Price discrepancies between the day-ahead and real-time markets represent a form of market inefficiency. To promote price convergence between the two markets, virtual trading was introduced in the U.S. electricity markets in early 2000s that allows market participants to arbitrage on the differences between the day-ahead and real-time prices. Empirical and theoretical studies have shown that increased competition due to virtual trading results in a level of price convergence, thus improving market efficiency. Currently, cleared virtual transactions represent a significant fraction of total energy trade.

In this talk, we present an online learning approach to algorithmic bidding for virtual trading in a two-settlement market where there are a large number of trading options defined by the location and the time of trades. Without assuming specific parametric models of day-ahead and real-time prices, we develop an online learning algorithm that maximizes the cumulative return from the bidding strategy under both risk-neutral and risk-averse performance measures. We demonstrate that the proposed strategy outperforms existing machine learning benchmarks and achieves significant profit consistently based on historical data from the NYISO and PJM markets over the eleven-year period between 2006 and 2016.