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# ИССЛЕДОВАНИЕ ВЛИЯНИЯ СТРУКТУРЫ НЕЙРОННОЙ СЕТИ И ЕЁ ТИПА НА ПАРАМЕТРЫ ПРОГНОЗА ОГРАНИЧЕННОГО ПО ПОЛОСЕ РАДИОТЕХНИЧЕСКОГО СИГНАЛА

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**Аннотация.** На сегодняшний день прогнозирование данных остается актуальным во многих сферах деятельности. Применительно к радиотехнике прогноз осуществляется при экстраполяции координат движения цели на этапе вторичной обработки информации, прогнозировании случайных процессов в приемных устройствах РЛС, прогнозировании параметров компонентов нелинейных элементов. Также прогнозирование используется в метеорологии, экономической статистике, социологических исследованиях, при анализе энергопотребления, при исследовании свойств химических элементов. В связи с постоянным усовершенствованием аппаратной части приборов их быстродействие измеряется порядками нано- пикосекунд. Это в свою очередь требует быстродействующих структур обработки сигналов. Искусственные нейронные сети (ИНС), благодаря возможности параллельной обработки данных, позволяют решать эти задачи без основательного синтеза/анализа математической модели. Кроме того, нейронные сети имеют уникальную возможность осуществлять построение нелинейных моделей любого уровня сложности, особенно в тех случаях, когда неизвестен общий вид аналитической зависимости. Целью работы является исследование качества прогноза динамических искусственных нейронных сетей при различных параметрах сигнала (ширина спектральной плотности) и параметров алгоритма обучения/адаптации, а также сравнительный анализ ИНС по значениям функционалов ошибки (СКО, СПО). Для моделирования работы ИНС был выбран пакет расширения Neural Network Toolbox.

***Ключевые слова:*** *адаптивный линейный нейрон; алгоритмы обучения/адаптации; искусственные нейронные сети; Neural Network Toolbox; оптимальное СКО и СПО; радиотехнический сигнал.*

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Original article

# INVESTIGATION OF THE INFLUENCE OF THE NEURAL NETWORK STRUCTURE AND ITS TYPE ON THE FORECAST PARAMETERS OF A BAND-LIMITED RADIO SIGNAL

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**Abstract.** At present, the theoretical information on the design of ANNs has been studied, software has been developed in MATLAB that allows one- and multi-step forecasting, signal predictions for all types of ANNs under study have been obtained, and a comparative analysis of networks has been carried out. With an increase in the number of harmonics in the spectrum, the optimal value of STR is not achieved for all types of networks. Also, an interesting feature of the convergence of all networks and algorithms is the achievement of a specific value of the minimum RMS for a type 4 signal. That is, we can say that the optimum has been reached and the accuracy for all structures can be improved by pre-processing the signal (for example, decimation) or taking a different number of samples. An adaptive linear neuron with an algorithm for minimizing the RMS (delta rule) shows itself stably for any width of the signal spectrum. That is, it is capable of adapting to the forecast of any type of signal with sufficient accuracy over a finite time period, but the adaptation time increases greatly with the increase in the complexity of the task. For ADALIN, in the course of the work, it was not possible to achieve the optimal RMSD and STR for the forecast of a broadband signal of the 4th type in a rational time. It can be concluded that when modeling an ANN, there is uncertainty in choosing the dimension of the hidden layer, the length of the delay line. Moreover, with an increase in the dimension of the structure, the potential accuracy increases, but the learning rate decreases and vice versa.

***Key words:*** *adaptive linear neuron, learning/adaptation algorithms, artificial neural networks, Neural Network Toolbox, optimal SSE and SPO, radio engineering signal*.

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## Introduction

Today, data forecasting remains relevant in many areas of activity. In relation to radio engineering, the forecast is carried out by extrapolating the coordinates of the target movement at the stage of secondary information processing, predicting random processes in radar receivers, and predicting the parameters of the components of nonlinear elements. Forecasting is also used in meteorology, economic statistics, sociological research, in the analysis of energy consumption, in the study of the properties of chemical elements. In connection with the constant improvement of the hardware of the devices, their speed is measured in the order of nano-picoseconds. This in turn requires high-speed signal processing structures. Artificial neural networks, thanks to the possibility of parallel data processing, allow solving these problems, in addition, without a thorough synthesis / analysis of the mathematical model. In addition, neural networks have a unique ability to build non-linear models of any level of complexity, especially in cases where the general form of the analytical dependence is unknown [1-5] .

The aim of the work is to study the quality of the prediction of dynamic artificial neural networks for various signal parameters (spectral density width) and parameters of the learning / adaptation algorithm, as well as a comparative analysis of the ANN by the values of the error functionals (RMS, STR).

To simulate the operation of the ANN, the Neural Network Toolbox extension package was chosen.

## 1. MATLAB Neural Network Toolbox

The Neural Network Toolbox contains all the main types of neural networks, as well as the most common adaptation, tuning and training algorithms, applied signal processing functions. In the course of the work, a program was developed that simulates a forecast using an adaptive linear neuron, a focused linear network and a nonlinear autoregressive network for 3 types of signals. To assess the adequacy of the prediction model, the modeling process is carried out on two samples (sets) of samples of the predicted signal - training and verification (post-test). Consider the first stage - training on the training set. When training networks of the FLS and HARS type, the training

set is divided into three subsets: evaluation, control and test and the network is trained on each of them.

The division of a set into subsets can be sequential or random (specified in MATLAB by the divideFcn function). It has been empirically established that when the network is retrained, the error on the control set begins to increase, and the network is then trained only by extraneous noise [1-5]. Therefore, the learning process is interrupted, considering that the minimum value of the functional is reached. The parameter that regulates the number of error increases on the control subset in the program is designated as maxfail [6-14].

The second stage consists in modeling the output signal of the network on the test set (post-test). If the standard deviation of the forecast on this sample takes an acceptable value, then the forecast can be considered satisfactory. In addition to RMS, there are also other error functionals: MAPE (the Mean Absolute Percentage Error) - the average relative error, CAO (Mean Absolute Deviation) - the average absolute deviation, SSE (Sum of Squared Error) - squared error, SPO (Mean Percentage Error) - the average percentage of error, etc. In the work, in assessing the quality of the forecast, in addition to the standard deviation, the functionals of the SAO and SPO are used. SAO is described by the following formula:

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|e_i|, \quad (1)$$

where n - is the number of samples of the vector supplied to the ANN;

$e_i$ - i-th sample value error.

And the SPO is calculated by the formula:

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\frac{e_i}{y_i}\cdot 100, \quad (2)$$

where is the $y_i$ - output of the ANN for the i-th sample. STR characterizes the relative degree of forecast bias and should not be more than 5% [15].

1.2. Pre-processing and post-processing of data

Since non-linear FAs have saturation limits, beyond which the output of a single neuron will be constant, therefore, it is necessary to bring the input sample vector to the interval of the function from -1 to 1.

In addition, the data vector must be normalized, that is, the average value over all sets must be equal to zero. Otherwise, this leads to looping of the values of the weights of neurons in the input layer [1]. After that, the input data are decorrelated (principal component analysis is performed). Correlation of input data leads to low data representativeness and correspondingly worse generalization. A detailed description of the principal component method is also described in [1]. After training and prediction, the value vectors must be processed in reverse order.

## 2. Model of an adaptive linear neuron

To demonstrate the operation of the program, let's model an adaptive linear neuron in the MATLAB environment (see Figure 2.3) with the following parameters: adaptation algorithm (AD); minimum standard deviation of approximation ($10^{-4}$); learning rate (0,3); number of adaptation cycles (10); the number of samples of the learning set (4300); number of counts of the post-verification set (1600); number of delay elements (5).

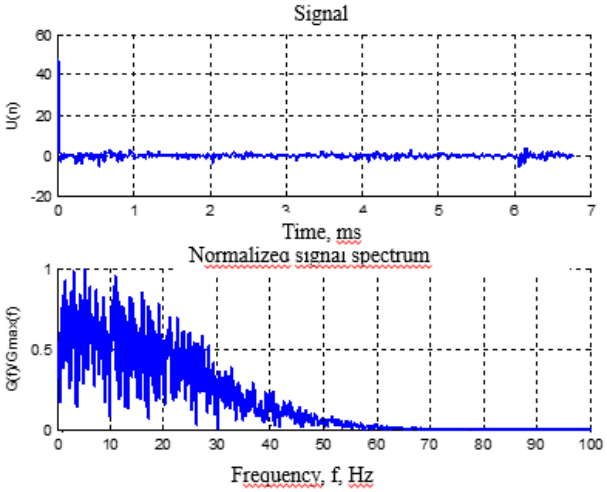



Figure 1 – Plot of a type 1 signal and its power spectral density

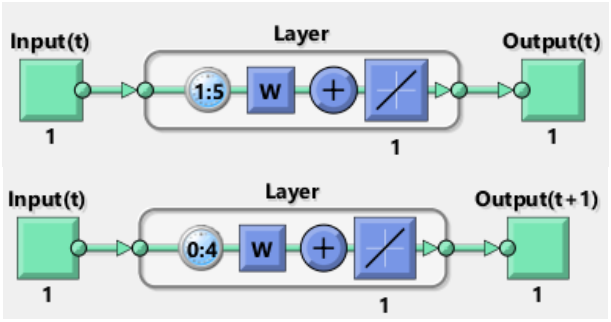



Figure 2 – Structure of ADALIN: during training (upper window); in forecast (lower window)

The training results are presented in Table 1. Thus, for 27 iterations, the RMS value was obtained with a specified accuracy of $10^{-4}$.

Table 1 – ALALINE training outcomes

| Learning Outcomes | | |
|---|---|---|
| Training time (seconds) | Number of iterations | Minimize parameter value |
| 185,712265 | 27 | 9,983163e–05 |
| Forecast result on the test set: Forecast errors | | |
| For the 1st neuron | | |
| SAO | SKO | SPO |
| 6,996076e–02 | 8,373748e–03 | –22,073857 % |

Figure 3 shows a graph of RSD changes depending on the epoch. Figure 4 shows the graph of the training signal approximation, and Figure 5 shows the prediction graph. On the test set, it is obvious that the forecast is worse (Figure 6).

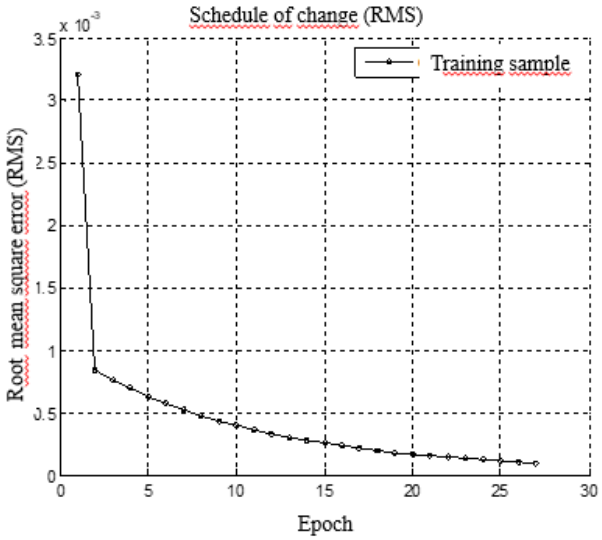



Figure 3 – Graph of RMS change

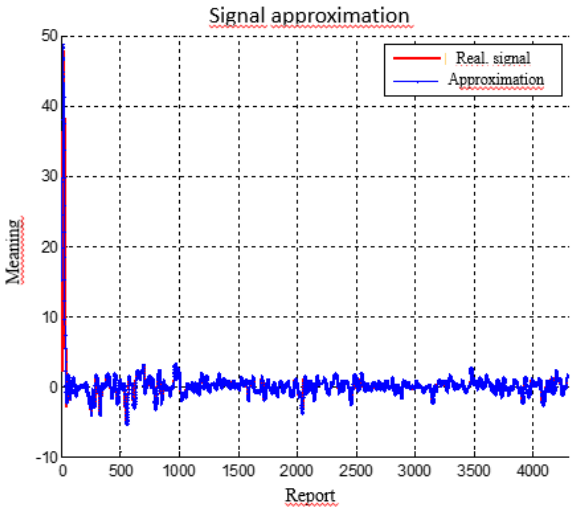



Figure 4 – Approximation of the training signal

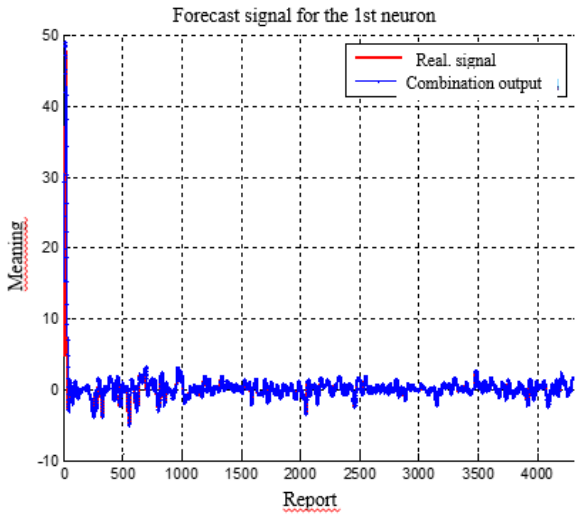



Figure 5 – Training Signal Prediction

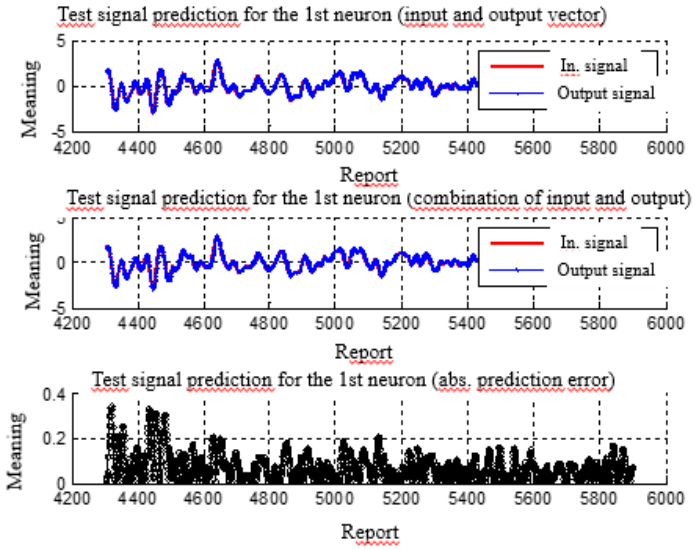



Figure 6 – Test signal prediction and prediction error

## 3. Linear network model

Let's model the ANN to demonstrate its ability to one-step prediction (the default values of the algorithm parameters): learning algorithm (LM); learning rate (0,01); number of training samples (4300); number of test readings (1600); distribution of samples (consecutive); number of hidden neurons (15); number of output neurons (predicted readings) (2); number of delay elements (5).

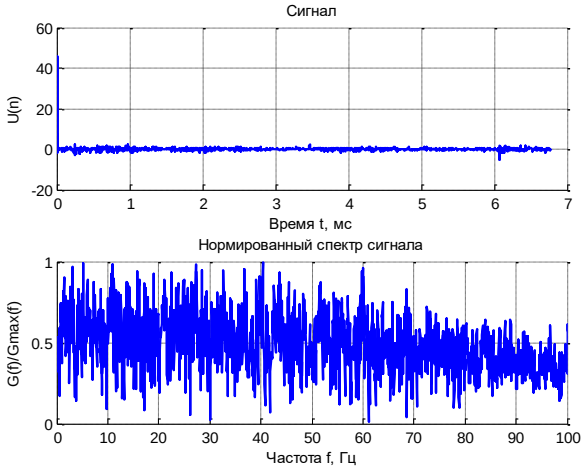



Figure 7 – Plot of a type 2 signal and its power spectral density

Table 2 – Results of training the FLS network and prediction for 2 samples

| Learning Outcomes | | | | |
|---|---|---|---|---|
| Training time (seconds) | Number of iterations | Stop reason | Gradient value | Minimize parameter value |
| 30,312 | 99 | Validation stop | 5,797341e–03 | 7,421479e–03 |
| Forecast result on the test set: Forecast errors | | | | |
| For the 1st neuron | | | | |
| SAO | | SKO | | SPO |
| 2,443811e–02 | | 1,208999e–03 | | –59,462451 % |

| For the 2nd neuron | | |
|---|---|---|
| SAO | SKO | SPO |
| 7,693391e–02 | 1,166122e–02 | 192,689217 % |

Figure 8 shows the learning window with the network structure and the network structure after delay removal. Figure 9 shows a graph of the RMS change, Figure 10 shows an approximation of the training signal, and Figure 11 shows the prediction of the training signal. Figures 12 and 13 show the signals from the outputs of the 1st and 2nd neurons, respectively, and the absolute prediction errors. As can be seen, the STRs of the prediction of output neurons differ greatly.

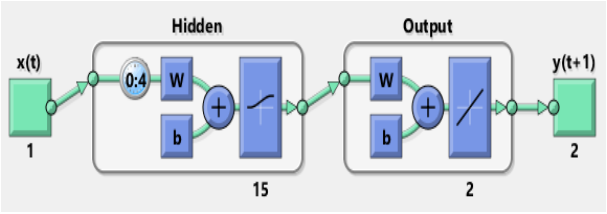



Figure 8 – Network structure after delay removal

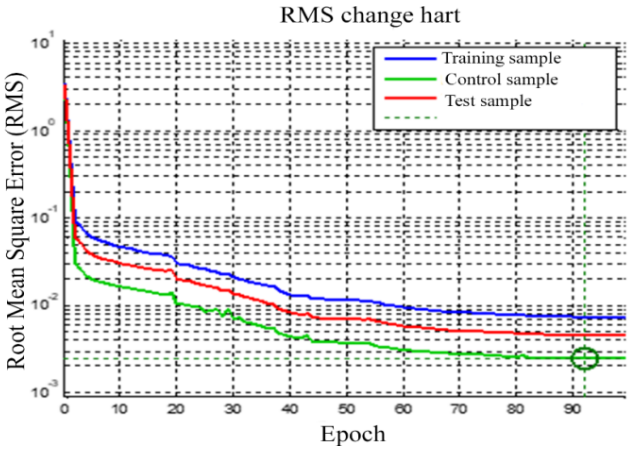



Figure 9 – Graph of change in RMS during training

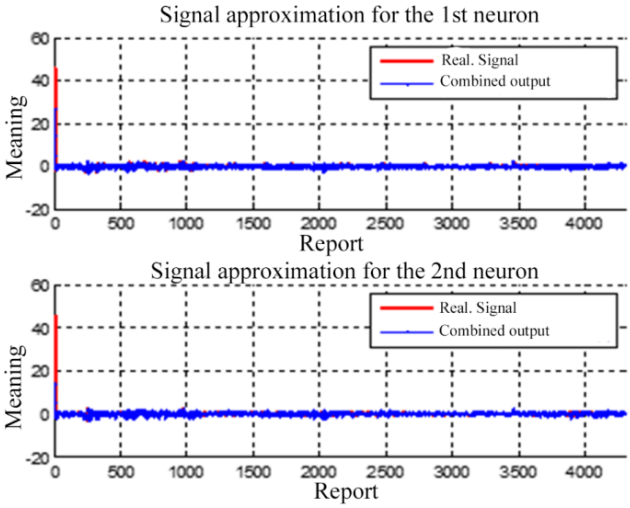



Figure 10 – Approximation of the training signal

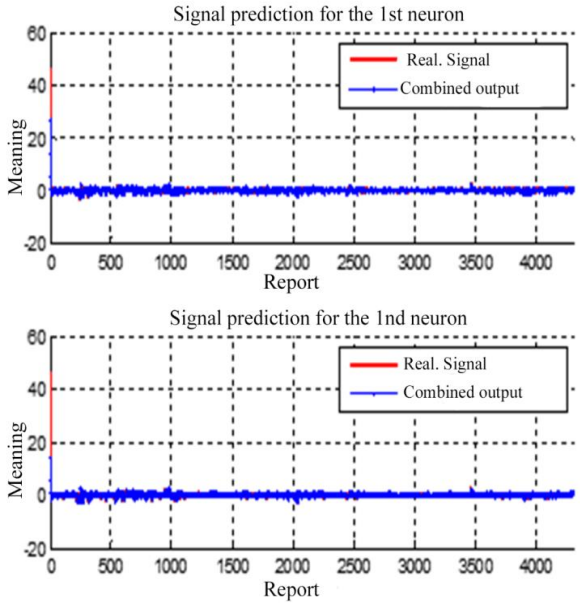



Figure 11 – Prediction of the training signal

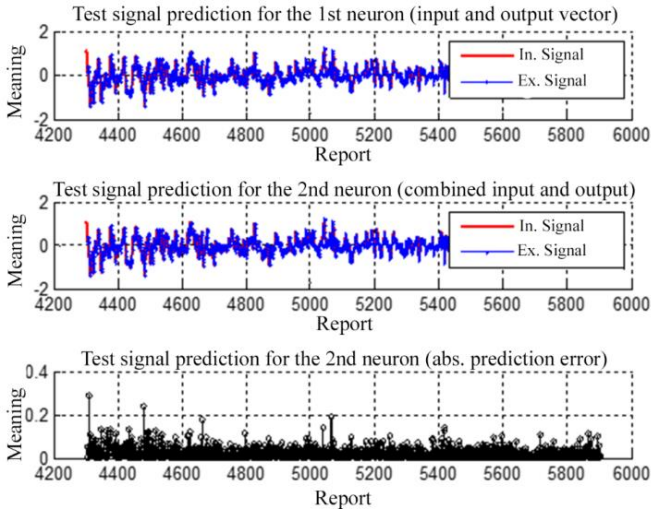



Figure 12 – Test signal prediction (output of the 1st neuron)

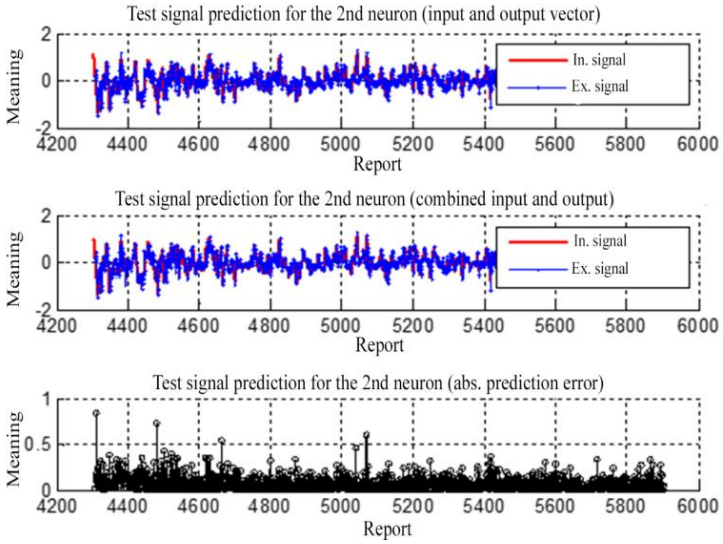



Figure 13 – Test signal prediction (output of the 2nd neuron)

## 4. Nonlinear autoregressive network model

Let's simulate the work of NARS, (algorithm parameters - by default): learning algorithm (BFGSh); one-dimensional search method (Charalambusa); learning rate (0,1); number of training samples (4300); number of test counts: (1600); distribution of samples (random); number of hidden neurons (9); number of output neurons (predicted readings) (4); number of delay elements (3).

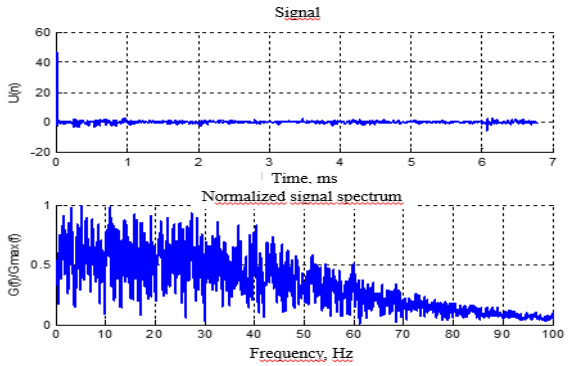



Figure 14 – Graph of a Type 3 signal and its power spectral density

Table 3 – Results of HARS network training and prediction for 4 samples

| Learning Outcomes | | | | |
|---|---|---|---|---|
| Training time (seconds) | Number of iterations | Stop reason | Gradient value | Minimize parameter value |
| 74,95 | 66 | Validation stop | 1,604297e–01 | 3,720646e–02 |
| Forecast result on the test set: Forecast errors | | | | |
| For the 1st neuron | | | | |
| SAO | | SKO | | SPO |
| 1,035035e–01 | | 2,657801e–02 | | 33,000326 % |
| For the 2st neuron | | | | |
| SAO | | SKO | | SPO |
| 1,154178e–01 | | 2,909257e–02 | | –1,197022 % |
| For the 3st neuron | | | | |
| SAO | | SKO | | SPO |
| 1,646659e–01 | | 5,293383e–02 | | –1,197022 % |
| For the 4st neuron | | | | |
| SAO | | SKO | | SPO |
| 2,348273e–01 | | 9,366414e–02 | | 157,485184 % |

The learning window with the network structure and the network structure after delay removal are shown in Figure 15. Figure 16 shows a plot of RMS change. Figures 17-20 show plots of the prediction and corresponding errors for the test set.

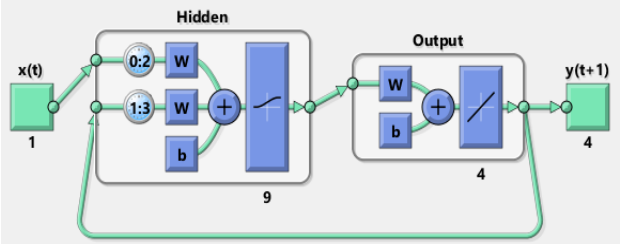



Figure 15 – Network structure after delay removal

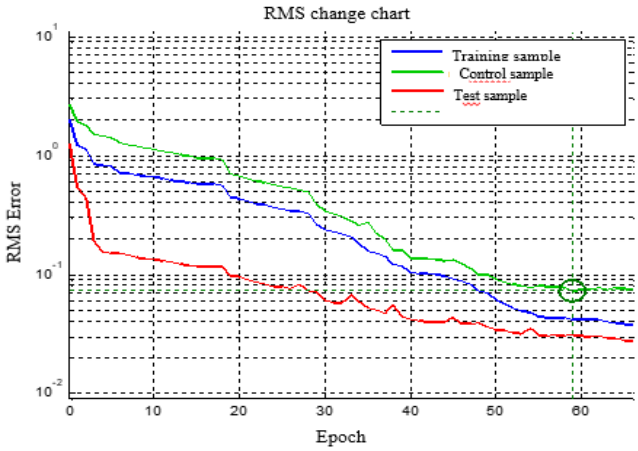



Figure 16 – Graph of change in RMS during training

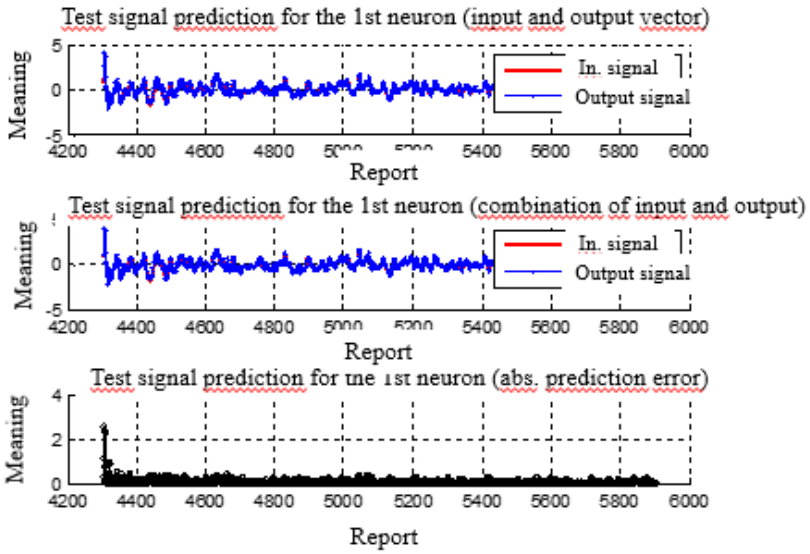



Figure 17 – Test signal prediction (output of the 1st neuron)

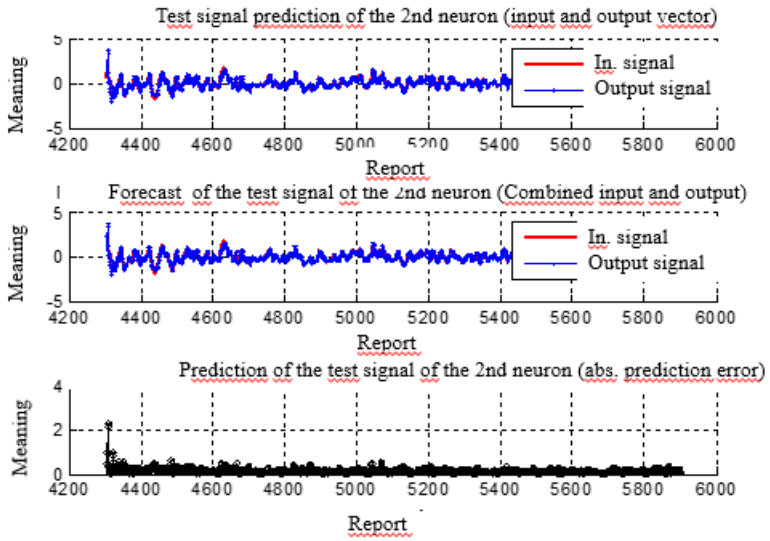



Figure 18 – Test signal prediction (output of the 2nd neuron)

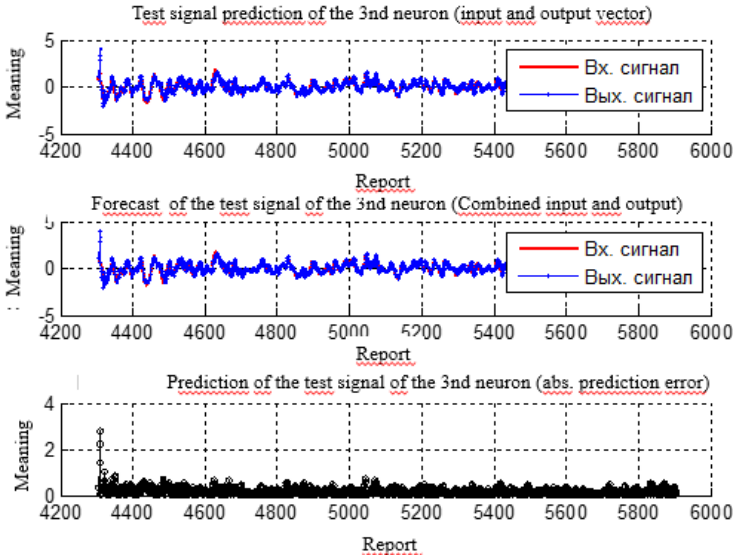



Figure 19 – Test signal prediction (output of the 3rd neuron)

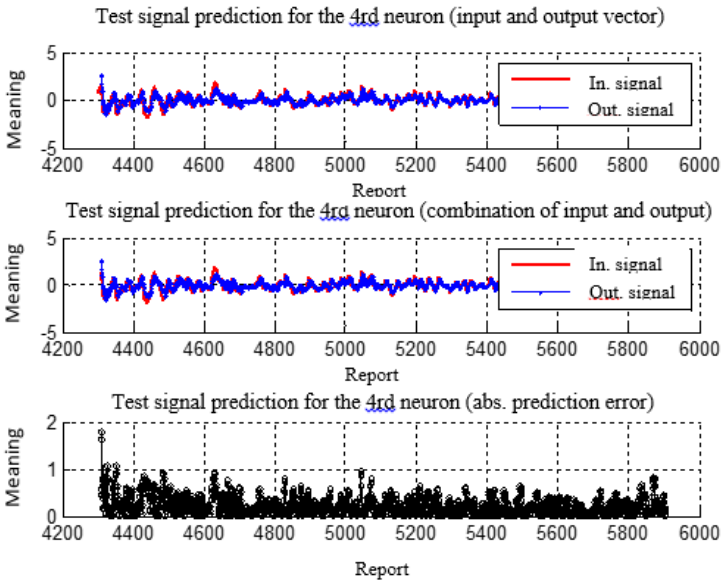



Figure 20 – Test signal prediction (output of the 4th neuron)

Comparative analysis of models. Finding the Best Model

We will consider the ANN model as the best one, in which the forecast errors and training time are minimal. The results of the comparative analysis are shown in Table 4, where the number indicates the order of quality of the model. As can be seen, the best ANN for single- and multi-step forecasting turned out to be a focused linear network with input delays with a random distribution of samples and the Levenberg-Marquardt learning algorithm. The nonlinear autoregressive network proved to be satisfactory only for multi-step forecasting and is generally unstable. The BFGN learning algorithm is ineffective with the default parameters.

Table 4 – Results of comparative analysis of ANN

| № | INS type | Learning algorithm | Sample distribution |
|---|---|---|---|
| 1 | FLS | LM | Random |
| 2 | FLS | LM | Sequential |
| 3 | FLS | BFGSh-PSV | Sequential |
| 4 | NARS | LM | Random |
| 5 | NARS | LM | Sequential |

| | | | |
|---|---|---|---|
| 6 | ADALIN | DP | Sequential |
| 7 | FLS | BFGSh-PSV | Random |
| 8 | NARS | BFGSh-PSV | Random |
| 9 | NARS | BFGSh-PSV | Sequential |

Study of the forecast quality of the best model

On the example of the most narrow-band signal of the 4th type (see Fig. 21), we study the quality of the forecast of the best model with a cumulative one-step forecast for a larger number of samples, in particular, for 20 samples simultaneously. The ANN parameters are as follows: the number of hidden neurons (15); learning rate (0,0005); number of delay elements (5).

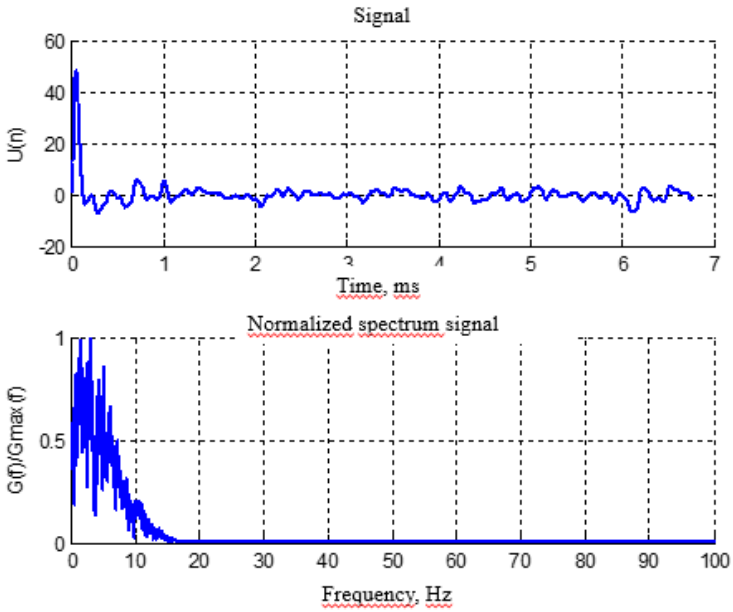



Figure 21 – Graph of Type 4 signal and its power spectral density

Table 5 – Results of training and one-step prediction with the number of output neurons equal to 20

| Learning Outcomes | | | | |
|---|---|---|---|---|
| Training time (seconds) | Number of iterations | Stop reason | Gradient value | Minimize parameter value |
| 3412,887 | 595 | Validation stop | 1,890482e–04 | 7,561870e–04 |
| Total Errors | | | | |
| SAO | | SKO | | SPO |
| 1,602018 | | 4,538997e–01 | | 43,513140 |

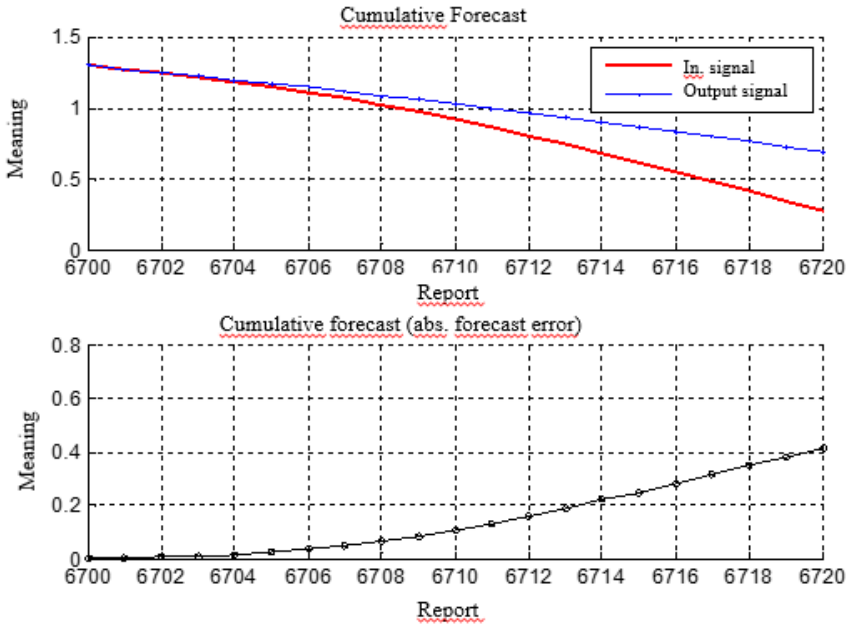



Figure 22 – Graph of the cumulative forecast for all samples with the number of output neurons equal to 20

**Conclusion**

At present, the theoretical information on the design of ANNs has been studied, software has been developed in MATLAB that allows one- and multi-step forecasting, signal predictions for all types of ANNs under study have been obtained, and a comparative analysis of networks has been carried out. With an increase in the number of harmonics in the spectrum, the optimal value of STR is not achieved for all types of networks. Also, an interesting feature of the convergence of all networks and algorithms is the achievement of a specific value of the minimum RMS for a type 4 signal. That is, we can say that the optimum has been reached and the accuracy for all structures can be improved by pre-processing the signal (for example, decimation) or taking a different number of samples.

An adaptive linear neuron with an algorithm for minimizing the RMS (delta rule) shows itself stably for any width of the signal spectrum. That is, it is capable of adapting to the forecast of any type of signal with sufficient accuracy over a finite time period, but the adaptation time increases greatly with the increase in the complexity of the task. For ADALIN, in the course of the work, it was not possible to achieve the optimal RMSD and STR for the prediction of a broadband signal of the 4th type in a rational time.

The linear network with delays turned out to be the most successful network model for both single-step and multi-step forecasts. Especially when using the high-speed Levenberg-Marquardt algorithm. The nonlinear autoregressive network can be unstable due to the presence of feedbacks and during the simulation gave relatively unsatisfactory forecast results.

The Levenberg-Marquardat algorithm, as recommended in the literature for use, is the best in terms of speed. Obviously, it is possible to increase the accuracy of the algorithm, but reduce the speed, by increasing the dimension of the hidden layer of the ANN.

The BFGS algorithm is the most time-consuming, because it is necessary to calculate the network response several times at each iteration. In [16], a comparative analysis of gradient methods is carried out and it is indicated that, for example, the conjugate gradient method is more efficient than quasi-Newtonian methods and is able to solve problems without additional calculations. The random distribution of samples during training allows you to quickly reach the minimum of the functional, but affects the stability of the convergence of algorithms.

It can be concluded that when modeling an ANN, there is uncertainty in choosing the dimension of the hidden layer, the length of the delay line. Moreover, with an increase in the dimension of the structure, the potential accuracy increases, but the learning rate decreases and vice versa.

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