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Original article

Intellectualization System for Information Resources Usability Testing

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Abstract
The article discusses the possibilities of predicting the state of the web resources usability. Next, modeling and predicting system the time series of the site page visitors number is proposed. The usability testing procedure is quite costly from both financial and time points of view. Thus, a system that reduces these costs is useful for modern organizations. Different approaches of forecasting the number of visitors: ARIMA model and Neural Networks are considered. An important time series property for ARIMA model being applicable is the stationarity of the series. It is shown that this model is not suitable enough for the investigated time series, some types of neural networks are also not suitable for various reasons. As a result, NARX networks are selected, which are successfully used for time series forecasting, providing an opportunity to use an exogenous variable. Proposed model using the NARX neural network. The developed application allows evaluating the usability of information resources according to the following parameters: page functionality, accessibility (convenience of location) of the main buttons on the page, colors, type and size of headings and body text. The application helps to predict the traffic of a web resource based on a time series of site visits without usability testing by experts, by comparing simulation results with the results of a full-fledged usability test.

Keywords: neural networks NARX, time series predicting, usability testing, intellectualization system for forecasting

Conflict of interests: The authors declare no conflict of interest.

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Оригинальная статья

Система интеллектуализации для тестирования юзабилити информационных ресурсов

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Аннотация
В статье рассматриваются возможности прогнозирования состояния юзабилити веб-ресурсов. Далее предлагается система моделирования и прогнозирования временного ряда количества посетителей страниц сайта. Процедура юзабилити-тестирования достаточно затратна как с финансовой, так и с временной точек зрения. Поэтому система, которая позволит сократить эти затраты, полезна для современных организаций. Рассмотрены различные варианты прогнозирования количества посетителей страниц сайта с помощью модели ARIMA и нейронный сетей. Важным свойством временного ряда для использования модели ARIMA является стационарность ряда. Выявлено, что для нашего временного ряда данная модель недостаточно подходит, некоторые виды нейронных сетей также не подходят по разным причинам. В итоге выбраны сети NARX, которые успешно применяется для прогнозирования временных рядов, предоставляют возможность использовать экзогенную переменную. Предложена модель с использованием нейронной сети NARX. Разработанное приложение позволяет оценивать удобство использования информационных ресурсов по следующим параметрам: функциональность страницы, доступность (удобство расположения) основных кнопок на странице, цветовая гамма, тип и размер заголовков и основного текста. Приложение помогает прогнозировать посещаемость веб-ресурса на основе временного ряда посещений сайта без юзабилити-тестирования экспертами, сравнивая результаты моделирования с результатами полноценного юзабилити-теста.

Ключевые слова: нейронные сети NARX, прогнозирование временных рядов, юзабилити-тестирование, интеллектуализация системы прогнозирования

Конфликт интересов: авторы заявляют об отсутствии конфликта интересов.

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Introduction

Internet marketing tools provide users with various applications that help to track the information resources usability [1-3]. We discussed this in more detail in [4]. Various methods are used to evaluate usability: heuristic evaluation methods, formal tests, think-aloud methods, cognitive walkthrough methods, informal testing, control experiments, sometimes surveys and other field studies[1] [5, 6]. But applications are required to simplify the usability testing procedure, by intellectualizing it. Such systems make it possible to automate the processes of assessing the company's resources, to understand how attractive the resource is for potential and real consumer goods and services. Before developing a usability testing system, it is necessary to propose criteria that must correspond to a web resource page. We have identified the main criteria: page functionality, availability of the main page buttons, especially the contacts, pages which reflect the basic assortment of goods, the pages describing the conditions of purchase behind, payment and delivery. The page headers size, the main text font size, the type of headers on the page, the type of main font, the page color scheme is also important [7]. The resulting indicator that characterizes the usability of a resource is page traffic. Website traffic depends on many external factors besides the usability of the resource: the time of the year, days of weeks and, holidays, etc. The most important external factor, which largely affects the number of visitors - it is the day of the week. Therefore, it was decided to develop a forecast of website traffic based on the previous period. It is desirable to take into account the exogenous variable – the days of the week in this forecast.

Intellectualization system for usability testing web resources allows to significantly simplify the testing procedure. With its help, the process of evaluating the company's information resources is automated. Accordingly, time and financial resources are saved in order to improve them and attract additional site visitors, some of whom become buyers.

In addition, a forecast for the next period was made, based on the data on the number of visitors to the company's website pages. The forecast is also used to evaluate the usability of an organization's web resource. The forecast is compared with the results of expert usability evaluations. If the site page receives positive ratings (we consider all ratings above 0 as positive), then the site's position in the search engine results is expected to improve, especially from organic traffic, which means there will be an increase in the number of site visitors and, as a result, an increase in sales. In turn, the developed application will allow predicting the number of site visitors based on the existing time series [8, 9]. If, according to the forecast, an increase in the number of visitors is expected, and this will coincide with the opinion of experts, then traditional usability testing can be omitted, and focus on the forecast data. Especially if later they were confirmed.

1. Methods of System Intellectualization

Different methods are used to intellectualize systems. These can be traditional methods: information retrieval, simulation modeling, situational analysis, regression methods. Some of these methods have been developed as part of artificial intelligence research.

The traditional forecasting methods are moving average, exponential smoothing, least square method and regression analysis [1, 2].

At present, the intellectualization of the system and forecasting can be carried out by rather new methods, in comparison with traditional methods: machine learning methods: ARIMA model, neural networks. We have considered various options for predicting the assessment of site usability.

The integrated model – Autoregressive Integrated Moving Average (ARIMA) - a model describing the time series and short-term forecasting. In general, ARIMA is described by the following equation (1), [10].

$$\phi_P(B)(1-B)^d z_t = \theta_q(B)a_t \,, \qquad (1)$$

Where ϕ_P and θ_q – are unknown parameters; z_t is a time series; B - is the backward shift operator, d - is the order of differentiation; and a_t – is a row that represents white noise [7].

The next common method is artificial neural networks. After the development of learning algorithms, the resulting models began to be used for practical purposes: in forecasting problems, for pattern recognition, in control problems. The network processes input information and forms a set of output signals in the process of changing its state in time. The work of the network consists in transforming input signals in time. Because of this, the internal state of the network changes and output effects are formed. Typically, the NN operates with digital, not symbolic values [5].

There are several types of neural networks that can be used in deep machine learning. Each type has its own advantages and disadvantages. The expediency of using one or the other type depends on the subject area and application tasks. The following main types of neural networks are distinguished, the main ones are systematized in the works [2], [11-14]. We discussed this in more detail in [7].

Consider the possibility of using the models to predict the number of site page visitors.

Usually consider two types of ARIMA model, stationary ARMA model and non-stationary ARIMA model [15, 16]. The stationarity of a time series is associated with the type of change in statistical temporal characteristics over time, so the probability distribution is constant over time. Stationarity or the so-called weak stationarity is defined as follows. The expected value of the time series is independent of time.

The autocovariance function is a function k, where for each k, $y_Z = Cov(z_t, z_{t+k})$.

Considering the equation (1), we can distinguish two components – autoregressive (AR) and moving average (MA). Thus, the ARIMA model can be the AR(p) model or the MA(q) model, or a combination of both, that is, ARMA(p,q), see (2).

We considered the autoregressive model and the moving average model more detail in [7].

The ARMA and ARIMA models have undoubted advantages. You can use several tools for their implementation: the Python, R- language, as well as the MATLAB computing environment [8].

[1] Hubbard E.A., Venkatramani K., Anderson D.P., Adiga A.K., Hewgill G.D., Lawson J.A. Dynamic coordination and control of network connected devices for large-scale network site testing and associated architectures. U.S. Patent Application No. 12/462,600. 2011.

The mathematical notation of the ARMA (p, q) model is reviewed by us in [7].

For time series that do not meet the requirements of criteria for stationary use differentiating. A series that can be modeled as a stationary ARMA(p, q) after differentiating in time D times is denoted ARIMA(p, D, q). Mathematically, the form ARIMA(p, D, q) is written in the following form (2) [7].

$$\Delta^D z_t = c + \phi_1 \Delta^D z_{t-1} + \ldots + \phi_p \Delta^D z_{t-p} + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \ldots + \theta_q a_{t-q}, \quad (2)$$

where denotes times the differentiated time series.

We have considered various types of neural networks [7]. The NARX network has been successfully used for time series forecasting. A conventional neural network consists of an input layer that receives external information, one or more hidden layers which provide nonlinearity of the model, and an output layer that provides the target value. Each layer consists of one or more nodes. All layers are connected through an acyclic arc [16]. Each input node in the input layer is associated with a corresponding weight. Activation function is applied to the weighted sum of the inputs to calculate the output. The activation function is either an identity function or a sigmoidal function [17-19]. In this type of neural networks, additional exogenous variables are used (in our case, it is a time factor). At the heart of NARX neural networks is the Levenberg-McGraft method, sometimes called the backpropagation algorithm, it was first used to minimize prediction errors. It is also currently used to determine the weight (synapse) of the NARX model. The algorithm combines the gradient descent method and Newton's method, and has fast convergence and stable performance [20, 21]. The main advantage of NARX in our case is the possibility of introducing an exogenous parameter. It make possible to predict website traffic not only taking into account its own changes, but also taking into account the time factor, which is especially important. Because page traffic often depends on the season, especially on the day of the week (off it or workday) NARX neural networks are suitable for the prediction of our time series.

The analysis result carried out, we choose the NARX model as a model for predicting traffic on the website pages.

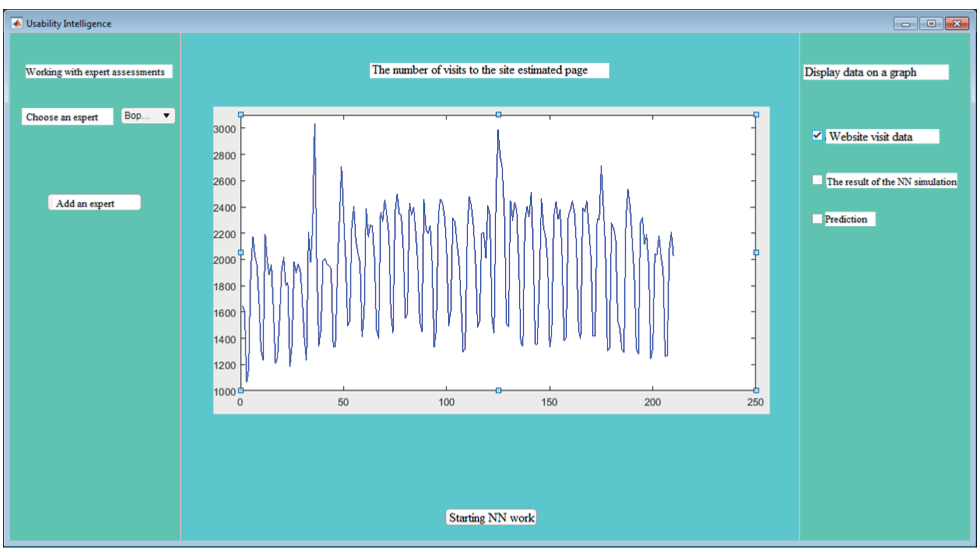
2. Interface of the Developed Application

The total number of site visitors is considered as a predicting parameter. Data on the number of page visitors is collected by Google Analytics. Feature Value - is the number of visitors of the main page, the time interval – daily, and sources data is the Google Analytics.

Data analysis in Google Analytics showed that the number of visitors varies significantly by day of the week, especially depending on whether it is a working day or a weekend. Accordingly, in the future, two options with indicators of time will be considered. This is the numbering of the days of the week - 1,2,3,4,5,6,7 and the numbering of workday and weekend days is 0 and 1. Next, we modeled the time series of site visitors in [4, 7] and determined, that the best method for modeling and predicting this time series is NARX neural networks [7].

The application allows you to conduct traditional usability testing, the results of which can be compared with the result obtained automatically using the NARX neural network. The respondent interacts with the developed application, who evaluates the usability site pages according to the parameters that are presented in the questionnaire in Figure 3. The administrator, who deals with the database, regulates the work of the expert. The first page of the application will be answers to questions directly about usability. Regular visitors can act as experts who evaluate the site's usability, it is especially easy to involve them in evaluating the b2b market.

First, the expert gets to the first page of the application, where he selects his last name in the drop-down list (Figure 1). If he participates in the survey for the first time, he selects the button to add an expert and gets to the page for filling in data about an expert (Figure 2).



F i g. 1. The application's first page – the entrance of an expert

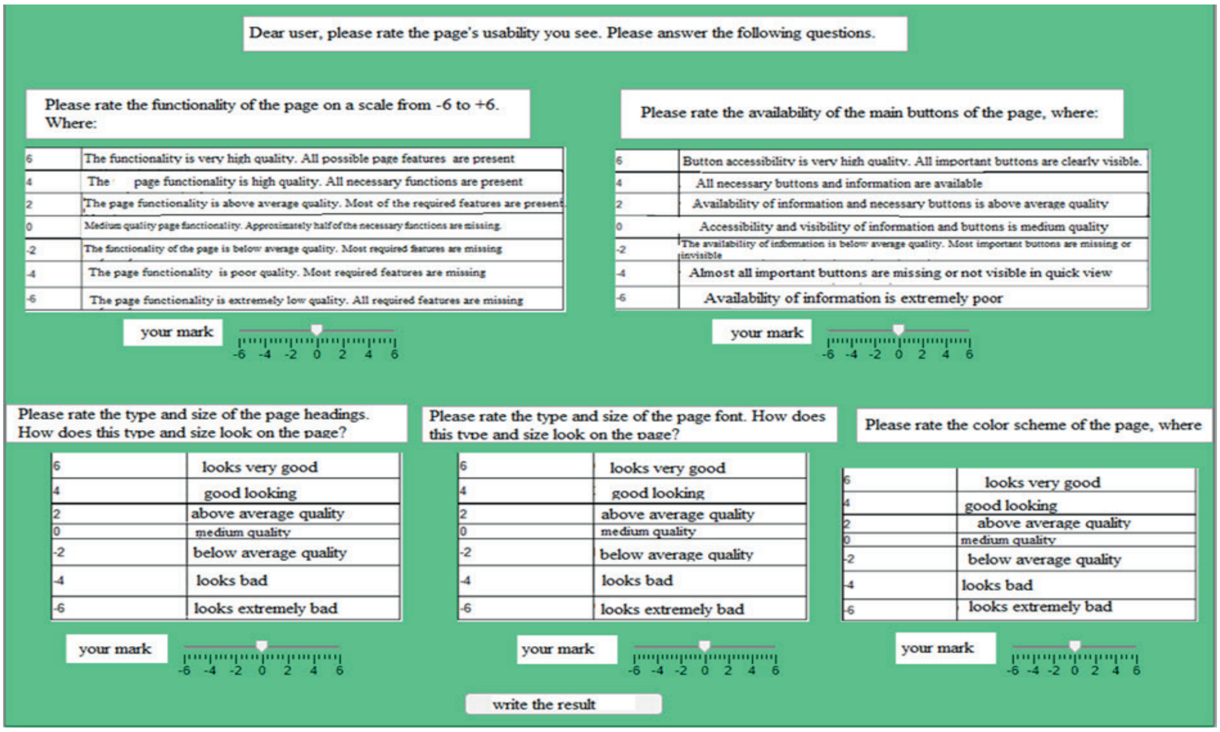
Source: Hereinafter in this article all figures were drawn up by the authors.

Источник: здесь и далее в статье все рисунки составлены авторами.

Here you need to enter the full name of the expert, his phone number, e-mail for possible further communication with him. Next, enter the name of the organization and the expert's position and other information about the organization that the expert represents for quick search at his customers. On the survey page for each question, the tables describe the answer options. Each question has its own answer options. At first, the answer options were the same for all questions, but testing the page usability testing system showed that experts don't always understand how one or another parameter can be assessed, for example, page functionality, or accessibility of basic elements.

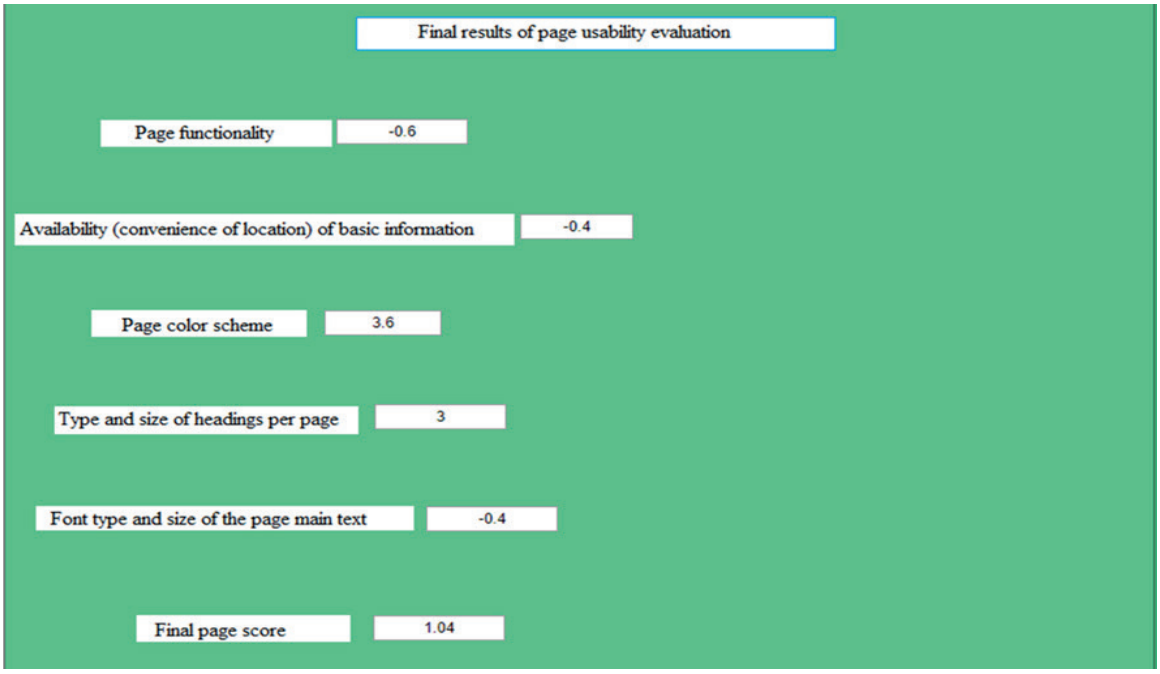
Each parameter is described in its own way, so it needs a separate detailed description.

F i g. 2. Application page where information about an expert is entered



F i g. 3. Questionnaire for evaluating the usability page of the site, which is filled out by experts – evaluators

The expert gives an assessment using the slider, which is located under each question (Figure 3). The slider allows you to reduce the average time to fill out the questionnaire. At the same time, it is convenient when choosing an assessment, the expert immediately sees all possible options in front of him.
Figure 4 shows the final result of evaluating the usability of the site page according to the considered parameters.



F i g. 4. The results of assessing the usability of the website page by all experts

The calculation was made based on the results of a survey of all experts (10 people). The final grades are calculated according to the geometric mean, as the *n*-th root of the product of n-numbers, that is, for a set of numbers $x_1, x_2, \ldots, x_n$ [20].

$$G(x_1, x_2, \ldots x_n) = \sqrt[n]{x_1 x_2 \ldots x_n} = (\prod_{i-1}^{n} x_i)1/2 \qquad (2)$$

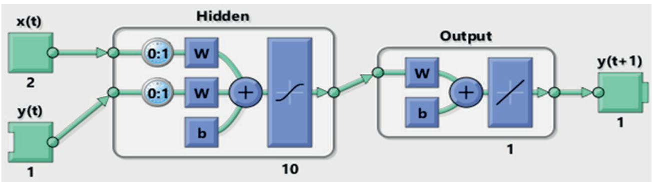
3. The Main Stages of Usability Testing System Intellectualization

The goal of intellectualization is to reduce the number of usability tests. To do this, we selected and refined the NARX neural network in the MATLAB environment. We have data on the number of visits to the site page, with their help we want to replace the usability testing of this page. The number of site's visits depends on many factors other than page usability.
In order to assess the impact of usability, it is necessary to highlight the rest of the factors influencing visits. In our case, the day of the week is selected as such: Monday, Tuesday Wednesday, Thursday, Friday, Saturday or Sunday. In addition, the second factor is highlighted - this is a day off or a workday. We will be able to determine with the help of such input data to the model, what will be the number of visits to the site in case of changes made to its page, depending on these two factors.
As a result of obtaining real data on the number of visitors after changing the page, it is possible to conclude how convenient the changes made to the site page are for users. It is necessary to compare the results of the forecast and the results of the actually collected information to do this.
Let's denote the input data to the neural network as x_1 – these are the days of the week, indicated by the numbers 1, 2. 3, 4, 5.6, 7, and also x_2 - a binary record of a day off or a working day - let's denote the day off as 1, let's de-note the day off as 0.
Then, we divided the data into 3 groups. The first group - 70% of the data is used to train the network
The second group - 15% is used to validate the model, that is, to check the correctness of its work. This group determines how correctly we have chosen a model for a given data series.
The third group of data - 15% - model testing, shows us how well the neural network is trained.
A usability testing system can be viewed as a dynamic system whose mathematical characteristics are unknown. We have at our disposal a set of data of input and output signals generated by the system in uniform discrete time intervals. We need to build an output signal model with multiple inputs and one output based on a single neuron. The neural model operates under the control of some algorithm that provides adjustment of the synaptic weights of the neuron. In this case, the following assumptions are made [10, 11].
The algorithm starts with arbitrary values of synaptic weights. Adjustment of synaptic weights in response to statistical variations in the system's behavior is performed continuously (time is built into the structure of the algorithm itself) [19, 20].
The calculation of the corrective values of the synaptic weights is performed at regular intervals. A neural network can be classified as an adaptive filter model.

The operation of the algorithm includes two sequential processes. A filtering process involving the calculation of two signals.
- An output signal, denoted as *Y(i)* and generated in response to an input vector *x(i)* with components $x_1, x_2, \ldots x_n$.
- The error signal, denoted as *e(i)* and calculated as the deviation of the output signal *y(i)* from the output signal of the real system *y(i)*, which is also called the target data (target) or the expected response.

Stage - The process of adaptation (validation), which includes automatic adjustment of the neuron synaptic weights based on the error signal *e(i)*, in our case, the error is denoted by - *b*. The combination of these two processes is called the feedback loop (Feed back loop) of the neuron [16].

Figure 5 uses the correction of neuron synaptic weights using the error signal application algorithm.



F i g. 5. The process of time series modeling, including the correction of neuron synaptic weights using the error signal application algorithm

4. Usability Testing System Prediction

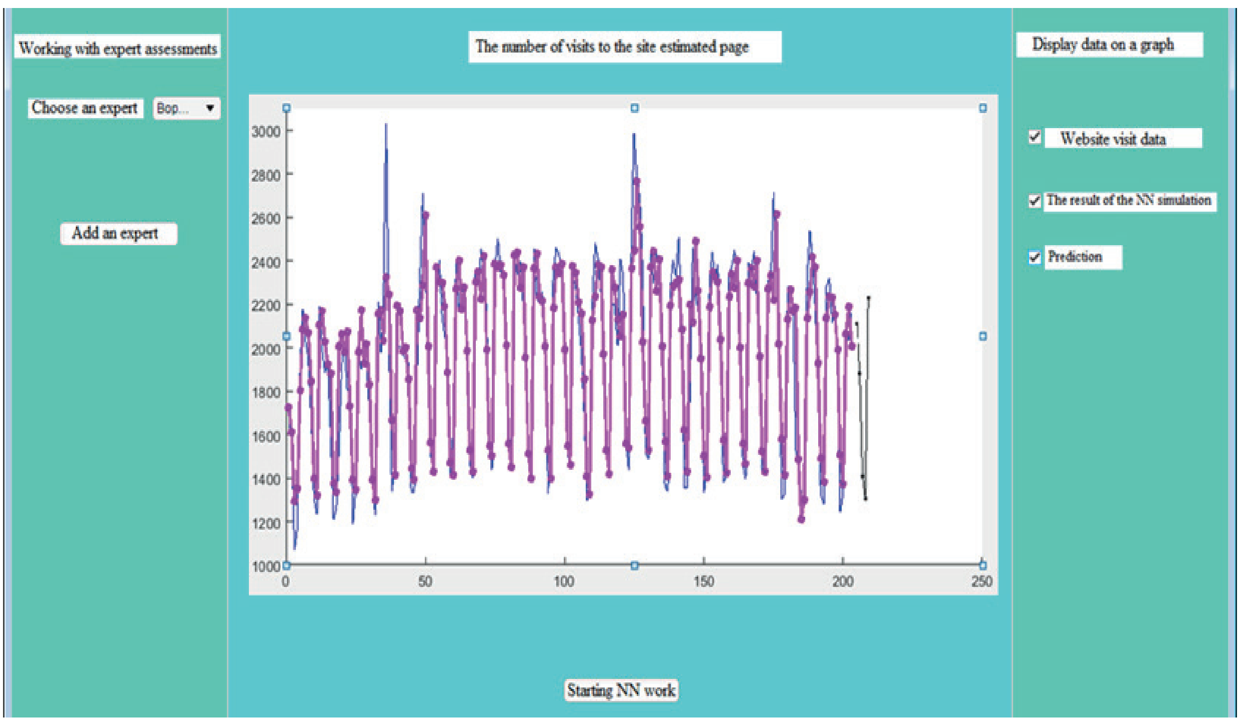
Thanks to the neural network, a forecast was made for 7 time periods. This will allow, in case of high accuracy of the forecast, not to conduct usability testing too often. The predict is shown in Figure 6.

The resulting forecast is marked in yellow on the graph. An analysis of the forecast for accuracy is required. The validation vectors are used to stop learning early, but if the network performance on the validation vectors fails to improve or stays the same for consecutive max_fail epochs. Test vectors are used as further validation which the network generalizes well but has no effect on training.

The NARX neural network uses the Levenberg-McGraft algorithm based on the gradient descent method. Gradient descent is a method of finding function local extremum (minimum or maximum) by moving along a gradient. To minimize the function in the direction of the gradient, one-dimensional optimization methods are used, for example, the golden section method. It is also possible to search not for the best point in the direction of the gradient, but for some better than the current one [8], [22-25].

After completing the network training, we can analyze the results of our model. We observe the best residuals at the third iteration, they are almost zero, which shows the iteration at which the check performance has reached a minimum. Training continued for 6 more iterations before it stopped. This figure doesn't indicate any major learning problems. The validation and testing curves are very similar. If the test curve increased significantly before the validation curve increased, then it is possible that some overfitting has occurred.

You can create a standard network that uses trainlm with feedforwardnet or cascadefor-wardnet. This function uses the jacobian for calculations, which assumes that the performance is the mean or the sum of the squared residuals. Therefore, networks trained with this feature must use either the MSE or the SSE performance feature.



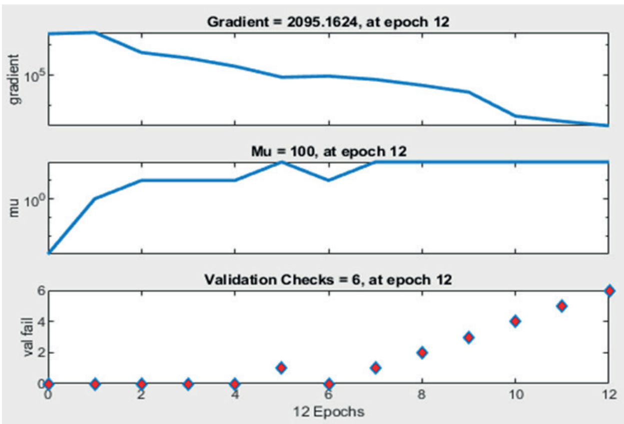
F i g. 6. Forecasting the site visitors number using the NARX neural network

Conclusion

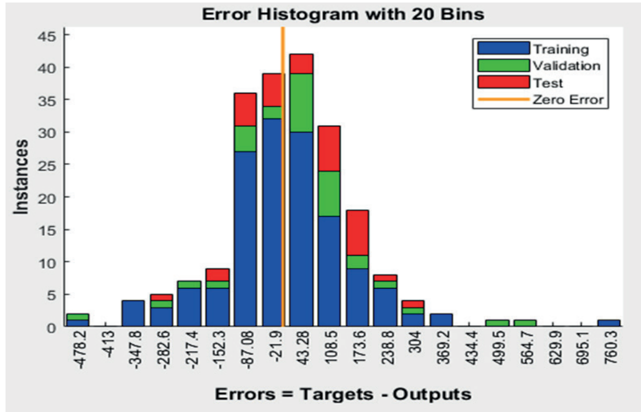
The performance of the resulting neural network is quite large - 31069,51. To find the gradient, you need to take the derivative of the graph at a given point. Moving in the direction of this gradient, we will smoothly move towards minimizing the error. The error tends to go down as quickly as possible and reduce its value. In the final case, we get the minimum error, as shown in Figure 7.

Mu - is the learning factor, it should be between 0.8-1. There is a slight discrepancy be-tween the data and the predict. So this model can be used. The forecast we received will allow us to adjust the organization's pricing policy in advance, depending on the growth or fall in the number of site visits.

Figure 8 shows the residuals when forecasting data for 20 periods.



F i g. 7. Model validation

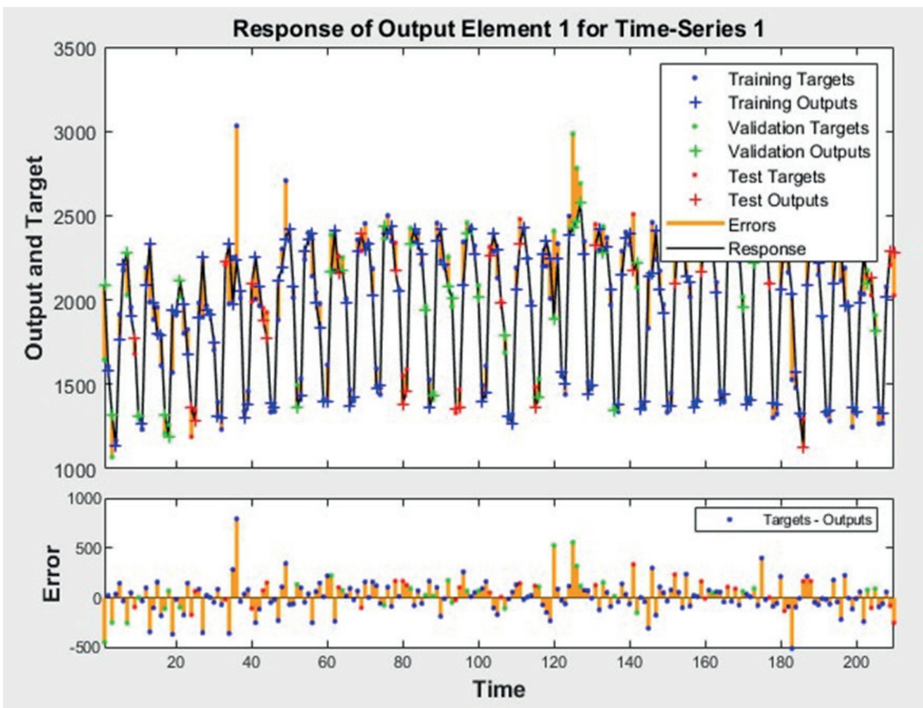


F i g. 8. Residuals when forecasting data over 20 time periods

Figure 9 shows the ratio of the time series and residuals in the case of a predict for 1 point. The figure shows that there is a slight discrepancy between the data and the predict, which confirms the possibility of using this model.

With the help of the model, it is possible to adjust the promotion policy certain products. For instance, on more visited pages of the site, links are placed to those pages that contain products that need to be sold as soon as possible.

The most important advantage of the developed system is the ability to refuse from periodic usability testing the site page. Usability - testing will need to be carried out only with significant page changes. Using this system, you can evaluate sites with a different number of pages, since a separate traffic forecast is compiled for each page.



F i g. 9. Relationship between time series and residuals

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