УДК 681.3: 004.89

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ANN DEPLOYMENT FOR THE EURO EXCHANGE RATE FORECAST

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In this paper presented non-iterative artificial neural network with the radial basis functions (RBF ANN) is used for the euro exchange rate forecast. The criteria to the preparing the training samples set for RBF ANN is formulated. In the end we got the forecast error less than 1,5 %.

Key words: ANN, RBF ANN, prediction, forecasting, euro.

Introduction

The financial markets analysis – is the mandatory component of the economical processes forecasts. Prognosis tasks in economics became especially actual due to the it's instability worldwide – e.g. not in Ukraine only. Significant stochastic deviations need more effective forecast tool in comparison to those are used traditionally. The reason of those – are permanent swinging on the world currency market. Ukraine involving to European structures and it proactive participation in the world financial and currency markets permanently increases requirements to the produced forecasts reliability [1].

The majority of the complicate mathematical model-based currency exchange forecast systems have the following issues: it's difficult to build mathematical model that would take into account that huge amount factors which could influence to the currency exchange rate; absence of the defined analytical dependencies between incoming and outcoming model's options and uncertainty between parameters that have influence to. Everything above mean that the euro exchange rate forecast is very complicate and actual task for Ukraine's market.

In this case the ideal solution – is deployment of the mathematical models are based on the usage the artificial neural networks (ANN) for the time series forecast. Deploying the artificial intellect systems has allowed us significantly improve the currency exchange rate forecast, euro in particular [2–4].

Algorithms

Flowchart time series forecasting algorithm in economic is presented in fig. 1.

The traditional approaches of short-, middle-, and long- term time series prediction are based on the usage of statistical methods (i.e. spectral, variance, covariance and factor analyses, correlation methods, regression etc). The most of these methods have serious limitations:

- The equations that describe dependences between different factors aren’t exact;
- It is difficult to define the criteria on the number of necessary and sufficient parameters;
- Because of uncertainty in the input data it is difficult to define exact mathematical model of the signal;
- Process complexity does not allow synthesis of mathematical model with necessary count of correction parameters.

Last time, in addition to known approaches of processes prediction, the methods that are based on the usage of artificial intellect become more and more popular. For example, the ANN are used successfully in the tasks of time series prediction, signal processing, clustering, approximation, optimization and in the decision-making systems. Unfortunately, the most of existent ANNs use iterative training methods. It significantly decreases possibilities to build an effective information analytical system for economic forecasts.

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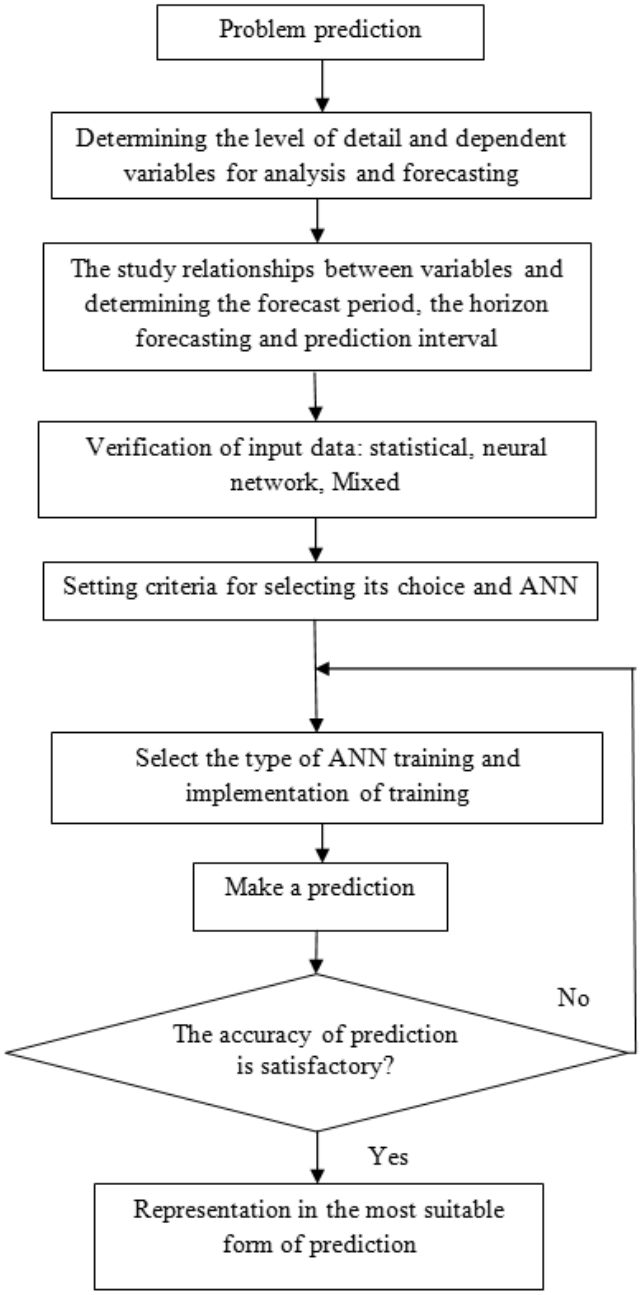

Fig. 1. Flowchart time series forecasting algorithm in economic

The euro exchange rate forecast is very complex and as a consequence it is very difficult to use ANN with iterative training method to solve prediction tasks. Generally, it's because of difficulties in initial data selection. We have deployed the non-iterative ANN with the radial basis functions (RBF ANN) is developed by prof. Tkachenko R.O. [5]. The major advantages of such ANN are:

- Faster ANN learning because of the non-iterative algorithm;
- This ANN can reproduce accurately the learning set elements;
- It allows to estimate the error of the forecast results;
- There are no practical limitations regarding the learning samples set selection that allows us to solve the high dimension tasks.

The offered ANN consists of the incoming neurons layer that receives the Initial objects classification signs $x_1, x_2, ..., x_n$. Of the hidden layer with the lateral connections between the neurons $u_1, u_2, ..., u_n$, signals at the hidden layer exits and outgoing signals that define the dependencies with the certain editors classes k_1, k_2. The sequence of forming output signals for the ANN like that could be described is Eq. 1, 2:

$$k = \sum_{m=1}^{n} f(KS_j^{(m)}) \cdot x_{Ei}^{(m)} \quad (1)$$

$$KS_j^{(m)} = \frac{\sum_{m=1}^{n} x_{ji} \cdot x_{Ei}}{\sum_{i=1}^{n+1} x_{Ei}^2} \quad (2)$$

where x_{Ei} is the vector-row of the training data matrix with the highest euclid distance.from the origin; f – function of the approximation.

The statistics for the euro exchange rate is taken here https://www.sberbank.ua/currency_archive/?filter [added][from]=2015-09-01&filter [added][to]=2016-03-02&x=72&y=59. With the purpose to optimize the training samples set we has excluded samples for Saturday and for Sunday since these days the exchange rate is not changing. Additionally the training set was complemented by the last known values for the official days-off during non-weekend days. This is necessary because we need set each ANN input with the appropriate exchange value for the appropriate weekday (fig. 2).

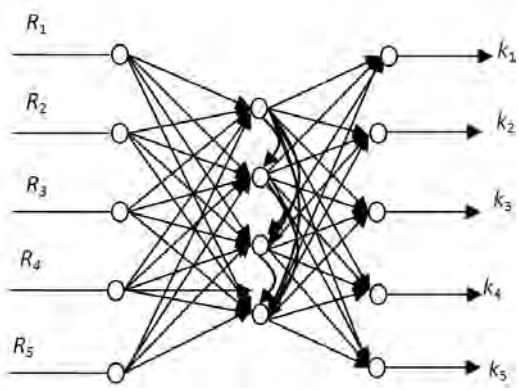

Fig. 2. RBF ANN with "bottle neck"

Thus, vector R contains the euro exchange rate values for all, R_1 – Mondays, R_2 – Tuesdays, R_3 – Wednesday, R_4 – Thursday, R_5 – Fridays. The values of the ANN outputs are prepared in the same way. So vector K_1 – Mondays, K_2 – Tuesdays, K_3 – Wednesday, K_4 – Thursday, K_5 – Fridays. In one step the RBF ANN produces forecasts of the eur exchange forecast for the following 5 (Mon.-Fri) days.

Table 1

Data for learning

The average rate for the euro					The average selling rate of euro				
R_1	R_2	R_3	R_4	R_5	R_1	R_2	R_3	R_4	R_5
24,28	24,38	24,48	24,52	24,31	26 ,63	26 ,66	26 ,54	26 ,29	26 ,34
24,59	24,60	24,47	24,13	24,36	26 ,48	26 ,25	26 ,04	26 ,28	26 ,31
24,53	24,68	24,74	24,35	24,33	26 ,29	26 ,32	26 ,18	26 ,26	26 ,48
24,47	24,23	23,97	24,02	24,01	26 ,27	25 ,90	25 ,74	25 ,51	25 ,39
23,99	24,01	23,99	23,61	23,51	25 ,58	25 ,57	25 ,58	25 ,10	25 ,19
23,50	23,60	23,80	23,80	23,90	25 ,53	25 ,46	25 ,52	25 ,61	25 ,74
24,36	24,43	24,65	24,46	24,07	26 ,18	26 ,34	26 ,48	26 ,37	26 ,27
24,30	24,80	25,30	25,00	24,80	26 ,20	26 ,74	26 ,90	26 ,37	26 ,42
24,99	25,01	24,99	24,91	25,11	26 ,50	26 ,47	26 ,23	26 ,50	26 ,76
25,20	25,11	25,00	24,80	24,30	26 ,72	26 ,52	26 ,38	26 ,34	26 ,11
24,26	24,25	24,16	24,43	24,62	26 ,05	26 ,24	26 ,38	26 ,41	26 ,62
24,78	25,02	25,28	25,22	25,21	26 ,60	26 ,78	26 ,91	26 ,97	26 ,72
25,36	25,23	25,10	24,86	25,08	26 ,72	26 ,84	26 ,89	26 ,93	26 ,82
25,10	25,15	25,05	24,60	25,50	26 ,67	26 ,56	26 ,35	27 ,02	27 ,01
25,20	24,90	25,00	25,40	26,00	26 ,85	27 ,05	27 ,14	27 ,13	27 ,25
25,96	25,75	25,46	25,33	25,42	27 ,41	27 ,08	26 ,87	26 ,87	27 ,04
25,44	25,21	24,99	25,11	25,21	27 ,11	27 ,17	27 ,17	27 ,37	27 ,40
25,82	25,78	25,82	25,98	25,39	27 ,50	27 ,83	27 ,83	27 ,68	27 ,46
25,17	25,31	25,16	25,44	25,97	27 ,92	27 ,83	27 ,70	28 ,00	28 ,40
K_1	K_2	K_3	K_4	K_5	K_1	K_2	K_3	K_4	K_5
26,589	26,368	26,594	26,489	26,739	28,889	28,799	28,862	28,849	28,799

Because of the huge amount of the statistical data, there was a decision to use the RBF ANN with the "narrow throat" type. ANNs like that performs the optimal data compression in the hidden layer -thus, despite the reducing the amount of the dimensions the amount of the information, in general, does not change.

The results

The training samples set was prepared of 6th training vectors. Each vector had 5 values e.g. for all working days (100 days training widow). The mean square error divided on the values of the training variation range (SQRtrain) is used as a measure of the forecast accuracy; and it's max value against all ANN outputs (SQR MAXforecast) is calculated in percents. In the end the accuracy (SQRtrain and SQR MAXforecast) was under 0,49 %.

The average rate for the maximum value |Real – Forecast| euro is 0,131788. After the training stage, the 21 testing vectors, with 5 exchange rate samples each, were passed through the ANN with the appropriate training results verification. The accuracy SQRforecast was under 0,18 % and SQR MAX forecast was under 0,37 %. The forecast results are represented on the fig. 3.

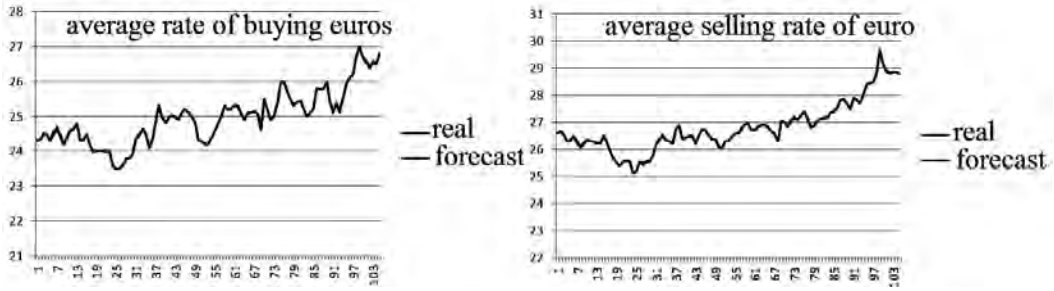

Fig. 3. Euro exchange rate forecast

Conclusion

1. The advantages and perspectivity of the ANN usage for the currency exchange rate estimation are admitted.
2. The effective deployment of the RBF ANN to solve the task of euro exchange rate forecast.
3. The criteria to the preparing the training samples set for RBF ANN is formulated.
4. The advantages of the RBF ANN with narrow throat in the resolution the tasks of currency exchange rate forecasts are shown.

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