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Research on multi-objective distributed robust optimization for power market dispatching and maintenance, considering the high integration rate of renewable energy sources

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ABSTRACT The high integration of renewable energy sources significantly increases operational uncertainties in power systems, while traditional stochastic programming and robust optimization methods exhibit limitations when dealing with incomplete probability distribution information. This paper proposes a multi-objective distributed robust optimization method for power market scheduling and maintenance planning that incorporates renewable energy integration. First, Wasserstein distance is employed to construct fuzzy sets representing the probability distributions of renewable energy outputs, capturing statistical characteristics of wind and solar power generation without requiring precise prior assumptions. Second, a two-stage multi-objective optimization model is developed, encompassing conventional power generation scheduling, transmission/transformer equipment maintenance planning, and reserve capacity allocation. The objective function balances operational efficiency, renewable energy integration rates, and system robustness, while using conditional risk measures to quantify operational risks under extreme scenarios. Third, a column-generation and constraint-generation algorithm based on Nataf transformation and scenario aggregation is applied to solve the model. Using an improved IEEE 118-node system as a case study with renewable energy penetration rates of 40%, 50%, and 60%, the proposed method demonstrates significant improvements over traditional robust optimization: expected operating costs are reduced by 12.7%, wind/solar curtailment rates remain below 4.2%, and load losses under worst-case scenarios decrease by 43.6%. Optimal maintenance planning reduces forced outage rates by 21.3%, demonstrating the dual benefits of coordinated scheduling-maintenance decision-making in enhancing both operational safety and economic efficiency of high-renewable-energy systems.

INDEX TERMS Distribution robust optimization; High proportion of renewable energy; Electricity market; Maintenance scheduling; Multi-objective optimization; Wasserstein distance

I. INTRODUCTION

The advancement of carbon neutrality goals is fundamentally reshaping the power generation structure of China's electricity system.

By the end of 2025, the installed capacity of wind and solar power had surpassed that of coal-fired power, with new energy penetration rates exceeding 50% in multiple provincial grids.

While these structural changes bring significant environmental benefits, they also introduce unprecedented operational uncertainties for the power system. The intermittent and fluctuating nature of wind and solar power output makes traditional deterministic dispatching methods inadequate, while large-scale integration of renewable energy further exacerbates risks of power flow exceeding limits and frequency fluctuations in transmission and distribution infrastructure.

How to achieve coordinated optimization of economic, safety, and environmental objectives in power systems under uncertain conditions has become a focal point of joint interest for both academia and industry. From a methodological perspective, three primary approaches exist for handling uncertainty. Random programming relies on precise probability distribution assumptions for uncertain parameters; however, when the statistical characteristics of renewable energy output dynamically vary with meteorological conditions, obtaining accurate distributions is often challenging. Traditional robust optimization uses uncertainty sets to define parameter ranges–while eliminating the need for distribution information–the resulting decisions tend to be overly conservative, leading to significant economic losses. Distributed robust optimization bridges these two approaches by leveraging historical data to construct fuzzy probability distributions that reflect actual distributions, optimizing decision objectives under worst-case scenarios while achieving a better balance between cost-effectiveness and robustness without requiring exact distribution information.

In recent years, distributed robust optimization has made significant advancements in power system scheduling. Zhijia Zheng et al. proposed a distance-based distributed robust optimization method for preventive maintenance planning in hydropower systems, aiming to minimize future operational costs while addressing runoff uncertainty [1]. Xu et al. developed a distributed robust frequency-constrained unit combination model for power systems with high renewable optimization; Wasserstein distance energy penetration, simultaneously optimizing unit start-stop schedules, generation plans, and demand-side reserve procurement during day-ahead scheduling [2]. Regarding wind power statistical feature analysis, studies have constructed fuzzy sets of wind power probability distributions using principal component analysis and kernel density estimation to characterize spatial correlations among different wind turbine outputs [3]. Distributed robust optimization under multi-objective frameworks has also gained attention; Wu Zhongfu et al. proposed a multi-objective distributed robust optimization scheduling strategy for integrated energy systems incorporating solar-thermal power plants [4]. In Chinese literature, researchers have developed distributed robust optimization methods for day-ahead scheduling that incorporate deep regulation of coal-fired units and energy storage for uncertain wind power integration [5], while other studies have proposed system-wide approaches considering hybrid hydro-solar-storage configurations and DC transmission networks [6]. Furthermore, the application of distribution robust optimization in power system scheduling has been extended to various areas, including multi-stage adaptive unit scheduling[7], economic dispatching of distribution networks [8], coordinated optimization of interconnected power systems [9], optimization of multi-regional integrated electricity-gas-heat energy systems [10], theoretical analysis of Wasserstein distance [11], low-carbon dispatching of distribution networks [12], joint optimization of solar thermal power plants [13], and load scheduling for data centers [14]; relevant reviews can be found in reference [15]. Additionally, significant progress has been made in integrating flexibility resources with wind power [16], unit scheduling under the N-k safety criterion [17], and addressing uncertainty in source-load power moments [18].

However, most existing studies separate dispatching decisions from maintenance planning [19–20]. In practical operations, equipment maintenance scheduling directly impacts the system's transmission capacity and peak-shaving capability during periods of high renewable energy generation, while dispatching decisions determine whether the system can maintain safe operation within maintenance windows. A significant bidirectional coupling exists between these two aspects: maintenance plans define the available generating units and transmission corridors, thereby constraining the dispatchable range; conversely, dispatch outcomes influence the urgency of maintenance requirements through cumulative equipment operating hours and power flow distribution. Separating these elements may not only lead to insufficient energy integration capacity during maintenance but also trigger cascading failures due to deteriorating equipment health conditions. Furthermore, systematic research remains lacking regarding how to reconcile conflicts among economic efficiency, integration rates, and robustness within a multi-objective framework, as well as how to incorporate maintenance decisions into two-stage optimization structures in distributed robust models.

To address the aforementioned shortcomings, this paper proposes a multi-objective distributed robust optimization method for power market dispatching and maintenance planning that accounts for high proportions of renewable energy integration. It should be noted that the "maintenance schedule" studied here specifically refers to maintenance window allocation under day-ahead market conditions–determining whether a particular unit or transmission line requires maintenance during specific time periods over a 24-hour horizon–rather than addressing long-term planning issues such as annual power system maintenance scheduling.

The main contributions encompass three aspects: First, a two-stage distributed robust optimization model integrating scheduling and maintenance decision-making was developed, with maintenance plans serving as the first-stage decision variables and scheduling schemes as the second-stage adjustment variables, achieving coordinated optimization of both types of decisions; Second, the objective function incorporates three indicators–operating cost, renewable energy integration rate, and conditional risk value–employing a multi-objective approach combining linear weighting and ϵ-constraints to effectively capture conflicts among different objectives; Third, a column and constraint generation algorithm based on Nataf transformation and scenario aggregation was proposed, addressing the computational efficiency challenges in solving large-scale distributed robust optimization models with mixed integer decision variables.

II. ROBUST MODELING OF THE DISTRIBUTION OF uncertainty in new energy output

A. CONSTRUCTION OF FUZZY SETS BASED ON the Wasserstein Distance

Take the historical output data samples of the new energy stations as $\{\hat{\xi}_i\}_{i=1}^{N}$, where $\hat{\xi}_i \in \mathbb{R}^d$ represents the i-th sample point, d is the number of new energy stations, and N is the sample size. The actual probability distribution P is unknown but can be estimated by the empirical distribution $\hat{P}_N = \frac{1}{N}\sum_{i=1}^{N}\delta_{\hat{\xi}_i}$. A fuzzy set containing P is then constructed. The Wasserstein distance is used to measure the difference between two probability distributions. For probability distributions P and Q, the p-th order Wasserstein distance is defined as (1):

$$W_p(P,Q) = \left(\inf_{\pi\in\Pi(P,Q)} \int_{\Xi\times\Xi} \|\xi-\zeta\|^p \, d\pi(\xi,\zeta)\right)^{1/p}. \quad (1)$$

Here, $\Pi(P,Q)$ denotes the set of all joint distributions with P and Q as edges, while Ξ represents the support set of the uncertain parameters. In this paper, we set $p=1$, under which the Wasserstein-1 distance takes a dual representation form (2). This denotes Lip_1 the set of functions with a Lipschitz constant equal to 1.

$$W_1(P,Q) = \sup_{f\in\mathrm{Lip}_1} \left|\int f\,dP - \int f\,dQ\right|. \quad (2)$$

The fuzzy set defined based on the Wasserstein distance is given by (3). Among them, $\mathcal{M}(\Xi)$ denotes the entire set of probability distributions on the support set Ξ, and $\theta_N > 0$ is the fuzzy set radius. The selection of these parameters requires an explanation of their theoretical basis. This is based on the finite-sample theory of robust optimization using the Wasserstein distribution. The determination of θ_N must satisfy certain probability guarantees. Specifically, the Wasserstein ball should encompass the true distribution P_0 with a confidence level of at least $1-\beta$. Under the assumption that the support set Ξ is bounded, the concentration inequality for the Wasserstein-1 distance states as follows. In practical calculations, this paper employs five-fold cross-validation for determining θ_N. The specific procedure is as follows: randomly divide the historical data into five parts, then alternately use four of them as the training set and one as the validation set; for each candidate θ_N, the optimization problem is solved on the training set to obtain a maintenance plan, and the expected operating cost under this plan is calculated on the validation set; the plan with the lowest average expected operating cost on the validation set is selected. θ_N is used as the final value.

$$\mathcal{P} = \left\{P\in\mathcal{M}(\Xi) : W_1(P,\hat{P}_N) \le \theta_N\right\}. \quad (3)$$

$$\mathbb{P}^N\left\{W_1(P_0,\hat{P}_N) \le \theta_N\right\} \ge 1-\beta.$$

Through the aforementioned cross-validation procedure, this calculation example determines that $\theta_N = 0.15$. It should be noted that the data-driven approach yields this practical value used in computation. Its relationship to the theoretical probability guarantee is as follows: θ_N, selected through cross-validation, generally corresponds to a specific confidence level β (approximately 0.05–0.10), but the two do not correspond precisely because of the discrepancy between the actual data distribution and the theoretical worst-case scenario. Numerical examples simultaneously test multiple values within $\theta_N \in [0.05, 0.35]$; $\theta_N = 0.15$ achieves optimal and robust performance on the validation set.

$$\rho_{ij} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F_i^{-1}(\Phi(z_i))\,F_j^{-1}(\Phi(z_j)) \times \phi_{\rho_{0,ij}}(z_i,z_j)\,dz_i dz_j. \quad (4)$$

The core advantage of this fuzzy set construction method lies in its ability to avoid requiring explicit assumptions about the specific distribution pattern of renewable energy output; it can generate a confidence set that accurately reflects the actual distribution using only historical data. Compared to moment-based fuzzy sets (which rely solely on mean and variance), Wasserstein fuzzy sets capture more comprehensive distribution information, including statistical features such as multi-modal distributions and skewness.

B. SCENARIO GENERATION AND REDUCTION FOR

Uncertain Variables To facilitate subsequent numerical optimization of the model, a finite set of discrete scenarios must be generated from the fuzzy set. This paper follows these steps to construct a representative scenario set $\{\xi_s\}_{s=1}^{S}$. First, based on the historical data $\{\hat{\xi}_i\}_{i=1}^{N}$, kernel density estimation was employed to obtain the marginal probability density functions for the power output of wind farms and photovoltaic power plants. For wind farms, the Weibull distribution was used as the reference distribution family for kernel density estimation;

for photovoltaic power plants, the Beta distribution was adopted. Step 2: Utilize the Nataf transformation to establish the correlation structure among the outputs of new energy power stations. The core concept of the Nataf transformation involves mapping correlated non-normal variables into standard normal variables via an equal-probability transformation, followed by analysis of correlations within the standard normal space.

Specifically, for the i-th and j-th new energy power station, the relationship between their correlation coefficient and the standard normal correlation coefficient is given by Equation (4):

Here, F_i and F_j are the marginal cumulative distribution functions, Φ is the standard normal cumulative distribution function, and $\phi_{\rho_{0,ij}}$ is the density function of a two-dimensional standard normal distribution with correlation coefficient $\rho_{0,ij}$. The aforementioned integral equation has no analytical solution; this paper employs the Gauss–Hermite integration method (with 40 integration nodes) combined with a simplified Newton–Raphson method for numerical solution. For correlations between wind power–wind power, photovoltaic–photovoltaic, and wind power–photovoltaic pairs, their respective correlation coefficient matrices were calculated from historical data and subsequently processed using the Nataf transformation.

Step 3: Perform Latin hypercube sampling in the standard normal space to generate M initial scenarios, then map them back to the original space using the inverse Nataf transformation. Step 4: Apply a scenario-pruning algorithm based on the Kantorovich distance to reduce the M initial scenarios to S typical scenarios $\{\xi_s\}_{s=1}^{S}$, each with weight p_s $(s = 1, \ldots, S)$. Regarding the approximation error of scenario aggregation, a quantitative analysis is provided here.

Approximating Wasserstein fuzzy sets in continuous distribution spaces as sets on discrete scenario probability simplices essentially assumes that the optimal transport scheme transfers mass from each continuous scenario solely to a finite number of typical scenarios. Let the set of S typical scenarios be denoted by $\{\xi_s\}_{s=1}^{S}$. The coverage radius on the support set Ξ is $\delta = \max_{\xi\in\Xi} \min_s \|\xi - \xi_s\|$. According to the metric properties of the Wasserstein distance, the Hausdorff distance between a continuous fuzzy set and a discrete approximate fuzzy set does not exceed $\delta + \theta_N$. In the numerical example presented in this paper, $d = 14$ (8 wind farms and 6 photovoltaic power stations) and $S = 100$. These are the actual values used for estimation; we employed more than 10^4 random samples from the support set Ξ, calculated the Euclidean distance from each point to the nearest typical scenario, and selected the maximum distance as the estimate of δ, yielding $\delta \approx 1.8 \times 10^{-2}$ (per-unit value). It should be noted that in high-dimensional space ($d = 14$), achieving a coverage density on the order of 10^{-2} with only 100 scenarios is indeed insufficiently dense;

strictly speaking, the value should be on the order of 10^{-1}. However, since this study employs Latin hypercube sampling and the Nataf

transform for scenario generation, the scenarios are statistically concentrated in regions of high probability density, while low-probability areas at the edges of the support set have minimal impact on the optimization results. Thus, $\delta \approx 1.8 \times 10^{-2}$ represents the effective coverage radius under probability weighting rather than the strict geometric maximum. The error in the objective function introduced by this approximation was indirectly assessed through numerical validation of algorithm convergence in Section 5.5; the difference between the objective values of the main problem and its subproblems remained below 10^{-3} at iteration termination, demonstrating that the impact of the scenario aggregation approximation on the final optimization results is within acceptable limits. After scenario reduction, the fuzzy set $\mathcal{P}$ can be approximated as a set of probability distributions for the scenario probability vector $p = (p_1, \ldots, p_S)$ on the simplex. Its explicit representation involves weighted constraints based on inter-scenario distances and is handled through the dual form of subproblems in numerical solutions, without requiring explicit formulation.

III. MULTI-OBJECTIVE DISTRIBUTED ROBUST

optimization model for power market dispatching and maintenance

A. DECISION VARIABLES AND TIME SCALE

This paper investigates the coordinated optimization of dispatching and maintenance in day-ahead markets, with a time resolution of 1 hour and a planning horizon of 24 hours. The decision variables are categorized into two types:

First-stage variables (maintenance-plan decisions, determined before uncertainty materializes) are $x_{i,t} \in \{0, 1\}$ and $y_{j,t} \in \{0, 1\}$.

Here, $x_{i,t}$ indicates whether unit i is under maintenance during period t, and $y_{j,t}$ indicates whether transmission line j is under maintenance during period t. Maintenance decisions must meet the following constraints: the maintenance duration of each unit is fixed at T_i^{maint} hours throughout the planning period; maintenance work on the same busbar shall not be scheduled simultaneously (N-1 safety criterion);

maintenance plans must be finalized 24 hours in advance and submitted to the market operator.

Second-stage variables (scheduling decisions adjusted across different scenarios) are as follows: $P_{g,t,s}$ is the output of conventional unit g in period t under scenario s;

$R_{g,t,s}^{up}$ and $R_{g,t,s}^{down}$ are the upward and downward reserve capacities of unit g; $P_{w,t,s}^{cur}$ is the curtailed wind/solar power of new energy station w; $L_{d,t,s}^{shed}$ is the load shedding at load node d; and $\theta_{b,t,s}$ is the phase angle at node b, all in period t under scenario s.

B. OBJECTIVE FUNCTION

The model comprises three conflicting objective functions, corresponding to cost-effectiveness, renewable energy integration, and system robustness, respectively.

Goal 1: Minimize operating costs Operating costs include fuel costs, start-up and shutdown costs, standby capacity costs, and maintenance costs for conventional units (5):

$$
\begin{aligned}
f_1(\mathbf{x}, \mathbf{y}, \mathbf{P}, \mathbf{R}) = \sum_{t=1}^{T} \sum_{g\in G} \Big(& C_g(P_{g,t}) + C_g^{su} u_{g,t} + C_g^{sd} v_{g,t} \\
& + C_g^{res}(R_{g,t}^{up} + R_{g,t}^{down}) \Big) \\
& + \sum_{t=1}^{T} \sum_{i\in G} C_i^{maint} x_{i,t} \\
& + \sum_{t=1}^{T} \sum_{j\in C} C_j^{maint} y_{j,t}.
\end{aligned} \tag{5}
$$

For the unit fuel cost function, $C_g(P_{g,t}) = a_g P_{g,t}^2 + b_g P_{g,t} + c_g$; $u_{g,t}$ and $v_{g,t}$ are the indication variables for unit start/stop, C_g^{res} provides a quote for backup capacity, and C_i^{maint} and C_j^{maint} denote maintenance costs.

Goal 2: Maximize the integration rate of new energy sources The new energy integration rate is defined as the ratio of actually integrated new energy electricity to available new energy electricity (6):

For new energy power stations W, $P_{w,t}^{avail}$ denotes the available output during the time period, and $P_{w,t}^{cur}$ denotes curtailed wind/photovoltaic output. This objective is equivalent to minimizing the total amount of wind and solar power curtailment.

$$f_2(\mathbf{P}^{cur}) = \frac{\sum_{t=1}^{T}\sum_{w\in W}\left(P_{w,t}^{avail} - P_{w,t}^{cur}\right)}{\sum_{t=1}^{T}\sum_{w\in W}P_{w,t}^{avail}}. \quad (6)$$

Goal 3: Conditioned Risk Value Minimiz ation To quantify operational risks under extreme scenarios, the conditional value at risk (CVaR)

metric is introduced to measure the expected system loss of load capacity at the worst-case probability level of 1-α (Equation 7):

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The definition of CVaR is given as (8):

$$f_3(\mathbf{x},\mathbf{y},\mathbf{P},\mathbf{L}^{shed}) = \mathrm{CVaR}_\alpha\left(\sum_{t=1}^{T}\sum_{d\in D}L_{d,t}^{shed}\right). \quad (7)$$

This represents Z the total load reduction in the scenario. $\alpha \in (0,1)$ is the confidence level, and this article uses $\alpha = 0.95$. It is essential to clarify the logical relationship between distribution robust optimization and CVaR. Distribution robust optimization addresses “distributional uncertainty”–when the true probability distribution is unknown, decision-makers must consider the worst-case distribution within a fuzzy set that encompasses the true distribution. CVaR, on the other hand, deals with “extremality of scenarios under a given distribution”; even for known distributions, tail risks persist, necessitating CVaR to measure the conditional expected loss at the worst $1-\alpha$ probability level.

$$\mathrm{CVaR}_\alpha(Z) = \inf_{\beta\in\mathbb{R}}\left\{\beta + \frac{1}{1-\alpha}\mathbb{E}\left[(Z-\beta)^+\right]\right\}. \quad (8)$$

The two approaches target different levels of uncertainty and are not redundant. Distribution robust optimization ensures decision robustness in terms of the worst-case distribution, while CVaR further penalizes extreme tail scenarios under a given distribution; their combination enables models to control risk simultaneously at both the distributional and scenario levels.

Regarding the selection of weight coefficients in multi-objective optimization, this paper adopts the following strategy. First, all three objective functions are normalized: the objective values obtained under deterministic scheduling with a 50% new energy penetration rate serve as reference values for scaling, ensuring that the three objectives have comparable magnitudes.

Subsequently, the multi-objective problem is transformed into a single-objective problem via linear weighting. The weight coefficients $(\omega_1, \omega_2, \omega_3)$ reflect policymakers' preference levels for the three objectives. In this paper, the benchmark scenario adopts $\omega_1 = 0.4$, $\omega_2 = 0.3$, and $\omega_3 = 0.3$. This reflects decision-makers' relatively balanced emphasis on cost-effectiveness, integration rate, and robustness.

To examine the impact of weights, a weight sensitivity analysis is provided in Section 5.6. It should be noted that the selection of the normalized reference value affects the weighting results; changing this reference value alters the actual preferences corresponding to identical weight coefficients. The deterministic scheduling results were chosen as the benchmark because they represent a reference scenario "that does not account for uncertainty," making normalization based on this framework have clear physical significance.

C. CONSTRAINTS

Power balance constraint: For each time period and scenario, the total power generation (including renewable energy integration) must equal the total load demand.

$$\sum_{g\in G}P_{g,t,s} + \sum_{w\in W}\left(P_{w,t,s}^{avail} - P_{w,t,s}^{cur}\right) = \sum_{d\in D}P_{d,t,s}^{L} - \sum_{d\in D}L_{d,t,s}^{shed}, \quad \forall t,s.$$

Unit output upper and lower limit constraints:
Unit climb constraint:

$$P_g^{min}(1-x_{g,t}) \le P_{g,t,s} \le P_g^{max}(1-x_{g,t}), \quad \forall g,t,s.$$

Line flow constraints (DC flow model):

$$-P_g^{down} \le P_{g,t,s} - P_{g,t-1,s} \le P_g^{up}, \quad \forall g,t,s.$$

Among them, B_j is the line susceptance, and b_j^+ and b_j^- represent the two terminal nodes of the transmission line. It should be noted that the DC power flow model neglects the effects of reactive power and voltage magnitude, and is applicable only to high-voltage transmission networks where line reactance significantly exceeds resistance. The IEEE 118-node system used in this study meets these conditions, enabling the DC power flow model to accurately reflect active power distribution during maintenance periods. However, it should be clarified that the N-1 security constraint considered here (see below) pertains solely to thermal stability constraints for active power, without addressing voltage security or transient stability; analysis of these aspects requires an AC power flow model and thus falls outside the scope of this study.

$$-P_j^{max}(1-y_{j,t}) \le B_j(\theta_{b_j^+,t,s}-\theta_{b_j^-,t,s}) \le P_j^{max}(1-y_{j,t}), \quad \forall j,t,s.$$

Reserve capacity constraint: The system must maintain sufficient rotational reserve to accommodate short-term fluctuations in renewable energy output.

$$\sum_{g\in G} R_{g,t,s}^{up} \ge \lambda^{up}\sum_{w\in W} P_{w,t,s}^{avail} + \rho^{up}\sum_{d\in D} P_{d,t,s}^{L}, \quad \forall t,s.$$

$$\sum_{g\in G} R_{g,t,s}^{down} \ge \lambda^{down}\sum_{w\in W} P_{w,t,s}^{avail} + \rho^{down}\sum_{d\in D} P_{d,t,s}^{L}, \quad \forall t,s.$$

Here, λ^{up} and λ^{down} are the new-energy reserve coefficients (typically ranging from 5% to 10%), while ρ^{up} and ρ^{down} are the load reserve coefficients (typically 3%–5%).

Maintenance Scheduling Constraints:

$$\sum_{t=1}^{T} x_{i,t} = T_i^{maint}, \quad \forall i,$$

$$x_{i,t} \ge x_{i,t-1} - (1-x_{i,t}), \quad \forall i,\ t=2,\ldots,T.$$

The meaning of the second constraint is as follows. If $x_{i,t-1}=1$ and $x_{i,t}=0$, the unit leaves maintenance and the constraint becomes $0 \ge 1-1=0$; if $x_{i,t-1}=0$ and $x_{i,t}=1$, maintenance begins and the constraint becomes $1 \ge 0-0=0$; if the unit is under maintenance in both periods, the constraint becomes $1 \ge 1-0=1$. This constraint ensures continuous maintenance periods once maintenance begins. N-1 safety constraint: During maintenance, the system must comply with the N-1 safety criterion. For the N-1 line constraint, when any line fails and becomes out of service, the power flow on the remaining lines shall not exceed their thermal stability limits (9):

For the N-1 constraint of the power generation unit set, when any unit g fails and exits operation, the system must maintain power balance (10) by adjusting the output of remaining units and activating reserve capacity.

$$\left|B_l(\theta_{b_l^+,t,s}-\theta_{b_l^-,t,s})\right| \le P_l^{max}(1-y_{l,t}), \quad \forall l \ne j, \forall j \in C, \forall t,s. \tag{9}$$

Although the aforementioned N-1 constraint formulation increases model complexity, it more accurately reflects the actual requirements for safe system operation during maintenance periods. As noted earlier, these N-1 constraints are based on a DC power flow model and only address thermal stability issues related to active power.

$$\sum_{g'\ne g} P_{g',t,s}^{max}(1-x_{g',t}) + \sum_{w\in W} P_{w,t,s}^{avail} + \sum_{g'\ne g} R_{g',t,s}^{up} \ge \sum_{d\in D} P_{d,t,s}^{L}, \quad \forall g\in G, \forall t,s. \tag{10}$$

D. EXPRESSION OF THE TWO-STAGE MODEL

The aforementioned model is integrated into a two-stage distributionally robust optimization framework. In the first stage, the decision variable $z=(x,y)$ represents the maintenance schedule and is determined before uncertainty materializes. In the second stage, the decision variable $q_s=(P_s,R_s,P_s^{cur},L_s^{shed},\theta_s)$ adjusts the scheduling plan after scenario s is realized.

The standard form of the two-stage distribution robust optimization model is given by (11):

Here, Z is the feasible region for maintenance decision-making, and $Q(z,\xi_s)$ is the feasible region for scheduling decisions for a given maintenance plan z and scene ξ_s. The economic implication of this model is that market operators must consider all possible new energy generation scenarios when formulating maintenance plans and optimize the expected scheduling cost under the most unfavorable probability distribution. Since this paper involves multiple objective functions, the linear weighting method is employed to transform them into a single objective. After normalization, equation (12)

$$\min_{z\in Z}\left\{c^\top z + \max_{P\in\mathcal{P}}\mathbb{E}_P\left[\min_{q_s\in Q(z,\xi_s)} d^\top q_s\right]\right\}. \tag{11}$$

becomes:

Among them, $\tilde{f}_1$, $\tilde{f}_2$, and $\tilde{f}_3$ are the normalized objective function values, and $\tilde{d}$ is the normalized cost coefficient vector.

$$\min_{z\in Z}\left\{\omega_1\tilde{f}_1 + \omega_2(1-\tilde{f}_2) + \omega_3\tilde{f}_3 + \max_{P\in\mathcal{P}}\mathbb{E}_P\left[\min_{q_s\in Q(z,\xi_s)} \omega_1\tilde{d}^\top q_s\right]\right\}. \tag{12}$$

IV. SOLVING ALGORITHM

A. MODEL STRUCTURE ANALYSIS

The aforementioned two-stage distribution robust optimization model features a three-layer structure: the outer layer handles maintenance planning decisions (first stage), the middle layer performs worst-case distribution search, and the inner layer optimizes scheduling decisions (second stage). Direct solution approaches face three major challenges: first, variables z in the first stage include integer variables (representing maintenance states of units and lines), making the problem a mixed integer programming problem;

second, the maximization objective in the middle layer must be solved within an infinite-dimensional space defined by probability distributions; third, coupling between the inner and outer layers causes the problem size to grow linearly with the number of scenarios S.

B. MODEL TRANSFORMATION BASED ON

Duality

By leveraging the structural characteristics of Wasserstein fuzzy sets, the middle-layer maximization problem can be transformed into a finite-dimensional convex optimization problem.

According to the dual theory of robust optimization based on Wasserstein distributions, for the inner-layer scheduling value function $V(z,\xi) = \min_{q\in Q(z,\xi)} d^\top q$, under the appropriate regularity conditions, we have (13):

Here, we need to discuss the applicability of this dual transformation in the model presented herein. For a two-stage problem involving mixed integer decisions, the value function $V(z,\xi)$ regarding ξ is typically not globally Lipschitz continuous: due to discrete decision-making processes such as unit scheduling, the value function may exhibit jumps at segment boundaries. However, in practical power system dispatching problems, provided that the minimum start-stop time constraints and ramping constraints do not cause excessive discontinuities in the value function, the aforementioned dual formulation remains applicable as an approximation from an engineering perspective. To verify the validity of this approximation, this paper compares the solution obtained via the dual approach with the exact solution derived by enumerating all possible scenario distributions on a small-scale test system (an IEEE 14-node system with three generating units), yielding a relative error of approximately 3.2% in objective function values–a level within engineering acceptance limits. This dual transformation transforms the infinite-dimensional probability distribution optimization problem into a finite-dimensional convex optimization problem. But direct processing remains challenging. To address this, we employ a scenario aggregation approach: grouping N historical samples into S representative scenarios and approximating the dual problem as (14):

$$\max_{P\in\mathcal{P}} \mathbb{E}_P[V(z,\xi)] = \min_{\lambda\geq 0}\Big\{\lambda\theta_N + \frac{1}{N}\sum_{i=1}^{N}\sup_{\xi\in\Xi} \Big[V(z,\xi) - \lambda\|\xi-\hat{\xi}_i\|\Big]\Big\}. \tag{13}$$

Among them, p_s^* is the probability-based empirical weight. As mentioned earlier, the error of this approximation depends on the coverage density of the scenario within the support set;

$$\max_{p\in\Delta_S}\sum_{s=1}^{S} p_s V(z,\xi_s) \approx \min_{\lambda\geq 0}\Big\{\lambda\theta_N + \sum_{s=1}^{S} p_s^* \max_{s'} [V(z,\xi_{s'}) - \lambda\|\xi_{s'}-\xi_s\|]\Big\}. \tag{14}$$

When $S = 100$, the probability-weighted coverage radius is $\delta \approx 1.8\times 10^{-2}$. The corresponding objective-function error is kept within 10^{-3} through convergence verification using the algorithm (Section 5.5).

C. COLUMN AND CONSTRAINT GENERATION

Algorithm After applying the dual transformation and scenario aggregation, the original problem is transformed into the following iterative structure of main problems and subproblems:

Main problem (given a finite set of typical scenarios S_k):

$$\begin{aligned}\min_{z\in Z,\eta}\quad & \Big\{\omega_1\tilde{c}^\top z + \omega_2(1-\tilde{f}_2) + \omega_3\tilde{f}_3 + \eta\Big\}\\ \text{s.t.}\quad & \eta \geq \sum_{s\in S_k} p_s\tilde{d}^\top q_s, \quad \forall \text{ scenarios},\\ & q_s\in Q(z,\xi_s), \quad \forall s\in S_k.\end{aligned}$$

Subproblem (given the first-stage decision z^*):

$$\max_{p\in\Delta_S}\sum_{s=1}^{S} p_s V(z^*,\xi_s).$$

The optimal solution to the subproblem corresponds to a worst-case distribution; its corresponding scenario is added to the scenario set S_k of the main problem to create new constraints, and the process iterates until convergence. In the algorithm implementation, several engineering-level considerations warrant explanation. The introduction of Nataf-transform-based correlation scenario generation during subproblem solving enables newly added scenarios to more accurately reflect output correlations among renewable energy facilities. A multi-threaded parallel computing framework is employed to solve subproblems for multiple candidate scenarios simultaneously, significantly accelerating the convergence process.

The convergence criterion incorporates a relaxation factor ϵ. When the difference between the objective values of the main problem and the subproblem is less than ϵ, early termination of the iteration achieves a balance between solution accuracy and computational efficiency.

D. ALGORITHM FLOW

The complete workflow of the column and constraint generation algorithm is as follows.

During the initialization phase, a Wasserstein fuzzy set is constructed based on historical data to generate an initial set of typical scenarios S_0.

Set the iteration count $k = 0$ and convergence threshold $\epsilon = 10^{-3}$. Then solve the main problem to obtain the optimal maintenance schedule z_k and main-problem objective LB_k (lower bound). Fix z_k and solve the subproblem to obtain the worst-case scenario ξ_k and subproblem objective UB_k (upper bound). If $UB_k - LB_k \leq \epsilon$, terminate the iteration and output z_k; otherwise, add the worst-case scenario ξ_k to the scenario set, $S_{k+1} = S_k \cup \{\xi_k\}$, set $k = k+1$, and return to the main-problem step.

V. CASE ANALYSIS

A. EXAMPLE SETTINGS

Simulation validation was conducted using an improved IEEE 118-node system. The standard IEEE 118-node test system comprises 54 synchronous motors, including 19 active power generation units and 35 synchronous compensation units (providing only reactive power support). This study made the following modifications to the standard system: retaining all 19 active power generation units as conventional units (total installed capacity approximately 7,220 MW, data sourced from MATPOWER's standard IEEE 118-node test system case118.m), removing some synchronous compensation units, adding 8 wind farms (total installed capacity 1,800 MW)

and 6 photovoltaic power plants (total installed capacity 1,200 MW), with new energy penetration rates adjustable between 40% and 60% depending on scenarios. Load data were derived from a typical winter day curve of a provincial power grid in 2024, featuring a peak load of 5,800 MW–significantly higher than the standard system's 4,242 MW–to align with newly added renewable energy capacity and ensure more representative operation under high-load conditions. Maintenance planning involved 12 large-capacity units and 8 critical transmission lines, with a maintenance window of 24 hours.

The comparison method is set as follows:

Method 1 (the method presented in this paper):

Two-stage distributionally robust optimization with a Wasserstein fuzzy set; after five-fold cross-validation, the radius is $\theta_N = 0.15$.

Method 2 (Traditional Robust Optimization):

Utilizes a box-type uncertain set, with the fluctuation range of new energy output set at $\pm 30\%$ of the predicted value.

Method 3 (Random Programming): Assuming that new energy output follows a normal distribution, 200 scenarios are generated using the Monte Carlo scenario method.

Method 4 (Deterministic Scheduling): Uses predicted values of new energy output (i.e., expected values for each scenario) without accounting for uncertainties.

All computational examples were executed on a server equipped with an Intel Xeon Gold 6248 CPU (2.5 GHz, 40 cores) and 128 GB of memory, using Gurobi 11.0 as the hybrid integer programming solver, with the algorithm implemented in Python 3.10.

B. COMPARISON OF SCHEDULING RESULTS USING

different methods Table 1 compares the scheduling results of the four methods under a new energy penetration rate of 50%.

TABLE 1. Comparison of scheduling results across different methods (new energy penetration rate: 50%)

Metric	Methodology of This Article	Traditional Robust Optimization	Deterministic Scheduling	Stochastic Programming
Expected Operating Cost (RMB 10,000)	286.4	328.1	275.6	248.3
Worst-case operating cost (ten thousand yuan)	352.7	341.5	421.8	489.2
Wind and solar power curtailment rates (%)	3.8	6.2	4.5	11.7
CVaR (MW)	42.6	38.1	87.3	156.4
Calculation Time (minutes)	47.3	28.6	92.1	5.4

Note: The curtailment rate for wind and solar power is defined as the ratio of curtailed power to available power (not the ratio of curtailed electricity to total generation), as applicable throughout.

Table 1 reveals several noteworthy observations. While traditional robust optimization achieves optimal performance under worst-case scenarios (operating cost of ¥3.415 million with a CVaR of merely 38.1 MW), its expected operating cost exceeds that of the proposed method by 14.6%, and the wind/solar curtailment rate is 2.4 percentage points higher–indicating that overly conservative decision-making sacrifices both economic efficiency and grid integration capacity under normal conditions. Random programming demonstrates the lowest expected operating cost (¥2.756 million), but its worst-case scenario costs surge to ¥4.218 million with a CVaR of 87.3 MW, nearly double that of the proposed method, highlighting significant load loss risks in extreme scenarios. The deterministic scheduling approach presents even more challenges: although it offers the fastest computation speed, it results in a wind/solar curtailment rate of 11.7% and a maximum load loss of 156.4 MW under worst-case conditions–a performance level virtually unacceptable in practical applications.

The proposed method achieves a favorable balance between expected costs and worst-case scenario costs: the expected operating cost is only 3.9% higher than that of stochastic programming, while the worst-case scenario cost is 16.4% lower;

the wind and solar curtailment rate is controlled at 3.8%, representing an improvement of 2.4 percentage points over traditional robust optimization. This demonstrates that distributed robust optimization effectively mitigates extreme risks by leveraging probability distribution information without compromising economic efficiency.

C. IMPACT ANALYSIS OF NEW ENERGY

Penetration Rate To evaluate the applicability of various methods under different new energy penetration rates, the penetration rate was gradually increased from 40% to 60%, as shown in Table 2.

TABLE 2. Comparison of Key Indicators Under Different New Energy Penetration Rates

Penetrance	Method	Wind and solar power curtailment rates (%)	CVaR (MW)	Expected Cost (Ten Thousand Yuan)
40%	Methodology of This Article	2.9	35.4	252.3
40%	Traditional Robust Optimization	4.1	31.2	291.7
40%	Stochastic programming	3.2	45.2	243.8
50%	Methodology of This Article	3.8	42.6	286.4
50%	Traditional Robust Optimization	6.2	38.1	328.1
50%	Stochastic programming	4.5	87.3	275.6
60%	Methodology of This Article	4.2	51.3	324.8
60%	Traditional Robust Optimization	8.4	44.6	372.5
60%	Stochastic programming	5.8	112.6	311.2

When the new energy penetration rate reaches 40%, the performance differences among methods remain relatively small: the wind and solar curtailment rate under traditional robust optimization is 4.1%, while that under our proposed method is 2.9%, a difference of merely

1.2 percentage points. This is primarily due to conventional power units still possessing sufficient regulation capacity to balance renewable energy fluctuations, resulting in limited impact of uncertainty on system operation.

However, when penetration increases to 60%, significant changes occur: the wind and solar curtailment rate under traditional robust optimization surges to 8.4%–more than double the 40% level; the CVaR under stochastic programming jumps from 45.2 MW to 112.6 MW, representing a 149% increase. Our method maintains a curtailment rate of only 4.2% and a CVaR of 51.3 MW at 60% penetration, demonstrating substantially less performance degradation compared to other approaches. These findings reveal a critical pattern: as new energy penetration rises, the impact of uncertainty on system operation exhibits nonlinear growth, making precise characterization of uncertainty distribution far more crucial than simply expanding uncertainty sets.

From the perspective of maintenance scheduling, as the penetration rate of renewable energy increases, maintenance plans undergo systematic adjustments. At a 40% penetration rate, maintenance activities are typically scheduled during nighttime off-peak hours (00:00–06:00);

whereas at 60% penetration rate, they are more frequently planned during peak solar generation periods (11:00–15:00). This is because excess solar power output during midday increases curtailment pressure, and scheduling maintenance for certain units during this period helps reduce curtailment while leveraging the regulation capacity of other units to maintain system balance.

These findings indicate that under high-renewable-energy scenarios, maintenance planning should no longer be merely a passive arrangement based on equipment status but rather an active strategy for optimizing system integration capacity.

D. THE VALUE OF COLLABORATIVE

Decision-Making Between Maintenance and Scheduling To verify the necessity of collaborative decision-making between maintenance and scheduling, a comparative experiment was conducted: the maintenance plan was decoupled from scheduling decisions (i.e., the maintenance plan was formulated independently first, followed by scheduling optimization), and compared with the collaborative optimization method proposed in this paper.

Under a scenario with a new energy penetration rate of 50%, the wind and solar curtailment rate of the decoupling method is 6.7%,2.9 percentage points higher than that of the collaborative method; the expected operating cost is 3.125 million yuan, 9.1% higher than that of the collaborative method; and the CVaR is 68.4 MW, 60.6% higher than that of the collaborative method. More notably, the decoupling method experienced line capacity exceedances in all three scenarios, due to insufficient consideration of transmission capacity constraints during periods of high renewable energy generation when formulating maintenance schedules, resulting in excessive load on certain lines during maintenance periods. In contrast, the collaborative method did not experience any such exceedances.

Further analysis of the differences in the maintenance plan reveals that the collaborative approach shifted the maintenance schedule for a critical line from midday (during peak photovoltaic generation periods) to early morning (during off-peak load periods). Although this increased the start-up and shutdown costs for nighttime units by approximately 42,000 yuan, it avoided losses due to solar curtailment caused by insufficient transmission capacity during midday hours–amounting to about 186,000 yuan–and yielded a net benefit of roughly 144,000 yuan.

This example vividly demonstrates that coordinated optimization between maintenance and dispatching is not merely a simple cost addition but achieves overall efficiency gains through cross-period and cross-scenario resource reallocation.

E. ALGORITHM CONVERGENCE AND

Computational Efficiency The convergence curve of the column and constraint generation algorithm demonstrates that after seven iterations, the difference between the objective values of the main problem and subproblems is less than 10^{-3}, with a total computation time of 47.3 minutes. Compared to the traditional C&CG algorithm (excluding Nataf transformation scenario generation), this algorithm requires three fewer iterations (versus ten iterations for the traditional method) and achieves a 32.6% reduction in computation time.

The improved computational efficiency stems primarily from two factors: Nataf transformations generate scenarios more closely aligned with real-world distributions, reducing the introduction of invalid scenarios; and multi-threaded parallel computing reduces the average solution time for each subproblem from 5.2 minutes to 2.8 minutes.

It should be noted that when the number of new energy stations exceeds 15 (i.e., $d > 15$), the selection of the Wasserstein fuzzy-set radius θ_N significantly affects both computational efficiency and result quality. When θ_N is too small, the model degenerates into stochastic programming; when θ_N is too large, the model approaches traditional robust optimization. This paper determines the optimal value $\theta_N = 0.15$ through five-fold cross-validation, achieving the best average performance on the test set.

F. WEIGHT SENSITIVITY ANALYSIS

To evaluate the impact of multi-objective weight coefficients on optimization results, three sets of key performance indicators were calculated under different weight configurations subject to $\omega_1 + \omega_2 + \omega_3 = 1$, as shown in Table 3.

TABLE 3. Optimization results under different weight configurations (new energy penetration rate of 50%)

Weight Configuration ($\omega_1, \omega_2, \omega_3$)	Expected Cost (Ten Thousand Yuan)	Wind and solar power curtailment rates (%)	CVaR (MW)
(0.6, 0.2, 0.2)	275.8	5.1	58.4
(0.4, 0.3, 0.3)	286.4	3.8	42.6
(0.2, 0.4, 0.4)	312.6	2.4	35.1

When the economic weight ω_1 is higher (0.6), the model is designed to reduce operational costs, but both wind and solar curtailment rates as well as CVaR increase;

when the integration-rate and robustness weights ω_2 and ω_3 are higher (0.4), wind and solar curtailment rates and CVaR improve significantly, though the expected cost increases by approximately 9%. These results indicate a clear conflict among the three objectives, requiring decision-makers to balance them based on actual operational needs. The benchmark scenario in this study employs the configuration $(\omega_1, \omega_2, \omega_3) = (0.4, 0.3, 0.3)$, which achieves a relatively balanced outcome across all objectives.

Regarding the impact of normalized reference values on the practical implications of weight allocation, a supplementary explanation is provided here. This study performs normalization using the target values obtained from deterministic scheduling under a new energy penetration rate of 50%. The baseline reference value for f_1 is 2.483 million yuan; the value for $1 - f_2$ is 0.117 (equivalent to a wind and solar curtailment rate of 11.7%); and the value for f_3 is 156.4 MW.

After normalization, all three targets fall within the range of 0 to 1 (potentially slightly above 1 in the worst-case scenario). Changing the baseline value (e.g., using results from stochastic programming) would affect the values accordingly. The same weight coefficients $(\omega_1, \omega_2, \omega_3)$ would then correspond to different actual preferences.

Therefore, the weight configuration in Table 3 of this paper is only comparable under this specific benchmark. In practical applications, decision-makers should select appropriate benchmarks and weights based on the operational characteristics and preferences of the specific system.

VI. CONCLUSION

This paper addresses the uncertainty challenges faced by power systems with high proportions of renewable energy under market-oriented operating conditions, proposing a multi-objective distributed robust optimization method for dispatching and maintenance that incorporates renewable energy integration. Through theoretical modeling, algorithm design, and numerical validation, the following insights are obtained.

Distribution robust optimization demonstrates distinct advantages over traditional robust optimization and stochastic programming in high-new-energy penetration scenarios. It eliminates the need for precise probability distributions of renewable energy output, effectively capturing uncertainty by constructing Wasserstein fuzzy sets based solely on historical data, while achieving a superior balance between expected cost and extreme risk compared to conventional approaches. Simulation results show that at a 60% new energy penetration rate, the proposed method reduces expected operating costs by 12.7% compared to traditional robust optimization and decreases peak load losses by 43.6% under worst-case scenarios.

The coordinated optimization of maintenance planning and dispatch decision-making holds significant value. Treating these two aspects separately not only increases wind and solar curtailment rates by 2.9 percentage points but may also lead to safety issues such as line overloading. In scenarios with high renewable energy penetration, maintenance planning should evolve from a passive equipment maintenance tool into an active system regulation mechanism; strategically scheduling maintenance periods can enhance the system's renewable energy integration capacity without additional investment.

It must be emphasized that the maintenance planning studied in this paper pertains to maintenance window allocation under day-ahead market conditions, rather than annual maintenance plan optimization–this research framework inherently limits the applicability of the conclusions.

From a methodological perspective, the integration of Wasserstein-distance-based distribution robust optimization with column and constraint generation algorithms provides a viable approach for solving large-scale distribution robust optimization problems involving mixed integer variables. The introduction of the Nataf transformation effectively captures output correlations among multiple renewable energy stations, while the scenario aggregation strategy achieves an optimal balance between computational accuracy and efficiency.

Certainly, this study leaves several areas worthy of further exploration. In real-world electricity markets, nodal prices dynamically fluctuate based on supply-demand dynamics, making the integration of price signals into a distributed robust optimization framework a natural and meaningful extension. Additionally, the coordination between multi-period coupled maintenance decisions and intra-day real-time dispatch requires deeper investigation. The implementation of pre-planned maintenance schedules during daily operations may introduce new uncertainties; therefore, developing robust maintenance strategies with online adjustment capabilities will be a key focus for future research.

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