Forecasting Indicators of Economic Development of Ukraine using an Artificial Neural Network

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Abstract. The article presents the results of forecasting indicators that characterise the economic development of Ukraine with the help of an artificial neural network developed by the author. For this purpose, a fully connected artificial neural network of direct signal propagation with a sigmoidal activation function was used. An inverse error propagation algorithm was used to train the artificial neural network. Used to assess the quality of the neural network Mean Squared Error and Mean Absolute Percentage Error. According to the forecasting results for the period 2022–2023, we have: a slight decline in Ukraine's GDP (US dollars), the growing role of the private sector in the structure of fixed assets of the country, and investment growth and growth in export earnings. At the same time, it is possible to reduce the amount of investment by the state and reduce the average salary (US dollars). Within the forecast period, the number of employed people in Ukraine will remain stable.

Keywords: prognostication; artificial neural network; sigmoidal activation function; inverse error propagation algorithm; Mean Squared Error; Mean Absolute Percentage Error.

INTRODUCTION

In the current development of the global economic system, the uncertainty of future growth vectors is increasing, and global financial crises are becoming increasingly unpredictable and large-scale. Ukraine's economy, which is under the influence of globalisation, is experiencing positive growth trends and damaging situations. This increases the uncertainty of options for further development of the national economic system. Consequently, domestic scientists are faced with the critical question of finding new methods for forecasting the growth of complex economic systems. One such method is neural networks, an effective tool for data analysis [1].

As Charkin Ye. notes, the rapid development of computer technology has opened access to the capabilities of the artificial neural network, which is rapidly expanding its scope [2].

According to [3], the use of neural networks is especially relevant for forecasting socio-economic phenomena and processes because their development patterns are formed under the influence of many interrelated factors and mass processes, which are not subject to experiments and are not available for direct observation.

Author [4] notes that neural networks and deep learning are becoming attractive for use in economics practice because, despite theoretical limitations, artificial networks have many positive qualities, which complement and improve traditional methods of economic assessment and forecasting.

Based on the statements of scientists, it is possible to give a definition – the artificial neural network is a model of biological neurons, that is, brain cells, which are shown through mathematical functions, written in the form of program code. However, interpreting the neural network through the classical algorithm of the interaction of mathematical functions simplifies it too much because the neural network is much more complex; many processes occur, not linearly. Still, in parallel, that is, at one point in time [5].

So, artificial neural networks can be represented as computational structures, able to learn through analysing negative and positive factors. The application of neural networks in economic modelling and forecasting allows to solve classes of problems: prognostication, optimisation, clustering and search for the optimal management mechanism.

MATERIALS AND METHODS

When writing the article, scientific achievements of Ukrainian and foreign scientists were used, and statistical information was taken from the State Statistics Service of Ukraine [6] and the Ministry of Economy of Ukraine [7]. A fully connected artificial neural network of direct signal propagation with a sigmoid activation function was used for modelling.

RESULTS AND DISCUSSION

For many years, no algorithm could be used to adjust the weights in a neural network during training. Only in the 70s of the XX century did authors [8] develop an algorithm for inverse error propagation. This algorithm is chosen for practical use in the presented article. Therefore, it requires a detailed description.

The algorithm for inverse error propagation involves the following steps [8, c. 55–60]:

1) the input set is read $x_1,\ldots,x_n$ and the corresponding source set $t_1,\ldots,t_m$;

2) the values of the input set to pass to the input layer of the network and become from the corresponding neurons the outputs of the input layer;

3) first, the total input is calculated In_j and total output o_j neurons of the first hidden layer, then all the hidden layers, in turn, moving from the input layer to the output, then calculations are performed for the source layer:

$$In_j = w_{0j} + \sum_{i=1}^{n} x_i\, w_{ij}, o_j = \frac{1}{1 + e^{-In_j}},$$

where j – the number of the hidden layer neuron, i – the number of the neuron of the input layer, n – the number of neurons in the input layer;

4) for all source neurons, the network error is calculated δ_j:

$$\delta_j = \left(t_j - o_j\right) \cdot \frac{e^{-o_j}}{(1 + e^{-o_j})^2},$$

where j – input neuron number;

5) for all hidden layers, in turn, moving from the source layer to the input, the error is calculated, coming to each neuron from the source layer:

$$\delta_i = \frac{e^{-o_j}}{(1 + e^{-o_j})^2} \cdot \sum_{j=1}^{m} w_{ij}\delta_j,$$

where i – the number of the hidden layer neuron, j – numbers of neurons of the source layer, m – the number of neurons in the source layer;

6) for all layers, the values of weights of each neuron are updated:

$$\Delta w_{ij}^{new} = \eta o_i \delta_j + \alpha \Delta w_{ij}^{old}, w_{ij}^{new} = w_{ij}^{old} + w_{ij}^{new},$$

where i – the number of the neuron of the previous layer, j – the neuron number of the next layer, new – new meaning, old – previous value;

7) if not, the last data set is used, the next stage is read, and the algorithm moves to point 2, and otherwise to point 8;

8) provided that the stop criterion is reached – the input set starts to be processed; first, from the first point of the algorithm.

The following prerequisites were used to forecast economic indicators using an artificial neural network:

1. Neural network training was conducted in overlapping areas; as a result, the number of samples for training was increased.

2. Used to assess the quality of the neural network Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). If you mark the actual network outputs o_i, and expected outputs t_i, then the following formulas are used to calculate these estimates:

$$MSE = \tfrac{1}{n}\textstyle\sum_{i=1}^{n}(o_i - t_i)^2, \quad (1)$$

$$MAPE = \tfrac{100}{n}\textstyle\sum_{i=1}^{n}\left|\tfrac{o_i - t_i}{o_i}\right|, \quad (2)$$

where n – the total number of considered outputs (the number of test samples multiplied by the number of outputs).

The relative values of these indicators were used as a criterion for stopping network learning, calculated based on absolute values obtained on the previous and current iterations:

$$MSE_{\%} = \left|\frac{MSE^{(t-1)} - MSE^{(t)}}{MSE^{(t-1)}}\right| \cdot 100, \quad (3)$$

$$MAPE_{\%} = \left|\frac{MAPE^{(t-1)} - MAPE^{(t)}}{MAPE^{(t-1)}}\right| \cdot 100. \quad (4)$$

In the formulas (3) and (4) superscript $(t-1)$ used for the value obtained in the previous iteration, (t) used for the value of the indicator obtained in the current iteration.

At least the number of iterations was empirically determined as the criteria for stopping learning 100 and achieving value improvement MSE% less than 0.0001.

3. Before using the neural network, the initial data was scaled to bring them to a segment [0,1]:

$$y_i = x_i - min(x), \quad (5)$$

$$t_i = \frac{y_i}{max(y)}. \quad (6)$$

The values obtained from the neural network can be returned to the previous scale using inverse formulas (5) and (6).

4. A network with one hidden layer was chosen as the basic topology of the neural network, containing three neurons, five input neurons and one output. The neural network will predict one value based on the previous 5, using a hidden layer of 3 neurons: topology [5x3x1]. The value of the learning coefficient was used for the neural network learning procedure 0.2, and the coefficient of inertia 0.75, which is selected empirically.

Not all series obtained satisfactory results using an artificial neural network of this topology. To forecast the amount of state capital, the network with topology showed the best results [7x3x1], and for predicting foreign direct investment, the best results of the topology [4x2x1].

5. Forecasting was performed three values ahead.

6. The forecasting procedure for one studied indicator consisted of the following stages: learning the neural network according to the available values of the time series; modelling time series values based on actual values. For every five values of the initial series, the next value is generated using the neural network, and a model line is formed; predicting the next value of the series based on the last five values of the initial series; adding the predicted value to the last four values of the initial series and predicting the second next value of the original series; forecasting the third value based on the last three values of the initial series and the two predicted.

The neural network can be started several times because the initial weights of intraneuronal connections are set randomly. During the training, the network entered a local stationary state, after which no improvement in its operation was observed. Therefore, after several launches, the best results were chosen, and the impact was evaluated using an evaluation MSE%.

First of all, the procedure described in paragraph 6 was applied to the time series of Ukraine's GDP. The results are shown in Figure 1.

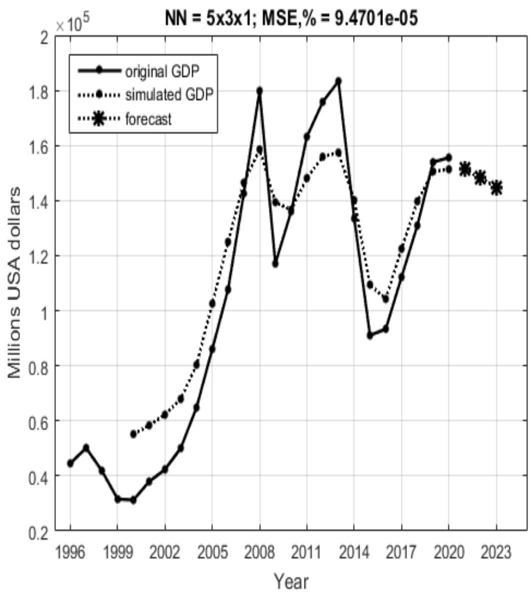


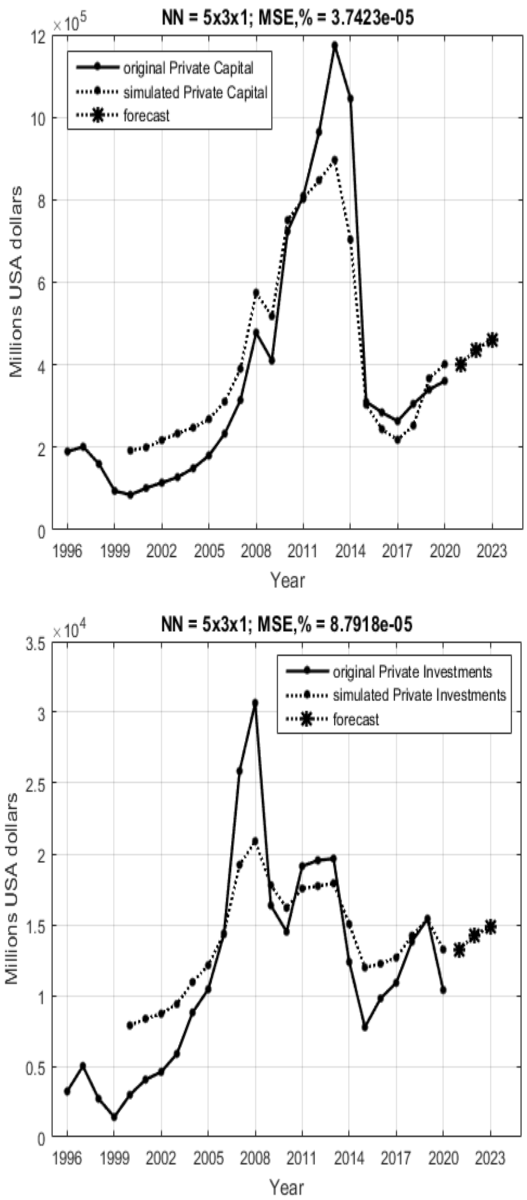
Figure 1 – Dynamics of input values of Ukraine's GDP, simulated by an artificial neural network series, and the following three predicted values

Figure 1 shows that the forecast network quite well repeats the shape of the initial series during the study period and coincides with its dynamics in different phases of economic cycles. Thus, the predicted values can be considered plausible. Forecasting using an artificial neural network for the period 2022 – 2023 showed a possible decrease in the real GDP of Ukraine in dollar terms. In Figure 1, the title indicates the topology of the neural network used and the achieved value of the relative standard deviation.

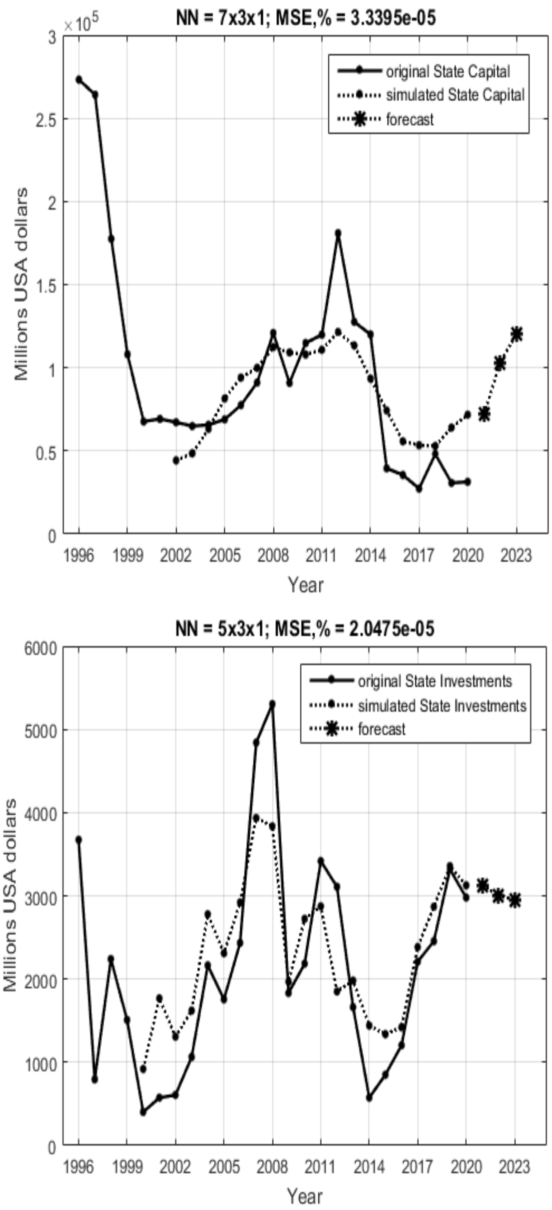
Figures 2-3 show the result of learning artificial neural networks for a time series of values of private capital, as well as the network predicted values for the period 2022 – 2023. In this case, the coincidence with the dynamics of the initial series is reached.

From Figure 3, it is seen that within the forecast period, it is possible to increase the inflow of investment resources at the expense of Ukrainian companies and private investors.

Figures 4-5 show the results of modelling the dynamics of public capital and public investment input values, series simulated by an artificial neural network.



Figures 2–3 – Dynamics of input values of private capital and private investment, series simulated by an artificial neural network, and the following three predicted values



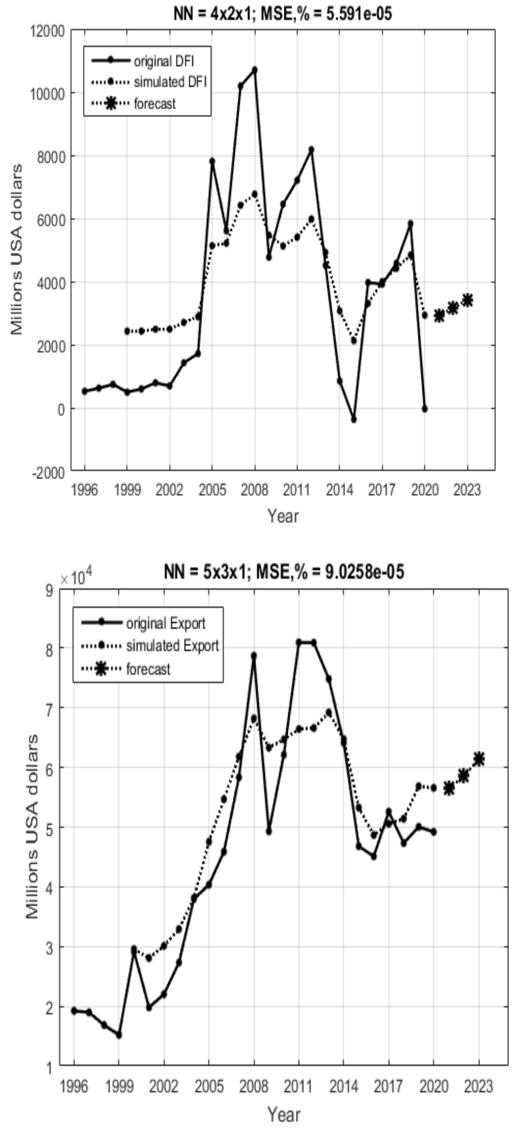
Figures 4–5 – Dynamics of input values of public capital and public investment, series simulated by an artificial neural network, and the following three predicted values

As can be seen from the figures, the neural network over the next three years predicts an increase in private capital in the overall structure of fixed assets in Ukraine.

At first glance, the predicted values from Figure 2 Figure 4 contradict each other because both dynamics tend to grow. At the same time, Ukraine is experiencing a steady decline in the public sector in the economy. Despite the contradictions, the results, on the contrary, confirm the correct operation of the network. Since the latter considers the entire time interval when calculating the simulated series, as shown in Figure 4, the amount of state capital in the periods 1996–1999 and 2009–2013 was significant.

They are analysing Figure 5; it is also possible to confirm the correct operation of the neural network because the series modelled by the network corresponds to the dynamics of input values of public investment. The forecast values tend to decline for future periods, and public institutions designed to regulate the investment process need to focus on stimulating public investment programs.

Figures 6-7 present the dynamics of input values of foreign direct investment and the importance of exports of goods and services.



Figures 6–7 – Dynamics of input values of foreign direct investment and values of exports of goods and services, series simulated by an artificial neural network, and the following three predicted values

Modelling the time series of foreign direct investment is significantly complicated by the presence of negative numbers observed in 2015 and 2020. Comparing the input values and the simulated ones, it is possible to notice the preservation of the primary trend, along with significant differences in fluctuations. The simulated series is more sloping. This confirms the existence of political and institutional influence on foreign direct investment, recalling at least a change in the calculation methodology in 2020, which led to a negative value in the dynamics.

As can be seen from Figure 7, projected values of exports of goods and services tend to increase in future periods, which is extremely important for the economic development of Ukraine.

The next step is to consider the simulated dynamics and projected values of the employed population (Figure 8) and the average wage in Ukraine (Figure 9).

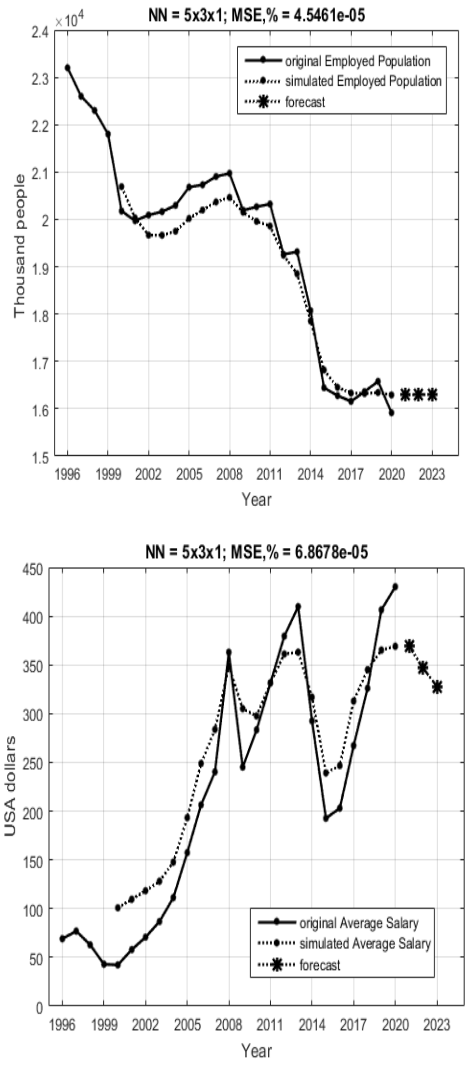


Figure 8–9 – Dynamics of input values of the employed population and the average wage in Ukraine, series simulated by an artificial neural network, and the following three predicted values

The number of employed people in Ukraine is constantly declining during the study period, undoubtedly hurting the economy. According to the forecast calculated by the neural network, the number of employed people will be stable for the next three years. Given the graph of input values, the lack of decline in the forecast can already be considered a positive phenomenon.

They are analysing the trends shown in Figure 9; you can see sharp fluctuations in the dynamics of average wages. Fallings occur during economic shocks, accompanied by inflation. The simulated dynamics of the artificial neural network perfectly repeat these cyclic oscillations, and therefore the forecast with its use should be considered plausible.

Based on the forecast results, it should be noted that the average wage in Ukraine in the coming years may tend to decline.

The projected values for the simulated time series for the period 2022-2023 are presented in Table 1.

Table 1 – Projected values of economic indicators of Ukraine (millions USA dollars)

Year	GDP	DFI	State Investments	Private Investments	Employed Population
2021	151368.19	2930.3725	3125.4214	13244.467	16291.212
2022	148154.73	3154.5253	3004.7095	14239.145	16298.719
2023	144734.43	3423.0747	2952.3312	14874.856	16298.248
Year	Total fixed Capital	Average Salary	Export	State Capital	Private Capital
2021	456533.56	369.07650	56577.571	71772.030	401544.38
2022	511410.11	346.79442	58536.265	10298.900	437104.64
2023	556902.62	327.84136	61387.916	12028.897	461360.19

CONCLUSIONS

Given the high accuracy of the constructed models, which confirms the synchronicity of time series and close in value forecasting results, it is possible to conclude that in 2022–2023: the growth of the private sector in the structure of the country's fixed assets will continue; the amount of investment from private national and foreign investors in Ukraine's economy will gradually increase; under constant conditions, the dynamics of public investment will tend to decline; income from exports of goods and services will grow; the number of employed will remain virtually unchanged; there may be a downward trend in the dynamics of the average wage; dynamics of Ukraine's GDP in dollar terms may lead to a slight decline.

It should be added that the calculations do not take into account the institutional influence of the state and show the state of the economy based on the input values of the time series. Ukraine's economy is experiencing times of crisis and is unbalanced. In the absence of concerted action to improve the situation on the part of the government and the public, the result will be a reduction in the absolute values of the studied macroeconomic indicators.

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