Fairness-Driven Optimal Scheduling of Aggregated Distributed Energy Resources

Xintian Wang
School of Electrical and Information Engineering
Tianjin University
Tianjin, China
2945166483@qq.com

Zhijie Yuan
Huadong Engineering Corporation Limited
PowerChina
Hangzhou, China
yuan_zj2@hdec.com

Hong Liu
School of Electrical and Information Engineering
Tianjin University
Tianjin, China
liuhong@tju.edu.cn

Junkai Li
School of Electrical and Information Engineering
Tianjin University
Tianjin, China
lijunkai6666@163.com

Xingtang He*
School of Electrical and Information Engineering
Tianjin University
Tianjin, China
power_hext@tju.edu.cn

***Abstract*—Fairness is crucial for sustainable electricity markets. However, existing optimal scheduling methods for distributed energy resources (DERs) that address renewable uncertainty often struggle to effectively balance fairness and economic efficiency. This paper proposes a fairness-driven optimal scheduling method for aggregated DERs. First, based on a dynamic distribution network operator (DNO)-aggregator framework, a sequential optimization model is designed with the threshold-based partitioning and lexicographic minimization (leximin) criterion. Then, a continuity correction technique and a mixed-integer linear programming (MILP) formulation are developed. The superiority of the method is validated with a modified DTU 25-bus–IEEE 33-bus system.**

Keywords—DERs, fair optimal scheduling, leximin criterion

I. INTRODUCTION

As distribution networks evolve from passive to active systems, distributed energy resources (DERs) play an increasingly prominent role in electricity markets [1]. After day-ahead market clearing, actual renewable generation may deviate from forecasts, potentially violating distribution network security constraints [2]. Scheduling DERs is thus necessary to ensure secure grid operation. While existing scheduling methods demonstrate good economic performance, fairness has increasingly emerged as a critical factor for effective distribution system operation and sustainable market development [3]. Therefore, it is essential to develop a scheduling approach for DERs that can simultaneously address economic efficiency and fairness.

Fair scheduling refers to the equitable allocation of system benefits (e.g., economic revenue, operational authority) and burdens (e.g., costs, responsibilities) [4]. Current research on fair scheduling of DERs primarily adopts three typical fairness principles—Equality, Meritocracy, and Min-Max Fairness [3]. Equality emphasizes uniform allocation of costs or benefits. For instance, in [5], PV users were assigned voltage regulation tasks proportional to their maximum reactive or active power capacity, ensuring equitable participation. However, this approach often overlooks the heterogeneity among participants and may lead to significant losses in economic efficiency. Meritocracy allocates benefits according to participants' actual contributions. Reference [6] employed the Shapley value in multi-microgrid scheduling, assigning power curtailment shares based on marginal contributions to voltage control. However, this method ignores inherent disparities such as resource endowment and response costs, potentially creating a Matthew effect, where advantages accumulate disproportionately. Min-Max Fairness, derived from Rawls' "Difference Principle" [7], protects the fundamental interests of the most disadvantaged participants by minimizing the maximum costs [8] or maximizing the minimum benefits [9]. For example, [8] minimized the maximum scheduling cost among aggregators in flexibility markets to limit extreme financial burdens, while [9] maximized the minimum response utility in a renewable-rich community to safeguard low-utility users. Although improving the fairness-economics trade-off, this approach still compromises total social welfare and focuses solely on the most disadvantaged, neglecting other vulnerable groups and thereby limiting further advancement in overall fairness. Therefore, there is an urgent need to develop improved DERs scheduling methods to better reconcile fairness with economic efficiency.

Recently, the lexicographic minimization (leximin) criterion has emerged as a novel equity modeling paradigm supported by well-established theoretical foundations [10]. By sequentially prioritizing the most to the least disadvantaged participants, it effectively addresses equitable allocation objectives among multiple vulnerable groups [11]. This method has found applications in economics, mathematics, and sociology [11], [12]. Despite its success in these domains, its introduction of discrete and nonlinear characteristics poses significant computational challenges in power system applications. Currently, there is a significant research gap in applying leximin criterion to optimal scheduling of DERs.

Building upon the preceding analysis, this paper proposes a fairness-driven optimal scheduling method for aggregated DERs. The key contributions are summarized as follows: (1) A sequential optimization model is formulated incorporating the threshold-based partitioning mechanism and the leximin criterion under a dynamic distribution network operator (DNO)-aggregator interaction framework, ensuring balanced fairness, economic efficiency, and incentive in DERs scheduling. (2) A continuity correction technique and a mixed-integer linear programming (MILP) formulation are developed, accompanied by a sequential optimization solution procedure.

This paper's organization continues below. Section II introduces the dynamic interaction framework while Section III describes the fairness-driven optimal scheduling model. Section IV presents the model solution methodology. Section V reports the cases, and Section VI concludes the work.

This work was supported by the Smart Grid National Science and Technology Major Project (2025ZD0804602).

XXX-X-XXXX-XXXX-X/XX/$XX.00 ©20XX IEEE
979-8-3315-8138-1

II. Dynamic Interaction Framework between DNO and DER Aggregators

As shown in Fig. 1, this paper considers two main entities: DNO and DER aggregators—which engage in iterative interactions. At each scheduling interval, the DNO solves a sequential optimization model that balances fairness, economic efficiency, and incentives to determine aggregated scheduling plans. Each aggregator performs local cost minimization by optimizing response strategies for diverse DERs, including photovoltaics (PVs), curtailable loads (CLs), shiftable loads (SLs), and combined heat and power units (CHPs). Prior to the coordinated optimization, each aggregator submits a one-time report of the feasible operation region of its DERs, providing accurate and quantifiable boundary conditions for the DNO. During the iterative process, the DNO transmits scheduling requirements to aggregators, who respond with their Distribution Locational Marginal Prices (DLMPs). Then, the DNO updates scheduling plans accordingly and repeats the process until convergence is achieved.

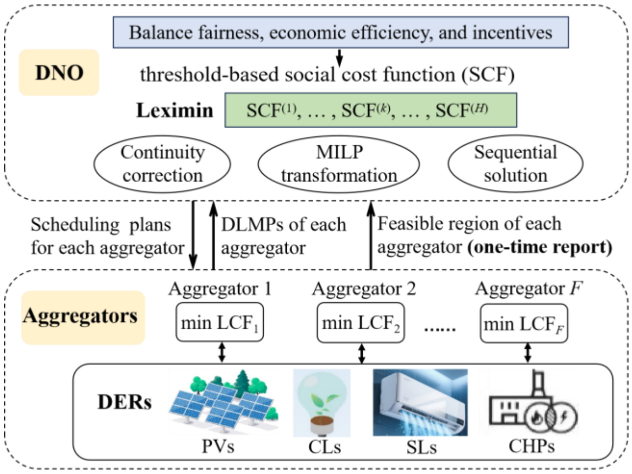


Fig. 1. Dynamic DNO-aggregator interaction framework

III. Fairness-Driven Optimal Scheduling Model for Aggregated DERs

Since the model has no temporal coupling and each time interval is optimized independently, the time subscript t is omitted throughout this section.

A. DER Aggregators

Each aggregator minimizes the total scheduling cost of its DERs according to DNO's instructions.

$$\min\ \mathrm{LCF}_f = \sum_{\mathcal{PDER}} C_f^{\mathcal{PDER}} + \sum_{\mathcal{QDER}} C_f^{\mathcal{QDER}}, f \in \mathcal{F} = \{1,\ 2,\ \ldots, F\}$$
$$\mathcal{PDER} = \{\mathrm{PV,CL,HVAC}\}, \mathcal{QDER} = \{\mathrm{PV,CL}\} \tag{1a}$$

$$s.t. V_i - V_j = P_{ij}^{\mathrm{L}} r_{ij} + Q_{ij}^{\mathrm{L}} x_{ij}, \forall i,j \in \mathcal{N}, \forall ij \in \mathcal{B} \tag{1b}$$

$$P_i = P_i^{\mathrm{G}} - P_i^{\mathrm{D}} = \sum_{ij\in\mathcal{B}} P_{ij}^{\mathrm{L}}, Q_i = Q_i^{\mathrm{G}} - Q_i^{\mathrm{D}} = \sum_{ij\in\mathcal{B}} Q_{ij}^{\mathrm{L}} \tag{1c}$$

$$\underline{V} \le V_i \le \overline{V}, \forall i \in \mathcal{N} \tag{1d}$$

$$\alpha_c P_{ij}^{\mathrm{L}} + \beta_c Q_{ij}^{\mathrm{L}} + \gamma_c \overline{S}_{ij} \le 0, c = \{1,2,\cdots,12\}, \forall ij \in \mathcal{B} \tag{1e}$$

$$\underline{P}_i^{\mathrm{D}} \le P_i^{\mathrm{D}} \le \overline{P}_i^{\mathrm{D}}, \underline{Q}_i^{\mathrm{D}} \le Q_i^{\mathrm{D}} \le \overline{Q}_i^{\mathrm{D}} \tag{1f}$$

$$\underline{P}_i^{\mathrm{G}} \le P_i^{\mathrm{G}} \le \overline{P}_i^{\mathrm{G}}, \underline{Q}_i^{\mathrm{G}} \le Q_i^{\mathrm{G}} \le \overline{Q}_i^{\mathrm{G}} \tag{1g}$$

where F is the number of aggregators. Constraints (1b)–(1c) denote the linearized branch power flow derived from [13], neglecting network losses and shunt admittance while assuming negligible phase differences ($\theta_{ij}\approx 0$) and a unity voltage profile ($V_i\approx 1$ p.u., $V_j\approx 1$ p.u.). V_i denotes the voltage magnitude at node i. Sets $\mathcal{N}$ and $\mathcal{B}$ encompass all network nodes and branches. P_i^{G} and Q_i^{G} represent the active and reactive power outputs of distributed generation at node i, while P_i^{D} and Q_i^{D} denote the active and reactive power demands, respectively. $\underline{V}$ and $\overline{V}$ are the lower and upper voltage limits. Constraint (1e) linearizes the line-capacity constraint using a polygonal inner approximation method with coefficients α_c, β_c and γ_c [13], where c denotes the number of polygon edges and $\overline{S}_{ij}$ defines the maximum allowable capacity of branch ij. Constraints (1f)–(1g) define the regulation limits of various DERs.

$$C_f^{\mathrm{PV}} = c_f^{\mathrm{PV,P}} P_f^{\mathrm{PV-}} + c_f^{\mathrm{PV,Q}} (Q_f^{\mathrm{PV+}} + Q_f^{\mathrm{PV-}}) \tag{2}$$

$$C_f^{\mathrm{CL}} = c_f^{\mathrm{CL,P}} P_f^{\mathrm{CL-}} + c_f^{\mathrm{CL,Q}} Q_f^{\mathrm{CL-}} \tag{3}$$

$$C_f^{\mathrm{HVAC}} = c_f^{\mathrm{HVAC}} \left(P_f^{\mathrm{HVAC+}} + P_f^{\mathrm{HVAC-}}\right) \tag{4}$$

where $c_f^{\mathrm{PV,P}}$, $c_f^{\mathrm{PV,Q}}$, $c_f^{\mathrm{CL,P}}$, $c_f^{\mathrm{CL,Q}}$ and c_f^{HVAC} denote marginal costs of the respective DERs, while $P_f^{\mathrm{PV-}}$, $Q_f^{\mathrm{PV+}}$, $Q_f^{\mathrm{PV-}}$, $P_f^{\mathrm{CL-}}$, $Q_f^{\mathrm{CL-}}$, $P_f^{\mathrm{HVAC+}}$ and $P_f^{\mathrm{HVAC-}}$ denote the upward or downward power adjustment.

According to Karush-Kuhn-Tucker (KKT) conditions, DLMPs $\pi_f^{\mathrm{PCC,P}}$ and $\pi_f^{\mathrm{PCC,Q}}$ for each aggregator are calculated [13], and subsequently iterated and updated as the DNO-level boundary conditions.

The vertex search method in [14] is used to construct an aggregated feasible region Π_f^* for each aggregator, which satisfies constraints (1b)–(1g) and characterizes the active and reactive power regulation capability, serving as additional boundary condition for DNO optimization.

$$\Pi_f^* = \left\{ \left(P_f^{\mathrm{PCC}}, Q_f^{\mathrm{PCC}}\right) \middle| \begin{array}{l} P_f^{\mathrm{PCC}} = \sum_{v=1}^{\mathcal{V}_t} \alpha_{f,v}^{\mathrm{P}} P_{f,v}^*, Q_f^{\mathrm{PCC}} = \sum_{v=1}^{\mathcal{V}_t} \alpha_{f,v}^{\mathrm{Q}} Q_{f,v}^*, \\ \sum_{v=1}^{\mathcal{V}_t} \alpha_{f,v}^{\mathrm{P}} = 1, \sum_{v=1}^{\mathcal{V}_t} \alpha_{f,v}^{Q} = 1, \alpha_{f,v}^{\mathrm{P}}, \alpha_{f,v}^{Q} \ge 0 \end{array} \right\} \tag{5}$$

where P_f^{PCC} and Q_f^{PCC} denote the active and reactive power of aggregator f. $P_{f,v}^*$ and $Q_{f,v}^*$ are vertices of feasible region, with weights $\alpha_{f,v}^{\mathrm{P}}$ and $\alpha_{f,v}^{\mathrm{Q}}$ ensuring operational points within Π_f^*。

The feasible region remains constant under fixed network and resource parameters, requiring only a one-time report before optimization.

B. DNO

1) Variable Definitions

The scheduling costs of the DNO for aggregators are defined as $\boldsymbol{C}_f = [C_1, C_2, \ldots, C_F]^{\mathrm{T}}$.

$$C_f = \pi_f^{\mathrm{PCC,P}} \left(P_f^{\mathrm{PCC}} - \tilde{P}_f^{\mathrm{PCC}}\right) + \pi_f^{\mathrm{PCC,Q}} \left(Q_f^{\mathrm{PCC}} - \tilde{Q}_f^{\mathrm{PCC}}\right) \tag{6}$$

where $\tilde{P}_f^{\mathrm{PCC}}$ and $\tilde{Q}_f^{\mathrm{PCC}}$ denote cleared schedules from the energy market.

Cost distribution among entities is a crucial concern in fair scheduling. Thus, a sorted vector of scheduling costs $\boldsymbol{C}_{<f>}$ $=[C_{<1>}, C_{<2>}, \ldots, C_{<F>}]^{\mathrm{T}}$, satisfying $C_{<1>}\ge C_{<2>}\ge\ldots\ge C_{<F>}$, is introduced. This vector is dynamically updated during optimization. To establish the mapping between original costs C_f and sorted costs $C_{<f>}$, an integer index set $\mathcal{R} = \{R_1, R_2, \ldots, R_F\}$ is introduced, satisfying $C_{<f>}=C_{R_f}$.

2) Threshold-Based Objective Function for Aggregated DERs Scheduling

979-8-3315-8138-1

In order to guide the fairness mechanism of scheduling among aggregators, this paper constructs a threshold-based social cost function (SCF). By introducing two threshold parameters, ε_1 and ε_2, the sorted costs are segmented, enabling differentiated optimization strategies within an objective function to integrate fairness, economic efficiency, and incentive compatibility.

$$\min\ \mathrm{SCF}=\sum_{f=1}^{H}(\max C_{<f>})+\sum_{f=H+1}^{F}C_{<f>}+\sum_{f=H+M+1}^{F}2\left(\varepsilon_2-C_{<f>}\right) \quad (7a)$$

$$s.t.\mathcal{C}^{\mathrm{High}}=\left\{C_{<f>}\middle|C_{<1>}-\varepsilon_1\le C_{<f>}\le C_{<1>},f=1,2,\cdots,F\right\} \quad (7b)$$

$$\mathcal{R}^{\mathrm{High}}=\{R_1,R_2,\ \ldots,R_H\} \quad (7c)$$

$$\mathcal{C}^{\mathrm{Med}}=\left\{C_{<f>}\middle|\varepsilon_2\le C_{<f>}<C_{<1>}-\varepsilon_1,f=1,2,\cdots,F\right\} \quad (7d)$$

$$\mathcal{R}^{\mathrm{Med}}=\left\{R_{H+1},\ \ldots,R_{H+M}\right\} \quad (7e)$$

$$\mathcal{C}^{\mathrm{Low}}=\left\{C_{<f>}\middle|0\le C_{<f>}<\varepsilon_2,f=1,2,\cdots,F\right\} \quad (7f)$$

$$\mathcal{R}^{\mathrm{Low}}=\left\{R_{H+M+1},\ \ldots,R_{H+M+L}\right\},H+M+L=F \quad (7g)$$

$\mathcal{C}^{\mathrm{High}}$ represents the high-cost segment where aggregators typically experience frequent and deep scheduling. In order to prevent over-concentration, a min-max fairness criterion is applied. $\mathcal{C}^{\mathrm{Med}}$ represents the medium-cost segment where aggregators exhibit neutral scheduling frequency and cost distribution. Accordingly, the model adopts conventional economic efficiency principles, aiming at total-cost minimization. $\mathcal{C}^{\mathrm{Low}}$ represents the low-cost segment associated with participation deficits and marginalization risks. To address these issues, additional incentive terms are incorporated into this segment while maintaining economic principles. Thresholds ε_1 and ε_2 reflect the fairness sensitivity of decision-makers, with larger values prioritizing fairness and smaller values emphasizing economic efficiency.

In the threshold selection process, the baseline optimal scheduling cost C_0 is obtained when ε_1=ε_2=0. Then, with ε_2 fixed at 0 and ε_1 gradually increased from 0, the cost increment is calculated as $\Delta C=C^*(\varepsilon_1,\ \varepsilon_2=0)-C_0$. The optimal threshold ε_1^* is identified at the knee point of ΔC where the rate of cost increase begins to diminish. In contrast, ε_2 serves as an incentive and policy-adjustment parameter for regional economic and development goal adaptation.

3) Sequential Optimization Model Based on Leximin Criterion

To further refine the fairness mechanism and enhance equity performance, this paper introduces a sequential optimization strategy based on the leximin criterion within the high-cost segment. The largest, second-largest, third-largest etc., sorted costs are sequentially determined, thereby establishing a hierarchically progressive optimization objective denoted as $\mathrm{SCF}^{(1)}$, …, $\mathrm{SCF}^{(k)}$, …, $\mathrm{SCF}^{(H)}$. The first and k-th (k≥2) stages are formulated as (8) and (9).

$$\begin{aligned}\min\ \mathrm{SCF}^{(1)}&=\min\ \mathrm{SCF}\\&=\sum_{f=1}^{H}C_{<1>}+\sum_{f=H+1}^{F}C_{<f>}+\sum_{f=H+M+1}^{F}2\left(\varepsilon_2-C_{<f>}\right)\end{aligned} \quad (8)$$

$$\begin{aligned}\min\ \mathrm{SCF}^{(k)}=&\sum_{f=1}^{k-1}\left(H-f+1\right)C^*_{<f>}+\sum_{f=k}^{H}C_{<k>}+\sum_{f=H+1}^{F}C_{<f>}\\&+\sum_{f=H+M+1}^{F}2\left(\varepsilon_2-C_{<f>}\right)\end{aligned} \quad (9)$$

where ε_1 and ε_2 are predefined, and $C_{<1>}$ is determined after solving $\min\mathrm{SCF}^{(1)}$, thereby fixing the high-cost segment for subsequent stages. At each stage, the previously determined sorted entities $\{R_1,\ R_2,\ \ldots,\ R_{k-1}\}$ and their corresponding scheduling results—namely $C^*_{<f>}$, $P^{\mathrm{PCC}*}_{R_f}$ and $Q^{PCC*}_{R_f}$ —are rigorously maintained as fixed parameters. Then, the sorted cost and scheduling plans for the current stage are optimized. The proposed sequential optimization approach thus accommodates the equity requirements of all participants within the high-cost segment, substantially strengthening the integration of fairness.

In summary, the DNO-level fairness-economics-incentives sequential model is formulated as follows: the objective functions are (8) and (9), subject to network security constraints (1b)–(1e), feasible region constraints (5), and segment partitioning constraints (7b)–(7h).

IV. Solution Algorithm

The solution procedure of the dynamic DNO-aggregator interaction model is illustrated in Fig. 2, and the three key steps A-C are detailed in the subsections below.

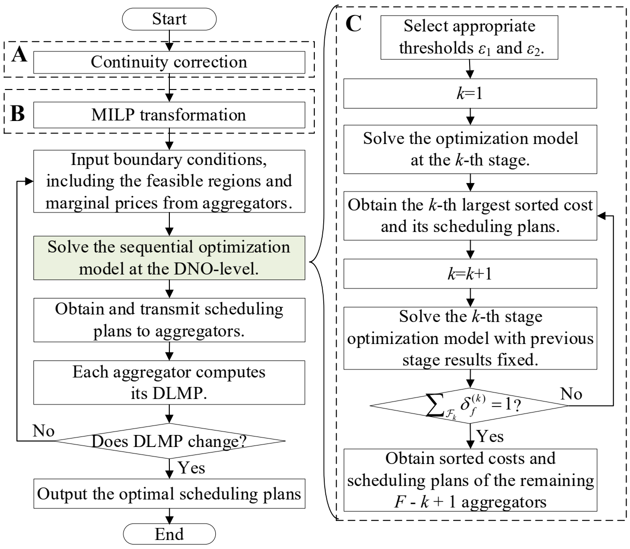


Fig. 2. Flowchart of the proposed algorithm

A. Continuity correction of the Model

Transitions between high and medium-cost segments will induce nonsmooth discontinuities in the objective function. To address this, a continuity correction is applied to the DNO-level optimization model. Based on boundary jump magnitudes, the correction terms $[-(H-1)\varepsilon_1]$, …, $[-(H-k+1)\varepsilon_1]$, … are respectively incorporated into each leximin optimization stage. Subsequently, through functional reconstruction and the omission of sorted constant terms $\Sigma_{f=1}^{k-1}(H-f+1)C^*_{<f>}$, the original objective functions (8)–(9) are transformed into smoothed formulations (10)–(11), thus ensuring the numerical tractability of the model.

$$\begin{aligned}\min\ \mathrm{SCF}^{(1)}&=-(F-1)\varepsilon_1+FC_{<1>}\\&-\sum_{f=1}^{F}\left(C_{<1>}-\varepsilon_1-C_{<f>}\right)^{+}+2\sum_{f=1}^{F}\left(\varepsilon_2-C_{<f>}\right)^{+}\end{aligned} \quad (10)$$

$$\begin{aligned}\min\ \mathrm{SCF}^{(k)}&=-(F-k+1)\varepsilon_1+\left(F-k+1\right)C_{<k>}\\&-\sum_{f=1}^{F}\left(C_{<1>}-\varepsilon_1-C_{<f>}\right)^{+}+2\sum_{f=1}^{F}\left(\varepsilon_2-C_{<f>}\right)^{+}\end{aligned} \quad (11)$$

B. MILP Transformation of the Model

To address the piecewise linearities inherent in sorting operations and the positive part operator, the sequential model is further transformed into MILP-compatible forms (12)–(13).

979-8-3315-8138-1

$$\min \ \mathrm{SCF}^{(1)} = \mathcal{H}^{(1)} \tag{12a}$$
$$s.t.\ \mathcal{H}^{(1)} \ge F\rho - \sum\nolimits_{f\in\mathcal{F}} \omega_f^{(1)} + \sum\nolimits_{f\in\mathcal{F}} \kappa_f^{(1)} \tag{12b}$$
$$\rho \ge C_f \tag{12c}$$
$$0 \le \omega_f^{(1)} \le \mathcal{M}\delta_f^{(1)} \tag{12d}$$
$$\omega_f^{(1)} \le \rho - \varepsilon_1 - C_f + \mathcal{M}\left(1-\delta_f^{(1)}\right) \tag{12e}$$
$$\kappa_f^{(1)} \ge \varepsilon_2 - C_f,\ \kappa_f^{(1)} \ge 0 \tag{12f}$$
$$C_{f_1} - C_{f_2} \le \mathcal{M},\quad \forall f_1, f_2, f \in \mathcal{F} \tag{12g}$$
$$\delta_f^{(1)} = \begin{cases} 0, & \rho - C_f \le \varepsilon_1 \\ 1, & \rho - C_f > \varepsilon_1 \end{cases} \tag{12h}$$

$$\min \ \mathrm{SCF}^{(k)} = \mathcal{H}^{(k)} \tag{13a}$$
$$s.t.\ \mathcal{H}^{(k)} \ge \left(F-k+1\right)\Theta^{(k)} - \sum\nolimits_{f\in\mathcal{F}_k} \omega_f^{(k)} + 2\sum\nolimits_{f\in\mathcal{F}_k} \kappa_f^{(k)} \tag{13b}$$
$$\Theta^{(k)} \ge C_f^{\dagger} \tag{13c}$$
$$\Theta^{(k)} \ge C_{<1>}^{*} - \varepsilon_1 \tag{13d}$$
$$C_f^{\dagger} \ge C_f \tag{13e}$$
$$C_f \ge C_f^{\dagger} - \mathcal{M}(1-\mu_f^{(k)}) \tag{13f}$$
$$\sum\nolimits_{f\in\mathcal{F}_k} \mu_f^{(k)} = 1 \tag{13g}$$
$$0 \le \omega_f^{(k)} \le \mathcal{M}\delta_f^{(k)} \tag{13h}$$
$$\omega_f^{(k)} \le C_{<1>}^{*} - \varepsilon_1 - C_f + \mathcal{M}\left(1-\delta_f^{(k)}\right) \tag{13i}$$
$$\kappa_f^{(k)} \ge \varepsilon_2 - C_f,\ \kappa_f^{(k)} \ge 0 \tag{13j}$$
$$C_{f_1} - C_{f_2} \le \mathcal{M}, \forall f_1, f_2, f \in \mathcal{F}_k \tag{13k}$$
$$(\delta_f^{(k)}, \mu_f^{(k)}) = \begin{cases} (0,0), & C_{<1>}^{*} - C_f \le \varepsilon_1,\ R_f \ne k \\ (0,1), & C_{<1>}^{*} - C_f \le \varepsilon_1,\ R_f = k \\ (1,0), & C_{<1>}^{*} - C_f > \varepsilon_1,\ R_f \ne k \\ (1,1), & C_{<1>}^{*} - C_f > \varepsilon_1,\ R_f = k \end{cases} \tag{13l}$$

where $\mathcal{H}^{(k)}$, $\Theta^{(k)}$, $\omega_f^{(k)}$, $\kappa_f^{(k)}$, $C_f^{\dagger}$, ρ are introduced as auxiliary variables for linearization. $\delta_f^{(1)}$, $\delta_f^{(k)}$, $\mu_f^{(k)}$ are binary variables, and $\mathcal{M}$ is a sufficiently large constant.

The equivalence of the MILP transformation at the k-th stage is justified covering feasibility and optimality, while the first stage can be proven similarly. Regarding feasibility, for any valid solution of the original problem, setting the binary variable corresponding to $C_{<k>}$ to 1 and others to 0 satisfies the Big-M constraints (13e)–(13g) and (13l). Likewise, valid assignments of auxiliary variables exist in (13c)–(13d) and (13h)–(13j), thereby confirming that the MILP formulation covers the original feasible region. Conversely, (13e)–(13g) and (13l) determine the unique aggregator corresponding to the k-th sorted cost $C_{<k>}$ at any given stage, thereby enforcing $C_f^{\dagger}=C_{<k>}$. In conjunction with the minimization objective, $\Theta^{(k)}$ is driven to its lower bound $\max\{C_{<1>}^{*}-\varepsilon_1,\ C_{<k>}\}$. Similarly, $\omega_f^{(k)}$ and $\kappa_f^{(k)}$ are enforced to capture the original terms $(C_{<1>}^{*}-\varepsilon_1-C_{<f>})^{+}$ and $(\varepsilon_2-C_{<f>})^{+}$. (13k) is a tightening constraint ensuring exact MILP representability. Therefore, the problem min $\mathcal{H}^{(k)}$ is equivalent to min$\mathrm{SCF}^{(k)}$, thus laying the algorithmic foundation for subsequent optimization.

C. Sequential Optimization Solution Strategy

After the mathematical transformation, the DNO-level sequential optimization model is reformulated as follows.

$$\begin{aligned} &\min \ \mathrm{SCF}^{(1)} \\ &\quad s.t. (1b)\text{-}(1e),(5),(7b)\text{-}(7g),(12b)\text{-}(12h) \end{aligned} \tag{14}$$

$$\begin{aligned} &\min \ \mathrm{SCF}^{(k)} \\ &\quad s.t. (1b)\text{-}(1e),(5),(7b)\text{-}(7g),(13b)\text{-}(13l) \end{aligned} \tag{15}$$

Upon completion of the first optimization stage, $C_{<1>}^{*}$ and corresponding scheduling plans are retained as boundary conditions for the subsequent stage. By the k-th stage, $\{R_1, R_2, \ldots, R_{k-1}\}$ have been sorted, with their respective sorted vectors and scheduling plans fixed. When there is only one unsorted DER aggregator remaining in the high-cost segment, a complete DNO scheduling plan for the current iteration can be obtained after solving the ongoing stage.

V. Case Studies

A. Basic Configuration

To investigate the performance of the proposed approach, numerical tests are conducted on a modified DTU 25-bus [15]–IEEE 33-bus multi-voltage-level system. As shown in Fig. 3, each medium-voltage bus in DTU 25 system hosts a DER aggregator, managing a 33-bus low-voltage network. Each aggregator coordinates a total load of 3.864MW+ 0.9524Mvar, comprising 1.932MW+0.635Mvar of time-sensitive load, 0.966MW+0.3175Mvar of CL, and 0.966MW of SL. Buses (12), (24), (27), and (32) in the 10kV network are each connected to a 1MW PV system. Parameters are moderately perturbed across aggregators to ensure diversity. The values of the segment partitioning parameters ε_1 and ε_2 are detailed in Fig. 4. The CPLEX solver is employed for solution.

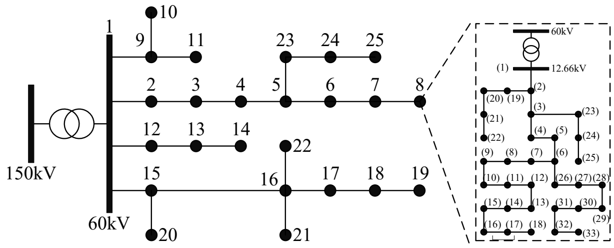


Fig. 3. Modified DTU 25-bus–IEEE 33-bus system topology

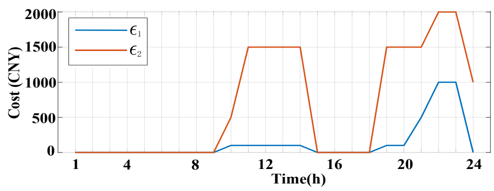
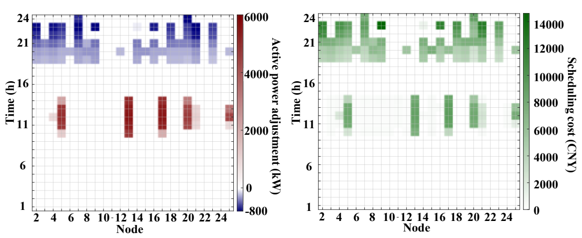


Fig. 4. Settings of thresholds

B. Effectiveness of Fairness-Economics Trade-off

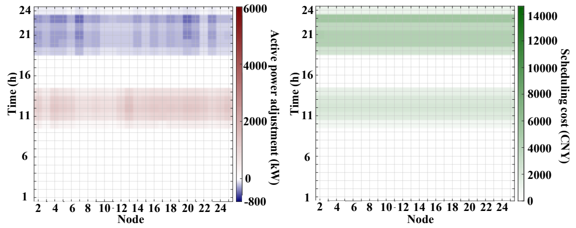
Figs. 5–7 compare the resource scheduling plans and cost distribution results of three different strategies under identical operational conditions. As illustrated, total-cost minimization focuses exclusively on economic efficiency, while the unsegmented leximin criterion prioritizes fairness. In contrast, the proposed method not only restricts the scheduling depth of high-cost aggregators to prevent excessive task allocation, but also employs incentives to motivate the DNO to actively schedule low-participation aggregators, thereby ensuring their fundamental market involvement.



(a) Resource scheduling plans (b) Resource scheduling costs

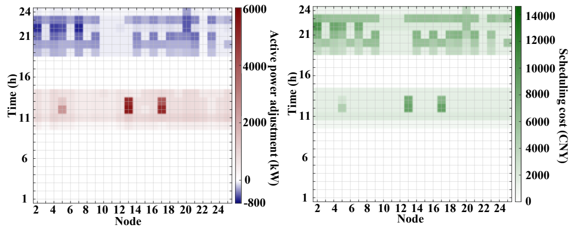
Fig. 5. Total-cost minimization method

979-8-3315-8138-1



(a) Resource scheduling plans (b) Resource scheduling costs

Fig. 6. Unsegmented leximin criterion



(a) Resource scheduling plans (b) Resource scheduling costs

Fig. 7. The proposed method

Tables I–III quantitatively evaluate the performance of the proposed method across four key metrics: total scheduled resource capacity S, total scheduling expenditure EXP, scheduling concentration $S_{K,t}$ (defined as the share of scheduled capacity from the top k aggregators during time interval t) and Jain's Index (JI). The proposed method exhibits consistently superior performance in balancing fairness and economic efficiency across all time intervals.

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT SCHEDULING METHODS ACROSS THE EVALUATION PERIOD

Scheduling Methods	S (MW·h)	EXP (k CNY)	JI
Total-cost minimization	123.17	620.2	0.661
Unsegmented leximin criterion	123.17	736.1 (+18.7%)	0.999
The proposed method	123.17	683.5 (+10.2%)	0.942

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT SCHEDULING METHODS ACROSS THE PEAK PERIODS（T=10–14，K=4）

Scheduling Methods	S (MW·h)	$S_{4,\,t=10\text{-}14}$ (%)	EXP (k CNY)	JI
Total-cost minimization	94.907	87	181.4	0.255
Unsegmented leximin criterion	94.907	16.7	205.4 (+13.2%)	1.0
The proposed method	94.907	29.16	202.4 (+11.6%)	0.84

TABLE III. PERFORMANCE COMPARISON OF DIFFERENT SCHEDULING METHODS ACROSS THE PEAK PERIODS（T=21–24，K=5）

Scheduling Methods	S (MW·h)	$S_{5,\,t=21\text{-}24}$ (%)	EXP (k CNY)	JI
Total-cost minimization	19.34	55.2	287.7	0.498
Unsegmented leximin criterion	19.34	20.8	353.3 (+22.8%)	0.999
The proposed method	19.34	37.05	325.7 (+13.2%)	0.871

Specifically, as observed in Table III, during peak scheduling periods (t=21–24), total-cost minimization strategy maintains the lowest EXP. However, 55% of the scheduled tasks are concentrated on only five buses: 2, 4, 7, 20, and 21, and it yields a JI of merely 0.498, indicating substantial fairness deficiencies. Meanwhile, in pursuit of absolute fairness, the unsegmented leximin criterion forcibly increases the scheduling capacity of low-participation aggregators, achieving near-perfect fairness (JI≈1.0) but at the cost of a 22.8% rise in EXP. In contrast, the proposed method restrains over-utilized participants while incentivizing under-engaged aggregators, which achieves an 18.15% reduction in $S_{K,t}$ with only 13.2% increase in EXP, demonstrating an effective trade-off between fairness and economic efficiency.

VI. CONCLUSION

This paper proposes a fairness-driven optimal scheduling method for aggregated DERs, which incorporates the threshold-based partitioning and the leximin criterion, and performs sequential optimization enabled by a continuity correction technique and MILP formulation. Case studies demonstrate that the proposed method reduces EXP by 7.1% over the unsegmented leximin criterion, while improves JI by 42.5% relative to the total-cost minimization method. Overall, it achieves a favorable trade-off between economic efficiency and fairness compared with conventional approaches. Future work will extend the method to time-coupled scenarios and develop more granular strategies to enhance the practical applicability of the scheduling management.

REFERENCES

[1] P. Olivella, E. Bullich, M. Aragüés, A. sumper, S. Ottesen, J. A. Vidal, et al., “Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources,” in *Applied Energy*, vol. 210, pp. 881-895, 2018.

[2] R. Messias, P. M. S. Carvalho, J. Sousa, “Hybrid distribution network planning to incorporate virtual capacity from distributed flexibility resources,” in *Utilities Policy*, vol. 93, pp. 101892, 2025.

[3] J. Soares, F. Lezama, R. Faia, S. Limmer, T. Rodemann, et al., “Review on fairness in local energy systems,” in *Applied Energy*, vol. 374, pp. 123933, 2024.

[4] K. Jenkins, D. McCauley, R. Heffron, H. Stephan, R. Rehner, “Energy justice: a conceptual review,” in *Energy Research & Social Science*, vol. 11, pp. 174-182, 2016.

[5] X. Sun, J. Qiu, Y. Tao, Y. Ma, J. Zhao, “Coordinated real-time voltage control in active distribution networks: An incentive-based fairness approach,” in *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 2650-2663, 2022.

[6] N. Gholizade, M. Abedi, H. Nafisi, M. Marzband, A. Loni, G. A. Putrus, “Fair-optimal bilevel transactive energy management for community of microgrids,” in *IEEE Systems Journal*, vol. 16, no.2, pp. 2125-2135, 2021.

[7] J. B. Rawls, “A theory of justice: Original edition,” in *Cambridge: Harvard University*, 2005.

[8] G. Tsaousoglou, J. S. Giraldo, P. Pinson, N. G. Paterakis, “Mechanism design for fair and efficient DSO flexibility markets,” in *IEEE Transactions on Smart Grid*, vol. 12, no.3, pp. 2249-2260, 2021.

[9] F. Jiao, Y. Zou, X. Zhang, B. Zhang, “Online optimal dispatch based on combined robust and stochastic model predictive control for a microgrid including EV charging station,” in *Energy*, vol. 247, pp. 123220, 2022.

[10] V. X. Chen, J. N. Hooker, “A guide to formulating fairness in an optimization model,” in *Annals of Operations Research,* vol. 326, no. 1, pp. 1-39, 2023.

[11] V. X. Chen, J. N. Hooker, “Combining leximax fairness and efficiency in a mathematical programming model,” in *European Journal of Operational Research*, vol. 299, no. 1, pp. 235-248, 2022.

[12] V. Gurvich, “Balanced flows for transshipment problems,” in *Discrete Applied Mathematics*, vol. 305, pp. 214-220, 2021.

[13] L. Bai, J. Wang, C. Wang, C. Chen, F. Li, “Distribution locational marginal pricing (DLMP) for congestion management and voltage support,” in *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 4061-4073, 2017.

[14] X. Liu, Y. Li, L. Wang, J. Tang, H. Qiu, A. Berizzi, et al., “Dynamic aggregation strategy for a virtual power plant to improve flexible regulation ability,” in *Energy*, vol. 297, pp. 131261, 2024.

[15] A. Baviskar, K. Das, M. Koivisto, A. D. Hansen, “Multi-voltage level active distribution network with large share of weather-dependent generation,” in *IEEE Transactions on Power Systems*, vol. 37, no. 6, pp. 4874-4884, 2022.

979-8-3315-8138-1