

Article

Accelerating Robust Power Grid Dispatch in Sustainable Energy Systems: Worst-Case Scenario Generation via a Physics-Guided Conditional Diffusion Model

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Abstract

The high penetration of sustainable energy integration leads to severe source-side uncertainty challenges in power system dispatch, and two-stage robust optimization is a critical tool for addressing this issue. However, traditional solution methods suffer from significant iterative computational bottlenecks and fail to meet the timeliness requirements of real-time grid dispatch. Therefore, this paper proposes a data-model hybrid-driven fast solution method for two-stage robust optimization. First, the method abandons the traditional iterative solution mode and directly identifies the worst-case scenarios within the uncertainty set based on a conditional diffusion model, which transforms the two-stage robust optimization into a single-stage deterministic optimization. Then, it constructs a physics-guided conditional diffusion model and proposes a worst-case scenario physics-guided operator to apply directional adversarial guidance during the reverse denoising stage to approach the worst-case operational boundary. Finally, by establishing a sensitivity allocation model for global active power imbalance, it reformulates the non-differentiable risk constraints in the gradient operator into efficient algebraic matrix operations. Experimental results show that the proposed method accurately generates worst-case scenarios and reduces the computation time to approximately 20% of the original while ensuring near-optimal economy, which provides a new solution paradigm for balancing decision robustness and timeliness.

Keywords: two-stage robust optimization; real-time grid dispatch; conditional diffusion model; worst-case scenario physics-guided operator; sustainability



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1. Introduction

To promote the green and low-carbon transformation of power systems, sustainable energy, represented by wind and solar power, accelerates large-scale grid integration [1]. However, as the penetration rate of sustainable energy continues to rise, its inherent randomness, volatility, and intermittency characteristics become increasingly prominent, which especially shows significant forecasting deviations in the intraday stage [2–4]. This not only restricts the full accommodation of sustainable energy, but also exacerbates power

balance and power flow security risks, which poses a severe test to intraday power system dispatch. How to formulate dispatch strategies that balance economy and security under the background of strong sustainable energy uncertainty has become the focus and difficulty of current research.

To cope with sustainable power uncertainty, robust optimization is widely applied in power dispatch decision-making [5,6]. Its core lies in describing the fluctuation range of random variables by constructing uncertainty sets and making decisions for the worst-case scenarios within the sets. Reference [7] proposes a sample-adaptive robust optimization method that introduces the probability of statistical feasibility to construct uncertainty sets and overcomes the problem where traditional robust optimization leads to overly conservative decisions due to inaccurate uncertainty set construction. Reference [5] proposes a robust look-ahead economic dispatch method considering conditional value-at-risk, which avoids excessive conservativeness of decisions while maintaining the high computational efficiency of robust optimization algorithms. However, optimal power system dispatch with high-proportion sustainable energy integration presents the following characteristics: (i) as the grid scale and dispatch objects grow, the model decision variables increase significantly; and (ii) thermal power ramping and energy storage state-of-charge limits introduce cross-temporal coupling constraints. These characteristics make the robust dispatch model an NP-Hard problem mathematically.

Considering the computational bottleneck of robust optimization in large-scale systems, existing research focuses on accelerating solution techniques, which mainly fall into two categories: model simplification and algorithm design. Model simplification focuses on reducing the model scale through pre-processing before solving, which includes decision variable aggregation [8–10] and redundant constraint reduction [11–13]. Algorithm design aims to improve the convergence speed of the solving process, and its core idea lies in performing convex approximation or decomposition and coordination. For example, the affine decision rule achieves the convexified solution of the model by restricting the form of the decision function, but approximation errors exist [14]; although the C&CG algorithm accelerates convergence by introducing dynamic cutting planes, the scale of the master problem increases gradually with the number of iterations [15,16].

In recent years, data-driven methods gradually become a new paradigm for solving complex optimization problems. Among them, deep reinforcement learning, as a typical representative, uses neural networks to construct end-to-end mapping from state to action and leverages the advantage of fast online decision-making [17]. Meanwhile, physics-informed or physics-guided learning methods receive extensive attention in energy system analysis. Such methods embed physical laws, network structures, or operational constraints into data-driven models, thereby improving the physical feasibility and interpretability of model results. For example, Reference [18] proposes a physics-informed neural network method for dynamic energy flow calculation in integrated electricity and gas systems, where differential-algebraic constraints are embedded into the neural operator to improve the satisfaction of physical constraints in energy flow calculation results. Reference [19] proposes a physics-informed graphical neural network method for power system state estimation that combines graph neural networks with physical knowledge based on branch-current equations to improve state estimation accuracy under sparse measurement conditions. These studies show that introducing physical knowledge into learning models helps improve model feasibility, generalization capability, and interpretability. However, existing physics-informed learning methods mainly embed physical equations, constraint residuals, or network topology information into the model training process through neural network architecture design or loss function constraints, and their applications mainly focus on tasks such as energy flow calculation and state estimation. Their ability to char-

acterize the distribution features and temporal fluctuation characteristics of sustainable energy output uncertainty remains limited. Simultaneously, generative models demonstrate significant potential in characterizing sustainable energy uncertainty. Generative adversarial networks (GANs) gradually approach the high-dimensional joint distribution of real output data through adversarial training between the generator and the discriminator [20,21]. Diffusion models achieve high-quality scenario generation based on the processes of forward noise addition and reverse denoising [22]. Compared to GANs, diffusion models effectively overcome the common convergence difficulty in adversarial training and exhibit superior sample diversity and training stability. Research in related fields falls into two categories: first, unconditional generation, which directly samples and generates sustainable energy output scenarios from noise and mainly applies to power grid planning and medium-to-long-term time-series simulation, such as in the References [23,24]; second, conditional generation, which provides uncertainty scenario sets fitting actual situations for dispatch by embedding information such as numerical weather forecasts as conditions, such as in Reference [25]. Reference [24] proposes a controllable GAN for modeling sustainable energy output scenarios targeting the volatility of sustainable energy, and this method achieves controllable scenario generation covering various statistical features. Reference [25] proposes a wind power output scenario generation method based on latent diffusion models, and experimental results show that its performance is superior to GANs.

The aforementioned conditional generation methods provide a new perspective for robust optimization. Considering that the solution difficulty of robust optimization lies in finding the worst-case scenario within the uncertainty set, this paper is inspired by this and proposes a two-stage robust optimization solution method based on physics-guided diffusion generation. The main contributions of this paper are as follows:

- (1) The Physics-Guided Diffusion based Two-Stage Robust Optimization (PGD-TSRO) solution framework: This framework uses a conditional diffusion model to generate the worst-case sustainable energy scenarios within the uncertainty set and then performs optimization based on the scenarios, which transforms the two-stage robust optimization problem into a deterministic optimization problem.
- (2) The Physics-Guided Conditional Diffusion Model (PhyCDM): This introduces the Worst-Case Scenario Physics-Guided Operator (WSPGO), embeds the objective function of the optimization model into the reverse denoising process of the diffusion model, and applies adversarial guidance along the ascent direction of the objective function gradient, which guides the generated scenarios to approach the boundary of the physical feasible region.
- (3) Global active power imbalance sensitivity allocation model (GAPISAM): To address the bottleneck where physical operational constraints—such as load shedding risk, sustainable power curtailment risk, and power flow violation risk—are difficult to differentiate, this model transforms these non-differentiable complex constraints into explicit algebraic matrix operations, which ensures the efficient execution of the SCVGO operator in the diffusion model and further improves computational efficiency.

2. Problem Statement and Solution Framework

2.1. Problem Statement

In the real-time dispatch stage, considering the power balance and power flow security risks brought by sustainable energy uncertainty, this paper adopts the two-stage robust optimization method for modeling. This paper adopts a min-max-min robust optimization model, and its standard form is as follows:

$$\begin{aligned}
 & \min_{\mathbf{x} \in X} \left(\mathbf{c}^\top \mathbf{x} + \max_{\mathbf{u} \in U} \min_{\mathbf{y} \in Y(\mathbf{x}, \mathbf{u})} \mathbf{d}^\top \mathbf{y} \right) \\
 & \text{s.t. } \mathbf{Ax} \leq \mathbf{b} \\
 & \quad \mathbf{Gy} \leq \mathbf{h} - \mathbf{Ex} - \mathbf{Mu}
 \end{aligned} \tag{1}$$

where decision variable $\mathbf{x}$ represents the adjustment amount relative to the day-ahead benchmark plan, which includes the increase and decrease commands for thermal unit power output and the adjustment of energy storage charging and discharging power. $\min_{\mathbf{x} \in X}$ is the first-stage decision problem, which typically aims to minimize the adjustment costs and reserve costs in the intraday stage, and considers constraints $\mathbf{Ax} \leq \mathbf{b}$, such as the power output limits and ramping constraints of thermal units. The uncertain variable $\mathbf{u}$ represents the deviation in real-time sustainable power output relative to the ultra-short-term forecasting value. $\max_{\mathbf{u} \in U}$ denotes that, given the first-stage decision $\mathbf{x}$, $\mathbf{u}$ searches within the uncertainty set U for the scenario that maximizes the objective function. Decision variable $\mathbf{y}$ represents the emergency decisions adopted when the worst-case scenario occurs, such as sustainable power curtailment and load shedding; this stage aims to minimize the penalties for sustainable power curtailment and load shedding, and considers constraints $\mathbf{Gy} \leq \mathbf{h} - \mathbf{Ex} - \mathbf{Mu}$, such as line active power flow constraints.

Since the aforementioned model presents a three-level nested structure, it is difficult to solve directly. When the inner problem $\min_{\mathbf{y} \in Y}$ satisfies convexity and the uncertainty set is a polyhedron, according to strong duality theory, the inner min problem transforms into an equivalent max problem. After transformation, the inner max–min structure of the original model merges into a single-level max problem, which reconstructs the original three-level problem into a bi-level min–max structure. For this structure, C&CG performs the solution through alternating iterations between the master and sub-problems. However, C&CG relies on the alternating iteration of master and sub-problems to identify worst-case scenarios and faces severe computational challenges in large-scale optimization problems. The uncontrollable number of iterations leads to decision timeouts, which is difficult to satisfy real-time dispatch scenarios with extremely high requirements for timeliness. Therefore, this paper adopts a data-driven approach and utilizes generative AI algorithms to construct a non-linear mapping between ultra-short-term forecasting data and worst-case scenarios. By directly generating worst-case scenarios, it replaces the tedious sub-problem iterations and reduces decision complexity while ensuring robustness.

2.2. Framework Description

For the two-stage robust optimization problem, this paper proposes the PGD-TSRO solution framework, which consists of two parts: worst-case scenario generation and deterministic optimization solution, as Figure 1 specifically shows.

In the worst-case scenario generation part, the ultra-short-term forecasting values of sustainable energy and the day-ahead planned output of units within the corresponding time window are input into the PhyCDM model. Since the PhyCDM model essentially belongs to conditional diffusion models, its scenario generation corresponds to the reverse denoising process, where the model approaches the true distribution of sustainable energy output through step-by-step gradient calculation. To achieve the directional generation of worst-case scenarios, this paper introduces WSPGO into the gradient calculation stage, which guides the scenario generation trajectory to gradually approach the boundary by applying specific directional corrections to the original denoising gradient. Finally, it outputs the extreme sustainable power output sequence $\mathbf{u}^*$ that maximizes the objective function. Section 3 introduces the specific implementation details of WSPGO in detail.

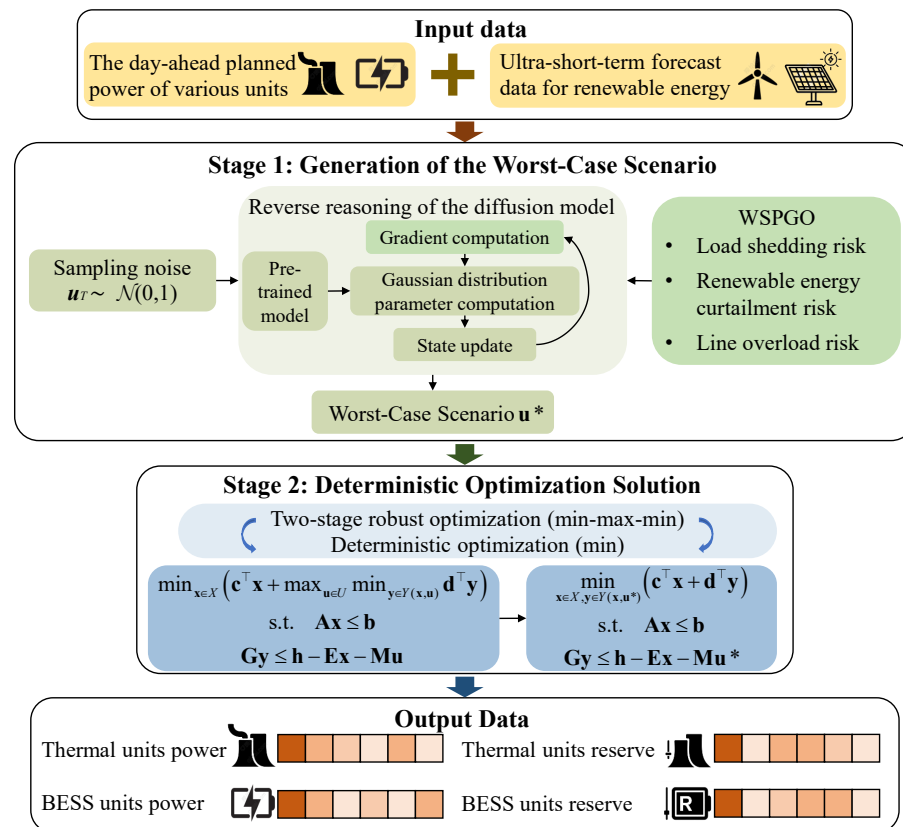


Figure 1. The physics-guided diffusion based two-stage robust optimization solution framework.

In the deterministic optimization solution part, after u^* is obtained, the $\max_{u \in U}$ layer in the original two-stage robust optimization model is completely eliminated. At this time, the two-stage nested problem is equivalent to a single-stage deterministic optimization model, and its mathematical form is

$$\begin{aligned} \min_{x \in X} & (c^T x + d^T y) \\ \text{s.t. } & Ax \leq b \\ & Gy \leq h - Ex - Mu^* \end{aligned} \quad (2)$$

Finally, the model outputs the power output and reserve capacity of various types of units in the system within the future time window. Through the aforementioned framework, the dispatch system only needs to substitute the generated u^* as a fixed parameter vector into Equation (2) and performs a deterministic solution through a commercial solver to output the optimal unit benchmark power output and reserve capacity allocation scheme that balances economy and extreme risk defense capability. This method can improve the computational efficiency of power grid intraday security dispatch decision-making.

3. Based on The Physical-Guided Conditional Diffusion Model

The identification of the worst-case scenario is essentially equivalent to the solution of the inner maximization problem of the robust optimization model. However, traditional conditional diffusion models only aim to fit the historical statistical distribution of uncertain variables and lack the perception capability of the maximization direction of the objective function. Therefore, this section proposes the PhyCDM, as Figure 2 shows. Considering that the inner maximization problem is a constrained optimization problem, this paper integrates the security constraints into the optimization objective using the penalty function

method. On this basis, it designs a worst-case scenario physics-guided operator, which applies adversarial guidance along the ascent direction of the objective function gradient to output the worst-case sustainable energy output.

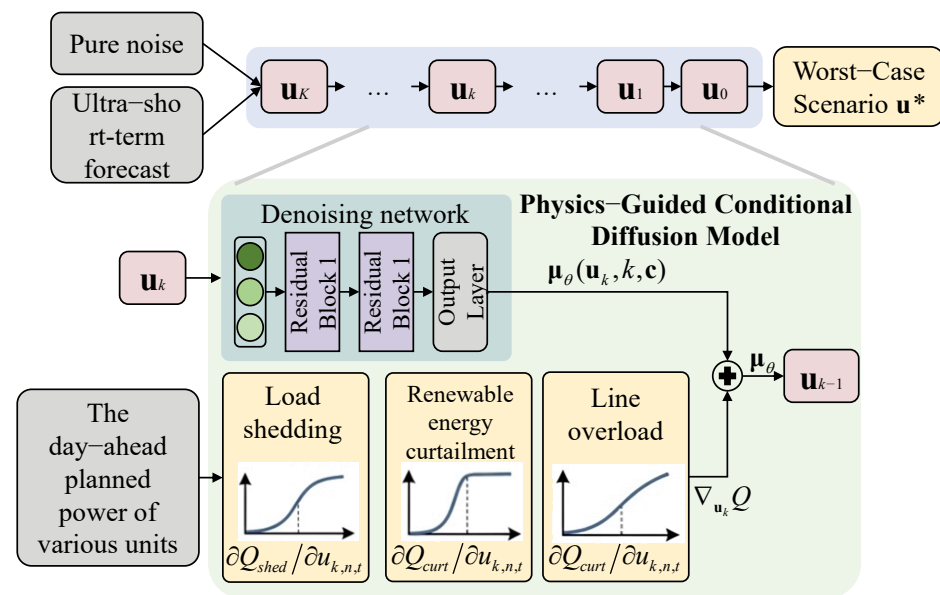


Figure 2. Physics-guided conditional diffusion model.

3.1. Conditional Diffusion Algorithm and Generation Mechanism

Denoising diffusion probabilistic models are a class of advanced generative frameworks based on stochastic differential and Markov evolution. Its core mechanism includes two stages: forward noise addition and reverse denoising. The forward stage is a continuous noise addition process, where the input is the real noise-free data $\mathbf{u}_0$, and it eventually evolves completely into a pure Gaussian noise distribution through the step-by-step injection of Gaussian noise ϵ . The reverse stage is an online inference generation process, where the input consists of randomly sampled pure Gaussian noise and given prior conditions, and the model eventually outputs the worst-case sustainable power output scenario $\mathbf{u}^*$ through the step-by-step prediction and removal of noise by a pre-trained neural network. In the model training stage, the neural network performs parameter iteration with the objective of minimizing the error between the predicted noise and the actual injected noise; in the online inference stage, the model completes end-to-end scenario generation based on the trained network, starting from a pure noise starting point combined with real-time boundary conditions.

Specifically, within the intraday dispatch time window, $\mathbf{u}_0 \in \mathbb{R}^{N \times T}$ represents the measured power values of N sustainable energy stations over T time periods during the training stage.

The forward stage is a parameter-free discrete Markov chain, which evolves the sequence that originally contains physical laws into Gaussian noise $\mathbf{u}_0$ through the gradual injection of Gaussian noise. The noisy state $\mathbf{u}_k$ after k steps of perturbation follows the following transition distribution:

$$q(\mathbf{u}_k | \mathbf{u}_0) = \mathcal{N}(\mathbf{u}_k; \sqrt{\bar{a}_k} \mathbf{u}_0, (1 - \bar{a}_k) \mathbf{I}) \quad (3)$$

where $\bar{a}_k = \prod_{s=1}^k a_s$. a_k represents the proportion of the original signal retained in the k -th step. $\mathbf{I}$ is the identity matrix.

Extracting the day-ahead dispatch plan $\mathbf{s}_{init}$ and the ultra-short-term power forecasting values $\mathbf{u}_{pred}$ forms the prior condition set $\mathbf{c} = \{\mathbf{u}_{pred}, \mathbf{s}_{init}\}$. Under this conditional con-

straint, the reverse inference stage is defined as the trajectory fitted by the neural network with parameters θ :

$$p_{\theta}(\mathbf{u}_{k-1} | \mathbf{u}_k, \mathbf{c}) = \mathcal{N}(\mathbf{u}_{k-1}; \boldsymbol{\mu}_{\theta}(\mathbf{u}_k, k, \mathbf{c}), \boldsymbol{\Sigma}_{\theta}(\mathbf{u}_k, k, \mathbf{c})) \quad (4)$$

where the covariance $\boldsymbol{\Sigma}_{\theta}$ is usually simplified to a constant matrix; the mean term $\boldsymbol{\mu}_{\theta}$ relies on the neural network's prediction of the current noise component $\varepsilon_{\theta}(\mathbf{u}_k, k, \mathbf{c})$ and is calculated analytically.

Based on score-based diffusion theory, the denoising process of the sample essentially proceeds along the gradient of the log-probability density of the data:

$$\nabla_{\mathbf{u}_k} \log p(\mathbf{u}_k | \mathbf{c}) \approx -\frac{\varepsilon_{\theta}(\mathbf{u}_k, k, \mathbf{c})}{\sqrt{1 - \bar{\alpha}_k}} \quad (5)$$

To shift the generation results toward the direction that maximizes the objective function, this paper additionally adds the worst-case scenario physics-guided operator $\nabla_{\mathbf{u}_k} Q(\mathbf{u}_k, \mathbf{c})$ on the basis of the original network-predicted mean. At this point, the mean update rule of reverse inference is corrected to

$$\tilde{\boldsymbol{\mu}}_{\theta}(\mathbf{u}_k, k, \mathbf{c}) = \boldsymbol{\mu}_{\theta}(\mathbf{u}_k, k, \mathbf{c}) + \gamma \cdot \boldsymbol{\Sigma}_{\theta} \nabla_{\mathbf{u}_k} Q(\mathbf{u}_k, \mathbf{c}) \quad (6)$$

where γ controls the intensity of the physical penalty guidance. The neural network mean term on the right side of Equation (6) is responsible for maintaining the temporal continuity and spatial correlation of the scenario, and the newly added gradient operator $\nabla_{\mathbf{u}_k} Q$ forces the sampling trajectory toward the extreme boundaries where system operational risk increases sharply.

3.2. Worst-Case Scenario Physics-Guided Model

Quickly and accurately obtaining the gradient of the cost function in Equation (6) is the key to the application of the physics-guided conditional diffusion model. To this end, this paper designs the WSPGO. This operator considers load shedding risk, sustainable power curtailment risk, and power flow violation risk, and transforms the originally non-differentiable physical operational constraints into explicit algebraic matrix operations, which achieves rapid calculation of the gradient.

3.2.1. Global Active Power Imbalance Sensitivity Allocation Model

In the real-time operation stage, when the actual output of sustainable energy such as wind and solar power deviates from the predicted trajectory, the system mainly relies on the reserve capacity of online units to maintain power balance. Assume that the global net power deficit of the system caused by forecasting errors in a given time period t is

$$\Delta P_t(\mathbf{u}_k) = \sum_{n=1}^N (u_{pred,n,t} - u_{k,n,t}) \quad (7)$$

where $u_{pred,n,t}$ represents the ultra-short-term forecasting value of sustainable energy node n in time period t , and $u_{k,n,t}$ is the power output scenario value generated in the k -th step of the diffusion model.

The power sharing coefficient of the adjustable unit i when facing a power deficit $\rho_{i,t}$ is set as the ratio of its available reserve to the total system reserve:

$$\rho_{i,t} = \frac{r_{i,t}^{up} + r_{i,t}^{down}}{\sum_{j \in G} r_{j,t}^{up} + r_{j,t}^{down}} \quad (8)$$

where $r_{i,t}^{up}$ and $r_{i,t}^{down}$ are the upper and lower reserve capacities of unit i in time period t , respectively; G is the set of conventional units in the system that provide reserve support. Thus, the approximate responsive regulation power of unit i is explicitly expressed as $\Delta P_{i,t} = \rho_{i,t} \cdot \Delta P_t(\mathbf{u}_k)$.

3.2.2. Worst-Case Scenario Physics-Guided Operator

The key idea of WSPGO is to transform non-differentiable operational risk judgments into differentiable algebraic gradient expressions. Specifically, the hard boundary judgments are replaced by the Softplus function, whose derivative is the Sigmoid function. Then, based on the global active power imbalance sensitivity allocation model, the effects of the generated sustainable scenario $\mathbf{u}_k$ on power imbalance, unit response, and line power flow are explicitly represented. Therefore, the gradients of load shedding, sustainable energy curtailment, and line-overload risks with respect to $\mathbf{u}_k$ can be derived by the chain rule. For power imbalance-related risks, $\frac{\partial \Delta P_t(\mathbf{u}_k)}{\partial u_{k,n,t}} = -1$. For line-overload risk, the DC-PTDF relationship provides the algebraic sensitivity coefficient $\Phi_{l,n}$. In this way, the three operational risks are converted into differentiable algebraic gradient expressions that can be directly used in the reverse denoising process.

First, the load shedding risk is quantified. If the global deficit exceeds the maximum upper reserve available in the entire grid, the system is forced to shed load. This part of the penalty function $Q_{shed}(\mathbf{u}_k)$ and its gradient with respect to the power output of any sustainable energy station are defined as

$$Q_{shed}(\mathbf{u}_k) = \sum_t \lambda_{shed} S\left(\Delta P_t(\mathbf{u}_k) - r_{total,t}^{up}, \tau\right) \quad (9)$$

$$\frac{\partial Q_{shed}}{\partial u_{k,n,t}} = -\lambda_{shed} \cdot \sigma\left(\tau(\Delta P_t(\mathbf{u}_k) - r_{total,t}^{up})\right) \quad (10)$$

where $r_{total,t}^{up} = \sum_{j \in G} r_{j,t}^{up}$ is the total upper reserve limit capacity that the entire grid can provide in time period t ; λ_{shed} is the penalty weight coefficient for load shedding; $S(x, \tau) = \frac{1}{\tau} \ln(1 + e^{\tau x})$ is the Softplus function, which replaces the logical judgment of hard boundaries and ensures the differentiability of the penalty function across the entire domain; τ is the smoothing factor; and $\sigma(\cdot)$ is the Sigmoid activation function, which is the derivative of $S(\cdot, \cdot)$. Equations (9) and (10) show that the closer the power deficit approaches the critical point of system reserve exhaustion, the stronger the negative gradient stimulus is fed back to the generative model.

If the increase in sustainable power output causes the system power surplus $-\Delta P_t$ to exceed the total lower reserve limit of the entire grid, it triggers the sustainable power curtailment penalty. This part of the penalty function $Q_{curt}(\mathbf{u}_k)$ and its gradient with respect to the output of any sustainable energy station are defined as

$$Q_{curt}(\mathbf{u}_k) = \sum_t \lambda_{curt} S\left(-\Delta P_t(\mathbf{u}_k) - r_{total,t}^{down}, \tau\right) \quad (11)$$

$$\frac{\partial Q_{curt}}{\partial u_{k,n,t}} = \lambda_{curt} \cdot \sigma\left(\tau(-\Delta P_t(\mathbf{u}_k) - r_{total,t}^{down})\right) \quad (12)$$

where $r_{total,t}^{down} = \sum_{j \in G} r_{j,t}^{down}$ is the total lower reserve limit capacity that the entire grid can provide in time period t ; λ_{curt} is the penalty weight coefficient for wind/solar power curtailment.

Additionally, the static security risk of line power flow violation needs to be considered. Based on DC network equations and the power transfer distribution factor (PTDF) matrix $\mathbf{H}$,

the power flow of the line l when facing sustainable energy fluctuations and unit response adjustments is

$$F_{l,t}(\mathbf{u}_k) = F_{l,t}^{bs} + \sum_{i \in G \cup N} H_{l,i} \Delta J_{i,t}(\mathbf{u}_k) \quad (13)$$

$$\Delta J_{i,t}(\mathbf{u}_k) = (u_{pred,i,t} - u_{k,i,t}) + \sum_{j \in N_i} \rho_{j,t} \Delta P_t(\mathbf{u}_k) \quad (14)$$

where $F_{l,t}^{bs}$ is the benchmark power flow of line l in time period t calculated based on ultra-short-term forecasting and the day-ahead plan; $H_{l,i}$ is the PTDF from node i to line l ; and $\Delta J_{i,t}(\mathbf{u}_k)$ is the change in net injection power at node i . When the line power flow exceeds its thermal stability limit capacity, the resulting power flow violation penalty $Q_{line}(\mathbf{u}_k)$ and the corresponding physical gradient are defined as

$$Q_{line}(\mathbf{u}_k) = \sum_t \sum_l \lambda_{line} S(|F_{l,t}(\mathbf{u}_k)| - F_l^{max}, \tau) \quad (15)$$

$$\frac{\partial Q_{line}}{\partial u_{k,n,t}} = \sum_l \lambda_{line} \cdot \text{sgn}(F_{l,t}) \cdot \Phi_{l,n} \cdot \sigma(\tau(|F_{l,t}(\mathbf{u}_k)| - F_l^{max})) \quad (16)$$

where F_l^{max} is the maximum thermal stability transmission capacity limit of line l ; λ_{line} is the penalty weight coefficient for power flow violation; $\Phi_{l,n} = \sum_{n=1}^N H_{n,l} (\mathbb{I}_{k \in n} - \sum_{i \in N_n} \rho_{i,t})$, and $\mathbb{I}_{k \in n}$ is the indicator function.

It should be noted that the absolute value in Equation (16) is used to describe the bidirectional line-overload constraint, that is, both forward and reverse line power flows should be penalized when they exceed the thermal stability transmission capacity limit. To avoid possible non-smooth points introduced by the absolute value and sign functions in practical gradient calculation, a differentiable smoothing treatment is adopted in the engineering implementation of WSPGO. Specifically, the absolute value term is approximated in the actual calculation as

$$|F_{l,t}(\mathbf{u}_k)| \approx \sqrt{F_{l,t}^2(\mathbf{u}_k) + \varepsilon_{WSPGO}} \quad (17)$$

where ε_{WSPGO} is a small positive constant used to ensure numerical smoothness. Accordingly, the sign function term is approximated as

$$\text{sgn}(F_{l,t}) \approx \frac{F_{l,t}(\mathbf{u}_k)}{\sqrt{F_{l,t}^2(\mathbf{u}_k) + \varepsilon_{WSPGO}}} \quad (18)$$

Therefore, in the practical engineering implementation, the gradient of the line-overload penalty is

$$\frac{\partial Q_{line}}{\partial u_{k,n,t}} \approx \sum_l \lambda_{line} \cdot \frac{F_{l,t}(\mathbf{u}_k)}{\sqrt{F_{l,t}^2(\mathbf{u}_k) + \varepsilon_{WSPGO}}} \cdot \Phi_{l,n} \cdot \sigma(\tau(\sqrt{F_{l,t}^2(\mathbf{u}_k) + \varepsilon_{WSPGO}} - F_l^{max})) \quad (19)$$

With the above smoothing treatment, the physical meaning of the bidirectional line-overload constraint remains unchanged, while the gradient used in the reverse denoising process has better continuity and numerical stability.

Integrating the aforementioned three types of risks, the complete gradient operator $\nabla_{\mathbf{u}_k} Q(\mathbf{u}_k, \mathbf{c})$ constituted by WSPGO is

$$\nabla_{\mathbf{u}_k} Q(\mathbf{u}_k, \mathbf{c}) = \left[\frac{\partial Q_{shed}}{\partial \mathbf{u}_k} \right] + \left[\frac{\partial Q_{curt}}{\partial \mathbf{u}_k} \right] + \left[\frac{\partial Q_{line}}{\partial \mathbf{u}_k} \right] \quad (20)$$

At this stage, in the k -th step of the reverse denoising process of the physics-guided conditional diffusion model, substituting the current diffused scenario feature matrix $\mathbf{u}_k$ into Equation (20) calculates the guidance vector pointing toward the risk maximization region. As the number of iteration steps decreases to 0, the model outputs the worst-case scenario $\mathbf{u}^*$ and inputs it into the deterministic optimization-solving model of Stage 2 to calculate the final dispatch decision. Specifically, the model takes the sustainable energy ultra-short-term forecasting and the grid day-ahead dispatch plan as inputs, and samples a pure noise sequence $\mathbf{u}_K$ from a standard Gaussian distribution as the starting point for reverse inference. During the reverse denoising iteration, the WSPGO operator is calculated based on Equation (20) using the grid day-ahead plan, and, subsequently, this gradient is superimposed onto the neural network-predicted mean $\tilde{\mu}_\theta$ based on Equation (6). As the diffusion step k decreases to 0, the model outputs the worst-case sustainable energy output sequence $\mathbf{u}^*$ that satisfies the grid's physical security boundary constraints. Finally, $\mathbf{u}^*$ is used as a constant parameter to solve Equation (2), which outputs the optimal intraday dispatch decision.

4. Case Study

4.1. Data Preparation and Experimental Setup

To verify the feasibility and effectiveness of the proposed strategy, this paper conducts an analysis based on an improved IEEE 118-bus system. Resource information is shown in Tables 1 and 2.

Table 1. System resource information.

Type	Number	Capacity/MW	Connected Bus Number
Wind	10	80	9, 14, 26, 33, 48, 58, 61, 73, 88, 115
Photovoltaics	10	70	17, 39, 41, 53, 55, 60, 69, 75, 76, 111
Energy Storage	6	100	4, 11, 31, 48, 58, 95

Table 2. Parameters of the thermal units considered in the dispatch model.

Name	Bus Number	Capacity/MW	Name	Bus Number	Capacity/MW
gen1	0	100	gen13	26	100
gen2	3	100	gen14	30	100
gen3	5	100	gen15	31	100
gen4	7	100	gen16	33	100
gen5	9	500	gen17	35	100
gen6	11	150	gen18	39	100
gen7	14	100	gen19	41	100
gen8	17	100	gen20	45	100
gen9	18	100	gen21	48	300
gen10	23	100	gen22	53	150
gen11	24	300	gen23	54	100
gen12	25	400			

The future time window rolls every 15 min to calculate the power output and reserve capacity of various types of units for the next 4 h. This setting is consistent with the standard time resolution of intraday dispatch and the current operation practice of provincial-level dispatch centers. The penalty weight coefficients λ_{shed} , λ_{curt} , and λ_{line} are set to 1500, 500, and 500, respectively, according to the relative priorities of different operational risks in practical dispatch. Since load shedding directly affects power supply reliability and user demand satisfaction, it is regarded as the most unacceptable outcome and is assigned the largest penalty weight. sustainable energy curtailment and line overload

are also undesirable operating conditions, but their impacts are relatively less critical than load shedding. Therefore, λ_{curt} and λ_{line} are set to the same value to balance sustainable energy accommodation and network security. The remaining parameters in PhyCDM are hyperparameters of the artificial intelligence model. To avoid subjective parameter selection, these hyperparameters are determined through an AutoML-based tuning process. Candidate configurations are evaluated based on the validation performance and training stability of the model, and the final configuration is selected as the best-performing setting. Accordingly, the maximum number of diffusion steps for the forward noise addition and reverse denoising of PhyCDM is 100, and the noise variance schedule adopts a cosine schedule. The main body of the denoising network uses the U-Net architecture with a hidden layer feature dimension of 128. Training employs the Adam optimizer, with the learning rate set to 0.0001, the batch size at 64, and the number of epochs at 500. The smoothing factor in the WSPGO operator τ is 10.

The scenarios are selected from the annual historical forecasting data of a regional power system in Southern China in 2020, including the day-ahead forecasts and intraday ultra-short-term forecasts of wind power, PV power, and load. To identify representative stressed operating conditions, the sustainable generation level, load power, and the forecasting deviations between the day-ahead and intraday stages are jointly considered. Therefore, this paper selects the three scenarios below as extreme scenarios and typical scenarios for experiments to verify the optimization performance of the proposed strategy under non-extreme operational conditions. The specific descriptions of the scenarios are shown in Figure 3:

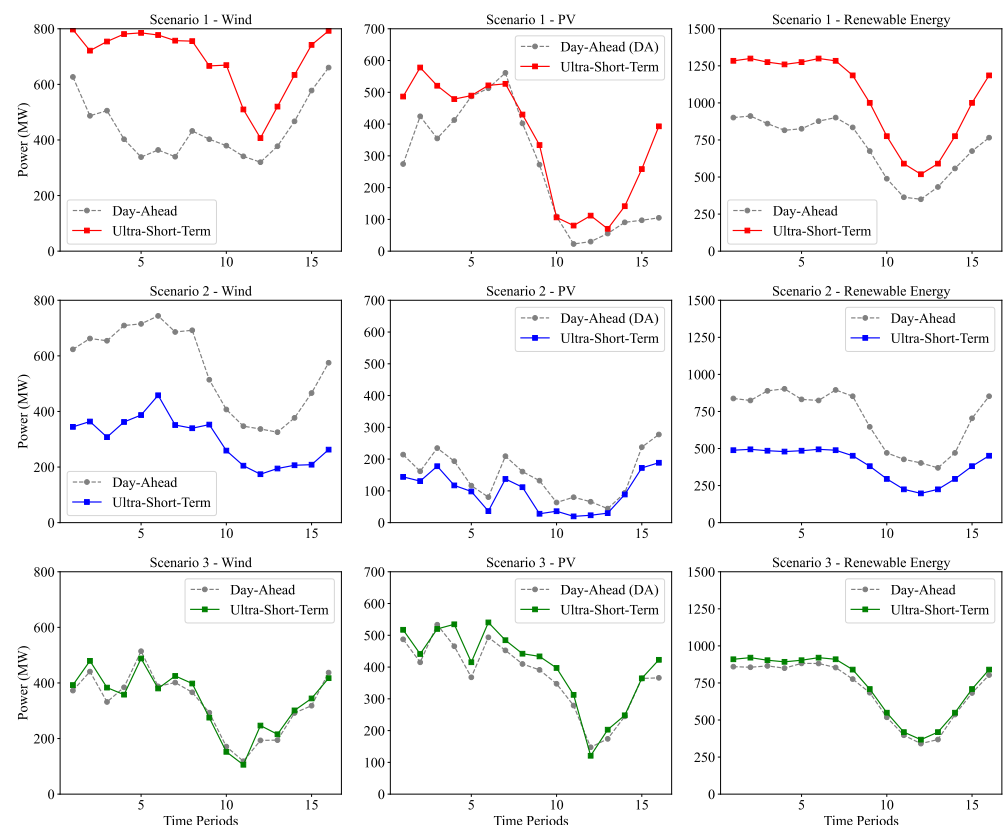


Figure 3. Detailed description of the three scenarios.

Scenario 1: The intraday ultra-short-term forecasting values of wind and PV output exceed the day-ahead forecasting values by 48.2%. The system source-side power is in severe surplus.

Scenario 2: The intraday ultra-short-term forecasting values of wind and PV output are 43.6% lower than the day-ahead forecasting values. The system source-side power is in severe shortage.

Scenario 3: The deviation between the day-ahead and intraday ultra-short-term forecasting data for wind and PV in this scenario is small.

4.2. Effectiveness Analysis of Worst-Case Scenario Generation

To verify the effectiveness of the proposed worst-case scenario generation method, the worst-case scenarios identified by the C&CG algorithm are used as the ground truth. Several representative methods are selected for comparison, including C&CG, Benders decomposition, GAN-based scenario generation, scenario-based robust dispatch, the conventional conditional diffusion model (Algorithm 1), and the proposed method. Among them, C&CG and Benders decomposition are used as optimization-based benchmarks. GAN represents a typical data-driven scenario generation method. The scenario-based robust dispatch method first constructs a finite scenario set containing 200 sustainable output scenarios and then selects the most adverse scenario according to the dispatch penalty cost of each candidate scenario. Algorithm 1 denotes the vanilla conditional diffusion model, which introduces predictive conditions to fit the regular error distribution of sustainable output, but does not include the proposed WSPGO. The proposed method further embeds WSPGO into the reverse denoising process, so that the generated scenarios are guided toward dispatch-risk-related worst-case boundaries. The normalized mean square error (NMSE) and mean absolute percentage error (MAPE) between the generated or identified worst-case scenarios and the ground truth are used as evaluation indicators. The comparison results are shown in Table 3. The total sustainable power curves generated by the three methods under the three scenarios described in Section 4.1 are illustrated in Figure 4.

Table 3. Error comparison of worst-case scenarios among different models.

Model	NMSE/%	MAPE/%
C&CG	0.00	0.00
Benders	0.00	0.00
GAN	27.36 (± 1.17)	25.59 (± 0.96)
Scenario	13.92 (± 0.63)	15.41 (± 0.81)
Algorithm 1	32.25 (± 1.23)	30.34 (± 1.48)
This paper	9.78 (± 0.58)	8.12 (± 0.71)

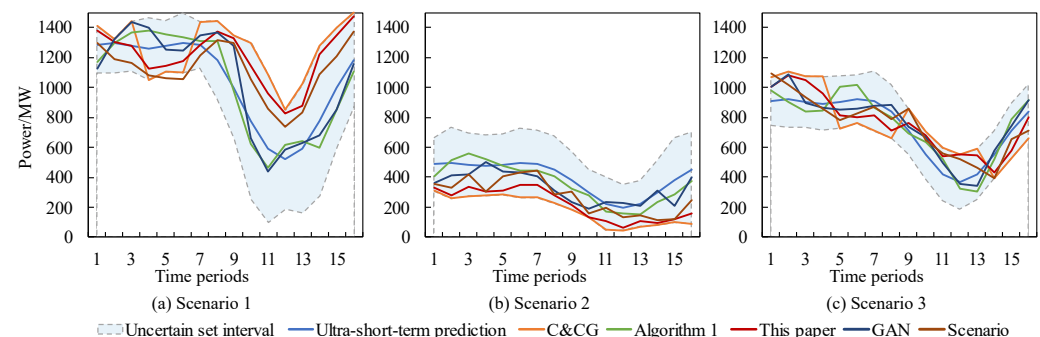


Figure 4. Total sustainable power curves generated by different methods.

As shown in Table 3, C&CG and Benders both obtain zero error because they identify the same worst-case scenarios as the optimization-based benchmarks. However, these methods usually require iterative mathematical optimization, which limits their applicability in fast online scenario generation.

For the data-driven methods, GAN achieves an NMSE of 27.36% and a MAPE of 25.59%. This indicates that GAN can learn the general distribution of sustainable output, but it lacks explicit dispatch-risk guidance and therefore has difficulty identifying worst-case boundary scenarios. Algorithm 1 shows the largest error, with an NMSE of 32.25% and a MAPE of 30.34%. This is because Algorithm 1 only introduces predictive conditions into the diffusion model and does not contain WSPGO, so its generated scenarios mainly reflect regular sustainable fluctuations rather than dispatch-critical worst-case conditions.

The scenario-based method achieves better accuracy than GAN and Algorithm 1, with an NMSE of 13.92% and a MAPE of 15.41%. This is because it selects the most adverse scenario from 200 candidate scenarios according to the dispatch penalty cost. However, the accuracy of this method is strongly limited by the sampling size. If the number of sampled scenarios is too small, the scenario set may fail to cover the true worst-case boundary, resulting in insufficient accuracy. If the number of sampled scenarios is too large, the computational time will increase significantly because each candidate scenario needs to be evaluated.

In comparison, the proposed method achieves the lowest error among the non-optimization-based methods, with an NMSE of 9.78% and a MAPE of 8.12%. Compared with Algorithm 1, the NMSE is reduced from 32.25% to 9.78%, which demonstrates the effectiveness of introducing WSPGO. By incorporating load shedding risk, sustainable curtailment risk, and line-overload risk into the reverse denoising process, the proposed method can guide scenario generation toward the physical security boundary related to dispatch risk. Therefore, the proposed PhyCDM achieves a better balance between worst-case scenario generation accuracy and online computational efficiency.

In Scenario 1 of Figure 4a, under the positive guidance of the power curtailment penalty gradient, PhyCDM shifts upward, thereby capturing the adverse boundary that causes the depletion of the system's lower reserve capacity. Similarly, in Scenario 2 of Figure 4b, under the negative guidance of the load shedding penalty gradient, PhyCDM shifts downward, thereby capturing the adverse boundary that leads to the exhaustion of the system's upper reserve capacity. In Scenario 3 of Figure 4c, the guidance gradient analyzed by WSPGO approaches zero. At this point, PhyCDM degenerates into regular probabilistic generation similar to Algorithm 1.

In summary, PhyCDM accurately generates worst-case scenarios under different operating conditions and maintains reasonable scenario diversity under secure operating conditions.

4.3. Comprehensive Evaluation of Economy and Robustness in Dispatch Results

To verify the comprehensive performance of the proposed PhyCDM method in ensuring operational economy and the capability to resist extreme risks, this section compares the optimized dispatch costs of the C&CG algorithm and the proposed model across three scenarios, as presented in Table 4. Furthermore, the dispatch results of the proposed model in different scenarios are shown in Figures 5 and 6.

Table 4. Dispatch costs of different algorithms in typical scenarios

Scenario	Model	Operating Cost/10 ⁴	Penalty Cost/10 ⁴	Total Cost/10 ⁴
1	C&CG	128.31	1.14	129.45
	This paper	119.06	1.28	120.34
2	C&CG	169.42	1.25	170.67
	This paper	158.34	1.36	159.7
3	C&CG	85.39	0.00	85.39
	This paper	84.26	0.00	84.26

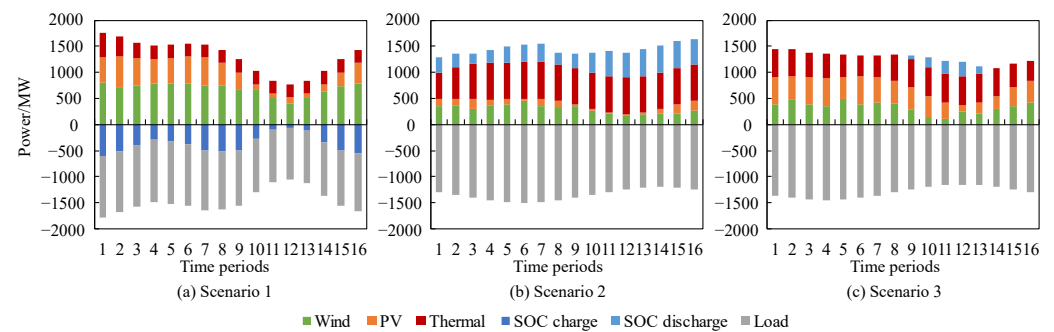


Figure 5. Dispatch results of unit power outputs in different scenarios.

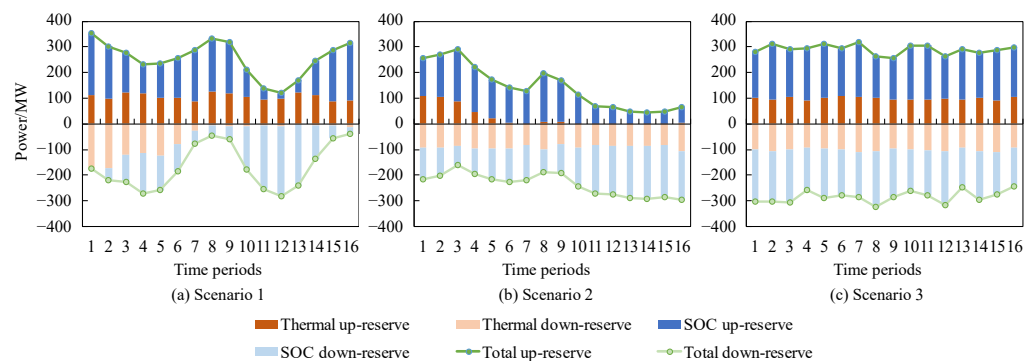


Figure 6. Reserve capacity allocation results for various units in different scenarios.

As shown in Table 4, across the three different scenarios, the total dispatch cost calculated by the proposed model is slightly lower than that of the C&CG algorithm, with an average cost reduction of approximately 6.87%. This is because the C&CG algorithm converges to the theoretical absolute optimal extreme boundary through rigorous mathematical programming and alternating iterations between master and sub-problems. In contrast, PhyCDM directly outputs the boundary, which inevitably possesses a certain optimality gap when approaching extremes. This leads to the system not reserving sufficient regulation margins compared to the C&CG method; consequently, the system operation cost is typically lower than that of C&CG, while the penalty cost is higher, resulting in a smaller overall total cost. Nevertheless, combined with the analysis in Section 4.3, the proposed model significantly reduces the solution time at the expense of partial computational accuracy to meet the time requirements of practical dispatch operations.

As shown in Figure 5, the dispatch decisions output by the proposed model are reasonable. In Figure 5a, due to the high sustainable energy output on the system source side, the power output of thermal units gradually decreases to the minimum technical output of 250 MW, while energy storage remains in a charging state to integrate sustainable energy, thereby reducing the risk of power curtailment. Simultaneously, as shown in Figure 6a, the downward reserve capacity of thermal units is depleted in the eighth period, and the upward reserve capacity is maintained at approximately 15% of the rated capacity due to thermal ramping constraints. Energy storage in the charging state possesses sufficient upward reserve capacity and flexible regulation capability overall, as it is not subject to strict ramping constraints. In Figure 5b, given the low sustainable output and the resulting large net load deficit, thermal units ramp up to the maximum output of 707 MW, and energy storage remains in a discharging state to prevent load shedding. Meanwhile, as illustrated in Figure 6b, the upward reserve capacity of thermal units is approximately 0 at the fifth hour, while the downward reserve remains in a stable state influenced by thermal ramping constraints. Energy storage in the discharging state has sufficient downward reserve

capacity overall. In Figure 5c, the source and load are basically balanced, and thermal power and energy storage exhibit a regular peak-shaving and valley-filling coordination, ensuring stable operation under regular conditions.

In summary, the proposed model significantly reduces the solution time at the expense of acceptable computational accuracy, which provides the possibility for practical application in the real-time operation of power grids with high penetration of sustainable energy.

4.4. Analysis of Computational Efficiency and Solution Accuracy

Intraday rolling dispatch imposes extremely high requirements on both computational timeliness and decision accuracy. Dispatch centers typically need to complete the online calculation of dispatch decisions for the next 4 h (16 time periods) within minutes. To verify the superiority of the proposed PhyCDM method in terms of computational efficiency and solution accuracy, this section randomly selects 100 historical intraday dispatch scenarios and records the online calculation times and various dispatch costs for both the C&CG algorithm and the proposed model across these scenarios. The specific quantitative breakdown of the calculation time is shown in Table 5, and the scatter regression distribution of the total costs is shown in Figure 7.

Table 5. Comparison of computational efficiency of different algorithms.

Model	C&CG	This Paper
Number of iterations	4~7	1
Online scenario generation time/s	N/A	3.42
Optimization solving time/s	65.21	8.23
Total calculation time/s	65.21	11.65
Speedup ratio compared to C&CG	1.0×	5.58×

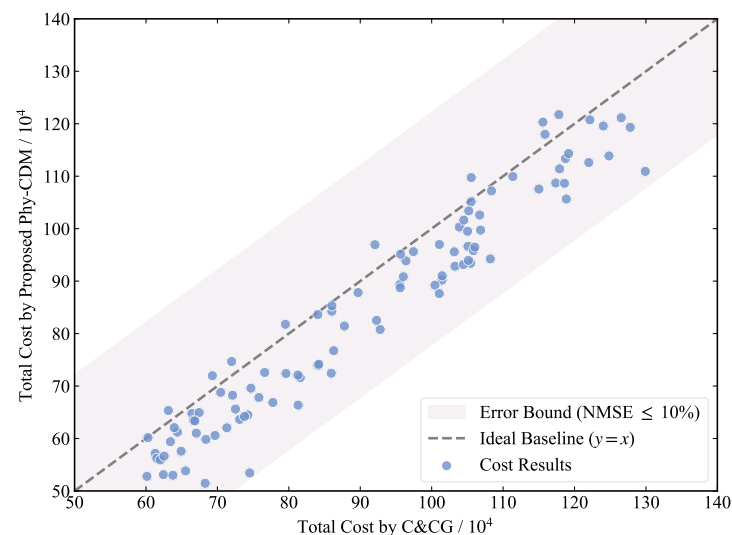


Figure 7. Scatter regression distribution of total costs.

According to Table 5, the average time of the C&CG algorithm is 65.21 s, and it requires 4–7 alternating iterations between the master and sub-problems as well as cutting-plane transfers to identify the extreme boundaries. In contrast, the proposed PhyCDM model has an average time consumption of 11.65 s with smaller variance. As indicated in Table 5, the reason for this is that, during the online calculation stage, the proposed model first leverages the extremely high inference speed of the neural network to directly output the worst-case scenario parameters in only 3.42 s. Subsequently, the originally nested complex robust model transforms into a regular single-layer deterministic economic

dispatch problem, achieving a significant 5.58-fold speedup compared to the traditional method. Therefore, the proposed method meets the time requirements for real-time online deployment in power grids.

As shown in Figure 7, the scatter points of the total dispatch costs calculated by the PhyCDM model cluster extremely closely around the ideal benchmark line. Furthermore, the NMSE between the costs calculated by the PhyCDM model and the C&CG model is within 10%, indicating that the approximate solution results of the proposed model possess high computational accuracy. Meanwhile, the costs calculated by the PhyCDM model are slightly lower overall than those of the C&CG model. The reason is that when a deep-driven model is used instead of traditional rigorous mathematical programming for online inference, it inevitably possesses a certain computational error relative to the actual worst-case scenario, which leads to the dispatch decisions output by the system being less conservative.

Meanwhile, the results in Table 3 and Figure 7 jointly indicate the optimality gap of the proposed method. Table 3 shows that the worst-case scenarios generated by PhyCDM are close to those identified by C&CG, with an NMSE of 9.78% and a MAPE of 8.12%. Figure 7 further shows that the total dispatch costs of PhyCDM are concentrated around the ideal baseline, and the NMSE of the total cost is within 10% over 100 historical intraday dispatch scenarios. These results indicate that the proposed method has a limited objective deviation from the C&CG benchmark. It should be noted that the lower operating cost of PhyCDM does not mean stronger robustness. Since PhyCDM directly generates worst-case scenarios through neural inference, its generated scenarios may slightly deviate from the theoretical extreme boundary obtained by C&CG, leading to a moderate reduction in conservativeness. Nevertheless, the scenario-generation error and objective-gap results show that this deviation remains within an acceptable range, enabling a practical balance between computational efficiency, economy, and robustness.

In summary, the proposed model maintains high computational accuracy while significantly reducing the calculation time, thereby effectively supporting higher-frequency intraday real-time dispatch operations.

4.5. Stress Test

To further distinguish between lower operating cost and sufficient robustness, an out-of-sample stress test is conducted under adverse sustainable deviations. For the three scenarios discussed above, the dispatch decisions obtained by C&CG and PhyCDM are first fixed. Then, these fixed decisions are applied to the stress-test scenario set for security verification, and the load shedding cost and sustainable energy curtailment cost are recorded. The stress-test scenario set is constructed by expanding the original uncertainty set. Let $\mathcal{U}_0$ denote the original sustainable uncertainty set used in the robust dispatch model. To generate adverse scenarios outside $\mathcal{U}_0$, the original sustainable deviation bounds are enlarged by a scaling factor $\alpha > 1$, resulting in an expanded uncertainty set $\mathcal{U}_\alpha$. The stress scenarios are then sampled from the set difference $\mathcal{U}_\alpha - \mathcal{U}_0$, ensuring that all of the tested scenarios are outside the original uncertainty set while still being within the predefined stress range. In this paper, α is set to 1.4, and the number of samples in the stress-test scenario set for each scenario is 100. The experimental results are shown in Figure 8.

As shown in Figure 8, under out-of-sample stress scenarios, the dominant penalty varies with the operating condition. In Scenario 1, the system is mainly affected by sustainable surplus, so the sustainable curtailment cost is relatively high while the load shedding cost remains close to zero. In Scenario 2, sustainable shortage becomes the main risk, leading to a higher load shedding cost and almost no sustainable curtailment. In Scenario 3, both penalty costs remain at moderate levels. Compared with C&CG, PhyCDM shows

slightly higher penalty costs in some cases, reflecting its lower conservativeness. However, the distributions of the two methods are close in all three scenarios, indicating that the performance degradation of PhyCDM under out-of-sample adverse sustainable deviations is limited.

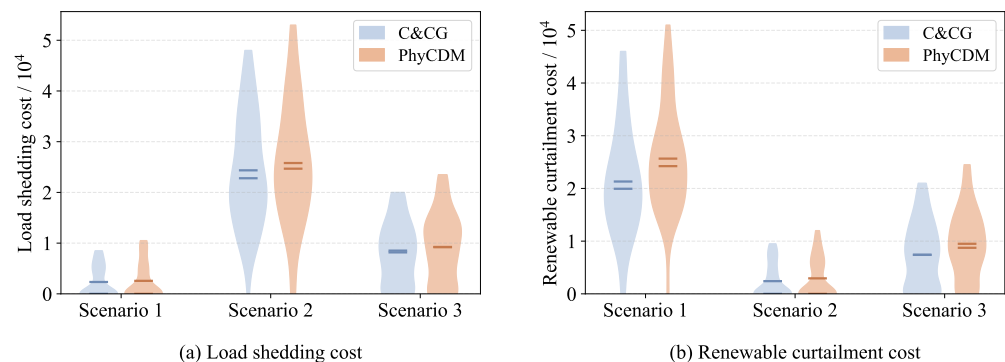


Figure 8. Results of the stress test.

5. Conclusions

To address the strong uncertainty brought by the high penetration of sustainable energy and the computational bottlenecks faced by traditional robust optimization dispatch in power systems, this paper first proposes a two-stage robust optimization solving framework based on physics-guided diffusion generation. This framework pre-positions the calculation process of the worst-case scenario, thereby transforming the two-stage robust optimization problem into a deterministic optimization problem. Then, a physics-guided operator for the worst-case scenario is proposed and embedded into a physics-guided conditional diffusion model. During the reverse denoising stage, directional adversarial guidance is applied, considering penalties for load shedding, sustainable power curtailment, and power flow limit violations. Finally, a sensitivity allocation model for global active power imbalance is proposed to accelerate the calculation of the physics-guided operator, thereby generating the worst-case scenario accurately and efficiently. Experimental results indicate that the worst-case scenarios generated by the proposed model are basically consistent with the precise search results of the traditional C&CG algorithm. The solving time is significantly reduced, and the computational efficiency is improved. Therefore, this method meets the timeliness requirements of real-time power grid dispatch while balancing economy and robustness.

Despite these advantages, an optimality gap inevitably exists when the directly generated scenarios in this paper approach theoretical extremes. Therefore, in future research, efforts should focus on optimizing the directional guidance mechanism to further reduce the optimality gap and improve its economy.

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