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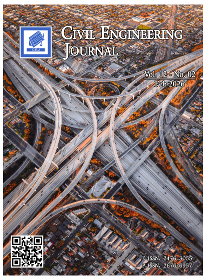

Hierarchical Learning-Based System Decomposition for Time-Dependent Structural System Reliability Assessment

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Abstract

Time-dependent reliability assessment of structural systems is challenging when degradation and multiple interacting failure modes govern failure. Under these conditions, the system limit state function (LSF) may be highly nonlinear, non-smooth, and available only implicitly through high-fidelity analysis. This paper proposes a system decomposition and hierarchical learning (DHL) framework to construct an evaluable surrogate system LSF for degradation-driven, time-variant reliability analysis. The structural system is decomposed into dominant failure modes and their connectivity. Artificial neural networks are trained hierarchically to learn the decomposed relationships. Mode-level surrogates approximate the LSF of each failure mode. A system-level surrogate then integrates the mode-level performance quantities and time to capture mode interaction and mechanism switching. The resulting surrogate is combined with Monte Carlo simulation and the probability density evolution method to compute time-dependent failure probabilities and, when required, the evolution of the system performance probability density. Two benchmark problems—a highly nonlinear parallel system and a rigid–plastic portal frame with correlated collapse mechanisms under degrading capacities—are used to evaluate the approach. DHL improves system-level surrogate fidelity relative to direct system-level ANN learning, with mean reliability prediction errors below 3.1% and 1.23% in the two benchmarks, respectively, while remaining compatible with both sampling-based and density-evolution propagation schemes.

Keywords: Artificial Neural Network; Failure-Mode Interaction; Hierarchical Surrogate; Limit State Function; Probability Density Evolution Method; Time-Variant Degradation.

1. Introduction

Reliability is a foundational measure for structural safety assessment, commonly defined as the probability that a structure performs its intended function without failure over a specified reference period [1]. With increasing system complexity and aging infrastructure, reliability evaluation has become more challenging because structural performance is affected by statistical dependence, multi-component interaction, and deterioration processes that evolve over time [2-5]. In many practical applications, reliability must be assessed at the system level rather than at the component level, because load redistribution and interaction among components can change the governing failure mechanisms after local damage occurs [6]. These characteristics often lead to highly nonlinear—and sometimes non-smooth—system failure boundaries, particularly when multiple competing failure modes are present and the dominant mechanism switches across the uncertainty space [4, 7].

Methods for structural system reliability can be broadly divided into event/logic-based formulations and sequential or search-based strategies [6]. Event-based methods include classical bounding approaches [8], Monte Carlo simulation

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(MCS) [9], matrix-based formulations that explicitly handle dependence and system topology [10], and surrogate-assisted approaches that reduce repeated expensive evaluations [11]. Sequential strategies, such as response-surface-based schemes and probabilistic search, can improve efficiency by iteratively focusing computations near critical regions [12-14]. Despite these advances, system reliability remains computationally demanding for large or strongly coupled systems, particularly when the system event involves multiple correlated failure modes and strong nonlinearity [4, 7].

A key modeling step in system reliability is defining mode-level limit state functions (LSFs) and the connectivity relationships that map mode failures to system failure [15, 16]. In this paper, time-dependent reliability refers to degradation-driven time-variant reliability, where capacity-related parameters evolve with time and the target quantity is the evolution of the system failure probability over the service horizon [17, 18]. Deteriorating structural systems have been studied extensively, and methodological reviews emphasize that time-varying resistance requires reliability to be evaluated as a function of time rather than at a single snapshot [2, 17]. Recent developments also demonstrate that machine-learning-assisted probabilistic propagation can improve accuracy and efficiency for time-dependent reliability evaluation under complex time effects [19-21].

For degradation-driven time-variant reliability, evolution-type methods provide a direct way to propagate uncertainty in time. The Probability density evolution method (PDEM) evolves the probability density of a performance quantity and has been used in structural reliability and life-cycle settings [22, 23]. Bayesian updating extensions of PDEM have further supported reliability assessment for deteriorating structures under inspection or information updates [24]. However, both PDEM and sampling-based propagation require an evaluable performance function. In many realistic structures, system performance is obtained from nonlinear numerical simulation or high-fidelity models, and explicit system LSFs are not available in closed form. In such cases, surrogate models are often required to enable repeated evaluation efficiently [11, 25].

A growing body of research has explored surrogate modeling for reliability, including kriging/Gaussian processes, polynomial chaos expansion (PCE), support vector machines, and neural networks [25-28]. Reviews highlight that surrogate selection should be aligned with problem dimensionality, nonlinearity, and downstream tasks such as rare-event estimation and time propagation [29]. Despite this progress, constructing accurate system-level surrogates remains more difficult than mode-level learning. System performance functions often involve extreme-value logic (e.g., series/parallel/compound behavior), which can produce non-smooth system responses and mechanism switching among competing failure modes [30, 31]. Equivalent system performance functions have been developed to address this, including moment-based system formulations [32] and equivalent extreme-value event representations [30, 31]. These formulations can be integrated naturally with time-variant reliability propagation, including PDEM-based system reliability assessment [18]. However, when the system response is implicit and must be learned, directly training a single surrogate for the system LSF can be fragile because the surrogate must simultaneously represent mode-level nonlinearities and the system-level switching interaction. Classical higher-moment reliability formulations and related approximation tools provide complementary perspectives on system performance representation, but they do not eliminate this learning difficulty when the system response is implicit or simulation-driven [33].

Recent work indicates that decomposition and multi-level modeling can improve robustness in complex reliability problems. Multilevel decomposition has been proposed for assembled stochastic structural systems [34], and rare-event reliability approaches continue to advance for complex system evaluations [35]. In parallel, adaptive sampling and active learning strategies have shown strong potential for improving surrogate efficiency by concentrating samples near failure boundaries [36, 37]. For high-dimensional reliability problems, dimension reduction and subspace-oriented active learning have also been proposed to improve scalability and sample efficiency [38]. Time-variant dependence across multiple failure modes, vine-copula-based formulations have also been explored [39]. System reliability methods and applications further extend across different domains, including imprecise probabilistic information [40], geotechnical reliability assessment under uncertainty [41], and fire-related reliability evaluation [42]. Foundational texts remain central for the formulation and interpretation of structural reliability in these settings [43], and classical service-life reliability studies continue to motivate deterioration-driven reliability evaluation [44].

Against this background, the present study proposes a system decomposition and hierarchical learning (DHL) framework for degradation-driven time dependent structural system reliability assessment. The method first decomposes the structural system into dominant failure modes and their connectivity, then trains surrogate models hierarchically: mode level surrogates approximate individual failure-mode LSFs, and a system-level surrogate integrates mode level performance values and time to represent system interaction and mechanism switching in a decomposition-consistent manner [30-32]. The resulting surrogate system LSF is designed to be compatible with both Monte Carlo simulation and probability density evolution for time-dependent reliability propagation [22, 23]. This formulation is consistent with ongoing developments in high-dimensional reliability prediction using deep-learning and multi-fidelity surrogates [45], and it is also complementary to recent system reliability strategies that use active learning and system sensitivity to improve efficiency [46] as well as enhanced active-learning kriging approaches for time-dependent system reliability [47].

The remainder of this paper is organized as follows. Section 2 presents the proposed DHL methodology and its integration with MCS and PDEM. Section 3 validates the approach using benchmark examples. Section 4 discusses results and practical implications. Section 5 concludes with key findings and future research directions.

2. Time-dependent Reliability Assessment Method for Structural Systems

This section presents the proposed system decomposition and hierarchical learning (DHL) framework for constructing a surrogate system limit state function (LSF) and integrating it with degradation-driven time dependent structural system reliability assessment. The fundamental difficulty in system reliability is that the system failure event is governed by multiple interacting failure modes; consequently, the effective system performance boundary in the basic random space may be highly nonlinear and may switch among dominant mechanisms across different regions. When the system LSF is implicit (e.g., obtained from high-fidelity numerical analysis), direct surrogate learning of a system-level mapping can become inaccurate or unstable. This challenge is consistent with observations in high-dimensional reliability prediction, where deep learning surrogates and multi-fidelity strategies have been introduced to improve approximation capability and computational efficiency [45]. Motivated by these considerations, DHL adopts a structured learning strategy aligned with system connectivity, decomposing the global learning task into a hierarchy of more tractable sub-problems.

Although various surrogate models (e.g., Gaussian processes/kriging and polynomial chaos expansion) can be used in reliability analysis, artificial neural networks (ANNs) are adopted here because they naturally support the compositional structure required by DHL. In DHL, the system mapping is represented as a hierarchy of functions (mode-level mappings followed by a system-level aggregation), and system behavior may exhibit mechanism switching induced by extreme-value-type failure logic. ANNs provide flexible parametric representations for such composed mappings and enable fast inference, which is attractive for repeated evaluations in MCS and PDEM. Importantly, the DHL framework is surrogate-agnostic: alternative regressors (e.g., kriging or PC-kriging) can be used at individual hierarchical levels when response smoothness and dimensionality make them advantageous [48].

2.1. Equivalent System LSF Representations and PDEM

To motivate system-level performance representations, Zhao & Ang [32] proposed a moment-based equivalent formulation. The corresponding equivalent performance function is expressed in Equation 1:

$$Z = G_m + \sum_{i=1}^{r}(G_i - G_m) \tag{1}$$

where, G_m represents the minimum value among the LSFs of all failure modes when all random variables in the system are assigned their mean values, G_i denotes the univariate LSF where all random variables except the i-th variable are assigned their mean values, leaving only the i-th variable to vary, and r represents the number of random variables. For system event representation based on mode-level LSFs, Li & Chen [30] and Chen & Li [31] introduced the equivalent extreme-value event, which provides equivalent system performance functions for typical system configurations. The series, parallel, and compound representations are summarized in Equation 2:

$$Z = \begin{cases} Z_{series} = \min\limits_{i=1,\dots,n}\{Z_i(\theta)\} \\ Z_{parallel} = \max\limits_{i=1,\dots,n}\{Z_i(\theta)\} \\ Z_{compound} = \max\limits_{i=1,\dots,n}\left\{\min\limits_{j=1,\dots,n}\{Z_{ij}(\theta)\}\right\} \end{cases} \tag{2}$$

where Z_{series}, $Z_{parallel}$, and $Z_{compound}$ represent the equivalent single LSFs for the series system, parallel system, and compound system, respectively, Z_i represents the LSF of the i-th failure mode, and θ denotes the vector of basic random variables. For degradation-driven time-dependent reliability, the PDEM provides a direct evolution formulation by propagating the probability density of the system performance quantity in time [22]. Given a system performance quantity $Z(\theta,t)$, the governing density evolution equation in PDEM is written as Equation 3:

$$\frac{\partial p_{Z\theta}(z,\theta,t)}{\partial t} + \dot{Z}(\theta,t).\frac{\partial p_{Z\theta}(z,\theta,t)}{\partial z} = 0 \tag{3}$$

where $p_{Z\theta}(z,\theta,t)$ denotes the joint PDF of (z,θ)at time t, and $\dot{Z}(\theta,t) = \partial Z/\partial t$ is the derivative of system LSF $Z(\theta,t)$ with respect to time. The marginal PDF of the system performance is obtained by integrating Equation 3 over the random-variable domain Ω_θ, as shown in Equation 4:

$$p_Z(z,t) = \int_{\Omega_\theta} p_{Z\Theta}(z,\theta,t)d\theta \tag{4}$$

In many practical applications, explicit expressions for $Z(\theta,t)$ and $\dot{Z}(\theta,t)$ are unavailable because the system response is computed numerically. Consequently, a surrogate model is required to approximate the system LSF with sufficient fidelity for both Monte Carlo estimation and density evolution.

2.2. Construction of the System Limit State Function via DHL

For a structural system, the limit state function (LSF) can generally be expressed as Equation 5, where θ denotes the vector of random variables, t is time, and $g(\cdot)$ represents the system LSF:

$$Z(t) = g(\theta, t) \tag{5}$$

In a structural system, the LSF of each component can be viewed as a failure surface in a multidimensional random space, which divides the sample points into different regions [23, 25]. Since multiple LSFs act simultaneously in the random variable space, the boundaries of the regions dividing the sample points may become non-smooth. Therefore, directly using the random variables and system limit state values as inputs and outputs might affect the accuracy of the constructed ANN function.

A more robust approach begins with the principles of system reliability analysis. The first step is to decompose the system to identify the connectivity among its failure modes. The rationale for this decomposition is to break down the complex system into smaller, relatively independent subsystems or components, allowing each to be analyzed or optimized separately and then recombined to represent the global response [16]. For example, the rigid-plastic portal frame in Figure 1 is subjected to two random loads [22, 40], H and V, with random moment capacities M_i, i=1,...,4. Through decomposition, the system LSFs are expressed by the four plastic failure modes shown in Figure 2 [40]. System failure occurs when any of these modes is activated.

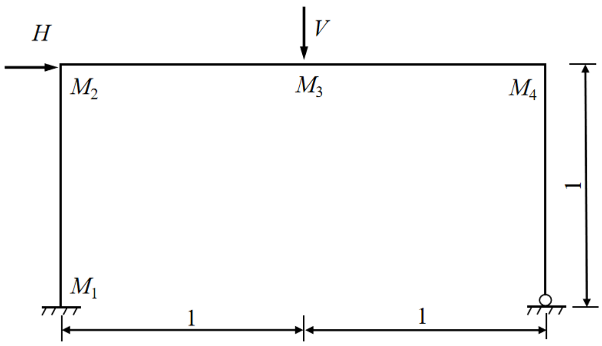


Figure 1. A single-story rigid frame

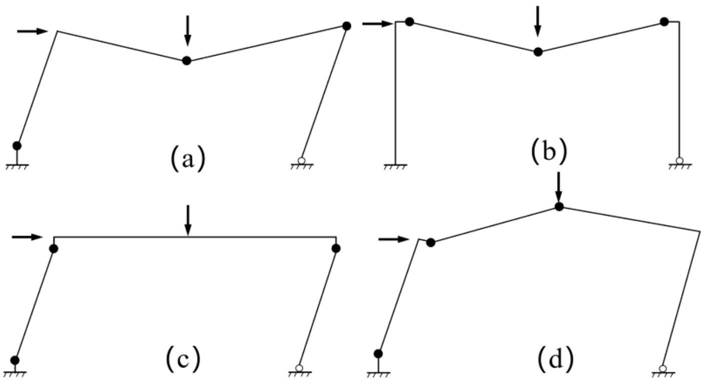


Figure 2. Four failure modes obtained through system decomposition

When constructing the system limit state function (LSF), the relationships identified through system decomposition can be captured using a hierarchical ANN framework. In this approach, the decomposition process reveals multiple levels of relationships that are recursively learned. At the first level, the relationship between the random parameters associated with each failure mode's LSF and its corresponding limit state value is modeled using an ANN. This is expressed in Equation 6:

$$Z_i(t) = g_i(\theta_i, t) \tag{6}$$

The second level of relationships corresponds to the connection between the limit state values Z_i of the failure modes and the system's limit state value Z. This connection, which incorporates the equivalent extreme value event, can also be learned via ANN, and is expressed as Equation 7 as follows:

$$Z(t) = g_{sys}(Z_i, t) \tag{7}$$

Together, Equations 6 and 7 define the system LSF constructed through the combination of decomposition-based hierarchical learning (DHL) and ANN. The hierarchical learning framework is illustrated in Figure 3.

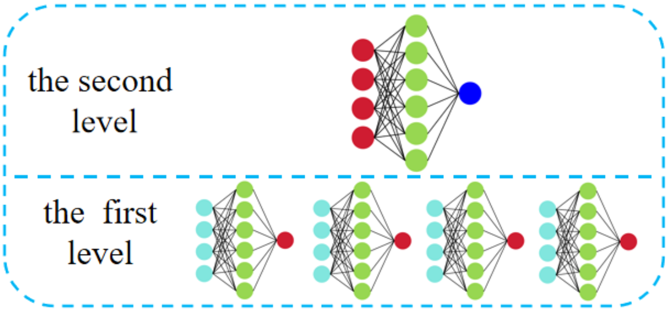


Figure 3. ANN learning after system decomposition

If additional subsystem-level information exists between the failure modes and the system, an extra hierarchical layer can be introduced and trained using ANN. By systematically capturing the hierarchical relationships revealed through system decomposition, and applying ANN at each level, a multi-level neural network representation of the system LSF can be developed. Compared to direct construction, this approach yields an equivalent system LSF with improved accuracy while relying on conventional ANN techniques.

2.3. Integration with Time-Dependent Reliability Analysis

Once the system LSF is established using DHL, it can be directly incorporated into existing reliability algorithms. In this work, two widely used approaches are considered: Monte Carlo simulation (MCS) and the PDEM. For MCS, samples of θ and t are drawn and evaluated through the constructed system LSF. The system failure probability at time t is estimated as Equation 8:

$$p_f(t) = N_f(t)/N \tag{8}$$

where, N is the total number of samples and $N_f(t)$ is the number of samples satisfying $\hat{Z}(\theta^{(k)}, t) \leq 0$. In surrogate-based MCS, the computational advantage arises from replacing expensive high-fidelity evaluations with surrogate predictions. Within this setting, DHL's primary contribution is improved system-level LSF accuracy and robustness relative to direct system-level surrogate learning, rather than a reduction in the number of surrogate evaluations per sample. For degradation-driven time-dependent reliability, the surrogate system LSF can also be incorporated into PDEM. Substituting $\hat{Z}(\theta, t)$ into the governing equation yields Equation 9:

$$\frac{\partial p_{Z\theta}(z,\theta,t)}{\partial t} + \dot{\hat{Z}}(\theta,t) \cdot \frac{\partial p_{Z\theta}(z,\theta,t)}{\partial z} = 0 \tag{9}$$

where, $\dot{\hat{Z}}(\theta,t) = \frac{\partial \hat{Z}(\theta,t)}{\partial t}$ the system performance density $p_Z(z,t)$ follows from Equation 4, and the time-dependent failure probability can be computed as $p_f(t) = \int_{-\infty}^{0} p_Z(z,t)\, dz$. In this study, MCS and PDEM are both employed to demonstrate that the DHL-based system LSF is compatible with conventional reliability propagation schemes and to validate the framework under different computational paradigms. In hierarchical surrogate modeling, approximation errors at lower levels may, in principle, propagate to higher-level predictions. In the proposed DHL framework, this risk is mitigated by decomposing a high-dimensional system-level mapping into a sequence of lower-dimensional and physically interpretable mappings. Mode-level surrogates approximate individual limit state functions, while the system-level surrogate operates on a small set of mode-level performance quantities. This transformation reduces the complexity of the learning task at the system level and limits sensitivity to small mode-level approximation errors.

2.4. ANN Configuration and Computational Workflow

To ensure a fair comparison between different system modeling strategies, this study does not aim to develop or optimize neural network algorithms. Instead, a fixed-architecture ANN regression model is adopted as a consistent numerical approximation tool. Specifically, each ANN uses three hidden layers with 30 neurons per layer, and an identical training procedure is applied across all compared strategies. This choice ensures that differences in reliability prediction primarily reflect the proposed DHL framework rather than hyperparameter tuning or architecture-specific advantages. The DHL framework reduces the dependence on network depth and neuron count by decomposing a complex system-level mapping into a hierarchy of lower-dimensional learning tasks. Consequently, as long as the chosen network provides sufficient representational capacity, moderate variations in depth or neuron count are not expected to significantly alter the relative performance of DHL. While problem-specific architecture optimization may further improve surrogate accuracy, it is not the focus of the present work. The overall computational workflow proceeds as follows. First, the system is decomposed to identify dominant failure modes and establish their connectivity. Second, mode-level ANN surrogates are trained according to Equation 6. Third, the system-level surrogate is trained according to Equation 7, using decomposition-consistent system targets (e.g., generated through Equation 2). Finally, time-dependent structural system reliability is computed using surrogate-based MCS (Equation 8) or surrogate-assisted PDEM (Equation 9). The complete workflow is summarized in Figure 4.

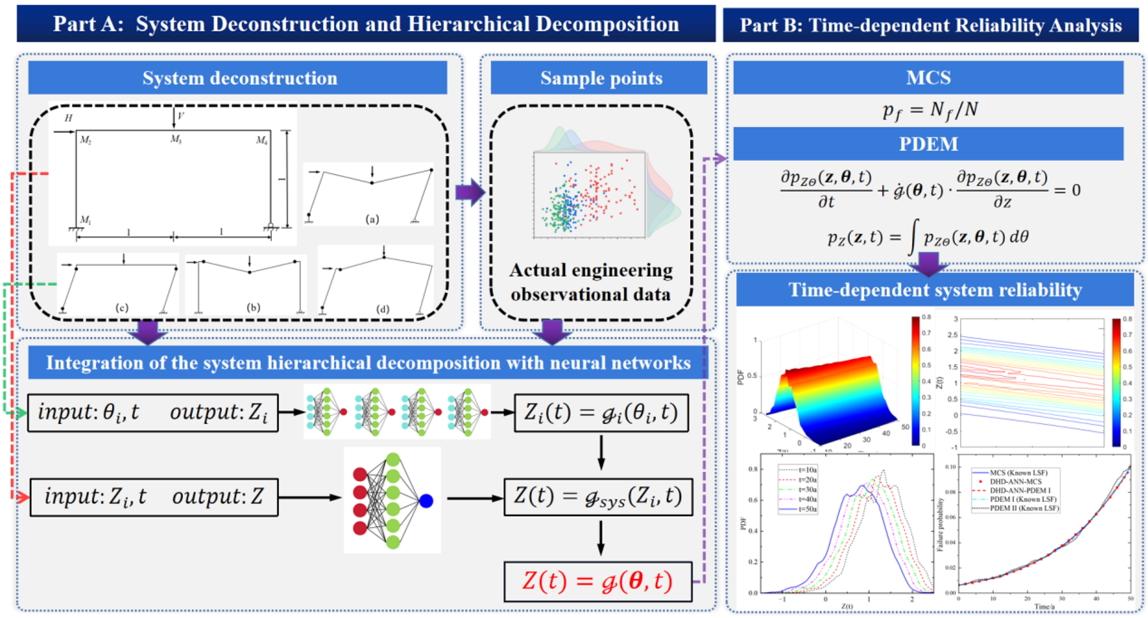


Figure 4. Flowchart of time-dependent system reliability assessment method

3. Case Study

This section evaluates the proposed DHL framework using two benchmark problems. The first problem is a highly nonlinear parallel system with analytically defined mode-level LSFs, enabling direct benchmarking against a reference Monte Carlo simulation (MCS). The second problem is a rigid-plastic portal frame with multiple correlated failure modes and degradation-driven time dependence, used to assess the method's performance in a representative structural system setting. Throughout both case studies, the ANN architecture and training procedure are kept fixed as described in Section 2.4, such that performance differences primarily reflect the system LSF construction strategy rather than network tuning. In this study, training samples are generated using a uniform random sampling strategy. This choice is made to focus on the effect of system decomposition and hierarchical learning, rather than on sampling optimization. It is noted that the proposed DHL framework is not restricted to a fixed sampling strategy. Owing to its hierarchical structure, adaptive or active learning approaches can be naturally incorporated by enriching samples near mode-level limit state boundaries or in regions where the dominant system failure mechanism switches. Such strategies are expected to further improve computational efficiency and accuracy, particularly for rare-event reliability problems, and will be considered in future work.

3.1. Case 1: Nonlinear Parallel System

The first case study involves a parallel system consisting of two components with nonlinear LSFs, expressed as Equations 10 and 11 [35]:

$$Z_1 = 2 - x_2 + exp(-0.1x_1^2) + (0.2x_1)^4 \quad (10)$$

$$Z_2 = 4.5 - x_1 x_2 \quad (11)$$

where, x_1 is time-dependent and defined as Equation 12 [44]:

$$x_1(t) = x_{1,0} \cdot \varphi(t) \quad (12)$$

With $\varphi(t) = 1 + 0.02t$ and $t = 0, \ldots, 50$. The basic variables $x_{1,0}$ and x_2 are mutually independent and follow standard normal distributions. The system performance quantity is defined according to the equivalent extreme-value event representation for a parallel system (Equation 2), which provides the system-level target for training and an explicit reference for reliability evaluation.

Training samples are generated by sampling $(x_{1,0}, x_2, t)$, where t is uniformly sampled over $[0, 50]$. For each sample, $x_1(t)$ is computed via Equation 12, and the corresponding mode-level performance values Z_1 and Z_2 are computed via Equations 10 ad 11. In the DHL framework, mode-level surrogates are first trained to approximate the mappings from $(x_{1,0}, x_2, t)$ to Z_1 and Z_2, consistent with Equation 6. Subsequently, a system-level surrogate is trained to approximate the mapping from (Z_1, Z_2, t) to the system performance quantity Z, consistent with equation 7, where the system-level target is generated using the parallel-system equivalent event in Equation 2. For comparison, a direct approach is implemented by training a single ANN to learn the mapping from $(x_{1,0}, x_2, t)$directly to the system performance quantity Z. After surrogate construction, the time-dependent failure probability is estimated for each time $t$using surrogate-assisted MCS according to Equation 8. The benchmark reference solution is obtained by direct MCS using the analytical definitions in Equations 10 to 12 and the system event definition implied by Equation 2.

Figure 5 compares the time-dependent failure probability curves obtained from DHL-ANN-MCS and ANN-MCS against the reference MCS results. The results indicate that DHL-ANN-MCS converges toward the reference solution as the number of training samples increases, whereas the direct ANN-MCS approach exhibits more persistent deviations for the same training sizes. This behavior is consistent with the intended effect of DHL, which reduces the difficulty of learning the system-level mapping by isolating mode-level nonlinearities prior to learning mode interaction at the system level.

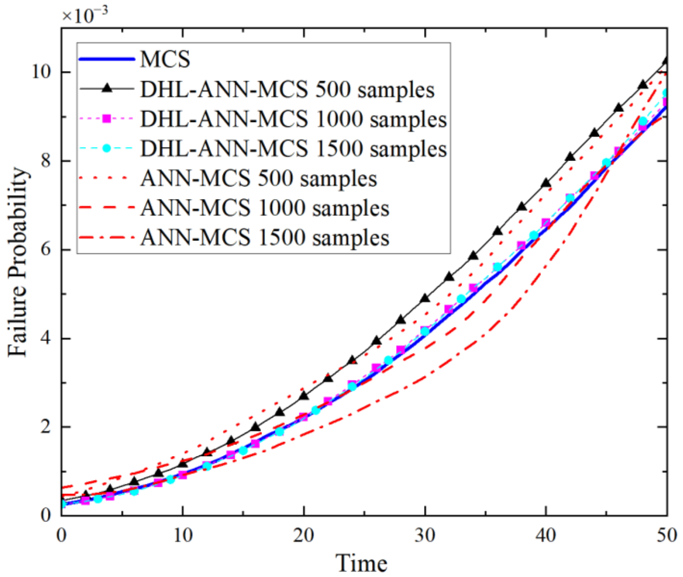


Figure 5. Time-dependent failure probability for Case 1

In addition, this behavior can be interpreted from the standpoint of system-event non-smoothness: the parallel-system response is governed by an extreme-value-type aggregation, so the active (governing) mode may switch across the uncertainty space. A monolithic system-level surrogate must approximate both the mode nonlinearities and the switching interaction simultaneously, which typically increases approximation instability. DHL separates these two sources of complexity, which explains the improved stability. Similar observations, namely that system surrogates are intrinsically harder than component surrogates because multiple failure modes contribute unevenly and the effective system event depends on configuration, have been emphasized in recent system active-learning studies [46].

It can be observed that DHL-ANN-MCS shows poor accuracy with 500 sample points but achieves good precision with 1000 and 1500 sample points. In contrast, the ANN-MCS method demonstrates only moderate accuracy across all three sample sizes. From an engineering-use viewpoint, this indicates that the DHL surrogate becomes suitable for time-dependent propagation once the training set covers both the strongly nonlinear regions of the mode responses and the mechanism-transition regions where the governing mode changes.

Consider varying the number of sample points to study the effect of sample size on the accuracy of constructing the system LSF. The number of sample points ranges from 50 to 2000, with an interval of 50 points for analysis. For each LSF fit, the calculation error of the system reliability is recorded. To further investigate sample size effects, the mean error in failure probability is quantified as Equation 13.

$$\varepsilon = \frac{1}{51}\sum_{t=0}^{50} |P_t - P_{t,MCS}|/P_{t,MCS} \tag{13}$$

where P_t is the predicted failure probability at time $t$and $P_{t,\mathrm{MCS}}$ is the reference solution from direct MCS. Figure 6 reveals that the mean error of the ANN-MCS method remains consistently elevated. Although its error generally decreases with additional observational data, significant fluctuations persist, preventing it from achieving reliable accuracy for time-dependent reliability analysis. In contrast, the mean error of the proposed DHL-ANN-MCS method exhibits a steady decline as more data are introduced. For the highly nonlinear parallel system examined in this case study, the calculation error stabilizes once the number of input sample points exceeds 950, yielding a maximum average error of merely 3.1%. These results demonstrate that the DHL framework, combined with an ANN to construct the system's limit state function (LSF), achieves high computational accuracy in time-dependent reliability assessments. Moreover, the persistent fluctuations of the direct ANN-MCS curve indicate that simply increasing samples does not guarantee stable improvement when a single surrogate must fit a composite system response with competing modes. This point is consistent with recent literature on system reliability surrogates, where instability is often linked to mode competition and system-event topology rather than to the smoothness of individual component LSFs [46-50].

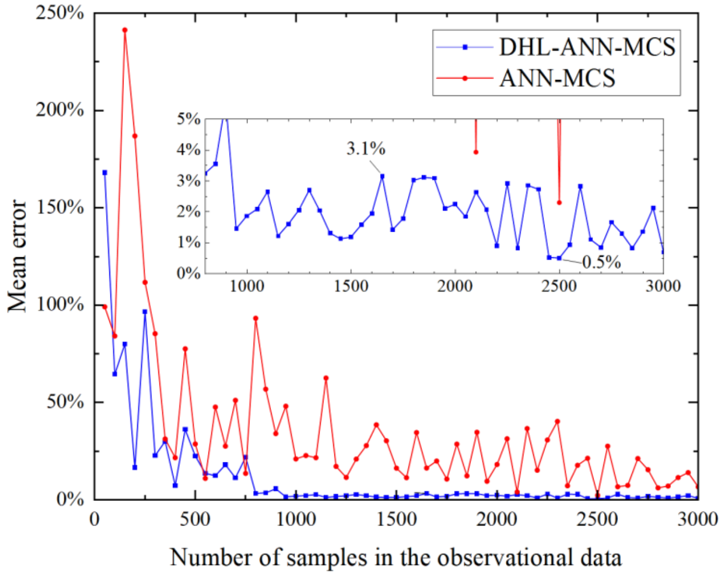


Figure 6. Mean error of system reliability in Case 1

The dependence between the two failure modes is established by the shared parameters, $x_{1,0}$ and x_2, in both Z_1 and Z_2. The proposed DHL framework inherently incorporates this statistical dependence. This is achieved by constructing the second-level surrogate model for the system limit state function (LSF) using the equivalent extreme value event, which intrinsically accounts for the correlation structure. The subsequent close agreement between the DHL results and the benchmark Monte Carlo simulation (MCS) validates the efficacy of this approach in handling correlated failure modes.

The results in Figures 5 and 6 also provide indirect evidence regarding error propagation in hierarchical learning. If approximation errors from mode-level surrogates were significantly amplified at the system level, the DHL-based results would exhibit increasing deviation or instability as training sample size varies. Instead, the observed convergence and improved stability of DHL-ANN-MCS compared with direct ANN-MCS suggest that error propagation remains controlled within the proposed framework for this benchmark problem.

3.2. Case 2: Rigid-Frame Structural System

The second example considers a single-story rigid-plastic portal frame (Figure 1) subjected to random horizontal and vertical loads H and V, with time-varying plastic moment capacities $M_i(t)(i = 1, \ldots, 4)$. System decomposition identifies four dominant plastic collapse mechanisms [40, 43], leading to the mode-level LSFs by Equations 14 to 17:

$$Z_1 = M_1 + 2M_3 + 2M_4 - H - V \quad (14)$$

$$Z_2 = M_2 + 2M_3 + M_4 - V \quad (15)$$

$$Z_3 = M_1 + M_2 + M_4 - H \quad (16)$$

$$Z_4 = M_1 + 2M_2 + 2M_3 - H + V \quad (17)$$

The moment capacities degrade with time as Equation 18:

$$M_i(t) = M_{i,0} \cdot \varphi(t) \quad i = 1, \ldots, 4 \quad (18)$$

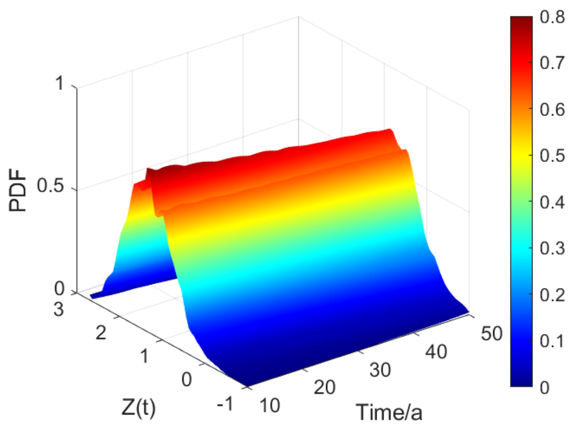
where the initial values $M_{i,0}$ follow normal distributions with a mean of 1.0 and a coefficient of variation of 0.15. The applied loads H and V are normally distributed with a mean of 1.5 and a coefficient of variation of 0.3 (Table 1).

Table 1. Random variable parameters involved in Case 2

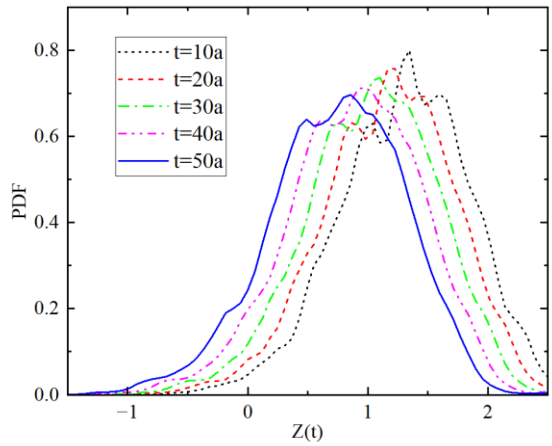
Random variable	Distribution pattern	Mean value	Coefficient of variation
$M_{1,0}$	Normal	1	0.15
$M_{2,0}$	Normal	1	0.15
$M_{3,0}$	Normal	1	0.15
$M_{4,0}$	Normal	1	0.15
H	Normal	1.5	0.3
V	Normal	1.5	0.3

Training samples are generated by sampling $(M_{1,0}, \ldots, M_{4,0}, H, V, t)$and computing the degraded capacities $M_i(t)$ using Equation 18. The mode-level LSF values Z_1–Z_4 are then computed from Equations 14 to 17. DHL constructs the system LSF by first training mode-level ANN surrogates for each of the four failure modes in accordance with Equation 6, and then training a system-level ANN surrogate in accordance with Equation 7. For the portal frame, system failure occurs when any collapse mechanism becomes active, and the system-level training targets are generated using a decomposition-consistent series-type system event (Equation 2). After surrogate construction, the time-dependent system failure probability is computed using surrogate-assisted MCS (Equation 8) and surrogate-assisted PDEM (Equations 4 and 9). For benchmarking, known-LSF computations are also performed using traditional PDEM and reference MCS based on the analytical expressions in Equations 14 to 18.

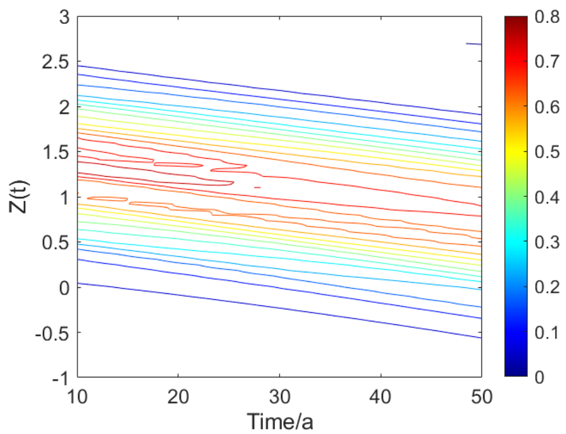
Figure 7 illustrates the evolution of the PDF of the system performance quantity obtained using DHL-ANN-PDEM. The results indicate that the DHL-constructed surrogate system LSF provides sufficiently smooth performance mapping to support density evolution and captures the degradation-driven evolution of the performance distribution over time. The PDF evolution shows a progressive shift of probability mass toward lower performance values as resistance degrades, which is physically consistent with monotonic capacity deterioration. Numerically, the absence of spurious oscillation in the evolved PDF provides evidence that the DHL surrogate is sufficiently regular for density evolution, which is an important practical requirement for PDEM-type propagation [22, 23, 51]



(a) 3D plot of the PDF evolution



(b) PDF evolution at typical points of time



(c) Contour plot of the PDF evolution

Figure 7. PDF evolution of Case 2 by DHL-ANN-PDEM

Figure 8 compares the time-dependent failure probability curves obtained from DHL-ANN-MCS, DHL-ANN-PDEM, traditional PDEM (known LSF), and the reference MCS (known LSF). The DHL-based results closely track the reference MCS solution across the full-time horizon, demonstrating that the DHL surrogate can accurately represent system behavior under multiple correlated failure modes and time-varying degradation. In addition, DHL-ANN-PDEM provides continuous distribution information with good agreement relative to the benchmark, indicating that the DHL surrogate is compatible with density evolution analysis.

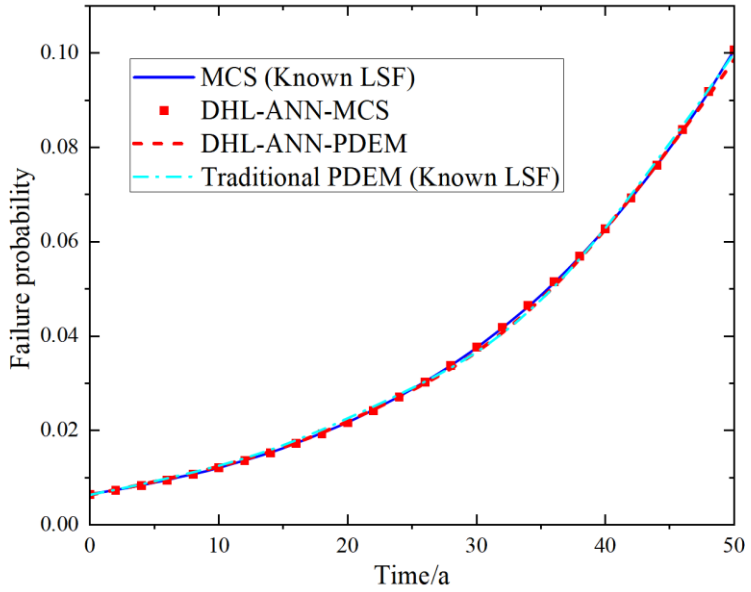


Figure 8. Time-dependent failure probability for Case 2.

For quantitative assessment, the error is evaluated at integer times using the mean relative error definition in Equation 13. The resulting error statistics are summarized in Table 2, showing that DHL-ANN-based approaches achieve lower average errors than the traditional PDEM baseline while maintaining computational efficiency for time-dependent reliability evaluation. Recent time-dependent system reliability studies have often pursued efficiency via adaptive/active learning Kriging strategies that focus samples near critical boundaries across time and multiple failure modes [47, 49, 52]. Those methods primarily reduce the number of high-fidelity calls by adaptive enrichment, whereas the present results show that DHL improves learnability and system-level surrogate robustness by enforcing a decomposition-consistent hierarchical structure (i.e., separating mode approximation from mode interaction). Therefore, DHL is complementary to active-learning strategies: active learning can be added to DHL to further reduce training cost, while DHL improves stability and accuracy of the system mapping under multi-mode interaction and mechanism switching [46, 47, 50].

Table 2. Comparison of mean error for several methods in Case 2

Parameter	MCS (Known LSF)	DHL-ANN-MCS	DHL-ANN-PDEM	Traditional PDEM (Known LSF)
Mean Error	-	0.52%	1.23%	2.16%

From a computational perspective, the cost of system reliability analysis consists of surrogate construction and reliability propagation. Known-LSF approaches avoid surrogate training but require repeated evaluations of explicit or high-fidelity limit state functions, which may be computationally expensive for complex structural systems. In contrast, surrogate-based approaches incur an upfront training cost but enable efficient reliability propagation. Compared with direct system-level ANN learning, the DHL framework distributes the learning task across multiple lower-dimensional surrogates. Although multiple networks are trained, each involves simpler mappings and faster convergence, resulting in a total training cost comparable to that of a single high-dimensional ANN. Once trained, DHL-ANN and direct ANN approaches exhibit similar computational efficiency during Monte Carlo simulation and PDEM, as both rely on inexpensive surrogate evaluations. Overall, DHL improves system-level accuracy and robustness without introducing a prohibitive increase in computational cost.

4. Discussion

Numerical studies confirm that a major challenge in system-level surrogate reliability analysis, particularly for systems governed by multiple interacting failure modes, is the accurate representation of the system performance boundary rather than the approximation of individual component or mode-level limit state functions (LSFs). When system behavior is defined through extreme-value type logic, such as series, parallel, or compound configurations (Eq. (2)), the resulting system LSF may exhibit non-smooth characteristics and switching dominant mechanisms across the random-variable space. In such cases, a direct surrogate for $Z(\theta, t)$ must approximate a composite mapping whose complexity arises from both the nonlinear behavior of individual modes and their competitive interactions, which can significantly degrade approximation accuracy. This observation aligns with recent system-surrogate literature, where the difficulty is attributed to multiple contributing failure regions and uneven mode contribution to the system event [46, 47].

The proposed system decomposition and hierarchical learning (DHL) framework alleviates this difficulty by aligning surrogate construction with the decomposition-defined system structure. By first approximating mode-level LSFs $Z_i(\theta_i, t)$ and subsequently learning the system-level aggregation $g_{\mathrm{sys}}(\cdot)$, DHL reduces the effective complexity of the learning task. Importantly, the system logic associated with extreme-value behavior is not replaced but is implicitly embedded in the system-level training targets generated in accordance with Eq. (2). This hierarchical strategy is consistent with the broader concept that decomposition-based or multilevel learning can improve approximation robustness by isolating localized nonlinearities before modeling higher-level interactions [34]. In Case 1, this effect is evidenced quantitatively: once the training size exceeds 950, the DHL error stabilizes below 3.1% (Figure 6), while the direct system-level ANN remains noticeably more sensitive to sample size, an indicator of the higher functional complexity of the monolithic system mapping.

The proposed DHL framework relies on a prior system decomposition that identifies dominant failure modes and their connectivity. As with any system reliability approach, omission or misidentification of critical failure modes may bias the resulting reliability estimates. In DHL, such bias manifests as a reduced system representation rather than numerical instability. Omitted failure modes may lead to non-conservative predictions in regions where they dominate system failure, while inaccuracies in individual mode formulations primarily affect the corresponding hierarchical branches. A notable advantage of the DHL framework is that decomposition-related uncertainties are not hidden within a single system-level surrogate. Instead, they remain localized and traceable within the hierarchical structure, facilitating diagnostic assessment and incremental refinement. In practical applications, the framework is therefore best used in combination with established failure mechanism identification procedures and may be progressively enhanced as additional failure modes are incorporated.

Comparison with related surrogate-based system reliability studies further clarifies the role of DHL. A major stream of recent work improves efficiency via adaptive learning, especially with Kriging or Gaussian process surrogates, by selecting samples near failure boundaries and by stabilizing updates when multiple failure modes exist. For example, Xu et al. [53] proposed an active-learning strategy that refines a specified number of component surrogates per iteration to improve stability in system reliability problems with multiple failure modes. For time-dependent system reliability, Zhan et al. [50] developed a parallel active-learning Kriging strategy to address time-dependent uncertainties and multiple failure modes more efficiently. These studies primarily reduce the number of expensive models calls through adaptive sampling and parallel enrichment, while still relying on accurate representation of component- and system-level interactions. In contrast, DHL targets a complementary bottleneck: it improves the representational accuracy and robustness of the system-level performance mapping under multi-mode interaction and mechanism switching, even under a fixed, non-adaptive sampling plan, by enforcing decomposition-consistent structure during learning. Practically, DHL can be combined with active learning: adaptive enrichment can be applied at the mode level (to refine Zi near Zi = 0) or at the system level (to refine regions where mechanism switching occurs).

From a time-dependent reliability perspective, the scope of the present study is limited to the degradation-driven evolution of system capacity, leading to an explicitly time-dependent performance function $Z(\theta, t)$. Under this setting, time-dependent reliability is evaluated by computing the failure probability $p_f(t)$ over the time horizon of interest. The proposed framework does not introduce stochastic-process models for loads or state trajectories; rather, it focuses on addressing the computational bottleneck associated with evaluating a time-varying system LSF when the underlying response model is implicit. This formulation is compatible with established time-variant reliability approaches that propagate probability distributions as the performance function evolves deterministically with time.

Once a smooth and evaluable surrogate representation of $Z(\theta, t)$ is constructed using DHL, it can be readily integrated with conventional reliability propagation methods. Monte Carlo simulation (MCS) provides a robust benchmark and is straightforward to implement, but it may become computationally demanding when fine temporal resolution or accurate estimation of small failure probabilities is required. The PDEM offers a complementary propagation paradigm by directly evolving the probability density of the system performance variable, thereby enabling continuous tracking of distributional changes over time. Prior studies have demonstrated the effectiveness of PDEM for deteriorating structural systems and reliability evolution problems, including applications involving surrogate representations [24]. Recent work has also focused on accelerating PDEM-based reliability analysis via learning-based enrichment and advanced learning functions. For example, Zhou et al. [54] integrated polynomial-chaos Kriging with PDEM using a look-ahead learning function (STVR) to reduce the computational burden of density evolution while maintaining accuracy. In dynamic reliability contexts, Wang et al. [55] combined an adaptive surrogate with PDEM for efficient reliability evaluation of coupled systems. These developments emphasize that an accurate and stable surrogate performance function is a prerequisite for reliable density evolution; the close agreement in Case 2 indicates that the DHL surrogate satisfies this requirement for multi-mode degrading systems.

Finally, DHL should be interpreted as a system-level modeling strategy rather than a neural-network innovation. Its primary contribution lies in enforcing a decomposition-consistent hierarchical structure in surrogate construction, thereby improving the reliability and robustness of system-level performance approximation under multi-mode interaction. While the present study employs artificial neural networks at each hierarchical level, the framework itself is not restricted to a specific surrogate type and can be extended to alternative regression models when appropriate. Moreover, intermediate hierarchical layers can be introduced when a subsystem structure exists, paralleling multilevel decomposition concepts commonly used in uncertainty propagation and large-scale system analysis [34]. This positioning is consistent with broader recent reviews emphasizing that surrogate choice and training strategy should be aligned with the dimensionality and nonlinearity of the response, the topology of the failure domain (e.g., multiple regions/mode switching), and the downstream reliability algorithm (e.g., rare-event estimation or time propagation) [29, 56]. For very high-dimensional reliability settings, additional scalability tools (e.g., subspace-oriented active learning) may be combined with DHL when needed [38].

5. Conclusion

This study proposed a system decomposition and hierarchical learning (DHL) framework for degradation-driven time-dependent structural system reliability assessment. The primary objective was to improve the construction of an evaluable system limit state function (LSF) in problems where system behavior is governed by multiple interacting failure modes and where direct, monolithic surrogate learning of the system LSF is prone to loss of accuracy. By decomposing the system into constituent failure modes and learning a hierarchy of surrogate mappings, mode-level LSFs followed by a system-level aggregation consistent with system connectivity, the DHL framework provides a structured and physically informed approach to system-level performance modeling.

Two benchmark problems were employed to evaluate the effectiveness of the proposed framework. In the nonlinear parallel system, the DHL-based surrogate combined with Monte Carlo simulation (MCS) demonstrated stable convergence toward the reference MCS solution as the number of training samples increased, while direct system-level ANN learning exhibited larger and more persistent deviations. In the rigid-plastic portal frame example with multiple correlated failure modes and degradation-driven time dependence, DHL produced time-dependent failure probability estimates that closely matched known-LSF reference solutions. In addition, the constructed surrogate system LSF supported probability density evolution analysis, enabling accurate prediction of both failure probability evolution and time-varying performance distributions. The results indicate that the principal benefit of DHL lies in its ability to reduce the effective complexity of system-level surrogate learning by isolating mode-level nonlinearities and embedding system logic through decomposition-consistent aggregation. This hierarchical construction improves robustness and accuracy in settings where the system performance boundary is non-smooth and governed by competing failure mechanisms. At the same time, the framework remains compatible with conventional reliability propagation techniques, including both MCS and the PDEM.

Several practical considerations should be noted. The accuracy of the DHL-based reliability assessment depends on the quality of the system decomposition and the completeness of the identified failure modes; omission of dominant mechanisms or incorrect connectivity definitions will inevitably bias system-level predictions. In addition, hierarchical surrogate construction introduces the possibility of error propagation across levels, underscoring the importance of robustness assessment through repeated training, validation, and appropriate sampling strategies. Overall, the proposed DHL framework provides a principled interface between the system reliability structure and surrogate modeling, offering a practical solution for the time-dependent reliability analysis of complex structural systems with implicit performance functions. Its decomposition-consistent formulation makes it naturally extensible to larger systems, alternative surrogate models, and more complex hierarchical structures. Future research will focus on extending the framework to higher-dimensional, simulation-driven systems, improving robustness quantification and adaptive sampling strategies, and exploring broader classes of time-dependent reliability problems involving more complex degradation and loading scenarios.

6. Declarations

6.1. Author Contributions

Conceptualization, B.Y. and B.H.; data curation, B.Y. and J.Y.; writing—original draft preparation, B.Y. and J.Y.; writing—review and editing, B.Y., B.H., H.X., and J.Y.; supervision, B.H. and H.X. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Conflicts of Interest

The authors declare no conflict of interest.

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