

Dynamic analysis for rigid-flexible multibody systems with random and interval fields

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Abstract: A nonintrusive dynamic response prediction method is proposed to deal with the rigid-flexible multibody systems involving hybrid uncertainties of random and interval fields. The high-dimensional discrete representations of random and interval fields are embedded into the multibody system dynamics modeling based on the absolute nodal coordinate formulation using the Karhunen-Loève expansion and truncation technique, enabling an effective description of spatially correlated uncertain parameters. To overcome the challenges induced by high-dimensional uncertain variables and long-time domain analysis, the local mean decomposition and high-dimensional model representation are applied to construct a nonintrusive surrogate model for the system dynamic response. The proposed approach improves prediction accuracy while considerably reducing computational cost and enhancing the efficiency of evaluating response statistics and boundary characteristics. The effectiveness and applicability of the proposed method are validated through two numerical examples of typical multibody systems involving one- and two-dimensional random-interval fields in handling spatial uncertainties and predicting system response ranges.

Key words: rigid-flexible multibody systems; random field; interval field; hybrid uncertainty dynamic analysis

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Accurate prediction of the dynamics of rigid-flexible multibody systems is crucial for the design and reliability of such systems. However, the parametric models upon which such predictions rely inevitably contain uncertainties, originating from sources such as geometric tolerances, material properties, initial/boundary conditions, and external excitations^[1-2]. These uncertainties can lead to inaccurate predictions or even catastrophic failures^[3-4]. Consequently, uncertainty analysis has be-

come a critical issue in assessing how these uncertain parameters influence the dynamic performance of the system^[5]. In multibody systems, uncertain parameters are typically classified as random variables^[6] or interval variables^[7]. For systems defined by precise probability distribution functions, probabilistic methods, such as Monte Carlo simulations, are the standard approach. However, in many practical scenarios, sufficient data to construct accurate probability distributions are challenging to obtain. When parameters are uncertain but bounded, treating them as interval variables is highly appropriate. For such systems with interval parameters, interval methods are employed to quantify the impact of uncertainty and determine the upper and lower bounds of the dynamic response.

However, existing studies often simplify uncertain parameters as independent random or interval variables. In practical engineering, the uncertainty of material properties such as elastic modulus and density often exhibits continuous spatial distribution characteristics, which can be mathematically defined as random fields^[8]. Owing to the inconvenience of continuous index sets in numerical computation, random fields must be discretized into a finite number of random variables. According to Ghanem et al.^[9], the mainstream method for achieving such discretization is the series expansion method, whose core idea is to expand any realization of a random field into a series composed of deterministic basis functions. Among various expansion methods, the Karhunen-Loève (K-L) expansion is considered to be a high-precision discretization method owing to its optimal convergence properties in the mean square sense^[10]. Random fields have been widely applied in structural dynamics, civil engineering, and environmental loading to model spatially varying uncertainties, such as material loads in concrete structures during construction^[11], the durability deterioration of reinforced concrete bridges^[12], and the simulation of non-stationary turbulent stochastic fields for exceptional winds^[13]. Notably, the theory of random fields has gradually been introduced into the field of multibody dynamics to analyze the impact of spatial randomness in material properties of flexible components on the overall dynamic response^[14-16]. For example, Wu et al.^[14] first combined random fields with flexible multibody model-

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ing, establishing an uncertainty analysis model considering the spatial random distribution of the material properties of flexible beams. Meng et al. [16] further proposed a dynamic computation method for flexible multibody systems considering imprecise random fields. This series of advancements provides an important theoretical foundation and modeling tools for more accurately describing the uncertainty propagation in complex multibody systems.

In practical engineering, when sample data are scarce and constructing complete random probability distributions is challenging, interval fields provide an effective mathematical tool for characterizing system inputs that are spatially dependent with unknown probability distributions [17]. Ni et al. [18] delved into the mathematical implications of interval fields, the interval K-L expansion method, and numerical techniques for solving eigenvalues and eigenfunctions, which form a complete modeling framework for interval fields and provide a standardized analytical approach for addressing spatial variability under epistemic uncertainty. However, most existing studies treat random fields and interval fields in isolation [19–20], which struggles to effectively address the hybrid uncertainty issues commonly encountered in practical engineering. Some scholars simultaneously considered random and interval fields in structural static uncertainty analysis [21–22]. However, similar studies in the dynamic field are urgently needed. Therefore, this paper focuses on introducing a unified analytical framework that incorporates random and interval fields, providing theoretical support and a methodological foundation for improving the accuracy of dynamic predictions for rigid-flexible multibody systems.

To achieve a unified analysis of random and interval fields, hybrid uncertainty quantification is required to be performed after uncertainty modeling. For the hybrid uncertainty problem in multibody systems, the polynomial-chaos-Chebyshev-interval (PCCI) method proposed by Wu et al. [23] combines the polynomial chaos expansion (PCE) with the Chebyshev theory, providing an effective numerical strategy for hybrid uncertainty propagation. Subsequently, Feng et al. [24] developed the polynomial chaos-Legendre metamodel (PCLM) method, which combines PCE theory with the Legendre polynomial surrogate model. For specific issues in flexible multibody systems, several modifications were made to the basic framework [25–28]. For example, to enhance computational efficiency, Guo et al. [25] proposed a sparse PCLM method based on compressed sensing. In response to scenarios where probabilistic information is incomplete in engineering practice, they further developed a data-driven PCLM method that integrates statistical moment orthogonal polynomial construction [26]. In addition,

to overcome the challenge of fitting accuracy decay with time in PCLM when dealing with periodic time-domain problems, Meng et al. [27] introduced the local mean decomposition (LMD) technique and proposed the PCLM-LMD method. To address the “curse of dimensionality” caused by high-dimensional inputs, the team also integrated high-dimensional model representation (HDMR) and proposed the PCLM-HDMR method, effectively achieving dimensionality reduction [28].

Addressing the high-dimensional variable problem resulting from the discretization of random and interval fields, as well as the accuracy degradation in long-time domain analysis, this paper proposes an efficient dimensionality reduction method based on the standard PCLM-LMD approach. The method reduces the dimensionality of the instantaneous amplitude (IA), instantaneous phase (IP), and trend terms obtained from the HDMR decomposition of the response, thereby improving the dynamic prediction accuracy and computational efficiency of rigid-flexible multibody systems under spatial hybrid uncertainties.

1 Spatially Dependent Uncertainty

1.1 Random field—A stochastic model for spatially dependent uncertainty

A random field is called a Gaussian random field $H_N(\mathbf{x}, \omega)$ if, for any $\mathbf{x}_p \in D$, the random variable $H_N(\mathbf{x}_p, \omega)$ follows a normal distribution:

$$H_N(\mathbf{x}_p, \omega) \sim N\left(\mu_{H_N(\mathbf{x}_p, \omega)}, \sigma_{H_N(\mathbf{x}_p, \omega)}\right) \quad \forall \mathbf{x}_p \in D \quad (1)$$

where $\mu_{H_N(\mathbf{x}_p, \omega)}$ and $\sigma_{H_N(\mathbf{x}_p, \omega)}$ represent the mean and standard deviation of the random variable at location $\mathbf{x}_p$, respectively; subscript N indicates a normal distribution; and $D \in \mathbf{R}^d$ is a bounded domain. Rather than focusing solely on the random variable at a single location $\mathbf{x}_p$, the collection of variables over the entire domain is considered. Thus, the correlation function of the random field is defined as

$$\rho(\mathbf{x}_1, \mathbf{x}_2) \equiv \frac{E[H(\mathbf{x}_1, \omega)H(\mathbf{x}_2, \omega)] - E[H(\mathbf{x}_1, \omega)]E[H(\mathbf{x}_2, \omega)]}{\sigma(\mathbf{x}_1)\sigma(\mathbf{x}_2)} \quad (2)$$

where $E[\cdot]$ represents the operation of computing the mean, and $\sigma^2(\mathbf{x}) = E[(H(\mathbf{x}, \omega) - \mu(\mathbf{x}))^2]$. For uncertainty modeling in beams and plates, one-dimensional (1D) and two-dimensional (2D) formulations of the random field are employed, with the corresponding correlation functions given respectively as follows [21]:

$$\rho(\mathbf{x}_1, \mathbf{x}_2) = \exp\left(\frac{-\|\mathbf{x}_1 - \mathbf{x}_2\|}{L_x}\right) \quad (3)$$

$$\rho(\mathbf{x}_1, \mathbf{x}_2) = \exp\left(\frac{-\|\mathbf{x}_1 - \mathbf{x}_2\|}{L_x} - \frac{-\|\mathbf{y}_1 - \mathbf{y}_2\|}{L_y}\right) \quad (4)$$

where L_x and L_y denote the correlation lengths in the x - and y -directions, respectively.

1.2 Interval field—A nonstochastic model for spatially dependent uncertainty

The mathematical model of an interval field is described by the following definition^[18]. Let $\{G(\mathbf{x}), \mathbf{x} \in D\}$ be an uncertain parameter varying in space. If for a given $\mathbf{x}_p \in D$, the uncertainty is expressed as an interval parameter $G^I(\mathbf{x}_p) = [G^L(\mathbf{x}_p), G^U(\mathbf{x}_p)]$, then the spatial uncertain parameter is an interval field, denoted as $\{G(\mathbf{x}) \in G^I(\mathbf{x}), \mathbf{x} \in D\}$. The midpoint function and radius function of the interval field are defined as

$$G^m(\mathbf{x}) = \frac{G^U(\mathbf{x}) + G^L(\mathbf{x})}{2}, \quad G^r(\mathbf{x}) = \frac{G^U(\mathbf{x}) - G^L(\mathbf{x})}{2} \quad (5)$$

The midpoint function $G^m(\mathbf{x}_p)$ represents the nominal value of the interval variable $G(\mathbf{x}_p)$, i. e. , the center of the interval, whereas the radius function $G^r(\mathbf{x}_p)$ reflects the magnitude of $G(\mathbf{x}_p)$, which indicates the range of variation around the nominal value.

To quantify the uncertainty correlation between $\mathbf{x}_1$ and $\mathbf{x}_2$, the correlation function $\rho_{G^I}(\mathbf{x}_1, \mathbf{x}_2)$ is defined as follows:

$$\rho_{G^I}(\mathbf{x}_1, \mathbf{x}_2) = \rho(G^I(\mathbf{x}_1), G^I(\mathbf{x}_2)) = \frac{\text{Cov}[G^I(\mathbf{x}_1), G^I(\mathbf{x}_2)]}{G^r(\mathbf{x}_1)G^r(\mathbf{x}_2)} \quad (6)$$

The interval K-L expansion represents an interval field as an infinite series of uncorrelated standard interval variables^[18]:

$$G^I(\mathbf{x}) = G^m(\mathbf{x}) + \sum_{i=1}^L G^r(\mathbf{x}) \sqrt{\lambda_i} \eta_i(\omega) \psi_i(\mathbf{x})$$

$$\eta_i(\omega) \in [-1, 1] \quad (7)$$

where $\eta_i \in [-1, 1]$, $i = 1, 2, \dots$ are the standard interval variables; L is the truncation order of the interval field; λ_i and $\psi_i(\mathbf{x})$ are the eigenvalues and eigenfunctions of the correlation function $\rho_{G^I}(\mathbf{x}_1, \mathbf{x}_2)$, respectively. The eigenvalues and eigenfunctions can be obtained by solving the Fredholm integral equation of the second kind, and an approximation degree κ is defined to assess the accuracy of the truncated K-L expansion:

$$\kappa = \frac{1}{|D|} \sum_{i=1}^L \lambda_i = \sum_{i=1}^L \lambda_i / \sum_{i=1}^{\infty} \lambda_i \quad (8)$$

where $|D|$ denotes the length (for a 1D interval field), area (for a 2D interval field), or volume (for a three-dimensional interval field) of the spatial domain D .

Fig. 1 visualizes sample realizations of 1D and 2D random and interval fields after K-L expansion. The 1D spatial domains are denoted as $D_x = [-0.5, 0.5]$, and the 2D spatial domains as $D_{xy} = [-0.5, 0.5] \times [-0.5, 0.5]$. To ensure consistency and comparability in the vi-

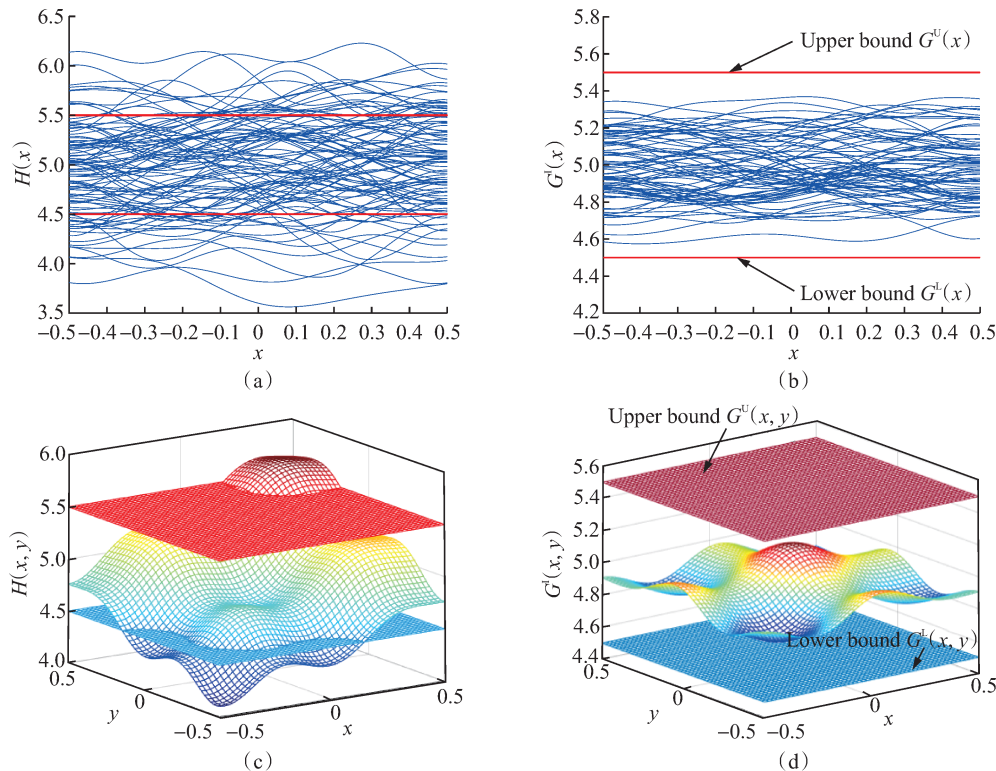


Fig. 1 Schematic and comparison of random and interval fields. (a) 1D random field; (b) 1D interval field; (c) 2D random field; (d) 2D interval field

sualization, the mean function of both random fields is set to $\mu(x) = 5$, $\mu(x, y) = 5$ and the standard deviation function $\sigma(x) = 0.1\mu(x)$, $\sigma(x, y) = 0.1\mu(x, y)$. Then, the midpoint function of the interval fields is set to $m(x) = 5$, $m(x, y) = 5$, and the radius function to $r(x) = 0.1m(x)$, $r(x, y) = 0.1m(x, y)$. The correlation length is uniformly set to $L_s = 2$ in all cases.

In Fig. 1, the interval field model explicitly defines upper and lower bounds to describe the fluctuation range of the uncertain parameter. By contrast, the random field model does not inherently impose such bounds. Moreover, the interval field model does not specify any particular probability distribution within the bounds, whereas the random field model requires a full characterization of the marginal probability distribution at each spatial location. Consequently, the random field model provides a highly refined representation of spatial uncertainty, albeit at the cost of greater demands on sample data. The interval field model, being coarser in its uncertainty representation, requires only upper and lower bounds of the uncertain variable.

2 Methodology for an Uncertain Rigid-Flexible Multibody System

2.1 Rigid-flexible multibody system with random-interval fields

According to absolute nodal coordinate formulation (ANCF)^[29-31], the dynamic differential algebraic equations (DAEs) for a rigid-flexible multibody system with uncertainties are written as follows:

$$\begin{cases} M(\xi^R, \eta^I) \ddot{q} + F(q, \xi^R, \eta^I) + \Phi_q^T(q, t) \lambda = \\ Q(q, \dot{q}, \xi^R, \eta^I) \\ \Phi(q, t) = 0 \end{cases} \quad (9)$$

where q is the vector of generalized coordinates; $\Phi(q, t)$ and $\Phi_q(q, t)$ denote the vector of constraints and the Jacobi matrix with respect to q , respectively; λ represents the vector of Lagrange multipliers; M , F , and Q stand for the mass matrix, the vector of generalized elastic forces, and the vector of other generalized forces, respectively.

The Young's modulus E and mass density ρ are considered as Gaussian random fields, whereas the plate thickness d and external loads f are treated as interval fields. Using the K-L discretization, the E , ρ , d , and f can be approximated by

$$\begin{aligned} E_H(\mathbf{x}, \xi^R) &= \mu_E + \sigma_E \sum_{i=1}^{K_E} \sqrt{\lambda_{E,i}} \xi_{E,i} \phi_{E,i}(\mathbf{x}) \\ \rho_H(\mathbf{x}, \xi^R) &= \mu_\rho + \sigma_\rho \sum_{i=1}^{K_\rho} \sqrt{\lambda_{\rho,i}} \xi_{\rho,i} \phi_{\rho,i}(\mathbf{x}) \\ d_{G^I}(\mathbf{x}, \eta^I) &= d^m + d^r \sum_{i=1}^{K_d} \sqrt{\lambda_{d,i}} \eta_{d,i} \psi_{d,i}(\mathbf{x}) \\ f_{G^I}(\mathbf{x}, \eta^I) &= f^m + f^r \sum_{i=1}^{K_f} \sqrt{\lambda_{f,i}} \eta_{f,i} \psi_{f,i}(\mathbf{x}) \end{aligned} \quad (10)$$

where the subscripts H and G^I are introduced as notational labels to identify quantities associated with a random field and an interval field, respectively, thereby distinguishing them from their deterministic counterparts. μ_E and μ_ρ are the mean values of $E_H(\mathbf{x}, \xi^R)$ and $\rho_H(\mathbf{x}, \xi^R)$, respectively; σ_E and σ_ρ are their standard deviations; d^m and f^m are the midpoint functions of $d_{G^I}(\mathbf{x}, \eta^I)$ and $f_{G^I}(\mathbf{x}, \eta^I)$, respectively; d^r and f^r are the radius functions; $\xi_{E,i}$ and $\xi_{\rho,i}$ represent the independent standard normal random variables; $\eta_{d,i}$ and $\eta_{f,i}$ are the independent standard interval variables; K_E , K_ρ , K_d , and K_f are the truncation order of the associated K-L expansion; and $\lambda_{E,i}$, $\lambda_{\rho,i}$, $\lambda_{d,i}$, $\lambda_{f,i}$, $\phi_{E,i}$, $\phi_{\rho,i}$, $\psi_{d,i}$, and $\psi_{f,i}$ denote the eigenvalues and eigenfunctions of the correlation function.

From Eq. (10), the constant mass matrix, the vector of generalized elastic forces, and the vector of other generalized forces in Eq. (9) are obtained as follows:

$$\begin{aligned} M^j &= \int_{V^e} \rho_H^j(\mathbf{x}, \xi^R) S_{G^I}^T(\mathbf{x}, \eta^I) S_{G^I}(\mathbf{x}, \eta^I) dV^e \\ F^j &= \int_{V^e} \boldsymbol{\varepsilon}; E_H^j(\mathbf{x}, \xi^R); \frac{\partial \boldsymbol{\varepsilon}}{\partial \mathbf{e}^j} dV^e \\ Q^j &= \int_{V^e} S_{G^I}^T(\mathbf{x}, \eta^I) f_{G^I}^j(\mathbf{x}, \eta^I) dV^e \end{aligned} \quad (11)$$

where ρ_H^j and V^e are the density and volume of the element, respectively; $\mathbf{e}^j$ is the vector of nodal coordinates of the j -th element; E_H^j is the fourth-order elastic tensor matrix; $\boldsymbol{\varepsilon}$ is the Green's strain tensor; f^j represents the external force vector.

Using the random field of Young's modulus for the fully parameterized beam as an illustrative example, the discretization of random and interval fields is demonstrated and embedded into the finite element formulation, treated during a preprocessing stage. Based on Eq. (10), the Lamé parameters of the material are expressed as

$$\lambda(\mathbf{x}, \xi) = \frac{E_H(\mathbf{x}, \xi) \nu}{(1 + \nu)(1 - 2\nu)}, \quad \mu(\mathbf{x}, \xi) = \frac{E_H(\mathbf{x}, \xi)}{2(1 + \nu)} \quad (12)$$

where ν denotes Poisson's ratio.

From Eqs. (10) and (12), each component E_{ijkl} of $E_H(\mathbf{x}, \xi)$ is expressed as

$$E_{ijkl}(\mathbf{x}, \xi) = \bar{E}_{ijkl} + \sum_{i=1}^{K_E} \tilde{E}_{ijkl}^i(\mathbf{x}) \xi_{E,i} \quad (13)$$

where

$$\bar{E}_{ijkl} = \frac{2\nu\delta_{ij}\delta_{kl} + (1-2\nu)(\delta_{ik}\delta_{jl} + \delta_{il}\delta_{jk})}{2(1+\nu)(1-2\nu)}\mu_E$$

$$\tilde{E}_{ijkl}^i(\mathbf{x}) = \frac{2\nu\delta_{ij}\delta_{kl} + (1-2\nu)(\delta_{ik}\delta_{jl} + \delta_{il}\delta_{jk})}{2(1+\nu)(1-2\nu)}\sigma_{E\sqrt{\lambda_{E,i}}}\phi_{E,i}(\mathbf{x}) \quad (14)$$

During the computation of the element elastic force and its Jacobian matrix, random variables $\xi_{E,i}$ in $\tilde{E}_{ijkl}^i(\mathbf{x})$ can be factored out of the integral. As a result, the integrand reduces to a spatial function that yields a constant matrix after integration over the element volume. Therefore, the $1 + K_E$ constant matrices corresponding to the components $E_{ijkl}(\mathbf{x}, \xi)$ can be precomputed and stored during the preprocessing stage to improve computational efficiency.

For fixed ξ^R and η^I , Eq. (9) is reduced to DAEs for a deterministic system. At each time step, the deterministic DAEs can be solved by the generalized- α integration algorithm.

2.2 Computational strategy

Considering the generalized coordinate $q(\xi^R, \eta^I)$ in Eq. (9), where $\xi^R \sim N(0, 1)^m$ and $\eta^I = [-1, 1]^n$, the output of $f(\xi^R, \eta^I)$ exhibits characteristics of both random and interval variables. Such a function can be expanded using the Hermite series of order p and the Legendre series of order q sequentially, in an approach referred to as the PCLM:

$$f(\xi^R, \eta^I) \approx \hat{f}(\xi^R, \eta^I) = \sum_{i=0}^{K-1} \left(\sum_{j=0}^{L-1} \beta_{i,j} \psi_j(\eta^I) \right) \phi_i(\xi^R) \quad (15)$$

where $K = \frac{(m+p)!}{m!p!}$ and $L = \frac{(n+q)!}{n!q!}$. The $\phi_i(\xi^R)$ ($i = 0, 1, \dots, K-1$) and $\psi_j(\eta^I)$ ($j = 0, 1, \dots, L-1$) denote the i -th term of the Hermite series and the j -th term of the Legendre series, respectively, and the coefficient matrix $\beta = (\beta_{i,j})_{K \times L}$ is obtained through the least squares method:

$$\beta = (\Psi^T(\eta^S) \Psi(\eta^S))^{-1} \Psi^T(\eta^S) F^T(\xi^S, \eta^S) \Phi(\xi^S) \cdot (\Phi(\xi^S) \Phi^T(\xi^S))^{-1} \quad (16)$$

where $\Phi(\xi^S)$ and $\Psi(\eta^S)$ denote the measurement matrices corresponding to random samples $\xi^S = \{\xi_1^S, \xi_2^S, \dots, \xi_M^S\}$ and interval samples $\eta^S = \{\eta_1^S, \eta_2^S, \dots, \eta_N^S\}$, respectively. The sample points of random variables are generated via the tensor product of the roots of univariate Hermite polynomials of order $p+1$ in the m -dimensional space, that is,

$$\hat{\xi} = \hat{\xi}_1 \otimes \dots \otimes \hat{\xi}_i \otimes \dots \otimes \hat{\xi}_m$$

$$\hat{\xi}_i = [\hat{\xi}_i^{(1)} \quad \hat{\xi}_i^{(2)} \quad \dots \quad \hat{\xi}_i^{(p+1)}]^T \quad (17)$$

The sample points of interval variables are generated via the tensor product of the roots of univariate Legendre polynomials of order $q+1$ in the n -dimensional space, that is,

$$\hat{\eta} = \hat{\eta}_1 \otimes \dots \otimes \hat{\eta}_j \otimes \dots \otimes \hat{\eta}_n$$

$$\hat{\eta}_j = [\hat{\eta}_j^{(1)} \quad \hat{\eta}_j^{(2)} \quad \dots \quad \hat{\eta}_j^{(q+1)}]^T \quad (18)$$

The resulting sample pool comprises $(p+1)^m(q+1)^n$ candidate points, from which $M = 2K$, $N = 2L$ are typically selected for analysis. Upon the β , the complete form of $\hat{f}(\xi^R, \eta^I)$ can be expressed and used to predict the dynamic response.

Using the PCLM-LMD method^[27], the surrogate model of response $f(\xi^R, \eta^I)$ is expressed as

$$\hat{f}(\xi^R, \eta^I) = \sum_{i_c=1}^s \hat{a}_{i_c}(\xi^R, \eta^I) \cos(\hat{\phi}_{i_c}(\xi^R, \eta^I)) + \hat{r}(\xi^R, \eta^I) \quad (19)$$

where $\hat{a}_{i_c}(\xi^R, \eta^I)$, $\hat{\phi}_{i_c}(\xi^R, \eta^I)$, and $\hat{r}(\xi^R, \eta^I)$ are corresponding surrogate models of IA, IP, and residual signal, respectively.

To solve the curse of dimensionality, the HDMR^[28] is introduced to deal with surrogate models of IA, IP, and residual signal. That is,

$$\hat{a}_{i_c}(\xi^R, \eta^I) = \frac{(m+n-1)(m+n-2)}{2} a_{i_c0} -$$

$$(m+n-2) \left(\sum_{i=1}^m \hat{a}_{i_c}^{\text{PCE}}(\xi_i) + \sum_{j=1}^n \hat{a}_{i_c}^{\text{LM}}(\eta_j) \right) +$$

$$\sum_{i_1=1}^{m-1} \sum_{i_2 > i_1}^m \hat{a}_{i_c}^{\text{PCE}}(\xi_{i_1}, \xi_{i_2}) + \sum_{j_1=1}^{n-1} \sum_{j_2 > j_1}^n \hat{a}_{i_c}^{\text{LM}}(\eta_{j_1}, \eta_{j_2}) +$$

$$\sum_{i=1}^m \sum_{j=1}^n \hat{a}_{i_c}^{\text{PCLM}}(\xi_i, \eta_j) \quad (20)$$

$$\hat{\phi}_{i_c}(\xi^R, \eta^I) = \frac{(m+n-1)(m+n-2)}{2} \phi_{i_c0} -$$

$$(m+n-2) \left(\sum_{i=1}^m \hat{\phi}_{i_c}^{\text{PCE}}(\xi_i) + \sum_{j=1}^n \hat{\phi}_{i_c}^{\text{LM}}(\eta_j) \right) +$$

$$\sum_{i_1=1}^{m-1} \sum_{i_2 > i_1}^m \hat{\phi}_{i_c}^{\text{PCE}}(\xi_{i_1}, \xi_{i_2}) + \sum_{j_1=1}^{n-1} \sum_{j_2 > j_1}^n \hat{\phi}_{i_c}^{\text{LM}}(\eta_{j_1}, \eta_{j_2}) +$$

$$\sum_{i=1}^m \sum_{j=1}^n \hat{\phi}_{i_c}^{\text{PCLM}}(\xi_i, \eta_j) \quad (21)$$

$$\hat{r}(\xi^R, \eta^I) = \frac{(m+n-1)(m+n-2)}{2} r_0 -$$

$$(m+n-2) \left(\sum_{i=1}^m \hat{r}^{\text{PCE}}(\xi_i) + \sum_{j=1}^n \hat{r}^{\text{LM}}(\eta_j) \right) +$$

$$\sum_{i_1=1}^{m-1} \sum_{i_2 > i_1}^m \hat{r}^{\text{PCE}}(\xi_{i_1}, \xi_{i_2}) + \sum_{j_1=1}^{n-1} \sum_{j_2 > j_1}^n \hat{r}^{\text{LM}}(\eta_{j_1}, \eta_{j_2}) +$$

$$\sum_{i=1}^m \sum_{j=1}^n \hat{r}^{\text{PCLM}}(\xi_i, \eta_j) \quad (22)$$

Combining with Eq. (19), the comprehensive coupled model for the system response is constructed. The lower and upper bounds of $\hat{f}(\xi^R, \eta^I)$ are described by

$$\begin{aligned} \underline{f}(\xi^R) &= \min_{\eta^I \in [-1, 1]^n} [\hat{f}(\xi^R, \eta^I)] \\ \bar{f}(\xi^R) &= \max_{\eta^I \in [-1, 1]^n} [\hat{f}(\xi^R, \eta^I)] \end{aligned} \quad (23)$$

Herein, the mean of bounds (MB) and the variance of bounds (VB) are defined as

$$\begin{aligned} \mu_{\underline{f}} &= E[\underline{f}(\xi^R)], \quad \mu_{\bar{f}} = E[\bar{f}(\xi^R)] \\ \sigma_{\underline{f}}^2 &= \text{Var}[\underline{f}(\xi^R)], \quad \sigma_{\bar{f}}^2 = \text{Var}[\bar{f}(\xi^R)] \end{aligned} \quad (24)$$

Based on the 3σ rule, which corresponds to a confidence interval of approximately 99.73% for a normal distribution, the range of the system output can be estimated from Eq. (24):

$$[f]_{\text{CI} = 99.73\%} = [\mu_{\underline{f}} - 3\sigma_{\underline{f}}, \mu_{\bar{f}} + 3\sigma_{\bar{f}}] \quad (25)$$

3 Examples

3.1 Rigid hub-flexible cantilever beam

In Fig. 2, a rigid hub-flexible cantilever beam system subjected to combined central driving torque τ and thermal radiation S_0 is analyzed. The flexible cantilever is modeled using 20 fully parameterized spatial beam elements of ANCF. The parameter values are listed in Table 1. The total simulation duration is set to 20 s, with an integration time step of 0.1 ms. The time-varying form of the central driving torque is given by

$$\tau = \begin{cases} 5\sin(\pi t) & t \leq 2 \\ 0 & t > 2 \end{cases} \quad (26)$$

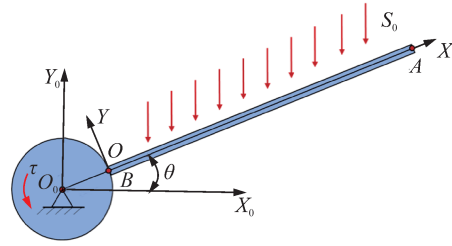


Fig. 2 Schematic view of the rigid hub-flexible cantilever beam system

Table 1 Characteristic parameters of rigid hub-flexible cantilever beam system

Parameter	Value
Length/m	5.0
Wall thickness/mm	2.35
Inner diameter/mm	10.92
Density/(kg·m ⁻³)	7 100
Young's modulus/GPa	69
Poisson ratio	0
Thermal expansion coefficient	4×10 ⁻⁵
Moment of inertia/(kg·m ²)	5.0
Specific heat capacity/(J·kg ⁻¹ ·K ⁻¹)	252
Thermal conductivity/(W·m ⁻¹ ·K ⁻¹)	16.61
Radiation absorptivity	0.5
Surface emissivity	0.13
Thermal radiation intensity/(W·m ⁻²)	3 500
Initial temperature/K	173
Ambient temperature/K	173
Stefan-Boltzmann constant	5.67×10 ⁻⁸

Fig. 3 shows the deterministic dynamic response of the system under combined central driving torque and thermal radiation.

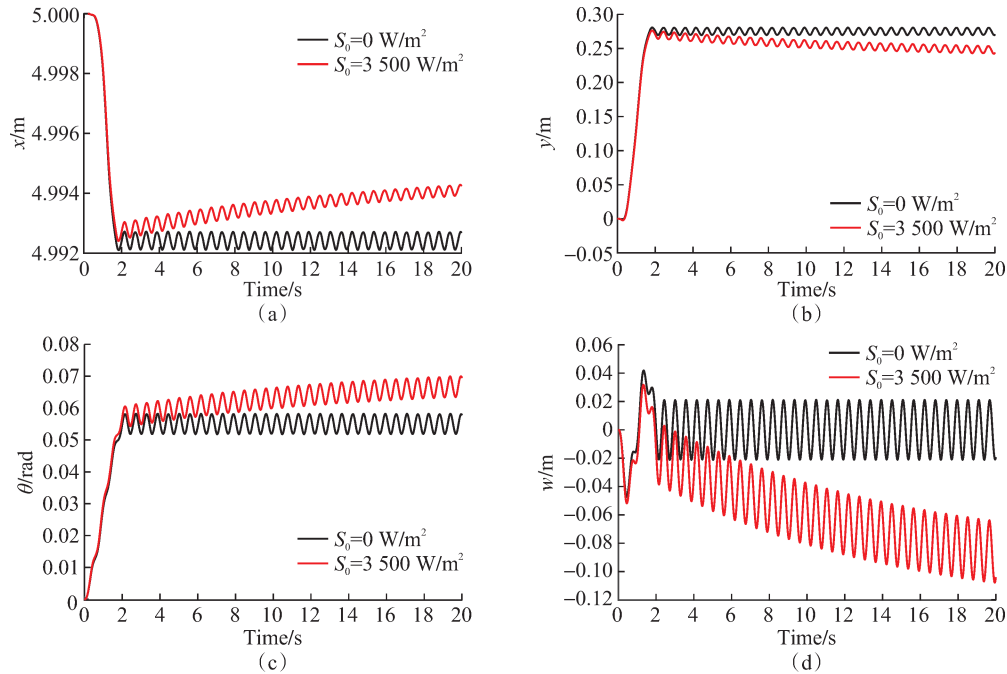


Fig. 3 Deterministic dynamic response of the system under combined central driving torque and thermal radiation. (a) Displacement in the x -direction at the endpoint A; (b) Displacement in the y -direction at the endpoint A; (c) Rotation angle of the rigid body; (d) Transverse deformation at the endpoint A

mal radiation. The red curve represents the system response with both thermal radiation ($S_0=3\,500\text{ W/m}^2$) and torque input, while the black curve represents the case without thermal radiation ($S_0=0\text{ W/m}^2$). During the initial 2 s, the central rigid body and the flexible beam driven by τ undergo rotation, leading to remarkable transverse deformation at the beam tip. Then, τ drops to 0, and the system enters free vibration, driven solely by inertia. Thermal radiation induces circumferential temperature differences along the beam, causing static deformation during free vibration. Thus, the tip displacement, rotation angle, and transverse deformation gradually increase.

Based on the expressions in Section 2, the Young's modulus of the flexible beam material is modeled as a random field with a correlation length $L_x^H = 5$. Simultaneously, thermal radiation intensity is modeled as an interval field with a correlation length $L_x^{G^I} = 5$. Using the K-L expansion, the random and interval fields are discretized as

$$\begin{aligned} E_H(x, \xi) &= \mu_E + \sigma_E \sum_{i=1}^4 \xi_i \sqrt{\lambda_{E,i}} \phi_{E,i}(x) \\ S_{G^I}(x, \eta) &= S^m + S^r \sum_{i=1}^4 \eta_i \sqrt{\lambda_{S,i}} \psi_{S,i}(x) \end{aligned} \quad (27)$$

where $\mu_E = 69 \times 10^9$ and $\sigma_E = 0.01\mu_E$ denote the nomi-

nal value and the standard deviation of Young's modulus; $S^m = 3\,500$ and $S^r = 0.1S^m$ indicate the nominal value and the interval radius of thermal radiation. The eigenvalues and eigenfunctions are obtained as

$$\begin{aligned} \lambda_{i,1} &= 3.694\,1, \quad \lambda_{i,2} = 0.690\,0, \quad \lambda_{i,3} = 0.225\,4 \\ \lambda_{i,4} &= 0.106\,6 \quad i = E, S \end{aligned} \quad (28)$$

$$\phi_{E,j}(x) = \psi_{S,j}(x) = \begin{cases} \frac{\cos(\omega_j x)}{\sqrt{L + \sin(2\omega_j L)/(2\omega_j)}} & j = 1, 3 \\ \frac{\sin(\omega_j x)}{\sqrt{L - \sin(2\omega_j L)/(2\omega_j)}} & j = 2, 4 \end{cases} \quad (29)$$

where $L = 2.5$; $\omega_1 = 0.261\,3$, $\omega_2 = 0.734\,6$, $\omega_3 = 1.316\,9$, and $\omega_4 = 1.926\,3$.

The surrogate models $\hat{a}^i(t)$, $\hat{\varphi}^i(t)$, and $\hat{r}^i(t)$ are constructed by the PCLM-HDMR method, where $i = x, y, \theta, w$. Based on the surrogate models, Figs. 4 and 5 present the predicted temporal evolution of MB and VB of the responses, respectively. In the presence of random and interval fields, the upper and lower bounds of responses exhibit remarkable randomness. The variance of these bounds increases gradually over time, making it essential to further investigate the dynamic response of the system.

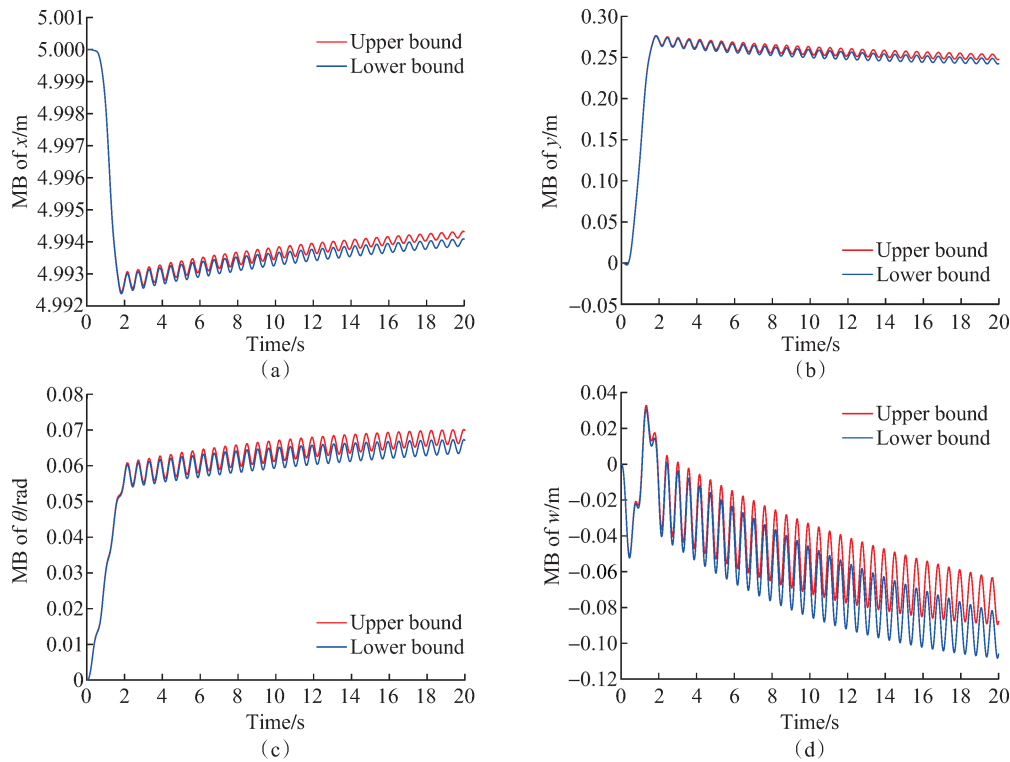


Fig. 4 MB results of the system response. (a) $x(t)$; (b) $y(t)$; (c) $\theta(t)$; (d) $w(t)$

Based on the MB and VB responses predicted by the complete surrogate models and the 3σ criterion, the predicted regions for all time-varying responses are pre-

sented in Fig. 6. The upper and lower bounds of the system responses progressively expand over time. This growth in uncertainty indicates an increasing influence of

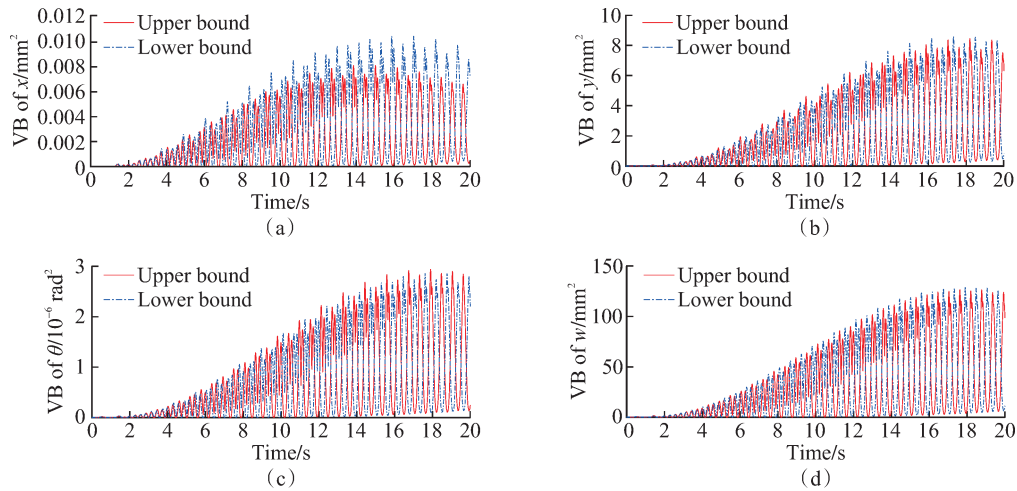


Fig. 5 VB results of the system response. (a) $x(t)$; (b) $y(t)$; (c) $\theta(t)$; (d) $w(t)$

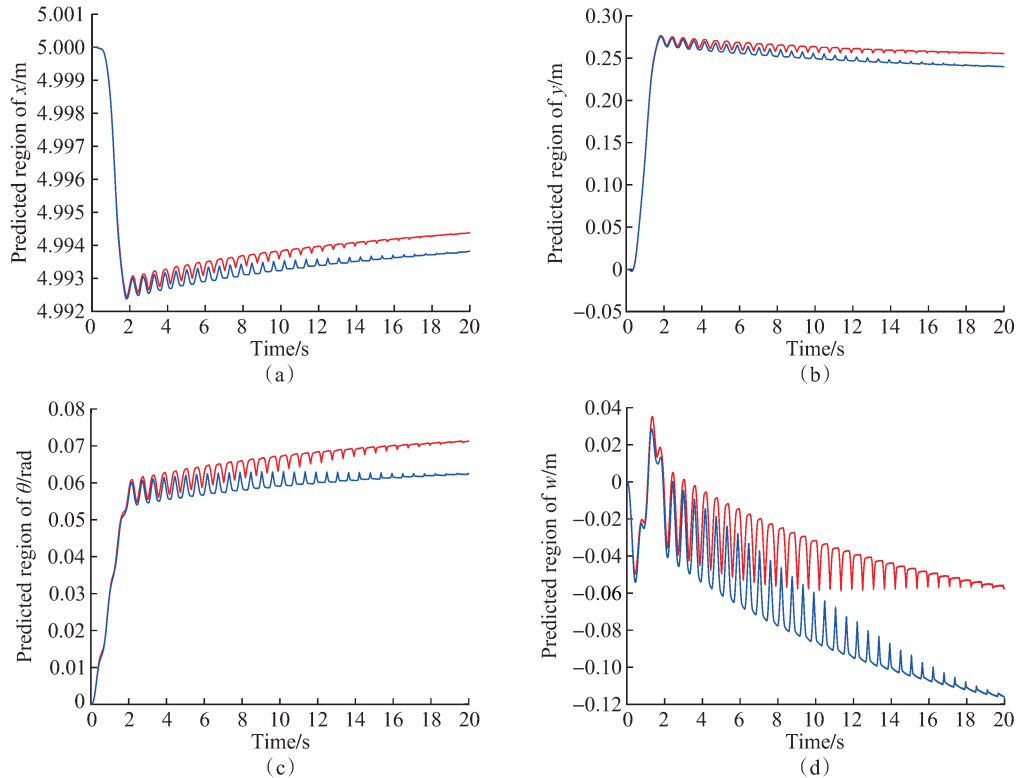


Fig. 6 Predicted regions of the responses. (a) $x(t)$; (b) $y(t)$; (c) $\theta(t)$; (d) $w(t)$

uncertain parameters on the dynamic response and a progressively stronger nonlinear input-output relationship. In general, the Monte Carlo scanning (MCS) method is used for comparison; however, it requires at least $N = 1.464 \times 10^8$ sample points, which is impractical for this problem. Therefore, Fig. 7 shows the real response results obtained from 5 000 randomly generated sample points using the sample pool of MCS. A comparison demonstrates that the nonintrusive surrogate modeling approach using the proposed method achieves long-time dynamic response prediction with only 481 sample points, enabling high-precision response prediction in hybrid uncertain systems while maintaining computational efficiency.

3.2 Rotating hub-inclined thin plate system

The inclined rotating thin plate system consists of a rectangular cantilever thin plate, with its left end fixed to a rigid rotating hub, as shown in Fig. 8. The hub rotates about a fixed axis according to a prescribed angular velocity profile. The time-dependent angular velocity function is given by

$$\Omega = \begin{cases} \Omega_s \left(\frac{t}{T_s} - \frac{1}{2\pi} \sin \frac{2\pi t}{T_s} \right) & t \leq T_s \\ \Omega_s & t > T_s \end{cases} \quad (30)$$

where $\Omega_s = 10 \text{ rad/s}$, $T_s = 5 \text{ s}$. Point O denotes the reference point of the rotating plate, with its distance to the

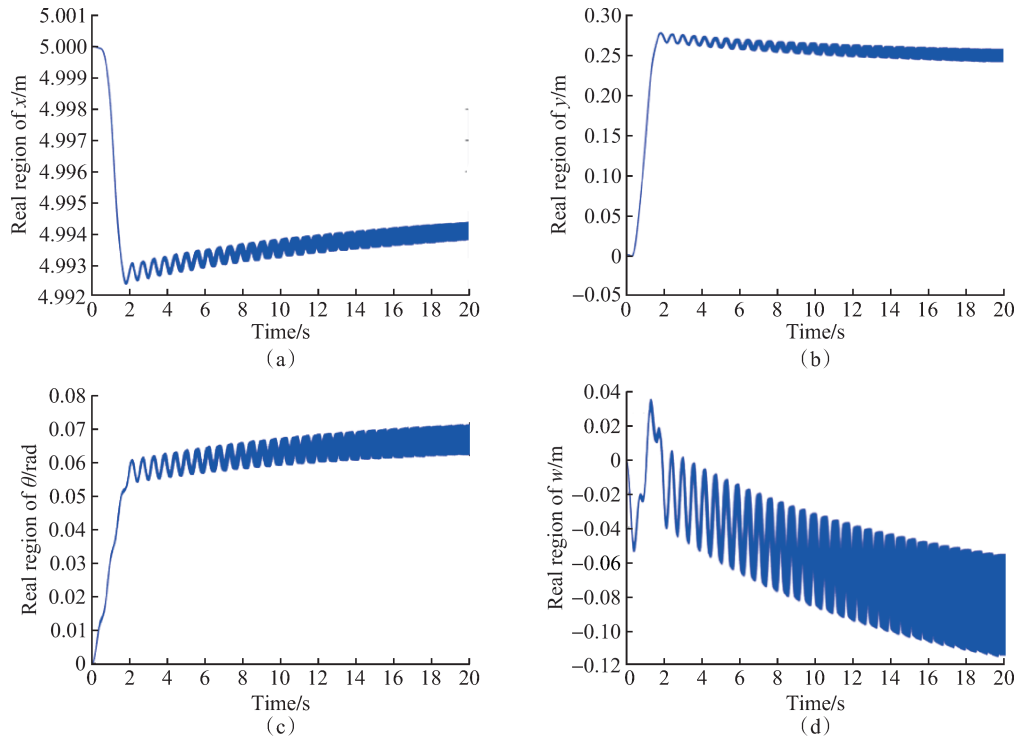


Fig. 7 Real regions of the responses. (a) $x(t)$; (b) $y(t)$; (c) $\theta(t)$; (d) $w(t)$

rotation axis set as $r = 0.2$ m. The frame $\{b_1, b_2, b_3\}$ is obtained from the local coordinate $\{a_1, a_2, a_3\}$ via a transformation defined by Euler angles, with the rotation angle set as $(0^\circ, 0^\circ, 30^\circ)$. The geometric and material parameters of the plate are listed in Table 2, and the rotating thin plate is modeled using 8×4 reduced plate elements of ANCF.

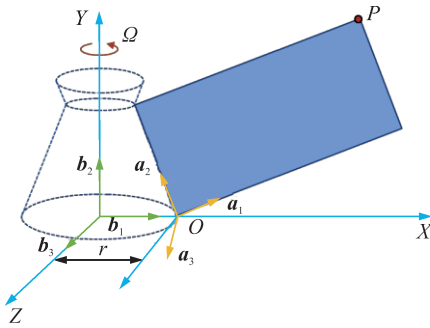


Fig. 8 Schematic view of the rotating hub-inclined thin plate system

Table 2 Parameters of the rotating hub-inclined thin plate system

Parameter	Value	Parameter	Value
Length/m	1.0	Density/(kg·m ⁻³)	3 000
Wide/mm	0.5	Young's modulus/GPa	70
Thickness/mm	2.5	Poisson ratio	0.3

The density of the flexible thin plate is modeled as a 2D random field, where $L_x^H = 1$, $L_y^H = 0.5$. Furthermore, to account for the inhomogeneity in plate thickness owing to practical manufacturing processes, the thickness is modeled as an interval field^[32] and its corre-

lation length is set as $L_x^G = 1$, $L_y^G = 0.5$. Through K-L expansion, the density random field and thickness interval field are expressed as

$$\begin{aligned} \rho_H(x, y, \xi) &= \mu_\rho + \sigma_\rho \sum_{i=1}^4 \xi_i \sqrt{\lambda_{\rho,i}} \phi_{\rho,i}(x, y) \\ d_{G^I}(x, y, \eta) &= d^m + d^r \sum_{i=1}^4 \eta_i \sqrt{\lambda_{d,i}} \psi_{d,i}(x, y) \end{aligned} \quad (31)$$

where μ_ρ is the nominal value and $\sigma_\rho = 0.02\mu_\rho$ is the standard deviation of the plate density; d^m and $d^r = 0.02d^m$ denote the nominal value and the radius of the interval field. The specific values and forms of eigenvalues and eigenfunctions are obtained as follows:

$$\begin{aligned} \lambda_{i,1} &= 0.2729, \lambda_{i,2} = 0.0510, \lambda_{i,3} = 0.0167 \\ \lambda_{i,4} &= 0.0095 \quad i = \rho, d \\ \phi_{\rho,1}(x, y) &= \psi_{d,1}(x, y) = \gamma_{11} \cos(\omega_{11}x) \cos(\omega_{21}y) \\ \phi_{\rho,2}(x, y) &= \psi_{d,2}(x, y) = \gamma_{12} \cos(\omega_{11}x) \sin(\omega_{22}y) + \\ &\quad \gamma_{21} \sin(\omega_{12}x) \cos(\omega_{21}y) \\ \phi_{\rho,3}(x, y) &= \psi_{d,3}(x, y) = \gamma_{13} \cos(\omega_{11}x) \cos(\omega_{23}y) + \\ &\quad \gamma_{31} \cos(\omega_{13}x) \cos(\omega_{21}y) \\ \phi_{\rho,4}(x, y) &= \psi_{d,4}(x, y) = \gamma_{22} \sin(\omega_{12}x) \sin(\omega_{22}y) \end{aligned} \quad (32)$$

where $\omega_{11} = 1.3065$, $\omega_{12} = 3.6732$, $\omega_{13} = 6.5846$, $\omega_{21} = 2.6131$, $\omega_{22} = 7.3464$, $\omega_{23} = 13.1692$, $\gamma_{11} = 1.3886$, $\gamma_{12} = 1.1426$, $\gamma_{13} = 1.0501$, $\gamma_{21} = 1.9974$, $\gamma_{22} = 1.2137$, $\gamma_{23} = 1.2666$.

The PCLM-HDMR method is used to construct surrogate models $\hat{a}_w(t)$, $\hat{\phi}_w(t)$, $\hat{r}_w(t)$. Then, a complete non-intrusive surrogate model $\hat{w}(t)$ is constructed for the deformation response under random-interval fields, and sta-

tistical analysis is performed on the distribution characteristics of the maximum transverse deformation response. As shown in Fig. 9(a), the combined spatially correlated random and interval field uncertainties cause the PDF of the maximum transverse deformation to be no longer represented by a single curve but by two separate

curves defining the upper and lower output bounds. Similarly, the cumulative distribution function (CDF) in Fig. 9(b) is now represented as an interval band, which reflects the uncertainty within a confidence range, exhibiting the dual characteristics of randomness and interval uncertainty.

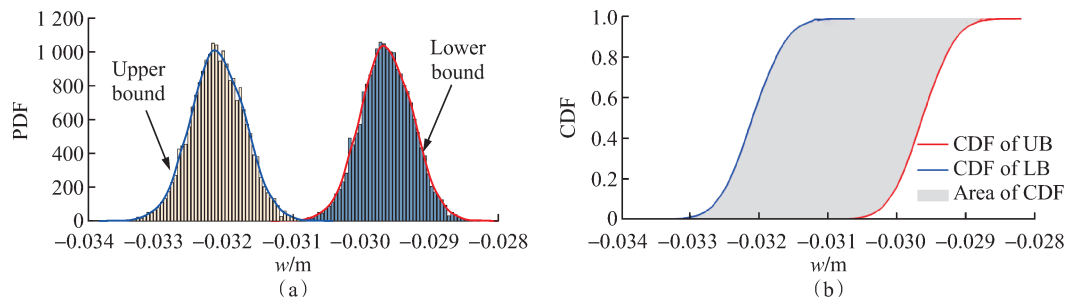


Fig. 9 PDF and CDF for bounds of the maximum lateral deformation. (a) PDF; (b) CDF

Figs. 10(a) and (b) illustrate the temporal evolution of MB and VB for the lateral deformation, respectively. The predicted region derived using the 3σ criterion is presented in Fig. 10(c). Fig. 10(d) provides reference responses obtained from 5 000 samples generated using the MCS sample pool, which serve as a benchmark for validating the prediction accuracy of the proposed method. Comparative results indicate that the DRPCLM-

LMD modeling strategy effectively captures the evolving boundary behavior of the system response under high-dimensional hybrid uncertainties. Furthermore, the approach demonstrates reliable predictive capability for extreme value statistics, highlighting its strong adaptability and practical utility in handling complex systems subjected to multiple sources of uncertain fields.

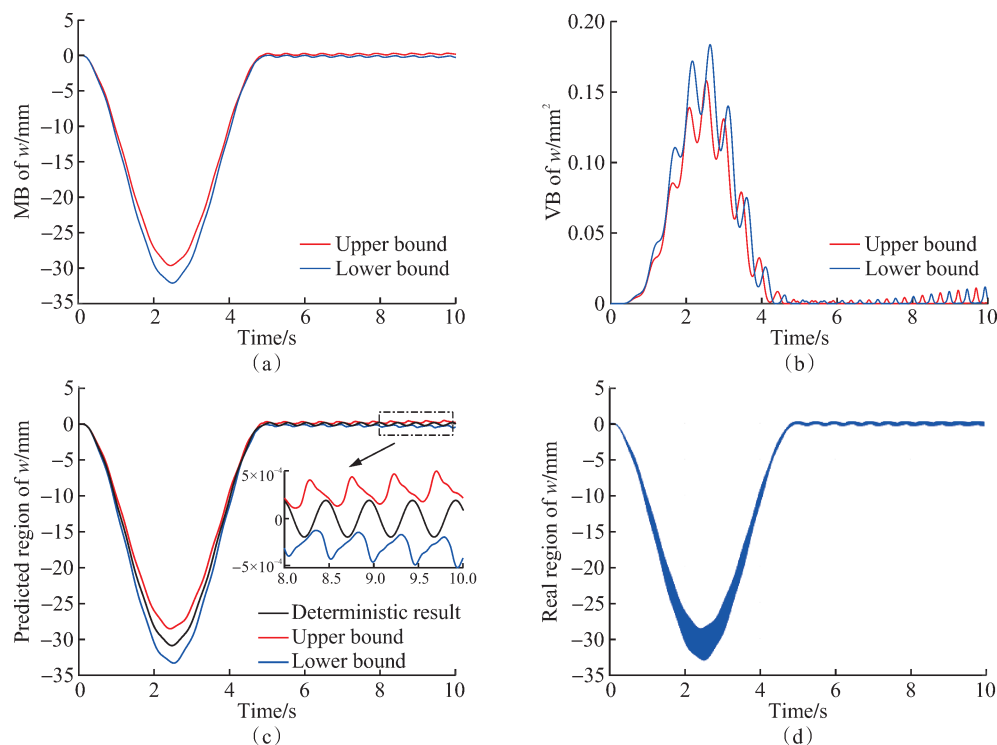


Fig. 10 Response prediction of lateral deformation at Point P. (a) MB; (b) VB; (c) Predicted region; (d) Real region

4 Conclusions

A nonintrusive computational framework is proposed to analyze the effects of random and interval fields on the dynamic response of multibody systems. By incorporat-

ing the K-L expansion, high-dimensional discrete representations of these fields are embedded into ANCF elements. Computational efficiency is further improved by precomputing constant matrices in the dynamic equations. To address challenges associated with high-

dimensional inputs and long-time domain simulations, PCLM is combined with the LMD technique, which decomposes the system response into IA, IP, and trend components. The HDMR technique is then employed to effectively reduce the dimensionality of these components, enabling accurate prediction of the overall system behavior via a fully constructed surrogate model. The validity and efficiency of the proposed methodology are demonstrated through two examples involving 1D and 2D random-interval field models. The results confirm that the proposed approach effectively captures spatially dependent uncertainties and considerably improves the accuracy and computational efficiency in predicting statistical characteristics and boundary envelopes of rigid-flexible multibody systems under hybrid spatial uncertainties. This work establishes the efficacy of the method on classical problems. Future research will extend its application to strongly nonlinear regimes, including systems with large deformations and non-smooth contact, to more rigorously benchmark its advantages for complex engineering analyses.

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考虑随机场与区间场的刚柔耦合多体系统动力学分析

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摘要: 针对刚柔耦合多体系统中包含随机场和区间场的混合不确定性问题, 本文提出了一种非侵入式动态响应预测方法。通过使用 Karhunen-Loève 展开及截断技术, 将随机场与区间场的高维离散表示嵌入基于绝对节点坐标法的多体系统动力学建模中, 实现了对空间相关不确定性参数的有效描述。在此基础上, 为应对高维不确定变量和长时域分析带来的挑战, 结合局域均值分解与高维模型表征方法, 构建了系统动态响应的非侵入式代理模型。该方法在提高预测精度的同时, 显著降低了计算成本, 提高了响应统计量与边界特征的求解效率。通过一维与二维随机场-区间场作用下的典型多体系统数值算例, 验证了所提方法在处理空间相关不确定性、预测系统响应范围等方面的有效性与适用性。

关键词: 刚柔耦合多体系统; 随机场; 区间场; 混合不确定性动力学分析

中图分类号: O313.7