Application of Neural networks for time series electrical consumption forecasts

Verica Babamova-Tsenova, Ognyan Andreev and Georgi Tsenov

***Abstract* — With introduction of IoT there is possible to use nowadays cheap measurement devices that can store information form actuators and store it in databases locally or online. With the recent opening of the electrical distribution markets, it will be possible to buy electrical energy on varying prices and from various suppliers. With big time intervals of data collection for the plant consumption and of the market price fluctuations done with IoT devices for a relatively small time intervals on the recorded samples a user electrical power profile can be created by using neural networks as time series forecasts predictor. With such plant/user power profile the predicted production can be shifted towards the intervals with cheaper electricity prices leading to reduced production costs. This paper presents the results for creating an energy consumption profile with electrical loads forecasts, when they are presented as time series and by using the MATLAB's Neural Networks Toolbox.**

***Index Terms*—Neural Networks, Time series prediction, Electric Load Optimization**

INTRODUCTION

Electricity is one of the most necessary products in the modern manufacturing plants. Electricity can be considered as one commodity and like all other commodities can be produced and traded on a market basis. Based on paragraph 15 of the Law on Implementation and Supplement to the Energy Act, published in issue 57 of the State Gazette of the Republic of Bulgaria from 26.06.2020, as of 1 October 2020 in Bulgaria started a procedure for selection of energy suppliers at freely negotiated prices for all non-domestic customers connected at low voltage level to the electricity distribution network. In the event that by July 1, 2021 the production enterprises do not conclude a contract with a trader of electricity at freely negotiated prices, then as of this date they will be supplied with electricity under the conditions of Art. 95a of the Energy Act by a supplier of last resort, which will increase their costs. The participants in the free energy electricity market are producers, distribution companies (EDPs), traders in their role of suppliers and end users.

Licensed companies, traders of electricity on the free market, offer their customers different prices, products, tariffs and services. In this way, they compete, and consumers have the opportunity to choose an electricity supplier and negotiate commercial terms. In order to achieve efficiency in the supply, distribution and consumption of electricity, i.e. different information is needed to be able to manage these processes. For example: information to the supplier about the amount of consumption, which are the loaded branches of the network, which are the loaded time zones, what is the quality of the supplied electricity, what is the size and structure of the losses, are there any attempts at manipulation and theft and information to the consumer, what is the amount of his current, daily and monthly consumption, what are his busy time zones, what is the quality of the electricity supplied to him, what is the effect of the measures taken by him to save electricity. energy, etc.

For this purpose, it is necessary to monitor and forecast the loads in the electricity networks, which is laid down in the rules for management of the electricity distribution networks of SEWRC [1] in Chapter 4. Successful accurate forecasting of electricity consumption is an important task for electricity distribution companies and manufacturing companies. in the current unplanned economy with free open markets.

Electric load forecasting finds many applications, such as in the planned switching on and off of power plants, in planning the future electricity transmission infrastructure, in the formation of electricity prices in the interstate markets for purchase / sale of electricity in determining the busy hours. areas with increased consumption and synchronization and production planning at a time when green energy suppliers have the highest yields, etc. which would lead to lower levels of carbon dioxide emissions and reduced costs with the direct priority use of electricity generated by wind turbines or solar panels.

In the monthly metering of electricity meters there is no way to make a correct forecast of consumption, because the report is made once and shows a report of the total consumed electricity, i.e. the electricity meters are one integrating unit, while for making forecasts it is necessary to measure the instantaneous power or an integral of the consumed power for short time intervals. By using devices for recording the consumed electric energy in short time intervals it is possible to apply methods for making forecasts.

Due to the fact that electrical consumption is traditionally presented as a time series, the team focused on the apparatus of neural networks, which have long proven that it is possible to successfully predict time series and in particular electrical loads [2], [3], [4], [5], [6].

This paper is organized in four chapters. Chapter Two shows a brief introduction to neural network theory. Chapter three shows the devices used for recording electricity and approximate results from the daily forecasting of electricity consumption in an enterprise presented as a time series using the function for creating neural networks with the right signal transmission and back propagation of the feedforward net error and Elman Neural Network by the Neural Networks

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Toolbox neural network package in the MATLAB desktop. Chapter Four includes the final conclusions.

I. A BRIEF INTRODUCTION TO NEURAL NETWORK THEORY

A neural network is a system for parallel information processing and it has the property of storing and using experimental knowledge. In general, neural networks consist of simple information processing elements called neurons or nodes. Neurons are connected and the weights of the connections between them determine the strength of the respective connections. The input information for each neuron is the weighted sum of the signals from the other neurons.

This information accumulates in the neuron and its output signal is determined by the so-called activation or trans-mission function. The information in a neural network is accumulated in the process of learning, as the strength of the connections between the individual nodes is modeled by the weights of the respective connections that are used to store the information.

Each neuron has many inputs and one output as shown on Figure1. At the inputs $x_1, x_2..., x_m$ the signals to the neuron arrive. They can be external signals or signals from the outputs of other neurons. Each input is connected to a weighting factor w_j, j = 1,2,…, m, modeling the strength of the connection during signal transmission. The aggregation of the input signals in the body of the neuron is modeled with the adder, whose output signal is calculated by the formula:

$$v = y_{in} = \sum_{j=1}^{m} w_j x_j + b \tag{1}$$

In the neuron model, a signal with a constant value b, called bias, is introduced. In most cases, the activation function is nonlinear and the output signal of a single neuron is calculated by:

$$y = f(y_{in}) = f\left(\sum_{j=1}^{m} w_j x_j + b\right) \tag{2}$$

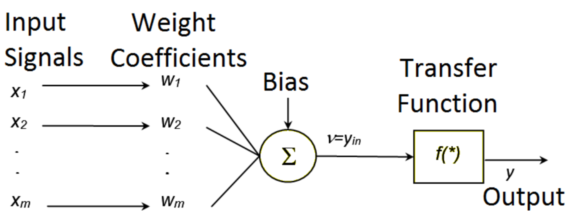


Fig. 1. Abstract mathematical model of a neuron

The main components of the neural networks to which they are connected and their different classifications are based on: the architecture of the network – it is set by the way of connection between the different neurons; the training algo-rithm – determines the way in which the weights of the connections between the neurons are adjusted so that the neural network performs the desired signal conversion; activation function - the mathematical rule by which the value of the output signal is determined.

For the purposes of prediction tasks, we are focused mainly on multilayer networks with feedforward signal transmission and error backpropagation, because it has been proven that with multilayer neural networks based on the error propagation method, all *L2* functions can be represented (approximated). At the same time, when solving various approximation problems, the generalizing properties of the networks are good, as long as the training sample is large enough.

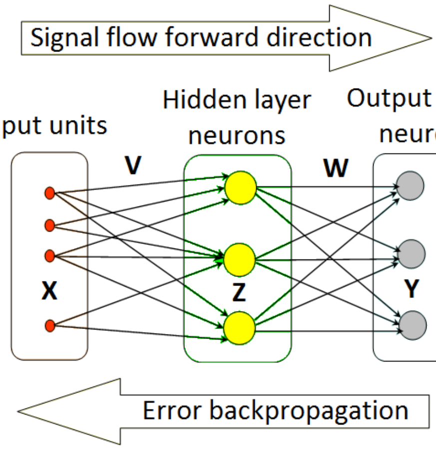


Fig. 2. Architecture of a two-layer neural network

In the exemplary structure of Figure 2, the neural network consists of one input layer of nodes, through which the input signals $X = [x_1\ x_2...\ x_n]$ are fed to the network, of one output layer of neurons, the vector of the output signals of which $Y = [y_1\ y_2\ ...\ Y_m]$ is the output vector of the network, and a hidden layer of neurons, the output signals of which are $Z = [z_1\ z_2...\ z_p]$ .In this type of network, the activation function of the output layer of neurons is linear, and of the hidden layer tangentially sigmoidal. The weighting factors are set by an algorithm including an iterative procedure changing the weighting factors from the output to the input layer based on the error obtained by comparing the obtained network output with the desired output. Multilayer neural networks based on the error backpropagation method work on the principle of the black box and with enough training data, the results in use are very good. Knowledge of the nature of the problem, which is approximated by the neural network, is not required, but only sufficient input-output data. Also, these neural networks are robust in terms of noise in the data and in the values of the weights of the network, in the absence of data and others. The number of neurons in the hidden layer is very important when using multilayer neural networks with error propagation. Usually the number of neurons is chosen for empirical reasons based on the Oja formula. If with Z we mark the number of neurons in the hidden layer, with P the number of elements from the training sample, m is the number of inputs and n is the number of outputs, then we will get according to Oja's formula that:

$$Z = \frac{P}{5(m+n)} \tag{3}$$

For comparison purposes an Elman recurrent neural network is also used. It is very similar with the exception that the hidden unit’s output response is fed back at the input of the hidden layer in the next time instance. This neural network type is generally suitable for time series prediction tasks and its architecture is shown in Figure 3.

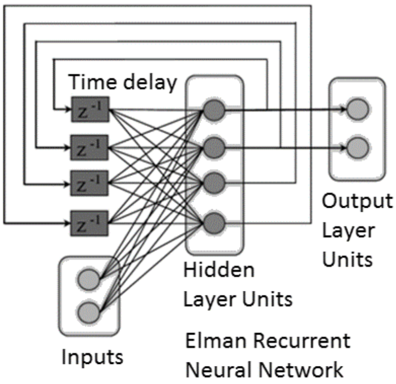


Fig. 3. Architecture of an Elman recurrent neural network

II. RESULTS OF FORECASTING OF ELECTRICAL LOADS

When forecasting electricity consumption, data from previous periods are needed to serve as a basis for forecasting consumption in future periods. To achieve this goal a smart electricity meter model SM-0001 is used, because it is offering the ability to record data at different time intervals.

Fig. 4. General view of the IoT smart electricity meter

The device is shown on Figure 4 and it has a built-in microcontroller with STM32F205 120 MHz processor and 128KB RAM. The microcontroller is supplied with a voltage of 3.3 V. 3 current-transformers are connected to the micro-controller, which allow for measuring installations up to 100 A. The transformers are connected non-invasively without making mechanical changes to the insulation of the con-ductors. The device is suitable for measuring the actual power in one, two or three phases.

Fig. 5. General view of the current transformer

Measurements and data collection can be performed in the smallest intervals of 5 minutes in increments of 5-minute steps. For one particular data collection example the smart meter was installed in one enterprise production SME where the data collection was performed at intervals of 15 minutes, using the MQTT protocol for data transfer. The use of IoT meters allows a web platform to process and visualize data provided by more devices.

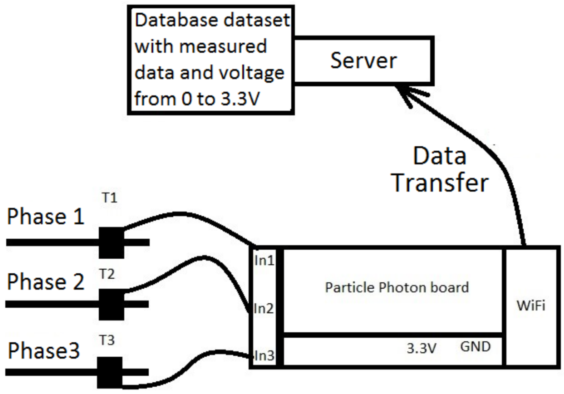


Fig. 6. Diagram of the software and hardware infrastructure

The more difficult task is to achieve adequate daily forecasting. The team had at its disposal field data taken over a period of one month for one enterprise. These data samples should be sufficient for the training of neural networks for daily reporting and forecasting, but for better results it is recommended to use data for longer periods of time.

The measurements measured and recorded in a database are in the following tabular form:

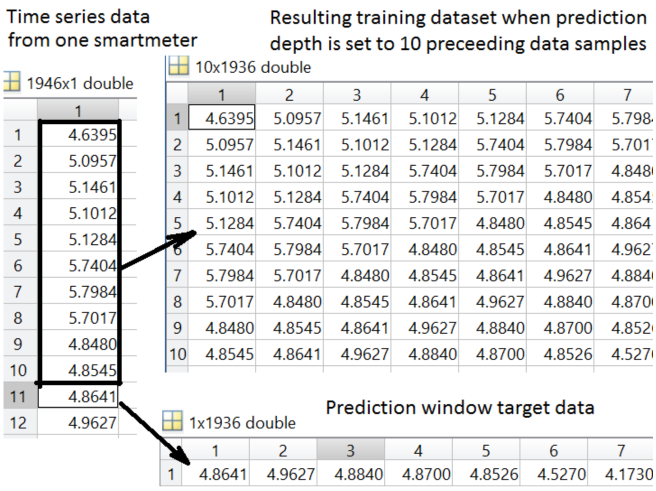
TABLE I

name	time	devId	value
sm-0001fifteen	2021-05-17T09:14:45.057462933Z	sm-0001	4.639475
sm-0001fifteen	2021-05-17T09:29:48.922862151Z	sm-0001	5.095667
sm-0001fifteen	2021-05-17T09:44:52.789837614Z	sm-0001	5.146074
sm-0001fifteen	2021-05-17T09:59:47.324949599Z	sm-0001	5.101224

In Table1 for each IoT smart electricity meter the consumption is available at 15-minute intervals, standardized and anonymized at the request of the enterprise. From this data a training sample is formed for submission to a neural network, each combination of 10 consecutive days being assembled as a sample of the training sample, in which the record of the next 11th report corresponds to its target function, as shown in Figure 7.

Once the training sample is formed, the training process of a neural network with the right signal transmission is started in MATLAB. Since the depth of the prediction window formed by the previous data is 10 reports, the inputs of the neural network are ten in number, i.e., report1 is input1, report2 is input2, etc. and the input layer will be made up of 10 neurons. The desired prediction window is a report forward in time and on this basis the output layer of the network must be made up of one neuron.

The number of neurons in the hidden layer is determined empirically by formula 3, which after elementary calculation leads to 35 neurons in the hidden layer. The resulting neural network structures for the Feedforward error backpro-pagation and for the Elman neural networks are created by using the feedforwardnet and newlm functions from the MATLAB neural network package and are shown in Fig. 8.



	1
1	4.6395
2	5.0957
3	5.1461
4	5.1012
5	5.1284
6	5.7404
7	5.7984
8	5.7017
9	4.8480
10	4.8545
11	4.8641
12	4.9627

	1	2	3	4	5	6	7
1	4.6395	5.0957	5.1461	5.1012	5.1284	5.7404	5.798
2	5.0957	5.1461	5.1012	5.1284	5.7404	5.7984	5.701
3	5.1461	5.1012	5.1284	5.7404	5.7984	5.7017	4.848
4	5.1012	5.1284	5.7404	5.7984	5.7017	4.8480	4.854
5	5.1284	5.7404	5.7984	5.7017	4.8480	4.8545	4.864
6	5.7404	5.7984	5.7017	4.8480	4.8545	4.8641	4.962
7	5.7984	5.7017	4.8480	4.8545	4.8641	4.9627	4.884
8	5.7017	4.8480	4.8545	4.8641	4.9627	4.8840	4.870
9	4.8480	4.8545	4.8641	4.9627	4.8840	4.8700	4.852
10	4.8545	4.8641	4.9627	4.8840	4.8700	4.8526	4.527

	1	2	3	4	5	6	7
1	4.8641	4.9627	4.8840	4.8700	4.8526	4.5270	4.1730

Fig. 7. Forming the training samples from the dataset

The number of neurons in the hidden layer is determined empirically by formula 3, which after elementary calculation leads to 35 neurons in the hidden layer. The resulting neural network structures for the Feedforward error backpropagation and for the Elman neural networks are created by using the feedforwardnet and newlm functions from the MATLAB neural network package and are shown in Fig.8.

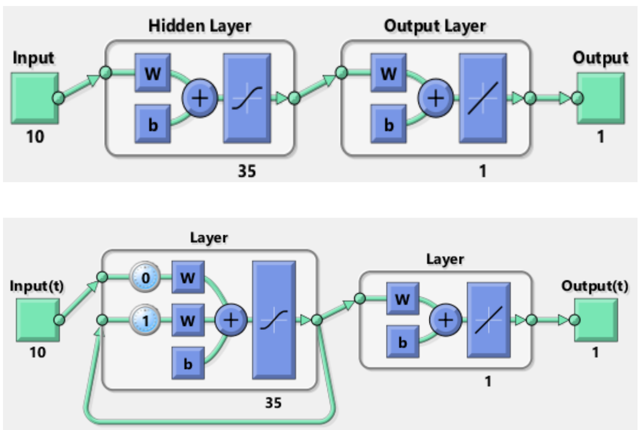


Fig. 8. Neural network architectures for electricity forecasting

After training the network with data obtained from one working month for its testing, the team used data on consumption measured for another month, the data from which did not participate in the training sample. Figure 9 shows a comparison between the predicted and actual value of electricity consumption from the two neural network models and moving average. From the graph of the comparison, it can be seen that the Feed-Forward error back propagation neural network very well approximates the data so that there are no large differences between the predicted and the actual value for the consumed electricity, while the Elman neural network provides good prediction rates, but not that good. This is reflected in the calculated performance; the Elman neural network is a little bit worse at 0.257 and the Feed-Forward error back propagation neural network is at 0.19.

The trained neural networks are performing well only for the node whose data are used in its training. If predictive assessment is needed for each node, it is necessary the creation of a software model of a neural network for each individual node or it is possible to combine all data for all nodes in a generalized neural network having m number of outputs, where each output represents the estimated value of one of the nodes.

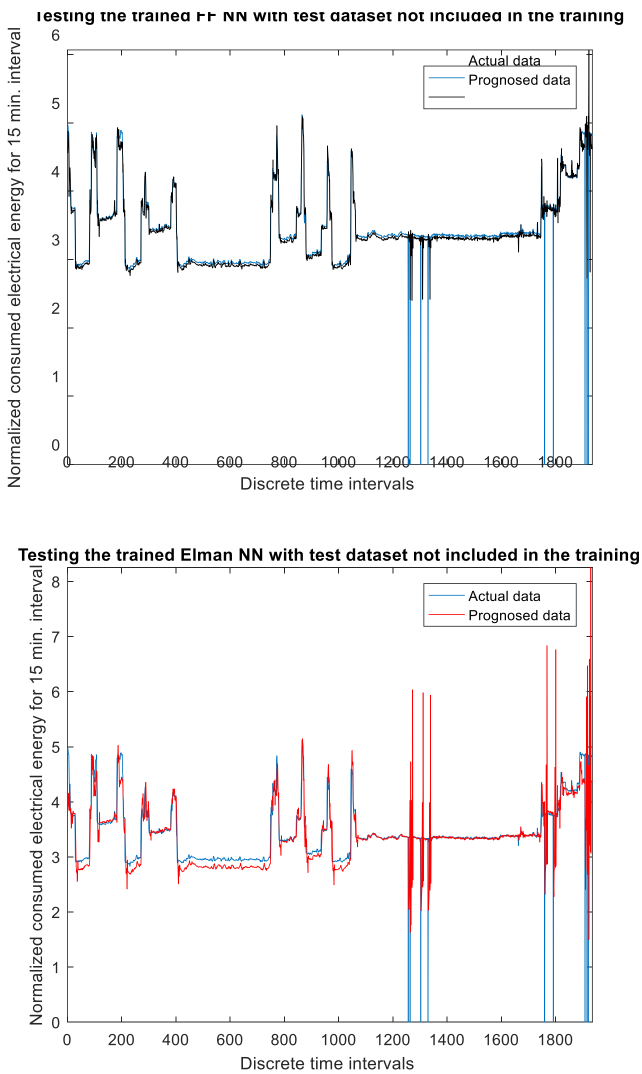


Fig. 9. Comparison of actual with the predicted consumption for a period of one month for the two neural networks trained

If such a production plant profile is paired with weather forecast predictor that can provide estimates of when the green energy generation will be at peak levels a much greener production levels can be reached with reduced CO2 emissions. This approach can lead to increased company competitiveness level by reducing the production costs and by reducing the company CO2 footprint to a lesser amount, thus requiring lesser number of tons of carbon dioxide emissions to be bought.

III. Conclusion

The trained forecasting neural network models shows that when a data for consumer consumption is available with the use of the neural networks it is possible to achieve quite accurate forecasting of the consumption of the electric power. On that basis a lower production costs can be achieved by scheduling the time of the production norms to coincide with the periods when the electricity is sold at a low price.

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