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OPEN ACCESS

DOI: 10.15199/48.2025.05.18

Neuro-short-term demand forecasting model of territorial communities energy islands with electricity and heat combined generation

Neuro-krótkoterminowy model prognozowania popytu na wyspy energetyczne społeczności terytorialnych z łączoną generacją energii elektrycznej i ciepła

Abstract: *The growing need to ensure the viability of energy islands of territorial communities requires the development of effective methods for short-term forecasting of energy demand. This problem becomes especially relevant in the context of warfare and an unstable energy situation. The paper is devoted developing a neural network model for short-term forecasting of demand energy islands of territorial communities with combined production of electricity and heat. The research used the architecture of long short-term memory, a recurrent neural network for manage sequential data with a time dependence. The model is trained using data history and integrated into an automated control system. The obtained results indicate a high accuracy of forecasting using the long short-term memory model. The average absolute forecast deviation is approximately 2.2%, R2 about 95%, and the root mean square (RMS) deviation is 0.0008. The model is superior in its efficiency for the support vector regression (SVR) models and random linear regression (Prophet). The implementation of the short-term forecasting model of energy demand in automated control systems of energy islands with combined production of electricity and heat allows collecting historical data and forecasting consumption in real time. This contributes the prompt coordination of the generation renewable energy sources (RES), form the balance of the energy system in combining production, adjustment of the load schedule, reduction of flows from the external grid and optimization energy costs.*

Streszczenie: *Rosnąca potrzeba zapewnienia żywotności wysp energetycznych społeczności terytorialnych wymaga opracowania skutecznych metod krótkoterminowego prognozowania zapotrzebowania na energię. Problem ten staje się szczególnie istotny w kontekście działań wojennych i niestabilnej sytuacji energetycznej. Artykuł poświęcony jest opracowaniu modelu sieci neuronowej do krótkoterminowego prognozowania zapotrzebowania na energię wysp terytorialnych społeczności przy skojarzonej produkcji energii elektrycznej i ciepła. W badaniach wykorzystano architekturę pamięci długoterminowej, rekurencyjną sieć neuronową do zarządzania sekwencyjnymi danymi z zależnością czasową. Model jest trenowany przy użyciu historii danych i zintegrowany z automatycznym systemem sterowania. Uzyskane wyniki wskazują na wysoką dokładność prognozowania przy użyciu modelu pamięci długoterminowej. Średnie bezwzględne odchylenie prognozy wynosi około 2,2%, R2 około 95%, a odchylenie średniej kwadratowej (RMS) wynosi 0,0008. Model ten jest lepszy pod względem wydajności dla modeli regresji wektorów nośnych (SVR) i losowej regresji liniowej (Prophet). Wdrożenie krótkoterminowego modelu prognozowania zapotrzebowania na energię w zautomatyzowanych systemach sterowania wysp energetycznych o skojarzonej produkcji energii elektrycznej i ciepła pozwala na zbieranie danych historycznych i prognozowanie zużycia w czasie rzeczywistym. Przyczynia się to do szybkiej koordynacji wytwarzania odnawialnych źródeł energii (OZE), kształtowania bilansu systemu energetycznego w skojarzonej produkcji, dostosowania harmonogramu obciążenia, redukcji przepływów z sieci zewnętrznej i optymalizacji kosztów energii.*

Keywords: Forecasting energy demand, smart grid, deep learning, energy island
Słowa kluczowe: Forecasting energy demand, smart grid, deep learning, energy island

Introduction

In the context of rapid technological development and global climate change, effective management of energy resources is an actual problem [1]. Forecasting short-term energy demand is particularly important to allow businesses planning energy production efficiently, thereby minimizing costs. In the context of warfare and unstable energy situation in Ukraine, short-term forecasting of energy demand, which is dominating for local enterprises and the country as a whole. Within the framework of modern energy management methods, energy islands are known. The energy island envisages the creation of a local energy supply system capable of operating offline, or connected to the main power supply grid. The implementation of an energy island requires accurate forecasting of energy demand, as it ensures using the optimal amount of available resources.

Supporting the viability, energy independence of energy islands territorial communities, combined production of electricity and heat, further increases the value of forecasting energy demand. The use of statistical data, the development of a neural network model make possibility to accept the available levels of generation of RES in terms of adjusting the load schedule with a decrease in flows from the external grid. It allows forming the balance of the power system in the conditions of joint combined production, thereby optimizing the cost of a unit of energy.

The purpose of research is to discuss the development of a neural network model for short-term forecasting of demand for energy islands territorial communities with combined production of electricity and heat.

Literature survey

Among the existing publications, well-known studies are devoted the energy islands and forecasting short-term energy demand. Kaplun et. al. [2] developed a method of reliable-cost optimization of the structure of micro-energy systems with heterogeneous sources, which is based using indicators of reliability and cost of electricity. The carried out research is based on modern methods of applied statistical analysis, reliability theory, synthesis of complex multi-aggregate systems. Computational experiments made it possible to obtain regularities in the evolution of the cost of electricity and show its dependence on the structure and algorithms functioning of sources. The cost of electricity is sensitive to the ratio availability RES of primary energy is proved. Practical application of the results is in increasing the efficiency of energy islands. Kurniawati et. al. [3] proposed a model of an energy island that combines various RES. The study focuses on the energy independence of the large island, illustrating a concept that refers the replacement of heat power plants with energy from sustainable production. Lüth et. al. [4] explored the trade-offs between the integration of energy islands through electricity and hydrogen infrastructure. A combined model of capacity expansion and dispatching of electricity, appreciated the role of electrolyzers and electrical cables, taking into account the availability of RES from the islands were created. Yan et. al. [5] researched the forecasting energy consumption by individual households on data base. The combination of the long-term memory ensemble neural network with the technique of steady-state wavelet transformation is proposed in a hybrid deep learning model. A steady-state wavelet transform reduces instability and increases the dimensionality of data, helping to improve forecasting accuracy. Alrasheedi et. al. [6] hybrid deep learning methods have been developed to improve load forecasting results in smart grids. A comparison strategy using different deep learning methods has been applied. It includes an artificial neural network, a recurrent neural network, conventional neural networks, long-term short-term memory, a recurrent gating unit, and various real-world datasets. Shachee et. al. [7] used the LSTM-RNN forecasting household electricity consumption two months from a given starting date. The model evaluates by comparing the projected and actual energy consumption values. Mubashar et al. [8] submitted a method for predicting the load in a smart grid using smart meters and the LSTM method has been proposed. The results of the research were compared with the methods of ARIMA and exponential smoothing. Miah et. al. [9] offer a deep learning-based approach to forecast energy demand in the smart grid, which can improve the integration of RES by providing accurate forecasts of energy demand. It uses a long network of short-term memory that combines well with time series data to capture complex patterns and dependencies in energy demand data. The short-term energy demand datasets from various power distribution companies are evaluated, including American Electric Power, Commonwealth Edison, Dayton Power and Light i Pennsylvania-New Jersey-Maryland Interconnection. The proposed model is compared with three state-of-the-art forecasting algorithms: Facebook Prophet, Support Vector Regression i Random Forest Regression. The results obtained indicate that the proposed model can accurately predict energy demand with an average absolute deviation 1.4%, indicating its potential to improve the stability and efficiency of the power grid.

Materials and methods

An approach based on deep learning for short-term forecasting of energy demand for energy islands of territorial communities with combined production of electricity and heat is proposed. A time series is adopted in the form of energy demand data, represented by a sequence of vectors [9]:

(1) $$< D = d_1, d_2, \dots, d_n >,$$

where d_n – vector of energy demand at a point in time.

Forecasting energy demand in the future is represented by a vector (Miah et. al., 2023):

(2) $$d_{n+h},$$

where h – number of steps to make predictions.

Projecting energy demand can be represented as a function of f (Miah et. al., 2023):

(3) $$f(D) = d_{n+h},$$

The implementation of the approach is in finding the optimal function f to minimize the forecasting deviation, which is the average absolute deviation between the forecasted and actual value of energy demand [9].

Hourly PJME energy consumption data available from open sources is used [10]. PJME – hourly energy consumption data, regional power transmission organization, Pennsylvania, New Jersey-Maryland in the United States. The data covers 13 states and the District of Columbia, includes variables like time, date, temperature, energy demand between December 2002 and January 2018 with a total of 145366 data points [9].

The architecture of long short-term memory, a recurrent neural network, is implemented to manage sequential data with a time dependence. The long short-term memory model is trained against the data history determining the ratio between the input data and the variables represented as energy demand in mW. The resulting dependencies are used for forecasting. Long short-term memory is a set of nonlinear transformations on the input and hidden states of the network, the gating mechanisms that regulate the passage of information through the network. A single cell of long short-term memory can be represented by the equation [9]:

(4) $$\begin{gathered} i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i), \\ f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \\ \tilde{C}t = \tanh\left(W_{xcx_t} + W_{hc}h_{t-1} + b_c\right) \\ C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}t \\ o_t = \sigma\left(W_{xox_t} + W_{ho}h_{t-1} + b_o\right) \\ h_t = o_t \odot \tanh(C_t) \end{gathered}$$

where x_t – entry point per time step t; h_{t-1} – latent state behind the previous time step; W – network weight; b – network offset; σ – sigmoid tangent activation function; tanh – hyperbolic tangent activation function; i_t – inlet valve; f_t – flow valve; o_t – outlet valve; C_t – cell status; h_t – latent state.

The structure of long short-term memory includes the input, extraction, and output layers. The neurons number in the input layer is equal the number of energy demand data. The number of layers is determined by cross-checking the grid search, which is a grid of possible values for each existing hyperparameter and a represent score for all possible combinations of hyperparameters. Productivity method is compared in all possible combinations, the neuron of the output layer represents the predict value of energy demand. The model is implemented using a programming language Python and library Keras [11]. RMS deviation and Adam's optimization are used in training model for a specified number of cycles, until productivity stops improving.

The average absolute deviation is the difference in forecast and actual energy demand and determined from the equation [9]:

(5) $$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}|,$$

Results

The results of research using data dividing into 80% learning objectives and testing objectives 20% were obtained. With using data were trained and tested machine learning models support vector regression (SVR) and random linear regression (Prophet). It was compared to the short-term energy demand forecasting model [12, 13]. The model of deep learning proposed in the paper was trained using long short-term memory architecture. It includes 200 units of memory. It was trained according to Adam's optimization algorithm with a speed of 0.001. The results of the experiment are shown in Table. 1.

Table 1. Experiment results

Model	R^2	Average absolute deviation	RMS deviation
Long short-term memory	0.951253	0.022566	0.000888
Support vector regression	0.986650	132.343542	85152.198802
Random linear regression	-14.407594	0.621314	0.412824

According to the results obtained, the model of long short-term memory is characterized by high accuracy of forecasting. The average absolute deviation is approximately 2.2 %, R^2 about 95 %, RMS is 0.0008. Compared to support vector regression, the model has a better exponent R^2. However, by the indicators of the average absolute deviation and the RMS, forecasting demand is not close to the actual one. The random linear regression model has a negative value R^2. It is an indicator of missing explanation for variability the independent variables. The obtained indicators of the average absolute deviation and RMS deviation indicate a lower forecasting ability and prediction accuracy compared to the long short-term memory model. The experimental results are presented in Fig. 1-3.

Fig. The 1-3 axis of the abscissa denotes the interval in time, the axis of the ordinate is the demand for energy. The long short-term memory model is highly accurate in forecasting energy demand based on industrial data. Forecasting values are the initial values of energy demand. The result presented in the paper is based on a specific set of data. The accuracy of the forecast depends on the data used training the model. The results demonstrate the potential for forecasting energy demand in the smart grid.

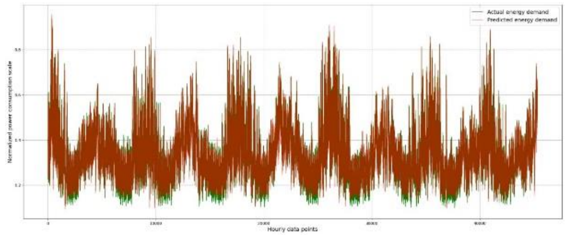

Fig. 1. The visual representation of the difference between actual and forecasting energy demand for a long short-term memory model

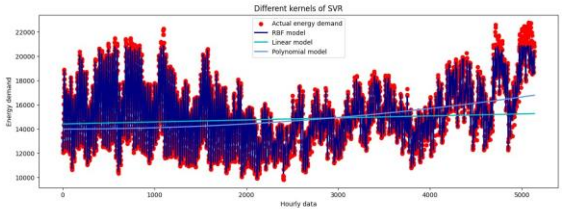

Fig. 2. The visual representation of the difference between actual and forecasting energy demand for a SVR model

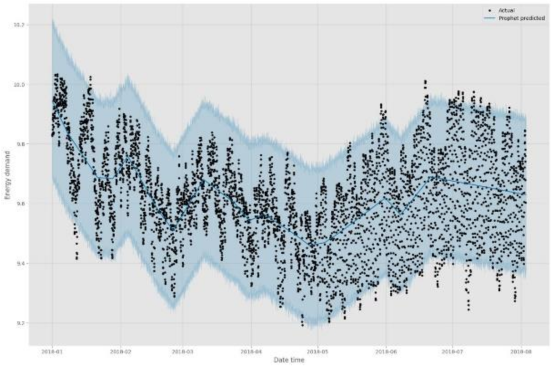

Fig. 3. The visual representation of the difference between actual and forecasting energy demand for a random linear regression model

The complete and high-quality datasets required to train the model are collected using controller SATEC PM180. It has been capable of measuring voltage, current, power frequency, unbalanced currents and voltages, neutral current. All this data, in the form necessary to train the model, using an application programming interface (API) are transferred to a local database and then used for training [14]. Connection controller is a part of an automated control system. The main task includes: collection of data on the state switching devices, the state of technological protections, general substation alarms; collection and primary processing of values technological quantities; operational control of power equipment; transfer of all received information to the system. The system is a cabinet that implements all necessary tasks and consists of the following components: information processing and exchange devices; teleinformation signal acquisition devices; communication channel connection devices; power supply devices.

The practical implementation of the neural network model for short-term forecasting demand of energy island territorial community with a combined production of electricity and heat was carried out in the Smila Community (Cherkasy region, Ukraine). For training and forecasting (Fig. 4-7) Data on the hourly consumption of electricity by the population was collected kWh for 2022 ·and hourly consumption of heat energy by the population in kWh for January-March 2022·. Learning outcomes and forecasting are shown in Table 2.

An input sequence is generated for the next month based on the training data sequence provided forecasting the electricity and heat energies demand for the next month. The long short-term memory model makes forecasting of energy demand for each hour following month. The forecasting occurs iteratively, returning the data to the input model and shifting the sequence by one hour at each step. Since the forecasting is made on the basis of normalized data, they are inversely converted to obtain the kWh value of energy demand.

Table 2. Learning outcomes and forecasting

Model	R^2	Average absolute deviation	RMS deviation
Electricity demand forecasting	0.814961	0.067728	0.009520
Heat energy demand forecasting	0.956163	0.046968	0.003814

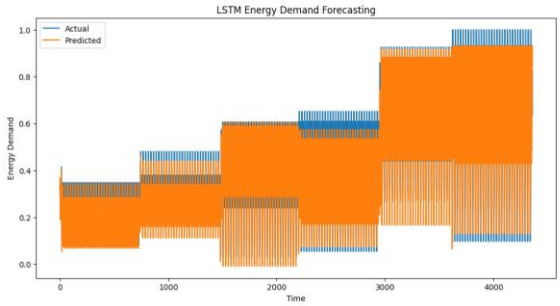

Fig. 4. The visual representation of the difference between actual and forecasting electricity demand for the long short-term memory model in Smila community

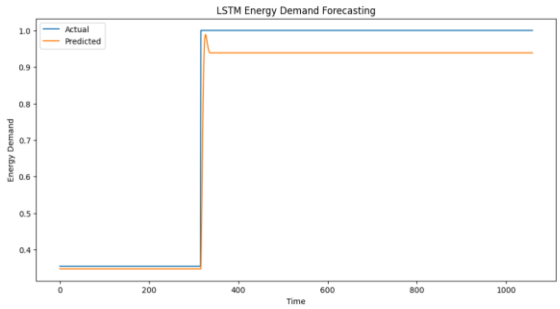

Fig. 5. The visual representation of the difference between actual and forecasting demand for heat energy for the long short-term memory model in Smila community

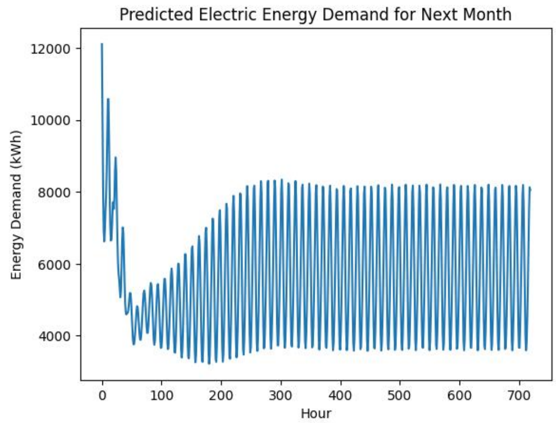

Fig. 6. Forecasting electricity demand for the next month relative data

With using the model, energy demand can be forecasting for hours, days, months in advance. The information is key for energy suppliers and grid operators for effectively plan and manage energy production, distribution and pricing. Accurate forecasts can optimize energy allocation, allow for production schedules adjustments, RES deployments, and optimize energy storage systems to meet demand while minimizing costs.

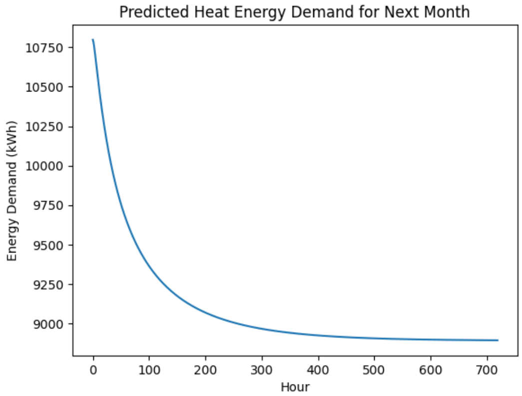

Fig. 7. Forecasting the demand for heat energy for the next month relative data

Using the example of the result (Fig. 6), a specialist of an energy generating company must plan the optimal work schedule, fulfill the demand, maximize energy production and minimize costs. In this case, generation schedules can be superimposed on the forecast energy demand. The graph shows periods of peak demand when forecasting demand exceeds power generation Grid overload alleviation is done by determining the time energy production. It helps to minimize costs, plan maintenance and repairs during periods of low energy demand, and adjust trading strategies based on market prices.

Conclusions

This paper is devoted a model of long short-term memory integrating into the architecture of supervisory control and data collection forecasting energy demand. A set of historical hourly energy consumption data was used to train the model PJME. The model compared to other existing support vector regression (SVR) and random linear regression (Prophet). The long short-term memory model obtained comparatively better results with an average absolute deviation 2.2 %, R2 approximately within 95 %, RMS deviation 0.0008. The results show high accuracy in forecasting energy demand when using complete datasets.

The introduction of a short-term energy demand forecasting model in existing or newly created automated control systems for the energy island of territorial communities with combined production of electricity and heat opens up opportunities for collecting historical datasets and forecasting energy demand at a specific point in time. It will allow in a short time to agree available levels of generation RES in terms of adjusting the load schedule with the reduction of flows from the external grid, form the balance of the energy system in combining production, thereby optimizing the cost of a unit of energy.

The research is supported by National Research Foundation of Ukraine call "Science for the Recovery of Ukraine in the War and Post-War Periods" grants №94/0129 «The formation of technological structures of decentralized energy systems in the post-war reconstruction of the infrastructure of territorial communities in the context of combating climate change».

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