Multi-failure reliability evaluation of wind turbine blades under extreme conditions

Xue-Qin Li[a,b], Qiu-Sheng Li[a*], Matthias G.R. Faes[b,c], Michael Beer[c,d,e]

[a] Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong, China

[b] Chair for Reliability Engineering, TU Dortmund University, Leonhard-Euler-Straße 5, Dortmund 44227, Germany

[c] International Joint Research Center for Resilient Infrastructure & International Joint Research Center for Engineering Reliability and Stochastic Mechanics, Tongji University, Shanghai, 200092, China

[d] Institute for Risk and Reliability, Leibniz Universität Hannover, Callinstr. 34, Hannover, 30167, Germany

[e] Department of Civil and Environmental Engineering, University of Liverpool, Liverpool L69 3BX, UK

Abstract: Wind turbine blades operating under extreme wind conditions are subjected to highly stochastic aerodynamic loading, which induces complex and strongly nonlinear structural responses and consequently introduces pronounced uncertainties into their structural behavior. To address these challenges, this study proposes an extreme-aware sparse Gaussian process regression with distributed collaborative (E-SGPR-DC) framework for system-level reliability analysis of wind turbine blades. The proposed framework combines a distributed collaborative strategy to effectively combine local sub-model information with global response characteristics and embeds an extreme-aware learning mechanism to enhance prediction fidelity in high-stress and near-failure regions. By further integrating probabilistic strength characterization and Gaussian Copula-based dependency modeling, a unified multi-failure reliability evaluation framework is established. Numerical investigations demonstrate that the proposed approach significantly improves prediction accuracy and computational efficiency compared with conventional surrogate methods, while providing more reliable estimates of structural reliability under correlated failure modes. These results indicate that the E-SGPR-DC framework offers a robust and efficient tool for structural reliability evaluation and design of wind turbine blades under realistic and extreme operational uncertainties.

Keywords: wind turbine blades; structural reliability; regression; correlation

1. Introduction

As critical components in renewable energy generation systems, wind turbine blades experience highly stochastic aerodynamic loads under extreme wind events such as hurricanes or typhoons [1-2]. These severe wind conditions

* Corresponding author: Prof. QS Li, email: bcqsli@cityu.edu.hk.

significantly amplify load fluctuations, potentially causing excessive deformation, elevated stress levels, and compromised structural strength, ultimately leading to premature or catastrophic failures [3-5]. Therefore, conducting comprehensive multi-failure mode analyses is crucial for accurately evaluating blade safety under extreme operational conditions. Furthermore, the inherent uncertainties in extreme wind loads, material variability, and manufacturing inconsistencies introduce substantial dispersion among multiple failure modes [6-8], posing considerable challenges to precise reliability predictions. Consequently, robust multi-failure mode reliability analysis methodologies are essential to effectively quantify safety margins, enhance prediction accuracy, and ensure reliable blade operation in realistic extreme scenarios.

Probabilistic reliability analysis methods have emerged as powerful tools to address uncertainties in structural systems [9-11]. These methods leverage statistical principles to capture the inherent randomness and variability in input parameters and response outcomes, thus enabling a reliability evaluation under stochastic conditions [12-14]. Among the various probabilistic approaches, Monte Carlo Simulation (MCS) is frequently utilized due to its straightforward conceptual implementation and ability to accurately characterize reliability under diverse uncertainty conditions [15-17]. However, MCS demands extensive computational resources, particularly when evaluating complex nonlinear structural responses or analyzing rare failure events, making it impractical for routine engineering analyses and design optimization [18-20]. Surrogate modeling has emerged as an effective tool for reducing computational cost in reliability evaluation [21-23]. Typical surrogate methods, including Quadratic Polynomial (QP) [24-26], Support Vector Regression (SVR) [27-29], Artificial Neural Networks (ANN) [30-32], Ensemble learning [33-35], Kriging models [36-38], have already demonstrated substantial benefits in reliability evaluation across conventional mechanical and civil engineering structures due to their computational effectiveness and accuracy [39-41]. Nevertheless, under highly stochastic aerodynamic conditions and strong nonlinear coupling among failure modes, conventional surrogate models frequently struggle to effectively capture extreme structural responses and intricate dependencies among various failure modes, thus limiting their predictive accuracy and efficiency in real-world engineering applications [42-44]. Related GP-based frameworks, including multi-output Gaussian Processes [45], co-kriging [46], and physics-informed Gaussian process regression [47], have also been developed for correlated-response prediction and surrogate modeling. However, these methods do not directly address the present setting, where heterogeneous structural responses, limited high-fidelity samples, and reliability-critical extreme responses must be handled simultaneously under extreme wind loading. Therefore, a distributed collaborative strategy is further introduced and combined with an extreme-aware sparse GP model in this study.

To address these limitations, the distributed collaborative (DC) strategy has emerged as an approach for accurately capturing complex interdependencies among structural responses and multiple failure modes[48-51]. DC-based frameworks have demonstrated the capability to effectively handle correlations among multiple failure modes. For instance, Song et al. [52] proposed a cascaded synchronous regression strategy to model dependent structural responses in aeroengine components, showing improved accuracy in multi-level reliability evaluation under coupled loading conditions. Xiao et al. [53] introduced a parallel learning Kriging framework with dependency-aware collaboration, effectively improving surrogate performance for systems with correlated outputs. Compared with traditional surrogate modeling approaches, these DC-based methods significantly enhance the capability to capture nonlinear correlations and improve predictive robustness for complex structural systems. However, when applied to wind turbine blades operating under extreme wind conditions, existing DC strategies still face substantial challenges in accurately resolving extreme structural behaviors.

To address the above challenges, this study proposes an extreme-aware sparse Gaussian process regression with distributed collaborative (E-SGPR-DC) framework for the system-level reliability analysis of wind turbine blades. The proposed framework integrates a distributed collaborative strategy to improve multi-response modeling of stress, strain, and deformation by reducing modeling complexity, and embeds an extreme-aware learning mechanism to explicitly enhance prediction fidelity in high-stress and near-failure regions. Overall, the technical route consists of three components: extreme-aware surrogate construction for nonlinear structural responses, distributed collaborative modeling for correlated outputs, and dependency-aware system reliability evaluation under multi-failure conditions. Accordingly, the novelty of this study lies in three aspects: (i) an extreme-aware sparse Gaussian process regression model for improving prediction fidelity in extreme-response regions under limited high-fidelity samples; (ii) a distributed collaborative strategy for improving multi-response modeling by reducing modeling complexity; and (iii) a system-level multi-failure reliability evaluation framework established by integrating the E-SGPR-DC surrogate with probabilistic strength characterization and Gaussian Copula-based dependency modeling.

The remainder of this paper is structured as follows: Section 2 elaborates the theoretical framework and methodologies of the proposed E-SGPR-DC. Section 3 outlines deterministic and probabilistic analyses for wind turbine blades under coupled aero-structural uncertainties. Section 4 systematically evaluates and compares the modeling accuracy, computational efficiency, and reliability prediction performance of the E-SGPR-DC framework. Finally, Section 5 summarizes the main conclusions.

2. Basic theory

This section establishes the theoretical foundation of the proposed framework, consisting of (i) an extreme-aware sparse Gaussian process regression model (E-SGPR), (ii) a distributed collaborative construction for multi-response decomposition (E-SGPR-DC), and (iii) a dependency-aware multi-failure probabilistic analysis scheme. Overall, the proposed workflow first constructs extreme-aware surrogate models for multiple structural responses, then characterizes their probabilistic dependencies, and finally performs system-level reliability evaluation under multiple failure modes.

2.1. *Extreme-aware sparse Gaussian process regression* (*E-SGPR*)

Wind turbine blades exhibit highly nonlinear responses under stochastic loading conditions, where stress, strain, and deformation often present localized peaks and heavy-tailed distributions[54]. Due to the high computational cost of fluid-structure simulations, only a limited number of training samples are available, making it difficult to construct accurate surrogate models in extreme-response regions. To address these challenges, this study adopts an extreme-aware sparse Gaussian process regression (E-SGPR) model, which enhances conventional sparse Gaussian processes with an extreme-aware likelihood formulation to improve predictive capability in high-risk regions. The principle of the E-SGPR model is illustrated in **Fig. 1**.

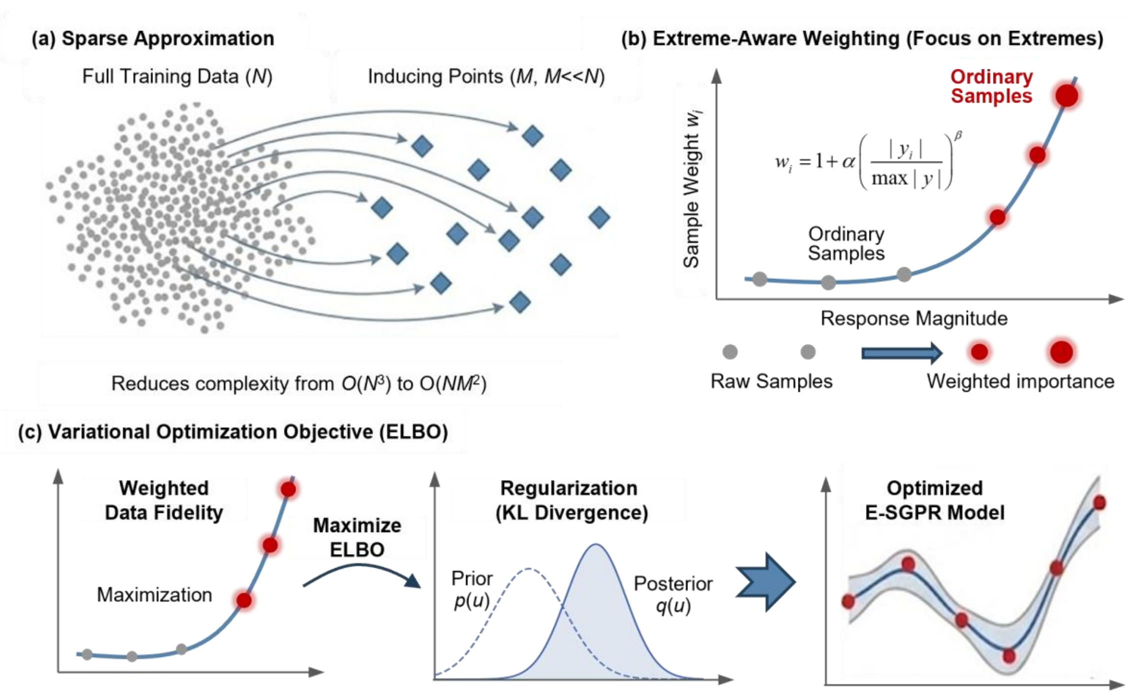


Fig. 1 The principle of E-SGPR model.

The mathematical modeling process is described as follows: Gaussian process regression [55] treats the structural response function $f(x)$ as a stochastic function with a Gaussian process prior

$$f(x) \sim GP(0, k(x, x')) \tag{1}$$

where $k(x, x')$ is a covariance kernel describing the correlation between any two input points. This formulation allows GPR to flexibly represent nonlinear variations in structural responses and to provide predictive uncertainty. However, the full GPR model requires inversion of an $N\times N$ covariance matrix, resulting in a computational cost of $O(N^3)$, which becomes prohibitive even for moderate dataset sizes. To improve computational tractability and stability, the sparse GPR approximation introduces a set of inducing points $Z = \{z_m\}_{m=1}^{M}$ with $M << N$. Letting $u = f(Z)$ denote the latent function values at these inducing points, the predictive mean for a test input x can be expressed as

$$\hat{f}\left(x\right) = k_Z^T K_{ZZ}^{-1} u \tag{2}$$

where k_z denotes the covariance vector between test input x and inducing inputs Z, and K_{ZZ} is the covariance matrix computed among the inducing points. This approximation significantly reduces the computational burden to $O(NM^2)$, while retaining the essential probabilistic characteristics of the full Gaussian process.

To avoid overfitting and improve numerical stability under small-sample conditions, variational inference (VI) [56] is employed to optimize kernel hyperparameters and inducing-point distributions. By introducing a variational posterior $q(u)$, VI maximizes the evidence lower bound ELBO

$$\mathcal{L}_{\text{ELBO}} = \mathbb{E}_{q(f)}[\log p(y \mid f)] - \text{KL}(q(u) \mid p(u)) \tag{3}$$

where the likelihood term promotes fidelity to observed data, and the Kullback-Leibler (KL) divergence regularizes the variational posterior for stable hyperparameter learning; $p(u)$ denotes the prior distribution of inducing points.

However, due to the imbalance between moderate and extreme responses in wind turbine simulations, the conventional likelihood term is dominated by moderate-response samples, leading to systematic underestimation of responses at extreme magnitudes. To enhance model sensitivity to extreme behavior, an extreme-aware weighting mechanism is incorporated into the likelihood. Each training sample is assigned a weight

$$w_i = 1 + \alpha \left(\frac{|\, y_i \,|}{\max_j |\, y_j \,|} \right)^{\beta} \tag{4}$$

where α is a baseline weighting coefficient introduced to ensure that all samples retain a minimum contribution during training, and β controls the sensitivity of the weighting function to the response magnitude. Since the response magnitude is normalized by $\max_j|y_j|$, the weighting remains scale-controlled. In this study, α and β are selected to balance overall fitting stability and prediction fidelity in extreme-response regions. Incorporating this weighting mechanism into the variational objective yields the extreme-aware ELBO

$$\mathcal{L}_{\mathrm{ELBO}}^{\mathrm{ext}} = \sum_{i=1}^{N} w_i, \mathbb{E}_{q(f_i)}[\log \mathcal{N}(y_i \mid f_i, \sigma_n^2)] - \mathrm{KL}(q(u) \mid p(u)) \tag{5}$$

where σ_n^2 denotes the observation noise variance. This formulation amplifies gradients associated with stress, strain, or deformation values, enabling the surrogate to more accurately capture sharp nonlinear transitions and localized peaks without compromising global stability. The resulting E-SGPR model therefore provides (i) robust nonlinear learning under limited training samples, (ii) enhanced fidelity in extreme-response regions, and (iii) predictive uncertainty required for reliability evaluation. As a result, E-SGPR serves as the core surrogate module in the proposed multi-failure analysis framework, providing reliable and physically meaningful predictions for downstream probabilistic evaluation.

2.2. E-SGPR with DC, E-SGPR-DC

In the multi-failure evaluation of wind turbine blades, the structural responses of stress, strain, and deformation exhibit distinct physical characteristics and heterogeneous nonlinear behaviors. Constructing a single monolithic multi-output surrogate often results in gradient interference and compromised accuracy, as the shared model structure cannot simultaneously accommodate the differing scales and nonlinearities of multiple failure-related responses. To resolve these conflicts, the distributed collaborative (DC) strategy is embedded into the E-SGPR framework, thereby establishing the E-SGPR-DC model, which decomposes the multi-output regression task into independent response-specific surrogate sub-models. Each sub-model is independently trained using the E-SGPR, while all sub-models share the same physical input variables, thereby maintaining physical coherence across responses. The method of E-SGPR-DC is summarized as follows:

Step 1: Identification of responses and input variables. Stress, strain, and deformation are defined as the key structural responses, and a unified set of random inputs describing wind loading, material properties, and geometric parameters is established.

Step 2: High-fidelity data generation. A small but accurate dataset is obtained through fluid-structure simulations, providing representative nonlinear structural responses for surrogate training.

Step 3: Distributed decomposition of multi-response regression. The original multi-output task is decomposed into three independent single-response problems, reducing interference among heterogeneous response behaviors.

Step 4: Construction of independent E-SGPR sub-models. For each response, an E-SGPR model is trained using sparse Gaussian processes with an extreme-aware mechanism to enhance learning in high-risk regions.

Step 5: Assembly of the distributed collaborative surrogate. The independently trained E-SGPR models are combined to form a coherent multi-response predictor through their shared input space.

Step 6: Large-scale surrogate-based propagation. A large number of input samples are evaluated using the E-SGPR-DC model to efficiently approximate multi-response behavior under uncertainty.

The proposed E-SGPR-DC mathematical model is summarized as follows: Let the input random variables be denoted by *x*, and define the three critical structural responses as

$$Y^{(1)} = \sigma, \quad Y^{(2)} = \varepsilon, \quad Y^{(3)} = d \tag{6}$$

where *σ*, *ε*, *d* denote stress, strain and deformation; Within the DC architecture, the multi-response regression problem is

$$x \rightarrow \{\sigma, \varepsilon, d\} \tag{7}$$

where *x* denotes the set of input random variables (e.g., material properties, geometric parameters, and operating conditions), which are reformulated as three independent single-response mappings:

$$\hat{\sigma} = f_{\sigma}(x), \qquad \hat{\varepsilon} = f_{\varepsilon}(x), \qquad \hat{d} = f_{d}(x), \tag{8}$$

where $f_\sigma(x)$, $f_\varepsilon(x)$, and $f_d(x)$ denote the response-specific surrogate mappings from the uncertain input variables to stress, strain, and deformation, respectively, which are constructed using the E-SGPR model. Specifically, for each response *Y*(*k*), an inducing-point set *Z*(*k*) and variational posterior $q(u^{(k)})$ are optimized by maximizing the extreme-aware evidence lower bound

$$\mathcal{L}_{\mathrm{ELBO}}^{\mathrm{ext}\,(k)} = \sum_{i=1}^{N} w_i^{(k)} \mathbb{E}_{q(f_i^{(k)})}\left[\log \mathcal{N}\left(Y_i^{(k)} \mid f_i^{(k)}, \sigma_n^{2(k)}\right)\right] - \mathrm{KL}\left(q(u^{(k)}) \| p(u^{(k)})\right) \tag{9}$$

where $\sigma_n^{2(k)}$ denotes the noise variance of the *k*-th response; $w_i^{(k)}$ is the weight of the *i*-th training sample corresponding to the *k*-th response. Yielding three calibrated single-response E-SGPR models. Because all sub-models share the same input variables but maintain independent kernel hyperparameters and inducing-point distributions, E-SGPR-DC is able to adaptively capture the distinct nonlinear patterns associated with stress concentration, localized strain amplification, and deformation gradients. Once each sub-model is trained, the distributed collaborative predictor is constructed by assembling the three E-SGPR estimators

$$\hat{Y}(x) = \left\{ f_{\sigma}(x),\, f_{\varepsilon}(x),\, f_{d}(x) \right\} \tag{10}$$

which provides a multi-response prediction. This “divide-and-collaborate” treatment retains the physical relationships among responses through their shared dependency on the same uncertain inputs, while preventing the convergence issues encountered in tightly coupled multi-output surrogates. By decomposing the multi-response task into several response surrogate modeling processes, the DC strategy reduces the modeling complexity of multi-response learning.

The distributed collaborative strategy provides two key advantages. First, it enables response-specific kernel learning and inducing-point placement, thereby improving predictive accuracy in regions where stress, strain, and deformation exhibit distinct nonlinear characteristics. Second, by decoupling heterogeneous responses into independent E-SGPR sub-models, the framework avoids gradient interference and parameter competition, which substantially enhances training stability under small-sample conditions. Response decoupling may reduce accuracy when multiple responses already share similar physical scales, smooth global trends, and a sufficiently stable common input-output mapping, so that a unified model can learn them effectively together. In this study, stress, strain, and deformation exhibit different physical scales and heterogeneous nonlinear behaviors, while all response-specific sub-models are trained using the same input sample set and paired outputs. Therefore, decomposition reduces modeling difficulty without losing the common data basis among responses. As a result, the E-SGPR-DC architecture offers an efficient, scalable, and physically interpretable surrogate for wind turbine blades reliability analysis.

2.3. The framework of multi-failure probabilistic analysis

The multi-failure probabilistic evaluation integrates the E-SGPR-DC surrogate predictions with statistical strength models and dependency formulations to establish a system-level reliability framework. In this setting, the E-SGPR-DC surrogate provides high-fidelity predictions of the stress, strain, and deformation responses at multiple critical blade locations, while the probabilistic analysis quantifies the likelihood that these responses exceed corresponding strength limits. By combining response prediction, strength randomness, and inter-location dependencies, the framework enables a dependency-aware reliability evaluation under extreme wind loading conditions. The specific modeling process is illustrated in **Fig. 2**.

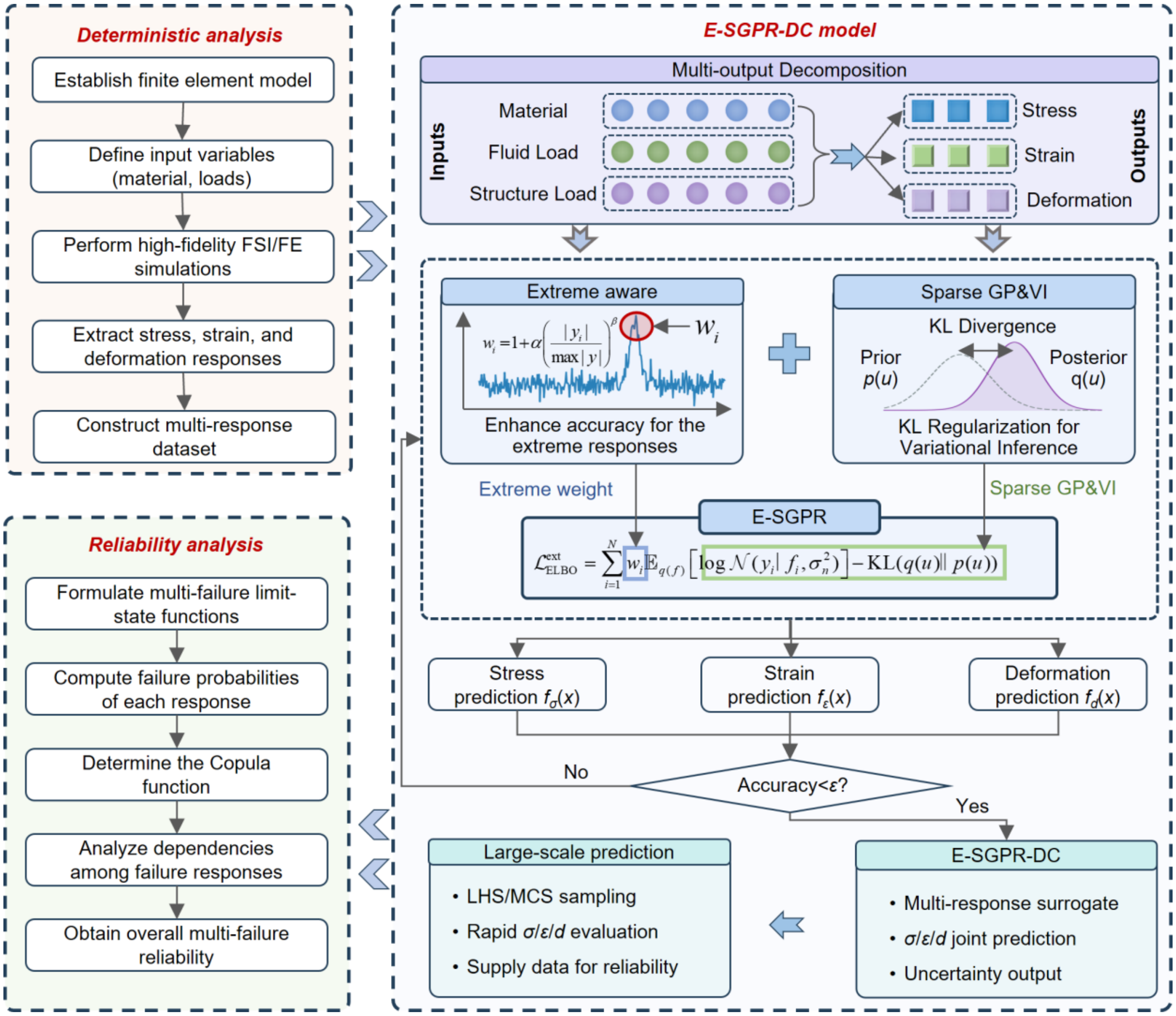


Fig. 2 The modeling process of E-SGPR-DC method

The E-SGPR-DC is applied independently at each critical blade location, producing the predicted multi-response vector $\hat{Y}_p(x)$. Let the blade contain P critical locations, and denote the E-SGPR-DC predicted responses at location p as

$$\hat{Y}_p(x) = \left(\hat{\sigma}_p(x), \hat{\varepsilon}_p(x), \hat{d}_p(x)\right) \tag{11}$$

where $\hat{\sigma}_p(x)$ the predicted stress at location p; $\hat{\varepsilon}_p(x)$ the predicted strain at location p; $\hat{d}_p(x)$ the predicted deformation at location p. Given the predicted structural responses, the limit state function for location p is defined as

$$g_p(x) = S_p - H_p\left(\hat{Y}_p(x)\right) \tag{12}$$

where S_p denotes the random structural strength, and $H_p\left(\hat{Y}_p(x)\right)$ denotes the response-to-strength measure. The reliability margin is governed by the gap between the structural resistance S_p and the response-derived demand

$H_p\left(\hat{Y}_p(x)\right)$. When the structural response enters an extreme-response region, $H_p\left(\hat{Y}_p(x)\right)$ increases and approaches S_p, so the local reliability margin decreases. As this gap decreases, the estimated failure probability becomes more sensitive to response variation. Therefore, the proposed extreme-aware mechanism places greater emphasis on extreme-response samples to enhance predictive fidelity in the region's most critical to reliability-margin evaluation. Failure at location p occurs when $g_p(x) \leqslant 0$. The corresponding indicator function is defined as

$$I_p(x) = \begin{cases} 1, & g_p(x) > 0 \\ 0, & g_p(x) \le 0 \end{cases} \tag{13}$$

For a Monte Carlo sample set $\{x_i\}_{i=1}^{N}$, the marginal reliability of location p is estimated as

$$R_p = \frac{1}{N}\sum_{i=1}^{N} I_p(x_i) \tag{14}$$

To account for statistical dependencies across multiple locations, the joint distribution of the strength demand H_p or of the responses $\hat{Y}_p$ is constructed using a Gaussian Copula. Let $F_p(\cdot)$ denote the marginal CDF of $H_p(\hat{Y}_p)$ and define

$$u_p = F_p\left(H_p(\hat{Y}_p)\right) \tag{15}$$

Then the joint distribution of $\{H_p\}_{p=1}^{P}$ is represented as

$$f(H_1,\ldots,H_P) = C(u_1,\ldots,u_P;\mathbf{R})\prod_{p=1}^{P} f_p(H_p) \tag{16}$$

where $C(\cdot)$is the Gaussian Copula density and $\mathbf{R}$ is the correlation matrix estimated from the E-SGPR-DC predictions. This construction captures the nonlinear, spatially correlated failure behavior across multiple critical locations. This dependency modeling is directly relevant to practical reliability evaluation, since the correlation among critical responses and locations affects joint failure probability and system-level reliability. For the extreme-loading scenario considered in this study, the blade system is modeled as a series system, since failure at any critical location may affect the overall structural reliability. Alternative formulations, such as parallel, load-sharing, or progressive-failure models, may also be considered when redundancy or damage evolution is involved. The system-level limit state function becomes

$$g_{\text{sys}}(x) = \min_{1\le p\le P} g_p(x) \tag{17}$$

Hence, system failure occurs when $g_{\text{sys}}(x) \le 0$. The system-level failure probability and reliability are then given by

$$\begin{cases} P_{\mathrm{f,sys}} = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} \mathbf{1}\left(g_{\mathrm{sys}}(x_i) \le 0\right) \\ R_{\mathrm{sys}} = 1 - P_{\mathrm{f,sys}} \end{cases} \tag{18}$$

By integrating (i) the response-level predictions from the E-SGPR-DC surrogate, (ii) location-specific strength uncertainty, and (iii) Gaussian Copula–based dependency modeling, the proposed framework provides an accurate and interpretable system-level reliability characterization. This formulation captures nonlinear multi-failure behavior, inter-location correlations, and extreme-response sensitivity, enabling robust reliability evaluation of wind turbine blades under severe stochastic wind excitation.

3. Deterministic analysis

To capture the structural responses of wind turbine blades under complex aerodynamic loading, a deterministic fluid-structure interaction (FSI) analysis was first performed. The blade geometry was based on the NREL 5-MW reference turbine, featuring a blade length of 61.5 m. For the fluid domain, a refined unstructured mesh was employed to ensure a high-fidelity representation of the flow characteristics. The solid domain, comprising the turbine blade structure, was discretized using structured hexahedral mesh techniques. This detailed mesh strategy effectively captured localized structural behaviors, including stress concentrations and deformation patterns. During the analysis, surface pressure distributions obtained from the fluid simulations were carefully mapped onto the structural finite element model, enabling an efficient FSI procedure. The deterministic results indicated a maximum stress of 46.9 MPa, a maximum strain of 1.17×10^{-3} m/m, and a maximum deformation of 1.79 m, as illustrated in **Fig. 3**. Spatially, the maximum deformation is concentrated near the blade tip, whereas the highest stress and strain are mainly observed in the blade root/transition region. This indicates that the critical failure-prone zone depends on the response type under the extreme-loading scenario considered.

Considering the inherent randomness and uncertainty associated with wind turbine operating conditions, a comprehensive probabilistic model of the input variables was subsequently established. Utilizing the Latin Hypercube Sampling (LHS) technique, 100 randomized input samples were generated based on the statistical characteristics of key input variables. Specifically, critical parameters including inlet velocity, turbulence intensity, turbulent-to-laminar viscosity ratio, air density, elastic modulus, Poisson's ratio, and rotational velocity were modeled as Gaussian random variables truncated at the physically admissible lower bound, i.e., truncated normal distributions [57]. The statistical descriptors, including means, standard deviations, kurtosis, and skewness of these variables, are detailed in **Table 1**. This rigorous probabilistic characterization provides a robust foundation for subsequent reliability evaluations of wind turbine blade systems under stochastic operating scenarios. These deterministic and probabilistic analyses together provide the high-fidelity input-output basis for subsequent E-SGPR-DC surrogate construction and reliability evaluation.

Table 1 Probabilistic characteristics of variables for wind turbine blades

Variables	Symbol	Unit	Distribution	Min	Max	Mean	Std.	Kurtosis	Skewness
Inlet velocity	U	m/s	Gaussian	28.733	31.521	29.986	0.568	-0.211	0.040
Turbulence intensity	I	-	Gaussian	0.143	0.159	0.150	0.003	0.563	0.347
Turbulent-to-laminar viscosity ratio	μ_t	-	Gaussian	9.430	10.472	9.984	0.228	-0.468	0.123
Air density	ρ_a	kg/m^3	Gaussian	1.142	1.280	1.222	0.025	0.100	-0.128
Dynamic viscosity of air	μ_a	kg/(m·s)	Gaussian	1.72e-05	1.91e-05	1.79e-05	3.89e-07	-0.006	0.484
Density	ρ	kg/m^3	Gaussian	1867	2047	1960	34	0.678	-0.225
Elastic Modulus	E	GPa	Gaussian	38	42	40	0.821	0.770	0.491
Poisson's Ratio	μ	-	Gaussian	0.212	0.230	0.221	0.004	-0.245	0.141
Rotational Velocity	ω	rad/s	Gaussian	2.386	2.640	2.496	0.049	0.008	0.332
Stress	σ	MPa	Gaussian	44.7	50.2	47.2	0.967	0.610	0.119
Strain	ε	m/m	Gaussian	1.10e-03	1.28e-03	1.18e-03	3.48e-05	0.182	-0.020
Deformation	d	m	Gaussian	1.685	1.928	1.800	0.048	0.037	-0.185

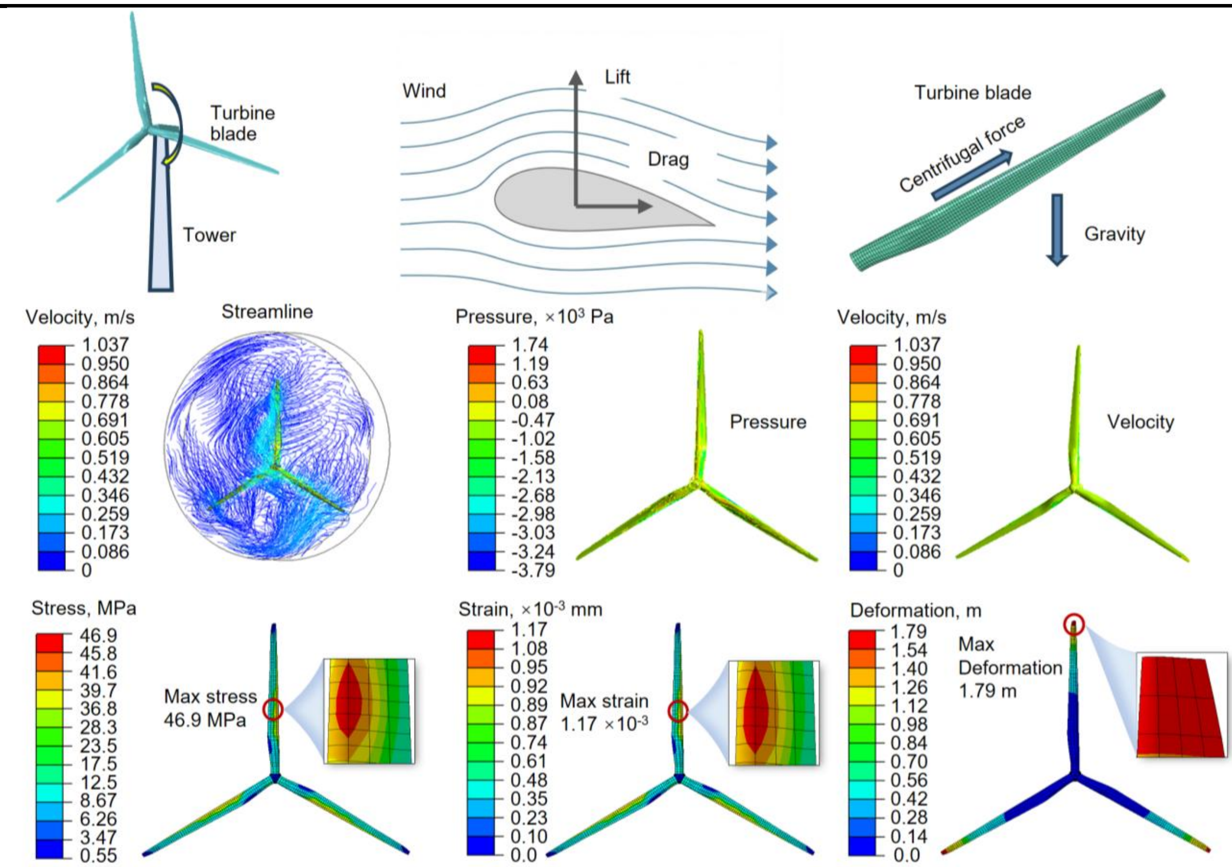


Fig. 3 Responses distributions on turbine blades

4. Multi-failure reliability evaluation of wind turbine blades

4.1. E-SGPR-DC modeling

To quantitatively evaluate the predictive accuracy of the proposed E-SGPR-DC framework, **Fig. 4** compares the regression performance of five representative surrogate models: Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGB), ANN with distributed collaborative (ANN-DC), extreme-aware sparse Gaussian process regression (E-SGPR), and the proposed E-SGPR with distributed collaborative (E-SGPR-DC). The results show that noticeable deviations between predicted and actual values for stress, strain, and deformation responses are observed for the ANN and XGB models, indicating limited generalization capability under extreme wind loading conditions. In contrast, the E-SGPR-DC model achieves near-perfect alignment of predictions and actual responses for both training and testing datasets. Specifically, predicted values closely follow the ideal reference line ($y = x$), demonstrating minimal scatter and exceptional consistency. These results confirm the effectiveness of the proposed extreme-aware with distributed collaborative strategies. Overall, the E-SGPR-DC approach exhibits superior accuracy and robustness, effectively addressing multi-response regression tasks under uncertainties inherent in wind turbine blade systems.

Fig. 5 illustrates the response surfaces constructed by the proposed E-SGPR-DC model to characterize the nonlinear relationships between representative input variables and key structural responses, including stress, strain, and deformation. Each surface depicts a bivariate mapping between a selected pair of input parameters (e.g., inlet velocity-rotational speed, material density-rotational speed, elastic modulus-rotational speed) and the corresponding output response, while the red markers denote the original simulation samples. It can be observed that the sampled data points are consistently distributed on or very close to the predicted response surfaces, indicating that the E-SGPR-DC model achieves high-fidelity approximation across the input domain without noticeable bias or dispersion. Moreover, the pronounced curvature, gradient variation, and asymmetric shapes of the surfaces clearly reveal the strong nonlinearity and complex coupling effects between aerodynamic, material, and operational parameters. These results demonstrate that the proposed E-SGPR-DC framework is capable of accurately capturing intricate nonlinear input-output dependencies in wind turbine blade systems, providing a reliable surrogate representation for subsequent uncertainty propagation and reliability analysis.

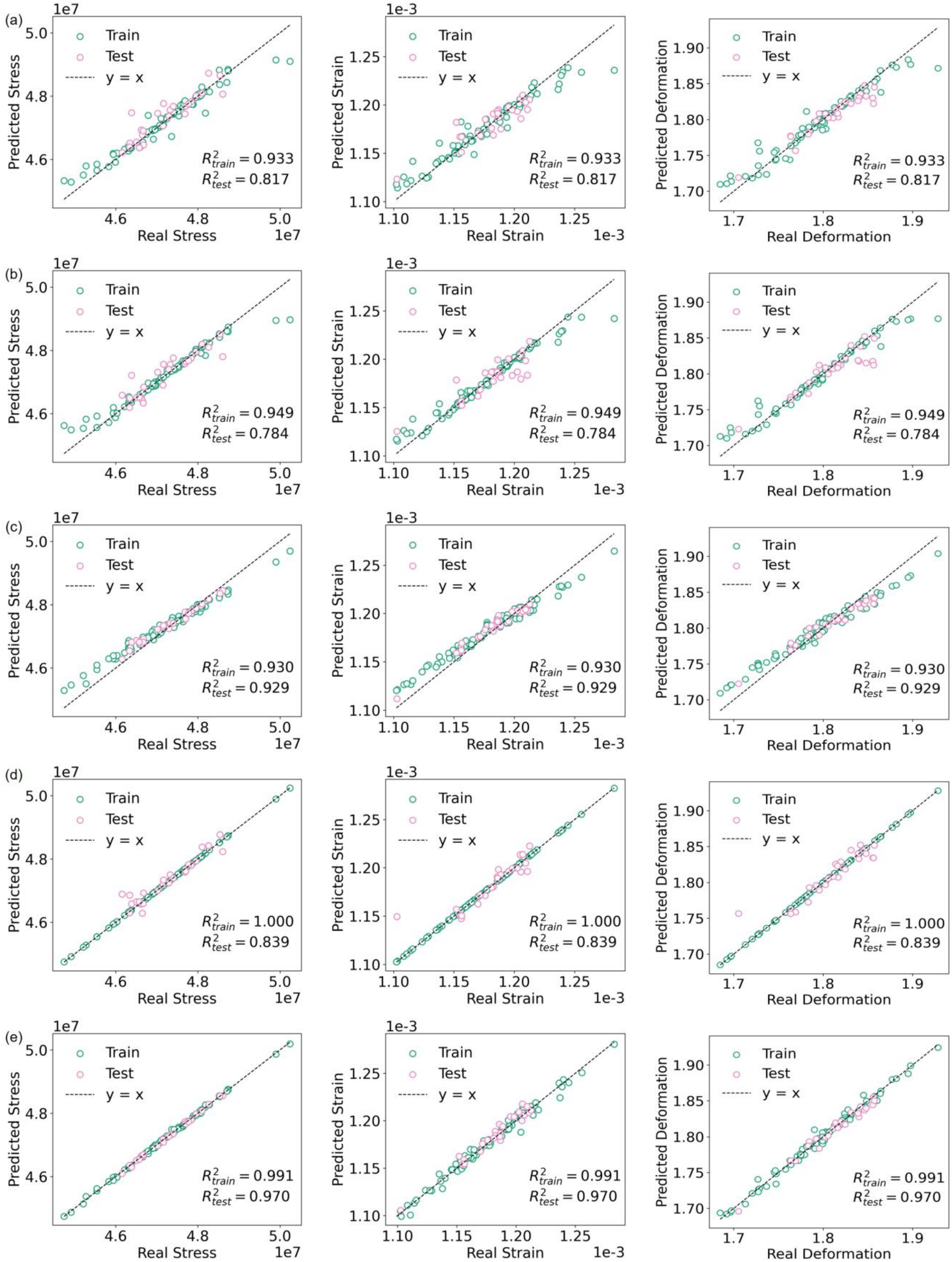


Fig. 4 E-SGPR-DC calculation accuracy. (a) ANN; (b) XGB; (c) ANN-DC; (d) E-SGPR; (e) E-SGPR-DC.

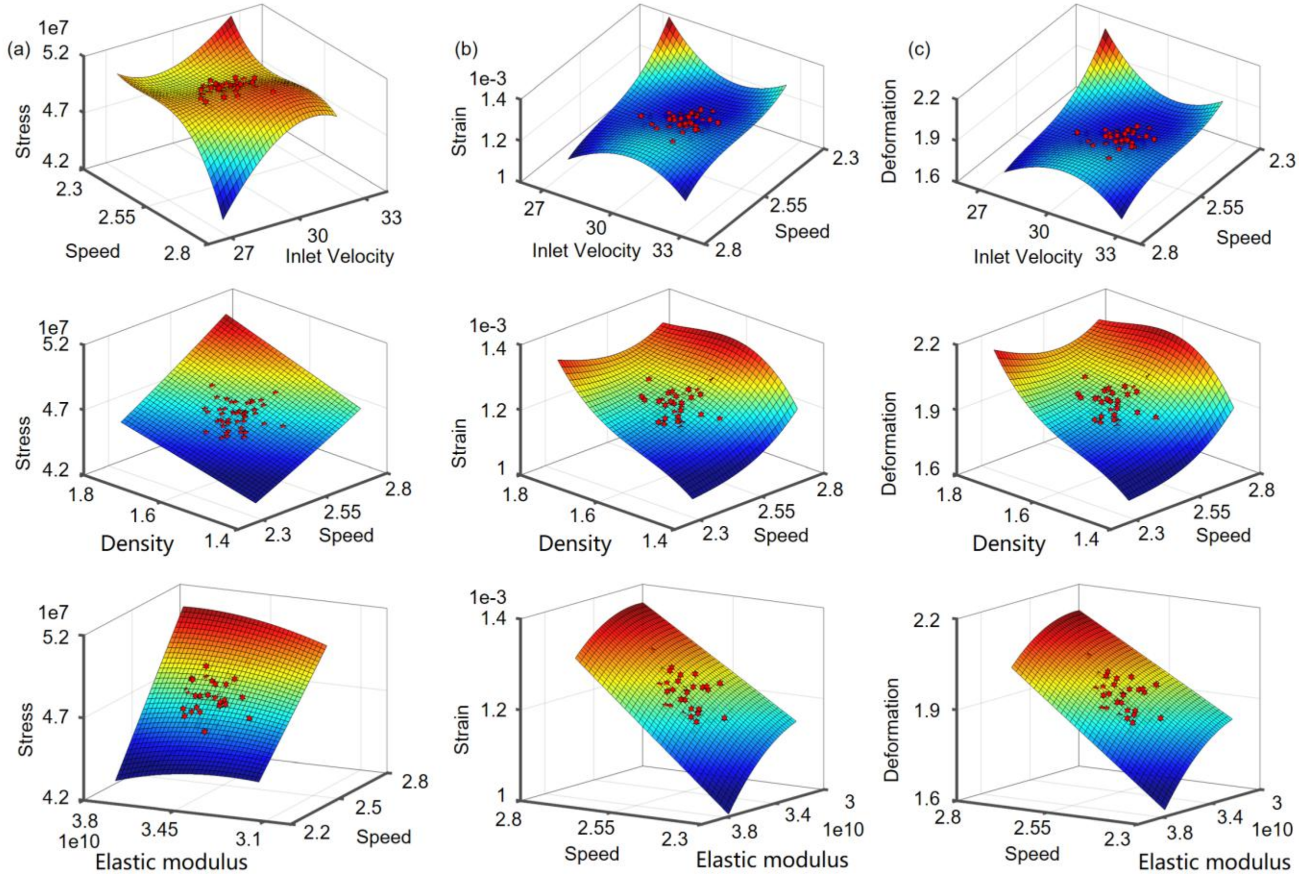


Fig. 5 Response surface between output responses and partial variables. (a) stress σ, Pa; (b)strain ε, m/m; (c)deformation d, m

4.2. Probabilistic analysis of wind turbine blades

Based on the probabilistic characteristics summarized in **Table 1**, a comprehensive dataset containing 10,000 samples of input variables was generated using the Latin hypercube sampling (LHS) technique. The corresponding deformation, stress, and strain responses were obtained by performing simulations with the established E-SGPR-DC model. As illustrated in **Fig. 6**, the resulting structural responses at the turbine blades closely follow Gaussian distributions. Specifically, the deformation response approximately follows a Gaussian distribution with mean μ = 1.79 m and standard deviation σ = 0.032 m; the stress response has $\mu = 4.74 \times 10^{7}$ Pa and $\sigma = 6.85 \times 10^{5}$ Pa; and the strain response shows $\mu = 1.18 \times 10^{-3}$ m/m and $\sigma = 2.30 \times 10^{-5}$ m/m. These probabilistic insights provide essential support for reliability evaluation and structural performance evaluation of wind turbine blades under realistic operating uncertainties.

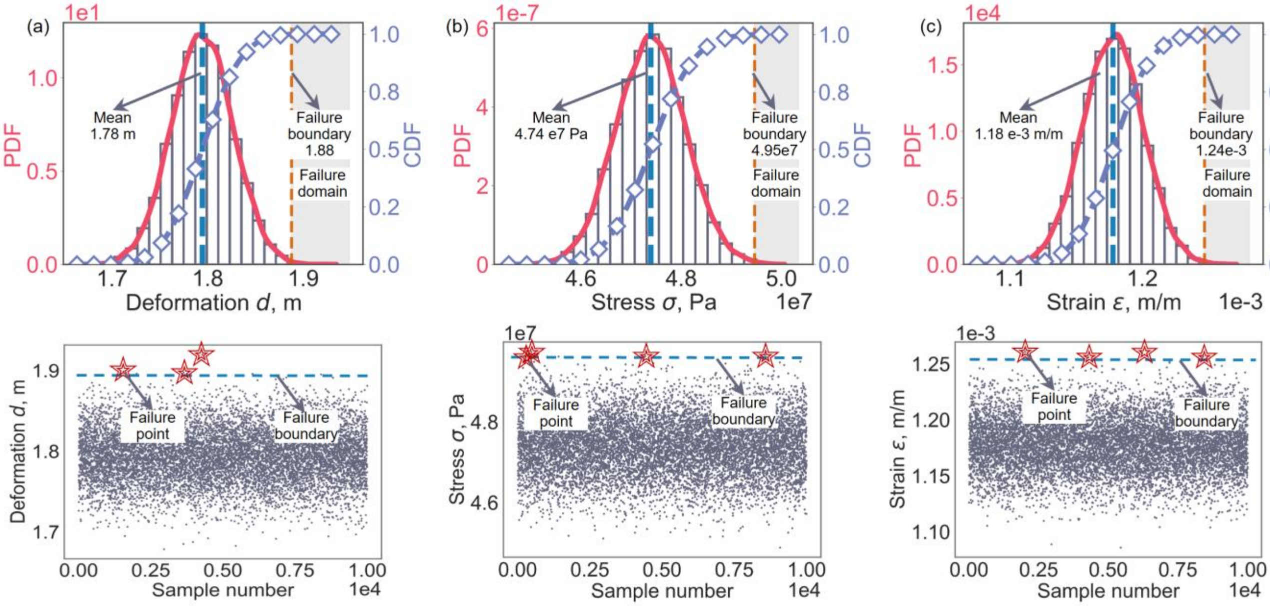


Fig. 6 Probabilistic distribution and simulation history of wind turbine blades. (a) deformation, (b) stress, and (c) strain

4.3. Correlation analysis of wind turbine blades

To explicitly identify and quantify the correlations between input uncertainties and critical structural output responses, a correlation analysis was conducted based on the 10,000 sample datasets generated through Latin Hypercube Sampling. The correlation heatmaps shown in **Fig. 7** illustrate the relationships between key input parameters and the primary structural responses. Ellipses illustrate correlation magnitude and direction, with red denoting positive and blue indicating negative correlations. As demonstrated, deformation, stress, and strain responses exhibit strong positive correlations (coefficients up to 0.9) with rotational velocity, highlighting the significant sensitivity of blade structural responses to rotational speed variations. Conversely, elastic modulus shows a clear negative correlation with all structural outputs, indicating a pronounced influence of material stiffness on deformation, stress, and strain. **Fig. 8** further illustrates the correlations between key input parameters (Rotational Velocity w, density ρ, and elastic modulus E) and structural responses (deformation, stress, and strain). Clearly, rotational velocity exhibits the strongest positive linear correlation with deformation, stress, and strain, indicating high sensitivity of structural responses to variations in aerodynamic loading conditions. Overall, rotational velocity can be identified as the dominant failure drivers, while density and elastic modulus are secondary factors.

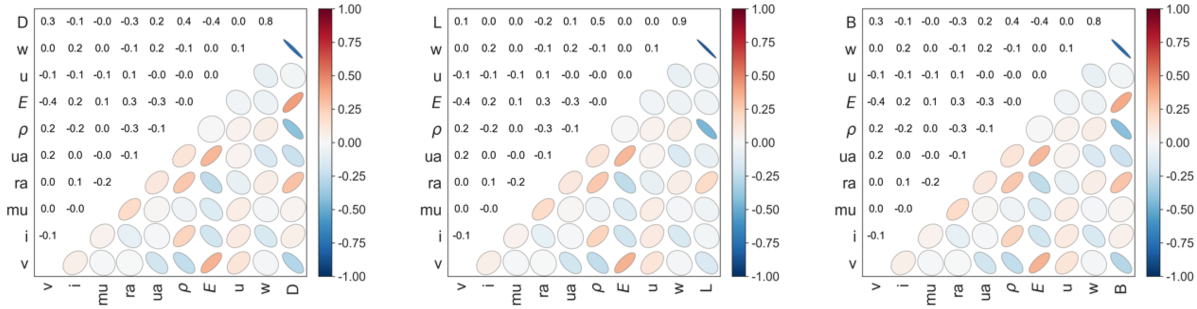


Fig. 7 Input-output correlation heatmap.

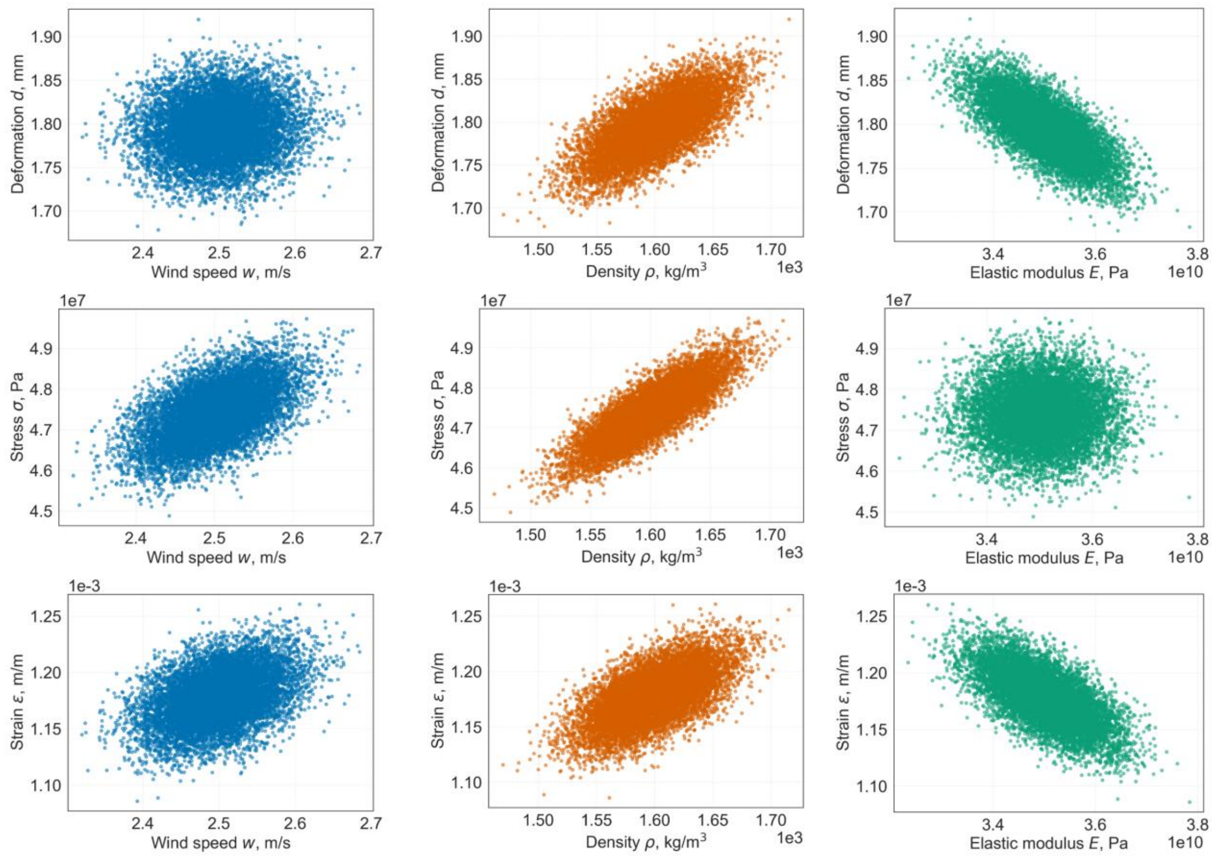


Fig. 8 Input-output correlation scatter plots.

Several candidate Copula families, including the Gaussian, t, Clayton, Frank, and Gumbel Copulas, were examined to characterize the dependence structure among the failure-related responses. As summarized in Table 2, for the stress-strain, stress-deformation, and strain-deformation response pairs, the Gaussian Copula consistently shows the highest log-likelihood and the lowest AIC and BIC values among the tested alternatives. Therefore, it was adopted as the dependence model in the subsequent correlation modeling and reliability analysis. As shown in **Fig. 9**, the first two columns depict contour plots of joint probability distributions between deformation-stress and deformation-strain, respectively, illustrating strong linear deformation-stress correlations and nonlinear deformation-strain relationships. The third column presents the fitting errors between stress and strain, highlighting regions of complex, nonlinear interaction adequately captured by the model. These results underscore the necessity of accurately modeling output correlations for precise and reliable structural evaluation.

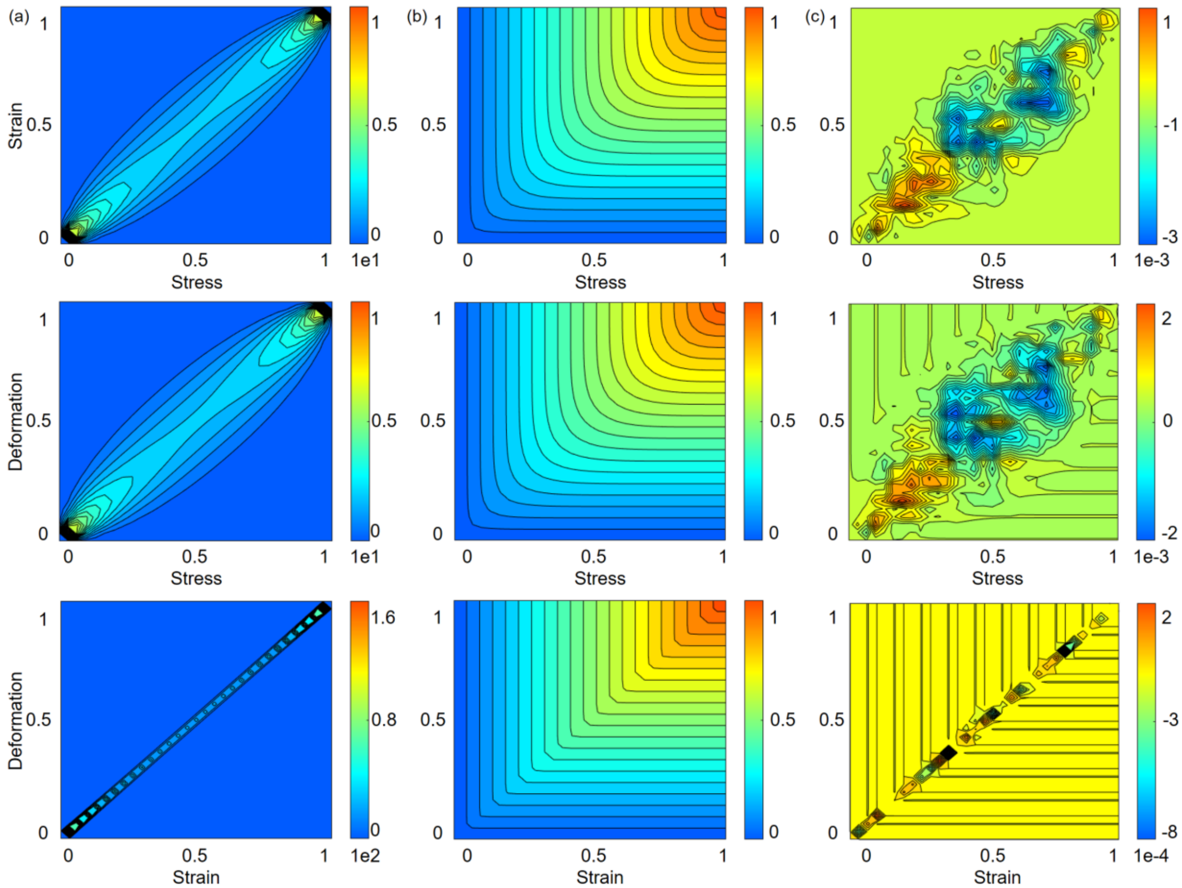


Fig. 9 Correlation analysis of output responses interdependencies. (a) joint probability density function (PDF); (b) joint cumulative distribution function (CDF); (c) fitting error distribution

Table 2 Comparison of candidate Copula models for response-pair dependency fitting

Responses	Copula	LogL	AIC	BIC
Stress-Strain	Gaussian	4145	-8288	-8280
Stress-Strain	t	4145	-8286	-8271
Stress-Strain	Clayton	3083	-6165	-6158
Stress-Strain	Frank	3735	-7469	-7462
Stress-Strain	Gumbel	3775	-7548	-7541
Stress-Deformation	Gaussian	2414	-4827	-4819
Stress-Deformation	t	2414	-4825	-4810
Stress-Deformation	Clayton	1787	-3572	-3565
Stress-Deformation	Frank	2182	-4362	-4355
Stress-Deformation	Gumbel	2132	-4262	-4255
Strain-Deformation	Gaussian	10925	-21848	-21841
Strain-Deformation	t	10925	-21846	-21832
Strain-Deformation	Clayton	8572	-17143	-17135
Strain-Deformation	Frank	9957	-19913	-19905
Strain-Deformation	Gumbel	10189	-20377	-20370

4.4. *Multi-failure reliability evaluation of wind turbine blades*

This section employs a multi-failure reliability analysis framework to systematically assess wind turbine blades reliability, considering correlated structural responses under multiple failure modes. **Fig. 10** presents joint distributions and marginal reliability behaviors for deformation, stress, and strain. The joint distributions in **Fig. 10 (a-c)** reveal complex nonlinear interactions among normalized structural responses, clearly indicating strong dependencies. Marginal distributions of maximum deformation, stress, and strain in **Fig. 10 (d-f)** exhibit pronounced sigmoidal shapes, highlighting significant reliability sensitivity near critical failure thresholds. Reliability predictions considering complete dependence versus independence scenarios are compared in **Fig. 10 (g-i)**, emphasizing the notable impact of correlation assumptions on reliability outcomes. The reliability analysis results underscore the necessity of explicitly accounting for interdependencies among structural responses, providing essential insights for accurate reliability evaluation and design optimization of wind turbine blades under realistic operational conditions.

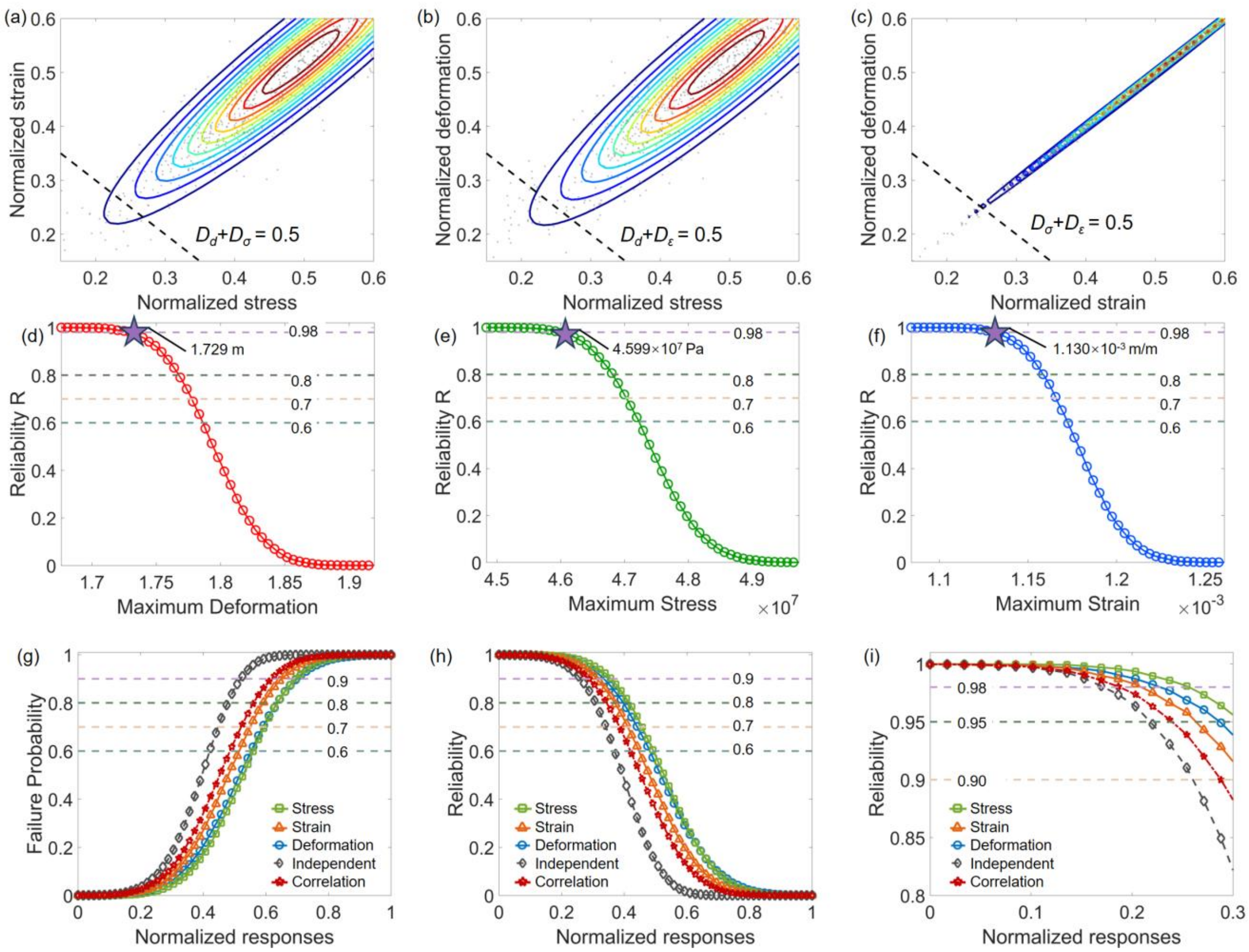
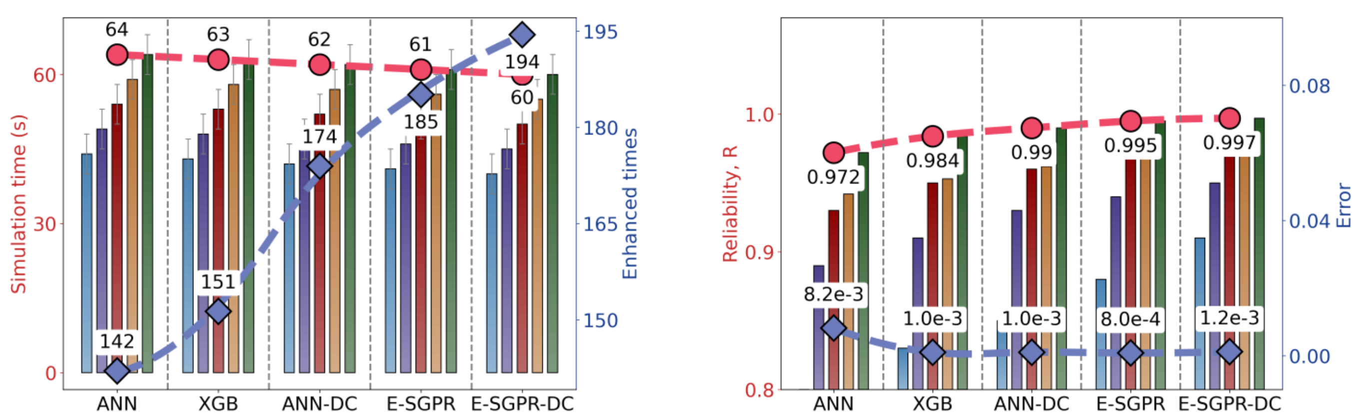


Fig. 10 Reliability of turbine blade

4.5. Methods comparison

To systematically evaluate the modeling accuracy, computational efficiency, and reliability prediction performance of the proposed E-SGPR-DC framework, a reliability analysis was conducted against four representative surrogate models: Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGB), ANN with distributed collaborative (ANN-DC), and Extreme-Aware Sparse Gaussian Process Regression (E-SGPR). As shown in **Fig. 11**, the proposed E-SGPR-DC approach demonstrates superior modeling accuracy, and computational efficiency (shortest computational time) compared to all other methods. Additionally, the reliability-error comparisons further highlight the superiority of the E-SGPR-DC method. For the proposed E-SGPR-DC framework, the computed reliability in **Fig. 11(b)** is R = 0.997, corresponding to a reliability index of $\beta \approx 2.75$. This value is slightly lower than the lower reference reliability level of β = 2.9 reported in the literature [58-59], which is consistent with the fact that the present study focuses on an extreme-loading scenario. Since the proposed E-SGPR-DC model shows the highest prediction accuracy and the smallest reliability error among the tested surrogate methods, the subsequent reliability evaluation is conducted based on this model, which helps reduce the influence of surrogate approximation error on the final reliability estimate.

The exceptional performance of the E-SGPR-DC approach can be attributed to the following methodological advantages. First, integrating extreme-aware strategy significantly enhances the accurate capture of extreme structural responses, thus improving prediction accuracy under critical operational conditions. Second, employing the distributed collaborative (DC) strategy effectively combines local and global response information, achieving an optimal balance between computational efficiency and model fidelity. These advancements verify that the E-SGPR-DC method can effectively handle complex, high-dimensional multi-response reliability analyses, providing robust theoretical and practical support for accurate structural evaluation of wind turbine blades under realistic operational uncertainties.



(a) Accuracy-efficiency comparison (b) Reliability-error comparison

Fig. 11 Comparison of accuracy, efficiency, and reliability for different methods

5. Conclusions

This study proposes an extreme-aware sparse Gaussian process regression with distributed collaborative (E-SGPR-DC) framework for accurate reliability evaluation of wind turbine blades under coupled, multi-dimensional uncertainties. The effectiveness and robustness of the proposed method were systematically validated through deterministic analysis, probabilistic modeling, correlation analysis, and multi-failure reliability evaluation. Key conclusions drawn from this research are summarized as follows:

(1) The proposed E-SGPR-DC model outperforms conventional surrogate methods (ANN, XGB, ANN-DC, and E-SGPR) in prediction accuracy and computational efficiency, demonstrating significant advantages in addressing high-dimensional multi-response regression problems.

(2) Probabilistic analysis shows that structural responses (deformation, stress, and strain) closely conform to Gaussian distributions, clearly reflecting sensitivity near critical operational thresholds. Quantitative probabilistic characteristics (mean and standard deviation) offer robust theoretical support for reliability evaluation under realistic operational uncertainties.

(3) Correlation analysis identifies rotational velocity as having the strongest influence on blade structural responses, while density and elastic modulus exhibit moderate yet notable impacts. These insights emphasize the critical role of input-response correlations in accurate reliability assessment.

(4) The multi-failure reliability framework effectively captures complex nonlinear dependencies among deformation, stress, and strain responses. Results highlight the substantial effect of response correlations on system-level reliability, reinforcing the necessity of explicitly considering multiple correlated failure modes in reliability evaluations.

The present results can support blade design optimization by identifying the critical regions and the dominant driving factors under extreme loading. They can also support maintenance planning by prioritizing inspection and preventive maintenance for high-risk regions. The proposed E-SGPR-DC framework may also be extended to other complex engineering systems involving correlated multi-response behaviors and multi-failure reliability problems, such as aerospace structures, composite components, and other large-scale load-bearing systems.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The research work described in this paper is fully supported by a grant from the Research Grants Council of Hong Kong (RIF Project No: R1006-23).

References

[1] Sanchez Gomez M, Portabella M, Stoffelen A, Lin W, Turiel A. Wind fields in category 1-3 tropical cyclones are not fully represented in current design standards, Journal of Geophysical Research: Atmospheres, 2023, 128: e2023JD039233.

[2] Dimitrov N, Kelly MC, Vignaroli A, Berg J. From wind to loads: wind turbine site-specific load estimation with surrogate models trained on high-fidelity load databases, Wind Energy Science, 2018, 3: 767-790.

[3] Rezaei A, Nejad AR. Probability assessment of static overload in wind turbine blade bearings considering turbulence, design, and manufacturing variability, Wind Energy Science, 2025, 10: 2947-2963.

[4] Hermansen SM, Lund E. Multi-material and thickness optimization of a wind turbine blade root section, Structural and Multidisciplinary Optimization, 2024, 67: 107.

[5] de Almeida IT, Lapa GVP, Gay Neto A, de Almeida SFM. Design and extreme structural analysis of wind turbine blades: beam and shell model comparison for a 10-mw reference turbine, Engineering Structures, 2025, 334: 120155.

[6] Behrendt M, Faes MGR, Valdebenito MA, Beer M. Estimation of an imprecise power spectral density function with optimised bounds from scarce data for epistemic uncertainty quantification, Mechanical Systems and Signal Processing, 2023, 189: 110072.

[7] Moustapha M, Marelli S, Sudret B. Active learning for structural reliability: survey, general framework and benchmark, Structural Safety, 2022, 96: 102174.

[8] Beer M, Valdebenito MA, Faes MGR, Straub D. Mixed uncertainties in engineering reliability: advances in modelling and computation, Structural Safety, 2022, 97: 102205.

[9] Gao HF, Zio E, Guo JJ, Bai GC, Fei CW. Dynamic probabilistic-based LCF damage assessment of turbine blades regarding time-varying multi-physical field loads, Engineering Failure Analysis, 2020, 108: 104193.

[10] Gao HF, Wang YH, Li Y, Zio E. Distributed-collaborative surrogate modeling approach for creep-fatigue reliability assessment of turbine blades considering multi-source uncertainty, Reliability Engineering & System Safety, 2024, 250: 110316.

[11] Song LK, Bai GC, Fei CW, Wen J. Reliability-based fatigue life prediction for complex structure with time-varying surrogate modeling, Advances in Materials Science and Engineering, 2018, 2018: 3469465.

[12] Dang C, Beer M. Semi-bayesian active learning quadrature for estimating extremely low failure probabilities, Reliability Engineering & System Safety, 2024, 246: 110052.

[13] Acevedo CH, Zhang XY, Valdebenito MA, Faes MGR. Reliability analysis combining method of moments with control variates, Probabilistic Engineering Mechanics, 2025, 81: 103771.

[14] Manque NA, Liedmann J, Barthold FJ, Valdebenito MA, Faes MGR. Interval isogeometric analysis for coping with geometric uncertainty, Computer Methods in Applied Mechanics and Engineering, 2025, 437: 117773.

[15] Papaioannou I, Straub D, Beer M. Rare event simulation for time-dependent reliability: state-of-the-art and open problems, Reliability Engineering & System Safety, 2022, 227: 108765.

[16] Li XQ, Song LK, Bai GC, Li DG. Physics-informed distributed modeling for CCF reliability evaluation of aeroengine rotor systems, International Journal of Fatigue, 2023, 167: 107342.

[17] Song LK, Li XQ, Zhu SP, Choy YS. Cascade ensemble learning for multi-level reliability evaluation, Aerospace Science and Technology, 2024, 148: 109101.

[18] Li XQ, Song LK, Bai GC. Vectorial surrogate modeling approach for multi-failure correlated probabilistic evaluation of turbine rotor, Engineering with Computers, 2023, 39: 1885-1904.

[19] Beer M, Broggi M, Goller B, Schöbi R, Sudret B. Surrogate modelling in reliability engineering: recent developments and open challenges, Mechanical Systems and Signal Processing, 2022, 171: 108861.

[20] Xiang F, Xie W, Ke S, Zuo Y, Tao F. Modeling and optimization of manufacturing service collaboration based on digital twins, The International Journal of Advanced Manufacturing Technology, 2025, 138: 5319-5344.

[21] Song LK, Bai GC. Multi-surrogate collaboration approach for creep-fatigue reliability assessment of turbine rotor, IEEE Access, 2020, 8: 39861-39874.

[22] Gao HF, Wang A, Zio E, Bai GC. An integrated reliability approach with improved importance sampling for low-cycle fatigue damage prediction of turbine disks, Reliability Engineering & System Safety, 2020, 199: 106819.

[23] Papadopoulos V, Giovanis DG, Lagaros ND, Fragiadakis M. Stochastic simulation methods for structural reliability under extreme loading, Probabilistic Engineering Mechanics, 2022, 70: 103345.

[24] Müller F, Becker C, Klein B, Hoffmann J. Quadratic surrogate models in reliability-based design optimization, Engineering Optimization, 2022, 54: 501-521.

[25] Khuri AI. Response surface methodology and its applications in engineering reliability, Quality Engineering, 2021, 33: 389-412.

[26] Li XQ, Song LK, Choy YS, Bai GC. Fatigue reliability analysis of aeroengine blade-disc systems using physics-informed ensemble learning, Philosophical Transactions of the Royal Society A, 2023, 381: 20220384.

[27] Shirzad S, Moaveni B. Support vector regression for fatigue life prediction under variable amplitude loading, Engineering Fracture Mechanics, 2022, 269: 108543.

[28] Zemed N, Cherradi T, Bouyahyaoui A, Mouzoun K. Enhanced active learning for structural reliability analysis: an ensemble SVR metamodel-Monte Carlo approach, Quality and Reliability Engineering International, 2025, 41: 1895-1912.

[29] Song LK, Bai GC, Li XQ. A novel metamodeling approach for probabilistic LCF estimation of turbine disk, Engineering Failure Analysis, 2021, 120: 105074.

[30] Song LK, Tao F, Li XQ, Yang LC, Wei YP, Beer M. Physics-embedding multi-response regressor for time-variant system reliability

assessment, Reliability Engineering & System Safety, 2025, 263: 111262.

[31] Xiang F, Shi J, Zhang M, Zuo Y, Tao F. A back propagation neural network based low frequency clustering man-hour prediction method for digital manufacturing, International Journal of Computer Integrated Manufacturing, 2026, 39(3): 405-423.

[32] Shi Y, Niu L, Beer M. Adaptive artificial neural network for uncertainty propagation, Journal of Reliability Science and Engineering, 2025, 1(1): 015002.

[33] Xiang F, Zhao YL, Zhang M, Zuo Y, Zou XF, Tao F. Ensemble learning-based stability improvement method for feature selection towards performance prediction, Journal of Manufacturing Systems, 2024, 74: 55-67.

[34] Li HM, Zhang SP, Huang S, Rong SL, Gao HF. An ensemble learning-enhanced collaborative surrogate modeling approach with improved particle swarm optimization for structural reliability assessment, Computers in Industry, 2026, 176: 104441.

[35] Alfarizi MG, Vatn J, Yin S. An extreme gradient boosting aided fault diagnosis approach: a case study of fuse test bench, IEEE Transactions on Artificial Intelligence, 2022, 4: 661-668.

[36] Gao HF, Zio E, Wang A, Bai GC, Fei CW. Probabilistic-based combined high and low cycle fatigue assessment for turbine blades using a substructure-based kriging surrogate model, Aerospace Science and Technology, 2020, 104: 105957.

[37] Meng DB, Yang SY, De Jesus AM, Zhu SP. A novel kriging-model-assisted reliability-based multidisciplinary design optimization strategy and its application in the offshore wind turbine tower, Renewable Energy, 2023, 203: 407-420.

[38] Gao HF, Wang Y, Xu J, Qin H. Fatigue strength reliability assessment of turbofan blades subjected to intake disturbances based on the improved kriging model, Eksploatacja i Niezawodność, 2025, 27(2): 194175.

[39] Li XQ, Song LK, Choy YS, Bai GC. Multivariate ensembles-based hierarchical linkage strategy for system reliability evaluation of aeroengine cooling blades, Aerospace Science and Technology, 2023, 138: 108325.

[40] Song LK, Tao F, Peng GZ. Mixed loss-guided modular regression for dependent system reliability, Reliability Engineering & System Safety, 2026, 267: 111898.

[41] Nogal M, O'Connor A, Teixeira R. Data-driven and physics-based hybrid reliability assessment for infrastructure systems, Structural Safety, 2022, 97: 102201.

[42] Teixeira R, Nogal M, O'Connor A. Review of surrogate modelling for reliability assessment of civil and mechanical structures, Engineering Structures, 2021, 245: 112823.

[43] Dimitrov N, Berg J, Kelly MC, Vignaroli A. Extreme-response modelling and uncertainty propagation for wind turbine blades, Wind Energy, 2022, 25: 1523-1546.

[44] Papakonstantinou KG, Straub D, Chatzi E. Physics-informed surrogate modelling for structural system reliability, Reliability Engineering & System Safety, 2024, 245: 110021.

[45] Alvarez M, Lawrence N. Sparse convolved Gaussian processes for multi-output regression, Advances in neural information processing systems, 2008, 21.

[46] Kennedy MC, O'Hagan A. Predicting the output from a complex computer code when fast approximations are available, Biometrika,

2000, 87(1): 1-13.

[47] Tartakovsky AM, Ma T, Barajas-Solano DA, Tipireddy R. Physics-informed Gaussian process regression for states estimation and forecasting in power grids, International Journal of Forecasting, 2023, 39(2): 967-980.

[48] Song LK, Tao F, Choy Y, Yang LC, Wei YF. Cascade sampling-driven block mapping for coupled reliability evaluation of turbine cooling systems, Mechanical Systems and Signal Processing, 2025, 236: 113008.

[49] Xiang F, Fan J, Zhang X, Zuo Y, Liu S. A digital twin-driven perception method of manufacturing service correlation based on frequent itemsets, The International Journal of Advanced Manufacturing Technology, 2024, 131: 5661-5677.

[50] Li XQ, Song LK, Bai GC. Deep learning regression-based stratified probabilistic combined cycle fatigue damage evaluation for turbine bladed disks, International Journal of Fatigue, 2022, 159: 106812.

[51] Song LK, Faes MGR, Tao F. Generative data-physics fusion for hierarchical reliability assessment, Reliability Engineering & System Safety, 2026, 272: 112642.

[52] Song LK, Bai GC, Li XQ, Wen J. A unified fatigue reliability-based design optimization framework for aircraft turbine disk, International Journal of Fatigue, 2021, 152: 106422.

[53] Xiao NC, Yuan K, Zhan H. System reliability analysis based on dependent kriging predictions and parallel learning strategy, Reliability Engineering & System Safety, 2022, 218: 108083.

[54] Slot RM, Sørensen JD, Sudret B, Svenningsen L, Thøgersen ML. Surrogate model uncertainty in wind turbine reliability assessment, Renewable Energy, 2020, 151: 1150-1162.

[55] Gentile R, Galasso C. Gaussian process regression for seismic fragility assessment of building portfolios, Structural Safety, 2020, 87: 101980.

[56] Burt DR., Rasmussen CE, Van Der Wilk M. Convergence of sparse variational inference in Gaussian processes regression, Journal of Machine Learning Research, 2020, 21(131): 1-63.

[57] Faes MGR, Sofi A, Valdebenito M. Avoiding two common pitfalls in uncertainty propagation, Journal of Reliability Science and Engineering, 2025, 1(2): 025005.

[58] Ghasemi SH, Nowak AS. Target reliability for bridges with consideration of ultimate limit state, Engineering Structures, 2017, 152: 226-237.

[59] Safari M, Ghasemi SH, Nowak AS. Performance-based target reliability analysis of offshore wind turbine mooring lines subjected to the wind and wave, Probabilistic Engineering Mechanics, 2024, 77: 103673.