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Transient Stability-Constrained Optimal Power Flow Model Considering Wind–Solar Output Correlation

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Abstract

To address the challenges of wind–solar output correlation, renewable-output uncertainty, transient stability, and economic optimization, this paper proposes a transient stability-constrained optimal power flow (TSCOPF) model considering wind–solar correlation. First, kernel density estimation (KDE) is employed to establish the marginal probability density functions of wind and photovoltaic outputs, and a Frank-Copula function is used to characterize the wind–solar correlation and construct a joint probability distribution model. A Wasserstein generative adversarial network with gradient penalty (WGAN-GP) is then used to generate wind–solar output scenarios, which are further reduced by K-means++ clustering. Second, a transient stability assessment method combining a graph convolutional network with attention mechanism (GCN-Attention) and conditional mutual information (CMI)-based feature selection is developed to extract key stability features, and a TSCOPF model considering renewable-energy integration is constructed. Third, an improved Coati Optimization Algorithm (ICOA) integrating refraction-based opposition learning, Levy flight, and spiral search strategies is proposed to enhance global optimization performance. Simulations on the modified Institute of Electrical and Electronics Engineers (IEEE) 39-bus system and the IEEE 118-bus system demonstrate the accuracy, effectiveness, and scalability of the proposed method.

Keywords: transient stability-constrained optimal power flow; wind–solar correlation; data-driven transient stability assessment; improved Coati Optimization Algorithm



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1. Introduction

Driven by the carbon peaking and carbon neutrality strategy, the power system is undergoing a critical transition from conventional fossil energy toward clean and low-carbon energy. Renewable energy represented by wind power and photovoltaic generation is gradually becoming a core component of electricity supply [1,2]. Large-scale grid integration of renewable generation effectively promotes ecological improvement and enhances energy supply security. However, the intermittency and stochastic fluctuation of renewable output also introduce new challenges to secure and stable power system operation [3–6]. In particular, the randomness of wind–solar output may reduce the transient stability margin of the system and thereby induce potential operational security risks [7,8]. Therefore, determining how to coordinate operating economy and transient stability under uncertainty

has become a key problem that urgently needs to be addressed in the power engineering field. This issue has important theoretical significance and engineering value for ensuring secure and reliable power system operation and supporting sustainable socioeconomic development [9,10]. Transient stability-constrained optimal power flow (TSCOPF) is an optimization framework that combines transient stability constraints describing system dynamic processes with the conventional optimal power flow model. It formulates an integrated optimization problem that accounts for both economy and security. This method can simultaneously satisfy static power flow constraints and transient stability requirements in operating strategies, and it has become an important technical path for ensuring secure power system operation [11–14]. With the increasing penetration of renewable energy, TSCOPF research has gradually extended from deterministic operating conditions to uncertainty-aware frameworks. Chen et al. proposed a robust TSCOPF model under renewable uncertainties, showing that coordinated generation redispatch and network-side control can improve transient stability robustness while maintaining operational economy [15].

Recent data-driven TSCOPF and stability-analysis studies have also provided important methodological references. Zou et al. proposed a probabilistic robustness verified data-driven transient-security-constrained optimal power flow method, in which data-driven security constraints were verified from a probabilistic robustness perspective to improve the reliability of transient security-constrained dispatch decisions [16]. Meng et al. developed a neural-network-based impedance identification and stability analysis method for double-sided feeding railway systems, demonstrating that neural networks can be used to identify system impedance characteristics and support stability analysis in complex power-electronic power supply systems [17]. Moreover, Meng et al. proposed a dissipativity-based multiport stability root-cause identification and mitigation method for solid-state transformers, which provides a useful reference for stability analysis and mitigation in power-electronic-interfaced systems and is relevant to the transient stability-oriented security constraints considered in this study [18]. These studies indicate the effectiveness of combining data-driven modeling with stability/security constraints. However, they do not simultaneously consider wind–solar output correlation, representative correlated scenario generation, and GCN-Attention-based transient stability constraints within a unified TSCOPF framework. This motivates the present study.

In recent years, research on TSCOPF has achieved progress in multiple aspects. Fuzzy set theory has been adopted to improve the TSCOPF model by maximizing satisfaction within a fuzzy framework, while a co-evolutionary particle swarm optimization algorithm has been used to improve computational efficiency [19]. The combination of deep learning and multi-objective intelligent optimization has promoted the development of new transient stability preventive-control frameworks. Deep learning is used to capture the complex relationship between operating variables and transient stability indices under fault conditions, thereby replacing traditional transient stability constraints and evaluation procedures; multi-objective algorithms are then employed for efficient solution [20]. Physics-informed neural networks (PINNs) have also been investigated as a new preventive-control method for transient stability. By embedding the preventive-control problem into a trained PINN framework, computational complexity is reduced and efficient decision-making is realized [21]. In addition, transient stability assessment methods based on nature-inspired optimization algorithms are being developed. For example, stacking ensemble multilayer perceptrons have been used as surrogate models to replace explicit transient stability constraints, avoiding the solution of complex differential-algebraic equation systems and reducing computational cost while maintaining prediction accuracy [22].

Meanwhile, feature selection methods have attracted extensive attention for addressing redundant high-dimensional input features in data-driven transient stability assessment. Reference [23] proposed an evolutionary wrapper-based screening framework that simultaneously considers temporal information and key feature search. Reference [24] used Powershap to select key steady-state features, improving the generalization capability of assessment for systems with renewable energy. Reference [25] constructed a two-stage feature selection method to realize integrated dimensionality reduction assessment of the transient rotor angle and voltage stability. These studies indicate that appropriate feature selection can effectively suppress interference from redundant information, reduce model training complexity, and improve the accuracy and robustness of transient stability assessment.

Although the above studies have made positive methodological progress, most of them are still based on deterministic modeling frameworks and fail to fully consider the inherent uncertainty and intermittency of renewable energy. As renewable energy penetration continues to increase, the multisource uncertainty introduced by renewable generation has exceeded the applicability boundary of the traditional deterministic paradigm, seriously affecting the applicability of existing TSCOPF methods in modern power systems. Therefore, developing uncertainty-aware TSCOPF methods has become an important research direction for adapting to the increasing complexity of power system operation [26,27].

In recent years, scholars have proposed various methods for uncertainty modeling and scenario generation in systems with renewable energy. Accurate renewable energy scenario generation is an important basis for uncertainty-aware dispatch. Dong et al. developed a controllable GAN-based method for wind and photovoltaic scenario generation, indicating that data-driven generative models can capture stochastic renewable-output patterns without relying heavily on predefined probability distributions [28]. Ma et al. proposed a WGAN-GP-based scenario generation method for wind and solar power complementary systems, which is closely related to the WGAN-GP-based wind–solar scenario generation module adopted in this paper and supports the applicability of Wasserstein adversarial learning to renewable-output scenario modeling [29]. In addition, recent studies have emphasized that wind and photovoltaic outputs should not always be treated as independent variables. Sørensen et al. reviewed multivariate wind and solar power forecasting methods and highlighted the importance of modeling dependence among renewable power outputs [30]. Lung et al. further pointed out that complementarity and spatial–temporal dependence are important characteristics of variable renewable energy and should be considered in modeling, planning, and operation [31]. Therefore, ignoring wind–solar correlation may lead to deviations between generated scenarios and actual operating conditions, which can further affect transient stability assessment and TSCOPF optimization results. Reference [32] generated wind–solar scenarios using Monte Carlo sampling and Latin hypercube sampling. However, such methods require predefined parametric distributions, such as Weibull or Beta distributions, making it difficult to accurately characterize the complex non-Gaussian distribution of wind–solar output, and they also entail high computational burden. Reference [33] used generative adversarial networks for wind–solar scenario generation, but such models are prone to mode collapse and vanishing gradients, resulting in insufficient scenario diversity. Reference [34] used the K-means clustering algorithm for scenario reduction, but this method requires a preset number of cluster centers and relies only on Euclidean distance while ignoring scenario occurrence probabilities, which may cause deviations in the probability distribution of reduced representative scenarios. In addition, most of the above studies treat wind and photovoltaic outputs as mutually independent and ignore their temporal complementary correlation induced by meteorological conditions, resulting in deviations between generated scenarios and actual operating conditions.

Based on the above analysis, this paper proposes a data-driven TSCOPF model considering wind–solar uncertainty. The main contributions of this study are summarized as follows:

- (1) A wind–solar joint probability distribution modeling framework based on kernel density estimation and the Frank-Copula function is established. Kernel density estimation is used to construct the marginal distributions of wind and photovoltaic outputs, and the Frank-Copula function is introduced to characterize wind–solar correlation. Based on the constructed joint distribution, WGAN-GP is employed to generate wind–solar scenarios, and K-means++ clustering is used for scenario reduction. This process effectively captures the uncertainty characteristics of wind–solar output and provides reliable data support for subsequent TSCOPF optimization.
- (2) A TSCOPF model considering wind–solar integration and transient stability constraints is constructed. On the basis of the conventional TSCOPF framework, the model accounts for the uncertainty of wind–solar output and introduces a data-driven transient stability constraint based on a graph convolutional network with an attention mechanism (GCN-Attention). Power system topology information is used, and the importance weights of key nodes are learned adaptively through the attention mechanism. In addition, CMI-based feature selection is used to identify key features with significant influence on transient stability from a large set of candidate variables, thereby enabling efficient and accurate assessment of system transient stability.
- (3) To improve the solution efficiency and global optimization capability of the TSCOPF model, an improved Coati Optimization Algorithm (ICOA) is proposed. The algorithm integrates a refraction-mechanism-based opposition learning population initialization scheme, a Levy flight path updating strategy, and a spiral local search mechanism. These improvements effectively enhance global exploration efficiency and convergence characteristics, avoid the tendency of conventional optimization methods to fall into local extrema, and realize efficient solution of the TSCOPF model with complex constraints.

Compared with existing uncertainty-aware TSCOPF studies, the novelty of this work lies in the integration of wind–solar correlation modeling, data-driven transient stability assessment, and intelligent optimization within a unified TSCOPF framework. The proposed method explicitly characterizes the joint uncertainty of wind and photovoltaic outputs through KDE and the Frank Copula, generates representative correlated scenarios using WGAN-GP and K-means++, and embeds a GCN-Attention-based stability constraint into the optimization model. The remainder of this paper is organized as follows: Section 2 presents wind–solar uncertainty modeling and scenario generation; Section 3 formulates the TSCOPF model; Section 4 introduces the improved Coati Optimization Algorithm; Section 5 presents the solution procedure; Section 6 provides case studies; and Section 7 concludes the paper.

2. Wind–Solar Uncertainty Processing

2.1. Wind–Solar Joint Probability Distribution Modeling

To accurately describe the uncertainty of wind–solar output, this paper adopts WGAN-GP to generate a large number of wind–solar output scenarios.

2.1.1. Marginal Distribution Modeling Based on Kernel Density Estimation

The wind and photovoltaic output data used in this study are obtained from historical renewable generation records collected from a wind–solar renewable energy base in Gansu Province, northwestern China. To protect the confidentiality of the station operator, the exact plant name and geographical coordinates are anonymized. The dataset covers the

period from 1 January 2023 to 31 December 2023, with an original sampling interval of 15 min. To make the data consistent with the 24 h dispatch horizon adopted in the TSCOPF model, the raw wind and photovoltaic output records are resampled into hourly data. After resampling, 8760 hourly wind power data points and 8760 hourly photovoltaic power data points are obtained.

Before probability modeling and scenario generation, data preprocessing is carried out. Missing values with short continuous durations are filled by linear interpolation, while records with long-term missing segments are removed. Abnormal values exceeding the physical output limits of the corresponding renewable units are eliminated. In addition, outliers that deviate significantly from the normal fluctuation range are identified and removed according to the three-sigma criterion. Finally, the processed wind and photovoltaic outputs are normalized by their installed capacities and then scaled to the rated capacities used in the modified IEEE 39-bus system. In this paper, a 200 MW wind farm is connected at bus 14 and a 100 MW photovoltaic power station is connected at bus 30. The processed dataset contains 365 valid daily wind–solar output profiles, each containing 24 hourly wind power and photovoltaic power values, which are used for kernel density estimation, Copula fitting, and WGAN-GP-based scenario generation.

To further improve reproducibility, the normalized hourly wind and photovoltaic output profiles, installed capacities, resampling rules, missing value processing method, outlier removal criterion, and scenario generation parameters are available from the corresponding author upon reasonable request. Owing to the confidentiality requirements of the renewable energy station operator, the raw plant-level SCADA records and exact geographical coordinates cannot be publicly released. However, the anonymized and normalized data are sufficient to reproduce the KDE fitting, Frank-Copula parameter estimation, WGAN-GP scenario generation, and K-means++ scenario reduction procedures used in this study.

Both wind power and photovoltaic generation exhibit evident temporal characteristics, and their outputs fluctuate stochastically under natural conditions such as wind speed and irradiance. To characterize wind–solar output distributions accurately, nonparametric kernel density estimation is introduced to construct marginal probability density curves for wind and photovoltaic outputs in each dispatching period. Assuming hourly historical records over the past n days are available, the probability density function of wind–solar output in period t is:

$$f_t(P_t) = \frac{1}{ns} \sum_{i=1}^n K\left(\frac{P_t - P_{t,i}}{s}\right) \quad (1)$$

where P_t denotes the wind–solar output at period t ; s is the bandwidth parameter determining the smoothness of the kernel function; $P_{t,i}$ is the historical wind–solar output value at period t on day i ; and K denotes the kernel function.

In this paper, the Gaussian kernel function is selected, and its expression is:

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right) \quad (2)$$

The Gaussian kernel is smooth and differentiable everywhere, enabling effective fitting of continuous probability distribution characteristics of wind–solar output.

2.1.2. Joint Distribution Modeling Based on Frank Copula

There is significant correlation between wind and photovoltaic outputs. Influenced by meteorological conditions in the same region, the two exhibit temporal complementarity: wind energy is generally weaker during the daytime and stronger at night, whereas photovoltaic output is higher in the daytime and zero at night. To accurately describe this correlation, a Copula function is used to establish a wind–solar joint output model.

A Copula function can couple several correlated random variables that follow non-normal distributions and thereby generate a joint distribution function. Let the wind power output be denoted P_w and the photovoltaic output P_{pv} . The corresponding wind–solar joint distribution function is defined as:

$$F(P_w, P_{pv}) = C(U_w(P_w), U_{pv}(P_{pv})) \quad (3)$$

$$f(P_w, P_{pv}) = c(u_w, u_{pv})f_w(P_w)f_{pv}(P_{pv}) \quad (4)$$

where $C(\cdot)$ is the selected Copula function; $U_w(P_w)$ and $U_{pv}(P_{pv})$ are the marginal cumulative distribution functions of wind and photovoltaic outputs, respectively; u_w and u_{pv} denote the probability density functions of wind and photovoltaic outputs, respectively; and $c(\cdot)$ is the density function of the Copula.

In existing studies, widely used Copula functions mainly include the Normal Copula, t-Copula, Clayton Copula, Frank Copula, and Gumbel Copula. Considering that wind and solar outputs exhibit a symmetric dependence structure in the tails of their probability distributions, the Frank-Copula function is finally adopted after goodness-of-fit comparison to characterize the dependence between wind and solar outputs. Its mathematical expression is:

$$C(U_w(P_w), U_{pv}(P_{pv}); \tau) = -\frac{1}{\tau} \ln \left[1 + \frac{(e^{-\tau U_w(P_w)} - 1)(e^{-\tau U_{pv}(P_{pv})} - 1)}{e^{-\tau} - 1} \right] \quad (5)$$

where $\tau \in (-1, 1)$ and $\tau \neq 0$ is the dependence parameter of $U_w(P_w)$ and $U_{pv}(P_{pv})$. When $\tau > 0$, $U_w(P_w)$ and $U_{pv}(P_{pv})$ are positively correlated; when $\tau < 0$, they are negatively correlated.

2.2. Scenario Generation Based on WGAN-GP

2.2.1. Basic Principle of Generative Adversarial Networks

A generative adversarial network (GAN) is a typical unsupervised deep-learning architecture [35,36]. It consists of two core modules: a generator G and a discriminator D . The generator G takes a random noise vector n as input and learns the statistical distribution and intrinsic features of real samples x , thereby outputting synthetic samples with a distribution similar to that of the real data. The discriminator D aims to distinguish generated data from real data.

Assume that the real historical observations of wind–solar output are denoted by x and follow the probability distribution P_d . A set of random noise vectors n is also introduced, satisfying the prior distribution P_n . During adversarial game training, GAN gradually establishes an implicit mapping from P_n to P_d , so that the synthetic samples output by the generator approach the statistical law followed by the real data and finally yield the generated distribution P_g . The generator and discriminator loss functions are defined as follows:

$$L_G = -\mathbb{E}_{n \sim P_n}[D(G(n))] \quad (6)$$

$$L_D = \mathbb{E}_{n \sim P_n}[D(G(n))] - \mathbb{E}_{x \sim P_d}[D(x)] \quad (7)$$

where L_G and L_D are the loss functions of the generator and discriminator, respectively; $E(\cdot)$ denotes mathematical expectation; $G(\cdot)$ is the mapping function of the generator network; and $D(\cdot)$ is the output function of the discriminator network.

The objective function of the adversarial game is expressed as:

$$\min_G \max_D V(G, D) = \mathbb{E}_{x \sim P_d}[D(x)] - \mathbb{E}_{z \sim P_z}[D(G(z))] \quad (8)$$

2.2.2. WGAN-GP Improvement

The GAN used in this paper employs the Wasserstein distance to measure the distance between real data and sample data generated by the original GAN. This effectively alleviates gradient dissipation and unstable convergence during GAN training [37]. On this basis, WGAN-GP further improves the probability distribution estimation strategy under extreme conditions based on sampled data. Specifically, WGAN-GP adds a penalty term to the discriminator gradient norm, thereby addressing the difficulty of strictly satisfying the 1-Lipschitz continuity constraint in the discriminator of the original WGAN.

The overall training optimization objective of WGAN-GP can be described as:

$$\min_G \max_D V(G, D) = \mathbb{E}_{x \sim P_d} [D(x)] - \mathbb{E}_{z \sim P_z} [D(G(z))] + \rho \mathbb{E}_{\hat{x} \sim P_{\hat{x}}} \left[(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2 \right] \quad (9)$$

where ρ is the penalty coefficient; $\hat{x} = \epsilon x + (1 - \epsilon)G(z)$; and $\|\nabla_{\hat{x}} D(\hat{x})\|_2$ is the discriminator gradient with respect to the interpolated sample.

Based on the wind–solar joint probability distribution model constructed in Section 2.1, the Frank-Copula joint distribution is used as the training data distribution P_d of WGAN-GP, enabling the generator to learn the joint probabilistic characteristics of wind and solar outputs. After training, the generator G can generate a set of wind–solar output scenarios, with size N_s , where each scenario contains hourly wind and photovoltaic power data for 24 h.

2.3. Scenario Clustering Based on K-Means++

2.3.1. Scenario Representation

Let the set of predicted scenarios of size N generated by WGAN-GP be:

$$S = \{S_1, S_2, S_3, \dots, S_N\} \quad (10)$$

A single scenario contains wind and solar power data over the 24 h scheduling horizon:

$$S_i = \{S_{wt,i,1}, S_{wt,i,2}, \dots, S_{wt,i,T}, S_{pv,i,1}, S_{pv,i,2}, \dots, S_{pv,i,T}\} \quad (11)$$

where $S_{wt,i,T}$ and $S_{pv,i,T}$ are the predicted wind and photovoltaic outputs of scenario i in period t , respectively.

2.3.2. K-Means++ Clustering Algorithm

Although the large-scale scenario set generated by WGAN-GP can comprehensively reflect the stochastic distribution of wind and solar outputs, directly applying it to the subsequent optimization model would cause excessive computational dimensionality. Therefore, clustering is required to screen representative typical scenarios from the original scenario set.

The K-means++ algorithm is selected in this paper to perform clustering-based reduction of wind–solar scenarios. Compared with classical K-means, K-means++ introduces a distance-probability weighting mechanism when selecting initial cluster centers, effectively avoiding the risk of being trapped in local optima due to improper initial-point selection. The implementation steps are as follows:

Step 1: Optimizing the number of clusters. The elbow method is used to determine an appropriate number of clusters, and the sum of squared errors (SSE) is used as the criterion:

$$SSE_n = \sum_{a=1}^L \sum_{g \in C_a} \|g - y_a\|^2 \quad (12)$$

where SSE_n is the cumulative squared deviation of samples in all clusters; g is a sample data point belonging to a cluster; C_a is the set of all points in cluster a ; y_a is the centroid coordinate of cluster a ; and L is the number of clusters.

The SSE decreases continuously as the number of clusters L increases. When the number of clusters exceeds the natural-category threshold of the data, the reduction in SSE becomes substantially smaller, forming an elbow on the curve. The number of clusters corresponding to this turning point is selected as the optimum.

Step 2: Selecting the initial center. One scenario is randomly selected from all scenarios as the first cluster center μ_1 .

Step 3: Calculating distance measures. Each scenario S_j in the scenario set is traversed, and the cumulative Euclidean distance from it to all selected cluster centers is calculated:

$$d_j = \sum_{a=1}^L \|S_j - \mu_a\|^2 \quad (13)$$

where S_j is the feature vector of candidate scenario j ; μ_a is the determined centroid of cluster a ; and d_j is the cumulative Euclidean distance from scenario j to all selected L cluster centroids.

Step 4: Weighted probability sampling. Sampling probabilities are constructed based on distance information, so that scenarios farther from the existing centers have a higher probability of being selected:

$$P(S_j) = \frac{d_j^2}{\sum_{i=1}^N d_i^2} \quad (14)$$

Step 5: Repeat Steps 2 to 4 until L initial cluster centers are selected.

Step 6: Iterative optimization. All scenarios are assigned to their corresponding clusters according to the nearest-distance criterion, the coordinates of each cluster center are recalculated, and the procedure is repeated until all cluster centers become stable.

2.3.3. Clustering Performance Evaluation

To comprehensively measure clustering quality, the following evaluation indices are introduced.

- The silhouette coefficient characterizes clustering performance in terms of intra-cluster cohesion and inter-cluster separation, with a value range of $[-1, 1]$; a value closer to 1 indicates better clustering.
- The Calinski–Harabasz index jointly considers the relative magnitude of within-cluster dispersion and between-cluster distance; a higher value indicates a better clustering result.
- The Davies–Bouldin index evaluates the balance between intra-cluster dispersion and inter-cluster distance; a smaller value indicates better clustering.

To eliminate evaluation bias caused by dimensional differences among indices, each index is positively normalized and uniformly converted into a maximization problem.

3. TSCOPF Model

The constructed TSCOPF model includes the objective function, power-flow balance equations, inequality constraints, and transient stability constraints. Its core purpose is to optimize the economic dispatch scheme of the power system.

3.1. Objective Function

Taking the minimization of fuel cost for thermal generating units as the optimization objective, this paper constructs a two-stage stochastic TSCOPF model. In order to avoid treating different renewable-output scenarios as independent dispatch problems, the active power output of conventional generators is divided into a scenario-independent base dispatch and a scenario-dependent redispatch term. The relationship is expressed as:

$$P_{G,i,t,s} = P_{G,i,t}^0 + \Delta P_{G,i,t,s} \quad (15)$$

Based on this decision structure, the expected fuel-cost objective function is formulated as:

$$\min F = \sum_{s=1}^S z_s \sum_{t=1}^T \sum_{i=1}^{N_G} \left[a_i \left(P_{G,i,t}^0 + \Delta P_{G,i,t,s} \right)^2 + b_i \left(P_{G,i,t}^0 + \Delta P_{G,i,t,s} \right) + c_i \right] \quad (16)$$

The scenario-dependent redispatch is limited by the regulation capability of each conventional generator:

$$-\Delta P_i^- \leq \Delta P_{G,i,t,s} \leq \Delta P_i^+ \quad (17)$$

Meanwhile, the actual active power output of each generator must satisfy its output limits:

$$P_{G,i}^{\min} \leq P_{G,i,t}^0 + \Delta P_{G,i,t,s} \leq P_{G,i}^{\max} \quad (18)$$

where F is the total expected fuel cost; s is the scenario index; S is the number of representative renewable-output scenarios; z_s is the occurrence probability of scenario s ; t is the scheduling-period index; T is the total number of scheduling periods; i is the generator index; N_G denotes the set of conventional generators; a_i , b_i , and c_i are the quadratic, linear, and constant fuel-cost coefficients of generator i , respectively; $P_{G,i,t}^0$ is the scenario-independent base active power dispatch of generator i at period t ; $\Delta P_{G,i,t,s}$ is the scenario-dependent redispatch of generator i at period t under scenario s ; $P_{G,i,t,s}$ is the actual active power output of generator i at period t under scenario s ; $-\Delta P_i^-$ and ΔP_i^+ are the downward and upward redispatch limits of generator i , respectively; and $P_{G,i}^{\min}$ and $P_{G,i}^{\max}$ are the minimum and maximum active power limits of generator i , respectively.

In this formulation, $P_{G,i,t}^0$ is a here-and-now decision shared by all scenarios, whereas $\Delta P_{G,i,t,s}$ is adjusted after the realization of renewable-output scenario s . Therefore, the five representative scenarios are not optimized independently, but are coupled through the common base dispatch $P_{G,i,t}^0$.

3.2. Static Equality Constraints

$$\begin{aligned} P_{G_i} + P_{W_i} + P_{PV_i} - P_{L_i} &= V_i \sum_{j=1}^{n_b} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\ Q_{G_i} + Q_{W_i} + Q_{PV_i} - Q_{L_i} &= V_i \sum_{j=1}^{n_b} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \end{aligned} \quad (19)$$

where n_b is the total number of buses in the system; P_{G_i} , P_{W_i} , P_{PV_i} , and P_{L_i} are the active power outputs of the thermal generator, wind generator, photovoltaic generator, and load, respectively; Q_{G_i} , Q_{W_i} , Q_{PV_i} , and Q_{L_i} are their reactive power outputs, respectively; V_i and V_j are the voltage magnitudes at buses i and j , respectively; θ_{ij} is the voltage phase-angle difference between buses; and G_{ij} and B_{ij} are the conductance and susceptance components of the admittance matrix between buses i and j , respectively.

3.3. Static Inequality Constraints

$$\begin{cases} P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}, & i = 1, 2, \dots, n_G, \\ Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max}, & i = 1, 2, \dots, n_G, \\ V_{L_q}^{\min} \leq V_{L_q} \leq V_{L_q}^{\max}, & q = 1, 2, \dots, n_L, \\ S_{L_q} \leq S_{L_q}^{\max}, & q = 1, 2, \dots, n_L. \end{cases} \quad (20)$$

where $P_{G_i}^{\max}$ and $P_{G_i}^{\min}$ are the upper and lower limits of generator active power output, respectively; $Q_{G_i}^{\max}$ and $Q_{G_i}^{\min}$ are the upper and lower limits of generator reactive power output, respectively; $V_{L_q}^{\max}$ and $V_{L_q}^{\min}$ are the upper and lower limits of the voltage magnitude at line node q , respectively; S_{L_q} and $S_{L_q}^{\max}$ are the apparent power and upper apparent power limits of branch q , respectively; n_G is the number of generating units; and n_L is the total number of transmission lines.

3.4. Transient Rotor-Angle Stability Constraint Based on GCN-Attention

Because time-domain simulation has relatively low computational efficiency, the transient stability constraint is constructed using the trained GCN-Attention model. For each scheduling period and each representative scenario, the constraint is expressed as:

$$\Phi(A_{t,s}) \geq \Omega, \quad t = 1, 2, \dots, T, \quad s = 1, 2, \dots, S \quad (21)$$

where $\Phi(\cdot)$ is the trained GCN-Attention assessment model; $A_{t,s}$ is the system operating feature vector in period t under scenario s , including generator active and reactive power, bus voltage magnitude and phase angle, line active and reactive power, generator rotor angle, load active and reactive power, wind and photovoltaic outputs, and voltage magnitudes at wind and photovoltaic grid-connection points; Ω denotes the normalized transient stability safety threshold. A larger Ω indicates a more conservative stability requirement and usually leads to a higher operating cost. Unless otherwise stated, $\Omega = 0.10$ is adopted in the following case studies. This value is selected by considering both transient stability margin and operating economy, and its sensitivity is further analyzed in Section 6.6. It should be noted that the constraint in (21) is imposed for all representative scenarios. Therefore, the dispatch solution must satisfy the transient stability requirement under each scenario simultaneously.

This paper focuses on rotor-angle stability. The transient stability index (TSI), denoted by η_{TSI} , is used to quantitatively reflect the transient stability level of the power system after a disturbance. Its mathematical expression is:

$$\eta_{TSI} = \frac{360 - \Delta\delta_{\max}}{360 + \Delta\delta_{\max}} \times 100 \quad (22)$$

where $\Delta\delta_{\max}$ is the maximum rotor-angle difference between any two thermal generating units during the fault. If $\eta_{TSI} > 0$, the system is judged to maintain transient stability under that operating condition; if $\eta_{TSI} < 0$, transient instability occurs.

In transient stability assessment, the number of unstable samples is usually smaller than the number of stable samples. If conventional binary cross-entropy is directly used, the model may be biased toward the majority stable class during training, weakening its ability to identify high-risk unstable conditions in the minority class. Therefore, a class-weighted binary cross-entropy loss function is introduced during GCN-Attention model training:

$$L_{\text{weighted}} = -\frac{1}{N} \sum_{i=1}^N w_i [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)] \quad (23)$$

$$w_i = \begin{cases} \frac{N_s}{N_u}, & y_i = 1, \\ 1, & y_i = 0. \end{cases} \quad (24)$$

where $L_{weighted}$ denotes the class-weighted binary cross-entropy loss function; N is the total number of training samples; i is the sample index; y_i is the true label of sample i , with $y_i = 1$ for transient instability and $y_i = 0$ for transient stability; $\hat{y}_i$ is the probability that sample i is predicted by the model to be unstable; and w_i is the class weight corresponding to sample i . Here, N_u is the number of unstable samples in the training set and N_s is the number of stable samples. Because $N_s > N_u$ usually holds, $w_i > 1$ when $y_i = 1$, increasing the penalty weight of misclassified unstable samples in the total loss and thereby alleviating the model bias toward the majority stable class.

3.5. CMI-Based Feature Selection Method

With large-scale renewable energy integration, the feature dimensionality of power systems increases significantly. To reduce computational burden and improve assessment accuracy, a conditional mutual information (CMI)-based feature selection method is introduced to screen key features that significantly affect transient stability from a large number of candidate features. The mutual information $I(J; H)$ is defined as:

$$I(J; H) = C(J) - C(J|H) \quad (25)$$

where $C(J)$ is the entropy of random variable J , and $C(J|H)$ is the conditional entropy of J given H .

CMI examines the information relationship between random variable J and another random variable H' under the condition of a given random variable H :

$$I(J; H'|H) = C(J|H) - C(J|H, H') \quad (26)$$

If H' and H carry the same information about J , the CMI is zero; if H' provides new information not contained in H , the CMI is nonzero. Based on this principle, the TSI is used as the target variable, and a forward greedy strategy is adopted to gradually construct the feature subset. In each selection round, the conditional mutual information between each candidate feature and the TSI is calculated using the selected features as conditions, and the feature with the largest CMI is preferentially selected. According to the definition, if the information of a candidate feature has already been covered by the selected features, its CMI approaches zero and it is naturally excluded. Thus, redundant variables are effectively removed. The iteration terminates when the CMI values of all candidate features are below the threshold, and the key features with independent contributions to transient stability assessment are retained, reducing input dimensionality while maintaining accuracy.

4. Improved Coati Optimization Algorithm “Coati Optimization Algorithm and Its Improvement”

4.1. Coati Optimization Algorithm

The Coati Optimization Algorithm (COA) is a metaheuristic algorithm inspired by the foraging and escape behaviors of coatis [38]. It performs solution-space exploration through hunting behavior and local exploitation through escape behavior.

The algorithm first generates an initial population within the feasible domain:

$$x_{i,j} = l_j + r \cdot (u_j - l_j) \quad (27)$$

where $x_{i,j}$ is the coordinate of individual i in dimension j ; l_j and u_j define the value range of the variable in dimension j ; and r is a uniformly distributed random variable in the interval $[0, 1]$.

After population initialization, the algorithm enters the hunting phase to achieve global exploration. In this phase, the first half of the population pursues the current best individual, regarded as the target prey. The position update rule is:

$$x_{i,j}^{P1} = x_{i,j} + r \cdot (I_j^G - I \cdot x_{i,j}) \quad (28)$$

The remaining individuals execute an escape strategy to maintain population diversity, and their position update formula is:

$$x_{i,j}^{P2} = x_{i,j} + r_1 \cdot (r_2 l_j^{local} + r_3 u_j^{local} - x_{i,j}) \quad (29)$$

where $x_{i,j}^{P1}$ and $x_{i,j}^{P2}$ are the new positions in the hunting and escape phases, respectively; I_j^G is the current best position; and l_j^{local} and u_j^{local} determine the local search radius.

4.2. Improved Coati Optimization Algorithm

To overcome the tendency of the standard COA to become trapped in local optima, this paper proposes an improved Coati Optimization Algorithm (ICOA).

- (1) Refraction-based opposition learning initialization. The search space is expanded by constructing refraction-based opposite solutions:

$$Q_i(j) = \frac{a_j + b_j}{2} + \frac{a_j + b_j}{2\lambda} - \frac{x_i(j)}{\lambda} \quad (30)$$

where λ is the refraction coefficient, and a_j and b_j are the lower and upper boundaries of dimension j in the search space, respectively.

- (2) Levy flight strategy. A Levy flight mechanism is introduced in the attack phase [39]:

$$\text{levy} = \frac{\mu}{|\nu|^{1/\beta}} \quad (31)$$

where β is a random number in $[0, 2]$; μ and ν follow normal distributions; and δ is the flight step size.

- (3) Spiral search mechanism. A spiral trajectory is adopted in the escape phase to approach the optimal solution:

$$R = \varphi e^{\kappa\theta} \cos(2\pi\theta) \quad (32)$$

$$x_i^{t+1}(j) = d_i^t(j) \cdot \delta \cdot \text{levy} \cdot r + \left(\text{Iguana}_{ground}^t(j) - R \cdot x_i^t(j) \right) \quad (33)$$

where φ is the current-position offset, κ is the compression factor, and θ is the angular factor.

Through these improvements, ICOA achieves a dynamic balance between exploration and exploitation and provides an efficient solution tool for the TSCOPF problem.

5. Solution Procedure of the TSCOPF Model

Step 1: Set the basic parameters of the power system, including line data, bus data, generator power limits, load data, and other relevant parameters. Initialize the WGAN-GP model parameters and ICOA algorithm parameters to provide basic data support for subsequent steps.

Step 2: Use kernel density estimation to fit the marginal probability distributions of wind and photovoltaic outputs, respectively, and establish their joint probability distribution model using the Frank-Copula function. Use the trained WGAN-GP model to generate the wind–solar output scenario set, and then reduce the initial scenarios using K-means++ clustering. The optimal number of clusters is determined by the elbow method, retaining representative scenarios that best characterize wind–solar uncertainty and correlation.

Step 3: Construct the TSCOPF model considering wind–solar uncertainty according to (15)–(21). The objective function minimizes the fuel cost of thermal generators, and the power-flow balance equality constraints and static inequality constraints are established.

Step 4: Use the trained GCN-Attention model for transient stability assessment. The system operating state is input to the GCN-Attention network; topology features of the power system are extracted through graph convolutional layers; importance weights of key nodes are adaptively learned through the attention mechanism; and the TSI value is output through weighted aggregation and fully connected layers to determine whether the system satisfies the transient stability constraint.

Step 5: Solve the TSCOPF optimization model using the proposed ICOA algorithm. Refraction-based opposition learning is used for population initialization, Levy flight path disturbance is incorporated in the exploration phase, and the spiral-trajectory approximation mechanism is introduced in the exploitation phase to update individual positions.

Step 6: Evaluate the fitness of each individual and update the current global optimal solution. If the convergence criterion is satisfied, output the optimal generator output scheme; otherwise, return to Step 5 and continue the iteration.

The solution procedure of the proposed TSCOPF model is illustrated in Figure 1.

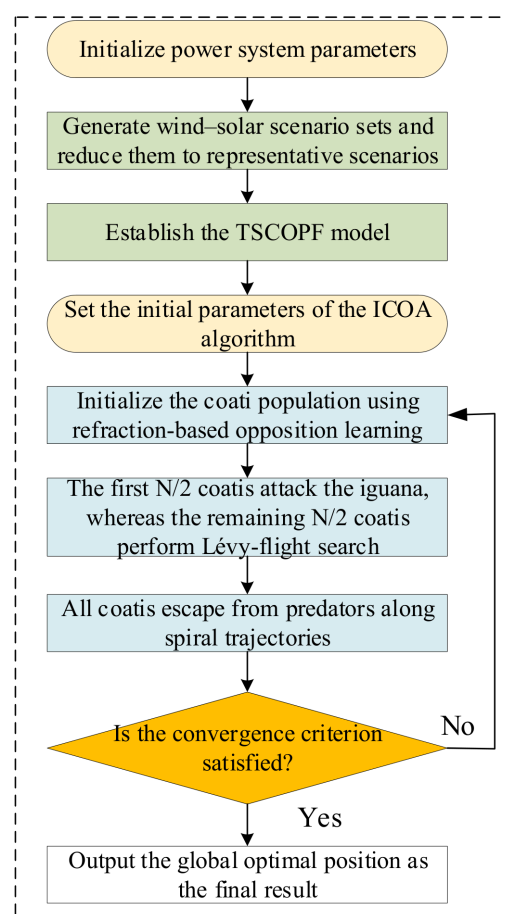


Figure 1. TSCOPF model solution process.

6. Case Analysis

The simulations in this paper are implemented on the MATLAB2023b platform and the PSASP 7.0 power system analysis software, and the modified IEEE 39-bus test system is used for effectiveness verification. The system contains ten thermal generators. To study the influence of wind and photovoltaic integration, a 200 MW wind farm is connected at bus 14 and a 100 MW photovoltaic power station is connected at bus 30. The system topology is shown in Figure 2. The test platform is a computer system equipped with an i9-14900HX processor (3.60 GHz) and 16 GB of memory.

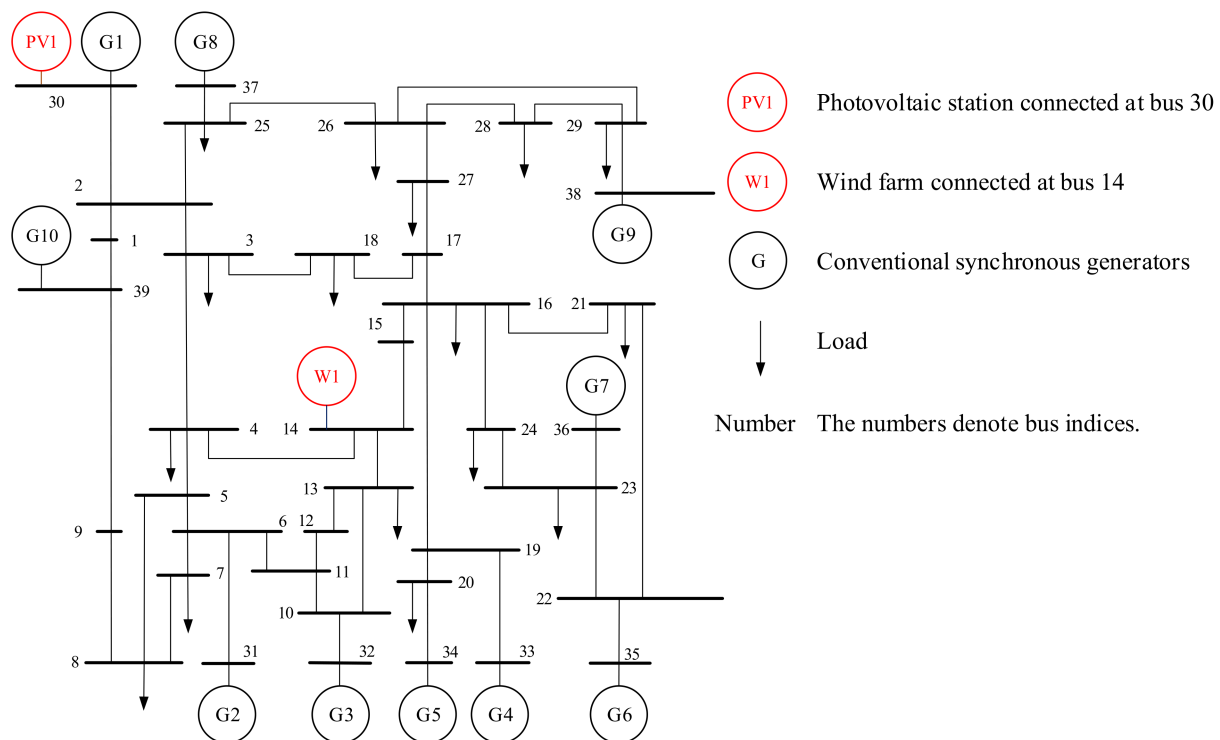


Figure 2. Modified IEEE 39-bus system.

6.1. Uncertainty Processing

The case studies are conducted on the modified IEEE 39-bus system. A 200 MW wind farm and a 100 MW photovoltaic power station are connected to bus 14 and bus 30, respectively. The scheduling horizon is set to 24 h with an hourly resolution. The renewable-output data used for probability modeling and scenario generation are described in detail in Section 2.1.1, including the data source, sampling interval, time span, preprocessing procedure, normalization method, and data availability statement. Based on the processed wind–solar output profiles, KDE and the Frank Copula are used to construct the joint probability distribution, WGAN-GP is adopted to generate wind–solar scenarios, and K-means++ is used to obtain representative scenarios for the TSCOPF case studies.

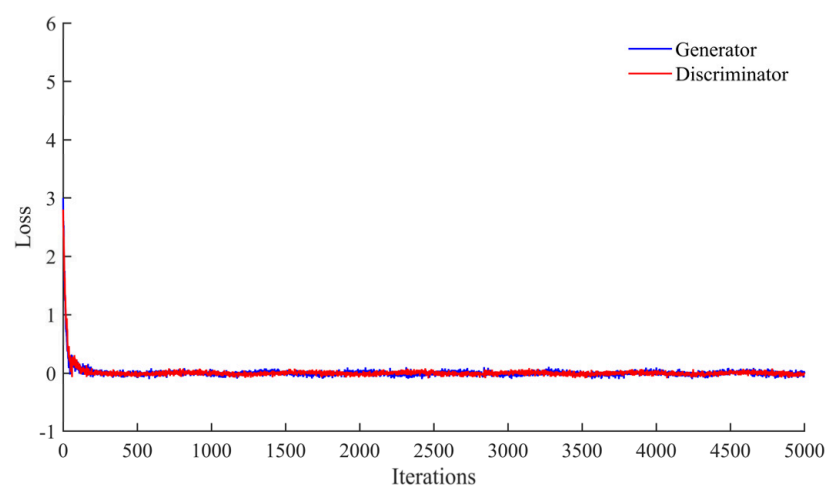
6.1.1. WGAN-GP Model Parameter Settings “Configuration of the WGAN-GP Model”

The generative adversarial network uses the following hyperparameters to complete the wind–solar output scenario generation task. The specific settings are given in Table 1.

Table 1. WGAN-GP model parameter settings.

Parameter	Value
Generator iterations	5000
Critic-to-generator iteration ratio	5:1
Gradient penalty coefficient λ	10
Number of intermediate interpolation points	10
Critic learning rate	1×10^{-4}
Generator learning rate	1×10^{-4}

As indicated by Table 1, in each iteration of WGAN-GP model training, the discriminator is trained more frequently than the generator. This helps improve the overall training performance, promotes a more stable convergence state of the optimization process, and finally yields a relatively smooth loss variation curve, as shown in Figure 3.

**Figure 3.** WGAN model loss curves.

6.1.2. Analysis of Wind–Solar Joint Probability Distribution Modeling

Before scenario generation, a joint probability distribution model of wind–solar outputs must first be established. Kernel density estimation is used to obtain the marginal probability density curves of wind and photovoltaic outputs, and the Copula function is used to characterize the correlation between the two output types.

To select the most suitable Copula function type, this paper compares the fitting performance of four typical functions: the Gaussian Copula, Clayton Copula, Gumbel Copula, and Frank Copula. The Kendall rank correlation coefficient, Spearman rank correlation coefficient, and squared Euclidean distance are used for comprehensive analysis. In addition, the log-likelihood value, Akaike information criterion, Bayesian information criterion, Cramér–von Mises statistic, and Kolmogorov–Smirnov statistic are further introduced to provide a more rigorous goodness-of-fit evaluation. The rank correlation coefficients reflect the degree of monotonic correlation between variables, whereas the squared Euclidean distance measures the deviation between the fitted distribution and the sample data distribution. The log-likelihood value reflects the overall fitting ability of each Copula function. The Akaike information criterion and Bayesian information criterion evaluate fitting performance while considering model complexity. The Cramér–von Mises statistic and Kolmogorov–Smirnov statistic measure the deviation between the fitted distribution and the empirical sample distribution. A larger log-likelihood value and smaller Akaike information criterion, Bayesian information criterion, Cramér–von Mises statistic, and

Kolmogorov–Smirnov statistic indicate better fitting performance. The fitting performance of each Copula function is compared in Table 2.

Table 2. Fitting performance of various Copula functions.

Function	Kendall Rank Correlation Coefficient	Spearman Rank Correlation Coefficient	Squared Euclidean Distance	Log-Likelihood	AIC	BIC	Cramér–Von Mises	KS Statistic
Clayton	8.236×10^{-5}	1.157×10^{-5}	2.127	18.42	−34.84	−27.76	0.0862	0.0715
Gumbel	2.453×10^{-5}	2.186×10^{-5}	2.143	20.16	−38.32	−31.24	0.0827	0.0689
Gaussian	−0.072	−0.083	0.485	74.63	−147.26	−140.18	0.0315	0.0441
Frank	−0.096	−0.148	0.273	96.84	−191.68	−184.60	0.0187	0.0294
Sample data	−0.088	−0.121	0	−	−	−	−	−

The comparison results in Table 2 show that, among the four candidate functions, the two rank correlation coefficients obtained by the Frank Copula have the smallest deviations from the statistical values of the original samples. Its squared Euclidean distance is only 0.273, the lowest among all functions, indicating the highest fitting accuracy for the wind–solar joint output distribution. The rank correlation coefficients of the Clayton Copula and Gumbel Copula are close to zero and deviate significantly from the negative correlation characteristics shown by the sample data; their squared Euclidean distances are also large, indicating poor fitting performance. Although the Gaussian Copula can reflect negative correlation to some extent, its fitting accuracy is still inferior to that of the Frank Copula. Furthermore, the Frank Copula obtains the largest log-likelihood value and the smallest AIC, BIC, Cramér–von Mises statistic, and Kolmogorov–Smirnov statistic among all candidate Copula functions. These additional goodness-of-fit indicators further confirm that the Frank Copula provides the best statistical fitting performance for the wind–solar joint output distribution. Therefore, the Frank Copula can more accurately capture the complementary correlation between wind and photovoltaic outputs and is selected to construct the wind–solar joint output model.

6.1.3. Initial Scenario Generation Based on WGAN-GP

The trained WGAN-GP model is used to generate 500 wind–solar output scenarios, each containing hourly output data over 24 h. Figures 4 and 5 show the three-dimensional distributions of wind and photovoltaic output scenarios generated by WGAN-GP, respectively.

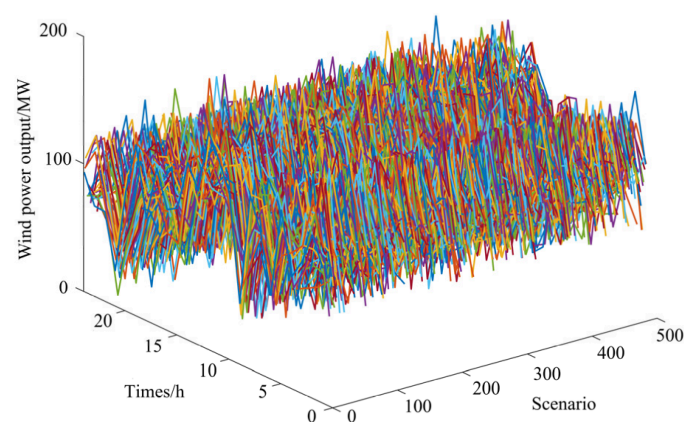


Figure 4. Wind power output scenarios generated by WGAN-GP.

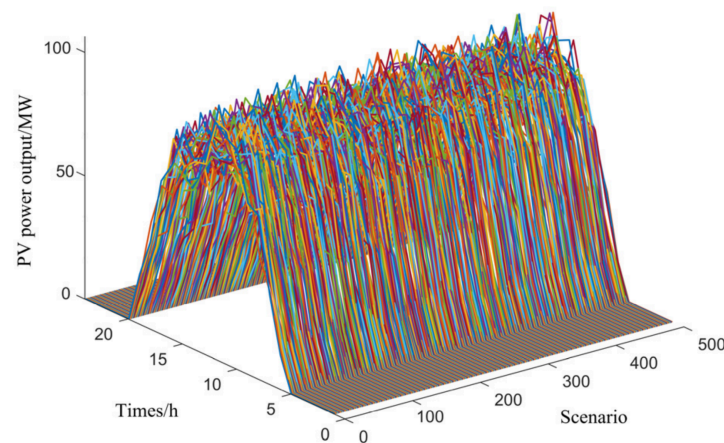


Figure 5. Photovoltaic output scenarios generated by WGAN-GP.

6.1.4. Scenario Clustering Analysis Based on K-Means++

The K-means++ clustering algorithm proposed in Section 2.3 is used to reduce the generated 500 wind–solar scenarios. The elbow method is used to observe the variation of SSE with the number of clusters, and multidimensional evaluation indices including the silhouette coefficient, the Calinski–Harabasz index, and the Davies–Bouldin index are introduced to comprehensively evaluate the clustering effect. The normalized variation curves of these indices are shown in Figure 6.

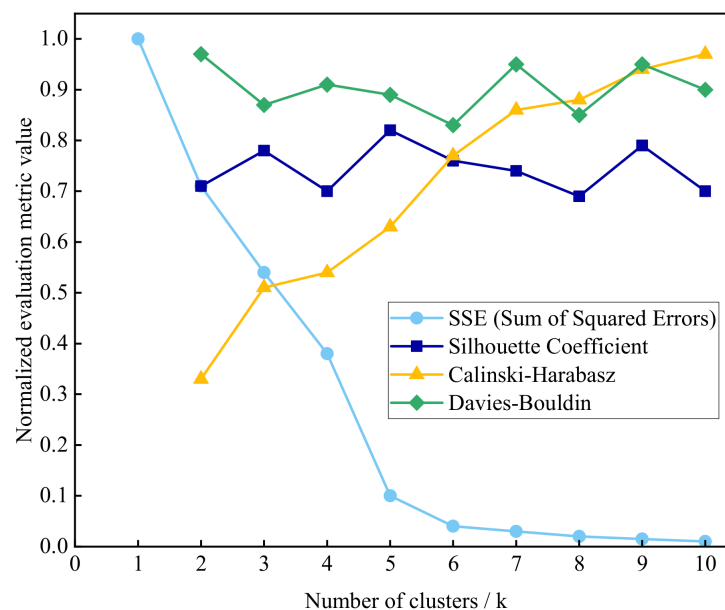


Figure 6. Trends of normalized evaluation indices with different numbers of clusters.

Figure 6 shows that, as the number of clusters increases, the silhouette coefficient and Calinski–Harabasz index increase, whereas the Davies–Bouldin index decreases, indicating gradual improvement in clustering quality. When the number of clusters is 5, the three indices reach the best balance. Further increasing the number of clusters yields limited improvement while increasing the computational burden. Combined with the elbow characteristic of the SSE curve, the optimal number of clusters is determined to be 5, and five typical scenarios are retained for subsequent TSCOPF optimization.

Figures 7 and 8 show the wind and photovoltaic output curves of the five typical scenarios obtained after K-means++ clustering.

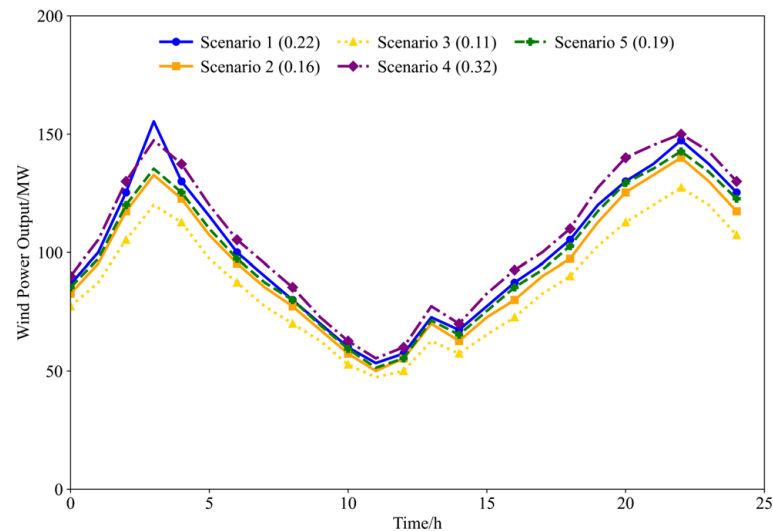


Figure 7. Representative wind power output scenarios.

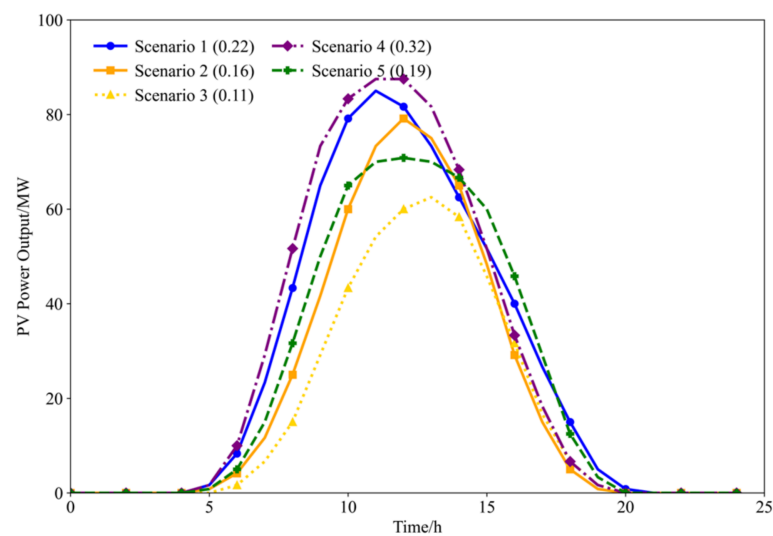


Figure 8. Representative photovoltaic output scenarios.

Figure 7 shows that the five wind output scenarios differ significantly in temporal characteristics and power levels, and wind power is generated throughout the day, with nighttime output generally higher than daytime output. Figure 8 shows that photovoltaic output is concentrated between 7:00 and 19:00, while output is zero during the remaining periods due to the absence of solar irradiation. A comparison of Figures 7 and 8 indicates a clear temporal complementary relationship between wind and photovoltaic outputs: when photovoltaic output is high during the daytime, wind output tends to be relatively low; when photovoltaic output is zero at night, wind output tends to increase. This negative correlation characterized by mutual compensation is consistent with the negative rank correlation coefficients fitted by the Frank Copula in Table 2, verifying the rationality of using a Copula function to characterize wind–solar correlation. The probability distributions of the scenarios are consistent with the actual statistical laws of wind and solar resources, indicating that the proposed scenario generation and clustering method can effectively represent the uncertainty and correlation characteristics of wind and solar outputs.

6.2. Analysis of CMI Feature Selection

The relationship among the feature dimension selected by the CMI algorithm, model accuracy, and training time is shown in Figure 9. As the feature dimension increases, the accuracy of the GCN-Attention model first rises rapidly and then tends to stabilize. When the number of features increases to 90, the accuracy reaches its peak; further increasing the feature dimension does not significantly improve accuracy, indicating that the feature information with key influence on transient stability has been essentially covered. At the same time, training time increases approximately linearly with feature dimension. These results show that CMI feature screening can effectively balance prediction accuracy and computational efficiency.

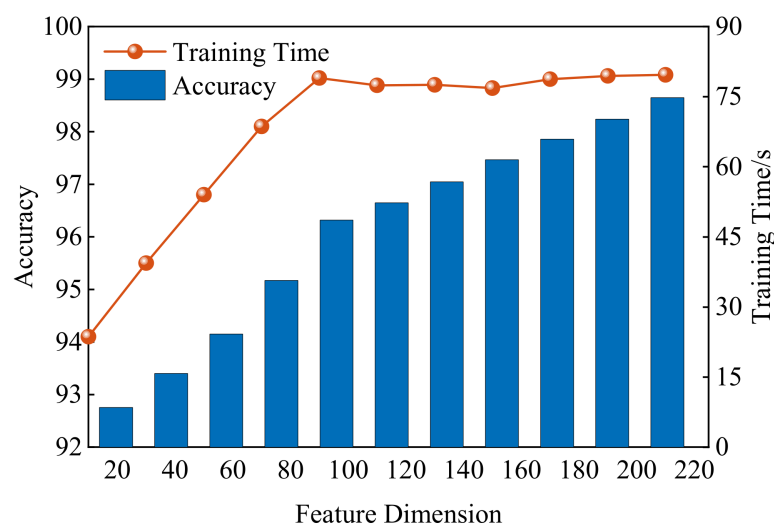


Figure 9. Accuracy and training time across different feature dimensions.

To further verify the effectiveness of the CMI feature selection method, this paper compares it with the maximum relevance minimum redundancy (MRMR) criterion and the mutual information (MI) criterion. Under the same experimental conditions, the three methods are used to screen the candidate feature set, and the comparison of model performance under different feature dimensions is shown in Figure 10.

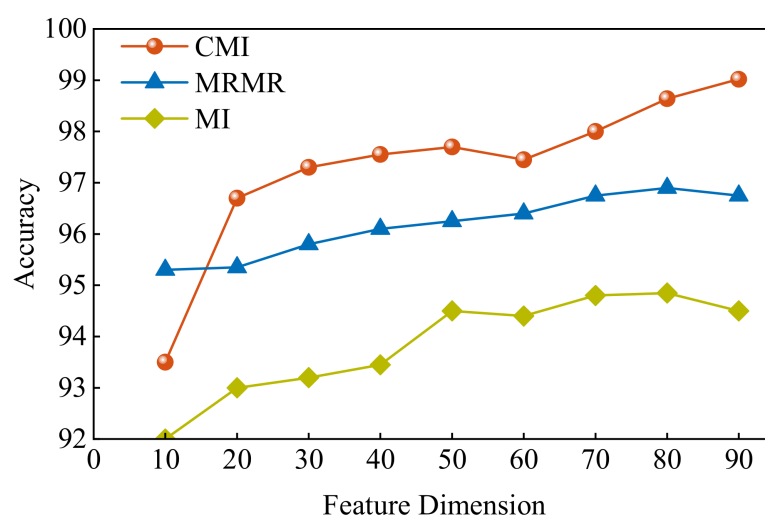


Figure 10. Comparison of model accuracy based on different feature selection algorithms.

Figure 10 shows that when the feature dimension does not exceed 20, the performance differences among the three methods are small. When the feature dimension exceeds 20,

the accuracy corresponding to the CMI method remains higher than that of MRMR and MI, and this advantage becomes more significant as the feature dimension increases. This is because CMI uses conditional mutual information to effectively identify and exclude candidate variables that are informationally redundant with selected features, thereby retaining the key feature subset with the greatest contribution to transient stability assessment. This verifies the superiority of the method in balancing assessment accuracy and dimensionality reduction.

6.3. Sample Construction and Training of the GCN-Attention Model

PSASP 7.0 software is used to conduct time-domain dynamic simulations of the power system, and training and testing data are generated from a large number of operating scenarios. The simulation time resolution is set to 0.01 s to accurately capture fast transient characteristics. To fully cover possible operating states of the system, the load fluctuation range is defined as 80–120% of the rated value, and generator outputs are adjusted accordingly to maintain power balance.

Considering the high risk of three-phase short-circuit faults and their representativeness for stability margin assessment, such faults are used as contingencies in this paper. The fault location is set at the sending end of a line, the fault duration is set to 0.1 s, and the overall simulation window extends to 10 s to observe the system recovery process. Among the generated typical wind–solar operating scenarios, five typical scenarios are obtained after K-means++ reduction. Based on these scenarios, time-domain dynamic simulations are further carried out by changing fault line types and fault locations, generating 6000 sets of system operating samples for model training. The deep-learning model is built using PyTorch 2.7.0. The specific configuration of the GCN-Attention assessment network is as follows: two graph convolutional layers, 64 neurons in each hidden layer, four multi-head attention heads, a final output dimension of 1, an optimizer learning rate of 0.001, and a batch size of 32. The samples are randomly divided into training and test sets in a ratio of 4:1. To avoid information leakage, the out-of-distribution test samples used in Section 6.4.4 were not involved in model training, feature selection, hyperparameter tuning, or threshold selection. The trained GCN-Attention model was directly tested on these unseen samples without retraining.

6.4. Performance Evaluation Indices for the GCN-Attention Model

6.4.1. Performance Evaluation of Different Models

To accurately evaluate the performance of the proposed GCN-Attention-based transient stability assessment model, accuracy, misdetection rate, and false alarm rate are used as model evaluation indices:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (34)$$

$$\text{Misdetection rate} = \frac{FN}{TP + FN} \quad (35)$$

$$\text{False alarm rate} = \frac{FP}{FP + TN} \quad (36)$$

where TP is the number of samples correctly identified as transiently unstable, TN is the number of samples correctly identified as transiently stable, FP is the number of stable samples misclassified as unstable, and FN is the number of unstable samples misclassified as stable. To reduce the randomness caused by random sample division, each result in Table 3 is the average of five independent random-split experiments.

Table 3. Performance comparison of different models.

Assessment Model	Accuracy/%	Misdetecation Rate/%	False Alarm Rate/%	Training Time/s
SVM	94.28	5.82	5.94	11.387
LSTM	96.63	3.36	3.42	58.624
GCN	97.48	2.19	2.31	36.752
GAT	98.16	1.47	1.58	41.286
Graph Transformer	98.63	1.32	1.21	86.412
Temporal GNN	98.48	1.41	1.35	93.578
PINN-based TSA	98.11	1.69	1.52	112.763
GCN-Attention	99.02	1.08	0.93	48.637

To verify the superiority of the proposed GCN-Attention model, it is compared with support vector machine (SVM), long short-term memory (LSTM), graph convolutional network (GCN), and graph attention network (GAT) models. In addition, three more recent transient stability assessment methods are introduced for a stronger comparison: Graph Transformer, Temporal Graph Neural Network, and PINN-based transient stability assessment. The Graph Transformer uses topology-aware self-attention to capture long-range dependencies among buses; the Temporal Graph Neural Network combines graph convolution with recurrent temporal modeling to represent electromechanical dynamic evolution; and the PINN-based model introduces swing-equation residuals as physical regularization during training. For fairness, all comparison models use the same training and testing samples, the same TSI-based labels, and the same CMI-selected feature set.

Table 3 shows that SVM has the lowest classification performance, with an accuracy of only 94.28%, mainly because it is difficult for SVM to fully characterize the complex nonlinear relationships among high-dimensional operating features. Although LSTM can use temporal information, it does not explicitly incorporate the power system topology; therefore, although its overall performance is better than that of SVM, it still has relatively high misdetection and false alarm rates. After introducing graph-structure information, GCN improves accuracy to 97.48%, while GAT further improves classification performance through a local attention mechanism. The Graph Transformer and Temporal GNN achieve higher accuracy than conventional GCN and GAT because they can capture longer-range spatial dependencies or temporal dynamic information. The PINN-based TSA model also improves the physical interpretability of transient stability assessment by introducing swing-equation constraints, but its training time is relatively long due to the additional physical residual calculation. Compared with these advanced models, the proposed GCN-Attention model achieves the highest accuracy of 99.02%, the lowest misdetection rate of 1.08%, and the lowest false alarm rate of 0.93%. This is because the proposed model combines topology-aware graph convolution, adaptive attention weighting, and CMI-based feature screening, thereby achieving a better balance between assessment accuracy and computational efficiency.

6.4.2. Robustness Analysis Under Different Noise Levels

To test model stability under noisy measurements, Gaussian white noise of different intensities is superimposed on the PMU measurement data of the test samples. Three signal-to-noise ratio scenarios, namely 40 dB, 20 dB, and 10 dB, are set. Robustness tests are conducted for SVM, LSTM, GCN, GAT, and the proposed GCN-Attention model, and the results are shown in Table 4.

Table 4 indicates that as noise intensity increases, the accuracy of all models decreases, but the proposed GCN-Attention model shows the smallest decline. When the signal-to-noise ratio decreases from 40 dB to 10 dB, the accuracies of SVM, LSTM, GCN, and GAT decrease by 2.18, 1.76, 1.71, and 1.35 percentage points, respectively, whereas the proposed

model decreases by only 0.86 percentage points. Under the 10 dB strong-noise scenario, the accuracy of the proposed model remains at 98.05%, significantly higher than those of the comparison models, indicating stronger robustness to noisy measurement disturbances.

Table 4. Comparison of model accuracy at different noise levels.

Model	40 DB	20 DB	10 DB
SVM	93.86	93.14	91.68
LSTM	96.37	95.75	94.61
GCN	97.29	96.72	95.58
GAT	97.96	97.34	96.61
GCN-Attention	98.91	98.57	98.05

6.4.3. Assessment Performance Under Imbalanced Sample Sets

Because transiently stable samples usually outnumber unstable samples in actual operation, relying only on overall accuracy may conceal identification bias for minority high-risk operating conditions. Therefore, three imbalanced training scenarios are further constructed, with ratios of unstable to stable samples of 1:2, 1:3, and 1:4, while the test set remains consistent with Section 6.3. To alleviate training bias caused by skewed sample distributions, a weighted binary cross-entropy loss function based on the inverse of class frequency is introduced in the comparative experiment.

Table 5 shows that as sample imbalance becomes more severe, the overall model accuracy remains high, but the misdetection rate gradually increases and the false alarm rate gradually decreases. This indicates that the model is more likely to misclassify minority unstable samples as stable samples. When the ratio of unstable to stable samples is 1:4, the model accuracy still reaches 98.61%, but the misdetection rate increases to 2.74%, indicating that skewed sample distributions weaken the model's ability to identify high-risk unstable conditions.

Table 5. Model performance on an unbalanced dataset without weighting.

Ratio of Unstable to Stable Samples	Accuracy/%	Misdetection Rate/%	False Alarm Rate/%
1:2	98.43	1.96	1.08
1:3	98.55	2.31	0.94
1:4	98.61	2.74	0.88

Table 6 shows that after class weighting is introduced, model accuracy under all three imbalance ratios improves slightly, and the misdetection rate decreases significantly. When the ratio is 1:4, model accuracy increases to 99.01% and the misdetection rate decreases to 0.96%. This indicates that class weighting can effectively enhance the model's ability to identify minority unstable samples without substantially increasing implementation complexity. The assessment results therefore better meet the engineering requirement of online risk warning: moderate early warning is acceptable, but unstable conditions should not be missed.

Table 6. Model performance after category weighting.

Ratio of Unstable to Stable Samples	Accuracy/%	Misdetection Rate/%	False Alarm Rate/%
1:2	98.71	1.24	1.17
1:3	98.92	1.08	1.06
1:4	99.01	0.96	1.09

6.4.4. Generalization Test Under Unseen Wind–Solar Distributions

To further examine whether the trained GCN-Attention model can generalize beyond the five representative scenarios used for training, an out-of-distribution (OOD) test was conducted. The model trained in Section 6.3 was directly applied to three unseen wind–solar distributions without retraining. OOD-1 was generated from WGAN-GP samples that were not selected by K-means++ clustering. OOD-2 was generated by changing the Frank-Copula dependence parameter from -0.096 to -0.140 , representing a stronger negative correlation between wind and photovoltaic outputs. OOD-3 was generated by broadening the KDE bandwidth by 20% and increasing the renewable-output fluctuation range to represent more extreme renewable scenarios. Each OOD test set contained 1200 samples, and the fault locations were randomly selected from candidate transmission lines. The test results are shown in Table 7.

Table 7. Generalization performance under unseen wind–solar distributions.

Test Set	Distribution Characteristic	Samples	Accuracy/%	Misdetection Rate/%	False Alarm Rate/%
In-distribution test set	Original five representative scenarios	1200	99.02	1.08	0.93
OOD-1	Unselected WGAN-GP scenarios	1200	98.41	1.52	1.31
OOD-2	Stronger wind–solar negative correlation	1200	98.08	1.73	1.46
OOD-3	Broadened marginal distribution and extreme renewable fluctuation	1200	97.66	2.05	1.72

As shown in Table 7, the proposed model maintains an accuracy higher than 97.5% under all unseen wind–solar distributions. Although the accuracy slightly decreases and the misdetection rate increases under OOD conditions, the degradation remains limited.

This indicates that the GCN-Attention model does not merely memorize the five representative training scenarios, but can preserve acceptable transient stability assessment performance under wind–solar distributions different from those used for training.

6.5. Ablation Experiment and Framework Effectiveness Analysis

To systematically verify the effects of the attention mechanism, CMI feature screening, and wind–solar grid-connection features on transient stability discrimination performance, multiple ablation models are constructed under the same training and test sets for comparison. The results are shown in Table 8.

Table 8 shows that the basic GCN model achieves an accuracy of only 97.36% without the attention mechanism and CMI feature screening. After the attention mechanism is introduced, the model can more effectively highlight the importance of key nodes, and the accuracy increases to 98.24%. When CMI is added without attention, the accuracy increases to 98.01%, indicating that feature screening effectively reduces interference from redundant information. When wind–solar grid-connection features are removed, the accuracy decreases to 97.62% and the misdetection rate increases to 2.07%, indicating that renewable-grid-side information is important for identifying critical instability conditions induced by wind–solar fluctuations. The proposed model achieves an accuracy of 99.02%, with misdetection and false alarm rates of 1.08% and 0.93%, respectively, verifying the synergistic contribution of each component to improving assessment accuracy.

Table 8. Results of the ablation experiments for the proposed model.

Model	Accuracy/%	Misdetecation Rate/%	False Alarm Rate/%
GCN	97.36	2.18	2.41
GCN-Attention (without CMI)	98.24	1.52	1.43
GCN + CMI (without attention)	98.01	1.74	1.58
GCN-Attention (wind–solar features removed)	97.62	2.07	1.95
GCN-Attention + CMI (proposed model)	99.02	1.08	0.93

To further examine the contribution of the integrated framework, a framework-level ablation analysis was conducted. This analysis was designed to determine whether the performance improvement of the proposed method arises from the coordinated integration of wind–solar correlation modeling, scenario generation, feature selection, transient stability assessment, and optimization, rather than from a simple combination of existing techniques.

Five comparative variants were constructed: (1) without wind–solar correlation modeling, where wind and photovoltaic outputs were assumed to be independent; (2) without WGAN-GP scenario generation, where scenarios were directly sampled from the fitted probability distributions; (3) without CMI feature selection, where all candidate variables were used as input features; (4) without the attention mechanism, where GCN-Attention was replaced by a basic GCN; and (5) without ICOA, where the original COA was used for optimization. All variants were evaluated under the same modified IEEE 39-bus system, representative scenarios, and contingency settings. The results are presented in Table 9.

Table 9. Framework-level ablation results.

Model Variant	Accuracy/%	Misdetecation Rate/%	False Alarm Rate/%	Optimal Cost/(\$/h)	Minimum TSI	Average Convergence Iterations
Full proposed framework	99.02	1.08	0.93	58,103.57	58.26	36.1
Without wind–solar correlation modeling	98.36	1.81	1.56	57,982.64	49.73	38.4
Without WGAN-GP scenario generation	98.52	1.63	1.48	58,176.39	53.42	39.6
Without CMI feature selection	98.24	1.52	1.43	58,165.28	55.17	37.9
Without attention mechanism	98.01	1.74	1.58	58,208.73	52.86	38.7
Without ICOA	99.02	1.08	0.93	58,418.94	56.41	47.8

As shown in Table 9, the removal of any key module leads to degradation in at least one performance indicator. When wind–solar correlation modeling is removed, the minimum TSI decreases from 58.26 to 49.73, indicating that neglecting the dependence between wind and photovoltaic outputs weakens the representation of high-risk operating conditions. Without WGAN-GP scenario generation, the stability margin decreases, suggesting that the generated scenarios become less representative. Without CMI feature selection, the assessment accuracy decreases and both the misdetecation rate and false alarm rate increase, indicating that redundant features adversely affect transient stability learning. Replacing GCN-Attention with a basic GCN reduces the assessment accuracy, which confirms the effectiveness of the attention mechanism in extracting critical topological information. When ICOA is replaced by the original COA, both the operating cost and the average number of convergence iterations increase.

These results indicate that the proposed method is not a direct accumulation of the Frank Copula, WGAN-GP, CMI, GCN-Attention, and ICOA. Rather, its effectiveness is achieved through the coordinated coupling of correlated scenario modeling, representative scenario generation, key feature extraction, transient stability assessment, and stochastic TSCOPF optimization.

6.6. TSCOPF Optimization Analysis

To verify the ability of the proposed TSCOPF model to maintain system transient stability under wind–solar integration, comparative experiments are conducted using the modified IEEE 39-bus system.

The benchmark is the conventional TSCOPF model without wind–solar integration. This model also uses GCN-Attention for transient stability assessment, but it is trained only on conventional thermal power operation samples and does not include wind–solar output features. In the proposed TSCOPF model, a 200 MW wind farm is connected at bus 14 and a 100 MW photovoltaic power station is connected at bus 30; its GCN-Attention transient stability assessment model is trained on operating samples with wind–solar integration. The two models are simulated and tested under six preselected fault lines, which are listed in Table 10. The comparison results of TSI values are shown in Table 11.

Table 10. Contingency fault lines.

System	Fault Line NO.	Fault Line
IEEE 39-bus system	1	Buses 1–39
IEEE 39-bus system	2	Buses 2–25
IEEE 39-bus system	3	Buses 3–18
IEEE 39-bus system	4	Buses 6–7
IEEE 39-bus system	5	Buses 17–27
IEEE 39-bus system	6	Buses 23–24

Table 11. TSI variations before and after optimization under various fault conditions.

Fault No.	Conventional Model TSI	Proposed Model TSI
1	47.23	68.51
2	32.47	63.08
3	−87.35	64.89
4	−91.28	61.73
5	−93.67	59.58
6	−95.91	58.26

Table 11 shows that the conventional TSCOPF model experiences severe instability under faults 3, 4, 5, and 6 ($TSI < 0$), whereas the proposed TSCOPF model maintains transient stability under all fault conditions ($TSI > 0$). Figures 11 and 12 show the rotor-angle comparison curves of the two models under fault scenarios 4 and 5, respectively.

To further investigate the influence of the transient stability threshold on the economy–security trade-off, the value of Ω was varied from 0 to 0.20 while keeping other parameters unchanged.

For each value of Ω , the TSCOPF model was solved by ICOA, and the minimum TSI among the six contingency faults in Table 10 was recorded. The results are shown in Table 12.

As shown in Table 12, increasing Ω improves the transient stability margin but also increases the operating cost.

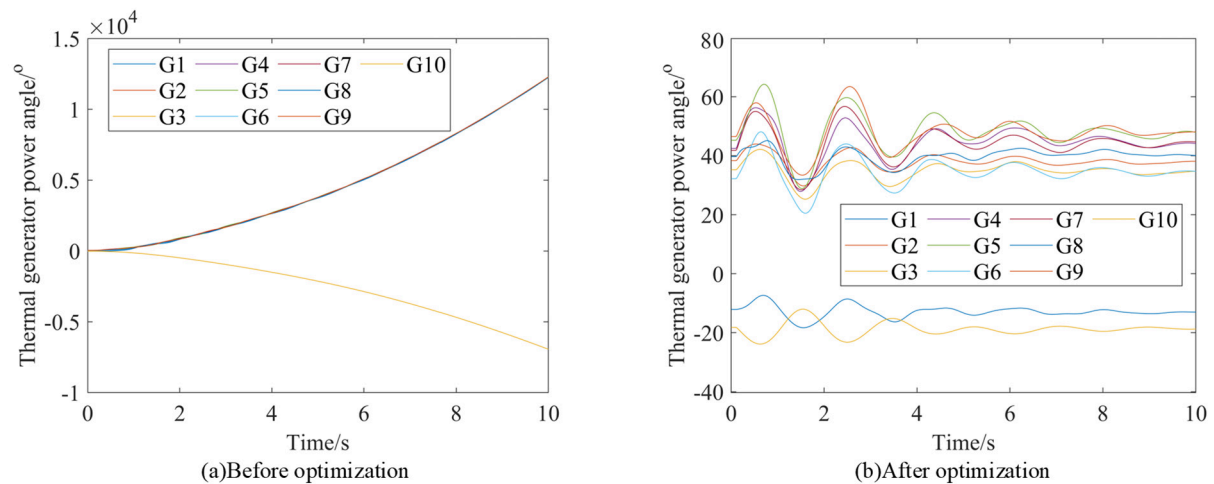


Figure 11. Trend in generator power angle before and after optimization in scenario 4.

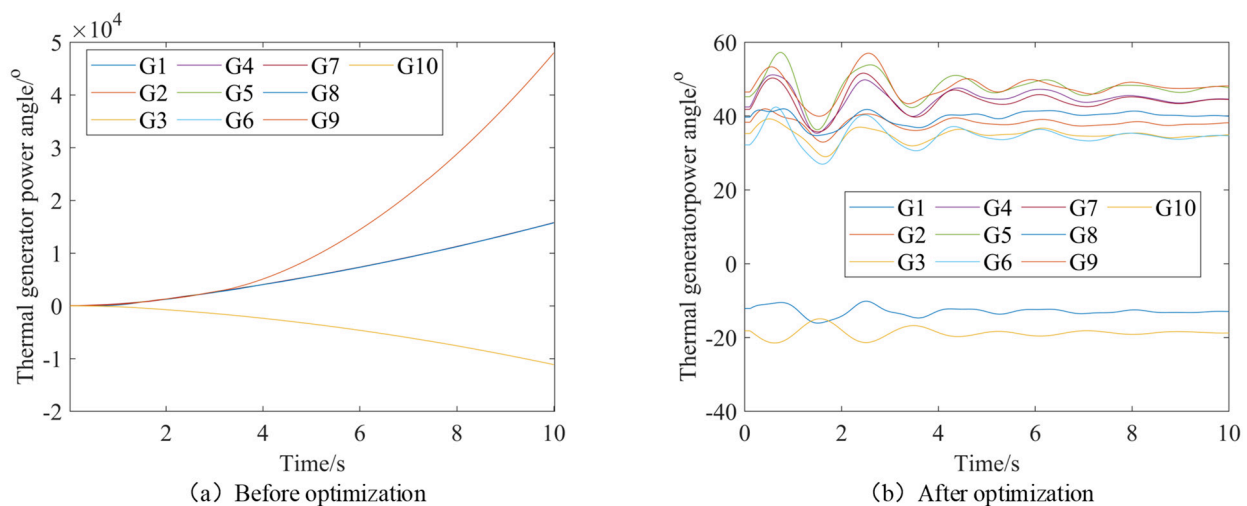


Figure 12. Trend in generator power angle before and after optimization in scenario 5.

Table 12. Sensitivity analysis of the transient stability threshold Ω .

Ω	Optimal Cost/(\$/h)	Cost Increase/%	Minimum TSI	Average TSI
0.00	57,936.42	0.00	48.73	55.84
0.05	58,014.29	0.13	53.19	59.21
0.10	58,103.57	0.29	58.26	62.68
0.15	58,247.85	0.54	62.94	66.03
0.20	58,432.61	0.86	66.58	69.52

When Ω increases from 0 to 0.10, the minimum TSI increases from 48.73 to 58.26, whereas the operating cost increases by only 0.29%. When Ω further increases to 0.20, the minimum TSI continues to improve, but the cost increase becomes more evident.

Therefore, $\Omega = 0.10$ is selected in this paper as a balanced threshold between stability conservatism and economic performance.

Figures 11a and 12a show that when the conventional TSCOPF model is used, the rotor angles of generators diverge after the fault occurs, and the maximum rotor-angle difference between any two machines exceeds the 360-degree critical value, indicating obvious loss of synchronism. In contrast, Figures 11b and 12b show that, after using the proposed method, transient stability is accurately assessed by the GCN-Attention model trained with wind–solar samples, and coordinated optimization considering wind–solar

output correlation converts the originally unstable system into a stable operating state. The generator rotor-angle curves gradually converge after a short oscillation, indicating that the proposed method can effectively handle the uncertainty introduced by wind–solar integration and ensure transiently stable system operation.

For fault scenario 4, the active-output adjustment strategy of the ten generating units after optimization by the proposed method is shown in Table 13.

Table 13. Comparison of generator output before and after optimization.

Generator	Output Before Optimization (MW)	Output After Optimization (MW)
G1	237.03	267.50
G2	622.57	612.87
G3	671.52	645.14
G4	642.04	620.88
G5	471.53	466.46
G6	638.57	602.76
G7	582.08	552.29
G8	521.58	548.19
G9	826.05	761.16
G10	988.03	1022.35

6.7. Scalability Validation on the IEEE 118-Bus System

To further evaluate the scalability and generalizability of the proposed method, an additional case study was conducted on the IEEE 118-bus system. The standard IEEE 118-bus system contains 118 buses, 186 branches, and 19 generators. Compared with the modified IEEE 39-bus system, it has a larger network scale and more operating constraints, and therefore provides a more rigorous benchmark for scalability verification.

The same modeling and solution procedure as that used for the modified IEEE 39-bus system was adopted. Specifically, KDE and the Frank Copula were used to model the joint probability distribution of wind and photovoltaic outputs. WGAN-GP was employed to generate wind–solar output scenarios, and K-means++ was used to obtain five representative scenarios. The GCN-Attention model was retrained using operating samples generated from the IEEE 118-bus system and was then embedded into the TSCOPF model as the transient stability constraint. The resulting optimization problem was solved using ICOA.

In the IEEE 118-bus case, a 600 MW wind farm and a 300 MW photovoltaic power station were connected to two load-intensive buses. Six severe contingency faults were selected for transient stability verification. The comparison results are summarized in Table 14.

Table 14. Scalability validation on different benchmark systems.

Test System	Buses	Branches	Generators	Renewable Capacity	Representative Scenarios	Accuracy/%	Misdetetection Rate/%	Optimal Cost/(\$/h)
Modified IEEE 39-bus system	39	46	10	200 MW wind + 100 MW PV	5	99.02	1.08	58,103.57
IEEE 118-bus system	118	186	19	600 MW wind + 300 MW PV	5	98.37	1.74	129,684.52

As shown in Table 14, the proposed method maintains satisfactory performance on the IEEE 118-bus system. Although the computation time increases from 42.37 s to 116.84 s because of the larger system scale, the GCN-Attention model still achieves an accuracy of 98.37%. Moreover, the minimum TSI remains positive under the selected contingency faults, indicating that the optimized operating points satisfy the transient stability requirement.

These results verify that the proposed framework is not limited to the modified IEEE 39-bus system and has applicability to larger benchmark systems.

6.8. Performance Analysis of the Optimization Algorithm

To further verify the optimization quality and robustness of the proposed ICOA algorithm, comparative experiments were conducted with COA, IWOA, and QPSO under fault scenario 4. Since metaheuristic algorithms are affected by random initialization and stochastic search processes, each algorithm was independently executed ten times under the same population size, maximum number of iterations, stopping criterion, and constraint-handling strategy. The final objective value of each run was recorded, and the statistical results are summarized in Table 15. In addition, the Wilcoxon rank-sum test was used to evaluate whether the difference between ICOA and each competing algorithm was statistically significant.

Table 15. Statistical comparison of optimization algorithms over ten independent runs.

Algorithm	Best Cost/(\$/h)	Mean Cost/(\$/h)	Std./(\$/h)	Worst Cost/(\$/h)	Average Convergence Iterations	<i>p</i> -Value vs. ICOA
ICOA	58,086.24	58,103.57	16.82	58,132.15	36.1	—
COA	58,332.76	58,418.94	68.47	58,536.21	47.8	2.7×10^{-4}
IWOA	58,511.38	58,612.73	83.95	58,744.66	51.3	8.6×10^{-5}
QPSO	58,711.54	58,835.26	101.42	58,982.89	52.0	3.1×10^{-5}

As shown in Table 15, ICOA obtains the lowest best, mean, and worst objective values among the four algorithms. The mean final cost of ICOA is 58,103.57 \$/h, which is 315.37 \$/h, 509.16 \$/h, and 731.69 \$/h lower than that of COA, IWOA, and QPSO, respectively. In terms of relative reduction, the mean operating cost is decreased by 0.54%, 0.87%, and 1.24%, respectively.

Moreover, ICOA shows the smallest standard deviation of 16.82 \$/h, while the standard deviations of COA, IWOA, and QPSO are 68.47 \$/h, 83.95 \$/h, and 101.42 \$/h, respectively. This indicates that ICOA has better repeatability and is less sensitive to stochastic search variations. In terms of convergence efficiency, ICOA requires only 36.1 iterations on average, which is fewer than COA, IWOA, and QPSO. The *p*-values obtained from the Wilcoxon rank-sum test are all lower than 0.05, confirming that the improvement of ICOA over the competing algorithms is statistically significant. Therefore, the proposed ICOA achieves better optimization quality, robustness, and convergence efficiency in solving the TSCOPF problem.

7. Conclusions

To address the influence of wind–solar output correlation and uncertainty on the economic and transiently stable operation of power systems, this paper proposes a transient stability-constrained optimal power-flow model considering wind–solar output correlation. The proposed framework integrates Frank-Copula-based wind–solar joint distribution modeling, WGAN-GP scenario generation, K-means++ scenario reduction, CMI-based feature selection, GCN-Attention transient stability assessment, and an improved Coati Optimization Algorithm. The modified IEEE 39-bus system is used to verify the effectiveness of the proposed method. The main conclusions are summarized as follows.

- The Frank-Copula-based wind–solar joint probability distribution model can effectively characterize the correlation and uncertainty of renewable output. Compared with other Copula functions, the Frank Copula better captures the negative correlation and temporal complementarity between wind and photovoltaic outputs. The wind–

solar scenarios generated by WGAN-GP and reduced by K-means++ retain the main statistical characteristics of renewable output, providing representative scenario data for the TSCOPF model.

- The CMI-based feature selection method improves the efficiency and accuracy of transient stability assessment. By removing redundant variables and retaining key features related to transient stability, the selected feature subset reduces the input dimension of the assessment model while maintaining high prediction accuracy. Compared with MI and MRMR methods, the CMI method shows better performance in balancing feature reduction and assessment accuracy.
- The proposed GCN-Attention transient stability assessment model achieves high accuracy and robustness. The model makes full use of power system topology information and adaptively learns the importance of key nodes through the attention mechanism. Compared with SVM, LSTM, GCN, and GAT models, the proposed model achieves better assessment performance, with an accuracy of 99.02%, a misdetection rate of 1.08%, and a false alarm rate of 0.93%. In addition, the model maintains good robustness under noisy measurement conditions and imbalanced sample distributions.
- The proposed TSCOPF model can effectively improve the transient stability margin under contingency faults. Compared with the conventional model, the proposed model maintains positive TSI values under all tested fault scenarios, while the conventional model becomes unstable in several cases. The generator rotor-angle curves further verify that the proposed method can suppress rotor-angle divergence and maintain system synchronism after disturbances.
- The proposed ICOA algorithm improves the solution quality and convergence performance of the TSCOPF model. By introducing refraction-based opposition learning, Levy flight, and spiral search strategies, ICOA enhances the global search capability and local exploitation ability of the standard COA. The optimization results show that ICOA converges faster and obtains a lower generation cost than COA, IWOA, and QPSO.

Overall, the proposed data-driven TSCOPF framework provides an effective method for coordinating economic dispatch and transient stability under wind–solar uncertainty. Future work will focus on validating the proposed method in larger-scale practical power systems, considering more types of renewable energy and energy storage resources, and further improving the online computational efficiency of the model for real-time dispatch applications.

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Nomenclature

Symbol	Description
P_w	Wind power output.
P_{pv}	Photovoltaic power output.
$U_w(P_w)$	Marginal cumulative distribution function of wind power output.
$U_{pv}(P_{pv})$	Marginal cumulative distribution function of photovoltaic power output.
$C(\cdot)$	Copula function used to describe the dependence between wind and photovoltaic outputs.
τ	Dependence parameter of the Frank-Copula function.
G	Generator network in the GAN/WGAN-GP model.
D	Discriminator network in the GAN/WGAN-GP model.
P_d	Probability distribution of real historical wind–solar output data.
P_g	Probability distribution of wind–solar output samples generated by the generator.
N_s	Number of wind–solar output scenarios generated by WGAN-GP.
S	Number of representative renewable-output scenarios retained after scenario reduction.
z_s	Occurrence probability of representative scenario (s).
L	Total number of scheduling periods.
$P_{G,i,t}^0$	Scenario-independent base active power dispatch of conventional generator (i) at period (t).
$\Delta P_{G,i,t,s}$	Scenario-dependent redispatch of conventional generator (i) at period (t) under scenario (s).
$P_{G,i,t,s}$	Actual active power output of conventional generator (i) at period (t) under scenario (s).
a_i, b_i, c_i	Quadratic, linear, and constant fuel-cost coefficients of conventional generator (i).
P_{G_i}, Q_{G_i}	Active and reactive power outputs of the thermal generator at bus (i).
P_{W_i}, Q_{W_i}	Active and reactive power outputs of the wind generator at bus (i).
P_{PV_i}, Q_{PV_i}	Active and reactive power outputs of the photovoltaic generator at bus (i).
P_{L_i}, Q_{L_i}	Active and reactive load demands at bus (i).
V_i, V_j	Voltage magnitudes at buses (i) and (j).
θ_{ij}	Voltage phase-angle difference between buses (i) and (j).
G_{ij}, B_{ij}	Conductance and susceptance elements of the bus admittance matrix.
$\Phi(\cdot)$	Trained GCN-Attention model used for transient stability assessment.
$A_{t,s}$	System operating feature vector at period (t) under scenario (s).
Ω	Normalized transient stability safety threshold.
η_{TSI}	Transient stability index used to quantify rotor-angle stability after a disturbance.
$\Delta\delta_{\max}$	Maximum rotor-angle difference between any two thermal generating units during the fault.
$I(J;H)$	Mutual information between random variables (J) and (H).

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