Stochastic Energy Market Price Forecasting with Recurrent Neural Networks

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ABSTRACT

This project proposes to construct a neural network that will forecast energy prices in the California Independent System Operator (CAISO). Accurate forecasting of energy prices in the CISO provides an economic opportunity for energy providers to incur profit and buyers to purchase at the lowest possible price. Traditional methods for forecasting have been used for many years to forecast these prices, but the recent advances in recurrent neural network time series forecasting presents a possible way to improve upon existing methods. The problem statement of this project is how to design a neural network to accurately predict stochastic energy prices.

KEYWORDS

machine learning, stochastic forecasting, recurrent neural networks, energy markets

ACM Reference Format:
Elmore, Clay and Kopp, Grace. 2019. Stochastic Energy Market Price Forecasting with Recurrent Neural Networks. In *Proceedings of ACM Conference (Conference'17).* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Energy markets are present all around the globe. Prices in these markets are extremely volatile due to a variety of different factors including but limited to market demand, erratic weather, natural resource availability, and so much more. Because of the large swings in these prices, participating in these energy markets presents an economic opportunity to both energy buyers and sellers alike. For an energy provider, knowing when the price of energy will be high is critical to knowing when to use valuable resources to produce energy. For an energy user, knowing when to buy energy on the market at a low price can be the difference between an industrial user being profitable or going under. With these considerations in mind, it is clear that energy price forecasting is a worthy venture for academics to study because of its direct applicability to the commercial world.

In this paper, we will explore a specific energy market: the California Independent System Operator (CAISO). The CAISO is an enormous, complex energy market system in which energy buyers and sellers schedule a multitude of energy related transactions. The CAISO had some 40 billion dollars in sales, and more than 260,000 gigawatts sold in 2015[2]. This complex system makes for a data-rich problem worthy for study by academics and industry professionals alike. A particularly interesting problem in the CAISO is the forecasting of Day-Ahead Market (DAM) prices which are notoriously stochastic. DAM prices are used to forecast energy prices a day in advance which energy buyers and sellers then use to schedule when they will buy and sell energy on the CAISO market. It has been shown that accurate forecasting is absolutely critical to profiting off DAM market prices[5].

Although prices in the CAISO DAM are quite volatile, they have very clear periodic tendencies. Figure 1 shows an example week of energy prices for an energy resource in the CAISO DAM for the first week of 2015. Note how the price is clearly periodic, but also has stochastic tendencies as well. Furthermore, Figure 1 shows the economic opportunity available to sell at high prices and buy at low prices. Some price swings are almost double the price. An accurate forecast would allow for large amounts of profit to be extracted from these systems.

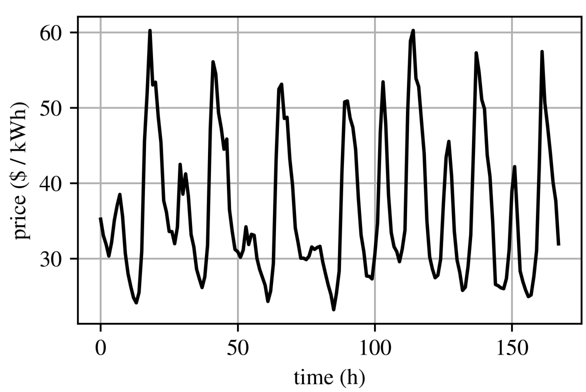

Figure 1: An example of time series behavior observed in the CAISO from January 1st, 2015 to January 7th, 2015.

Many standard time series forecasting methods have been used to predict DAM prices in the CAISO and other energy markets across the globe. For example, standard autoregressive integrated moving average (ARIMA) forecasting methods have been used to differing degrees of success in the CAISO market and the Spanish DAM. Conejo et al. have used ARIMA models to predict prices in

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Conference'17, July 2017, Washington, DC, USA
© 2019 Association for Computing Machinery.
ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

the Spanish market with a 10% error for the 2002 market [4]. Furthermore, ARIMA has been shown to generate forecasts in the 2000 CAISO DAM with an error of around 13% [6]. Another standard method for time series forecasting that has been used in the Generalized autoregressive conditional heteroskedasticity (GARCH) method. Similar to ARIMA models, an error rate of around 10% for the Spanish DAM has been reported when using GARCH [6]. More advanced hybrid methods have also been used for DAM forecasting. These methods include the usage of wavelet decompositions in order remove noise from data as well as the incorporation of ARIMA models in conjunction with GARCH methods [1, 3, 7, 8]. These various hybrid methods have error rates reported that range from as low as 1% to as high as 25%.

Recent advances in Recurrent Neural Networks (RNN) in the past 5 to 10 years have motivated this project to investigate their potential ability to predict CAISO DAM prices. The remainder of the paper will be organized in the following manner.

- Section 2: A problem statement along with the design of the RNN, an explanation of the dataset, and software implementation details.
- Section 3: Results of the forecasting performance of our RNN forecaster is presented.
- Section 4: A discussion of how RNN forecasting compares to existing methods and other insights from this project.
- Section 5: Major findings from the paper are summarized.

2 MODELING APPROACH

2.1 Problem Statement

INCLUDE HOW ERROR IS CALCULATED!

2.2 Neural Network Methodology

Outline:

- Basic explanation of an RNN.
- How does an RNN relate to energy prices.
- Figure: How does our RNN look in relation to energy prices.
- What are the specifics of the RNN we use.
- What was the methodology we used to determine the this design.

2.3 Data Sources

The dataset for this project was kindly provided by the Dowling Lab for Uncertainty Quantification and Mathematical Optimization at the University of Notre Dame in the Department of Chemical and Biomolecular Engineering. The dataset is comprised of over 6500 energy vendors, called nodes, participating in the CAISO. There is a full year's worth of data for each node in 2015, and price measurements are recorded at 1 hour intervals. Latitude and longitude coordinates are known for around 2000 of these nodes for visualization purposes. However, because of the limited timeline of this project, only 50 of these nodes will be used, and only a single week of data in January 2015 will be used for testing purposes. This is a reasonable thing to do as many papers report error values for single weeks in Janurary [4, 6, 7]. Furthermore, these papers only report results for single nodes in the DAM. Because our results include 50 nodes, it can be concluded that the results obtained for this dataset are statistically significant.

2.4 Software Implementation

Outline:

- Tensorflow
- CRC GPUs
- Code available at: GitHub

3 RESULTS

Figures and Tables we will need:

- Figure: Example of what a price forecast looks like (good and bad).
- Figure: Histogram of error values for all nodes.
- Figure: Histogram of what adding more training data does for testing.
- Figure: Histogram of error values for the single node across the whole year.
- Table: Aggregated statistics of all nodes with low and high amounts of training.
- Table: Aggregated statistics of single node across the year.
- Table: Aggregated statistics on CPU time.

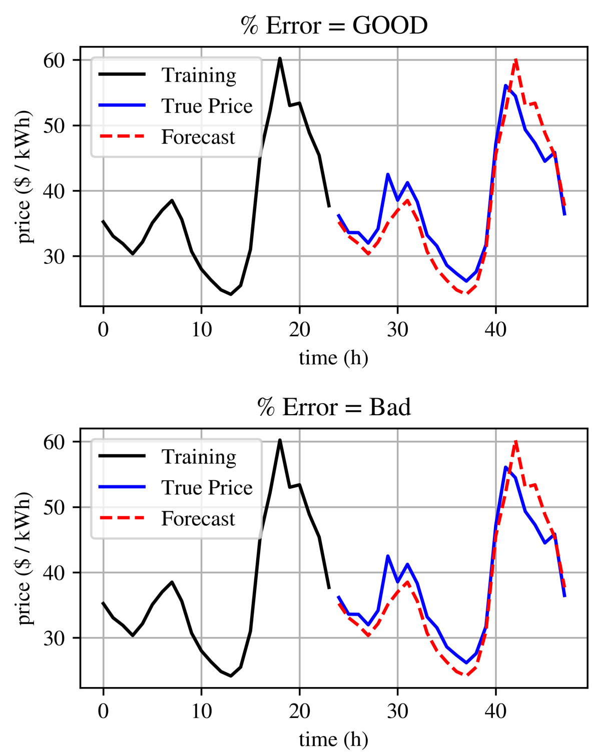

Figure 2: Example price forecasting using our RNN.

4 DISCUSSION

Figures and Tables we will need:

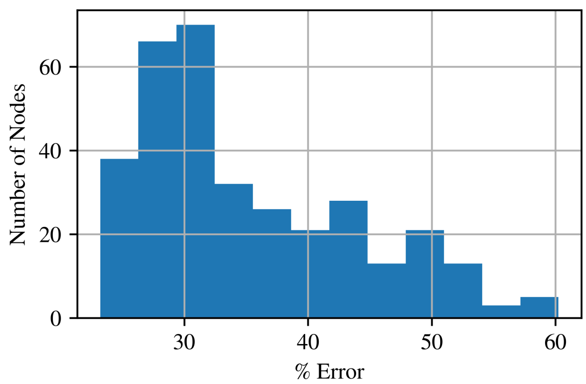

Figure 3: Histogram of all nodes.

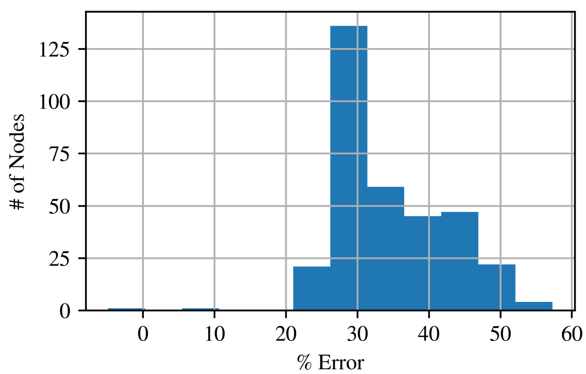

Figure 4: Histogram of all nodes now with larger amounts of training data.

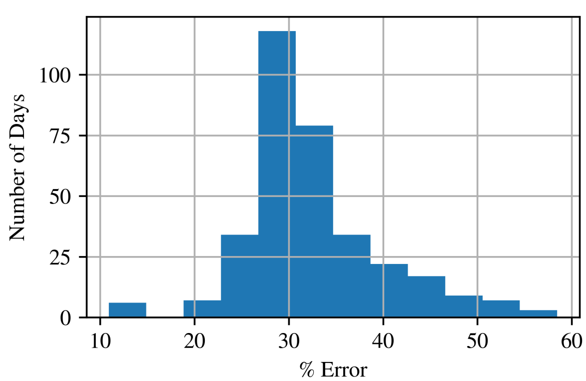

Figure 5: Histogram of a single node run through the whole year.

- Figure: Graphical comparison of how backcasting does not do what the RNN can do.
- Figure/Table: Comparison to techniques that have been mentioned earlier in the paper and backcasting.

5 CONCLUSIONS

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