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SPECTRUM NEURAL NETWORK FILTRATION TECHNOLOGY FOR IMPROVING THE FORECAST ACCURACY OF DYNAMIC PROCESSES IN ECONOMICS

The universal method for improving measurement, evaluation and forecast accuracy of dynamic processes in economics based on spectrum neural network technology is developed. Simulation model for determining the optimal parameters for spectrum neural network filtration system has been created. The approach to adaptation of developed tools to specific application requirements is proposed.

Keywords: *spectrum neural network filtration; forecasting; dynamic processes; time series; principal components method.*

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ТЕХНОЛОГІЯ НЕЙРОМЕРЕЖЕВОЇ СПЕКТРАЛЬНОЇ ФІЛЬТРАЦІЇ ДЛЯ ПІДВИЩЕННЯ ТОЧНОСТІ ПРОГНОЗУВАННЯ ДИНАМІЧНИХ ПРОЦЕСІВ В ЕКОНОМІЦІ

У статті розроблено універсальний метод підвищення точності вимірювання, оцінювання та прогнозування динамічних процесів в економіці на основі технології нейромережевої спектральної фільтрації. Побудовано імітаційну модель визначення оптимальних параметрів системи для здійснення нейромережевої спектральної фільтрації. Запропоновано підхід до адаптації розроблених засобів до вимог конкретного застосування.

Ключові слова: *нейромережева спектральна фільтрація; прогнозування; динамічні процеси; часові ряди; метод головних компонент.*

Рис. 2. Літ. 13.

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ТЕХНОЛОГИЯ НЕЙРОСЕТЕВОЙ СПЕКТРАЛЬНОЙ ФИЛЬТРАЦИИ ДЛЯ ПОВЫШЕНИЯ ТОЧНОСТИ ПРОГНОЗИРОВАНИЯ ДИНАМИЧЕСКИХ ПРОЦЕССОВ В ЭКОНОМИКЕ

В статье разработан универсальный метод повышения точности измерения, оценки и прогнозирования динамических процессов в экономике на основе технологии нейросетевой спектральной фильтрации. Построена имитационная модель определения оптимальных параметров системы для осуществления нейросетевой спектральной фильтрации. Предложен подход к адаптации разработанных средств к требованиям конкретного применения.

Ключевые слова: *нейросетевая спектральная фильтрация; прогнозирование; динамические процессы; временные ряды; метод главных компонент.*

Introduction. For quality control in complex technical systems, it is important to obtain forecast information on future states of such systems. This allows eliminating potential failures and other shortcomings in their functioning.

Often it is necessary to control the changing conditions that lead to uncertainties in the processes within systems. Such conditions may have uncertain impact of

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uncontrollable factors, the lack of sufficient knowledge on the environment and external factors, the uncertainty of the model structure of the system and other types of uncertainties. As a result, it is more complicated to make a state forecasting and to perform efficient management of such systems.

For tasks when the output values depend on previous input values and system has its internal dynamics, there are problems of effective noise removal from various sources. Such problems are related to the influence of many factors on input data, each having a different degree of influence on the result. Especially difficult is the problem, when it is impossible to clearly identify the influencing factors and when the impact magnitude of these factors on the result is unknown. One of these problems is increasing the prediction accuracy in economics (Cao et al., 1996; Kaastra and Boyd, 1996; Clements and Hendry, 1998).

That is why the development of methods and tools to improve the accuracy of dynamic processes forecast is an important task.

Literature review. Currently new scientific approach to the analysis of processes occurring in complex systems is actively developing, based on multidimensional samples of real processes in a matrix convolution (set of copies of time sequences taken with certain displacements). Singular decomposition of that matrix can describe the dynamics of a complex system and predict its future behavior. This approach is called the singular spectrum analysis (SSA). An important contribution to its development has been made in particular by N. Golyandina et al. (2010), J. Elsner and A. Tsonis (1996). The advantage of singular spectrum analysis is the ability to present time sequence as the sum of independent components such as trend, periodic fluctuations, noise in the absence of precise knowledge of the process model parameters.

General ideas of SSA are considered in (Golyandina and Zhigljavsky, 2013; Elsner and Tsonis, 1996). In particular, N. Golyandina and A. Zhigljavsky (2013) show that this method is effective for noise filtering in time series. There are many publications on use of SSA in solving problems in various fields because SSA is a powerful methodology that can be used for various applications, e.g., for predicting energy consumption (Kumar and Jain, 2010), noise reduction and restoration of seismic data (Oropeza and Sacchi, 2011), short-term forecast of exchange rates (Hassani, Soofi and Zhigljavsky, 2010) etc.

Unresolved issues. Classic singular spectrum analysis has several disadvantages that often make impossible its practical application. In particular, the known methods of singular spectrum analysis are difficult to apply to many prediction problems due to significant restrictions on the dimensions and the volume of data describing the background of processes since the appearance of each new time count requires re-execution of the entire amount of necessary calculations. These disadvantages can be eliminated by using neural network technology.

The purpose of this study is to develop a universal neural network data filtering technologies for dynamic processes of measurement, evaluation and prediction and its adaptation to a specific application.

Key research findings. To achieve the research goal the following tasks have been resolved:

- instruments for short-term forecasting of dynamic processes in economics has been selected and adapted;

- neural network paradigm for the implementation of spectrum filtration has been chosen;
- universal neural network tools for realization of spectrum neural network filtration of dynamic data has been developed;
- method for adapting the universal neural network tools for specific application has been developed;
- developed tools have been used to improve the accuracy of short-term prediction of generalized integral influence index of internal and external factors on the enterprise.

The main stages of the developed spectrum neural network filtration technology for improving the prediction accuracy are:

1. Making prediction of the generalized integral influence index of internal and external factors on an enterprise for one year.
2. Formation of reference (actual) set of initial data to assess the accuracy of prediction.
3. Adaptation of neural network spectrum filtering tools for a specific application.
4. Filtration of incoming data using adapted neural network tools.
5. Making a prediction using the filtered input data.

To implement the spectrum neural network filtration technology for improving the forecast accuracy of dynamic processes in economics the basic structure of neural network tools has been developed (Figure 1), which consists of 3 main components:

- input time sequence to matrix delay conversion module;
- neural network based on geometric transformations models (GTM) for the selection of principal components and dynamic filtering;
- neural network for implementation of forecasting – you can use different types of networks, such as GTM, RBF and others.

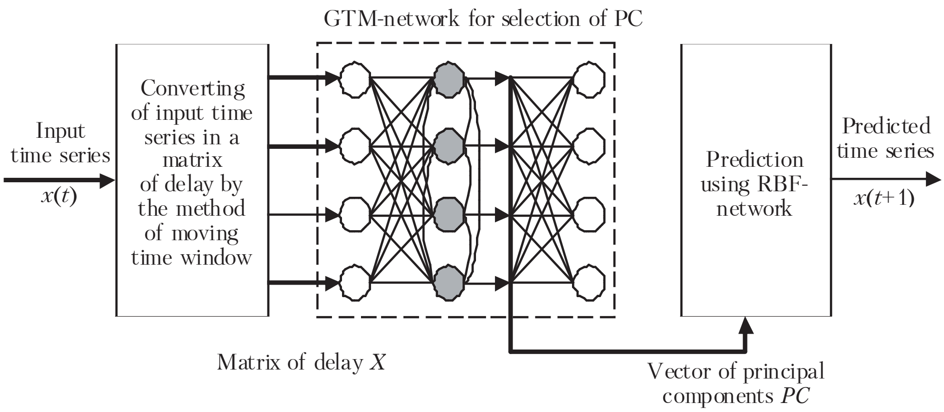

Figure 1. **Basic structure of neural network tools for improving the forecast accuracy of dynamic data,** *developed by the authors*

The essence of the developed neural network tools is that the input time sequence, based on which we perform the forecasting, is filtered using the decomposition on principal components and the components which are noise is discarded.

Thus, to the input of neural network, which provides the forecasting, data get cleared of noise and due to this the forecast accuracy is increased.

Neural network tools for improving the forecast accuracy of dynamic processes in economics operate as follows.

The very first step in dynamic filtering implementation is to transform the input time sequence into a matrix (Golyandina and Osipov, 2007). To do this, windows size K should be selected. The optimal value of K depends on the problem that is solved, and can be determined experimentally. The first row of the matrix consists of elements $1..K$ of input time series. Then, at each step, the window moves by one element. Thus, the second row will consist of elements $2..K + 1$, the third – $3..K + 2$, etc. As a result of processing the matrix K principal components will be obtained, some of which are informative, and some are noise.

To perform the spectrum neural network filtration of dynamic data GTM neural network is used (Tkachenko et al., 1999). At the basis of GTM paradigm is the principle of response hypersurfaces presentation in orthogonal coordinate systems that best match with the main hypersurfaces dimensions. A close analogue of neural network based on GTM paradigm is a two-layer perceptron of the autoassociative type which is constructed by the method in formation bottleneck. In the general case of bottleneck, when the number of hidden layer neural elements are less than the number of inputs, the transformation of input vectors into identical output vectors occurs with some error. The advantage of GTM network is that a "bottleneck" mode is not mandatory for its implementation, so there is a possibility of exact (with zero methodological error) display of input signal vectors in output vectors, simultaneously selecting the signals of all the components of an information object on the outputs of hidden layer neural elements.

The inputs of GTM network received all components of existing vectors of the sample simultaneously; the same components are used as input signals for network training vectors for implementation of training. Output signals of neural elements represent the signals of principal components.

After the filtering stage the data arrives at the inputs of the neural network, which makes the forecasting. For prediction of dynamic processes in economic RBF neural network has been used (Caiqing et al., 2008; Teslyuk et al., 2011).

The adaptation of developed tools for implementation of spectrum neural network filtration technology of dynamic data to specific use occurs in a few steps.

On the first step you need to select the size of a time window K, i.e., on how many principal components we will decompose our signal. This value is selected by iterating all possible values of K, and then you select the value at which the output error is minimal. Manual determination of this parameter is difficult and long, so we develop a simulation model for determining the optimal parameters.

In the next step input signal is decomposed into principal components by means of the GTM network. It should be noted that if we decompose a value on K principal components, the sum of these components will match the original value.

Each principal component is an independent additive part of the original signal. The first component is the trend and some others are useful signals, some are noise.

In the next step the principal components which are noise are discarded. To do this, we reject some of the main components in turn and check how the actual error

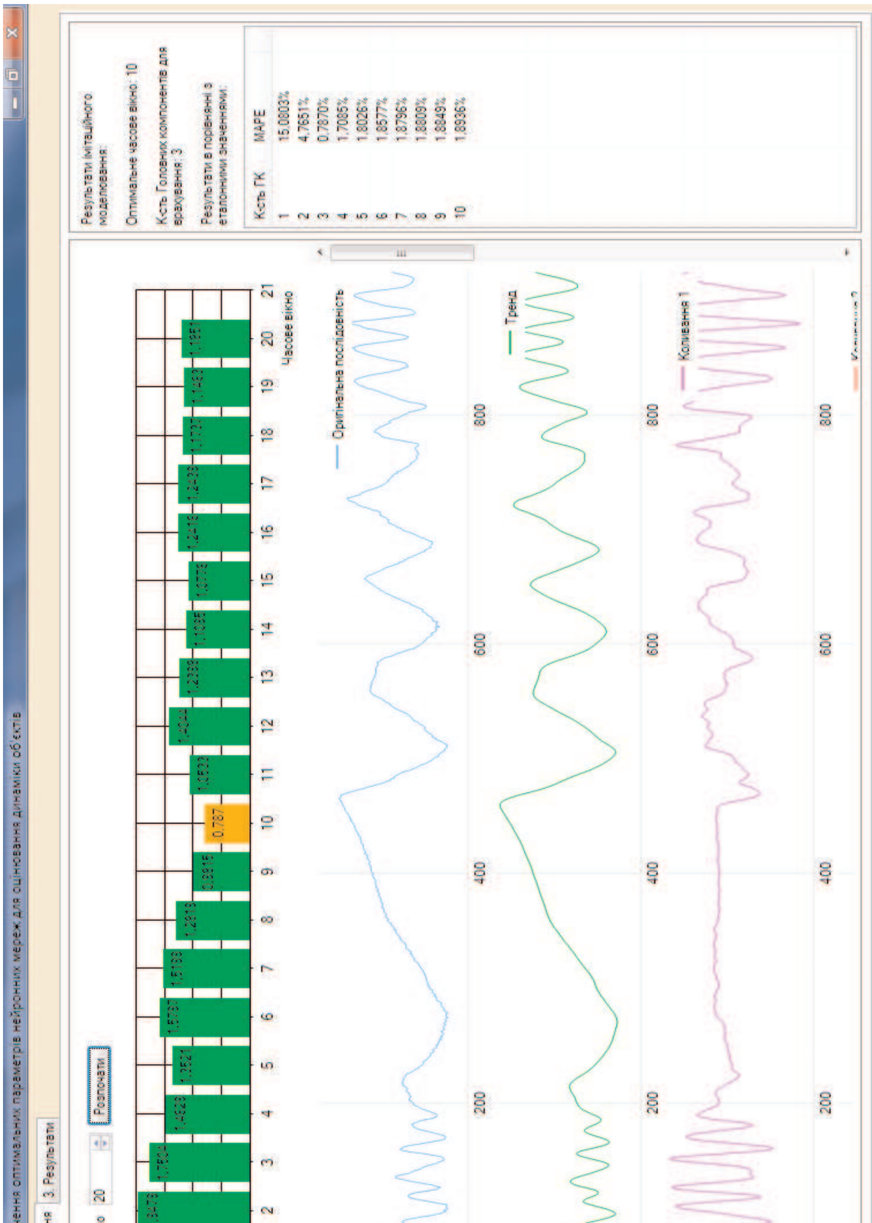

Figure 2. **Main window of the simulation model for determining the optimal filtration options,** *developed by the authors*

value decreased as compared to the reference value. If we reject the principal components which are noise, the accuracy of the input data increases, and thus the quality of prediction that we can make based on this data will increase as well.

To determine the optimal filtering parameters, we have developed a simulation model (Figure 2). Software implementation of the simulation model is developed in the C# programming language. To determine the optimal parameters you should provide two time sequence – actual and reference – to the input of application. As a result, the application shows on how many principal components the input signal should be decomposed, and which of these principal components are to rejected.

To test the tools for dynamic processes forecasting in economics the prediction of generalized integral influence index on the enterprise "Energoterm" (Lviv) has been carried out. The generalized integral influence index on enterprise takes into account the hierarchical interaction and interdependence of all groups and impacts that act on the enterprise.

Using the simulation model, it was determined that for dynamic filtering of the generalized integral influence index input temporal sequence should be divided into 7 principal components. After calculations, it was found that only the first 4 principal components contain useful data, while others are noise. Thus, it is required to reject the last 3 principal components to implement filtering of input sequences, and consider only the first 4.

Using the developed spectrum neural network filtration technology of dynamic processes in economics improves the forecast accuracy of generalized integral influence index by 9%.

Conclusions:

1. For the first time spectrum filtration technology of dynamic processes based on neural network models of geometric transformations has been developed, which is universal and based on the research of the input time series using the principal components method. Application of this technology enhances the forecast accuracy of dynamic processes in economics.

2. The structure of neural network tools for improving the forecast accuracy of dynamic processes consists of 3 main components: 1) tools for converting the input time sequence to the delay matrix; 2) neural network based on geometric transformations models for selection of principal components and rejection of noise components; 3) tools for prediction using purified data.

3. The adaptation of developed tools of neural network dynamic filtering for specific applications includes the following steps: 1) choosing the size of a time interval; 2) decomposition of the input signal to principal components; 3) discarding those principal components that are noise.

4. Further research and development should be carried out in the direction of using neural network tools for recovering lost data under noise and incomplete information conditions, which should provide further growth of forecast accuracy of dynamic processes in economics.

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