Flexible Bidding in Local Energy Markets: Simulation-Based Insights into the FAPO Bidding Strategy

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***Abstract*— The effective integration of distributed energy resources (DERs) into the energy system is a key pathway for reducing CO_2 emissions by decreasing reliance on fossil fuel-based generation. Local Energy Markets (LEMs) provide the financial framework for DER integration, enabling trading of locally generated renewable energy between prosumers in residential communities. This activity, known as Peer-to-Peer (P2P) trading, requires effective incentives for prosumer participation. In this work, we explore the Flexible Aggressiveness Probabilistic Optimization (FAPO) bidding strategy, formulated as a stochastic optimization problem aimed at maximizing prosumers' financial satisfaction through market interaction.**

The performance of FAPO bidding was tested in a LEM simulation environment structured as a Continuous Double Auction (CDA) conducted over 80 auction rounds. Each order was submitted through the FAPO mechanism based on the trader's intent to buy or sell power. The submission considers a randomly assigned trader limit price within a reasonable range, along with a specified quantity of electricity in kilowatt-hours (kWh).

In the LEM simulation, FAPO bidding demonstrated high efficiency, achieving a 97–98% order-clearing rate, facilitating the trading of 948 kWh across 352 bids and 339 asks. Furthermore, while clearing prices exhibited significant variability, the FAPO mechanism dynamically adjusted order prices to prevent prolonged deviations from satisfactory market levels, maintaining market stability and liquidity. Finally, no direct correlation between prices and trade volumes was observed, highlighting FAPO's adaptability.

***Index Terms*—electrification, microgrids, flexibility, electricity trading, P2P**

I. Introduction

According to the International Energy Agency, electrification plays a pivotal role in reducing CO2 emissions and achieving Net Zero by 2050 [1]. Among the many aspects of electrification, home electrification has garnered increasing attention, driving discussions in global energy forums. A key component in this transformation is the integration of Distributed Energy Resources (DERs) into the power grid. This integration is fundamental to decrease reliance on fossil fuel-based power generation and transitioning to a more sustainable energy landscape.

To support the effective integration of DERs, Local Energy Markets (LEMs) have emerged as promising financial structures. These markets facilitate energy trading among prosumers - individuals or entities that both produce and consume energy - through a mechanism commonly referred to as Peer-to-Peer (P2P) trading.

While the penetration of DERs into the grid is essential [2], the success of LEMs as a mechanism for achieving this depends heavily on incentivizing participation. Financial gain is a particularly compelling motivator for prosumers to engage with a market [3]. In the context of a LEM, this financial benefit can be maximized through the adoption of effective bidding strategies tailored to prosumers' unique roles as both buyers and sellers of energy.

Different bidding strategies show promise depending on the clearing mechanism of the market. Among these, the Continuous Double Auction (CDA) is the most widely used clearing mechanism in Local Energy Markets (LEMs) [4],[5]. It allows peers to individually set prices to request energy for consumption or offer it for sale. Common bidding strategies in CDA-based markets include the Zero Intelligence (ZI) strategy [6], where traders make random, non-optimized bids; intelligent bidding methods with reinforcement learning [7]-[10], in which traders adapt and optimize their bidding strategies over time based on market feedback; and Adaptive Aggressiveness (AA) [11]. AA stands out as a versatile approach for CDA-cleared markets, introducing "aggressiveness" - the degree to which traders are willing to sacrifice potential profit for the sake of executing a trade quickly [11]. This allows participants to adapt their bidding behavior dynamically. Researchers have successfully applied this strategy in CDA-cleared LEMs, such as Wang et al.'s blockchain-safeguarded LEM [12] and Stańczak et al.'s self-sufficient microgrid electricity market [13].

This study builds on the novel bidding strategy, Flexible Aggressiveness Probabilistic Optimization (FAPO), which was first introduced in prior work [14]. FAPO leverages probabilistic principles, optimization theory and the AA logic to enhance the bidding behavior of prosumers. In this paper, FAPO is applied in a unique case study involving a LEM operated as a CDA over 80 rounds. The results of this study provide key insights regarding the impact of FAPO on the engagement and efficiency of the LEM.

II. Bidding Methodology

The FAPO bidding algorithm is separated into three key steps:

- The fitting of the historical clearing price data of the market into a beta distribution.
- The optimization model for the determination of target price, τ.
- The determination of the order price (bid or ask) eventually submitted.

The key parameters and variables used for the development of the strategy along with the symbols used to express them are presented in Table I.

TABLE I

SYMBOLS USED IN FAPO BIDDING STRATEGY AND THEIR MEANINGS.

Symbol	Meaning
ask	New ask price
bid	New bid price
C_a	Empirical constant for ask formulation with FAPO bidding
C_b	Empirical constant for bid formulation with FAPO bidding
c_j	Buyer's limit price
l_i	Seller's limit price
N	Number of auction round
o_a	Outstanding ask
o_b	Outstanding bid
p^*	Clearing price (from historical data)
$\hat{p}^*$	Trader's clearing (equilibrium) price estimate
$\hat{p}_n^*$	Normalized clearing price (from historical data)
p_b	Basic price prediction
p_f	Feed-in price
p_M	Maximum bid or ask allowed in market
$P_t(\tau_n)$	Probability of transaction of trader
r	Degree of aggressiveness
t_g	Grid retail tariff
U_b	Buyer's utility
U_s	Seller's utility
α	Alpha parameter of beta distribution
β	Beta parameter of beta distribution
γ_1	Skewness of beta distribution
θ	Property of aggressiveness model
$\underline{\theta}$	Function of θ
λ	Auxiliary variable
σ	Standard deviation of beta distribution
τ	Target price of trader

A. Historical Clearing Price Fitting with Beta Distribution

A critical element of FAPO bidding is the probability of transaction of a trader, $P_t(\tau_n)$. This is considered when deciding on the order price to be submitted based on a historical clearing price distribution for the market. The selected distribution is the beta distribution, due to its high versatility as a result of its dependence on two free positive parameters, alpha (α) and beta (β), with probability density function (PFD):

$$P(x) = \frac{(1-x)^{\beta-1}x^{\alpha-1}}{B(\alpha,\beta)}, x \in [0,1] \quad (1)$$

where $B(\alpha,\beta)$ is the beta function, and cumulative distribution function (CDF):

$$D(x) = I(x;\alpha,\beta), x \in [0,1] \quad (2)$$

where $I(x;\alpha,\beta)$ is the regularized beta function [15].

The domain of the beta distribution is [0,1]. Hence, the historical clearing prices (p^*) are normalized with the aid of the feed-in price (p_f) and the grid retail tariff (t_g):

$$p_n^* = \frac{p^*-p_f}{t_g-p_f} \quad (3)$$

B. The Optimization Model

The optimization model is divided into two sub-models, each addressing a distinct optimization problem: one for the buyer and one for the seller. While both sub-models share the same overall structure, their equations vary based on the type of order. These models were developed using the Pyomo environment (version 6.8.0) [16].

The aim of both optimization problems is the maximization of the trader's satisfaction from interacting with the market. This is quantified through their utility, $U_b(\tau(r))$ for a buyer and $U_s(\tau(r))$ for a seller. Consequently, the objective function of the buyer is (4) and the seller is (5):

$$\max_r \quad U_b(\tau(r)) = \left(l_i - \tau(r)\right) P_t(\tau_n(r)) \quad (4)$$

$$\max_r \quad U_s(\tau(r)) = \left(\tau(r) - c_j\right) P_t(\tau_n(r)) \quad (5)$$

The primary decision variable for which the optimization problem is solved is the degree of aggressiveness, r, since the target price τ is a function of r. The degree of aggressiveness is in the range [-1,1] and is a concept introduced by Vytelingum et al. for AA [11]. For $r \in [-1,0)$, the trader is considered passive, prioritizing high-reward transactions over the probability of transacting. When $r = 0$, the trader is classified as active, interacting with the market similarly to ZI. Finally, when $r \in (0,1]$, the trader is considered aggressive, valuing more the probability of transacting over high-reward transactions.

The first optimization constraint entails the bidding equations used to derive τ. These are the AA bidding equations, (6), (7), (8), (9), which are defined for both intra- and extra-marginal traders [11]. This classification depends on the relationship between the trader's limit price and their estimated clearing price. The intra-marginal buyer and extra-marginal seller have limit prices greater than $\hat{p}^*$ whereas the extra-marginal buyer and intra-marginal seller less than $\hat{p}^*$. The case when l_i and c_j are equal to $\hat{p}^*$ falls under the intra-marginal category for both cases.

Intra-marginal Buyer

$$\tau = \begin{cases} \hat{p}^* \left(1 - \frac{\exp(-r\underline{\theta})-1}{\exp(\underline{\theta})-1}\right) & if\ r \in [-1,0], \\ \hat{p}^* + (l_i - \hat{p}^*)\left(\frac{\exp(r\theta)-1}{\exp(\theta)-1}\right) & if\ r \in [0,1]. \end{cases} \quad (6)$$

where $\underline{\theta}$ is calculated such that the function is continuous as $r = 0$, namely, $\lim_{r\to 0^-} \frac{d\tau}{dr} = \lim_{r\to 0^+} \frac{d\tau}{dr}$.

Extra-marginal Buyer

$$\tau = \begin{cases} l_i \left(1 - \frac{\exp(-r\theta)-1}{\exp(\theta)-1}\right) & if\ r \in [-1,0], \\ l_i & if\ r \in [0,1]. \end{cases} \quad (7)$$

Intra-marginal Seller

$$\tau = \begin{cases} \hat{p}^* + (p_M - \hat{p}^*)\left(\frac{\exp(-r\underline{\theta})-1}{\exp(\underline{\theta})-1}\right) & if\ r \in [-1,0], \\ c_j + (\hat{p}^* - c_j)\left(1 - \frac{\exp(r\theta)-1}{\exp(\theta)-1}\right) & if\ r \in [0,1]. \end{cases} \quad (8)$$

where $\underline{\theta}$ is calculated such that the function is continuous as $r = 0$, namely, $\lim_{r\to 0^-} \frac{d\tau}{dr} = \lim_{r\to 0^+} \frac{d\tau}{dr}$.

Extra-marginal Seller

$$\tau = \begin{cases} c_j + (p_M - c_j)\left(\frac{\exp(-r\theta)-1}{\exp(\theta)-1}\right) & if\ r \in [-1,0], \\ c_j & if\ r \in [0,1]. \end{cases} \quad (9)$$

For FAPO bidding, parameter θ, which is crucial for incorporating market event triggers, is defined differently from AA in (6), (7), (8) and (9). Specifically, θ is determined based on the skewness (γ_1) and standard deviation (σ) of the clearing price fitted beta distribution [14]:

$$\theta = \frac{\gamma_1}{\sigma} \quad (10)$$

Furthermore, another equation of this optimization constraint, involves the clearer mathematical definition of $\underline{\theta}$ to facilitate the effective solution of an otherwise complex equation for the optimization environment. Specifically, $\underline{\theta}$ is defined in (11) and (12) for the buyer and seller respectively. $\underline{\theta}$ is expressed with a Lambert W function, $W(z)$, a multivalued function with only two partially real branches, W_0 which is real for $z \in \left(-\frac{1}{e}, \infty\right)$ and branch W_{-1} which is real for $z \in \left(-\frac{1}{e}, 0\right)$. Equations 11 and 12 are solved in both branches and only the real solution occurring from either branch every time is assigned to $\underline{\theta}$ [14].

$$\underline{\theta} = -W(-\lambda_1 \exp(-\lambda_1)) - \lambda_1 \quad (11)$$

where

$$\lambda_1 = \begin{cases} \frac{l_i - \hat{p}^*}{\hat{p}^*} & if\ \theta = 0, \\ \frac{l_i - \hat{p}^*}{\hat{p}^*} \frac{\theta}{\exp(\theta)-1} & otherwise. \end{cases}$$

and

$$\underline{\theta} = -W(-\lambda_2 \exp(-\lambda_2)) - \lambda_2 \quad (12)$$

where

$$\lambda_2 = \begin{cases} \frac{\hat{p}^* - c_j}{p_M - \hat{p}^*} & if\ \theta = 0, \\ \frac{\hat{p}^* - c_j}{p_M - \hat{p}^*} \frac{\theta}{\exp(\theta)-1} & otherwise. \end{cases}$$

The second constraint defines $P_t(\tau_n)$ at the trader's desirable τ. This is achieved through the application of (2) which requires the normalization of τ as presented in (3) [14]. It is the normalized clearing price, τ_n, that will be used for the determination of $P_t(\tau_n)$:

$$\tau_n = \frac{\tau - p_f}{t_g - p_f} \quad (13)$$

C. *Determination of New Bid/Ask*

Upon completion of the optimization, τ may represent the target price for each trader, but it does not necessarily reflect a competitive price for the prevailing market conditions. Therefore, it requires further mathematical manipulation to derive a final order price that is sufficiently competitive for both buyers and sellers to submit. The set of rules used for this purpose are presented in Table II. The constants C_b and C_a in (15), (16) and (19), (20) respectively are empirical constants critical to the adjustment of the bid and ask price accounting for o_b and o_a as well as τ every time to facilitate trading. C_b and C_a are both empirically set to 0.1, to enable the initiation and continuity of trading activity.

TABLE II
RULES FOR FINAL BID AND ASK FORMULATION [14].

Bidding Rules for Buyer (Bid Formulation)			
if $\tau \geq o_a$:			
		$bid = o_a$	(14)
else:			
	if $N = 0$:		
		$bid = o_b + C_b l_i$	(15)
	else:		
		$bid = o_b + C_b \tau$	(16)
if $bid \geq t_g$:			
		$bid = \tau$	(17)
Bidding Rules for Seller (Ask Formulation)			
if $\tau \leq o_b$:			
		$ask = o_b$	(18)
else:			
	if $N = 0$:		
		$ask = o_a - C_a c_j$	(19)
	else:		
		$ask = o_a - C_a \tau$	(20)
if $ask \leq p_f$:			
		$ask = \tau$	(21)

III. Implementation of FAPO in an Energy Market Simulation Environment

A simple CDA-based energy market simulation was formulated in the simulation modeling software AnyLogic [17], whereby orders accompanying various small volumes of electricity were constantly submitted over multiple auction rounds. The simulation was configured to automatically execute ten auction rounds each time once uncleared orders were reduced below five. The underlying logic is illustrated in Fig. 1.

```
run 10 rounds:
    if number of uncleared bids < 5:
        add 10 new bids per round
    if number of uncleared asks < 5:
        add 10 new asks per round
```

Figure 1. Algorithm for order submission frequency during the automatic execution of ten auction rounds.

A random limit price and electricity volume to be traded were assigned to each order. Regarding the limit price of the seller: $c_j \in [p_f, p_b]$ and of the buyer: $l_i \in [p_b, t_g]$where p_b is the midpoint between p_f and t_g. FAPO requires preliminary historical clearing price data before it is readily applicable for the fitting of the beta distribution. To obtain these data, the order prices were first formulated with the AA bidding strategy due to the logical similarities between AA and FAPO. Since it is only in the beginning of the CDA that AA is utilized, parameter θ which is related to market event triggers is assumed to be zero. Consequently, for the determination of τ with AA, (6), (7), (8) and (9) are applied with $\theta = 0$. As for the determination of order prices based on τ, certain AA specific equations were used, found in Vytelingum et al.'s AA development work [11]. Finally, in the initial stage of trading when AA is employed, it is crucial that trading commences promptly to meet the electricity demands of the prosumers. It was observed that when traders were assigned values of $r \in [-1,1]$, the passive traders ($r \in [-1,0]$) either significantly slowed down the trading process or entirely prevented it from starting. Consequently, the decision was made that $r \in [0,1]$). Once 10 clearing prices were obtained, AA bidding was terminated and FAPO bidding initiated. This transition was made because 10 clearing prices provide sufficient data to fit the historical price beta distribution FAPO requires. The FAPO optimization problems for each buyer and seller were solved in the Pyomo environment [16] and the solver used was the Interior Point Optimizer (IPOPT), a widely used open-source software package for large-scale nonlinear optimization [18].

This study examined the performance of FAPO bidding in a small-scale energy market with $p_f = £0.075$ and $t_g = £0.28$. Moreover, each order was accompanying a volume of electricity in the range of 1 to 5 kWh. A total of 80 auction rounds were documented. In the first 12 rounds, order price formulation was carried out with AA bidding, resulting in the recording of 10 clearing prices. Next, FAPO bidding was initiated.

IV. Results and Discussion

For the 80-round energy market simulation, a total of 948 kWh were traded. This was the result of 352 cleared bids and 339 cleared asks. In total 98% of all bids and 97% of all asks were cleared. This is a promising result, highlighting that FAPO bidding leads to a high order-clearing frequency, indicating increased market engagement.

Subsequently, the trading behavior across the 80 auction rounds was examined. Fig. 2 presents the clearing prices formulated during the 80 auction rounds. In the first 12 rounds, which were run with AA bidding, minimal price deviation from p_b is observed, consistently below it by 2.0% to 9.9%. Once FAPO bidding was initiated, clearing prices fluctuated by approximately 42% above and 49% below p_b, with half of them exceeding p_b and the other half falling below it. Despite this balanced distribution, the lower prices exhibited a wider range of fluctuation. However, this difference is not significant enough to directly attribute it to the FAPO bidding mechanism formulation. It is more likely a result of the specific market conditions selected for this study (random order limit prices and volumes), in conjunction with the flexibility inherent in the FAPO bidding mechanism. Nevertheless, the greater fluctuation below p_b aligns with a greater number of cleared bids compared to asks. In fact, it is logical for more buyers to be willing to purchase electricity at these lower prices compared to sellers willing to sell at the same price.

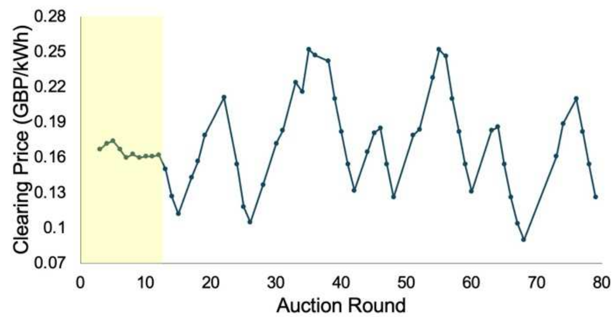

Figure 2. Clearing prices against 80 auction rounds. The first 12 rounds (in yellow box) are run with preliminary AA whereas the rest with FAPO bidding.

In general, a total of 58 clearing prices were recorded demonstrating that for certain auction rounds no trading took place. This is more evident in Fig. 3 that showcases the electricity volumes of bids, asks and traded per round. AA-regulated trading starts in round 3 and consistently occurs until round 12. FAPO bidding is then initiated.

With FAPO, some rounds experience no trades. Typically, these trade-free rounds occur either as isolated instances or in pairs. Trade-free rounds result in increase of traders' aggressiveness, prompting them to readjust order prices, which leads to trading activity in the following round. There is only one instance where four consecutive rounds remain trade-free, rounds 69 to 72. These rounds are observed after the absolute minimum clearing price of 0.09 GBP/kWh was reached in round 68. This is potentially a direct result of the flexibility and probabilistic nature of FAPO bidding at extreme prices. Once the price nears p_f the probability of transaction decreases for both buyers and sellers, as the system relies on a historical beta distribution with few occurrences of such low prices. Therefore, this price point triggers a temporary standoff where traders are unwilling to engage at those prices, despite the flexible nature of FAPO. In response, traders adjust their order prices, leading to a subsequent clearing price that falls more in line with the typical range of clearing prices in round 73. In general, the uncertainty FAPO traders face in assessing whether extreme orders are acceptable leads them to adjust their order prices. This adjustment is beneficial in the broader market context, fostering greater market stability, liquidity, and facilitating the balanced satisfaction of both sellers and buyers from their interactions with the market.

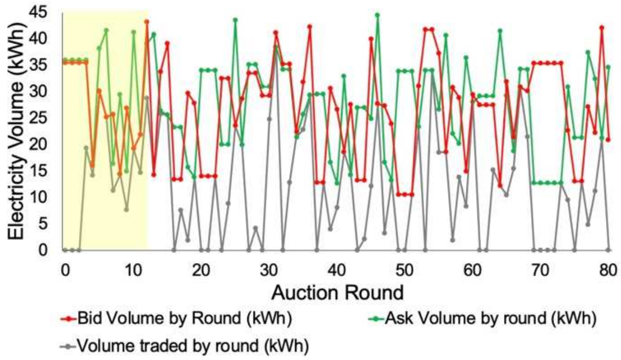

Figure 3. Volume of electricity traded against 80 auction rounds. The first 12 rounds (in yellow box) are run with preliminary AA whereas the rest with FAPO bidding applied. The red and green lines represent the bid and ask volumes by round respectively while the gray line depicts the volume traded by round.

Furthermore, while FAPO bidding introduces volatility in traded energy volumes between auction rounds, this does not necessarily pose a significant concern for traders in the long term. Given that up to 80 auction rounds can occur within a single timeslot in a full LEM, volume fluctuations from one round to the next are not alarming but rather expected. It is indicative of how participants have multiple opportunities to engage in trading activity within a single timeslot.

Finally, in Fig. 4 the total number of cleared orders and the average clearing prices for every 10 rounds are presented for rounds 11-80, focusing solely on FAPO-regulated bidding. No clear pattern is observed connecting the number of cleared bids and asks to the average clearing price. This suggests that the FAPO bidding mechanism does not establish a predictable relationship between market activity and price outcomes. Given that FAPO is formulated as an optimization problem with stochastic elements, it is expected that no clear correlation will emerge between clearing prices and electricity volumes. This lack of predictability further underscores the flexibility inherent in the bidding mechanism.

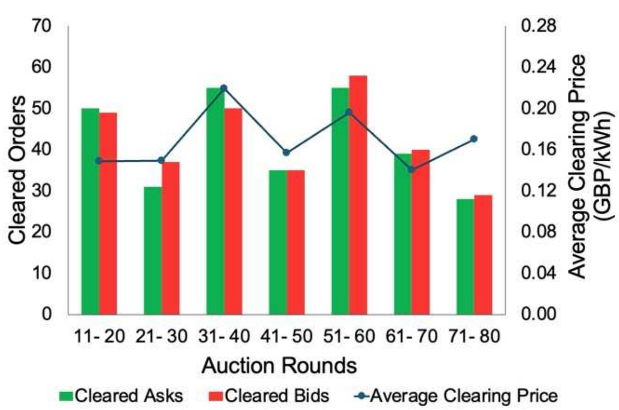

Figure 4. Number of cleared orders and average clearing prices for every 10 auction rounds. Only rounds 11-80 are presented since FAPO is applied from round 12. The columns represent the cleared bids and asks while the line represents the average clearing price.

V. Conclusions

In this paper, the FAPO bidding strategy is presented and its impact in a CDA-cleared LEM is evaluated [14]. FAPO combines probabilistic principles with optimization theory, enabling prosumers to interact with the market in a flexible manner. Its mechanism incorporates three key components: distribution fitting based on historical clearing price data, an optimization model tailored separately for buyers and sellers, and a set of rules to align the optimization outcomes with prevailing market conditions, ultimately determining the final order price of the trader for the particular auction round.

To evaluate the performance of FAPO in a CDA-cleared LEM, a simulation environment was designed with a total of 80 auction rounds. Orders were submitted automatically every 10 rounds, with additional orders generated and submitted whenever the number of uncleared bids or asks fell below five. Each order was assigned a randomly determined limit price and electricity volume. The first 12 rounds were conducted using the AA bidding mechanism to record 10 preliminary clearing prices, providing the necessary data for beta distribution fitting to initiate FAPO.

The simulation results demonstrated the effectiveness of the FAPO bidding strategy in enhancing market engagement and flexibility. Over 80 auction rounds, 98% of bids and 97% of asks were successfully cleared, highlighting FAPO's ability to drive active participation in the LEM. The analysis of clearing prices revealed balanced fluctuations around p_b, reflecting adaptability to varying market conditions. Furthermore, the absence of a clear correlation between the number of cleared orders and average clearing prices observed highlighted FAPO's stochastic optimization design and inherent flexibility. Finally, occasional trade-free rounds, often at extreme price points, further demonstrated the probabilistic nature of the strategy as traders adjusted orders to align with typical market conditions. Overall, these results suggest that FAPO fosters market liquidity and balances the satisfaction of buyers and sellers.

Although the LEM simulation results are promising for FAPO bidding, further experimentation within a more realistic LEM environment is needed to evaluate the strategy's practical applicability and impact. Future studies should span multiple timeslots and could incorporate detailed household energy consumption and generation profiles to assess the financial gains of households utilizing FAPO. Moreover, integrating external factors such as grid constraints, renewable energy variability, and policy-driven incentives could provide deeper insights into FAPO's performance and scalability. These considerations should facilitate a comprehensive evaluation of FAPO's potential to enhance household participation, profitability, and market stability while fostering a competitive marketplace.

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