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Resilience Assessment of Drilling Risers in Extreme Marine Environments

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ABSTRACT

Resilience, as a comprehensive evaluation concept, assesses the overall post-event response capability of a system, providing theoretical foundations and decision support for system design optimization and disaster emergency management. Extreme marine environments characterized by violent winds, strong currents, and large waves significantly increase the failure probability of deepwater drilling riser systems. These extreme loads induce excessive stress, fatigue, and fracture, heightening the risk of structural failure. This paper proposes a resilience assessment method for drilling risers under extreme sea conditions. The method first employs high-precision hydrodynamic simulation to fit and process acquired time-varying load data, deriving riser failure probabilities. It then quantifies degradation processes using a dynamic Bayesian network model. Subsequently, a dynamic recovery process encompassing fault diagnosis, resource allocation, and maintenance models is established. Two metrics—failure rate and recovery capability—are selected as single-stage resilience indicators for each process, with resilience calculated using the area method. Using a drilling riser in the South China Sea as a case study, the proposed resilience framework demonstrates validity and applicability. Results confirm the method effectively quantifies riser performance degradation and recovery capacity, providing critical guidance for engineering design and operational management.

KEYWORDS

Drilling Riser; Resilience; Performance Quantification; Dynamic Bayesian Networks.

1. INTRODUCTION

Deep-water drilling riser systems serve as critical connecting structures between subsea wellheads and floating drilling platforms, constituting an essential component of offshore drilling operations. They are tasked with critical functions such as transporting drilling fluids and maintaining well control integrity. Structurally, the riser system comprises telescopic joints, multiple riser segments, lower marine riser packages (LMRP), along with flex and ball joints. Due to their slender and complex design, these systems are highly susceptible to external environmental loads. Particularly in regions prone to tropical storms, such as the South China Sea, operational risks associated with riser systems are significantly elevated. Intense marine environmental changes induced by storms, including heightened wind, wave, and current actions, impose substantial hydrodynamic loads on the riser, markedly increasing the risks of structural fatigue, fracture, and even catastrophic failure. Such risks threaten operational continuity and pose serious safety hazards. In recent years, as the nation has increasingly prioritized disaster prevention and mitigation in major engineering projects, the safety assessment of marine structures has gained greater significance. To safeguard national deep-sea energy development and meet strategic demands, it is imperative to study the disaster prevention and mitigation capabilities of drilling riser systems during operation, as well as to develop effective safety assessment methodologies.

During long-term operations, drilling risers may be subjected to extreme marine environmental conditions, which can disrupt normal platform activities. In severe cases, such conditions may cause structural damage to the platform and even endanger personnel safety as well as the security of equipment and assets. While substantial research has been conducted on the resilience assessment of onshore structures or systems, studies on the resilience of marine structures remain in their early stages, particularly with respect to riser systems, which have yet to be thoroughly investigated[1,6]. Therefore, it is essential to study the ability of drilling risers to withstand loads and recover rapidly under extreme sea conditions, which can further enhance the safety and operational reliability of riser systems.

To address these challenges, this study aims to develop a comprehensive resilience assessment methodology for deep-water drilling riser systems under extreme marine environments. The structure of this paper is organized as follows: Section 2 outlines the methodology for drilling riser resilience assessment and introduces a foundational framework. The proposed approach involves constructing a degradation process model of the riser, obtaining time-varying load data through high-fidelity hydrodynamic simulations, fitting failure probabilities using the generalized extreme value distribution, and implementing dynamic probabilistic inference of performance degradation via Dynamic Bayesian Networks (DBN). Additionally, the resilience triangle theory is introduced to establish a multi-stage recovery model encompassing fault diagnosis, resource allocation, and maintenance operations, with the area method employed to quantify system resilience metrics[6]. The degradation and recovery models are subsequently integrated to reflect the residual performance of the riser throughout extreme sea conditions. Section 3 presents a case study to demonstrate the practical application and effectiveness of the proposed methodology. Section 4 summarizes the main findings and conclusions of the study.

2. BACKGROUND

A typical deep-water drilling riser system is illustrated in Figure 1. The top of the riser is suspended from the drilling platform via tensioners, which apply a predefined top tension in the vertical direction. The bottom of the riser is connected to the LMRP, Blowout Preventer (BOP), wellhead, conductor, and other subsea equipment.

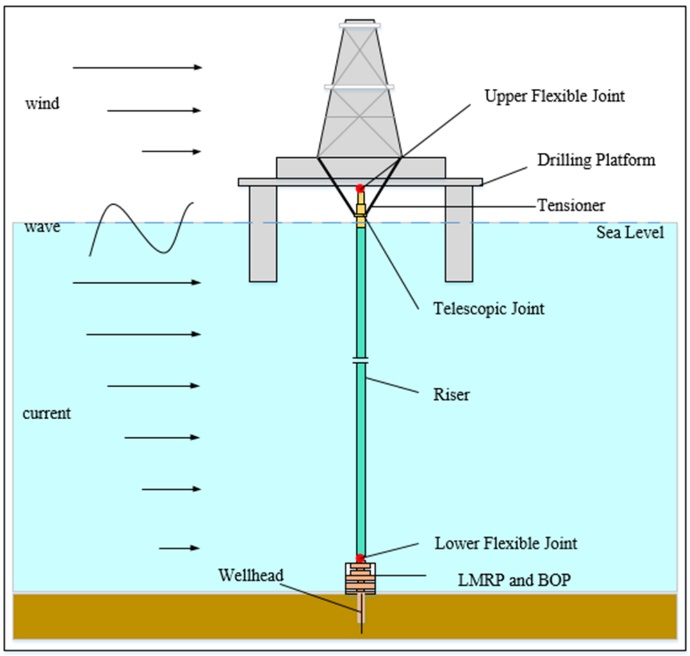


Fig 1. Schematic diagram of a typical drilling riser system

The dynamic behavior of deep-water drilling riser systems is influenced by a variety of marine environmental factors. Due to the considerable length of the riser and the substantial top tension required to support the entire riser string, deep-water drilling operations are highly sensitive to ocean currents. Under high-flow conditions, riser operations are severely constrained, as increased drag loads may exceed the material strength of the riser, leading to potential damage and subsequent drilling incidents. Wave action affects riser design primarily in two ways: first, by imposing hydrodynamic loads directly on the riser; second, by influencing platform motion through the Response Amplitude Operator (RAO) of the platform, which in turn affects the dynamic boundary conditions at the top of the riser. Studies indicate that platform motion and wave loading are the primary dynamic loads considered in riser dynamic response analysis, with platform motion representing the dominant contribution, while wave effects are generally localized along the riser span. The influence of wind speed on deep-water drilling risers is mainly manifested through wind loads acting on the drilling platform. High wind speeds can induce significant sway or lateral displacement of the platform, thereby altering the dynamic loading and stress state of the riser. Under extreme wind conditions, platform motion may amplify riser bending and oscillation, increasing the risk of fatigue damage and potentially leading to structural failure.

The quantification of extreme marine environmental conditions is typically based on probabilistic statistics. In this study, the concept of "return period" is employed to characterize the rarity and severity of extreme events [5]. This approach provides an intuitive representation of the potential risk associated with such events while offering a unified quantitative standard for environmental conditions across different regions.

3. METHOD

3.1. Resilience Assessment Model

The core of resilience assessment for risers under extreme environmental conditions lies in quantifying their resistance and recovery capacities. This paper proposes a resilience evaluation method under extreme sea conditions that integrates physical mechanisms and data-driven approaches. First, a resilience assessment model for the riser is established, comprising a degradation process model and a recovery process model. These models construct single-stage performance curves based on failure rates and recovery capacities, respectively, and resilience values are then calculated by integrating these performance curves. For the degradation process, a riser analysis model is developed using OrcaFlex software. High-fidelity hydrodynamic simulations are employed to obtain time-series response data of key riser nodes under various sea conditions. Through data processing and fitting methods, the failure probability of the riser under specific environmental conditions is derived. Subsequently, a DBN is integrated to simulate the time-varying transition process of structural performance. This approach combines the deterministic physical laws from finite element analysis with the probabilistic inference capability of Bayesian networks, enabling the dynamic evolution of the riser failure process to be captured. The recovery process includes three stages: fault diagnosis, resource allocation, and repair. A component-level recovery model can be established by integrating physical models with Bayesian networks. Through the aforementioned process, the performance loss and recovery efficiency of the riser under extreme sea conditions can be quantified, revealing trends in performance variation.

3.2. Degradation Process Analysis.

3.2.1. Failure Criteria and Probability of Riser Systems

Under extreme marine environments, such as sea conditions associated with high return periods, the mechanical response of the riser is significantly intensified. This amplification increases the likelihood of the riser exceeding its operational envelope. Common failure modes include yielding of the riser body, fatigue failure of the top structure, local buckling at the bottom of the riser or damage to the wellhead, and seal failure of the telescopic joint[2,4].

Methods for obtaining the mechanical response of a riser typically include numerical simulation and condition monitoring. In this paper, hydrodynamic simulation is employed to provide data support for failure analysis of the riser under extreme sea conditions, with a typical simulation duration of 3 hours.

(1) For yielding failure of the riser, the failure probability can be calculated based on the equivalent stress response of the riser. The failure probability of the riser under a given environmental condition is given as:

$$P_{yield} = P(\sigma \geq [\sigma] \mid EN) \tag{1}$$

In the equation, *EN* denotes the marine environment, σ represents the equivalent stress at critical locations of the riser, and $[\sigma]$ signifies the allowable stress of the riser. Their distributions are based on.

$$[\sigma] = \frac{\sigma_s}{SF} \tag{2}$$

where σ_s represents the yield strength of the riser, and *SF* denotes the safety factor of the riser, which is influenced by sea state and operational conditions.

(2) When the angular displacement of the Upper Flexible Joint (UFJ) in the riser exceeds permissible limits, it may lead to fatigue failure of the top structure. Excessive angular displacement indicates that the upper section is subjected to significant bending and torsional stresses, which can induce crack initiation and propagation due to fatigue in the top material, ultimately resulting in failure. Additionally, seals and connecting components of the ball joint may also sustain damage under excessive stress. The failure probability can be expressed as:

$$P_{TFIF} = P(\theta \geq [\theta] \mid EN) \tag{3}$$

In the equation, θ represents the angular displacement of the Upper Flexible Joint (UFJ) of the riser, and $[\theta]$ denotes the angular displacement limit.

(3) Excessive angular displacement of the Lower Flexible Joint (LFJ) may subject the bottom of the riser to significant bending and torsional stresses, potentially leading to local buckling, especially in sections with reduced wall thickness or insufficient structural strength. Moreover, excessive angular displacement can cause damage to the wellhead system, compromising its sealing integrity and stability. The failure probability is expressed as:

$$P_{WID} = P(\psi \geq [\psi] \mid EN) \tag{4}$$

In the equation, Ψ represents the angular displacement of the Lower Flexible Joint (LFJ) of the riser, and $[\Psi]$ denotes the angular displacement limit.

3.2.2. Dynamic Bayesian Network Modeling

Bayesian networks are widely used in probabilistic inference to evaluate the safety of complex systems [3]. In Bayesian networks, nodes, arcs, and conditional probability tables (CPTs) are the three key components, which are employed to represent a set of random variables in a system and the conditional dependencies among them. The relationship between parent nodes and child nodes can be defined through conditional dependencies and a series of established rules. The joint probability distribution of the variables $U=\{A1,A2,....,An\}$ can be expressed as follows:

$$P(U) = \prod_{i=1}^{n} P\left(A_i \mid P_a\left(A_i\right)\right) \tag{5}$$

In a Bayesian network, the probability calculation and node states are interconnected. Once the states of certain nodes within the network are adjusted, the Bayesian network can compute the state probabilities of other related nodes based on conditional dependencies and probability propagation mechanisms.

Extending a static Bayesian network along a time series yields a dynamic Bayesian network, which accounts for the temporal evolution of variables. As shown in Fig. 2, where t denotes the current time slice and t+1 denotes the next time slice, the transition network depends conditionally on the initial network via transition probabilities. In a Dynamic Bayesian Network (DBN), the transition probability between adjacent time slices is given by the following expression:

$$P(X_t | X_{t-1}) = \prod_{i=1}^{N} P(X_t^i | Pa(X_t^i)) \tag{6}$$

In the equation, X_t^i represents the *i*-th node at the *t*-th time slice, and $Pa(X_t^i)$ denotes the parent nodes of X_t^i.

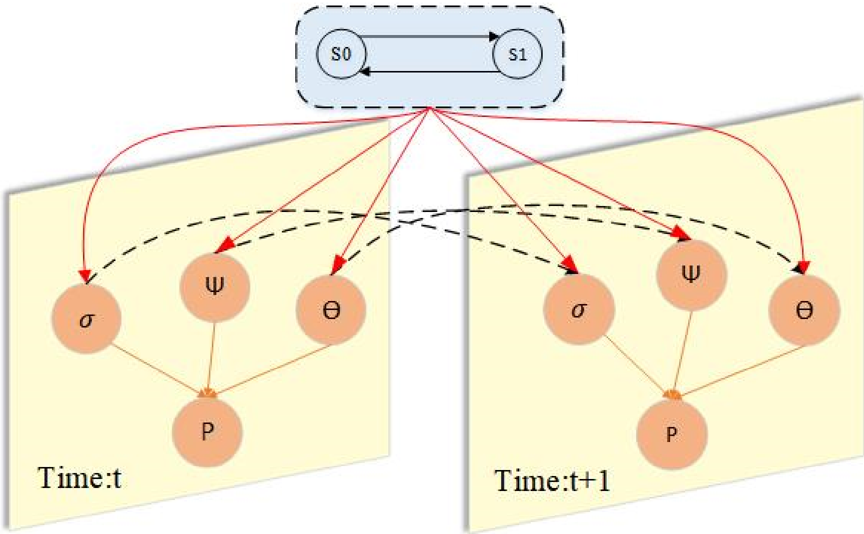


Fig 2. Dynamic Bayesian network model for the riser

3.2.3. Introduction to Markov Processes

Dynamic Bayesian Networks possess the Markov property, which enables them to effectively describe systems with multiple states and simulate the transition relationships between those states. When structural degradation is considered, it is assumed that the structural state space is finite, and as degradation progresses, the structural performance either remains unchanged or decreases to a lower state at discrete time points. Under these conditions, structural performance can be modeled as a Markov chain. A Markov chain is a discrete stochastic process that satisfies the Markov property, meaning that the next state of the structure depends solely on its current state and is independent of its historical states. All information required to predict the state of the next time slice is contained within the current time slice.

$$p = e^{-\lambda \Delta t} \tag{7}$$

In the equation, *P* represents the state transition probability of the node, and *λ* denotes the failure rate of the riser.

3.3. Analysis of Recovery Process.

The performance recovery process of a drilling riser can be divided into three phases: fault diagnosis, resource allocation, and physical repair. The corresponding Dynamic Bayesian Network (DBN) model is illustrated in Fig. 3. During the fault diagnosis phase, methods such as acoustic emission testing, non-destructive testing, and real-time monitoring systems (standard equipment on modern deep-water platforms) are used to rapidly locate the failure mode and its specific position, typically completed within 6 to 8 hours. The resource allocation phase involves mobilizing repair equipment, technical personnel, and support vessels based on the diagnostic results. Due to the offshore operational nature of deep-water platforms, this process usually takes 24 to 48 hours, and may extend further in remote sea areas. The repair phase, based on data from the OREDA reliability handbook, shows that the average actual repair time for a riser is 73.4 hours, excluding downtime and resource allocation time[7].

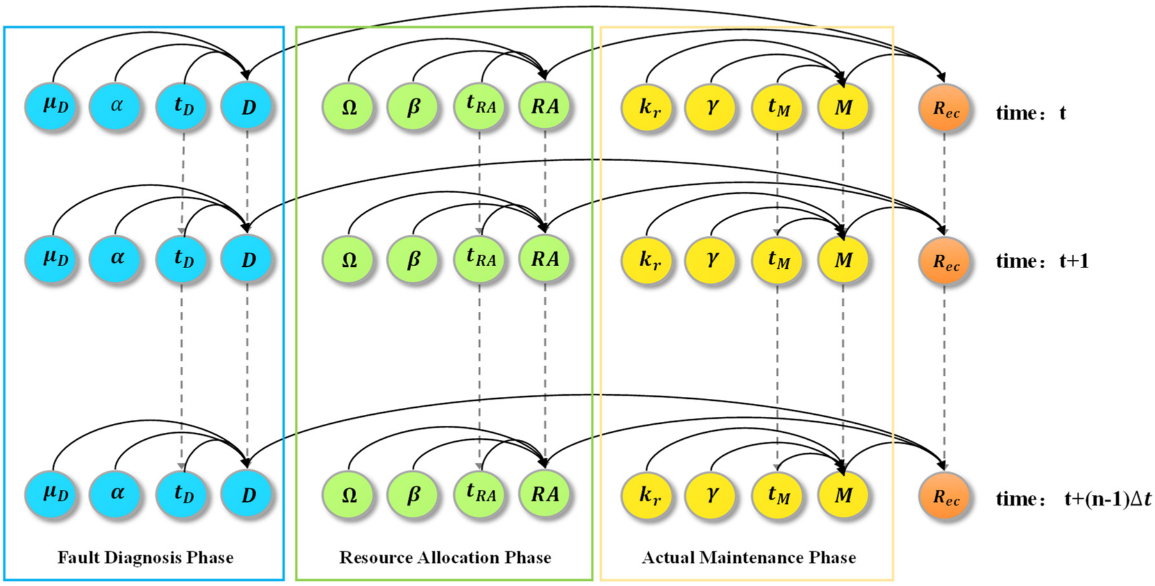


Fig 3. Dynamic Bayesian network model of the recovery process

Diagnostic capability is expressed as

$$D(t_D) = \mu_D \times e^{-\alpha t_D} \tag{8}$$

where α is the coefficient of the exponential function, and t_D is used to account for the time effect. μ_D represents the accuracy of fault diagnosis.

The quantification of diagnostic capability depends on the required resource demand (Req), the available resources (Ava), and the time required to acquire resources (t_{RA}). The resource availability is expressed as:

$$RA(t_{RA}) = \Omega(\text{Ava}, \text{Req}) \times e^{-\beta t_{RA}} \tag{9}$$

where β is the coefficient of the exponential function, and t_{RA} is influenced by factors such as infrastructure design, resource allocation, and additional resource requirements. For instance, well-designed infrastructure and rational resource configuration can ensure rapid resource transfer. $\Omega(\cdot)$ is a functional definition of the resource metric. Within a certain threshold, this metric increases with the addition of stored or available resources. Beyond this threshold, however, adding extra resources may degrade the metric due to congestion effects. During the degradation phase following an external shock, necessary materials for the offshore platform can be mobilized from onshore sources, enabling the deployment of external resources required for the repair process. Therefore, in this model, the resource metric $\Omega(\cdot)$ is assigned a value of 1.

Repair capability is expressed as:

$$M(t_M) = k_r \times e^{-\gamma t_M} \tag{10}$$

where γ is the coefficient of the exponential function, and k_r is the success rate of equipment repair.

Diagnostic capability, resource availability, and repair capability together constitute the recovery process of the system. Therefore, the restorability of the system can be measured as follows:

$$\mathrm{R}_{ec} = D(t_D) + RA(t) + M(t_M) \tag{11}$$

The dynamic Bayesian network model for the system recovery process is also established based on structural modeling methods and parametric modeling methods. The structural models for the degradation process and the recovery process are identical, as they pertain to the same system. By integrating the Markov model with the dynamic Bayesian network, a comprehensive model for the performance recovery process can be developed. The recovery process also adheres to the Markov property, where the recovery rate μ is calculated based on the component repair time, which is determined by referencing historical data and expert knowledge. All information necessary to predict the state at time t+Δt is contained within the state at time t, with no need for information from earlier times. The transition relationship for the recovery process between time slice t and t+1 is expressed by the following formula:

$$p = 1 - e^{-\mu \Delta t} \tag{12}$$

3.4. Resilience Quantification

Through the simulation results of the dynamic Bayesian network, the relationship between system performance and time during both the degradation and recovery processes can be obtained, enabling real-time simulation of the trend in system performance variation. The system performance curve is illustrated in Fig. 4.

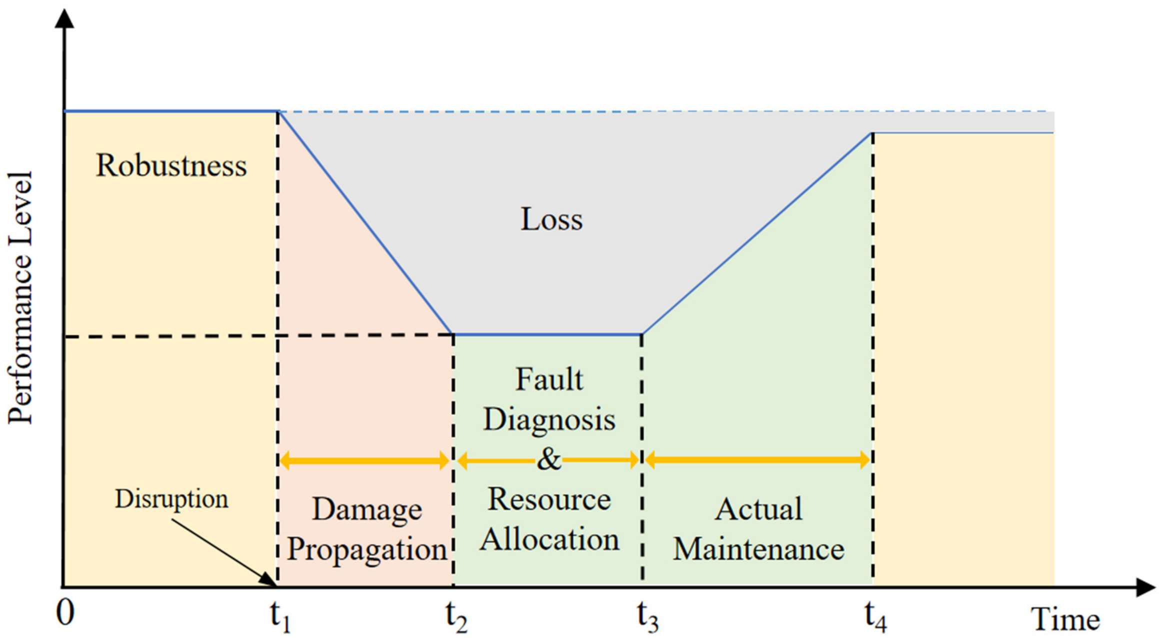


Fig 4. Full-cycle performance curve of the riser under extreme environmental conditions

The time period from t_1 to t_2 is referred to as the degradation phase of the system; the time period from t_2 to t_4 is referred to as the recovery phase of the system. At time t_1, the structural system is subjected to the impact of extreme sea conditions, leading to a decline in system performance. At time t_2, maintenance of the structural system begins, and system performance gradually recovers. The time period from t_2 to t_3 constitutes the fault diagnosis phase of the recovery process and the resource allocation phase; and from t_3 to t_4, the equipment repair phase of the recovery process. System resilience is expressed as the ratio of the area of the shaded portion to the area of the rectangle formed by the dashed lines.the resilience R of the drilling riser can be calculated as the ratio of the area enclosed by P(t) and the time axis to the area enclosed by P_0 and the time axis. The calculation formula is as follows:

$$R = \frac{\int_{t_1}^{t_5} P(t)dt}{P \times (t_5 - t_1)} \tag{13}$$

4. CASE STUDY

4.1. Structural Information.

To validate the effectiveness of the proposed method and further investigate the resilience performance of the riser under extreme sea conditions, this study conducted detailed numerical simulations of a deepwater drilling riser in the South China Sea based on OrcaFlex software. The simulation scenarios encompassed combined wind, wave, and current conditions corresponding to different return periods to comprehensively assess the riser's performance under varying degrees of extreme environmental conditions.

OrcaFlex software was employed to perform time-domain irregular wave analysis of the dynamic behavior of the deepwater riser[8]. By mapping the physical model, a finite element model of the deepwater drilling riser was constructed within the software, as shown in Fig. 5.

Taking a drilling riser system with a water depth of 1500 m as an example for investigation, the total length of the riser system used is 1,520 m. The bottom is connected to the BOP via the LMRP, with a vertical height of 20 m above the mudline and an above-water length of 20 m. The outer diameter of the riser is 0.5334 m, and the wall thickness is 0.02225 m. The steel density of the riser is 7,850 kg/m³, the elastic modulus is 210 GPa, and the submerged weight per unit length is 3081.7 N. The drilling fluid density is 1,400 kg/m³, and the seawater density is 1,025 kg/m³.

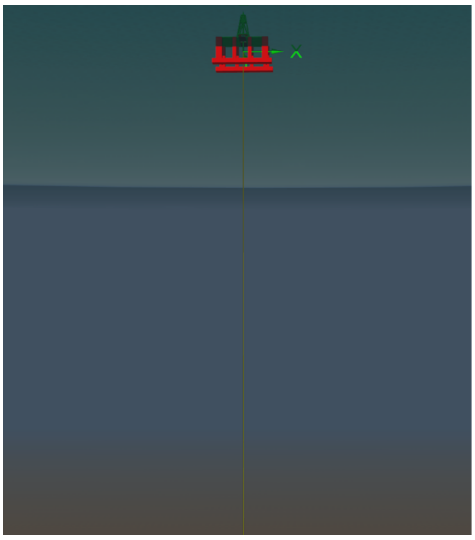


Fig 5. Finite element analysis model of the riser

4.2. Environmental Data.

In this case study, the marine meteorological data were sourced from the China offshore engineering research project. The extreme environmental conditions considered include the extreme wind, wave, and current conditions in the South China Sea under both tropical cyclone and non-tropical cyclone scenarios. In all operating conditions, the directions of waves and currents are consistent, aligned along the X-axis of the coordinate system, with the severity characterized using return periods. The specific environmental data are presented in Table 1.

Table 1. Extreme conditions in the South China Sea under tropical cyclone conditions

Type	Return Period (Years)	25	50	100	200
Wind	Spectrum	NPD			
	Speed(m/s)in 1-min	35.4	39.4	43.8	45.7
	Spectrum	JONSWAP			
Wave	Hs(m)	11.7	12.7	13.6	14.5
	Tz(s)	10.4	11.0	11.6	12.2
	Depth (m)	Velocity (m/s)			
Current	0m	1.75	1.89	2.02	2.14
	25	1.68	1.82	1.94	2.06
	247	1.16	1.24	1.31	1.38
	411	0.64	0.66	0.68	0.69
	576	0.64	0.66	0.68	0.69
	740	0.63	0.66	0.67	0.69
	1m above seabed	0.37	0.39	0.4	0.4

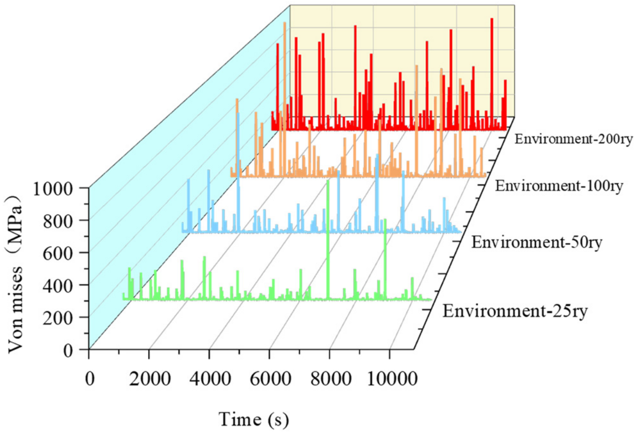
The hydrodynamic coefficients used in drilling riser analysis are critical parameters, as the analysis results can be sensitive to the selection of these values. According to API specifications, the recommended hydrodynamic coefficients are provided in Table 2.

Table 2. Hydrodynamic Analysis Parameters

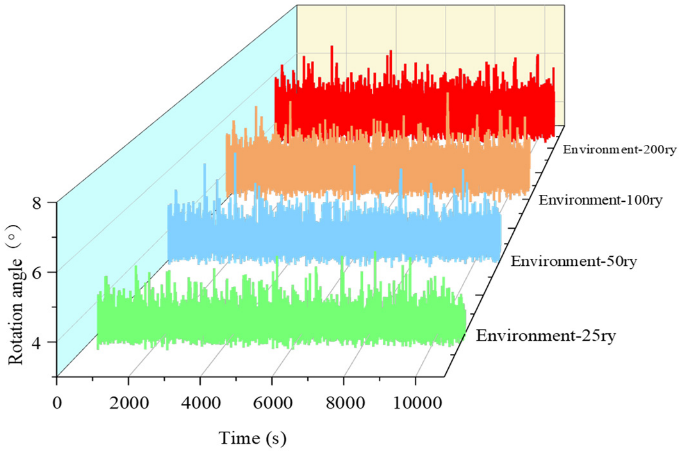
Name	Symbol	Parameter Value
Drag Force Coefficient	C_D	1.2
Lateral Drag Coefficient	C_r	0.02
Inertia Force Coefficient	C_M	2.0

The time histories of the riser's equivalent stress, the angular displacement of the bottom flexible joint, the angular displacement of the top ball joint, and the displacement of the telescopic joint are illustrated in the figures, respectively.

Clarifying the operational window criteria is a crucial prerequisite for calculating the failure probability of the riser. Referring to API RP 16Q specifications and relevant research findings, the established window limit criteria are presented in Table 3.



(a)



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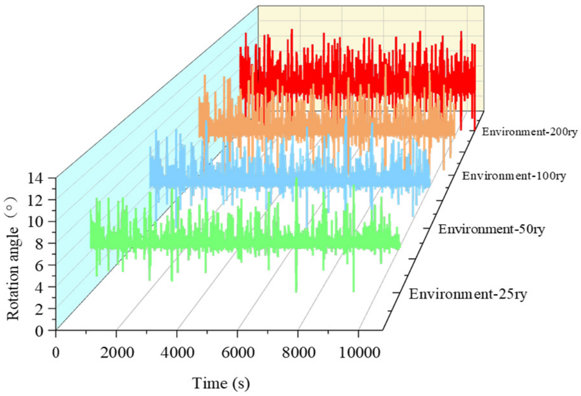

(c)

Fig 6. Distribution of 3-hour hydrodynamic response data under different return periods: (a) equivalent stress, (b) top ball joint rotation angle, (c) bottom flexible joint rotation angle.

By fitting the simulation results with the generalized extreme value distribution, the probabilities of key failure modes of the riser under different return periods are calculated.

The trend of performance change in the marine drilling riser during the degradation and recovery processes is illustrated in Fig. 7. The structural performance is calculated based on the failure rate. Degradation phase: as the storm return period increases from 25 years to 200 years, the riser's performance within 24 hours degrades to 69.7 %, 38.7 %, 7.4 %, and 0.47 %, respectively, with the

200-year event approaching complete failure. During the recovery phase, the final recovery levels decrease with the degree of degradation, reaching 94 %, 88 %, 82 %, and 80 %, respectively. There is a significant positive correlation between the severity of the marine environment (reflected in the increase of the return period) and the rate of performance degradation of the riser: the more severe the environment, the greater the decline in performance within the same time window (24 hours). Under a given maintenance strategy, the more severe the performance degradation the system experiences, the lower the final achievable recovery rate. This indicates that, despite repair work being carried out as planned, the deep damage caused by extreme events limits the ability to fully restore performance.

Table 3. Drilling riser operational window limit criteria

Name	Extreme Operating Conditions
Equivalent Stress	<368
UFJ	<6
LFJ	<10

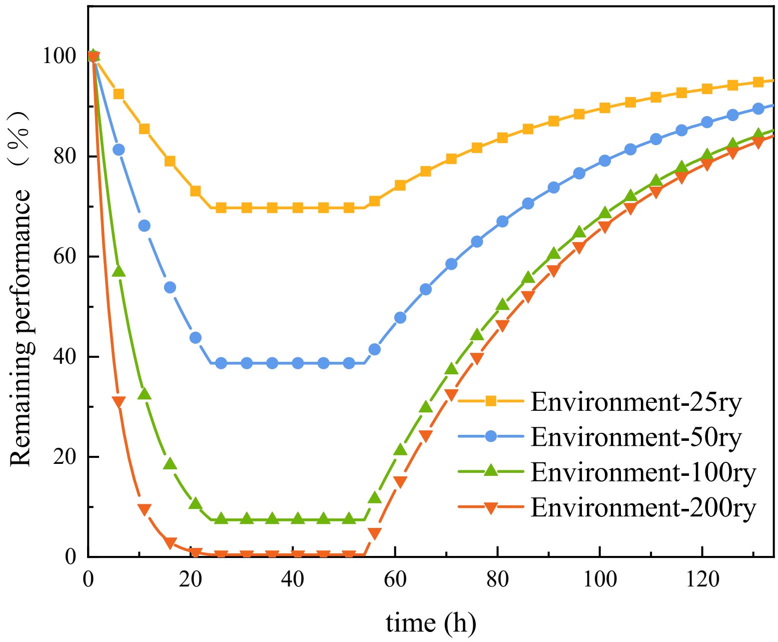

Fig 7. Riser performance variation curves under different return periods.

Fig. 8 shows the resilience values of the riser under different return periods. The results indicate that the resilience of the riser gradually decreases as the return period increases. When the return period is 25 years, the system resilience is 81.4%; when the return period is 50 years, the system resilience is 62.7%; when the return period is 100 years, the system resilience is 42.2%; and when the return period is 200 years, the system resilience is 35.8%. For return periods of 100 years or more, the change in resilience is minimal. This is because the riser can reach a near-complete failure state during the degradation process, and their recovery trends during the restoration phase are similar.

The above analysis indicates that the resilience value of the riser significantly decreases under extreme marine environmental conditions. In practical engineering, when encountering marine environments with a return period of 25 years or longer, it is necessary to shut down the riser system and implement evacuation measures.

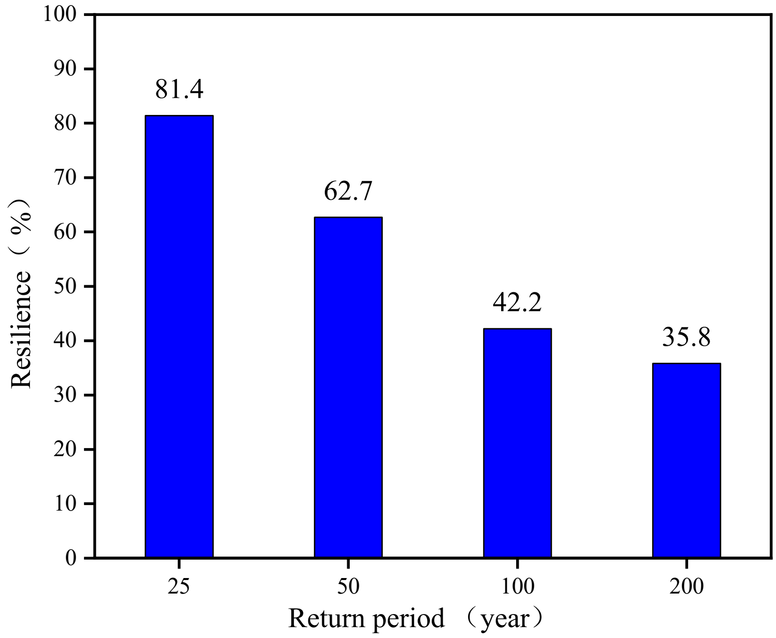

Fig 8. Resilience values of the riser under different return periods.

5. SUMMARY

These research findings provide valuable references for the engineering design and operational management of risers. During the design phase, it is recommended to increase wall thickness or use high-strength materials in areas sensitive to equivalent stress, such as the midsection of the riser, to enhance its fatigue resistance. In terms of operation and maintenance, sufficient repair resources should be pre-positioned before the typhoon season, and the repair response time should be reduced to within 18 hours to improve system resilience. Additionally, real-time monitoring of the rotation angles of the top ball joint and the bottom flexible joint of the riser is essential. Exceeding the limits of these parameters serves as a critical warning for the degradation of riser resilience, helping to implement timely measures to avoid potential failure risks.

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