

Electric Vehicle Incentivization Framework to Provide Local Reserve Capacity for PV Power Generation in Green Power Direct Supply

Zhan Liu, Yue Zhou, Wei Gan, Hongtao Ren, and Fushuan Wen

Abstract—Low-voltage photovoltaic (PV) expansion reduces energy revenue of utility grid but leaves reserve capacity and costs unchanged and hard to quantify. To address this issue, the utility grid promotes the green power direct supply scheme that deliver PV energy to consumers in behind-the-meter (BTM) community without relying on public transmission lines. With a clear ownership boundary, the utility grid can accurately measure and share the previously neglected cost of providing reserve capacity, thereby encouraging PV power generation to seek local reserve capacity in the BTM community to reduce cost. Dedicated slow-charging electric vehicle (EV) facilities in the BTM community, servicing EVs that have fixed arrival and departure schedules and long parking durations, can offer local reserve capacity to mitigate PV power deviations. This paper proposes an EV incentivization framework to provide local reserve capacity for PV power generation in the green power direct supply scheme. First, a stochastic optimization model is established to evaluate expected residual PV power deviation costs and determine the corresponding local reserve capacity demand. Second, a bi-level Stackelberg game model is formulated to describe the multi-round bargaining between the charging facility operator (CFO) and EV users. Simulation results demonstrate that the proposed EV incentivization framework effectively aggregates EV adjustable power, reduces PV power deviation penalties, and alleviates the reserve capacity burden of the utility grid.

Index Terms—Behind-the-meter (BTM) community, electric vehicle (EV), stochastic optimization, photovoltaic (PV), green power direct supply, incentive price, reserve capacity, Stackelberg game.

I. INTRODUCTION

IN low-voltage distribution areas of the utility grid, the increasing integration of distributed green power generation such as photovoltaic (PV) power generation promotes local power supply-demand balance and helps relieve the supply pressure on the utility grid [1], [2]. Many generators and consumers bypass the unified settlement mechanism of the utility grid through peer-to-peer (P2P) or bilateral trading [3], [4] to increase electricity income or reduce costs. With uncertain power outputs [5], [6] and within the scope of the demand-side management (DSM) responsibilities of the utility grid [7], [8], the distributed green power generators naturally enjoy the reserve capacity support of the utility grid either unconditionally or at very low cost, e.g., they rely on the utility grid to balance generation deviations during real-time operation. As a result, the energy revenue of the utility grid decreases, while its responsibility for providing reserve capacity support to distributed green power generators remains unchanged, with a cost that is easily overlooked or underestimated. To address this, the utility grid encourages distributed green generation operators to develop their own reserve capacity and rely less on the utility grid [9], [10].

The green power direct supply scheme [11]–[13] in a behind-the-meter (BTM) community features clear physical boundaries, which makes it more adaptable to new regulations and facilitate consensus with the utility grid on sharing reserve capacity responsibilities. In such a scheme, distributed green power generators build dedicated supply lines that connect generators and consumers directly, avoiding the utility grid as a transmission path. This arrangement reduces the natural responsibility of the utility grid to guarantee supply for this scheme [14], [15]. At the same time, all power facilities in the BTM community line to the utility grid through a single metering point, which defines a clear ownership boundary [16], [17] and ensures that the power flow across the connection point is accurately captured by the meter. In cases regarding consuming distributed PV power generation [11]–[13], the utility grid uses economic penalties to limit real-time deviations, causing PV power generation operators (PGOs) to incur extra costs associated with the reserve capacity support of the utility grid when they fail to manage deviations effectively [18], [19]. Therefore, if PGOs can explore the flexibility of other distributed energy resources

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(DERs) in the BTM community to obtain local reserve capacity, it will help them reduce the reliance on utility grid [20].

In this context, dedicated slow-charging (with long parking durations) EV facilities in the BTM community can provide local reserve capacity for green power [21]–[23]. Being dedicated means EVs connect to fixed chargers with stable schedules, yielding predictable demand. A baseline charging plan can thus be established to meet essential charging needs. Furthermore, EV users can be incentivized to offer spare battery capacity, allowing the charging facility operator (CFO) to aggregate EV adjustable power as local reserve to support PV power generation.

Since the CFO and EV users are usually independent entities, CFO must design reasonable incentive price to effectively aggregate the EV adjustable power for providing local reserve capacity support for PV power generation. Existing studies generally adopt two types of models as follows.

1) Single-layer optimization model focuses on the optimization objective of the CFO, and estimates the available local reserve capacity by establishing a functional relationship between incentive price and the power response of EVs. Reference [24] focuses on reserve capacity support for the utility grid and considers the operator's bidding strategy. Stevens' law from psychology is used to model the relationship between frequency regulation subsidies and EV power response rates, determining the optimal charging discount. Similarly, [25] addresses the spinning reserve ancillary service market, similarly focusing on the operator's day-ahead bidding. Psychological assumptions about EV users' social behavior patterns are applied to model the relationship between charging discounts and response willingness of EVs, identifying the optimal discount.

2) Bi-level optimization model simulates the CFO and EV users as a Leader-Follower structure. Reference [26] introduces a Stackelberg game pricing model between the CFO and EV users, accounting for EV users' anxiety costs caused by flexible EV usage time. The willingness of EV clusters participating in power adjustment is evaluated and an optimization model is developed aiming at maximize the CFO's benefits.

In the single-layer optimization model, the CFO estimates power responses from typical EV profiles without direct communication or multi-round interactions with individual EVs. This fits large, geographically dispersed EV clusters with mixed vehicle types across distribution network nodes. In the bi-level optimization model, the CFO and EV users engage in a multi-round bargaining game. It is typically applied to chargers connected to the same distribution network node, located in the same or adjacent areas, serving a single vehicle type.

For dedicated charging facilities in the BTM community, the bi-level optimization model is more appropriate. However, the model proposed in [26] has limitations: it characterizes EV user's response behavior through flexible usage time and jointly optimizes necessary charging demand and optional reserve capacity, but works only when both charging start

time and end time can be flexibly adjusted.

In addition, a bi-level Stackelberg game model that uses the incentive price set by CFO for incentivizing EVs still leaves gaps. The model implies repeated bargaining and assumes that in each round, EV users optimize power response to maximize their payoff at the posted price signal. In practice, EV users first decide whether to accept the price. If the price in a bargaining round falls below expectation, they may refuse to participate, yielding zero EV adjustable power. Therefore, each bargaining round must capture EV users' response-triggering characteristics in the lower-level model and explicitly model accept-or-reject behavior associated with the CFO's price decision variables in the upper-level model.

This paper is set against the background of green power direct supply scheme in the BTM community. An EV incentivization framework is established to provide local reserve capacity for PV power generation. The main contributions are as follows:

1) The expected residual PV power deviation metric is established, and stochastic optimization is leveraged to quantify the residual PV power deviation costs, including curtailment and supply shortage penalties. This provides a basis for estimating the local reserve capacity demand, that is, the maximum local reserve capacity the PGO expects from the charging facility.

2) A bi-level Stackelberg game model is formulated to simulate the multi-round bargaining process of pricing and adjustable power response between the CFO and EV users.

Based on the price-response behavior, EV users are categorized and modeled as Followers, Takers, and Refusers. In particular, since providing EV adjustable power is not mandatory for EV users, Followers may temporarily decline to respond when the incentive price in a given bargaining round falls below their expectation, resuming response only once the price becomes acceptable. To capture this behavior, a response price threshold is introduced. When the CFO's incentive price is lower than this threshold, the Followers' adjustable power is set to be zero.

However, this characteristic cannot be directly represented in a standard Stackelberg game model. It requires introducing non-convex constraints that determine whether the lower-level EV adjustable power equals zero based on the response price threshold and CFO's price decision variables in the upper-level model. Such non-convexity then makes the model unsolvable by commercial solvers. To address this issue, this paper introduces lost adjustable power decision variables for EV users and reformulates the lower-level utility function to linearize the complex non-convex constraints. Finally, the lower-level model can be reformulated through the Karush-Kuhn-Tucker (KKT) conditions, enabling the overall bi-level Stackelberg game model to be solved using commercial solvers.

The rest of the paper is organized as follows. Section II outlines the overall framework. Section III presents the mathematical modeling. Section IV introduces the modeling and solving of the bi-level Stackelberg game. Section V shows the case study. Finally, Section VI concludes the paper.

II. OVERALL FRAMEWORK

The involved participants of the EV incentivization framework collaborate with each other while maintaining independent decision-making, including the PGO, CFO, and EV user, as shown in Supplementary Material A Fig. SA1. PV systems suffer from uncertain power deviations: positive deviations cause power shortages and negative deviations trigger curtailment, both incurring economic losses. Traditionally, these deviations are balanced by the utility grid. Now, the utility grid is shifting reserve responsibility locally by urging PV systems in the BTM community to handle their own power deviations.

In the proposed EV incentivization framework, the PGO contracts with the CFO to aggregate EV adjustable power as local reserve capacity.

The CFO acts as an intermediary, aggregating EV adjustable power. By setting a reasonable incentive price, the CFO incentivizes EV users to adjust charging and discharging behaviors relative to the baseline to balance the PV power deviation. The price is made via multi-round bargaining between the CFO and EV users.

EV users are the local reserve capacity providers, adjusting charging and discharging power in response to incentive price signals of the CFO. Followers adjust their power according to price signals, Takers make adjusting decisions based on their preferences rather than price signals, and Refusers follow their baseline charging schedules, declining to offer additional adjustable power. In this paper, we focus on Followers and Takers as local reserve capacity providers, with Followers participating in multi-round bargaining with the CFO as well as Takers directly accepting the final incentive price.

The day-ahead interactions among multiple entities are summarized as follows.

Step 1: the PGO obtains the PV forecasting data, including forecasted power and potential PV power deviation ranges.

Step 2: EV users submit charging parameters to the CFO, who develops a proper pricing strategy to guide users in scheduling their baseline charging and discharging power.

Step 3: based on the potential PV power deviation ranges, the PGO calculates its local reserve capacity demand, serving as the maximum upward and downward boundaries of aggregated EV adjustable power.

Step 4: after multi-round bargaining with EV users, the CFO sets incentive prices to motivate EV users to adjust their charging and discharging profiles beyond the baseline, thereby providing local reserve capacity to manage PV power deviation.

In this paper, we focus on the EV incentivization process, i.e., *Steps 3* and *4*, assuming that *Steps 1* and *2* have been completed and their results are given as known inputs.

III. MATHEMATICAL MODELING

A. Calculation of PGO's Local Reserve Capacity Demand

The forecasted PV power $P_t^{\text{PV,power}}$ is decomposed as:

$$P_t^{\text{PV,power}} = P_t^{\text{PV,point}} + \varepsilon_t^{\text{PV}} \quad (1)$$

where $t \in [1, T]$ denotes a specific time period within the total T periods; $P_t^{\text{PV,point}}$ is the forecasted PV point power; and $\varepsilon_t^{\text{PV}}$ is the forecasted PV power deviation. The probability density function (PDF) of $\varepsilon_t^{\text{PV}}$ is assumed to follow a normal distribution $f_t(x)$ with a mean of 0, describing PV power deviation ranges and calculating the corresponding local reserve capacity demand.

Forecasted PV power deviations are classified into two types.

1) Positive deviation: actual PV power falls below the forecast, necessitating additional supply or load reduction to cover deficits.

2) Negative deviation: actual PV power exceeds the forecast, requiring extra load to absorb surplus PV power generation.

The PGO needs to purchase reserve capacity (i.e., aggregated EV adjustable power) provided by the CFO based on its price. No penalty will be incurred as long as the actual PV power deviation stays within the adjustable range of reserve capacity.

Given the PGO's local reserve capacity demand, any PV power deviation exceeding this demand is defined as the residual PV power deviation, as illustrated by Supplementary Material A Fig. SA2. The expected residual PV power deviation $E_t^{\text{PV,dev},\pm}$, which is derived from the PDF of PV power deviation, denotes the average PV power deviation unmitigated by local reserve capacity, as formulated in (2)-(4).

$$E_t^{\text{PV,dev},+} = \int_{P_t^{\text{PV,dem},+} + \Delta P_t^{\text{PV},+}}^{+\infty} (x - P_t^{\text{PV,dem},+} - \Delta P_t^{\text{PV},+}) f_t(x) dx \quad (2)$$

$$E_t^{\text{PV,dev},-} = \int_{-\infty}^{P_t^{\text{PV,dem},-} + \Delta P_t^{\text{PV},-}} (P_t^{\text{PV,dem},-} + \Delta P_t^{\text{PV},-} - x) f_t(x) dx \quad (3)$$

$$\Delta P_t^{\text{PV},\pm} = \Delta \delta^{\text{PV},\pm} P_t^{\text{PV,point}} \quad (4)$$

where $E_t^{\text{PV,dev},+}$ is the expected power curtailment due to unmitigated positive deviation; $E_t^{\text{PV,dev},-}$ is the expected power shortage due to unmitigated negative deviation; $P_t^{\text{PV,dem},+}$ and $P_t^{\text{PV,dem},-}$ are the positive and negative local reserve capacity demands, respectively; and $\Delta \delta^{\text{PV},+}$ and $\Delta \delta^{\text{PV},-}$ are the given ratios of allowable positive deviation $\Delta P_t^{\text{PV},+}$ and negative deviation $\Delta P_t^{\text{PV},-}$ relative to $P_t^{\text{PV,point}}$, respectively.

A piecewise linearization method is used in (5) to linearize (2) and (3).

$$\begin{cases} E_t^{\text{PV,dev},\pm} \geq a_{s,t}^{\pm} P_t^{\text{PV,dem},\pm} + b_{s,t}^{\pm} \\ a_{s,t}^{\pm} = \frac{E_{s,t}^{\text{PV,dev},\pm} - E_{s-1,t}^{\text{PV,dev},\pm}}{P_{s,t}^{\text{PV,dem},\pm} - P_{s-1,t}^{\text{PV,dem},\pm}} \\ b_{s,t}^{\pm} = -a_{s,t}^{\pm} P_{s,t}^{\text{PV,dem},\pm} + E_{s,t}^{\text{PV,dev},\pm} \end{cases} \quad (5)$$

where the subscript s denotes the number of segments in the piecewise linearization; and $a_{s,t}^+$, $b_{s,t}^+$, $a_{s,t}^-$, and $b_{s,t}^-$ are the coefficients associated with the linearization constraints.

Building on this, this subsection employs stochastic optimization model to estimate the local reserve capacity demand, considering the tradeoff between the purchase cost of local reserve capacity and the PV power deviation cost:

$$\min f = \left(\pi_t^{\text{PV, Fle}} P_t^{\text{PV, dem, +}} \Delta t + \pi_t^{\text{PV, Fle}} P_t^{\text{PV, dem, -}} \Delta t + \pi_t^{\text{PV, punish}} E_t^{\text{PV, dev, +}} \Delta t + \pi_t^{\text{PV, punish}} E_t^{\text{PV, dev, -}} \Delta t \right) \quad (6)$$

where $\pi_t^{\text{PV, Fle}}$ is the purchase price for local reserve capacity; $\pi_t^{\text{PV, punish}}$ is the penalty coefficient for PV power deviation; and Δt is the time interval between adjacent periods.

The PGO's local reserve capacity demand sets the boundary for aggregated EV adjustable power. Upward adjustment is defined to address PV power shortages by increasing discharging power or reducing charging power. Conversely, downward adjustment mitigates PV power surplus by boosting charging power or reducing discharging power. The detailed illustration is provided in Supplementary Material A Fig. SA2. In addition, two indicators are introduced to evaluate the economic value of local reserve capacity.

1) Hypothetical PV penalty C_t^{Hyp} without local reserve capacity: the expected PV penalty from power curtailment and shortage without local reserve capacity, measuring the potential economic losses from unbalanced PV power deviations.

$$C_t^{\text{Hyp}} = \pi_t^{\text{PV, punish}} \left(\int_{\Delta P_t^{\text{PV, +}}}^{P_t^{\text{PV, dem, +}} + \Delta P_t^{\text{PV, +}}} x f_t(x) dx + \int_{-P_t^{\text{PV, dem, -}} - \Delta P_t^{\text{PV, -}}}^{-\Delta P_t^{\text{PV, -}}} x f_t(x) dx \right) \Delta t \quad (7)$$

2) Net benefit R_t^{Avoided} from avoiding PV penalty via local reserve capacity: the savings from avoiding PV penalty through local reserve capacity minus the cost of purchasing them. This reflects the net benefit of local reserve capacity.

$$R_t^{\text{Avoided}} = -\pi_t^{\text{PV, Fle}} (P_t^{\text{PV, dem, +}} + P_t^{\text{PV, dem, -}}) \Delta t + C_t^{\text{Hyp}} \quad (8)$$

B. Incentive Price-driven Response Model of EV Users

EV adjustable power is aggregated to serve as local reserve capacity for PV power generation. The decision-making characteristics comprise two aspects: intrinsic time willingness and external price responsiveness.

For the time willingness, EV users are categorized as time-closed or time-open. Time-closed users strictly adhere to baseline charging schedules, unwilling to provide additional EV adjustable power. Time-open users, however, are willing to offer extra EV adjustable power beyond their baseline. Binary constant $v_{n,t}^{\text{time}}$ is used to indicate the time willingness of EV user n , with 1 and 0 representing time-open and time-closed types, respectively. For time-open users, a time preference ranking, i.e., $R_t^{\text{rank}} \in \{1, 2, \dots, T\}$, and $R_t^{\text{rank}} \neq R_{t'}^{\text{rank}}, t \neq t'$, is introduced, reflecting their time willingness to provide EV adjustable power during different time periods.

For the price responsiveness, EV users are categorized as price-sensitive or price-tolerant. Price-sensitive users adjust their power in response to the incentive price signal π_t^{Fle} until an agreement is reached with the CFO. In contrast, price-tolerant users formulate their decisions solely on time preferences, unaffected by the incentive price signal.

Since providing EV adjustable power is an optional service, price-sensitive users have the right to decline participation if π_t^{Fle} does not reach a certain level. To model this response-triggering characteristic, the response price threshold

$\pi_n^{\text{Fle, min}}$ is introduced, representing the minimum incentive prices these users are willing to accept.

Assume that after K rounds of bargaining, an agreement is reached between the CFO and EV users. During the k^{th} round of bargaining, the incentive price set by the CFO is $\pi_t^{\text{Fle, (k)}}$, and the adjustable power response of EV user n is $P_{n,t}^{\text{EV, Dir, (k)}}$, $\text{Dir} \in \text{DIR}$. Here, $\text{DIR} = \{\text{ch, +}, \text{ch, -}, \text{dis, +}, \text{dis, -}\}$ denotes the set of adjustment directions, covering charging upward, charging downward, discharging upward, and discharging downward adjustments, respectively. Each element in the set is a signed identifier (e.g., ch, +) that explicitly indicates the adjustment type. Note that the comma ($\cdot, \cdot$) is an integral part of the identifier and must not be omitted.

In this paper, upward and downward adjustments are defined relative to the direction of PV power value. When actual PV power is lower than the forecasted PV power, an upward adjustment is needed to relieve supply pressure by reducing load—either by lowering charging power or increasing discharging power. Conversely, when actual PV power exceeds the forecasted PV power, a downward adjustment is needed to absorb the excess achieved by increasing charging or reducing discharging power. These clarify how CFO and EV users offer local reserve capacity to PV power deviations in the BTM community.

Considering EV users' feedback toward the incentive price set by the CFO, and based on their time willingness and price responsiveness, EV users can be categorized into three types.

1) Refusers. When EV users are time-closed, they do not provide EV adjustable power, regardless of their price responsiveness:

$$P_{n,t}^{\text{EV, Dir, (k)}} \leftarrow 0 \quad (9)$$

$$t \in \emptyset \quad (10)$$

2) Followers. This type of EV users is time-open and also price-sensitive. When π_t^{Fle} is not lower than $\pi_n^{\text{Fle, min}}$, they adjust the power to maximize the profits. $v_{n,t}^{\text{time}}$ indicates whether the user adjusts the power during this period.

$$P_{n,t}^{\text{EV, Dir, (k)}} \leftarrow \begin{cases} P_{n,t}^{\text{EV, Dir, (k)}} & \pi_t^{\text{Fle, (k)}} \geq \pi_n^{\text{Fle, min}}, \forall k \\ 0 & \pi_t^{\text{Fle, (k)}} < \pi_n^{\text{Fle, min}}, \forall k \end{cases} \quad (11)$$

$$t \in \{t_n^{\text{time}} \in [1, T] | v_{n,t_n^{\text{time}}}^{\text{time}} = 1\} \quad (12)$$

3) Takers. This type of EV users is time-open and also price-tolerant. They do not engage in bargaining but instead determine their power response based on their own time preferences.

$$P_{n,t}^{\text{EV, Dir, (k)}} \leftarrow \begin{cases} P_{n,t}^{\text{EV, Dir, (k)}} & k = K, \forall \pi_t^{\text{Fle, (k)}} \\ 0 & k < K, \forall \pi_t^{\text{Fle, (k)}} \end{cases} \quad (13)$$

$$t \in \{t_n^{\text{time}} \in [1, T] | v_{n,t_n^{\text{time}}}^{\text{time}} = 1\} \quad (14)$$

Followers and Takers are the providers of local reserve capacity for PV power generation and therefore participate in bargaining with the CFO, whereas Refusers are excluded from this process. Additionally, subsequent price-sensitive

and price-tolerant users are implicitly assumed to be time-open. Thus, the set of available EVs is defined as $\Omega = \{1, 2, \dots, n, \dots, N\}$, $j \in \Omega$. The EV user type set is $OBJ = \{\text{Follower}, \text{Taker}\}$, $obj \in OBJ$. Let Ω^{Follower} and Ω^{Taker} denote the corresponding subsets. Each EV belongs to exactly one type, satisfying:

$$\begin{cases} \bigcap_{obj \neq obj'} (\Omega^{\text{Follower}} \cap \Omega^{\text{Taker}}) = \emptyset \\ \bigcup_{obj \in OBJ} \Omega^{obj} = \Omega \end{cases} \quad (15)$$

C. Revenue Model of EV Users

As is shown in Supplementary material A Fig. SA3, EV adjustable power $P_{n,t}^{\text{EV},Dir} \in \{P_{n,t}^{\text{EV},ch,+}, P_{n,t}^{\text{EV},ch,-}, P_{n,t}^{\text{EV},dis,+}, P_{n,t}^{\text{EV},dis,-}\}$ is defined as the adjustment relative to the baseline charging and discharging power $\{P_{n,t}^{\text{EV},ch}, P_{n,t}^{\text{EV},dis}\}$.

The revenue function calculates the economic returns $R_n^{\text{EV},Fle}$ that the EV users gain from providing EV adjustable power:

$$R_n^{\text{EV},Fle} = \sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} P_{n,t}^{\text{EV},Dir} \right) \Delta t \quad n \in \Omega, Dir \in DIR \quad (16)$$

Some variables describe the feasibility of power adjustment, i.e., $v_{n,t}^{\text{ch},+}$, $v_{n,t}^{\text{ch},-}$, $v_{n,t}^{\text{dis},+}$, and $v_{n,t}^{\text{dis},-}$ represent whether EV user n can provide charging upward, charging downward, discharging upward, and discharging downward adjustable power, respectively.

The assignment rules for these variables are defined in (17), avoiding conflicts between the direction of charging and discharging, as shown in Supplementary material A Fig. SA3.

$$v_{n,t}^{\text{Dir}} = \begin{bmatrix} v_{n,t}^{\text{ch},+} \\ v_{n,t}^{\text{ch},-} \\ v_{n,t}^{\text{dis},+} \\ v_{n,t}^{\text{dis},-} \end{bmatrix} = \begin{cases} [0 \ 0 \ 0 \ 0]^T & v_{n,t}^{\text{time}} = 0 \\ [1 \ 1 \ 0 \ 0]^T & v_{n,t}^{\text{time}} = 1, P_{n,t}^{\text{EV},ch} > 0, P_{n,t}^{\text{EV},dis} = 0 \\ [0 \ 0 \ 1 \ 1]^T & v_{n,t}^{\text{time}} = 1, P_{n,t}^{\text{EV},ch} = 0, P_{n,t}^{\text{EV},dis} > 0 \\ [0 \ 1 \ 1 \ 0]^T & v_{n,t}^{\text{time}} = 1, P_{n,t}^{\text{EV},ch} = 0, P_{n,t}^{\text{EV},dis} = 0 \end{cases} \quad (17)$$

The power adjustment constraints are expressed as:

$$0 \leq P_{n,t}^{\text{EV},ch,+} \leq v_{n,t}^{\text{time}} v_{n,t}^{\text{ch},+} P_{n,t}^{\text{EV},ch} \quad (18)$$

$$0 \leq P_{n,t}^{\text{EV},ch,-} \leq v_{n,t}^{\text{time}} v_{n,t}^{\text{ch},-} (P_{n,t}^{\text{EV},ch,\max} - P_{n,t}^{\text{EV},ch}) \quad (19)$$

$$0 \leq P_{n,t}^{\text{EV},dis,+} \leq v_{n,t}^{\text{time}} v_{n,t}^{\text{dis},+} (P_{n,t}^{\text{EV},dis,\max} - P_{n,t}^{\text{EV},dis}) \quad (20)$$

$$0 \leq P_{n,t}^{\text{EV},dis,-} \leq v_{n,t}^{\text{time}} v_{n,t}^{\text{dis},-} P_{n,t}^{\text{EV},dis} \quad (21)$$

where $P_{n,t}^{\text{EV},ch,\max}$ and $P_{n,t}^{\text{EV},dis,\max}$ are the maximum allowable charging and discharging power for EV n , respectively.

State of charge (SOC) changes dynamically due to power adjustment. SOC variations from upward and downward power adjustments, i.e., $SOC_{n,t}^{\text{EV},\pm}$, are calculated as:

$$SOC_{n,t}^{\text{EV},\pm} = SOC_{n,t-1}^{\text{EV},\pm} + \left(\eta_{\text{EV},ch} \frac{P_{n,t}^{\text{EV},ch,\pm}}{Cap_n^{\text{EV}}} + \frac{1}{\eta_{\text{EV},dis}} \frac{P_{n,t}^{\text{EV},dis,\pm}}{Cap_n^{\text{EV}}} \right) \Delta t \quad (22)$$

where $\eta_{\text{EV},ch}$ and $\eta_{\text{EV},dis}$ are the charging and discharging effi-

ciencies of the EVs, respectively; and Cap_n^{EV} is the battery capacity of EV n .

SOC variations must remain within the given maximum allowable upper and lower bounds $SOC_{n,t}^{\text{Fle},\pm,\max}$:

$$0 \leq SOC_{n,t}^{\text{EV},\pm} \leq SOC_{n,t}^{\text{Fle},\pm,\max} \quad (23)$$

$SOC_{n,t}^{\text{EV}}$ serves as the reference, and its upper limit $SOC_{n,t}^{\text{EV},UL}$ and lower limit $SOC_{n,t}^{\text{EV},LL}$ define the safe range for SOC during adjustable power responses:

$$SOC_{n,t}^{\text{EV},UL} = SOC_{n,t}^{\text{EV}} + SOC_{n,t}^{\text{EV},-} \leq SOC^{\text{max}} \quad (24)$$

$$SOC_{n,t}^{\text{EV},LL} = SOC_{n,t}^{\text{EV}} - SOC_{n,t}^{\text{EV},+} \geq SOC^{\text{min}} \quad (25)$$

where SOC^{max} and SOC^{min} are the maximum and minimum allowable SOC, respectively.

Simplifying (23) - (25), the SOC variation constraints are expressed as:

$$0 \leq SOC_{n,t}^{\text{EV},+} \leq \min \left\{ SOC_{n,t}^{\text{Fle},+,\max}, (SOC_{n,t}^{\text{EV}} - SOC^{\text{min}}) \right\} \quad (26)$$

$$0 \leq SOC_{n,t}^{\text{EV},-} \leq \min \left\{ SOC_{n,t}^{\text{Fle},-,\max}, (SOC^{\text{max}} - SOC_{n,t}^{\text{EV}}) \right\} \quad (27)$$

D. Revenue and Cost Models of CFO

This subsection constructs revenue and cost functions for the CFO, incorporating time-of-use pricing constraints to quantify the economic benefits. The aggregated upward and downward adjustable power $P_t^{\text{CF},\pm}$ must satisfy constraints defined by the boundaries of $P_t^{\text{PV},\text{dem},\pm}$.

$$P_t^{\text{CF},\pm} = \sum_{n=1}^N P_{n,t}^{\text{EV},ch,\pm} + \sum_{n=1}^N P_{n,t}^{\text{EV},dis,\pm} \leq P_t^{\text{PV},\text{dem},\pm} \quad (28)$$

The total revenue $R^{\text{CF},Fle}$ from providing aggregated EV adjustable power as PGO's local reserve capacity can be expressed as:

$$R^{\text{CF},Fle} = \sum_{n=1}^N \sum_{t=1}^T \left(\pi_t^{\text{PV},Fle} \sum_{Dir \in DIR} P_{n,t}^{\text{EV},Dir} \right) \Delta t \quad (29)$$

The cost for aggregating EV adjustable power $C^{\text{EV},Fle}$ can be expressed as:

$$C^{\text{EV},Fle} = \left\{ \sum_{n \in \Omega^{\text{Taker}}} \sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} P_{n,t}^{\text{EV},Dir} \right) \Delta t + \sum_{n \in \Omega^{\text{Follower}}} \sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} P_{n,t}^{\text{EV},Dir} \right) \Delta t \right\} \quad (30)$$

The total cost function for CFO is:

$$C^{\text{CF},Fle} = C^{\text{EV},Fle} - R^{\text{CF},Fle} \quad (31)$$

The time-of-use pricing constraints are:

$$\pi^{\text{Fle},\min} \leq \pi_t^{\text{Fle}} \leq \pi^{\text{Fle},\max} \quad (32)$$

$$\frac{1}{T} \sum_{t=1}^T \pi_t^{\text{Fle}} = \pi^{\text{Fle},\text{fixed}} \quad (33)$$

where $\pi^{\text{Fle},\min}$ and $\pi^{\text{Fle},\max}$ are the lower and upper bounds of the pricing range, respectively; and $\pi^{\text{Fle},\text{fixed}}$ is a constant denoting fixed daily average incentive price. Equation (32) constrains the incentive price within a range. Equation (33) ensures that the average incentive price in a day remains $\pi^{\text{Fle},\text{fixed}}$.

IV. MODELING AND SOLVING OF Bi-level STACKELBERG GAME

The multi-round bargaining between the CFO and EV users are modeled as a bi-level Stackelberg game, as shown in Fig. 1. Given the EV users' response-triggering characteristics, some EV users may opt out when the incentive price drops below their response price threshold. To better incentivize EV users to participate, CFO must set appropriate incentive price.

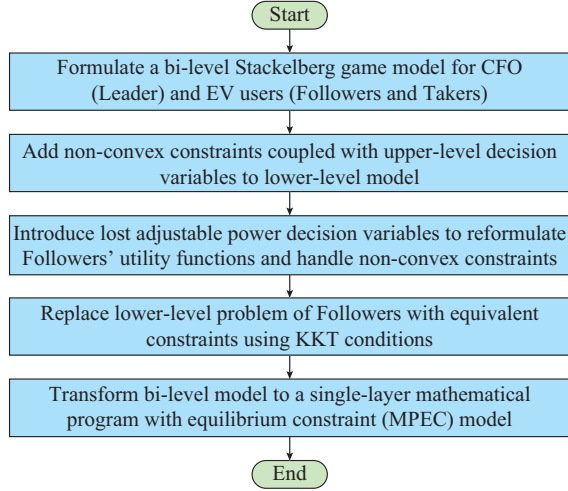


Fig. 1. Modeling and solving of bi-level Stackelberg game.

A. Formulation of Utility Functions for Takers and Followers

For Takers, the utility function is not constructed using the revenue function, since their power response is unaffected by incentive prices and is instead guided by their time preferences.

To capture this, as shown in (34), π_t^{Fle} is replaced with a constant $\pi_n^{\text{Fle, tol}}$ across all time periods, ensuring that price signals no longer influence their decisions.

$$\hat{R}_n^{\text{Taker, Fle}} = \sum_{t=1}^T \left[\left(\pi_n^{\text{Fle, tol}} - \zeta_{n,t}^{\text{Fle}} \right) \sum_{Dir \in DIR} P_{n,t}^{\text{EV, Dir}} \right] \Delta t \quad n \in \Omega^{\text{Taker}} \quad (34)$$

where $\hat{R}_n^{\text{Taker, Fle}}$ denotes the total utility (total reserve revenue) of Taker n from providing local reserve capacity, which is determined by time preferences rather than incentive price signals; and $\zeta_{n,t}^{\text{Fle}}$ is the minimal time preference coefficient, which is generated based on the time preference ranking R_t^{rank} and a minimal constant ζ_0^{Fle} , and is combined linearly with the coefficient of power variables.

$$\zeta_{n,t}^{\text{Fle}} = \zeta_0^{\text{Fle}} R_t^{\text{rank}} \quad (35)$$

Thus, π_t^{Fle} set by the CFO no longer influences the decisions of Takers. Their power adjustment responses are determined solely by $\zeta_{n,t}^{\text{Fle}}$. EV users prioritize charging and discharging during periods with a higher $\zeta_{n,t}^{\text{Fle}}$, realizing time-based priority scheduling.

The utility function of Takers $\hat{C}^{\text{Taker, Fle}}$ and Followers $\hat{C}^{\text{Follower, Fle}}$ are summarized as:

$$\hat{C}^{\text{Taker, Fle}} = - \sum_{n \in \Omega^{\text{Taker}}} \sum_{t=1}^T \left[\left(\pi_n^{\text{Fle, tol}} - \zeta_{n,t}^{\text{Fle}} \right) \sum_{Dir \in DIR} P_{n,t}^{\text{EV, Dir}} \right] \Delta t \quad (36)$$

$$\hat{C}^{\text{Follower, Fle}} = - \sum_{n \in \Omega^{\text{Follower}}} \sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} P_{n,t}^{\text{EV, Dir}} \right) \Delta t \quad (37)$$

B. Transformation of Nonlinear Problem Involving Response Price Threshold

Ideally, the utility function of Followers can be expressed as in (37), built from the revenue function in (16). However, owing to $\pi_n^{\text{Fle, min}}$ in (11), the lower-level model cannot be kept negative. Hence, we employ a linearization approach to incorporate the characteristic of response price threshold.

The original $P_{n,t}^{\text{EV, Dir}}$ is split into two components:

1) Real adjustable power variable $\hat{P}_{n,t}^{\text{EV, Dir}} \in \left\{ \hat{P}_{n,t}^{\text{EV, ch, +}}, \hat{P}_{n,t}^{\text{EV, ch, -}}, \hat{P}_{n,t}^{\text{EV, dis, +}}, \hat{P}_{n,t}^{\text{EV, dis, -}} \right\}$ is denoted as the price-accepted power, which is fed back to the CFO's upper-level objective.

$$\hat{P}_t^{\text{CF, } \pm} = \sum_{n=1}^N \hat{P}_{n,t}^{\text{EV, ch, } \pm} + \sum_{n=1}^N \hat{P}_{n,t}^{\text{EV, dis, } \pm} \quad (38)$$

2) Lost adjustable power variable $\hat{P}_n^{\text{EV, Dir, loss}} \in \left\{ \hat{P}_{n,t}^{\text{EV, ch, +, loss}}, \hat{P}_{n,t}^{\text{EV, ch, -, loss}}, \hat{P}_{n,t}^{\text{EV, dis, +, loss}}, \hat{P}_{n,t}^{\text{EV, dis, -, loss}} \right\}$ is denoted as the power rejected due to price constraints, which do not affect the CFO's upper-level objective. These decision variables are subject to (39) and (40).

$$\hat{P}_{n,t}^{\text{EV, Dir}} + \hat{P}_{n,t}^{\text{EV, Dir, loss}} = P_{n,t}^{\text{EV, Dir}} \quad \forall Dir \in DIR \quad (39)$$

$$\begin{cases} 0 \leq \hat{P}_{n,t}^{\text{EV, Dir}} & \forall Dir \in DIR \\ 0 \leq \hat{P}_{n,t}^{\text{EV, Dir, loss}} & \forall Dir \in DIR \end{cases} \quad (40)$$

As shown in (41), the utility function of lower-level model of EV users multiplies these two types of variables with π_t^{Fle} and $\pi_n^{\text{Fle, min}}$, respectively.

$$\hat{R}_n^{\text{Follower, Fle}} = \left\{ \sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} \hat{P}_{n,t}^{\text{EV, Dir}} \right) \Delta t + \sum_{t=1}^T \left[\left(\pi_n^{\text{Fle, min}} - \zeta^{\text{Fle, min}} \right) \sum_{Dir \in DIR} \hat{P}_{n,t}^{\text{EV, Dir, loss}} \right] \Delta t \right\} \quad (41)$$

where $\hat{R}_n^{\text{Follower, Fle}}$ is the total utility of Follower n from providing local reserve capacity, accounting for both realized reserve revenue and the value of lost adjustable power due to unmet response price threshold. In the process of minimizing the utility function, the lower-level model of EV users dynamically adjusts the two types of variables according to their respective associated coefficients, namely, the incentive price and the response price threshold. For Followers, when the incentive price is lower than response price threshold, the real adjustable power variable becomes zero, and the lost adjustable power variable equals the original adjustable power. When the incentive price exceeds the response price threshold, the lost adjustable power variable becomes zero, and the real adjustable power variable equals the original adjustable power.

To ensure that EV users remain engaged in power response when the incentive price matches their response price threshold, $\zeta^{\text{Fle, min}}$ is added to the coefficient of lost power, as shown in (41). Thus, this linearized approach effectively models the strategy of Followers under different time and

price conditions. Then, the revenue function of the Followers can be substituted to compute the actual revenue.

To reduce the number of decision variables in (39)-(41), the lost adjustable power can be replaced with real adjustable power and original adjustable power. Finally, the utility function of lower-level model of the Follower $\hat{C}^{\text{Follower, Fle}}$ can be expressed as:

$$\begin{aligned} \hat{C}^{\text{Follower, Fle}} = & -\hat{K}^{\text{Follower, Fle}} = -\sum_{n=1}^N \hat{K}_n^{\text{Follower, Fle}} = \\ & -\sum_{n=1}^N \left[\sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} \hat{P}_{n,t}^{\text{EV, Dir}} \right) \Delta t + \right. \\ & \left. \sum_{t=1}^T \left(\left(\pi_n^{\text{Fle, min}} - \zeta^{\text{Fle, min}} \right) \sum_{Dir \in DIR} \left(P_{n,t}^{\text{EV, Dir}} - \hat{P}_{n,t}^{\text{EV, Dir}} \right) \right) \Delta t \right] \end{aligned} \quad (42)$$

$$0 \leq \hat{P}_{n,t}^{\text{EV, Dir}} \leq P_{n,t}^{\text{EV, Dir}} \quad Dir \in DIR \quad (43)$$

The utility function of upper-level model of CFO $\hat{C}^{\text{CF, Fle}}$ is also reformulated as shown in (44). This highlights that, in the bi-level Stackelberg game model, the CFO, as the Leader, interacts solely with EV users as Followers in multiple rounds of game.

$$\begin{aligned} \hat{C}^{\text{CF, Fle}} = & \sum_{n \in \mathcal{Q}^{\text{Follower}}} \sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} \hat{P}_{n,t}^{\text{EV, Dir}} - \pi_t^{\text{PV, Fle}} \sum_{Dir \in DIR} \hat{P}_{n,t}^{\text{EV, Dir}} \right) \Delta t + \\ & \sum_{n \in \mathcal{Q}^{\text{Taker}}} \sum_{t=1}^T \left(\pi_t^{\text{Fle}} \sum_{Dir \in DIR} P_{n,t}^{\text{EV, Dir}} - \pi_t^{\text{PV, Fle}} \sum_{Dir \in DIR} P_{n,t}^{\text{EV, Dir}} \right) \Delta t \end{aligned} \quad (44)$$

C. Transformation of Bi-level Model into Single-layer MPEC Model

The set of decision variables for Takers and Followers can be defined as:

$$\mathcal{A}^{\text{Taker}} = \left\{ P_{n,t}^{\text{EV, ch, +}}, P_{n,t}^{\text{EV, ch, -}}, P_{n,t}^{\text{EV, dis, +}}, P_{n,t}^{\text{EV, dis, -}} \right\} \quad n \in \mathcal{Q}^{\text{Taker}} \quad (45)$$

$$\mathcal{A}^{\text{Follower}} = \left\{ \hat{P}_{n,t}^{\text{EV, ch, +}}, \hat{P}_{n,t}^{\text{EV, ch, -}}, \hat{P}_{n,t}^{\text{EV, dis, +}}, \hat{P}_{n,t}^{\text{EV, dis, -}}, P_{n,t}^{\text{EV, ch, +}}, P_{n,t}^{\text{EV, ch, -}}, P_{n,t}^{\text{EV, dis, +}}, P_{n,t}^{\text{EV, dis, -}} \right\} \quad n \in \mathcal{Q}^{\text{Follower}} \quad (46)$$

In summary, the bi-level Stackelberg game model between the CFO and EV users is formulated as follows.

1) Upper-level objective of Leader

$$\begin{cases} \min_{\{\pi_t^{\text{Fle}}, \mathcal{A}^{\text{Follower}}\}} \hat{C}^{\text{CF, Fle}}(\pi_t^{\text{Fle}}, \mathcal{A}^{\text{Follower}}, \mathcal{A}^{\text{Taker*}}) \\ \text{s.t. (32), (33), (44), (48), and (49)} \end{cases} \quad (47)$$

where $\mathcal{A}^{\text{Taker*}}$ denotes the optimal set of decision variables for Takers that obtained by solving their lower-level optimization problem.

$$\mathcal{A}^{\text{Follower}} \in \arg \min_{\mathcal{A}^{\text{Follower}}} C^{\text{Follower, Fle}}(\pi_t^{\text{Fle}}, \mathcal{A}^{\text{Follower}}, \mathcal{A}^{\text{Taker*}}) \quad (48)$$

$$\mathcal{A}^{\text{Taker*}} \in \arg \min_{\mathcal{A}^{\text{Taker}}} \hat{C}^{\text{Taker, Fle}}(\mathcal{A}^{\text{Taker}}) \quad (49)$$

2) Lower-level objective of Followers

$$\begin{cases} \min_{\mathcal{A}^{\text{Follower}}} \hat{C}^{\text{Follower, Fle}}(\pi_t^{\text{Fle}}, \mathcal{A}^{\text{Follower}}, \mathcal{A}^{\text{Taker*}}) \\ \text{s.t. (18)-(22), (26)-(28), (42), (43), and (49)} \end{cases} \quad (50)$$

3) Lower-level objective of Takers

$$\begin{cases} \min_{\mathcal{A}^{\text{Taker}}} \hat{C}^{\text{Taker, Fle}}(\mathcal{A}^{\text{Taker}}) \\ \text{s.t. (18)-(22), (26)-(28), and (36)} \end{cases} \quad (51)$$

In the bi-level Stackelberg game model, Takers do not engage in bargaining with the CFO. Instead, they determine $\mathcal{A}^{\text{Taker}}$ directly based on their individual time preferences and the boundary constraints imposed by the PGO's local reserve capacity demand. Consequently, prior to the CFO's negotiation of pricing and power decisions with Followers, the adjustable power provided by Takers can be regarded as pre-determined.

To align with this practical setup, the bi-level Stackelberg game model is simplified by decoupling Taker-related components: first, calculate $\mathcal{A}^{\text{Taker}}$, then solve the optimization model of the CFO and Followers. For the above bi-level Stackelberg game model, the lower-level model of Followers is a continuous linear optimization model with convex properties, and its optimal solution can be expressed through the KKT conditions. This transforms the lower-level model of Followers into linear constraints in the upper-level model, thereby converting the bi-level model into a single-layer MPEC model [27], [28]. The detailed steps and model can be found in Supplementary Material B.

V. CASE STUDY

A. Parameter Setting

Taking the BTM community involving PGO, CFO, and EV users as an example. The PGO provides renewable energy with power purchase agreements and balances PV power deviation through an EV incentivization framework offered by the CFO. In the day-ahead stage, the CFO aggregates EV adjustable power to provide the PGO with necessary local reserve capacity to address the uncertainties of PV power generation. Relevant model parameters and values are detailed in Supplementary Material C.

B. Analysis of Aggregation and Pricing of EV Adjustable Power

Figure 2 shows the pricing results and the aggregated EV adjustable power. Supplementary material A Fig. SA4 further visualizes the contribution rate of EV reserve capacity, which is calculated as the ratio of aggregated EV adjustable power to the PGO's local reserve capacity demand. In Fig. 2 (b), the blue area denotes the PGO's local reserve capacity demand, obtained via stochastic optimization. A 31-segment piecewise linear function is adopted to approximate the expected residual PV power deviation. The selection of segmentation and its justification are detailed in Supplementary Material D. The orange, yellow, and gray areas represent the Followers' real adjustable power, the Takers' real adjustable power, and the EV users' lost adjustable power, respective-

ly. Note that the blue area is presented separately and not stacked with the other three areas. The uncovered portion of the blue area in Fig. 2(b) indicates unmet PGO's local reserve capacity demand. The radar chart in Supplementary material A Fig. SA4 further illustrates the reserve capacity contribution of EV.

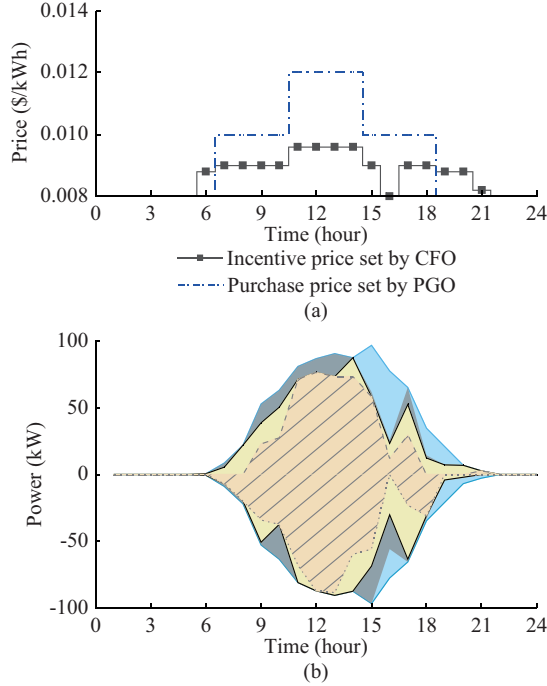


Fig. 2. Analysis of results. (a) Pricing results. (b) Aggregated EV adjustable power.

Followers provide the majority of aggregated EV adjustable power, as evident in the stacked areas of Fig. 2(b) and the contribution rate in Supplementary material A Fig. SA4.

Comparing Fig. 2(a) and (b), from a pricing perspective, the incentive price closely tracks the PGO's purchase price for local reserve capacity. This linkage enables the CFO to transmit PGO's purchase price signals to EV users, maximizing CFO's total revenue while driving EV user participation. Notably, higher incentive price during peak PGO's local reserve capacity demand significantly enhances EV users' responsiveness.

Takers adjust their response mainly based on time preferences, showing little sensitivity to price fluctuations. As illustrated in Supplementary Material A Fig. SA4, their downward adjustable power contribution forms a scattered pattern, reflecting no clear link to price changes. In contrast, Followers exhibit a strong correlation between their response and the incentive price set by the CFO, showing clear price-driven behavior. In addition, as shown in Supplementary Material C Table SCI, EV11-EV50 are designated as Followers and EV1-EV10 are designated as Takers. Their adjustable power results are presented in Supplementary Material D.

C. Analysis of Impact of EV Users' Response Price Threshold

To investigate the influence of EV users' response price thresholds on the CFO's optimal pricing, Scenario 1 (S1) is

established to incorporate the threshold effects. Accordingly, Scenario 2 (S2) is constructed to exclude the impacts of such threshold. In S2, the CFO ignores Followers' response-triggering characteristic and assumes a response price threshold of zero for all such EV users, meaning that they respond to any incentive level. With other parameters unchanged, the CFO's pricing strategy is first obtained by solving the bi-level Stackelberg game model. Then, the actual response price thresholds of EV users are reintroduced, and the EV adjustable power is recalculated directly based on the lower-level model of EV users, enabling a posterior analysis of EV users' responses under the given incentive prices.

Table I presents the economic performance comparison of S1 and S2. In S1, the CFO earns \$13.80 in reserve revenue, netting \$2.19 after paying \$11.62 to EV users. Compared with S2, ignoring Followers' response price thresholds leads to suboptimal pricing, which fails to fully activate Followers' adjustable power and reduces reserve revenues for both EV users and the CFO.

TABLE I
ECONOMIC PERFORMANCE COMPARISON OF S1 AND S2

Scenario	$R^{CF, Fle}$ (\$)	$R^{EV, Fle}$ (\$)	$C^{CF, Fle}$ (\$)	C_t^{Hyp} (\$)	$R_t^{Avoided}$ (\$)
S1	2.19	11.62	13.80	19.64	5.83
S2	1.96	9.44	11.41	15.29	3.89

As detailed earlier, (39) and (40) define the lost adjustable power variables to resolve the nonlinearity from response price thresholds. Analyzing these values further clarifies the performance gap between the two scenarios.

Figure 3(a) compares the total lost reserve energy and real reserve energy for both scenarios over the 24-hour period. Reserve energy is calculated by integrating hourly adjustable power over time, representing the cumulative reserve capacity provided by EV users; it is distinct from the kWh unit used to quantify traded electrical energy. Figure 3(b) illustrates the loss rates, defined as the ratio of total lost reserve energy to total real reserve energy. The results demonstrate that the pricing strategy in S1 achieves superior EV incentivization performance. Specifically, S1 yields a total lost reserve energy of 178.59 kWh, which is significantly lower than 417.52 kWh observed in S2. Correspondingly, the loss rate in S1 decreases to 0.15, compared with 0.42 in S2. Furthermore, the total real reserve energy in S1 reaches 1182.72 kWh, exceeding 988.17 kWh in S2. This confirms that S1, which explicitly accounts for EV users' response price thresholds, effectively unlocks the full potential of EVs for local reserve capacity provision.

Therefore, Followers' response price thresholds influence the CFO's pricing decision, as illustrated in Fig. 4, leading to a careful balance between incentivizing more EV to provide adjustable power and lower aggregation cost to optimize net profit.

This also indicates that EV users' response price threshold is a factor that CFO cannot afford to overlook when designing incentive price. A pricing decision that takes response price thresholds into account can more effectively unlock the flexible adjustment potential of EVs, thereby improving the overall efficiency in utilizing flexibility resources.

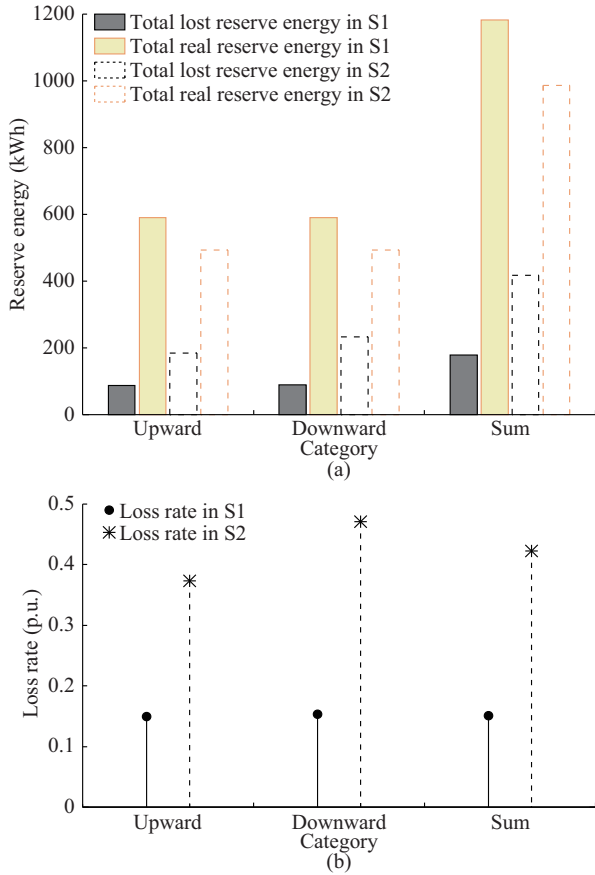


Fig. 3. Comparison of S1 and S2. (a) Total lost reserve energy and real reserve energy. (b) Loss rate.

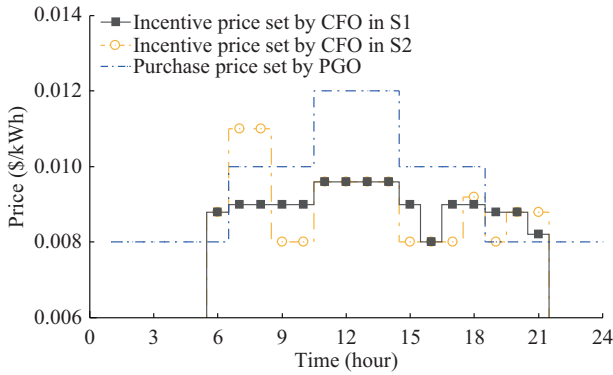


Fig. 4. Comparison of incentive price set by CFO in S1 and S2 and purchase price set by PGO.

In addition, in terms of PV power deviation balancing, Table I also presents two key metrics for the PGO. When real-time PV power generation falls within the blue range in Fig. 2, the aggregated EV adjustable power can serve as local reserve capacity and cover the PV power deviations, avoiding economic penalties from power curtailment or shortages. C_i^{Hyp} quantifies the economic losses that should have been caused by power curtailment or shortages within the EV power adjustment range, while R_i^{Avoided} captures the net gains after reducing these penalties.

Table I shows that EV users' response price threshold is

considered to enable the CFO to design a more effective pricing strategy. This not only increases the earnings of the operator and EV users, but also further reduces the PGO's potential penalties, verifying the feasibility and superiority of the pricing strategy. Under this setup, EV users are willing to provide adjustable power not only to reduce their overall charging costs through additional reserve revenue, but also to benefit from the green power direct supply scheme in the BTM community. In the BTM community, PGO typically supplies electricity to local users through green power direct contracts, taking on corresponding supply related obligations. Therefore, as long as EV users' regular charging needs are satisfied, they can adjust their charging and discharging behaviors to help stabilize the local consumption of clean energy provided by the PGO.

As shown in Supplementary Material C Table SCII, the CFO achieves a net revenue of \$41.33 from basic charging services. By aggregating EV adjustable power as local reserve capacity for PV systems, the CFO's total revenue increases by 5.30%, with a direct reserve income of \$2.19. Although this additional income is relatively modest, it is acceptable given that the CFO's primary revenue stems from basic charging. Furthermore, this service enhances EV users' stickiness to the charging facility and supports the sustainable consumption of green power in the BTM community.

D. Sensitivity Analysis of Impact of PV Power Profiles and Battery Capacity

This subsection illustrates the sensitivity analysis results for EV users, CFO, and PGO, as shown in Figs. 5-7, respectively. The horizontal axis indicates the PGO's total reserve energy demand, which rises with increasing uncertainty due to the larger variance of the PV forecast probability distribution. The PGO's total reserve energy demand is employed as a proxy for PV forecasting uncertainty. A larger reserve energy demand indicates higher uncertainty in PV power output, which requires more local reserve capacity to mitigate potential power deviations. As shown in Fig. 5(a), EV users' reserve revenue increases rapidly with PGO's total reserve energy demand and then plateaus. Together with Fig. 5(b), it shows that as the PGO's total local reserve energy demand increases, the total reserve energy of EV first rises and then stabilizes, leading to a similar stabilization in EV users' reserve revenues. The battery capacity of 32 kWh shows negligible revenue growth due to battery limitations. Under identical uncertainty, larger battery capacities provide higher reserve energy and thus higher reserve revenues, although reserve revenues are constrained by PGO's total reserve energy demand rather than battery capacity at low reserve levels.

Figure 6(a) indicates that CFO's total revenue rises with PGO's total reserve energy demand and then saturates, except for the battery capacity of 32 kWh. As illustrated in Fig. 6(b), the utilization rate of battery adjustment range follows the same trend. Larger battery capacities consistently improve CFO's total revenue, which is jointly limited by PGO's total reserve demand and battery capacity.

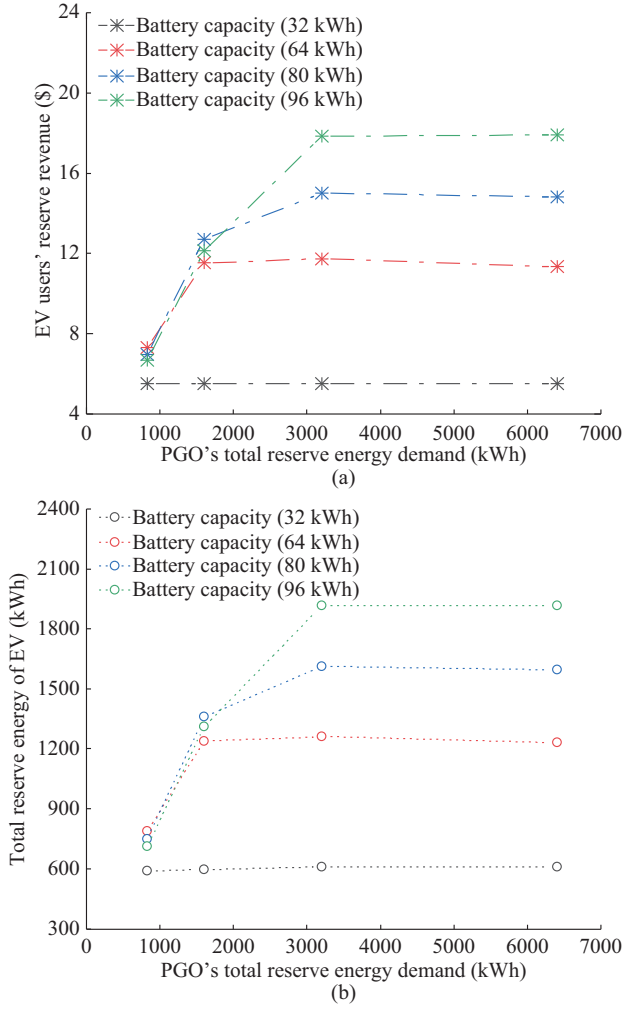


Fig. 5. Sensitivity analysis result for EV users. (a) EV users' reserve revenue. (b) Total reserve energy of EV.

Figure 7(a) depicts the PGO's net benefit from avoiding PV penalty via local reserve capacity, with the orange line indicating the optimal value. For a given battery capacity, PGO's net benefit first increases and then decreases as PGO's total reserve energy demand (uncertainty in PV power output) rises, even turning negative at high reserve energy demand. This occurs because PGO's total reserve energy demand grows faster than the total reserve energy of EV, as reflected in the declining ratio shown in Fig. 7(b). When PGO's total reserve energy demand is low, battery capacities match reserve energy demand well, while when PGO's total reserve energy demand is high, EV resources fail to satisfy the sharply increased PGO's total reserve energy demand, resulting in poor economic efficiency. In summary, battery capacity and PGO's total reserve energy demand jointly determine the revenues of all stakeholders. EV users' revenues and CFO's total revenues increase and then saturate with the rising PGO's total reserve energy demand, while PGO's net benefit exhibits an inverted-U trend and can become negative if the reserve capacity of EV is insufficient. Larger battery capacities effectively improve the revenues of all participants, yet the PGO must arrange additional reserve capacity to maintain profitability when PGO's total reserve energy demand is high.

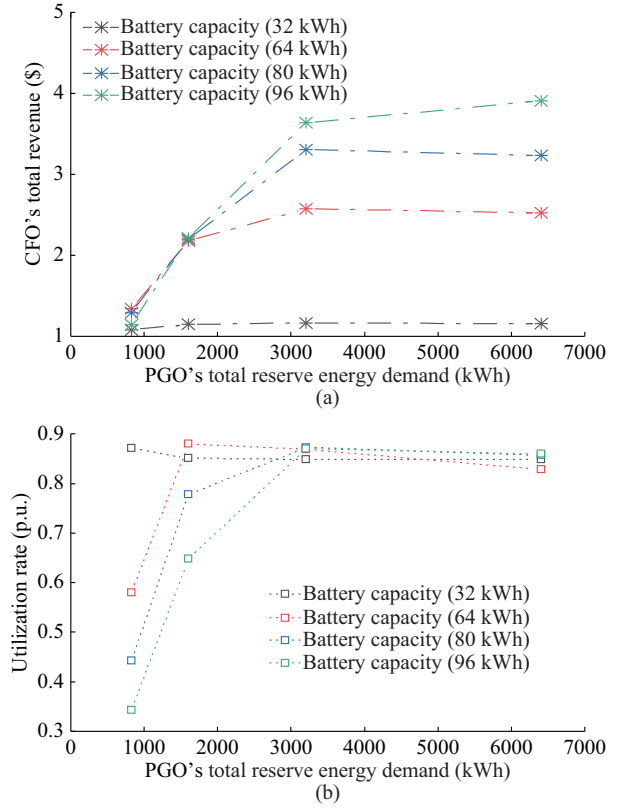


Fig. 6. Sensitivity analysis result for CFO. (a) CFO's total revenue. (b) Utilization rate of battery adjustment range.

VI. CONCLUSION

This paper proposes an EV incentivization framework in a green power direct supply scheme, where the CFO sets the incentive price to aggregate EV adjustable power as local reserve capacity for PV power generation. The PGO optimizes the local reserve capacity demand, which serves as the boundary for the aggregated EV adjustable power. The CFO employs incentive price signals to encourage EV users to provide upward and downward adjustable power. EV users are categorized as Followers, Takers, or Refusers. The multi-round bargaining process between the CFO and EV users is modeled as a bi-level Stackelberg game. To address the non-linearity caused by response price thresholds in the lower-level model, additional decision variables representing lost adjustable power are introduced. Key conclusions from the case study are as follows:

1) The proposed EV incentivization framework successfully aggregates 1182.72 kWh of reserve energy of EV in a day, enabling the PGO to avoid \$19.64 in potential penalties by paying \$13.80 to the CFO for reserve. At the same time, the CFO earns a net profit of \$2.19 after compensating EV users \$11.62, demonstrating clear economic benefits for all stakeholders.

2) Incorporating EV users' response price thresholds into the CFO's pricing strategy can more effectively unlock the flexible adjustment potential of EVs. Compared with S2, the total lost reserve energy is reduced from 417.52 kWh to 178.59 kWh, and the aggregated reserve energy supply increases from 988.17 kWh to 1182.72 kWh.

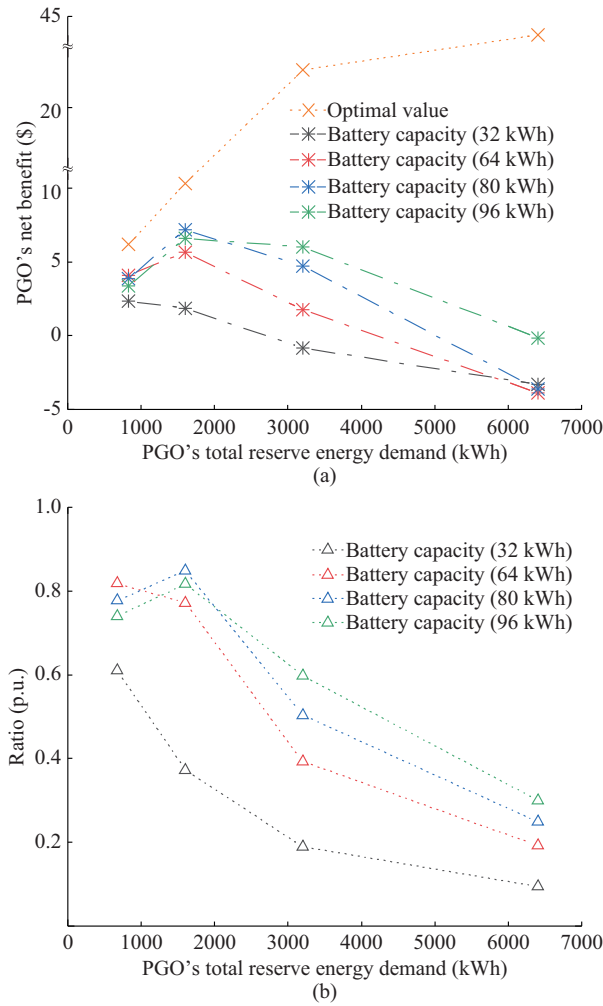


Fig. 7. Sensitivity analysis result for PGO. (a) PGO's net benefit from avoiding PV penalty via local reserve capacity. (b) Ratio of total reserve energy of EV to PGO's total reserve energy demand.

3) When the uncertainty of PV power output is fixed and battery capacity varies, larger battery capacities deliver more local reserve capacity and higher revenues for both EV users and the CFO, though their marginal gains taper off. When battery capacity is fixed and the uncertainty of PV power output rises, the revenues of EV users and the CFO grow at first and then level off, revealing the upper limit of reserve capacity benefits. However, as uncertainty deepens, the PGO's net benefit climbs before falling. Once local reserve capacity can no longer offset PV power deviations, PGO's net benefit may turn negative. These results underline the need to align battery capacity with the uncertainty of PV power output to keep the PV system both balanced and profitable.

In summary, the proposed EV incentivization framework effectively incentivizes EVs to provide local reserve capacity for PV power generation in a green power direct supply scheme. Future work will explore real-time implementation and scalability to multi-community systems, advancing the integration of renewable energy in distributed energy networks.

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