POSSIBILITIES OF USING ARTIFICIAL RADIAL BASIS FUNCTION NEURAL NETWORKS FOR MODELING ECONOMIC PROCESSES

Tomasz Wołowiec[1]
Volodymyr Martyniuk[2]

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Abstract: *The possibility of using artificial radial basis function neural networks for modeling of economic phenomena and processes is shown. The basic characteristics and parameters of an artificial radial basis function neural network are shown and the advantages of using this type of artificial neural networks for modeling economic phenomena and processes are emphasized. Using an artificial radial basis function neural network, together with official statistics for 2010-2017, the modeling of the influence caused by work efficiency indicators of the customs authorities of Ukraine on the indicators of economic security of Ukraine was carried out. The results obtained showed good analytical and prognostic properties of an artificial radial basis function neural network when modeling the impact of customs authorities' performance on the state's economic security indicators.*

Keywords: *Economic security of the state, Radial Basis Function Neural Networks, Customs system, Indicators of economic security of the state, Macroeconomic forecasting.*

1. INTRODUCTION

In the context of the constantly changing global economic development trends and the daily occurrence of internal and external threats that can suddenly change the trajectory of each country's economic development (e.g., coronavirus pandemic, dramatic change in energy prices, etc.), not only the current state of the national economy is an important task for both science and practice, but also the prediction of its values for the near future. Such a prediction is not possible without taking into account the influence of various factors both on particular branches and on the general state of the economy of the state. Developing an appropriate scientific and methodological framework will make it possible to quite accurately predict the value of macroeconomic indicators, and consequently to implement appropriate management decisions to minimize the negative impact of certain global processes.

Most often, regression models are used to model economic phenomena and processes. However, under conditions of non-stationarity of processes, nonlinearity of relationships between indicators that are characteristic of most economic phenomena and processes, as well as in the absence of objective statistics using a stochastic approach, and in particular, regression analysis does not allow to obtain scientific results that would reflect objective economic reality. In addition, applications such as Statistica, MS Excel, which can be used for modeling, require the study of the statistical characteristics of both the studied economic indicators and the factors influencing them, which, in the case of limited statistics, can sometimes be a difficult practical task.

[1] University of Economics and Innovation in Lublin, Projektowa str. 4, 20-209 Lublin, Poland
[2] University of Economics and Innovation in Lublin, Projektowa str. 4, 20-209 Lublin, Poland

2. THEORETICAL BACKGROUND

Recently, artificial neural networks (ANNs) have become widely used to model economic systems. In particular, perceptron-type networks, which provide good approximation capabilities of the model, are used for these purposes. Among the scientists whose studies deal with the problems of using these networks for modeling economic phenomena and processes, the works of Bodiansky E., Oliver Nelles, Rudenko O., Dyvak M. should be mentioned.

Among a large number of types of neural networks (Kohonen Maps, Carpenter & Grossberg Networks, and those of Hopfield), the Radial Basis Function Neural Networks (RBFNs) are a special class from the standpoint of modeling the development of different economic phenomena and processes, as well as the influence of various factors on them. As the results of the studies show, this type of artificial neural network is not only a powerful mean of approximating the nonlinear functions of many variables, but also allows us to predict the processes successfully. Such networks have a fairly simple architecture and high training speed.

RBF networks are known as networks with locally configured processing units, that is, networks where the output signal is „local" or „tuned" to some narrow-confined area of the input space. (Rudenko & Bodiansky, 2006)

Radial basis transfer function - this type of function accepts as the argument the distance between the input vector and some preset center of the activation function. The closer the input vector is to the center, the higher is the value of this function. (Yasnitsky, 2008) Gaussian function in this case can be used as a radial basis:

$$y = \exp - \frac{(S-R)^2}{2\sigma^2} \tag{1}$$

where $S = \|X - C\|$ is the distance between the center C and the vector of the input signals X. The scalar parameter σ determines the decay rate of a function when the vector is distant from the center and is called the width of the window, the parameter R determines the shift of the activation function along the abscissa axis. Different metrics can be used as a distance between vectors (Kruglov & Borisov, 2001), although it is the Euclidean distance that is most commonly used:

$$S = \sqrt{\sum_{j=1}^{N} (x_j - c_j)^2} \tag{2}$$

where x_j is the jth component of the vector fed to the input of the neuron, and c_j is the jth component of the vector that determines the position of the center of the transfer function.

The RBF network consists of an input, a single hidden (radial basis) and a linear (output) layer. The input layer consists of sensors (synaptic contacts) that connect the network to the external environment. The neurons of the hidden layer act on the principle of centering on the elements of the training sample. The weighting matrix functions as the centers. There is an area called radius around each center. The radius (network sensitivity) is adjusted using the vector of smoothing coefficients (σ_1, ... ,σ_m). The transformation function (Gaussian function):

$$f(x) = e^{\frac{(x-c)^2}{2\sigma^2}},$$

which takes values in the range from 0 to 1, determines the output of the hidden layer. The source layer contains ordinary linear or sigmoid neurons. The weight setting determines the output of the network.

The properties of such an artificial neural network are completely determined by the radial basis functions used in the hidden layer neurons and form some basis for the input vectors x. The radial basis function $\varphi(x) = \hat{O}(\|x - c\|, \sigma) = \hat{O}(r, \sigma)$ – is a multidimensional function that depends on the distance between the input vector x and its own center c and the width (scale) parameter σ. (Nelles, 2001) Thus each neuron of the hidden layer determines the distance between the input vector and its center and performs some nonlinear transformation $\hat{O}(r, \sigma)$ over it.

In most practical cases, the node centers c_i and width parameters σ_i are fixed and only the synoptic weights w_i are adjusted. To solve more complex problems, all three sets of parameters $c_i \in R^n$, σ_i, $w_i \in R^1$, $i = 0, 1, 2, \dots, h$ are taken into account.

The main advantages of using RBFNs compared to other ANNs are the next (Bodiansky & Rudenko, 2004): there is only one hidden layer in the RBFN, which simplifies the network structure; high learning speed; training ability on a heterogeneous sample of data; possibility of modeling systems with deep instability; ability to build models of dynamics of non-stationary objects; prognostic properties; capability of modeling and predicting random processes.

It is the presence of these advantages that led to the choice of this type of ANN for the study of economic phenomena and processes.

3. METHODOLOGY OF RESEARCH

The RBFN behavior depends largely on the number and position of the radial basis functions of the hidden layer. Indeed, for any valid n-dimensional input vector x = $(x_1, x_2, \dots, x_n)$, where $x \in X \subset R_n$ the network output will be determined as follows:

$$y_i = \sum_{k=1}^{m} w_{ik}^l f_k \left(dist\left(x, w_k^r\right), \sigma_k\right) \tag{3}$$

where, $w^l_{ik} \in W^l$, $i = \overline{1, p}$ – the weights of the linear layer, are the centers of radial-basis functions.

The artificial neural network with RBF is characterized by three types of parameters (Rudenko & Bodiansky, 2006; Bodiansky & Rudenko, 2004):

1. Linear weight parameters of the source layer w_{ij} (included in the network description linearly);
2. Centers c_i – nonlinear (included in the description of the neural network in nonlinear way) parameters of the hidden layer;
3. Deviations (radial of basic functions) σ_{ij} – nonlinear parameters of the hidden layer.

So, as we can see, the advantage of using such ANNs for modeling economic phenomena and processes is a significant simplification of the model structure, since radial basis functions are used, and the training task involves determining the weight coefficients and synoptic connections of the output layer of the network. In this case, the neural network has one hidden layer with nonlinear activation functions having configurable parameters. This ensures the simplicity of the model structure on the one hand and the approximate and predictive properties, on the other hand, with small „noisy" data samples. That is why, as an experiment with the use of RBFN, we modeled the impact of the customs system of Ukraine performance indices on the indicators of economic security of the state.

Based on official statistical information (State Statistics Service of Ukraine, 2018; EUROSTAT, 2019), eight indicators for 2010–2017, which characterize the customs authorities of Ukraine work efficiency were selected as factors of influence (input data). Among them: the amount of transfer of customs payments to the state budget, the number of cargoes completed, the number of customs declarations issued, the number of vehicles issued, the number of preliminary declarations issued, the number of preliminary notices issued, cases of violation of customs rules, cases of smuggling. Eighteen most effective indicators of economic security of Ukraine in 2010–2017, which comprehensively characterize the economic status of the country in terms of production, social, financial, food, transport, energy, foreign economic security, grouped on the basis of performance, were selected (State Statistics Service of Ukraine, 2028; Institute for European Environmental Policy, 2013). The list of these indicators is provided by the Methodological recommendations for calculating the level of economic security of Ukraine, which were approved by the Order of the Ministry of Economic Development and Trade of Ukraine of October 29, 2013 No. 1277.

MATLAB was used to train the network and shape its structure, as it allows for the rapid processing of large amounts of statistics, and its tools provide a wealth of data analysis capabilities covering almost all areas of mathematics, including ANN.

Both the one-step Widerow-Hoff training algorithm (Nelles, 2001), and the multi-step learning algorithm are most commonly used for RBFN training. When training a neural network using a one-step algorithm, the network structure is formed in such a way that the number of neurons in the hidden (radial basis) layer is equal to the number of elements of the training sample, and the learning error is zero (Nelles, 2001). A significant disadvantage of the one-step training algorithm is that it forms a network with a number of radial-base-level neurons equal to the number of training sample elements. With this neural network training algorithm, it is not possible to obtain adequate simple models when dealing with large volumes of training samples. Therefore, in our study, we used a multi-step learning algorithm.

The multi-step network learning algorithm generates an RBFN model with optimal number of hidden level neurons. It creates a bi-level network. The first level consists of radial-base neurons, and calculates its weighted inputs using the Euclidean distance *dist* function as well as its specific inputs. The second layer consists of simple linear neurons ($y = f(x) = x$) and calculates its weighted input and its specific inputs using the appropriate functions.

At the beginning of the algorithm, the radial basis level does not contain neurons. Neurons are added to the hidden layer until the sum of squares of the mean square errors of the network is less than the specified value or the maximum number of neurons is used. In the next step, the network forecast is calculated:

1. An input vector (in our case it is the realization of inputs in one or another month) with the largest value of the root mean square error is found;
2. A radial basis neuron with weights equal to this vector is added;
3. The linear scale weights are reorganized in such a way as to minimize the root mean square error.

Fig. 1 shows the initial structure of the RBFN, where $x_1 - x_8$ – the indicators characterizing the efficiency of the customs system functioning, and $y_1 - y_{18}$ – indicators of economic security of the state.

As the figure shows, the structure of RBFN 8:36:18 is formed when the root mean square error of training is set to equal to zero. The number of neurons in the hidden level is equal to the number of elements of the training sample. From the conducted research it is possible to conclude that the given structure of a network is too complicated.

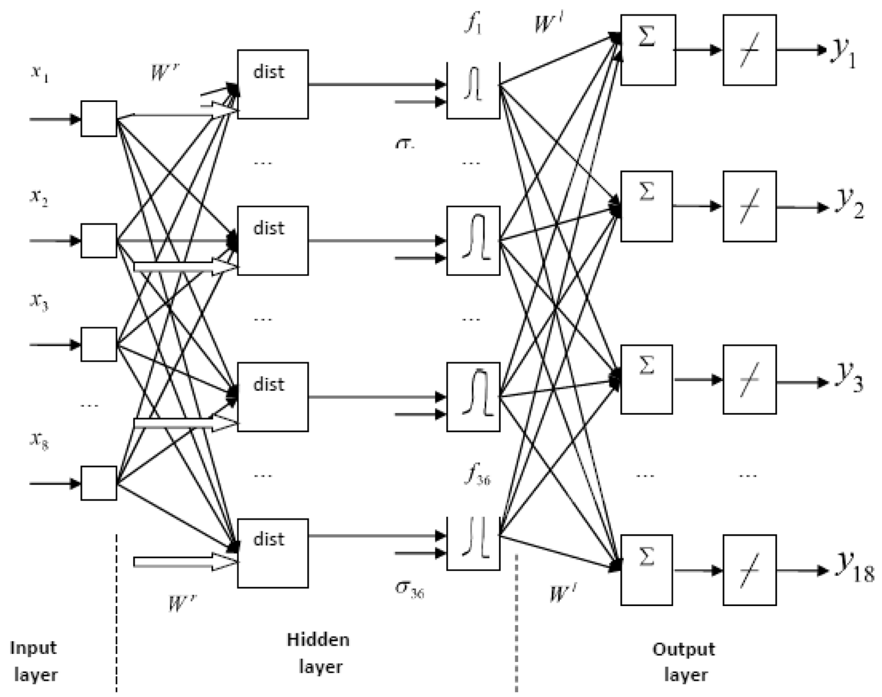

Figure 1. The initial structure of RBFN (the root mean square error of training is zero)

Source: Own elaboration

With a root mean square error of network training of 10% the number of neurons of the hidden level will be equal to 30; an error of 20% equals to 21 neurons; errors of 30%, 40%, and 50% result in 14, 6 and 2 neurons of the hidden level respectively. Although at 40% and 50% network training error, the RBFN structure is optimized to 6 and 2 hidden level neurons, however, as the results of the experiments, this structure does not provide sufficient prognostic properties. (European Commission, 2012, 2013)

The formation of the network structure is also influenced by the smoothing factor (the width parameter of the RBF window), which is usually chosen experimentally. The parameter value must be large to override the active areas of the basic functions. This provides the necessary smoothness of the approximating curves and precedes the situation of retraining the network. However, the influence parameter value should not be so large that the radial basis function shows all the input values equal.

The choice of the smoothing coefficient is completely empirical, and when incorrectly set its value complicates the RBFN structure and deteriorates its prognostic properties.

As a result of the conducted research, the optimal value of the impact parameter (RBF window width parameter) was set at 600000 (Institute for European Environmental Policy, 2013), which made it possible to predict rather complicated dynamics of economic security indicators, depending on the factors characterizing the activity of the customs authorities of Ukraine. An example of such a model is shown in Fig. 2.

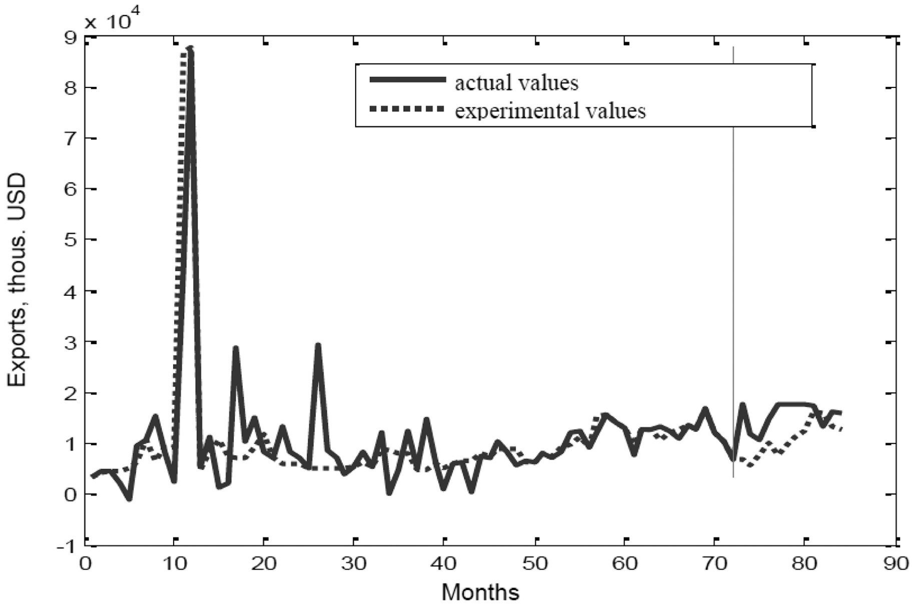

Figure 2. Forecasting the ES export indicator values

Source: Own elaboration

4. FUTURE RESEARCH DIRECTIONS

On the whole, the obtained results of the conducted experiments give grounds to conclude that the given RBFN structure well describes the tendency of change of economic security indicators of the country for future periods. This, in turn, will allow future studies to accurately establish the relationship and interaction between performance indicators of the customs system and certain economic security indicators of the state.

5. CONCLUSION

As a result of the research, the optimal RBFN structure is 8:14:18 (the allowed root mean square error of network training is 30%, the influence parameter is 600000).

To further check the adequacy of the obtained model structure, a computational experiment was conducted: an attempt was made to forecast the values of economic security indicators of Ukraine with the help of RBFN for 2018-2019 based on a training sample of data (performance indicators of the customs authorities of Ukraine and economic security indicators of Ukraine) for 2010–2017.

The results of forecasting the values of economic security indicators of Ukraine were compared with their actual values given in official statistical sources.

As the results of the experiment show, there is no significant error in the obtained results of forecasting the values of the economic security indicators of Ukraine. The neural network, in training, describes well the actual trend of individual economic security indicators of Ukraine.

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