

Article

Comprehensive Evaluation of Power Grid Renewable Energy Hosting Capacity Based on the EWM-GRA-TOPSIS Method

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Abstract

To address the supply–security pressures and hosting capacity assessment challenges arising from the high penetration of renewable energy into power systems, this paper proposes a comprehensive evaluation method for grid renewable energy hosting capacity based on the entropy weight method, technique for order preference by similarity to ideal solution, and grey relational analysis (EWM-GRA-TOPSIS). First, a multi-dimensional comprehensive evaluation index system is established, encompassing security and stability, operational economy, flexible power supply security, and renewable energy penetration. Subsequently, a comprehensive hosting capacity evaluation model is formulated. Within the operational simulation layer, key evaluation metrics across diverse renewable energy deployment alternatives are quantified based on time-series production simulation and power flow calculations. In the data processing layer, the EWM is employed to determine index weights, while GRA measures the morphological similarity between alternatives and the ideal sequence. Concurrently, TOPSIS evaluates their geometric proximity, enabling a coordinated trade-off among multi-dimensional metrics and the final ranking of the alternatives. Finally, the result output layer yields the comprehensive assessment outcomes and the prioritized ranking of the proposed scenarios. Simulation results demonstrate that the proposed method effectively evaluates the hosting capacity of various development scenarios, thereby providing a robust decision-making basis for power system planning and operation that balances high grid capacity with optimal comprehensive benefits.

Keywords: Evaluation of Renewable Energy Hosting Capacity; technique for order preference by similarity to ideal solution (TOPSIS); grey relational analysis (GRA); comprehensive benefit index; ranking of optimal alternatives

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1. Introduction

With the global proliferation of dual-carbon goals [1], transitioning toward renewable energy-dominated power systems has become a critical objective. Although large-scale renewable energy integration supplies clean energy to the grid [2,3], it simultaneously introduces operational challenges to grid expansion planning, dispatch scheduling, and protection configurations [4–6]. As the penetration level of renewable energy

escalates, its inherent stochasticity, intermittency, and uncontrollability pose growing risks to grid operational security [7–9]. Consequently, electric utilities and regulatory authorities are increasingly focusing on the grid's renewable energy hosting capacity, initiating adaptability assessments and technical upgrades to facilitate further integration and sustainable development.

Currently, the renewable energy hosting capacity following grid integration has been extensively investigated by researchers worldwide. In the literature, hosting capacity is generally defined as the maximum allowable installed capacity that a modern power system can accommodate while maintaining secure, reliable, and economic operations under given conventional generation configurations, network topologies, and load distributions. To quantify this capacity, three main methodology streams are utilized: analytical methods, intelligent optimization techniques [10], and stochastic scenario simulation approaches. Analytical methods mathematically transform the capacity assessment into an optimal power flow (OPF) problem [11], with interior point methods [12], non-linear programming [13], and simple gradient methods serving as key sub-branches. Meanwhile, intelligent optimization approaches primarily employ particle swarm optimization (PSO) [14], genetic algorithms (GA) [15], and robust optimization (RO) [16,17]. Based on a time-series production simulation model, the literature [18] formulated a calculation methodology for renewable energy accommodation capacity that explicitly accounts for the utilization levels of inter-provincial tie-lines. Literature [19] presented a generalized framework that conceptualizes power system optimization as a history matching problem, employing statistical surrogate models and Bayesian linear analysis to achieve computational efficiency and uncertainty quantification. Additionally, the literature [20] proposed a photovoltaic (PV) hosting capacity assessment method utilizing interval overvoltage probability (IOP) and interval overvoltage risk (IOR), thereby yielding less conservative appraisal outcomes compared to traditional methodologies.

The increasing complexity of modern power systems has motivated research toward multi-scenario indicator systems and multi-criteria comprehensive assessment methods. Literature [21] proposes a data-driven hosting capacity analysis framework using active learning to explore how DER adoption patterns and control/management strategies significantly affect grid hosting capacity. Literature [22] presented a rapid assessment methodology for distributed generation capacity in smart distribution networks based on distributed dispatching, incorporating a steady-state security region to achieve bilateral optimal operations for both distribution networks (DN) and microgrids (MG). Furthermore, the literature [23] investigated three reliability evaluation techniques to evaluate the impacts of renewable energy integration on power system reliability profiles. Literature [24] established a flexibility assessment framework for distribution networks that accounts for the large-scale clustered integration of flexible resources, constructing a flexibility metric framework from the generation, network, and load perspectives. Regarding multi-criteria assessment, the literature [25] constructed a comprehensive benefit evaluation index system encompassing economic, environmental, energetic, and social dimensions, and proposed a hybrid multi-criteria decision-making (MCDM) model based on the grey DEMATEL and modified difference quotient grey relational analysis (DQ-GRA) approach. However, the research objective mainly focuses on multi-dimensional benefit analysis rather than renewable hosting capacity under power system operational constraints.

To address existing research gaps, this study investigates a power grid featuring high-penetration renewable energy export and proposes a comprehensive evaluation framework for its hosting capacity based on a hybrid EWM-GRA-TOPSIS approach. This methodology establishes a multi-dimensional evaluation index system, employing the entropy weight method to determine metric weights and resolve inter-dimensional coupling. By integrating GRA and TOPSIS, the framework evaluates and ranks the candidate

renewable deployment alternatives according to their comprehensive performance. Finally, case studies on a modified IEEE 118-bus system with high renewable energy penetration validate the feasibility and effectiveness of the proposed approach.

The remainder of this paper is organized as follows: Section 2 establishes a four-dimensional comprehensive index system for grid renewable energy hosting capacity, followed by the mathematical formulation of each individual metric. Section 3 constructs the comprehensive evaluation model, which incorporates a time-series production simulation under critical operational constraints and delineates the EWM-GRA-TOPSIS-driven decision workflow. Section 4 evaluates renewable deployment alternatives under representative operating scenarios, estimates their renewable energy hosting capacities and associated operational indicators, and identifies the preferred alternative through comprehensive evaluation. Finally, Section 5 concludes the paper with key research findings.

2. Establishment of the Comprehensive Evaluation Index System for Renewable Energy Hosting Capacity

2.1. Construction of the Multi-Dimensional Index System

To comprehensively account for the impacts of high-penetration renewable energy integration and the critical determinants of grid hosting capacity, a multi-dimensional evaluation index system is developed. This hierarchical framework comprises three levels: the target level, the criterion level, and the indicator level. Specifically, the target level aims to identify the preferred renewable energy deployment scheme by jointly considering renewable energy hosting capacity, security and stability, power-supply reliability, operational economy, system flexibility, and renewable energy utilization. The criterion level encompasses four dimensions—security and stability, operational economy, flexible power supply security, and renewable energy characteristics—which are further refined into specific granular metrics within the indicator level. The detailed structure of this evaluation index system is illustrated in Figure 1.

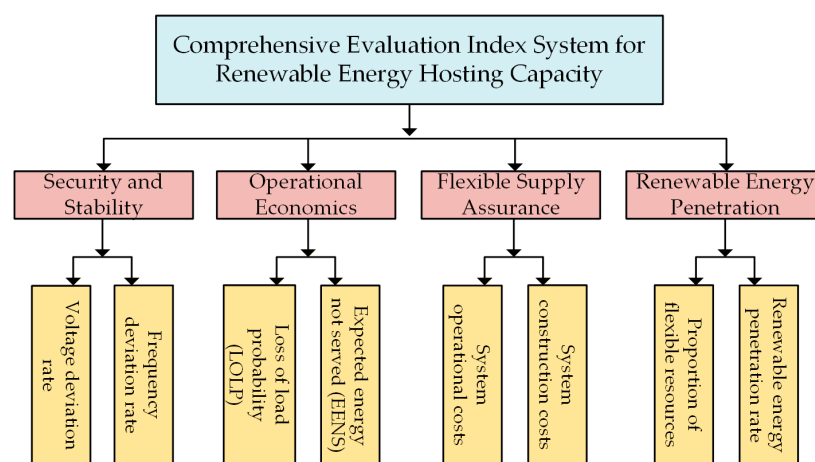


Figure 1. Comprehensive evaluation index system for grid renewable energy hosting capacity.

The selection of evaluation indicators is based on the operational characteristics of high-penetration renewable energy systems and the key factors affecting renewable energy hosting capacity. Since renewable integration involves interactions among system security, economic operation, flexibility requirements, and renewable generation characteristics, the proposed indicator system considers these four aspects comprehensively. Specifically, security and stability indicators are selected to characterize operational constraints caused by renewable integration, economic indicators reflect the cost-related impacts of renewable deployment, flexibility-related indicators describe the regulation

capability required to accommodate renewable generation fluctuations, and renewable energy characteristic indicators represent the utilization and integration level of renewable resources.

2.2. Quantitative Calculation of Evaluation Indexes

1. Voltage deviation rate;

To characterize the most critical voltage deviation under each renewable deployment alternative and operating scenario, the maximum absolute voltage deviation across all buses and calculation periods is used.

$$A_1 = \frac{|U_0 - U_N|}{U_N} \times 100\% \quad (1)$$

where A_1 represents the voltage deviation rate; U_0 represents the actual operational voltage of the system; U_N indicates the rated voltage of the system.

2. Frequency deviation rate;

$$A_2 = \frac{|f - f_N|}{f_N} \times 100\% \quad (2)$$

where A_2 represents the frequency deviation rate; f represents the actual operational frequency of the system; f_N indicates the rated frequency of the system.

3. Loss of Load Probability (LOLP);

$$B_1 = \frac{1}{T} \sum_{t=1}^T \text{sgn}\{P_{\text{available},t} < P_{\text{load},t}\} \quad (3)$$

where B_1 signifies the loss of load probability (LOLP); T represents the total number of statistical time periods; sgn denotes the sign function (or indicator function), which takes a value of 1 when the condition inside the parentheses is satisfied, and 0 otherwise; $P_{\text{available}}(t)$ indicates the available capacity of the system during time period t ; $P_{\text{load}}(t)$ represents the total load demand of the system during time period t .

4. Expected Energy Not Served (EENS);

$$B_2 = \sum_{t=1}^T \max(P_{\text{load}}(t) - P_{\text{available}}(t), 0) \cdot \Delta t \quad (4)$$

where B_2 signifies the expected energy not served (EENS); Δt represents the duration of each time period; $\max(\cdot, 0)$ denotes the function ensuring that only the part where the load demand exceeds the available capacity is calculated.

5. System construction costs;

$$C_1 = c_{sg}e_{g1} + c_{sw}e_{w1} + c_{sp}e_{p1} + c_{sb}e_{b1} \quad (5)$$

where C_1 represents the system construction cost; e_{g1} , e_{w1} , e_{p1} , and e_{b1} denote the unit construction costs of thermal power, wind power, photovoltaic (PV) power, and

energy storage systems, respectively; C_{sg} , C_{sw} , C_{sp} , C_{sb} represent the total installed capacities of thermal power, wind power, PV power, and energy storage systems, respectively.

The construction costs of various generation technologies are summarized in Table 1.

Table 1. Capital expenditures of various generation technologies.

Technology Type	Capital Expenditure
Thermal Power	4000 (RMB/kW)
Wind Power	4000 (RMB/kW)
PV Power	2500 (RMB/kW)
Energy Storage	1000 (RMB/kW)

6. System operational costs;

$$C_2 = E_{sg}e_g + E_{sw}e_w + E_{sp}e_p + E_{sb}e_b \quad (6)$$

where C_2 represents the system operational cost; e_g , e_w , e_p , and e_b denote the unit operational costs of thermal power, wind power, PV power, and energy storage systems, respectively; E_{sg} , E_{sw} , and E_{sp} indicate the total power generation of thermal power, wind power, and PV power, E_{sb} , respectively; represents the total charging and discharging energy of the storage system.

7. Proportion of flexible resources;

$$D_1 = \frac{P_{\text{flex}}}{P_{\text{total}}} \times 100\% \quad (7)$$

where D_1 represents the proportion of flexible resources. P_{flex} represents the total power capacity of the flexible regulation resources within the system, including energy storage systems and regulable thermal units; P_{total} indicates the total installed power capacity of the system.

8. Renewable energy penetration rate.

$$D_2 = \frac{E_{\text{new}}}{E_{\text{total}}} \times 100\% \quad (8)$$

where D_2 denotes the renewable energy penetration rate; E_{new} represents the total power generation from renewable energy sources, including wind power and PV power; E_{total} indicates the total electricity consumption of the system.

3. Comprehensive Evaluation of Renewable Energy Hosting Capacity Based on EWM-GRA-TOPSIS

3.1. Overall Framework of the Evaluation Model

Figure 2 illustrates the evaluation model framework, which consists of three main components: the operational simulation layer, the data processing layer, and the output layer.

1. Operational Simulation Layer: For each renewable deployment alternative and representative operating scenario, chronological production simulation and power-flow analysis are performed to obtain the renewable energy hosting capacity and the associated operational evaluation indicators, which together form the initial decision matrix for the subsequent comprehensive evaluation;
2. Data Processing Layer: Formulates the hosting capacity evaluation index system and executes metric weight allocation alongside comprehensive scheme ranking utilizing the EWM, GRA, and TOPSIS algorithms;
3. Result Output Layer: Yields the definitive multi-dimensional assessment outcomes and the prioritized ranking of all alternative scenarios.

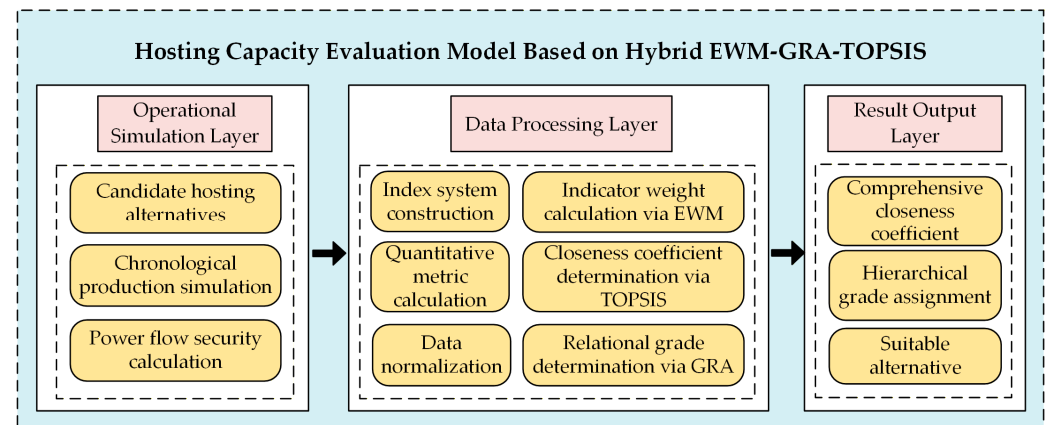


Figure 2. Structural framework of the proposed hosting capacity evaluation model.

3.2. Estimation of Renewable Energy Hosting Capacity Based on Chronological Production Simulation

3.2.1. Objective Function

In this study, renewable energy hosting capacity refers to the maximum total renewable installed capacity that can be accommodated by the power system under a given renewable deployment alternative and operating scenario while satisfying the specified operational constraints. Renewable installed capacity represents the predetermined physical deployment scale of each alternative, whereas hosting capacity represents the maximum feasible renewable capacity under the corresponding system configuration and operating condition.

Accordingly, the objective function is defined as follows:

$$HC_{p,q} = \sum_{i=1}^N (S_{i,w}^{p,q} + S_{i,pv}^{p,q}) \quad (9)$$

where $HC_{p,q}$ denotes the renewable energy hosting capacity of alternative P_p under operating scenario Q_q ; p and q denote the indices of the renewable deployment alternative and operating scenario, respectively; N denotes the total number of buses in the system; and $S_{i,w}^{p,q}$ and $S_{i,pv}^{p,q}$ denote the wind and PV capacities accommodated at bus i , respectively, when alternative P_p is evaluated under scenario Q_q .

For each alternative under each operating scenario, the predefined wind and PV capacities and ESS rated power of alternative P_p are introduced as alternative-specific model parameters. During the chronological production simulation, wind and PV capacities are increased from their predefined levels, and system operation is evaluated under

the specified operational constraints. The maximum feasible total wind and PV capacity is determined as the renewable-energy hosting capacity $HC_{p,q}$.

3.2.2. Constraints

The operational constraints primarily encompass nodal power balance constraints, operational limits of various power generation units, network security constraints, and renewable energy power output constraints.

1. Nodal Power Balance Constraints;

$$\sum_{g \in G_i} p_{g,t}^{gen} + \sum_{w \in W_i} p_{w,t}^{wind} + \sum_{v \in V_i} p_{v,t}^{pv} + \sum_{s \in S_i} p_{s,t}^{dis} = \sum_{s \in S_i} p_{s,t}^{ch} + P_{i,t}^{load} \quad (10)$$

where G_i , W_i , V_i , and S_i represent the sets of conventional units, wind power units, PV power units, and energy storage units connected to the bus within the system, respectively; $p_{g,t}^{gen}$ denotes the active power output of the conventional unit g during time period t ; $p_{w,t}^{wind}$ and $p_{v,t}^{pv}$ represent the active power outputs of the wind unit w and PV unit v during the time period t , respectively; $p_{s,t}^{ch}$ and $p_{s,t}^{dis}$ indicate the maximum charging and discharging power limits of the energy storage unit s , respectively; $P_{i,t}^{load}$ represents the load demand of bus i during time period t .

2. Operational Constraints of Conventional Units;

These limits include upper and lower output bounds, unit ramping constraints, and reserve capacity constraints.

$$P_g^{\min} \leq P_{g,t} \leq P_g^{\max} \quad (11)$$

$$-\Delta_g^{down} \leq P_{g,t} - P_{g,t-1} \leq \Delta_g^{up} \quad (12)$$

$$\begin{cases} \sum_{g \in G_i} r_{g,t}^{up} \geq R_t^{up} \\ \sum_{g \in G_i} r_{g,t}^{down} \geq R_t^{down} \end{cases} \quad (13)$$

where $P_g^{\max}$ and $P_g^{\min}$ represent the upper and lower limits of the power output for conventional units, respectively; Δ_g^{down} and Δ_g^{up} denote downward and upward ramp limits, respectively; $r_{g,t}^{up}$ and $r_{g,t}^{down}$ represent the upward and downward spinning reserve capacities reserved by conventional units during time period t , respectively; R_t^{up} and R_t^{down} indicate the positive and negative spinning reserve capacities required by the system during time period t , respectively.

3. Operational Constraints of Energy Storage Units;

These limits include the energy storage constraints of the storage station and the charge/discharge constraints of the storage units.

$$E_s^{\min} \leq E_{s,t} \leq E_s^{\max} \quad (14)$$

$$\begin{cases} 0 \leq p_{s,t}^{ch} \leq (1 - \delta_{s,t}) P_s^{\max} \\ 0 \leq p_{s,t}^{dis} \leq \delta_{s,t} P_s^{\max} \end{cases} \quad (15)$$

where $E_s^{\max}$ and $E_s^{\min}$ represent the maximum and minimum energy storage limits of storage unit s , respectively; $P_s^{\max}$ denote the maximum charging and discharging power limits of storage unit s ; $\delta_{s,t}$ indicates a binary variable, where 1 signifies discharging, and 0 represents charging.

4. Network Security Constraints;

These limits include the nodal voltage constraints and branch power flow constraints.

$$U_{\min}(i, t) \leq U_i(t) \leq U_{\max}(i, t) \quad (16)$$

$$\begin{cases} P_{i,j}^{\min} \leq P_{i,j}(t) \leq P_{i,j}^{\max} \\ Q_{i,j}^{\min} \leq Q_{i,j}(t) \leq Q_{i,j}^{\max} \end{cases} \quad (17)$$

where $U_{\max}(i, t)$ and $U_{\min}(i, t)$ represent the upper and lower limits of the voltage magnitude at bus i for secure operation, respectively; $P_{i,j}(t)$ and $Q_{i,j}(t)$ denote the active power and reactive power flowing through branch ij at time t from bus i to bus j , respectively; $P_{i,j}^{\max}$ and $P_{i,j}^{\min}$ represent the upper and lower limits of the active power flowing through branch ij , respectively; $Q_{i,j}^{\max}$ and $Q_{i,j}^{\min}$ indicate the upper and lower limits of the reactive power flowing through branch ij , respectively.

5. Output Constraints of Renewable Energy Units.

Only the upper bounds of wind and PV generation are considered, neglecting ramping processes and start-stop dynamics. To ensure that the capacity estimation is conducted within the renewable development range considered in this study, the total renewable capacity is restricted by a system-level planning-search ceiling.

$$\begin{cases} 0 \leq p_{i,t}^{w,p,q} \leq \alpha_t^{w,q} S_{i,w}^{p,q} \\ 0 \leq p_{i,t}^{pv,p,q} \leq \alpha_t^{pv,q} S_{i,pv}^{p,q} \\ \sum_{i=1}^N (S_{i,w}^{p,q} + S_{i,pv}^{p,q}) \leq C_U \end{cases} \quad (18)$$

where $\alpha_t^{w,q}$ and $\alpha_t^{pv,q}$ denote the available wind and PV output coefficients under scenario Q_q , respectively. Therefore, the feasible renewable output and the resulting hosting capacity vary with the operating scenario. C_U denotes the upper limit of the renewable capacity search adopted in this case study, set at 13,000 MW.

6. Renewable Energy Curtailment Constraint.

To prevent the hosting-capacity result from increasing through excessive renewable-energy curtailment, a maximum allowable curtailment-rate constraint is imposed. The renewable-energy curtailment rate of alternative P_p under operating scenario Q_q is expressed as:

$$R_{\text{curt}}^{p,q} = \frac{E_{\text{ava}}^{p,q} - E_{\text{disp}}^{p,q}}{E_{\text{ava}}^{p,q}} \times 100\% \leq R_{\text{curt}}^{\text{max}} \quad (19)$$

where $E_{\text{ava}}^{p,q}$ denotes the total available wind and PV energy determined by the renewable installed capacities and the scenario-specific availability coefficients; $E_{\text{disp}}^{p,q}$ denotes the renewable energy actually dispatched and accommodated by the system; and $R_{\text{curt}}^{p,q}$ denotes the maximum allowable renewable-energy curtailment rate, which is set to 15% in this study.

3.3. Comprehensive Evaluation Methodology Based on EWM-GRA-TOPSIS

3.3.1. Indicator Weight Calculation Based on the Entropy Weight Method

The evaluation indicators for renewable energy hosting capacity comprise positive and negative metrics; positive metrics denote those where higher values signify superior performance, whereas negative metrics represent those where lower values are preferred. In this study, the positive metrics include the proportion of flexible resources and renewable energy penetration. Conversely, the negative metrics encompass the voltage deviation rate, frequency deviation rate, LOLP, EENS, system construction costs, and system operational costs.

Given that these indicators feature varying dimensions and conflicting optimization directions, a data standardization procedure is required. Assuming there are m renewable energy hosting capacity alternatives and n evaluation metrics, the initial indicator matrix derived from the metric calculation phase is defined as $X = (x_{ij})_{m \times n}$.

It should be noted that the alternatives considered in this study are not statistical samples but representative renewable energy planning scenarios. The objective of the entropy weight method is to determine the relative importance of evaluation indicators based on the information variation among these scenarios rather than to estimate statistical characteristics of a large population.

For positive indexes:

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (20)$$

For negative indexes:

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (21)$$

where r_{ij} denotes the normalized value of alternative i with respect to the j indicator.

Following the data standardization procedure, the normalized decision matrix $R = (r_{ij})_{m \times n}$ is constructed:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (22)$$

To determine the indicator weights using the EWM, the entropy value of the j metric is formulated as follows:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (23)$$

$$p_{ij} = r_{ij} / \sum_{i=1}^m r_{ij} \quad (24)$$

where e_j is the entropy value of the j index. When $p_{ij} = 0$, $p_{ij} \ln p_{ij} = 0$ is defined. Then the difference coefficient is $g_j = 1 - e_j$.

Finally, the objective weights are calculated to yield the definitive objective weight vector:

$$w_{oj} = \frac{g_j}{\sum_{j=1}^n g_j} \quad (25)$$

$$w_{oj} = (w_{o1}, w_{o2}, \dots, w_{on})^T \quad (26)$$

where w_{oj} denotes the objective weight of the indicator j .

3.3.2. Optimal Alternative Evaluation Combining TOPSIS and GRA Methods

TOPSIS evaluates alternatives based on their geometric proximity to the ideal solution, whereas GRA measures the relational similarity between alternatives and the ideal sequence. Integrating both methods enables the evaluation to consider both distance-based performance and relational characteristics.

For different renewable energy integration alternatives, the weighted normalized decision matrix is constructed as:

$$V = [v_{ij}]_{m \times n}, v_{ij} = w_{oj}^* \cdot r_{ij} \quad (27)$$

where v_{ij} denotes the weighted normalized value of alternative i with respect to the indicator j .

Considering the optimization directions of the indicators, the positive and negative ideal solutions are determined as:

$$A^+ = (v_1^+, v_2^+, \dots, v_n^+), v_j^+ = \max_i v_{ij} + \delta_j^+ \quad (28)$$

$$A^- = (v_1^-, v_2^-, \dots, v_n^-), v_j^- = \min_i v_{ij} - \delta_j^- \quad (29)$$

where A^+ and A^- represent the positive and negative ideal solution vectors, respectively; δ_j^+ and δ_j^- denote the positive and negative adjustment offsets for the indicator j , respectively; if no adjustment is required, it can be set as $\delta_j^+ = \delta_j^- = 0$.

In conventional TOPSIS methods, the Euclidean distance is commonly adopted to measure the separation between alternatives and ideal solutions. However, Euclidean distance treats each evaluation indicator as an independent dimension after normalization and does not explicitly consider the correlations among indicators.

In renewable energy hosting capacity assessment, the evaluation indicators are derived from the same power system operational process and may exhibit inherent coupling

relationships. For example, increasing renewable energy penetration can improve renewable energy utilization, while it may simultaneously increase operational costs, flexibility requirements, and potential security risks. Therefore, considering the correlation information among indicators can provide an additional perspective for characterizing the relative differences between alternatives and ideal solutions.

To incorporate such correlation information, this study introduces Mahalanobis distance into the TOPSIS framework. Unlike Euclidean distance, Mahalanobis distance considers the covariance relationship among indicators and provides a correlation-aware measurement of the distance between alternatives and ideal solutions.

The covariance matrix is calculated from the weighted normalized decision matrix:

$$\Sigma = \text{cov}(V) \quad (30)$$

where V denotes the weighted normalized decision matrix.

Considering that the number of alternatives in this case study is limited, the covariance matrix may suffer from singularity and may not provide a sufficiently reliable estimation of the covariance structure among evaluation indicators. Therefore, a regularization strategy is introduced to ensure numerical stability during matrix inversion.

$$\Sigma_{\lambda} = \Sigma + \lambda I \quad (31)$$

where I represents the identity matrix and λ is the regularization coefficient. In this study, λ is initially set to 10^{-6} , and its influence on the evaluation results is further examined in Section 4.4.1.

The Mahalanobis distances to the positive and negative ideal solutions are calculated as:

$$D_i^+ = \sqrt{(V_i - A^+)^T \Sigma_{\lambda}^{-1} (V_i - A^+)} \quad (32)$$

$$D_i^- = \sqrt{(V_i - A^-)^T \Sigma_{\lambda}^{-1} (V_i - A^-)} \quad (33)$$

The grey relational coefficient for alternative i with respect to indicator j is formulated as:

$$\xi_{ij}^+ = \frac{\min_i \min_j |v_j^+ - v_{ij}^+| + \rho \max_i \max_j |v_j^+ - v_{ij}^+|}{|v_j^+ - v_{ij}^+| + \rho \max_i \max_j |v_j^+ - v_{ij}^+|} \quad (34)$$

$$\xi_{ij}^- = \frac{\min_i \min_j |v_j^- - v_{ij}^-| + \rho \max_i \max_j |v_j^- - v_{ij}^-|}{|v_j^- - v_{ij}^-| + \rho \max_i \max_j |v_j^- - v_{ij}^-|} \quad (35)$$

where ξ_{ij}^+ and ξ_{ij}^- represent the grey relational coefficients with respect to the positive and negative ideal solutions, respectively; ρ denotes the distinguishing coefficient, which is typically set to 0.5.

Then, the grey relational grade for alternative i is derived as:

$$G_i^+ = \frac{1}{n} \sum_{j=1}^n \xi_{ij}^+ \quad (36)$$

$$G_i^- = \frac{1}{n} \sum_{j=1}^n \xi_{ij}^- \quad (37)$$

where G_i^+ and G_i^- indicate the grey relational grades of alternative i with respect to the positive and negative ideal solutions, respectively.

Based on the aforementioned formulations, the relative closeness coefficient C_i for alternative i based on the TOPSIS method can be obtained as follows:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (38)$$

Concurrently, the relative relational grade R_i for alternative i based on GRA is derived as:

$$R_i = \frac{G_i^+}{G_i^+ + G_i^-} \quad (39)$$

By applying a combination coefficient, the outcomes of TOPSIS and GRA are integrated to calculate the comprehensive closeness coefficient via:

$$S_i = \eta \cdot C_i + (1 - \eta) \cdot R_i \quad (40)$$

where S_i denotes the comprehensive closeness coefficient of alternative i , with a value range of $[0, 1]$; η indicates the combination coefficient.

Consequently, the final comprehensive evaluation index set for the alternatives m is obtained, and these alternatives are prioritized in descending order based on their comprehensive closeness coefficients.

$$\{S_1, S_2, \dots, S_m\} \quad (41)$$

To provide an intuitive relative classification of the alternatives in addition to their continuous ranking, the relative dominance degree is calculated by normalizing the comprehensive closeness coefficient between the worst-performing and best-performing alternatives:

$$AD_i = \frac{S_i - \min S_i}{\max S_i - \min S_i} \times 100\% \quad (42)$$

where AD_i denotes the relative dominance degree of alternative i .

The alternative with the minimum comprehensive closeness coefficient is assigned a relative dominance degree of 0%, whereas the alternative with the maximum coefficient is assigned 100%. The remaining alternatives are positioned proportionally within this interval. Since the grading is intended to describe the relative performance of the investigated alternatives, the normalized interval is divided into three equal-width grades. The corresponding grading criteria are summarized in Table 2.

Table 2. Hierarchical grading criteria based on the relative dominance degree.

Grade	Relative Dominance Degree Range
I	$AD_i \geq 66.67\%$
II	$33.33\% \leq AD_i < 66.67\%$
III	$AD_i < 33.33\%$

3.3.3. Evaluation Workflow of Renewable Energy Hosting Capacity Indicators

The comprehensive evaluation workflow for grid renewable energy hosting capacity is detailed in Figure 3. This framework ultimately yields the optimal deployment scheme, alongside its corresponding hosting capacity and hierarchical grade assignment. The systematic evaluation procedure consists of the following specific steps:

1. Initialization and normalization of the initial decision matrix;

2. Calculation of indicator weights utilizing the entropy weight method (EWM);
3. Construction of the weighted normalized decision matrix;
4. Determination of the positive and negative ideal solutions;
5. Calculation of the positive and negative distance matrices based on Mahalanobis distance;
6. Derivation of the grey relational grades with respect to the ideal solutions;
7. Computation of the comprehensive closeness coefficient for each alternative;
8. Final alternative ranking and relative-dominance-based hierarchical grading.

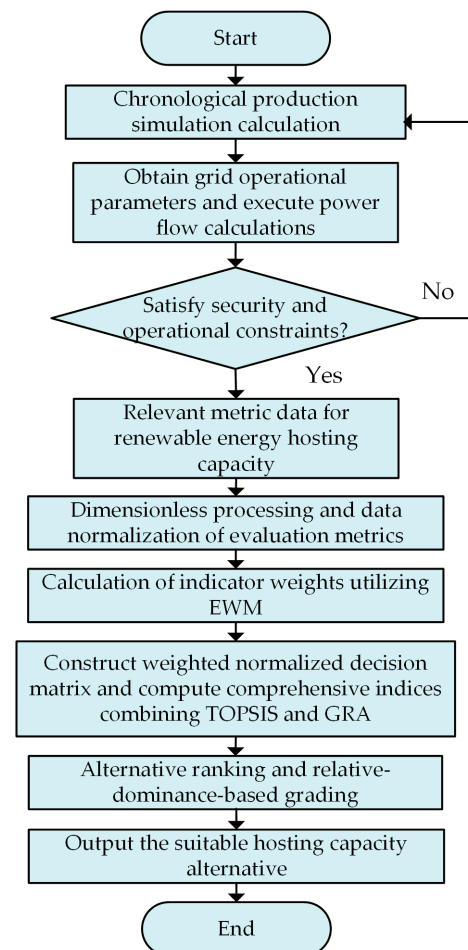


Figure 3. Operational flowchart of the systematic evaluation procedure.

4. Simulation Analysis

4.1. Simulation System and Scenario Settings

The case study is implemented on a modified IEEE 118-bus system, where a high-penetration renewable energy integration scenario is constructed for simulation validation. The modified IEEE 118-bus system consists of 7 thermal generators, 24 wind power plants, 16 PV power plants, and 5 energy storage units. The original network topology and load distribution are maintained, while renewable energy resources and storage units are integrated at designated buses to construct different renewable deployment scenarios.

Specifically, the thermal generators are located at buses 10, 12, 25, 26, 31, 49, and 54. The wind power plants are installed at buses 1, 4, 6, 8, 15, 18, 19, 27, 32, 34, 36, 40, 42, 55, 56, 62, 65, 66, 69, 70, 72, 73, 74, and 76. The PV power plants are located at buses 24, 77, 80, 82, 85, 87, 89, 90, 91, 92, 99, 100, 103, 104, 105, and 107. The energy storage units are installed at buses 101, 106, 112, 115, and 117. All remaining buses are categorized as load

buses or pure transmission buses. The detailed electrical topology is illustrated in Figure 4.

The operational assessment is implemented in MATLAB R2024a integrated with MATPOWER 8.0 and the CPLEX optimization solver. Representative operating scenarios are employed to characterize variations in renewable generation, load demand, and conventional generation availability.

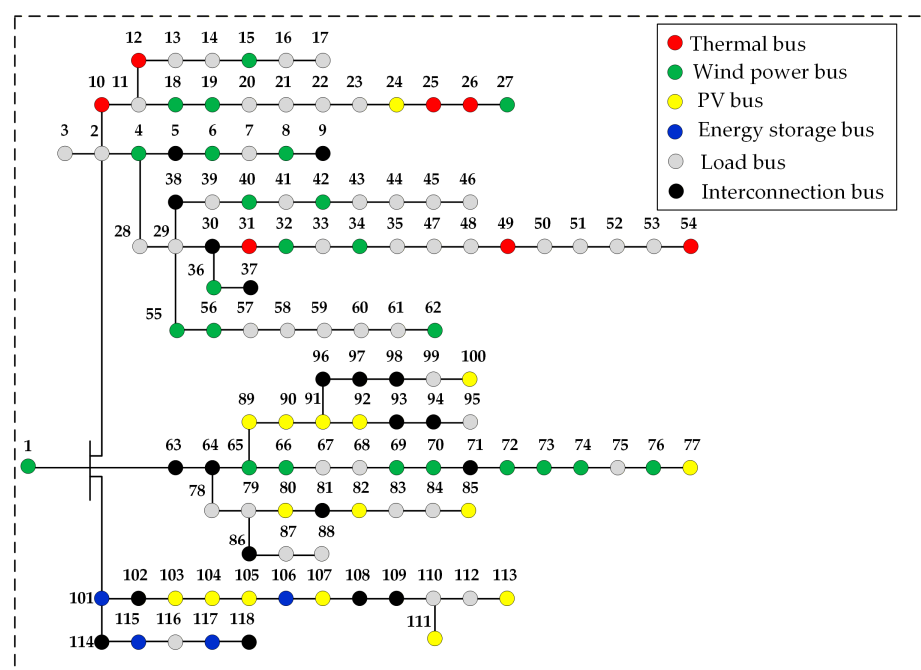


Figure 4. Topological structure of the tested power system.

The existing generation and load scales of the region are defined as the baseline scenario (P0). Specifically, the annual peak load is approximately 4550 MW; the total installed capacity is around 11,000 MW, comprising 3000 MW of thermal power, 4800 MW of wind power, and 3200 MW of PV power, with renewable energy accounting for 72% of the installed generation capacity. Additionally, the energy storage system (ESS) capacity is 1500 MW, with no pumped-hydro storage available.

To investigate the effects of progressive renewable expansion on renewable-energy hosting capacity and comprehensive system performance, three additional planning alternatives, P1–P3, are predefined to represent low, medium, and high penetration development stages, respectively. Across the four alternatives, the total renewable installed capacity is increased in approximately equal increments. Considering the increasing flexibility requirements associated with renewable expansion, the ESS rated power is progressively reinforced according to the cumulative increase in renewable installed capacity relative to P0, while the ESS connection buses and other operational parameters remain unchanged. The installed wind, PV, and ESS capacities of the four alternatives are summarized in Table 3.

Table 3. Summary of installed renewable-energy capacities and ESS rated power under different alternatives.

Alternative	Wind Capacity (MW)	PV Capacity (MW)	ESS Rated Power (MW)	Renewable Installed Capacity Share (%)
P0 (Baseline)	4800	3200	1500	72.73
P1 (Low)	5531	3687	1683	75.45
P2 (Medium)	6261	4174	1865	77.67
P3 (High)	6992	4661	2048	79.53

To validate the effectiveness of the proposed model, power flow calculations and time-series simulations are executed across four distinct operating scenarios to contrast the evaluation metrics. These scenarios include:

- Q1 (minimum online generation capacity and valley load);
- Q2 (maximum online generation capacity and peak load);
- Q3 (high renewable output and low load);
- Q4 (extremely low renewable output and high load).

Q1–Q4 are constructed by combining different conventional-generation output levels, system capacity factors, load levels, and renewable-generation availability conditions. These scenarios are used to compare the operational performance of the deployment alternatives. The corresponding simulation parameters are provided in Table 4.

Table 4. Parameter settings for the representative operating scenarios (p.u.).

Parameter	Q1	Q2	Q3	Q4
Thermal output coefficient	0.35	1	0.35	1
System capacity factor	0.55–0.60	0.60–0.65	0.62–0.67	0.65–0.70
Peak-to-valley load ratio	0.2	0.8	0.2	0.8
Wind output coefficient	0.85	0.25	0.85	0.15
PV output coefficient	0.9	0.1	0.9	0.05

Furthermore, Figures 5–7 present the wind power, PV generation, and load curves for each typical scenario, with all power data expressed in per-unit (p.u.) values.

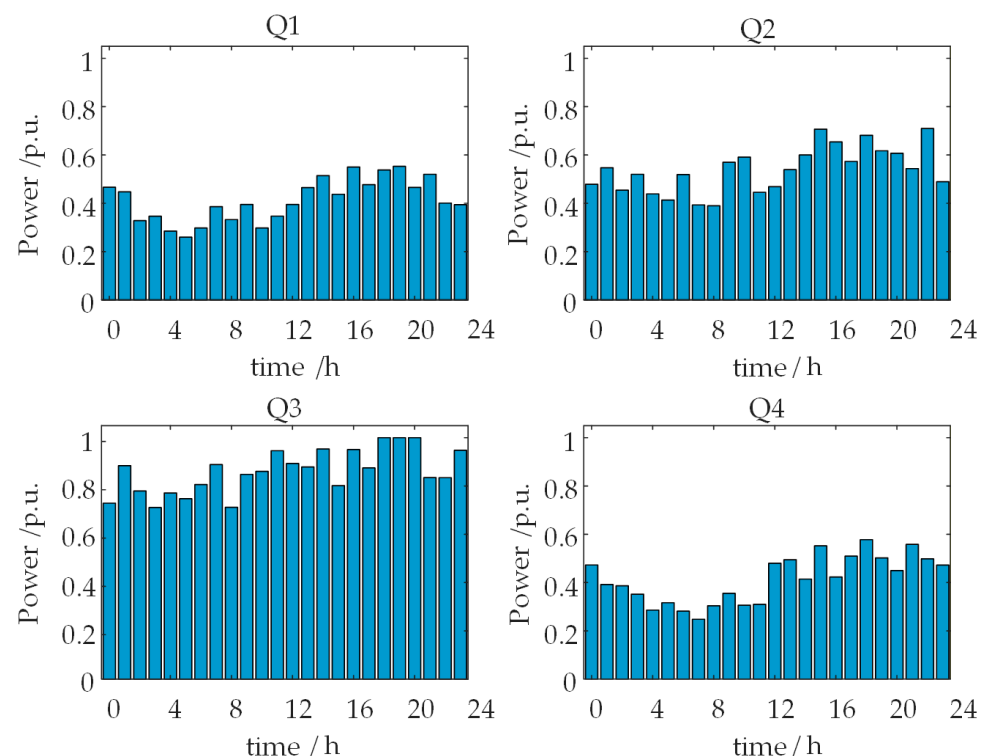


Figure 5. Representative daily wind-power profiles under Q1–Q4.

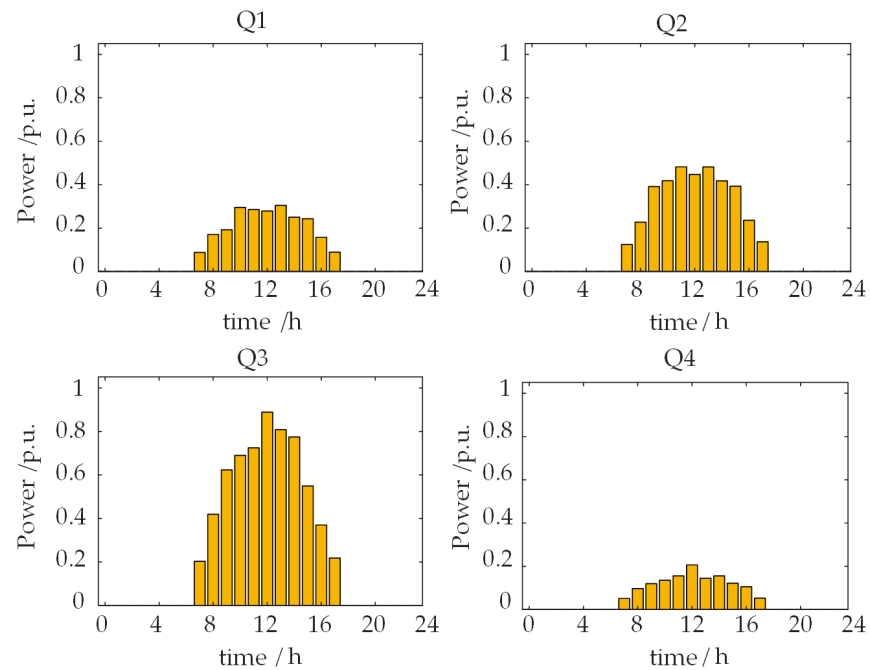


Figure 6. Representative daily Photovoltaic (PV) generation profiles under Q1–Q4.

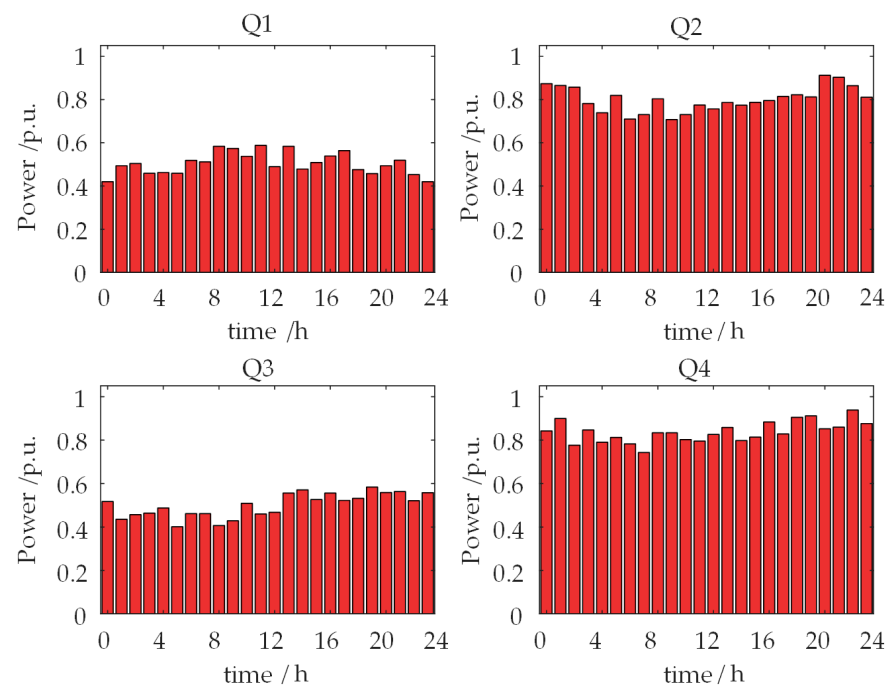


Figure 7. Representative daily load profiles under Q1–Q4.

4.2. Simulation Results and Discussion for Typical Scenarios

4.2.1. Chronological Characteristics of Power Balance

To contrast the chronological profiles of the power balance, the typical anti-peak-shaving scenario (Q3) is chosen to compare the baseline alternative against the high-penetration alternative. In this study, the maximum allowable curtailment rate is set to 15%. The power balance trajectories for both alternatives on a typical day are illustrated in Figures 8 and 9.

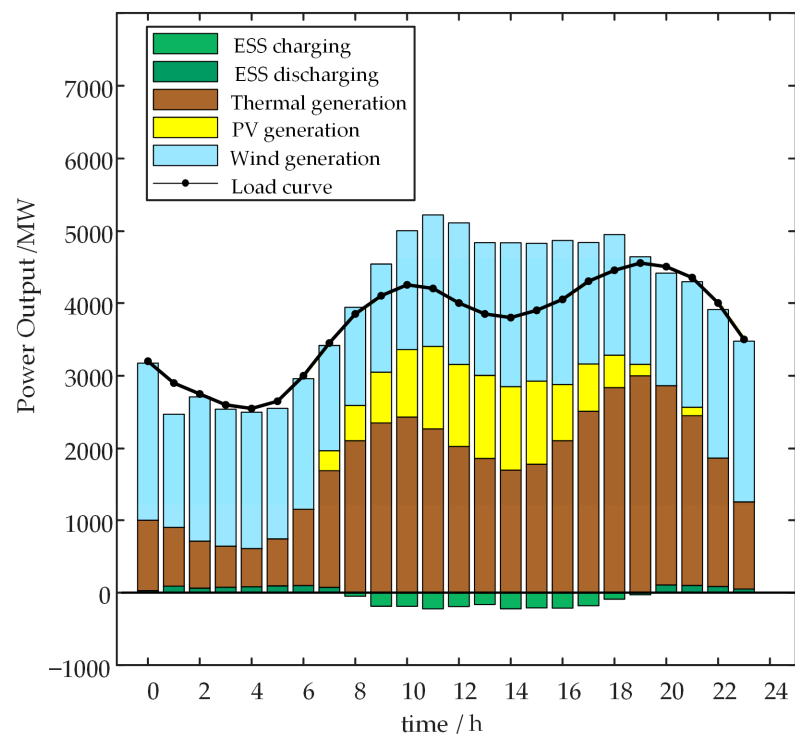


Figure 8. Chronological profiles of power balance on a typical day under the baseline alternative P0.

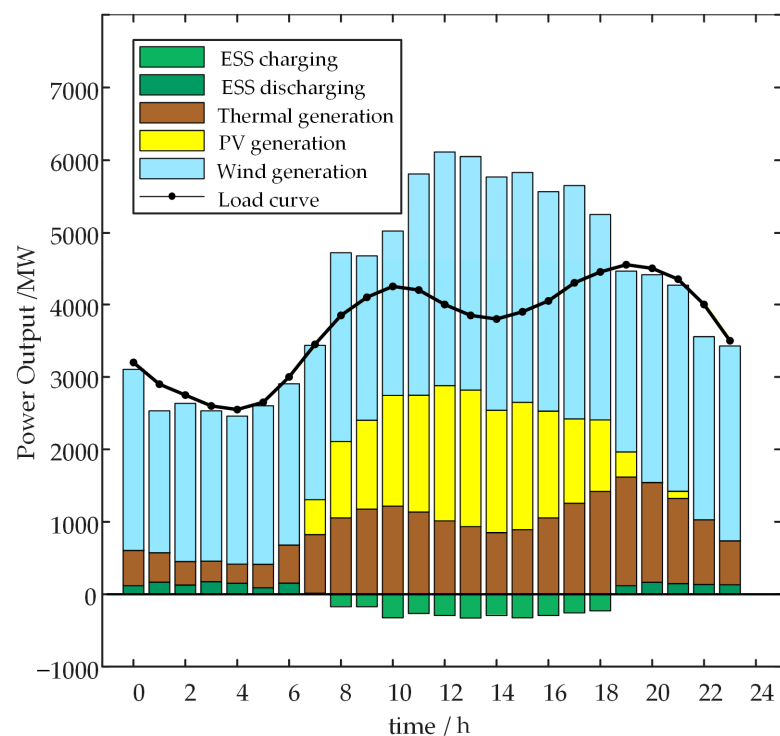


Figure 9. Chronological profiles of power balance on a typical day under the alternative P3.

Figures 8 and 9 compare the representative power-balance profiles of P0 and P3 under scenario Q3. Under P0, the renewable curtailment rate is approximately 12.1%. As renewable installed capacity increases, P3 exhibits a larger renewable-power surplus during high-output periods, resulting in greater reliance on thermal minimum-output operation, ESS charging, and renewable curtailment. This result indicates that the high-penetration alternative experiences greater renewable accommodation pressure, even though it remains within the curtailment constraint adopted in the hosting-capacity assessment.

4.2.2. Voltage Deviation Analysis of Renewable Deployment Alternatives

To further examine the influence of renewable penetration on system voltage performance, the voltage deviation characteristics of the baseline alternative P0 and the high-development alternative P3 are compared under Q1–Q4. Figures 10 and 11 present representative voltage-distribution profiles consistent with the voltage deviation rates of P0 and P3, respectively.

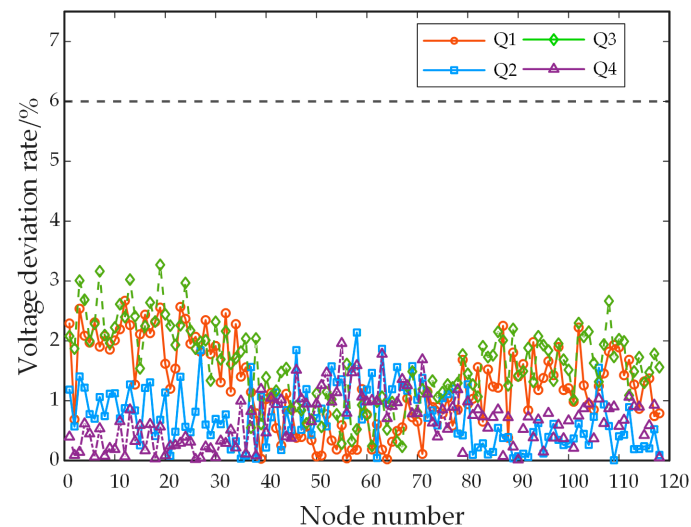


Figure 10. Representative voltage-distribution profiles of P0 under Q1–Q4.

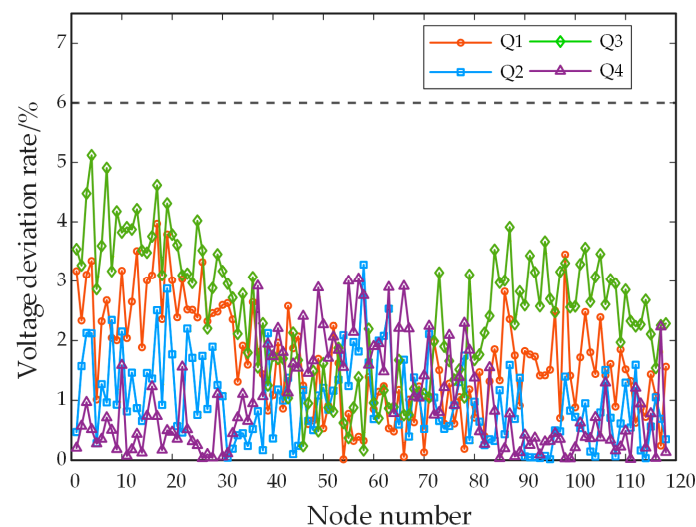


Figure 11. Representative voltage-distribution profiles of P3 under Q1–Q4.

Figures 10 and 11 compare the bus-voltage profiles of the baseline alternative P0 and the high-penetration alternative P3 under Q1–Q4. All bus voltages remain within 0.94–1.06 p.u., but the voltage deviations become substantially larger as the deployment level increases from P0 to P3. Among the four scenarios, Q3 consistently exhibits the largest deviation, followed by Q1, while Q2 and Q4 show comparatively smaller deviations. This pattern reflects the scenario characteristics: Q3 combines high renewable output with low load, causing larger nodal injection variations; Q1 also suffers from a shrunken absorption space under low-load conditions. The maximum deviation rates rise from the range of 1.96–3.27% under P0 to 3.04–5.12% under P3. These results indicate that higher renewable penetration increases voltage-regulation pressure and further reduces the remaining voltage-security margin.

4.3. Comprehensive Evaluation of Renewable Energy Hosting Capacity

4.3.1. Quantification of Evaluation Indicators

The renewable energy hosting capacity and associated performance metrics for each alternative are quantitatively calculated.

The metric values across various scenarios are compiled in Tables 5–8 from which the following conclusions can be drawn:

(1) The hosting capacity upper bounds across all scenarios generally exceed the baseline alternative. As the installed capacity scales up, the growth rate of the hosting capacity decelerates due to the insufficient allocation of flexible resources. This implies that a further development potential for renewable energy remains untapped under the existing network topology and generation infrastructure.

(2) Across all four deployment alternatives, Q2 yields the highest estimated hosting capacity, whereas Q4 yields the lowest. This result indicates that hosting capacity is jointly influenced by load demand, renewable availability, conventional-generation status, and system flexibility. Therefore, no single operating scenario can fully represent the accommodation capability of a deployment alternative.

Table 5. Evaluation metric values under the baseline alternative P0 across distinct scenarios.

Scenario	Q1	Q2	Q3	Q4
A1 (%)	2.67	2.14	3.27	1.96
A2 (%)	0.21	0.25	0.28	0.17
B1	0.0014	0.0018	0.0005	0.0041
B2 (MWh)	1648	2037	597	4218
C1 (10 ⁸ RMB)	450.8	450.8	450.8	450.8
C2 (10 ⁸ RMB/year)	37.9	39.3	35.4	42.1
D1 (%)	33.8	39.1	35.2	37.6
D2 (%)	35.2	41.1	48.3	27.6
Renewable energy hosting capacity (MW)	9147	9382	9213	8927

Table 6. Evaluation metric values under alternative P1 across distinct scenarios.

Scenario	Q1	Q2	Q3	Q4
A1 (%)	3.08	2.48	3.82	2.31
A2 (%)	0.24	0.28	0.33	0.2
B1	0.0011	0.0015	0.0004	0.0034
B2 (MWh)	1382	1731	494	3486
C1 (10 ⁸ RMB)	496.6	496.6	496.6	496.6
C2 (10 ⁸ RMB/year)	39.6	41.2	37.1	43.9
D1 (%)	29.4	34.2	30.8	33.1
D2 (%)	37.4	43.5	50.6	29.2
Renewable energy hosting capacity (MW)	10,123	10,377	10,241	9927

Table 7. Evaluation metric values under alternative P2 across distinct scenarios.

Scenario	Q1	Q2	Q3	Q4
A1 (%)	3.54	2.86	4.43	2.67
A2 (%)	0.27	0.31	0.37	0.23
B1	0.0009	0.0013	0.0003	0.0029
B2 (MWh)	1132	1423	388	2827

C1 (10 ⁸ RMB)	542.4	542.4	542.4	542.4
C2 (10 ⁸ RMB/year)	41.4	43.2	38.8	45.9
D1 (%)	25.1	29.9	26.7	28.9
D2 (%)	39.7	45.9	53.1	31.1
Renewable energy hosting capacity (MW)	11,236	11,514	11,362	11,018

Table 8. Evaluation metric values under the alternative P3 across distinct scenarios.

Scenario	Q1	Q2	Q3	Q4
A1 (%)	3.97	3.28	5.12	3.04
A2 (%)	0.3	0.34	0.41	0.26
B1	0.0007	0.0011	0.0002	0.0025
B2 (MWh)	937	1182	296	2389
C1 (10 ⁸ RMB)	588.2	588.2	588.2	588.2
C2 (10 ⁸ RMB/year)	43.3	45.4	40.6	48.2
D1 (%)	21.7	26.3	23.2	25.4
D2 (%)	42.1	48.2	55.6	33.2
Renewable energy hosting capacity (MW)	12,387	12,674	12,493	12,158

For each alternative, the negative metrics take the maximum values across all scenarios, while the positive metrics take the minimum values, thereby establishing the comprehensive hosting capacity evaluation index vector as presented in Table 9.

Table 9. Comprehensive evaluation index vectors for the proposed alternatives.

Alternative	P0	P1	P2	P3
A1 (%)	3.27	3.82	4.43	5.12
A2 (%)	0.28	0.33	0.37	0.41
B1	0.0041	0.0034	0.0029	0.0025
B2 (MWh)	4218	3486	2827	2389
C1 (10 ⁸ RMB)	450.8	496.6	542.4	588.2
C2 (10 ⁸ RMB/year)	42.1	43.9	45.9	48.2
D1 (%)	33.8	29.4	25.1	21.7
D2 (%)	27.6	29.2	31.1	33.2
Renewable energy hosting capacity (MW)	8927	9927	11,018	12,158

Table 9 reveals that the variations in hosting capacity among the alternatives are relatively minor, with an overall upward trend matching the expansion of renewable energy installations. However, an enhanced hosting capacity does not imply unrestricted integration; thus, further multi-criteria evaluation is indispensable to strike an optimal trade-off between economics and security.

From the perspective of power system planning, the variation trends of these indicators provide important guidance for renewable deployment decisions. Although increasing renewable installed capacity can continuously improve the physical hosting capacity of the system, it simultaneously increases flexibility requirements and economic investment demands. Therefore, renewable expansion should not be determined solely based on the maximum achievable hosting capacity. Instead, coordinated consideration of renewable accommodation capability, system security margins, flexibility resource allocation, and economic costs is required to identify a more sustainable development pathway.

4.3.2. Indicator Weight Analysis

To ensure the objectivity and comparability of the assessment results, these evaluation metrics undergo dimensionless processing and normalization. Utilizing the range normalization method, each metric is scaled into the range of 0 to 1, as tabulated in Table 10.

Table 10. Normalized evaluation indicator matrix.

Alternative	P0	P1	P2	P3
A1	1	0.7027	0.373	0
A2	1	0.6154	0.3077	0
B1	0	0.4375	0.75	1
B2	0	0.4003	0.7605	1
C1	1	0.6673	0.334	0
C2	1	0.7049	0.377	0
D1	1	0.6364	0.281	0
D2	0	0.2857	0.625	1
Renewable energy hosting capacity	0	0.3095	0.6473	1

Subsequently, the indicator weights are calculated based on the EWM, with the results detailed in Table 11.

Table 11. Calculation results of indicator weights based on EWM.

Indicator	Entropy Value	Coefficient of Information Divergence	Weight	Rank
A1	0.7681	0.2319	0.1053	9
A2	0.7467	0.2533	0.115	4
B1	0.7543	0.2457	0.1116	5
B2	0.7402	0.2598	0.118	2
C1	0.7269	0.2731	0.124	3
C2	0.7639	0.2361	0.1072	6
D1	0.6613	0.3387	0.1538	1
D2	0.7635	0.2365	0.1074	7
Renewable energy hosting capacity	0.7626	0.2374	0.1078	8

As indicated in Table 11, the overall weight distribution is relatively balanced, governed by the dispersion degree of the underlying data. Notably, the proportion of flexible resources commands the highest weight at 0.1538, reflecting that flexible resources—such as energy storage systems and regulable thermal units—constitute the critical bottlenecks limiting this high-penetration renewable power system. Economic metrics rank second; as the renewable installation scales up by approximately 46% from P0 to P3, construction costs increase noticeably. The weights for the frequency deviation rate, LOLP, EENS, and construction costs are highly comparable and positioned in the mid-range, indicating that the system attaches equal importance to operational security and economics.

Based on the weighted normalized matrix, the performance radar chart illustrating the strengths and weaknesses of each alternative across different metrics is displayed in Figure 12.

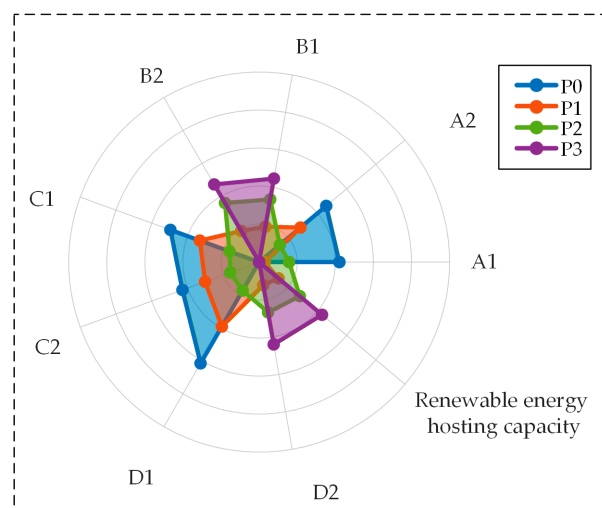


Figure 12. Performance radar chart illustrating metrics across different alternatives.

4.3.3. Alternative Ranking and Hierarchical Grading

By constructing the weighted normalized decision matrix, the TOPSIS closeness coefficient and the GRA relative relational grade for each alternative are computed. Applying a combination coefficient of 0.5, the comprehensive closeness coefficients of all alternatives are obtained, as illustrated in Figure 13.

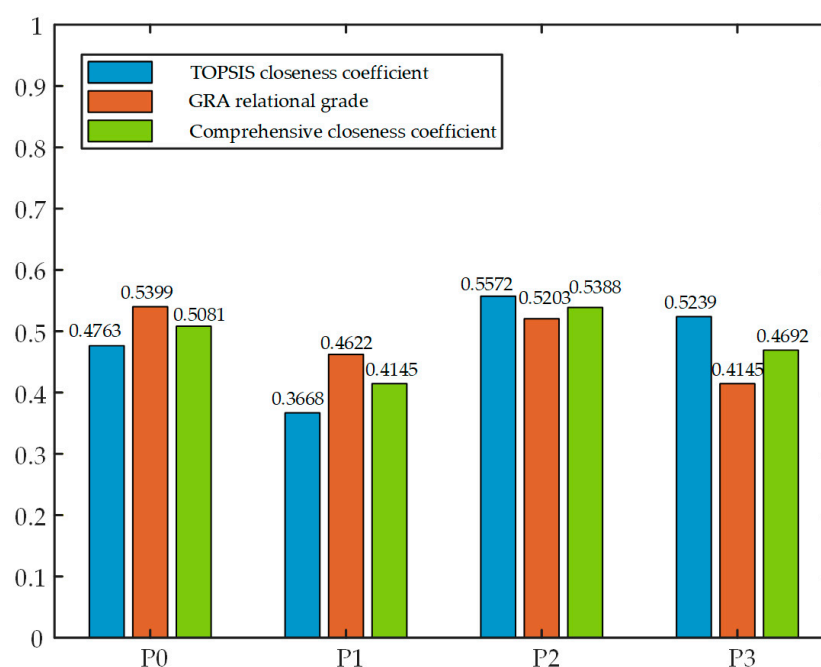


Figure 13. Alternative ranking based on the comprehensive closeness coefficients.

According to Figure 13, the comprehensive closeness coefficients follow the priority order of $P2 > P0 > P3 > P1$. Specifically, alternative P2 achieves the highest comprehensive closeness coefficient of 0.5388, outperforming the other scenarios, whereas alternative P1 exhibits the lowest value at 0.4145.

To provide a more intuitive relative classification in addition to the continuous ranking, the relative dominance degree is calculated from the comprehensive closeness coefficients. According to the grading criteria defined in Table 2, the relative dominance degrees and hierarchical grades of the alternatives are presented in Table 12.

Table 12. Relative-dominance-based hierarchical grading results for the alternatives.

Alternative	P0	P1	P2	P3
Relative dominance degree	75.22%	0%	100%	44.01%
Grade	I	III	I	II

Table 12 indicates that alternative P2 is assigned to Grade I, yielding a renewable energy hosting capacity of 11,018 MW with the optimal comprehensive benefit. Alternative P2 balances minimal construction cost increments against improved security margins and operational cost reductions, achieving a balanced trade-off among security, supply guarantee, and economics. If a further increase in renewable penetration is required, alternative P3 serves as the sub-optimal choice. Through the rational allocation of energy storage, P3 can smooth renewable output fluctuations and alleviate both peak-shaving and peak-load supply pressures, albeit at the expense of a slight degradation in certain economic and security indicators.

These results provide practical insights for renewable energy planning. The alternative with the highest hosting capacity is not necessarily the most suitable scheme, as excessive renewable expansion may introduce additional flexibility requirements and economic burdens. The hierarchical grading results enable planners to distinguish between different renewable deployment stages and determine whether further grid reinforcement measures, such as additional flexibility resources or network enhancement, are required before increasing renewable penetration.

4.4. Additional Validation and Sensitivity Analysis

4.4.1. Distance Metric Comparison and Regularization Sensitivity Analysis for TOPSIS Evaluation

Considering that the covariance matrix used in Mahalanobis distance is estimated from a limited number of renewable energy hosting capacity alternatives, a sensitivity analysis of the regularization coefficient is further conducted to examine its influence on the evaluation results. In this study, Mahalanobis distance is adopted as a correlation-aware distance measurement to incorporate the correlations among evaluation indicators. Six regularization coefficients ranging from 10^{-8} to 10^{-3} are selected, and the corresponding Mahalanobis-distance TOPSIS results are presented in Table 13.

Table 13. Sensitivity analysis of Mahalanobis-distance TOPSIS results under different regularization coefficients.

Regularization Coefficient λ	P0	P1	P2	P3
10^{-8}	0.729	0.391	0.853	0.646
10^{-7}	0.730	0.391	0.854	0.647
10^{-6}	0.731	0.392	0.854	0.648
10^{-5}	0.732	0.393	0.855	0.649
10^{-4}	0.735	0.395	0.857	0.652
10^{-3}	0.740	0.399	0.860	0.656

As shown in Table 13, the comprehensive closeness coefficients exhibit slight variations under different regularization coefficients. However, the ranking order of all alternatives remains unchanged. This indicates that the final decision ranking remains stable within the investigated range of regularization coefficients. Based on this stable regularization setting, the results obtained using Euclidean distance and Mahalanobis distance are further compared in Table 14.

Table 14. Comparison of TOPSIS evaluation results using different distance metrics.

Alternative	Euclidean-Distance TOPSIS	Rank	Mahalanobis-Distance TOPSIS	Rank
P0	0.612	2	0.731	2
P1	0.438	4	0.392	4
P2	0.823	1	0.854	1
P3	0.596	3	0.648	3

As shown in Table 14, both distance metrics identify P2 as the optimal alternative and P1 as the least preferred alternative. Although the calculated closeness coefficients differ due to different distance formulations, the ranking results remain consistent. This indicates that incorporating covariance information changes the numerical distance representation among alternatives, but does not affect the final decision ranking in this case study.

4.4.2. Comparison with Other MCDM Methods

To further examine the stability of the evaluation results under different multi-criteria decision-making (MCDM) frameworks, comparative analyses with representative MCDM methods are conducted. Specifically, AHP-TOPSIS, EWM-TOPSIS, and AHP-GRA-TOPSIS are selected as benchmark approaches. All methods employ the same renewable energy deployment alternatives and evaluation indicators, while different weighting strategies and decision-making mechanisms are adopted. The comparison results are summarized in Table 15.

Table 15. Comparison of comprehensive evaluation results using different MCDM frameworks.

Method	P0	P1	P2	P3	Ranking
AHP-TOPSIS	0.521	0.372	0.603	0.534	P2 > P3 > P0 > P1
EWM-TOPSIS	0.503	0.391	0.621	0.458	P2 > P0 > P3 > P1
AHP-GRA-TOPSIS	0.495	0.403	0.617	0.472	P2 > P0 > P3 > P1
EWM-GRA-TOPSIS	0.482	0.415	0.539	0.45	P2 > P0 > P3 > P1

As shown in Table 15, different MCDM frameworks produce variations in comprehensive evaluation values and partial ranking positions due to differences in weighting strategies and decision-making mechanisms. However, the overall preference tendency among renewable energy deployment alternatives remains consistent across different evaluation frameworks. The results indicate that the ranking obtained by the proposed evaluation framework is consistent with those of other MCDM methods, providing a valuable reference for comprehensive renewable energy hosting capacity assessment.

4.4.3. Sensitivity Analysis of Combination Coefficient η

The combination coefficient η determines the relative contribution of the TOPSIS-based distance evaluation and the GRA-based relational analysis in the comprehensive evaluation process. In this study, $\eta = 0.5$ is adopted to assign equal importance to the two evaluation components. To investigate the influence of this parameter selection on the evaluation results, a sensitivity analysis is conducted by varying η from 0 to 1 with an interval of 0.1. The comprehensive evaluation scores of different renewable deployment alternatives under different η values are calculated and compared. The variation trends of the comprehensive evaluation scores for different alternatives under different η values are illustrated in Figure 14.

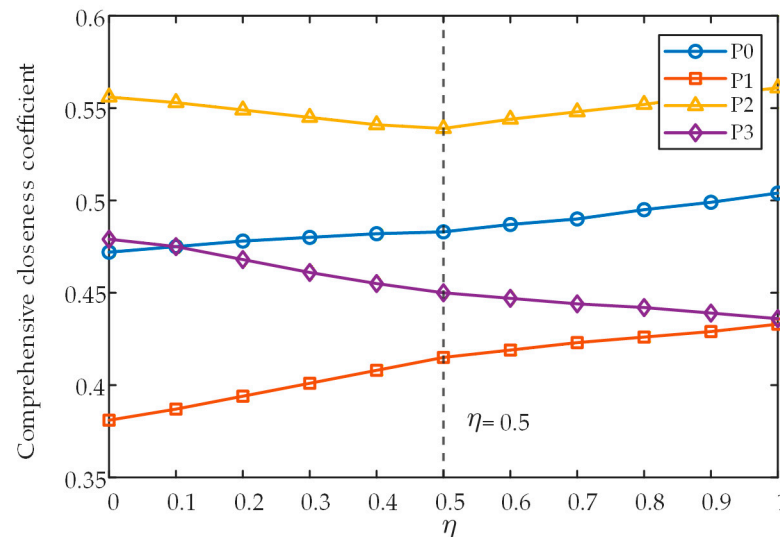


Figure 14. Sensitivity analysis of comprehensive evaluation scores with respect to the combination coefficient η .

As shown in Figure 14, the comprehensive closeness coefficients of all alternatives vary with the increase of η , reflecting the different influences of TOPSIS-based distance evaluation and GRA-based relational analysis. When η is close to 0, the evaluation results are mainly dominated by GRA, and P3 exhibits a relatively higher performance due to its advantages in relational similarity. As η increases, the contribution of TOPSIS gradually strengthens, leading to a more significant advantage of P0 in terms of overall proximity to the ideal solution. Throughout the variation range of η , P2 consistently maintains the highest evaluation value, while P1 remains the lowest-ranked alternative. The selected value of $\eta = 0.5$ provides a balanced contribution of the two evaluation mechanisms, avoiding excessive dependence on either relational characteristics or distance-based preferences, and thus offers a reasonable parameter setting for comprehensive evaluation.

5. Conclusions

This paper presents a comprehensive evaluation framework for the renewable energy hosting capacity of power grids. By utilizing the EWM to determine indicator weights and integrating the complementary advantages of GRA and TOPSIS, the proposed approach systematically accounts for the impacts of various factors on the decision-making objective. This hybrid framework offers a holistic appraisal of multi-criteria problems and provides a feasible assessment approach when applied to high-penetration renewable energy integration scenarios. Based on the simulation and verification analysis, the following core conclusions are drawn:

1. A multi-dimensional evaluation index system is established to assess renewable energy hosting capacity from security, flexibility, and economic perspectives. The results indicate that insufficient flexible resources and economic constraints are the main factors limiting further hosting capacity improvement. Therefore, coordinated planning of flexible resources and renewable energy installations is recommended to achieve sustainable capacity expansion.
2. By configuring parameters across varying operational scenarios, alternative evaluations under typical conditions are conducted. This approach rationally accounts for renewable energy fluctuations and load uncertainties, thereby contributing to the credibility and robustness of the evaluation outcomes. Although the proposed

framework has been validated using representative renewable deployment scenarios, the number of candidate alternatives remains limited. Future studies will further investigate large-scale scenario generation methods considering renewable uncertainty, load variations, and operational constraints to improve the scalability and applicability of the proposed framework.

3. The developed methodology yields intermediate and final analytical outputs, including indicator weights, TOPSIS closeness coefficients, GRA relational grades, comprehensive scores, and relative-dominance-based grade assignments. The assessment results indicate that alternative P2 achieves the highest comprehensive closeness coefficient, demonstrating improved operational security and maximized economic benefits under the test conditions, thereby serving as a suitable alternative that balances security and economics. Furthermore, to balance evaluation comprehensiveness and model complexity, some detailed dynamic characteristics, such as renewable power ramping constraints and energy storage degradation effects, are not explicitly considered in the current framework. Future research will further incorporate refined dynamic models and additional operational factors to improve the accuracy and applicability of renewable energy hosting capacity assessment.

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References

1. Eltohamy, M.S.; Aldawsari, M.S.M.; Sadek, A.R.A.; Hegazy, H.Y.A.H.; Ahmed, I.; Alsenani, T.R.; Kim, Y.S.; Ahmed, M.M.R. Enhancing Electric Grid Flexibility for the Integration of Variable Renewable Energy: Challenges, Innovations, and Future Directions. *IEEE Access* **2026**, *14*, 23080–23109. <https://doi.org/10.1109/ACCESS.2026.3660837>.
2. Khezri, R.; Mahmoudi, A.; Aki, H. Resiliency-Oriented Optimal Planning for a Grid-Connected System with Renewable Resources and Battery Energy Storage. *IEEE Trans. Ind. Appl.* **2022**, *58*, 2471–2482. <https://doi.org/10.1109/TIA.2021.3133340>.
3. Su, H.Y.; Liu, J.H.; Chu, C.C.; Lee, S.H.; Hong, Y.Y.; Lin, Y.J.; Liao, C.J. Developing an Optimal Scheduling of Taiwan Power System with Highly Penetrated Renewable Energy Resources and Pumped Hydro Storages. *IEEE Trans. Ind. Appl.* **2021**, *57*, 1973–1986. <https://doi.org/10.1109/TIA.2021.3057300>.
4. Wang, D.; Zhang, C.; Li, J.; Zhu, L.; Zhou, B.; Zhou, Q.; Cheng, L.; Shuai, Z. A Novel Interval Power Flow Method Based on Hybrid Box-Ellipsoid Uncertain Sets. *IEEE Trans. Power Syst.* **2024**, *39*, 6111–6114. <https://doi.org/10.1109/TPWRS.2024.3391921>.
5. Balobaid, A.; Abd-Elhafiez, W.M.; Nagy, S.M.; Trabay, D.W. Integrating Multi-Criteria Decision-Making Techniques in Assessing Renewable Energy Potential: A Case Study of Egypt. *IEEE Access* **2024**, *12*, 103594–103605. <https://doi.org/10.1109/ACCESS.2024.3434604>.
6. Junlong, L.; Chenghong, G.; Yue, X.; Furong, L. Edge-cloud Computing Systems for Smart Grid: State-of-the-art, Architecture, and Applications. *J. Mod. Power Syst. Clean Energy* **2022**, *10*, 805–817. <https://doi.org/10.35833/MPCE.2021.000161>.

7. Li, H.; Liu, D.; Yao, D. Analysis and Reflection on the Development of Power System Towards the Goal of Carbon Emission Peak and Carbon Neutrality. *Proc. CSEE* **2021**, *41*, 6245–6258. <https://doi.org/10.13334/j.0258-8013.pcsee.210050>.
8. Li, B.; Chen, M.; Zhong, H.; Ma, Z.; Liu, D.; He, G. A Review of Long-term Planning of New Power Systems with Large Share of Renewable Energy. *Proc. CSEE* **2023**, *43*, 555–580. <https://doi.org/10.13334/j.0258-8013.pcsee.212716>.
9. Xiang, Y.; Han, W.; Zhang, J.; Liu, J.; Liu, Y. Optimal Sizing of Energy Storage System in Active Distribution Networks Using Fourier-Legendre Series Based State of Energy Function. *IEEE Trans. Power Syst.* **2018**, *33*, 2313–2315. <https://doi.org/10.1109/TPWRS.2017.2779042>.
10. Strielkowski, W.; Vlasov, A.; Selivanov, K.; Muraviev, K.; Shakhnov, V. Prospects and Challenges of the Machine Learning and Data-Driven Methods for the Predictive Analysis of Power Systems: A Review. *Energies* **2023**, *16*, 4025. <https://doi.org/10.3390/en16104025>.
11. Zhang, C.; Wang, D.; Zhang, W.; He, L.; Zhou, K.; Li, J.; Zhu, L.; Zhou, B.; Zhou, Q.; Shuai, Z. A Novel Optimal Power Flow Method Considering Interval Uncertainties Under High Renewable Penetration Based on Security Limits Definition. *IEEE Trans. Sustain. Energy* **2026**, *17*, 926–938. <https://doi.org/10.1109/TSTE.2025.3602456>.
12. Wang, S.; Chen, S.; Ge, L.; Wu, L. Distributed Generation Hosting Capacity Evaluation for Distribution Systems Considering the Robust Optimal Operation of OLTC and SVC. *IEEE Trans. Sustain. Energy* **2016**, *7*, 1111–1123. <https://doi.org/10.1109/TSTE.2016.2529627>.
13. Zeng, Y.; Li, J.; Luo, Y.; Yu, Y.; Zhang, C.; Zhu, L. Frequency Dynamics-Constrained Renewable Energy Hosting Capacity Evaluation with Synthetic Inertia and Multi-Resource Frequency Support. *IEEE Trans. Ind. Appl.* **2025**, *61*, 7780–7789. <https://doi.org/10.1109/TIA.2025.3559029>.
14. Ganguly, S.; Samajpati, D. Distributed Generation Allocation on Radial Distribution Networks Under Uncertainties of Load and Generation Using Genetic Algorithm. *IEEE Trans. Sustain. Energy* **2015**, *6*, 688–697. <https://doi.org/10.1109/TSTE.2015.2406915>.
15. Pereira, B.; da Costa, G.R.M.; Contreras, J.; Mantovani, J.R.S. Optimal distributed generation and reactive power allocation in electrical distribution systems. In Proceedings of the 2017 IEEE Power & Energy Society General Meeting, Chicago, IL, USA, 16–20 July 2017; p. 1.
16. Louca, R.; Bitar, E. Robust AC Optimal Power Flow. *IEEE Trans. Power Syst.* **2019**, *34*, 1669–1681. <https://doi.org/10.1109/TPWRS.2018.2849581>.
17. Lin, C.; Wu, W.; Shahidehpour, M.; Guo, Y.; Wang, B. A Non-Iterative Decoupled Solution of the Coordinated Robust OPF in Transmission and Distribution Networks with Variable Generating Units. *IEEE Trans. Sustain. Energy* **2020**, *11*, 1579–1588. <https://doi.org/10.1109/TSTE.2019.2931908>.
18. Li, G.; Li, G.; Zhou, M. Model and Application of Renewable Energy Accommodation Capacity Calculation Considering Utilization Level of Inter-Provincial Tie-Line. *Prot. Control Mod. Power Syst.* **2019**, *4*, 1–12. <https://doi.org/10.1186/s41601-019-0115-7>.
19. Du, H.; Sun, W.; Goldstein, M.; Harrison, G.P. Optimization via Statistical Emulation and Uncertainty Quantification: Hosting Capacity Analysis of Distribution Networks. *IEEE Access* **2021**, *9*, 118472–118483. <https://doi.org/10.1109/ACCESS.2021.3105935>.
20. Wang, S.; Dong, Y.; Wu, L.; Yan, B. Interval Overvoltage Risk Based PV Hosting Capacity Evaluation Considering PV and Load Uncertainties. *IEEE Trans. Smart Grid* **2020**, *11*, 2709–2721. <https://doi.org/10.1109/TSG.2019.2960335>.
21. Lee, K.; Zhao, P.; Bhattacharya, A.; Mallick, B.K.; Xie, L. An Active Learning-Based Approach for Hosting Capacity Analysis in Distribution Systems. *IEEE Trans. Smart Grid* **2024**, *15*, 617–626. <https://doi.org/10.1109/TSG.2023.3290414>.
22. Sun, B.; Jing, R.; Ge, L.; Zeng, Y.; Dong, S.; Hou, L. Quick Hosting Capacity Evaluation Based on Distributed Dispatching for Smart Distribution Network Planning with Distributed Generation. *J. Mod. Power Syst. Clean Energy* **2024**, *12*, 128–140. <https://doi.org/10.35833/MPCE.2022.000604>.
23. Akhtar, I.; Kirmani, S.; Jameel, M. Reliability Assessment of Power System Considering the Impact of Renewable Energy Sources Integration Into Grid with Advanced Intelligent Strategies. *IEEE Access* **2021**, *9*, 32485–32497. <https://doi.org/10.1109/ACCESS.2021.3060892>.

24. Zhang, J.; Tan, J.; Liu, Z.; Li, M.; Tao, Y.; Luo, T. Active Distribution Network Flexibility Evaluation Method Considering Flexibility Resource. In Proceedings of the 2022 12th International Conference on Power and Energy Systems (ICPES), Guangzhou, China, 23–25 December 2022; pp. 62–66.
25. Li, P.; Hu, D.; Hou, L.; Wang, J.; Pan, Y. Comprehensive Benefits Evaluation of Renewable Energy Based on Grey-DEMATEL and DQ-GRA. *IEEE Access* **2024**, *12*, 98660–98671. <https://doi.org/10.1109/ACCESS.2024.3429242>.

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