Empirical Analysis of Financial Transmission Right Trading Behavior

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***Abstract*—Financial transmission rights (FTRs) serve as important financial instruments for risk mitigation and congestion arbitrage in the electricity market. Although substantial research has investigated the bidding strategies associated with many market products such as energy, ancillary services and virtual bids, a comprehensive study from a proprietary trading company (PTC)'s perspective for FTRs is lacking. To fill the research gap, this paper investigates the bidding strategies of PTCs in the Midcontinent Independent System Operator (MISO)'s annual FTR auctions from 2021 to 2022. First, we develop a matching algorithm to map asset owner identification numbers to entity codes of PTCs. Then, we deploy the K-medoids clustering algorithm to analyze the FTR bidding behavior of the top 10 PTCs. Our study identifies a unique approach used by some PTCs that leverages an unconventional strategy to arbitrage the differences between settlement prices of FTRs between rounds of the annual auction.**

***Index Terms*—Data mining, trading behavior, electricity market, financial transmission right.**

I. Introduction

In the United States, electricity markets comprise wholesale and retail markets, where the wholesale markets are usually managed by independent system operators (ISOs). The ISOs, as independent non-profit organizations, ensure the fairness of the wholesale electricity market and maintains the energy adequacy and stability of the power system. Currently, there are seven ISOs in the United States, namely Midcontinent Independent System Operator (MISO), Pennsylvania New Jersey Maryland Interconnection (PJM), California Independent System Operator (CAISO), New England Independent System Operator (ISO-NE), Electric Reliability Council of Texas (ERCOT), Southwest Power Pool (SPP), and New York Independent System Operator (NYISO), each managing the electricity market within a specific region [1]. Although similar electricity market products are offered by ISOs, they can vary slightly. The following products are offered by almost all ISOs: the energy market (comprised of day-ahead and real-time markets), the capacity market, the ancillary services market, and financial instruments such as virtual bid (VB) [2] and financial transmission right (FTR) [3], [4].

The day-ahead market (DAM) allows market participants (MPs) to buy and sell electricity one day before the operating day. In DAM, the locational marginal price (LMP) reflects the incremental cost associated with supplying the next increment of power at a given location [5], [6]. It is composed of three price components: the marginal energy component, the marginal congestion component, and the marginal loss component. In scenarios where transmission lines reach their maximum capacity, the ability to meet electricity demand using the most cost-effective generators becomes compromised. In such situations, ISOs are forced to dispatch generators with higher marginal operational costs to fulfill the additional demand, incurring congestion costs that contribute to the marginal congestion component of LMP [7].

FTR is a financial instrument used by MPs such as proprietary trading companies (PTCs), investor-owned utilities, and municipal utilities to hedge financial risk or arbitrage congestion in the electricity market. FTR entitles the holders to receive a stream of revenues (or charges) based on the day-ahead LMP congestion components' differences across the source and sink nodes of various paths. ISOs assign auction revenue rights (ARRs) to MPs, which entitle them to receive the proceeds from the FTR auctions [8]. MPs may acquire FTR in a few ways: annual FTR auction, long-term FTR auction, monthly FTR auction, and FTR secondary market [9]. In many ISO markets, FTRs can be acquired in two forms: FTR obligation and FTR option. The FTR obligation mandates that MPs must either pay or receive the hourly congestion value, whereas the FTR option holder only enjoys FTR benefit when the hourly congestion value is positive. The economic value of FTR is derived by calculating the product of the trading quantity and the difference between the LMP at the sink node and the LMP at the source node [10]–[12]. MISO holds auctions for FTR obligations that cover the contract duration of one month, one quarter, and several months/quarters [9]. In this research, we will focus on the PTC's bidding strategies and behaviors in annual FTR auction from 2021 to 2022 in MISO.

Prior research papers have investigated the bidding strategies associated with the energy product, the ancillary services, and financial instruments such as virtual bids. Many researchers developed virtual bid trading strategies to maximize the expected profit subject to portfolio budget and risk constraints [13]–[16]. The authors in [17] present an optimization algorithm to determine spinning reserve bidding curves from the perspective of the generation companies.

A stochastic model was developed to construct the optimal bids of wind farms [18]. A reinforcement learning algorithm was leveraged to model the trading behavior of generators to generate energy and ancillary service bids [19]. The bidding behaviors of individual generators in Australian energy market were analyzed in [20]. The authors identified several energy bidding behaviors including energy-preferred, price-preferred, and capacity-withholding. However, there remains a major gap in the study of PTCs' bidding strategies in FTR auction markets.

To fill this knowledge gap, we analyze the FTR bidding behaviors of PTCs in the MISO market using publicly available data. The contributions of this paper are summarized as follows:

1) We developed an algorithm to associate MPs' entity codes with their unique asset owner identification number encrypted by MISO.
2) We investigated the FTR auction bid curves by performing clustering analysis, which helps identify different bidding approaches of PTCs.
3) We explored the correlation between trading volumes and profits in FTR paths from 2021 to 2022 and discover an unconventional but profitable bidding strategy to arbitrage differences in FTR settlement prices in different auction rounds.

The remainder of the paper is organized as follows: Section II provides an overview of the FTR market in MISO, including the annual auction, the real-world dataset, and the categorization and identification of MPs. Section III investigates the FTR auction bids, awards, and profits, the clustered bidding curves, and the bidding strategies. Section IV concludes the paper.

II. Overview of the FTR Market in MISO

A. Annual FTR Auction

MPs of MISO acquire the bulk of FTR obligations by participation in the three-round annual FTR auction. In this study, we focus on those MPs who procure seasonal FTRs via the annual auction. The annual FTR auction in MISO spans from June in the current year to May in the next year, enabling the trading of FTRs for the upcoming planning year.

The inputs to the annual FTR auction clearing process from MISO include: the transmission system maintenance and outage schedules, list of contingencies, pre-existing FTRs, transmission network model, reliability-relate constraints, and valid FTR bidding paths [21]. The MPs are required to submit FTR bids with the following information: FTR bid type (buy or sell), FTR path (sink node or source node), season (summer, fall, winter, or spring), time-of-use (peak or off-peak), round (first, second, or third), quantity (in MW) and price ($/MW) of bidding curves (up to 9 segments). The FTR supply offer curve must be monotonically non-decreasing, and the FTR demand bid curve must be monotonically non-increasing [21].

The FTR auction clearing engine solves an optimization problem that maximizes the bid value of a set of simultaneous feasible FTR bids and offers. The market clearing price of an FTR is the sum over all transmission constraints of the product of the power transfer distribution factor (PTDF) and the shadow price of the transmission constraint in the direction of the PTDF [21]. The FTR market clearing price and the winning FTR bids/offers are communicated to all auction participants. MISO reveals the FTR bids and offers information to the public 90 days after the auction. However, the identities of the FTR bidders and offerors are concealed.

B. Publicly Available Dataset

In this study, we analyze MISO market data from 2021 to 2022. The dataset includes day-ahead ex-post LMPs, annual FTR auction results, annual FTR auction bids and offers, and a list of certified MPs. The hourly day-ahead ex-post LMPs from every pricing node are made available by MISO.

In the annual FTR auction results, MISO categorizes the data by seasons (fall, spring, summer, and winter) and auction rounds (one, two, and three). Each FTR award record contains the FTR identification number, the MP, source node, sink node, start date, end date, bid type, time-of-use (TOU) class, cleared quantity, clearing price, and auction round. Each FTR bid/offer record includes market name, source node, sink node, bid type, TOU class, start date, end date, round, price and quantity pairs of the bidding curve, and asset owner identification number. Lastly, the list of certified MP provides a compilation of MPs and their entity codes.

C. Categorization and Identification of Market Participants

Using the list of certified MPs, we looked up each MP and categorized them into one of the following groups: PTCs, municipal utilities, investor-owned utilities, renewable energy developers, cooperatives, independent power producers, energy service providers, and others. We summarized the annual market clearing results and the annual auction bids and offers by MP type and investigate the bidding strategies and trading behaviors of the PTCs.

The annual FTR auction results data are organized by MPs' entity codes where as the FTR bid and offer records are arranged by the asset owner identification number. We propose an algorithm that matches the asset owner identification numbers with the MPs' entity codes, which is a necessary step before analyzing individual MP's trading strategy. For season s and auction round r, we define the annual FTR auction results as a set $M_{s,r}$ and the annual auction bids and offers as another set $B_{s,r}$. For each element $m \in M_{s,r}$, it has the following attributes: source node $source$, sink node $sink$, TOU class $class$, bid type $type$ (buy or sell), cleared quantity $quant$, clearing price $price$. Similarly, for each element $b \in B_{s,r}$, it has all the same attributes as $m \in M_{s,r}$ except that there are multiple bid steps. Each bid step i is represented by a bid quantity q_i and bid price p_i. In addition, the bid type $type$ also includes self-schedule. These attributes are the data inputs to the matching algorithm.

Algorithm 1 takes $M_{s,r}$ and $B_{s,r}$ as inputs and returns $R_{s,r}$ which contains the matching results between asset owner identification number and the MP's entity code for season s

TABLE I

SUMMARY OF FTR TRADING VOLUME FOR ALL MARKET PARTICIPANTS IN 2021 AND 2022 BY ON/OFF PEAK, SEASONS, AND FLOWS

Bid Vol. (TWh)				**Cleared Vol. (TWh)**			
15,803				4,239			
Peak		**Off-Peak**		**Peak**		**Off-Peak**	
10,898		4,905		2,917		1,323	
PF	**CF**	**PF**	**CF**	**PF**	**CF**	**PF**	**CF**
8,116	2,783	3,630	1,273	1,994	923	655	668
Seasonal Vol. (TWh)							
Summer	**Fall**	**Winter**	**Spring**	**Summer**	**Fall**	**Winter**	**Spring**
4,041	4,088	3,771	3,903	1,107	1,065	1,023	1,044

TWh: terawatt hour, Vol.: volume, PF: prevailing flow, and CF: counter flow

Algorithm 1 Matching Algorithm

$Input : Market\ result := M_{s,r},\ Bid\ file := B_{s,r}$
$Output : Matched\ entity := R_{s,r}$
$Initialization : G^m_{s,r} \leftarrow \varnothing,\ \forall m \in M_{s,r},\ R_{s,r} \leftarrow \varnothing$
for each $m \in M_{s,r}$ **do**
  $C \leftarrow \{b | b \in B_{s,r},\ b.source = m.source,\ b.sink = m.sink,\ b.type \in T_{m.type},\ b.class = m.class\}$
  for each $c \in C$ **do**
    for $i = 2$ to 10 **do**
      if $b.type$ = Self-Schedule and $m.quant = b.q_{i-1}$ **then**
        $err \leftarrow 0$
        $G^m_{s,r} \leftarrow G^m_{s,r} \cup \{(err,\ b.q_{i-1},\ b.id)\}$
      else if ($b.type$ = Buy and $m.price < b.p_{i-1}$ and $m.price > b.p_i$) or ($b.type$ = Sell and $m.price < b.p_i$ and $m.price > b.p_{i-1}$) **then**
        $err \leftarrow m.quant - b.q_{i-1}$
        $G^m_{s,r} \leftarrow G^m_{s,r} \cup \{(err,\ b.q_{i-1},\ b.id)\}$
      else if $m.price = b.p_i$ **then**
        $\mu \leftarrow (b.q_{i-1} + b.q_i)/2$
        $err \leftarrow \|m.quant - \mu\|$
        $G^m_{s,r} \leftarrow G^m_{s,r} \cup \{(err,\ \mu,\ b.id)\}$
      end if
    end for
  end for
  $e_{min} = \infty$
  for each $(err,\ q,\ id) \in G^m_{s,r}$ **do**
    if $err < e_{min}$ **then**
      $e_{min} \leftarrow err$
      $r \leftarrow (m,\ id,\ err)$
    end if
  end for
  $R_{s,r} \leftarrow R_{s,r} \cup \{r\}$
end for

and auction round r. We initialize an empty set $G^m_{s,r}$ that stores tuples (error, quantity, asset owner ID) of possible matches associated with $m \in M_{s,r}$ and an empty set for matched result $R_{s,r}$. Then we define the set $T_{Buy} := \{\text{Buy}, \text{Self-Schedule}\}$ and $T_{Sell} := \{\text{Sell}\}$, because self-schedule bids can only be cleared as demand bids. For convenience, we construct a temporary set C that stores all possible candidates with matched attributes of $source$, $sink$, $type$, and $class$ except for quantity and price. Next, we use the following conditions to determine if there is mismatch between the bid/offer record and the FTR award. If the bid type is self-schedule, we only need to match the bid quantity and the cleared FTR quantity. If it is a demand bid, we check if the bid price is greater than the clearing price. If it is a supply offer, we check if the bid price is lower than the clearing price. If the bid price is exactly the same as the clearing price, we approximate the cleared quantity by taking an average of the lower and upper bounds of that bid segment. Once we finish all the inner loops and derive the possible matches $G^m_{s,r}$ associated with m, we search for the one with the minimum error and store it in $R_{s,r}$. Mathematically, the algorithm aims to find the matching between MP entity code and asset owner identification number such that the expected clearing quantity of the submitted bids from the PTC with asset owner identification number id equals to the cleared quantity of the published market result m:

$$quant^{submit}_{id} = quant^{clear}_{m}$$

III. TRADING BEHAVIOUR ANALYSIS AND DISCOVERIES

A. FTR Auction Bids, Awards and Profits

The analysis of bids and cleared quantities in the annual FTR auction for the years 2021 and 2022 shows similar trends. As presented in Table I, the total bid volume is 15,803 terawatt hours (TWh). Specifically, 68% of these FTR bids occurred during the peak hours, with the prevailing flow bid volume account for 74% of the total volume during the peak hours. A similar proportion of 74% was observed for the prevailing flow bid volumes during the off-peak hours. Meanwhile, bid volumes across different seasons are very similar and stay around 4,000 TWh. Unlike the substantial bid volume, the volume of FTRs cleared in the auctions of 2021 and 2022 was significantly lower. The total cleared FTR volume in the two years is 4,239 TWh, accounting for 27% of the total bid volume. For the cleared volume, 69% was attributed to peak hours. 68% of the peak volume is associated with prevailing flow. In contrast, approximately 50% of the volume cleared during the off-peak hours was prevailing flow, and the distribution of the cleared volumes across the seasons was relatively uniform.

Fig. 1 and Fig. 2 give an overview of PTCs' bids and cleared volumes in 2021 and 2022 respectively. The distribution within

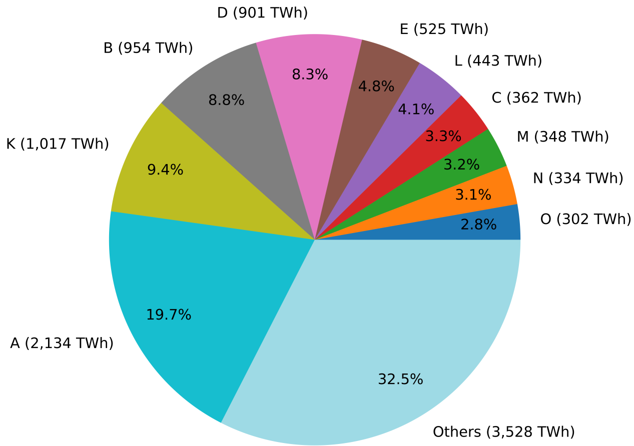

Fig. 1. 2021 - 2022 bid volume for proprietary trading companies.

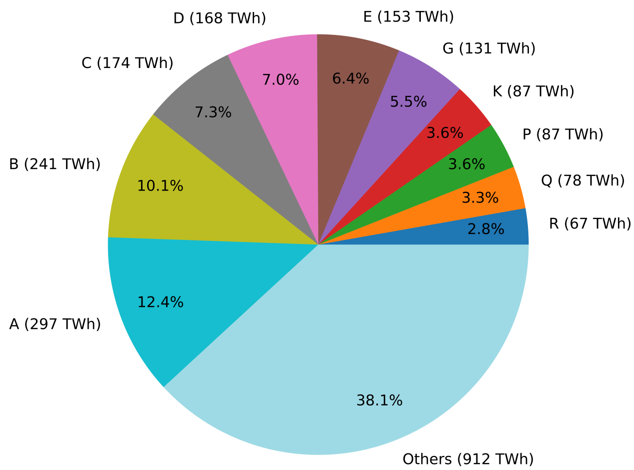

Fig. 2. 2021 - 2022 cleared volume for proprietary trading companies.

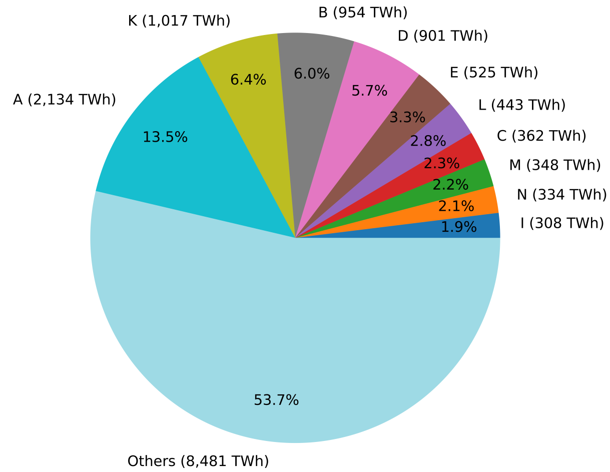

Fig. 3. 2021 - 2022 bid volume for all market participants.

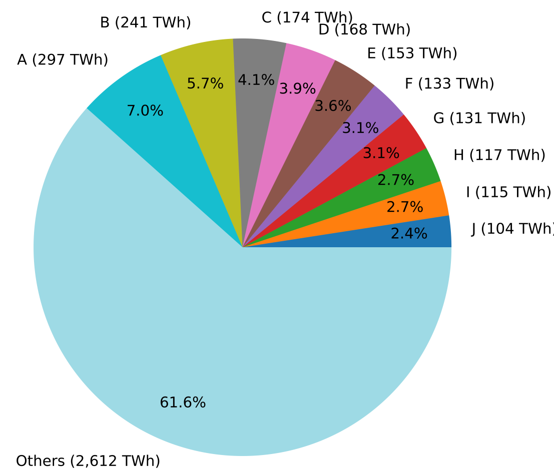

Fig. 4. 2021 - 2022 cleared volume for all market participants.

both pie charts indicates a balanced allocation among PTCs, with no single entity dominating the share of bids or cleared volumes. Additionally, an interesting observation is that a large volume of bids does not guarantee a great cleared volume. For instance, the market participant C is ranked 7th in bid volume, but ranked 3rd in cleared volume. Fig. 3 and Fig. 4 expand this analysis to include all MPs' bids and cleared volumes for the same period, which shows a similar pattern of market shares. To quantitatively assess the concentration of market power within the annual FTR auctions, the Herfindahl-Hirschman Index (HHI) is calculated. As shown in Table II, the HHI for both FTR bids and clear quantity are well below 1500. Thus, the MISO FTR market is considered a competitive marketplace.

Table III shows the cleared volume, bid volume and profit of the top 10 highest-earning PTCs in FTR annual auction market for 2021 and 2022. As shown in the table, some MPs such as S, A, B, and Q maintained their competitive advantages in both trading years. However, due to the high level of uncertainty in the market congestion patterns, it is not easy to preserve robust profitability. Furthermore, it can be observed from Table III that some PTCs' FTR bidding strategy are quite opportunistic. For example, MP M and K's cleared volume is less than 10% of their bid volume.

Table IV presents the top 10 most profitable node pairs in the period of 2021 to 2022. It can be seen that a large portion of the market-wide FTR profits are made from a small number of FTR paths. Fig. 5 illustrates the geographical proximity of the top 10 most profitable FTR paths. Note that some lucrative FTR paths are within close spatial vicinity. For instance, the path (EAI.ANO2, EAI.EAMP_1.AZ) and (EAI.ANO1, EAI.EAMP_1.AZ) are adjacent to each other, yielding a total revenue of $73M in 2021 and 2022.

Figure 6 shows the profit and bid count of all FTR paths for

TABLE II
HERFINDAHL-HIRSCHMAN INDEX FROM 2021 TO 2022

	All MPs	PTCs Only
HHI for Bid	425.22	738.89
HHI for Cleared	229.96	527.12

TABLE III
TOP 10 HIGHEST-EARNING PROPRIETARY TRADING COMPANIES IN 2021 AND 2022

	2021				2022			
Rank	MP	Cleared Vol. (TWh)	Bid Vol. (TWh)	Profit (M $)	MP	Cleared Vol. (TWh)	Bid Vol. (TWh)	Profit (M $)
1	S	20	94	74.6	A	129	974	45.8
2	A	167	1159	67.5	K	46	499	34.8
3	T	14	108	57.0	B	127	484	27.2
4	B	114	470	34.3	D	141	826	24.9
5	M	18	186	30.4	W	66	151	19.0
6	Q	34	91	28.4	G	87	140	15.5
7	E	75	263	27.5	X	19	112	15.3
8	U	21	29	25.0	C	73	139	11.3
9	V	15	26	24.5	S	15	62	10.8
10	K	39	520	22.5	Q	43	82	10.2

MP: market participant, C.: cleared, B.: bid, TWh: terawatt hour, Vol.: volume

TABLE IV
TOP 10 MOST PROFITABLE NODE PAIRS IN THE PERIOD OF 2021 TO 2022

Rank	Source	Sink	Total Cleared Vol. (TWh)	Total Bid Vol. (TWh)	Total Profit (M $)
1	EAI.ANO2	EAI.EAMP_1.AZ	14.9	30.9	37.6
2	EAI.ANO1	EAI.EAMP_1.AZ	13.8	27.7	35.9
3	OTP.BIGSTON1	OTP.AZ	4.4	10.5	35.7
4	MEC.NEALN_3	MEC.AZ	11.3	23.4	30.2
5	AMMO.CALLAWAY1	AMMO.UE.AZ	20.8	41.9	28.1
6	CONS.MCV	CONS.AZ	9.9	20.4	28.1
7	DECO.FERMI2	DECO.AZ	18.5	42.5	26.3
8	AMIL.CLINTO51	AMIL.CNE	14.3	25.1	23.2
9	AMIL.PSGC1.PPI	SIPC.SIPC	1.7	5.1	21.1
10	CONS.CAMPBELL3	CONS.AZ	8.9	18.2	21.0

TWh: terawatt hour, Vol.: volume

2021 and 2022. It can be seen from the figure that when the number of bid count is higher, the FTR path's profitability's variability is lower. In other words, it is important for PTC to identify profitable FTR path that did not catch the attention of the other MPs. Finally, it can be seen that PTCs are less risk-averse than the non-PTCs. PTCs are more likely to bid on a FTR path with higher volatility in profit. Figures 7 and 8 show the geographical distribution of the top-earning FTR sources and sinks for 2021 and 2022 respectively. The figures reveal a predominant clustering of these nodes in the Midwestern United States, particularly in the state of Iowa, Minnesota, Illinois, Michigan, Wisconsin, and Indiana.

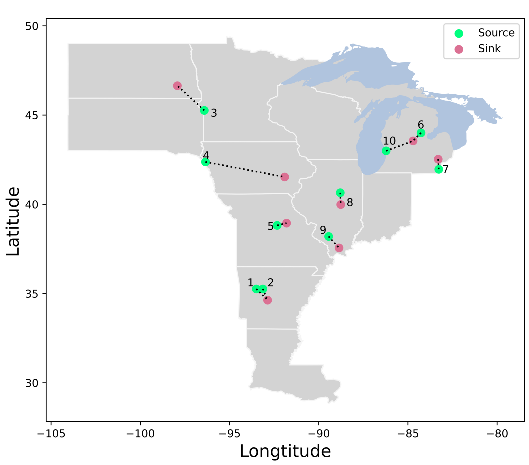

Fig. 5. 2021 - 2022 top 10 most profitable FTR paths.

B. Clustering of FTR Demand Bid Curves

Majority of the trades in the annual FTR auction market are demand bids. To perform clustering analysis of FTR demand bid curves, we need to first normalize the lengths/volumes of all bid curves. A conventional bid curve comprises up to 9 segments with 10 price-quantity pairs. To address the issue of having bid curves with different lengths, we normalize each bid curve to encompass 80 equidistant segments, using a

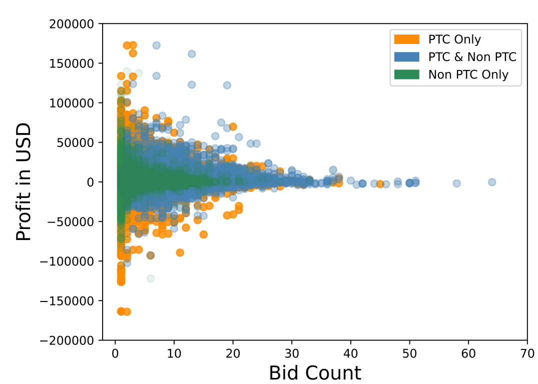

Fig. 6. Profit and bid count of all FTR paths in 2021 and 2022.

TABLE V
PROFITABILITY OF STRATEGIES ONE AND TWO IN 2021 AND 2022

Year	Strategy One Profit (%)	Strategy Two Profit (%)	Demand Bid Vol. (TWh)	Supply Offer Vol. (TWh)
2021	99.51	0.49	7378.05	555.35
2022	99.41	0.59	7355.95	513.68

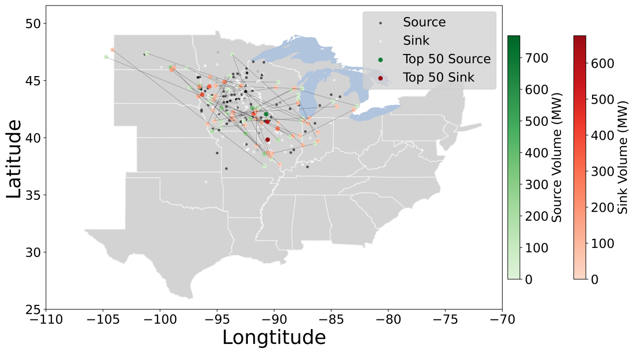

Fig. 7. Top-earning FTR paths in 2021.

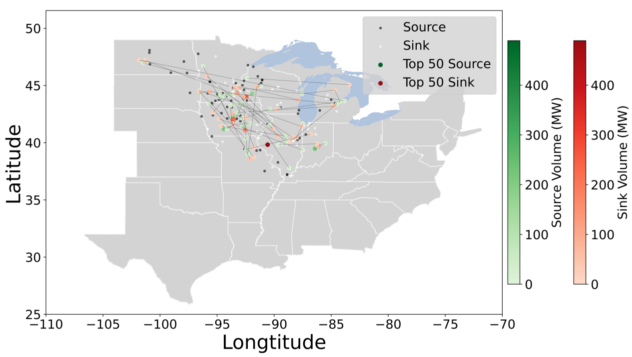

Fig. 8. Top-earning FTR paths in 2022.

nearest-neighbor interpolation function [20]. In this study, the K-medoids clustering algorithm is selected to partition the bid curves after normalization [22].

Moreover, we use the average absolute bid price difference to quantify the discrepancy between any two bid curves ϕ_i and ϕ_j within the ensemble of N bid curves, denoted as $\{\phi_k\}_{k=1}^{N}$. All bid curves are represented by a tuple:

$$\boldsymbol{P}^{\phi_l} = [P_1^{\phi_l}, P_2^{\phi_l}, \cdots, P_K^{\phi_l}], \tag{1}$$

where $P_k^{\phi_l}$ is denoted as the k-th price for the bid curve ϕ_l with the bid prices satisfying the following relationships $P_1^{\phi_l} \geq P_2^{\phi_l} \geq \cdots \geq P_K^{\phi_l}$. The distance between bid curves ϕ_i and ϕ_j, denoted by d_{ϕ_i,ϕ_j}, can calculated as follows:

$$d_{\phi_i,\phi_j} = \frac{1}{K}\sum_{k=1}^{K} \|P_k^{\phi_i} - P_k^{\phi_j}\|. \tag{2}$$

When applying the K-medoids clustering algorithm, we designate three categories of centroids (low, medium, and high), which separates the bids curves based on price sensitivity and FTR pricing strategy [20].

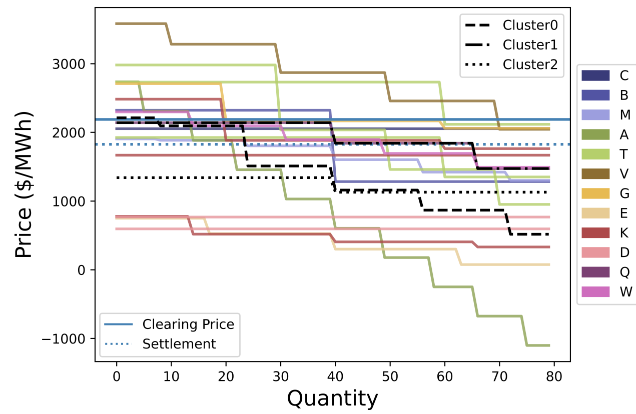

Fig. 9. Top 10 PTCs' quantity-normalized bid curves in Fall 2022 round 2. TOU: on-peak. Source: AMIL.MERDS.MVP. Sink: AMIL.MRDSA.ARR.

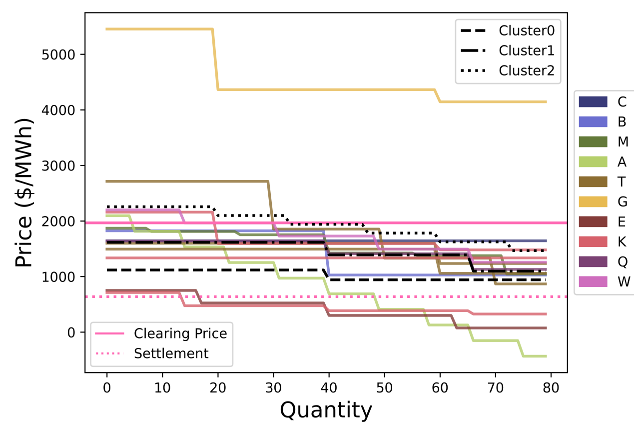

Fig. 10. Top 10 PTCs' quantity-normalized bid curves in Fall 2022 round 2. TOU: off-peak. Source: AMIL.MERDS.MVP. Sink: AMIL.MRDSA.ARR.

After examining the most popular FTR paths by season and round from 2021 to 2022, we find that the path from AMIL.MERDS.MVP (source) to AMIL.MRDSA.ARR (sink) has the highest bid volume in fall 2022 round 2, winter 2022 round 2, and fall 2022 round 3. As illustrated in Fig. 9 and Fig. 10, the quantity-normalized bid curves of the top 10 PTCs in fall 2022 round 2 show that the majority of PTCs used an opportunistic bidding strategy by setting demand bid price lower than the FTR clearing price. In other words, PTCs often set lower FTR bidding prices so that the expected gain is greater if the FTR demand bids are cleared. If the FTR demand bids are not cleared, then PTCs' opportunistic bids will not incur any loss. It can also be observed that the MP A' bidding curve is more price sensitive than the others in both the on-peak and off-peak periods.

C. Two Types of Bidding Strategies

Upon conducting detailed analysis, we identified two types of bidding strategies used by PTCs in MISO's annual FTR auction. The first strategy, which is well-known, involves arbitrage between the FTR clearing price and the average difference in the source and sink's day-ahead LMP. The second strategy involves arbitrage of FTR clearing price among the three rounds of the annual auction. Although the second approach is uncommon among PTCs in the annual FTR auction, it is frequently used by MP A, B, and V to procure a good amount of revenue in 2021 and 2022.

To make profits using the second strategy, the PTC needs to accurately predict the change in the FTR clearing price between difference rounds of FTR auctions. For example, some MPs correctly predicted that in 2021 and 2022 the FTR path AMIL.MERDS.MVP (source) to AMIL.MRDSA.ARR (sink) and the path from NSP.REDPINE (source) to NSP.LYONC.MVP (sink) exhibit consistent shifts in clearing prices between the three rounds. Table V highlights that the second strategy contributed approximately 0.49% of the total profit in 2021 and 0.59% in 2022. MP A and B collected an average revenue of approximately $1M from 2021 to 2022. MP V achieved a profit of $0.23M in 2021 and $0.57M in 2022 by using strategy two.

IV. Conclusion

In conclusion, this paper analyzed the publicly available MISO annual FTR auction market data and investigated the trading behavior of PTCs in the annual FTR auction market from 2021 to 2022. We developed an algorithm to decode the asset owner identification numbers and matched them to the MPs' entity codes. The high-level FTR auction market data show that the top 10 PTCs dominated the annual FTR auction market in terms of profits. However, the FTR auction market is considered to be competitive based on the bid and cleared FTR volume. We also identified the most profitable FTR paths and how it changes from year to year. More detailed analysis shows that the most frequently-bid FTR paths typically result in negligible profits. Thus, in order to achieve sizable profit, a PTC needs to consider bidding on FTR paths that did not draw a high level of interest from other MPs. The clustering analysis on the FTR bid curves show that many PTCs' bidding behaviors are opportunistic on the popular FTR paths. Finally, we discovered a unique FTR trading strategy used by PTCs to arbitrage the FTR clearing prices among the three different rounds of FTR auctions.

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