Day-Ahead Price Forecasting in ERCOT Market Using Neural Network Approaches

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ABSTRACT

Electricity is the "blood" of society. Electricity is a special commodity that is not storable, so its production and load should always be balanced to maintain a tightly regulated system frequency. Electricity production and load both depend on many factors, such as the weather, temperature, and wind. These characteristics make the dynamics of electricity price very different from that of any other commodities or financial assets. The electricity price can exhibit hourly, daily, and seasonal fluctuations, as well as abrupt unanticipated spikes. Now almost all electricity market participants use wind/load/price forecasting tools in their daily operations to optimize their operation plans, and bidding and hedging strategies, in order to maximize the profits and avoid price risks. However, the unreliable and inaccurate predictions with current forecasting tools have caused many serious problems, which can cause system instabilities and result in extreme prices even in the absence of scarcity. This paper presents an implementation of state of the art machine learning approaches into the forecasting tools for the ERCOT Day-Ahead market to improve the reliability and accuracy of electricity price prediction.

CCS CONCEPTS

• **Computing methodologies** → *Neural networks.*

KEYWORDS

Electricity Price Forecasting, Machine Learning, Neural Networks

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1 INTRODUCTION

Price forecasting tools and technologies are used by market participants to help optimize market operations. In the longer term, bilateral contracts are priced based on forecasts of future Day-Ahead (DA) and Real-Time (RT) market prices [1]. Large electricity consumers can minimize wholesale purchase costs by operating during low price hours. The accuracy of electricity price forecasting is therefore very important [2]. Hong [3] estimates that a 1% improvement of the short-term forecasting can result in about $0.5 million savings per year for a utility company with 1 GW peak load. However, due to the special characteristics of electricity, the forecasting of the electricity prices is very challenging. Many modeling and statistical methods have been proposed during the last few decades, but it is very difficult to build a model with good prediction accuracy that can cover the characteristics of the whole system. It is difficult to make progress in electricity price forecasting using classical models and statistical approaches. However, newly developed approaches like machine learning, especially neural network methods, might make substantial improvements in electricity price forecasting. Neural networks have proven strength in handling complexity and non-linearity as the technology keeps developing and computing power becomes cheaper, and are already applied in energy forecasting researches [4–17]. Advanced recurrent neural networks like "Long-short term memory network" (LSTM) and "Gated Recurrent Units" (GRU) have shown strength in time sequence forecasting, but are not yet fully explored in electricity price forecasting. This paper focuses on exploring the forecasting capability of neural network models for the ERCOT Day-Ahead market.

Table 1: Selected input features

Selected Input	Comments
Load forecast	DA Market uses load forecast to run unit commitment.
Wind forecast	DA Market uses load and wind forecast to calculate net load.
Previous DA prices	Provide price and system condition reference.
Month, Day	Provide seasonal information, temperature range.
Hour	Provide peak and off-peak information, and temperature information.

Table 2: Example of input data for day-ahead price forecasting

Time	DA Price of Day d-1 ($/MWh)	Wind forecast of Day d (MW)	Load of Day d-1 (MW)	Month	Day	Hour
01/01/2018 01:00	24	1,000	32,000	1	1	0
01/01/2018 02:00	25	900	32,400	1	1	1
01/01/2018 03:00	22	900	32,800	1	1	2
01/01/2018 04:00	25	920	33,780	1	1	3

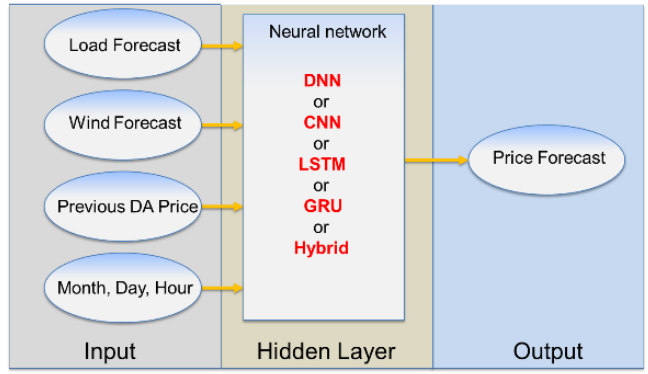

Figure 1: Machine learning data flow

2 MODEL DESCRIPTION AND PRELIMINARY RESULTS

2.1 Data Input

The following information is available and can be used for Day-Ahead price forecasting in the ERCOT Market: Day-Ahead cleared prices of previous days, wind and load long-term forecasting information from ERCOT, transmission information from ERCOT, and weather and temperature forecasts. Weather and temperature information were not used explicitly in this paper. Instead the models used month/day/hour information, which not only implicitly represents temperature information (since the month and day will reflect average temperature range and seasonal information) but also represents peak and non-peak information into the neural network models. In particular, the hour will reflect peak and non-peak hours of the day, with ERCOT peak hours being 7:00-22:00 of weekdays, and non-peak hours being 22:00-7:00 next day and weekends. Based on the data availability, the selected input features for this paper are as in Table 1.

ERCOT can be roughly divided into four zones: West, North, South, and Houston. A testing dataset from the ERCOT South Load Zone was used to train, test, and validate the models.

2.2 Model Architectures

Models of all popular neural networks like Deep Neural Network (DNN), Convolutional Neural Network (CNN), Long-short term memory network (LSTM) and Gated Recurrent Units (GRU) were set up for testing and comparison. As shown in Figure 1, all the model architectures can be simplified into three parts: input, hidden layers, and output. The design of hidden layers is the core, which will determine how the model adapts the trainings, and the consistency between training and testing.

Based on the design of neural networks they can be divided into two groups: feed-forward neural networks and recurrent neural networks. DNN and CNN belong to the first group while LSTM and GRU belong to the second. Figures 2 and 3 show examples of the two kinds of neural networks. It can be seen from the figures that RNN has better capability in studying the time sequential influences from the input features compared to feed-forward neural networks.

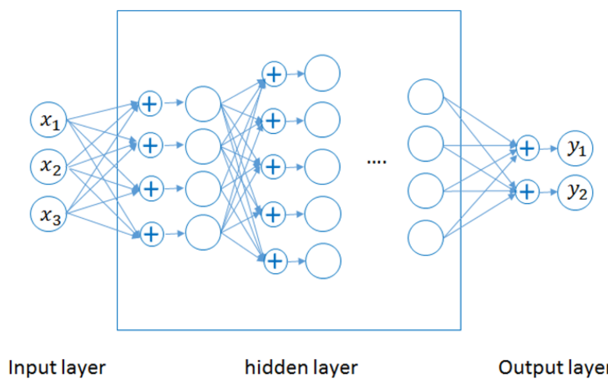

Figure 2: Feed-forward neural network (DNN)

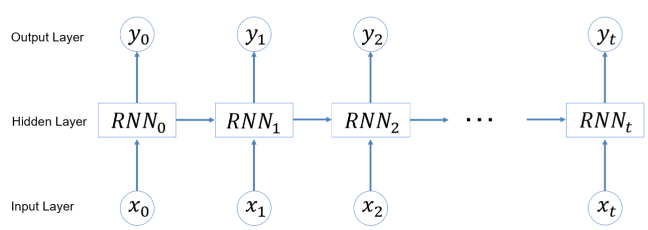

Figure 3: Recurrent neural network

Hidden layers of a LSTM model is one of the most complex structures because of the recurrent structure of the LSTM cells [18]. Figure 4 shows the data flow structure of a simple three hidden layers, three nodes per layer LSTM model. The

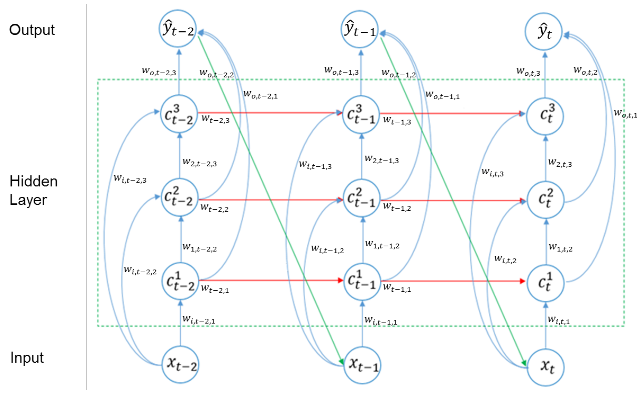

Figure 4: A simple LSTM data flow

input sequential vectors are sent to the hidden layers and the hidden sequential vectors will be calculated, and then the output vectors will be calculated. Each output vector $\hat{y}_t$ will be passed to the next input vector x_{t+1} for parameterizing a predictive distribution of the input [18].The value at the cell at time sequence t of the layer n is:

$$c_t^n = H(w_{t-1,n} \times c_{t-1}^n + w_{i,t,n} \times x_t + w_{n-1,t,n} \times c_t^{n-1}) \quad (1)$$

where H is the hidden layer function and the w terms are weights as shown in Figure 4. The forecast, $\hat{y}$ is the output at time t and is determined by the output layer function using all the layers:

$$\hat{y} = \sum_{k=1}^{n} w_{o,t,k} \times c_t^k \quad (2)$$

The LSTM model used in this paper has more than three layers, and each layer has over 100 nodes. Moreover, the inputs are vectors instead of scalars as illustrated in the simple model in Figure 4. Vector inputs require huge calculations for every training. Figure 5 shows an example of time sequence data flow of LSTM.

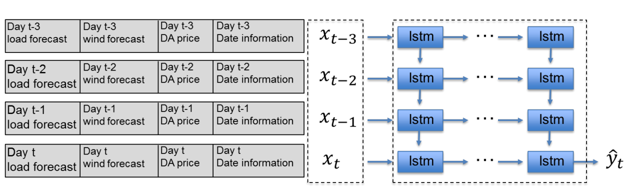

Figure 5: Time sequence data flow of LSTM

2.3 Testing of the Models

All the four neural network models, DNN, CNN, LSTM, and GRU, will be trained/validated using the equivalent settings and the same set of data. Once the model has been trained, a set of (different) testing data will be fed to the trained model to predict the Day-Ahead prices. The error is calculated by statistically comparing the forecasted Day-Ahead prices to the actual Day-Ahead prices during the same time window. Mean absolute error (MAE) was used to evaluate the results in the tests. If the testing data set has T hours in total, y_t is the actual Day-Ahead price at hour t, and $\hat{y}_t$ is the forecasted Day-Ahead price at hour t , then MAE can be calculated as follows:

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |(y_t - \hat{y}_t)| \quad (3)$$

3 RESULT AND DISCUSSION

3.1 Performance Testing of Different Neural Networks

Performance of each neural network has been tested for comparison. Hybrid models combining feedforward neural network and recurrent neural network have also been tested to see how the hybrid models can improve the forecasting capability. Testing result of each neural network is shown in Figure 6.

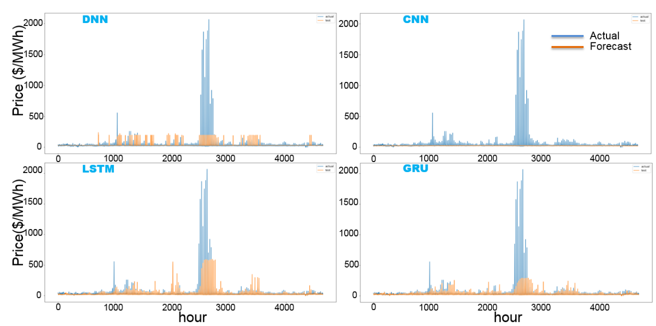

Figure 6: Performance of each neural network

A hybrid model can be constructed by using the outputs of a feedforward neural network as the inputs for a recurrent neural network. Hybrid models studied in this paper are LSTM-DNN and LSTM-CNN. Figure 7 shows how the structures of the two neural networks for the case of LSTM-DNN. LSTM-CNN is analogous.

The testing results of the hybrid neural networks are shown in Figure 8, and all the testing data are summarized in Table 3 for comparison.

From the results, GRU performs best, which is consistent with the statement in [19] that GRU has better performance

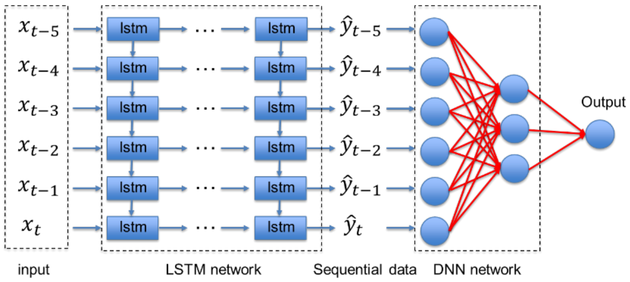

Figure 7: Hybrid model architecture

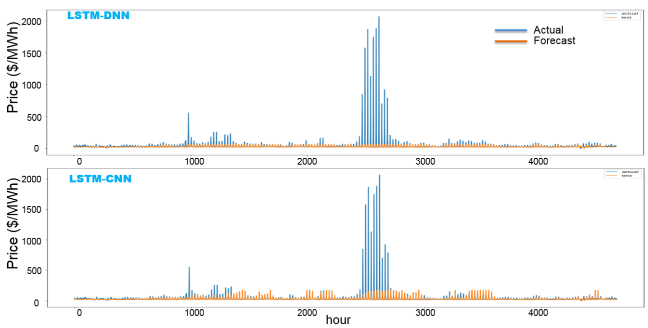

Figure 8: Performances of hybrid neural networks

Table 3: Summary of testing results for different neural networks

Neural Network	MAE	Finishing time with CPU (minutes)
DNN	19.328	202
CNN	16.532	607
LSTM	15.838	2,487
GRU	14.863	2,316
LSTM-DNN	15.394	3,015
LSTM-CNN	16.092	2,482

than LSTM in many cases. Hybrid models LSTM-DNN and LSTM-CNN do not improve forecasting accuracy much compared to LSTM alone and are not superior to GRU.

3.2 Study of the Impact of Peak Price on the Forecasting

Sudden "spike" prices are challenging to predict, both from the perspective of timing and from the perspective of the peak price reached. The previous section utilized all data, including both "normal" prices and price spikes. This section analyzes how removing peak prices will affect forecasting accuracy of normal prices. Price spikes over \$100/MWh occur about 200 times a year in the ERCOT South Load Zone, which is less than 2% of the total hours. It is believed that the sporadic high price events will affect the ability of neural networks to forecast normal prices, if the high prices are included in the training and validation data set. Figure 9 shows the price distribution in each month during 2013-2018, omitting price spikes above \$100/MWh.

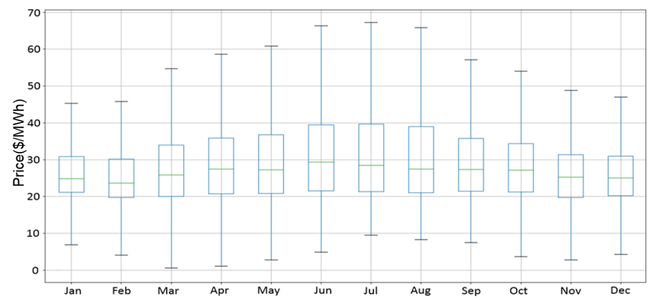

Figure 9: Boxplot omits price outliers (2013 - 2018)

Figure 10 shows the spike price numbers in different price ranges. Prediction of timing and magnitude of price spikes apparently needs to be done separately to prediction of normal prices, and needs to consider more inputs like transmission conditions, system conditions and wind fluctuations than forecasting of normal price occurrences. If the main goal is to predict prices during the 98% of time when they are normal, then the price spikes can usefully be excluded. Future work will address the important issue of predicting timing and magnitude of price spikes.

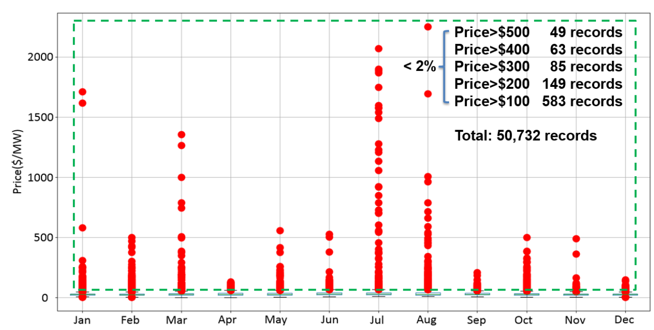

Figure 10: Boxplot includes price outliers (2013 - 2018)

Part of testing results using GRU omitting price spikes are as in Figure 11. Since recurrent neural networks are first picks for time sequential price forecasting, GRU, which is a popular recurrent neural network, is selected for testing and comparison in this section. The results are also summarized in Table 4.

The testing results have shown that the prediction of the normal conditions can be improved in accuracy if the price spikes are excluded. In practice, there can be two sets of

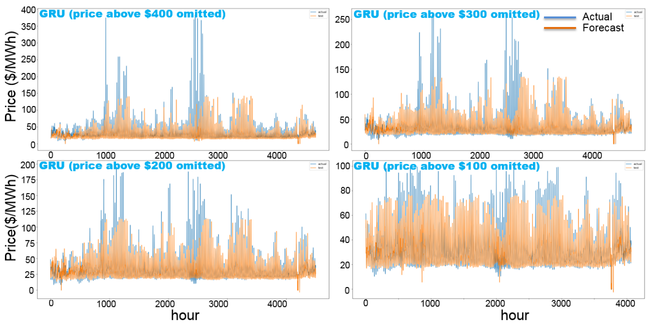

Figure 11: Testing result of GRU omitting peak prices

Table 4: Summary of testing results for GRU omitting peak prices

Neural Network	Filter	MAE of testing
GRU	Price over $500 omitted	13.750
	Price over $400 omitted	8.324
	Price over $300 omitted	5.979
	Price over $200 omitted	5.146
	Price over $100 omitted	4.528

forecasting algorithms: one focuses on forecasting the normal conditions, and another can focus on forecasting the peak prices. Since the peak prices themselves show great variability, it is easier to predict the times when price spikes will occur than it is to forecast the actual peak prices.

3.3 Neural Networks Compared to Other State of the Art methods

This section compares state of the art classical forecasting methods to the advanced neural network methods. Data used in this testing omits records with price above $100/MWh and so is comparable to the ANN results from Section 3.2 corresponding to the last row in Table 4. The state of the art classical forecasting methods for comparison are: Autoregressive Integrated Moving Average (ARIMA), Holt Winter's Exponential Smoothing (HWES), Autoregressive Moving Average (ARMA) and Persistence Algorithm (the "naive" forecast).

The results for the statistical methods are shown in Table 5. From the results we can see GRU has MAE 4.528 for the same data set, which is an approximately 10% improvement over other state of the art forecasting methods.

4 CONCLUSION

The overall accuracy of neural networks has outperformed classical forecasting approaches in several contexts [20]. This paper shows that the same is true in the context of electricity price forecasting. However, different neural networks have different performances, and recurrent neural networks perform the best among all the neural networks, and are better than state of the art statistical methods in forecasting ERCOT Day-Ahead prices. The empirical performance of the hybrid models was not significantly improved compared to the best non-hybrid model. Using more inputs, such as transmission conditions, may help improve the forecasting accuracy further and it is possible that the hybrid models might show better performance when there is an even greater variety of input data to be used in the forecast. If the models are not designed to forecast the 2% of time when there are spike prices, then the removal of the spike prices as noise from the training data set can improve the accuracy of the forecasting those prices that are under $100/MWh. To forecast the price spikes accurately, more inputs need to be included. This will be explored in future work.

Table 5: Summary of testing results for other state of the art methods

Method	MAE
ANN(GRU)	4.528
ARIMA	5.408
HWES	6.367
ARMA	10.719
NAIVE	5.756

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