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Increasing The Credibility Of Forecasting Random Time Series Based On Fuzzy Inference Algorithms

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Abstract – Methods for the identification of linear, nonlinear dependencies help models of fuzzy logic and neural network (NN), data preprocessing, design of a computational training scheme for a five-layer neuro fuzzy network (NFN) are proposed. A software and algorithmic complex has been implemented, including modules for computational circuits of the NFN, parametric and structural identification. The effectiveness of methods for forecasting random time series is shown using the example of numerical results.

Keywords – Random Time Series, Forecast, Fuzzy Model, Database, Knowledge Base, Neuro-Fuzzy Network, Identification, Optimization.

Relevance Of The Topic

Existing models, algorithms for predicting random time series (RTS) are based on the use of methods for imitations dynamic processes based on complex analytical dependencies represented by various mathematical expressions such as differential, difference equations, etc. [1].

Finding an adequate model of the forecasting object in conditions of insufficient a priori information, parametric uncertainty becomes difficult to describe modeling task, which will be associated with complex calculations [2, 3].

An effective and promising approach to increasing the reliability of the forecast is to use the properties and features of random time series (RTS), fuzzy sets, models, fuzzy logic algorithms, neuro-fuzzy networks (NFN) [4, 5].

NFSs manifest themselves on the positive side when identifying and approximating non-stationary processes, large structure uncertainty, and limited information about the parameters.

Methods for forecasting RTS based on NFN require the implementation of modified computational schemes for structural and parametric identification, fuzzy logic models, and the use of a knowledge base (KB), including a wide set of fuzzy rules instead of complex analytical functions and equations describing a nonstationary process [6].

The formal model for the identification of RTS in the data mining system (DMS) based on the NFN is generally represented as

$$J = F(u(t - \Delta t), w, a), \quad (1)$$

where $u(t-\Delta t)$ – parameter obtained to configure the process of identifying the RTS according to the values set in the previous step of the system execution; w – vector of unknown parameters and random disturbances; a – vector of known parameters.

When a priori information about the parameters, structure, properties, and distribution laws of the RTS is insufficient, or even absent, then in these cases an approach is considered effective, which is aimed at building methods and algorithms for increasing the reliability of the forecast based on the use of the properties of models of fuzzy inference.

The introduction of fuzzy modeling is due to the fact that modeling methods based on statistical approaches do not take into account complex nonlinearities, parameter measurement errors, information distortions, time delays in the real dynamics of nonstationary objects. Under these conditions, algorithms with fuzzy rules successfully perform the tasks of ensuring the accuracy of analysis and data processing, as well as increasing the reliability of the forecast of the RTS through the use of the unique properties of self-adaptation, self-organization, and approximation [7].

The system under study implements the Sugeno fuzzy inference model of zero-order and NN with five layers, which perform the following functions: the first layer - forms the terms of the input variables; the second layer - antecedents (premises) of fuzzy rules; the third layer - normalizes the degree of rule execution; the fourth layer is the conclusion of the rules; fifth layer - aggregation of the result obtained according to different rules [8].

NN training with the determination and adjustment of the parameters of the membership function (FP) is performed with backpropagation of the error according to the hybrid model, which is a combination of the least-squares method and the gradient method [9].

Initially, to execute the algorithm, the data set is transformed

$$X = [x_1, x_2, ..., x_p] \quad (2)$$

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$$Z = [z_1, z_2, ..., z_p], \quad (3)$$

represented in the range (-1, 1) with a uniform distribution law.

At the next stage, the input data normalization algorithm is implemented, which includes the following steps [10].

Step 1. Determine the mean and standard deviation of the set (3):

$$\bar{x} = \frac{1}{p}\sum_{i=1}^{p} x_i\ ; \quad (4)$$

$$\sigma = \frac{1}{p}\sum_{i=1}^{p} (x_i - \bar{x})^2\ , \quad (5)$$

where p – number of RTS measurements; x_i – input variable $(i = \overline{1 ... p})$; $\bar{x_i}$ – average value; σ – standard deviation of the input variable.

Step 2. The set (3) is normalized according to the function:

$$z_i = \frac{2}{1 + \exp[-K(x_i - \bar{x})]} - 1 \quad (6)$$

where K – adjustable normalization factor; z – transformed variable.

Step 3. The entropy of the resulting set is determined by K. Shannon's formula:

$$H(Z) = -\sum_{j=1}^{h} P_j(z) \log P_j(z), \qquad (7)$$

where h – the number of options in the variation range; $P_j(z) = a_j / a$ – frequency of occurrence of variable z in the set; a_j – the number of measurements included in the training sample; a – total number of measurements.

Step 4. The $K := K + 0{,}01$ coefficient is increased and steps 2 and 3 are recalculated until the functional (7).

The belonging of the transformed set to the range (-1,1) is guaranteed by function (6), and the uniformity of the distribution law is ensured by searching for the coefficient K by functional (7).

The next stage of training the NN is to launch the algorithm for determining the rational size of the training sample and the architecture of the NN [11].

The algorithm is presented in the following steps.

Step 1. The rational size of the training data set is determined by the formula

$$p \approx [2^d (4d+1)]^2 / d, \qquad (8)$$

where p – the number of measurements in the training sample; d – the size of the vector of measurements submitted for training.

Step 2. The number and values of nodes in the NNS layers are determined, when $t_k \le 0$ and $m_k = 1$ according to the system:

$$\begin{cases} m_1 = (m_0 - t_1)/d, \\ m_2 = (m_1 + t_1 - t_2)/d, \\ m_3 = (m_2 + t_2 - t_3)/d, \\ \vdots \\ m_k = (m_{k-1} + t_{k-1} - t_k)/d. \end{cases} \qquad (9)$$

$$M = [m_1, m_2, \dots, m_k],$$

where k – number of network layers; m_k – the number of nodes in the k-layer, rounded to the lower integer from division m_{k-1}/d; $t = m_{k-1} - d \cdot m_k$ – remainder of division, which determines the number of unused features in the k-layer and passing to the next layer $m_0 = n$.

Step 3. For the j node of the l layer, a training sample is formed:

$$y_i = [x_1, x_2, \dots, x_d]_{l,j,i}, \; l = \overline{1 \dots k}, \; j = \overline{1 \dots m_1}, \; i = \overline{1 \dots p}. \qquad (10)$$

In the work, the results of identification of a certain conditional technological indicator are obtained, at which the implemented algorithms for learning neural networks based on the Sugeno and Mamdani models are tested [12].

It is determined that the optimal value of the identification quality functional without the use of fuzzy rules is equal to 275; for the Sugeno fuzzy model - 675 and for the Mamdani fuzzy model - 650. The Sugeno model gives the best result when calculating the predictive reliability of the conditional RTS.

The results of testing the computational schemes of the network show that the problem of learning the neural network remains the possible "noise" of the training data. The implemented methods of training NN create an opportunity for automatic correction of the parameters of the RTS model and more accurate results of analysis and processing of information are obtained with strong variations in statistical parameters and non-stationary properties of the RTS.

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