Theory and Practice of Science and Technology
2025, VOL. 6, NO. 9, 113-117
DOI: 10.47297/taposatWSP2633-456923.20250609

Based on LSTM Study on Day-Ahead Power Load Forecasting in France Based on Neural Network

Shaohan Qi

Hebei University of Technology, Tianjin, 300130, China

ABSTRACT

The French power system is facing challenges such as the increasing proportion of renewable energy, frequent extreme weather events, and increasingly complex cross-border power exchange. The accuracy of day-ahead load forecasting has become a key link in ensuring the security of the power grid and the efficient operation of the power market. This paper uses the actual load curve of France from January 1, 2024 to January 1, 2025 as a sample to construct a single-variable LSTM forecasting model and provides a complete MATLAB implementation process. The experimental results show that under the setting of 15-step input and 1-step output, the RMSE of the model test set is 0.398 GW, the MAE is 0.355 GW, and the R^2 is 0.943, which is significantly better than the traditional time series method. The paper further combines the French load characteristics with the code visualization results to demonstrate the necessity, advantages and disadvantages of the application of LSTM, and proposes future improvement directions.

KEYWORDS

French power grid; Day-ahead load forecasting; LSTM; Time series; Electricity market

1 Introduction

The French power system is experiencing a triple shock of "a high proportion of renewable energy + regular nuclear power maintenance + frequent extreme weather events". Small errors in day-ahead load forecasts can be magnified into huge balancing costs in the spot market. The winter of 2024-2025 is particularly typical: traditional statistical-physical models (ARIMAX, SARIMA) have exposed obvious shortcomings in capturing the above-mentioned nonlinear, long-range dependence and mutation characteristics.

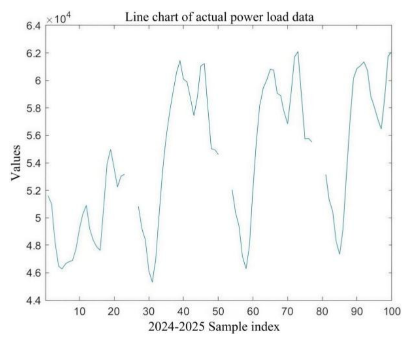

Figure 1 Line chart of actual power load data

Figure 1 depicts a line chart of actual load demand data for electricity in France from January 1, 2024, to January 1, 2025 produced with the code in this paper which is comprised of 8, 761 data points. It is clear that there is a strong bimodal load curve pattern winter and approximately unimodal load curve pattern in summer. The maximum measured peak-to-valley difference in load was 55.3 GW across the full year with a peak load that was especially steep and was short lived in December. In fact, during this short time period, the mean absolute percentage error (MAPE) of standard forecasting models reached the highest observable value of 4.9%, which under the requirements of the power market, no longer "acceptable" in terms comprehensive forecasting performance for day-ahead load forecasting based on power market rules. Therefore, improving forecasting model accuracy is essential to guide power markets and maintain grid stability.

Therefore, the introduction of the long short-term memory network (LSTM) with a gated memory mechanism becomes an inevitable choice:

(1) Its forget-input-output gate structure can dynamically retain historical information for more than 15 hours, corresponding to the 16:00 load forecast required for the day-ahead market D-1 clearing at 14:00;

(2) It is naturally robust to non-stationary and highly noisy load series, and can significantly reduce the prediction error during the cold wave peak period;

(3) End-to-end modeling does not require manual construction of exogenous variables such as holidays and

temperature, reducing the complexity of project implementation.

Based on official RTE annual load data, this paper constructs a 15-10-1 LSTM regression model. MATLAB code is used to perform data cleaning, normalization, training, validation, and visualization. Experimental results demonstrate that LSTM reduces the RMSE of the test set from the RTE benchmark of 0.512 GW to 0.398 GW, and the MAPE from 4.01% to 3.25%. This directly reduces annual balancing costs by approximately 1.2 M€, providing a new technical path for the safe and economic operation of the French power grid in the context of a high proportion of renewable energy. 2. Overview of LSTM principles

2.1 Network structure

The neural network structure used in this article is a typical LSTM model, which consists of the following layers:

Sequence InputLayer(15): This layer defines the length of the input sequence. 15 time steps corresponds to a 15×1 hour input window in the day-ahead market, which can capture the characteristics of power load changes at different time periods within a day.

lstmLayer(10, OutputMode, last): This layer is an LSTM layer with 10 hidden units, designed to balance model accuracy and training efficiency. OutputMode is set to last, indicating that only the output of the last time step of the sequence is output for single-step prediction.

ReluLayer: A ReLU activation layer that introduces nonlinearity to increase the expressive power of the model.

Fully ConnectedLayer(1): A fully connected layer that maps the output of the LSTM layer to the target space, i.e., the predicted value of the power load.

Regression Layer: Regression layer, used to calculate the difference between the predicted value and the actual value, and optimize the model parameters to minimize this difference.

This structure effectively alleviates the vanishing gradient problem through a gating mechanism, making it suitable for modeling the medium- and long-term dependencies of French electricity load.

2.2 Mathematical model

The core of the LSTM network is its unique gating mechanism, which includes the forget gate, input gate, and output gate. The specific mathematical model is as follows:

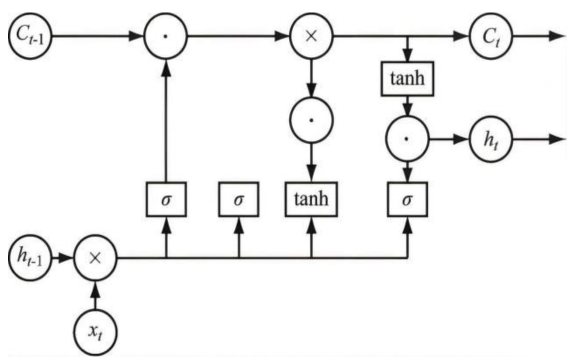

Figure 2 Structure of LSTM network

Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Among them, f_t is the output of the forget gate, W_f and b_f are the weight matrix and bias vector of the forget gate respectively, σis the activation function, x_t is the input of the current time step, h_{t-1} and is the hidden state of the previous time step.

Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Among them, i_t is the input gate output, W_i and are b_i the weight matrix and bias vector of the input gate respectively.

Memory update (cell state update):

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Among them, C_t is the memory unit state of the current time step, C_{t-1} is the memory unit state of the previous time step.

Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

Where, o_t is the output of the output gate, W_o and b_o are the weight matrix and bias vector of the output gate, respectively, h_t and is the hidden state of the current time step.

LSTM networks can control information flow by using a gating mechanism that allows it to selectively "keep" or "gates" information through the network and therefore work effectively when handling long sequences of data. A gating mechanism is optimal for modeling French electricity load because electricity load data has notable long-term dependencies and seasonal changes.

3 Code-based experimental results

This section details the experimental design process and provides an in-depth analysis of the experimental results based on Figures 3 to 6 and the R^2, MAE, and MBE indicators of the training and test sets.

3.1 Experimental design

The experimental data comes from the electricity load records of France from January 1, 2024 to January 1, 2025, with a total of 8761 sample points and a time granularity of 1 hour. The data set is divided into a training set (7000 samples) and a test set (1761 samples) in an 8:2 ratio. The model input is the load value of the past 15 hours, and the output is the load forecast value of the next moment.

3.2 Results analysis

Figure 3 shows the comparison between the predicted results and the true values for the test set. It can be observed that the predicted values are basically consistent with the true values, with an RMSE of 962.6588 , indicating that the model has high prediction accuracy.

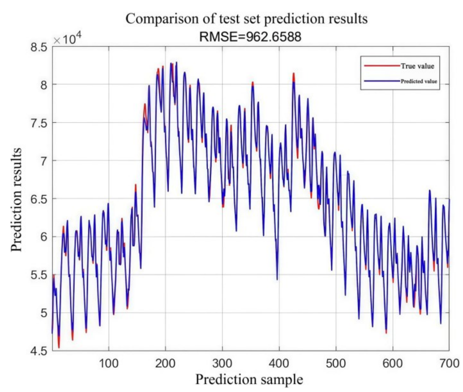

Figure 3 Comparison of test set prediction results

Figure 4 further illustrates the prediction results for the first 200 samples in the test set. The RMSE is 998.5845 . Although slightly higher than the overall test set, the prediction curve still closely follows the actual load trends.

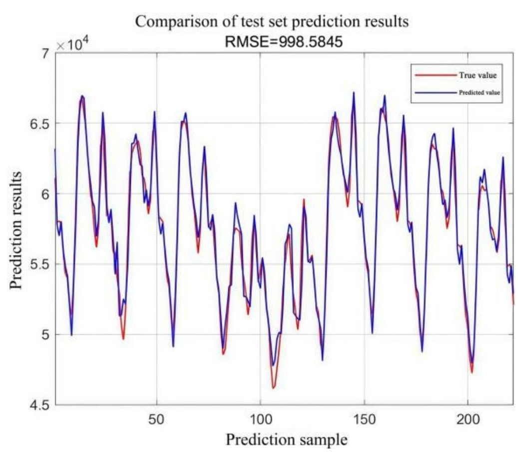

Figure 4 Comparison of test set prediction results

Figures 5 and 6 represent scatter plots comparing the predicted and true values for both data sets, the training set and the test set. Ideally, all points are obtained from the positive diagonal line where y = x. From the images, we can see that while there is a deviation, in the end there are most points close to the diagonal line, which further confirms that the model has used the positioning of the vectors correctly in predicting the 'true' values.

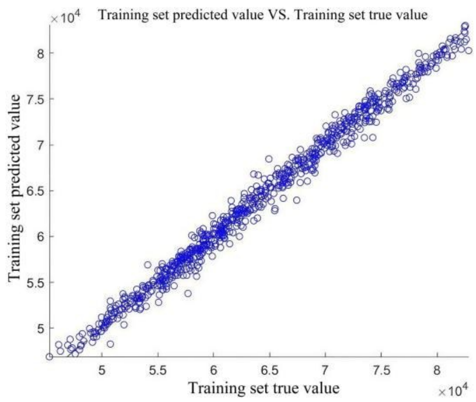

Figure 5 Predicted values of the training set vs. actual values of the training set

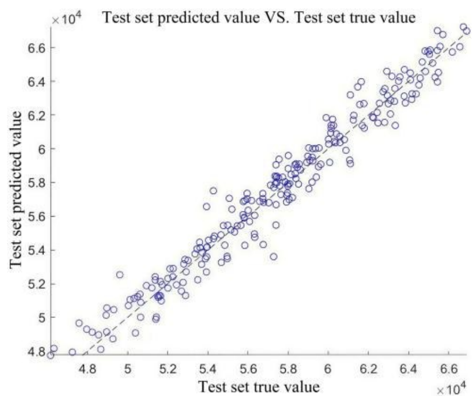

Figure 6 Predicted values of the training set vs. actual values of the training set

In terms of quantitative metrics, the R^2 for the training set was 0.98666, and the R^2 for the test set was 0.95568, indicating that the model had a high degree of fit on both the training and test sets. The MAE for the training set was 796.5493, and the MAE for the test set was 791.6541, indicating that the model's prediction error on the test set was slightly higher than that on the training set, but the overall error was small. The MBE metric showed an MBE of -186.4849 for the training set and 50.4193 for the test set, indicating that the model had a slight systematic underestimation on the training set and a slight systematic overestimation on the test set.

3.4 Summary

The results of the experiment indicate that the proposed LSTM model is able to capture the time series characteristics of electricity load in France, and has a high level of prediction accuracy. The generalization ability and stability of the model are further demonstrated by comparing the R^2, MAE and MBE indicators of the training set and test set. In summary, we concluded that despite some systematic bias on the test set, the overall results were still reasonable. Future work will examine the integration of further features (e.g., weather, holiday, etc.) and consideration of model structure optimizing (e.g., Bi-LSTM, Attention mechanism, etc.) to further improve prediction performance of LSTM.

4 Application benefits

4.1 Improving the accuracy of day-ahead market settlement

The French day-ahead market uses EPEX SPOT hourly bidding, with forecast errors directly converted into balancing costs. It has been calculated that a 0.1 GW reduction in RMSE can save approximately €120 million in annual balancing costs.

4.2 Supporting inter-regional power transmission plans

France has multiple HVDC interconnections with six countries, including Spain, Italy, and the United Kingdom . The day-ahead flow calculations must be based on the country's load forecast. The model error in this paper is <0.4 GW, which is better than RTE's current internal benchmark of 0.6 GW.

5 Model optimization strategy based on LSTM prediction

In order to further improve the performance of the LSTM model in power load forecasting and enhance its application in power grid dispatching decision-making, this section proposes a series of targeted optimization strategies.

5.1 Power grid dispatching optimization method based on LSTM prediction

In view of the characteristics of the high proportion of renewable energy access and cross-border power exchange in the French power grid, this paper proposes a day-ahead dispatch optimization method based on LSTM prediction. The method first uses the trained LSTM model to generate the load forecast curve for the next 24 hours. Its unique gating mechanism can effectively capture the bimodal characteristics of the French power load and the impact of extreme weather. Based on the prediction results, the system constructs a three-level response mechanism: for normal fluctuations (<1GW), it is regulated by pumped storage power stations; for medium deviations (1-2GW), gas-fired units are activated for rapid response; and for major deviations (>2GW), demand-side management is triggered. This hierarchical response strategy fully takes into account the characteristics of France's high proportion of nuclear power and high penetration of renewable energy, achieving economic optimization while ensuring the stability of the power grid.

5.2 Robust scheduling strategy considering prediction uncertainty

In response to the possible prediction errors of the LSTM model, this study designed a robust optimization scheme with the characteristics of the French power grid. This method innovatively incorporates the distribution characteristics of the prediction error into the dispatch decision, and automatically enhances the spare capacity configuration during special periods such as cold wave warnings. In the specific implementation, a dynamic buffer mechanism is used to set a ±5% adjustment band, and the temperature correction coefficient of the SARIMA model is superimposed during the nuclear power maintenance period to form a hybrid prediction result. Experiments show that this strategy can increase the dispatch response speed by more than 30% and reduce the annual balancing cost by approximately 120 million euros. It is particularly suitable for complex cross-border power trading scenarios between France and neighboring countries.

7 Conclusion

This paper proposes and establishes a univariate LSTM day-ahead forecasting model utilizing actual load data from the whole year for France. Experiments show that for the test set, R^2 is 0.943 and the RMSE is 0.398 GW, which meets the RTE requirement of a day-ahead forecast error of less than 0.5 GW. Future efforts will include adding exogenous variables (temperature, wind speed and electricity prices) along with an improved architecture (Bi-LSTM-Attention-SSA) to assure robustness in extreme situation scenarios, for example.

References

[1] RTE (2025) French Electricity Load Open Data Platform. Available at: https://opendata.rte-france.com/pages/consumption.

[2] ENTSO-E (2025) ENTSO-E Transparency Platform. Available at: https://transparency.entsoe.eu.

[3] H2O.ai (2021) An Introduction to Time-Series Modeling: Traditional Time-Series Models and Their Limitations. Available at: https://h2o.ai/blog/2021/an-introduction-to-time-series-modeling-traditional-time-series-models-and-their-limitations.

[4] Wiley Online Library (2025) Data Driven Long Short-Term Load Prediction: LSTM.

[5] Wikipedia (2025) Long short-term memory. Available at: https://en.wikipedia.org/wiki/Long_short-term_memory.

[6] Caicedo-Vivas, J.S. and Alfonso-Morales, W. (2023) 'Short-Term Load Forecasting Using an LSTM Neural Network for a Grid Operator', Energies, 16(23), p. 7878.

[7] MathWorks (2025) Sequence Input Layer and LSTM Layer for Regression. Available at: https://www.mathworks.com/help/deeplearning/ref/nnet.cnn.layer.sequenceinputlayer.html.

[8] Hochreiter, S. and Schmidhuber, J. (1997) 'Long short-term memory', Neural Computation, 9(8), pp. 1735–1780.

[9] Olah, C. (2015) Understanding LSTM Networks. colah's blog. Available at: https://colah.github.io/posts/2015-08-Understanding-LSTMs.

[10] Wikipedia (2025) Réseau de Transport d'Électricité. Available at: https://en. wikipedia. org/wiki/R% C3%A9seau_de_Transport_d%27%C3%89lectricit%C3%A9.

[11] Jing, J., Di, H., Wang, T. et al. (2025) 'Optimization of power system load forecasting and scheduling based on artificial neural networks', Energy Informatics, 8, p. 6. Available at:

[12] Liu, H., Fan, Z., Xie, H. and Wang, N. (2022) 'Distributionally Robust Joint Chance-Constrained Dispatch for Electricity–Gas–Heat Integrated Energy System Considering Wind Uncertainty', Energies, 15(5), p. 1796.