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A Non-Iterative Reliability-Constrained Generation Expansion Planning: A Multi-Cluster Risk Surrogate Model

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Abstract

Reliability-constrained generation expansion planning (GEP) is crucial to balance economy and reliability for power systems with high renewable penetration. Most of the existing reliability-constrained GEP methods treat reliability indices as exogenous constraints, which yields subjective and empirical results. Endogenous methods are computationally intractable due to the substantial computational burden caused by massive samples and the complexity of transmission networks. This work develops an efficient non-iterative GEP framework with endogenous reliability assessment built upon a novel risk surrogate model. The implicit relationship among high-dimensional uncertainties, installation capacity, and expected energy not served (EENS) is characterized by the proposed risk surrogate model based on polynomial chaos expansion (PCE), which incorporates network constraints. To enhance approximation precision, a multi-cluster PCE strategy is proposed to construct piecewise analytical formulations that accurately represent the underlying non-convex risk function. Relying on this surrogate model, an efficient non-iterative reliability-constrained GEP framework is proposed, which eliminates iterative solving and balances economy and reliability. Embedding the reliability analytical formulations into the GEP model, the two-level optimization model is transformed into a single-level optimization model. The simulation results demonstrate the effectiveness of the proposed method.

Keywords: generation expansion planning; polynomial chaos expansion; reliability-constrained; risk surrogate model

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1. Introduction

Environmental policies, such as renewable targets and carbon emission reductions [1], have driven the large-scale integration of renewable energy into power systems. Generation expansion planning (GEP) is a classical long-term optimization problem, which determines the optimal mix of generations and other energy infrastructures, such as wind turbines (WT), photovoltaic (PV), and energy storage systems (ESS), to meet the growing electricity demand and replace retired units [2,3]. However, the inherent variability of renewable generation and load poses significant challenges to the planning problem. On the one hand, the planning method should accurately model the uncertainties of the renewable energy and loads to ensure reliability [4]. On the other hand, the complexity in-

troduced by the uncertainty model can lead to computational intractability. To address these issues, many inspiring studies have been conducted.

To consider uncertainties of renewable energy and loads, scenario-based stochastic planning (SP), robust optimization (RO), chance-constrained (CC) programming, and their hybrid approaches have been proposed in recent years [5–15]. SP considers a finite set of scenarios, each represented by occurrence probabilities and uncertain parameters [5,6]. Despite its popularity for uncertainty modeling, this method substantially expands the problem dimensions and results in heavy computational burdens [7]. RO makes decisions based on the worst scenarios of uncertainty [8–10], which ensures reliability in extreme cases but sacrifices economy and yields a conservative investment scheme [11]. CC constrains the event probability under probability distribution to exceed a confidence threshold [12]. However, confidence threshold settings rely on empirical judgement. To address these limitations, hybrid methods are being investigated. For instance, the distributionally robust optimization (DRO) constructs an ambiguity probability set of uncertainty and minimizes the expected cost under the worst probability distribution within this set [13–15]. However, reliability is a key constraint in the planning process [16]. The above approaches mitigate operational risks, yet still do not explicitly quantify the reliability level of the investment scheme.

Integrating reliability assessment into the planning problem to quantify the risk of uncertainty has garnered increasing attention [17–22]. In general, a series of candidate planning schemes is initially generated to satisfy the reliability requirement. The optimal scheme is then screened by comparing each candidate's reliability and economic cost [17–19]. To further improve the optimality of the result, an iteration-based approach is proposed to embed the reliability into a two-level planning model. In this approach, the upper-level model outputs planning schemes. The lower-level model subsequently evaluates the corresponding reliability indices, which are fed back to the upper level. This iterative process continues until the convergence criteria are satisfied [20–22]. However, reliability assessment becomes computationally intractable under large-scale uncertainty scenarios. Whether post-screening or iterative adjustments are adopted, reliability is processed as an exogenous index separated from the planning optimization, which introduces subjectivity and empiricism into the process.

To address the above-mentioned challenges, non-iterative approaches have been proposed [23–28]. These approaches actively incorporate reliability as an optimization objective and constraint, which endogenously considers reliability in the planning model. In [23–25], the reliability assessment process is simplified under radial distribution network expansion planning, establishing planning models with embedded reliability indices. These models approximate the relationship between candidate lines and reliability indices by considering failures in existing/candidate lines and utilizing annual load duration curves. Building upon this, References [26–28] developed expansion planning models for loop-structured distribution networks. In these models, downstream load demand is derived from power balance relationships under open-loop operation modes. However, these methods rely on the unique structural properties of distribution networks to derive the analytical relationship between reliability and planning decisions, which renders them hard to generalize to transmission networks with complex topologies.

To address the above drawbacks, surrogate modeling has been adopted in transmission expansion planning. This technique builds approximation functions via neural networks or regression methods. These functions connect planning decisions with load, generation, operation costs, and reliability indices and serve as surrogates to replace either the entire optimization or its computationally intensive parts [29–34]. Reference [29] proposed a deep learning method that takes load and generation data as inputs and outputs line expansion schemes. Nevertheless, it ignores physical constraints and fails to guaran-

tee the operational feasibility of schemes. References [30–32] fit the relationship between planning decisions and operational costs. Then, the relationship is embedded into the stochastic planning model to establish a neural two-stage stochastic programming framework. This approach avoids massive scenario evaluations for operational cost calculation and efficiently achieves a trade-off between investment and operational costs. However, none of the above methods embed reliability into the planning model. References [33,34] employed a regression-based approach to capture the implicit relationship between reliability indices and planning decisions. This method integrates reliability into the optimization model and supports rapid non-iterative expansion planning. Nevertheless, they do not fully account for the uncertainties of renewable energy outputs and the impact of N-1 contingencies on reliability. Such simplifications lead to inaccurate reliability evaluation results.

Existing works are summarized as follows. (i) Uncertainty-based methods (i.e., SP, RO, CC, and DRO) are commonly used to address the variability of renewable energy and load. These methods do not explicitly quantify the reliability level of the planning scheme. (ii) Iteration-based approaches that embed reliability into a bilevel optimization model can quantify reliability accurately. However, they incur a high computational burden. (iii) Non-iterative methods integrate analytical reliability formulation into the planning model, including distribution network-specific analytical methods [23–28] and surrogate-based methods for transmission network [33,34], significantly improving the solution efficiency. However, all of these methods rely on simplified reliability approximations or fail to fully account for complex network structures, high-dimensional uncertainties, and N-1 contingencies. Moreover, the complex topology of transmission networks renders the relationship among planning variables, uncertainty variables, and reliability distinctly non-convex and discontinuous. Existing non-iterative methods rely on a single surrogate model, struggling to capture this characteristic and leading to insufficient accuracy in reliability assessment.

To fill these gaps, this paper proposes an efficient non-iterative reliability-constrained GEP method that incorporates reliability based on a novel surrogate model. The main contributions are summarized as follows:

- (1) A novel surrogate model is developed to quantify reliability indices under network constraints with respect to high-dimensional uncertainty parameters and installation capacity. By establishing explicit expressions between reliability indices and related variables in transmission networks, the model significantly reduces the computational complexity of reliability assessment.
- (2) A multi-cluster PCE analytical strategy is proposed to construct a multi-segment nonlinear analytical formulation. The approach captures the non-convex relationship between high-dimensional inputs and outputs, significantly improving the fitting accuracy of the surrogate model.
- (3) An efficient non-iterative reliability-constrained GEP framework is proposed to alleviate the computational burden. The proposed method transforms the traditional two-level optimization into a single-level framework, enabling the efficient processing of massive scenarios while avoiding iterative solutions.

2. Problem Statement and Solution Framework

Most existing reliability-constrained GEP methods employ a two-level optimization framework, as illustrated in Figure 1. In the first level, planning schemes for renewable generation units and ESS are determined. The objective minimizes the total investment and expected operational costs subject to operational constraints over typical scenarios. The second level evaluates the reliability of the planning scheme: if the reliability criteria are met, the scheme is output; otherwise, a reliability cut is generated and fed back to the

first level for scheme revision. The first level then regenerates planning schemes within an updated decision space. Reliability assessment requires enumerating massive scenarios and relies on an optimal power flow (OPF) model to quantify minimal load shedding. The compact form of the OPF model is shown in Equations (1)–(5), and EENS is calculated by Equation (6).

$$\min_{\chi, \mathbf{P}_s} ENS_s \quad (1)$$

$$s.t. \mathbf{B} \cdot \mathbf{P}_s = \mathbf{D} \quad (2)$$

$$\mathbf{E} \cdot \mathbf{P}_s \geq \mathbf{F} \quad (3)$$

$$\mathbf{G} \cdot \boldsymbol{\chi} + \mathbf{I} \cdot \mathbf{P}_s \geq \mathbf{J} \quad (4)$$

$$\boldsymbol{\chi} = \mathbf{X}^{inv}; \quad \tau_s \quad (5)$$

$$EENS = \sum_s \rho_s ENS_s, s \in \Omega^s \quad (6)$$

where $\boldsymbol{\chi}$ represents the vector of auxiliary variables; $\mathbf{P}_s$ is the vector of generator power outputs under scenario s ; ENS_s is the total energy not supplied in scenario s ; $\mathbf{B}, \mathbf{D}, \mathbf{E}, \mathbf{F}, \mathbf{G}, \mathbf{I}$, and $\mathbf{J}$ are coefficient matrices and vectors associated with the operational constraints of the OPF model; $\mathbf{X}^{inv}$ is the vector of investment decisions; τ_s represents the vector of dual variables for the constraint $\boldsymbol{\chi} = \mathbf{X}^{inv}$ of scenario s ; ρ_s is the probability of scenario s ; Ω^s is the set of all reliability assessment scenarios. However, this framework encounters significant computational bottlenecks. The OPF-based reliability assessment must handle complex network constraints, temporal coupling relationships, and a large number of scenarios, resulting in substantial computational effort. This burden is further intensified by the iterative interaction between the reliability assessment and the first level planning process.

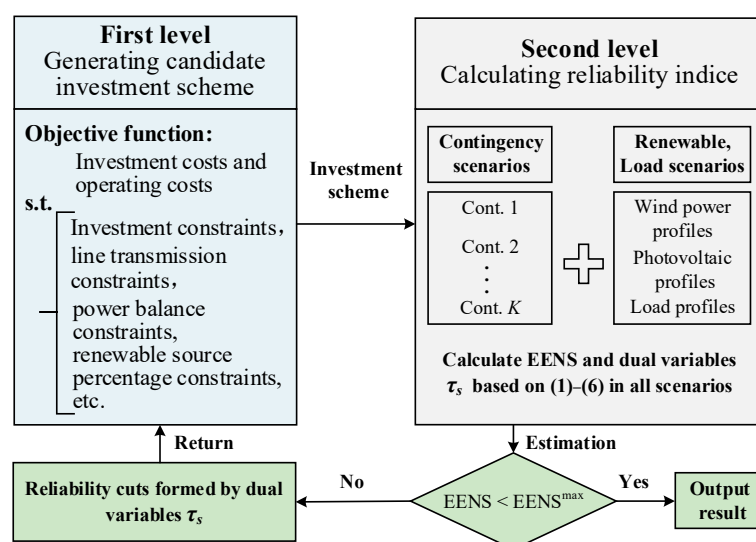


Figure 1. Two-level solution framework.

Throughout the iterative process, reliability represents an implicit function of WT generation, PV output, load demand, and planning decisions. If the implicit function can be inscribed in an explicit expression, then the optimization of massive scenarios can be avoided, and the above bottlenecks can be overcome. This paper attempts to replace the second level with a surrogate model while embedding it in the first level to create a non-

iterative reliability-constrained GEP model, as shown in Figure 2. However, constructing the surrogate model faces two critical challenges. (1) The reliability function depends not only on stochastic renewable generation and load demand, but also on the planning variables. The variables feature high dimensionality and tight coupling, which makes it hard to derive explicit analytical functions. (2) The reliability function exhibits strong nonlinearity and non-convexity driven by the intricate mechanism through stochastic variables affecting system risks. It may include discontinuous and non-smooth segments, which further impede precise analytical fitting.

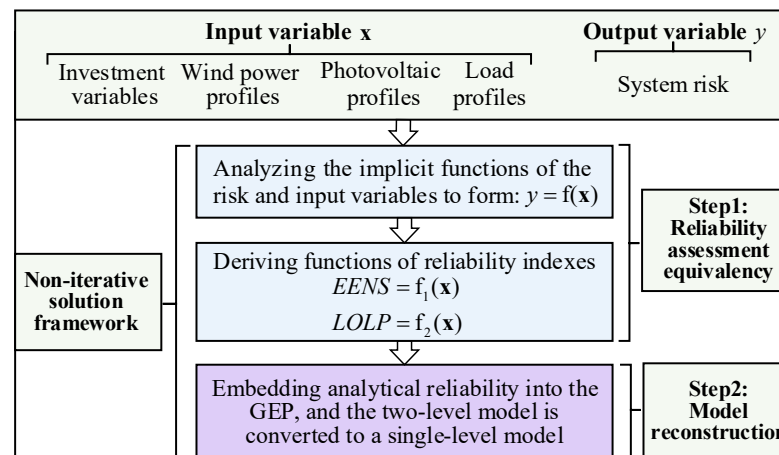


Figure 2. Non-iterative solution framework.

3. A Multi-Cluster Risk Surrogate Model

This section develops a PCE-based risk surrogate model to equivalently characterize the reliability assessment, accounting for high-dimensional stochastic variables. To capture the discontinuities and non-smooth characteristics between high-dimensional input space and reliability indices, a multi-cluster risk analysis strategy is further proposed.

3.1. PCE-Based Risk Surrogate Model

PCE is an uncertainty quantization method based on the expansion of orthogonal polynomial series. This approach approximates the implicit parameter-output relationship through an explicit polynomial representation that achieves global optimality. Furthermore, the explicit polynomial function, usually obtained at a relatively small computational cost, is accurate and easy to sample [35]. Sparse PCE construction techniques further improve scalability, making the method suitable for high-dimensional stochastic systems [36].

The advantages of PCE provide strong support to construct surrogate models for reliability assessment with simplified and accurate calculations. The steps to develop a PCE-based risk surrogate model are detailed as follows: (i) constructing input variables, (ii) generating the analytical formulation and PCE basis, (iii) calculating the coefficients of the analytical formulation, and (iv) calculating the reliability indices.

(1) *Constructing input variables*: The wind power, PV, and load profiles each contain 24 hourly values per scenario. To reduce the input dimension, we aggregated them into a single net-load profile. After this dimension reduction, the probability distribution of the net-load is needed. Assuming the original variables are independent and normally distributed, the net-load is also normal, and its mean and variance can be obtained via convolution, leading to the expressions in Equations (7) and (8). The convolution simplifies the distribution calculation under the independence assumption, while the dimension reduction is achieved by variable aggregation.

$$\mu_{nl} = \mu_l - \mu_w - \mu_{pv} \quad (7)$$

$$\sigma_{nl}^2 = \sigma_l^2 + \sigma_w^2 + \sigma_{pv}^2 \quad (8)$$

where μ_{nl} and σ_{nl}^2 denote the mean and variance of the net-load, and μ_w , σ_w^2 , μ_{pv} , σ_{pv}^2 , μ_l , σ_l^2 represent those of wind power, PV, and load, respectively. It should be noted that independent normal distributions fail to fully capture the complicated spatio-temporal stochastic features of power system uncertainties. In fact, wind speed fluctuations present complex temporal and spatial vertical variations [37]. More flexible scenario-based methods are required to handle the complex features of renewable generation [38]. If practical WT power, PV output, and load variables obey bounded, skewed, or correlated distributions, the net-load distribution can be established via moment matching or copula functions [39,40]. In this work, core theoretical analyses and case studies adopt the independent normal distribution assumption. Testing the proposed model under non-Gaussian profiles, correlated random variable and extreme renewable generation scenarios will be explored in future research.

The net-load profiles and planning variables together constitute the input variables $\mathbf{x} = [x_1, x_2, \dots, x_{N_{nl}}, x_{N_{nl}+1}, \dots, x_{N_{nl}+1} + x_{N_{nl}+N_l}]$. Equation (9) is used to transform them into standardized random variables, as follows:

$$x_i = F_i^{-1}(\Phi(\xi_i)), i = 1, 2, \dots, N \quad (9)$$

where x_i represents the i -th component of $\mathbf{x}$. F_i is the cumulative probability function of x_i , and F_i^{-1} is its inverse. ξ_i denotes the i -th standardized random variable. Φ stands for the cumulative probability function of the standard random variable ξ_i . N is the sum of the number of net-load variables N_{nl} and the number of planning variables N_l , denoting the total number of random variables.

(2) *Constructing analytical formulation and PCE basis:* In PCE, the system output-load shedding is represented for each contingency k using a dedicated analytical expression. Each expression is formulated as a finite weighted sum of orthogonal polynomial basis functions $h_{k,j}(\xi_s)$, as presented in Equation (10):

$$y_{k,s} = \sum_{j=0}^{N_p} a_{k,j} h_{k,j}(\xi_s) \quad (10)$$

where $y_{k,s}$ denotes the load shedding under scenario s given contingency k . $a_{k,j}$ denotes the coefficient of the polynomial term. N_p represents the total number of coefficients. The total number of terms in the PCE is expressed as $(N+P)!/(N!P!)$, where P denotes the maximum order of the PCE basis functions. The selection of basis functions is determined by the probability distribution of the input variables. The Askey scheme [41,42] provides many typical probability distributions and corresponding orthogonal polynomials, as shown in Table 1.

Table 1. Orthogonal polynomial bases corresponding to common distribution types.

Random Variable	Orthogonal Polynomial	Domain
Normal	Hermite	$(-\infty, +\infty)$
Uniform	Legendre	$[-1, 1]$
Gamma	Laguerre	$[0, +\infty)$
Beta	Jacobi	$[0, 1]$

The multi-dimensional PCE basis function is constructed as a tensor product of one-dimensional orthogonal bases, as shown in Equation (11). Each univariate basis corresponds to a single independent input variable. These basis functions $h_i(\xi_i)$ are orthogonal with respect to a specific weight function $w(\xi_i)$, as shown in Equation (12).

$$h_{k,j}(\xi) = h_{j,1}(\xi_1) \otimes h_{j,2}(\xi_2) \otimes h_{j,i}(\xi_i) \otimes \cdots \otimes h_{j,N}(\xi_N) \quad (11)$$

$$\int h_{i,o}(\xi_i) h_{i,q}(\xi_i) w(\xi_i) d\xi_i = \begin{cases} 0, & o \neq q \\ > 0, & o = q \end{cases} \quad (12)$$

where o and q represent the order of the basis function.

(3) *Calculating coefficients of analytical formulation:* The least squares method is employed to calculate the coefficients. This approach requires only the input variables (collocation points) and their corresponding system outputs, without the need to analyze the internal characteristics of the system. The specific steps are as follows:

- (i) Select the appropriate collocation points. The selection of collocation points is significantly related to the PCE accuracy. These points are generally obtained in the roots of a high-order univariate polynomial. For higher accuracy, the number of collocation points, denoted as N_{cp} , is set to twice the quantity of unknown PCE coefficients. Collocation points in use are randomly sampled from all combinations constructed by roots of each high-order univariate polynomial.
- (ii) Substitute the collocation points into the coefficient matrix $\mathbf{H}_k$, which comprises all terms of the PCE basis. The matrix has dimensions of $N_{cp} \times N_p$, as:

$$\mathbf{H}_k = \begin{bmatrix} h_{k,0}(\xi_1) & h_{k,1}(\xi_1) & \cdots & h_{k,N_p}(\xi_1) \\ h_{k,0}(\xi_2) & h_{k,1}(\xi_2) & \cdots & h_{k,N_p}(\xi_2) \\ \vdots & \vdots & \vdots & \vdots \\ h_{k,0}(\xi_{N_{cp}}) & h_{k,1}(\xi_{N_{cp}}) & \cdots & h_{k,N_p}(\xi_{N_{cp}}) \end{bmatrix} \quad (13)$$

- (iii) Using the formulations in Equations (1)–(5), the minimum load shedding is computed for each collocation point. The load shedding vector is generated as follows:

$$\mathbf{Y}_k = [y_{k,1}, y_{k,2}, \dots, y_{k,N_{cp}}]^T \quad (14)$$

- (iv) The coefficient vector $\mathbf{A}_k$ is derived from Equation (15) using the load shedding vector $\mathbf{Y}_k$ and the coefficient matrix $\mathbf{H}_k$.

$$\mathbf{A}_k = [a_{k,0}, a_{k,1}, \dots, a_{k,N_p}]^T = (\mathbf{H}_k^T \mathbf{H}_k)^{-1} \mathbf{H}_k^T \mathbf{Y}_k \quad (15)$$

(4) *Calculating reliability indices:* Substituting the basis functions and coefficients identified in Steps (2) and (3) into Equation (10), an explicit formulation of load shedding can be constructed as shown in Equation (16). Combined with the scenario probabilities, the reliability indices EENS and loss of load probability (LOLP) can be calculated by Equations (17) and (18).

$$ENS_{k,s} = \max\{0, y_{k,s}\} \quad (16)$$

$$EENS = \sum_{k \in \Omega^K} \sum_{s \in \Omega^S} \rho_{k,s} ENS_{k,s} \quad (17)$$

$$LOLP = \sum_{k \in \Omega^K} \sum_{s \in \Omega^S} \rho_{k,s} l_{k,s} \quad (18)$$

where $l_{k,s}$ is a binary variable indicating whether load shedding occurs. Specifically, $l_{k,s} = 1$ if $y_{k,s}$ exceeds a small positive number σ , and $l_{k,s} = 0$ otherwise. EENS and LOLP are widely accepted standard indices in transmission expansion planning because they capture energy shortage risk with mature computational frameworks. However, renewable-rich systems can experience reliability concerns beyond energy not supplied [43], such as voltage violations and frequency deviations. Frequency fluctuations are primarily caused by active power imbalances. The system restores frequency by adjusting generator outputs or load levels, which eventually translates into renewable curtailment or load shedding. Thus, the severity of frequency events is indirectly reflected in EENS and LOLP. Voltage violations are mainly related to reactive power distribution, and such risks cannot be quantified within the current modeling framework.

The PCE-based risk surrogate model significantly reduces the computational burden associated with reliability assessment while maintaining acceptable accuracy. However, high-order PCE expansions bring practical obstacles to optimization. The derived nonlinear formulations cannot be solved efficiently by state-of-the-art solvers. Furthermore, implicit functions of reliability may exist with non-convex discontinuities. There is still an error in the global scope of variables when using a single risk surrogate model. Therefore, Section 3.2 provides further handling of the risk surrogate model.

3.2. Multi-Cluster Risk Surrogate Model

To improve the accuracy of the surrogate model, this paper groups scenarios with similar regularity. Each cluster is then assigned an individual risk surrogate model to handle the non-smoothness and discontinuities of the implicit function, as illustrated in Figure 3.

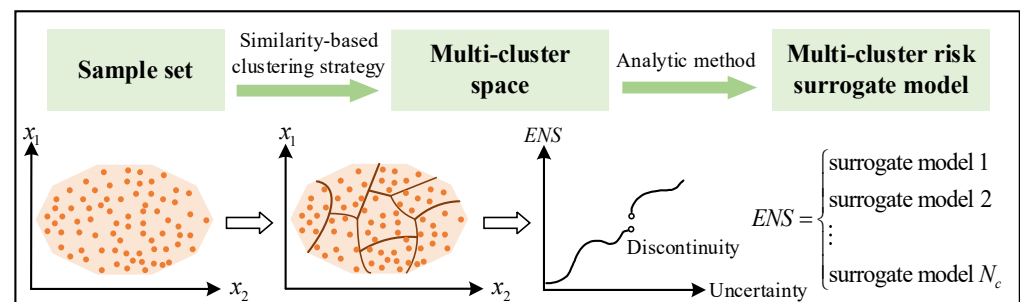


Figure 3. Constructing process of the MRSM.

The multi-cluster risk surrogate models (MRSMs) are constructed in two steps:

(1) *Clustering and reconstruction of random variables*: Assuming that the number of reliability assessment scenarios is N_{ra} and each scenario contains N_{rv} random variables, all scenarios are assembled into an $N_{ra} \times N_{rv}$ matrix marked as $\mathbf{W}$. To enhance the local smoothness of the relationship between random inputs and load shedding, we first perform Z-score standardization on net-load curves, followed by K-means++ clustering with Euclidean distance [44]. This ensures that scenarios within the same cluster exhibit similar net-load profiles. The scenario set $\mathbf{W}$ is thus divided into N_c clusters, expressed as:

$$\mathbf{W} = [\mathbf{W}_1; \mathbf{W}_2; \dots; \mathbf{W}_c; \dots; \mathbf{W}_{N_c}] \quad (19)$$

where $\mathbf{W}_c$ represents all scenarios within cluster c . After clustering, the probability distributions of the random input variables are refitted within cluster c . The standard random variables ξ_c are then reconstructed following the approach in Section 3.1. By partitioning the stochastic space into smaller subregions, the PCE can select suitable polynomial orders and basis functions for each cluster, improving the approximation accuracy and avoiding unnecessary computation [45,46]. Note that the contribution of this paper focuses on the MRSM framework rather than clustering algorithms. Therefore, general configurations are adopted for feature standardization and distance metric selection. Unlike conventional cluster validation relying on silhouette coefficient or Davies–Bouldin index, the optimal cluster number and clustering quality are determined according to the surrogate fitting result and the precision of the final planning results. The reasons for this approach are as follows:

- (i) The goal of clustering is to guarantee the accuracy of surrogate models and planning results. It is more intuitive that these results are adopted as evaluation standards of the optimal cluster number and clustering quality.
- (ii) Conventional cluster validity criteria do not directly correlate with the performance of the surrogate model and introduce additional computational cost.
- (iii) Directly assessing surrogate accuracy avoids selecting a cluster number that optimizes the conventional index but is unsuitable for surrogate construction.

(2) *Reformulation of PCE analytical formulation for each cluster:* After clustering, Hermite polynomial bases are adopted for net-load variables that follow normal distributions. The planning variables, including the installed capacities of WT, PV, and ESS, follow a uniform distribution within feasible ranges. The Legendre polynomial basis is applied. The first- and second-order polynomial expressions of the Hermite and Legendre bases are presented in Equation (20) and Equation (21), respectively.

$$\begin{cases} h_0(\xi) = 1 \\ h_1(\xi) = \xi \\ h_2(\xi) = \xi^2 - 1 \end{cases} \quad (20)$$

$$\begin{cases} h_0(\xi) = 1 \\ h_1(\xi) = \xi \\ h_2(\xi) = (3\xi^2 - 1) / 2 \end{cases} \quad (21)$$

To obtain a sparse representation of the PCE coefficients, we employed the orthogonal matching pursuit algorithm [47], which iteratively selects the most significant polynomial terms and updates their coefficients using least-squares. For power system optimization problems, second-order truncated PCE is widely adopted to strike a balance between approximation accuracy and computational complexity [36,48]. By substituting the finally retained polynomial terms and their coefficients back into Equation (10), a second-order sparse PCE formulation is obtained as follows:

$$y_{c,k,s} = a_{c,k,0} + \sum_{j=1}^N a_{c,k,j} \xi_{c,k,s,j} + \sum_{j=N+1}^{N+N_{qt}} a_{c,k,j} \xi_{c,k,s,m} \xi_{c,k,s,n} + \sum_{j=N+N_{qt}+1}^{N+N_{qt}+N_I^*} a_{c,k,j} (3\xi_{c,k,s,j-N-N_{qt}}^2 - 1) / 2 + \sum_{j=N+N_{qt}+N_I^*+1}^{N+N_{qt}+N_I^*+N_{nl}^*} a_{c,k,j} (\xi_{c,k,s,j-N-N_{qt}-N_I^*}^2 - 1) \quad (22)$$

where $m, n = 1, 2, \dots, N, n \neq m$. The term N_{qt} represents the number of bilinear terms. For clusters where the probability distributions are unknown or do not belong to the distributions listed in Table 1, the Stieltjes procedure can be employed to generate the PCE basis

functions and coefficients [49]. Nevertheless, relevant investigations into non-independent normal distribution assumptions are not covered within the scope of the present work.

Based on the above, the computationally heavy OPF-based reliability assessment is replaced by MRS. The use of low-order polynomial expansions improves tractability. In addition, the MRS addresses the challenge that a single risk surrogate model encounters in dealing with non-smoothness and discontinuities.

4. Non-Iterative Reliability-Constrained GEP Model

The non-iterative reliability-constrained GEP model is proposed based on the above risk surrogate models, considering reliability endogenously. By efficiently incorporating massive scenarios, the planning model obtains accurate results while maintaining a balance between economy and reliability.

4.1. Objective Function

The objective of the proposed model is to minimize the total cost associated with renewable energy deployment, ESS investment, system operation, and reliability penalty, as shown in Equation (23). The investment costs of candidate WT, PV, and ESS units are computed using Equation (24), where ϖ denotes the present value coefficient. The operating cost, including thermal generation cost, renewable energy curtailment penalty, and ESS operating cost, is evaluated through Equation (25). The penalty cost associated with EENS under a given planning scheme is expressed in Equation (26).

$$\min C^{\text{total}} = C^{\text{inv}} + C^{\text{op}} + C^r \quad (23)$$

$$C^{\text{inv}} = \varpi \left(\sum_{g \in \Omega^{\text{WT}}} IC_g^{\text{WT}} P_g^{\text{WT,inv}} + \sum_{g \in \Omega^{\text{PV}}} IC_g^{\text{PV}} P_g^{\text{PV,inv}} + \sum_{b \in \Omega^{\text{ES}}} (IC_b^{\text{ES,e}} E_b^{\text{ES,inv}} + IC_b^{\text{ES,p}} P_b^{\text{ES,inv}}) \right) \quad (24)$$

$$C^{\text{op}} = 365 / N_{\text{TD}} \times \left(\sum_{s \in \Omega^{\text{TS}}} \rho_s \sum_{d \in \Omega^{\text{TD}}} \left(\sum_{t \in T} \sum_{g \in \Omega^{\text{TH}}} OC_g^{\text{TH}} P_{g,t,d,s}^{\text{TH}} + \sum_{t \in T} \sum_{g \in \Omega^{\text{WT}}} C_g^{\text{WT,cur}} P_{g,t,d,s}^{\text{WT,cur}} + \sum_{t \in T} \sum_{g \in \Omega^{\text{PV}}} C_g^{\text{PV,cur}} P_{g,t,d,s}^{\text{PV,cur}} + \sum_{t \in T} \sum_{b \in \Omega^{\text{ES}}} OC_b^{\text{ES}} (P_{b,t,d,s}^{\text{ES,ch}} + P_{b,t,d,s}^{\text{ES,dis}}) \right) \right) \quad (25)$$

$$C^r = 365 \times \text{VOLL} \times \text{EENS} \quad (26)$$

4.2. Constraints

(1) *Investment constraints*: Considering environmental policies and techno-economic factors, a reasonable upper bound is defined for the maximum installable capacity. The planned capacity of each resource type is constrained within this upper limit, as follows:

$$\begin{cases} 0 \leq P_g^{\text{WT,inv}} \leq P_g^{\text{WT,max}}, g \in \Omega^{\text{WT}} \\ 0 \leq P_g^{\text{PV,inv}} \leq P_g^{\text{PV,max}}, g \in \Omega^{\text{PV}} \\ 0 \leq E_b^{\text{ES,inv}} \leq E_b^{\text{ES,max}}, b \in \Omega^{\text{ES}} \end{cases} \quad (27)$$

(2) *Operating constraints*: The proposed model introduces annual typical scenarios and seasonal typical days to separately capture seasonal uncertainties and patterns. Operational constraints are enforced on each seasonal typical day under each annual typical scenario. The corresponding operational constraints are presented as follows:

$$\sum_{g \in \Omega^{\text{TH}}} P_{g,t,d,s}^{\text{TH}} + \sum_{g \in \Omega^{\text{PV}}} P_{g,t,d,s}^{\text{PV}} + \sum_{g \in \Omega^{\text{WT}}} P_{g,t,d,s}^{\text{WT}} + \sum_{b \in \Omega^{\text{ES}}} (P_{b,t,d,s}^{\text{ES,dis}} - P_{b,t,d,s}^{\text{ES,ch}}) = \sum_{n \in \Omega^{\text{B}}} D_{n,t,d,s}, \quad t \in T, d \in \Omega^{\text{TD}}, s \in \Omega^{\text{TS}} \quad (28)$$

$$\mathbf{f}_{t,d,s} = \mathbf{PTDF}[\mathbf{P}_{t,d,s}^{\text{TH}} + \mathbf{P}_{t,d,s}^{\text{WT}} + \mathbf{P}_{t,d,s}^{\text{PV}} + \mathbf{P}_{t,d,s}^{\text{ES,dis}} - \mathbf{P}_{t,d,s}^{\text{ES,ch}} - \mathbf{D}_{t,d,s}], t \in T, d \in \Omega^{\text{TD}}, s \in \Omega^{\text{TS}} \quad (29)$$

$$\mathbf{f}^{\min} \leq \mathbf{f}_{t,d,s} \leq \mathbf{f}^{\max}, t \in T, d \in \Omega^{\text{TD}}, s \in \Omega^{\text{TS}} \quad (30)$$

$$\sum_{d \in \Omega^{TD}} \sum_{t \in T} \left(\sum_{g \in \Omega^{WT}} P_{g,t,d,s}^{WT} + \sum_{g \in \Omega^{PV}} P_{g,t,d,s}^{PV} \right) \geq \beta \sum_{d \in \Omega^{TD}} \sum_{t \in T} \sum_{n \in \Omega^B} D_{n,t,d,s}, s \in \Omega^{TS} \quad (31)$$

$$\begin{cases} SR_{t,d,s}^{up} \geq \tau \sum_{n \in \Omega^B} D_{n,t,d,s} + \varsigma \left(\sum_{g \in \Omega^{WT}} P_g^{WT,inv} \eta_{t,d,s}^{WT} + \sum_{g \in \Omega^{PV}} P_g^{PV,inv} \eta_{t,d,s}^{PV} \right) \\ SR_{t,d,s}^{down} \geq \tau \sum_{n \in \Omega^B} D_{n,t,d,s} + \varsigma \left(\sum_{g \in \Omega^{WT}} P_g^{WT,inv} \eta_{t,d,s}^{WT} + \sum_{g \in \Omega^{PV}} P_g^{PV,inv} \eta_{t,d,s}^{PV} \right) \\ \sum_{g \in \Omega^{TH}} (P_g^{TH,max} - P_{g,t,d,s}^{TH}) \geq SR_{t,d,s}^{up} \\ \sum_{g \in \Omega^{TH}} (P_{g,t,d,s}^{TH} - P_g^{TH,min}) \geq SR_{t,d,s}^{down}, t \in T, d \in \Omega^{TD}, s \in \Omega^{TS} \end{cases} \quad (32)$$

$$s.t. \begin{cases} \text{Power limits and ramp limits of generators} \\ \text{Power limits of WT and PV} \\ \text{Operating constraints of ESS} \end{cases} \quad (33)$$

Constraint Equation (28) enforces power balance in period t of typical day d under typical scenario s . This condition guarantees full load supply by prohibiting load shedding in all time intervals of the typical scenario. Constraint Equation (29) specifies the transmission line power flows, and constraint Equation (30) imposes the corresponding operational limits for each line. Constraint Equation (31) ensures that renewable generation supplies at least a predetermined proportion β of the total load in scenario s . Constraint Equation (32) requires the thermal unit reserves to satisfy the combined load and renewable fluctuation requirements during period t , where τ and ς represent fluctuation coefficients. Constraint Equation (33) corresponds to device-level operational constraints, whose detailed formulations are referenced from [33].

(3) *Reliability Constraints*: According to the risk surrogate models Equations (7)–(22) developed in Section 3, the reliability constraints are formulated as:

$$0 \leq ENS_{c,k,s}, c \in \Omega^C, k \in \Omega^K, s \in \Omega^S \quad (34)$$

$$y_{c,k,s}(\xi_{c,k,s}) \leq ENS_{c,k,s}, c \in \Omega^C, k \in \Omega^K, s \in \Omega^S \quad (35)$$

$$y_{c,k,s}(\xi_{c,k,s}) \leq M \times l_{c,k,s}, c \in \Omega^C, k \in \Omega^K, s \in \Omega^S \quad (36)$$

$$y_{c,k,s}(\xi_{c,k,s}) \geq \sigma - M \times (1 - l_{c,k,s}), c \in \Omega^C, k \in \Omega^K, s \in \Omega^S \quad (37)$$

$$EENS = \sum_{c \in \Omega^C} \sum_{k \in \Omega^K} \sum_{s \in \Omega^S} \rho_{c,k,s} ENS_{c,k,s} \leq EENS^{\max} \quad (38)$$

$$LOLP = \sum_{c \in \Omega^C} \sum_{k \in \Omega^K} \sum_{s \in \Omega^S} \rho_{c,k,s} l_{c,k,s} \leq LOLP^{\max} \quad (39)$$

Massive reliability scenarios substantially increase the bilinear and quadratic terms in Equation (22), which in turn raises the computational complexity and leads to a significant reduction in solution efficiency. To mitigate this issue, a linearization procedure is applied to $y_{c,k,s}$. Net-load variables are predetermined under specified scenarios, hence their self-quadratic terms, as well as bilinear cross terms between net-load and planning variables, are kept in the original form without linearization. Only the bilinear terms of distinct planning variables and self-quadratic terms of single planning variables are substituted with auxiliary variables, as follows:

$$mc_{c,k,s,j} = \begin{cases} \xi_{c,k,s,m} \xi_{c,k,s,n}, j = N + N_{qt1} + 1, N + N_{qt1} + 2, \dots, N + N_{qt1} + N_{qt2} \\ \xi_{c,k,s,n}^2, j = N + N_{qt1} + N_{qt2} + 1, \dots, N + N_{qt1} + N_{qt2} + N_{qt2}^* \end{cases} \quad (40)$$

$$m, n = N_{nl}, N_{nl} + 1, \dots, N_{nl} + N_I, m \neq n$$

where $mc_{c,k,s,j}$ denotes the auxiliary variable introduced for the j -th expansion term of the surrogate model under cluster c , contingency k , and scenario s ; $\xi_{c,k,s,m}$ and $\xi_{c,k,s,n}$ re-

fer to the m -th and n -th standardized random input variable of the surrogate model within the same cluster, contingency, and scenario; N_{qt1} donates the count of bilinear terms formed by net-load and planning variables; N_{qt2} stands for the number of bilinear terms in different planning variables; N_I^* represents the quantity of quadratic terms belonging to planning variables after sparse expansion. By substituting Equation (40) into Equation (22), the risk surrogate model is reconstructed as follows:

$$y_{c,k,s} = a_{c,k,0} + \sum_{j=1}^N a_{c,k,j} \xi_{c,k,s,j} + \sum_{j,n,m=N+1,n \neq m}^{N+N_{qt1}} a_{c,k,j} \xi_{c,k,s,n-N} \xi_{c,k,s,m-N} + \sum_{j=N+N_{qt1}+1}^{N+N_{qt1}+N_{qt2}} a_{c,k,j} mc_{c,k,s,j} \\ + \sum_{j=N+N_{qt1}+N_{qt2}+1}^{N+N_{qt1}+N_{qt2}+N_I^*} \frac{a_{c,k,j}}{2} (3mc_{c,k,s,j} - 1) + \sum_{j=N+N_{qt1}+N_{qt2}+N_I^*+1}^{N+N_{qt1}+N_{qt2}+N_I^*+N_{nl}^*} a_{c,k,j} (\xi_{c,k,s,j-N-N_{qt1}-N_{qt2}-N_I^*}^2 - 1) \quad (41)$$

where N_{nl}^* is the number of quadratic terms of net-load variables after sparse expansion. Subsequently, Equation (40) is handled by the McCormick convex relaxation method [50]. Planning variables follow a uniform distribution within their feasible installation ranges and are normalized to the standard interval $[-1, 1]$, thus yielding unified lower bounds $\xi_{c,k,s,m}^L = -1$ and upper bounds $\xi_{c,k,s,m}^U = 1$; $m = N_{nl} + 1, \dots, N_{nl} + N_I$. These bounds are adopted to construct McCormick convex constraints for auxiliary variable $mc_{c,k,s,j}$, as shown in Equations (42) and (43):

$$\begin{cases} mc_{c,k,s,j} \geq \xi_{c,k,s,m}^L \xi_{c,k,s,n} + \xi_{c,k,s,m} \xi_{c,k,s,n}^L - \xi_{c,k,s,m}^L \xi_{c,k,s,n}^L \\ mc_{c,k,s,j} \geq \xi_{c,k,s,m}^U \xi_{c,k,s,n} + \xi_{c,k,s,m} \xi_{c,k,s,n}^U - \xi_{c,k,s,m}^U \xi_{c,k,s,n}^U \\ mc_{c,k,s,j} \leq \xi_{c,k,s,m}^U \xi_{c,k,s,n} + \xi_{c,k,s,m} \xi_{c,k,s,n}^L - \xi_{c,k,s,m}^U \xi_{c,k,s,n}^L \\ mc_{c,k,s,j} \leq \xi_{c,k,s,m} \xi_{c,k,s,n}^U + \xi_{c,k,s,m}^L \xi_{c,k,s,n} - \xi_{c,k,s,m}^L \xi_{c,k,s,n}^U \end{cases} \quad (42)$$

$$j = N + N_{qt1} + 1, \dots, N + N_{qt1} + N_{qt2}, n, m = N_{nl} + 1, \dots, N_{nl} + N_I, n \neq m$$

$$\begin{cases} mc_{c,k,s,j} \geq 2\xi_{c,k,s,m}^L \xi_{c,k,s,m} - \xi_{c,k,s,m}^L \\ mc_{c,k,s,j} \geq 2\xi_{c,k,s,m}^U \xi_{c,k,s,m} - \xi_{c,k,s,m}^U \\ mc_{c,k,s,j} \leq (\xi_{c,k,s,m}^U + \xi_{c,k,s,m}^L) \xi_{c,k,s,m} - \xi_{c,k,s,m}^U \xi_{c,k,s,m}^L \\ mc_{c,k,s,j} \leq (\xi_{c,k,s,m}^U + \xi_{c,k,s,m}^L) \xi_{c,k,s,m} - \xi_{c,k,s,m}^L \xi_{c,k,s,m}^U \end{cases} \quad (43)$$

$$j = N + N_{qt1} + N_{qt2} + 1, \dots, N + N_{qt1} + N_{qt2} + N_I^*, m = N_{nl} + 1, \dots, N_{nl} + N_I$$

4.3. Solution of the Proposed Model

Based on the above procedure, the surrogate model was employed to evaluate the reliability indices, which substantially reduces the number of constraints in the proposed reliability-constrained GEP model. By incorporating high-dimensional influencing factors and a multi-cluster analytical strategy, system risk is accurately quantified through several low-order surrogate models. Directly computing the variable $y_{c,k,s}$ for a large number of scenarios would generate extensive nonlinear terms. Therefore, the McCormick convex relaxation is applied to reformulate the problem for mixed-integer linear programming (MILP). Consequently, the proposed model can be solved in a non-iterative manner using state-of-the-art optimization solvers. The flowchart of the proposed non-iterative reliability constrained GEP model is illustrated in Figure 4.

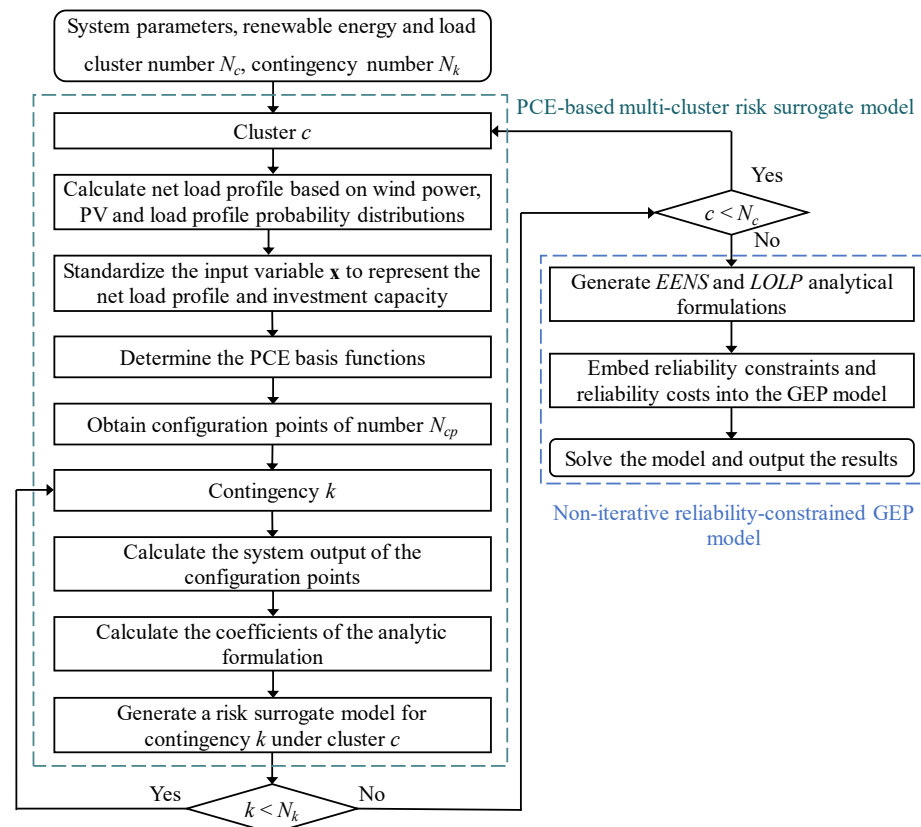


Figure 4. Flowchart of the proposed non-iterative reliability-constrained GEP model.

To focus on the contribution of surrogate modeling, the framework employs the DC OPF model while simplifying treatments for flexible loads and converter interfaces. Nevertheless, existing research indicates that these factors exert non-negligible impacts on power system planning with high renewable penetration. Reference [51] demonstrated that flexible loads significantly alter the optimal planning schemes of wind-integrated power systems. Reference [52] verified that hybrid AC/DC operating modes determine the practical accuracy of renewable generation planning models. Furthermore, References [53,54] revealed that offshore wind farms and converter-dominated resources introduce intricate practical constraints within GEP problems. Incorporating all of the above characteristics falls beyond the scope of the current work and will be reserved for future extensions.

5. Numerical Study

5.1. Simulation Configuration and Parameter Settings

To validate the effectiveness of the proposed model and methodology, case studies were carried out on the IEEE 39-bus and IEEE 118-bus test systems. Five methods are presented in Table 2 for comparison. The specific details of simulation configuration and parameter settings are as follows:

- (1) *Renewable and load scenario generation:* The forecasting errors of WT power, PV power, and system load follow zero-mean normal distributions, with a standard deviation of 17.5% of the corresponding predicted values. Under the probability distributions, forecasting error samples are generated, superimposed on the predicted values, and truncated within a range $[0, 1]$ to construct stochastic scenarios.
- (2) *Sample configuration for surrogate model construction:* The training set and test set consist of 1600 and 400 samples, respectively, which are uniformly generated via the above scenario generation method.

- (3) *Scenario probability calculation*: The probability of each reliability scenario is determined by coupling the stochastic source-load probability with the N-1 line outage probability, covering both normal conditions and single-line contingency scenarios.
- (4) *Typical scenario generation*: A total of 1000 annual hourly scenarios are clustered into four annual typical scenarios, whose probabilities are determined by the proportion of intra-cluster samples. Each typical scenario is further clustered to extract four seasonal typical days.
- (5) *N-1 contingency set*: For the IEEE 39-bus test system, lines 2, 7, 9, 18, and 22 are selected as candidate outage lines. For the IEEE 118-bus test system, lines 2, 12, 24, 42, and 58 are adopted as candidate outage lines.
- (6) *System parameter modification*: The transmission limit of all lines in the IEEE 118-bus system is set to 200 MW. The IEEE 39-bus test system remains unchanged.
- (7) *Candidate planning buses and lifespan*: In the IEEE 39-bus system, WT, PV, and ESS are allowed to be installed at candidate buses {1,4,5,19,26}, {8,13,14,19,26}, and {1,5,9,21,27}, respectively. In the IEEE 118-bus test system, the candidate buses for WT, PV, and ESS are {5,7,38,83,106}, {2,20,67,88,103}, and {5,20,67,83,106}, respectively. All equipment is assumed to have a lifespan of 15 years.
- (8) *Economic parameters*: The unit investment costs for WT and PV installations are \$260/kW and \$220/kW, respectively. For ESS, the energy capacity cost is \$174/kWh, and the power capacity cost is \$278/kW. The unit costs of load shedding and renewable curtailment are set to \$3850/MW and \$3150/MW, respectively. The operating costs are specified as \$25/MW for thermal units and \$6/MW for ESS.
- (9) *Solver and convergence settings*: All optimization models are solved using Gurobi 10.0.3 and MATLAB R2023b on a work-station with a 12th Gen Intel Core i5-12600KF @ 3.70 GHz, 32 GB RAM, and Windows 11. The Mixed Integer Programming (MIP) gap is uniformly set to 2% for all methods.
- (10) *Reliability constraint setup*: The upper limit of EENS in reliability constraints for M4–M5 is set equal to the converged EENS value obtained from M2 after iterative computation. In this paper, $EENS^{max} = 18,406.40$ MWh. M3 is infeasible under this constraint, so the reliability bound is relaxed accordingly.
- (11) *ESS model*: The ESS is modeled following the common formulation, with detailed model implementation referring to References [33,55–57].
- (12) *Renewable energy penetration and fluctuation coefficients*: The renewable penetration rate β is set to 30%. The load fluctuation coefficient τ and renewable fluctuation coefficient ζ are assigned as 5% and 10%, respectively.

Table 2. Methodology.

Method	Detail
M1	Stochastic planning without considering reliability [6].
M2	Two-level iterative planning model, considering reliability using the Monte Carlo simulation [22].
M3	The non-iterative model uses simplified surrogate method neglecting wind power and line outage effects [33].
M4	The proposed method without the MRSM framework.
M5	The proposed method with the MRSM framework comprises four clusters.

5.2. IEEE 39-Bus Test System

To evaluate the performance of the proposed method, the IEEE 39-bus test system was employed. The cost components and installed capacities of each planning method are summarized in Table 3 and Table 4, respectively. The reliability costs of M1 and M2 are obtained through post-planning assessments, while M3–M5 embed reliability into the op-

timization model. M2 calculates reliability via the DC OPF model and adopts iterative optimization to generate high-quality solutions, which serves as the benchmark reference. Acceleration methods in network-constrained optimization must be judged by decision accuracy and robustness, not only by faster solution time [58,59]. We quantified the decision quality of the proposed method according to how closely their optimized results approximated the outcomes of M2. Partial simulation results may benefit from approximation errors, leading to planning solutions that outperform M2. However, the target of this work is to accelerate computation while retaining satisfactory solution accuracy, rather than pursuing superior planning results beyond the benchmark level.

Table 3. Cost comparison of different methods in the IEEE 39-bus test system.

Method	Investment Cost (k\$)	Operating Cost (k\$)	Reliability Cost (k\$)	Total Cost (k\$)
M1	93,537.97	402,024.36	998,761.51	1494,323.84
M2	106,356.33	391,543.97	70,864.65	568,764.95
M3	129,806.07	392,583.30	73,725.64	596,115.01
M4	93,861.28	401,998.15	70,864.65	566,724.08
M5	100,165.65	396,823.44	70,864.65	567,853.74

Table 4. Installed capacity comparison of different methods in the IEEE 39-bus test system.

Unit	Bus	Installed Capacity of Different Methods (MW)				
		M1	M2	M3	M4	M5
WT	1	500	471.94	380.73	433.03	444.67
	4	500	436.23	380.73	437.21	394.72
	5	0	166.62	380.73	148.05	171.13
	19	0	215.13	380.73	200.82	205.07
	26	456.25	274.42	380.73	237.97	242.78
	sum	1456.25	1564.52	1903.65	1457.08	1458.37
PV	8	342.29	499.14	205.82	492.07	496.34
	13	500	330.09	205.82	303.79	308.08
	14	0	317.40	205.82	316.10	310.82
	19	0	99.24	205.82	99.50	95.07
	26	500	126.71	205.82	128.49	125.95
	sum	1342.29	1372.58	1029.10	1339.95	1336.26
ESS	1	137.47	203.90	400	297.62	187.74
	5	181.54	202.95	400	170.96	214.02
	9	79.84	247.98	400	97.00	213.52
	21	149.91	307.40	400	184.57	270.46
	27	400	300.56	400	210.29	285.29
	sum	948.76	1262.79	2000	960.44	1170.03

Table 3 shows that M1 exhibited the highest reliability cost and total cost, indicating the poorest reliability performance, as reliability is not accounted for in this method. By incorporating OPF-based reliability assessments, M2 achieved accurate results. Relative to M1, M2 increased investment by 12,818.36 k\$, but reduced the reliability cost by 927,896.86 k\$, leading to a considerable decrease in total cost and achieving a balance between economic efficiency and reliability. M3 resulted in higher investment, operational, and reliability costs compared with M2, which contradicts the practical expectations. Typically, adding renewable units reduces thermal generation, and increasing the ESS capacity enhances system reliability. Therefore, higher investment should be accompanied by a decrease in operational cost, reliability cost, or both. The unreasonable phenomenon ob-

served in M3 occurred because its simplified surrogate model failed to correctly compute reliability, leading to significant errors. A comparison of M4 and M5 with M2 shows that their investment cost errors were 11.75% and 5.82%, respectively, while the total cost errors were 0.36% and 0.16%. Clearly, M5 achieved higher accuracy than M4. Without the MRSM structure, M4 failed to capture the discontinuous characteristics of the reliability function, resulting in greater assessment errors relative to M5.

In Table 4, the installed capacity was analyzed from two perspectives. The first was the allocation of capacity among candidate buses, and the second was the total installed capacity of WT, PV, and ESS. In M1, the concentrated allocation of WT and PV capacity increased network vulnerability, thereby reducing system reliability. In contrast, M2–M5 demonstrated a more balanced capacity distribution, which effectively enhances reliability by mitigating network congestion. Among them, M3 exhibited uniform capacity deployment across all candidate buses, which deviated from the practical expectations. This allocation was caused by the defects of the simplified surrogate model, which cannot handle high-dimensional variables and equivalently simplifies all candidate buses of each device type as identical nodes. Moreover, the ESS in M3 was deployed at its maximum capacity, showing a notable discrepancy compared with M2. In comparison, the capacity allocations of M4 and M5 were closer to those of M2. The largest deviation in M5 occurred at WT bus 4 (less than 42 MW), while that in M4 appeared at ESS bus 9 (below 151 MW). Overall, the results show that the capacity allocation of M5 is more reasonable compared to M1, M3, and M4.

Regarding the total installed capacities of WT, PV, and ESS, M2 exceeded M1 by 108.27 MW, 30.29 MW, and 314.03 MW, respectively. This confirms that an appropriate increase in investment enhances system reliability, with ESS providing the greatest contribution. Relative to M2, M3 cut the renewable installation by 4.35 MW yet deployed an extra 737.21 MW of ESS, which explains its higher investment and operational costs. For M4 and M5, the total installed capacities of WT and PV were similar and close to those of M2. However, in terms of ESS, the deviation of M5 from M2 was only 92.76 MW, while that of M4 reached 302.35 MW. The deviations in cost and capacity of M5 mainly originate from the fitting error of the surrogate model and the numerical error of the McCormick relaxation. These deviations are acceptable in engineering practice. Because long-term GEP involves uncertainties such as load forecast errors, policy changes, and fuel price fluctuations, the influential magnitude of these uncertainties is typically much larger than the deviation between M5 and M2. Moreover, as discussed in Section 5.3, M5 offers significant computational improvements over M2. In summary, the analyses of cost and installed capacity demonstrate that the proposed method achieves a balance between economy and reliability through reasonable investment decisions.

To verify the effectiveness of MRSM, four surrogate modeling schemes were compared. PCE1 (2nd-order) and PCE1 (3rd-order) were constructed with second- and third-order polynomials, respectively, while PCE2 (2nd-order) and PCE4 (2nd-order) adopted two-cluster and four-cluster frameworks combined with second-order polynomials. Figure 5 presents the root mean square error (RMSE) of load shedding under various training set sizes. The error bars denote the standard deviation from six independent repeated tests. PCE1 (2nd-order) produced the largest overall RMSE. Nevertheless, its simple structure with fewer parameters suppressed parameter fluctuation induced by random sampling, leading to narrower error bars than PCE1 (3rd-order) and PCE2 (2nd-order). The RMSE of PCE1 (3rd-order) and PCE2 (2nd-order) rose sharply once the sample size exceeded 960 and 640, respectively, accompanied by severe fluctuations across distinct independent tests. As the sample quantity increased, neither the high-order polynomials nor low-order polynomials with insufficient clusters could precisely approximate the complicated implicit function. In contrast, PCE4 (2nd-order) maintained a consistently low

RMSE accompanied by negligible error bars, which verifies that the MRSMS improves the fitting accuracy by establishing dedicated surrogate models for separate subdomains of stochastic space.

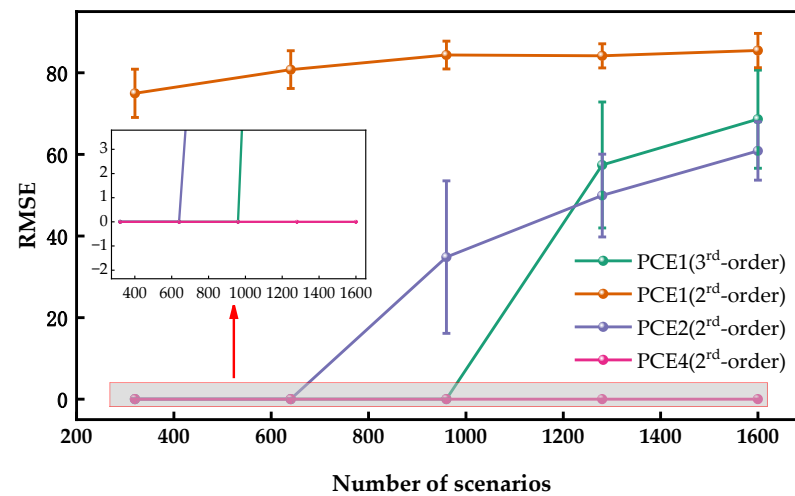


Figure 5. RMSE for different methods and number of scenarios in the IEEE 39-bus test system.

As indicated in [60,61], independent validation and uncertainty sensitive error reporting are mandatory when predictive models are used for engineering decisions. Therefore, 1600 test samples were adopted to conduct independent validation of the MRSMS, and none of these samples were involved in any of the training procedures. The load shedding results of all test samples covered the range of 0–6500.99 MWh, with an overall average load shedding of 259.09 MWh. Among them, the top 10% high-risk scenarios with the largest load shedding were the critical scenarios determining system reliability, with an average load shedding of 1864.03 MWh. Six independent training samples were used to train separate MRSMSs, and all trained models were applied to predict load shedding on the identical test set. All benchmark load shedding was obtained via the DC OPF model. Five quantitative metrics were adopted to validate the proposed MRSMS, including the mean absolute error (MAE), maximum error, tail RMSE of the top 10% high-risk scenarios, relative EENS error, and relative LOLP error. The statistical results are shown in Table 5.

Table 5. Multi-index validation results of MRSMS from six independent repeated trials.

Trial Number	MAE (MWh)	Max Error (MWh)	Tail RMSE (Top 10%) (MWh)	Relative EENS Error	Relative LOLP Error
1	70.03	1151.69	409.92	2.46%	3.40%
2	65.59	1275.73	388.26	2.51%	2.95%
3	61.49	1207.39	369.95	2.40%	2.49%
4	62.66	1170.10	371.92	2.34%	4.40%
5	63.80	1175.40	380.66	2.38%	3.31%
6	75.33	1283.08	448.79	2.62%	4.08%

Table 5 shows the relative EENS errors between 2.34% and 2.62%, while the relative LOLP errors varied from 2.49% to 4.40%. The MRSMS delivered reliable EENS and LOLP estimates for planning optimization. The tail RMSE of the top 10% high-risk scenarios was controlled within 448.79 MWh, which was only 24.07% of the average load shedding of high-risk scenarios. The MAE was in the range of 61.49–75.33 MWh, which was only 23.73–29.07% of the average load shedding of all samples and 3.30–4.04% of the average load shedding of the top 10% scenarios. The maximum error was 1283.08 MWh, account-

ing for merely 19.74% of the maximum load shedding (6500.99 MWh). Admittedly, the MRSM has limited fitting performance for individual extreme scenarios with large errors. As weighted statistical metrics, EENS and LOLP dilute the bias and yield small overall errors. However, this characteristic underestimates the impact of high-risk scenarios on planning outcomes and masks potential operational risks in planning schemes. In fact, high-risk scenarios dominate investment decisions in reliability-constrained GEP, even with low occurrence probabilities. Tighter upper bounds of EENS and LOLP are therefore recommended as safety margins for practical engineering applications in the proposed model. Raising the reliability standards guides the optimization model to deploy extra capacity, which alleviates risk in high-risk scenarios.

5.3. IEEE 118-Bus Test System

The IEEE 118-bus test system was further examined to demonstrate the scalability of the proposed approach. Table 6 summarizes the costs obtained from methods M1–M5. The results are similar to those observed in the smaller test system. M1 yielded the lowest investment cost but incurred the highest reliability cost. For M3, both investment and reliability costs were higher than those in M2, indicating that its reliability assessment method is inadequate and leads to overinvestment. Between M4 and M5, the latter provided results closer to M2, with relative errors of 0.67%, 0.08%, and 0.06% in investment cost, operating cost, and total cost, respectively. The installed capacity results are shown in Table 7. Among all methods, M5 produced capacity allocations at candidate buses that most closely matched those of M2. Although some deviations remain, such discrepancies are acceptable given the substantial improvements in computational efficiency. The results confirm that the proposed model remains effective for planning renewable energy and ESS in large-scale systems while accounting for reliability.

Table 6. Cost comparison of different methods in the IEEE 118-bus test system.

Method	Investment Cost (k\$)	Operating Cost (k\$)	Reliability Cost (k\$)	Total Cost (k\$)
M1	57,305.01	267,555.61	218,357.12	543,217.74
M2	62,874.75	262,157.90	53,871.02	378,903.67
M3	78,914.68	235,337.06	71,473.40	385,725.14
M4	67,039.32	257,106.63	53,871.02	378,016.97
M5	62,455.60	262,365.04	53,871.02	378,691.66

Table 7. Installed capacity comparison in the IEEE 118-bus test system.

Unit	Bus	Installed Capacity of Different Methods (MW)				
		M1	M2	M3	M4	M5
WT	5	500	199.20	308.28	194.17	197.94
	7	0	235.65	308.28	266.03	223.38
	38	366.98	274.05	308.28	292.70	279.34
	83	216.48	195.83	308.28	207.93	197.94
	106	0	193.46	308.28	188.94	197.94
	sum	1083.46	1098.19	1541.40	1149.77	1096.54
PV	2	0	284.93	167.56	255.83	261.26
	20	186.46	274.11	167.56	289.15	261.26
	67	0	0	167.56	5.17	0
	88	326.15	185.73	167.56	196.43	179.71
	103	377.83	201.52	167.56	172.95	197.94
	sum	890.44	946.29	837.80	919.53	900.18
ESS	5	189.10	198.71	149.58	229.11	197.05
	20	3.38	139.38	149.58	177.23	142.50

67	23.19	0	149.58	0	0
83	26.46	169.47	149.58	190.94	179.41
106	157.01	0	149.58	24.49	8.59
sum	399.14	507.56	747.9	621.77	527.55

To demonstrate the improvement in computational efficiency of the proposed method, Table 8 presents the computation time of M1–M5 for different test systems. The computation time of M3–M5 consists of the analysis time of the polynomial and the solution time. A total of 3500 reliability assessment scenarios were considered in M2–M5. These scenarios were used for separate surrogate model training yet generated via an identical approach. Furthermore, the set of N-1 contingencies adopted remained consistent with the contingency set Ω^k utilized in MRSIM construction. As system scale increased, the computation time for all methods grew accordingly. M1 achieved the shortest computation time because it does not integrate reliability assessment into the GEP model. M2 required the longest computation time while delivering the highest accuracy. Although M3–M5 provided substantially lower computation times, M5 yielded results closest to those of M2. With acceptable accuracy, M5 reduced the computation time by 47,020.35 s and 54,047.72 s relative to M2 in the two test systems. These results demonstrate that the proposed method substantially enhances the computational efficiency while preserving solution accuracy.

Table 8. Computation time comparison of different methods in different test systems.

Method	IEEE 39-Bus Test System		IEEE 118-Bus Test System	
	The Analysis Time of the Polynomial (s)	Solution Time (s)	The Analysis Time of the Polynomial (s)	Solution Time (s)
M1	-	5.46	-	143.10
M2	-	47,180.61	-	54,530.08
M3	10.58	266.47	12.43	2731.57
M4	17.34	23.69	19.27	286.56
M5	65.09	95.17	76.02	406.34

5.4. Sensitivity Analysis

Apart from fitting accuracy, stability and decision reliability are essential for surrogate-based optimization [58–62]. Accordingly, the sensitivity analysis of parameter N_c was carried out to quantify how this parameter affects the economic performance, reliability, and computational efficiency of the proposed model. Multiple cases with $N_c = \{2, 4, 6, 8, 12, 16, 20\}$ were simulated on the IEEE 39-bus test system. An identical upper bound of EENS was adopted for cases with $N_c \geq 4$, while the EENS limit was moderately relaxed for $N_c = 2$, since no feasible optimal solution can be obtained under the original reliability constraint. Detailed numerical results are summarized in Table 9.

Table 9. Solution results of the proposed model under different cluster numbers.

N_c	Total Cost (k\$)	Investment Cost (k\$)	Operating Cost (k\$)	Total Computation Time (s)	EENS (MWh)	LOLP (%)
2	621,765.68	80,111.69	458,933.63	111.05	21,485.80	1.94
4	567,853.74	100,165.65	396,823.44	160.26	18,406.40	3.13
6	566,384.49	93,488.90	402,030.93	361.33	18,406.40	4.96
8	571,453.91	95,993.72	404,595.54	322.01	18,406.40	1.19
12	568,185.30	99,549.81	397,770.83	1010.81	18,406.40	1.84
16	567,255.28	98,678.14	397,712.49	1029.20	18,406.40	2.49

20	567,275.91	98,681.36	397,729.89	1257.92	18,406.40	3.56
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Apparently, remarkable discrepancies exist in total cost, investment cost, and operating cost between the case of $N_c = 2$ and other configurations with $N_c = 4, 6, 8, 12, 16, 20$. The surrogate model under $N_c = 2$ lacked sufficient fitting capacity to capture the non-convex and discontinuous relationship between random variables and system reliability, which led to large assessment errors for reliability indices. No feasible solution could be obtained under the uniform reliability limit $EENS^{\max} = 18406.40$ MWh. The corresponding EENS constraint must be relaxed individually, which reflects the unstable performance of the MRSMS framework at this cluster setting. For $N_c \geq 4$, total cost, investment cost and operating cost fluctuated within a narrow range, and all of these configurations yielded identical EENS values. Compared with $N_c = 20$, $N_c = 4$ reduced the total computation time by 1097.66 s, while the relative errors of total cost, investment cost, and operating cost were merely 0.10%, 1.48% and 0.23%, respectively. Furthermore, the LOLP gap between $N_c = 20$ and $N_c = 4$ was only 0.0043. The above results verify that $N_c = 4$ enables a trade-off between numerical accuracy and computational burden with stable model performance and reliable results.

5.5. Reliability Verification

To further verify the true reliability of the planning decisions obtained by the proposed method, we substituted the planning schemes derived by M3, M4, and M5 into the DC OPF model. The 3500 reliability assessment scenarios were re-evaluated to obtain accurate true EENS values. These scenarios were used for separate surrogate model training yet generated via an identical approach. Furthermore, the set of N-1 contingencies adopted remained consistent with the contingency set Ω^K utilized in MRSMS construction. The results are shown in Table 10. For M3, substantial gaps existed between the true EENS and predicted EENS across both test systems. M3 adopted a simplified surrogate model. This model drastically overstates the real operational risks and neglects uncertainties from wind volatility and transmission line outages, which yielded a conservative planning scheme. Though this scheme delivers high reliability, it suffers poor economic efficiency and cannot satisfy the target of coordinated economic and reliable operation. For M4, the actual EENS was 101.75 MWh on the IEEE 39-bus system, 101.76% higher than its predicted value of 50.43 MWh. On the IEEE 118-bus system, its actual EENS was 17.03 MWh, 55.60% lower than the predicted value of 38.36 MWh. The single risk surrogate model cannot capture the non-convex, non-smooth traits of the reliability function, leading to heavily skewed operational risk estimations. In contrast, for M5 with MRSMS, the relative errors between predicted EENS and true EENS were only 4.14% and 4.01% for the IEEE 39-bus and IEEE 118-bus systems, respectively, which fall within an acceptable error range. To ensure that the planning solution strictly meets the actual reliability requirements, the reliability constraint can be appropriately tightened to account for potential deviations.

Table 10. True and predicted EENS obtained from different solution methods.

Test System	M3		M4		M5	
	True EENS (MWh)	Predicted EENS (MWh)	True EENS (MWh)	Predicted EENS (MWh)	True EENS (MWh)	Predicted EENS (MWh)
IEEE 39	17.39	52.46	101.75	50.43	52.61	50.43
IEEE 118	3.41	50.86	17.03	38.36	36.82	38.36

5.6. Validation of the Effectiveness of Relaxation

To verify the effectiveness of relaxation, three EENS indices, including non-relaxed EENS, relaxed EENS derived from M5, and true EENS, were compared. First, the planning solution of M5 was obtained, which contains the installed capacities of WT, PV, and ESS at each candidate node. Second, with the identical reliability assessment scenarios adopted in M5, the planning scheme and scenarios were inputted into the original unrelaxed PCE Formula (22). Polynomial values were calculated to acquire the load shedding of each scenario, based on which the non-relaxed EENS was further computed. Finally, a comparison among non-relaxed EENS, relaxed EENS, and true EENS is presented in Table 11. The relaxed EENS from M5 was 6.15 MWh lower than the non-relaxed result on the IEEE 39-bus system and 4.56 MWh lower on the IEEE 118-bus system. These differences are negligible for power systems with installed capacities on the order of thousands of megawatts. In addition, the relaxed EENS were consistently lower than the non-relaxed ones. This occurs because the solver, under looser variable bounds, tends to find solutions with lower reliability, making it easier to satisfy the reliability constraints. Furthermore, regardless of whether relaxation was applied, the EENS computed using the surrogate model deviated from the true EENS. This is because the M5 results are from the combined effects of PCE fitting error and relaxation error. Under the combined effects, they may sometimes cancel each other out, making the result closer to the actual value. The non-relaxed EENS always exceeds the true EENS, which guarantees that the actual system reliability outperforms the pre-set reliability. In contrast, the relaxed formulation may lead to unpredictable deviation in practical reliability performance.

Table 11. EENS calculated using different methods.

Test System	Non-Relaxed EENS (MWh)	Relaxed EENS (MWh)	True EENS (MWh)
IEEE 39	56.58	50.43	52.61
IEEE 118	42.92	38.36	36.82

6. Discussion

The surrogate model is reliable not only statistically, but also as a decision-support tool. This section assesses the practicability of the proposed surrogate model for engineering decision-making through four aspects: input–output interpretability, benchmark comparisons, reproducibility, and diverse evaluation dimensions.

6.1. Discussion of Input–Output Definition, Benchmark Comparison, and Reproducibility

Transparent input–output definition, benchmark comparison, and reproducibility constitute three indispensable prerequisites for an intelligent surrogate model [63]. First, the proposed MRSM establishes fully transparent input–output logic: its input set covers net-load stochastic variables, installed capacities, and N-1 contingency scenarios, while system EENS and LOLP are defined as explicit risk outputs. Moreover, the proposed surrogate model yields an explicit analytical expression linking input and output variables. Second, reliability assessment results solved via DC OPF take both network constraints and temporal coupling constraints into account, which therefore serve as a high-precision benchmark. Multiple error metrics are introduced to measure the prediction bias of MRSM under the test set, realizing benchmark comparisons. Third, Sections 3.1 and 3.2 present complete mathematical derivations of the MRSM, and Figure 4 visualizes the whole workflow from surrogate construction to embedding planning. All critical experimental settings, including scenario generation rules, training/test sample allocation, N-1 contingency set, scenario probability calculation, and solver parameters, are documented in Section 5.1, enabling reproducibility of the numerical cases.

6.2. Discussion of Diverse Assessment Dimensions

As stated in [64], a complete assessment containing sensitivity, validation, and robustness tests is required to fully reflect the engineering practicability of intelligent surrogate models. (1) In terms of sensitivity, targeted tests of cluster number N_c were carried out on the IEEE 39-bus system. Results prove that $N_c = 4$ delivers high prediction accuracy and stability. The fluctuation of planning outcomes is negligible when adopting larger cluster numbers. Corresponding sensitivity analysis on the IEEE 118-bus test system are left for future tests. (2) From the validation perspective, M5 with MRSM was validated on both IEEE 39-bus and IEEE 118-bus test systems. Compared with the benchmark method (M2), the proposed method maintained minor errors on both systems. The four-cluster strategy accurately captures discontinuous and non-convex reliability function, which verifies its generalization capacity across different networks. (3) Regarding robustness, the effectiveness of the proposed method under variable renewable penetrations, reliability thresholds, and network congestion conditions is discussed via mechanism analysis. On the one hand, the MRSM can be reused for varying renewable penetration and reliability thresholds without retraining. On the other hand, the optimized planning capacities under various constraints fall within the investment constraints. The surrogate training samples are uniformly sampled over investment constraints, thus guaranteeing steady accuracy under diverse reliability and renewable targets for both test systems. In addition, variations in network congestion exert ambiguous impacts on the nonlinearity of the implicit input–output function. Although $N_c = 4$ has been proven effective under fixed congestion modes of the IEEE 39-bus and IEEE 118-bus test system, its adaptability to variable congestion requires further numerical verification. Severe degradation of fitting precision under complex congestion can be mitigated by increasing the cluster number as an effective measure.

In summary of the above discussions, the proposed surrogate model achieves transparent input–output relationships, valid benchmark comparisons, and full reproducibility. However, supplementary sensitivity, validation, and robustness examinations remain necessary prior to its adoption for engineering decision-making.

7. Conclusions

This paper introduces a non-iterative reliability-constrained GEP model that aims to achieve a desirable trade-off between reliability and economy for power systems with high renewable penetration. Firstly, an MRSM is developed to represent the nonlinear and nonconvex relationships among uncertain variables, planning decisions, and system risks, replacing the OPF-based reliability assessment. Subsequently, the MRSM is embedded into the GEP framework to realize non-iterative solutions. The case results demonstrate the following. (1) The proposed method effectively allocates installed capacity to balance economy and reliability. (2) It significantly accelerates the solution process while maintaining acceptable accuracy. Specifically, on the IEEE 118-bus system, compared with the benchmark method (M2), it achieved errors of 0.67% in investment cost, 0.08% in operating cost, and 0.06% in total cost, reducing the computation time by 54,047.72 s. If further discussion is required regarding the sustainability contributions, it is necessary to correlate the planning model with measurable sustainability outcomes such as curtailment reduction, emissions, life cycle cost, or implementation feasibility [65,66].

The proposed framework carries several inherent limitations. First, it relies on simplified uncertainty assumptions, DC power flow approximations, and a static single-year planning formulation. Furthermore, flexible demand resources and detailed converter models are not incorporated within the GEP model. The fitting performance of the surrogate model under high-risk scenarios also still leaves considerable room for improvement. To expand the adaptability of the proposed method for high-renewable power systems,

future research will be carried out in the following aspects. (1) Develop source-load uncertainty models that better reflect practical operating conditions, while fully capturing the boundedness, correlation, and seasonal features of uncertain parameters. (2) Develop reliability-constrained GEP methods compatible with the AC OPF model. (3) Construct high-fidelity converter models and detailed flexible demand models, embedding them into the planning problem. (4) Extend the static single-year model to multi-stage dynamic GEP. (5) Develop an embedded clustering optimization strategy. The optimal cluster number will be set as an endogenous decision variable and solved simultaneously with planning variables to avoid repeated trial calculation for cluster selection. (6) Establish a multi-dimensional reliability assessment framework. Apart from EENS and LOLP, more risk indices such as voltage sag will be incorporated to quantify operational risks. Dedicated reliability indices will also be developed to strengthen the guiding role of high-risk scenarios in planning decisions.

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Nomenclature

The following variables are used in this manuscript:

Indices and Sets

$b/g/n$	Index of ESS/generators/buses.
$t/s/k$	Index of discrete periods/operation scenarios/contingencies.
$i/j/c$	Index of random variables/PCE coefficients/clusters.
$\Omega^{TH} / \Omega^{WT} / \Omega^{PV} / \Omega^{ES} / \Omega^B$	Set of indices of all thermal unit/WT/PV/ESS/buses.
$\Omega^{TD} / \Omega^S / \Omega^{TS} / \Omega^K / \Omega^C$	Set of typical days/reliability assessment scenarios/typical scenarios/contingencies/clusters.
T	Set of the periods.
Variables	
$x_{(\cdot)}$	Random input variable.

$\mathbf{x}$	Vector of random input variable.
$\xi_{(\cdot)}$	Standardized random input variable.
ξ	Vector of standardized random input variable.
$ENS_{c,k,s}$	Energy not supplied in scenario s , contingency k , and cluster c .
$EENS$	Expected energy not served.
$LOLP$	Loss of load probability.
$\mathbf{P}_s$	Vector of operation variables in scenario s .
$\mathbf{X}^{inv}$	Investment variables determined by the first level.
C^{total}	Total system cost of the proposed model.
C^{inv}	Investment cost of the proposed model.
C^{op}	Operation cost of the proposed model.
C^r	Reliability cost of the proposed model.
$P_g^{WT,inv} / P_g^{PV,inv}$	Installed capacity of WT/PV g .
$E_b^{ES,inv} / P_b^{ES,inv}$	Installed capacity of energy/power facility to ESS b .
$P_{g,t,d,s}^{TH}$	Power output of thermal unit g in period t , typical day d , and scenario s .
$P_{g,t,d,s}^{WT} / P_{g,t,d,s}^{PV}$	Power output of WT/PV g in period t , typical day d , and scenario s .
$P_{g,t,d,s}^{WT,cur} / P_{g,t,d,s}^{PV,cur}$	Power curtailments of WT/PV g in period t , typical day d , and scenario s .
$P_{b,t,d,s}^{ES,dis} / P_{b,t,d,s}^{ES,ch}$	Discharging/charging power of ESS b in period t , typical day d , and scenario s .
$SR_{t,d,s}^{up} / SR_{t,d,s}^{down}$	Upward/downward spinning reserve in period t , typical day d , and scenario s .
$\mathbf{f}_{t,d,s}$	Vector of line transmission power flow in period t , typical day d , and scenario s .
$\mathbf{P}_{t,d,s}^{TH}$	Vector of power output of thermal unit in period t , typical day d , and scenario s .
$\mathbf{P}_{t,d,s}^{WT} / \mathbf{P}_{t,d,s}^{PV}$	Vector of power output of WT/PV in period t , typical day d , and scenario s .
$\mathbf{P}_{t,d,s}^{ES,dis} / \mathbf{P}_{t,d,s}^{ES,ch}$	Vector of discharging/charging power of ESS in period t , typical day d , and scenario s .
$l_{c,k,s}$	Binary variable indicating whether load shedding occurs in scenario s , contingency k , and cluster c .
$y_{c,k,s}$	Load shedding of scenario s in contingency k , cluster c .
$mc_{c,k,s,j}$	Auxiliary variables for the j -th term of the surrogate model in scenario s , contingency k , and cluster c .
Parameters	
$\mathbf{B}, \mathbf{D}, \mathbf{E}, \mathbf{F}, \mathbf{G}, \mathbf{I}, \mathbf{J}$	Matrices of coefficients.
$N_c / N_k / N_{TD}$	Number of all clusters/all contingencies/all typical days.
N_{nl} / N_{nl}^*	Number of quadratic terms of the net-load variables before/after sparse expansion.
N_I / N_I^*	Number of quadratic terms of the installed variables before/after sparse expansion.
$\rho_{c,k,s}$	Scenario probability in scenario s , contingency k , and cluster c .
$\mathbf{f}^{\min} / \mathbf{f}^{\max}$	Vector of maximum/minimum line transmission power flow.
IC_g^{WT} / IC_g^{PV}	Unit installed cost of WT/PV g .
$IC_b^{ES,e} / IC_b^{ES,p}$	Unit installed cost of energy capacity/power capacity in the ESS b .
OC_g^{TH} / OC_b^{ES}	Unit operation cost of thermal unit g /ESS b .
$C_g^{WT,cur} / C_g^{PV,cur}$	Penalty cost of power curtailment for WT/PV g .
$P_g^{TH,max} / P_g^{TH,min}$	Maximum/minimum power output of thermal unit g .
$P_g^{WT,max} / P_g^{PV,max}$	Maximum installed power capacity of WT/PV unit g .

$E_b^{ES,max}$	Maximum installed energy capacity of ESS b .
$D_{n,t,d,s}$	Predicted load of bus n in period t , typical day d , and scenario s .
$\mathbf{D}_{t,d,s}$	Vector of predicted nodal loads in period t , typical day d , and scenario s .
M	A large constant.
$VOLL$	Value of load loss, representing the cost coefficients of load shedding.
$EENS^{max}$	Maximum of the expected energy not served.
$LOLP^{max}$	Maximum loss of load probability.
$\mathbf{PTDF}$	Power transfer distribution factors.
$\eta_{t,d,s}^{WT} / \eta_{t,d,s}^{PV}$	The output power coefficients of the WT/PV g in period t , typical day d , and scenario s .
$\xi_{c,k,s,m}^U / \xi_{c,k,s,n}^L$	Upper/lower bounds for standardized planning variables.

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