

Multi-market Demand Response Bidding Strategy for Load Aggregators Based on Bilateral Time Granularity Matching Framework

Simian Pang, Yongbiao Yang, Qingshan Xu, Jiao Du, Jiancheng Yu, and Chao Pang

Abstract—Power systems with renewable energy penetration increasingly rely on flexible loads to provide ancillary services, including emergency DR, renewable energy consumption, peak shaving, and valley filling. However, the demand response (DR) characteristics of diversified loads such as long DR delay time and ramp-up time do not match the high-resolution bidding and fast-response requirements of ancillary services. To address this challenge, this paper proposes a multi-market DR bidding strategy for load aggregators (LAs). First, the specific bidding resolution and response frequency rules of emergency DR, renewable energy consumption, peak shaving, and valley filling are analyzed, leading to the establishment of a market-side time granularity model. Meanwhile, the DR characteristics of flexible loads, including DR delay time, ramp-up time, and duration, are reformulated into a load-side time granularity model based on DR deviation penalty rules. A bilateral time granularity matching framework is then constructed to enable coarse-grained loads to participate in fine-grained markets through co-ordinated aggregation. To enable the distributed optimization of DR bidding plans and load response schedules under the management of LAs, a multi-market DR bidding strategy based on bilateral time granularity matching framework is developed. Case studies demonstrate that the proposed strategy effectively unlocks the time flexibility of diversified loads, allowing them to participate in multiple markets and maximize economic benefits.

Index Terms—Ancillary service, demand response, deviation penalty, distributed optimization, flexible load, bilateral time granularity matching, flexibility, load aggregator.

NOMENCLATURE

A. Indexes and Sets

i, I Index and set of markets in which load aggregator (LA) participates

I' Index between 1 and I
 j, J Index and set of loads managed by LA
 k Index of iteration
 n, n_j Time indexes of market and load
 N^+ Set of positive integers
 t_1, t_2 Sets of demand response (DR) bidding period
 t' Time index between 0 and T
 T Time scale of DR
 T_i The maximum number of bids within the period $[t_1, t_2]$

B. Variables

λ Dual variable in alternating direction method of multipliers (ADMM)
 E_i, E_j Response energy of market i and load j
 E_i^D Energy deviation settled in market i
 E_{LA} Total response energy of LA
 L_P Lagrangian function of ADMM
 P_i^D Power deviation settled in market i
 P_{LA} Power of LA
 P_j^L, P_j Load response schedule and real DR power of load j
 P_i^M, P_i DR bidding plan and real DR power in market i
 P_{ij} Matching power of load j bidding in market i

C. Parameters

α_i, α_j DR ratios of market i and load j
 $\alpha_{\max}, \alpha_{\min}$ The maximum and minimum ranges of DR ratio
 β_i, β_j Discount factors of market i and load j
 ρ Penalty parameter in ADMM
 δ_j Response power potential of load j
 γ_j Response energy potential of load j
 $\varepsilon^{\text{dual}}, \varepsilon^{\text{pri}}$ Dual and primal residuals of ADMM
 b_i, b_j DR subsidies of market i and load j
 B_{LA}, B_i, B_j Benefits of LA, market i , and load j
 c_j, c_{TOU} Response cost and time-of-use price

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$E_j^{C,\min}, E_j^{C,\max}$	The minimum and maximum cumulative energy limits of load j
G_i, G_j	Time granularities of market i and load j
M	A very large positive value in big- M method
P_j^B	Baseline power of load j
$P_j^{\max}, P_j^{\min}$	The maximum and minimum power of load j
t_{DT}, t_{CT}, t_{ST}	DR delay time, ramp-up time, and duration
$\Delta t_i, \Delta t_{I'}$	Bidding time resolutions in markets i and I'
$\Delta t_{\min}$	The minimum bidding time resolution of multiple markets
v_j	Ramp-up speed limit of load j

D. Matrices

A, B, C, D	Coefficient matrices in ADMM
$\mathbf{x}, \mathbf{y}, \mathbf{z}$	Decision variable matrices in ADMM

I. INTRODUCTION

THE ongoing reform of the electricity market in China has transformed demand-side management, shifting it from traditional load dispatch to price-based incentive mechanisms [1]. Auxiliary service markets, including renewable energy consumption, peak shaving, and valley filling, have emerged as key approaches for utilizing power loads to enhance grid flexibility, gradually replacing direct load control methods [2]. This transition also provides flexible load managers with opportunities to participate in multiple markets, thereby reducing electricity costs. Nevertheless, the shift from passive load dispatch to active demand response (DR) introduces several challenges.

On the demand side, load flexibility is constrained by DR characteristics such as regulation speed and DR delay time, resulting in deviation penalties in demand-side management [3]. From the market perspective, ancillary services exhibit diverse requirements for bidding time resolution and response frequency [4]. These time-based requirements, collectively referred to as time granularity, define the minimum time units for scheduling on the load side and bidding on the market side, respectively. However, when the time granularity of market rules does not align with the DR characteristics of flexible loads, it leads to lower DR efficiency, increased response deviations, and higher penalty risks. To address this challenge, this paper proposes a multi-market DR bidding strategy for load aggregators (LAs) based on bilateral time granularity matching framework. The proposed strategy models the characteristics of heterogeneous loads and matches them with market bidding rules through a bilateral time granularity matching framework, aiming to reduce entry barriers, mitigate deviations, and improve settlement revenues for LAs in multi-market participation.

Demand-side resources are characterized by small capacities, large numbers, and wide distribution [5]. Consequently, these flexible loads participate in DR through agents such as virtual power plants (VPPs) or LAs [6]. It is crucial to note that different types of loads exhibit diverse DR characteristics [7]. Regarding DR delay time, [8] and [9] model load

flexibility by considering monitoring and communication delays, and analyze their impacts on DR performance. Furthermore, the ramp-up speed and ramp-up time of DR are investigated in [10] and [11], emphasizing the time required for loads to transition from initial power values to target power values. DR duration, another critical characteristic, is discussed in [12] and [13], where the minimum duration requirements are linked to entry thresholds for ancillary services, and the maximum durations are incorporated as constraints in DR bidding strategies. However, modeling these characteristics remains challenging due to their strong coupling and continuity in the time dimension. In this context, [14] and [15] propose time granularity models for thermal and industrial production device processes. However, the relationship between time granularity and DR characteristics remains insufficiently explored.

Flexible loads have traditionally participated in single-market transactions after aggregation, achieving considerable benefits [16], [17]. In recent years, increasing attention has been paid to LAs engaging in DR within complex market environments. For instance, [18] and [19] explore co-optimization strategies for LAs participating in day-ahead, intraday, and real-time markets, improving DR benefits across multiple timescales. References [20] and [21] further expand the scope of DR by leveraging load flexibility for ancillary services such as frequency regulation and three-phase imbalance mitigation. In addition, [22] investigates DR strategies with separate considerations for penalty-charged and penalty-free market mechanisms. Despite these advancements, the issue of differing time granularities across multiple markets remains insufficiently studied. Existing studies often assume uniform time resolutions and response frequencies across markets, which deviates from real-world conditions. Although [4] and [23] highlight the significance of market-side time granularity, they lack detailed DR modeling methodologies. This limitation hinders LAs from coordinating resources across diverse markets, thereby reducing their ability to fully exploit load flexibility.

To enhance DR benefits, it is essential to enable aggregated bidding of fast- and slow-response loads across markets with varying time granularities [24]. Given the aforementioned heterogeneity in market rules and DR characteristics, it is crucial to address the bilateral matching problem of time granularity. Distributed optimization algorithms have been increasingly adopted in DR research involving multiple agents, including markets and loads. These algorithms enable DR scheduling or trading through localized computation while preserving data privacy [25]. For example, [26] applies the alternating direction method of multipliers (ADMM) to coordinate adjustable load trading in electricity and gas markets, facilitating iterative exchanges of shared variables. Similarly, [27] proposes a distributed optimization model for joint electricity-carbon trading among VPPs, leveraging ADMM to exploit the spatio-temporal complementarity of flexible resources. While existing studies explore the matching of trading products with load types, there remains a gap in integrating DR characteristics with market-side time granularities [28].

Table I provides a detailed comparison of existing literature and this paper. First, most existing studies overlook market-side time granularity in multi-market co-bidding processes and typically fix the trading frequency across different markets at 15 or 60 min. This simplification may cause slow-response loads to incur larger deviation penalties when participating in markets with higher trading frequencies. Moreover, limited research considers DR characteristics of loads. The strong coupling and nonlinearity among the three charac-

teristics, including DR delay time, ramp-up time, and duration, pose challenges for the optimization. Simplifying these characteristics often prevents certain loads from accurately responding to rapidly changing commands. Notably, there is still a lack of bilateral matching framework to address the mismatch between multi-market bidding time rules and multi-load response characteristics. This gap leads to increased deviation penalties in DR, thereby reducing the overall economic benefits for LAs.

TABLE I
COMPARISON OF EXISTING LITERATURE AND THIS PAPER

Reference	Market-side time granularity	DR characteristic	DR deviation management
[8], [9]	×	DR delay time	×
[10], [11]	×	DR ramp-up time	×
[12], [13]	×	DR duration	×
[14], [15]	×	Time granularity	×
[20]	√	×	×
[23]	√	×	×
[3]	×	DR delay time and speed	Energy storage compensation
This paper	√	Coupled DR delay time, ramp-up time, and duration	Bilateral time granularity matching

Note: √ and × indicate whether this item has been considered or not.

In summary, this paper addresses the above gap by proposing a multi-market DR bidding strategy for LAs based on a bilateral time granularity matching framework, formulated as a distributed optimization problem. The main contributions are as follows.

1) We develop a market-side time granularity model based on bidding resolution and response frequency rules, and a load-side time granularity model that incorporates DR characteristics (DR delay time, ramp-up time, and duration).

2) We construct a bilateral time granularity matching framework that overcomes the limitations of DR characteristics and market rules, enabling flexible matching between markets and loads with varying time granularities to achieve precise DR.

3) We propose a multi-market DR bidding strategy based on ADMM to optimize DR bidding plans and load response schedules across different time granularities. This strategy preserves data privacy and enables loads to participate in various ancillary services, breaking the constraints of bilateral time granularity and enhancing DR benefits for LAs.

The remainder of this paper is organized as follows. Section II presents the problem formulation of bilateral time granularity, including the market-side time granularity model, the load-side time granularity model, and the bilateral time granularity matching framework. Section III describes multi-market DR bidding strategy based on ADMM. Section IV presents case studies. Finally, Section V concludes the paper.

II. PROBLEM FORMULATION OF BILATERAL TIME GRANULARITY

To address the mismatch between DR characteristics and bidding resolutions, this section focuses on modeling the bi-

lateral time granularity of loads and markets. Firstly, the time resolutions of different ancillary services are analyzed and characterized using a generalized time granularity model. Then, based on deviation penalty rules, the impacts of DR delay time, ramp-up time, and duration on the market response ratio are explored. These characteristics are further integrated into the time granularity model. Finally, the bilateral time granularity matching framework is formulated through a series of constraints.

A. Market-side Time Granularity Model

Market bidding rules related to the time granularity model include time resolution requirements [4] and deviation penalty mechanisms [29]. First, different time resolutions are adopted across various ancillary services. For instance, time resolutions of 5, 15, and 60 min are commonly used in ancillary services of China, including emergency DR, renewable energy consumption, peak shaving, and valley filling. In this context, LAs participate in multiple ancillary services with distinct time resolutions to maximize their benefits. However, many existing studies on participation of LAs in multi-market bidding assume uniform time resolutions across all markets, which simplifies the modeling and solution process. This assumption does not align with actual market rules and may lead to impractical bidding strategies, thereby increasing the risk of DR deviations.

In traditional DR bidding models, the time resolution of DR is expressed as:

$$\begin{cases} E_{LA} = \sum_{i=1}^I \Delta t P_i^M \\ B_{LA} = \sum_{i=1}^I \Delta t P_i^M b_i \end{cases} \quad (1)$$

Building on these DR bidding models, the time granulari-

ty G_i is introduced to distinguish various bidding time resolutions Δt_i in each market. This enables the multi-market DR bidding variables for the period $[t_1, t_2]$ to be defined as:

$$\begin{cases} E_{LA} = \sum_{i=1}^I \sum_{G_i=1}^{T_i} \Delta t_i P_i^M(G_i) \\ B_{LA} = \sum_{i=1}^I \sum_{G_i=1}^{T_i} \Delta t_i P_i^M(G_i) b_i(G_i) \\ T_i = \frac{t_2 - t_1}{\Delta t_i} \end{cases} \quad (2)$$

To ensure precise DR, the power of LA P_{LA} and DR bidding plan P_i^M must satisfy the condition in (3) at any moment t .

$$\begin{cases} P_{LA}(t) = \sum_{i=1}^I P_i^M(G_i(t)) \\ G_i(t) = \left\lfloor \frac{t - t_1}{\Delta t_i} \right\rfloor \quad \forall t \in [t_1, t_2] \end{cases} \quad (3)$$

Following the bidding process, the DR ratio α_i of the LA is used to refine the benefit B_i in the energy dimension, accounting for deviation penalties [22]. The DR ratio α_i , which is related to the time granularity G_i , is calculated as:

$$\alpha_i(G_i) = \frac{\int_0^{\Delta t_i} P_i(t) dt}{\Delta t_i P_i^M(G_i)} \times 100\% \quad (4)$$

The DR ratio α_i and benefit B_i are then linked through a discount factor β_i , as described in (5). Specifically, when α_i approaches 100%, market i compensates the LA at the DR subsidy b_i . However, when the DR ratio is low, the LA incurs a penalty determined by the discount factor.

$$B_i(G_i) = \beta_i(\alpha_i(G_i)) b_i(G_i) \Delta t_i P_i^M(G_i) \quad (5)$$

Finally, the DR penalty mechanisms detailed in [29] are incorporated into the time granularity model for China. Specifically, a stepwise discount factor based on DR ratio intervals is applied to reflect deviation penalties, expressed as:

$$\beta_i(\alpha_i) = \begin{cases} \alpha_i & \alpha_i \in [\alpha_{\min}, \alpha_{\max}] \\ 0 & \alpha_i \in (-\infty, \alpha_{\min}) \cup (\alpha_{\max}, +\infty) \end{cases} \quad (6)$$

Although this paper focuses on the Chinese market, the proposed market-side time granularity model can also be applied to ancillary service markets in Europe and the United States. These markets similarly feature diverse DR bidding time granularities and energy-based settlement mechanisms [4], [30].

B. Load-side Time Granularity Model

Under the management of the LA, diversified loads collaborate to track DR bidding plans across multiple markets. Conventional multi-market DR bidding strategies primarily focus on static flexibility constraints such as response power and energy. However, DR characteristics hinder the ability of flexible loads to accurately track evolving DR bidding plans, resulting in DR deviations. In precise DR scenarios, a lower DR ratio leads to greater deviation penalties for the

LA [31]. To address this issue, this subsection incorporates the deviation penalty rules from (4)-(6) into constraints on three DR characteristics. Figure 1 illustrates typical DR deviations between DR schedule and actual load response. In conjunction with Fig. 1, a load-side time granularity model is then developed to ensure that LAs are not penalized due to their inherent characteristics.

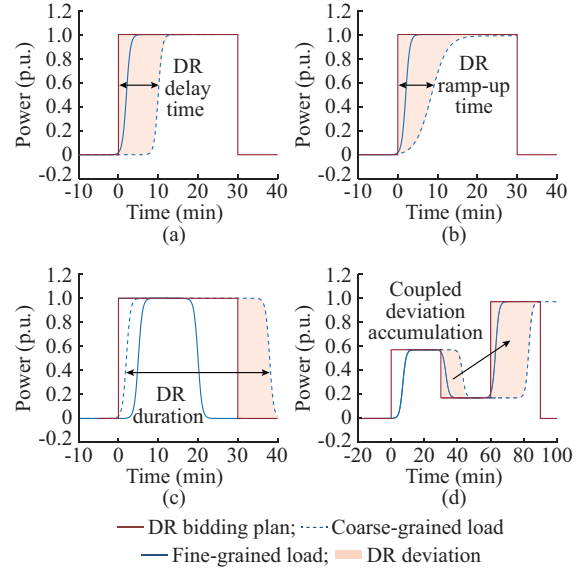


Fig. 1. Typical DR deviations between DR schedule and actual load response. (a) DR deviation caused by DR delay time. (b) DR deviation caused by DR ramp-up time. (c) DR deviation caused by DR duration. (d) Coupled deviation accumulation under multi-characteristic constraints.

The DR delay time t_{DT} refers to the expected time interval between the issuance of a DR schedule and the start of response of the user, as described in (7). This delay is typically influenced by operational and communication latency [7].

$$P_j = \begin{cases} 0 & 0 \leq t \leq t_{DT} \\ P_j^L & t_{DT} < t \leq \Delta t \end{cases} \quad (7)$$

Figure 1(a) illustrates the DR deviation caused by t_{DT} . As the DR delay time increases and the DR ratio decreases to the penalty range $(-\infty, \alpha_{\min})$ defined in (6), DR subsidies decline from b_j to $\beta_j b_j$. Consequently, the load benefit B_j can be expressed using the piecewise function as:

$$B_j = \begin{cases} (b_j - c_j)(\Delta t - t_{DT}) P_j^L & \alpha_j > \alpha_{\min} \\ (\beta_j b_j - c_j)(\Delta t - t_{DT}) P_j^L & \alpha_j \leq \alpha_{\min} \end{cases} \quad (8)$$

In (8), the sign of B_j determines the willingness of load j to participate in DR. Specifically, the load will not participate if $b_j \leq c_j$, and it will always participate if $\beta_j b_j \geq c_j$. The relationship between the DR delay time and DR ratio is given as:

$$\alpha_j = (\Delta t - t_{DT}) / \Delta t \quad (9)$$

In addition, the expected DR ramp-up time is determined by the ramp-up speed limit of DR. In most DR-related studies, this speed limit is treated as a key constraint, typically expressed as:

$$-v_j \leq P_j^L \leq v_j \quad (10)$$

However, with the introduction of the deviation penalty rule in (6), the traditional speed constraint becomes insufficient. When the DR ramp-up time reaches the constraint bound, the DR ratio caused by deviation is only 50%, which is unacceptable for most ancillary services. To address this issue, the real DR power detailed in (7) is refined to (11), accounting for the coupled effects of DR delay time and ramp-up time.

$$P_j = \begin{cases} 0 & 0 \leq t < t_{DT} \\ 0 + v_j(t - t_{DT}) & t_{DT} \leq t < t_{CT} + t_{DT} \\ P_j^L & t_{CT} + t_{DT} \leq t \leq \Delta t \end{cases} \quad (11)$$

The relationship among t_{DT} , t_{CT} , and α_j is given as:

$$\alpha_j \Delta t = \Delta t - t_{DT} - 0.5t_{CT} \quad (12)$$

The DR duration refers to the minimum time interval during which the load must maintain the DR power. The time resolution of DR Δt cannot be shorter than t_{ST} . Otherwise, the load will be unable to track rapidly changing response schedules, leading to the deviation accumulations across different bidding periods. The duration constraint is given as:

$$P_j = P_j^L \quad \Delta t \geq t_{ST} \quad (13)$$

Finally, as depicted in Fig. 1(d), to track rapidly changing response schedules and avoid deviation accumulation, the load must satisfy the time-domain constraint defined as:

$$(n-1)\Delta t_{\min} \leq t_{DT} + t_{CT} + t_{ST} \leq n\Delta t_{\min} \quad n \in N^+ \quad (14)$$

However, the time-domain constraint in (14) is insufficient to fully address deviation issues. An improved load-side time granularity model that incorporates deviation penalty rules is formulated in (15). With this model, the LA can track response schedules without penalty, even when the time resolution is greater than $n_j \Delta t_{\min}$.

$$\begin{cases} G_j(t) = \left\lfloor \frac{t}{n_j \Delta t_{\min}} \right\rfloor & n \in N^+ \\ (2t_{DT} + t_{CT}) \leq 2n_j \Delta t_{\min} (1 - \alpha_i) \end{cases} \quad (15)$$

C. Bilateral Time Granularity Matching Framework

Figure 2 illustrates the proposed bilateral time granularity matching framework. In this framework, the LA functions as a central coordinator that facilitates alignment between load-side and market-side time granularities. As described in Section II-B, load-side time granularity is determined by three DR characteristics: DR delay time, ramp-up time, and duration. Meanwhile, market-side time granularity is determined by corresponding bidding rules, as detailed in Section II-A. The proposed framework allows the LA to decompose and aggregate load response schedules, thereby achieving n -to- n alignment with DR bidding plans even when their time granularities differ.

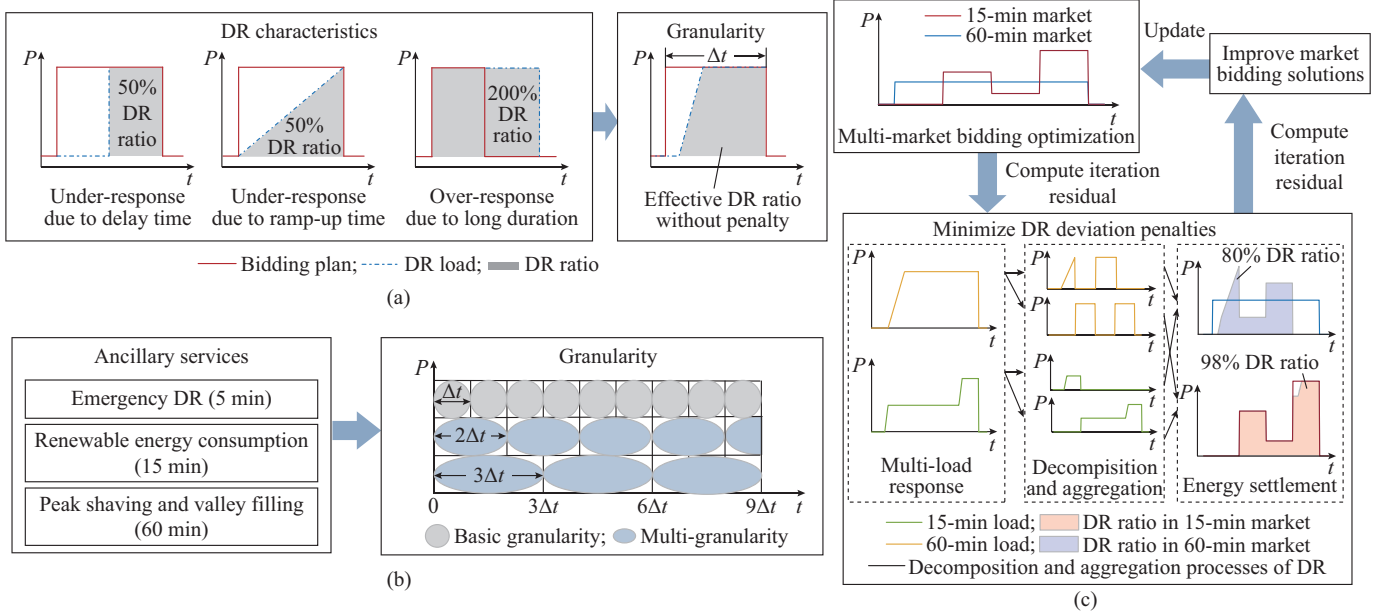


Fig. 2. Proposed bilateral time granularity matching framework. (a) Load-side time granularity. (b) Market-side time granularity. (c) Bilateral time granularity matching.

To ensure direct matching between loads and markets with the same time granularity, constraint (16) is introduced.

$$\begin{cases} P_i(G_i(t)) = P_j(G_j(t)) \\ \Delta t_i = n_j \Delta t_{\min} \end{cases} \quad (16)$$

To ensure that loads can participate in both coarse-grained and fine-grained markets, (17) is imposed. Specifically, to prevent under-response deviation, the real DR power P_j of

load must exceed the maximum real power P_i of the market. Additionally, to prevent over-response deviation, the response energy must not exceed the cleared energy across all markets.

$$\begin{cases} P_j(G_j(t)) \geq \max_{t \in [0, n_j \Delta t_{\min}]} P_i(G_i(t)) \\ \int_0^{n_j \Delta t_{\min}} P_j(G_j(t)) dt \leq \sum_{i=1}^I \int_0^{n_j \Delta t_{\min}} P_i(G_i(t)) dt \end{cases} \quad (17)$$

Then, (18) ensures that diversified loads can participate in coarse-grained markets.

$$\begin{cases} P_j(G_j(t)) \geq 0 & \Delta t_i \geq n_j \Delta t_{\min} \\ P_j(G_j(t)) = 0 & \text{otherwise} \end{cases} \quad (18)$$

Finally, to achieve hybrid bilateral time granularity matching, the constraint in (19) is introduced.

$$\begin{cases} \sum_{i=1}^P E_i(G_i(t)) \leq \sum_{j=1}^J \int_{t_1}^{t_2} P_j dt \\ t_2 - t_1 = \Delta t_I \end{cases} \quad (19)$$

III. MULTI-MARKET DR BIDDING STRATEGY BASED ON ADMM

ADMM is a distributed optimization algorithm that decomposes a centralized problem into smaller subproblems, each of which can be solved independently and in parallel [32]. This feature makes ADMM particularly suitable for scenarios involving multiple decision-making entities such as diversified loads and multiple markets. To preserve data privacy during computation, ADMM is adopted to solve the two-layer problem in a distributed and iterative manner. Under this algorithm, all sensitive information such as DR characteristics, baseline load profiles, and response potentials is processed locally by each DR participant and does not need to be centrally uploaded or shared with other entities. Only shared or consensus-related variables are exchanged during iterations, thereby preventing the leakage of private parameters while ensuring global convergence of the optimization [33].

This section develops a multi-market DR bidding strategy based on ADMM that enables bilateral time granularity matching. The flowchart of multi-market DR bidding strategy based on ADMM is illustrated in Fig. 3. This process achieves bilateral time granularity matching by using DR ratio as the coordination bridge between upper-layer market bidding and lower-layer load response. Matching constraints are reformulated into the objective functions of both layers and iteratively updated via ADMM.

A. Upper Layer: Multi-market Bidding

In the upper layer, the LA manager submits the day-ahead bidding plans to multiple markets. The objective is to maximize the total DR benefits while accounting for deviation penalties caused by insufficient DR potential. The decision variables in this layer include bidding plans, incentive prices, deviation power, and deviation energy.

$$\begin{cases} \max \sum_{i=1}^I \int_t^T B_i dt \\ \text{s.t. (2)-(6), (16)-(19), and (21)-(23)} \end{cases} \quad (20)$$

The benefit B_i in (20) consists of the response subsidy $\beta_i b_p$, as formulated in (21). This term also reflects the incentives associated with renewable energy consumption in the corresponding market.

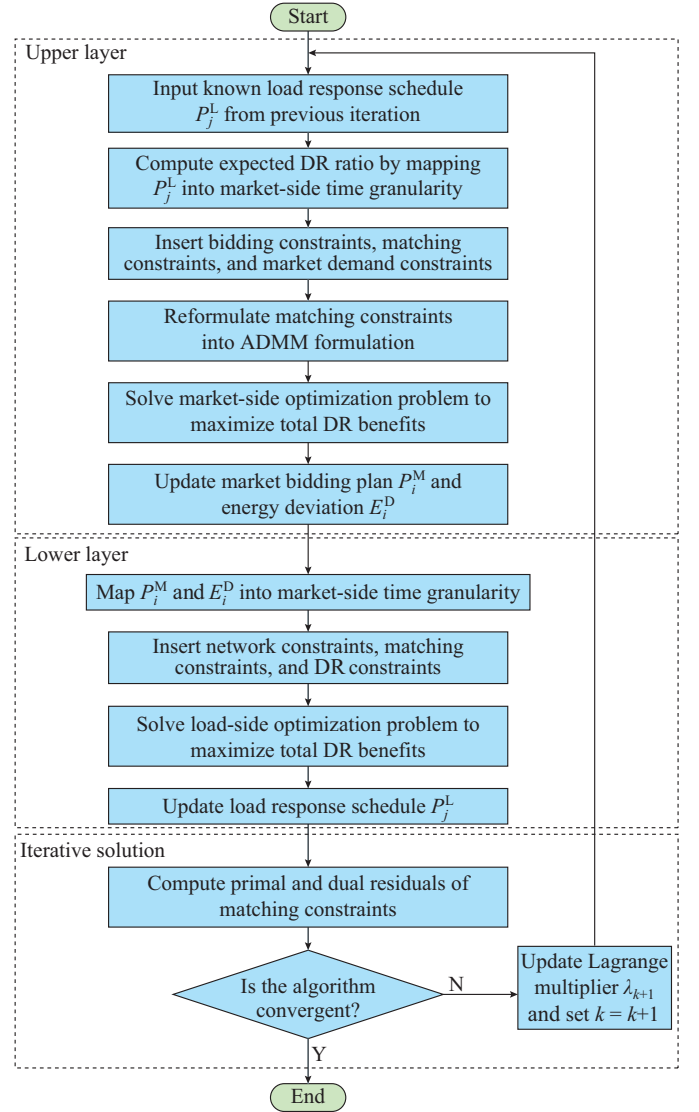


Fig. 3. Flowchart of multi-market DR bidding strategy based on ADMM.

$$B_i = \beta_i b_i (P_i^M - P_i^D) \Delta t_i \quad (21)$$

However, (21) introduces a nonlinear term, making direct computation difficult. To address this issue, (22) applies convex relaxation, where M is a sufficiently large positive constant.

$$\beta_i b_i (P_i^M - P_i^D) \geq b_i P_i^M - M P_i^D \quad (22)$$

In addition to the bidding constraints in (2)-(6) and the matching constraints in (16)-(19), the deviation constraints in (23) are introduced to link the upper-layer bidding plans with the lower-layer response power.

$$\begin{cases} P_i^D = P_i^M - \sum_{j=1}^J P_{i,j} & P_i^D \geq 0 \\ E_i^D = \int_{t_1}^{t_2} \left(P_i^M - \sum_{j=1}^J P_{i,j} \right) dt & E_i^D \geq 0 \\ t_2 - t_1 = \Delta t_i \end{cases} \quad (23)$$

B. Lower Layer: Multi-load Response

Based on the DR bidding plan, the LA manager decom-

poses DR commands among various flexible loads in the lower layer. This layer also focuses on mitigating deviations caused by DR characteristics using the time granularity model. The objective function of the lower layer, as formulated in (24), aims to maximize total DR benefits by jointly optimizing DR subsidies and electricity price arbitrage.

$$\begin{cases} \max \sum_{j=1}^J \int_t^T B_j dt \\ \text{s.t. (7)-(15), (16)-(19), (25), and (26)} \end{cases} \quad (24)$$

The load benefit B_j consists of DR subsidy b_j , response cost c_j , and time-of-use price c_{TOU} . The response cost c_j includes both energy-shifting and power-shedding costs, and if additional linear cost terms are considered, it can be extended as:

$$B_j = (b_j - c_{\text{TOU}} - c_j) P_j^L \quad (25)$$

In addition to DR delay time, ramp-up time, and duration within the time granularity constraints, all flexibility resources must satisfy the DR constraints in (26), including rated power limits, response power limits, energy shiftability, cumulative energy limits, and ramp-up speed limits. This unified formulation is general to approximate the response behavior of load clusters. For instance, cumulative energy limits can model electric vehicle (EV) charging queues [34] and thermal energy storage devices [35], while energy constraints can represent daily production schedules of industrial production devices.

$$\begin{cases} P_j^{\min} \leq P_j^B + P_j^L \leq P_j^{\max} \\ -\delta_j P_j^B \leq P_j^L \leq \delta_j P_j^B \\ -\gamma_j \int_t^T P_j^B dt \leq \int_t^T P_j^L dt \leq \gamma_j \int_t^T P_j^B dt \\ E_j^{C, \min} \leq \int_t^{t'} (P_j^L + P_j^B) dt \leq E_j^{C, \max} \quad \forall t' \in [0, T] \\ -v_j \leq P_j^L(G_j(t')) - P_j^L(G_j(t - n_j \Delta t_{\min})) \leq v_j \quad \forall t' \in [0, T] \\ 0 \leq \delta_j \\ \gamma_j \leq 1 \end{cases} \quad (26)$$

To ensure that the DR scheduling results comply with distribution network operation limits, the lower-layer optimization further incorporates linearized DistFlow constraints, as detailed in [36].

C. Iterative Solution: Bilateral Time Granularity Matching

In this subsection, ADMM is used to iteratively solve the upper- and lower-layer problems, thereby achieving bilateral time granularity matching. The original problems in (20) and (24) are first transformed into the standard ADMM form in (27), where $f(\mathbf{x})$ is the upper-layer objective, $g(\mathbf{y})$ is the lower-layer objective, and $\mathbf{z}$ is the shared variable introduced by the coordinator. Specifically, $\mathbf{z}$ captures the total energy deviation between the LA response results and the multi-market bidding plan, and serves as the coupling variable that aligns decisions across different time granularities.

$$L_p(\mathbf{x}, \mathbf{y}, \mathbf{z}) = f(\mathbf{x}) + g(\mathbf{y}) + \lambda(\mathbf{Ax} + \mathbf{By} + \mathbf{Cz} - \mathbf{D}) + \frac{\rho}{2} \|\mathbf{Ax} + \mathbf{By} + \mathbf{Cz} - \mathbf{D}\|_2^2 \quad (27)$$

The iterative solution process of the proposed framework consists of the steps outlined in (28)-(31). The updates in (28) and (29) are executed independently by the load cluster and the market operator using only their local information. Equations (30) and (31) are performed by the LA coordinator, who updates the shared variables without accessing any private operational data of participating entities.

$$\mathbf{x}^{k+1} = \arg \min_{\mathbf{x}} L_p(\mathbf{y}^k, \mathbf{z}^k, \lambda^k) \quad (28)$$

$$\mathbf{y}^{k+1} = \arg \min_{\mathbf{y}} L_p(\mathbf{x}^{k+1}, \mathbf{z}^k, \lambda^k) \quad (29)$$

$$\mathbf{z}^{k+1} = \arg \min_{\mathbf{z}} L_p(\mathbf{x}^{k+1}, \mathbf{y}^{k+1}, \lambda^k) \quad (30)$$

$$\lambda^{k+1} = \lambda^k + \rho(\mathbf{Ax}^{k+1} + \mathbf{By}^{k+1} + \mathbf{Cz}^{k+1} - \mathbf{D}) \quad (31)$$

The proposed framework is guaranteed to converge to a primal-dual optimal solution [37], as indicated in (32), provided that the local subproblems are convex and the updates are performed in parallel within ADMM. In addition, each local computational task remains essentially constant, ensuring stable convergence performance even as the number of loads and markets increases.

$$\begin{cases} \|\mathbf{Ax}^{k+1} + \mathbf{By}^{k+1} + \mathbf{Cz}^{k+1} - \mathbf{D}\|_1 \leq \epsilon^{\text{pri}} \\ \|\rho \mathbf{B}(\mathbf{y}^{k+1} - \mathbf{y}^k)\|_1 \leq \epsilon^{\text{dual}} \end{cases} \quad (32)$$

IV. CASE STUDIES

A. Case Description

The proposed strategy is implemented on a modified IEEE 33-bus system, as shown in Fig. 4. Specifically, the standard IEEE 33-bus topology and parameters are adopted, while the original load profiles at each node are replaced with four typical DR loads collected from Hebei Province, China. In addition, the LA manages different types of flexible load clusters at specific nodes: EV charging stations at node 6, heating, ventilation, air-conditioning, and cooling (HVAC) systems at node 10, electric heating stations at node 19, and industrial production devices at node 23. These load clusters participate in the day-ahead DR market. Time granularities of loads and markets are detailed in Table II and aggregation parameters of different loads are provided in Table III. On the market side, the bidding time granularity varies across different markets, as shown in Table II. All tests were conducted using MATLAB 2024b on a PC with a 3.5 GHz Intel Core i5 processor and 32 GB of RAM.

Based on the above system configuration and experimental environment, six cases are designed to evaluate the effectiveness and economic performance of the proposed strategy, which are shown in Table IV.

Specifically, Case 1 applies the proposed framework and serves as the benchmark for all comparisons. Cases 2-4 employ typical DR bidding strategies commonly used in prior studies as alternatives.

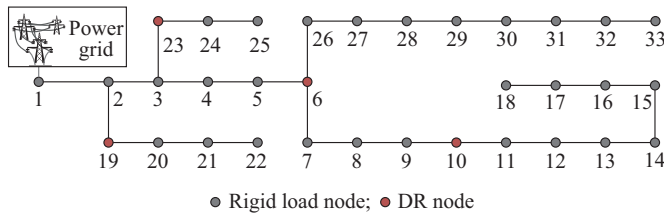


Fig. 4. Modified IEEE 33-bus system.

TABLE II
TIME GRANULARITIES OF LOADS AND MARKETS

Side	Load or market type	Time granularity (min)
Load	EV charging station	5
	HVAC system	10
	Electric heating station	30
	Industrial production device	120
Market	Emergency DR	5
	Renewable energy consumption	15
	Peak shaving and valley filling	60

Note: time granularity indicates time interval of load response/market bidding.

TABLE III
AGGREGATION PARAMETERS OF DIFFERENT LOADS

Load	Rated capacity (MW)	DR power (MW)	Transfer energy (MWh)	DR delay time (min)	DR ramp-up speed (MW/min)	The minimum DR duration (min)
EV charging station	0.55	0.10	0.00	0-0.5	0.10	0-5
HVAC system	1.20	0.20	0.50	0.5-1	0.10	5-10
Electric heating station	1.95	0.30	2.50	1-3	0.05	10-30
Industrial production device	2.80	0.40	25.00	3-12	0.02	30-120

TABLE IV
CASE STUDY COMPARISON

Case	Time granularity model	DR bidding strategy
1	Bilateral	Time granularity matching
2	Bilateral	Power tracking
3	Bilateral	P2P trading
4	Bilateral	Exclusive market bidding
5	Market-side	Time granularity matching
6	Load-side	Time granularity matching

Case 2 adopts a power tracking strategy that enforces strict alignment between load response schedules and DR bidding plans in the power dimension. Case 3 applies a peer-to-peer (P2P) trading strategy, in which each load is restricted to a single market based on its classification. Case 4 simulates exclusive market bidding, where all loads are directed to the market with the highest return. Additionally, Cases 5 and 6 examine the proposed framework under different time granularity modeling assumptions. Case 5 fixes the market-

side time granularity at 5 min, while case 6 fixes the load-side time granularity at 5 min.

B. Strategy Comparison

Compared with conventional power tracking, P2P trading, and exclusive market bidding strategies in Cases 2-4, this paper verifies the effectiveness of the proposed strategy in enhancing load co-response flexibility and improving multi-market bidding economics. The evaluation is conducted through detailed case studies covering three market time granularities and four load time granularities, where peak shaving and valley filling are treated as a single market due to their identical time granularity, as shown in Table II.

Figure 5 illustrates the DR bidding plans in multiple markets. These plans are optimized by the LA across multiple markets for Cases 1-6. Notably, all four strategies in Cases 1-4 incorporate market time granularities. In Fig. 5(a), the LA manager optimizes DR bidding plans to ensure that total DR energy satisfies DR bidding plans, prioritizing the emergency DR market a 5-min time granularity, which generally provides higher subsidies to incentivize rapid responses. In contrast, as shown in Fig. 5(b), Case 2 enforces real-time power tracking and tends to favor bidding in the renewable energy consumption market, which generally provides lower subsidies than the emergency DR market. Compared with these multi-market bidding strategies, the P2P trading strategy in Case 3 restricts each load to a single market, thereby reducing bidding flexibility in all three markets, as illustrated in Fig. 5(c). Meanwhile, although the exclusive market bidding strategy in Fig. 5(d) maximizes the participation in the peak shaving and valley filling, it results in a lack of participation in other types of markets. From a qualitative perspective, the proposed strategy improves bidding efficiency in highly subsidized, fine-grained markets compared with conventional strategies.

Figure 6 presents the response schedules for diversified loads across different cases, highlighting the differences between conventional strategies and the proposed strategy. Each strategy considers the time granularities of load in Table II to mitigate deviation risks caused by DR characteristics. In Fig. 6(a), the proposed strategy effectively schedules multi-granularity flexibility by coordinating fine-grained high-cost loads and coarse-grained low-cost loads to enhance co-response bidding while minimizing response costs. Figure 6(b) also utilizes coarse-grained flexibility but adopts a more conservative scheduling strategy for fine-grained loads (e.g., 5-min and 10-min loads) due to real-time power tracking constraints.

In contrast, Fig. 6(c) restricts each load to a fixed market, preventing industrial production devices with the time granularity of 120 min from participating in fast-bidding markets, making it the least effective strategy. Additionally, Fig. 6(d) fails to fully utilize the flexibility of fine-grained loads, as all loads are confined to the exclusive market bidding, resulting in relatively flat response schedules of 5-min and 10-min loads. Overall, the proposed strategy significantly enhances the flexibility of loads with different time granularities compared with the three conventional strategies.

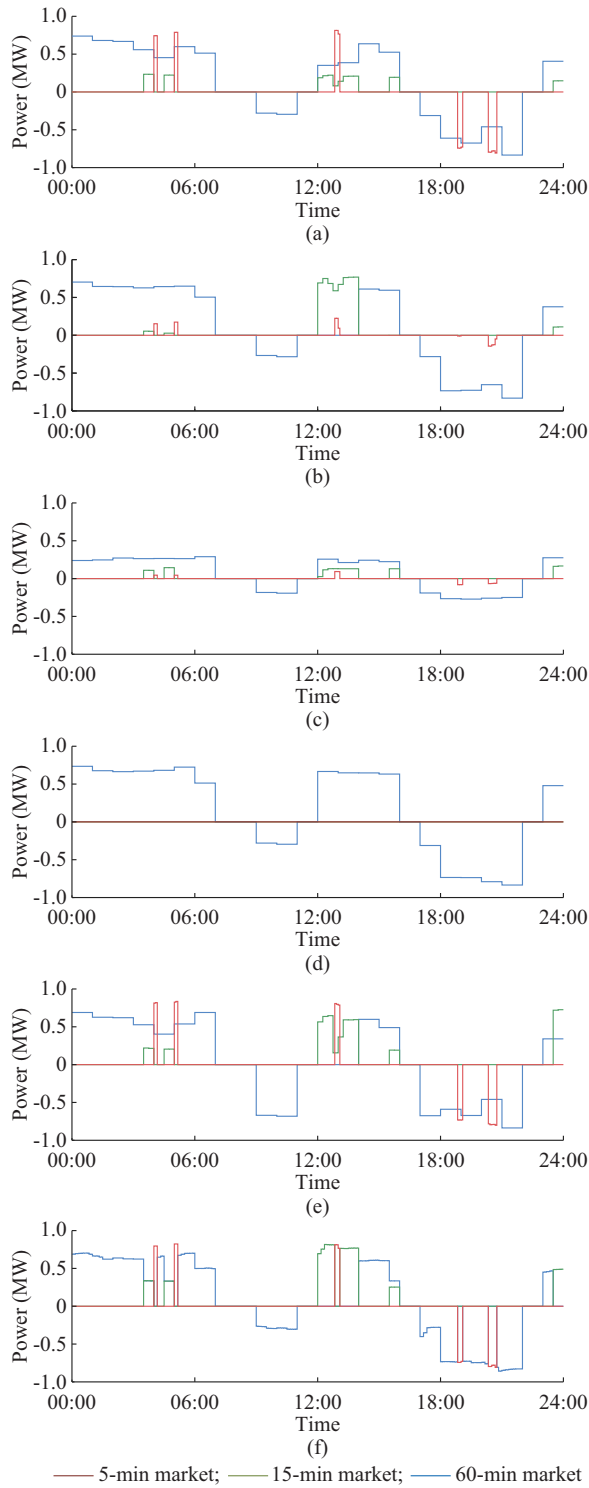


Fig. 5. DR bidding plans in multiple markets. (a) Case 1. (b) Case 2. (c) Case 3. (d) Case 4. (e) Case 5. (f) Case 6.

To further validate the proposed framework between DR bidding plans and response schedules, Fig. 7 presents bilateral time granularity matching results in different DR bidding strategies. In Fig. 7(a), although power deviations occur during 03:00-04:00, the settlement deviation remains zero due to the offsetting of positive and negative deviations. This demonstrates that coarse-grained loads can flexibly participate in fine-grained markets and vice versa.

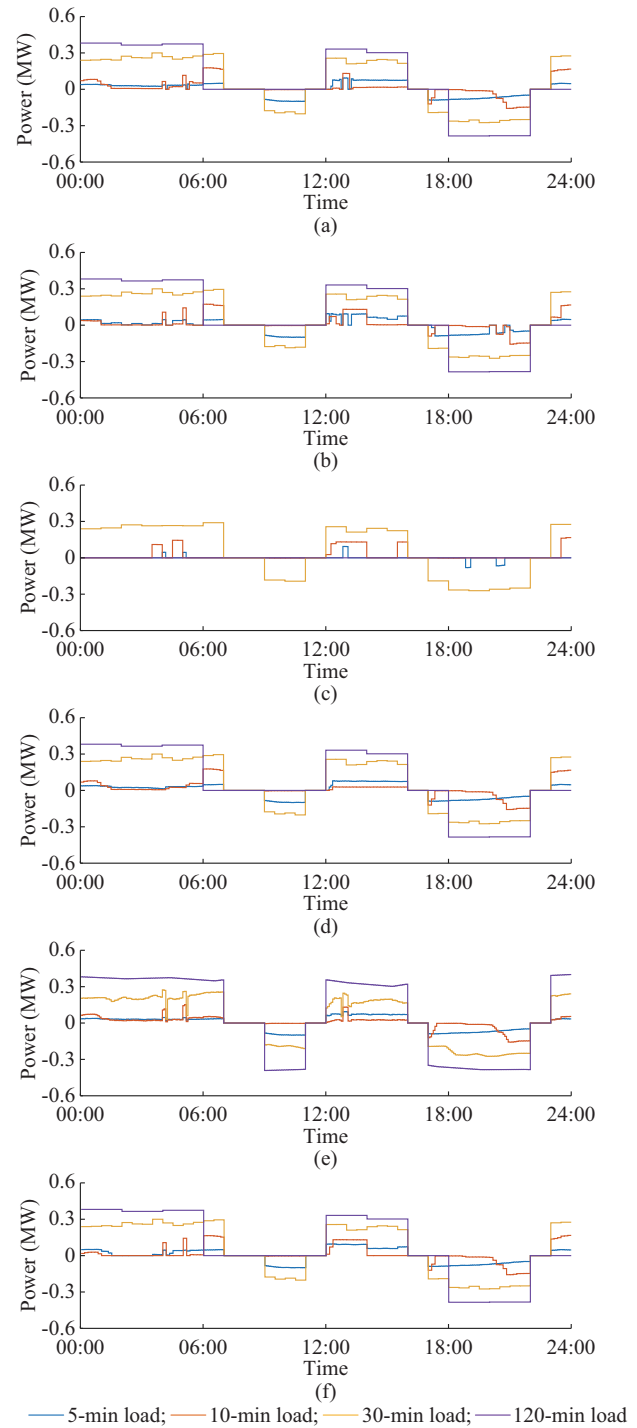


Fig. 6. Response schedules for diversified loads across different cases. (a) Case 1. (b) Case 2. (c) Case 3. (d) Case 4. (e) Case 5. (f) Case 6.

Figure 7(b) shows a strictly enforced real-time power balance, eliminating deviations but significantly restricting optimization flexibility. In Fig. 7(c), only electric heating loads participate in the 60-min market. The P2P trading strategy between markets and loads ensures no DR deviation when fine-grained loads are matched with coarse-grained markets. Meanwhile, Fig. 7(d) allocates all loads solely to peak shaving and valley filling, wasting the flexibility of fast-response and high-cost loads.

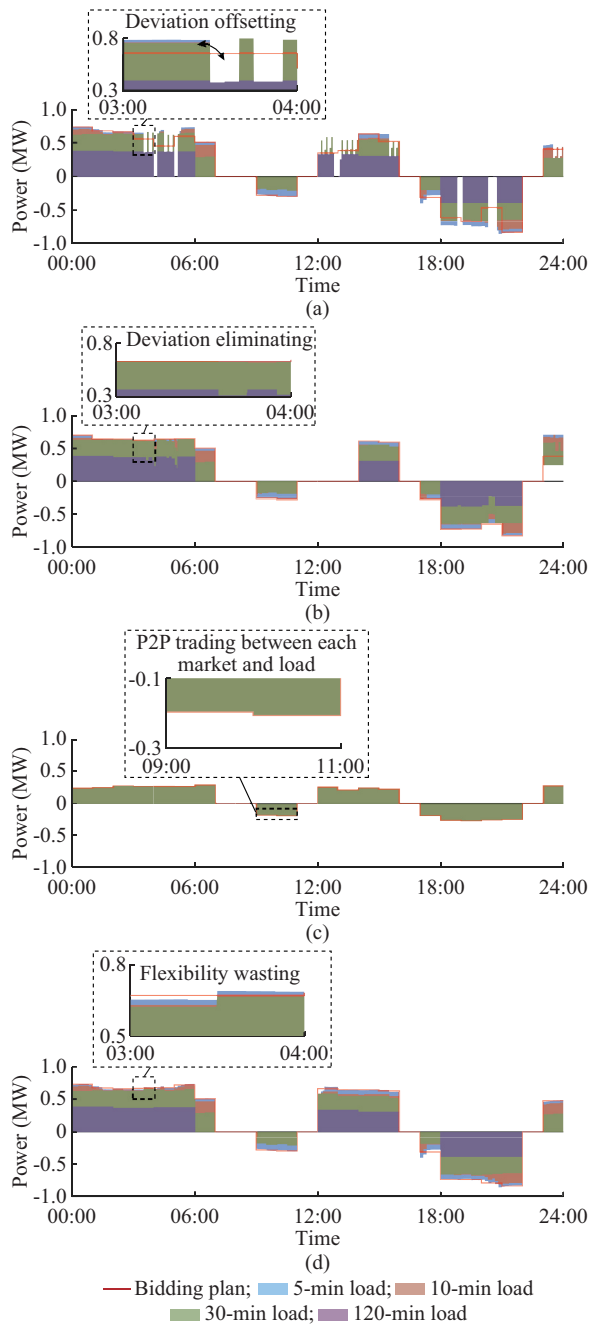


Fig. 7. Bilateral time granularity matching results in different DR bidding strategies. (a) Case 1. (b) Case 2. (c) Case 3. (d) Case 4.

Overall, the proposed strategy in Case 1 effectively integrates market rules and DR characteristics through the time granularity models, achieving more flexible and efficient bilateral time granularity matching via ADMM compared with conventional strategies.

Table V presents a quantitative analysis of DR bidding plans and load response schedules. In market bidding results, the proposed strategy in Case 1 achieves a cleared energy of 0.98 MWh in the emergency DR market, outperforming the conventional strategies. The power tracking strategy in Case 2 performs best in the renewable energy consumption market, reaching a cleared energy of 1.61 MWh, while the exclusive market bidding strategy in Case 4 achieves the highest a cleared energy of 11.72 MWh in peak shaving and valley filling. However, P2P trading strategy in Case 3 underperforms across all markets. These results, consistent with Fig. 5, highlight the effectiveness of the proposed framework in enhancing participation in fine-grained and highly subsidized markets. For load response scheduling, both Cases 1 and 4 fully utilize load flexibility. Case 1 achieves the highest response schedules for EV charging station (1.10 MWh), HVAC system (0.90 MWh), electric heating station (4.67 MWh), and industrial production device (5.04 MWh). In contrast, the power tracking strategy in Case 2 limits the response of most loads except industrial production devices, while P2P trading strategy in Case 3 results in the lowest response levels across all load types.

Table VI summarizes the overall economic and technical indicators for the LA. In terms of LA bidding volume, Cases 1, 2, and 4 exceed 11 MWh, whereas Case 3 achieves only 5.27 MWh due to the absence of industrial production device participation. From the perspective of LA benefits, Case 1 yields ¥5730 in DR, primarily driven by the emergency DR market, outperforming other cases. Regarding computational time, Case 1 requires 43.8 s, which is shorter than 69.7 s required by Case 2 but longer than 8.8 s required by Case 3. Figure 8 further illustrates convergence performance across different cases. For all cases, ADMM is implemented with a penalty parameter of 10, a maximum of 15 iterations, and a convergence tolerance of 0.1 for both primal and dual residuals. These settings ensure stable convergence and enable fair comparison. Cases 1 and 4 converge within 7 and 6 iterations, respectively, whereas Case 2 stabilizes at a higher residual level of around 1 MWh, indicating slower convergence.

TABLE V
QUANTITATIVE ANALYSIS OF DR BIDDING PLANS AND LOAD RESPONSE SCHEDULES

Case	Load response energy (MWh)				Market settlement energy (MWh)		
	EV charging station	HVAC system	Electric heating station	Industrial production device	Emergency DR	Renewable energy consumption	Peak shaving and valley filling
1	1.10	0.90	4.67	5.04	0.98	0.71	10.02
2	0.98	0.80	4.65	5.04	0.15	1.61	9.70
3	0.09	0.51	4.67	0.00	0.09	0.51	4.67
4	1.10	0.90	4.67	5.04	0.00	0.00	11.72
5	1.10	0.73	4.05	6.91	0.98	1.69	10.12
6	1.10	0.90	4.67	5.04	0.97	2.06	8.67

TABLE VI
OVERALL ECONOMIC AND TECHNICAL INDICATORS FOR LA

Case	LA bidding energy (MWh)	Load deviation (MWh)	DR subsidy (¥)	DR cost (¥)	DR penalty (¥)	LA benefit (¥)	Computational time (s)
1	11.72	0.87	9040	3050	260	5730	43.8
2	11.46	0.88	6490	2990	330	3160	69.7
3	5.27	0.40	2880	2120	210	550	8.8
4	11.72	0.81	5380	3050	180	2150	48.5
5	12.80	2.90	9830	3100	1570	5160	39.9
6	11.72	0.85	9640	3050	1730	4860	28.9

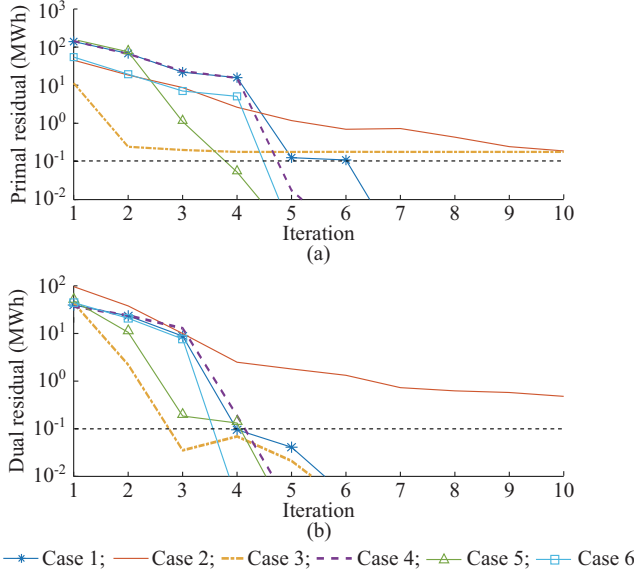


Fig. 8. Convergence performance across cases. (a) Primal residual. (b) Dual residual.

C. Time Granularity Model Comparison

This subsection compares the bilateral time granularity model in Case 1 with the single market-side or load-side time granularity models in Cases 5 and 6 to assess its effectiveness in reducing DR deviation. In all cases, market settlements are based on actual response volumes when the DR ratio exceeds 75%, while no subsidies are provided if the DR ratio falls below this threshold.

Figure 5(a), (e), and (f) compares multi-market DR bidding plans under three cases. Cases 1 and 5 incorporate multi-market time granularities, whereas Case 6 applies a uniform 5-min time granularity across all markets. For example, the peak shaving and valley filling market requires a DR bidding plan with 60-min time granularity, and Cases 1 and 5 successfully generate the results that meet this requirement. In contrast, Case 6 optimizes a DR bidding plan with a 5-min time granularity for this 60-min market, resulting in a mismatch with the actual market requirements. Figure 9 illustrates DR deviation between bidding plan and real power. During 12:00-13:00, Case 6 exhibits significant negative deviation in the renewable energy consumption market, resulting in economic penalty because the DR ratio does not reach 70%. In contrast, Case 1 avoids economic penalty by offset-

ting positive and negative DR deviations. This demonstrates that ignoring market-side time granularity increases DR deviation and reduces subsidies.

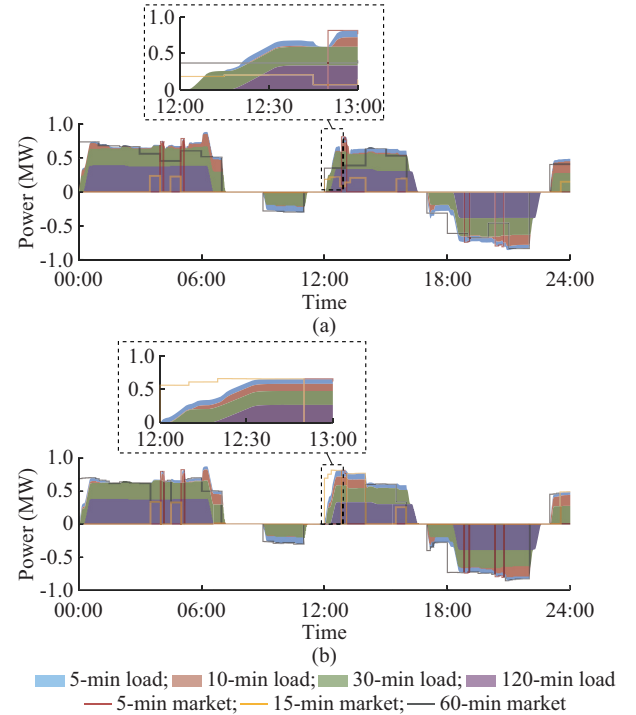


Fig. 9. DR deviation between bidding plan and real power. (a) Case 1. (b) Case 6.

Figure 6(a), (e), and (f) presents multi-load response results, illustrating how Case 5 ignores load-side time granularity by applying a uniform 5-min time granularity to all loads, while Cases 1 and 5 avoid this shortcoming through multi-granularity scheduling. Due to inherent DR characteristics, including DR delay time, ramp-up time, and duration, actual load responses inevitably deviate from the 5-min load response schedules issued by the LA. Figure 10 illustrates deviation between response schedule and real power of industrial production device. Specifically, Case 1 effectively controls load DR deviations caused by t_{DT} and t_{CT} to 22.1%, thereby avoiding deviation penalties, whereas Case 5 results in substantial deviations, particularly for industrial production devices with limited t_{DT} , t_{CT} , and t_{ST} . This confirms that proper modeling of load-side time granularity reduces DR mismatches and deviation penalties.

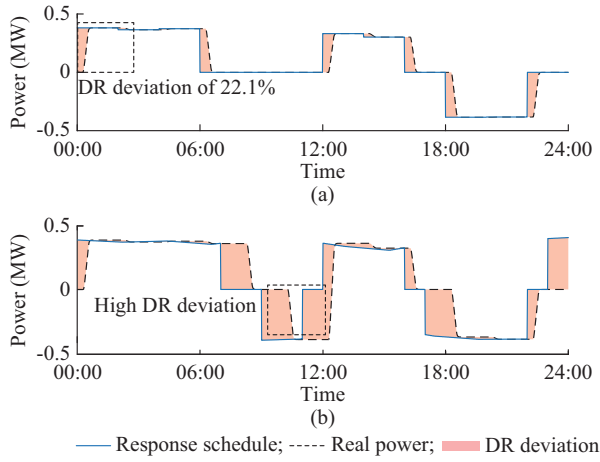


Fig. 10. DR deviation between response schedule and real power of industrial production device. (a) Case 1. (b) Case 5.

TABLE VII
LOAD AND MARKET DR DEVIATIONS ACROSS CASES

Case	Load DR deviation (MWh)				Market DR deviation (MWh)		
	EV charging station	HVAC system	Electric heating station	Industrial production device	Emergency DR	Renewable energy consumption	Peak shaving and valley filling
1	0.03	0.11	0.35	0.38	0.03	0.01	0.35
2	0.04	0.12	0.34	0.38	0.00	0.10	0.27
3	0.02	0.06	0.32	0	0.01	0.04	0.18
4	0.02	0.07	0.35	0.38	0	0	0.37
5	0.02	0.04	0.15	2.69	0.04	0.12	1.61
6	0.02	0.10	0.35	0.38	0.02	0.22	1.25

In terms of computational performance, Table VI and Fig. 8 compare convergence characteristics across different cases. Case 5 and Case 6 require convergence time of 39.9 s and 28.9 s, respectively, both faster than Case 1. This is attributed to the faster convergence of the unilateral time granularity models, which converge within 5 iterations. In contrast, the bilateral time granularity model in Case 1 requires 7 iterations due to the increased complexity of coordinating both market-side and load-side time granularities.

The comparison of Cases 1, 5, and 6 demonstrates that the bilateral time granularity models significantly reduce deviations from both DR characteristics and market rules. By resolving time granularity mismatches, it minimizes DR deviation penalties and maximizes LA benefits, highlighting its practical advantages in DR markets.

V. CONCLUSION

This paper proposes a multi-market DR bidding strategy for LAs to address the mismatch between market rules and DR characteristics in terms of bilateral time granularity. Specifically, bilateral time granularity models are developed, a bilateral time granularity matching framework is constructed, and a multi-market DR bidding strategy is formulated as a distributed optimization problem. The main conclusions are as follows.

1) Market bidding benefit improvement. The proposed strategy enhances LA participation in fine-grained and high-

In the previous Table V, Case 5, which neglects load-side time granularity, heavily relies on industrial production devices (6.91 MWh), exceeding the 5.04 MWh allocation in the bilateral model. Similarly, Case 6, which ignores market-side time granularity, overemphasizes the renewable energy consumption market (2.06 MWh), nearly three times that of Case 1. However, Table VII further quantifies load and market deviations across cases. Furthermore, Case 5 results in a DR deviation of industrial production device of 2.69 MWh due to violations of load constraints, significantly higher than 0.38 MWh in Case 1. Case 6 leads to a 0.22 MWh deviation in the renewable energy consumption market due to mismatched bidding rules, compared with only 0.01 MWh in Case 1. Therefore, both Cases 5 and 6 incur larger DR deviation penalties and LA benefits, as reflected in Table VI.

ly subsidized markets, resulting in at least an 11% increase in overall economic benefits compared with conventional strategies.

2) Load flexibility enhancement. By enabling coordinated response of both coarse-grained and fine-grained loads, the proposed strategy overcomes the limitations imposed by DR characteristics.

3) Deviation penalty reduction. The DR bidding strategy based on ADMM reduces deviation between DR bidding plans and actual load responses to below 8%, thereby mitigating deviation penalties under day-ahead DR market rules of China.

This paper focuses on optimizing DR benefits, but several trading mechanisms such as carbon emission reduction and frequency regulation are not considered. Moreover, the current model does not incorporate long-term degradation costs associated with frequent DR participation such as EV battery aging or increased wear on industrial equipment. Future work will explore multi-objective optimization algorithms that incorporate these factors, enabling LAs to participate more effectively in a wider range of markets with varying bidding granularities.

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