Short-term electricity price forecasting G-LSTM model and economic dispatch for distribution system

Zheng Lyu¹, Yushan Wang³³, Jiayu Wang¹, Lin Zhang¹, Jian Shen¹ and Xu Wang²

¹ Pudong Power Supply Company, State Grid Shanghai Municipal Electric Power Company;
² Key Laboratory of Control of Power Transmission and Conversion, Ministry of Education, Shanghai Jiao Tong University
³ Email: 896670390@qq.com

Abstract. In electricity market, electricity prices play an important role. The short-term electricity trading accounts for a large part in the market. Thus, this paper studied the short-term electricity price forecasting and proposed a new method -- G-LSTM (LSTM with error correction using GARCH model). Using this model, we achieve good performance on the LMPs (locational marginal prices) forecasting in the PJM power market. And based on our electricity price forecasting results, we calculate the ED (economic dispatch) plan of an IEEE 33-bus distribution system which contains wind power generation and photovoltaic power generation as an example.

1. Introduction
Since the appearance of power market, it has demonstrated its outstanding advantages, like introducing competition, improving efficiency, and promoting the rational use of resources. Electricity price is one of the key components in power market, and have a huge impact on the interests of multilateral market participants like power producers, consumers and energy trading centers. Therefore, electricity price forecasting is a significant task in power market.

There are many methods for electricity price forecasting at home and abroad. Literature [1] classifies and generalizes various electricity price forecasting methods, roughly divides these methods into: time series method, neural network method, wavelet prediction method and various combination methods. Also, many papers proposed these models in detail: the combination of wavelet transform and support vector machine [2], application of seasonal ARIMA model to short-term electricity price prediction [3], and literature [4] gives prediction model based on EEMD (Ensemble Empirical Mode Decomposition). But, compared with load forecasting, the volatility of electricity prices is larger, so the prediction accuracy of traditional prediction methods can hardly achieve a satisfactory result. In recent years, deep learning has been widely used in various fields and has demonstrated excellent performance in problem solving; for example, people use deep learning for image matching [5], text recognition in images [6], and the price forecasting can also take advantages of this technology. In deep learning technology, different numbers of neural network layers can provide different levels of abstraction to improve learning ability and task performance [7]. In this paper, we use the LSTM (long short-term memory) recurrent neural network (RNN), this model (RNN) was first introduced by
Hochreiter and Schmidhuber [8]. It showed good performance on the prediction of time series such as load, stock price, electricity price, etc.

In addition, under the background of the ubiquitous power Internet of things, it has gradually become a trend that new energy power generations access to the distribution system. Therefore, research on the economic dispatching problem of the distribution system containing new energy power generation is also a demand for power grid. Literature [9] introduces the optimal dispatching of active distribution network considering demand response, taking account of consumer psychology. Literature [10] uses genetic algorithm to deal with the optimal scheduling problem of regional microgrid. And literature [11] solved the security-constrained unit commitment problem in AC/DC transmission systems using linear programming.

In this paper, we first use the G-LSTM model to do electricity price forecasting and make a horizontal comparison on results of different models. Then we’ll use the predicted electricity price as the distribution system's electricity selling price, and then solve the economic dispatch or unit commitment problem using the modified IEEE 33-bus distribution system containing the photovoltaic and wind power generations.

2. Background study
This paper aims to improve electricity price prediction accuracy by studying the existing methods, and use the prediction results for solving economic dispatch or unit commitment problem.

Most of the existing studies on electricity price forecasting used time series method and wavelet prediction method such as wavelet transform combined with ARMA model [12]. While the literature [13] proposed an Adam-optimized LSTM prediction method combined with wavelet transform. Inspired by its thinking, this paper adds an error-correction model to the basic LSTM neural network, which further improves the prediction accuracy of the day-ahead electricity price. Our model has reference value for the future development of electricity price forecasting using neural network technology.

The examples in our paper select the PJM power market (Literature [14] introduces the PJM power market from many aspects) in America instead of the domestic power market. The main reasons are two:

1. The foreign power market has developed for longer time than the power market in China, so its market system is more consummate, the rules are clearer.
2. The PJM power market platform are open and transparent in load data, node electricity price and other data, which is conducive to select data for use in our research.

In the rest part of this paper, we’ll learn the rules of DA (day-ahead) hourly locational marginal prices (LMPs) and make prediction on it. Finally, we’ll solve the ED problem.

3. Data processing & model building

3.1. Data selection and processing
In the PJM power market, electricity price is settled using the node price and it doesn’t consider the system losses and congestion. In deep learning, the size of training set will have a great impact on the accuracy of the prediction model. Therefore, when we make selection among these nodes, it is necessary to select a node that has been operate for a long time — through our previous research and selection, we chose the node named TEXAS E (which named TEXAS2 before June 2006) and all LMPs data from its record began to February 2019 is selected.

For comparison, this paper also applies ARIMA model (Autoregressive Integrated Moving Average model), wavelet transform-ARMA model (Autoregressive moving average model) and EMD decomposition-ARMA model to do forecasting. The ARIMA/ARMA models requires stable time series data, and the stable time series can be expressed as follow in ARMA model:
\[ y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \\
\epsilon_t = \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \]  
(1)

where \( y_t \) and \( \epsilon_t \) are the actual value and the random error at time \( t \), \( \phi_i \) (\( i = 1, \ldots, p \)) and \( \theta_j \) (\( j = 0, 1, \ldots, q \)) are parameters; \( p \) and \( q \) are integers, which represent the order of the model.

We can judge whether the data is stable by observing the mean value, variance and auto-covariance of the time series. If the data is not stable, we can smooth it by differential operation. Equation (2) shows the first-order difference as an example, where \( Y_t \) is the original time series, \( Y_{t-1} \) is the sequence got by shifting \( Y_t \) back one time step on the time axis, and \( y_t \) is the new sequence after differential operation. As a specific explanation, if we have time series \( Y_t = [\cdot, 2, 3, 4, \cdot] \), then \( Y_{t-1} = [\cdot, 1, 2, 3, \cdot] \).

\[ y_t = y_t - y_{t-1} \]  
(2)

Based on previous research, when predicting the electricity price of multiple future time points using LSTM, it is more accurate to use the time-segment prediction method than the rolling prediction method. Thus, before build and train the neural network model, we should divide the training data into 24 groups and make normalization.

### 3.2. Construction of neural networks

Electricity price forecasting belongs to the "regression task" in deep learning. To solve this kind of problem, the learning algorithm needs an output function like:

\[ f : \mathbb{R}^n \rightarrow \mathbb{R} \]  
(3)

We know the RNN (Recurrent Neural Network) model is a structure that designed to deal with the modeling of time series. And LSTM (long short-term memory) is used to solve the shortcomings of gradient disappearance or gradient explosion in the simple RNN structure.

According to equation (3), we need to separate \( x \) and \( y \). \( x \) represents the input in \( \mathbb{R}^n \) space, \( y \) represents the output in \( \mathbb{R} \) space and \( n \) represents the value of "lookback". The relationship between input \( x \) and output \( y \) can be expressed as follow (\( n=3 \) as an example):

\[ y_{t+1} = w_1 x_t + w_2 x_{t-1} + w_3 x_{t-2} \]  
(4)

where \( w_n \) is the weight that will be adjusted during the training process.

Finally, we built a LSTM model in Python consisting of 7 layers: the input layer, the output layer, two dropout layers, two LSTM layers containing 16 neurons and one full-connected layer. The structure of our LSTM model is showed in Figure 1.

![Figure 1. Structure of LSTM neural network.](image)

### 3.3. GARCH model for error correction

ARCH (Autoregressive conditional heteroskedasticity model) model is a popular volatility modeling method. The GARCH model is the generalized ARCH model. When build an ARMA model for prediction, the difference between the real value and fit value is called the residual. By modeling the square of residual, the ARCH model is transformed into a GARCH (p, q) model:
Where the $\sigma^2_t$ represents the conditional heteroscedasticity, and $\varepsilon_t$ represents the residual of data at time $t$ in ARMA modeling.

If we want to build a GARCH model in Python, first we need to obtain a residual sequence $a_t$, then perform an ARCH effect test on $a^2_t$, and select parameters to build models when the sequence has ARCH effect, here ARCH effect was introduced in detail by literature [15]. Then the GARCH model will give us the square of the residual of the predicted values.

3.4. Algorithm and model of G-LSTM

Since the prediction accuracy of the neural network method is already high, it can largely reflect the true electricity price level. Therefore, we build two LSTM models with different precisions. In rest of our paper, we refer to the LSTM model with higher precision as Model A and the one with lower precision as Model B. Model B is used as the prediction model, model A is used as the reference model, and GARCH model is used as the correction model. The logic diagram is shown in Figure 2.

![Figure 2. Logical block diagram of G-LSTM.](image)

The logic of the comparison part is performed according to the following formula (6):

$$
\left\{ \begin{array}{l}
y_{\text{pre}} = Y_t + \varepsilon_t, \quad Y_t - y_t > Q \\
y_{\text{pre}} = Y_t - \varepsilon_t, \quad Y_t - y_t < -Q \\
y_{\text{pre}} = Y_t, \quad Q \geq Y_t - y_t \geq -Q 
\end{array} \right.
$$

where $Q$ is a threshold value.

4. Forecasting case analysis

All data in our paper is taken from the DA hourly electricity price of node TEXASE in the PJM market. Here we list the prediction results using the traditional prediction models in Table 1.

It can be seen from Table 1 that the most basic ARMA model and ARIMA model have relatively poor prediction accuracy. The ARIMA model combined with wavelet transform are not as accurate as we expect, but the trend of the predicted price change is basically the same as the actual price. The ARIMA model combined with EMD is more reasonable and precise.

In Table 2, we show the prediction results of the LSTM model and G-LSTM model. For further comparison and confirmation, a summer day is selected for testing, too.
Taking February 27, 2019 as an example, Figure 3 is the forecasting diagram, the last 24 points represent the test day, the red line is the corrected prediction result.

**Table 1.** Electricity price forecasting by traditional models.

| The target day | Model (24 points/day) | Maximum error | Minimum error | Mean squared error |
|----------------|------------------------|----------------|---------------|-------------------|
| Feb. 27, 2019  | ARMA (1,2)             | 57.87%         | 0.24%         | 14.26%            |
|                | ARIMA (1,0,1)          | 37.78%         | 0.15%         | 14.08%            |
|                | ARIMA + wavelet transform | 41.39%     | 0.09%         | 16.62%            |
|                | ARIMA + EMD            | 39.76%         | 0.49%         | 12.08%            |
| Sep. 10, 2018  | ARMA (1,2)             | 54.67%         | 0.34%         | 16.09%            |
|                | ARIMA (1,0,1)          | 39.86%         | 0.17%         | 15.45%            |
|                | ARIMA + wavelet transform | 40.20%     | 0.21%         | 15.98%            |
|                | ARIMA + EMD            | 34.73%         | 0.31%         | 13.12%            |

**Table 2.** Electricity price forecasting by LSTM & G-LSTM models.

| The target day | Model (24 points/day) | Maximum error | Minimum error | Mean squared error |
|----------------|------------------------|----------------|---------------|-------------------|
| Feb. 27, 2019  | LSTM (Model A)         | 16.98%         | 0.20%         | 5.74%             |
|                | LSTM (Model B)         | 16.07%         | 0.32%         | 6.93%             |
|                | G-LSTM                 | 13.06%         | 0.21%         | 3.91%             |
| Sep. 10, 2018  | LSTM (Model A)         | 17.23%         | 0.75%         | 5.88%             |
|                | LSTM (Model B)         | 17.12%         | 0.25%         | 9.05%             |
|                | G-LSTM                 | 13.25%         | 0.28%         | 4.78%             |

**Figure 3.** Electricity price forecasting by LSTM and G-LSTM model.
5. Economic dispatch case study

This paper adopts the modified IEEE 33-bus distribution system, as shown in Figure 4, bus 1 is the connection point between the distribution network and the main network. There are small power producers G1, G2, G3 on the bus 4, 7, and 14, respectively. The generator parameters were taken from the paper [16] and have been changed according to the actual situation. The photovoltaic power station data on bus 32 is taken from the paper [17] and taken averaging operation. The wind power generation data on the bus 21 is taken from the hourly measured data of the southern part of the PJM power market on February 27. And the node load data of the original IEEE 33-bus distribution system was proportionally converted based on the hourly load forecast data of the southern part of the PJM power market on February 27.

The output of the wind power station and the photovoltaic power station on February 27, 2019 is shown in Figure 5. We assume the PV and wind power in Figure 5 are the predicted values (actually we can build LSTM model to do the forecasting if we have ways to get enough training data), thus the electricity price, PV energy and wind power are all predicted values in this system. And parameters of the three generators are shown in Table 3. We take the maximum distribution network’s revenue $R$ as the objective function, and consider the power flow constraint, unit output constraint, unit climbing rate constraint and the power balance constraint, then use the quadratic programming model to solve the unit commitment problem (only G1, G2, G3 can be scheduled).

![Figure 4. The modified IEEE 33-bus distribution system.](image)

![Figure 5. Output of wind power and photovoltaic power (2019/2/27).](image)

| Generator | $P_{\text{max}}$ | $P_{\text{min}}$ | Climbing rate | Cost $a$ | Cost $b$ | Cost $c$ |
|-----------|-----------------|-----------------|--------------|--------|--------|--------|
| G1        | 1365            | 450             | 120          | 0.00021| 17.50  | 0      |
| G2        | 1365            | 450             | 120          | 0.00031| 17.26  | 0      |
| G3        | 1365            | 450             | 150          | 0.00048| 17.19  | 0      |
The objective function and constraints of this Security Constraint Unit Commitment (SCUC) problem for our distribution network can be written as follows:

\[
\max \{ R \} = \max \{ P_{\text{load}} \times \lambda_{\text{sell}} - P_0 \times \lambda_{\text{buy}} - \sum_{j=1}^{3} C_{G_i} \}
\]

\[
s.t. \quad P_{G_i,\text{min}} \leq P_{G_i,t} \leq P_{G_i,\text{max}}
\]
\[
- P_{L,\text{max}} \leq P_{\text{line}} \leq P_{L,\text{max}}
\]
\[
r_i \leq P_{G_i,t} - P_{G_{i-1},t} \leq r_i
\]
\[
P_{L,i,t} = P_{0,i} + \sum_{i=1}^{3} P_{G_i,t} + P_{\text{wind},t} + P_{\text{pv},t}
\]

Here \( \lambda_{\text{sell}} \) means the electricity sell price of the distribution network, it’s the price that the distribution network sell power to users and also it is our previous forecasted price; \( \lambda_{\text{buy}} \) means the electricity purchase price from the superior grid (bus1), it’s the price that the distribution network buy power from the main network and is set by the main network. \( C_{G_i} \) represents the cost for \( G_i \), \( P_0 \) represents the power that received from the superior grid (bus1) and \( r \) represents the unit climbing rate.

Then we expect to find the optimal solution of \( P_{G_i,t} \) so we should design matrix \( H, f, A, b, A_{eq}, b_{eq} \) in the following formula (8):

\[
\min_x \frac{1}{2} x^T H x + f^T x
\]
\[
s.t. \quad A \cdot x \leq b,
\]
\[
A_{eq} \cdot x = b_{eq},
\]
\[
1b \leq x \leq ub.
\]

Then we can solve the UC problem according to the flow shown in Figure 6.

![Figure 6. The process of solving the SCUC problem.](Image)

Through the steps, we get the final unit commitment result shown it in Figure 7.
6. Conclusions

From the examples, we see that the accuracy of the neural network model is higher than that of the traditional electricity price forecasting models, but at the same time we should also realize that this is an accuracy improvement obtained by sacrificing the training time, it’s a trade-off between time and precision.

By horizontal comparison with the conventional LSTM model in typical summer and winter day, we can see that the G-LSTM model proposed in this paper can do electricity price prediction more accurate. Moreover, depending on different markets, determining an appropriate comparison logic and thresholds allows the model to be applied to electricity price forecasts in most power markets. This method is a new attempt in the direction of electricity price forecasting under the background of big data. For future work, we need to study more different power markets and look for comparative logic and thresholds to further improve the applicability of the method.

At the same time, we can also see that predictions such as electricity price forecasting and distributed power forecasting are helpful and can guide for economic dispatching and unit scheduling. In the future, as ubiquitous power Internet of things and big data technology continues to develop, combining forecasting with scheduling/dispatching will be a necessary practice for grid dispatchers.

Acknowledgements
The authors gratefully acknowledge the financial support from Pudong Power Supply Company, State Grid Shanghai Municipal Electric Power Company (No. 52092119002H).

References
[1] Zhao Jing 2013 Summary of electricity price forecasting methods in electricity market[J] Enterprise Technology Development 32(18) 118-119
[2] Li Qiupeng, Li Yan 2013 Simulation of clearing electricity price forecast based on wavelet-support vector machine[J] Lanzhou University of Technology newspaper 39(02) 86-89
[3] PAN Yurong, JIA Chaoyong 2018 Short-term electricity price forecast based on seasonal ARIMA model[J] Journal of Baicheng Teachers College 32(12) 18-24
[4] Zhang Jinliang, Tan Zhongfu 2013 Mixed Forecasting Model of Short-Term Electricity Price[J] East China Electric Power 41(05) 916-918
[5] Islam M T, Siddique B M N K, Rahman S, et al. 2018 Image Recognition with Deep Learning[C] 2018 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS) IEEE Computer Society,
[6] A Sevik, P Erdogmus and E Yalein 2018 Font and Turkish Letter Recognition in Images with
Deep Learning 2018 International Congress on Big Data, Deep Learning and Fighting Cyber Terrorism (IBIGDELFIT), ANKARA, Turkey 61-64

[7] Y Bengio, A Courville and P Vincent 2013 Representation learning: A review and new perspectives IEEE Trans. Pattern Anal. Mach. Intell. 35(8) 1798-1828 Aug. 2013

[8] S Hochreiter and J Schmidhuber 1997 Long short-term memory Neural Comput. 9(8) 1735-1780

[9] Wang Peng, Liu Min 2019 Optimal Scheduling of Active Distribution Network Considering Demand Response[J] Electric Power Science and Engineering 35(08) 17-23

[10] Xu Bin, Xu Bin, Liu Hongxin, Ma Jun, Ding Qian 2018 Optimal Scheduling of Regional Microgrid Based on Demand Response[J] Journal of Electric Power Science and Technology 33(01) 132-140

[11] Lotfjou A, Shahidehpour M, Fu Y, et al. 2010 Security-Constrained Unit Commitment With AC/ DC Transmission Systems[J] IEEE Transactions on Power Systems 25(1) 531-542

[12] Jia Yan, Wang Wei, Wang Yifei, Zhao Meng, Zhang Chi, Li Wenxiong 2019 Short-term wind speed prediction based on wavelet transform and time series method considering random components[J] Journal of Inner Mongolia University of Technology(Natural Science Edition) 38(02) 115-121

[13] Chang Zihan 2019 Research on LSTM electricity price prediction based on wavelet transform and Adam optimization[D] Lanzhou University

[14] Ott A L 2003 Experience with PJM market operation, system design, and implementation[J] IEEE Transactions on Power Systems 18(2) 528-534

[15] Li Zhulin 2018 Research on ARCH effect of China's stock market volatility[D] Anhui Agricultural University

[16] Zhang Buhan, Zeng Ciling, Xie Peiyuan, Wang Lijie 2006 Power Generation Quotation Strategy Considering Unit Climbing Rate Constraint[J] Hydropower Energy Science 2006(03) 58-61+100

[17] Solar Radiation Monitoring Laboratory, University of Oregon. Download Solar Data [EB/OL].[2019-05-13]. http://solardata.uoregon.edu/SolarData.htm