Algorithm for predicting the evolution of series of dynamics of complex systems in solving information problems

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Abstract. In the development of information, systems and programming to predict the series of dynamics, neural network methods have recently been applied. They are more flexible, in comparison with existing analogues and are capable of taking into account the nonlinearities of the series. In this paper, we propose a modified algorithm for predicting the series of dynamics, which includes a method for training neural networks, an approach to describing and presenting input data, based on the prediction by the multilayer perceptron method. To construct a neural network, the values of a series of dynamics at the extremum points and time values corresponding to them, formed based on the sliding window method, are used as input data. The proposed algorithm can act as an independent approach to predicting the series of dynamics, and be one of the parts of the forecasting system. The efficiency of predicting the evolution of the dynamics series for a short-term one-step and long-term multi-step forecast by the classical multilayer perceptron method and a modified algorithm using synthetic and real data is compared. The result of this modification was the minimization of the magnitude of the iterative error that arises from the previously predicted inputs to the inputs to the neural network, as well as the increase in the accuracy of the iterative prediction of the neural network.

1. Introduction

In the development of information systems and programming in solving problems of forecasting the state of the system and, accordingly, to implement the possibility of influencing the development of the dynamic system, neural network methods have recently been applied. They are used where it is necessary to forecast parameters and parameters of the system for some pre-emptive period. Neural network methods are more flexible than existing analogues and are capable of accounting for the nonlinearities of series. Now, there is a wide variety of approaches to predicting the series of dynamics, for example, the use of statistical methods described in [1-10]. Of particular popularity recently acquired more flexible, in comparison with existing analogs, and capable of taking into account the nonlinear nature of the series of dynamics, neural network methods, for example, presented in [11-17]. When predicting the dynamics series, various neural network approaches, such as the use of recurrent neural networks, the use of generalized regression neural networks (the GRNN method), the use of RBF networks, the use of multilayer perceptrons [18-23] are also used. In order to obtain the maximum forecasting effect, several approaches and different types of neural networks are usually used at once. In this paper, we offer a unifying approach to predicting the series of dynamics, including the method of training neural networks, the method of describing and presenting input data,
based on approaches to forecasting based on a multilayer perceptron. The proposed method can act both as an independent approach to predicting the series of dynamics, and be one of the parts of the forecasting system.

2. Statement of the problem with the traditional method of describing a number of dynamics
The predicted series of dynamics can be specified in the form of some sequence:

\[ x_1, x_2, \ldots, x_t. \]  

(1)

It is required to define its continuation in the form:

\[ x_{t+1}, x_{t+2}, \ldots \]  

(2)

In this case, the predicted nonlinear model can be defined as follows:

\[ x_t = F(x_{t-1}, x_{t-2}, \ldots, x_{t-k}), \]  

(3)

where \( t = k + 1, \) \( n; \) \( F \) – nonlinear functional dependence, constructed on the basis of artificially created neural network; \( k \) – the size of the sliding window, numerically equal to the number of neurons entering the network \( n \).

To predict a number of dynamics for given values, a **multilayer perceptron** (MLP, Multilayer Perceptron) can be used as the main architecture. In [24] it was proved that an artificially created neural network could approximate with any desired accuracy any continuous function. Another no less important characteristic of a multilayer perceptron is the possibility of generalizing information that is in the set of training. Thus, the multilayer perceptron is a powerful tool for predicting the evolution of the series of dynamics of complex systems. In fig. 1 shows a multilayer perceptron used in the present work to predict the evolution of the series of dynamics.

![Figure 1. The multilayer perceptron.](image)

When using the traditional method of describing the predicted series of dynamics, only the previous values (1) set in the sequence will be taken into account in predicting subsequent values. In
the present work, the prediction was carried out on images that differed from the sample of images fed from the set of training. To ensure the correct functioning of the neural network, it is required to normalize the input data. There are many options for carrying out such an operation. Some of the best results are achieved by projecting the domain of the definition of the set of input data \((1)\) into a segment \([0; 1]\).

3. Statement of the problem with a modified method for describing a number of dynamics
This method consists in a special approach to learning the neural network in forecasting, as well as in a special way of specifying the input data set. At the first stage of the evolution prediction, the following transformation of a number of dynamics is performed.

1. In a number of dynamics only the extremum values are chosen for forecasting: the maximum points and the minimum points.
2. The value at the extremum point and the time interval that has elapsed since the appearance of the previous extremum value are time-value pairs, which are further used as inputs to the neural network. In fig. 2 shows a method for specifying time-value pairs.

Thus, to construct a neural network as input data, it is expedient to use the values of a number of dynamics at the extremum points and time values corresponding to them and formed on the basis of the sliding window method. As a result, time-value pairs \(n\) are formed and fed to the network input, which are the values of a number of dynamics. Each such pair includes the value at the very extremum, and the time interval elapsed from the previous extremum to the moment of the present appearance. The output layer in the multilayer perceptron, respectively, contains both series of such values, and the output is as follows:

\[
x_{n+1} = F(x_1, x_2, ..., x_n),
\]

\[
t_{n+1} = F(t_1, t_2, ..., t_n).
\]

In fig. 3 is an image of the implemented neural network architecture.

The proposed modification of the approach to learning a neural network is that the classical traditional neural network learning process is first conducted on the basis of the accepted master sample data, and then the training is based on a sample of the predicted data. The result of this modification is the minimization of the error value resulting from the previously predicted inputs to the inputs to the neural network, the so-called iterative error. As a result, the learning process of a neural network is first performed on reference values, and then, once the iterative error reaches an acceptable level, the learning process of the neural network is started on the predicted data. The result of this approach is a reduction in the forecast error as a whole, as well as an increase in the accuracy of the iterative prediction of the neural network.
4. Results of the experimental study

In the course of the experimental study of the proposed approach, the evolution of chaotic series of dynamics based on the use of a multilayer perceptron with the use of synthetic data, as well as the use of real data, was predicted. As an explored chaotic system of synthetic data, the Enon attractor was used. To describe the Enon process, the following equations are applied:

\[
\begin{aligned}
  x_{n+1} &= 1 - \alpha \cdot x_n^2 + y_n \\
  y_{n+1} &= \beta \cdot x_n
\end{aligned}
\]

where the coefficients of the chaotic behavior of the system are \( \alpha = 1.4 \), \( \beta = 0.3 \).

In fig. 4 shows the first 200 elements of the Enon dynamics series.

The coordinate \( X \) of a number of dynamics of Enon is applied as a set of input data. When demonstrating the evolution of the series in the process of training the neural network, the first 400 elements of a series of dynamics and 300 elements other than the elements involved in training were used. The neural network was trained on the basis of the sliding window method. The forecasting process was performed on data that was different from the elements in the set of data used in training the network. This is necessary in order to make the results compare more clearly. The work used a multi-step and one-step forecast types. A one-step forecast is necessary for short-term forecasting of evolution, forecasting one step in time. When implementing this type of forecasting, only the reference actual data was used. Inputs from the neural network were fed from the data sample for forecasting. In fig. 5 is a diagram of a short-term one-step forecast of a number of dynamics.
Figure 5. Scheme of short-term one-step forecasting of the evolution of a number of dynamics.

A multi-step view of predicting the evolution of the dynamics series, carried out by repeating the iterations, was carried out using a series of data obtained at the output from the previous stage of the forecasting process. In fig. 6 is a diagram of a long-term multi-step forecast of a number of dynamics. Estimation of the quality of forecasting the evolution of a number of dynamics was carried out using the MAP (Mean absolute percentage error) error and the MSE total root-mean-square error. The MAPE error is the average absolute error expressed in percentages and, as a rule, is used to estimate the accuracy of predicting the dynamics series for large volumes of statistical data. The calculation of the MARE error was carried out using the formula:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right|,$$  

where $A_i$ – real value of the data set; $F_i$ – the value obtained as a result of predicting the evolution of a number of dynamics.

Calculation of the mean square error MSE was carried out by the formula:

$$\text{MSE} = \frac{1}{2n} \sum_{i=1}^{n} (A_i - F_i)^2.$$  

When predicting the evolution of a number of dynamics of Enon with the help of the classical algorithm of a multilayer perceptron, the neural network showed the best results using architecture 28-12-1.

Figure 6. Scheme of long-term multi-step prediction of the evolution of a number of dynamics.

In single-step forecasting, the results of forecasting are presented in fig. 7, the average value of the MAPE error was 38.4%, and the average MSE error was 0.033. In fig. 7, in order to better visualize the calculated data, only the first 20 values obtained are shown.
In the multi-step prediction of the evolution of the dynamics series due to iteration repeatability under the classical algorithm of the multilayer perceptron, the average value of the MAPE error was 237.2%, and the average MSE error value was 0.96. The results of multi-step prediction of a number of Enon dynamics are shown in fig. 8. For the best visibility of the calculated data in fig. 8 only the first 20 predictions are shown.

![Figure 7](image7.png)

**Figure 7.** Results of a one-step prediction of a number of dynamics of Enon using the classical algorithm of a multilayer perceptron.

![Figure 8](image8.png)

**Figure 8.** Results of multi-step prediction of a number of dynamics of Enon using the classical algorithm of a multilayer perceptron.

The results obtained for the short-term one-step and long-term multi-step prediction of the evolution of the dynamics series indicate the possibility of using the traditional classical multi-layer perceptron method for short-term one-step prediction of the evolution of a number of dynamics and the impossibility of using it for long-term forecasting, since by the fifth step of the iteration the MARE error was 125.9%.

The proposed modified forecasting method is implemented using the network architecture 30-13-2 and using the sigmoid function of nonlinear transformations in the output and hidden layers. In fig. 9 presents the results of a one-step short-term forecast. The average value of the MARE error was 37.1%, and the average value of the MSE error was 0.086. For the best visibility of the calculated data, only the first 20 values obtained as a result of the prediction are shown.
Figure 9. Results of a one-step short-term prediction of a number of dynamics of Enon using a modified algorithm of a multilayer perceptron.

As can be seen from comparing the values of the MARE error criterion for the classical and modified methods, the neural network performs a prediction with the modified algorithm more accurately than with the help of the classical algorithm. The MAPE error is 38.4%. Further, a multi-step long-term iterative forecasting study was conducted, since the main goal of the proposed modified training is to minimize the error of the iteration. The experimental results for the first 20 values are shown in fig. 10. The average value of the MAPE error was 47.7%, and the average MSE error value was 1.159. As can be seen from fig. 10, the forecast accuracy for 20 values is small, but there is no accumulation of the error value as a whole. That is, the received error value is kept constant throughout the entire duration of the prediction process. It does not increase.

Figure 10. Results of multi-step prediction of a number of dynamics of Enon using a modified algorithm of a multilayer perceptron.

In order to confirm this conclusion, fig. 11 shows calculated and reference data for 120 consecutive iterations. Thus, an estimation of the prediction error by 120 steps forward is made. Based on the data presented, it can be concluded that the quality of the iterative training of the neural network is quite high. In addition to this statement, the average value of the MARE error, which is 47.6%, is indicative.
Therefore, we can assume that the modified algorithm with multi-step prediction shows much better results than the classical algorithm of the multilayer perceptron. For clarity of comparison, the results of the study are shown in table 1 and 2. Table 1 shows the values of the MARE error criterion, and in table 2 – the values of the MSE error criterion.

![Figure 11. Estimation of the prediction error at 120 consecutive iterations of the modified multilayer perceptron algorithm.](image)

**Table 1. Values of the MARE error**

| Type of algorithm    | Method of forecasting       | one-step short-term forecast | multi-step long-term forecast |
|----------------------|-----------------------------|------------------------------|-------------------------------|
| Multilayer Perceptron|                             | 38.4%                        | 237.2%                       |
| Modified algorithm   |                             | 37.1%                        | 47.7%                        |

**Table 2. MSE error values**

| Type of algorithm    | Method of forecasting       | one-step short-term forecast | multi-step long-term forecast |
|----------------------|-----------------------------|------------------------------|-------------------------------|
| Multilayer Perceptron|                             | 0.033                        | 0.96                          |
| Modified algorithm   |                             | 0.086                        | 1.159                         |

Verification of the operability and quality level of the proposed modified algorithm was carried out on the real experimental data proposed in [25]. For this purpose, a perceptron with architecture 28-13-1 with sigmoid function of nonlinear transformations, activating neurons in the output and hidden layers was considered. As training data, the first 400 elements of the proposed series of dynamics were taken, which was 60% of all available elements. In order to assess the quality of the forecast, the remaining 40% of the series was used. With a one-step short-term forecast, the average MAP error obtained was 63.4%, and the average MSE error was 296.823. The results of the forecast for the first 20 values are shown in fig. 12.
Figure 12. The results of a one-step prediction of a number of dynamics on the basis of real data using the classical algorithm of a multilayer perceptron.

Comparison of the shape of the graphs presented in fig. 12, as well as the average value of the MSE error, indicates that this architecture can not be applied to such forecasts due to a sufficiently large amount of error occurring at the first step of the prediction. Next, we will consider the application of the proposed modified multilayer perceptron algorithm for a one-step short-term prediction based on the 30-13-2 network architecture. Based on the results of the prediction of the evolution of a number of dynamics on the basis of real data, presented for 20 values in fig. 13, the average value of the MAPE error was 31.8%, and the average value of the MSE error was 72.04.

Figure 13. Results of a one-step short-term forecasting of a number of dynamics on the basis of real data using the modified algorithm of a multilayer perceptron.

The use of the modified forecasting algorithm gives better results, in favor of which low values of the MARE error criterion testify. Based on this, it can be concluded that this neural network architecture can be used for short-term one-step forecasting of the dynamics series.

The results of multi-step prediction of a number of dynamics using the modified multilayer perceptron algorithm for the first 20 values are shown in fig. 14. The average value of the MARE error criterion for this algorithm was 27.8%, and the mean value of the MSE error criterion was 34.02. Comparing these results with those for the classical algorithm (the average value of the MAPE error is 68.953%, the average value of the MSE error is 332.197), one can conclude that the proposed
modified algorithm for predicting the evolution of the dynamics series in comparison with the classical algorithm is undeniable.

![Graph showing multi-step prediction of dynamics series](image)

**Figure 14.** The results of multi-step prediction of a number of dynamics on the basis of real data using the modified algorithm of a multilayer perceptron.

5. **Conclusion**

The paper proposed a unifying approach to forecasting the series of complex system dynamics, which includes a method for training neural networks, a method for describing and presenting input data, based on approaches to forecasting based on a multilayer perceptron. In the course of the research it was shown that the modified neural network algorithm is able to compete with existing analogs presented in [18-26]. It is flexible enough compared to existing analogs [24-26] and has the ability to take into account the nonlinearity of a complex chaotic system. As inputs to the construction of a neural network, it is suggested to use the values of a number of dynamics at the extremum points, as well as the corresponding time values obtained by computation using the sliding window method. This algorithm can be used both as an independent approach to predicting the series of dynamics, and as part of the forecasting system. The efficiency of predicting the evolution of the dynamics series for a one-step and multi-step forecast based on the classical multilayer perceptron method and on the basis of the modified algorithm considered is compared. For comparison, synthetic chaotic data were used, as well as real data obtained from experiments [10, 14, 22].

Thus, the study showed that the modified algorithm of the multilayer perceptron is a powerful tool for predicting the evolution of chaotic series of the dynamics of complex systems. The result of this modification is to minimize the criterion of the iterative error that occurs when the previously predicted data is applied to the inputs of the neural network. A positive result is an increase in the accuracy of the iterative prediction of the neural network.

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