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FORECASTING OF SHORT-TERM POWER DEMANDS IN POLISH POWER SYSTEM USING ENSEMBLE OF LSTM NETWORKS

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Abstract – The article presents and discusses the results of the research of forecasting power demands in Polish Power System with time horizon of one hour ahead in conditions of limited availability of forecasting model input data, covering only three months. The prediction was carried out using deep neural networks - LSTM (Long Short-Term Memory) connected to an ensemble. The performance of the ensemble is much more efficient than individual networks working separately. The numerical experiments were conducted using MATLAB computing environment. The accuracy of the predictions was estimated using such statistical measures as MAPE, MAE, RMSE, Pearson correlation coefficient *R*.

Key words – LSTM, neural networks, Polish Power System, power demand, time series forecasting

INTRODUCTION

Accurate forecasting of hourly demand plays a key role in planning the generation, transmission, distribution and use of the electricity. Information about the demand in next hour can ensure the possibility of distributing power from power plants, functionally connected to each other in a system that allows for the implementation of electricity supplies throughout the country in a continuous and uninterrupted manner. It allows for the planning of time interruptions in energy supplies in order to perform necessary repairs or redirect power in emergency situations.

1. POWER FORECASTING METHODS

Load forecasting is the subject of many scientific studies. Various methods are widely used for time series forecasting. The most common ones are: linear methods such as ARMA, SARIMA, ARMAX [1], nonlinear methods especially neural networks: MLP (Multilayer Perceptron), RBF (Radial Basis Function), SVM (Support Vector Machine) [2, 3], random forest [4] or ANFIS model [5]. In recent years, methods based on deep learning, such as convolutional networks [6, 18] or LSTM [7, 10, 11, 20] have been increasingly applied. This article will focus on the application of LSTM neural networks connected to an ensemble, in conditions of limited availability of historical input data, covering only three months. Main difference between the current study and the available literature is the significant limitation of the input data. In contrast to the approach presented in [17, 18, 19, 20], the current study includes input data for the entire country (Poland) and does not include other parameters, such as temperature or wind speed in examined area.

2. DATABASE USED FOR NUMERICAL EXPERIMENTS

The database [13] used for the research contains real power demands in Polish Power System that covers three months: December 2023, January 2024 and February 2024 (total 91 days).

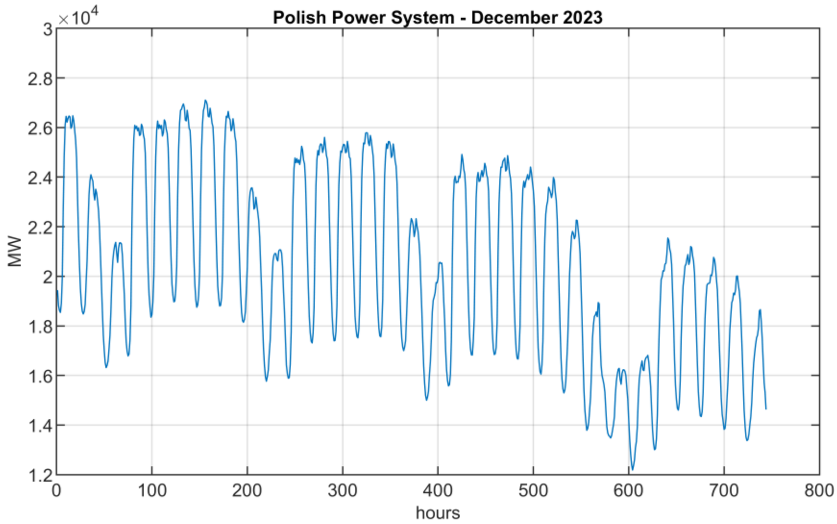

Fig. 1. Power demand in Polish Power System in December 2023 (744 hours)

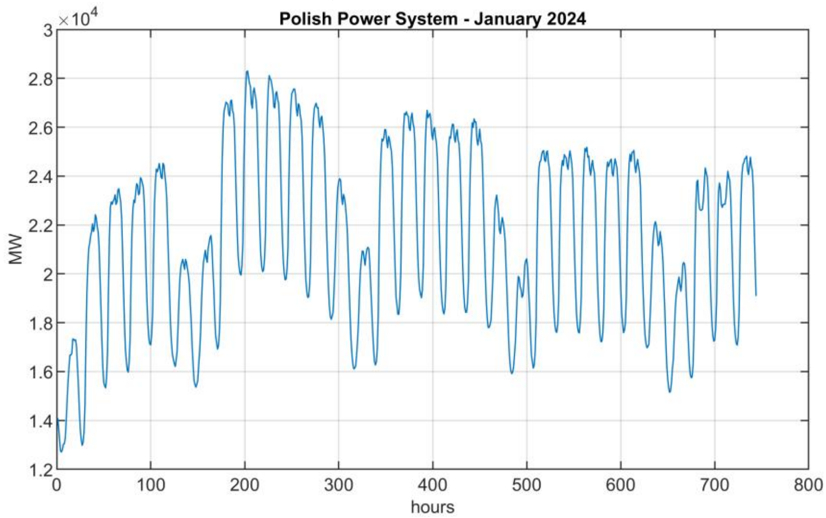

Fig. 2. Power demand in Polish Power System in January 2024 (744 hours)

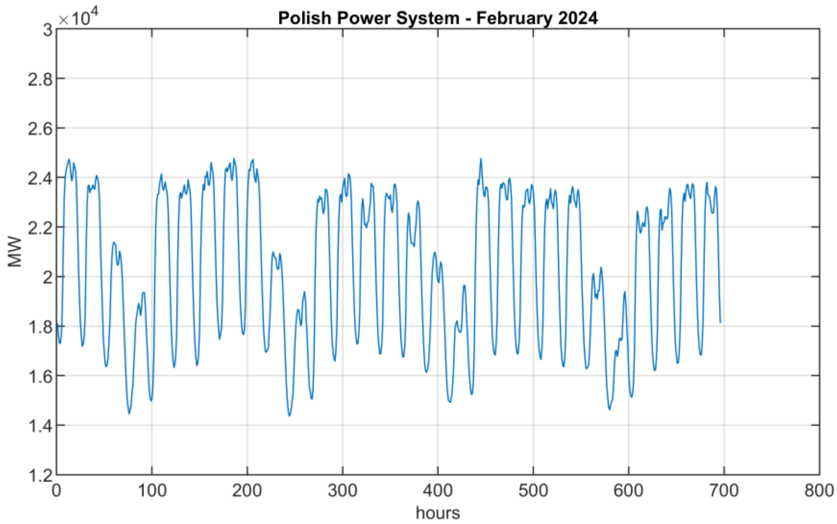

Fig. 3. Power demand in Polish Power System in February 2024 (696 hours)

The whole data set was divided for learning data (80%) and testing data (20%). Time series of true power demands in Polish Power System are presented in Fig. 1, Fig. 2, Fig. 3 corresponding to the three succeeding months. In Fig. 1 we can see significant irregularity of the curve shape for specific days of the month, especially the 24th, 25th, 26th and 31st December which are holidays. Such irregularity occurs also in two specific days in January – 1st and 6th (Fig. 2). These irregularities increase the difficulty of power forecasting. On the other hand, February (Fig. 3) is an example of a month without specific holiday breaks.

Statistical values of power demands in Polish Power System of the analysed period have been presented in Table 1. The highest standard deviation was calculated for December (3773 MW, which is 18,5% of the mean value) and the lowest for February (2950 MW, which is only 14,5% of the mean value). The range of data in December (14923 MW) and in January (15596 MW) is higher than the minimum power demand in corresponding months, which makes forecasting even more difficult.

Table 1. Statistical values of power demand in Polish Power System (PPS) calculated for three succeeding months

Month	Power demand in PPS [MW]				
	Minimum	Mean	Maximum	Range (max-min)	Standard deviation
December 2023	12183	20437	27106	14923	3773
January 2024	12708	21470	28304	15596	3573
February 2024	14369	20285	24777	10408	2950

3. RESEARCH METHOD AND ACCURACY METRICS

The LSTM was developed by Hochreiter and Schmidhuber [8, 9, 10]. It belongs to the group of recurrent networks (RNN). The signal from the input layer is propagated through the hidden layer with mutual feedback between the neurons (Fig. 4). Recurrent neural networks use quite different feedback loops than feedforward networks (FNN), such as MLP.

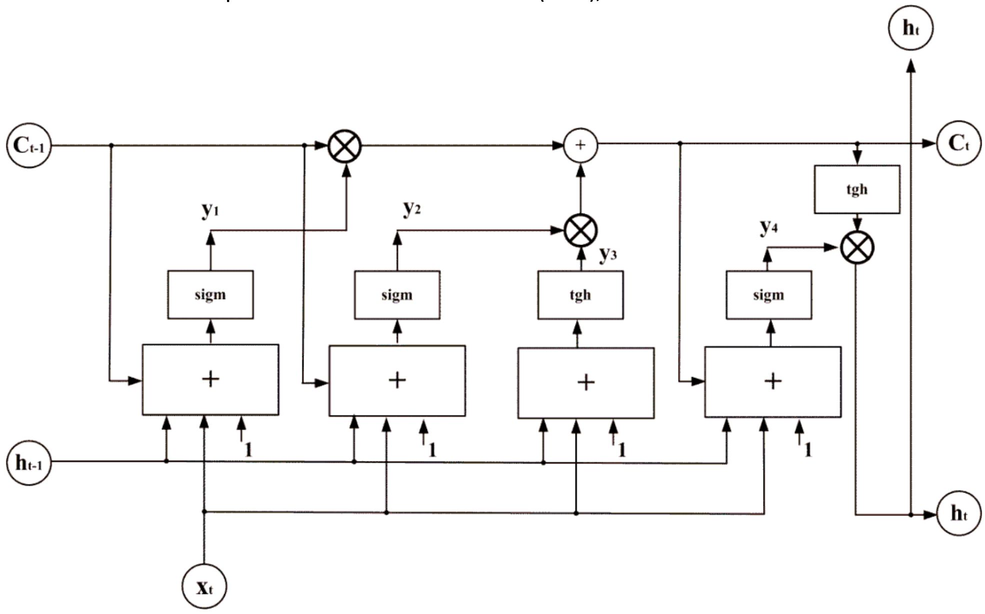

Fig. 4. The general structure of single LSTM cell [7]

In structure of single LSTM cell, $\mathbf{x}_t$ is the vector of input signals in the time point *t,* C_{t-1} and C_t represent cell states in the previous *t*-1 and actual *t* time points, h_{t-1} and h_t are output signals of the cell in *t*-1 and *t* time points, respectively, 1 represents the bias. The symbol **×** represents the multiplication and **+** is the summation of signals [7].

To analyse the forecast model performance, several metrics are commonly used [5, 15, 16], such as mean absolute percentage error (MAPE) (1):

$$\mathrm{MAPE} = \frac{1}{n}\sum_{h=1}^{n}\frac{|T(h) - P(h)|}{T(h)} \cdot 100\% \tag{1}$$

mean absolute error (MAE) (2):

$$\mathrm{MAE} = \frac{1}{n}\left(\sum_{h=1}^{n}|T(h) - P(h)|\right) \tag{2}$$

and root mean square error (RMSE) (3):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{h=1}^{n}(T(h) - P(h))^2} \tag{3}$$

where: $T(h)$ represents the true value of the hth hour, $P(h)$ is the corresponding value predicted by the system, and n is the number of hours taking part in the testing stage. In the case of an ensemble of predictors, the MAPE value of the ensemble ($\mathrm{MAPE_{ens}}$) is calculated differently (4):

$$\mathrm{MAPE_{ens}} = \frac{1}{p}\sum_{i=1}^{p}\frac{|y_m(i) - d(i)|}{d(i)} \cdot 100\% \tag{4}$$

where p represents the number of hours for which the predictions were made, $y_m(i)$ is the mean of values predicted for an ith hour by all members of the ensemble, and $d(i)$ is the true value of the load at the ith hour [12]. The fifth accuracy measure presented in the article is the Pearson correlation coefficient R.

4. Results of numerical experiments

The introductory experiments allowed to select the best hyperparameters of the network. The adaptive moment estimation (Adam) method was used in the research. This approach combines momentum and root mean square propagation (RMSProp), as the optimization method [4]. Different values of: hidden neurons (from 80 to 220), initial learning rate in Adam (from 0.003 to 0.008), learning rate drop factor (from 0.25 to 0.75) were tried in this stage of experiments. The arrangement of the best performing network setting was selected in this way. The number of hidden neurons was chosen randomly: from 80+50*rand(1) to 220+50*rand(1), initial learning rate in Adam equal to 0.005, learning rate drop factor equal to 0.5, and 80 learning cycles were found sufficient.

Statistical results of the numerical experiments for the case of five individual predictors have been presented in Table 2. The best results obtained at this stage were: MAE=(354.63±26.69) MW at 200+50*rand(1) hidden neurons of LSTM network, RMSE=(446.21±28.20) MW and R=(0.989±0.001) at 220+50*rand(1) hidden neurons and MAPE=(1.77±0.16)% at 180+50*rand(1) hidden neurons.

Table 2. Statistical results of numerical experiments in in the case of individual predictors and five repetitions of experiments (testing data cover 20% of the year)

Number of hidden neurons of individual networks	MAE (mean ± std.) [MW]	RMSE (mean ± std.) [MW]	MAPE (mean ± std.) [%]	R (mean ± std.)
80+50*rand(1)	407.0042 ±56.5699	504.9762 ±60.0824	2.0151 ±0.2772	0.9846 ±0.0033
100+50*rand(1)	406.8114 ±43.8146	511.7893 ±60.4941	2.0091 ±0.2150	0.9841 ±0.0040
120+50*rand(1)	390.9952 ±32.2848	484.1646 ±36.3398	2.3702 ±0.1479	0.9861 ±0.0024
140+50*rand(1)	358.9266 ±20.8421	459.1525 ±20.7351	1.7782 ±0.1136	0.9874 ±0.0009
160+50*rand(1)	377.8686 ±28.2228	474.1553 ±31.6932	1.8810 ±0.1312	0.9869 ±0.0019
180+50*rand(1)	355.5840 ±29.7334	457.2248 ±28.1207	**1.7663 ±0.1556**	0.9888 ±0.0011
200+50*rand(1)	**354.6292 ±26.6929**	450.8896 ±30.3972	1.7780 ±0.1328	0.9884 ±0.0014
220+50*rand(1)	355.0559 ±25.6143	**446.2129 ±28.1983**	1.7814 ±0.1306	**0.9891 ±0.0011**

The application of the ensemble significantly improved the accuracy of the forecasting. The accuracy measures of the ensemble have been presented in Table 3. The best results obtained were: MAEens=319.59 MW, RMSEens=410.18 MW, MAPEens = 1.59% at 200+50*rand(1) hidden neurons and Rens=0.9899 at 220+50*rand(1) hidden neurons.

Sample results of the ensemble model performance for the testing data, not involved in training, were presented in Fig. 5. Upper plot shows real and predicted demand curves which are well-fitted in whole tested period, covering 436 hours. The lower plot presents errors calculated in MW, for every hour of testing period. The differences do not exceed the value of 1500 MW for a single hour.

Table 3. Statistical results of prediction of the ensemble composed of five members of the prediction model (testing data cover 20% of the year)

Number of hidden neurons in ensemble of predictors	MAE_{ens} [MW]	$RMSE_{ens}$ [MW]	$MAPE_{ens}$ [%]	R_{ens}
80+50*rand(1)	391.4793	480.9653	1.9342	0.9859
100+50*rand(1)	385.3509	475.7166	1.8946	0.9862
120+50*rand(1)	364.0612	453.0392	1.7919	0.9875
140+50*rand(1)	339.9565	434.2687	1.6778	0.9885
160+50*rand(1)	351.8599	441.3109	1.7427	0.9882
180+50*rand(1)	325.1296	421.9777	1.6070	0.9897
200+50*rand(1)	**319.5870**	**410.1765**	**1.5867**	0.9898
220+50*rand(1)	320.7967	410.4573	1.5973	**0.9899**

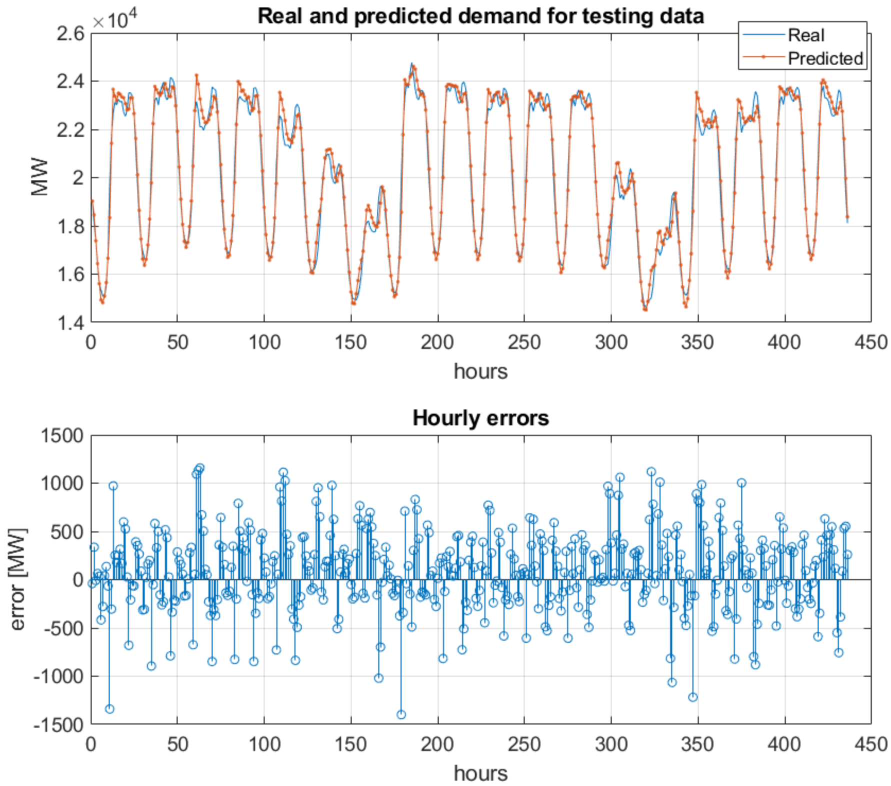

Fig. 5. Real and predicted power demand in Polish Power System for testing data (plot at the top) and hourly prediction errors (plot at the bottom), calculated for the ensemble model

The learning and testing research was performed using a laptop with Windows 10 64-bit operating system with the following parameters: CPU: Intel Core i7-6700HQ 2.60 GHz, GPU: Nvidia GeForce 940MX, RAM memory: DDR4-2133 16 GB, disk: HDD 1 TB. All experiments were conducted using the MATLAB R2023b computing environment [14].

5. CONCLUSIONS

The paper has presented a study concerning electrical power time series prediction based on its historical values with time horizon of 1-hour ahead power value. The results of numerical experiments confirmed the high performance of the LSTM networks in the task of forecasting the power demands in Polish Power System, assuming limited availability of the input data covering only 3 months. The application of an ensemble increases the accuracy, compared to the individual predictors. The MAPE error decreased from 1.77% for individual predictors to 1.59% for the ensemble, at different number of hidden neurons.

Further research will examine power forecasting for even shorter time horizon, using series of neural methods. The proposed method may also find application for prediction of renewable energy sources such as wind or photovoltaic. The system can be expanded by adding new input attributes such as atmospheric parameters.

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