Credibility Copula-based Robust Multistage Plan for Industrial Parks Under Exogenous and Endogenous Uncertainties

Zehao Shi, Jiajia Chen, *Member, CSEE*, Yanxin Wang, Yanlei Zhao, and Bingyin Xu

***Abstract*—The integration of photovoltaic and energy storage in industrial parks enhances economic benefits. However, uncertainties in photovoltaic output and future electricity prices pose challenges to optimal configuration. To address these issues, this paper develops a credibility copula-based robust multistage plan. Firstly, it addresses endogenous uncertainties in electricity pricing and exogenous uncertainties in photovoltaic output. Meanwhile, the copula function is used to couple endogenous uncertainties of the time-of-use, on-grid and demand power prices. Secondly, based on credibility theory, a fuzzy chance constraint model of endogenous uncertainties of future electricity prices and exogenous uncertainties of the PV output is derived. Finally, the method transforms fuzzy chance constraints into deterministic robust optimization through clear equivalence classes. Simulation analyses using data from an industrial park validate the applicability and effectiveness of the proposed approach.**

***Index Terms*—Copula coupling, credibility theory, industrial park, multistage planning, uncertainties.**

I. Introduction

In recent years, photovoltaic (PV) and energy storage (ES) technologies have been driving a revolutionary change in power technology [1]. In industrial parks, the integration of PV and ES systems can significantly reduce electricity costs while lowering carbon emissions [2]–[4]. The role of PV and ES in achieving carbon neutrality in industrial parks is explored in [5], with successful applications in various industrial parks worldwide. The study in [6], [7] demonstrates that configuring ES on the user side in conjunction with PV can enhance the proportion of local PV consumption and reduce electricity bills. Therefore, the strategic configuration of PV and ES is crucial for promoting low-carbon and sustainable development, offering significant economic benefits to industrial parks.

It is well understood that uncertainties are the primary factor affecting the optimal configuration of PV and ES systems. However, most studies have predominantly focused on impacts of exogenous uncertainties, such as the volatility, randomness, and intermittency of the PV output. Reference [8] considers impacts of load uncertainties on ES configuration, and proposes an operation strategy of industrial park ES based on random clustering and dynamic identification. Similarly, Reference [9] addresses impacts of uncertainties of the PV output on ES systems, and offers a solution for cost-effective configuration and operation in industrial parks. Despite these advancements, existing studies primarily address exogenous uncertainties of the PV output while neglecting endogenous uncertainties of electricity prices in planning schemes. This oversight is critical, as the configuration of PV and ES can significantly influence future electricity price uncertainties.

With the large-scale access of distributed PV, electricity price uncertainties are further exacerbated, directly affecting the benefits of PV and ES configuration [10]. Reference [11] develops a probabilistic scenario model considering uncertainties of electricity prices, demonstrating a reduction in operating costs for residential energy centers. Similarly, Reference [12] studies impacts of electricity price uncertainties and proposes a two-stage spread arbitrage strategy to balance the interests of users and virtual power plants. Most existing studies regard uncertainties of electricity prices as exogenous uncertainties. However, in practical planning, the configuration of PV and ES significantly affects future electricity price uncertainties [13]. In addition, industrial parks follow a two-part tariff, including a demand tariff charged according to the maximum power consumption of the gateway meter and an electricity tariff charged according to the actual power consumption of the user. Therefore, recognizing the correlation between multiple endogenous electricity prices is crucial, as it will inevitably affect the optimal planning of PV and ES in industrial parks.

The concept of endogenous uncertainties originates from modern economics and can be expressed as decision dependence [14], [15]. Generally speaking, there are two types [16]. The first type is the distribution in which the decision results directly affect future uncertainties. For example, the power generation capacity of PV affects the distribution of future electricity prices [17]. The second type involves decision-making that renders uncertain parameters meaningful through action, where the true value of uncertainties is revealed only after decisions are made [18]. Studies on power systems increasingly consider endogenous uncertainties [19]. Reference [20] incorporates endogenous uncertainties into operational reliability assessment, highlighting impacts of system operation decisions on reliability metrics. Similarly, Reference [21]

Manuscript received December 16, 2024; revised February 6, 2025, accepted March 7, 2025. Date of online publication May 16, 2025, date of current version May 25, 2025. This work was supported by the National Natural Science Foundation of China (No. 52377110).

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DOI: 10.17775/CSEEJPES.2024.09120

examines the interaction between uncertainties and decision-making, and proposes a stage-dependent distribution network plan. In this paper, endogenous uncertainties belong to the first category. That is, uncertainties of future electricity prices will be affected by the configuration of PV and ES.

In the uncertainties planning of PV and ES integrated industrial parks, the main methods used are stochastic programming, robust optimization and fuzzy optimization. Robust optimization describes uncertainties of parameters by uncertain sets, focusing primarily on worst-case scenarios and often neglecting decision-makers' preference characteristics. Reference [22] proposes robust stochastic optimization to ensure user demand by dealing with different degrees of PV uncertain parameters. However, random optimization requires repeated sampling, and the solution efficiency is reduced [23]. Fuzzy optimization uses the basic idea of fuzzy mathematics to model uncertain parameters [24]. Reference [25] develops an energy management model using fuzzy set theory, characterizing electricity price uncertainties with triangular fuzzy numbers. Conventional fuzzy optimization's lack of self-duality in membership functions can lead to decision-making confusion [26]. Unlike conventional methods, credibility theory integrates fuzzy and random measures [27]. In the configuration PV and ES in industrial parks, developing models for endogenous and exogenous uncertainties based on credibility theory is crucial. This involves effectively controlling violations within allowable ranges by defining the credibility level, thereby balancing risks and costs [28]. This research area is significant and currently underexplored in literatures.

To highlight the innovation of this study, Table I presents a comprehensive comparison between this work and relevant literatures in this field. From existing literatures, we note that: 1) PV and ES planning mostly focuses solely on exogenous uncertainties of the PV output while neglecting endogenous price uncertainties. This oversight can reduce the predictability of decision-making outcomes and affect a park's economic benefits. 2) Industrial parks operate under a two-part electricity pricing system, with economic benefits influenced by the on-grid, time-of-use (TOU), and demand prices. However, existing studies often limit their analysis to a single electricity price uncertainty, with few addressing the coupling of multiple types of prices. 3) Conventional uncertainty planning often overlooks fuzzy and random measures. The lack of self-duality in conventional fuzzy optimization membership functions can lead to decision-making confusion. Additionally, planning in industrial parks frequently emphasizes one-time planning while rarely considering multistage approaches.

TABLE I
COMPARISON BETWEEN THIS WORK AND RELEVANT LITERATURE

Reference	Endogenous/ exogenous uncertainties	Demand price/ TOU price/ on-grid price	Price coupling	Fuzzy/ stochastic measure	Multistage planning
[10]	×/√	√/√/×	×	×/×	×
[12]	×/√	×/√/√	×	×/√	×
[13]	×/√	×/√/×	×	×/×	×
[14]	√/×	×/√/√	×	×/√	×
[20]	√/√	×/√/√	×	×/√	×
[21]	√/×	×/×/×	×	×/√	×
[22]	×/√	×/√/×	×	×/×	×
[23]	×/√	×/×/√	×	×/√	×
[25]	√/×	√/√/×	×	×/√	×
[27]	×/√	×/√/√	×	√/×	×
This work	√/√	√/√/√	√	√/√	√

In this context, this paper proposes a credibility copula-based robust multistage plan (CCbRMP) for industrial parks to address both exogenous and endogenous uncertainties. Copula functions provide flexible modeling of dependencies between variables, which is crucial for capturing the intricate relationship among on-grid, TOU, and demand power prices. Credibility theory combines fuzzy and random measures, offering a robust framework for integrating expert judgment and historical data. Thus, the proposed CCbRMP effectively balances economic and robustness considerations, while clarifying the relationship between endogenous uncertainties and decision variables. The main contributions of this paper are as follows:

1) This paper explores the mathematical characteristics of endogenous and exogenous uncertainties using martingale theory. It comprehensively examines impacts of the PV output's exogenous uncertainties and electricity price's endogenous uncertainties on industrial park planning, providing a dynamic framework for optimal PV and ES configuration.

2) A copula function based credibility distribution is developed to couple on-grid, TOU, and demand power prices, leading to an integrated fuzzy chance constraint model. This enhances the accuracy and reliability of uncertainty modeling, which is crucial for effective planning.

3) An innovative aspect is transforming fuzzy chance constraints into deterministic robust optimization through clear equivalence classes. This approach simplifies complex uncertainties, making them more manageable for effective and accurate optimization in the planning process.

The rest of this article is organized as follows. Section II introduces the characteristics of endogenous and exogenous uncertainties variables, and develops a fuzzy chance constraint model based on credibility theory. Section III proposes a credibility copula-based robust multistage industrial park planning model. Section IV analyzes the type proposed in this paper. Section V draws a conclusion.

II. Uncertainty Evaluation Model Based on Credibility Theory

The large-scale integration of PV into industrial parks leads to increased peak-valley fluctuations. The configuration of PV and ES is influenced by uncertainties in electricity prices and the PV output. This, in turn, raises both electricity and demand tariffs, ultimately affecting the economic viability of an industrial park. To address these challenges, this paper proposes the CCbRMP model as depicted in Fig. 1. An industrial park operates under a two-part tariff, with excess output sold to the power grid at the on-grid price. Due to exogenous uncertainties in the PV output from each workshop and endogenous uncertainties in electricity prices, industrial parks must strategically allocate PV and ES to optimize peak-valley arbitrage and enhance economic performance. Therefore, a multistage planning approach is derived, considering

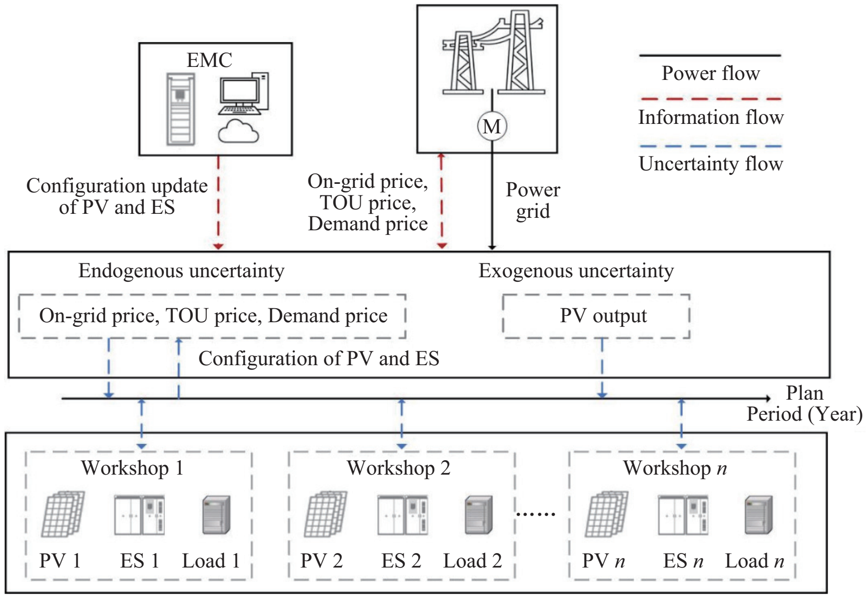

Fig. 1. Multistage planning framework for industrial parks.

how PV and ES configuration affects future endogenous electricity price uncertainties. This approach aims to balance the park's investment with electricity price fluctuations, ultimately improving the park's economic efficiency.

A. Characterization of Endogenous and Exogenous Uncertainties

In planning PV and ES integrated industrial parks, endogenous uncertainties of future electricity prices not only affect the current configuration of PV and ES but are also influenced by it, unlike exogenous uncertainties of the PV output. To better analyze these uncertainty attributes and facilitate subsequent modeling, this subsection mathematically describes endogenous and exogenous uncertainties using martingale theory.

For variable M_n, let $\{X_n\}$ be the adaptive sequence. It meets the following condition:

$$E(M_{n+1}|X_0, X_1, \cdots, X_n) = M_n \tag{1}$$

where M_n is said to be a martingale with respect to $\{X_n\}$ [29]. If it is assumed that u_n is the uncertainty variable, d_n is the decision variable, and k represents the time increment in probability space, the martingale process is defined as follows:

$$\begin{cases} E(u_n|\{d_0, d_1, \cdots, d_n\}) = u_n \\ E(u_{n+k}|\{d_0, d_1, \cdots, d_n\}) = u_n \end{cases} \tag{2}$$

If the uncertainty variable u_n and the decision variable d_n satisfy (2), the process is considered a martingale, that is, the uncertainty variable is exogenous. Specifically, (2) implies that given the decision variable $\{d_0, d_1, \cdots, d_n\}$, the conditional expectation of the uncertainty variable u_n to the decision variable $\{d_0, d_1, \cdots, d_n\}$ remains u_n. And for the uncertainty variable u_{n+k}, the conditional expectation is still u_n, indicating that the conditional expectation is independent of the decision variable, that is, the decision variable does not affect the uncertainty variable. In this paper, this process suggests that the expectation of endogenous uncertainty in future electricity prices is affected by PV and ES configuration. However, the configuration decision of PV and ES will not affect exogenous uncertainties of the PV output, nor will it change the expected distribution of the PV output in the future.

To further analyze the relationship between endogenous uncertainties and decision variables, we have introduced the concepts of super-martingale and sub-martingale to mathematically describe endogenous uncertainties:

$$\begin{aligned} &\text{Sup:} \begin{cases} E[u_n^-] < \infty \\ E(u_{n+k}|\{d_0, d_1, \cdots, d_n\}) \le u_n, \ \forall n \ge 0 \end{cases} \\ &\text{Sub:} \begin{cases} E[u_n^+] < \infty \\ E(u_{n+k}|\{d_0, d_1, \cdots, d_n\}) \ge u_n, \ \forall n \ge 0 \end{cases} \end{aligned} \tag{3}$$

Super-martingale and sub-martingale represent decreasing and increasing expectations, respectively. This framework allows us to model how decision-making affects the expectations of uncertain variables both presently and in the future. For instance, in the context of large-scale PV and energy storage integrated industrial parks, the downward trend in electricity price expectations due to increased renewable energy penetration is represented by a super-martingale. This approach enhances our understanding of the interaction between endogenous uncertainties and decision variables. By employing martingale theory alongside super-martingales, we provide a standardized mathematical interpretation of both endogenous and exogenous uncertainties.

B. Fuzzy Chance Constraint Model of Exogenous Uncertainties

Conventional fuzzy decision-making often results in inconsistent or contradictory conclusions due to the absence of a comprehensive axiomatic system [30]. Credibility theory employs a credibility measure to describe the likelihood of fuzzy events, avoiding the decision confusion associated with conventional membership calculations.

The credibility measure is defined as follows: For any set $A \in R$, A^{c} is an opposing set of A, and the credibility measure can be given by:

$$\mathrm{Cr}\{\xi \in A\} = \frac{1}{2}\Big(\sup_{x\in A}\mu(x) + 1 - \sup_{x\in A^{\mathrm{c}}}\mu(x)\Big) \tag{4}$$

where $\mathrm{Cr}(\cdot)$ denotes the credibility measure, $\mu(x)$ is the membership function of fuzzy variable ξ, and sup represents the upper bound.

This subsection first derives the credibility distribution of the PV output, accounting for the prediction error, and then develops the fuzzy chance constraint of exogenous uncertainties based on credibility theory.

Step 1: The initial distribution of the PV output is generated from the historical data of the industrial park, and its membership function is characterized by a triangular distribution as follows:

$$\mu_\chi = \begin{cases} 0, & \chi \le r_1 \\ \dfrac{\chi - r_1}{r_2 - r_1}, & r_1 < \chi \le r_2 \\ \dfrac{r_3 - \chi}{r_3 - r_2}, & r_2 \le \chi < r_3 \\ 0, & \chi \ge r_3 \end{cases} \tag{5}$$

where r_1, r_2, r_3 denote the membership parameters that control the shape of the membership function. The credibility distribution of the prediction error is derived from (4). The triangular credibility distribution function is expressed as follows:

$$\mathrm{Cr}\{\xi \le \chi\} = \begin{cases} 0, & \chi \le r_1 \\ \dfrac{\chi - r_1}{2(r_2 - r_1)}, & r_1 \le \chi < r_2 \\ \dfrac{\chi + r_3 - 2r_2}{2(r_3 - r_2)}, & r_2 \le \chi \le r_3 \\ 1, & r_3 \le \chi \end{cases} \tag{6}$$

The proving processes are given as follows:

If $\chi > r_3$, according to the triangle membership function shown by (5), it can be seen that $\sup_{y\le\chi}\mu(y) = \max\{\sup_{y<r_1}\mu(y), \sup_{r_1\le y\le r_2}\mu(y), \sup_{r_2<y\le r_3}\mu(y), \sup_{r_3<y\le\chi}\mu(y)\} = 1$, $\sup_{y>\chi}\mu(y) = 0$, and according to (4), we have $\mathrm{Cr}\{\varepsilon\} = \frac{1}{2}(1+1-0) = 1$.

If $r_2 \le \chi \le r_3$, $\sup_{y\le\chi}\mu(y) = \max\{\sup_{y<r_1}\mu(y), \sup_{r_1\le y\le r_2}\mu(y), \sup_{r_2<y\le\chi}\mu(y)\} = 1$, $\sup_{y>\chi}\mu(y) = \max\{\sup_{\chi\le y\le r_3}\mu(y), \sup_{r_3<y}\mu(y)\} = \frac{r_3-\chi}{r_3-r_2}$, according to (4), we have $\mathrm{Cr}\{\varepsilon\} = \frac{1}{2}(1+1-\frac{r_3-\chi}{r_3-r_2}) = \frac{\chi+r_3-2r_2}{2(r_3-r_2)}$.

If $r_1 < \chi < r_2$, $\sup_{y\le\chi}\mu(y) = \max\{\sup_{y<r_1}\mu(y), \sup_{r_1\le y\le\chi}\mu(y)\} = \frac{\chi-r_1}{r_2-r_1}, \sup_{y>\chi}\mu(y) = \max\{\sup_{\chi\le y\le r_2}\mu(y), \sup_{r_2\le y\le r_3}\mu(y), \sup_{r_3<y}\mu(y)\} = 1$, $\sup_{y\le\chi}\mu(y) = \max\{\sup_{y<r_1}\mu(y), \sup_{r_1\le y\le\chi}\mu(y)\} = \frac{\chi-r_1}{r_2-r_1}$, according to (4), we have $\mathrm{Cr}\{\varepsilon\} = \frac{1}{2}(\frac{\chi-r_1}{r_2-r_1}+1-1) = \frac{\chi-r_1}{2(r_2-r_1)}$.

If $\chi \le r_1$, $\sup_{y\le\chi}\mu(y) = \max\{\sup_{y<r_1}\mu(y)\} = 0$, $\sup_{y>\chi}\mu(y) = \max\{\sup_{y<r_1}\mu(y), \sup_{r_1\le y\le r_2}\mu(y), \sup_{r_2<y\le r_3}\mu(y), \sup_{r_3<y\le\chi}\mu(y)\} = 1$, according to (4), we have $\mathrm{Cr}\{\varepsilon\} = \frac{1}{2}(0+1-1) = 0$.

Step 2: Based on credibility theory, the fuzzy chance constraint of exogenous uncertainties of the PV output is:

$$\mathrm{Cr}\left(\sum_{k=1}^{K} P_{t,k}^{\mathrm{PV}} + P_t^{\mathrm{Buy}} + P_t^{\mathrm{d}} = \sum_{k=1}^{K} P_{t,k}^{\mathrm{Load}} + P_t^{\mathrm{Sell}} + P_t^{\mathrm{c}}\right) \ge \alpha \tag{7}$$

where α indicates the reliability of the PV output, typically ranging from 0.95 to 0.99. $P_{t,k}^{\mathrm{PV}}$ and $P_{t,k}^{\mathrm{Load}}$ are the PV output and load demand of workshop k at time t, respectively. P_t^{c} and P_t^{d} represent the charging and discharging power at time t, respectively.

Solving the fuzzy chance constraint in (7) ensures that the solution matches the specified credibility under PV output uncertainties, keeping violation behavior within the allowable range. Since the fuzzy chance constraint contains uncertain variables, it cannot be solved directly. This paper derives its deterministic equivalent class, transforming the credible fuzzy chance constraint into deterministic robust optimization [31].

Suppose the function has the following form:

$$g(x,\zeta) = h_1(x)\zeta_1 + h_2(x)\zeta_2 + \cdots + h_t(x)\zeta_t + h_0(x) \tag{8}$$

where $\zeta, \cdots, \zeta_t$ represent the trapezoidal fuzzy variables associated with $(r_{k1}, r_{k2}, r_{k3}, r_{k4})$, and $h_1, \cdots, h_t$ denote the membership parameters.

When $\alpha \ge 1/2$, the clear equivalence class of $\mathrm{Cr}\{g(x,\xi) \le 0\} \ge \beta$ is represented as follows:

$$(2-2\beta)\sum_{k=1}^{K}\begin{bmatrix} r_{k3}h_k^+(x) - \\ r_{k2}h_k^-(x) \end{bmatrix} + (2\beta-1)\sum_{k=1}^{K}\begin{bmatrix} r_{k4}h_k^+(x) - \\ r_{k1}h_k^-(x) \end{bmatrix} + h_0(x) \le 0 \tag{9}$$

where $h_k^+(x) = h_k(x) \vee 0$, $h_k^-(x) = -h_k(x) \wedge 0$.

The fuzzy chance constraint adopts an equivalent model, simplified as:

$$(2-2\alpha)\sum_{k=1}^{K} P_{t,k}^{\mathrm{PV}} + (2\alpha-1)\gamma\sum_{k=1}^{K} P_{t,k}^{\mathrm{PV}} + P_t^{\mathrm{Buy}} + P_t^{d} = \sum_{k=1}^{K} P_{t,k}^{\mathrm{Load}} + P_t^{\mathrm{Sell}} + P_t^{\mathrm{c}} \tag{10}$$

where γ indicates the proportional coefficient, derived from historical PV output data.

The fuzzy chance constraint of exogenous uncertainties in (7) is transformed into the deterministic robust constraint in (10). This transformation simplifies complex uncertainties into a more manageable form, facilitating more effective and accurate optimization in the planning process.

C. Fuzzy Chance Constraint Model of Endogenous Uncertainties

The industrial park operates under a two-part tariff system, with economic benefits influenced by the on-grid, TOU, and demand prices [32]. The correlation between these three electricity prices is crucial for optimal planning. Therefore, this subsection first couples the three prices using a copula function, and then examines how the configuration of PV and

ES affects the coupled electricity prices. Finally, it derives the credibility distribution of electricity prices with the prediction error and develops a fuzzy chance constraint model for endogenous uncertainties based on credibility theory.

Step 1: Copula theory is a method for describing multivariate uncertain variables, linking marginal and joint distributions [33], [34]. In this paper, the copula function is used to couple the on-grid, TOU, and demand prices.

First, it is assumed that electricity prices follow a multivariate normal distribution under ideal conditions [35], as shown below:

$$\tau = (\tau_1, \tau_2, \cdots, \tau_s)^{\mathrm{T}} \sim N(\mu_\tau, B) \tag{11}$$

where $\mu_\tau = (\mu_1, \mu_2, \cdots, \mu_s)^{\mathrm{T}}_{s\times 1}$ is the mean vector of the electricity price, $B = \mathrm{Cov}(\tau)_{s\times s}$ denotes the covariance matrix of the electricity price, and s represents the total number of electricity price categories. The joint probability density function $\phi(\tau)$ with respect to electricity prices can be expressed as:

$$\phi(\tau) = \frac{1}{\sqrt{(2\pi)^S |B|}} \mathrm{e}^{-\frac{1}{2}(\tau-\mu)^{\mathrm{T}} B^{-1} (\tau-\mu)} \tag{12}$$

Then, $\forall x \in (0, \tau_s)$, and the probability distribution of the price is $\phi(x)$. Thus, the coupling price error of the price $\rho(\tau_s^{\mathrm{c}})$ can be expressed as:

$$\rho(\tau_s^{\mathrm{c}}) = \int_0^{\tau_s^0} (\tau_s^0 - x)\phi(x)\mathrm{d}x \tag{13}$$

where τ_s^0 indicates the historical electricity price. The coupled electricity price can be expressed as: $\tau_s^{\mathrm{c}} = \tau_s^0 + \rho(\tau_s^{\mathrm{c}}) \sim N(\mu^{\mathrm{c}}, B^{\mathrm{c}})$.

Step 2: The large-scale integration of renewable energy into industrial parks inevitably increases uncertainties in future electricity prices. It is well known that higher renewable energy penetration often results in a downward trend in electricity prices [36]. Therefore, this paper examines the impact of PV and ES configuration on future electricity prices. The copula-endogenous electricity price τ_s^{ce} can be expressed as:

$$\tau_s^{\mathrm{ce}} \sim N\left(\mu^{\mathrm{c}} - \sum_{k=1}^{K} E_k^{\mathrm{PV}} \cdot \frac{1}{P_{\mathrm{load}}^{\max}} \cdot \Delta\vartheta, B^{\mathrm{c}} + \Delta B\right) \tag{14}$$

where $\Delta\vartheta$ and ΔB indicate the correction factors of mean and covariance, respectively. E_k^{PV} is the PV capacity of workshop k, and $P_{\mathrm{load}}^{\max}$ represents the maximum load of the park.

Step 3: The membership degree μ_ε of the actual electricity price considering the prediction error is characterized by a Gaussian distribution shown as follows:

$$\mu_\varepsilon = \begin{cases} \mathrm{e}^{-\left(\frac{w(\varepsilon/E_+)}{\sigma}\right)^2}, & \varepsilon \geq 0 \\ \mathrm{e}^{-\left(\frac{w(\varepsilon/E_-)}{\sigma}\right)^2}, & \varepsilon \leq 0 \end{cases} \tag{15}$$

where E_+ and E_- represent the statistical average of the percentage of positive and negative errors, respectively. And ω is the weight, and meets the condition $0 \leq \omega \leq 1$. According to (3) and (14), the Gaussian credibility distribution function can be expressed as:

$$\mathrm{Cr}\{\xi \leq \varepsilon\} = \begin{cases} 1 - \dfrac{1}{2}\mathrm{e}^{-\left(\frac{w(\varepsilon/E_+)}{\sigma}\right)^2}, & \varepsilon > 0 \\ \dfrac{1}{2}\mathrm{e}^{-\left(\frac{w(\varepsilon/E_-)}{\sigma}\right)^2}, & \varepsilon \leq 0 \end{cases} \tag{16}$$

The proving processes are given as follows:

If $\varepsilon > 0$, according to the Gaussian function shown in (15), it can be seen that $\sup_{y\leq\varepsilon}\mu(y) = \max\{\sup_{0<y\leq\varepsilon}\mu(y), \sup_{y\leq 0}\mu(y)\} = 1$, $\sup_{y>\varepsilon}\mu(y) = \mathrm{e}^{-(\frac{w(\varepsilon/E_+)}{\sigma})^2}$, and according to (4), we have $\mathrm{Cr}(\varepsilon) = \frac{1}{2}(1 + 1 - \mathrm{e}^{-(\frac{w(\varepsilon/E_+)}{\sigma})^2}) = 1 - \frac{1}{2}\mathrm{e}^{-(\frac{w(\varepsilon/E_+)}{\sigma})^2}$. Similarly, if $\varepsilon < 0$, $\sup_{y\leq\varepsilon}\mu(y) = \mathrm{e}^{-(\frac{w(\varepsilon/E_-)}{\sigma})^2}$, $\sup_{y>\varepsilon}\mu(y) = \max\{\sup_{\varepsilon<y\leq 0}\mu(y), \sup_{y\geq 0}\mu(y)\} = 1$, according to (4), we have $\mathrm{Cr}(\varepsilon) = \frac{1}{2}(\mathrm{e}^{-(\frac{w(\varepsilon/E_-)}{\sigma})^2} + 1 - 1) = \frac{1}{2}\mathrm{e}^{-(\frac{w(\varepsilon/E_-)}{\sigma})^2}$.

Step 4: Based on credibility theory, the fuzzy chance constraint of endogenous uncertainties of future electricity prices is:

$$\mathrm{Cr}(\tau_s = (1+\varepsilon)\tau_s^{\mathrm{ce}}) \geq \beta_s \tag{17}$$

where β_s indicates the reliability of the electricity price, typically ranging from 0.95 to 0.99.

According to [29], we have the following theorem: Assuming ξ degenerates into a one-dimensional fuzzy variable, its membership function is μ. If the form of function $g(x,\xi)$ is $g(x,\xi) = h(x) - \xi$, then $\mathrm{Cr}(g(x,\xi)) \leq \alpha$, if and only if $h(x) \leq K_\alpha$, where x and g are decision vectors and constraints, respectively. This is represented as follows:

$$K_\alpha = \begin{cases} \sup\{K | K = \mu_\varepsilon^{-1}(2\alpha)\}, & \alpha < 1/2 \\ \inf\{K | K = \mu_\varepsilon^{-1}(2(1-\alpha))\}, & \alpha \geq 1/2 \end{cases} \tag{18}$$

The equivalent model of the fuzzy chance constraint shown in (17) can be expressed as:

$$\begin{cases} \tau_s = (1 + K_\beta)\tau_s^{\mathrm{ce}} \\ K_\beta = \mu_\varepsilon^{-1}(2(1-\beta)) \geq 0 \end{cases} \tag{19}$$

Through (18), the fuzzy chance constraint for electricity price uncertainties can be transformed into a deterministic robust constraint in (19), facilitating more effective and accurate optimization in the planning process. Additionally, Fig. 2 illustrates the process from deterministic planning (DP) to CCbRMP planning, considering uncertain electricity price coupling. In the DP model, electricity prices are simplified to follow a normal distribution. The conventional uncertainty planning (UP) model addresses exogenous factors like PV output using methods such as stochastic programming, robust optimization, and fuzzy optimization, each with distinct advantages and limitations. The Copula-UP model builds on the UP model by incorporating correlations between multiple electricity prices using a copula function, describing these uncertainties as a normal distribution under the credibility copula framework. The CCbRMP advances this by integrating both endogenous and exogenous uncertainties, establishing a fuzzy chance-constrained model based on credibility theory. By considering these uncertainty attributes, the CCbRMP

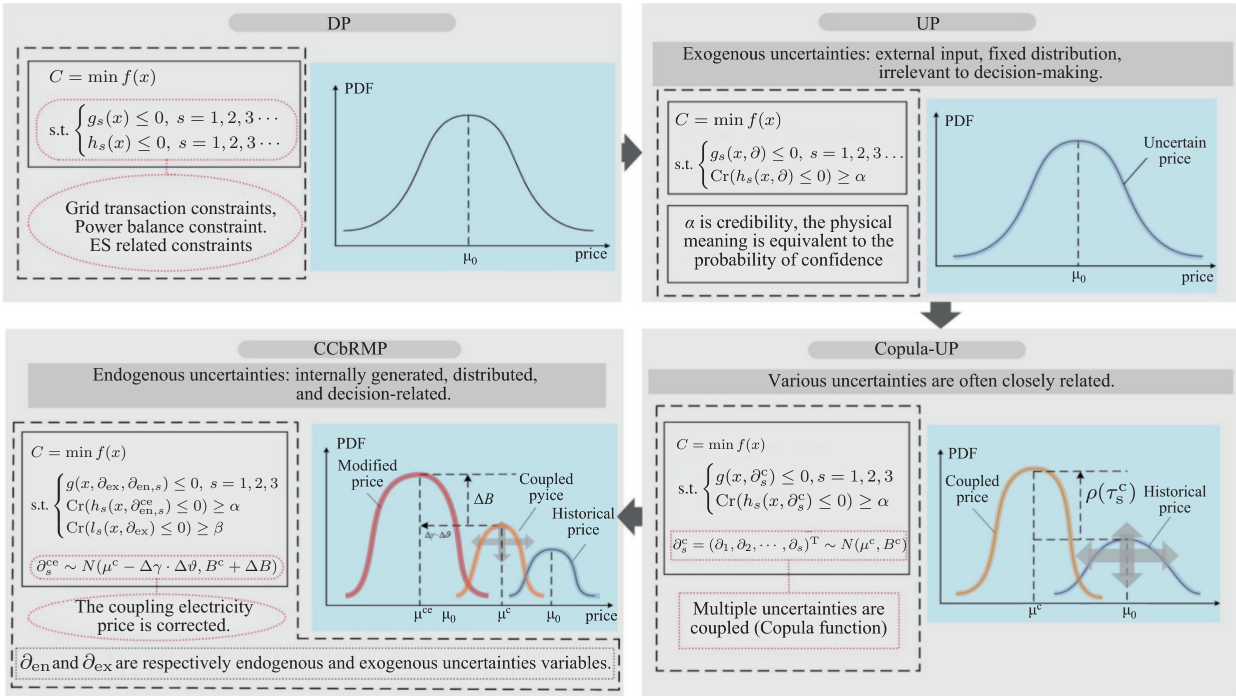

Fig. 2. Evolution path from DP to CCbRMP planning.

aligns constraints and decision variables more closely with real-world planning scenarios, resulting in more economical decision-making outcomes.

III. Robust Multistage Planning of Industrial Park

This paper considers impacts of exogenous uncertainties in the PV output and endogenous uncertainties on electricity prices under a two-part tariff system, aiming to maximize the return on investment in PV and ES within an industrial park. Fig. 3 presents the flowchart of the proposed robust multistage planning, and the detailed optimization model is outlined as follows:

$$\min C = \sum_{n=1}^{N} \left[\frac{\nu(1+\nu)^n}{(1+\nu)^n - 1} (C_n^{\mathrm{PV}} + C_n^{\mathrm{ES}}) + C_n^{\mathrm{OM}} + C_n^{\mathrm{TOU}} + C_n^{\mathrm{DP}} - C_n^{\mathrm{OG}} \right]$$

$$\text{s.t.}\quad C_n^{\mathrm{PV}} = \sum_{k=1}^{I} u^{\mathrm{PV}} E_k^{\mathrm{PV}}$$

$$C_n^{\mathrm{ES}} = \sum_{k=1}^{I} u^{\mathrm{ES}} E^{\mathrm{ES}}$$

$$C_n^{\mathrm{OM}} = \sum_{k=1}^{K} m^{\mathrm{PV}} E_k^{\mathrm{PV}} + m^{\mathrm{ES}} E^{\mathrm{ES}}$$

$$C_n^{\mathrm{OG}} = \sum_{t=1}^{8760} \tau_t^{\mathrm{OG}} P_t^{\mathrm{Sell}}$$

$$C_n^{\mathrm{TOU}} = \sum_{t=1}^{8760} \tau_t^{\mathrm{TOU}} P_t^{\mathrm{Buy}}$$

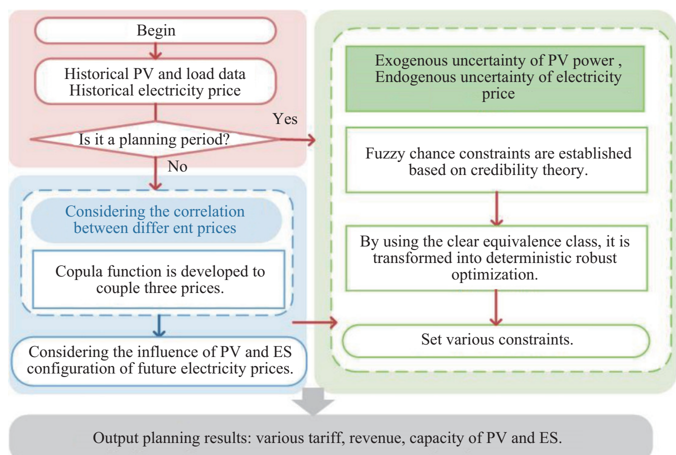

Fig. 3. Flow chart of robust multistage planning for industrial park under endogenous and exogenous uncertainties.

$$C_n^{\mathrm{DP}} = \sum_{t=1}^{8760} \tau_t^{\mathrm{Demand}} P_t^{\mathrm{Buy,max}} \tag{20}$$

where C_n^{PV} and C_n^{ES} indicate the fixed investment cost of PV and ES in year n, respectively. v represents the discount rate. u^{PV} and u^{ES} are the investment cost coefficients of PV and ES, respectively. E_k^{PV} is the PV capacity installed in workshop k. E^{ES} denotes the ES capacity of the park. C_n^{OM} represents the operation maintenance cost of the park in year n. m^{PV} and m^{ES} represent the maintenance cost coefficients of PV and ES, respectively. Under the two-part tariff system, the electricity tariff of the industrial park includes electricity and demand tariffs [37]. When distributed power generation has a surplus to meet the demand of the park, it can be sold back to the grid at the grid price [38]. Therefore, this paper does not consider PV power curtailment. C_n^{OG}, C_n^{TOU} and C_n^{DP} denote the on-grid, TOU and demand tariffs in year n, respectively. τ_t^{OG}, τ_t^{TOU} and τ_t^{Demand} indicate on-grid price, TOU price and demand prices at time t, respectively. P_t^{Buy} and P_t^{Sell} are the buying power and selling power of the park at time t, respectively.

To ensure normal operations, the planning model must satisfy power balance constraints, operational constraints, and both endogenous and exogenous uncertainty constraints, which are expressed as follows:

1) Power balance constraints

$$\sum_{k=1}^{K} P_{t,k}^{\mathrm{PV}} + P_t^{\mathrm{Buy}} + P_t^{d} = \sum_{k=1}^{K} P_{t,k}^{\mathrm{Load}} + P_t^{\mathrm{Sell}} + P_t^{\mathrm{c}} \tag{21}$$

where $P_{t,k}^{\mathrm{PV}}$ and $P_{t,k}^{\mathrm{Load}}$ indicate the PV output and load demand of workshop k at time t, respectively. P_t^{c} and P_t^{d} represent the charging and discharging power at time t, respectively.

2) Grid transaction constraints

$$\begin{aligned} &\sum_{t=1}^{T} P_t^{\mathrm{Buy}} P_t^{\mathrm{Sell}} = 0 \\ &0 \le P_t^{\mathrm{Buy}} \le P_{\max}^{\mathrm{Buy}} \\ &0 \le P_t^{\mathrm{Sell}} \le P_{\max}^{\mathrm{Sell}} \end{aligned} \tag{22}$$

where $P_{\max}^{\mathrm{Buy}}$ and $P_{\max}^{\mathrm{Sell}}$ denote the maximum buying and selling power, respectively.

3) ES constraints

$$\begin{cases} E^{\mathrm{ES}} = \theta P_{\max}^{\mathrm{ES}} \\ P_t^{d} + P_t^{\mathrm{c}} \le P_t^{\mathrm{ES}} \le P_{\max}^{\mathrm{ES}} \\ SOE(0) = \lambda E^{\mathrm{ES}} \\ SOE(t) = SOE(t-\Delta t) + \left(\eta^{\mathrm{c}} P_t^{\mathrm{c}} - \dfrac{1}{\eta^{\mathrm{d}}} P_t^{\mathrm{d}}\right)\Delta t \\ SOE(ts) = SOE(ts+24), ts \in (0, 24, 48, \cdots) \\ P_{\min}^{\mathrm{c}} \le P_t^{\mathrm{c}} \le P_{\max}^{\mathrm{c}} \\ P_{\min}^{\mathrm{d}} \le P_t^{\mathrm{d}} \le P_{\max}^{\mathrm{d}} \\ P_t^{\mathrm{c}} P_t^{\mathrm{d}} = 0 \end{cases} \tag{23}$$

where $E_{\max}^{\mathrm{ES}}$ and $E_{\min}^{\mathrm{ES}}$ indicate the upper and lower limits of the ES capacity, respectively. θ is the maximum energy rate of ES. $P_{\max}^{\mathrm{ES}}$ represents the maximum ES output power. $P_{\max}^{\mathrm{c}}$ and $P_{\min}^{\mathrm{c}}$ are the upper and lower limits of the ES charging power, respectively. $P_{\max}^{\mathrm{d}}$ and $P_{\min}^{\mathrm{d}}$ represent the upper and lower limits of the ES discharging power, respectively. $SOE(t)$ denotes the state of energy of ES at time t. The time interval Δt represents the duration between these intervals. $SOE(ts)$ represents the time of energy conservation, where $ts \in (0, 24, 48, \cdots)$. To ensure the health of the ES battery, the initial ES energy cannot be lower than the capacity limit threshold λ. η^{c} and η^{d} denote the efficiency of charging and discharging power, respectively.

4) Endogenous and exogenous uncertainties constraints

$$\begin{aligned} &(2-2\alpha)\sum_{k=1}^{K} P_{t,k}^{\mathrm{PV}} + (2\alpha-1)\gamma \sum_{k=1}^{K} P_{t,k}^{\mathrm{PV}} \\ &\quad + P_t^{\mathrm{Buy}} + P_t^{d} = \sum_{k=1}^{K} P_{t,k}^{\mathrm{Load}} + P_t^{\mathrm{Sell}} + P_t^{\mathrm{c}} \\ &\tau_s = (1+K_\beta)\tau_s^{\mathrm{ce}} \\ &K_\beta = \mu_\varepsilon^{-1}(2(1-\beta)) \ge 0 \end{aligned} \tag{24}$$

where α represents the reliability of the PV output, and β_s is the reliability of electricity prices, usually within the range of 0.95–0.99. γ denotes the proportional coefficient, which can be obtained from the historical data of the PV output.

IV. Numerical Studies

To verify the validity and reliability of the model, we conduct a simulation analysis on a PV and ES integrated industrial park. Fig. 4 illustrates the PV output and load of the park on four typical days representing spring, summer, autumn, and winter. Each season is assumed to last 90 days, with a discount rate of 0.1. The specific parameters for each workshop are detailed in Table II.

TABLE II
Parameters Related to ES and PV

Parameter	Value	Parameter	Value (CNY/(kW))
ε	2.67	m^{PV}	14.60
λ	0.15	m^{ES}	3.65
η^{d}	0.95	u^{ES}	1300
η^{c}	0.95	u^{PV}	3000

A. Cost Comparison Between the CCbRMP and ES Planning

Due to significant differences in light resources between summer and winter, and high average load demand, this paper analyzes typical days in these seasons. The output results are shown in Figs. 5 and 6.

The results demonstrate that ES can effectively implement a strategy of charging at low prices and discharging at high prices in response to TOU price and load demand changes, thereby achieving peak-valley arbitrage. Specifically, ES charges during the first 8 hours, with the SOC rising. During hours 8 to 12, as load demand increases and the PV output becomes insufficient, the TOU price peaks, causing ES to discharge, reducing the SOC. During hours 12–18, the TOU price drops to a flat rate, allowing the PV output to meet the load demand and charge ES, raising the SOC for the next peak. Additionally, excess energy can be sold to the grid at the on-grid price. During hours 18–22, the TOU price peaks again, and the PV output cannot meet the demand, causing ES to discharge to its minimum level before electricity is purchased from the grid. During hours 22–24, the TOU price drops, and to follow the recycling principle, ES maintains a constant SOC without charging or discharging.

The trend on typical summer days is similar to that in winter, indicating the model's wide applicability across seasons. Furthermore, this paper compares the cost of the CCbRMP with deterministic programming (DP), robust programming (RP), fuzzy programming (FP), stochastic programming (SP) and one-time planning. Detailed planning costs for different models are presented in Table III.

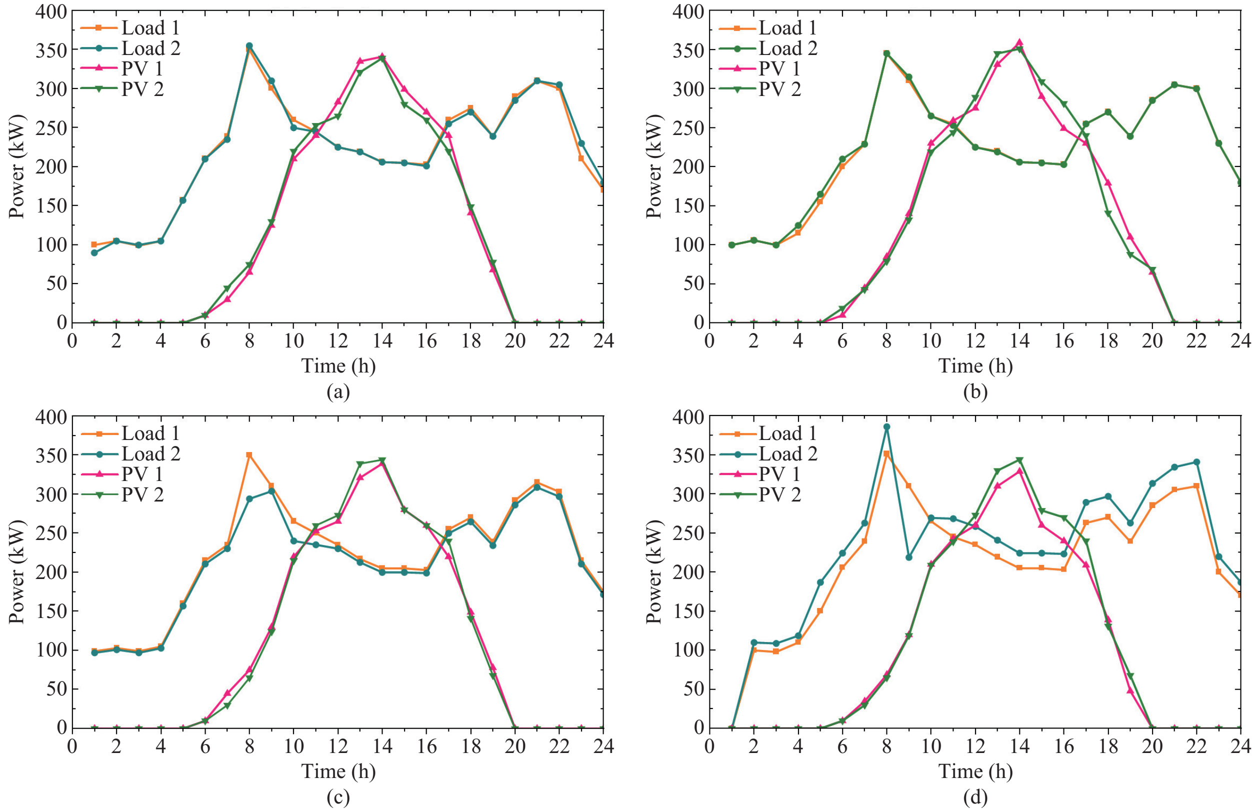

Fig. 4. PV and load values of typical days in four seasons. (a) Spring. (b) Summer. (c) Autumn. (d) Winter.

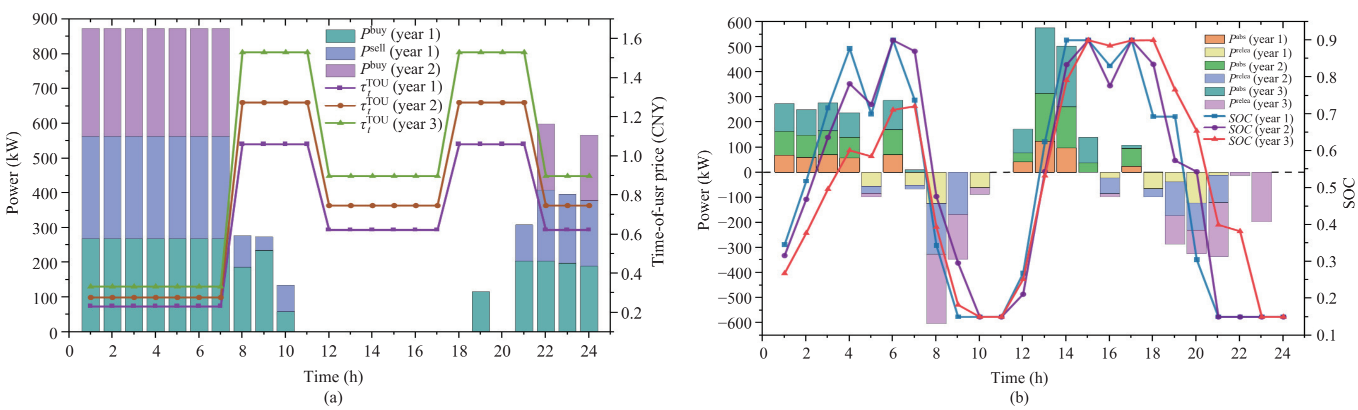

Fig. 5. Grid and ES outputs in summer. (a) Industrial park output power. (b) ES output power.

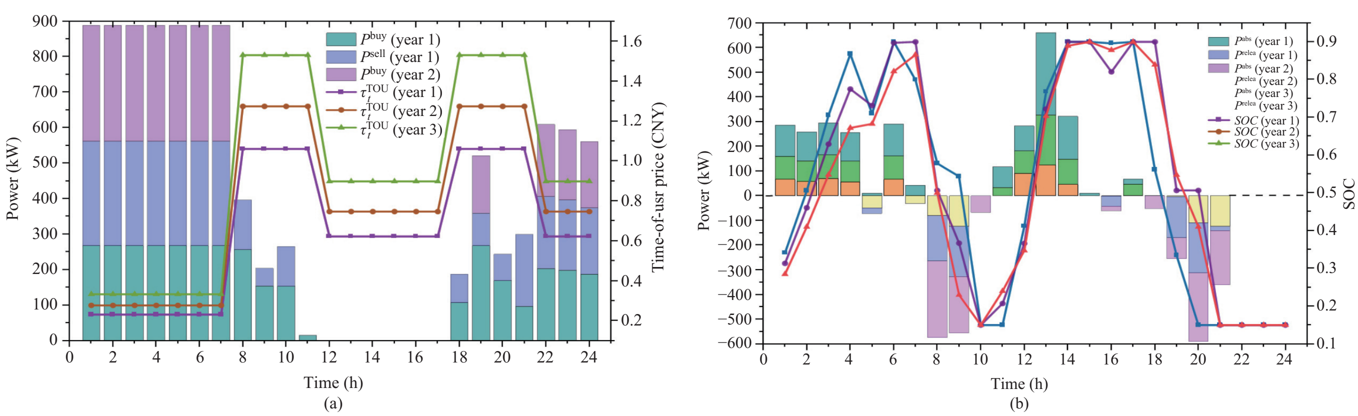

Fig. 6. Grid and ES outputs in winter. (a) Industrial park output power. (b) ES output power.

TABLE III
COMPARISON OF DIFFERENT MODELS ON ES PLANNING OF INDUSTRIAL PARK

ES model	Maintenance cost (CNY)	Operation cost (CNY)	Total cost (CNY)	Time (s)
DP	24631.040	5323598.094	8240005.330	9.737
FP	33338.594	7709561.500	9250562.572	13.044
RP	35240.211	8260772.275	9656329.131	15.269
SP	32595.209	7659380.995	8929606.158	5164.607
CCbRMP (90%)	29953.710	6750295.633	8245331.640	10.242
CCbRMP (95%)	30759.577	6976518.626	8409897.391	11.894
CCbRMP (99%)	31415.243	7160991.758	8567046.016	12.142

As shown in Table III, while the DP model has lower costs compared to the RP, FP, and CCbRMP models, it fails to account for the uncertainty of the PV output, resulting in lower PV and ES configuration. This makes the DP model overly idealistic and not reflective of real-world operations.

In contrast, the CCbRMP demonstrates superior economic benefits, with total costs 11.281% to 14.612% lower than RP, 4.060% to 7.663% lower than SP and 7.389% to 10.867% lower than FP. This is achieved by optimizing the PV and ES capacities to meet specific confidence levels, thereby effectively reducing costs. Maintenance costs are 10.854% to 15.001% lower than RP, 3.620% to 8.104% lower than SP and 5.769% to 10.153% lower than FP, while operation costs are 13.313% to 18.284% lower than RP, 6.507% to 11.869 lower than SP, and 7.115% to 12.443% lower than FP.

Moreover, the solution efficiency of the CCbRMP is comparable to that of the RP, FP, and DP models. The SP model, however, requires repeated sampling, leading to very low computational efficiency. The computational efficiency of the CCbRMP is only 0.198% to 0.235% of that of the SP model, highlighting its superior solution efficiency.

Table IV indicates that, compared to one-time planning, the total cost of the CCbRMP is reduced by 22.212% to 23.850%, with maintenance costs reduced by 34.848% to 35.665% and operation costs reduced by 20.984% to 23.375%. Online revenue increases by 11.215% to 13.463%. This multistage planning method better adapts to uncertainty fluctuations and provides higher economic benefits.

Overall, compared to conventional models, the CCbRMP offers high potential revenue in PV and ES configuration, achieving a balance between economy and robustness.

B. Analysis of Endogenous and Exogenous Uncertainties

Exogenous uncertainties of the PV output and endogenous uncertainties of electricity prices significantly influence PV and ES configuration in parks. This paper compares the configuration results of different planning models over the planning period, as shown in Tables V and VI.

Firstly, from the PV configuration in Table V, it is evident that the DP model, which does not account for PV output uncertainties, shows significant differences compared to the RP, SP, and CCbRMP models. Specifically, the PV capacity of the RP model exceeds that of the DP model by 30.705%, and the PV capacity of the CCbRMP model exceeds that of the DP model by 16.870%. The capacity planning results of the CCbRMP model show minimal variation across different confidence levels, with a PV capacity difference of not more than 3.458% within the 90% to 99% confidence interval. This is because the CCbRMP model ensures that PV power constraints are met with high confidence, even under the most unfavorable conditions, thereby ensuring the stability and reliability of PV and ES configuration.

Secondly, Table VI shows variations in ES configuration across different models. Specifically, the DP model results in a relatively low ES capacity due to its lack of consideration for uncertainties, leading to an overly optimistic prediction of supply and demand balance, thereby reducing the ES capacity. Among the models analyzed, the RP model has the highest ES capacity, 23.388% to 94.670% higher than those of the other models, as it prioritizes maintaining power supply reliability under extreme conditions. The CCbRMP model has a smaller ES capacity compared to other models. Its ES capacity is reduced by 27.569% to 57.771% compared to the SP model and increases annually. This is because the CCbRMP model fully accounts for the impact of PV and ES configuration on the endogenous uncertainties of electricity prices. As PV penetration increases, future electricity prices are expected to

TABLE V
PV CAPACITY UNDER DIFFERENT MODELS AND CONFIDENCE LEVELS IN DIFFERENT PERIODS (KWH)

Year	DP	RP	FP	CCbRMP		
				90%	95%	99%
First year	781.000	890.340	874.720	843.480	851.290	857.538
Second year	781.000	1014.988	979.687	910.958	919.393	941.57
Third year	781.000	1157.086	1097.249	983.835	1011.418	1033.851

TABLE VI
ES CAPACITY UNDER DIFFERENT MODELS AND CONFIDENCE LEVELS IN DIFFERENT PERIODS (KWH)

Year	DP	RP	FP	CCbRMP		
				90%	95%	99%
First year	168.084	420.584	384.512	312.369	330.405	344.834
Second year	168.084	902.729	756.790	472.661	507.532	599.240
Third year	168.084	1711.541	1318.307	773.941	887.970	983.992

TABLE IV
COMPARISON OF CCBRMP AND ONE-TIME PLANNING (CNY)

ES model	CCbRMP			One-time planning		
	90%	95%	99%	90%	95%	99%
Maintenance cost	29953.710	30759.577	31415.243	46559.106	47480.854	48218.252
Operation cost	6750295.633	6976518.626	7160991.758	8809560.816	8950189.968	9062693.290
Total cost	8245331.640	8409897.391	8567046.016	10827767.064	10930453.079	11013393.844
On-grid revenue	156524.474	167436.454	176050.590	140740.323	148493.606	155161.459
TOU tariff	1190514.086	1127911.562	1095357.045	1733226.944	1700926.452	1676016.035
Demand tariff	431092.685	442144.080	455332.558	385907.701	387486.162	389076.132

decrease. Thus, the CCbRMP model adjusts ES decisions to find the optimal balance between investment costs and on-grid revenue.

Finally, based on the results of electricity prices and ES capacity decisions, this paper conducts a reverse verification analysis to explore the correlation between ES capacity decisions and endogenous uncertainties of electricity prices. Since the trends of the on-grid, TOU, and demand prices are consistent, the on-grid price is used as an example. Fig. 7 illustrates the electricity price trend of the CCbRMP model at different confidence levels.

According to Fig. 7, in the first year, large-scale PV integration leads to a decrease in electricity prices due to increased PV penetration. In the second and third years, electricity prices rebound. As shown in Table VII, as the ES capacity increases, electricity prices trend upward. This is because an increased ES capacity raises the originally lower fixed costs, which are reflected in the on-grid price. Similarly, an increased PV capacity boosts the originally lower on-grid revenue, thereby affecting the TOU and demand prices.

Additionally, comparing the electricity price trends of the CCbRMP model at different confidence levels reveals that a higher confidence level results in a slighter downward trend in electricity prices. Although increased PV penetration tends to lower future electricity prices, this effect is offset by the investment costs of PV and ES configuration. This further explains the correlation between the ES and PV capacities, and endogenous uncertainties of electricity prices.

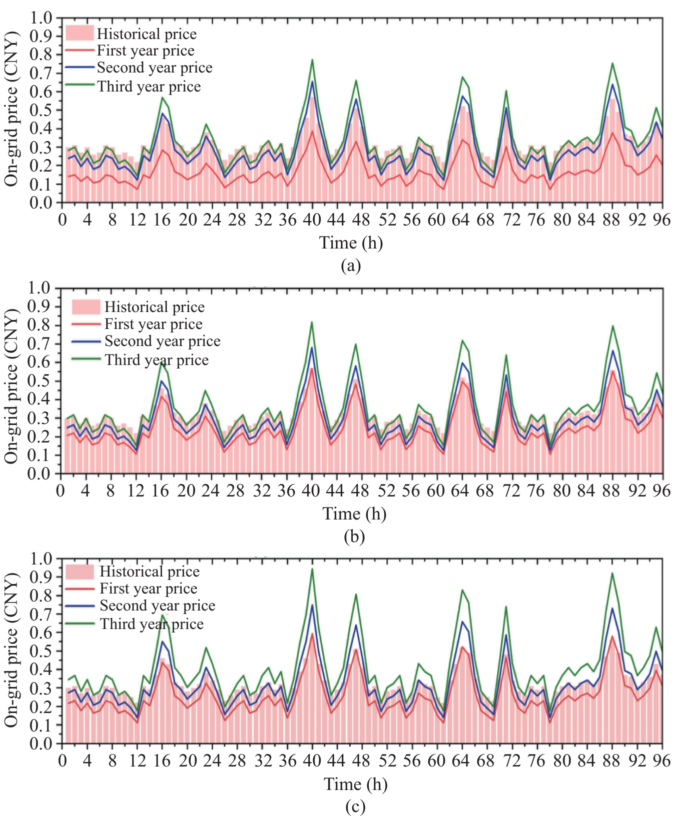

Fig. 7. On-grid price of CCbRMP model under different confidence levels. (a) Model with 90% confidence. (b) Model with 95% confidence. (c) Model with 99% confidence.

TABLE VII
COMPARISON OF CCBRMP AND COPULA-FREE MODEL (CNY)

ES model		Total cost	On-grid revenue	TOU tariff	Demand tariff
CCbRMP	90%	8245331.640	156524.474	1190514.086	431092.685
	95%	8409897.391	167436.454	1127911.562	442144.080
	99%	8567046.016	176050.590	1095357.045	455332.558
Copula-free planning	90%	8362386.329	167422.808	1318281.134	431278.659
	95%	8515716.119	179178.974	1245282.069	442334.821
	99%	8666227.845	188448.864	1206740.718	455528.989

C. Analysis of Copula Coupling and Endogenous Uncertainties

To examine the significance of considering the correlation between the on-grid, TOU, and demand prices, this study compares the costs and revenues of the CCbRMP with a copula-free model at different confidence levels. The optimal cost and revenue results for both models are presented in Table VII.

Table VII demonstrates that the total cost of the CCbRMP model is 1.144% to 1.400% lower than that of the copula-free model, with the net transaction price of the power grid reduced by 6.730% to 7.399%. This indicates that accounting for the correlation between the on-grid, time-of-use, and demand electricity prices allows for more efficient trading with the power grid, thereby reducing electricity costs.

To emphasize the importance of considering endogenous uncertainties of electricity prices, this paper compares the costs of three models at different confidence levels. The MEUP model treats both PV output and electricity price uncertainties as exogenous, while the SEUP model considers PV output as exogenous and the on-grid price as endogenous. Fig. 8 presents a total cost comparison of the models during the planning period at different confidence levels.

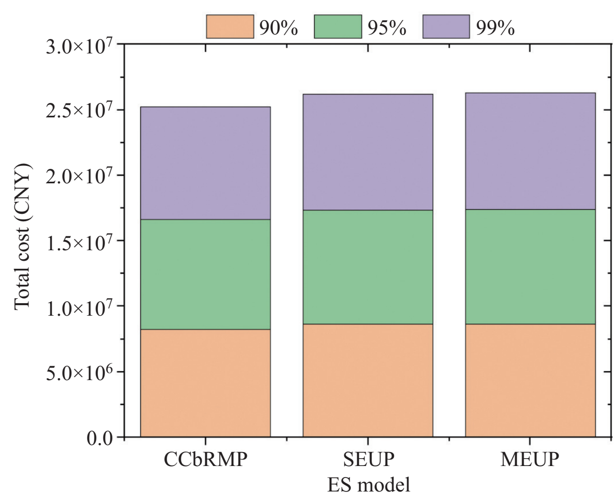

Fig. 8. Comparison of total cost of ES model under different credibility.

Figure 8 shows that the total cost of the MEUP model is significantly higher than those of the CCbRMP and SEUP models at the same confidence level. This is because the MEUP model treats both electricity prices and the PV output as exogenous uncertainties, resulting in greater robustness against price fluctuations, with a total cost 3.686% to 4.754% higher than that of the CCbRMP. The total cost of SEUP is 2.878% to 4.594% higher than that of the CCbRMP because it only considers endogenous uncertainties of the on-grid price while neglecting the impact of PV and ES configuration on the TOU and demand prices.

Additionally, as the confidence level of the CCbRMP increases, its cost rises. When credibility increases from 90% to 95%, its cost rises by 1.957%. At a confidence level of 99%, the cost increases by 3.755%. This is because higher confidence levels reflect lower tolerance for constraint violations, compelling the model to adopt more conservative and costly strategies to ensure operational stability and safety. This conservatism naturally leads to increased costs.

V. Conclusion

This paper proposes a credibility copula-based robust multistage planning approach for industrial parks, addressing both endogenous uncertainties in electricity prices and exogenous uncertainties in the PV output. The simulation results demonstrate the effectiveness of the proposed model. The main conclusion is as follows:

1) Compared with the RP, SP and one-time planning models, the CCbRMP model effectively reduces the total peak cost by 14.84%, 11.42% and 24.51%, respectively, highlighting its superior economic performance.

2) Impacts of endogenous and exogenous uncertainties on PV and ES configuration are analyzed. The CCbRMP model ensures stable PV configuration with high confidence, while maintaining smaller ES configuration than the other models, which increase annually. Additionally, reverse verification shows that an increased ES capacity leads to rising electricity prices.

3) Compared to the MEUP, SEUP, and copula-free models, the CCbRMP model offers greater economic benefits. This underscores the importance of fully considering the correlation between electricity prices and prioritizing various endogenous uncertainties in decision-making.

The primary limitation of our model is the exclusion of power exchange dynamics and electricity trading among workshops within an industrial park. Future research will focus on extending the model to incorporate these trading acts, and integrate both renewable energy sources and electricity market dynamics in order to enhance its robustness and applicability.

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