Recurrent Adaptive Neuro-Fuzzy Models for predicting time series with fuzzy trends

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Abstract

The article presents the recurrent neuro-fuzzy models of a new type of RecANFIS (Recurrent Adaptive Neuro-Fuzzy Inference System), designed for the analysis and forecasting of time series (TS) taking into account fuzzy trends. The proposed models differ from models of the ANFIS (Adaptive Neuro-Fuzzy Inference System) type in that they: firstly, store the predicted values of TS in the lag range of the "sliding window"; secondly, fuzzy trends are identified in accordance with the results of the analysis of the values of TS in the lag range of the "sliding window"; thirdly, the identified fuzzy trends are taken into account due to the corresponding fuzzy mappings when forecasting TS. The developed RecANFIS models adaptively adapt to the features of specific TS in the process of their forecasting, automatically take into account dynamically changing trend components of time series and allow solving the problem of their non-stationarity. An original method for training RecANFIS models is proposed, which differs from the known ones by the additional step of preliminary setting fuzzy mappings to identify fuzzy trends. Experimental studies of the use of RecANFIS models for forecasting TS were carried out using the example of forecasting electric energy consumption in the Smolensk region, according to which it was possible to increase the forecast accuracy by an average of 10-15% compared to neural network and ANFIS models. Based on the composition of RecANFIS, it is possible to synthesize a model for analyzing and predicting a multidimensional time series.

Keywords 1

Recurrent neuro-fuzzy model, time series forecasting, fuzzy trend, fuzzy transform

1. Introduction

For forecasting time series (TS), various models and methods are used, including statistical, regression, based on Kalman filters, wavelet transforms, artificial neural networks, neuro-fuzzy models, evolutionary and bioinspired models [1-3]. In this case, the main directions of increasing the accuracy of forecasting TS are the substantiation and use of significant factors that directly or indirectly affect the predicted TS, taking into account the nonlinearity of the relationships of factors, their uncertainty, as well as the non-stationarity of the TS.

Artificial neural networks (ANNs) are effectively used for short-term forecasting of TS. However, their application for medium-term and long-term forecasts is problematic due to the complexity of forecasting in conditions when the values of the factors go beyond the values used in their training, as well as insufficient possibilities to take into account the TS trends [4]. A separate class of ANNs that are quite effectively used for short- and medium-term forecasting includes recurrent neural networks focused on advanced capabilities for accounting for retrospective data [5]. At the same time, the limitations of recurrent neural network models (in addition to the indicated general limitations

Russian Advances in Fuzzy Systems and Soft Computing: selected contributions to the 8-th International Conference on Fuzzy Systems, Soft Computing and Intelligent Technologies (FSSCIT-2020), June 29 – July 1, 2020, Smolensk, Russia
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inherent in neural network models) are the complexity of identifying and taking into account trends in conditions of nonstationary TS.

Use neuro-fuzzy Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [6] and forecasting methods based on them eliminates the limitations of artificial neural networks associated with the uncertainty of factors, however, it does not completely eliminate the problem caused by the nonstationary TS and the need for adaptive tuning to the features of specific TS in the process of their prediction.

The article proposes recurrent neuro-fuzzy models of a new type *Rec*ANFIS (Recurrent Adaptive Neuro-Fuzzy Inference System/Models), designed for analysis and forecasting of TS with fuzzy trends. The proposed models differ from ANFIS in that they: firstly, keep the predicted values of TS in the range of the "sliding window"; secondly, fuzzy trends are identified in accordance with the results of the analysis values TS in the "sliding window"; thirdly, the identified fuzzy trends are taken into account due to the corresponding fuzzy mappings when predicting TS. The developed *Rec*ANFIS adaptively adjust to the features of specific TS in the process of forecasting, automatically take into account the dynamically changing fuzzy trend TS component and allow solving the problem non-stationarity. For training *Rec*ANFIS, a method is proposed, characterized by an additional stage of preliminary assignment of fuzzy mappings to identify fuzzy trends. The article presents the results of experimental studies of *Rec*ANFIS for predicting TS (using the example of predicting the consumption of electric energy in the Smolensk region) in comparison with neural network, as well as ANFISs.

2. Structure of Recurrent Adaptive Neuro-Fuzzy Inference System/Model

The proposed models of the new type *Rec*ANFIS are intended for the analysis and forecasting of multidimensional time series, in which the predicted series depends on factors that influence directly or indirectly. Taking into account the identified fuzzy trend within the "sliding window" allows for a more accurate forecast because the influence of the fuzzy tendency is carried out in the neuro-fuzzy model, immediately before the fuzzy production rule base.

The structure of a recurrent neuro-fuzzy production model based on fuzzy inference algorithms and the theory of fuzzy tendencies [4], [7], in accordance with the example considered in Figure 1, can be described as follows.

Layer 1. At the output of the elements of this layer, the degrees of truth for the current values of the input variables are determined with respect to the corresponding fuzzy statements of the premises of all the rules of the model:

$$\mu_{\tilde{L}}\left(\tilde{s}_1^{(t-1)}\right)=\tilde{s}_1^{(t-1)}\cap\tilde{L},\dots,\mu_{\widetilde{H}}\left(\tilde{s}_1^{(t-1)}\right)=\tilde{s}_1^{(t-1)}\cap\widetilde{H},\dots,\mu_{\widetilde{H}}\left(\tilde{s}_N^{\left(t-L_i^j\right)}\right)=\tilde{s}_N^{\left(t-L_i^j\right)}\cap\widetilde{H},$$
$$\mu_{\tilde{L}}\left(\tilde{s}_1^{(t-1)}\right)=\tilde{s}_1^{(t-1)}\cap\tilde{L},\dots,\mu_{\widetilde{H}}\left(\tilde{s}_i^{(t-\tau)}\right)=\tilde{s}_i^{(t-\tau)}\cap\tilde{L},$$
$$\mu'_{\tilde{L}}\left(\tilde{s}_i^{(t-1)}\right)=\varphi\left(\mu_{\tilde{L}}\left(\tilde{s}_i^{(t-1)}\right),\tilde{T}_1\right),\dots,\mu'_{\tilde{L}}\left(\tilde{s}_i^{(t-\tau)}\right)=\varphi\left(\mu_{\tilde{L}}\left(\tilde{s}_i^{(t-\tau)}\right),\tilde{T}_\tau\right),$$

where $\tilde{s}_i^{(t-1)}$ – predicted fuzzy time series; $\cap$ – fuzzy union operator; $\mu_{\tilde{L}}\left(\tilde{s}_i^{(t-1)}\right)$– linguistic term of the input variable; $\tilde{T}_j, j\in 1..\tau$ – fuzzy tendency obtained by fuzzy transformation; τ – depth of analyzed historical data; $\mu'_{\tilde{L}}\left(\tilde{s}_i^{(t-1)}\right)$– refined linguistic term based on a fuzzy trend; φ – operator for displaying a fuzzy variable with a fuzzy trend; $\tilde{L},\widetilde{M},\widetilde{H}$ – examples of linguistic terms of input variables.

The fuzzy operator transforms the incoming fuzzy variables in accordance with the detected fuzzy trend. For example, the following can be presented as types of fuzzy trends: "Growth", "Weak Growth", "Stability", "Slight Fall", "Fall". An illustration of the transformation of a triangular number taking into account five types of trend is shown in Figure 2. The resulting fuzzy number depends on the shape of the transformation curve set in accordance with the fuzzy trend and can change both the shape and the range of the output fuzzy values.

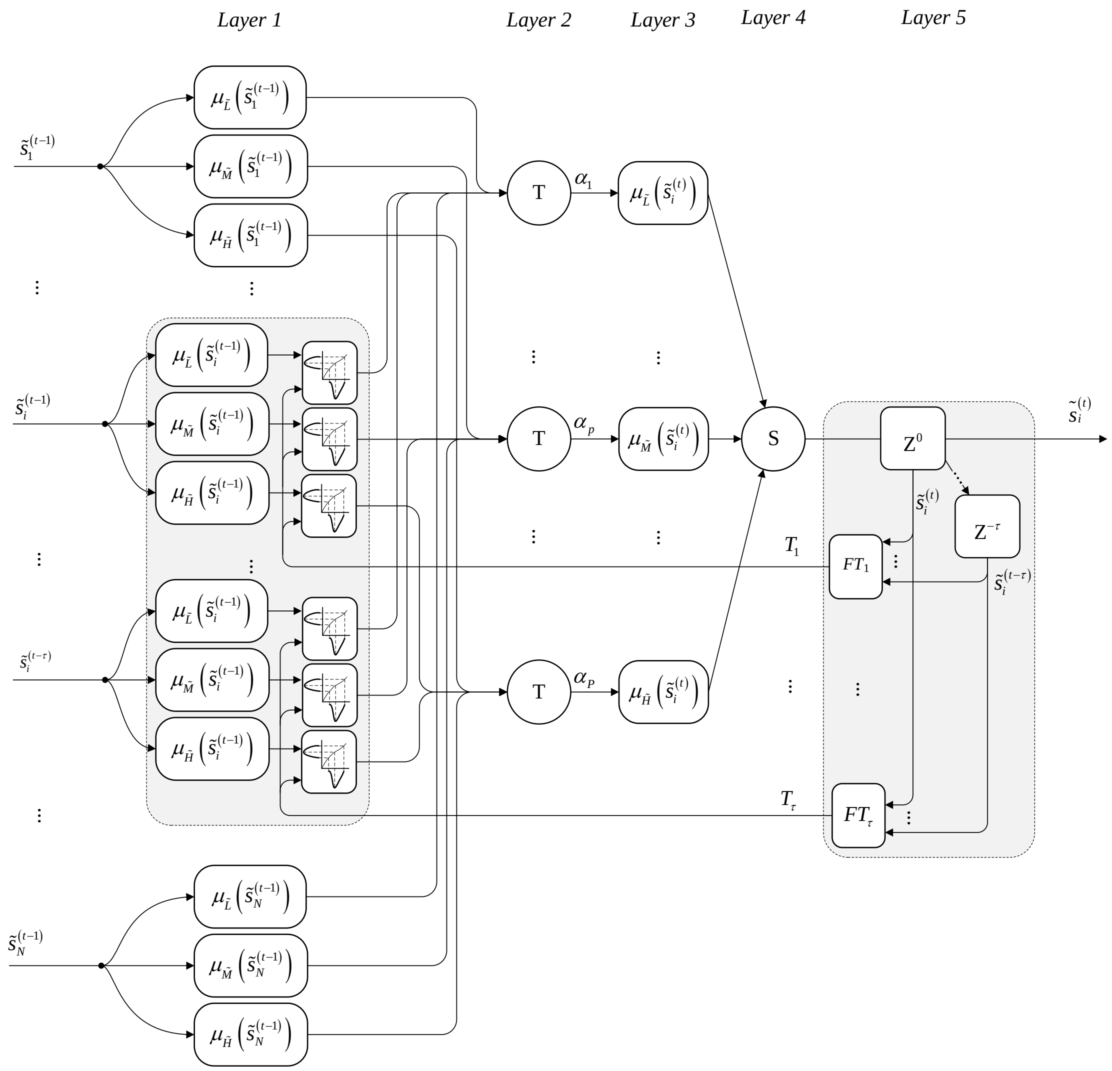

Figure 1: The structure of the proposed model of the new type RecANFIS

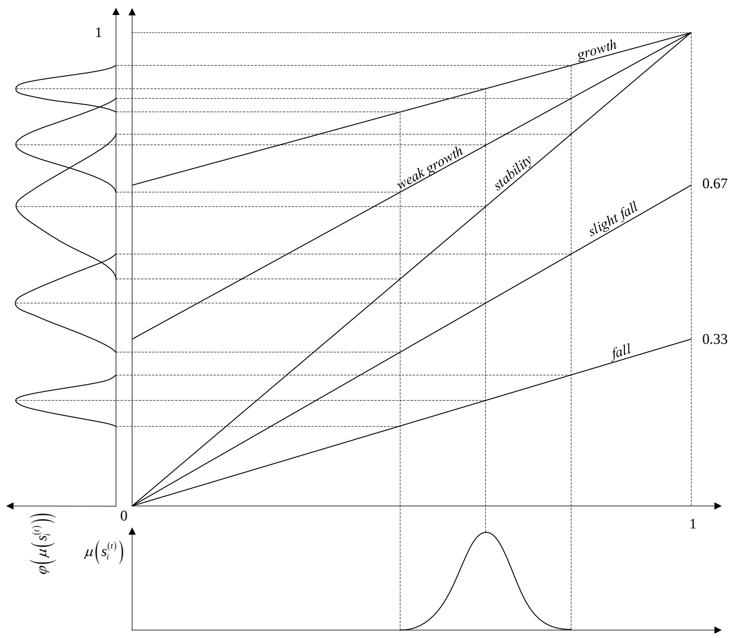

Figure 2: Fuzzy transformation illustration depending on the detected fuzzy trend

Layer 2. The elements of this layer are intended for aggregation based on the T-norm operation (here, min-conjunction) of the degrees of truth of the premises of the rules and serve as a production knowledge base. Here's an example of a fuzzy production rule:

$$If \ \left(\tilde{s}_1^{(t-1)} is\ \tilde{L}\right) AND \ldots AND \left(\tilde{s}_i^{(t-1)} is\ \tilde{L}\right) AND \ldots$$
$$AND \left(\tilde{s}_i^{(t-\tau)} is\ \widetilde{M}\right) AND \ldots AND \left(\tilde{s}_N^{(t-1)} is\ \widetilde{H}\right)\ Then\ \tilde{s}_i^{(t)}\ is\ \widetilde{M}.$$

Layer 3. Elements of this layer activate the conclusions of the corresponding rules in accordance with the degrees of truth of their premises based on the implication operation (for example, the operation min- or prod-activation). For the rule in question:

$$\mu_{\widetilde{M}}\left(\tilde{s}_i^{(t)}\right) = \min\left(\alpha_p, \widetilde{M}\right).$$

Layer 4. The only element of this layer performs the operation S-norms (for example, max-disjunctions), accumulating the activated **conclusions** of all model rules:

$$\tilde{s}_i^{(t)} = \max\left(\mu_{\tilde{L}}\left(\tilde{s}_i^{(t)}\right), \ldots, \mu_{\widetilde{M}}\left(\tilde{s}_i^{(t)}\right), \ldots, \mu_{\widetilde{H}}\left(\tilde{s}_i^{(t)}\right)\right).$$

Layer 5. The elements of this layer are designed to detect a fuzzy trend based on the output values $Z^0\left(\tilde{s}_i^{(t)}\right), \ldots, Z^{-\tau}\left(\tilde{s}_i^{(t)}\right)$ with a time delay τ, implemented using memory elements Z:

$$\tilde{T}_j = FT_j\left(Z^0\left(\tilde{s}_i^{(t)}\right), \ldots, Z^{-\tau}\left(\tilde{s}_i^{(t)}\right)\right), j \in 1..\tau,$$

where FT_j – neuro-fuzzy model for detecting a fuzzy trend.

In addition to the above, the value of the output fuzzy variable of the recurrent adaptive neuro-fuzzy model is defuzzified to a clear value using the “center of gravity” method [8].

3. Algorithm for training Recurrent Adaptive Neuro-Fuzzy Inference System/Model

In *Rec*ANFIS, which is based on algorithms of fuzzy inference and detection of fuzzy trends, the adjustable parameters are modal values and the degree of blurring of the membership functions of the assumptions and conclusions of the rules, as well as models for detecting fuzzy tendencies, which in turn also represent neuro-fuzzy models.

If the structural and parametric adjustment is made by an expert of the subject area, the expert is faced with the task, firstly, to adjust the linguistic terms of input and output fuzzy variables, secondly, to build a production base, and thirdly, to determine the number of analyzed values of “sliding window” τ for detecting fuzzy tendencies, fourthly, adjust neuro-fuzzy models to identify fuzzy tendencies, fifthly, configure transformation functions that influence the prerequisites of fuzzy production rules. If a part of the parameters is adjusted by an expert, and the other part of the learning elements is retrained in an automated way, with the parameters fixed by the expert, *Rec*ANFIS blended learning is performed. If there is a training sample, expert edits can be applied after automated training, which is carried out using data analysis algorithms. Let us take a closer look at the automated training algorithm *Rec*ANFIS based on data analysis algorithms, which consists of the following steps.

Step 1. Based on the retrospective data of the predicted BP, the size of the analyzed data τ window is determined to identify fuzzy trends. The size of the analyzed data window is selected based on expert opinion or in the process of analyzing the predicted time series. If necessary, various, both statistical and intelligent models with different windows can be built τ. For example, an autoregressive model can be used, in which time lags are alternated in order to reconstruct a time series with minimal error, which can be represented as follows:

$$\forall\{l_i, i \in 1..L\} | \delta s_i \rightarrow min,$$

where L – maximum value of analyzed time lags; δs_i– error in restoring the predicted time series; $\{l_i, i \in 1..L\}$– many negative time lags of the predicted variable, for example {0, -1, -3}.

Step 2. Based on the selected analyzed window, neuro-fuzzy models $\{FT_1, \ldots, FT_\tau\}$ will be built to identify fuzzy trends. Based on retrospective data, training samples are constructed for each neuro-fuzzy model, an example of which is presented in Table 1.

After the formation of training sets of neuro-fuzzy models, the construction of ACL-scales is performed according to the initial time series [8].

After the process of evaluating the fuzzy values of TS according to the ACL-scale, a fuzzy production base of the rules of the neuro-fuzzy model is built, which is based on the algorithm of neuro-fuzzy inference. Neuro-fuzzy model is a collection of fuzzy set and production rules that unite them. Examples of fuzzy production rules for detecting fuzzy trends are presented as follows:

$$\text{if } \tilde{s}_i^{(t)} \text{ is } \tilde{L} \text{ and } \ldots \text{ and } \tilde{s}_i^{(t-\tau)} \text{ is } \tilde{L} \text{ then } \tilde{T} \text{ is } \textbf{fall},$$
$$\vdots$$
$$\text{if } \tilde{s}_i^{(t)} \text{ is } \tilde{M} \text{ and } \ldots \text{ and } \tilde{s}_i^{(t-\tau)} \text{ is } \tilde{M} \text{ then } \tilde{T} \text{ is } \textbf{stability},$$
$$\vdots$$
$$\text{if } \tilde{s}_i^{(t)} \text{ is } \tilde{H} \text{ and } \ldots \text{ and } \tilde{s}_i^{(t-\tau)} \text{ is } \tilde{H} \text{ then } \tilde{T} \text{ is } \textbf{growth},$$

where $\tilde{L}, \tilde{M}, \tilde{H}$ – examples of linguistic terms of input variables; *fall*, *stability*, *growth* – examples of linguistic terms of the output variable. The conclusion of fuzzy rules of neuro-fuzzy models for detecting fuzzy trends determine the fuzzy transformation function of the fuzzy transformation operator, an example of the transformation of which is presented above.

Table 1

An example of constructing training samples of neuro-fuzzy models FT_i, $i \in 1..\tau$ to identify fuzzy trends

Neuro-fuzzy models	Training sample: Input values	Training sample: Output values
FT_1	$s_i^{t-\tau}(k)$, $s_i^{t-\tau+1}(k)$, ..., $s_i^{t-1}(k)$	$s_i^{t}(k)$
FT_2	$s_i^{t-\tau}(k)$, $s_i^{t-\tau+1}(k)$, ..., $s_i^{t-2}(k)$, $s_i^{t}(k)$	$s_i^{t-1}(k)$
…	…	
FT_τ	$s_i^{t-\tau+1}(k)$, ..., $s_i^{t-1}(k)$, $s_i^{t}(k)$	$s_i^{t-\tau}(k)$

Such fuzzy production rules are built personalized for each neuro-fuzzy model with time shifts $j \in 1..\tau$ without taking into account external factors. Depending on τ and the tasks being solved, a fuzzy tendency can be elementary, local or basic [9]. In addition, the identification and use of a fuzzy trend eliminates the problem of non-stationarity of the predicted time series, it is a feedback makes the system stable.

Step 3. Based on the established dependence with predetermined time lags, a training sample is built to form a fuzzy rule base:

$$\left\{\left(s_j^{(t-1)}(k), \ldots, s_j^{(t-L_j)}, \tilde{T}_1, \ldots, \tilde{T}_\tau, s_i^{(t)}(k)\right) \middle| j \in 1..N\right\},$$

where $s_i^{(t)}$ – value of the predicted time series; k – number of training sample examples; N – number of univariate time series; L_j – time shift of the j-th time series.

Step 4. For the automated formation of the fuzzy rule base, the mountain clustering algorithm is used. The main feature of this algorithm is that the number of clusters and their centers are determined during operation [11]. The formed clusters are represented in the following form:

$$\left\{\left(a_j^{(c)}/b_j^{(c)}\right) \middle| j \in 1..N, c = 1..C\right\},$$

where C – number of clusters found; $a_j^{(c)}$– center of the g-th cluster of the j-th input or output variable; $b_j^{(c)}$– radius of the g-th cluster of the j-th input or output variable.

Step 5. Then, the error function is calculated for all examples of the training sample. In accordance with the used learning algorithm (for example, the backpropagation algorithm or the genetic algorithm), the position of the linguistic terms is adjusted. By sequentially changing the slope of the display function, the linguistic terms of the predicted fuzzy variable are corrected.

Step 6. After setting up the fuzzy rule base and adjusting the linguistic terms, fuzzy trends are identified. The algorithm for training an adaptive neuro-fuzzy production model to identify a fuzzy trend is described in detail in [10].

The process of adjusting the parameters of linguistic terms continues until an acceptable error is reached, after which *Rec*ANFIS is ready for use.

4. Results of predicting electrical load based on Recurrent Adaptive Neuro-Fuzzy Inference System/Model

The proposed *Rec*ANFIS has been tested on historical data when solving problems of short-term prediction of electrical loads, taking into account the temperature and humidity of the environment in the city of Smolensk.

Graph comparing the electrical load obtained using ANN-based prediction and the proposed RecANFIS for 24 hours shows on Figure 3. The ANN was a three-layer perceptron with three neurons in the input layer (load, temperature and lighting) and seven neurons in the hidden layer, as well as the neuro-fuzzy ANFIS system.

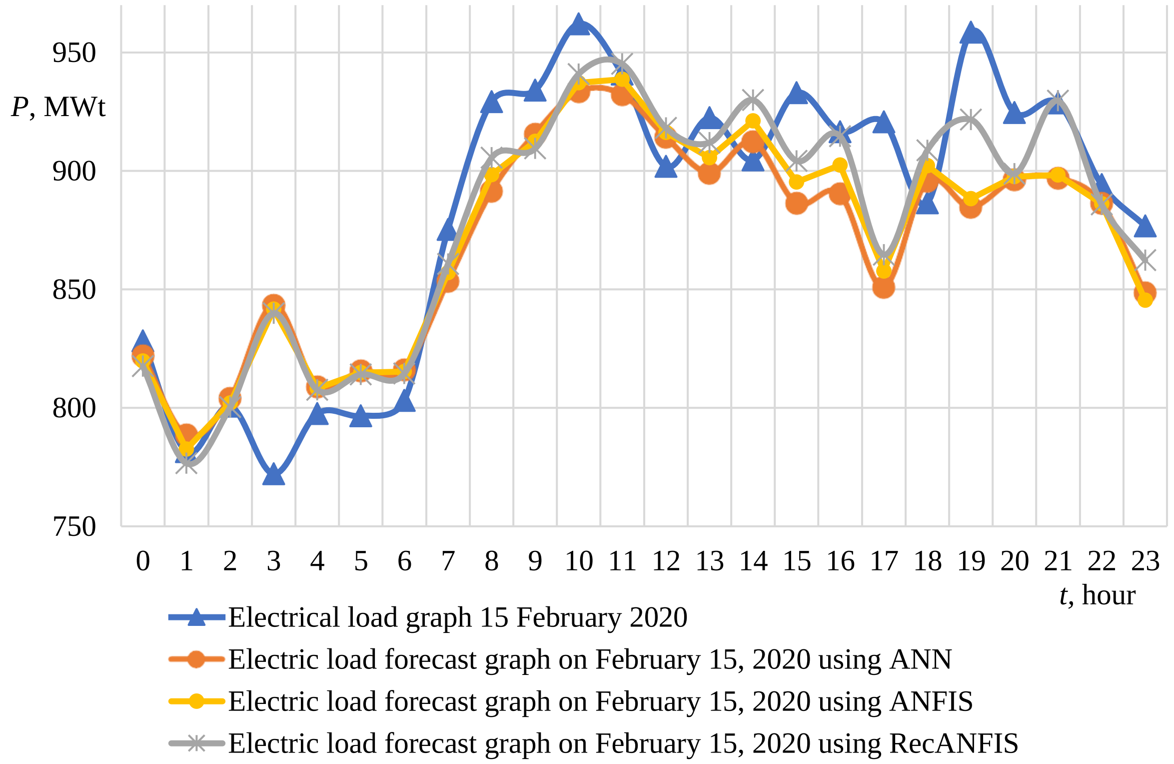

Figure 3: Comparison of the prediction of electrical loads using ANN, ANFIS and the proposed RecANFIS

Table 2 presents the results of prediction errors using ANN, ANFIS and the proposed RecANFIS.

Table 2
The result of comparing errors in predicting electrical load on August 01, 2019 using ANN, ANFIS and RecANFIS.

Prediction errors	Prediction models		
	ANN	*ANFIS*	*RecANFIS*
MAPE, %	2,86	2,64	2,17

5. Conclusion

The paper presents a new type of recurrent neuro-fuzzy models (*Rec*ANFIS - Recurrent Adaptive Neuro-Fuzzy Inference System) for predicting multidimensional time series with fuzzy trends. The internal memory of the "sliding window" serves as a data source for the formation and use of fuzzy trend, which solves the problem of non-stationarity of time series.

The resulting effect is achieved by expanding the classical apparatus of fuzzy production inference with a recurrent layer under uncertainty conditions, which, due to internal memory, allows one to take into account sequential connections of arbitrary length.

*Rec*ANFIS is tested on historical data on the example of electricity consumption in the city of Smolensk. The test results allow to increase the forecast accuracy by an average of 10-15% in comparison with the presented ANN and ANFIS.

The proposed new type of *Rec*ANFIS and the forecasting results are planned to be used in the future to develop and substantiate recommendations for increasing the accuracy of forecasting operational forecasts, taking into account temperature and humidity in conditions of uncertainty.

6. Acknowledgements

The reported study was funded by RFBR, project No.19-31-90054.

7. References

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