Nonlinear Temperature Effects and Weather-Based Trading in the MISO Minnesota Hub

Jack Hardiman

Department of Economics

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Dana Golden

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1. Introduction:

Electricity markets are very dependent on the weather, because temperature directly drives heating and cooling demand. Unlike most commodities, electricity cannot be stored economically. With various ways of storing being invented, this solution is not yet common. So, short-term fluctuations in demand have to be met in real time. This results in unexpected changes in temperature that often lead to sharp movements in electricity prices. This happens most in real-time markets.

In an organized electricity market, such as the Midcontinent Independent System Operator (MISO), prices are determined by both day-ahead (DA) market and a real-time (RT) market. The DA market relies on forecasts of electricity demand, generation availability, and weather conditions. The RT market reflects actual system conditions as they occur. When forecasts deviate from current conditions, especially during periods of the extreme heat or cold, there are significant price differences that can emerge between the DA and RT prices. These are called “incs and decs”, the basis for virtual trading strategies.

This project takes a look into temperature-based indicators, such as Heating Degree Days (HDD), and Cooling Degree Days (CDD). These can be used to predict deviations between real time and day ahead electricity prices at the MISO Minnesota Hub. The hypothesis is that these temperature driven demand shocks create predictable forecast errors in the DA market, and that these errors are the largest during extreme weather events.

To test this hypothesis, multiple weather based trading strategies are developed to compare the effects. This includes linear, nonlinear extreme-weather, peak versus off-peak hours, and anomaly-based approaches. After evaluating the profitability and risk-adjusted performance of

each strategy, the hypothesis will be aimed to identify which weather signals provide the strongest, and most reliable trading opportunities in electricity markets.

2. Data:

This analysis uses hourly electricity price data and weather observations for the MISO Minnesota Hub covering the period from January 1, 2023 to December 31, 2024. All data sets were aligned at an hourly frequency to get the short-term temperature demand changes. Weather data was taken from NOAA and consist of hourly temperature observations also from the Minneapolis area. Temperature data was given in hourly temperature, and HDD and CDD hourly temperature.

All of the datasets were merged using consistent hourly timestamps, with little outliers. This resulted in approximately 17,000 hourly observations. For each hour, the data included the DA prices, RT prices, the RT-DA spread, temperature, HDD, CDD, and the datetime used to distinguish between peak and off-peak hours. This merged dataset forms the foundation I used for constructing and evaluating the purely weather-based strategies in the following sections.

3. Methodology:

For all of the trading strategies, trading is conducted through virtual positions in the RT minus DA price spread, known as incs and decs. When a strategy generates a trading signal, a fixed notional position of 1 MWh is taken for that hour. Profit or loss is determined by the difference in the incs and decs for that hour.

3.1 Weather Variables:

To examine the unexpected weather conditions that affect the outcomes differently, temperature anomalies were created by subtracting the average seasonal HDD and CDD values from the observed values. This allows the comparison between the strategies to be based on the absolute temperature stress and those based on deviations from the climatological norms.

3.2 Trading Strategy Design

Four different weather based strategies were created and tested in this project:

1. Linear Weather Strategy

   This base strategy assumes that any deviation from temperatures increases electricity demand. A trade is executed whenever HDD or CDD is positive. This results in frequent market participation.

2. Nonlinear Extreme-Weather Strategy

   To capture nonlinear demand effects, this strategy trades only when there are extreme temperature conditions. These trades are done when HDD or CDD falls within the most extreme quartile of observed values. This concentrates the most exposure during periods of high stress.

3. Peak versus Off-Peak Strategy

   Electricity demand varies a lot by the time of day it is. The nonlinear strategy was further divided into peak hours, of 7:00 - 22:00. Off peak hours were 23:00 - 6:00. This separation allows for the examination of how system load conditions affect the strength of weather-driven price deviations.

4. Anomaly-Based Strategy

This strategy only traded when the temperature deviates tremendously from the seasonal norms. This was measured by the HDD and CDD anomalies.

3.3 Performance Evaluation

For each strategy, the hourly profit and loss is calculated as the difference between RT and DA prices, then multiplied by the trading position. The hourly returns are then accumulated to make capital curves, using an initial balance of $100,000.

Also, to calculate the evaluation of risk-adjusted performance, Sharpe ratios were made. By comparing average hourly returns to their volatility and annualizing the result, the Sharpe ratio is here for insight in the consistency of each strategy's performance.

4. Results:

4.1 Capital Curve Performance:

The capital curves reveal that the strategies focused on the extreme temperature conditions outperformed the simpler approaches. The linear weather strategy generated steady gains. However, there was relatively slow capital growth due to the frequent exposure during mild weather periods when the incs and decs are small.

To differ, the nonlinear extreme-weather strategy produced significantly higher returns. When restricting trades to the coldest and hottest hours, this strategy sought periods when demand stress is greatest and DA forecasts are most likely to underestimate the RT conditions. The capital growth of this was more concentrated and less noisy.

The anomaly-based strategy, however, performed very poorly in comparison. Although anomalies identify unusual weather events which could make good profit, this strategy failed to recognize that many periods of high temperature stress prolonged the drawdowns.

4.2 Peak versus Off-Peak Performance

Separating trades from the time of the day further clarifies when profit can be made. The nonlinear strategy performs far better during the peak hours than during off-peak hours. Peak hours trades for the most of the cumulative gains. This reflects higher electricity demand, tighter system constraints, and greater volatility.

Off peak trading generated very minimal returns, and overall poor performance. This suggested that weather-driven demand shocks are the most impactful when the grid is heavily loaded with noise. The overnight hours, however, show very limited sensitivity to temperature changes.

4.2 Risk-Adjusted Performance

Sharpe ratios showed the conclusions that were taken from the capital curves. The nonlinear extreme-weather strategy achieved the highest Sharpe ratio of 1.92. This indicates a very strong and consistent risk adjusted performance. The linear strategy, and peak hour strategy, produced moderate Sharpe ratios of slightly above 1.0. This suggests that the returns are stable but less efficient returns.

By comparison, the anomaly-based strategy and off-peak strategy exhibited very low Sharpe ratios, of 0.25 and 0.11. This showed there was very high volatility relative to the average returns. These results confirm that not all weather signals are equally valuable, and that absolute temperature stress during high-demand periods provide the most reliable trading signal.

5. Conclusion:

This project shows that weather-based trading strategies can predict deviations between RT and DA electricity prices, when temperature effects are modeled. Strategies like these that focus on extreme heating and cooling have outperformed the simpler linear rules. Trading during the peak hours also strengthen performance, while anomaly-based and off-peak strategies provide very little value for predictions. Overall, the results confirm that absolute temperature stress during high-demand periods create the most reliable signals in the MISO Minnesota Hub.