CS230

Spike Prediction for Electricity Market Prices

Lingyu ren
Department of Computer Science
Stanford University
renlingy@stanford.edu

June 10, 2020

Abstract

Electricity market leverages real time locational nodal prices to regulate power system operation and balance the generation and demands. For electricity market participants, accurate price forecast will help them create most profitable bidding and purchasing strategy and manage risks. This project intends to develop an algorithm to accurately predict the electricity prices, especially the spikes where most current algorithms fail to capture. The solution will be an ad hoc ABC model where A model predicts the appearance of spikes, B model predicts the non-spike curve and C model predicts the spike curve. This algorithm is tested and compared with the state-of-the-art LSTM and transitional RFR, SVR, MLP and Persistent (PS) model for evaluation. It shows improvement in spike prediction while maintaining satisfactory average MSE.

1 Introduction

Electricity market takes the sensor data from power grids and use them to generate regional electricity prices. By doing so, the market operators can encourage more generation by increasing prices of certain area where demands surpass supplies, and vice versa. Those generators with the current highest acceptable bids are called marginal units and they decide the prices for each dispatch interval. Under extreme cases, when there is a big gap of generation, reserve generators will be launched to fill the gap and keep system stable. This mechanism indicates the electricity prices are predictable using load data, historical trend and other features, such as reserve or margin values. Accurate electricity price prediction is important for all market participants and market operators. For example, authors in [1] studied how market prediction helps industrial load to gain financial benefits by smart load shifting.

Electricity price curves are usually smooth with some spikes due to sudden lack of generation (generator outages) or load surge, shown in Fig. 1. Note in this figure, Locational Marginal Price (LMP) equals to the sum of Marginal Loss Component (MLC), Marginal Congestion Component (MCC) and Marginal

Energy Component (MEC). LMP is the total price and the prediction target in this project. These spikes are harder to predict using historical behavior of the price data since they are rare events compared to the data length. There are some research on spike prediction. For example,[2] explored the statistics of price spikes and built a rule-based spike detection, separate from the neural network based normal curve prediction. Authors in [3] adopted the autoregressive conditional hazard model to predict spikes. As mentioned in the recent research [4], spike prediction remains the bottleneck for electricity price prediction.

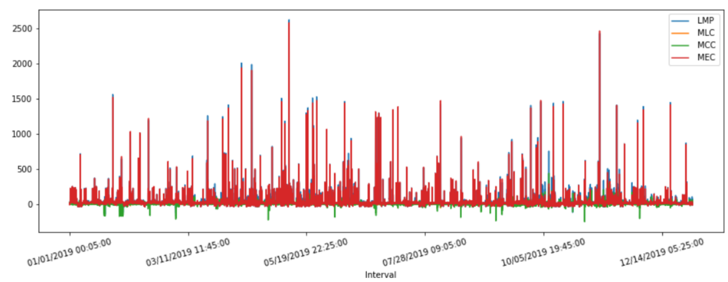

Figure 1: Real-time Locational Marginal Price (LMP) curve of 2019 from Southwest Power Pool (SPP)

2 Related work

As mentioned before, there are research work on spike prediction but it is still the most challenging part of electricity price prediction. Even the industry benchmark Genscape [5] fails to predict the spikes.

3 Dataset and Features

The data sets are downloaded from Southwest Power Pool (SPP), one of the major power system operators. The data repository of year 2019 is downloaded from SPP website through Python Request function. Specifically, the five minute load forecast and actual measurement are downloaded from operational data. The five minute LMP and its three components (in Fig. 1) are downloaded from market data. Following the mechanism behind the market operation, the LMP is impacted by load changing rate and load discrepancy between "real" and "forecast" data. Two features are added as "difference" (one step difference) and discrepancy (actual load minus forecast load). Also, five time step lagging features (t-1, t-2, t-3, t-4, t-5) are added for each LSTM component to incorporate the temporal correlations of historical LMP data. Additionally, to predict the appearance of spikes, spike labels are added using a threshold of 200$, which means any LMP above 200$ will be labeled as 1, otherwise 0. All features are standardized before feeding into the model. Since this is a relatively small feature set (only 24 in total), there is no need for advanced feature selection.

4 Methods

Initially, the traditional algorithms are tested as baseline. The random forest regression (RFR), support vector regression (SVR), multi-layer perceptron (MLP) and persistent model (one step prediction) are tested on 60 days of training data, 14 days of validation data and 14 days of testing data. Similarly, an LSTM model is tested for comparison. To capture the spikes, the loss function is modified with high weight on the spike loss. The modified LSTM is not robust in non-spike prediction. Then intuitively, an ad hoc model combining both spike and non-spike prediction is designed. This model followed an ABC structure where A model predicts the appearance of spike, B model predicts the non-spike data and C model predicts the spike data, as illustrated in Fig. 2

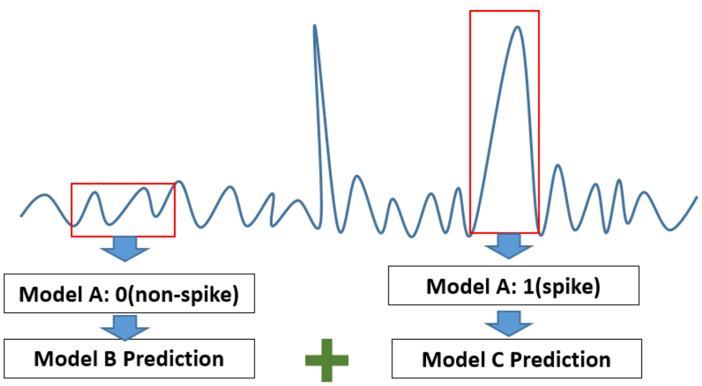

Figure 2: Structure of an ad hoc ABC model to predict both spike and non-spike LMP

5 Experiments/Results/Discussion

This section is discussed in two subsections: the baseline model, and the ABC model.

5.1 The baseline model test

First, the four algorithms (RFR, SVR, MLP and PS) are used for time-series LMP prediction using features mentioned above. Keras architecture is used to test the LSTM model. The LSTM model is two layers: one LSTM layer with 50 output and one Dense layer with one output. Adam is used for optimization and mean-squared-error is used for loss function in the beginning. The learning rate

(LR) and batch size are selected using hyper parameter searching. A random search from 0.0001 to 1 is used to find the proper LR band, followed by a fine tune in the range of 0.0001 to 0.001. Similarly, the batch size is selected through searching from 1 to 512. The final parameter is 0.0003 for LR and 32 for batch size.

We then define a spike mean-squared error (spike MSE) to be the MSE of spike only. A special loss function is defined as *0.5*MSE if not spike, 0.5*MSE + 0.5*Spike MSE if spike*. The LSTM with new loss function is named spike-LSTM. The quantified results are compared in Table 1.

	RFR	SVR	MLP	PS	LSTM	Spike-LSTM
MSE	795	838	1069	1101	746	927
Spike MSE	93053	118638	105609	123213	99542	87326

Table 1: MSE and Spike MSE Comparison for LMP prediction

It is shown that with new loss function the loss prediction is improved but the normal MSE is worse than before. We need a robust algorithm that handles both spike and non-spike prediction.

5.2 ABC Model

We design a hybrid model with Model A as a classification model to predict the appearance of spikes. If it is not a spike, Model B will predict the LMP, otherwise, Model C will predict the LMP. The results is a combination of ABC model prediction. First, we need to prepare data to train each model. We added label for the spikes for Model A. Note, there is a bias in the spike training data since there are much less spike data than non-spike data. The test results show using MLP is better than LSTM in spike prediction. This is because the spike data is segmented from the original and they do not have temporal correlations which best captured by LSTM. Also,for Model A, the labels are biased since more ”0” than ”1” in the data. The threshold for softmax is selected as 0.9 for zero prediction to balance the bias. The results are shown in Table 2. Note the test data are different from Table 1.

	RFR	SVR	MLP	PS	Spike-LSTM	ABC
MSE	984	1005	1637	1261	1889	1262
Spike MSE	316239	473983	277223	379727	464995	272633

Table 2: MSE and Spike MSE Comparison for LMP prediction

Note, Model A accuracy rate is 0.996; Model B MSE is 101 and Model C MSE is 230353 for their own test data.

The prediction results on spike and non-spike data are shown in Fig. 3 and Fig. 4, respectively.

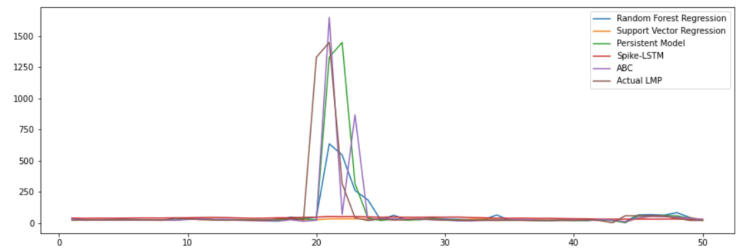

Figure 3: Prediction comparison on spike data

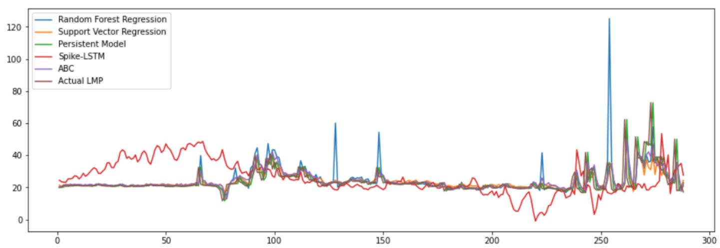

Figure 4: Prediction comparison on non-spike data

As shown in Fig. 4, the spike-LSTM deviate far from the actual LMP due to the modification of the loss function. Meanwhile, the ABC model fits the real data better since it uses a more accurate model.

6 Conclusion/Future Work

The ABC model is more robust than the spike-LSTM and it performs better than traditional machine learning algorithms. In the future, The data bias needs to be handled more carefully. Some figures are attached in Appendix due to page limit.

7 Contributions

This is a one person team. I had enjoyed the project work.

8 Appendix

The LR fine tune result is shown in Fig. 5.
The ABC separate model prediction result is shown in Fig. 6.
The results of traditional ML algorithms are illustrated in Fig. 7.

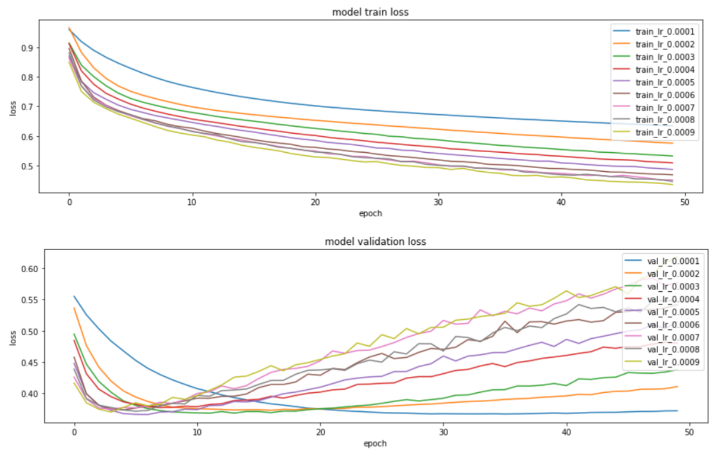

Figure 5: Training and Validation Loss during each epoch of LR fine tune

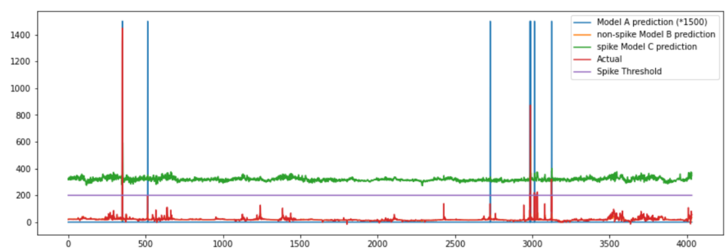

Figure 6: Model A, B, C prediction, Actual LMP and Threshold comparison

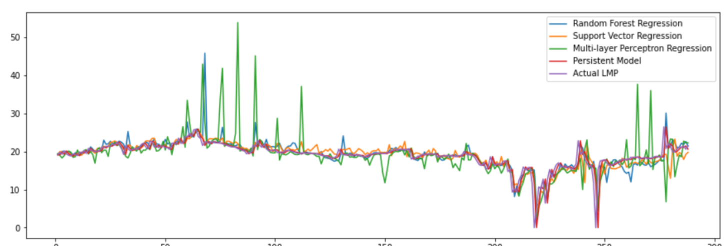

Figure 7: One day LMP prediction using traditional time series prediction algorithms

References

[1] T. Mathaba, X. Xia, and J. Zhang, "Analysing the economic benefit of electricity price forecast in industrial load scheduling," *Electric Power Systems Research*, vol. 116, pp. 158–165, 2014.

[2] X. Lu, Z. Y. Dong, and X. Li, "Electricity market price spike forecast with data mining techniques," *Electric power systems research*, vol. 73, no. 1, pp. 19–29, 2005.

[3] T. M. Christensen, A. S. Hurn, and K. A. Lindsay, "Forecasting spikes in electricity prices," *International Journal of Forecasting*, vol. 28, no. 2, pp. 400–411, 2012.

[4] A. Radovanovic, T. Nesti, and B. Chen, "A holistic approach to forecasting wholesale energy market prices," *IEEE Transactions on Power Systems*, vol. 34, no. 6, pp. 4317–4328, 2019.

[5] "Genscape," *https://www.genscape.com/*.