Electricity consumption forecasting using neural networks for low-carbon power systems planning

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Abstract. Power systems require the continuous balance of energy supply and demand for their appropriate functioning, which makes electricity forecast a necessary process for the successful planning of operation and expansion of modern power systems, especially with the increase of renewable energy resources to be accommodated in order to realize low-carbon power systems. The task of predicting electricity consumption is complex because electricity demand patterns are intricate and involve various factors such as weather conditions. Recurring Neural Networks (RNN), such as Long Short-Term Memory (LSTM) networks, can learn long sequence patterns and make multi-step forecasts at once considering several variables, which can be especially useful for time series forecasts such as electricity consumption. This paper presents the application and assessment of a multivariate multi-step times series forecasting model based on LSTM neural networks for short-term prediction of electricity consumption using a dataset that encompasses data on energy load and meteorological elements from Belgorod Oblast in Russia as a case study.

1 Introduction

Forecasting electricity consumption is necessary to adequately balance supply and load demand in modern power systems and, therefore, to plan operations and infrastructure expansion [1], especially in the context of the current transformation of the energy sector aiming at realizing low-carbon or carbon-neutral power systems with high penetration of variable renewable energy and large electrification of energy loads, as a major strategy of climate change mitigation.

The appropriate forecast of electricity consumption in power systems is essential for the effective application of demand response programs and demand-side flexibility strategies to balance supply and demand allowing higher participation of variable renewable generation in the energy mix.

The prediction of electricity consumption can be defined as time series forecasting problem [2] where the complexity of temporal dependence between observations is considered and the estimation of future loads is made based on previous data. Conventional time series forecasting methods focus on single-variable data with linear relationships and static dependence [3]; neural networks offer the capability to learn and approximate arbitrary non-linear functions supporting multivariate and multi-step forecasting [4], and especially Recurrent Neural Networks (RNN) could handle ordered observations and learn time-dependent context.

In this order, Long Short-Term Memory (LSTM) networks, a type of RNN, are claimed to be able to automatically learn the characteristics and patterns of the time series dataset, supporting multiple variables to generate multi-step predictions [3]. To confirm this assumption, we applied and assessed a time series forecasting model based on LSTM for the prediction of electrical energy consumption using past sequences of consumption data as well as past weather conditions records. A set of real data from Belgorod Oblast, in Russia, is used as a case study and this paper presents the results obtained.

2 Methodology

To evaluate the suitability and performance of RNN for power consumption prediction, an LSTM forecasting model [5] has been adapted and applied to a dataset of actual power consumption and weather conditions over a year from the Belgorod Oblast to make predictions on consumption for the following 24 hours using the previous 72 hours. The model is developed using Python and Keras, a deep learning application programming interface (API) that runs on top of the TensorFlow machine learning platform [6].

This is a multivariate multi-step time series forecasting problem and it is defined by the following function:

$$[Y_t, Y_{t+1}, \ldots, Y_{t+n-1}] = f\,(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}, X_{t-1}, X_{t-2}, \ldots, X_{t-p}) \quad (1)$$

where Y is a variable to be predicted n steps (hours) ahead using data from the previous p hours. In this case, Y is the power load; X represents the weather variables

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that influence the value of Y, in this case, air temperature, atmospheric pressure, humidity, and day length; n is 24 hours, and p is 72 hours.

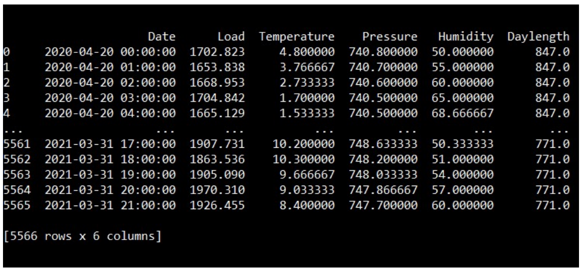
There are several stages in our time series forecasting analysis:

1. Data visualization and preparation for the model
2. LSTM model definition and fitting
3. Model training and testing
4. Future forecasting beyond the dataset

2.1. Data visualization and preparation

Belgorod Oblast is a constituent entity of the Russian Federation with an area of 27134 km2. The power load dataset was collected every hour from 2020.20.04 to 2021.03.31 (working days). Data on weather characteristics were collected at the meteorological station located at Belgorod International Airport [7], 4 km north of Belgorod city, the administrative center of Belgorod Oblast. The dataset includes the hourly past values of air temperature (°C), atmospheric pressure (mmHg), and humidity (%). Lastly, the dataset also integrates day length, in minutes, for each day for the city of Belgorod [8].

There are a total of 5566 data points and Figure 1 shows the first and last rows of the dataset.



	Date	Load	Temperature	Pressure	Humidity	Daylength
0	2020-04-20 00:00:00	1702.823	4.800000	740.800000	50.000000	847.0
1	2020-04-20 01:00:00	1653.838	3.766667	740.700000	55.000000	847.0
2	2020-04-20 02:00:00	1668.953	2.733333	740.600000	60.000000	847.0
3	2020-04-20 03:00:00	1704.842	1.700000	740.500000	65.000000	847.0
4	2020-04-20 04:00:00	1665.129	1.533333	740.500000	68.666667	847.0
...	...	...	...	...	...	...
5561	2021-03-31 17:00:00	1907.731	10.200000	748.633333	50.333333	771.0
5562	2021-03-31 18:00:00	1863.536	10.300000	748.200000	51.000000	771.0
5563	2021-03-31 19:00:00	1905.090	9.666667	748.033333	54.000000	771.0
5564	2021-03-31 20:00:00	1970.310	9.033333	747.866667	57.000000	771.0
5565	2021-03-31 21:00:00	1926.455	8.400000	747.700000	60.000000	771.0

[5566 rows x 6 columns]

Fig. 1. Electrical load, air temperature, atmospheric pressure, humidity, and daylength dataset - Belgorod Region.

Figure 2 presents all the data points representing the hourly power load throughout the year, and Figure 3 shows the data points representing day length. Introducing the daylength dataset into the forecasting model, allows the system to consider the seasonal fluctuations in electricity demand, as demand is generally higher in winter than in summer.

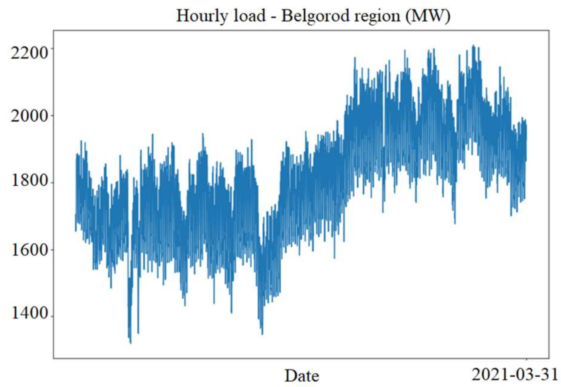


Fig. 2. Hourly power load for the past year – Belgorod Region.

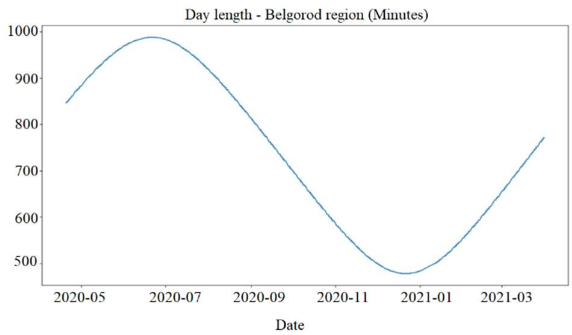


Fig. 3. Daylength in minutes for the past year - Belgorod Region.

The dataset must first be divided into a training set and a testing set. 90% of the datapoint will be used for training the model, and then the model should forecast the remaining 10% to be compared with the real values in the testing set and evaluate the performance.

```
test_share = 0.1 # testing share:
10% of dataset
```

The input to an LSTM model is a three-dimensional array: (Samples, Timesteps, Features).

– Samples are the total number of sequences built for training.
– Timesteps is the time length of each sample.
– Features are the number of variables used in the model.

In this case, the model uses 5 variables which are power load, temperature, pressure, humidity, and daylength. Since the total number of data points is 5566 and 72 hours back are used to produce each 24-hour forward prediction, the input training data shape is as follows:

- Shape of training data: (4923, 72, 5)
- Shape of the output data: (547, 24)

Training samples = (5566 – 72 – 24) * 90% = 4923
Output samples = (5566 – 72 – 24) * 10% = 547

2.2 LSTM Model Definition and Fitting

2.2.1 Selecting the model hyperparameters

The LSTM model is defined to use 10 neurons for 19 training epochs with a batch size of 8. A batch is a set of samples (size) that the RNN process, after which the model weights are updated, in other words, the model makes predictions for each sample in the batch, calculates the error by comparing the prediction to the actual value, estimates an error gradient and the weights are updated. An epoch involves one pass over the entire training set [3]. In this case, one epoch is comprised of 597 batches.

```
epochs = 19
batch_size = 8
n_layer = 10
lag = 72 #hours back for making each
24-hour prediction
n_ahead = 24 #24-hour ahead
prediction
```

2.2.2 Defining the model

The model uses the Adam optimization algorithm to update the network weights based on the training data in an iterative process. To evaluate the operation during training and testing, the model uses Mean Absolute Error (MAE) loss function [9]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

where y_i and $\hat{y}_i$ are the actual value and predicted value at time t; n is the total number of data points used. MAE provides the average of the absolute values of the individual prediction errors for all data points in the testing set.

```
empty_model = self.model
optimizer = keras.optimizers.Adam()
empty_model.compile(loss=losses.Mean
AbsoluteError(),
optimizer=optimizer)
```

2.3 Model Training and Testing

Once the model is trained using the 90% of data points, i.e., the training set, the performance is evaluated by forecasting the remaining 10% of data and comparing the predictions against the actual values in the testing set of data. For this, the model calculates the Root Mean Square Error (RMSE) metric [9]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

where y_i and $\hat{y}_i$ are the actual load and predicted value at time t; n is the total number of data points used. RMSE provides the spread of the prediction errors.

2.4 Future forecasting

After applying the model to make predictions against the testing set and evaluating its performance, the model now should study the entire dataset to forecast the future, 24 hours forward beyond the time frame of the dataset, as developed in other applications of LSTM models [10]. The model is then also trained and applied to predict electricity consumption for one week beyond the timeframe.

3 Results

3.1. Training and testing result

Figure 4 shows the energy consumption forecast plot against actual consumption values after training and testing. Figure 5 shows the curves of losses for each epoch during the training and testing processes.

It can be seen how the loss curves converge and tend to 0.27. The model can be tuned by changing the hyperparameters according to the train and test loss curves to avoid overfitting or underfitting the model, i.e., learning random noise during training or not learning enough of the sequence pattern structure, thus affecting the prediction.

The model also calculates the RMSE and a value of 0.285 is obtained. When training and testing the model for a one-week prediction, a RMSE equal to 0.314 is obtained.

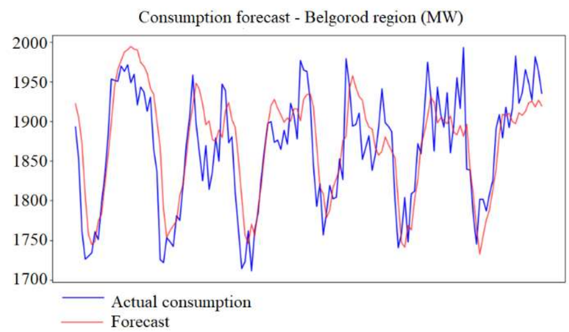


Fig. 4. Electricity consumption forecast against actual consumption dataset - Belgorod Region.

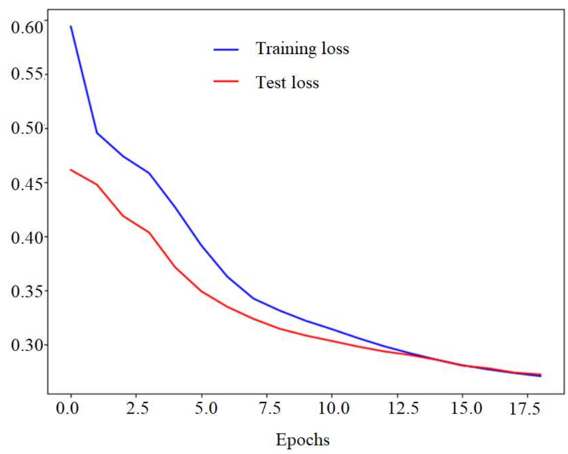


Fig. 5. Training and test loss over the epochs.

3.2. Future forecasting result

Finally, Figure 6 shows the curve obtained when applying the model to forecast electricity consumption 24-hours forward beyond the time frame of the dataset.

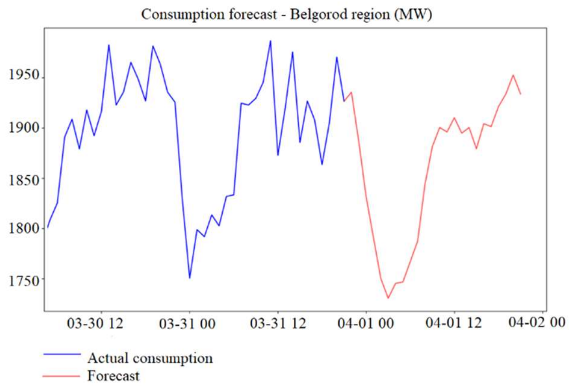


Fig. 6. 24-hour ahead electricity consumption forecast beyond dataset.

LSTM-based neural networks have short-term and long-term learning capabilities, making them suitable for short-term time series prediction applications taking into account the seasonal fluctuations and trends of electricity consumption. The data handling with a LSTM model is simple and can surpass other traditional forecasting methods explored [11]. The use of the TensorFlow software library for machine learning with Python, with the option to modify the training features for the given dataset, allows the improvement of the accuracy of the LSTM forecasting model presented. Future work should include applications with the use of longer datasets and for specific types of consumers, such as commercial buildings, hospitals, or universities.

4 Application Programming Interface

In addition, an Application Programming Interface (API) has been built with the use of Postman Platform [12] to be able to access the dataset of power load over the internet, build the forecasting model, run the model, test it, and create a power consumption forecast.

Using the API, it is also possible to update the dataset when new electricity consumption data have been added and create a new forecasting model with the updated dataset. Figure 7 shows the interface of the API.

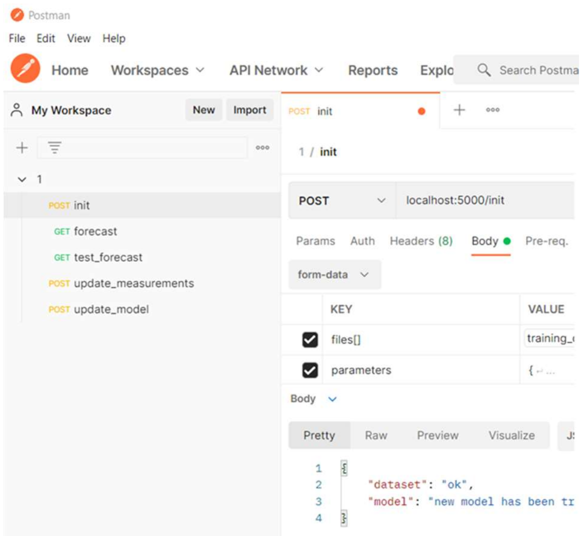


Fig. 7. Application Programming Interface (API).

5 Conclusion

Neural Network models based on Long Short-Term Memory (LSTM) architecture can accommodate multivariate multi-step time series forecasting problems with suitable results and can be used as short-term electricity consumption prediction techniques. An analysis of a 24-hour ahead electricity consumption forecast methodology using LSTM is carried out using a year-long dataset of hourly power load and weather conditions; the results obtained demonstrate that the proposed LSTM model offers valuable prediction results, and the methodology could be used to develop more specialized electricity consumption forecasting models required by modern power systems nowadays.

Adequate electricity consumption forecasting is essential to achieve the power balance in energy systems with high integration of renewable energy sources, in the context of the current transformation of power systems based on fossil fuels to low-carbon systems to achieve climate change mitigation targets.

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