A calculation method for flexible resource baseline power based on Nash Bargaining Game

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***Abstract*—The participation of demand-side flexible resources in the power balancing ancillary service market has been realized. A baseline power calculation model based on the Nash Bargaining Game is proposed, which can balance the interests of the power system operator and flexible resource aggregators and find the fairest solution for both stakeholders on the Pareto frontier. Subsequently, a golden section and alternating direction method of multipliers nested iterative solution method is proposed, which calculates the game's equilibrium under the condition of limited data interaction. Numerical simulations are carried out based on the actual data of the power balancing market in the North China Power Grid, which verifies the effectiveness of the proposed method.**

***Keywords*—Demand-side flexible resources; power balancing ancillary services; baseline power; Nash Bargaining Game; Pareto frontier; alternating direction method of multipliers**

I. INTRODUCTION

In ancillary services markets, baseline power is a critical parameter for both the power system dispatcher (PSD) and demand-side flexible resource aggregators, as it directly influences the willingness of flexible resources to provide services and their market revenues [1]. The baseline should reflect the electricity-use pattern that a load aggregator would exhibit absent participation in ancillary services. The baseline is primarily computed by the PSD, and prevailing methods estimate it by averaging the load during intervals without ancillary-service provision or by mathematical fitting. For example, California Independent System Operator (CAISO) applies 10/10 and 5/10 methods, which select the median from 10 or 5 days out of the past 10 days [2]. However, baselines computed via averaging or curve fitting can be manipulated by participants, potentially imposing significant losses on PSD [3].

In recent years, machine learning methods have also been employed for baseline estimation [4]–[6]. Most of these methods take as key inputs the power trajectories observed when the aggregator is not providing peak-shaving ancillary services. However, missing data is a common issue in demand-side load profile processing. To tackle the problem, a load profile inpainting network for baseline estimation is proposed [6]. Besides, the ongoing development of new-type power systems implies that demand-side participation in ancillary services will become routine. In that regime, non-participation load data may be scarce and stale, failing to capture an aggregator's current power characteristics [7]. Facing data sparse, PSD commonly infer baselines from resource type, yet for emerging, highly flexible resources such as electric vehicles, such baselines are difficult to justify under traditional methods.

Some studies depart from the conventional baseline-setting paradigm and thus alleviate the difficulty of computing baselines when historical data are scarce. For example, [8] proposes that electricity customers self-report their baseline power, while the PSD employs an optimization model to accept those baselines that deliver better peak-shaving performance. Reference [9] replaces the baseline with a load reference trajectory and evaluates user contribution by the similarity between the realized load and this trajectory. Although this approach captures, to a reasonable extent, the alignment between user load and system needs, it cannot accurately assess the user's incremental contribution toward meeting system requirements.

This paper proposes a baseline power calculation approach based on the Nash Bargaining Game (NBG) [10]. The method dispenses with reliance on load data from non-participation intervals, making it suitable for aggregators that engage in peak shaving on a sustained basis. By adopting the Nash bargaining equilibrium between the PSD and the aggregator as the baseline, the solution balances both parties' interests and yields outcomes that are fair to both sides. We further develop a nested iterative scheme that combines golden section search with the Alternating Direction Method of Multipliers (ADMM) [11] to compute the NBG equilibrium, safeguarding the aggregator's data privacy. Finally, numerical experiments based on real data from the North China Power Grid validate the effectiveness of the proposed approach.

II. NASH BARGAINING GAME MODEL BETWEEN FLEXIBLE RESOURCE AGGREGATORS AND PSD

The participants in the NBG are all aggregators and the PSD, who negotiate the baseline and planning power of all aggregators. The objective functions and feasible domains in the optimization models correspond to the utility functions and strategy sets of the game.

A. Optimization problem of aggregator

Energy consumed by demand-side resources is settled at the retail electricity tariff, while providing peak-shaving

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ancillary services yields additional revenue settled at the market-clearing price. Each aggregator selects its baseline and planning power to minimize net operating cost. Accordingly, the objective function of aggregator i is:

$$\min g_i^{\mathrm{A}} = \sum_{t=1}^{T} \left[P_{i,t}^{\mathrm{r}} c_t - \left(P_{i,t}^{\mathrm{r}} - P_{i,t}^{\mathrm{b}} \right) \pi_{i,t} \right] \Delta T \tag{1}$$

where, $P_{i,t}^{\mathrm{b}}$ and $P_{i,t}^{\mathrm{r}}$ respectively denote the baseline and panning power of aggregator i in period t which are the decision variables，and the full trajectories are presented by $\left\{P_{i,t}^{\mathrm{b}}\right\}_{1\le t\le T}$ and $\left\{P_{i,t}^{\mathrm{r}}\right\}_{1\le t\le T}$, respectively. T is the number of time intervals and ΔT is the interval duration. c_t is the end-use tariff. $\pi_{i,t}$ is aggregator i's forecast of the market-clearing price in the peak-shaving market.

Feasible aggregate-power set is presented by

$$\left\{P_{i,t}^{\omega}\right\}_{1\le t\le T} \in X_i, \forall \omega \in \{\mathrm{r},\mathrm{b}\} \tag{2}$$

where, P^{ω} denotes the power trajectory under scenario ω. X_i denotes the feasible set of the aggregator's load trajectory, and superscripts r and b indicate the planning and baseline power, respectively. Constraint (2) requires both trajectories to lie in X_i. The set X_i can be described by aggregate power and energy bounds which is equal to

$$\underline{P}_{i,t} \le P_{i,t}^{\omega} \le \overline{P}_{i,t}, \forall 1 \le t \le T \tag{3}$$

$$\underline{E}_{i,t} \le \sum_{\tau=1}^{t} P_{i,\tau}^{\omega} \Delta T \le \overline{E}_{i,t}, \forall 1 \le t \le T \tag{4}$$

where $\underline{P}_{i,t}$, $\overline{P}_{i,t}$ are the lower/upper boundary on total power, $\underline{E}_{i,t}$ and $\overline{E}_{i,t}$ are the lower/upper boundary on cumulative energy.

The basic economic rationality of aggregators needs to be satisfied, which can be given by

$$\sum_{t=1}^{T} P_{i,t}^{\omega} c_t \Delta T \le C_i^*, \forall \omega \in \{\mathrm{r},\mathrm{b}\} \tag{5}$$

where C_i^* is the optimal energy cost of self-planning when the aggregator does not participate in peak shaving, obtained from

$$C_i^* = \min \left\{ \sum_{t=1}^{T} P_{i,t} c_t \Delta T, \text{s.t.} \left\{P_{i,t}\right\}_{1\le t\le T} \in X_i \right\} \tag{6}$$

Constraint (5) formalizes economic rationality which means that after participating in peak shaving, the aggregator's net cost should not be worse than its optimal electricity cost under non-participation. When $\omega = \mathrm{b}$, it requires the baseline power to minimize the electricity bill. When $\omega = \mathrm{r}$, it requires that the planning power trajectory after participation should not increase the energy bill. In other words, only the peak-shaving revenue component in (1) is negotiated, while the energy-cost component is not, thereby safeguarding the aggregator's basic interests. Mathematically, (5) states that both the baseline and planning profiles are selected from the solution set of (6). Because c_t is typically time-of-use or flat, multiple periods share identical prices and problem (6) usually admits multiple solutions. Thus (5) does not unduly restrict the feasibility of the baseline or planning power.

Accordingly, the aggregator's objective in (1) can be rewritten without loss of optimality as

$$\max f_i^{\mathrm{A}} = \sum_{t=1}^{T} \left(P_{i,t}^{\mathrm{r}} - P_{i,t}^{\mathrm{b}} \right) \pi_{i,t} \Delta T \tag{7}$$

where f_i^{A} denotes the revenue earned by aggregator i from participating in peak-shaving market.

B. Optimization Problem of the PSD

a) The original optimization problem of the PSD

The PSD aims to maximize the weighted total peak-shaving contribution of all aggregator, measured as the deviation of each aggregator's planning power from a system-referenced trajectory, i.e.,

$$\max f^{\mathrm{G}} = \sum_{i\in\mathcal{A}} \sum_{t=1}^{T} \left(P_{i,t}^{\mathrm{r}} - L_{i.t} \right) \gamma_t \Delta T \tag{8}$$

where f^{G} denotes the PSD's weighted peak-shaving capacity. $\mathcal{A}(i \in \mathcal{A}, |\mathcal{A}| = N)$ is the set of aggregators. The reference $L_{i,t}$ follows the trend of the system load factor while preserving aggregator i's minimum energy requirement $\underline{E}_{i,T}$, which is given by

$$L_{i,t} \triangleq \underline{E}_{i,T} \cdot L_t \Big/ \left(\Delta T \sum_{t=1}^{T} L_t \right), \forall 1 \le t \le T \tag{9}$$

where L_t is the system load factor in period t. The weight γ_t reflects the PSD's scarcity at time period t for peak shaving and is computed by

$$\gamma_t \triangleq \frac{\max\left(0, \hat{L} - L_t\right)}{\max\limits_{1\le t\le T} \left[\max\left(0, \hat{L} - L_t\right) \right]}, \forall 1 \le t \le T \tag{10}$$

with $\hat{L}$ is the average load factor over the T periods.

Because the feasibility of each aggregator's trajectory is guaranteed by the aggregator model, the PSD's model only needs bounds on the aggregate regulation volume

$$\underline{\Delta P}_t \le \sum_{i\in\mathcal{A}} P_{i,t}^{\mathrm{r}} - \sum_{i\in\mathcal{A}} P_{i,t}^{\mathrm{b}} \le \overline{\Delta P}_t, \forall 1 \le t \le T \tag{11}$$

where $\underline{\Delta P}_t$ and $\overline{\Delta P}_t$ are the lower/upper boundaries on the total regulation in period t.

b) Decoupling of optimization problems of the PSD

Since (11) couples all aggregators' baseline and planning power, directly embedding it in a multiple-to-one NBG would lead to high dimensionality and computational complexity. Accordingly, we replace the PSD's peak-shaving capacity upper/lower boundaries constraint (11) with per-aggregator boundaries (12), thereby decoupling each aggregator's baseline and planning power.

$\forall i \in \mathcal{A}$:

$$\underline{\Delta P}_{i,t} \le P_{i,t}^{\mathrm{r}} - P_{i,t}^{\mathrm{b}} \le \overline{\Delta P}_{i,t}, \forall 1 \le t \le T \tag{12}$$

where $\underline{\Delta P}_{i,t}$ and $\overline{\Delta P}_{i,t}$ are the lower/upper boundaries on aggregator i's regulation in period t. Let $\underline{\Delta P}_{i,t} = \beta_{i,t} \underline{\Delta P}_t$, $\overline{\Delta P}_{i,t} = \beta_{i,t} \overline{\Delta P}_i$ with allocation coefficient.

$$\beta_{i,t} \triangleq \frac{\left(\overline{P}_{i,t} - \underline{P}_{i,t} \right)}{\sum_{j\in\mathcal{A}} \left(\overline{P}_{j,t} - \underline{P}_{j,t} \right)}, \forall 1 \le t \le T, \forall i \in \mathcal{A} \tag{13}$$

This rule proportionally allocates the PSD's capacity to aggregators according to their available headroom. Evidently, the constraints before and after decoupling are not equivalent. However, once decoupled, the feasible sets for different aggregators become independent, i.e., one aggregator's baseline and planning power no longer affect the others' decisions. This reformulation converts the original multiple-to-one NBG into a collection of independent one-to-one NBGs, thereby substantially reducing computational complexity. Besides, since $\sum_{i\in\mathcal{A}}\beta_{i,t}=1$, the decoupled feasible set induced by (12) lies inside that of (11), ensuring feasibility. After this decoupling, the objective in the bilateral NBG with aggregator *i* becomes

$$\max f_i^{\mathrm{G}}=\sum_{t=1}^{T}\left(P_{i,t}^{\mathrm{r}}-L_{i.t}\right)\gamma_t\Delta T \tag{14}$$

where f_i^{G} denotes the weighted peak-shaving quantity contributed by aggregator *i* to the PSD.

c) Bilateral NBG Between a Single Aggregator and the PSD

In the bilateral NBG between the PSD and aggregator *i*, let x_i denote the strategy vector $\left\{P_{i,t}^{\mathrm{b}}\right\}_{1\le t\le T}$ and $\left\{P_{i,t}^{\mathrm{r}}\right\}_{1\le t\le T}$. x_i must satisfy the aggregator's constraints (2) and (5) and the PSD's decoupled constraint (12).

Let S_i^{A} denote the feasible region induced by (2) and (5), and let S_i^{G} denote the feasible region induced by (12). Define $S_i=S_i^{\mathrm{A}}\cap S_i^{\mathrm{G}}$, then $x_i\in S_i$. Let x_i^{A} and x_i^{G} be

$$x_i^{\mathrm{A}}\triangleq\arg\max_{x_i} f_i^{\mathrm{A}}\ \text{ s.t. }\ x_i\in S_i \tag{15}$$

$$x_i^{\mathrm{G}}\triangleq\arg\max_{x_i} f_i^{\mathrm{G}}\ \text{ s.t. }\ x_i\in S_i \tag{16}$$

The worst solutions (negotiation breakdown points) for the PSD and aggregator are $d_i^{\mathrm{G}}=f_i^{\mathrm{G}}(x_i^{\mathrm{A}})$ and $d_i^{\mathrm{A}}=f_i^{\mathrm{A}}(x_i^{\mathrm{G}})$. The Nash solution is the point on the Pareto frontier that maximizes the product of gains over the disagreement point, which is the optimal solution to the following optimization problem

$$\max_{x_i\in\Gamma_i}\xi_i=\left(f_i^{\mathrm{G}}(x_i)-d_i^{\mathrm{G}}\right)\left(f_i^{\mathrm{A}}(x_i)-d_i^{\mathrm{A}}\right) \tag{17}$$

where ξ_i is the bargaining objective and Γ_i denotes the Pareto set of the bi-objective problem $\mathcal{P}_i^{\mathrm{G\&A}}:\left\{\max_{x_i}\left(f_i^{\mathrm{G}},f_i^{\mathrm{A}}\right),\ \text{s.t. } x_i\in S_i\right\}$. Here, the NBG of the PSD and aggregator *i* has been modeled and solved (17) to obtain the baseline power of aggregator *i*.

III. Distributed Algorithm for Soving the Nash Bargaining Game

A. Basic Solution Procedure of the NBG

The key to computing the NBG equilibrium is to obtain the Pareto frontier Γ_i of problem $\mathcal{P}_i^{\mathrm{G\&A}}$. Since $\mathcal{P}_i^{\mathrm{G\&A}}$ is a linear multi-objective program, its Pareto frontier can be generated by weighted-sum scalarization, i.e., by solving the following single-objective problem.

$$\max_{x_i\in S_i}\lambda f_i^{\mathrm{G}}(x_i)+(1-\lambda)f_i^{\mathrm{A}}(x_i) \tag{18}$$

where λ is the weighting coefficient. For any given $\lambda\in[0,1]$, solving optimization problem (18) yields a solution $x_i^*(\lambda)\in\Gamma_i$ and the corresponding values $f_i^{\mathrm{G}}\left(x_i^*(\lambda)\right)$ and $f_i^{\mathrm{A}}\left(x_i^*(\lambda)\right)$. The bargaining function at $\xi_i(\lambda)$ is given by

$$\xi_i(\lambda)=\left(f_i^{\mathrm{G}}\left(x_i^*(\lambda)\right)-d_i^{\mathrm{G}}\right)\left(f_i^{\mathrm{A}}\left(x_i^*(\lambda)\right)-d_i^{\mathrm{A}}\right) \tag{19}$$

which defines a mapping from λ to $\xi_i(\lambda)$. Hence, computing the NBG equilibrium reduces to the following one-dimensional optimization:

$$\max_{\lambda\in[0,1]}\xi_i(\lambda) \tag{20}$$

Because the mapping from λ to $\xi_i(\lambda)$ entails solving (18) at each evaluation, gradient-based methods are not directly applicable. One classical approach replaces (18) with its KKT conditions and uses big-M linearization method for the complementarity constraints, leading to a centralized mixed-integer formulation-unsuitable here due to data-privacy requirements between the PSD and aggregators. A second approach employs a one-dimensional search (e.g., the golden section method) to solve (20), with (18) solved at each step via a distributed optimizer that preserves privacy.

B. Distributed Optimization via ADMM

We solve (18) using the classical ADMM so that the PSD and aggregator exchange only a small amount of information. Problem (18) is split into an aggregator subproblem and a PSD subproblem, linked by coupling constraints. Let the aggregator's variables be $P_{i,t}^{\mathrm{b}}$ and $P_{i,t}^{\mathrm{r}}$ (collected in x_i), create copies in the PSD subproblem $\overset{\mathrm{b}}{P}_{i,t}$ and $\overset{\mathrm{r}}{P}_{i,t}$ (collected in $\tilde{x}_i$). The two subproblems and the coupling constraint are given by

$$\min -(1-\lambda)f_i^{\mathrm{A}}(x_i)\ \text{ s.t. }\ x_i\in S_i^{\mathrm{A}} \tag{21}$$

$$\min -\lambda f_i^{\mathrm{G}}(\tilde{x}_i)\ \text{ s.t. }\ \tilde{x}_i\in S_i^{\mathrm{G}} \tag{22}$$

$$P_{i,t}^{\omega}-\overset{\omega}{P}_{i,t}=0,\forall 1\le t\le T,\forall\omega\in\{\mathrm{r,b}\} \tag{23}$$

At iteration *k*+1, the aggregator solves the augmented-Lagrange subproblem

$$\left(P_{i,t}^{\mathrm{r},(k+1)},P_{i,t}^{\mathrm{b},(k+1)}\right)=\arg\min\left\{\begin{aligned}&-(1-\lambda)\sum_{t=1}^{T}\left(P_{i,t}^{\mathrm{r}}-P_{i,t}^{\mathrm{b}}\right)\pi_{i,t}\Delta T\\&+\sum_{t=1}^{T}u_t^{(k)}\left(P_{i,t}^{\mathrm{r}}-\overset{\mathrm{r}}{P}{}_{i,t}^{(k)}\right)+\sum_{t=1}^{T}v_t^{(k)}\left(P_{i,t}^{\mathrm{b}}-\overset{\mathrm{b}}{P}{}_{i,t}^{(k)}\right)\\&+\frac{\rho}{2}\sum_{t=1}^{T}\left[\left(P_{i,t}^{\mathrm{r}}-\overset{\mathrm{r}}{P}{}_{i,t}^{(k)}\right)^2+\left(P_{i,t}^{\mathrm{b}}-\overset{\mathrm{b}}{P}{}_{i,t}^{(k)}\right)^2\right]\end{aligned}\right\} \tag{24}$$

s.t. (2), (5)

where superscript (*k*) denotes the value from iteration *k*. $u_t^{(k)}$, $v_t^{(k)}$ are dual variables and ρ is the penalty parameter.

The PSD solves

$$\left(\overset{\mathrm{r}}{P}{}_{i,t}^{(k+1)},\overset{\mathrm{b}}{P}{}_{i,t}^{(k+1)}\right)=\arg\min\left\{\begin{aligned}&-\lambda\sum_{t=1}^{T}\left(\overset{\mathrm{r}}{P}{}_{i,t}^{(k+1)}-L_{i,t}\right)\gamma_t\Delta T\\&+\sum_{t=1}^{T}u_t^{(k)}\left(P_{i,t}^{\mathrm{r},(k+1)}-\overset{\mathrm{r}}{P}_{i,t}\right)+\sum_{t=1}^{T}v_t^{(k)}\left(P_{i,t}^{\mathrm{b},(k+1)}-\overset{\mathrm{b}}{P}_{i,t}\right)\\&+\frac{\rho}{2}\sum_{t=1}^{T}\left[\left(P_{i,t}^{\mathrm{r},(k+1)}-\overset{\mathrm{r}}{P}_{i,t}\right)^2+\left(P_{i,t}^{\mathrm{b},(k+1)}-\overset{\mathrm{b}}{P}_{i,t}\right)^2\right]\end{aligned}\right\} \tag{25}$$

s.t. $\underline{\Delta P}_{i,t}\le\overset{\mathrm{r}}{P}_{i,t}-\overset{\mathrm{b}}{P}_{i,t}\le\overline{\Delta P}_{i,t},\forall 1\le t\le T$

Dual variables are then updated by

$$\begin{cases} u_t^{(k+1)} = u_t^{(k)} + \rho\left(P_{i,t}^{\mathrm{r},(k+1)} - P_{i,t}^{\mathrm{r},(k+1)}\right) \\ v_t^{(k+1)} = v_t^{(k)} + \rho\left(P_{i,t}^{\mathrm{b},(k+1)} - P_{i,t}^{\mathrm{b},(k+1)}\right) \end{cases} \tag{26}$$

Convergence is declared when both the primal and dual residuals fall below prescribed tolerances.

$$\delta_{\mathrm{prim}}^{(k+1)} \triangleq \sum_{\omega\in\{\mathrm{r,b}\}} \sum_{t=1}^{T} \left(P_{i,t}^{\omega,(k+1)} - P_{i,t}^{\omega,(k+1)}\right)^2 \le \varepsilon_{\mathrm{prim}} \tag{27}$$

$$\delta_{\mathrm{dual}}^{(k+1)} \triangleq \sum_{\omega\in\{\mathrm{r,b}\}} \sum_{t=1}^{T} \left(P_{i,t}^{\omega,(k+1)} - P_{i,t}^{\omega,(k)}\right)^2 \le \varepsilon_{\mathrm{dual}} \tag{28}$$

where $\delta_{\mathrm{prim}}^{(k+1)}$ and $\delta_{\mathrm{dual}}^{(k+1)}$ denote the primal and dual residuals at iteration k+1. $\varepsilon_{\mathrm{prim}}$ and $\varepsilon_{\mathrm{dual}}$ are their respective tolerance thresholds. A sufficiently small primal residual indicates that the coupling variables exchanged between the aggregator and the PSD are nearly consistent, whereas a sufficiently small dual residual signifies that the iterates are stabilizing.

Because the original subproblems (21)-(22) and the coupling (23) are linear, strong duality holds and ADMM can converge to the global optimum of (18).

C. Overall Nested Iteration

Embedding the ADMM solver for (18) inside the golden-section search for (20) yields a privacy-preserving distributed algorithm to compute the NBG equilibrium between the PSD and each aggregator. Given the search tolerance ε and the ADMM tolerances $\varepsilon_{\mathrm{prim}}$, $\varepsilon_{\mathrm{dual}}$, the nested procedure iterates outer golden-section steps on λ and runs ADMM to solve (18) to the required accuracy at each step.

IV. Case Studies

A. Setup

This study uses the actual clearing prices of the peak-shaving ancillary service market with third-party participation in the North China Power Grid for August 2021, together with the average system load factor over the same period. Each aggregator's forecast $\pi_{i,t}$ of the next-day clearing price is taken as the 10-day moving average of historical clearing prices. The forecast of L_t is the average load factor of day 11, from which γ_t and $L_{i,t}$ are computed. The tariff c_t adopts the summer time-of-use (TOU) tariff for general industrial/commercial customers in Beijing. The interval length is set to ΔT =15 min.

The PSD's aggregate regulation boundaries are $\overline{\Delta P_t} = 200$ MW and $\underline{\Delta P_t} = -200$MW. Ten aggregators participate including five EV aggregators (EVA1-EVA5) and five air-conditioning load aggregators (ACA1-ACA5). Each EVA aggregates 10,000 EVs, and each EV has 7 kW maximum charging power and 50 kWh battery capacity. Arrival/departure times and initial/target SOC are generated via Monte Carlo simulation. Each ACA aggregates 10,000 air-conditioners (rated 5 kW, set-point range 20-24°C).

B. Analysis of Convergence and Decoupling Effects

Because all aggregators show similar behavior, the result of EVA1 is shown for analysis. For different λ, the inner-loop ADMM exhibits similar patterns. For λ=0.382, ADMM converges in 44 iterations with a runtime of 7.0947s. The convergence process is shown in Fig.1. At convergence,

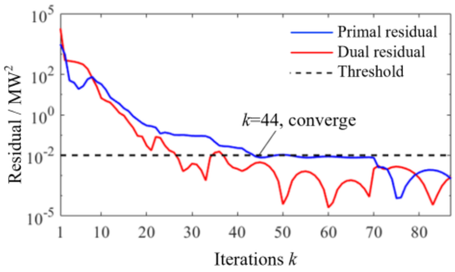


Fig. 1. The convergence process of ADMM algorithm

$f_i^{\mathrm{G}} = 111.87$ MWh and $f_i^{\mathrm{A}} = 2580.1$ CNY, matching the centralized benchmark and confirming that ADMM attains the optimal solution of (18). In addition, to directly quantify the decoupling impact by Section II-B, a centralized non-decoupled benchmark is calculated. The solution yields $f^{\mathrm{G}} = 844$ MWh and $f^{\mathrm{A}} = 35201$ CNY. The decoupled solution yields $f^{\mathrm{G}} = 843$ MWh and $f^{\mathrm{A}} = 34929$ CNY when summing across all aggregators. The relative differences are only 0.12% (energy) and 0.77% (revenue), demonstrating that the decoupling has negligible practical impact on system-level outcomes.

Figure 2 shows the golden section search used to compute the NBG equilibrium. The search interval shrinks monotonically and terminates after 16 iterations at $\lambda^* = 0.1185$, and the total runtime is 262.3s which is sufficient for day-ahead baseline computation.

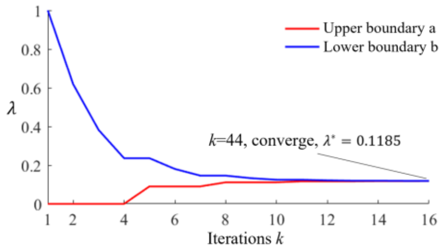


Fig. 2. The convergence process of solving NBG equilibrium by the golden section method

C. Equilibrium Results

a) Baseline and planning Power Trajectories

Figure 3 plots the total baseline power and the total planning power across all aggregators at equilibrium. Consistent with TOU trends, both totals peak in low-price periods, aligning with demand-side operating principles. Differences between baseline and planning power concentrate in the peak-shaving periods (00:30–07:00 and 12:30–16:00). When both the market price and the operator's weighting γ_t are high (e.g., around 03:00 and 15:00), planning power exceeds the baseline. When they are

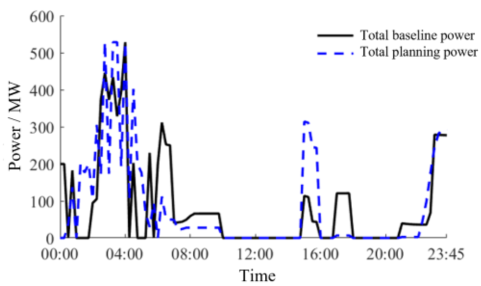
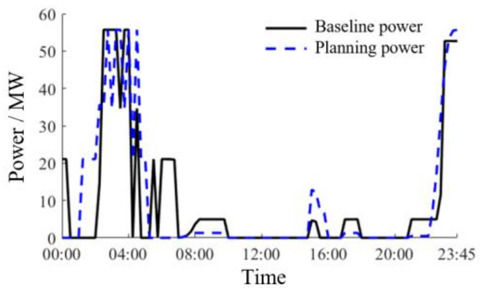
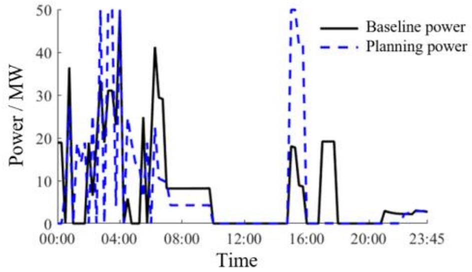


Fig. 3. The convergence process of solving NBG equilibrium by the golden section method



(a) EVA1



(b) ACA1

Fig. 4. Baseline power and planning power of EVA1 and ACA1

relatively low (e.g., around 06:00 and 09:00), the planning power may fall below the baseline. High planning power peaks occur at night and near 16:00, which is counter cyclical to the system load factor and thus favorable for peak-shaving services.

Figure 4 shows individual results for EVA1 and ACA1 follow the same qualitative pattern as the aggregate, with quantitative differences due to distinct flexibility envelopes. For example, around 15:00, a period with high price and high γ_t, ACA1's regulation relative to its baseline is much larger than EVA1's. Because the available EV count is limited and the EVA's flexibility is lower in that period, peak-shaving there is primarily provided by ACA.

b) Economic Performance

Using EVA1 as an example, we evaluate the PSD's and aggregator's equilibrium payoffs under the NBG. For comparison, we also compute results using

1. Stackelberg Game (SKG): a non-cooperative formulation with the PSD as leader and the aggregator as follower, modeled as a bilevel program. Upper level determines the baseline and lower level optimizes the aggregator's planning power given the baseline.

2. Averaging Method (AVG): the baseline equals the mean of 10 days in which the aggregator does not participate in peak shaving but self-schedule to minimize energy cost. The planning power is then obtained by solving the aggregator's model in Section *II.B.* with the baseline fixed.

From Table I, the three methods' objective values for the PSD and EVA1, as well as the Nash bargaining value. Under SKG, the PSD's objective is slightly larger than under NBG, but EVA1's profit is much smaller, so the bargaining value becomes negative. Under AVG, EVA1's profit exceeds the NBG result, but the PSD's objective is far smaller, leading to a low bargaining value. Compared with AVG, which tends to favor aggregators, and SKG, which tends to favor the system operator, NBG explicitly balances PSD and aggregators' utilities by maximizing the product of their improvements over the disagreement point, thereby yielding a compromise that is both more efficient and fairer.

TABLE I. COMPARISON OF OBJECTIVES AND THE NEGOTIATION VALUE BY THREE CALCULATION METHODS

Method	f_i^{G} / MWh	f_i^{A} / CNY	ξ_i / (MWh • CNY)
NBG	110.96	2898.3	38376.0
SKG	112.26	233.9	-7590.5
AVG	98.16	3354.2	11501.4

V. CONCLUSION

In this paper, a NBG-based model is proposed, together with a nested golden section and ADMM algorithm that enables the PSD and aggregators to compute the equilibrium baseline while exchanging only limited information. Case studies show that the algorithm converges within minutes, satisfying the time requirements of day-ahead operation. Unlike conventional methods, the NBG model does not rely on historical non-participation load data, making it suitable for scenarios where aggregators participate in peak shaving on a routine basis. Moreover, the proposed approach achieves a more balanced allocation of benefits between the PSD and aggregators, demonstrating stronger applicability to real-world peak-shaving ancillary service markets.

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