UDC 004.048

DEVELOPMENT OF THE MODEL FOR NEURAL NETWORKTIME SERIES FORECASTING

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Purpose. When forecasting time series, it is vital to study the processes of knowledge hidden in the time series. The current study examined information technology for hidden patterns using neural networks and fuzzy interpreters to simplify the process of obtaining the hidden patterns of time series and databases by creating information technology interpretations of knowledge stored in the neural network. **Results and originality.** The results of the study are: developed animproved predictive model based on aneural network which, unlike existing layer containing receptors of moving average model, reduces the error in forecasting time series with atrend. **Practical value.** Advanced knowledge extraction method with aneural network, which, in contrast to the known, involves iterative setting limits fuzzy sets simplifies the verification rules and updating the knowledge base.

Key words: time series, fuzzy logic, fuzzy sets, neural network, artificial intelligence.

РОЗРОБКА НЕЙРОННОЇ МЕРЕЖІ ДЛЯ МОДЕЛІ ПРОГНОЗУВАННЯ ЧАСОВИХ СЕРІЙ

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Розглянуто інформаційні технології для прихованих моделей з використанням нейронних мереж та нечітких логік для спрощення процесу отримання прихованих моделей часових рядів та баз даних шляхом створення інформаційних технологій інтерпретації знань, що зберігаються в нейронній мережі. При прогнозуванні часових рядів важливо вивчити процеси знань, сховані в часових рядах. Результати дослідження: розроблена покращена прогностична модель на базі нейронної мережі, яка, на відміну від існуючого шару, що містить модель експоненціального згладжування нейронів, зменшує похибку в прогнозуванні часових рядів з тенденцією; розширений метод виявлення знань з нейронною мережею, який, на відміну від відомих, передбачає ітераційне обмеження нечітких множин, що спрощує правила перевірки та оновлення бази знань.

Ключові слова: часові ряди, нечітка логіка, нечіткі множини, нейронна мережа, штучний інтелект.

PROBLEM STATEMENT. Fuzzy logic and neural networks (NNs) have been used successfully to solve real-life problems in various fields. In recent years, NNs and fuzzy logic have become essential methods to solve forecasting and time series (TS) forecasting problems in particular. Hence, there has been growing interest in these forecasting models as artificial intelligence (AI) techniques. Because of the growing interest in AI techniques, we need to examine some specific methods such as NNs and FL for TS forecasting and modelling. The main reasons for increasing interest in these techniques are that modelling the nonlinear relationship between variables is becoming more and more accurate than that of traditional statistical and econometrical models and they do not require any assumptions for the data set.

The task of the automated knowledge receiving is a fundamental part of the engineering of knowledge – the field of information technologies that refers to the system of artificial intelligence. Solving the task of the automated knowledge mining from databases is connected to the development and exploitation of the decision taking support intelligence systems (DTSIS) and expert systems (ES) [1]. The received knowledge can enrich the existing database of some expert system or can be used for forming recommendations for making decisions.

Forecasting is an independent scientific field widely applied in all spheres of the human activity. There is a range of kinds and ways of forecasting developed with taking into consideration the character of the studied tasks, research goals, and information state. Since forecasting assessments are approximate, there appears doubt in the rationality of forecasting in the whole. So, primary requirements for any forecast are the possible minimisation of errors in the appropriate assessments.

Scientifically proved forecasts are doubtlessly more accurate and efficient in comparison to the random and intuitive ones. These are the forecasts based on the use of methods and models of statistical analysis. We can state that they are the most trusted among all ways of forecasting because the statistical data are the solid base for taking decisions concerning future.

TS (or dynamics series) are statistic material about some indicators of the studied process collected at various moments of time. Each unit of the statistic material is called measurement or record; we also can call it the level on the stated moment of time. The measurement time or the number of records in succession should be indicated in the TS [1].

EXPERIMENTAL PART AND RESULTS OBTAINED.With the advent of innovative technologies, accessibility of data and calculation power have increased significantly. Associated with this, the usage of artificial intelligence techniques has been increased for forecasting objectives [2]. NNs were first used in cognitive science and engineering. In recent years, artificial NNs have become increasingly popular in economic forecasting [3], risk rating [4] and TS forecasting [5] problems.

Associated with the transition from general logic system to alternative logic system, this has dominated modern scientific understanding of fussy logic (FL) based on uncertainty. Together with this understanding, FL has progressed swiftly [6]. It is possible to separate fuzzy logic systems (FLS), as simple fuzzy systems and hybrid fuzzy systems. FL algorithms can be defined as systems that use linguistic variables and rules. FLs consist of fuzzifier, inference engine, defuzzifier and knowledge base. FLs have been commonly used in expert systems, pattern recognition, TS analysis, data classifications and decision analysis.

The study of [3] is based on NNs for financial and economic TS forecasting. It presents a guide to constructing an NN forecasting model in TS. It proposes an eight-step procedure of NN design taking into the consideration parameter variable selection, determining learning momentum rate and discusses some argued topics between practitioners. The research [7] studied forecasting with artificial neural networks (ANNs). The purpose of the study was three fold: evaluate previous research; provide insights on ANN modelling issues; and suggest future research.

The work [8] introduced the type-2 fuzzy logic system (FLS) as a modified and improved type-1 FL system, which could deal with rule uncertainties and focused on 'output processing'. The paper [9] presented a study that evaluated the theory and design of interval type-2 FL system. The authors proposed a method to calculate the input and antecedent operations for FL systems. The work [10] proposed a hybrid model by combining NNs and autoregressive integrated moving average (ARIMA) models. The researcher developed a hybrid model that could produce more accurate forecasts comparing to ARIMA or NNs models separately. Later, [11] studied seasonal and trended TS forecasting with NNs. In this study, authors argued the number of limited empirical studies on seasonal TS. NN model and Box-Jenkins seasonal ARIMA model were applied and compared to each other. As a result, NNs were not able to model seasonal and trend TS without any data pre-processing (deseasonalization and detrending). Data pre-processing has reduced the forecasting error dramatically.

One more study on type1-2 FL system was carried out by [12]. Type 1 models were utilised for one variable in TS. In this study, the authors proposed a Type 2 fuzzy TS model with improved forecasting performance based on Type 1 model in which further observations were used to enrich or to refine the fuzzy relationships. The research used the dataset collected from the Taiwan stock index within the three-year period. Analysis showed that the Type 2 model outperformed the Type 1 model. Another research [13] developed Type 2 fuzzy NN, claiming it is a promising strategy and offered a novel multi-step-ahead time series prediction model based on a combination of the Bayesian filtering model (BFM) and the type-2 fuzzy neural network.

Wang, Chau, Cheng, & Qiu [14], to develop a forecasting model for monthly discharge TS, have compared several forecasting models including ARMA, NNs and adaptive neural-based fuzzy inference system (ANFIS). The obtained results revealed that the best performance was respectively achieved by ANFIS, Genetic Programming and Support Vector Machine based on different evaluation criteria during the training and validation phases. Another related research [15] analysed monthly reservoir inflow data using autoregressive (AR), NNs and ANFIS models. To train the ANFIS model data set divided different input vector sets and in all cases, the ANFIS model produced more accurate forecasts than the NNs and AR models. Yan [16], concerning not having any systematic way to determine the parameters of NNs, proposed an automatic artificial NNs modelling scheme based on the generalised regression NN. The proposed model was compared to nearly 60 different models worldwide and got the best model award. A study made by [5] aimed to forecast electricity generation using ARIMA and NNs. As a result of the study, the authors revealed that both models could be used to forecast electricity generation, but NN was more preferable.

One of the recent studies [17] argued that most of the nowadays time series models often have unknown nonlinear structure, rather than linear. The study demonstrated that the typical neural networks were not efficient for recognising the behaviour of nonlinear or dynamic time series, which have moving average terms and hence low forecasting capability. The researchers came up to a conclusion on the importance of formulating new models of neural networks such as Deep Learning neural networks with or without hybrid methodologies such as Fuzzy Logic.

The related works review enabled the following conclusions: NNs and FL models are convenient for the real lifetime series forecasting. NNs models or FL models are convenient to solve time series problems, but the hybrid models such as ANFIS can show better performance. However, this proposal cannot be valid for all-time series problems. Statistical, econometrical and mathematical models show better performance when the number of independent variables is the lowest. Therefore the variable selection methodology is critical in forecasting performance. At this point AI techniques can be helpful, since they do not need any data or distribution assumption, but, if they examine historical data such as time series, data pre-processing, such as deseasonalization, detrending or data normalisation, improve the model performance.

Figure 1 shows the scheme of the NN of the class perceptron that is a powerful instrument of forecasting in the conditions of the lack of information about statistical features of the TS.

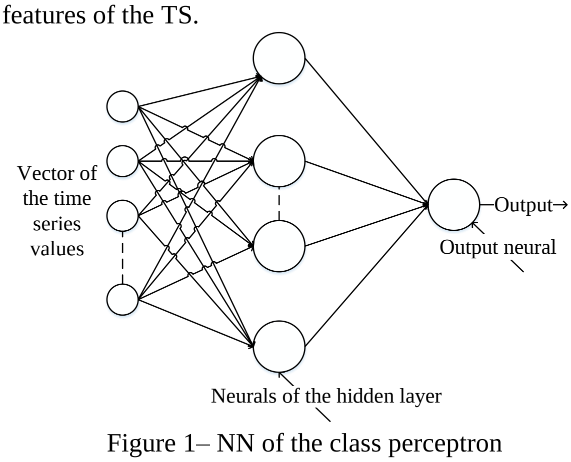

Figure 1– NN of the class perceptron

Network training is a purposeful process of changing values of the coefficients of inter-layer relations. This process lasts till the network acquires relevant features. The training is based on the usage of training data combined with templates. Besides the training data, the teacher also has data for testing that is selected from the same volume of data.

Each template includes the vector of known input signals of the network and the appropriate vector of the output signals corresponding to it. Of course, the data from the training set of templates are sent consequently on the input of the NN during the training. If the vector of network output signals does not comply with the appropriate one, the modification of the network parameters with the help of a particular rule or algorithm takes place to minimise the error. The process repeats until the network adequately reacts to all templates of the training set.

Due to the training, the network acquires the ability to react correctly not only to the templates during the training but also the testing examples that it has never seen before. So, the network has the feature of generalisation.

The NNs for forecasting are trained on the examples comprising several values of elements of TS (window) and the value of the TS level that is next after the window that is a template of the output signal for the outgoing neuron.

The NN disadvantages in the tasks of forecasting TS are complications of generalisation if there is a trend in TS, i.e., the TS should be transformed into the permanent form.

From a mathematical point of view, developing the model that forecasts is the task of identification has two stages. On the first stage, we should develop the structure, i.e., content and the way of combining separate parts of the model.

When choosing the model structure, we will apply the following requirements:

- the model should be simple in parameter adjustment;
- the model should take into consideration the trends without the necessity to delete them and transform the TS to the stationary type.

On the second stage, we should determine the optimal values of the model parameters, i.e., solve the task of optimisation. We choose the average sum of the square of differences between the values of the input data and the values of the model function corresponding to the same stage of measurement as a criterion of the quality of the task solving.

$$Q = \frac{1}{n}\sum_{i=n}^{n}(y_i - y_i^m)^2 \to min. \qquad (1)$$

We determine limits for the change of values of the function parameters and the weight coefficients of some functions that are included in the combined model:

$$\alpha_i \geq a_i \geq \beta_i, \qquad (2)$$

where α_i, $\beta_i$arecoefficients limit values.

We determine the general type of the model in the following way:

$$F(x) = w_1 f_1(x) + w_2 f_2(x) + \cdots + w_i f_i(x) + \cdots + w_n f_n(x), \qquad (3)$$

where a separate constituent of the forecasting model that influences approximation of regularity hidden in the TS.

The optimal values of the parameter values of each constituent function$f_i(x)$, as well as the weighting coefficients $w_1, w_2, \ldots, w_n$ should be calculated when using such "collective" model.

Considering the requirements, we build the model in the following way. The base of the model is an NN of the class "perceptron" with one hidden layer and non-linear transferring functions of neurons. According to [18], such network can approximate practically any non-linear regularity hidden in the input data.

The second constituents of the model are a model of moving average (MA) built into the NN. Neural outputs of the NN hidden layer and MA model should be connected to the output neural with the linear transfer function. The aim of the output neural is determining the weight coefficients of the linear combination of outputs of the two models.

The NN of direct distribution is chosen for solving the tasks of identification and forecasting more often [19]. The input layer of NN consists of some number of receptors according to the dimension of the window, i.e., the number of values of the previous elements of the TS. The number of neurons of the hidden layer is selected experimentally. The existence of the unique neural playing the role of the generator of the floating displacement in the hidden layer is the peculiarity of the model. This neural calculates the moving average of the time window. The input vector of the network comprises a time window with the width from 2 to 20 previous values. Figure 2 shows the structure of the developed model.

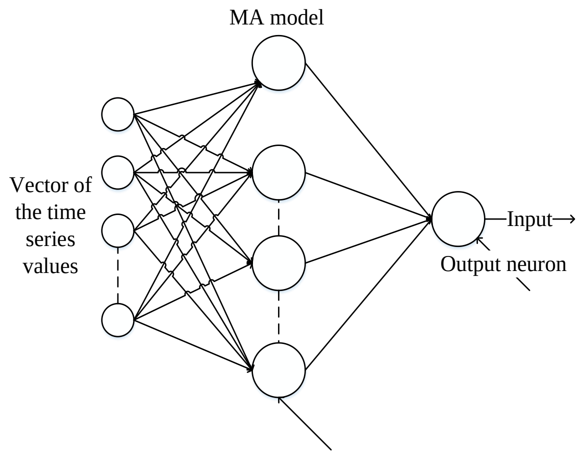

Figure 2 – Structure of forecasting model

We use the shifted sigma function as an activation function of the hidden layer:

$$Y = \frac{2}{1+e^{-S}} - 1.0, \qquad (4)$$

where *S* is thesum of weighted input signals.

Training this model has been conducted by the method of reverse errors spreading with taking into consideration the peculiarities of the commitment structure.

The algorithm includes the following steps:

STEP 1. Loading elements of TS into the NN window (vector of the TS values).

STEP 2. Calculating the output value of MA and outputs of neurons of the hidden layer.

STEP 3. Calculating output of the model (of the output neuron).

STEP 4. Calculating error of the model output.

STEP 5.If the output error does not exceed the constant E0 determined beforehand, the transfer to step 9 takes place. Otherwise, the transfer to step6 takes place.

STEP 6. Calculating errors of the neurons of the hidden layer and error of the E0 model.

STEP 7. Calculating new values of the weight coefficients between the neuron of the hidden layer, MA model and output neuron.

STEP 8. Calculating new values of the weight coefficients between the neurons of the hidden layer and receptors of the time window. Transfer to step 2.

STEP 9. If the current example is the last one, the END takes place. Otherwise, the transfer to step 1 takes place.

From the formal point of view, the outputof NN is a universal approximating model in the form of a graph. Modelling a real object, such graph can enhance its adequacy to this object by training and due to modification of the weight of connections between neurons. The existence of the formal methods of training (if there is a training selection in the form of experimental pair "inputs–outputs") is the leading advantage of NNs.

Developing experiment systems based on the rules [20] requires 12~18 months and NNs require time from several weeks to months that is an essential advantage of NNs. However, NNs as a tool for data mining has some disadvantages:

1) Weight coefficients of inter-neural connections of the trained NN cannot be interpreted qualitatively and meaningfully;

2) Nowadays the models of NNs using qualitative inputs are not developed very well to model complicated objects successfully;

3) Gradient method that is traditionally used for training the NN does not always allow achieving a global minimum in the dividing model and experimental values of the output.

The last disadvantage is eliminated with the use of evolution methods of correcting the network weight coefficients.

Fuzzy systems of logical output can also be used for data mining. The works [21, 22] suggest the method of building fuzzy databases by their mining from the experiment data. The described method uses a neuron-fuzzy network that adapts to the studied object by optimising values of the parameters of the function of the membership of input values and the values of the weight coefficients of fuzzy rules. The generic algorithm is used for searching optimal values of the mentioned parameters. However, the database should be filled with rules beforehand to develop a neuron-fuzzy expert system, i.e., create a system prototype that should be additionally trainedby way of parameter optimisation. If priory formulations of rules are absent, the method is useless.

The work [23] describes a simple method of mining scientific knowledge from "raw" numerical data with the help of fuzzy interpretation of the hidden regularities. Using the formalism of the theory of fuzzy sets, the method can be described in the following way:

1. The range of acceptable values is specified for each input and output.

$$X_i = \left|\underline{x_i}, \bar{x}_i\right|, Y = \left|\underline{y}, \bar{y}\right|. \qquad (5)$$

2. Each value receives a semanticinterpretation, and the range of its change is divided into fuzzy intervals named with the terms:

a) term-set of the value *Xi*:

$$A_i = \{a_i^1, a_i^2, \dots, a_i^{l_i}\}, i = \overline{1, n}. \qquad (6)$$

b) term-set of the value *Y*:

$$D = \{d_1, d_2, \dots, d_m\}, \qquad (7)$$

where a_i^p – p^{th} linguistic term of the variable x_i; $p = \overline{1, l}, i = \overline{1, n}$; d_j– j[th] linguistic term of the variable *y*; *m* – number of different solutions in the given area.

Capacity of terms-sets A_i in general case can be different, i.e.,$l_1 \neq l_2 \neq \dots \neq l_m$

3. The function of membership ensures each fuzzy interval. So, fuzzy sets a_i^p and d_j are determined as:

$$a_i^p = \sum_{k=1}^{q_i} \mu^{a_i^p}\left(x_i^k\right)/x_i^k$$
$$d_j = \sum_{r=1}^{q_m} \mu^{d_j}\left(y^r\right)/y^r, \qquad (8)$$

where $\mu^{a_i^p}\left(x_i^k\right)$– level of membership of the element $x_i^k \in X_i$ in the term $a_i^p \in A_i, p = \overline{1, l}, i = \overline{1, n}, k = \overline{1, q_i}$; $\mu^{d_j}(y^r)$ – level of membership of the element $y^r \in Y$in the term-decision $d_j \in D, j = \overline{1, m}$

4. Numerical data are grouped in the form of pairs "input-output": $(X_l, y_l), l = 1 \dots, M$, where $X^l = (x_1^l, x_2^l, \dots, x_n^l)$– input vector and the corresponding value of the output of the variable y^l forl^{th}pair "input-output" $y^l \in \left[\underline{y}, \overline{y}\right]$

5. The value of the function of membership is calculated for each pair "input-output." $\mu^{a_i^p}\left(x_i^l\right)$of the vector X^l and$\mu^{d_j}(x_1^*, x_2^*, \dots, x_n^*)$for all fuzzy intervals the range of acceptable values$\left[\underline{y}, \overline{y}\right]$is divided into of the output variable *y*.

6. Terma_i^p is found for each output x_i^kvariable, where the function of membership$\mu^{a_i^p}\left(x_i^l\right)$ has the maximum $\mu^{a_{imax}^p}\left(x_i^l\right)\mu^{d_j}(y^l)d_j^l$ value. Term $\mu^{d_{jmax}}(y^l)$is found for each output variable where the function of membership has the maximum value.

7. There appears a rule of the type "IF-ELSE" that connects linguistic values$a_{imax}^1, a_{imax}^2, \dots, a_{imax}^{l_i}$of the input variables with linguistic values of the output variable d_{jmax}^l

$$\left[\bigcap_{i=1}^n\left(x_i^l = a_{imax}^{jp}\right)\right] \to y = d_{jmax}^l, j = \overline{1, m}. \qquad (9)$$

8. The level of truth is calculated for the received rule.

$$R^l = \mu^{d_{jmax}}(y^l) \prod_i \mu^{a_{imax}^p}\left(x_i^l\right). \qquad (10)$$

9. Rule selection. If there is already a rule with number *t* with the same ues $a_{imax}^1, a^2_{\langle max}, \dots, a_{imax}^{l_i}$ and d_{jmax}^l in the collected data base and the condition$R^l > R^t$ is fulfilled, so the rule *l* is fixed in the data base instead of the rule *t*.

This is the way for collecting data in the linguistic form based on fuzzy analysis of the raw numerical data.

The simplicity of realisation is an undoubted advantage of the method. Although, this method has reserves of enhancing efficiency and accuracy that can be realized if a trained NN is used as a rule generator and an improved algorithm for selecting and verifying rules is applied.

The iteration human-machine procedure of specifying the limits of fuzzy sets is used for improving the method. The procedure has the following steps:

1. Determining the initial value of the limit. Each expert specifies this value. The range of values $x_{bmin}<x_b<x_{bmax}$ appears in the result of these actions.

2. Calculating the average value for the received range [x_{bmin}, x_{bmax}] as a new limit. If the received value differs from the previous one in less than the specified value ε, the limit point is found. If not, there is a transition to the step 1.

The value $\varepsilon$is chosen with the condition that the limits of fuzzy sets cover each other. It ensures the continuation of the fuzzy membership functions.

If there is a task to create a database of the linguistic type (for example, for the system of fuzzy logical output), there is an issue of the procedure of the rule selection. It is reasonable not to put aside the rules with a difference (even small values of the degree of truth) and to collect a significantly full set of examples of the rule on all or the more significant part of pairs “input-output” of the training selection of the NN. Let us discuss the verification and selection of rules.

If the developer finds out that after the testing the system has a significant number of errors, theyhave several waysof correcting the rules. First, the structure[24] of the NN can be changed. Second, membership of function parameters can be corrected using the methods described in work [25]. The rules received on the output of interpreter can be verified and selected as it is suggested in the method described above. However, substitution of the previous rule with a new one with the increased value of the level of truthiness is not suggested to be a single and a correct approach. We believe that the values of the truth of all found similar rules should be collected and the average level of the truth in the whole selection should be calculated according to the following rules:

1. If the number of the mined similar rules is quite significant, the truth of the resulting rule is determined by the average value of the level of truth R.

2. If the number of the mined similar rules does not exceed the determined limit value A that is established on the results of the frequency analysis of the collected set of rules, the average level of truth R for similar rules is calculated as $R=k/A$, where k is the number of similar rules in the selection. The limit value of the level of truth Rn is established for selecting reliable rules. The rules with $R \geq R_n$get into the data base.

3. If there is selection of controversial rules in the collected set of rules with equal left parts but the d_j ($d_j$is jth linguistic term of the variable y) conclusions are different, there should be conducted additional analysis to solve the issues: whether to choose one of the variants or to delete both variants of the rules from the data base. The following methods are suggested for solving this task.

3.1. The vector of average values of all input variables for selections 1 and 2is calculated:

$$\left(\overline{x}_1^1, \overline{x}_2^1, \dots, \overline{x}_n^1\right) i \left(\overline{x}_1^2, \overline{x}_2^2, \dots, \overline{x}_n^2\right). \qquad (11)$$

3.2. The vector of the average values on all input variables of both selections is calculated:

$$\left(\overline{x}_1, \overline{x}_2, \dots, \overline{x}_n\right). \qquad (12)$$

The vector received in p.3.2 is sent onto the input of the NN, and the numerical value of the net output is calculated.

3.3. Input and output of the net are interpreted into the linguistic form.

3.4. If the received rule coincides with one of the competing ones, the advantage is given to the rule that had won. If the new rule does not coincide with any of the competing ones, both competing rules are deleted from the database.

Figure 3 demonstrates the functional structure of the necessary software means that must realise the developed technology of mining and interpreting.

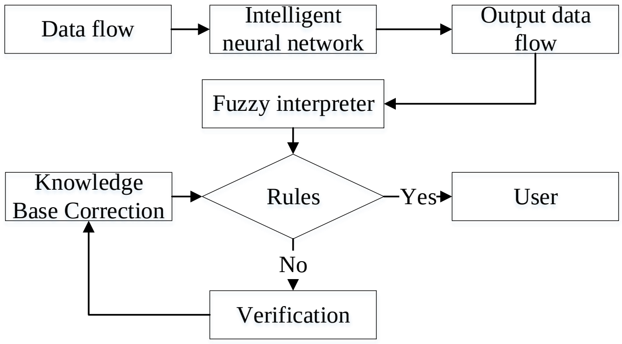

Figure 3 – Functional structure of the instrumental software means

Knowledge collected by the NN. The structure does not require additional explanations.

RESEARCH RESULTS. In the research, we have compared a usual neural net and the combined model that consists of the neural net and the model of the moving average.

Figure 4 demonstrates the time series that does not have an apparent tendency for decreasing or increasing but has a certain periodical constituent. It is evident that the trained neural net makes a forecast with a minor error which is seen in Figure 4.

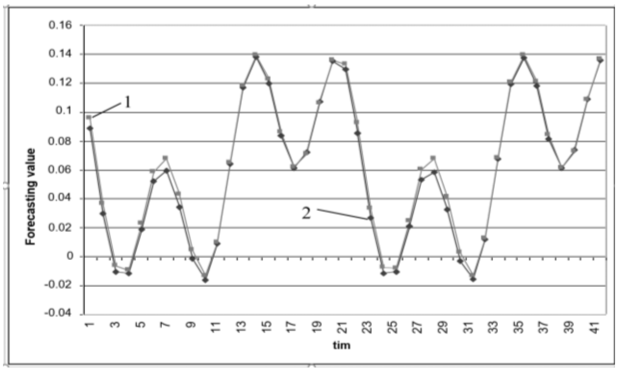

Figure 4– Testing the neural net on the periodical time series without a trend: 1– value of the time series; 2 – forecast values

However, if the time series contains a trend, the usual neuron net will have a significant error of forecasting as shown in Figure 5.The incoming data was chosen manually to represent a trend. Hence, the use of the usual neural net for forecasting time series that contain a trend has proven to be inefficient.

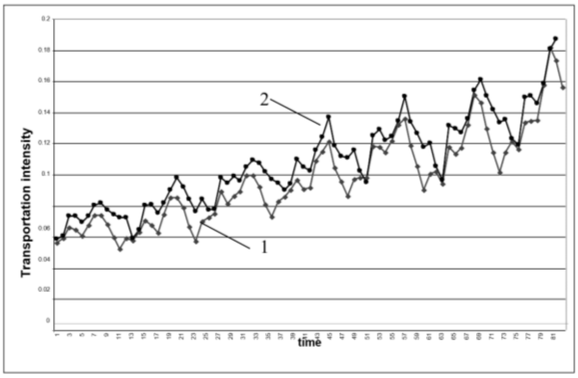

Figure 5– Testing the neural net on the periodical time series with a trend: 1 – value of the time series; 2 – forecast values

Having applied the combined model, we could see it had a significantly smaller error of forecasting as shown in Figure 6.

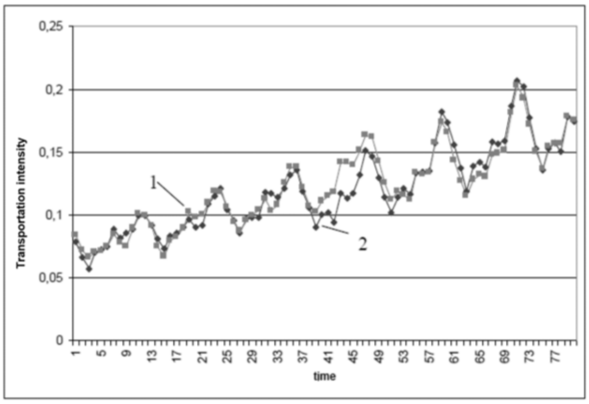

Figure 6– Testing the combined model on the periodical time series with a trend: 1 – value of the time series; 2 – forecast values

Summing up the results of the experiments, we have calculated the mean square error of the neural net model of the suggested combined model as shown in Figure 7.

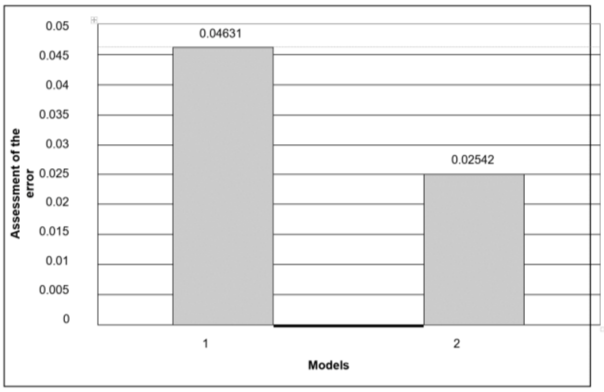

Figure 7– Comparison of the neural net model (1) and the combined model (2) with the criteria of the mean square error

As it is seen from the Figure 7, the suggested combined model has significantly fewer errors on the time series with a trend. This means that the user can receive the action plan or the possible variant of the situation developed that will help to develop the most appropriate decision for the situation.

CONCLUSIONS. The developed model allows experimenting with neural nets and combined forecast models. Experiments prove that the suggested combined forecasting model has advantages over the usual neural net, i.e. if there is a trend in the TS, the combined model ensures significantly smaller error of forecasting than the classical neural net.

Next step of the research will be developing of the program that would allow experimenting with a fuzzy interpreter that transforms precise inputs and outputs of the neural net into the verbal assessments that are the basis for the rules on forecasting the following fuzzy values of the time series.

ACKNOWLEDGEMENT: The authors would like to thank the reviewers for their valuable comments. This work is supported by National Natural Science Foundation of China under grant No. 61462059, and Technology Foundation for Selected Overseas Chinese Scholar, Ministry of Human Resources and Social Security of China under grant No. 2013277.

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РАЗРАБОТКА НЕЙРОННЫХ СЕТЕЙ ДЛЯ МОДЕЛИ ПРОГНОЗИРОВАНИЯ ВРЕМЕННЫХ СЕРИЙ

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При прогнозировании временных рядов важно изучить процессы знаний, скрытые во временных рядах. В исследовании рассмотрены информационные технологии для скрытых моделей с использованием нейронных сетей и нечетких логик для упрощения процесса получения скрытых моделей временных рядов и баз данных путем создания информационных технологий интерпретации знаний, хранящихся в нейронной сети. Результаты исследования: разработана улучшенная прогностическая модель на базе нейронной сети, которая, в отличие от существующего слоя, содержащего модель экспоненциального сглаживания нейронов, уменьшает погрешность в прогнозировании временных рядов с тенденцией; расширенный метод выявления знаний по нейронной сетью, который, в отличие от известных, предусматривает итерационном ограничения нечетких множеств, упрощает правила проверки и обновления базы знаний.

Ключевые слова: временные ряды, нечеткая логика, нечеткие множества, нейронная сеть, искусственный интеллект.

Стаття надійшла 09.11.2017.