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FORECASTING TIME SERIES WITH NOTICEABLE FRACTALITY

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The article considers the main stages of forecasting by neural networks, opportunities and benefits of their use for prediction of time series with a visible fractality. In the examples predictability is determined by the R/S-analysis and can be used to select an appropriate prediction method, including the method of neural networks.

Keywords: *artificial neural networks, methods of forecasting, R/S analysis, predictability, training samples, sliding window, persistent value.*

PREVIZIUNEA SERIILOR DINAMICE CU FRACTALITATE VIZIBILĂ

În articol sunt abordate principalele etape de previziune prin reţelele neuronale, oportunităţile şi avantajele de utilizare a acestora pentru previziunea a serii de timp cu o fractalitate vizibilă. În exemplele aduse o predictibilitate se determină prin R/S-analiză şi poate fi utilizată pentru a selecta o metodă de predicţie adecvată, inclusiv metoda reţelelor neuronale.

Cuvinte-cheie: *reţele neuronale artificiale, metode de previziune, analiza R/S, predictibilitate, eşantion de formare, fereastră glisantă, valoare persistentă.*

I. Introduction. In modern conditions, issues of short-term and medium-term forecasting becomes especially relevant. This is due to insufficiently high stability of the economic situation in the world market due to the redistribution of production capacity, high rates of progress in science and technology, the general aging of the population, poor global environmental situation, the emergence of new diseases, strengthen the political process in many countries, including Moldova.

Many traditional methods of forecasting in a constantly changing operating conditions of enterprises give low accuracy or inapplicable. In such a situation more acceptable results with less time getting predictions have so- called artificial neural networks [1-8], which allows to take into account factors not formalized, rebuild the object model, with new information, simplify and make more accurately forecast economic indicators on the functioning of the enterprise in the relevant market their profiles.

The subject of the study is algorithmization of short-and medium-term forecasting using neural networks: an analysis of the domain and problem-solving methods of forecasting economic indicators facilities, demonstration of the technology of neural networks in series with a notable example of the fractality.

II. Characteristics forecasting methodology using neural networks

Forecasting is one of data mining tasks related to the problem of insufficient quality and quantity of data flow changes in the environment of the studied process, the influence of subjective factors and the model used.

Any forecast is always a certain error. Really there is no possibility to reduce the prediction error is below a certain level, regardless of the method used forecasting. Determination and prediction error allows (in certain situations) to reduce the risk of decision-making.

With the help of neural networks can solve some problems of processing and analysis. However, for predicting neural networks requires a certain expertise to develop user models of neural networks and their use. First of all, requires the correct formulation of the problem, namely, the sense of correct formulation of the problem , the correct choice of solutions, selection of the structure of a neural network learning algorithm and the quality criterion for solving the problem. Second, to obtain the optimum settings of neural network methods and finding the right solutions to relatively complex problems of time series forecasting, it is necessary to develop along with the theory of statistical prediction , and appropriate software.

Key features, characteristics and advantages of the use of neural networks over other existing methods, the following:

a) for solving ill-formalized or non-formalized problems always get a result. Of the advantages of methods based on neural networks is the lack of need for a rigorous specification of the model, which is especially characteristic for predicting poorly formalized processes (for example, in the areas of finance, business, and others);

b) the merits of neural networks lies in the resistance to the frequent changes in the environment in which there is a predictable process, and the nature of the effects of influencing factors. Therefore, neural networks are recommended to meet the challenges of forecasting trends in the stock market, which is characterized by constantly changing and influenced by many factors;

c) the ability to give acceptable results for the prediction of time series with a large amount of information or conflicting information. Neural networks are more preferred in the case where the analyzed data hidden patterns and also can take into account non-linear interactions between factors is especially important for pre-analysis or selection input data, detecting errors in the decision-making;

d) used to solve problems with incomplete information or subject to random effects;

e) work with neural networks to explore the dependence of the predicted values of the independent variables;

f) The advantage of neural networks is that the construction of a neural network model is adaptively during training.

Forecasting, carried out with the use of neural networks, comprising the steps of:

a) isolating the maximum number of significant influencing the prognosis factors;

b) the choice of the observation period, that is, it turns out the number of previous time series values for the implementation of the forecast;

c) carrying out preliminary processing to improve the quality of prediction, i.e. eliminated non-essential, do not affect or have little effect on the forecast, data recovery of missing information, the removal of abnormal (outlying observations);

d) selection of the appropriate neural network structure for this process analyzed, as well as the parameters of the algorithm and its training;

e) obtaining predictive values by sliding windows.

Method sliding window characteristic for neural networks involves two windows V_0 and V_1 with fixed dimensions n and m, respectively. These windows are moved in steps *s* slip on the temporal sequence of the available data, starting with the first element. Thus a first window V_0 of length n forms the input vector of the neural network, and the window V_1 - output vector dimension m. Sequence (V_0, V_1) form a block of training samples. For example, suppose we are given information on the level of output $R_1, R_2, ..., R_k$ for k periods. It is natural to assume the existence of hidden non-linear dependencies among the speakers. Predictive estimate of production (for one period, and then at some periods it is recommended to get a neural network with the parameters of n, m, s, where n - number of neurons in the input layer (the width of the window), m - the number of neurons in the output layer, s - step slide.

Thus, by using the sliding window for the neural network unit formed of $p = k + 1 - n$ training samples shown in Table 1. Another training sample is obtained by shifting the windows V_0 and V_1 right by one element. The neural network is trained using samples by adjusting their rates and forms as a result of the required function of the forecast.

Table 1

Block of training samples of neural network

Number of training samples	The input layer				The output layer
	1	2	…	n	
1	R_1	R_2	…	R_n	R_{n+1}
2	R_2	R_3	…	R_{n+1}	R_{n+2}
…	…	…	…	…	…
$p-1$	R_{p-1}	R_p	…	R_{n+p-2}	R_{n+p-1}
p	R_p	R_{p+1}	…	R_{n+p-1}	R_{n+p}

The forecasting process is performed after the training of the neural network, conducted on the same principle as the process of forming a training set. The neural network trained on the temporal sequence using the $R_1, R_2, ..., R_k$ unit training samples when submitting it to the entrance of the last known samples of $R_{k-n+1}, R_{k-n+2}, ..., R_k$, predicts R_{k+1}-th element of the sequence.

There are two ways of forecasting:

1) one step forward, when the current next step as the initial information the only objective data, that is, the next step is for the time sequence of $R_1, R_2, ..., R_k$ projected level of R_{k+1};

2) several steps (at predetermined intervals) when the prediction results as the input data to predict the next timing. Multi-step prediction of continued feeding the input of the neural network sampling $R_{k-n+2}, R_{k-n+3}, ..., R_k, R_{k+1}$, in which the last element is the result of the forecast in the previous step. The training set increases per time window. A process of re-education network in the enlarged training set, during which defines new synaptic connections weights and the transfer functions of neurons.

III. The use of neural networks and R/S analysis in forecasting. Application of neural networks for poorly predicted time series with a noticeable fractality, with a low value of the Hurst exponent. As this series has many consider a number of interpretations, let's call him on the volume of production and number of characteristic of currency exchange rates.

The scheme of calculation of the Hurst exponent (H) for a time series of observations y_t:

$$H = \frac{\log(R/s)}{\log(an)},$$

where H – the indicator Hirst,

R – the scope of accumulated deviations,

s – the standard deviation of a set of observations y_t,

n – the number of observation periods,

$a(>0)$ – given constant ($a = 0,5$ for a relatively short time-series, and, in general, to calculate H recommended to take $a = \pi / 2$).

The scope of the accumulated deviations R is generally calculated as follows:

$$R = \max_{1 \le u \le n}(X_u) - \min_{1 \le u \le n}(X_u),$$

where X_u - the accumulated deviation from the mean number of $\bar{y}$,

$$X_u = \sum_{t=1}^{u}(y_t - \bar{y}).$$

In [5], [8] for the Hurst exponent range with a small number of observations is calculated as the slope of the regression line was built on a set of points

$$\left(Log\left(R/S\right), Log\left(n/2\right)\right).$$

For the Hurst exponent is recommended to take a number to the number of levels of n about 100.

1. We apply the technology outlined above to receive the weather data for the n ($t = 1, ..., n$) periods relative to production y_t (m.u.) products by "R":

The data in Table 2 are characterized by the following indicators: average output equal to $\bar{y}$ *=574,5* m.u.; maximum and minimum of the accumulated deviations are, respectively *-11786,5* and *1156,5*; standard deviation s equal to *699,5177*; scale *R = 12943*; normalized scale *R/S = 18,5028*. As a result, the Hurst exponent *H* is equal to *0,5817*. According to the characteristics of the data series for different values of the Hurst exponent, a time series (t, y_t) with $0,326 < H < 0,674$ with high probability (*99.73*%), is considered to be random (Fig. 1), ie, weak forecast.

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They used a neural network method using the module STATISTICA (SNN) [7]. For the period of a forecast of production, equal to *1551* m.u.

Table 2

The volume of production of goods firm "R"

t	y_t	t	y_t	t	y_t	t	y_t	t	y_t	t	y_t
1	137	17	1847	33	1405	49	431	65	389	81	2772
2	16	18	22	34	810	50	16	66	198	82	638
3	474	19	87	35	656	51	155	67	7	83	416
4	473	20	1716	36	731	52	345	68	56	84	1483
5	139	21	59	37	455	53	574	69	223	85	473
6	242	22	2476	38	643	54	1	70	62	86	18
7	88	23	368	39	1483	55	117	71	1449	87	605
8	63	24	219	40	29	56	176	72	105	88	9
9	221	25	467	41	233	57	409	73	84	89	372
10	156	26	277	42	36	58	133	74	2645	90	1454
11	256	27	1406	43	287	59	84	75	1218	91	8
12	199	28	412	44	62	60	299	76	1996	92	1454
13	437	29	125	45	102	61	45	77	1614	93	1141
14	56	30	729	46	640	62	4	78	3112	94	3
15	238	31	453	47	31	63	1453	79	1857	95	88
16	83	32	221	48	1528	64	44	80	1148	96	476

2. The second row refers to the exchange rate of MDL against the U.S. dollar [9]. The experiment consisted of two stages:

a) the formation of the sample, ie determined by the presentation of the projected data (the actual rate or the relative change)

$$R_{t+1/t} = K_{t+1} / K_t - 1 = I_{t+1/t} - 1,$$

where K_t - the exchange rate for the day t, and

b) assessing the predictability of the course MDL/USD.

Some data for the three months to June, July, August 2013.

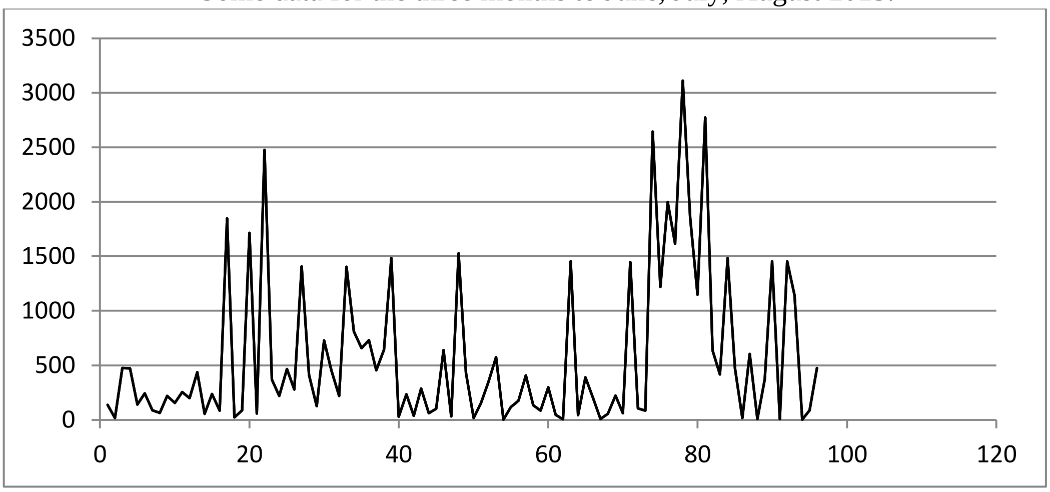

Fig.1. Graph of production volumes.

Index Hirst calculated for random series, regardless of their configuration, are 0.5. Such series are characteristic of many phenomena (in the economy and in nature). Another group of rows - it is linear and cyclic series. They have certain characteristics trending, at least for some period of time. These rows are usually exchange rates. For any straight rows Hurst reaches the persistent values in (the series is likely to manifest trendiness). For any straight rows Hurst reaches persistent values for $n > 20$ (the series is likely to manifest trendiness).

At time intervals from *40* to *100* observations Hurst index calculated for the linear series is in the range of from *0,707* to *0,755*. For a pair of *MDL/USD* for June- August 2013, which corresponds to *92* observations (linear increasing trend), the Hurst exponent *H = 0,7476*, ie *0,707*-*0,755* ranges, for nonrandom series of natural phenomena . Data on the currency pair MDL/USD are not random events and at other intervals of *100* values of the pair for the period from 2007 to August 2013 and are in the majority of cases, about the same value, ie rate *MDL/USD* has no more than the average predictability.

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