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Intelligent system for time series forecasting

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Abstract

The paper presents a mathematical model of processing and forecasting time series data. The mathematical model based on the methods of artificial neural networks and preliminary data processing using wavelet transforms discribed.

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Keywords: time series; forecasting; artificial neural networks; wavelet transform.

1. Introduction:

The most optimal and reliable method of forecasting is predicting at short intervals. The purpose is to optimize the activity of industrial enterprise in planning and carrying out activities aimed at minimizing the environmental, material damages and the general negative impact on the environment.

In order to predict the value of the time series is not enough just to apply these values to the neural network. Reducing the influence of parasitic noise is added to the useful signal noise component, it requires the use of low-pass filtering. Wavelet filtering (W-filter) was used for this purpose. After processing, they are fed to the neural network. The latter, in turn, must be formed and trained according to the task. Once the neural network has been initialized and is ready to fill the required number (needed for foresight) of the wavelet expansion coefficients obtained by using W-filter, connects the memory unit required for constant adjustment of the neural network coefficients. To receive as a result of the predicted values of the time series, it is required to restore the approximate coefficients. Thus, automated monitoring system includes three main phases of functioning: pre-processing at the

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wavelet W-filter forming and training the neural network and restoring the time series data of the predicted coefficients.

2. Processing and analysis of time series by wavelet transform

Consider multiresolution wavelet decomposition nonstationary signal in a time-series of samples *x(k)* to the level n. In this case, the signal *x(k)* is decomposed into two projections - projection onto the space V^n (approximating coefficients representing the low-frequency component of the signal) and the space W^n (detailing the factors responsible for the transmission of high-frequency part of the signal)[4,5].

Expressions for calculating approximate and detail coefficients of the wavelet decomposition of the first decomposition level are of the form:

$$C_1(k) = \frac{1}{p}\big(u(k)+\xi(k)\big)\varphi_1(k),$$
$$d_1 = \frac{1}{p}\big(u(k)+\xi(k)\big)\psi_1(k) \tag{1}$$

where *u(k)=x(k)-n(k)* - the actual value of count, n(k) - noise component),$\xi(k)$ - the reference fluctuation component,$\varphi_1(k)$ - scaling function, $\psi_1(k)$- the wavelet function.

The approximation and detail coefficients of higher expansion levels are calculated by the following expressions:

$$C_{i+1}(k) = \frac{1}{p}C_i(k)\varphi_{i+1}\left(2^{i+1}t-k\right),$$
$$d_{i+1}(k) = \frac{1}{p}C_i(k)\psi_{i+1}\left(2^{i+1}t-k\right). \tag{2}$$

Recovery time series is carried out by the formula [4,5]:

$$s(k) = d_1 + d_2 + .. + d_n + C_n, \tag{3}$$

where $C_n = \frac{1}{p}C_{n-1}\varphi_n\left(2^n t-k\right)$.

Considering the (1), (2) and (3), the mathematical model of the reduced experimental time series with the wavelet decomposition to a level n is given by [6,4]

$$s(k) = \frac{1}{2}\left[\left(u(k)+\xi_k\right)\psi_1(k) + \left[\sum_{i=1}^{n-1}\left(C_i\psi_{i+1}(k)\right)\right] + C_i\psi_{i+1}(k)\right] \tag{4}$$

Fig. 1 shows the results of investigation approximate autocorrelation coefficients $C_i(k)$. As can be seen from Figure 1, graphs ACF approximating coefficients $C_i(k)$ show an increase in the correlation time with an increase in the level of wavelet decomposition[5,7].

Figure 2 shows results of studies of the time series according to the attenuation component and noise variance, respectively, reduce the error from the neural network learning level wavelet processing the input time series signals, where β(τ)=σ2n,W/σ2n,inthe variance of the noise components at the output of filter W-wavelet processing.

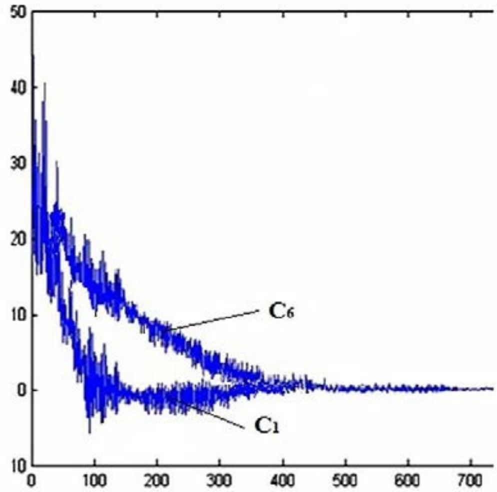

Fig. 1. Graphs autocorrelation functions

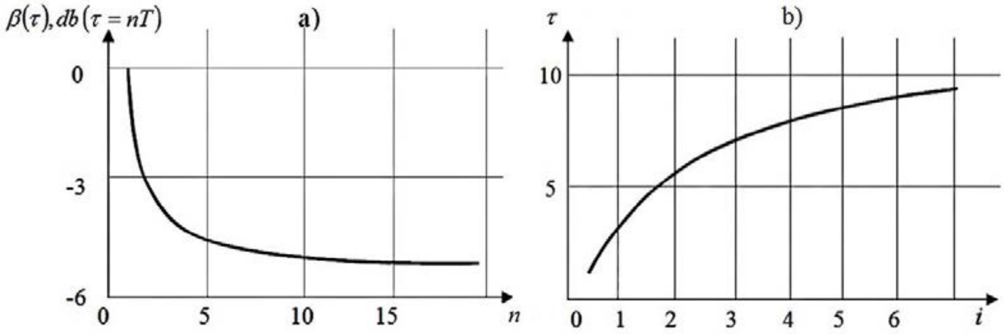

Fig. 2. Dependence of the noise attenuation component of time series on the level decomposition of the wavelet processing

Figure 2 “a” reducing the dependence of the resulting neural network training error of the correlation time of the noise component; Figure 2 “b” - dependence of correlation timeof the noise component of the time series at the output of the filter W-level wavelet - decomposition of an *i*-approximated coefficients C_i.

By plotting the attenuation of a neural network training and the error (Fig. 2, “a”) that the largest component of the noise attenuation and dispersion, respectively, the greatest reduction of the resulting neural network learning error can be obtained by increasing the correlation time of the noise component to the value $\tau=(5\div10)T$.

The graph in Fig. 2 "b", depending on the correlation time of the noise component of the time series data on the level of wavelet decomposition (i) approximating coefficients C_i, it can be noted that the greatest increase of the correlation time of the noise component for $\tau=(6\div8)T$can be obtained by the wavelet expansion approximating the coefficient of 3 to 6 levels. When $C3$;$\tau=6T$and when$C6$, $\tau=8T$. Thus, the pre-processing of the wavelet transform of the time series of samples can be carried out with the help of wavelet decomposition to the $C_6(k)$ coefficients.

With regard to (3), as well as the prediction samples r-mathematical model with experimental time series wavelet decomposition level to i = 6, it can be represented as:

$$s(k+r)=\frac{1}{p}\left[u(k)*\psi_1(k)+\left[\sum_{i=1}^{n=4}(C_i)*\psi_{i+1}(k)\right]+\left(C_5-C_6^{*r}\right)+C_6^{*r}\right] \tag{5}$$

3. Research, development and training of a neural network. Mathematical model of the automated monitoring.

In the simulation, the prediction algorithm according to the scheme of the neural network feedforward multilayer perceptron algorithm which follows.

3.1. Determine outputs one layer

Resultant vector of the first layer outputs where l = 1,2, ..., 64, in accordance with the number of neurons in the 1st layer:

$$y_1 = \begin{pmatrix} y_1^1 \\ y_1^2 \\ \dots \\ y_1^{64} \end{pmatrix} = \begin{pmatrix} \varphi\left(w_{1,1}^T \boldsymbol{C}_6 + w_{0,1}^1\right) \\ \varphi\left(w_{1,2}^T \boldsymbol{C}_6 + w_{0,2}^1\right) \\ \dots \\ \varphi\left(w_{1,64}^T \boldsymbol{C}_6 + w_{0,64}^1\right) \end{pmatrix},$$

where C_6 - vector approximating coefficients, $C_6 = [C_6^1, ..., C_6^{64}]$.

3.2. Determine the layer 2 outputs

Outputs a resultant vector of the second layer, l = 1,2, ..., 10, in accordance with the number of neurons in the 2nd layer, and depends on:

$$y_2 = \begin{pmatrix} y_2^1 \\ y_2^2 \\ \dots \\ y_2^{10} \end{pmatrix} = \begin{pmatrix} \varphi\left(w_{2,1}^T \boldsymbol{y}_1 + w_{0,1}^2\right) \\ \varphi\left(w_{2,2}^T \boldsymbol{y}_1 + w_{0,2}^2\right) \\ \dots \\ \varphi\left(w_{2,10}^T \boldsymbol{y}_1 + w_{0,10}^2\right) \end{pmatrix},$$

where y_1 - vector outputs the first neural network layer, $y_1 = [y_1^1, ..., y_1^{10}]^T$.

3.3. Determine outputs 3 layer

A third layerof the resulting output vector y_3^l , l = 1,2, ..., 10 in accordance with the number of neurons on the 3rd layer, and depends on y_3^l .

The last third layer outputs correspond to the ten predicted coefficients approximating the sixth level of wavelet decomposition.

$$y_3 = \begin{pmatrix} y_3^1 \\ y_3^2 \\ \dots \\ y_3^{10} \end{pmatrix} = \begin{pmatrix} \varphi\left(w_{3,1}^T \boldsymbol{y}_2 + w_{0,1}^3\right) \\ \varphi\left(w_{3,2}^T \boldsymbol{y}_2 + w_{0,2}^3\right) \\ \dots \\ \varphi\left(w_{3,10}^T \boldsymbol{y}_2 + w_{0,10}^3\right) \end{pmatrix} = \begin{pmatrix} \boldsymbol{C}_6^{*1} \\ \boldsymbol{C}_6^{*2} \\ \dots \\ \boldsymbol{C}_6^{*10} \end{pmatrix},$$

where y_2 - the vector of the second layer of the neural network outputs, $y_2 = [y_2^1, ..., y_2^{10}]^T$, C_6^{*r} - the result of predictions on r - return periods.

3.4. Determine the error

Reverse run: $e_{j-1} = W_j \phi_j e_j$, $j = n, n-1, \dots, 2$, $e_n = \varphi(s_n) - d$, where Φ_j-sigmoid activation function of neuron j[1,p.53]

$$s_j = W_j^T y_{j-1} + w_{j0} = \left(s_{j1}, s_{j2}, \dots, s_{jm_j}\right)^T .$$

Then adjust the synaptic coefficients[3].

$$w_{jl}(k+1) = w_{jl}(k) - \alpha h_{jl}(s_{jl}) e_{jl} y_{j-1} ,$$
$$w_{j0}(k+1) = w_{j0}(k) - \alpha \Phi_j e_j ,$$
$$W_j = \left(w_{j1} w_{j2} \dots w_{gm_1}\right),$$
$$\frac{\partial \varphi^T(s_j)}{\partial s_j} = diag\left(\frac{\partial \varphi(s_{j1})}{\partial s_{j,1}} \frac{\partial \varphi(s_{j1})}{\partial s_{j,1}} \dots \frac{\partial \varphi(s_{jm_j})}{\partial s_{j,m_j}}\right) = \Phi_j ,$$
$$h_{jl}(s_{jl}) = \frac{\partial \varphi(s_{jl})}{\partial s_{j,l}} .$$

The Figure 3 shows the graphs of the two-layer error learning, three-layer and four-layer neural network of the number of training iterationsn for different values of tuning steps.

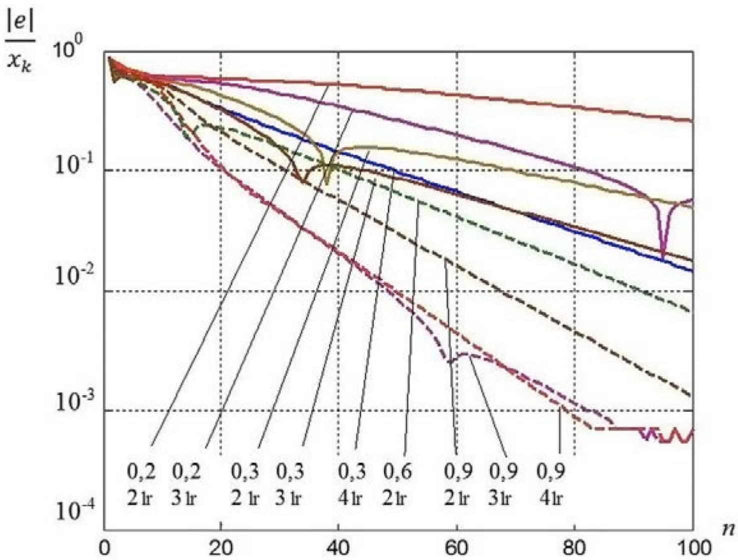

Fig. 3. Plots of the training error | e | /x_k the number of training iterations n for different values of α configuration step from 0.2 to 0.9.

From a graph of error learning in Figure 3 shows that the three-layer neural network has the best characteristics learning criterion prediction error (the difference reaches 37%). Fig. 4 shows the three-dimensional graphics error learning curves depending on the number of training cycles q and the number of neurons in the network m.

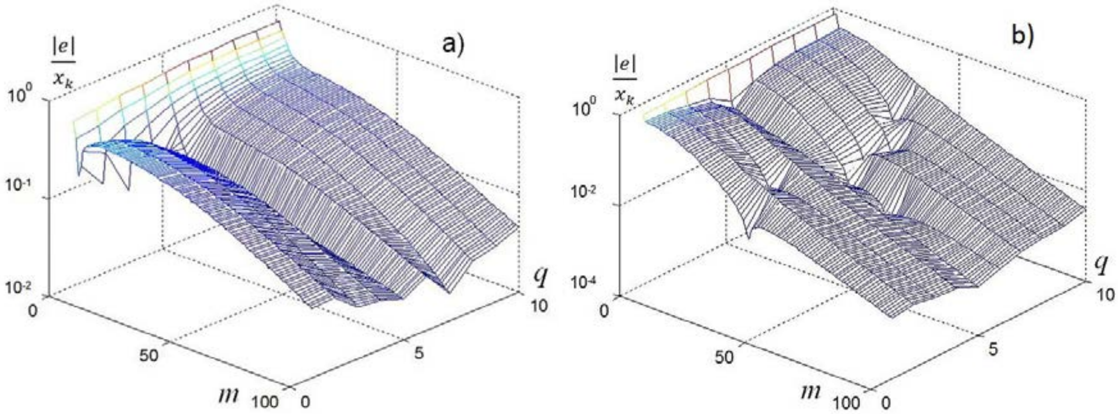

Fig. 4. Plots of the training error of the number of cycles of q and m the number of neurons in the network configuration step for values: a*)* $\alpha = 0.3$; b) $\alpha = 0,9$

The graphs in Fig. 4 shows that the number of cycles of the neural network training may be in the range of 1-3. A further increase in the number of cycles does not substantially increase the training options. Also from the graphs in Figure 3 shows that the parameters to obtain satisfactory education network should contain 50-80 neurons. According to the schedule, "b" shows that the network of learning setting step allows you to get the best results. Thus, the study results showed that the prediction model using neural networks of direct distribution to be realized before, preferably a three-layer perceptron scheme[3]. The neural network in this case consists of three layers, the first layer 64 comprises a neuron, a second layer of neurons ten, and ten third layer of neurons.

4. Recovery time series values. The structure of the implementation model, channel processing and forecasting information

On the basis of mathematical processing and forecasting models developed structural processing and forecasting channel timing circuits series obtained at the output of a sensor control system shown in Figure 5.

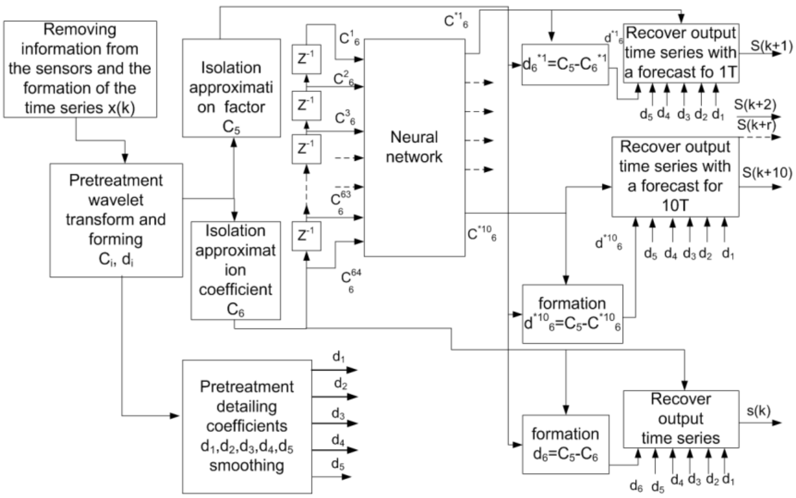

Fig. 5. The structural scheme of the channel prediction model

As seen from the block diagram in Fig. 5, recorded information forms the time series of counts. Thus, the input signals in the form of a time series x(k) are supplied to W-filter pretreatment wavelet transform. The wavelet filter is formed by approximating the coefficients Ci and detailing coefficients di, i-level wavelet decomposition. Dedicated sixth level approximating coefficients (C6 (k)) are input to a 64-bit shift register which generates sampled input signals of the neural network as a moving window of 64 data samples, formed in the wavelet filter. Detailing coefficients to the fifth level (d1, d2, ..., d5) after thresholding smoothing algorithm, supplied to the output units recovery time series forecast.

5. Conclusion

Thus, the pure interference output time series in real time and output time series prediction with a lower accuracy of information in display devices, and in decision-making system.

The studies developed a mathematical model and the structural model of the processing circuit and the time series prediction monitoring system. The main functional subsystems and their interrelationships. Based on wavelet transform algorithm was developed pretreatment time series, which provides a more correct set of training samples for subsystems using artificial neural network forecasting. Combined algorithm for prediction of time series values has been developed to improve the accuracy of the forecast, even after prolonged extrapolation. The results recovery time series show a high prediction accuracy. In an automated forecasting with high accuracy monitoring system is carried out (the prediction error is not more than 5.3%). Time predictions up to 10 periods of the time series, but may increase the prediction time in the application of this method of construction of an artificial neural network model

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