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## FORECASTING OF ELECTRICITY CONSUMPTION USING NEURAL NETWORK TECHNOLOGIES

## ПРОГНОЗУВАННЯ ОБСЯГІВ ЕЛЕКТРОСПОЖИВАННЯ З ВИКОРИСТАННЯМ НЕЙРОМЕРЕЖЕВИХ ТЕХНОЛОГІЙ

*At work, the issue of hourly forecasting of electricity consumption has been examined. Based on the input data in the form of a time series of electricity consumption over a specific period, short-term forecasting has been performed using a recurrent neural network (RNN). The choice of RNN architecture, the number of layers, as well as the choice of activation functions and optimization algorithms are considered in detail. The selection of hyperparameters, such as learning rate, is also discussed. The training and validation process is described, including the division of data into training, validation, and testing sets. It discusses the use of relevant metrics to evaluate the accuracy of forecasting using RNN.*

***Keywords****: recurrent neural network, multilayer perceptron, artificial neural network, Elman network, error backpropagation algorithm.*

*Враховуючи зростання навантаження на енергетичні системи та зношеність інфраструктури самих мереж, перед сучасними дослідниками постало завдання навчитися ефективно управляти та розподіляти навантаження між споживачами у просторовому та тимчасовому контексті у новому енергетичному просторі. Потрібно створити нові системи управління, які в реальному часі будуть не тільки налаштовувати параметри окремих вузлів енергомережі, а й реорганізовувати її структуру на всіх рівнях, майже до зміни обсягів для самих споживачів. Для таких систем управління необхідний точний прогноз споживання енергії, щоб заздалегідь створити план перерозподілу навантаження. Найбільшу точність прогнозу дають системи, побудовані на основі штучного інтелекту. Точність прогнозу, заснованого на використанні нейронних мереж, залежить від наявних вихідних даних, що визначають архітектуру мережі, ступеня достовірності даних та необхідного періоду прогнозування.*

*В даній роботі розглянуто проблему погодинного прогнозування споживання електроенергії. На основі вхідних даних у вигляді часового ряду споживання електроенергії за певний період, здійснено короткострокове прогнозування за допомогою нейронної рекурентної мережі*

*(RNN). Детально розглядається вибір архітектури RNN, кількості шарів, а також вибір функцій активації та алгоритмів оптимізації. Також обговорюється вибір гіперпараметрів, як-от швидкість навчання. Описується процес навчання та перевірки, включаючи поділ даних на навчальні, перевірочні та тестові набори. У ньому обговорюється використання відповідних показників для оцінки точності прогнозування за допомогою RNN.*

*Побудовано мережу і підібрано оптимальні параметри для її роботи. А також спроектовано UML діаграми, в яких чітко відображено, як саме повинна працювати система і яким вимогам повинна відповідати, розроблені сценарії роботи системи та виконано їх програмну реалізацію.*

*Представлені результати та оцінка ефективності моделі прогнозування споживання електроенергії на основі RNN. Це забезпечує аналіз точності та ефективності моделі при прогнозуванні споживання електроенергії для різних часових горизонтів. В рамках дослідження розглянуто проблему погодинного прогнозування споживання електроенергії. Представлено емпіричні результати дослідження, які демонструють ефективність рекурентних нейронних мереж в порівнянні із традиційними методами, такими як ARIMA та SV у прогнозуванні споживання електроенергії.*

***Ключові слова**: рекурентна нейронна мережа, багатошаровий персептрон, штучна нейронна мережа, мережа Елмана, алгоритм зворотного поширення похибки.*

## Problem's Formulation

In the conditions of the formation of market relations in electricity, the task of improving the methods of short-term forecasting of electricity consumption and creating appropriate software to increase the accuracy of planning optimal modes of electricity systems is important and relevant. Increasing the accuracy of planning involves ensuring the most economical operation of electric power systems with rational consumption of energy resources and meeting the requirements of reliability of energy supply and quality of electricity. Load forecasts play a crucial role in electricity pricing in the wholesale electricity market and capacity planning, becoming increasingly important for both electricity producers and consumers.

Considering the increasing load on power systems and the aging infrastructure of the networks themselves, modern researchers face the task of efficiently managing [1] and distributing [2] the load among consumers in a spatial and temporal context in the new energy landscape. The issue of overall energy system stability in Ukraine has become particularly acute following the onset of a large-scale invasion. To address these challenges, management based on load forecasting in different parts and at different times of system operation, as well as flexible resource reallocation, is necessary. For the new energy grid, new management systems need to be developed that will not only adjust the parameters of individual nodes in the energy grid in real-time but also restructure it at all levels, even to the extent of altering the volumes for consumers themselves. Accurate energy consumption forecasting is essential for such management systems to proactively create load redistribution plans.

## Analysis of recent research and publications

The accuracy of forecasting depends on the calculation methods. There is a wide range of models and methods for short-term load forecasting. At the current stage of development of short-term load forecasting, a large number of methods and models are proposed. The main ones include methods of mathematical statistics, data processing, regression analysis, neural networks, fuzzy logic, hybrid systems, database theory, and relational database construction technology [3].

The highest forecast accuracy is provided by systems built with artificial intelligence in mind. The accuracy of the forecast based on the application of artificial intelligence methods depends on the available initial data that determine the network architecture, the degree of reliability of the data and the required forecasting period. The application of hybrid networks shows promise [2].

For example, works [4,5] investigate the problem of improving the hybrid approach to the development of informal mathematical models for forecasting electricity consumption of a large regional supplier based on the combined application of modern information technologies using the apparatus of artificial neural networks and Kalman filters.

Articles [6, 7] are dedicated to the use of neural networks for energy consumption forecasting. In the study [6], the author employed deep learning neural networks and used an error function that is a combination of mean squared error and quantile regression error for their training. The results of the studies confirm that using neural networks for energy consumption forecasting is an effective method due to the time-dependent and random nature of electrical load variations, which are influenced by various internal and external factors.

In the work [8], the application of artificial neural networks for forecasting energy consumption in production systems, considering archival data for a set of energy efficiency indicators, is discussed. The use of neural networks allows for the prediction of energy consumption in complex production systems by considering an input vector of parameters without explicitly investigating their relationships with the consumed energy. This is achieved through the formation of the network architecture and its training based on historical data.

In many practical forecasting tasks, time series are commonly used, which are characterized by high levels of nonlinearity, nonstationarity, irregular trends, abrupt changes, and anomalous outliers. In such conditions, rigid statistical assumptions about the properties of time series often limit the capabilities of classical forecasting methods. In the study [9], a neural network training method is proposed to address the task of time series forecasting. The results of the simulation modeling confirmed that the proposed neural network training method significantly improves the accuracy of time series forecasting.

A new hybrid approach based on machine learning, combining multilayer perceptron (MLP), support vector regression (SVR), and CatBoost, is proposed in the study [10] for power forecasting. The authors analyzed the trends in electricity consumption from renewable and non-renewable energy sources and combined them.

In the article [11], neural networks are used by the authors for forecasting and detecting anomalies in energy consumption indicators. For this purpose, adaptive and continuous training of the neural network is proposed. The authors have demonstrated that the performance of neural networks exceeds clustering algorithms.

The success of artificial neural networks in the discussed problem can be attributed to the nonlinear nature of the forecasted processes and the neural network's ability for self-learning and generalization. It handles high levels of uncertainty, stochasticity, and chaos. Currently, there are numerous successful examples of using neural networks in electricity consumption forecasting, both domestically and internationally. In the majority of cases, the forecasting system is based on a multilayer perceptron with all its variations, unified by a common architecture with feedforward information transmission.

An alternative to neural networks with direct information transfer in forecasting tasks can be recurrent neural networks that include both global and local (at the level of layers) feedback in their architecture and are trained using specialized procedures [12]. Thanks, first of all, to its universal approximating and extrapolating capabilities and the ability to learn in conditions of significant structural and parametric uncertainty of the characteristics of the forecasted processes. In most cases, recurrent neural networks from a computational point of view are much more efficient than networks with direct information transfer [13]. To date, three types of recurrent neural networks have been most widely used in the tasks of processing nonlinear time series: Williams-Zipser [14], Ellman [15], and Jordan networks. To solve the problems of analyzing and predicting time series and detecting changes in their properties, these networks require significant modification, which concerns, first of all, the learning algorithms, since all the specified neural networks are trained in batch mode and do not foresee the situation when the data of time series observations are received on processing sequentially one after the other.

In general, electrical load is a stochastic process, with dominant causal factors being time of day and weather conditions. The ongoing development of computer technologies enables the implementation of complex and branching neural networks that provide high forecasting accuracy for stochastic processes. An analysis of numerous studies leads to the conclusion that there is no universal method capable of solving the problem of forecasting characteristics of random processes of various natures. However, established approaches, when applied to specific practical tasks, allow for the construction of models that provide acceptable reliability and accuracy.

## Formulation of the study purpose

The purpose of this study is to enhance the operational efficiency of power supply companies through the development of algorithmic and software solutions for short-term electricity consumption forecasting based on recurrent neural networks. To achieve this, the article investigates multilayer neural networks that can provide forecasts with minimal deviation from actual electricity consumption values.

## Presenting main material

Within this research, it is necessary to construct a recurrent neural network. Based on this mechanism, it is possible to predict the values of variables that are important in the decision-making process. The use of a neural network for time series forecasting involves forming a neural network with a specific structure, adjusting its parameters based on the behavior of the studied system at known time points, and predicting the future behavior of the system based on previous observations. The choice of the neural network structure is determined by the specificity and complexity of the problem being addressed. To construct a neural network model capable of adequately and accurately solving the given task, it is necessary to describe the object that serves as the input signal to the neural network. This can be the output values of variables or initial values of defined quantities. In our case, the input signal will consist of data on electricity consumption from a previous analogous period.

Let the sequence of time series observations be given $y_0, y_1, ..., y_t$ for forecasting the next values of this series $y_{t+1}, y_{t+2}, ..., y_{t+K}$ with an absolute error smaller than a certain value $\varepsilon$ :

$$\left|\tilde{y}_{t+i} - y_{t+i}\right| < \varepsilon, \quad i = \overline{1, K}. \tag{1}$$

The time series of electricity consumption is characterized by chaotic dynamics. We assume that all transient processes in the system have settled, and the time series reflects the trajectories in the vicinity of a strange attractor. In multi-step forecasting, it should be taken into account that for a chaotic time series, the forecast can be performed properly up to a certain limit (forecast horizon). The existence of the horizon is explained by the fact that for chaotic series, the data error, which was small at the initial time point, grows in a geometric progression due to the divergence of trajectories that were initially close. If the system's trajectory moves within the same region of the attractor associated with that section, the series is considered to be normalized.

Recurrent Neural Networks (RNNs) are a class of artificial neural networks in which connections between nodes form a directed cycle. This creates an internal state within the network, allowing it to exhibit dynamic behavior over time. Unlike feedforward neural networks, RNNs can utilize their internal memory to process arbitrary input sequences.

As a test model, we choose the Elman network because it has the ability to learn and solve numerous practical problems. The Elman network can also maintain a form of state, enabling it to perform tasks such as sequence prediction that are beyond the capabilities of a standard feedforward perceptron. The dynamics of the model can be formally described as follows:

$$p(t) = f(w_1 x(t) + w_2 p(t-1)), \tag{2}$$

$$y(t) = f(w_3 p(t)), \tag{3}$$

where $x(t)$ — the input signal vector with a dimension of *m*, $p(t)$ — the output signal vector of the hidden layer with a dimension of *q*, $f(\bullet)$ — the non-linear function that characterizes the hidden layer., $w_1$ — Matrix of synaptic weights connecting the hidden layer and the input. $w_2$ — Matrix of synaptic weights connecting the hidden layer and the context, $w_3$ — matrix of synaptic weights connecting the output layer and the hidden layer, $y(t)$ — output signal of the network.

The network has recurrent connections between hidden neurons and a context layer. These context elements store the outputs of the hidden neurons at the previous time step, and then pass them to the output layer. This allows the neurons to remember their previous actions. The hidden neurons also transmit information to the output neurons, which shape the network's response to external stimuli. Since the nature of the feedback is solely associated with the hidden neurons, they can propagate repeated cycles of information throughout the network over a large number of time steps, thus accessing an abstract representation of time. At time step t, the input neurons receive the first input of the sequence sequentially. Each input can be scalar or vector, depending on the nature of the task. The context elements are initially set to 0.5. The input neurons and context activate the hidden neurons, which in turn activate the output layer. The hidden neurons also send signals to the context. During the next time step t + 1, the sequence is repeated. This time, the context contains the values of the hidden layer at time t. These context blocks can provide memory to the network.

To train the network, we use the backpropagation algorithm. First of all, the recurrent connections are fixed at 1.0 and are not subject to adjustment.

Training with the backpropagation method involves two passes through all the layers of the network: forward and backward. During the forward pass, the input vector (image) is presented to the sensory nodes of the network, and it propagates through the network layer by layer. As a result, a set of output signals is generated, which represents the network's actual response to the given input image. During the forward pass, all synaptic weights of the network remain fixed.

During the backward pass, all synaptic weights are adjusted according to the error correction rule. Specifically, the actual network output is subtracted from the desired response, resulting in an error signal. This error signal is then propagated through the network in the opposite direction of the synaptic connections. Hence the name "backpropagation" algorithm. The synaptic weights are adjusted to maximize the approximation of the network's output signal to the desired output. The learning process implemented by this algorithm is known as backpropagation learning.

Let the training sample be represented as: $(u(k), d(k)),\quad k=\overline{1,K}$, де $d(k)$ — the expected result of the network. After a direct move, we calculate the network error for the current vector:

$$E=\frac{1}{2}\sum_{j=1}^{N_L}\left(y_j^{(L)}-d_j\right)^2, \tag{4}$$

where $y_j^{(L)}$ — network output, $d_j$ — expected result.

The task boils down to minimizing the error function. To achieve this, we use the gradient descent method:

$$w_{ij}^{(l)}(t+1)=w_{ij}^{(l)}(t)-\gamma\Delta w_{ij}^{(l)}; \tag{5}$$

$$\Delta w_{ij}^{(l)}=\delta_i^{(l)}\,y_j^{(l-1)},\qquad \left(l=\overline{0,L},\quad i=\overline{0,N},\quad j=\overline{0,M}\right), \tag{6}$$

where $\gamma$ — learning rate $\delta_i^{(l)}$ — the error of the $i$-th neuron in the $l$ -th layer. For the last layer $\delta_i^{(l)}$ it will take the form:

$$\delta_i^{(l)}=f'\left(s_i^{(L)}\right)\cdot\left(y_j^{(L)}-d_j\right), \tag{7}$$

where $f'\left(s_i^{(L)}\right)$ — the derivative of the activation function.

The neuron activation function is selected as: $f(s)=\tanh(s)=\dfrac{1-e^{-s}}{1+e^{-s}}$. For all other layers, the neuron's error function will look like this:

$$\delta_i^{(l)}=f'\left(s_i^{(l)}\right)\cdot\sum_{j=1}^{N_{l+1}}\delta_j^{(l+1)}\,w_{ij}^{(l+1)}. \tag{8}$$

The training procedure needs to be repeated multiple times. Sometimes even going through all the vectors in the training set may not have sufficient effect on weight changes. Going through all the vectors in the training set with weight updates is called an epoch of training. The number of epochs can reach hundreds of thousands. The operation of the network is divided into two stages:

1) the training stage;

2) the functioning stage in real situations.

The ability of the network to function based on data it hasn't been trained on is called generalization ability. The method of testing the generalization ability is referred to as a learning strategy.

For the Elman network, we will use the following strategy. The entire dataset is divided into subsets:

1) a training set (70 %);

2) a testing set (30 %).

The distribution of vectors across the datasets is random. After each epoch, we record the weights and pass through the entire training set first and then the testing set. For each dataset, we calculate the average error across all vectors (training error and generalization error, respectively). As the number of epochs increases, the errors should converge. The network is considered trained if the errors remain close in value for an extended period. This provides a criterion for stopping the training. The value to which the errors converge is referred to as the capacity of the network. It characterizes the network's ability to work with the given dataset. However, if the errors reach asymptotic curves and hardly change over a large number of epochs, it indicates that the network's capacity is insufficient for working with the data.

Let's construct an algorithm for solving the prediction problem using the Elman network. We will choose the network architecture as follows: the number of neurons in the output layer will be one, and for the input and hidden layers, we will experimentally select the number of neurons, evaluating the prediction error for each variant using the formula:

$$MSE = \sum_{i=1}^{n_l} \left( \frac{y_i - d_i}{y_i} \right)^2 , \tag{9}$$

where MSE — the value of the relative root mean square error, $y_i$ — the output of the network at the $i$-th step, $d_i$ — preferred network feedback.

Then the algorithm can be represented in the following steps:

1. Preparing the data for feeding into the neural network. Since the dataset needs to be normalized, we can do it using the following formula:

$$\tilde{x}_i = \frac{2 \cdot \left( x_i - \frac{1}{2} \left( \min_{x \in X} x - \max_{x \in X} x \right) \right)}{\left( \min_{x \in X} x - \max_{x \in X} x \right)} , \tag{10}$$

where $\tilde{x}_i$ — normalized value of the input signal $x_i$.

2. Specify the number of neurons in the input and hidden layers and create the network.

3. Train the network using the following steps.

3.1 Prepare the training dataset. In our case, it consists of 20,000 values. Randomly divide them into vectors for training and testing.

3.2 Feed the training dataset vector into the network input.

3.3 Perform a forward pass using the backpropagation algorithm.

3.4 Evaluate the error of the obtained results using formula (4).

3.5 Perform a backward pass using the backpropagation algorithm.

3.6 Fix the network weights.

3.7 Pass the entire training dataset through the network and calculate the training error.

3.8 Pass the entire testing dataset through the network and calculate the generalization error.

3.9 Repeat steps 3.1—3.8 for a sufficient number of epochs until the training and generalization errors converge with the desired accuracy.

4. After completing the training phase, we can test the network for prediction. We choose the number of steps ahead we want to forecast: one, five, or ten. We input the dataset for processing into the network. Then, using a forward pass of the network, we obtain the forecasted values.

5. We evaluate the error of the obtained result using formula (9).

Based on the constructed algorithm, the design of a software system for electricity consumption forecasting will be conducted. During the system design, it is necessary to clearly define all usage scenarios, all possible use cases, and develop the system architecture, among other things. Therefore, a use case diagram was created, which is a graphical representation of various application scenarios of the system by the user (Fig. 1).

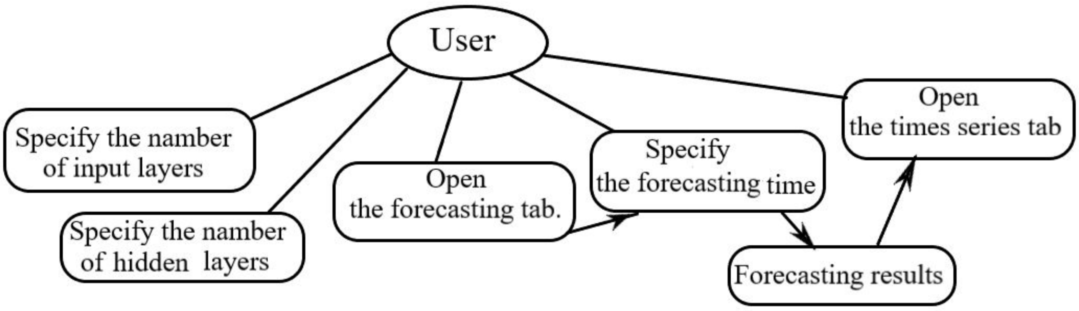


*Fig. 1.* Chart Use Case of forecasting electricity use

The developed program consists of three main parts: "Interface," "Calculation Block," and "Information Block." They are further divided into modules.

The "Interface" block is divided into 6 modules, each performing its specific function. The "Calculation Block" consists of 5 modules, including "Elman Network Training," where the training of the neural network takes place, and "Error Calculation," where the relative error is computed. The next module is "Forecasting for 1, 5, and 10 hours," which performs forecasting using the trained neural network. The final module is "Graph Plotting," where graphs are constructed based on the forecasting results.

The program was tested on real data of hourly electricity consumption in Ukraine. Since the data used corresponds to a specific time of observation, it can be considered to reflect the temperature regime characteristic of a particular forecasting moment (excluding anomalous phenomena). The training dataset size for each series is 20,000 values. The network's learning rate is 0.01. When constructing the network, there are 4 input neurons, 8 hidden neurons, and one output neuron. The training results of the network are presented in Fig. 2.

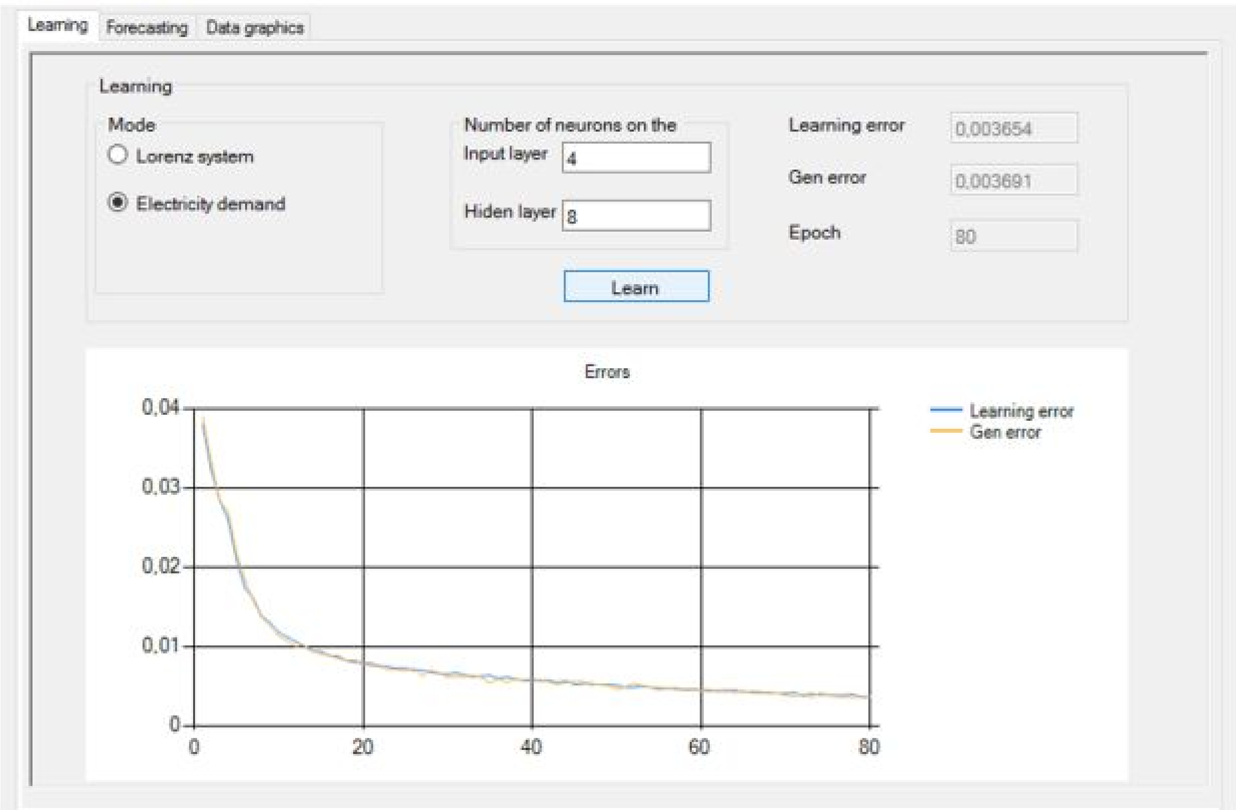


*Fig. 2.* Results of neural network training

The next stage is forecasting. The forecasting results for one step ahead are shown in Fig. 3.

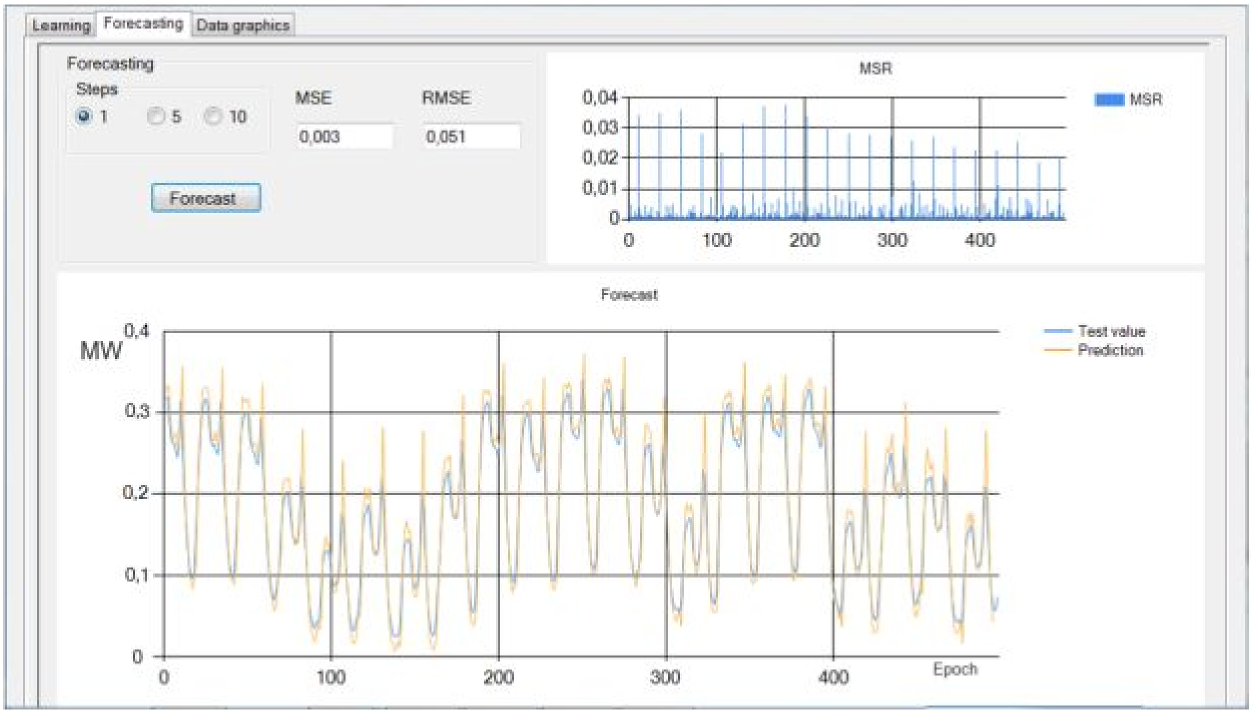


*Fig. 3.* Results of forecasting electricity consumption are one step ahead

The execution time of training and forecasting using this program is 30 seconds. This forecasting time, even with training, is acceptable as it constitutes 1/120th of the minimum time interval for forecasting.

The relative training error of the neural network is 0.003654, while the forecasting error on real data is 0.003015. Thus, the forecasting error does not exceed the training error.

**Conclusions**

As a result of the conducted work, algorithmic and software solutions for time series forecasting of electricity consumption using a recurrent neural network have been developed. The network has been constructed, and optimal parameters have been chosen for its operation. UML diagrams have been designed to clearly illustrate how the system should work and the requirements it must meet. Scenarios for the system's operation have been developed and implemented in the software.

The findings of this research contribute to the advancement of energy forecasting and provide practical guidance for implementing RNN models in real-world energy management scenarios. The interpretability analysis enhances our understanding of the factors influencing electricity consumption and enables better decision-making in energy planning and resource allocation.

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