COMP 652: Project

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Presented to Dr. Doina Precup

Geoffrey Stanley
Student ID: 260645907

Introduction

The reliability of modern day energy markets is the responsibility of independent system operators (ISO) who are tasked with the governance of the energy network within a pre-definied geographic region. PJM Interconnection is such an organization. It is responsible for the proper functioning of the electric grid in Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia.

It ensures that loads on the system, such as cities, are serviced by a sufficient amount of generators, such as nuclear, natural gas or wind power plants at any given hour of the day. It does so by holding hourly auctions requesting that producers offer the quantity of megawhatts they are capable of producing and at what cost. Next, based on the demand for a given hour the ISO will request that the producers bring their generators online, prioritizing the most inexpensive power first while also ensuring that the grid operates at a sufficient level of reliability and redundancy.

The first priority of the ISO is the reliability of the system. If it does not provide a sufficient amount of power to satisfy the loads in the system it risks causing a brown out or a black out in the entire system. It also must ensure a certain level of redundancy as if a line or a power plant suddenly fails the energy grid must continue to operator as a whole. It's second priority is to provide loads with the most inexpensive power that it can find, nuclear is cheaper then natural gas, and natural gas cheaper then coal.

As such, the price of power through out the energy grid can be seen as being driven by three categories of variables: demand, supply and physical. With in the demand component variables will be ones that influence the amount of power being drawn from the grid. These will be things such as weather, season, day of the week, hour of the day, weather it's a holiday or normal work week. Supply will be made up of all factors influencing how generators are changing their bidding behavior. This will mostly be driven by fuel costs; uranium, natural gas, coal and the amount of wind. Physical variables will be the current status of the network; what outages and constraints there are on the system.

Congestion in the electricity grid will occur when the price of energy between two nodes is different. This will occur when different types of generation power different load zones. For example, take cities A and B both of which consume 100mwh and let's assume that city A is connected to generator E while city B is connected to F which also produces 200mwh. In a situation where E can produce 200mwh at 15$ and F at 20$ there will be no congestion so long as 100mwh can freely flow between city A and city B. However, if only 50mwh can flow from A to B then generator F will need to be turned on to produce the remaining 50mwh required by city B. This results in a cost of energy of 20$ in city B and a congestion of 5$ between the two cities.

In order to protect generators from unforseen congestion events a product called up to congestion (UTC) contracts were created. The holder of these contracts will receive payments when more congestion occurs then expected and have to make payments when less congestion the expected occurs.

Which creates the problem of how to accurately evaluate the value of these contracts.

Methodology

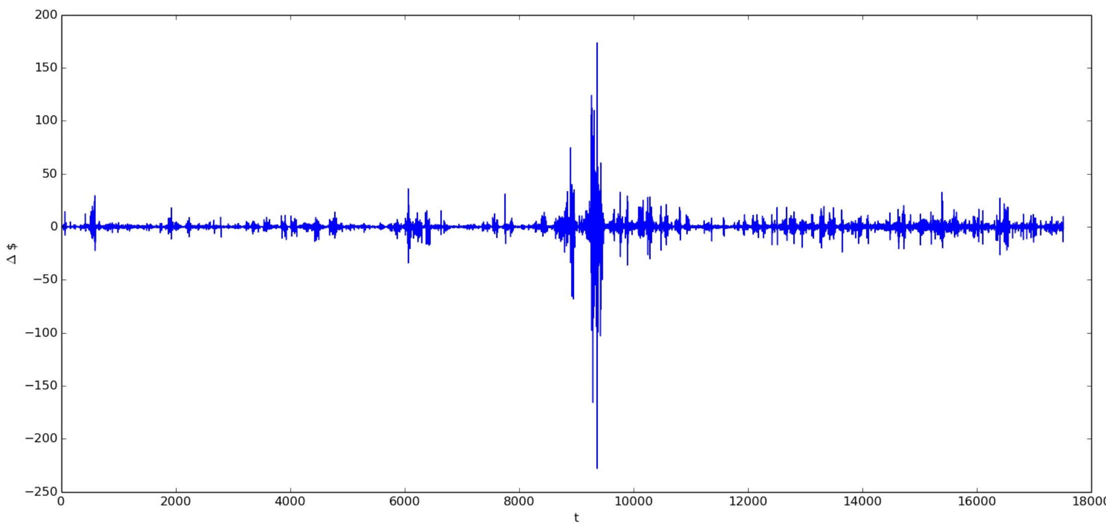
Ignoring potential variables such as fuel costs, weather and outages; as a first attempt in trying to evaluate the value of a UTC contract a Markov Chain Monte Carlo (MCMC) approach will be used. The objective will be to use the previous distribution of differences between UTC contract prices and the last known price to estimate the most likely value in the future. A similar method to the one used by Landauskas [2] to evaluate future stock prices will be used.

The first step will be the estimation of the distribution for price differences for a particular time range. This will be done using SciPy's [1] implementation of Gaussian kernel density estimate (KDE). This implementation will also allow for the generation of a set of random samples from the distribution. Once the random samples are generated, they will be added to the previous known price of the contract and the Gaussian KDE will again be used to infer the distribution of potential future contract prices. The price with the greatest likelihood will be used as the forecasted price. The evaluation of the model's accuracy will be done by summing the squared error of the differences between the forecasted prices and the actual prices.

Due to the seasonality of the prices the amount of history used to estimate the probability distribution of price differences will need to be optimized. As such, a time series validation procedure will need to be used. This procedure will be implemented as follows: at t_0 the price at t_1 will be predicted using price difference distributions between $t_{0-n} \rightarrow t_0$ where n will vary in days between one week and one year.

In order to attempt to reduce the effect of variables outside of normal seasonality aggregates of nodes were selected; Eastern Hub and Western Hub. These hubs are an average of a few hundred different pricing nodes within their regions.

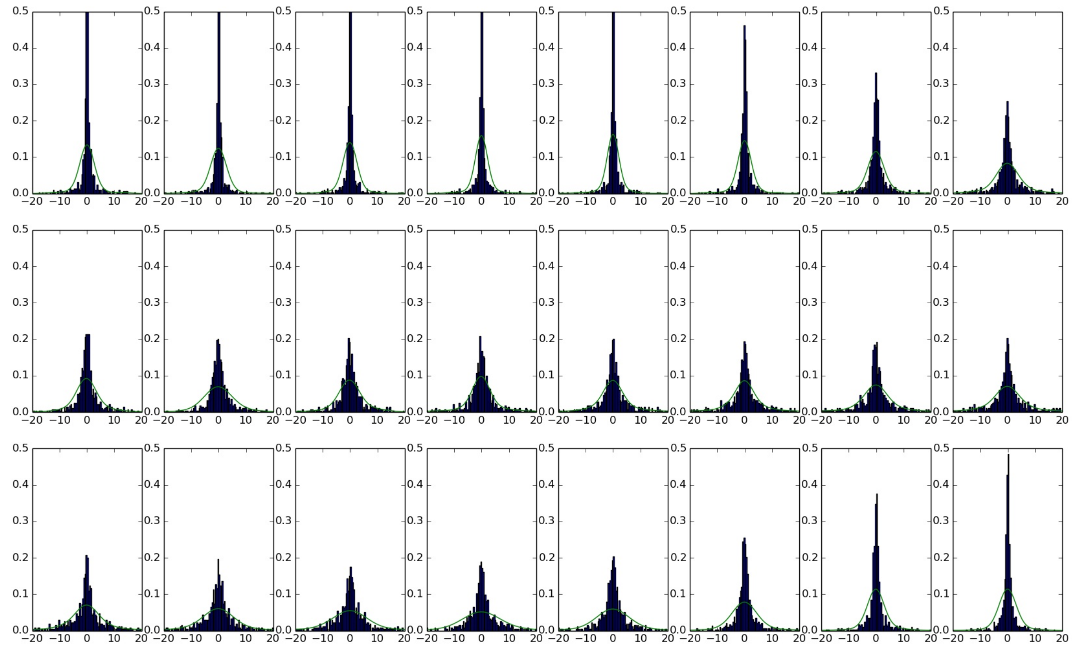
Price differences between Eastern Hub and Western Hub from January first 2013 and January first 2015 can be seen in the following figure:



Differences were consistent except for a period in January 2014. Because of the tendency of the differences to be within a rather tight range the next optimization problem will be deciding how many of the outliers to remove when evaluating the data distribution.

As a second step, after the optimal amount of history to be used is identified, the same use the same process described previously for forecasting a ptice at t_1 however in this approach the amount of outliers removed will vary. From the bottom and top 0% to 25%.

Lastly, the differences in price distributions between hours of the day is significant:



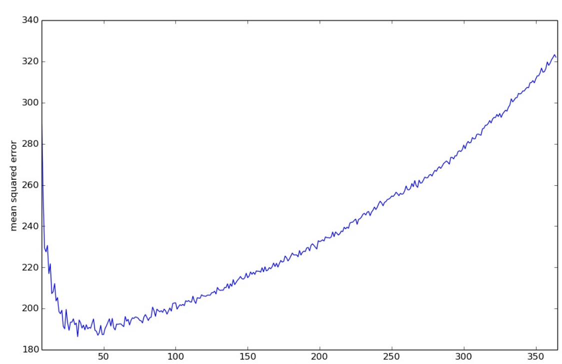
The figure above shows the price differences for hours ending 0 through 23. The x-axis is the difference in price and the y-axis is the probability 0 to 1 of that difference. Evening hours 22, 23 and 0 through 6 are much less volatile then the others. As such, the UTC contracts should be evaluated on an hourly basis given the price it was worth at the same hour the previous day.

Experimental Set-up

Data was obtained from the PJM website [3]

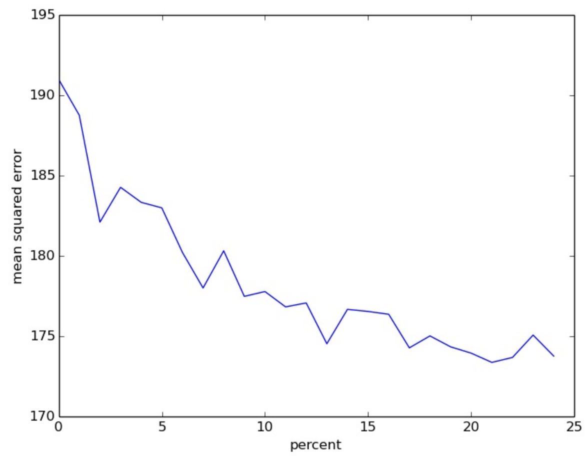
Results

The following figure shows the means squared error produced by the model as a function of the amount of history used to fit the model.



This shows that the optimum amount of history to be used is about 30 days.

The next figure shows the improvement of mean squared error as outliers are removed:



The interpretation of this graph leads me to believe that predictive feature for future prices is no the distribution of price differences but in fact the actual price at t_{0-1}. This is because accuracy continues to increase as fewer and fewer data points are used to evaluate the price difference distribution. I believe this is caused by the mean reverting nature of the price of the contracts.

Conclusions

One of the weaknesses of this approach is that it does not take into account the mean reverting tendency of energy prices. In other words, when a price suddenly jumps this approach to modelizing the price behavior assumes that the price will maintain the price it moved to. A more robust approach would need to take into account how strong the tendency is to revert to a mean price and what that mean is.

Further work would also need to take into account more of the features. One potential avenue would be to look at price differences given particular outages in the system. As well as incorporate supply and demand drivers such as fuel costs and weather.

Bibliography

[1] Eric Jones, Travis Oliphant, Pearu Peterson, et al. SciPy: Open source scientific tools for Python, 2001–. [Online; accessed 2015-04-20].

[2] Mantas Landauskas and Eimutis Valakevicius. Modelling of stock prices by the markov chain monte carlo method. *Intellectual Economics*, 5(2(10)):244–256, 2011.

[3] PJM. Pjm - home. http://www.pjm.com. Accessed: 2015-04-26.

[4] Q. Tang and D Gu. Day-ahead electricity prices forecasting using artificial neural networks. *Artifical Intelligence and Computation Intelligence*, 2:511–514, 2009.