, trailers, semi-trailers and other vehicles	0,039	25,415	0,961	0,209	1,000	0,041	-0,207	-1,000	-0,041
Production of furniture, other products, repair and installation of machinery and equipment	0,015	68,215	0,985	0,001	1,000	0,000	-0,153	-1,000	-0,019
Retail trade turnover	0,075	13,368	0,925	0,124	1,000	0,0034	-0,128	-1,000	-0,035
Wholesale and retail Motor gasoline	0,002	540,8	0,998	1,061	1,000	0,0046	-0,578	-1,000	-0,025
Estimation of changes in sales volume (turnover) for the previous three months, balance%	0,011	94,411	0,989	0,459	1,000	0,047	-0,299	-1,000	-0,031
Expected changes in sales (turnover) in the next three months, balance%	-0,00								
Estimation of the current volume of stocks of goods, balance%	-0,00								

Source: own construction.

Analysis of the beta coefficients – column Unemployed population, thousand people) indicates the feasibility to range predictors by the degree of their impact on the response as follows: Employed population aged 15-70 years, thousand people; 2) Natural increase (reduction); 3) Wholesale and retail Motor gasoline; Sale of light oil products and gas through gas stations thousand UAH; 4) Estimation of changes in sales volume (turnover) for the previous three months, balance%; 5) migratory increase (decrease), axis; 6) Funds from foreign investors; 7) Fisheries; 8) Telecommunications; 9) Production of motor vehicles, trailers, semi-trailers and other vehicles; 10) Production of furniture, other products, repair and installation of machinery and equipment; 11) Production of electrical equipment; 12) Production of coke and refined petroleum products; 13) Water transport; 14) Retail trade turnover; 15) Postal and courier activities; 16) funds of the population for individual housing construction; 17) The need for workers, thousand people; 18) Production of computers, electronic and optical products; 19) Rights to commercial designations, objects of industrial property, copyrights and related rights, patents, licenses, concessions, etc .; 20) Expected changes in sales (turnover) in the next three months, balance%; 21) Estimation of the current volume of stocks of goods, balance%.

Besides, partial correlation coefficients (columns Gross Domestic Product, excluding Crimea, actual prices of million UAH and Unemployed population, thousand people, Table 1) show the degree of influence of one predictor on the regressor provided that the other predictors are fixed. This indicator's calculated values confirm the significant degree of all 21 regressors' influence on the studied regressands.

Analyzing the determination coefficient (column R square of Table 1), i.e., the square of the multiple correlation coefficient between this variable and all others, we note the high significance of all except two: Expected changes in sales (turnover) in the next three months, balance%; Estimation of the current volume of goods stocks, balance%. At the same time, the correlation matrix study enables to conclude the following:

the strong direct relationship of gross domestic product with the following indicators: Production of coke and refined products; Production of motor vehicles, trailers, semi-trailers and other vehicles; Expected changes in sales (turnover) in the next three months, balance %; Estimation of the current volume of stocks of goods, balance%;

strong inverse relationship of the unemployed population with the following indicators: Employed population aged 15-70 years, thousand people; Expected changes in sales (turnover) in the next three months, balance%;

the average direct relationship of gross domestic product with the following indicators: The need for workers, thousand people; funds of the population for individual housing construction; Production of computers, electronic and optical products; Production of electrical equipment;

the average inverse relationship of the unemployed population with the following indicators: Production of coke and refined petroleum products; Production of motor vehicles, trailers, semi-trailers and other vehicles.

The authors proposed to evaluate the direction of economic and social development trajectory transformation in the country due to the quarantine restrictions through the data mining by building a neural network. The neural network's economic and mathematical models regarding the dependence between gross domestic product and the unemployed population on factor features are presented using a multilayer perceptron MLP with the BFGS algorithm and based on radial basis functions RBF with the RBFT algorithm.

The economic and mathematical model of the neural network is as follows:

$$f(x) = F\left(\sum_{i_N} w_{i_N j_N N} \dots \sum_{i_2} w_{i_2 j_2 2} F\left(\sum_{i_1} w_{i_1 j_1 1} x_{i_1 j_1 1} - \theta_{j_1 1}\right) - \theta_{j_2 2} \dots - \theta_{j_N N}\right) \tag{1}$$

where $F\left(\sum_{i_1} w_{i_1 j_1 1} x_{i_1 j_1 1} - \theta_{j_1 1}\right)$ – layer 1;
$\sum_{i_2} w_{i_2 j_2 2} F\left(\sum_{i_1} w_{i_1 j_1 1} x_{i_1 j_1 1} - \theta_{j_1 1}\right) - \theta_{j_2 2}$ – layer 2;
$F\left(\sum_{i_N} w_{i_N j_N N} \dots \sum_{i_2} w_{i_2 j_2 2} F\left(\sum_{i_1} w_{i_1 j_1 1} x_{i_1 j_1 1} - \theta_{j_1 1}\right) - \theta_{j_2 2} \dots - \theta_{j_N N}\right)$ – layer N;
i – input number;
j – number of the neuron in the layer;
$x_{i_1 j_1 1}$ – i-input signal of j-neuron in the layer 1;
$w_{i_N j_N N}$ – weigh coefficient of the i-input of the j-neuron in layer N;
$\theta_{j_N N}$ – the threshold level of the j-neuron in layer N.

The economic-mathematical model of the neural network based on radial basis functions is as follows (Michael, 1977; Broomhead & Lowe, 1988):

$$f(x) = \sum_{i=1}^{N} w_i \varphi(\|x - x_i\|) \tag{2}$$

where w_i – weigh coefficient of the i-input signal;

x_i – centers of radial basis functions.

Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm is used to build a neural network of the multilayer perceptron MLP. It is one of the most common quasi-Newton methods for implementing an iterative numerical optimization procedure to find a nonlinear function's local extremum without restrictions. The BFGS algorithm involves the following steps (Zhang et al., 2020):

determination of weight coefficients by random small quantities and the initial value of the inverse Hessian approximation V - matrix of n x n size, where n is the length of the gradient vector g.

calculation of the gradient g.

calculation of the weight coefficients correlation $\Delta W = g \cdot \tau, W_{k+1} = W_k - \Delta W$, where τ is the parameter of learning speed.

determining the new value of the gradient $g = g(W)$, considering the previous value of g_p, and calculating the change in the gradient $\Delta g = g - g_p$.

calculation of the inverse Hessian (r change of gradient, s change of weights):

$$V_{k+1} = V_k - \frac{V_k \cdot s \cdot s^T \cdot V_k}{s^T \cdot V_k \cdot s} + \frac{r \cdot r^T}{s^T \cdot s}, \tag{3}$$
$$r = \Delta g_k = g_k - g_{k-1}$$
$$s = \Delta W_k = W_k - W_{k-1}$$

calculation of changes in weight coefficients $\Delta W = W \cdot g$ and adjustment of parameters $W \quad = W \quad - \Delta W$.

determination of the error. If the error of the specified accuracy exceeds, it is necessary to repeat the algorithm, starting with step 4. Otherwise, the algorithm stops.

The RBFT algorithm is used to build a neural network based on the radial basis functions of RBF.

It is proposed to use the Statistica program's capabilities, the Analysis package, the Neural Networks tab, and the Regression tab to implement this stage.

3. Empirical results

For practical approbation of the design calculations to forecast the levels of gross domestic product and unemployed population from the first quarter of 2020 to the fourth quarter of 2022 in Ukraine, the authors conducted economic and mathematical modeling of two types of neural networks (multilayer MLP perceptron and network based on radial basis functions) of regression dependence of gross domestic product and the unemployed population on the relevant regressors. They systematized the results in tabular form (table 2).

Table 2 shows a much greater range of constructed neural networks in the form of a multilayer perceptron MLP (9 of 13, 69.23% of models), than networks based on radial basis functions RBF (30.77% of models). All presented models (except for 6, 7 and 8, 11) are characterized by a high level of adequacy, evidenced by the criteria in the columns "Productivity training", "Productivity control". At the same time, the performance of MLP models has a much smaller variation range of correlation coefficients - from 0.9368 to 0.9999 (training sample), from 0.9702 to 0.9845 (test sample) than RBF models - respectively, from

0.1829 to 0.7086 (training sample), from 0.5379 to 0.9846 (test sample). The reliability of the constructed neural networks is also confirmed by the error rate within the training, control and test sample, which takes values close to zero.

The authors chose all 13 models for forecasting the gross domestic product and the unemployed population from the first quarter of 2020 to the fourth quarter of 2022. The BFGS algorithm is used to construct a neural network of the MLP multilayer perceptron type, and respectively, the RBFT algorithm is used for a neural network based on the radial basis functions of RBF. We will demonstrate a fragment from the neural network architecture regarding the perspective layer of 21 layers with five hidden layers of MLP 21-5 in Figure 1.

Table 2. The results of neural network models for regression dependence of gross domestic product and unemployed population on relevant regressors

Index	Architecture	Producti-vity training	Productivity control	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 21-5-2	0.973187	0.977594	0.004519	0.012485	BFGS 13	SOS	Sine	Identity
2	MLP 21-5-2	0.999999	0.975184	0.000000	0.006793	BFGS 131	SOS	Exponential	Sine
3	MLP 21-6-2	0.936821	0.970242	0.009444	0.013917	BFGS 11	SOS	Sine	Tanh
4	MLP 21-5-2	0.991670	0.980823	0.001399	0.012250	BFGS 18	SOS	Tanh	Sine
5	MPL 21-5-2	0.984664	0.975821	0.002429	0.014108	BFGS 26	SOS	Logistic	Logistic
6	RBF 21-5-2	0.182852	0.537886	0.074342	0.123409	RBFT	SOS	Gaussian	Identity
7	RBF 21-5-2	0.463001	0.652043	0.074342	0.123409	RBFT	SOS	Gaussian	Identity
8	RBF 21-5-2	0.446046	0.735705	0.074342	0.123409	RBFT	SOS	Gaussian	Identity
9	MLP 21-5-2	0.999841	0.979002	0.000026	0.010508	BFGS 35	SOS	Exponential	Exponential
10	MLP 21-5-2	0.964678	0.983086	0.005649	0.012953	BFGS 9	SOS	Identity	Tanh
11	RBF 21-5-2	0.708576	0.975072	0.037124	0.043064	RBFT	SOS	Gaussian	Identity
12	MLP 21-6-2	0.991946	0.976478	0.001359	0.011874	BFGS 27	SOS	Logistic	Logistic
13	MLP 21-6-2	0.968505	0.984588	0.005201	0.008732	BFGS 8	SOS	Identity	Sine

Source: own construction.

Table 3. Fragment from the neural network architecture of the MLP 21-5-2 (multilayer perceptron of 21 layers with five hidden layers)

	Network weights	
	Connections 1. MLP 21-5-2	Weight values 1. MLP 21-5-2
1	The need for workers, thousand people → hidden neuron 1	-0,057008
2	The need for workers, thousand people → hidden neuron 2	-0,174539
3	The need for workers, thousand people → hidden neuron 3	-0,010515
4	The need for workers, thousand people → hidden neuron 4	0,011973
5	The need for workers, thousand people → hidden neuron 5	-0,036693
6	Population aged 15-70 years, thousand people → hidden neuron 1	-0,029574
7	Population aged 15-70 years, thousand people → hidden neuron 2	0,152916
8	Population aged 15-70 years, thousand people → hidden neuron 3	0,202181
9	Population aged 15-70 years, thousand people → hidden neuron 4	0,007077
10	Population aged 15-70 years, thousand people → hidden neuron 5	0,199111
11	Natural increase (reduction) → hidden neuron 1	-0,129421
12	Natural increase (reduction) → hidden neuron 2	0,086522
13	Natural increase (reduction) → hidden neuron 3	0,158329
14	Natural increase (reduction) → hidden neuron 4	0,005035
15	Natural increase (reduction) → hidden neuron 5	0,007741
16	Migration increase (reduction) → hidden neuron 1	0,014024
17	Migration increase (reduction) → hidden neuron 2	-0,086780
18	Migration increase (reduction) → hidden neuron 3	-0,044901
19	Migration increase (reduction) → hidden neuron 4	0,146937
20	Migration increase (reduction) → hidden neuron 5	0,046278
21	Rights to commercial designations, industrial property objects, copyrights and related rights, patents, licenses, concessions, etc. → hidden neuron 1	0,087118
22	Rights to commercial designations, industrial property objects, copyrights and related rights, patents, licenses, concessions, etc. → hidden neuron 2	0,415536

23	Rights to commercial designations, industrial property objects, copyrights and related rights, patents, licenses, concessions, etc. → hidden neuron 3	0,283452
24	Rights to commercial designations, industrial property objects, copyrights and related rights, patents, licenses, concessions, etc. → hidden neuron 4	-0,258651
25	Rights to commercial designations, industrial property objects, copyrights and related rights, patents, licenses, concessions, etc. → hidden neuron 5	0,254409

Source: own construction.

The scattering diagram of theoretical (obtained by using constructed neural networks) and actual gross domestic product values and the unemployed population is in Fig. 1-2. Based on the visual ratio of neural networks to forecast gross domestic product and the unemployed population, it is possible to conclude about the reliability of the selected models, as evidenced by the closeness of actual values compared to theoretical ones (predictive, found using models except for the 8th model).

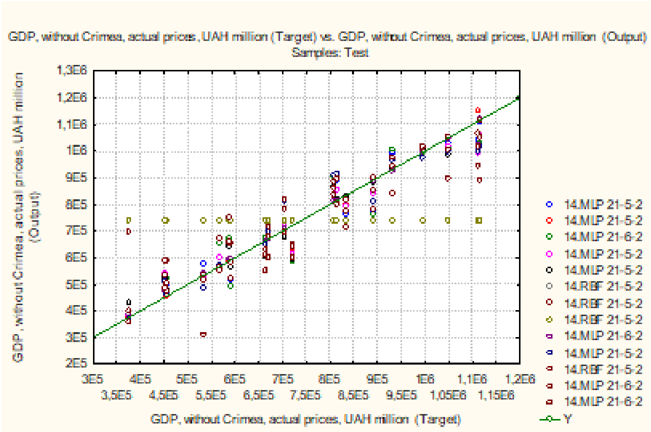

Figure 1. The ratio of actual and predicted gross domestic product
Source: own construction.

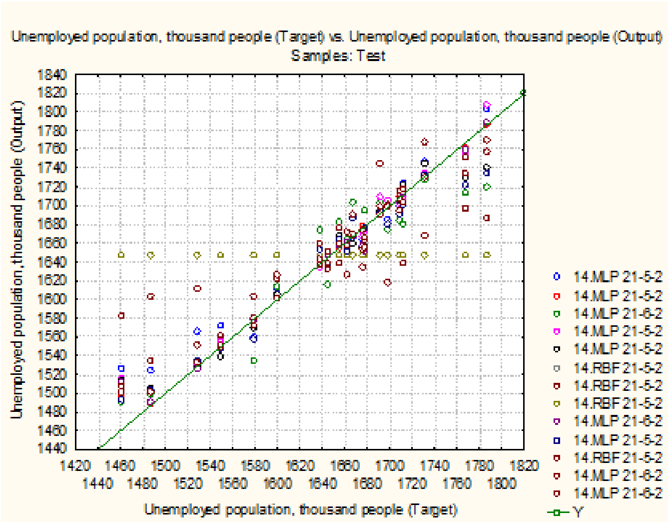

Figure 2. The ratio of actual and forecast levels of the unemployed population
Source: own construction.

In terms of calculation approbation to forecast the gross domestic product levels and the unemployed population during the 3rd quarter of 2020 – the 4th quarter of 2022, we will conduct economic and mathematical modeling of two neural networks (multilayer MLP perceptron and RBF network) regression dependence of gross domestic product and the unemployed population on relevant regressors and systematize the results in Table 3. The data from Table 4 shows a much greater range of constructed neural networks via multilayer perceptron MLP (10 of 13, 76.92% of models), than networks based on radial basis functions RBF (23.08% of models). A high level of adequacy characterizes all presented models (except for 6, 7 and 8), as evidenced by the criteria in the columns "Productivity training", "Productivity control". At the same time, the performance of MLP models has a smaller range of correlation coefficients variation - from 0.8831 to 0.9989 (training sample), from 0.8136 to 0.9335 (test sample), than RBF models - respectively, from - 0.0433 to 0.0.2837 (training sample), from -0.2485 to 0.1971 (test sample). The reliability of the constructed models of neural networks is also confirmed by the error rate within the training, control and test sample, which takes values close to zero. We will choose all thirteen models to forecast gross domestic product and the unemployed population during the third quarter of 2020 - the fourth quarter of 2022.

Table 4. The results of neural network models for regression dependence of gross domestic product and the unemployed population on regressors during the first quarter of 2015 – the second quarter of 2020

Index	Architecture	Productivity training	Productivity control	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 18-12-2	0.927752	0.854923	0.016645	0.015460	BFGS 8	SOS	Logistic	Sine
2	MLP 18-17-2	0.920189	0.838053	0.015770	0.012349	BFGS 9	SOS	Logistic	Tanh
3	MLP 18-8-2	0.994539	0.860934	0.000944	0.009592	BFGS 25	SOS	Tanh	Tanh
4	MLP 18-8-2	0.910821	0.876994	0.014532	0.016738	BFGS 4	SOS	Exponential	Logistic
5	MPL 18-13-2	0.965576	0.829655	0.008444	0.012170	BFGS 9	SOS	Identity	Identity
6	RBF 18-5-2	-0.043267	0.197068	0.081188	0.043034	RBFT	SOS	Gaussian	Identity
7	RBF 18-5-2	0.283654	-0.222331	0.081188	0.043034	RBFT	SOS	Gaussian	Identity
8	RBF 18-5-2	0.203114	-0.248472	0.081188	0.043034	RBFT	SOS	Gaussian	Identity
9	MLP 18-9-2	0.965931	0.813610	0.006140	0.014978	BFGS 10	SOS	Sine	Sine
10	MLP 18-9-2	0.883066	0.824617	0.022561	0.012645	BFGS 6	SOS	Tanh	Identity
11	MLP 18-14-2	0.911598	0.842332	0.014001	0.013891	BFGS 6	SOS	Tanh	Logistic
12	MLP 18-8-2	0.998924	0.933467	0.000177	0.011308	BFGS 29	SOS	Tanh	Sine
13	MLP 18-14-2	0.920963	0.893228	0.016035	0.005787	BFGS 6	SOS	Sine	Identity

Source: own construction.

The scattering diagram of theoretical (obtained by using the formed 13 neural networks) and actual gross domestic product values and the unemployed population is shown in Figures 3-4.

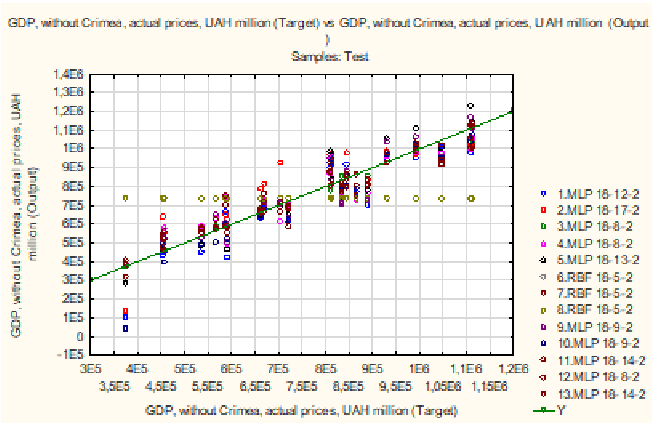

Figure 3. The ratio of actual and forecast levels of the gross domestic product during the third quarter of 2020 - the fourth quarter of 2022
Source: own construction.

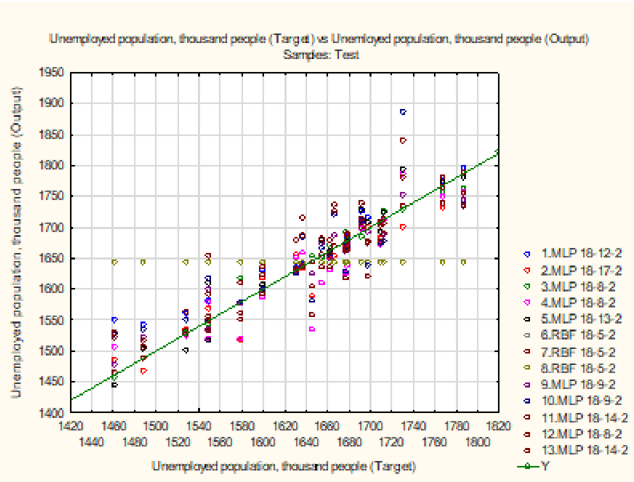

Figure 4. The ratio of actual and forecast levels of the gross domestic product during the third quarter of 2020 - the fourth quarter of 2022
Source: own construction.

The quality of the constructed neural network models is based on data from Table 5 – correlation coefficients of actual and forecast levels in terms of 13 neural network models to predict the levels of gross domestic product and unemployed population during the first quarter of 2015 – second quarter of 2020. The third quarter of 2020 – fourth quarter of 2022 is the best period to forecast: for gross domestic product - the third model with MLP architecture 18-8-2, the fifth model with MLP architecture 18-13-2, the ninth model with MLP architecture 18-9-2, the twelfth model with MLP 18-8-2 architecture; for the unemployed population – the second model with the architecture MLP 18-17-2, the third model with the architecture MLP 18-8-2, the fifth model with the architecture MLP 18-13-2, the ninth model with the architecture MLP 18-9-2, the twelfth model with the MLP 18-8-2 architecture.

Table 5. Correlation coefficients in the context of 13 constructed neural network models for forecasting the gross domestic product and the unemployed population levels during the first quarter of 2015 - the second quarter of 2020

Index	Architecture	GDP, without Crimea, actual prices, UAH million Train	Unemployed population, thousand people Train
1	MLP 18-12-2	0.924098	0.931405
2	MLP 18-17-2	0.875098	0.965281
3	MLP 18-8-2	0.994321	0.994757
4	MLP 18-8-2	0.916550	0.905092
5	MLP 18-13-2	0.966086	0.965067
6	RBF 18-5-2	-0.496990	0.410456
7	RBF 18-5-2	0.513691	0.053616
8	RBF 18-5-2	0.050744	0.355485
9	MLP 18-9-2	0.965781	0.966080
10	MLP 18-9-2	0.947420	0.818713
11	MLP 18-14-2	0.947584	0.875612
12	MLP 18-8-2	0.998991	0.998856
13	MLP 18-14-2	0.955512	0.886414

Source: own construction.

The authors compared two scenarios having predicted the value of the gross domestic product and the unemployed population in different scenarios considering the first and second quarters of 2020 and without considering it, i.e., the first quarantine wave and without it. Figure 5 and Table 6 present the obtained values.

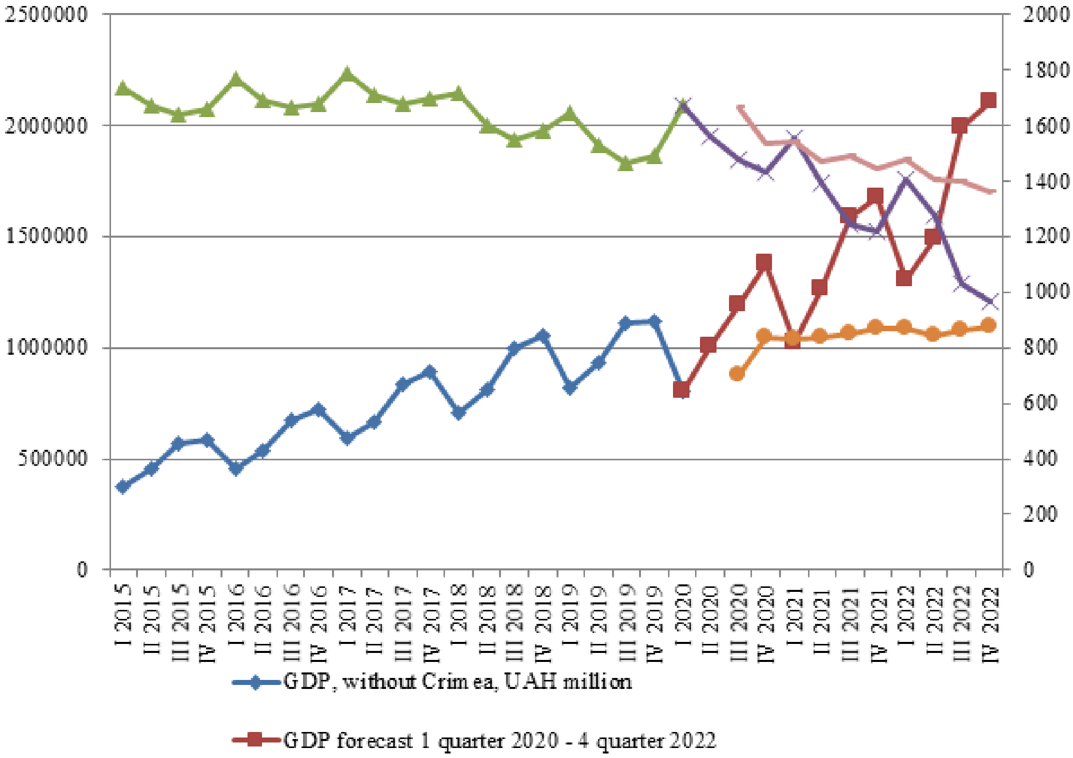

Figure 5. The ratio of actual (up to the 2nd quarter of 2020 and the 4th quarter of 2019) and forecast levels (from the 3rd quarter of 2020 and the 1st quarter of 2020) in terms of gross domestic product and unemployed population

Source: own construction.

Table 6. Comparison of actual and forecast values of gross domestic product and unemployed population in different scenarios (considering the first and second quarters of 2020 and without considering it)

Period	GDP, without Crimea, UAH million	GDP forecast 1 quarter 2020 – 4 quarter 2022	UP, thousand people	UP forecast 1 quarter 2020 - 4 quarter 2022	GDP, without Crimea, UAH million	GDP forecast 3 quarter 2020 - 4 quarter 2022	UP, thousand people	UP, forecast 3 quarter 2020 - 4 quarter 2022
1	2	3	4	5	6	7	8	9
I 2015	375,991		1731.53		375,991		1731.53	
II 2015	456,715		1667.3		456,715		1667.3	
III 2015	566,997		1637.6		566,997		1637.6	
IV 2015	588,841		1654.7		588,841		1654.7	
I 2016	455,298		1767.4		455,298		1767.4	
II 2016	535,701		1691.5		535,701		1691.5	
III 2016	671,456		1662.2		671,456		1662.2	
IV 2016	722,912		1678.2		722,912		1678.2	
I 2017	592,523		1786.9		592,523		1786.9	
II 2017	665,233		1709.7		665,233		1709.7	
III 2017	834,287		1676.9		834,287		1676.9	
IV 2017	891,839		1698		891,839		1698	
I 2018	705,977		1712.8		705,977		1712.8	
II 2018	810,174		1600.4		810,174		1600.4	
III 2018	994,810		1549.3		994,810		1549.3	
IV 2018	1,049,635		1578.6		1,049,635		1578.6	
I 2019	815,123		1645.8		815,123		1645.8	
II 2019	932,677		1528.4		932,677		1528.4	
III 2019	1,111,862		1461.8		1,111,862		1461.8	
IV 2019	1,114,902		1487.7		1,114,902		1487.7	
I 2020	800,106	800,106	1670.001	1670.001	845,829		1548.9	
II 2020		1,004,658		1560.546	867,782		1630.6	
III 2020		1,187,562		1474.36	873,664	873,664	1660.887	1660.887
IV 2020		1,376,318		1428.437		1,045,236		1533.188
I 2021		1,018,460		1552.818		1,034,628		1541.794
II 2021		1,259,700		1391.175		1,0437,39		1466.629
III 2021		1,587,115		1240.777		1,062,303		1491.793
IV 2021		1,674,015		1214.733		1,084,077		1445.972
I 2022		1,305,531		1406.675		1,083,250		1474.098
II 2022		1,491,635		1275.096		1,053,416		1402.191
III 2022		1,990,795		1030.87		1,079,408		1399.283
IV 2022		2,101,626		963.243		1,092,791		1357.648

Source: own construction.

Conclusions

Adjustment of national and local post-quarantine recovery programs requires considering the time factor regarding macro indicators changes and deep deformation resulting from quarantine and cause macroeconomic trends in 2020-2022. The authors formalize the dependence of the GDP and unemployment levels on social and economic development indicators of Ukraine through neural networks of two types: 1) in the form of a multilayer MLP perceptron (the weight coefficients of the input channels will be determined by small random values, the correlation of weights is considered when estimating the parameter "learning speed", the possible dynamic change of weight coefficients is considered by adjusting the parameters, the error thresholds are determined); 2) based on the radial basis functions of RBF using the RBFT algorithm (considering the weight coefficients of each input signal, the centers of radial basis functions, and the threshold levels of each neuron in the corresponding layer). Constructed neural networks differ in architecture (number of layers and hidden neurons), performance and error, learning algorithm and error functions, active hidden and active source neurons. The authors' approach is fundamentally different from the existing ones due to the application of an iterative procedure of numerical optimization, taking into account the possible dynamic change of input parameters and parallel processing of this information by a large number of neurons. Consideration in the process of modeling migration processes and the need for workers creates a basis for operational and targeted decisions to limit the mobility of the population in the event of new waves of the pandemic and adjust government programs to stimulate job creation in the regions. Considering the complexity of economic parameters and their connection with the level of vulnerability from COVID-19 will allow adjusting the initiatives of sectoral and functional support to increase the regions' financial and economic self-sufficiency.

Thus, the urgent task is to forecast the trajectory of significant economic and social indicators development affected by the COVID-19 pandemic based on the neural networks. This approach is a powerful and flexible tool for ensuring an effective system of anti-epidemic government measures. The method proposed by the authors makes it possible to identify complex dependencies of socio-economic processes within the state to predict the possible results of the approved quarantine measures. Its use can increase the initial validity of public administration decisions, preventing the pandemic's negative impact. The author's approach effectively predicts quarantine measures on changing individual countries' social and economic development in different future epidemiological threats.

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