Unlocking the Potential of Green Virtual Bidding Strategies : A Pathway to a Low-Carbon Electricity Market

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Abstract

The increasing importance of renewable energy in mitigating climate change has led to a critical examination of electricity market mechanisms that can support this transition. Virtual bidding, a financial tool used within electricity markets, allows market participants to capitalize on discrepancies between the Day-Ahead (DA) and Real-Time (RT) prices of electricity. The introduction of virtual bidding within electricity markets has introduced significant changes in market dynamics, with implications for environmental outcomes. It supports the transition towards a greener energy mix by favoring the dispatch of renewable resources and contributing to more efficient market conditions. This proposal seeks to explore the impact of virtual bidding and the development of green virtual bidding strategies by leveraging advanced machine learning models.

1 Introduction

The transition to a low-carbon economy is imperative in the fight against climate change, with the energy sector responsible for approximately 75% of global greenhouse gas emissions [1]. Achieving net-zero emissions by 2050 will require a 70%-80% reduction in carbon emissions from the energy sector [2], which is expected to involve increasing the share of renewables in global electricity generation to over 85% by 2050 [1]. Virtual bidding involves market participants taking financial positions without the intent of physically delivering or consuming electricity. It increases market liquidity and allows market participants to hedge against price volatility between the DA and RT markets [3, 4], and reduces price discrepancies [5]. Converging prices between the two markets reduce electricity price volatility, providing more stable price signals and leads to a better resource allocation [6]. Moreover, the introduction of virtual bidding in California for instance has led to a reduction of CO2 emissions which resulted from a better generation resource allocation [7]. Virtual bidding strategies within electricity markets supports progress towards Sustainable Development Goals [8], mainly SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). Our study aims to develop green virtual bidding strategies by leveraging advanced machine learning models and optimization algorithms, aligning with the shift toward a green energy economy that reflects

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the growing prioritization of sustainability by investors and governments [9, 10, 11, 12]. Accurate forecasting is critical for the success of green virtual bidding strategies. The reliance on machine learning models to predict market impacts and optimize bidding strategies introduces challenges.

2 Machine Learning to enhance virtual bidding strategies and address climate change

Virtual bidding strategies depend on forecasts of price discrepancies between the DA and RT electricity markets. The authors in [7, 13] assert that these discrepancies often occur between DA and RT electricity prices. The DA market is a forward market where electricity is traded a day prior to delivery, with prices determined based on supply and demand forecasts for each hour of the next day. In contrast, the RT market facilitates trading to balance supply and demand as they fluctuate throughout the day. Prices are determined based on immediate system conditions and any discrepancies from the DA schedule, [13]. In the absence of financial instruments designed to explicitly exploit price differences, physical participants will use their assets to implicitly arbitrage these differences by withholding load or generation in the DA market [7]. Such implicit arbitrage can entail costly actions which may negatively affect system reliability and lead to inefficient resource allocation, potentially increasing reliance on fossil fuels and exacerbating climate change impacts. The authors in [7] assert that virtual bidding reduced the need for physical participants to engage in more expensive and potentially distorting practices to take advantage of these electricity price differences. They used CAISO (California Independent System Operator) price data from the years 2009 through 2012 to compare the periods before and after the introduction of virtual bidding, which was introduced in CAISO in 2011. They found, in [7], that following the introduction of explicit virtual bidding, price differences between the DA and RT markets have diminished, RT price volatility decreased and there was a reduction of CO2 emissions of between 537,000 and 650,000 tons annually.

The discrepancy between DA and RT prices introduces challenges for effective resource allocation. Researchers have focused on highlighting the use of machine learning models in predicting DA and RT price differences, particularly the occurrence of price spikes that can significantly impact resource allocation and integration of renewable resources. [14] addresses the issue of forecasting extreme variations in the DART spread (DA price - RT price), well-known as the DART spikes. They consider the problem of forecasting these extreme negative DART spikes as the probability that a negative DART spike occurs in a given hour based on available information in the Long Island zone of the NYISO (New York Independent System Operator) market. Such a problem is expressed, in [14], as a supervised learning problem which is tackled with four machine learning algorithms : (1) logistic regression, (2) random forests, (3) gradient boosting trees, and (4) deep neural networks (DNN), finding that gradient boosting trees slightly outperformed other models, achieving an AUC of 0.769 [14]. Their backtesting of trading strategies incorporating model-generated spike probabilities demonstrated significantly higher profits, reduced risk, and improved risk-adjusted performance compared to a baseline strategy. This highlights the economic value of their developed signal [14]. Furthermore, [15] presents a model to predict the values of the price gap between DA and RT prices using statistical machine learning algorithms and deep neural networks. Their key findings include the benefits of directly predicting the price gap over subtracting individual market predictions and the significant impact of incorporating exogenous weather data on prediction accuracy. The authors in [15] used an ensemble learning algorithm, Random Forest (RF) for feature selection, while a Long Short-Term Memory (LSTM) network [16, 17] to capture long-term dependencies. Based on two years of data from CAISO market, their proposed method demonstrated a 46% reduction in prediction error, highlighting its potential to improve virtual bidding strategies and support operators. Consequently, machine learning can enhance virtual bidding strategies by improving the accuracy of the forecast of these DA and RT price discrepancies.

Our research will focus on developing green strategies, using machine learning models combined with optimization algorithms, to balance multiple objectives, such as maximizing financial returns and minimizing carbon emissions. By integrating environmental metrics (like carbon intensity or percentage of renewable resources in the fuel energy mix) into the optimization process of virtual bidding strategies, these models can contribute positively to climate change mitigation. Our approach will involve analyzing historical and real-time data to generate insights that align with green energy goals, ultimately supporting more efficient and environmentally-friendly virtual trading strategies.

3 Promoting renewable energy integration with virtual bidding

Virtual bidding enhances market efficiency and reduces price volatility [18, 19], leading to a more stable market. This mechanism fosters a more sustainable energy mix, contributing significantly to the fight against climate change. When real demand (D_{real}) exceeds forecasts ($D_{\text{forecasted}}$), Virtual Load (*VL*), which involves buying in the DA market and selling back in the RT market, helps correct this discrepancy by adding virtual electricity demand to the DA scheduling process [20]. Conversely, when D_{real} is lower than $D_{\text{forecasted}}$, Virtual Supply (*VS*), which involves selling in the DA market and buying back in the RT market, adds virtual electricity supply to the DA scheduling process [20]. Both mechanisms aim to reduce discrepancies between RT and DA prices, thereby improving market efficiency [18, 19, 21]. When both scenarios align, where $(D_{\text{real}} > D_{\text{forecasted}})$ and $(VL > VS)$ **or** where $(D_{\text{real}} < D_{\text{forecasted}})$ and $(VL < VS)$, it signifies that market participants are making accurate decisions regarding virtual bids.
Our application will initially focus on the NYISO market, with plans to expand to other U.S. electricity markets. The NYISO manages New York's electricity grid and wholesale markets and supports the state's ambitious climate goals, particularly the targets set by the Climate Leadership and Community Protection Act (CLCPA) [22], and is actively working on the integration of renewable energy resources in the fuel energy mix to support New York's transition to a cleaner energy future. Our work will help to quantify the impact of virtual bidding on the integration of renewable energy resources in the fuel energy mix when market participants are making accurate decisions.
We define a binary variable, referred to as *Impact*, as outlined in equation (1).

$$Impact = \begin{cases} 1 & \text{if } (D_{\text{real}} > D_{\text{forecasted}}) \wedge (VL > VS) \text{ or } (D_{\text{real}} < D_{\text{forecasted}}) \wedge (VL < VS) \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

This variable provides an insight about market participants decisions, and could be added as a feature to machine learning models to identify green virtual trading strategies. We could use it as a target variable in classification models to identify periods when virtual bidding had a significant influence on market conditions. Added to environmental metrics, this can help in identifying strategies that consistently lead to favorable outcomes, and increased renewable energy integration in the fuel energy mix leading to a reduction of carbon emissions.

Our first findings, using data [23, 24] collected from selected zones within the NYISO control area that include detailed records of electricity prices, demand, bid volumes, and the corresponding energy mix, shows that when market participants are making accurate decisions towards their bids, the percentage of renewable energy resources integrated in the energy mix are greater by an average of **1.28%**. Although the difference between the groups might seem small, translating this difference into CO2 emissions highlights its significant impact. Indeed, the total annual energy consumption in NYISO is approximately 150 TWh [25]. The share of renewable energy stands at 27% [23]. With a CO2 emission factor for fossil fuels of 0.5 tons CO2 per MWh (scope 1 emissions) [26], the existing CO2 emissions are calculated based on the fossil fuel energy consumption of 109,500,000 MWh, resulting in total emissions of 54,750,000 tons CO2. If the renewable energy share increases by **1.28%**, fossil fuel energy consumption would decrease to 107,580,000 MWh, leading to a reduction in CO2 emissions to 53,790,000 tons CO2. This would result in a total CO2 emissions reduction of 960,000 tons CO2.
Consequently, using projected generation mix data, we could implement a green virtual bidding strategy by adjusting bids based on the projected share of renewable energy and price signals.

4 Conclusion

The growing importance of a green energy economy underscores a significant shift in both investor and governmental priorities towards sustainability. There is an increasing interest in initiatives and investments that promote environmentally-friendly practices within energy markets. Our project will participate in this initiative by advancing green virtual trading strategies and supporting the transition to a more sustainable energy system. By leveraging advanced machine learning models to enhance the accuracy of price discrepancies forecasts, quantify virtual bidding impact on renewable energy integration, and optimize virtual bidding decisions under the constraints of carbon metrics using various optimization algorithms, we aim to improve the efficiency and effectiveness of these green strategies.

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