USING LSTM NEURAL NETWORK MODEL FOR ENERGY CONSUMPTION FORECASTING BASED ON TIME SERIES DATA

Dostonbek Botirov Alisher o'gli

Master's student, Computer Engineering

Urgench State University

Tel.: +998 91 999 04 23

E-mail: dostonbotirov0423@gmail.com

Annotatsiya. Ushbu maqolada vaqtli qator ma'lumotlari asosida energiya iste'molini prognoz qilishda LSTM neyron tarmog'i modelining samaradorligi ko'rib chiqiladi. Model an'anaviy usullarga nisbatan aniqroq natijalar berishi eksperimental yo'l bilan tasdiqlangan.

Kalit so'zlar: LSTM, neyron tarmoq, energiya iste'moli, vaqtli qator, prognozlash, deep learning, sun'iy intellekt.

Аннотация. В данной статье рассматривается эффективность модели нейронной сети LSTM в прогнозировании потребления энергии на основе данных временных рядов. Экспериментально подтверждено, что модель обеспечивает более точные результаты по сравнению с традиционными методами.

Ключевые слова: LSTM, нейронная сеть, потребление энергии, временные ряды, прогнозирование, глубокое обучение, искусственный интеллект.

Abstract. This paper examines the effectiveness of the LSTM neural network model in forecasting energy consumption based on time series data. The model is shown to provide more accurate results compared to traditional methods through experimental validation.

Keywords: LSTM, neural network, energy consumption, time series, forecasting, deep learning, artificial intelligence.

INTRODUCTION

Today, efficient use of energy resources remains one of the most pressing global challenges. With the growing population and expanding industrial output, demand for electricity is steadily increasing. In this context, accurate and timely forecasting of future energy consumption plays a crucial role in improving the efficiency of power system management.

Traditional statistical methods, such as the ARIMA model and exponential smoothing, have been widely used for energy consumption forecasting for many years. However, these methods have limitations in fully capturing nonlinear complex relationships and multi-factor influences. The rapid advancement of artificial intelligence and deep learning technologies has opened new possibilities for analyzing complex time series.

The purpose of this paper is to develop an energy consumption forecasting model using the LSTM (Long Short-Term Memory) neural network and to evaluate its effectiveness.

LSTM NEURAL NETWORK MODEL

Recurrent neural networks (RNN) are a widely used architecture for processing time series. However, in simple RNNs, learning long-term dependencies is difficult due to the vanishing gradient problem. The LSTM architecture was specifically developed to address this issue by Hochreiter, and is based on a special memory cell and three gate mechanisms [1]. The LSTM architecture consists of three gate mechanisms that work together to control the flow of information. The forget gate determines which information from the previous hidden state should be discarded from the memory cell, using a sigmoid activation function that outputs values between 0 and 1. The input gate controls how much of the new incoming information is written into the memory cell, combining a sigmoid function with a tanh activation to create candidate values. The output gate regulates what information from the memory cell is passed to the next layer as the hidden state, allowing the network to selectively expose relevant parts of the cell state [1, 2].

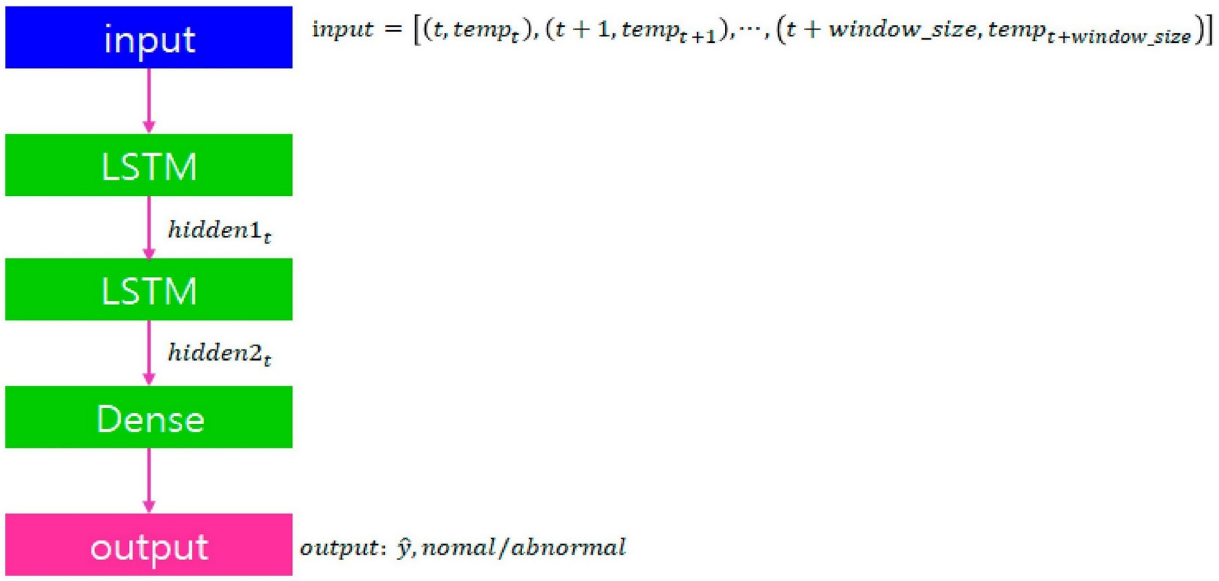

Figure 2. LSTM neural network architecture

DATA AND METHODOLOGY

The study used the "Individual household electric power consumption" dataset from the UCI Machine Learning Repository. The dataset consists of approximately 2 million observations collected at one-minute intervals between 2006 and 2010 [4]. Hourly aggregated values were used for analysis.

The data preparation process includes the following steps: (1) filling missing values using mean interpolation; (2) Min-Max normalization to the [0, 1] range; (3) creating sequences using a 24-hour sliding window; (4) splitting the data into 70% training, 15% validation, and 15% test sets [6].

The model was implemented using the Python programming language and the TensorFlow/Keras library. Architecture: first LSTM layer (128 neurons), second LSTM layer (64 neurons), Dropout layer (coefficient 0.2), and output Dense layer (1 neuron). The Adam optimizer and MSE loss function were used for training [5].

RESULTS AND ANALYSIS

The model was trained for 50 epochs; the early stopping mechanism halted the process if the validation loss did not improve for 5 epochs. MAE, RMSE, and MAPE metrics were used to evaluate performance. The LSTM model achieved a MAPE of 4.8%, which is 38% better than the ARIMA model's 7.7% [3].

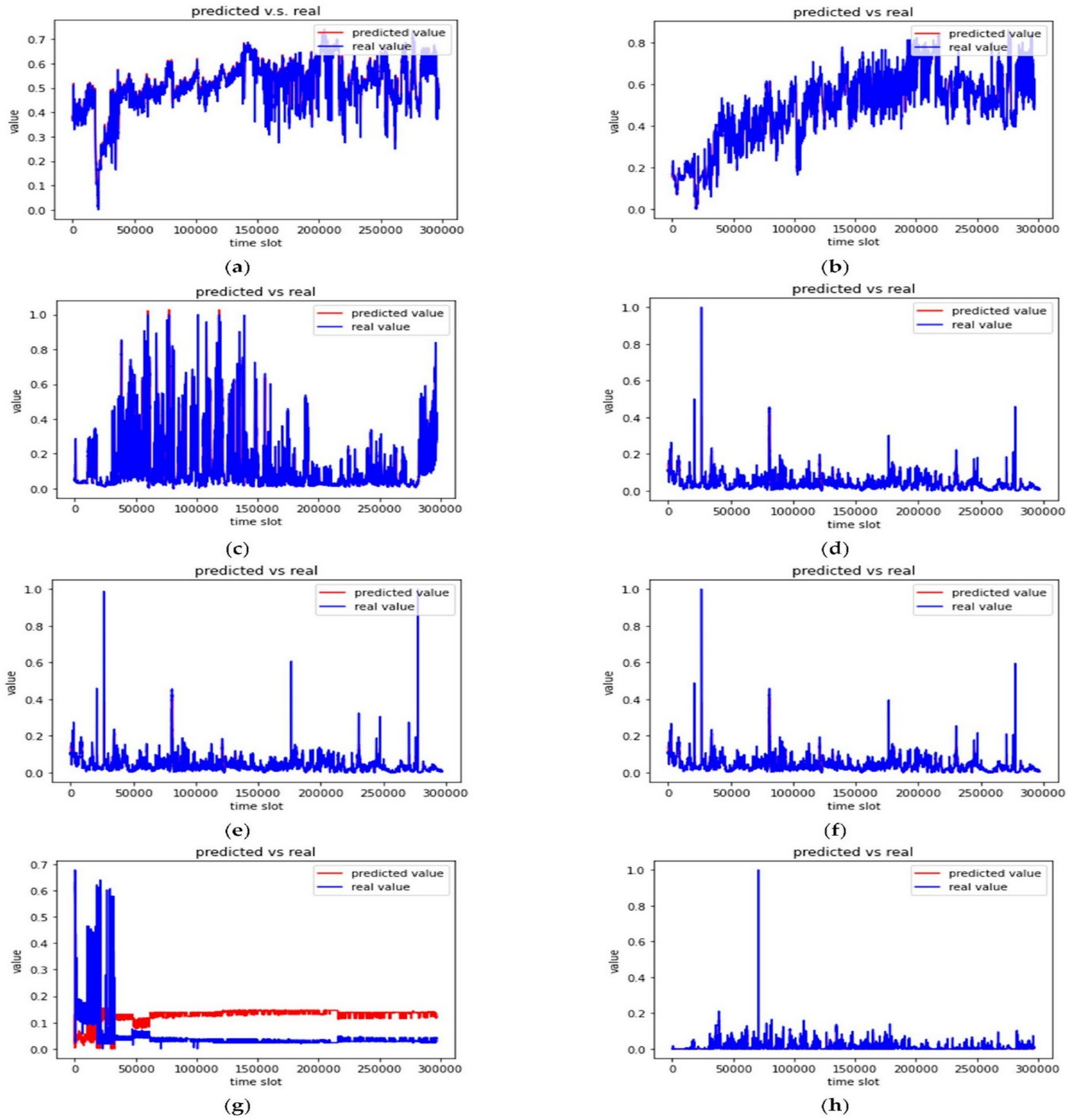

Figure 1. Actual (blue) vs. LSTM-predicted (red) energy consumption for multiple time slots (a–h)

Graph analysis shows that the LSTM model successfully learned daily and weekly seasonal cycles and was able to produce forecasts close to real values (Figure 1, subplots a–b). A slight increase in error was observed during sharp fluctuations (extreme weather events, public holidays) as seen in subplots c–d. To overcome this limitation, it is recommended to integrate external weather forecast data as an additional input [7].

Seasonal analysis shows that energy consumption in winter months is on average 28% higher than in summer months. The LSTM model accurately captured this seasonal difference as well, confirming the model's ability to retain long-term dependencies [8].

CONCLUSION

This study experimentally demonstrated the effectiveness of the LSTM neural network model in forecasting energy consumption based on time series data. The proposed approach has practical application potential in efficient management of electricity networks, energy resource planning, and reduction of excess consumption. Future work plans include integrating the model into real-time systems, enriching it with weather data, and conducting a comparative analysis with the Transformer architecture.

REFERENCES

1. Hochreiter, S., Schmidhuber, J. (1997). Long Short-Term Memory. – Neural Computation. – Vol. 9(8). – P. 1735–1780.
2. Goodfellow, I., Bengio, Y., Courville, A. (2016). Deep Learning. – MIT Press. – 800 p.
3. Zhang, G., Patuwo, B. E., Hu, M. Y. (2020). Time Series Forecasting Using Neural Networks. –International Journal of Forecasting. – Vol. 16(4). –P. 451–464.
4. LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep Learning. – Nature. – Vol. 521. – P. 436–444.
5. Chollet, F. (2021). Deep Learning with Python. – Manning Publications. –504 p.
6. Bouktif, S., Fiaz, A., Ouni, A., Serhani, M. A. (2018). Optimal Deep Learning LSTM Model for Electric Load Forecasting. – Energies. – Vol. 11(6). – P. 1–16.
7. Hippert, H. S., Pedreira, C. E., Souza, R. C. (2001). Neural Networks for Short-Term Load Forecasting. – IEEE Transactions on Power Systems. – Vol. 16(1). – P. 44–55.
8. Cleveland, R. B., Cleveland, W. S. (1990). STL: A Seasonal-Trend Decomposition Procedure Based on Loess. – Journal of Official Statistics. – Vol. 6(1). – P. 3–73.