# 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, neural networks, energy markets

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## 1 INTRODUCTION

The California Independent System Operator (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[1]. This 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[3].

Recent advances in recurrent neural networks (RNN) for time series learning suggest that RNN's could be a potential way to produce more accurate forecasts of energy prices. In this project, we propose to build a RNN that can accurately predict stochastic energy prices in the CAISO across various energy providers. In order to evaluate this challenge, we will compare against reported literature values of standard time series forecasting such as backcasting and ARIMA predictions[2]. Due to the recent success of RNN's, we expect an RNN to perform as well or better than current methods.


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## 2 APPROACH

Because the dataset contains sequential information in the form of energy prices at different time increments, a recurrent neural network would be well suited to predicting future prices for this problem. This is because unlike in traditional neural networks, in recurrent neural networks there are loops that allow information about previous inputs to persist. In other words, it can use its memory from a previous time step to make a decision in a future time step. This is essential when working with time series data where order and contextual information is extremely important for accuracy. At a high level, the proposed model would utilize long short-term memory recurrent neural network architecture. Long short-term memory networks are ideal for making time series predictions because they allow the model to decide what information to keep and what information to forget. This allows them to deal with gaps of unknown duration between notable events in a time series. Our network will accept an input vector of past time series values and then return an output vector of predicted prices over the next 48 hours.

### 2.1 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.

## 3 EVALUATION PLAN

Fortunately, there is a lot of published work on forecasting DAM markets, so evaluation of our RNN will be somewhat easy to compare with reported literature accuracies. Furthermore, the DAM dataset that was provided is sufficiently large enough to test our RNN's performance on a large amount of geographically separated nodes while still having enough training data to fully learn DAM dynamics. Furthermore, it will be important to evaluate the CPU time needed to train our RNN. CPU time can easily be compared with existing literature values reported. We have determined that success for this project will be defined as the successful implementation of a RNN that forecasts DAM prices in the CAISO. However, as time is somewhat limited for this project, success is not going to be defined as constructing a RNN that performs as well or better than current time-series forecasting methods.

## 4 PROJECT IMPLEMENTATION PLAN

By the first milestone on April 7th, we plan to have our data split into training, testing, and validation sets. We also will solidify the initial architecture of our neural network and begin to implement it on a small scale in a Jupyter Notebook in order to identify roadblocks as soon as possible.

By the second milestone on April 17th, we plan to extend our implementation across all of the nodes in our data set. We will also perform error analysis to evaluate our work and make any changes necessary from those results.

By April 27th we will turn in our paper drafts for peer review with detailed analysis of our findings from the first and second milestones.

On May 5th, we will turn in our final paper with edits based on peer feedback and any model developments. This paper will outline the implementation of a neural net for energy forecasting. We will also turn in reproducible code to verify our findings.

## REFERENCES

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