Algorithmic Trading Strategy with Virtual Bids in Electricity Markets

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Outline

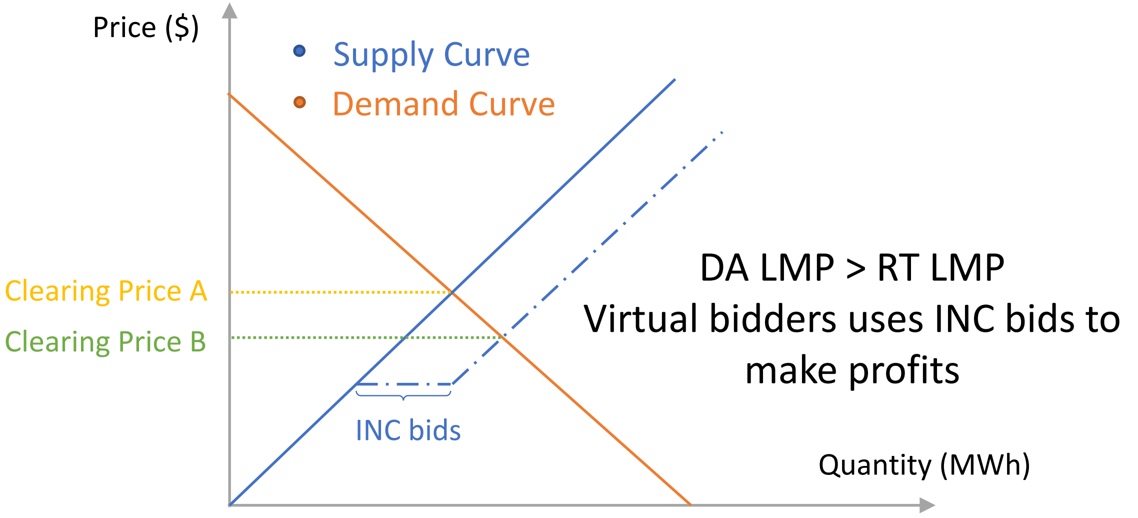
- Background and Objectives
- Literature Review
- Overall Framework
- Forecast of Price Spread and Price Sensitivity
- Portfolio Optimization
- Extension to Congestion Arbitrage to Avoid Uplift Cost
- Conclusion

Background and Objectives

- Background
  - Regional wholesale electricity markets in the U.S. adopt the two-settlement system
    - Day-ahead market: Forward market that determines the hourly DA locational marginal prices (LMPs), the unit commitment plans, and the DA dispatch schedules using supply offers and demand bids submitted by market participants
    - Real-time market: Spot market that calculates the RT LMPs and the unit/resource dispatch schedules based on the updated supply offers and actual operating conditions described by the state estimator.
  - Virtual bids
    - Financial product (do not have to be backed by physical assets)
    - Allow market participants to buy or sell energy in DA market with an explicit requirement to sell or buy it back in RT market
- Objectives
  - Develop an algorithmic trading strategy with virtual bids from the perspective of proprietary trading companies
    - Maximize expected portfolio profit subject to budget and risk constraints
  - Evaluate and compare the market efficiencies of different regional electricity markets in the U.S.

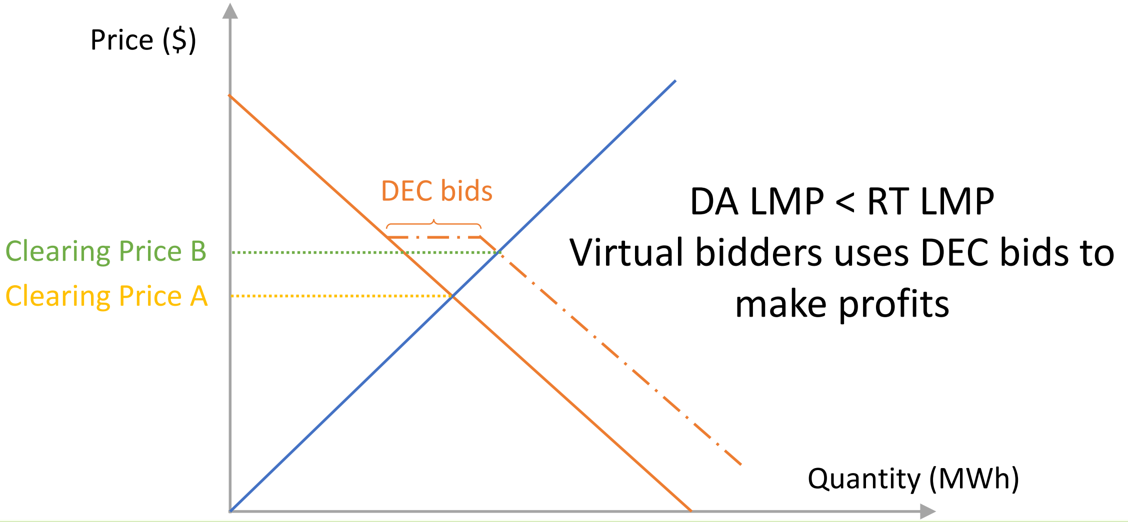
Virtual Bids and Its Impacts on Market

- Two Types of Virtual Bids
  - Incremental Offer (INC) also known as Virtual Supply
    - Enable virtual bidders to sell energy in DA market and buy the same amount of energy back in RT market at the same pricing node.
  - Decrement Bid (DEC) also known as Virtual Demand
    - Enable virtual bidders to buy energy in DA market and sell the same amount of energy back in RT market at the same pricing node.
- Impacts of Virtual Transactions
  - Promote price convergence, improve market efficiency, provide hedging instrument, enhance market liquidity
  - Inappropriate market designs (e.g., modeling discrepancies & virtual bids on interties) led to inefficient market solutions.



INC bids lower DA LMP to promote price convergence

DEC bids raise DA LMP to promote price convergence



Market Efficiency Definitions

- The Efficient Markets Hypothesis (EMH)
  - Brought up by Eugene Fama in 1970 book “Efficient Capital Markets: A Review of Theory and Empirical Work”
  - Current asset prices fully reflect all currently available relevant information
- Three Forms of Market Efficiency Hypothesis
  - Weak Form: all previous market price information is reflected by the current market price
    - With early access to public and insider information, one can exceed normal returns.
  - Semi-strong Form: all readily available information is reflected by the current market price
    - Asset price immediately adjusts to the release of new public information
  - Strong Form: all relevant information is reflected by the current market price
    - Even insider information cannot help exceed normal returns.
- In this work, we use all readily available information to identify arbitrage opportunities with virtual bids and test the semi-strong form of market efficiency hypothesis in electricity market.

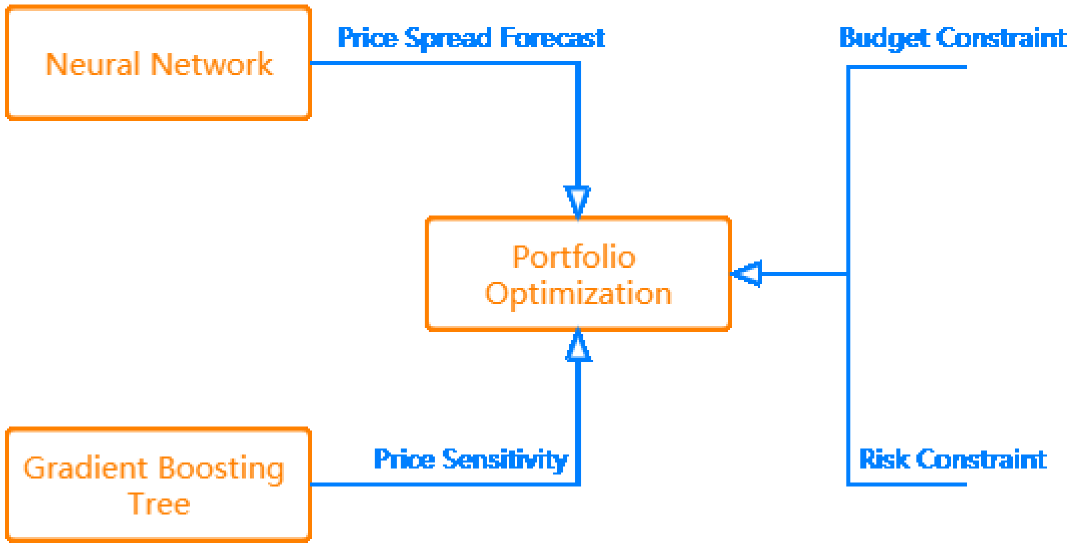
Literature Review

- Identified profitable virtual bid trading strategy based solely on historical prices
  - Underestimate the potential profitability of virtual bids and overestimate market efficiency by limiting the available information for virtual traders to historical LMPs only [1] [2] [3].
  - Overestimate potential profitability of virtual bid strategy
    - Neglected virtual bid transaction fees [3]
    - Missed uplift costs of virtual bids [2]
- Develop algorithmic trading strategy for virtual bidding with all publicly available information
  - Ignored impacts of virtual bidders' trading activities on electricity market prices [4]

1. A. Jha and F. Wolak, "Testing for market efficiency with transactions costs: An application to convergence bidding in wholesale electricity markets," *Industrial Organization Seminar*, Yale University, May 2013.
2. R. Li, A. Svoboda, and S. Oren, "Efficiency impact of convergence bidding in the California electricity market," *Journal of Regulatory Economics*, vol. 48, no. 3, pp. 245–284, 2015.
3. S. Baltaoglu, L. Tong, and Q. Zhao, "Algorithmic bidding for virtual trading in electricity markets," *IEEE Transactions on Power Systems*, vol. 34, no. 1, pp. 535–543, 2019.
4. W. Wang and N. Yu, "A machine learning framework for algorithmic trading with virtual bids in electricity markets," *2019 IEEE Power & Energy Society General Meeting (PESGM)*. IEEE, 2019, pp. 1–5.

Overall Framework*

- Three Key Technical Components
  - Forecast of price spread between DA and RT market with deep neural network
  - Model price sensitivity with respect to virtual bid quantity with gradient boosting tree
  - Portfolio optimization that determines bidding positions to maximize profit considering price sensitivity with risk and budget constraints



* Y. Li, N. Yu, and W. Wang, "Machine learning-driven virtual bidding with electricity market efficiency analysis," *IEEE Transactions on Power Systems*, vol. 37, no. 1, pp. 354-364, Jan. 2022.

Forecast of Price Spread

- A separate price spread model is trained for each pricing node
- Model Inputs
  - Load, weather, fuel price, import forecast, generation outage
  - Hourly timestamp, wind and solar generation forecast
  - Batch normalization
- Model Outputs
  - Price spread between DA and RT LMPs at each nodes
  - Address volatile and spiky price spread with pre-processing using sigmoid function $f(x) = 1/(1 + \exp(-x/\theta))$
- Model Selection
  - Feed-forward neural network (computationally efficient for large-scale demonstration with thousands of pricing nodes)
  - Long short-term memory model captures the temporal correlations on the time series price spread data
  - Mixture density model to capture the multi-modality of the price spread distribution
  - Graphical learning model can be developed if detailed network topology information is made available

Portfolio Optimization Formulation*

$$\max_{\boldsymbol{z}} E[\pi_{daily}(\boldsymbol{z})]$$

Maximize the expected portfolio profit

s.t. $$\sum_{i=1}^{N}\sum_{h=1}^{24}[Prox_{i,h}^{I}\, z_{i,h}^{I} + Prox_{i,h}^{I}\, z_{i,h}^{D}] \le \mathcal{B}$$

Portfolio budget constraint

$$\sum_{h=1}^{24} CVaR_{\alpha}\left(f_h\left(\boldsymbol{z_h}, \boldsymbol{\lambda_h^{dif}}\right)\right) \le \mathcal{C}$$

Portfolio risk constraint

$$f_h\left(\boldsymbol{z_h}, \boldsymbol{\lambda_h^{dif}}\right) = -\sum_{i=1}^{N}[r_{i,h}^{I} z_{i,h}^{I} + r_{i,h}^{D} z_{i,h}^{D}]$$

Portfolio loss function

$$E\left[\pi_{daily}(\boldsymbol{z})\right] = \sum_{i=1}^{N}\sum_{h=1}^{24}[z_{i,h}^{I} E[r_{i,h}^{I}(\boldsymbol{z_h})] + z_{i,h}^{D} E[r_{i,h}^{D}(\boldsymbol{z_h})]]$$

Portfolio daily expected profit

$$E\left[r_{i,h}^{I}\right] = E[(\lambda_{i,h}^{dif} - \gamma^{I})\mathbf{1}(\lambda_{i,h}^{bid,I} \le \lambda_{i,h}^{DA})]$$

$$E\left[r_{i,h}^{D}\right] = E[(-\lambda_{i,h}^{dif} - \gamma^{D})\mathbf{1}(\lambda_{i,h}^{bid,D} \ge \lambda_{i,h}^{DA})]$$

Expected profit of 1MW of INC/DEC bid without considering price sensitivity

* W. Wang and N. Yu, "A machine learning framework for algorithmic trading with virtual bids in electricity markets," *IEEE Power and Energy Society General Meeting*, pp. 1-5, 2019.

Modeling of Price Sensitivity w.r.t. Virtual Bids

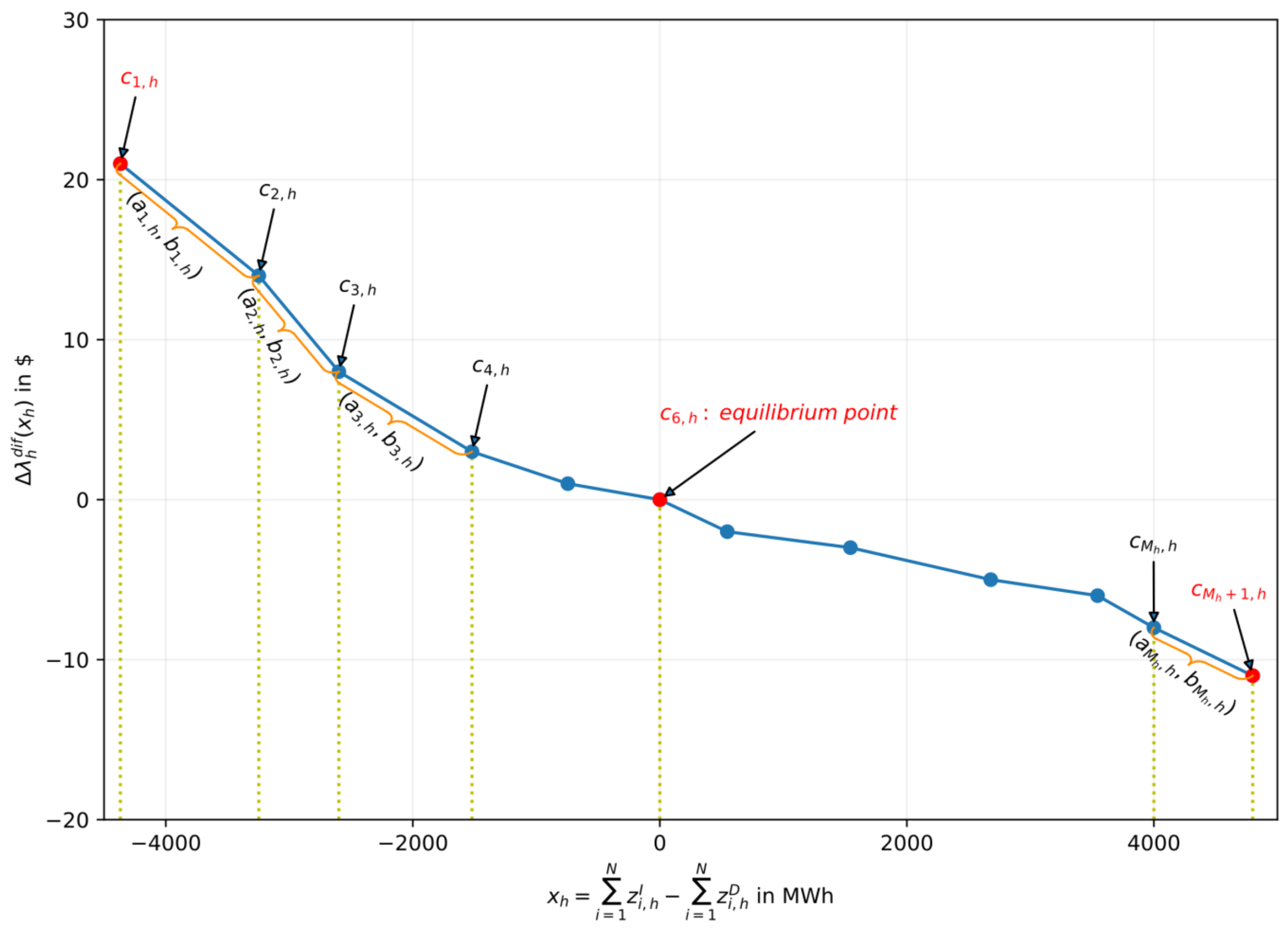
- The change in price spread is a function of market-wide virtual bidding quantity

$$\Delta\lambda_h^{dif}(\boldsymbol{z}_h) = \Delta\lambda_h^{dif}(x_h + \widehat{y_h}) - \Delta\lambda_h^{dif}(\widehat{y_h})$$

  - $x_h = \sum_{i=1}^{N} z_{i,h}^{I} - \sum_{i=1}^{N} z_{i,h}^{D}$ denotes the trader's bidding quantity in hour h
  - $\widehat{y_h}$: Estimation of exogenous virtual bidding quantity in hour h
- Need an interpretable and piece-wise linear model with the ability to enforce the monotonicity of the price sensitivity function.
  - i.e. the price spread monotonically decrease w.r.t. INC bids and monotonically increase w.r.t to DEC bids
- Adopted gradient boosting tree (GBT)
  - Greedy search is performed on all candidate variables for each iteration to find the maximum gain that also complies with monotonicity requirement.
  - A split is made at a node if the inequality of scores complies with monotonicity requirement

Estimation and Integration of Price Sensitivity

Illustration of Piece-wise Linear Price Sensitivity Function



- From the trained GBT model, derive the price sensitivity function as a piece-wise linear function of bidding quantity

$$\Delta\lambda_h^{DA}(\boldsymbol{z_h}) = \sum_{j=1}^{M_h} (a_{j.h} x_h + b_{j,h}) d_{j,h}$$

- $a_{j.h}$: Function slope of j-th piece in hour h
- $b_{j,h}$: Function y-intersect of the j-th piece in hour h
- $d_{j,h}$: Binary indicator variable of j-th piece in hour h

Numerical Study - Setup

- Three Independent System Operators
  - PJM with 1,101 pricing nodes
    - 3 years of data from Jan. 2015 to Dec. 2017; Uplift cost: 0.325 \$/MWh for INC bids, 0.395 \$/MWh for DEC bids
  - ISO-NE with 994 pricing nodes
    - 3 years of data from Jan. 2015 to Dec. 2017; Uplift cost: 1.25 \$/MWh for all virtual bids
  - CAISO with 395 aggregated pricing nodes
    - 3 years of data from July 2017 to June 2020; Uplift cost: 0.61 \$/MWh for all virtual bids
- Training, Validation and Testing
  - For neural network training and validation, one year of data is used
  - A rolling training/validation and testing framework with monthly update frequency is used
  - The last two years’ data is used for out of sample testing

Neural Network & Virtual Bid Portfolio Setup

- Feed-Forward Neural Network
  - Key Hyperparameters
    - No. Training Epoch: 1,000
    - Batch size: 1,024; Optimizer: Adam

Market	Hidden Units	Dropout %	Activation
PJM	[128, 64, 32]	20	tanh
ISO-NE	[64, 32]		
CAISO	[128, 64, 32]		

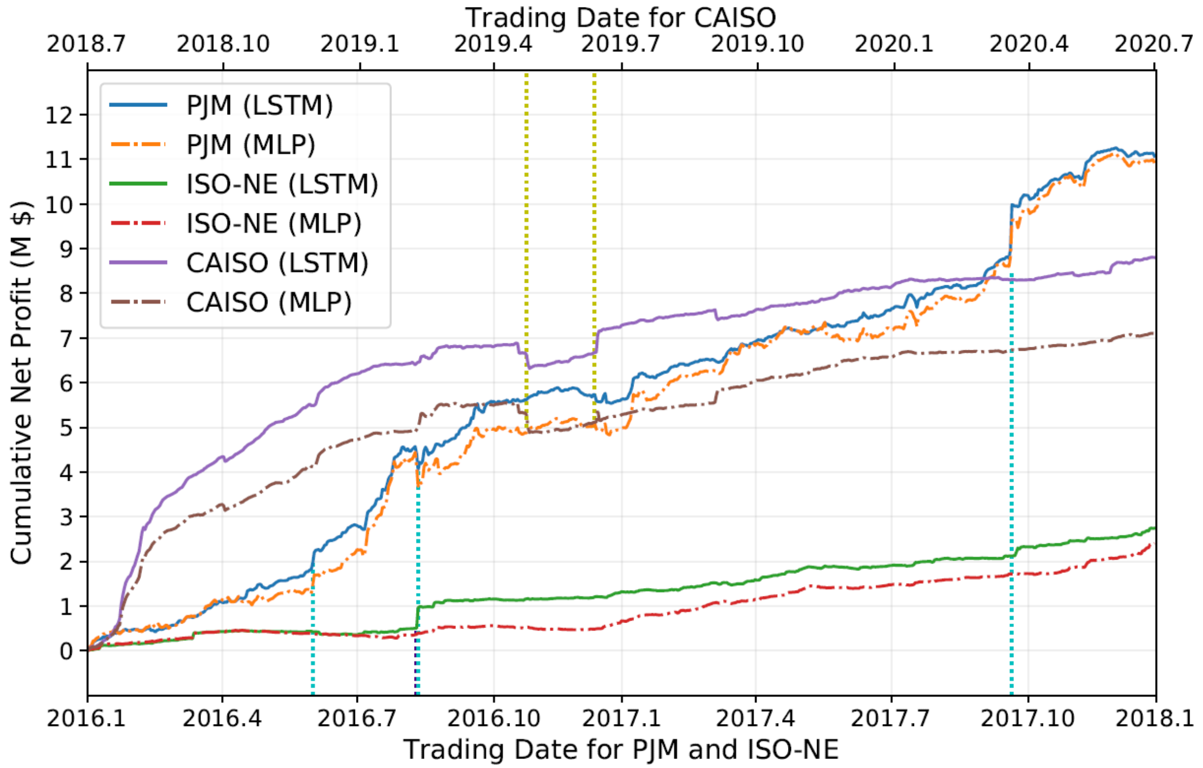
- Long Short-term Memory Model
  - Key Hyperparameters
    - No. Training Epoch: 50; Batch size: 1,024
    - Optimizer: Adam; Window Size: 4

Market	Hidden Units	Dropout %	Activation
PJM	[64, 128, 128, 64, 32]	20	tanh
ISO-NE	[32, 64, 64, 32]		
CAISO	[64, 128, 128, 64, 32]		

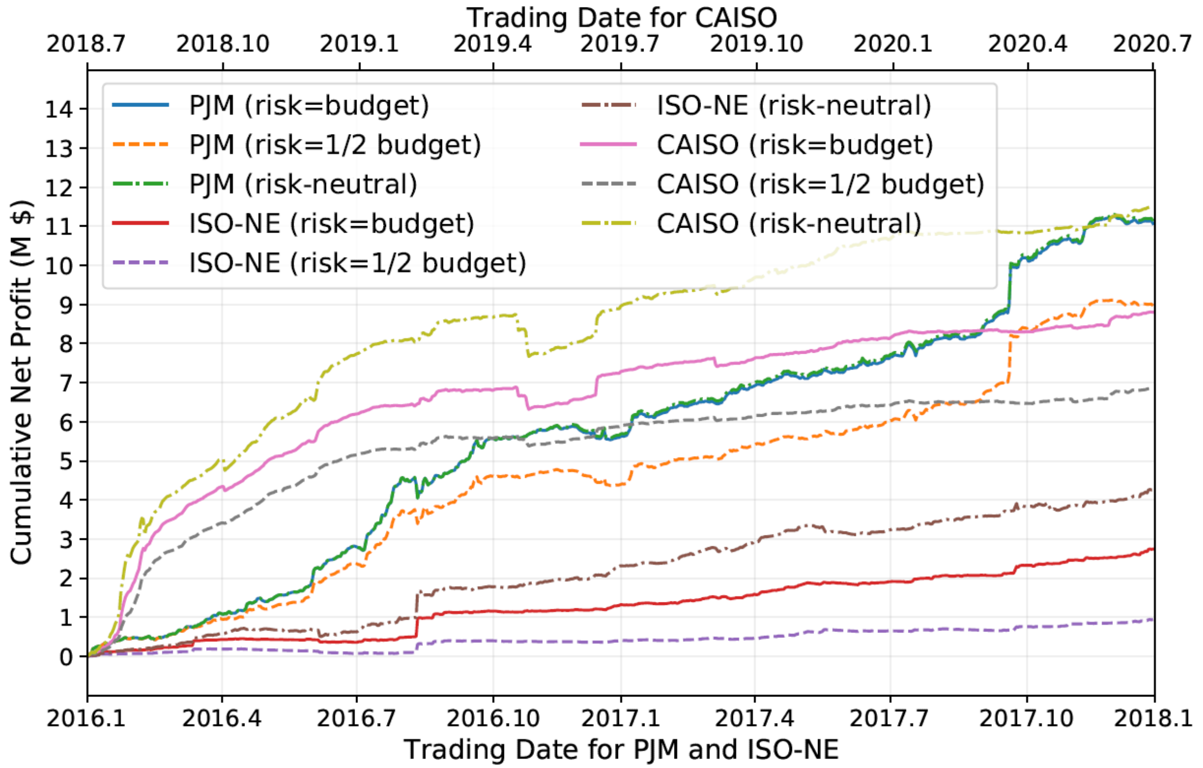
- Virtual Bid Portfolio Setup
  - Portfolio budget set at 5% of the market share for virtual bids
  - PJM $330,000; ISO-NE $25,000; CAISO $85,000.

Results: Cumulative Profit of Algorithmic Trading Strategy without Considering Price Sensitivity

Comparison between Two Price Spread Prediction Models



Impact of Portfolio Risk Limit on Profitability

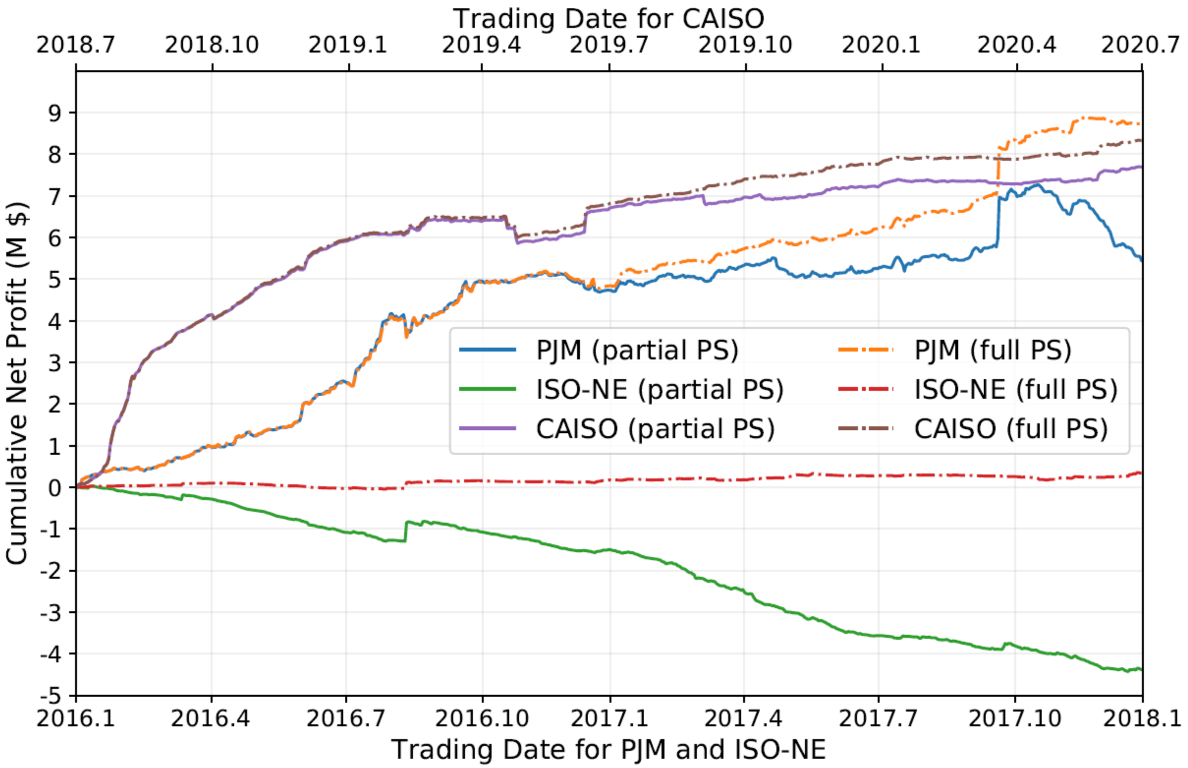


- LSTM outperforms MLP by 1.4%, 14.1% and 23.9% for PJM, ISO-NE and CAISO
- Algorithmic trading strategy yields $11M, $3M, and $9M for PJM, ISO-NE and CAISO

- Doubling the risk limit from one half of the budget to the budget limit leads to 18%, 60%, and 22% higher virtual bid portfolio profit for PJM, ISO-NE, and CAISO.

Results: Impacts of Price Sensitivity on Portfolio Profitability and Price Convergence

Profitability of Algorithmic Trading Strategies Considering Price Sensitivity



- Trading company's virtual bidding activity reduces profit in PJM, CAISO, ISO-NE by $2M, $0.7M, and $2.5M.
- Considering price sensitivity in portfolio optimization increases profit for ISO-NE, PJM, and CAISO by $4M, $2.5M, and $0.9M.

LMP Convergence Considering Price Sensitivity

Market	Year	Average Absolute LMP Spread ($/MWh)	
		without virtual bidding	with virtual bidding
PJM	yr 1	6.37	6.25
	yr 2	6.07	5.84
ISO-NE	yr 1	9.39	8.45
	yr 2	10.38	9.18
CAISO	yr 1	13.25	12.97
	yr 2	7.11	6.96

- Impact from algorithmic virtual bids with quantity equal to 5% of the market share
- The presence of virtual bid does lead to some reduction in LMP spread between DA and RT market.

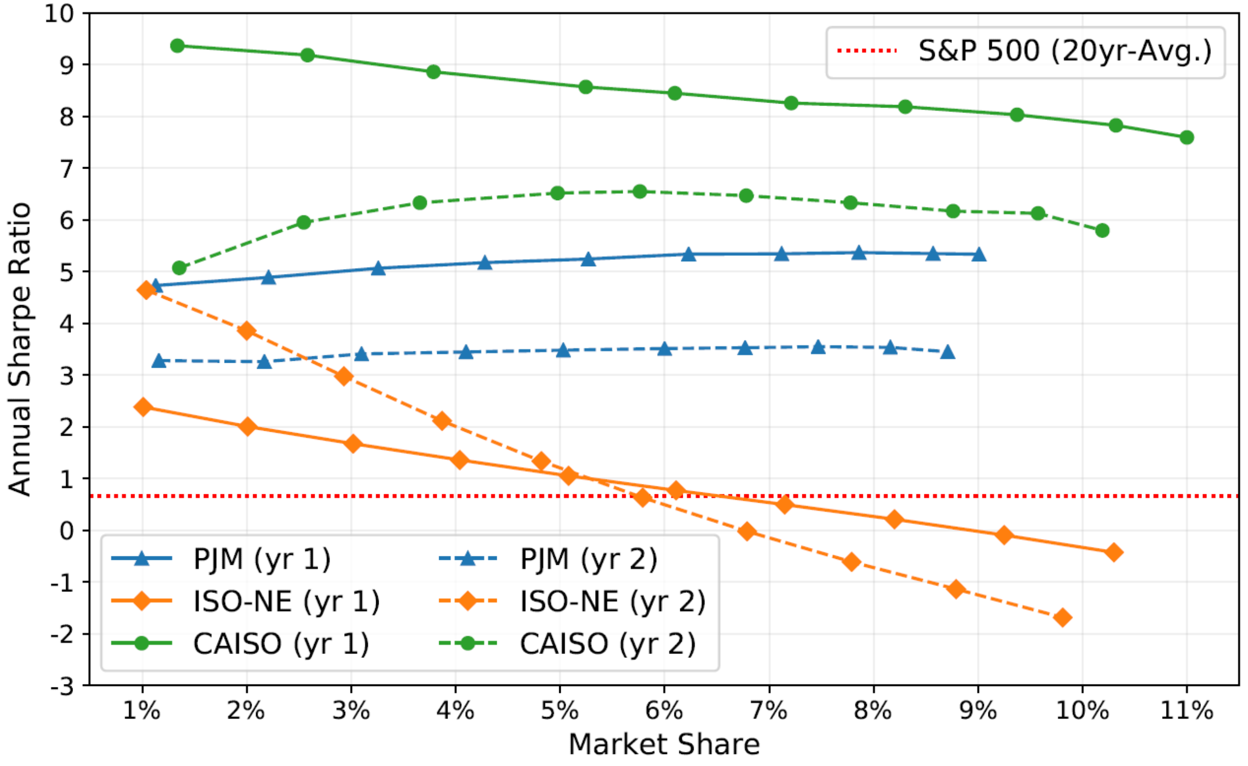
Sharpe Ratio and Market Efficiency

- Definition of Sharpe Ratio (S_p)

$$S_p = \frac{E[R_a - R_f]}{\sqrt{var(R_a - R_f)}}$$

  - R_a is the virtual bid portfolio's rate of return
  - R_f is the rate of return of risk-free asset
- Measures the performance of the virtual bids portfolio compared to a risk-free asset after adjusting for its risk.
- If the algorithmic trading strategy achieves a high Sharpe ratio, then the corresponding market's efficiency should be low.
- Compare against S&P 500 index measuring the stock performance of 500 large companies listed on stock exchanges in the United States.

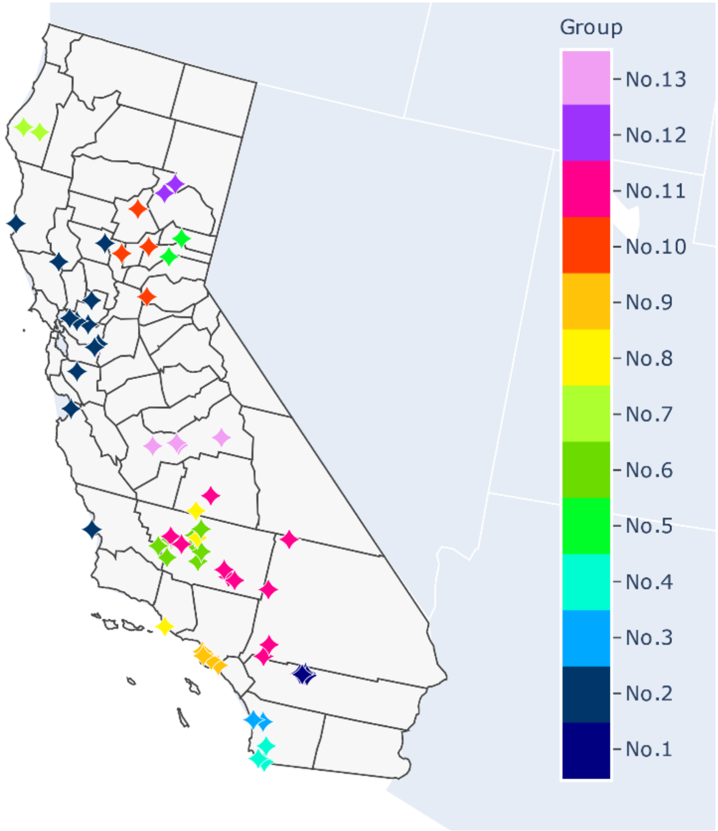
Sharpe Ratios of Algorithmic Virtual Bids Trading Portfolio



- The Sharpe ratio of virtual bid portfolios for CAISO and PJM are much higher than that of the S&P 500 index for all market shares.
- The electricity markets' two settlement systems are in general much less efficient than the stock market.

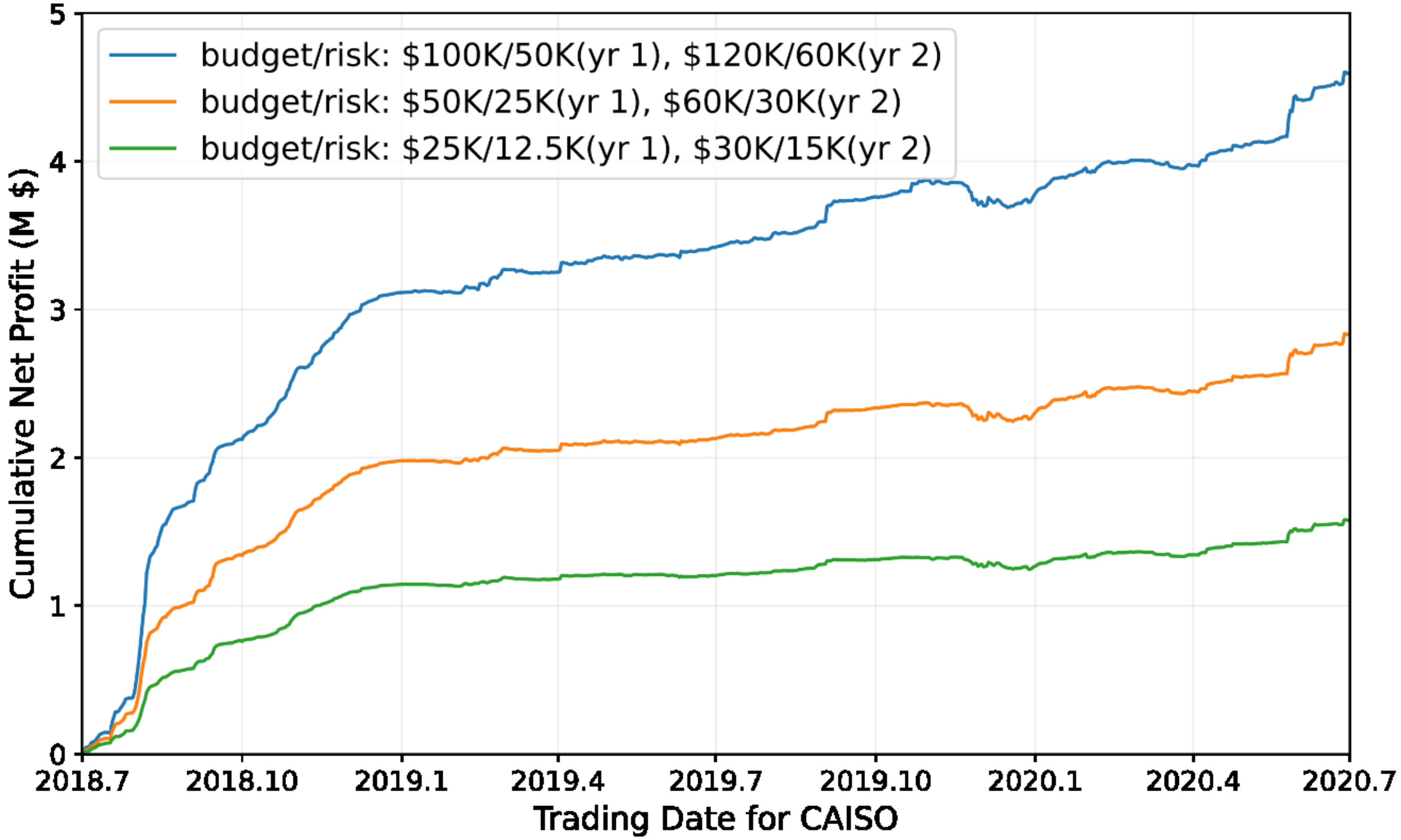
Extension to Congestion Arbitrage*

- Motivation: Uplift cost unpredictable and varies significantly with time
- Need to find a way to completely remove the risk of high uplift cost



Geographical Information of Clustered Bidding Nodes

Cumulative Profit of Congestion Arbitrage



- A 5.48% of virtual bid market share budget limit corresponds to $4.59 M of cumulative profit

*Y. Li and N. Yu, "Learning to arbitrage congestion in electricity market with virtual bids," *IEEE ISGT Europe*, 2021.

Conclusion

- A risk and budget constrained algorithmic virtual bid trading strategy that considers the impacts of virtual bids on LMPs is developed
- The proposed algorithmic virtual bid trading strategy achieves very high profits for PJM and CAISO.
- Comprehensive empirical studies on 3 U.S. electricity markets show that proposed strategy considering price sensitivity outperforms the one that ignores it.
- The Sharpe ratios of virtual bid portfolios for 3 electricity market are all significantly higher than that of S&P 500 index when the virtual bidder’s market share is lower than 5%.
- An algorithmic trading strategy to arbitrage congestion with virtual bids in the wholesale electricity market is proposed.
- The empirical results with CAISO managed electricity market demonstrate that the proposed framework is capable of capturing the congestion differences in node pairs and making notable profits by arbitraging the congestion.

Reference

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Thank You

UCR Ph.D. Students: Yinglun Li and Wei Wang

Portfolio Optimization - Notations

- $\lambda_{i,h}^{DA}, \lambda_{i,h}^{RT}$: DA LMP and RT LMP at node i in hour h
- $\lambda_{i,h}^{dif} = \lambda_{i,h}^{DA} - \lambda_{i,h}^{RT}$: Price spread at node i in hour h
- $r_{i,h}^{I}, r_{i,h}^{D}$: Net earnings of INC bids and DEC bids at node i in hour h
- $z_{i,h}^{I}, z_{i,h}^{D}$: Binary decision variable INC bids and DEC bids at node i in hour h
- γ^{I}, γ^{D}: Uplift cost of INC bids and DEC bids
- $prox_{i,h}$: Collateral required for bidding 1 MW of virtual bid at node i in hour h
- $\mathcal{B}$: Daily virtual bid portfolio budget limit
- $\mathcal{C}$: Daily virtual bid portfolio risk limit
- $\pi_{daily}(\boldsymbol{z})$: Daily portfolio profit