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Multi-objective Distributionally Robust Optimization for Power Market Scheduling and Maintenance Considering High Proportion of Renewable Energy Accommodation

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Article

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ABSTRACT

With the large-scale integration of renewable energy, power systems are facing profound changes in operational modes that directly necessitate more flexible energy management strategies within energy-intensive textile manufacturing facilities. This paper proposes a multi-objective distributionally robust optimization method for power market scheduling and maintenance that accounts for high proportion of renewable energy accommodation. This method adopts a data-driven approach to construct a probability distribution ambiguity set considering renewable energy correlations, introduces fuzzy chance constraints to characterize photovoltaic output uncertainty, and builds a multi-objective optimization model that minimizes total cost, maximizes renewable energy accommodation, and minimizes risk. Meanwhile, considering the coupling relationship between power grid maintenance and operation, the system topology is optimized and strictly maintained throughout the entire maintenance duration. While the primary switching actions occur at the start and end times of maintenance plans to avoid frequent operations, continuous N-1 security constraints and power flow balance are enforced across the full maintenance horizon to prevent mid-term reliability violations. The improved IEEE 118-bus system is used as a test case to verify the effectiveness of the proposed method. Results show that compared with traditional methods, the proposed method reduces system operating costs while improving renewable energy accommodation rate by 8.2%, reducing wind and solar curtailment rate by 22.6%, and significantly improving system voltage levels, providing a new solution for scheduling and maintenance of power systems with high proportion of renewable energy.

KEYWORDS

high proportion of renewable energy, power market scheduling, distributionally robust optimization, fuzzy chance constraints, textile manufacturing

INTRODUCTION

The power system is undergoing an unprecedented transformation. By the end of 2023, China's renewable energy power generation installed capacity exceeded 1.45 billion kilowatts, accounting for more than 51% of the total installed capacity [1]. The integration of a high proportion of renewable energy has changed the operational characteristics of traditional power systems, bringing a series of new technical challenges for energy-intensive textile manufacturing processes that require a highly stable and continuous power supply. These fluctuations necessitate advanced energy management systems within textile factories to ensure that the precision of high-speed weaving and chemical dyeing operations is not compromised by the intermittent nature of green energy sources. The intermittency and volatility of renewable energy increase the difficulty of system peak load regulation, and prediction errors significantly increase uncertainty, putting traditional scheduling and maintenance methods to a severe test. In the power market environment, renewable energy participation in market trading makes the problem more complex. On one hand, to pursue economic efficiency, market participants tend to maximize renewable energy generation; on the other hand, system security and reliability requirements necessitate sufficient reserve capacity [2]. Traditional deterministic optimization methods struggle to adapt to these changes, while stochastic optimization methods rely on precise probability distributions, which may lead to suboptimal or even unsafe decisions when historical data is insufficient or distributions change significantly [3].

In recent years, distributionally robust optimization methods have provided new ideas for handling uncertainty problems. This method does not rely on a single probability distribution but considers a set of probability distributions (ambiguity set), optimizing the expected objective under the worst-case distribution. Literature [4] proposed a data-driven distributionally robust optimization method based on ellipsoidal uncertainty sets, effectively handling wind power correlation problems. Literature [5] constructed a coordinated optimization model for maintenance and reconfiguration of distribution networks with high photovoltaic penetration considering fuzzy chance constraints, but did not consider the multi-objective characteristics in market environments. Literature [6] studied the application advantages of energy storage technology in power systems with high renewable energy proportions, but did not deeply explore the coordinated optimization of scheduling and maintenance. Literature [7] proposed a maintenance scheduling preparation mode for power generation units based on maintenance willingness curves, but did not consider uncertainty in high renewable energy scenarios.

Current research has obvious shortcomings: first, scheduling and maintenance plans are often considered separately, ignoring the coupling relationship between them; second, renewable energy uncertainty is mostly modeled using single probability models, which are difficult to adapt to actual complex scenarios; third, existing methods often focus on a single objective, lacking multi-objective coordinated optimization of economy, security, and renewable energy accommodation.

To address these problems, this paper proposes a multi-objective distributionally robust optimization method for power market scheduling and maintenance that incorporates the energy-intensive demand profiles of textile manufacturing plants alongside high proportions of renewable energy accommodation. This framework enables the synchronization of fluctuating green power supplies with the continuous operational requirements of weaving and dyeing facilities to ensure both grid stability and industrial production efficiency. The innovations are as follows: using kernel density estimation to establish a probability distribution ambiguity set considering renewable energy correlations; introducing fuzzy chance constraints to characterize photovoltaic uncertainty; constructing a multi-objective optimization model that minimizes total cost, maximizes renewable energy accommodation, and minimizes risk; considering the coupling relationship between grid maintenance and operation, optimizing system topology with a focus on temporal consistency. The model ensures that the optimal topology remains secure under N-1 contingencies for every time interval within the maintenance window, rather than only at the start and end times of maintenance, thereby bridging the gap between operational efficiency and continuous grid reliability.

PROBLEM MODELING

Characteristics of Power Systems with High Proportion of Renewable Energy

Power systems with high proportion of renewable energy exhibit obvious nonlinear, stochastic, and complex characteristics. Wind power and photovoltaic output are affected by weather conditions, showing strong spatiotemporal correlation and uncertainty. Figure 1 shows the correlation characteristics of typical wind power and photovoltaic output. It can be seen that geographically adjacent wind farms have strong positive correlation, and photovoltaic output also shows highly correlated characteristics in sunny weather. Ignoring these correlations will lead to overly conservative or risky scheduling decisions.

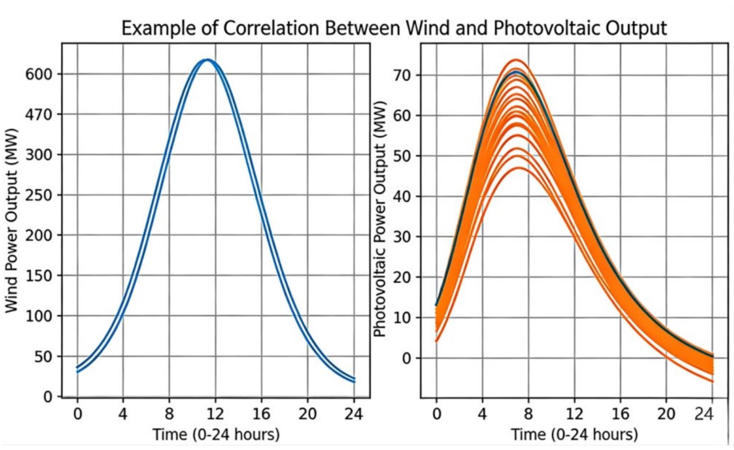

Figure 1. Correlation characteristics example of wind power and photovoltaic output.

Multi-Objective Optimization Problem Formulation

The optimization problem of power market scheduling and maintenance considering high proportion of renewable energy accommodation can be formulated as a multi-objective optimization problem:

$$\min x, y\{f_1(x,y), f_2(x,y), f_3(x,y)\} \tag{1}$$

Where x represents first-stage decision variables (such as unit on/off status, line maintenance status $y_{l,t}$, and maintenance schedules), while y represents second-stage decision variables including active/reactive power output adjustment, transformer tap positions, and reserve capacity. This classification ensures that discrete maintenance commitments are fixed before uncertainty is revealed. The objective functions include:

- Total cost minimization:

$$f_1(x,y) = C_{gen} + C_{maint} + C_{loss} + \lambda C_{curt} \tag{2}$$

- Renewable energy accommodation maximization (Strategic Objective):

$$f_2(x,y) = -\sum_{t=1}^{T} \sum_{i \in N_{\mathrm{RES}}} p_{i,t}^{\mathrm{RES}} \tag{3}$$

While f_1 includes a curtailment penalty (C_{curt}) to ensure basic economic feasibility, f_2 is explicitly defined as a distinct strategic objective to prioritize green energy penetration beyond mere cost-avoidance. By decoupling the environmental target from the economic penalty, the model allows decision-makers to explore a Pareto frontier where renewable accommodation can be maximized even if the marginal cost of doing so exceeds the unit curtailment penalty. Risk minimization (using conditional value-at-risk model):

$$f_3(x,y) = CVaR_\alpha[Violation(x,y,\xi)] \tag{4}$$

Where C_{gen} is generator operating cost, C_{maint} is maintenance cost, C_{loss} is network loss cost, C_{curt} is wind and solar curtailment cost; $p_{i,t}^{\mathrm{RES}}$ is the actual output of renewable energy source i at time period t ; $CVaR_\alpha$ is the conditional value-at-risk at confidence level a; $Violation(x,y,\xi)$ represents constraint violation degree.

Constraint Conditions

System operation constraints include power balance constraints, generator output limits, and power flow constraints. To ensure the economic results accurately reflect the flexibility of energy storage, a time-varying discharge and state-of-charge (SoC) model is explicitly integrated into the scheduling framework using the following temporal coupling constraints:

- Maintenance duration constraint:

$$\sum_{t\in T}(1-y_{l,t}) = T_{maint,l}, \forall l \in L \tag{5}$$

This formulation, alongside continuous power flow equations, ensures that once a maintenance-induced topology change occurs, its impact on system security is validated for every dispatch interval until the line is restored, explicitly accounting for potential N-1 violations during the maintenance state.

- Maintenance mutual exclusion constraint:

$$\sum_{l\in\Omega}(1-y_{l,t}) \le N_{max}, \forall t \in T \tag{6}$$

- Reserve capacity constraint:

$$R_t^{+} \ge \max_{\xi\in\Xi}\left\{\sum_{i\in N_{RES}} \xi_{i,t}^{up} - \sum_{j\in G} r_{j,t}^{up}\right\} \tag{7}$$

- Fuzzy chance constraint:

$$Pr\{p_{i,t}^{PV} \le \hat{p}_{i,t}^{PV} + \eta\} \ge 1-\epsilon, \forall i \in N_{PV}, t \in T \tag{8}$$

Where $y_{l,t} \in \{0,1\}$is a binary component of the first-stage decision vector x,represents the online status of line 1 at time period t; $T_{maint,l}$ is the required maintenance time for line 1; Ω is the set of lines that can be maintained simultaneously; N_{max} is the maximum number of lines that can be maintained simultaneously; R_t^{+} is the positive reserve capacity; $\xi_{i,t}^{up}$ is the upper bound of renewable energy prediction error; $r_{j,t}^{up}$denotes the upward regulation capability of the unit; $Pr\{\cdot\}$represents probability;$\hat{p}_{i,t}^{PV}$is the predicted photovoltaic output; η and ϵ are ambiguity parameters..where $\hat{p}_{i,t}^{PV}$ denotes the nominal predicted PV output; $\eta_{i,t}$ represents the fuzzy admission deviation variable belonging to a fuzzy set characterized by a membership function; and $\epsilon \in \{0,1\}$ is the risk tolerance level. Unlike traditional chance constraints, Eq. (8) requires the probability of constraint satisfaction to be met for all probability distributions P within the ambiguity set P_{set}, ensuring distributional robustness.

DISTRIBUTIONALLY ROBUST OPTIMIZATION METHOD

Construction of Probability Distribution Ambiguity Set

Kernel density estimation (KDE) is used to construct the probability distribution ambiguity set. Given historical data$\xi^1, \xi^2, \dots, \xi^N$, the probability density function estimation is:

$$f_0(\xi) = \frac{1}{N\|\mathbf{H}\|^{1/2}} \sum_{i=1}^{N} K\left[\mathbf{H}^{-1/2}(\xi - \xi^i)\right] \tag{9}$$

where H is a symmetric positive definite bandwidth matrix, and K is the kernel function. This paper uses the Gaussian kernel function:

$$\mathrm{K(u)} = (2\pi)^{-\mathrm{n}/2} \exp(-\frac{1}{2}\mathrm{u^T u}) \tag{10}$$

The probability distribution ambiguity set is defined based on the L_1-norm distance from the KDE-generated reference distribution $\mathrm{f_0(\xi)}$, constrained by the ellipsoidal support set Ξ_{ell} to bridge density estimation with correlation constraints:

$$\mathcal{P}_{\mathrm{set}} = \left\{\mathrm{P} \in \mathcal{P}: \int \Xi_{ell} \, |\mathrm{f(\xi)} - \mathrm{f_0(\xi)}| \mathrm{d\xi} \le \mathrm{d_K}, \mathrm{supp(P)} \subseteq \Xi_{ell}\right\} \tag{11}$$

Where d_K is the distance parameter controlling the size of the ambiguity set, and Ξ_{ell} represents the ellipsoidal uncertainty set defined in Section Ellipsoidal Support Set Considering Correlations, which ensures that all distributions within the set respect the observed spatiotemporal correlations of wind and solar output.

Ellipsoidal Support Set Considering Correlations

To capture correlations between wind farms and provide a bounded support for the ambiguity set, the minimum volume enclosing ellipsoid (MVEE) is used to construct the ellipsoidal support set Ξ_{ell}:

$$\mathcal{E}_{G,c_0} = \{\xi \in \mathbb{R}^n : (\xi - c_0)^T G (\xi - c_0) \le 1\} \tag{12}$$

where G is a symmetric positive definite matrix, and c_0 is the center vector. The parameters are determined by solving the following optimization problem:

$$\min \log \det \mathrm{G}^{-1}$$

$$\mathrm{s.t.}\ (\xi^{i} - c_0)^{T} G(\xi^{i} - c_0) \leq 1, i = 1,2, \ldots, N \tag{13}$$

Multi-Objective Problem Transformation and Solution

By integrating the KDE-based density constraints with the MVEE-based support set, the model minimizes the expected objective value under the worst-case distribution P within P_{set}.

The ϵ- constraint method is used to transform the multi-objective problem into a single-objective problem:

$$\min f_1\,(x, y) \tag{14}$$

$$f_2(x, y) \leq \epsilon_2 \tag{15}$$

$$f_3(x, y) \leq \epsilon_3 \tag{16}$$

Where ϵ2 and ϵ3 are preset thresholds. The threshold values are adjusted according to risk aversion degree and environmental priority. Specifically, ϵ2 is utilized to enforce a minimum accommodation level that may surpass the purely economic equilibrium defined by the curtailment cost in f_1, thereby addressing the non-linear policy requirements for green energy transition in textile manufacturing.

Algorithm Flow

The distributionally robust optimization solution process proposed in this paper is as follows:

① Input historical data, system parameters, ambiguity set parameter dK ;

② Construct probability distribution ambiguity set using equations (9)-(10);

③ Construct ellipsoidal uncertainty set using equations (12)-(13);

④ Establish multi-objective distributionally robust optimization model (equations (1)-(8));

⑤ Transform to single-objective problem using epsilon-constraint method (equation (14));

⑥ Call optimization solver (this paper uses Gurobi 10.0) to solve;

⑦ Output scheduling and maintenance plans, objective function values, system operating status.

CASE ANALYSIS

System Parameters

The modified IEEE 118-bus system is used as the test case, containing 48 generator units, 186 branches, and 91 load nodes. To support voltage stability, the model incorporates 54 reactive power compensation buses and 9 adjustable transformers, ensuring that the "Voltage Deviation" metrics reported in the results are achieved through active voltage regulation rather than remaining as passive outputs. The system is connected to 12 wind farms and 8 photovoltaic power stations, with renewable energy total installed capacity being 35% of the system peak load. It is assumed that 20 lines need maintenance within 30 days, with each line requiring 3-5 days for maintenance. The optimization solver is Gurobi 10.0, running on Intel Core i9-13900K CPU @ 5.8 GHz, 64 GB RAM, Windows 11 system. Table 1 presents a comparison of parameters for different types of energy storage technologies, used to assist in analyzing the role of energy storage systems in power systems with high renewable energy proportion [8].

Table 1. Comparison of energy storage technology parameters

Energy Storage Type	Energy Density (Wh/kg)	Power Density (W/kg)	Efficiency (%)	Lifetime (years)	Cost per kWh (yuan/kWh)
Lithium-ion Battery	150-200	250-350	85-90	8-10	0.6-0.8
Pumped Hydro Storage	0.2-2.0	300-500	70-85	40-60	0.2-0.3
Compressed Air	30-50	50-100	55-70	25-30	0.3-0.4
Supercapacitor	4-8	3000-5000	90-95	15-20	1.5-2.0
Flywheel Energy Storage	5-30	150-200	85-90	15-20	0.8-1.2

Data source: National Energy Administration's "Energy Storage Industry Development Report (2023)"

Results Analysis

- To verify the effectiveness of the proposed method, four comparison scenarios were designed:
- Scenario 1: Traditional deterministic optimization method
- Scenario 2: Stochastic optimization method
- Scenario 3: Robust optimization method
- Scenario 4: The distributionally robust optimization method proposed in this paper

Table 2 shows the comparison of system performance indicators under different scenarios.

Table 2. Comparison of system performance indicators under different scenarios

Indicator	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
Total Cost (10,000 yuan)	985.6	936.2	1087.3	952.8
Wind and Solar Curtailment Rate (%)	12.3	9.8	5.2	7.6
Renewable Energy Accommodation (MWh)	4823	5016	4958	5215
Voltage Deviation (%)	7.8	6.9	5.2	5.8
Risk Value (10,000 yuan)	178.4	145.6	86.3	93.5

From Table 2, it can be seen that Scenario 4 (the method proposed in this paper) shows good comprehensive performance in terms of total cost, renewable energy accommodation, and risk control. By incorporating the time-varying discharge model, the total cost of 952.8 (10,000 yuan) represents a realistic dispatch that respects the physical state-of-charge limits of the integrated pumped hydro and battery systems, rather than an idealized unconstrained optimization. Compared with Scenario 1, the renewable energy accommodation increased by 8.1%; compared with Scenario 2, the risk value decreased by 35.7%; compared with Scenario 3, the total cost decreased by 12.4%. This shows that the proposed method can effectively balance the objectives of economy, renewable energy accommodation, and risk control. Specifically, the inclusion of reactive power coordination allows the proposed method (Scenario 4) to maintain a superior voltage profile (5.8% deviation) even during periods of high renewable fluctuation, as shown in Table 2.

Figure 2 shows the comparison of system daily net load curves under different methods. It can be seen that the method proposed in this paper can better track load changes and reduce net load fluctuations, which is beneficial for improving system operating efficiency. Especially during midday and evening periods, due to the uncertainty of photovoltaic output and load peaks, traditional methods struggle to balance supply and demand, while the method proposed in this paper significantly improves system operation status through coordinated scheduling and optimized reserves [9-11].

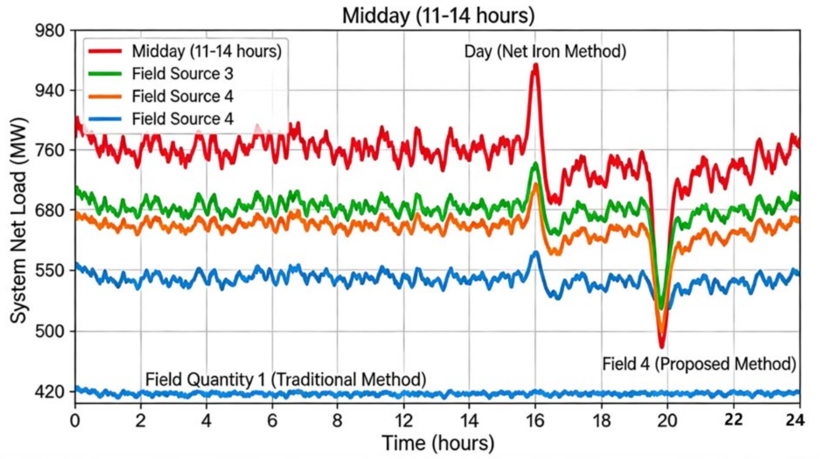

Figure 2. Comparison of system daily net load curves under different methods

Figure 3 shows the changes in system reserve capacity requirements under different correlation coefficients. When the wind power correlation coefficient increases from 0 to 0.9, the required reserve capacity significantly increases from 125MW to 218MW, an increase of 74.4%. This indicates that ignoring wind power correlation will lead to insufficient reserve capacity configuration, threatening system security operation. The ellipsoidal uncertainty set used in this paper can effectively capture this characteristic, automatically increasing reserve capacity when correlation strengthens, ensuring system security [12,13].

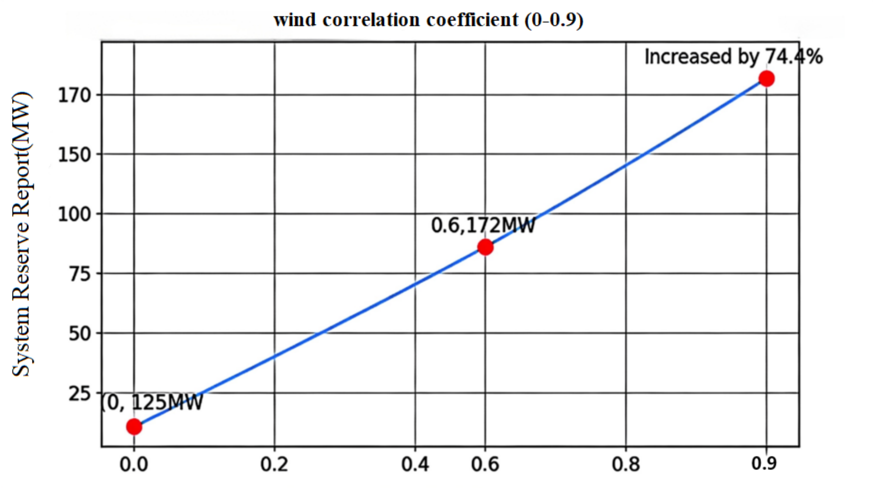

Figure 3. System reserve capacity requirements under different correlation coefficients

CONCLUSION AND OUTLOOK

Aiming at the scheduling and maintenance challenges of power systems with a high proportion of renewable energy, this paper proposes a multi-objective distributionally robust optimization method to ensure the stable power supply required for energy-intensive textile production processes. This approach optimizes the coordination between intermittent green energy and the continuous operational loads of high-speed weaving and dyeing machinery to maintain industrial productivity and energy efficiency. Research results show that:

- Using a data-driven method to construct a probability distribution ambiguity set considering renewable energy correlations can effectively capture the uncertainty characteristics of renewable energy output with limited historical data, improving the robustness of decisions.
- Introducing fuzzy chance constraints to characterize photovoltaic uncertainty and constructing a multi-objective optimization model can coordinate economic, renewable energy accommodation, and risk control objectives, achieving comprehensive performance improvement of the system.
- Considering the coupling relationship between grid maintenance and operation, and optimizing the system topology consistently throughout the maintenance period can reduce network losses while guaranteeing N-1 security. By expanding the optimization focus from discrete time points (start/end) to the entire maintenance trajectory, the proposed method provides a more robust guarantee for the continuous stable power supply required by textile manufacturing.
- Case analysis verifies the effectiveness of the proposed method in various scenarios, with more obvious advantages in high volatility and strong correlation scenarios.

Future research directions include: further considering multi-time scale coordination, deeply studying the optimal configuration of energy storage systems in maintenance scheduling, exploring resilient scheduling methods considering extreme weather events, and researching collaborative optimization mechanisms for cross-regional power markets. With the deepening of power market reform and advances in renewable energy technology, scheduling and maintenance optimization methods must evolve to accommodate the high energy demands of intelligent textile manufacturing while adapting to the development needs of new power systems. This continuous innovation ensures that textile enterprises can capitalize on green energy transitions to power precision weaving and dyeing processes with greater stability and cost-efficiency.

Author Contributions

Conceptualization –Yixing Chen, Xuchen Tang, Guoliang Zhang, Rui Yang, Bo Bao, Cong Fu and Gang Luo; methodology – Yixing Chen, Xuchen Tang, Rui Yang, Bo Bao, Cong Fu and Gang Luo; investigation – Yixing Chen, Xuchen Tang, Guoliang Zhang, Rui Yang, Bo Bao, Cong Fu and Gang Luo; writing-original draft preparation – Yixing Chen, Xuchen Tang, Guoliang Zhang, Rui Yang, Bo Bao, Cong Fu and Gang Luo. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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