

Distribution Market Trading Optimization for High-Energy-Consuming Industrial Park Microgrids via Distributionally Robust Chance Constraints

Linlin Shao, Guoqing Li, and Song Zhang

Abstract—Uncertainty in photovoltaic (PV) output disrupts energy management decisions for a high-energy-consuming industrial park microgrid (HEIMG) and increases operational risk when it participates in distribution market transactions. This paper proposes an HEIMG energy management scheme adapted to distribution market contexts by leveraging distributionally robust chance constraints (DRCC) and fully considering the adjustable demand response characteristics of industrial production processes. An HEIMG energy management formulation integrating production-side demand response constraints is developed, and a bi-level optimization model is further derived under distribution market interaction. Wasserstein-distance-based DRCC is introduced to quantify PV generation uncertainty, thereby balancing the over-reliance of stochastic optimization on complete probability information and the excessive conservatism of traditional robust optimization. Conservative conditional value-at-risk (CVaR) approximation combined with duality theory is adopted to transform DRCC into tractable second-order cone programming (SOCP) formulations. Karush–Kuhn–Tucker (KKT) optimality conditions combined with the big-M method are then utilized to linearize complementary slackness constraints, transforming the bi-level formulation into a tractable mixed-integer second-order cone programming (MISOCP) model. Numerical simulations verify that the proposed method achieves a favorable trade-off between operational risk control and economic performance for park energy management.

Index Terms—HEIMG, production process demand response, distributionally robust chance constraints, mathematical programs with equilibrium constraints.

ABBREVIATION

PV	photovoltaic
HEIMG	high-energy-consuming industrial park microgrid
DRCC	distributionally robust chance constraints
CvaR	conditional value-at risk
SOCP	second-order cone programming

KKT	Karush–Kuhn–Tucker
MISOCP	mixed-integer second-order cone programming
HEIPO	high-energy-consuming industrial park operator
DG	distributed generators
HEIP	high-energy-consuming industrial parks
DLMP	distribution locational marginal price
DSO	distribution system operator
DRO	distributionally robust optimization

I. INTRODUCTION

Driven by the global clean energy transition and the dual carbon goals of carbon peaking and carbon neutrality, microgrids have gradually become key participants in distribution market transactions [1], [2]. As a typical microgrid form, high-energy-consuming industrial park microgrid (HEIMG) features concentrated energy loads, large operational capacity, and high controllability, which significantly improves the flexibility of load-side demand response [3], [4], [5], [6]. While satisfying industrial production constraints and guaranteeing stable operation of the industrial park, the high-energy-consuming industrial park operator (HEIPO) can implement refined energy management to coordinate and regulate multiple resources, including building temperature control systems, production processes, energy storage devices, and combined heat and power units [7]. This fully exploits the time-shifting adjustment potential of various industrial loads. Such management methods can reduce the overall power purchase costs and total energy expenditure of HEIMG, smooth system power consumption fluctuations via peak shaving and valley filling, and effectively relieve the peak regulation pressure of upstream distribution networks [8]. Nevertheless, the output uncertainty of distributed generators (DG) brings potential risks to the energy management of high-energy-consuming industrial parks (HEIP) and poses challenges for peak-shaving capacity provision in distribution markets [9].

To improve the dispatch performance of the HEIMG system and enhance its economic efficiency, [10] incorporates

Manuscript received 17 July, 2026; accepted 1 September, 2026.
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Color versions of one or more of the figures in this paper are available online at <https://doi.org/10.26599/PEF.2026.9650022>.

Digital Object Identifier 10.26599/PEF.2026.9650022

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thermostatically controlled loads in HEIP and the flexible charging potential of on-site electric vehicles. A mixed-integer linear programming framework is developed for industrial park energy optimization, which effectively realizes peak shaving and cuts the overall electricity purchase cost of the park. Reference [11] introduces a regret metric to construct a stochastic energy dispatch framework that takes into account the temporal sequence of industrial production. Reference [12] develops a demand response scheduling optimization model for industrial microgrids integrated with photovoltaic (PV) generation, energy storage devices, and discrete manufacturing lines. The model jointly optimizes production process arrangements and charge–discharge profiles of energy storage, explicitly incorporating battery degradation costs to prolong the service lifetime of storage units and cut their full-lifecycle expenses. Nevertheless, these works only concentrate on the internal resource coordination within microgrids, without considering bidirectional power–price coupling between industrial parks and distribution networks, as well as distribution-grid operational constraints including power flow and voltage limits.

HEIMG is highly susceptible to uncertainty shocks caused by output fluctuations of DG during operational scheduling and market trading, which gives rise to various operational risks. Existing domestic and international research primarily employs two mathematical methods: stochastic optimization [13], [14], [15] and robust optimization [16], [17], [18] to address the stochastic characteristics of DG. Reference [13] adopts chance-constrained stochastic optimization to tackle stochastic fluctuations of distributed generation outputs, where coordinated energy storage deployment mitigates the adverse impacts of random disturbances on distribution network operation. Reference [14] develops a two-stage stochastic optimization model for the operational scheduling of renewable-powered microgrids. This work characterizes the stochastic uncertainty of renewable generation via stochastic optimization, thereby optimizing the economic operation of microgrids. Reference [15] proposes a risk-averse stochastic optimal scheduling model. References [16], [17] establish a two-stage robust optimization solution framework for microgrid scenarios. Reference [18] proposes a robust scheduling strategy based on time-series correlations, leveraging the coupling patterns observed in historical output data.

Both mainstream optimization algorithms have significant limitations: Stochastic optimization solutions rely heavily on complete probability distribution information for wind and solar power output, yet they are often difficult to accurately obtain these distribution parameters in real-world engineering settings. Robust optimization, in order to cover all extreme fluctuation scenarios, generates overly conservative scheduling strategies, which can increase the system's overall operating costs and reduce overall economic benefits.

To address these challenges, this paper proposes an economic and risk-balanced energy management strategy for HEIMG based on distributionally robust chance constraints

(DRCC). First, an overall energy management framework is established for HEIMG participation in distribution-level electricity market transactions. Second, fully considering production-side demand response and PV output uncertainty, a bi-level optimal scheduling model is constructed for distribution market trading scenarios. The upper-level model maximizes the overall economic benefit of HEIMG, while the lower-level model minimizes the operating cost of the distribution system. Based on the above derivation, the two-stage optimization model is restructured into an MPEC formulation, which can be further equivalently recast as a mixed-integer second-order cone programming (MISOCP) model. Numerical simulations are implemented via the YALMIP toolbox with the CPLEX solver. Finally, an IEEE 33-bus distribution network integrated with a practical HEIMG is adopted for case validation, which verifies the feasibility and effectiveness of the proposed scheduling model and optimization strategy. Simulation results demonstrate that the energy management scheme for HEIMG designed in this work can reduce the comprehensive power cost of industrial entities, relieve distribution network congestion, and mitigate the peak–valley regulation pressure of the power grid.

II. ENERGY MANAGEMENT FRAMEWORK FOR HEIMG IN THE DISTRIBUTION MARKET

A. The entire industrial production process at the HEIP

HEIP features diversified energy consumption demands, which cover basic energy resources such as electricity and natural gas, together with multiple end-consumption energy forms consisting of heating, cooling, and compressed air. In terms of load composition, the energy system can be mainly classified into production energy consumption and non-production energy consumption. Non-production energy consumption primarily refers to energy usage for office operation, lighting, cooling, and heating. Although such loads only account for a small proportion of total energy consumption, their variation characteristics are consistent with conventional load curves. By contrast, production energy consumption mainly consists of electric loads for production machinery operation, compressed air loads for production line conveyor belts, and thermal loads for equipment drying, curing, and other production processes. Restricted by inherent production process requirements, these loads follow fixed operation cycles and consume massive amounts of energy. Scientific scheduling of production plans and active participation of HEIPO in production process regulation can effectively reduce overall production costs.

This paper selects a lithium-ion battery manufacturing industrial park as the research object. The manufacturing procedure of lithium-ion batteries mainly includes three core stages: electrode preparation, cell assembly, and battery aging. As illustrated in Fig. 1, material storage links are arranged among the three production stages, with operation restricted

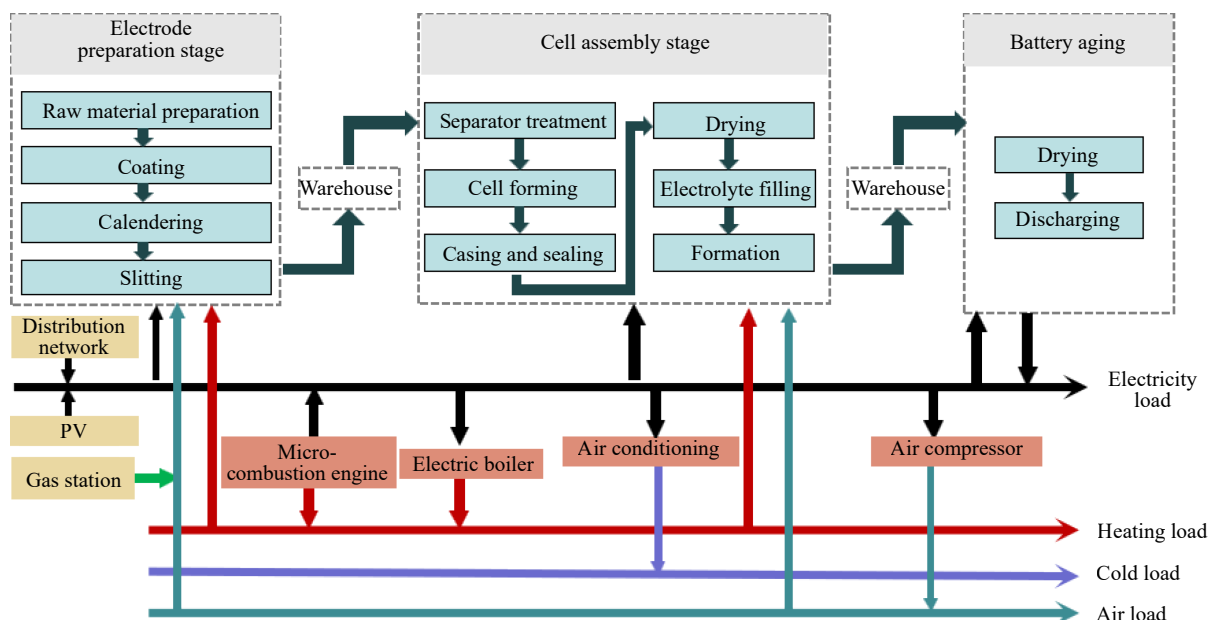


Fig. 1. Production process and structure of the HEIMG.

by input and output capacity limits. Since finished products from the former stage serve as raw materials for the subsequent stage, the production sequence must be strictly followed.

According to operational characteristics, the above production stages can be categorized into continuous and discrete types. Electrode preparation and cell assembly belong to continuous production processes, which require uninterrupted operation after startup. When participating in demand response, such processes act as fixed-power loads with load shifting potential, while their operation is limited by raw material and finished product storage capacity to guarantee stable production. By comparison, the battery aging stage is a discrete production process involving charging and discharging behaviors. It supports intermittent operation and can be equivalent to an energy storage system. Under the premise of satisfying raw material capacity limits and production sequence constraints, this discrete production stage exhibits higher scheduling flexibility than continuous production stages.

The energy consumption characteristics of the three production stages mentioned above are shown in Fig. 1. Electrical energy is supplied through three channels: on-site photovoltaic power generation, micro-gas turbine generation, and electricity purchased from the upstream grid-effectively meeting both production electricity demands and the park's basic electrical load. Thermal energy, provided by micro-gas turbines and electric boilers, serves as a stable heat source for temperature control in production processes and hot water supply. Cooling is provided by the air conditioning system, which maintains a constant temperature in both production and office environments through precise regulation. Compressed air, a critical power source for production, is continuously and stably supplied by air compressors to fully meet the air demand of core production processes such as electrode preparation and cell assembly.

B. Bidding and trading framework of HEIMG based on distribution market

This section elaborates on the framework for HEIMG to participate in distribution market clearing transactions, as illustrated in Fig. 2. HEIPO undertakes system-level energy management for HEIMG while conducting power purchase transactions in the distribution market. Specifically, the energy management strategy adopted by HEIPO is subject to the operational status of distribution networks and the distribution locational marginal price (DLMP) at grid coupling nodes. Such external factors adjust the power purchase volume from the distribution system operator (DSO) and further modify nodal load profiles accordingly.

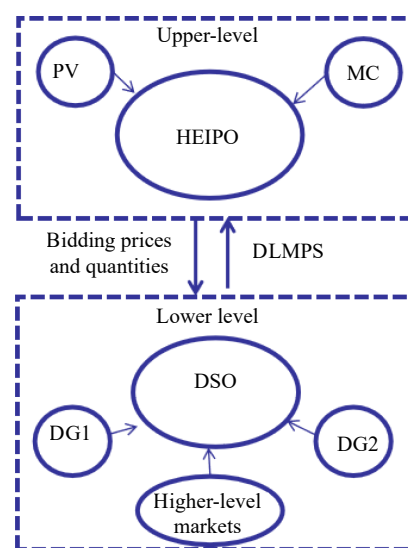


Fig. 2. Market participation structure for HEIMG in distribution market clearing.

In distribution network operations, the DSO integrates DG bid information, settlement prices from upper-level markets, and load forecasts at each node to determine the DLMP for each node, where DLMP refers to the marginal power cost at each distribution node, mathematically equal to the dual multiplier $\mu_{1,j,t}$ of nodal active power balance constraints in the lower market clearing model, which in turn influences the energy management strategy of HEIPO. Thus, the bidding strategy of HEIMG and the clearing results of the distribution market influence each other: The former affects the market clearing results, while the latter, in turn, affects the trading process of HEIMG.

III. BI-LEVER BIDDING MODEL FOR HEIMG IN DISTRIBUTION MARKET CLEARING

On the basis of the trading framework for HEIMG to engage in distribution market clearing, a bi-level bidding model targeting HEIMG's market participation is established.

A. Upper-level model: HEIMG energy management model considering production process response

The upper-level model is the energy management model for HEIMG that considers production process responses. This model minimizes the total energy cost of the park subject to constraints on production process responses and the multi-energy balance of the park.

A.1 Objective function

The objective function of the upper-level model is to minimize the total operating cost of HEIMG

$$\min \sum_{t=1}^{N_t} (C_{e,t} + C_{g,t} + C_{p,t}) \quad (1)$$

$$\begin{cases} C_{e,t} = C_{grid,t} P_{grid,t} \\ C_{g,t} = \sum_{m=1}^{N_{MT}} (C_{gas} P_{MT,m,t} / \eta_{MT}) \\ C_{p,t} = \sum_{ep=1}^{N_{ep}} (C_{ep,on} S_{iep,t}) + \sum_{ca=1}^{N_{ca}} (C_{ca,on} S_{ica,t}) + \sum_{ag=1}^{N_{ag}} (C_{ag,on} S_{iag,t}) \end{cases} \quad (2)$$

where $C_{e,t}$, $C_{g,t}$, and $C_{p,t}$ denote the electricity procurement cost, natural gas procurement cost, and operation and maintenance cost of the HEIMG, respectively; N_t denotes the total number of scheduling periods; $C_{grid,t}$ is the electricity settlement price for power purchased by the park from distribution network nodes; $P_{grid,t}$ stands for the active power purchased by the park from the distribution network; C_{gas} refers to the unit price of natural gas; $P_{MT,m,t}$ represents the output power of the microturbine at time t ; η_{MT} denotes the energy conversion efficiency of the microturbine; $C_{ep,on}$, $C_{ca,on}$, and $C_{ag,on}$ are the

operation and maintenance costs corresponding to the electrode preparation, cell assembly, and battery aging processes, respectively; $S_{iep,t}$, $S_{ica,t}$, and $S_{iag,t}$ represent the operating state variables of the electrode preparation, cell assembly, and battery aging production lines, respectively; N_{MT} is the numbers of microturbines; N_{ep} , N_{ca} , and N_{ag} represent the number of electrode preparation, cell assembly, and battery aging production lines, respectively.

A.2 Constraints

(1) Modeling the production process response

As described above, the lithium-ion battery production process is divided into three stages, with a buffer phase between adjacent stages. This model simultaneously accounts for the dynamic changes in production status within each stage.

Electrode preparation and cell assembly correspond to continuous manufacturing lines that share identical modeling logic. Taking the cell assembly stage as an illustration, Eqs. (3) and (4) impose continuity constraints on the startup and shutdown status of each production line and prohibit simultaneous startup and shutdown actions. Equations (5) and (7) denote the maximum runtime and minimum runtime constraints, respectively, and Eq. (6) describes the minimum idle time constraint. Equation (8) constrains the total output of cell-assembly lines to satisfy the total production demand.

$$y_{ca,t} - y_{ca,t-1} = q_{ca,t} - ti_{ca,t} \quad (3)$$

$$ti_{ca,t} + q_{ca,t} \leq 1 \quad (4)$$

$$\sum_{t=h}^{h+T_{ca,on}^{\max}-1} ti_{ca,t} \geq q_{ca,h}, \forall h \in [1, N_t] \quad (5)$$

$$\sum_{t=h}^{h+T_{ca,off}^{\min}-1} (1 - y_{ca,t}) \geq T_{ca,off}^{\min} ti_{ca,h}, \forall h \in [1, N_t] \quad (6)$$

$$\sum_{t=h}^{h+T_{ca,on}^{\min}-1} y_{ca,t} \geq T_{ca,on}^{\min} q_{ca,h}, \forall h \in [1, N_t] \quad (7)$$

$$\sum_{t=1}^{N_t} \sum_{ca=1}^{N_{ca}} y_{ca,t} V_{ca} = V_{sum} \quad (8)$$

where $ti_{ca,t}$, $q_{ca,t}$, and $y_{ca,t}$ denote the shutdown, startup, and operating state variables of the cell assembly stage at time t , respectively; $T_{ca,on}^{\min}$ and $T_{ca,on}^{\max}$ stand for the minimum and maximum operating time of the cell assembly process, respectively; $T_{ca,off}^{\min}$ denotes the minimum idle time for cell assembly lines; V_{ca} refers to the unit-time output of each cell assembly line; V_{sum} is the total production demand to be fulfilled; h denotes any time point within the scheduling horizon; N_{ca} represents the number of cell assembly lines; and N_t corresponds to the total number of scheduling periods.

The third stage of the lithium-ion battery manufacturing pro-

cess is the battery aging stage, which is a discrete production stage. This stage performs battery charging and discharging operations. Equation (9) describes the power balance constraint for charging and discharging at time t . Equations (10) and (11) guarantee that the quantity of charged and discharged cells in the battery aging stage satisfies the total production demand constraint.

$$y_{ag,t}^c P_{ag}^c - y_{ag,t}^f P_{ag}^f = P_{ag,t} \quad (9)$$

$$\sum_{t=1}^{N_t} \sum_{ag=1}^{N_{ag}} y_{ag,t}^c V_{ag}^c = V_{sum} \quad (10)$$

$$\sum_{t=1}^{N_t} \sum_{ag=1}^{N_{ag}} y_{ag,t}^f V_{ag}^f = V_{sum} \quad (11)$$

where $y_{ag,t}^c$ and $y_{ag,t}^f$ are the charging and discharging state variables at time t during the battery aging stage, respectively; P_{ag}^c , P_{ag}^f , and $P_{ag,t}$ are the charging power, discharging power, and total operating power at time t , respectively; and V_{ag}^c and V_{ag}^f represent the number of charged and discharged cells during the battery aging stage, respectively.

The above three production stages follow a fixed production sequence, as defined by Eqs. (12)–(14), which represent the production sequence constraints for the electrode preparation stage, cell assembly stage, and battery aging stage, respectively. The processing order of the three manufacturing links cannot be arbitrarily swapped due to the physical flow of semi-finished products.

$$\sum_{t=1}^{h+m} \sum_{ca=1}^{N_{ca}} y_{ca,t} V_{ca} G_{ca} \leq \sum_{t=1}^h \sum_{ep=1}^{N_{ep}} y_{ep,t} V_{ep}, \forall h \in [1, N_t] \quad (12)$$

$$\sum_{t=1}^{h+n} \sum_{ag=1}^{N_{ag}} y_{ag,t}^f V_{ag}^f \leq \sum_{t=1}^h \sum_{ca=1}^{N_{ca}} y_{ca,t} V_{ca}, \forall h \in [1, N_t] \quad (13)$$

$$\sum_{t=1}^{h+1} \sum_{ag=1}^{N_{ag}} y_{ag,t}^c V_{ag}^c \leq \sum_{t=1}^h \sum_{ag=1}^{N_{ag}} y_{ag,t}^f V_{ag}^f, \forall h \in [1, N_t] \quad (14)$$

where V_{ep} and V_{ca} represent the hourly output of the electrode preparation stage and the cell assembly stage, respectively; G_{ca} represents the number of cells in the cell assembly stage; m represents the minimum sum of the production time of the electrode preparation stage and the waiting time in warehouse 1; n represents the minimum sum of the production time of the cell assembly stage and the waiting time in warehouse 2; and l represents the minimum sum of the production time of the battery aging discharging operation and the waiting time between the discharging and charging operations.

(2) Modeling warehouse states

Warehouses act as material storage buffers connecting the three production stages. Equations (15) and (16) impose upper

and lower capacity bounds on warehouse inventory levels, while Eqs. (17) and (18) formulate the material balance constraints.

$$S_t^{ew,min} \leq S_t^{ew} \leq S_t^{ew,max} \quad (15)$$

$$S_t^{cw,min} \leq S_t^{cw} \leq S_t^{cw,max} \quad (16)$$

$$S_t^{ew} - S_{t-1}^{ew} = \sum_{ep=1}^{N_{ep}} y_{ep,t} V_{ep} - \sum_{ca=1}^{N_{ca}} y_{ca,t} V_{ca} G_{ca} \quad (17)$$

$$S_t^{cw} - S_{t-1}^{cw} = \sum_{ca=1}^{N_{ca}} y_{ca,t} V_{ca} - \sum_{ag=1}^{N_{ag}} y_{ag,t} V_{ag}^f \quad (18)$$

where S_t^{ew} stands for the inventory level of the warehouse between the electrode preparation stage and the cell assembly stage, while S_t^{cw} refers to the inventory level of warehouse 2. In addition, $S_t^{ew,max}$ and $S_t^{ew,min}$ denote the upper and lower capacity bounds of the intermediate warehouse, and $S_t^{cw,max}$ and $S_t^{cw,min}$ represent the maximum and minimum storage capacities of warehouse 2, respectively.

(3) Modeling the air compression system

In electrode preparation and cell assembly, pneumatic manipulators and conveyors operate on compressed air. Apart from steady uninterrupted air supply, cylinder pressure constraints need to be fulfilled. Equation (19) depicts the storage tank's operational status, Eq. (20) restricts the variation of stored air volume between the start and end of the optimization horizon, and Eq. (21) sets its maximum and minimum storage capacities. Under extreme tank pressure conditions, Eq. (22) dictates that compressors shut down at peak pressure to stop air inflow, whereas Eq. (23) requires compressors to resume operation at the minimum pressure to refill the tank.

$$E_{cas,t-1} - E_{cas,t} = D_{cas,t} \Delta t - \eta_{cas} P_{cas,t} \Delta t \quad (19)$$

$$0.8 E_{cas,0} \leq E_{cas,end} \leq 1.2 E_{cas,0} \quad (20)$$

$$V_{ocas} P_{cas,min} \leq E_{cas,t} \leq V_{ocas} P_{cas,max} \quad (21)$$

$$E_{cas,t} + y_{cas,t} V_{ocas} P_{cas,max} \leq 1.1 V_{ocas} P_{cas,max} \quad (22)$$

$$1.1 V_{ocas} P_{cas,min} \leq E_{cas,t} + y_{cas,t} V_{ocas} P_{cas,min} \quad (23)$$

where $E_{cas,t}$ and $D_{cas,t}$ denote the storage volume and air consumption of the compressed air system, respectively, and η_{cas} refers to its operational efficiency. $P_{cas,t}$ stands for the power consumption of air compressors. $E_{cas,0}$ and $E_{cas,end}$ correspond to the tank air volume at the start and end of the optimization horizon, respectively, while V_{ocas} is the physical volume of the storage tank. $y_{cas,t}$ represents the operating state variable of air compressors. $P_{cas,min}$ and $P_{cas,max}$ are the lower and upper pressure bounds of the tank, respectively.

(4) Building heating and cooling load model

This paper assumes the factory space to be a single thermal zone, whereas the office area is divided into multiple thermal zones [19]. Equations (24) and (25) set the upper and lower temperature bounds for the factory and office zones, Eqs. (26) and (27) define the output upper and lower limits of the two zones' HVAC systems, Eqs. (28) and (29) formulate heat balance constraints for factory and office areas, and Eqs. (30) and (31) are heat balance constraints for interior partition walls ($v = 2$ and 3) and exterior walls ($v = 4$ and 5), respectively. Only wall 5 is equipped with windows, hence the window heat transfer and solar gain terms in Eq. (29) are formulated with the fixed wall index $v = 5$.

$$T_{ir,min} \leq T_{ir,t} \leq T_{ir,max} \quad (24)$$

$$T_{or,min} \leq T_{or,t} \leq T_{or,max} \quad (25)$$

$$0 \leq P_{ic,t} \leq P_{ic,max} \quad (26)$$

$$0 \leq P_{rc,t} \leq P_{rc,max} \quad (27)$$

$$C_{ir}(T_{ir,t+1} - T_{c,t}) = \Delta t \left(\frac{T_{out,t} - T_{ir,t}}{R_{wa}} + \frac{T_{out,t} - T_{ir,t}}{R_w} + C_{GP} \cdot P_{ic,t} + M_t^{rad} \cdot k_c \cdot F_w + Q_{in} \right) \quad (28)$$

$$C_{or}(T_{or,t+1} - T_{or,t}) = \Delta t \left(\sum_{v \in N_u} \frac{T_{u,v}^{wa,t} - T_{or,t}}{R_{u,v}^{wa}} + \frac{T_{out,t} - T_{or,t}}{R_{u,5}^w} + C_P P_{rc,t} + Q_{or,t} + k_c F_{u,5}^w Q_{u,5,t}^{rad} \right) \quad (29)$$

$$C_{u,v}^{wa} R_{u,v}^{wa} T_{u,v}^{wa,t+1} - (C_{u,v}^{wa} R_{u,v}^{wa} - 2) T_{u,v}^{wa,t} = \Delta t (T_{or,t} + T_{or,t,t}) \quad v = 2, 3 \quad (30)$$

$$C_{u,v}^{wa} R_{u,v}^{wa} T_{u,v}^{wa,t+1} - (C_{u,v}^{wa} R_{u,v}^{wa} - 2) T_{u,v}^{wa,t} = \Delta t (T_{or,t} + T_{out,t} + s_{u,v} a_{u,t} A_{u,v}^{wa} Q_{u,v,t}^{rad} R_{u,v,t}^{rad}) \quad v = 4, 5 \quad (31)$$

Here, $T_{ir,min}$ and $T_{ir,max}$ denote the lower and upper bounds of indoor comfort temperature for the factory building, respectively, and $T_{ir,t}$ is the factory indoor temperature at time t . $T_{or,min}$ and $T_{or,max}$ represent the lower and upper comfort temperature limits for office zones, respectively, and $T_{or,t}$ stands for the office indoor temperature at time t . $P_{ic,t}$ is the factory air-conditioning power consumption, and $P_{ic,max}$ is the rated power of the factory air-conditioning system. $P_{rc,t}$ denotes the power consumption of office air-conditioning systems, with $P_{rc,max}$ being its rated power. Δt represents the simulation time step. C_{ir} refers to the thermal capacitance of the factory building, and $T_{out,t}$ is the outdoor ambient temperature at time t . R_{wa} and R_w are the thermal resistances of factory walls and external windows, respectively. C_{GP} is the performance coef-

ficient of factory air-conditioning equipment. k_c stands for window solar transmittance. F_w is the total exterior window area of the factory, M_t^{rad} characterizes the solar heat gain received by the factory at time t , and Q_{in} represents internal heat gain within the factory building. C_{or} is the thermal capacitance of a single office thermal zone. N_u denotes the set of wall nodes adjacent to indoor thermal node u . $R_{u,v}^{wa}$ is the thermal resistance between office indoor node u and wall node v , and $R_{u,v}^w$ represents the thermal resistance of windows arranged on wall v of zone u . C_P is the performance coefficient of office air-conditioning equipment. $Q_{u,v,t}^{rad}$ corresponds to the solar heat gain acting on wall v of zone u at time t . $F_{u,v}^w$ is the window area on wall v within zone u , and $Q_{or,t}$ refers to the internal heat gain inside office zone u at time t . $C_{u,v}^{wa}$ stands for the thermal capacitance of wall v belonging to zone u , and $T_{u,v}^{wa,t}$ characterizes the temperature of wall node v in zone u at time t . $T_{or,t}$ denotes the indoor temperature of the adjacent office thermal zone l separated by the interior partition wall at time t . $s_{u,v}$ is a binary variable representing the solar-exposed state of wall v in zone u , where $s_{u,v} = 1$ indicates the wall receives solar radiation and $s_{u,v} = 0$ otherwise. $\alpha_{u,v,t}$ denotes the time-varying solar heat absorption coefficient of wall v in zone u , $A_{u,v}^{wa}$ is the area of wall v in zone u , and $R_{u,v,t}^{rad}$ is the solar radiation thermal resistance of wall v at time t . In Eqs. (30) and (31), $v = 2$ and 3 correspond to internal partition walls, while $v = 4$ and 5 correspond to external building envelope walls. Only wall 5 is equipped with windows.

(5) Energy balance constraints

Equation (32) expresses the overall energy balance constraint of the industrial park. The total electrical load covers power demands from all production links, air compressors, electric boilers, HVAC systems, and basic domestic loads. The power supply-demand balance is maintained jointly by micro-cogeneration units, photovoltaic generation, and power purchased from the upper distribution network.

$$\sum_{m=1}^{N_{MT}} P_{MT,t} + P_{PV,t} + P_{grid,t} = \sum_{ag=1}^{N_{ag}} P_{ag,t} + \sum_{ca=1}^{N_{ca}} P_{ca,t} + \sum_{ep=1}^{N_{ep}} P_{ep,t} + \sum_{cas=1}^{N_{cas}} P_{cas,t} + \sum_{ir=1}^{N_i} P_{ic,t} + \sum_{r=1}^{N_r} P_{rc,t} + P_{br,t} + P_{load,t} \quad (32)$$

where $P_{PV,t}$ stands for the photovoltaic power output at time t , $P_{load,t}$ denotes the basic electrical load, N_i denotes the number of factory buildings, N_r represents the quantity of office buildings, $P_{br,t}$ characterizes the output power of electric boilers at time t , and $P_{ca,t}$ and $P_{ep,t}$ correspond to the power consumption of the cell assembly line and electrode preparation line at time t , respectively.

Equation (33) governs the overall thermal energy balance constraint of the industrial park. Total heat demand includes process heat loads from baking, drying, and other manufacturing procedures across all production stages, alongside the

basic heat load for daily routine demands. Thermal supply-demand equilibrium is jointly satisfied by micro combined heat and power units and electric boilers.

$$\frac{P_{MT,t}}{R_{MT}} + \eta_{br} P_{br,t} \geq J_{base,t} + J_{ep} \cdot \sum_{ep=1}^{N_{ep}} y_{ep,t} + J_{ca} \cdot \sum_{ca=1}^{N_{ca}} y_{ca,t} \quad (33)$$

where R_{MT} stands for the heat-to-power ratio of the micro-combustion engine; $J_{base,t}$ denotes the basic heat load; J_{ep} and J_{ca} denote the heat load per unit operation of each electrode preparation line and cell assembly line, respectively; and η_{br} refers to the thermal efficiency of the electric boiler.

Equation (34) enforces the compressed air balance constraint, which characterizes the supply-demand equilibrium of pneumatic systems throughout electrode preparation and cell assembly processes.

$$D_{cas,t} = D_{ca} \cdot \sum_{ca=1}^{N_{ca}} y_{ca,t} + D_{ep} \cdot \sum_{ep=1}^{N_{ep}} y_{ep,t} \quad (34)$$

where D_{ca} denotes the compressed air consumption of the cell assembly process, and D_{ep} stands for the compressed air consumption of the electrode preparation process.

B. Lower-level model: Power distribution market clearing model

This submodel takes the minimum operating cost of the distribution system as its optimization objective, and a distribution market clearing model is established with second-order cone relaxation introduced.

(1) Objective function

Distribution system operating costs consist of three components: electricity procurement costs from the upstream utility grid, power purchase expenses from DG, and sales revenue for HEIMG. The lower-level model takes the minimum operating cost of the distribution system as its objective function, as formulated in Eq. (35)

$$\min \sum_{t=1}^{N_t} \left(C_{G,t} P_{G,t} + \sum_{DG=1}^{N_{DG}} C_{DG,t} P_{DG,t} - C_{grid,t} P_{grid,t} \right) \quad (35)$$

where $C_{G,t}$ denotes the settlement price of electricity purchased by the distribution network from the upstream grid; $P_{G,t}$ stands for the power volume purchased from the upstream grid; $C_{DG,t}$ refers to the power bidding price of distributed generation; and $P_{DG,t}$ represents the output power of distributed generation.

(2) Constraints

Equations (36) and (37) are the active and reactive power balance equations for distribution network nodes; Eq. (38) is the voltage drop equation; Eq. (39) is the second-order cone programming constraint after relaxing the power flow constraints [20]; Eqs. (40)–(43) are the limits on the active and reactive power output of generators and DG; and Eq. (44) is the node voltage safety constraint.

$$\sum_{\substack{i \in m_1 \\ j \in m_2}} P_{ij,t} - I_{ij,t} R_{ij} - \sum_{\substack{j \in m_1 \\ k \in m_2}} P_{jk,t} + P_{G,j,t} + P_{DG,j,t} - P_{L,j,t} + P_{grid,t} = 0 : [\mu_{1,j,t}] \quad (36)$$

$$\sum_{\substack{i \in m_1 \\ j \in m_2}} Q_{ij,t} - I_{ij,t} X_{ij} - \sum_{\substack{j \in m_1 \\ k \in m_2}} Q_{jk,t} + Q_{G,j,t} + Q_{DG,j,t} - Q_{L,j,t} = 0 : [\mu_{2,j,t}] \quad (37)$$

$$U_{j,t} = U_{i,t} - 2(R_{ij} P_{ij,t} + X_{ij} Q_{ij,t}) + ((R_{ij})^2 + (X_{ij})^2) I_{ij,t} : [\mu_{3,ij,t}] \quad (38)$$

$$\left\| \begin{array}{c} 2P_{ij,t} \\ 2Q_{ij,t} \\ I_{ij,t} - U_{i,t} \end{array} \right\|_2 \leq I_{ij,t} + U_{i,t} : [B_{1,ij,t}, B_{2,ij,t}, B_{3,ij,t}, B_{4,ij,t}] \quad (39)$$

$$P_{G,j,\min} \leq P_{G,j,t} \leq P_{G,j,\max} : [\lambda_{1,t}, \lambda_{2,t}] \quad (40)$$

$$Q_{G,j,\min} \leq Q_{G,j,t} \leq Q_{G,j,\max} : [\lambda_{3,t}, \lambda_{4,t}] \quad (41)$$

$$P_{DG,j,\min} \leq P_{DG,j,t} \leq P_{DG,j,\max} : [\lambda_{5,t}, \lambda_{6,t}] \quad (42)$$

$$Q_{DG,j,\min} \leq Q_{DG,j,t} \leq Q_{DG,j,\max} : [\lambda_{7,t}, \lambda_{8,t}] \quad (43)$$

$$(U_{j,\min})^2 \leq U_{j,t} \leq (U_{j,\max})^2 : [\lambda_{9,t}, \lambda_{10,t}] \quad (44)$$

where m_1 and m_2 denote the sets of branch starting node i and terminal node j in the distribution network, respectively; $P_{ij,t}$ and $Q_{ij,t}$ stand for the active and reactive power flowing through line ij , respectively; R_{ij} and X_{ij} refer to the resistance and reactance of line ij , respectively; $I_{ij,t}$ represents the squared current magnitude of line ij ; $U_{i,t}$ and $U_{j,t}$ are the squared voltage magnitudes at nodes i and j , respectively; $P_{L,j,t}$ and $Q_{L,j,t}$ correspond to the active and reactive power loads at node j , respectively; $P_{G,j,t}$ and $Q_{G,j,t}$ stand for the active and reactive power injected from the upstream grid at node j , respectively; $U_{j,\min}$ and $U_{j,\max}$ are the lower and upper bounds of voltage magnitude at node j , respectively; $P_{G,j,\min}$, $P_{G,j,\max}$, $Q_{G,j,\min}$, and $Q_{G,j,\max}$ define the minimum and maximum limits of power exchange between the distribution network and the upstream grid; $P_{DG,j,\min}$, $P_{DG,j,\max}$, $Q_{DG,j,\min}$, and $Q_{DG,j,\max}$ represent the minimum and maximum active and reactive power outputs of distributed generation units. The colons attached to each constraint correspond to the dual variables of the proposed model. In Eqs. (36)–(44), the symbols after colons denote corresponding dual variables for each constraint: $\mu_{1,j,t}$ and $\mu_{2,j,t}$ are dual multipliers of nodal active/reactive power balance equations; $\mu_{3,ij,t}$ corresponds to voltage drop equality constraints; $B_{1,ij,t}$ sim $B_{4,ij,t}$ are dual variables for second-order cone power flow relaxation; and $\lambda_{1,t}$ sim $\lambda_{10,t}$ represent dual multipliers of generator, DG, and nodal voltage upper/lower bound inequalities.

IV. CONSTRUCTION AND SOLUTION OF DRCC-BASED DISTRIBUTION MARKET CLEARING MODEL FOR HEIMG

To address bidding risks arising from volatile photovoltaic generation in HEIMG operations, this section embeds the DRCC framework into the bidding formulation. In addition, to resolve computational difficulties stemming from the model's non-convexity and nested bi-level structure, primal-dual optimality conditions are employed to convert the bi-level model into a single-level MPEC, which is further recast as a tractable MISOCP formulation.

A. Construction of the bidding model

Faced with PV output uncertainty in HEIMG, inflexible execution of trading strategies derived from deterministic PV scenarios will increase system operating costs and may result in load shedding for internal demands. This paper characterizes PV generation uncertainty via chance constraints and adopts a distributionally robust optimization approach to cope with the corresponding power balance constraints.

A.1 Development of a DRCC model based on Wasserstein distance

To handle the output uncertainty of distributed photovoltaic generation, the random variable $\xi_t = P_{PV,t}$ is defined. The corresponding chance constraint originally shown in Eq. (32) is formulated as Eq. (45).

$$\mathbb{P}\{a(x_t)\xi_t + b_t(x_t) \leq 0\} \geq 1 - \eta \quad (45)$$

$$a(x_t) = 1 \quad (46)$$

$$b(x_t) = \sum_{m=1}^{N_{MT}} P_{MT,t} + P_{grid,t} - \sum_{ag=1}^{N_{ag}} P_{ag,t} - \sum_{ca=1}^{N_{ca}} P_{ca,t} - \sum_{ep=1}^{N_{ep}} P_{ep,t} - \sum_{cas=1}^{N_{cas}} P_{cas,t} - \sum_{ir=1}^{N_i} P_{ir,t} - \sum_{r=1}^{N_r} P_{rc,t} - P_{br,t} - P_{load,t} \quad (47)$$

where the decision variable is denoted by x_t , $\mathbb{P}\{\cdot\}$ is the probability that the inequality constraint holds, and $1 - \eta$ is the confidence level of the chance constraint.

Since the exact probability distribution of the random variable ξ_t cannot be easily acquired, Eq. (45) cannot be solved directly. Most existing studies simplify this problem by approximating the uncertainty with a fixed deterministic probability distribution. Equation (45) can be converted into a DRCC model based on historical operation data in practical modeling. The core concept of distributionally robust optimization (DRO) is to guarantee constraint feasibility under the worst-case probability distribution within an ambiguity set constructed from historical sample data [21]. This paper adopts the Wasserstein metric to build the DRCC model. The Wasserstein metric can accurately quantify the divergence between different probability distributions and has been extensively utilized for the formulation and solution of distribution-

ally robust optimization models in recent years [22]. The detailed implementation steps are presented as follows.

First, Eq. (45) is conservatively approximated by into a CvaR constraint, as formulated in Eq. (48). This transformation converts the probabilistic constraint into an expectation-based form and simplifies subsequent solving procedures. Furthermore, the expectation term in Eq. (48) is expressed as the maximum of two linear functions, as given in Eq. (49)

$$\inf_{\beta_t} (\mathbb{E}[(a(x_t)\xi_t + b(x_t) - \beta_t)_+] + \eta\beta_t) \leq 0 \quad (48)$$

$$(a(x_t)\xi_t + b(x_t) - \beta_t)_+ + \eta\beta_t = \max_{v=1,2} \{a_{t,v}\xi_t + b_{t,v}(x_t, \beta_t)\} \quad (49)$$

where $\mathbb{E}[\cdot]$ is the expected value under distribution $\mathbb{P}$, $(\cdot)_+ = \max\{\cdot, 0\}$, and $\inf\{\cdot\}$ denotes the infimum over the auxiliary variable β_t . $a_{t,1}(x) = a(x_t) = 1$, $b_{t,1}(x, \beta_t) = b(x_t) - (1 - \eta)\beta_t$, and $a_{t,2}(x) = 0$; $b_{t,2}(x, \beta_t) = \eta\beta_t$.

The DRCC based on the Wasserstein metric belongs to the DRO framework [23]. This method constructs ambiguity sets via the Wasserstein metric to characterize uncertainties and guarantees decision-making reliability against distribution perturbations through chance constraints [24], [25]. Specifically, taking ε as the radius of the Wasserstein ball, the l_1 -norm is adopted to quantify the distance between probability distributions, and the polyhedron containing random variable ξ_t is defined as $\Xi = \{\xi_t | C\xi_t \leq d\}$. Here, a larger ε corresponds to a wider coverage of probability distributions within the ambiguity set, higher risk aversion of the model, and more conservative scheduling strategies [26], [27]. To satisfy the physical characteristic that distributed generators yield non-negative power output, we set $C = -I$ and $d = 0$. On this basis, the original CVaR equivalent expression of the chance constraint is converted into the following DRCC formulation by applying strong duality theory and linear decomposition techniques

$$\begin{cases} \lambda_t \varepsilon + \frac{1}{N} \sum_{u=1}^N s_{t,u} \leq 0 & \forall t \leq T \\ b_t(\mathbf{x}_t) - (1 - \eta)\beta_t + (1 + \gamma_{t,u,1})\hat{\xi}_t \leq s_{t,u} \\ \eta\beta_t + \gamma_{t,u,2}\hat{\xi}_t \leq s_{t,u} \\ \|\gamma_{t,u,1} + 1\|_\infty \leq \lambda_t \\ \|\gamma_{t,u,2}\|_\infty \leq \lambda_t \\ \gamma_{t,u,v} \geq 0 & \forall t \leq T, \forall u \leq N, \forall v \leq 2 \end{cases} \quad (50)$$

where $\gamma_{t,uv}$ is the dual vector corresponding to the polyhedral set, $s_{t,u}$ is the slack auxiliary variable for sample u at time t , λ_t is the dual variable associated with the Wasserstein ball radius, $\hat{\xi}_t$ is the u^{th} sample of the random variable ξ_t , and N is the total number of samples.

The above CVaR approximation method under DRCC constraints transforms the HEIMG bidding model, which incorporates the uncertainty of PV output, into a SOCP that can be solved directly. The model is expressed as follows

$$\begin{cases} \min \sum_{t=1}^{N_t} (C_{e,t} + C_{g,t} + C_{p,t}) \\ \text{s.t. (2)–(31), (33), (34), (47), (50)} \end{cases} \quad (51)$$

B. DRCC-based HEIMG bidding MPEC model for the distribution market

For the bi-level bidding problem of HEIMG participating in the distribution market, direct acquisition of the global optimal solution is challenging owing to its nested structure and non-convex characteristics. To lower the computational complexity of solving this bi-level programming problem, this paper adopts the primal-dual equivalence transformation to recast the lower-level optimization into an MPEC model. The detailed transformation steps are presented as follows.

To derive the dual constraints corresponding to the line flow constraints after second-order conic relaxation, two auxiliary variables $l_{1,ij,t}$ and $l_{2,ij,t}$ are introduced, as defined in Eqs. (52) and (53), where $\chi_{ij,t}$ and $\delta_{ij,t}$ are the dual variable. Subsequently, the first-order partial derivatives of variables in the lower-level Lagrangian function are calculated to yield the equality constraints of the dual problem, as shown in Eqs. (54)–(64). Meanwhile, the inequality constraints of the dual problem are formulated in Eqs. (65) and (66).

$$l_{1,ij,t} = I_{ij,t} - U_{i,t} : \chi_{ij,t} \quad (52)$$

$$l_{2,ij,t} = I_{ij,t} + U_{i,t} : \delta_{ij,t} \quad (53)$$

$$\mu_{1,j,t} - \mu_{1,i,t} - 2R_{gj}\mu_{3,ij,t} - 2B_{2,ij,t} = 0 \quad (54)$$

$$\mu_{2,j,t} - \mu_{2,i,t} - 2X_{gj}\mu_{3,ij,t} - 2B_{3,ij,t} = 0 \quad (55)$$

$$C_{G,t} + \mu_{1,j,t} - \lambda_{1,t} + \lambda_{2,t} = 0 \quad (56)$$

$$\mu_{2,j,t} - \lambda_{3,t} + \lambda_{4,t} = 0 \quad (57)$$

$$C_{DG,t} + \mu_{1,j,t} - \lambda_{5,t} + \lambda_{6,t} = 0 \quad (58)$$

$$\mu_{2,j,t} - \lambda_{7,t} + \lambda_{8,t} = 0 \quad (59)$$

$$-C_{grid,t} + \mu_{1,j,t} = 0 \quad (60)$$

$$-R_{ij}\mu_{1,j,t} - X_{ij}\mu_{2,j,t} + (R_{ij}^2 + X_{ij}^2)\mu_{3,ij,t} - \chi_{ij,t} - \delta_{ij,t} = 0 \quad (61)$$

$$-\mu_{3,ij,t} + \mu_{3,jk,t} - \lambda_{9,t} + \lambda_{10,t} = 0 \quad (62)$$

$$-B_{4,ij,t} + \chi_{ij,t} = 0 \quad (63)$$

$$B_{1,ij,t} + \delta_{ij,t} = 0 \quad (64)$$

$$\|B_{2,ij,t}, B_{3,ij,t}, B_{4,ij,t}\|_2 \leq B_{1,ij,t} \quad (65)$$

$$\lambda_{1,t}, \lambda_{2,t}, \lambda_{3,t}, \lambda_{4,t}, \lambda_{5,t}, \lambda_{6,t}, \lambda_{7,t}, \lambda_{8,t}, \lambda_{9,t}, \lambda_{10,t} \geq 0 \quad (66)$$

As dictated by the strong duality theorem, the primal and dual lower-level optimization models yield the same objective value. The equality constraint satisfying strong duality for the lower model is therefore given in Eq. (67).

$$\begin{aligned} C_{G,t}P_{G,t} + \sum_{DG=1}^{N_{DG}} C_{DG,t}P_{DG,t} - C_{grid,t}P_{grid,t} = \\ -(\mu_{1,j,t}P_{L,j,t} + \mu_{2,j,t}Q_{L,j,t}) + (\lambda_{1,t}P_{G,j,\min} - \lambda_{2,t}P_{G,j,\max}) \\ + (\lambda_{3,t}Q_{G,j,\min} - \lambda_{4,t}Q_{G,j,\max}) + (\lambda_{5,t}P_{DG,j,\min} - \lambda_{6,t}P_{DG,j,\max}) \\ + (\lambda_{7,t}Q_{DG,j,\min} - \lambda_{8,t}Q_{DG,j,\max}) + (\lambda_{9,t}(U_{j,\min})^2 - \lambda_{10,t}(U_{j,\max})^2) \end{aligned} \quad (67)$$

Finally, the DRCC-based HEIMG bidding MPEC model for distribution power markets is formulated as follows

$$\begin{cases} \min \sum_{t=1}^{N_t} (C_{e,t} + C_{g,t} + C_{p,t}) \\ \text{s.t. (2)–(31), (33), (34), (47), (50), (52)–(66)} \end{cases} \quad (68)$$

C. Model linearization

In the DRCC-based HEIMG bidding MPEC model for the distribution market, the objective function and constraints involve the nonlinear term $C_{grid,t}$ and $P_{grid,t}$, which can be eliminated by virtue of the relation presented in Eq. (67). Moreover, the dual variables in Eq. (67) are linearized via the complementarity constraints derived from the KKT conditions of the primal lower-level problem. Linearization is further performed via the big-M method, where y stands for the binary variable and M is a sufficiently large positive constant. Following this transformation, the complementarity constraints are ultimately reformulated as Eqs. (69)–(78).

$$\begin{cases} 0 \leq P_{G,j,t} - P_{G,j,\min} \leq (1 - y_{1,t})M \\ 0 \leq \lambda_{1,t} \leq y_{1,t}M \end{cases} \quad (69)$$

$$\begin{cases} 0 \leq P_{G,j,\max} - P_{G,j,t} \leq (1 - y_{2,t})M \\ 0 \leq \lambda_{2,t} \leq y_{2,t}M \end{cases} \quad (70)$$

$$\begin{cases} 0 \leq Q_{G,j,t} - Q_{G,j,\min} \leq (1 - y_{3,t})M \\ 0 \leq \lambda_{3,t} \leq y_{3,t}M \end{cases} \quad (71)$$

$$\begin{cases} 0 \leq Q_{G,j,\max} - Q_{G,j,t} \leq (1 - y_{4,t})M \\ 0 \leq \lambda_{4,t} \leq y_{4,t}M \end{cases} \quad (72)$$

$$\begin{cases} 0 \leq P_{DG,j,t} - P_{DG,j,\min} \leq (1 - y_{5,t})M \\ 0 \leq \lambda_{5,t} \leq y_{5,t}M \end{cases} \quad (73)$$

$$\begin{cases} 0 \leq P_{DG,j,max} - P_{DG,j,t} \leq (1 - y_{6,t})M \\ 0 \leq \lambda_{6,t} \leq y_{6,t}M \end{cases} \quad (74)$$

$$\begin{cases} 0 \leq Q_{DG,j,t} - Q_{DG,j,min} \leq (1 - y_{7,t})M \\ 0 \leq \lambda_{7,t} \leq y_{7,t}M \end{cases} \quad (75)$$

$$\begin{cases} 0 \leq Q_{DG,j,max} - Q_{DG,j,t} \leq (1 - y_{8,t})M \\ 0 \leq \lambda_{8,t} \leq y_{8,t}M \end{cases} \quad (76)$$

$$\begin{cases} 0 \leq U_{j,t} - U_{j,min}^2 \leq (1 - y_{9,t})M \\ 0 \leq \lambda_{9,t} \leq y_{9,t}M \end{cases} \quad (77)$$

$$\begin{cases} 0 \leq U_{j,max}^2 - U_{j,t} \leq (1 - y_{10,t})M \\ 0 \leq \lambda_{10,t} \leq y_{10,t}M \end{cases} \quad (78)$$

In summary, the HEIMG bidding nonlinear programming problem, which accounts for the uncertainty in PV output, is transformed into a mixed-integer SOCP for solution:

$$\begin{cases} \min \sum_{t=1}^{N_t} \left[C_{g,t} + C_{p,t} + (\mu_{1,j,t} P_{L,j,t} + \mu_{2,j,t} Q_{L,j,t}) - \right. \\ \left. (\lambda_{1,t} P_{G,j,min} - \lambda_{2,t} P_{G,j,max}) - (\lambda_{3,t} Q_{G,j,min} - \lambda_{4,t} Q_{G,j,max}) - \right. \\ \left. (\lambda_{5,t} P_{DG,j,min} - \lambda_{6,t} P_{DG,j,max}) + C_{G,t} P_{G,t} - (\lambda_{7,t} Q_{DG,j,min} - \right. \\ \left. \lambda_{8,t} Q_{DG,j,max}) - \lambda_{9,t} (U_{j,min})^2 + \lambda_{10,t} (U_{j,max})^2 + \right. \\ \left. \sum_{DG=1}^{N_{DG}} C_{DG,t} P_{DG,t} \right] \\ \text{s.t. } (2)-(31), (33), (34), (47), (50), (52)-(67), (69)-(78) \end{cases} \quad (79)$$

V. CASE STUDY ANALYSIS

To test the practical performance of the HEIMG bidding formulation proposed in this paper, a case study is conducted based on a 33-bus distribution network and a practical HEIMG. The system configuration is illustrated in Fig. 3. The HEIMG is connected to bus 4 of the IEEE 33-bus distribution network for subsequent nodal-price calculation and market-bidding analysis. The outdoor temperature and solar irradiance profiles are presented in the Fig. 4.

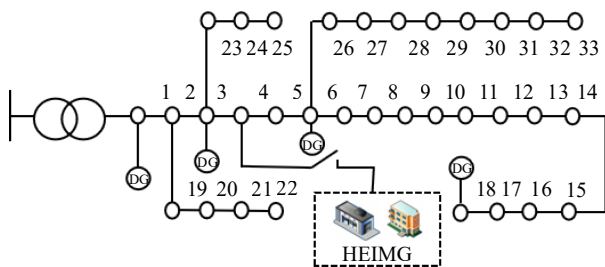


Fig. 3. Structure of the 33-bus distribution system.

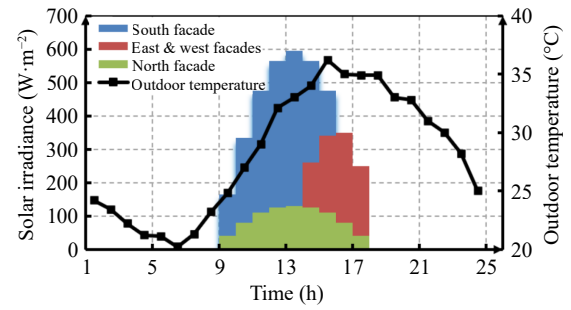


Fig. 4. Solar radiation of building wall and ambient temperature.

As shown in Table 1, the HEIMG consists of a 600 kW PV system, a heating system equipped with a 600 kW micro-gas turbine and a 200 kW electric boiler, a cooling system composed of six 500 kW air-conditioning units, and a 300 kW compressed air system. The industrial park comprises six factory buildings and four office buildings, with indoor temperature ranges of 38–40 and 20–25 °C, respectively. The production task parameters and building envelope parameters are adopted from [28] and [19], respectively.

TABLE 1
SYSTEM PARAMETERS OF THE INDUSTRIAL PARK MICROGRID.

Equipment name	Rated power (kW)	Quantity
Micro gas turbine	600	1
Photovoltaic system	600	1
Electric boiler	200	1
Air conditioning system	500	6
Compressed air system	300	1

To verify the feasibility of the HEIMG bidding strategy that accounts for PV output uncertainties, this paper designs three cases and conducts a comparative analysis of the bidding schemes, distribution market clearing outcomes, and system economic performance.

Case 1: PV output is modeled as deterministic, the controllability of industrial production processes is not considered, and production equipment operates according to a fixed daily schedule.

Case 2: PV output is modeled as deterministic, while the controllability of industrial production processes is considered.

Case 3: HEIMG applies the bidding model proposed in this paper, which incorporates DRCC ($\varepsilon = 0.15$, $\eta = 0.1$).

A. Analysis of HEIMG bidding strategies

A.1 Impacts of HEIMG production process regulation on HEIMG energy management

To analyze how adjustable production processes affect the energy management of HEIMG, Fig. 5 presents the production power consumption in cases 1 and 2. The production equipment inside the park includes two electrode preparation units, two cell assembly units, three battery aging units, and one compressed air system.

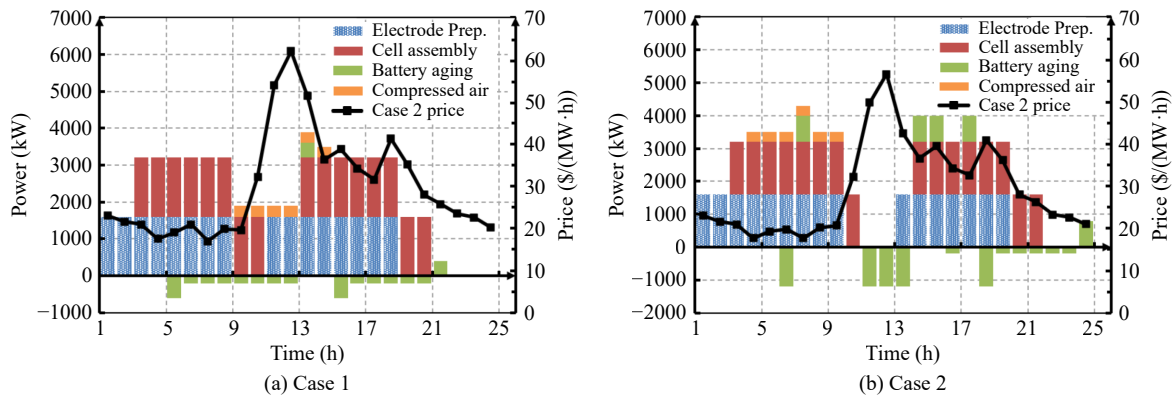


Fig. 5. Power consumption of production processes in different cases.

In case 1, production processes do not participate in demand response, and the operation periods of each production unit are fixed. In case 2, the production schedule can be flexibly adjusted to optimize power consumption in response to electricity price signals. Considering time-varying electricity prices, the following section analyzes the differences in park-level electric load profiles between the two cases to reveal the impacts of production-side demand response on the park's power management strategies.

Under the constraints of total daily output and hourly unit capacity, each electrode preparation unit and each cell assembly unit operate for a fixed duration of 16 h per day. Compared with case 1, case 2 optimizes the operation schedules of these production units by shifting operation across time intervals. During the peak electricity price window of 10:00–14:00, the output of electrode preparation units and cell assembly units drops substantially, and the overall production load is transferred to the low-price period 16:00–21:00. Notably, all these units fully halt production from 11:00 to 13:00 when prices reach their peak. Despite the favorable electricity prices during 21:00–24:00, the system does not schedule operation for these production units within this window. The core goal is to reserve sufficient lead time for the three downstream battery aging units and guarantee seamless coordination of the full production sequence.

Compared with case 1, all three battery aging units are scheduled to perform discharge aging during the peak-price window of 11:00–13:00 in case 2. Charge aging is prioritized during relatively low-price hours, namely, 07:00 and 24:00. It is noteworthy that multiple battery aging units are still scheduled for charge aging during 14:00–15:00 and 17:00 under relatively high electricity prices, while discharge aging is scheduled at 06:00 when prices remain low. Such scheduling decisions do not merely follow price signals; the primary motivation is to satisfy process sequence constraints and guarantee the orderly coordination of the entire production sequence.

Conveying equipment in both electrode preparation units and cell assembly units is driven by compressed air. In case 1 without production-side demand response, the air compressor operates synchronously with production schedules to maintain continuous air supply during production periods. By contrast,

case 2 fully accounts for electricity price variations across time slots and leverages the energy storage capability of compressed air tanks to shift the air consumption load over time. The optimization results reveal that case 2 reschedules air compressor operation to the low-price window of 04:00–09:00. Compressed air is produced and stored in tanks in advance during off-peak hours at low electricity prices. In subsequent high-load periods of electrode preparation and cell assembly units, stored compressed air is released to meet air demand. This strategy fully exploits the peak-shaving potential of air storage facilities and reduces the overall electricity cost of the industrial park.

The case study results verify that when production-side demand response is incorporated, each production process can flexibly adjust its power consumption schedule in response to electricity price fluctuations to realize peak shaving and valley filling. By boosting production loads during off-peak periods and appropriately curbing power consumption at peak-price hours, the proposed strategy fully exploits the economic benefits of price differences, which markedly reduces the overall electricity cost of the industrial park. These results provide an effective optimization scheme for industrial consumers to participate in distribution market transactions and reduce overall energy costs.

A.2 Analysis of HEIMG bidding strategies

As introduced in Section 2.2, DLMP is represented by the dual multiplier $\mu_{1,j,t}$ associated with nodal active power balance constraints. The time-series DLMP curves illustrated in Fig. 6(b) correspond to the values of $\mu_{1,4,t}$ at bus 4. Figure 6 presents the power trading decisions of cases 1 and 2, where the traded power volumes are shown in Fig. 6(a). Without considering the demand response capability of industrial production, all production schedules in case 1 are fixed, and the electric loads cannot be dynamically optimized in response to electricity price signals. Consequently, the park's hourly purchased power remains relatively flat throughout the day, failing to capture economic benefits from peak-valley electricity price differences. As shown in Fig. 6(b), case 2 schedules the battery aging units to operate in discharge mode during the price peak window of 11:00–13:00, generating reverse power flow in which the industrial park delivers electricity back to

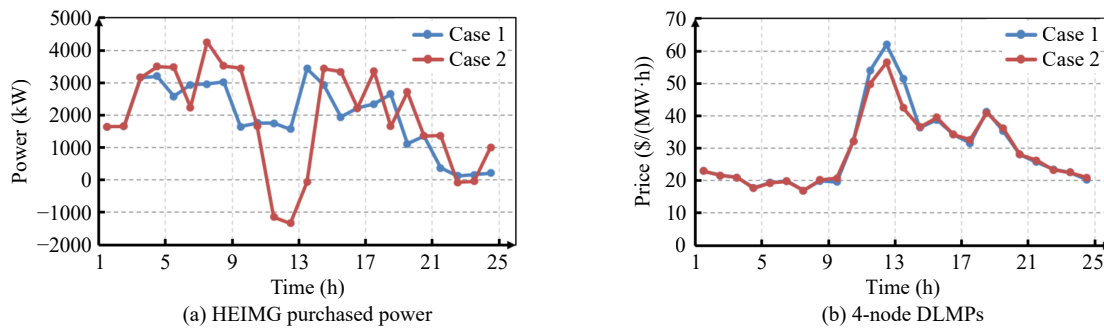


Fig. 6. HEIMG trading results under different cases.

the upstream distribution network. During the relatively low-price period of 15:00–21:00, the purchased power of case 2 is generally higher than that of case 1. The model schedules production processes within this time window to shift power loads to this low-price period.

Beyond power-dispatch optimization, noticeable improvements can also be observed from the electricity-price perspective. As shown in Fig. 6(b), during 11:00–13:00, when the industrial park feeds power back to the upstream distribution network in case 2, the DLMP at bus 4 drops considerably compared with case 1. By shifting flexible production loads away from peak-price intervals, the production-side demand response reduces net power injection at bus 4 and relieves local branch congestion around this connection node. Consequently, congestion during peak hours is effectively alleviated, further lowering the nodal price for this period.

In summary, the bi-level optimal scheduling model for the HEIMG established in this paper possesses twofold advantages. On the one hand, it leverages flexible resources from lithium-ion battery production processes to optimize the park's power consumption profiles and reduces the comprehensive operating cost of the industrial-park microgrid by responding to electricity-price signals. On the other hand, load-profile reconstruction improves the power flow conditions of the distribution network, mitigates line congestion, and reduces the DLMP. Thus, coordinated optimal operation between the industrial-park microgrid and the upstream distribution network is achieved.

B. Economic and risk analysis

Differences in the HEIMG bidding schemes simultaneously affect the economic benefits and operational risks for both HEIMG and the distribution network. Table 2 presents the economic and risk comparisons among the three scenarios for HEIMG and the distribution network. Case 1 adopts a deter-

ministic bidding strategy. Without exploiting the demand response capability of industrial production processes, the power-purchase plan is formulated solely based on the forecasted PV output. Consequently, the HEIMG's power-purchase cost and total operating cost are \$1543 and \$1957, respectively, while the operating cost of the DSO is as high as \$3883. The system fails to shift energy-intensive production processes to periods with high PV generation and low electricity prices, resulting in high power-purchase volumes during peak hours. Consequently, the operating costs of both the microgrid and the distribution network are the highest among the three cases.

Case 2 also performs bidding optimization based on a deterministic PV model. It fully leverages flexible industrial loads to realize load peak-shifting. Production processes are rescheduled to periods with abundant PV output, which effectively reduces the peak power demand from the external grid. The microgrid's power-purchase cost and total operating cost drop to \$1146 and \$1552, respectively. With smoothed load profiles, branch congestion and line losses in the distribution network are reduced simultaneously, and the DSO operating cost decreases to \$3410. Thus, case 2 yields the best economic performance within the deterministic framework.

Case 3 adopts the proposed DRCC-based bidding model. The optimization considers PV output fluctuations, and power reserves are allocated in advance to handle extreme low-irradiance conditions. The microgrid's power-purchase cost and total operating cost increase slightly to \$1152 and \$1559, respectively, and the DSO operating cost rises to \$3417. Compared with case 2, the total operating cost of the microgrid in case 3 increases by only 0.523%, while the distribution-network operating cost grows by only 0.26%. The additional cost required to mitigate PV output fluctuations is relatively small.

To quantify the operational risks of different scheduling strategies against PV uncertainties, CVaR is calculated offline

TABLE 2
ECONOMIC AND RISK COMPARISON RESULTS UNDER DIFFERENT CASES

Case No.	HEIMG power purchase cost (\$)	HEIMG total operating cost (\$)	DSO operating cost (\$)	CVaR (kW)
Case 1	1543	1957	3883	61.79
Case 2	1146	1552	3410	45.25
Case 3	1152	1559	3419	25.63

via the Monte Carlo sampling method. One hundred random samples are generated based on the PV forecast series. Cases 1 and 2 perform deterministic scheduling using forecast values, whereas case 3 adopts the proposed DRCC-based HEIMG bidding model with $\varepsilon = 0.15$ and a confidence level of 0.9. After the optimal scheduling strategies for the three cases are obtained, all random samples are imported into the simulation. Only positive power deficits are counted for each case, and CVaR is computed as the average of the top 10% most extreme samples.

The simulation results show that the CVaR values of cases 1–3 are 61.79, 45.25, and 25.63 kW, respectively. Case 1 lacks flexible load adjustment measures and yields the largest power deficit under PV disturbances. Case 2 reduces operational risks moderately through industrial demand response; however, random PV disturbances are not incorporated into its optimization, and the bidding strategy has no adaptive adjustment capability. Hence, considerable power deficit risks still exist under extreme irradiance conditions. By contrast, case 3 proactively avoids extreme scenarios in the optimization stage. It jointly leverages industrial demand response, micro gas turbines, and purchased power to hedge against power deficits. Its CVaR decreases by 58.52% and 43.36% compared with cases 1 and 2, respectively, which substantially mitigates economic losses caused by stochastic PV fluctuations.

C. Sensitivity analysis of DRCC parameters

C.1 Impacts of confidence level on scheduling

The confidence level directly determines the coverage of stochastic PV scenarios by the ambiguity set, which further results in different optimization benchmarks for PV output. It alters the power-balance constraints and day-ahead scheduling of the industrial-park microgrid, and significantly affects the system's power-purchase cost and expected operating cost in terms of load dispatch and external power purchase.

Figure 7 presents the PV output samples and the corresponding power curves of case 3 under different confidence levels. Figure 7(a) shows 100 stochastic PV output samples generated from the baseline PV forecast time series. All samples fluctuate around the baseline output curve. Daytime PV fluctuations mainly occur from 9:00 to 19:00, with the output peak appearing near 15:00. The dispersion of samples intuitively

reflects the stochastic fluctuation characteristics of PV generation during the day.

Figure 7(b) presents the equivalent available PV output from the optimization in case 3 when the confidence level is set to 0.75, 0.8, 0.9, 0.95, and 0.99. The equivalent available PV output exhibits an overall negative correlation with the confidence level. A lower confidence level relaxes the uncertainty constraints and increases PV accommodation. The daily equivalent PV output shifts upward, and the scheduling scheme becomes more aggressive. However, the probability of power imbalance under stochastic disturbances increases, and the system's operational risk rises accordingly.

Conversely, a higher confidence level imposes stricter constraints on extreme PV drop scenarios. To guarantee system power balance with high probability, the conservative available PV output gradually decreases, and the corresponding output curve shifts downward. Under such circumstances, HEIMG sacrifices part of its PV generation revenue to obtain a bidding strategy with higher robustness and lower power-deficit risk. In engineering practice, lower confidence levels correspond to higher available PV power and larger operational risks, while higher confidence levels reduce available PV generation but effectively mitigate power deficit risks. In summary, tuning the confidence level can directly adjust the constraint boundary of conservative available PV output and flexibly adjust the conservativeness of HEIMG scheduling strategies. It provides a parameter-tuning tool for scheduling decisions under diverse operating conditions and various risk-control requirements.

As a core risk constraint parameter of the distributionally robust optimization model, the confidence level directly modifies the intraday optimal power trading strategies of HEIMG. Figure 8 illustrates the power-purchase cost of HEIMG under different confidence levels when the Wasserstein ball radius is set to 0.15. At low confidence levels, the system can fully accommodate PV output and reduce power purchased from the external grid, thereby effectively cutting the power-purchase cost. As the confidence level increases, the model imposes tighter control over extreme low-PV-output scenarios. The available PV output is reduced, and the internal power deficit of the system grows. More power needs to be procured from the external grid to fill the supply-demand gap, which ultimately drives up the power-purchase cost.

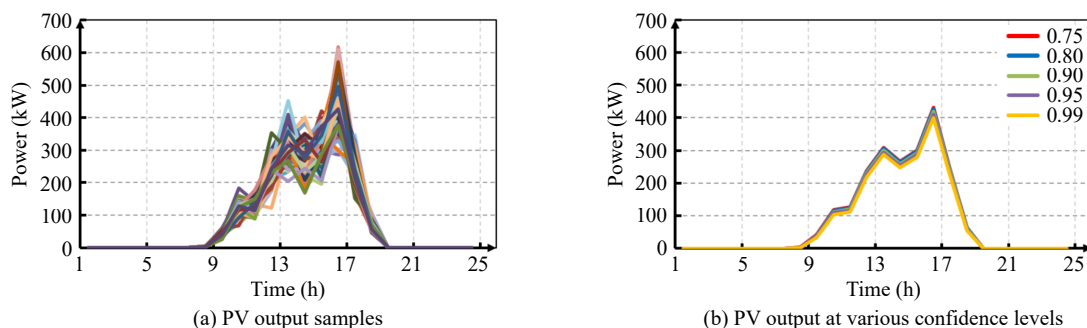


Fig. 7. PV Output samples and profiles at various confidence levels.

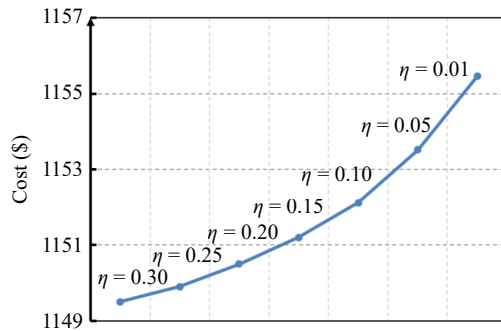


Fig. 8. Costs under various confidence levels.

Meanwhile, the increase in power-purchase cost is most pronounced within the confidence-level range of 0.9–0.99, while cost variations become moderate in other intervals. Within this range, the conservatism of the model rises sharply, the available PV output shrinks, and power procurement from the external grid increases. Accordingly, the slope of the power-purchase cost curve is larger than that in other intervals. When the confidence level drops to 0.9, the available PV output approaches the sample mean, and the daytime PV generation potential is almost fully exploited. Further reducing the confidence level to 0.75 relaxes the chance constraints and increases the conservative available PV output. The model no longer needs to hold substantial power reserves against extreme low-PV scenarios, so distributed PV can achieve a higher degree of on-site accommodation, and the power-purchase cost continues to decline moderately. This characteristic prevents HEIMG from blindly adopting low-confidence-level bidding strategies in exclusive pursuit of economic benefits and guarantees the rationality and stability of bidding strategies.

C.2 Impacts of Wasserstein-ball radius on scheduling

Compared with the deterministic model without uncertainty constraints, the adoption of DRCC leads to a higher system power-purchase cost, which is positively correlated with the Wasserstein ball radius ε . Figure 9 presents the HEIMG power-purchase cost under different ball radii when the confidence level is fixed at 0.9. A smaller ball radius results in less conservative robust constraints. The optimization results approach the deterministic optimal solution and achieve better

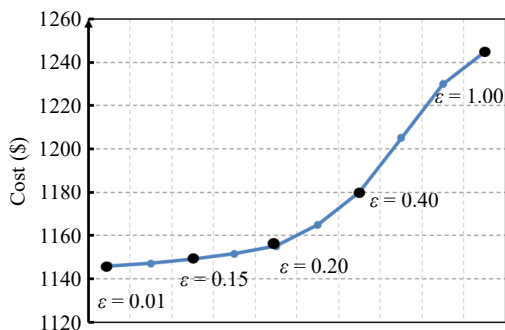


Fig. 9. Costs under various ball radii.

economic performance. As the ball radius increases, more extreme PV output scenarios are covered by the ambiguity set, the scheduling strategy becomes more conservative, and the power-purchase cost increases. Furthermore, the cost evolves through three successive stages with increasing radius: gentle growth, rapid growth, and plateau.

When ε lies in the gentle-growth interval of 0.01–0.20, a small ε limits the maximum allowable deviation of probability distributions from the empirical distribution, so the model considers only a narrow range of extreme output scenarios. To satisfy the chance constraints, only a small amount of demand-response resources or additional power procurement from the distribution network needs to be deployed for selected time periods, resulting in mild cost growth. As the radius expands gradually into the rapid-growth interval of 0.20–0.40, ε accurately covers the main distribution range of historical PV forecast errors. The ambiguity set encompasses most pessimistic PV-output scenarios. The economic cost of further expanding the ambiguity set keeps increasing, whereas the marginal gains from robustness improvement keep diminishing.

After crossing the rapid-growth region, ε enters the plateau region ranging from 0.4 to 1.0. The worst-case distribution corresponding to this region covers not only the most severe scenarios observed in historical samples, but also harsher physically feasible operating conditions not observed in historical samples. The boundary of the ambiguity set reaches the upper limit for this case. The room for covering additional pessimistic scenarios is greatly reduced, and accordingly the growth rate of scheduling cost slows down significantly.

In summary, ε plays a decisive role in the economic performance of the DRCC scheduling scheme. If an excessively small radius is adopted, the system operating cost is close to the deterministic result. Nevertheless, the coverage of the ambiguity set becomes insufficient. When the actual PV output drops significantly below the forecast value, active power deficits occur, and the high cost of temporary power procurement introduces extra economic losses. By contrast, an overly large radius leads to an excessively conservative scheduling strategy and a rapid increase in power-purchase cost. According to the case-study results, setting ε around 0.2 balances operating cost and robustness, which is the recommended parameter range that balances system economic performance and robustness. From the perspective of parameter influence scope, the Wasserstein ball radius exerts a dominant macroscopic effect on the power-purchase cost, whereas the confidence level serves as a fine-tuning variable. Under most operating conditions, the cost variation induced by adjusting the confidence level is less than \$10.

VI. CONCLUSION

To mitigate dispatch risks induced by photovoltaic output uncertainty when HEIMG participates in distribution market transactions, this paper develops a Wasserstein-distance-based DRCC bi-level optimization framework, where industrial pro-

duction demand response is incorporated into industrial park energy management to balance the economic performance and operational risks of scheduling schemes. Conservative CVaR approximation and duality theory are utilized to convert the original bi-level DRCC model into a tractable MISOCP formulation for numerical computation. The proposed energy management strategy fully exploits the adjustable demand response characteristics of industrial production processes. Production loads are dynamically regulated in response to DLMP signals: energy-intensive production processes are scheduled in low-price periods, whereas production power consumption is reduced in high-price intervals, substantially lowering the total operating cost of HEIMG. Simulation results demonstrate that reasonable confidence levels and Wasserstein ball radii selected from historical PV sample data can achieve a flexible trade-off between system conservatism and operational costs. The proposed framework provides rigorous theoretical and technical support for market-driven optimal dispatch of high-energy-consuming industrial microgrids under volatile PV generation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work is carried out without the support of any funding agency.

Use of AI statement

None.

REFERENCES

- [1] A. Muhtadi, D. Pandit, N. Nguyen, and J. Mitra, "Distributed energy resources based microgrid: review of architecture, control, and reliability," *IEEE Trans. Ind. Appl.*, vol. 57, no. 3, pp. 2223–2235, May/Jun. 2021.
- [2] M. Mansourlakouraj, M. Shahabi, M. Shafie-Khah, and J. P. S. Catalão, "Optimal market-based operation of microgrid with the integration of wind turbines, energy storage system and demand response resources," *Energy*, vol. 239, pp. 122156, Jan. 2022.
- [3] X. Ding, J. Xu, Y. Z. Sun, S. Y. Liao, and J. W. Zheng, "A demand side controller of electrolytic aluminum industrial microgrids considering wind power fluctuations," *Prot. Control Mod. Power Syst.*, vol. 7, no. 1, pp. 49, Dec. 2022.
- [4] Y. M. Ding, S. H. Hong, and X. H. Li, "A demand response energy management scheme for industrial facilities in smart grid," *IEEE Trans. Ind. Inf.*, vol. 10, no. 4, pp. 2257–2269, Nov. 2014.
- [5] F. Y. Xu and L. L. Lai, "Novel active time-based demand response for industrial consumers in smart grid," *IEEE Trans. Ind. Inf.*, vol. 11, no. 6, pp. 1564–1573, Dec. 2015.
- [6] X. X. Long, Y. Z. Li, Y. Li, L. J. Ge, H. B. Gooi, and C. Chung, "Collaborative response of data center coupled with hydrogen storage system for renewable energy absorption," *IEEE Trans. Sustainable Energy*, vol. 15, no. 2, pp. 986–1000, Apr. 2024.
- [7] S. Paudyal, C. A. Cañizares, and K. Bhattacharya, "Optimal operation of industrial energy hubs in smart grids," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 684–694, Mar. 2015.
- [8] J. D. Wei, Y. Zhang, J. X. Wang, and L. Wu, "Distribution LMP-based demand management in industrial park via a bi-level programming approach," *IEEE Trans. Sustainable Energy*, vol. 12, no. 3, pp. 1695–1706, Jul. 2021.
- [9] S. Das, O. B. Fosso, and G. Marafioti, "Probabilistic planning of distribution networks with optimal DG placement under uncertainties," *IEEE Trans. Ind. Appl.*, vol. 59, no. 3, pp. 2731–2741, May/Jun. 2023.
- [10] J. D. Wang, Y. C. Shi, and Y. Zhou, "Intelligent demand response for industrial energy management considering thermostatically controlled loads and EVs," *IEEE Trans. Ind. Inf.*, vol. 15, no. 6, pp. 3432–3442, Jun. 2019.
- [11] R. F. Zhang, G. Q. Li, T. Jiang, H. H. Chen, X. Li, W. Pei, and H. Xiao, "Incorporating production task scheduling in energy management of an industrial microgrid: a regret-based stochastic programming approach," *IEEE Trans. Power Syst.*, vol. 36, no. 3, pp. 2663–2673, May 2021.
- [12] C. Huang, H. C. Zhang, Y. H. Song, L. Wang, T. Ahmad, and X. Luo, "Demand response for industrial micro-grid considering photovoltaic power uncertainty and battery operational cost," *IEEE Trans. Smart Grid*, vol. 12, no. 4, pp. 3043–3055, Jul. 2021.
- [13] Y. Li, B. Feng, G. Q. Li, J. J. Qi, D. B. Zhao, and Y. F. Mu, "Optimal distributed generation planning in active distribution networks considering integration of energy storage," *Appl. Energy*, vol. 210, pp. 1073–1081, Jan. 2018.
- [14] H. Abunima, W. H. Park, M. B. Glick, and Y. S. Kim, "Two-stage stochastic optimization for operating a renewable-based microgrid," *Appl. Energy*, vol. 325, pp. 119848, Nov. 2022.
- [15] H. H. Chen, D. Wang, C. Q. Lin, R. F. Zhang, T. Jiang, and X. Li, "Risk-averse optimal scheduling of regional electricity-heating integrated energy system considering interface with microgrids," *CSEE J. Power Energy Syst.*, vol. 11, no. 5, pp. 2117–2127, Sep. 2025.
- [16] J. Yang and C. Q. Su, "Robust optimization of microgrid based on renewable distributed power generation and load demand uncertainty," *Energy*, vol. 223, pp. 120043, May 2021.
- [17] A. Sahebi and S. Jadid, "A robust model of local energy market under a security constraint-based approach for distribution system operator and multi-energy microgrids," *Electr. Power Syst. Res.*, vol. 217, pp. 109164, Apr. 2023.
- [18] H. F. Qiu, W. Gu, X. C. Xu, G. S. Pan, P. X. Liu, and Z. Wu, "A historical-correlation-driven robust optimization approach for microgrid dispatch," *IEEE Trans. Smart Grid*, vol. 12, no. 2, pp. 1135–1148, Mar. 2021.
- [19] R. F. Zhang, T. Jiang, G. Q. Li, X. Li, and H. H. Chen, "Stochastic optimal energy management and pricing for load serving entity with aggregated TCLs of smart buildings: a Stackelberg game approach," *IEEE Trans. Ind. Inf.*, vol. 17, no. 3, pp. 1821–1830, Mar. 2021.
- [20] H. H. Chen, L. B. Fu, L. Q. Bai, T. Jiang, Y. S. Xue, and R. F. Zhang, "Distribution market-clearing and pricing considering coordination of DSOs and ISO: an EPEC approach," *IEEE Trans. Smart Grid*, vol. 12, no. 4, pp. 3150–3162, Jul. 2021.
- [21] P. Mohajerin Esfahani and D. Kuhn, "Data-driven distributionally robust optimization using the Wasserstein metric: performance guarantees and tractable reformulations," *Math. Program.*, vol. 171, no. 1–2, pp. 115–166, Sep. 2018.
- [22] Z. C. Shi, H. Liang, S. J. Huang, and V. Dinavahi, "Distributionally robust chance-constrained energy management for islanded microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2234–2244, Mar. 2019.
- [23] Y. Li, M. Han, M. Shahidepour, J. Z. Li, and C. Long, "Data-driven distributionally robust scheduling of community integrated energy systems with uncertain renewable generations considering integrated demand response," *Appl. Energy*, vol. 335, pp. 120749, Apr. 2023.
- [24] Y. Q. Zhou, W. B. Yu, S. Y. Zhu, B. Yang, and J. P. He, "Distributionally robust chance-constrained energy management of an integrated retailer in the multi-energy market," *Appl. Energy*, vol. 286, pp. 116516, Mar. 2021.
- [25] Y. Guo, K. Baker, E. Dall'Anese, Z. C. Hu, and T. H. Summers, "Data-based distributionally robust stochastic optimal power flow—Part II: Case studies," *IEEE Trans. Power Syst.*, vol. 34, no. 2, pp. 1493–1503, Mar. 2019.

- [26] W. J. Xie, "On distributionally robust chance constrained programs with Wasserstein distance," *Math. Program.*, vol. 186, no. 1-2, pp. 115–155, Mar. 2021.
- [27] S. Zymmler, D. Kuhn, and B. Rustem, "Distributionally robust joint chance constraints with second-order moment information," *Math. Program.*, vol. 137, no. 1-2, pp. 167–198, Feb. 2013.
- [28] X. Ma, W. Pei, H. Xiao, W. Deng, H. W. Xiao, and W. Sun, "Integrated energy network and production management optimization operation of battery production industrial estate considering complex production constraints," *Power Syst. Technol.*, vol. 42, no. 11, pp. 3566–3575, Nov. 2018.



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