Article ID：1007−7294(2026)06−0995−30

Recent Advances in Pitting Morphology Characterization in Corrosion-Fatigue Coupling: A Review

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Abstract: Corrosion-fatigue coupling presents significantly greater risks than damage mechanisms in isolation. This review synthesizes recent research advancements in theoretical frameworks, computational simulations, and experimental methodologies, with a focus on the pitting evolution and crack propagation stages. Existing models of pitting morphology are commonly constrained by single-defect assumptions and geometric regularization, which hinder a comprehensive and multidimensional characterization of pits. In the modeling of crack propagation, three primary paradigms have emerged: mechanism-driven models, data-driven models, and hybrid-enhanced models. Among these approaches, physics-informed neural networks demonstrate considerable potential in addressing complex interactions between corrosion and fatigue. A critical issue identified is the empirical oversimplification in pitting characterization, particularly the assumption of geometric regularity, which serves as a key bottleneck in quantifying corrosion-fatigue synergies. To overcome this limitation, there is a need to develop integrated multidimensional quantification methods that incorporate size, shape, irregularity, and statistical distribution. This area represents a pivotal research frontier. Advancements in this field will lead to transformative insights into the fundamental coupling mechanisms and the assessment of structural integrity for engineering systems. Ultimately, this will facilitate the development of highly accurate corrosion-fatigue life prediction models, which are essential for ensuring the safety of infrastructure.

Key words: corrosion-fatigue coupling; multidimensional morphology characterization; pitting corrosion; in-situ monitoring

CLC number: U663.1 **Document code:** A **doi:** 10.3969/j.issn.1007−7294.2026.06.011

0 Introduction

Corrosion fatigue poses a significant interdisciplinary challenge, extensively documented in various engineering applications[1−6]. This phenomenon arises from the combined effects of cyclic mechanical loads and corrosive environments, leading to the initiation and propagation of pitting corrosion and subsequent fatigue cracks. The risk of corrosion fatigue failure is particularly pronounced in safety-critical industries including oil and gas (O&G)[7−8], aerospace[9−11], nuclear power[12−14], marine systems[15−16], civil engineering,

Received date：2025−09−10
Foundation items：Supported by the Natural Science Foundation of Hubei Province (2025AFB870) and the National Natural Science Foundation of China (52201388); the Stable Support Project Fund (WDZX70202030207)
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energy, and transportation. In these sectors, infrastructure components are routinely exposed to concurrent corrosive media (such as seawater, atmospheric pollutants, and chemical agents) and cyclic loads induced by operational conditions (like wave dynamics and mechanical vibrations). The interaction between corrosion and fatigue damage mechanisms gives rise to intricate synergistic effects, where localized defects—notably pitting sites—act as potent stress concentrators and preferential sites for crack initiation. Consequently, structures may undergo premature failure at stress levels substantially below their nominal in-air fatigue strength or during early stages of service[6], incurring severe economic and safety consequences.

Corrosion fatigue phenomena are broadly categorized based on the sequence of exposure to corrosive media and fatigue loading: pre-corrosion fatigue and corrosion-fatigue. Pre-corrosion fatigue assesses the residual fatigue life of pre-corroded structures subsequently tested in inert environments, a domain well-established in the literature [17−18]. The term corrosion-fatigue, however, is designated specifically to describe the process where corrosion and fatigue loading occur simultaneously, thereby giving rise to complex, synergistic coupling mechanisms. This process is characterized by bidirectional interactions: corrosive environments accelerate fatigue damage mechanisms, such as pitting evolution, crack-tip anodic dissolution, or hydrogen embrittlement, while cyclic stresses and associated plastic deformation actively modulate electrochemical responses through processes like passive film rupture, slip-dissolution, or alterations in mass transport. Such dynamic interactions fundamentally distinguish corrosion-fatigue from isolated damage mechanisms, necessitating integrated multidisciplinary approaches across electrochemistry, metallurgy, mechanics, and surface science to address its inherent complexities.

Corrosion-fatigue is prevalent in critical engineering systems operating under harsh conditions. Marine infrastructure suffers from seawater-induced degradation—including chemical corrosion, biofouling, and microbiologically influenced corrosion (MIC)—while concurrently experiencing cyclic wave and wind loading. Aerospace structures withstand atmospheric corrosion in conjunction with flight-induced mechanical and vibratory stresses. Similarly, nuclear power systems face combined challenges from high-temperature pressurized water corrosion and thermomechanical fatigue. Extensive research demonstrates that the severity of damage resulting from corrosion-fatigue surpasses the cumulative effects of isolated corrosion and fatigue mechanisms[9,19–21], establishing it as a predominant failure mode in engineered systems and a central focus of multidisciplinary research.

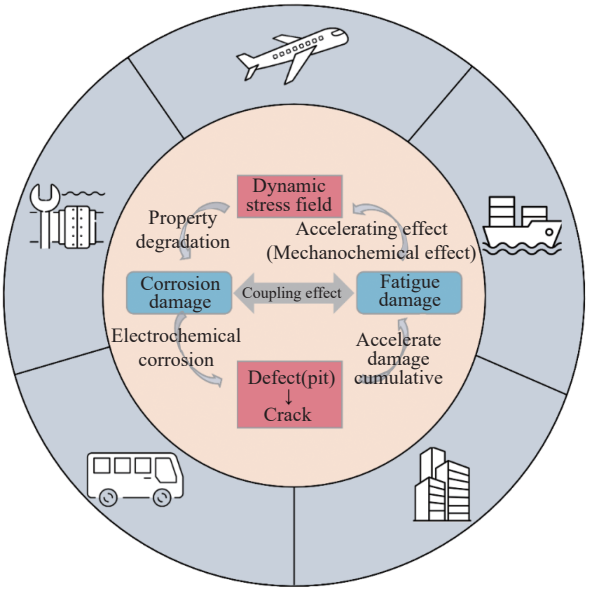


Fig.1 Schematic illustration of the corrosion-fatigue coupling process and its application scenarios

During the early stages of corrosion-fatigue (see Fig.1), modest accumulation of fatigue damage enables corrosion-driven formation of localized surface defects, particularly pitting corrosion. These defects function as geometric discontinuities, creating significant stress concentrations while establishing micro-electrochemical activity gradients in adjacent plastic zones. This process accelerates localized corrosion and the evolution of pits[22–24]. As pits grow and their morphology develops under cyclic loading,

they often lead to the initiation of fatigue cracks at the roots of these defects, significantly accelerating the early stages of crack propagation. Thus, the morphology of pits serves two diagnostic functions: it constitutes primary physical evidence of the synergy between corrosion and fatigue, and it provides a quantifiable indicator for mechanistic analysis. Critically, pit evolving characteristics intrinsically encode bidirectional acceleration phenomena wherein cyclic loading enhances corrosion kinetics while corrosive environments degrade fatigue resistance, particularly during crack initiation stages.

Research has shown that key parameters of pitting morphology—such as depth[25−26], aspect ratio[27−29], three-dimensional (3D) geometry[26], irregularity index[30], and the spatial distribution of pit clusters[28−29]—are significantly correlated with a material's resistance to the nucleation and early growth of fatigue cracks. Therefore, the selection of appropriate morphological descriptors can effectively capture both cyclic load-enhanced corrosion acceleration and corrosion-driven fatigue damage, while facilitating a quantitative assessment of the severity of corrosion-fatigue coupling. Moreover, monitoring pit morphology is more practical for direct in-situ evaluations compared to tracking crack initiation or internal damage, underscoring its substantial engineering value for rapid integrity assessments.

Contemporary characterization methodologies, however, remain constrained by their reliance on unidimensional metrics (e.g., depth, width) or overly simplified statistical parameters. These approaches lack robustness in comprehensively quantifying the complex 3D morphology of pits and their dynamic evolution under cyclic stresses. They also fail to establish reliable quantitative correlations between pit morphology and corrosion-fatigue damage. Consequently, advancing multidimensional characterization frameworks for pitting morphology and quantitatively resolving the mechanisms and effects of corrosion-fatigue coupling remains a significant challenge in contemporary engineering science.

This review article systematically evaluates the current landscape of corrosion-fatigue coupling research, encompassing theoretical frameworks, computational models, and experimental investigations, while critically addressing their limitations, notably the challenges associated with quantifying pitting morphology. Based on this analysis, we synthesize key advances and delineate future research trajectories aimed at developing effective multidimensional methodologies for pitting quantification. These efforts seek to overcome the prevailing characterization bottlenecks, providing a robust theoretical foundation for accurately assessing corrosion-fatigue coupling across engineering disciplines, with the conceptual research framework detailed in Fig.2.

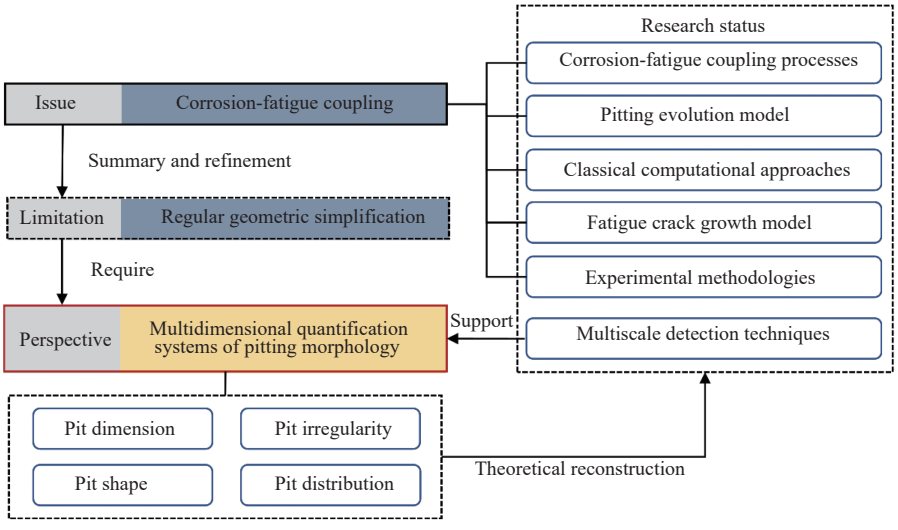


Fig.2 Research framework for corrosion-fatigue coupling analysis

1 Research progress on corrosion-fatigue coupling

1.1 Corrosion-fatigue coupling processes

Corrosion damage can be fundamentally classified into uniform and localized forms[31]. Uniform corrosion results in a generalized reduction of thickness, a phenomenon with established prediction strategies and comparatively lower risk profiles[32–34]. In contrast, localized corrosion, especially pitting corrosion, poses significantly greater hazards owing to extreme localization and stress concentration effects[35–36]. In corrosion-fatigue systems, pits serve as primary pre-crack defects and preferred nucleation sites for fatigue cracks[37–39]. Therefore, this study emphasizes pitting corrosion as a critical form of localized damage.

Corrosion-fatigue failure can be broadly categorized into two primary phases: crack initiation and crack propagation[5,40]. More specifically, this process involves surface film rupture, pit nucleation and growth, pit-crack transition, and crack propagation (which includes both small and long crack regimes), as schematized in Fig.3.

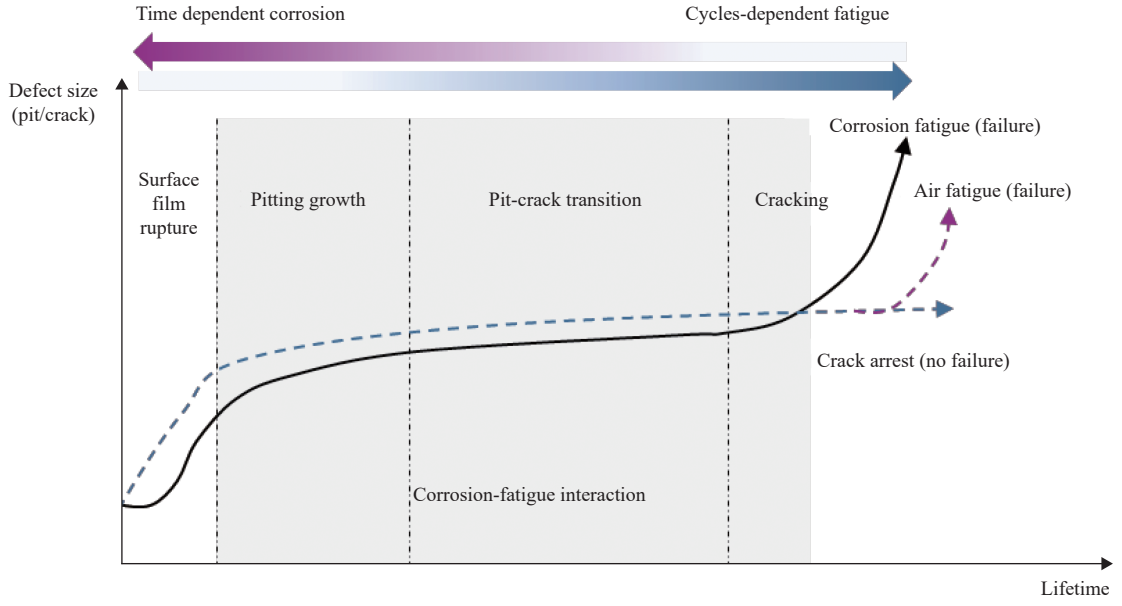


Fig.3 Schematic diagram of corrosion-fatigue process[40]

During the initial stages dominated by pitting, the accumulation rates of fatigue damage are relatively low, with pitting serving as the primary form of damage. Notably, cyclic loading markedly accelerates the morphological evolution of pits, highlighting the coupling between corrosion and fatigue processes. The pivotal phases of pit growth, the transition from pit to crack, and the propagation of small cracks involve intense interactions between corrosion and fatigue mechanisms. These damage mechanisms are heavily influenced by complex interactions among environmental and mechanical factors. Upon transitioning to long crack propagation, crack growth rates become much higher than pit evolution rates, establishing fatigue fracture mechanics as the dominant governing framework. While corrosive media continue to influence crack propagation through mechanisms such as crack-tip electrochemical reactions or hydrogen embrittlement, the impact of these factors is significantly diminished or altered during long crack propagation compared to earlier stages that involve pit initiation and the early phases of crack propagation. Therefore, a thorough understanding of corrosion-fatigue coupling mechanisms must concentrate on the stages of pit growth, pit-crack transition, and small crack propagation.

Pit growth is a critical stage in corrosion-fatigue coupling. The synergistic interactions between corrosive media and cyclic loading drive the morphological evolution of pits, which is characterized by pronounced stochasticity, complexity, and anisotropy. Key research findings reveal the following aspects of pit morphology:

(1) Localized plastic strain caused by cyclic loading substantially modifies surface electrochemical states (e.g., anodic equilibrium potential), thereby accelerating localized dissolution and the kinetics of pit evolution[22,24].

(2) Directional growth anisotropy[41] is observed, with significantly higher evolution rates in the perpendicular orientations (width and depth) compared to the parallel orientation (length direction) relative to the primary loading axis. This anisotropy stems fundamentally from distinct mechanical constraints (stress state, strain amplitude) and electrochemical microenvironments (mass transport efficiency) across different orientations.

(3) The morphology of pits provides macroscopic evidence of the interaction between corrosion and mechanical processes. Research confirms that material degradation caused by corrosion at pit surfaces—such as dissolution or hydrogen embrittlement—can be equivalently quantified through enlarged effective pit dimensions[42]. Consequently, quantitative characterization of morphological parameters, including depth, width, aspect ratio, shape, irregularity, and spatial distribution, is crucial for evaluating localized corrosion damage evolution under coupled conditions. The dynamic evolution of pits visually manifests corrosion-fatigue coupling, with the accuracy of characterization directly determining the precision of corrosion-fatigue life predictions.

The mechanistic dependencies of corrosion-fatigue coupling are critically governed by the material-environment systems (such as metal composition and electrolyte chemistry), stress parameters (mean stress and stress amplitude), loading frequency, and temperature. Simultaneous exposure to corrosive media and cyclic loading induces premature crack nucleation and accelerated propagation through coupled mechano-electrochemical processes, including stress corrosion cracking, hydrogen-assisted cracking, and corrosion fatigue[23−24]. The primary theories regarding crack initiation include pit stress concentration theory[37–39], slip dissolution theory[39], protective film rupture theory[43], and adsorption theory[44], each offering distinct mechanistic insights with inherent advantages and limitations. The pit stress concentration theory centers on the geometric discontinuity of pits, which induces localized stress and plastic strain concentration under cyclic loading to promote crack nucleation, with the strength of clear mechanical logic and broad material adaptability but the limitation of neglecting electrochemical coupling effects. The slip dissolution theory posits that cyclic loading triggers slip steps to rupture the passive film, and the exposed fresh metal undergoes anodic dissolution, with the repeated cycle driving pit growth and crack initiation—effectively revealing mechano-electrochemical coupling but struggling to explain complex pit morphologies and multi-defect interactions. The protective film rupture theory focuses on local film fracture induced by stress or microstructural inhomogeneities, forming micro-galvanic cells to initiate pitting, which accurately interprets passivating metal pitting but ignores dynamic film repair under cyclic fatigue. The adsorption theory attributes pitting to selective adsorption of aggressive ions (e.g., Cl^-) on the passive film, weakening film-substrate bonding—clarifying environmental ion effects but lacking quantitative description of mechano-electrochemical coupling.

Given its broad applicability, the pit stress concentration theory is extensively utilized to interpret

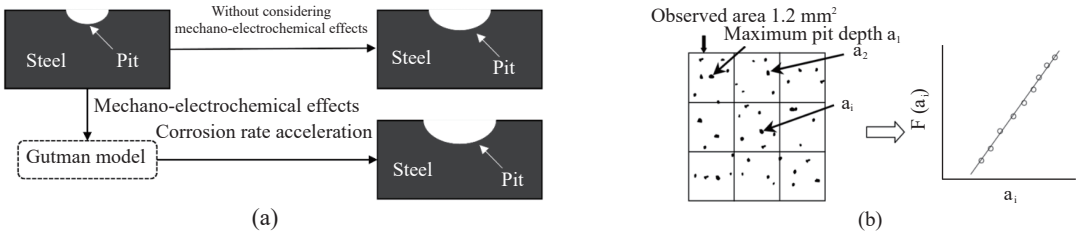
corrosion-fatigue crack initiation in stainless steels, carbon steels, aluminum alloys, and other metals in diverse service environments[45–49]. The theory posits that cyclic loading generates significant localized stress concentrations at pit defects, resulting in plastic deformation. This plastically deformed region becomes anodic due to enhanced electrochemical activity, thereby accelerating the dissolution of metal[22,50]. This process not only stimulates pit growth and morphological evolution but also establishes conditions vital for the transition from pit to crack. Once cracks nucleate and progress into the small crack propagation stage, the tips of these cracks remain within high-strain zones, where the combined effects of corrosive media (due to electrochemical reactions or hydrogen permeation) and mechanical loading continue to significantly impact crack propagation behavior. Consequently, the stages of pit growth, the pit-crack transition, and small crack propagation collectively represent the most intense and complex characteristics of corrosion-fatigue coupling.

From a macroscopic perspective, the effects of coupling are primarily manifested through the dynamic evolution of pit morphology (size, shape, distribution) during pit growth. In contrast, during the transition from pit to crack and small crack propagation, the focus shifts to characterization of nucleation sites, initiation rates, and early propagation paths. This stage-dependent dichotomy profoundly impacts both experimental research and engineering applications. In laboratory studies employing small polished specimens, the process from pit initiation through growth to crack transition typically accounts for over 90% of the total fatigue life[49]. Therefore, accurately characterizing the evolution of pit morphology is crucial. On the other hand, for engineered structures that contain inherent manufacturing defects or service-induced cracks, understanding corrosion-affected crack propagation behavior becomes essential for assessing residual life and managing structural integrity.

1.2 Theoretical modelling of corrosion-fatigue coupling

1.2.1 Pitting evolution under cyclic loading

Research on pitting evolution under cyclic loading constitutes a fundamental component in understanding corrosion-fatigue coupling mechanisms, primarily addressing pitting evolution modeling and pit-crack transition criteria. Contemporary theoretical frameworks employ three principal methodologies: 1) Mechano-electrochemical models establish physical correlations between stress fields and pitting growth rate (e.g., depth, width) by quantifying mechanical influences on electrochemical processes, as exemplified by Gutman's framework[22−24] (see Fig.4(a)); 2) Empirical and semi-empirical formulations calibrate stress amplitude, frequency, and related parameters against pitting evolution patterns through statistical fitting of corrosion-fatigue test data (notably pit depth progression versus exposure duration or cycle count), demonstrated in Ishihara's model[51] (see Fig.4(b)); and 3) Energy-based paradigms conceptualize pitting evolution as an irreversible thermodynamic process driven by synergistic contributions of strain energy, surface energy, and electrochemical energy, from which shape parameter evolution (particularly aspect ratio) is derived[52] (see Fig.4(c)). Researchers have implemented these methodologies across diverse disciplinary fields and material systems.



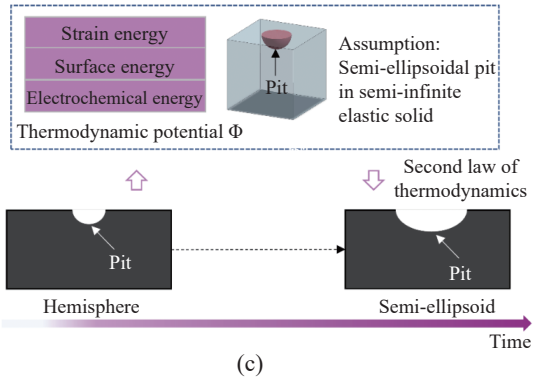


Fig.4 Schematic diagram of contemporary theoretical frameworks

(1) Research by Hu et al[52–54]

Hu et al proposed a methodology for predicting the initiation life of corrosion-fatigue in aluminum alloys, based on Continuum Damage Mechanics (CDM). This approach integrated three key modules: an improved pitting evolution model, a coupled damage elastoplastic constitutive model, and a fatigue damage evolution model. The pitting evolution model, grounded in electrochemical kinetics, described the progression of pit depth over time as follows

$$a^3 = A^A \Pi \frac{3MI_{p0}}{2\pi\lambda^2\rho nF} \exp\left[-\frac{\Delta H}{RT}\right] t + a_0^3 \tag{1}$$

where a denotes pit depth, M is the material's molecular mass, I_{p0} represents the pre-exponential factor in the Arrhenius relationship, λ signifies ellipticity, ρ is density, n is the valence electron count, F is Faraday's constant, ΔH corresponds to the activation energy, R is the gas constant, T represents absolute temperature, t is time, and a_0 is the initial pit depth.

The constitutive model employed the Chaboche kinematic hardening model[55–57] and incorporated a damage variable through the strain equivalence hypothesis[58]. Fatigue damage evolution was calculated by separately considering the elastic and plastic damage components. Specifically, a stress-controlled fatigue damage evolution model and a strain-controlled fatigue damage evolution model were utilized, as expressed in Eqs.(2) and (3), respectively. The cumulative damage was then determined as the maximum value of these components, with crack initiation defined by the criterion $D \geqslant D_c$. This approach simplifies pit morphology through two-parameter ellipsoidal regularization, exemplifying the application of CDM theory for predicting corrosion fatigue life.

$$\frac{\mathrm{d}D_e}{\mathrm{d}N} = \left[1-(1-D)^{\beta+1}\right]^{\alpha} \cdot \left[\frac{\sigma_a}{M_0(1-b_2\sigma_m)(1-D)}\right]^{\beta} \tag{2}$$

$$\frac{\mathrm{d}D_p}{\mathrm{d}N} = \left[\frac{(\sigma^*_{max})^2}{2ES(1-D)^2}\right]^{m} \cdot p \tag{3}$$

Here, D_e and D_p represent the elastic and plastic fatigue damage components, respectively. N is the number of cycles, while β, M_0, b_2, S, and m are material constants. Additionally, σ_a and σ_m denote the stress amplitude and mean stress, respectively. The parameter α can be calculated based on material properties and the fatigue limit, and σ^*_{max} represents the maximum value of the damage equivalent stress.

(2) Study by Ishihara et al[51]

Ishihara et al established an empirical model for stress amplitude-dependent pit depth through corrosion fatigue tests on aluminum alloy specimens submerged in a 3% sodium chloride (NaCl) solution. The model can be expressed with the following equations

$$\gamma = A'(\sigma_{\mathrm{a}})\, t^{B} \tag{4}$$

$$A' = 2.34 \times 1.014^{\sigma_{\mathrm{a}}} \tag{5}$$

where γ is the location parameter, σ_{a} represents the applied stress amplitude, B denotes an experimentally fitted parameter, and t corresponds to corrosion exposure time.

For irregular corrosion pits, a novel fracture mechanics-based transformation criterion[59] was proposed

$$K_{p\to c} = 0.65\sigma_{\mathrm{a}} \sqrt{\pi \sqrt{(area)_{p\to c}}} \tag{6}$$

This model specifically addresses corrosion pit irregularity in aluminum alloys and provides an empirically derived methodology that is applicable for engineers.

(3) Investigations by Huang and Xu et al[60–63]

Huang and Xu et al developed an energy-based theoretical framework that conceptualized the evolution of pits as a driven process involving strain energy, surface energy, and electrochemical energy. The governing equation for this framework is given by

$$\Phi = U_{\mathrm{E}} + U_{\mathrm{S}} - U_{\mathrm{C}} \tag{7}$$

Based on this framework, a morphological evolution model for semi-ellipsoidal corrosion pits in a two-dimensional infinite elastic medium was developed. The model leads to the derivation of the crack initiation lifetime, represented by

$$N_i = \frac{2\pi nF\rho}{3MI_{\mathrm{p0}}} f \left[\left(\frac{1-m_{\mathrm{cr}}}{1+m_{\mathrm{cr}}} \right)^{3/2} a_{\mathrm{cr}}^3 - \left(\frac{1-m_0}{1+m_0} \right)^{3/2} a_0^3 \right] \exp\left(\frac{\Delta H}{RT} \right) \tag{8}$$

where a_{cr} and a_0 denote the critical pit depth and initial pit depth, respectively. m_{cr} and m_0 represent the corresponding ellipsoidal shape parameters at these depths.

This theory elucidates an energy competition mechanism where both strain energy and electrochemical energy promote pit growth and encourage morphological flattening, resulting in transition from hemispherical to semi-ellipsoidal geometries, as illustrated in Fig.4(c). In contrast, surface energy acts to inhibit this progression.

The establishment of criteria for the transition from pit to crack requires balancing physical mechanisms with engineering applicability. There are three predominant criteria to consider which are explained herewith

(1) Stress intensity factor (SIF) criterion: Crack initiation occurs when the effective SIF amplitude (ΔK) at the pit exceeds the material's fatigue crack growth threshold.

(2) Competitive growth criterion[64]: This criterion is defined by the condition where the fatigue crack growth rate surpasses the pit propagation rate.

(3) Critical damage accumulation criterion: This criterion is triggered when cumulative damage reaches a critical value.

Chen et al suggested a dual-criterion framework that required simultaneous satisfaction of both the SIF criterion and competitive growth criterion[45]. This approach has been extensively validated for its physical soundness[60–63,65]. However, significant limitations still exist. The effectiveness of these criteria is highly sensitive to the actual 3D pit morphology (e.g., depth, aspect ratio, sharpness). Simplifying the morphology of pits can lead to distorted stress field calculations, resulting in biased predictions of SIF amplitude and ultimately an inaccurate assessment of damage accumulation. Such oversimplifications may generate erroneous predictions for the transition from pit to crack, constituting a primary source of error in life prediction models. Therefore, developing improved criteria that incorporate high-fidelity characterization of pit morphology is crucial for overcoming these quantitative limitations. The pit evolution models and pit-crack transition criteria proposed by the aforementioned researchers are summarized in Tab.1.

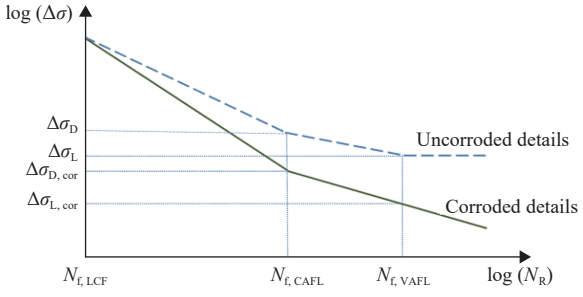
Tab.1 Summary of representative pit evolution models under alternating loads

Literature	Pit simplification	Basis	Pit Evolution Model	Pit-crack criterion	Application scope	Accuracy	Limitations
Wu et al[123]	Hemispherical pit	Faraday's law	$\frac{\mathrm{d}V}{\mathrm{d}t}=\frac{MI_{\mathrm{p}}}{nF\rho}$, $N_{\mathrm{f}}=\alpha_{\mathrm{c}}N_{\mathrm{cf}}+(1-\alpha_{\mathrm{c}})N_{\mathrm{ff}}$,	$\Delta K\geqslant\Delta K_{\mathrm{th}}$	Material: FV520B stainless steel; Environment: distilled water spray/5% NaCl salt spray	Fatigue life predictions agree with test results within a factor of ±2	Only valid for single-pit dominated corrosion fatigue conditions
Ishihara et al[51]	–	Corrosion fatigue tests (3% NaCl solution)	$\gamma=A'(\sigma_{\mathrm{a}})t^{B}$, $A'=2.34\times1.014^{\sigma_{\mathrm{a}}}$	$K_{p\to c}=0.25\mathrm{MPa}\sqrt{\mathrm{m}}$	Material: 2024-T3 aluminum alloy; Environment: 3% NaCl solution	Estimated crack initiation/total life matches test results, with error < 20% at low stress amplitude	Exclusive to the target alloy-salt solution system
Hu et al[54]	Bivariate ellipsoidal pit	Faraday's law & Gutman model	$\frac{\mathrm{d}V}{\mathrm{d}t}=\frac{MI_{\mathrm{p0}}}{nF\rho}\exp\left[-\frac{\Delta H}{RT}\right]A^{A_{II}}$	$D_{\mathrm{c}}=1$	Material: 2024-T3 aluminum alloy, Environment: 5% NaCl solution (pH=4)	Predictions of pit depth and fatigue life both deviate < 10% from test results	Relies on ABAQUS dedicated user subroutines for simulation
Amiri et al[65]	Bivariate ellipsoidal pit	Faraday's law & Gutman model	$\frac{\mathrm{d}V}{\mathrm{d}t}=\frac{MI_{\mathrm{p0}}}{nF\rho}\exp\left[-\frac{\Delta H}{RT}\right]A^{\sigma_{\mathrm{a}}}$	$\Delta K\geqslant\Delta K_{th}$ and $\left(\frac{\mathrm{d}a}{\mathrm{d}t}\right)_{\mathrm{crack}}\geqslant\left(\frac{\mathrm{d}a}{\mathrm{d}t}\right)_{\mathrm{pit}}$	Material: AA2024-T3 aluminum alloy; Environment: Cl^--containing corrosive medium	Predicted pit-to-crack transition life covers test data with a 95% confidence interval	Plastic deformation acceleration on pitting growth is not considered
Huang et al[60–63]	Bivariate semi-ellipsoid	Energy criterion & Faraday's law	$\Phi=U_{\mathrm{E}}+U_{\mathrm{S}}-U_{\mathrm{C}}$, $\frac{\mathrm{d}\Phi}{\mathrm{d}m}=0$	$\Delta K\geqslant\Delta K_{\mathrm{th}}$ and $\left(\frac{\mathrm{d}a}{\mathrm{d}t}\right)_{\mathrm{crack}}\geqslant\left(\frac{\mathrm{d}a}{\mathrm{d}t}\right)_{\mathrm{pit}}$	Material: Aluminum alloy; Environment: unspecified corrosive medium	Calculated critical pit size deviates < 10% from the stress intensity factor criterion	Lacks direct experimental validation for the theoretical model
Ma et al[41]	–	Corrosion fatigue tests (3.5% NaCl solution)	$f(t)=a+bt^{n}$	–	Material: A537 steel; Environment: 3.5% NaCl solution (pH=6.5)	Simulated 3D pit dimensions match measured values with a consistency > 90%	Only applicable to MnS inclusion-dominated pitting evolution
Kondo[64]	Aspect ratio=0.7	Corrosion fatigue data	$2c\propto t^{1/3}$	$\left(\frac{\mathrm{d}a}{\mathrm{d}t}\right)_{\mathrm{crack}}\geqslant\left(\frac{\mathrm{d}a}{\mathrm{d}t}\right)_{\mathrm{pit}}$	Material: Low-alloy steel; Environment: deionized water at 90 ℃	Calculated critical ΔK and residual life predictions both fit well with test results	Synergistic evolution effect of multiple pits is not considered

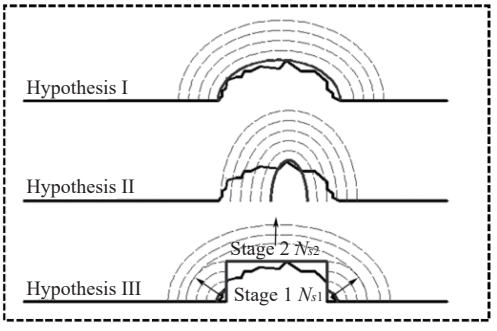
1.2.2 Fatigue crack growth models in corrosive environments

The development of models for corrosion fatigue crack propagation poses significant challenges stemming from multi-scale phenomena and multi-physics field coupling. Existing methodologies can be classified into three primary paradigms: mechanism-driven models, data-driven models, and hybrid-enhanced models. Mechanism-driven approaches focus on the physical characterization of synergistic damage mechanisms. Data-driven models leverage nonlinear mapping to uncover complex underlying correlations, while hybrid-enhanced models integrate physical constraints with data learning to address the limitations associated with single-method strategies.

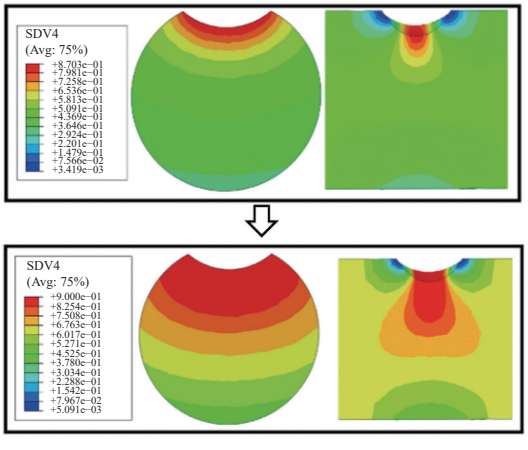
Mechanism-driven models are based on corrosion kinetics, fracture mechanics, or CDM theory. Depending on their scale and theoretical framework, these models can be further classified into *S-N* curve-based empirical models (see Fig.5(a)), fracture mechanics-based models (see Fig.5(b)), CDM-based methods (see Fig.5(c)), and phase field models (see Fig.5(d)). Specifically, *S-N* curve-based empirical models, modify traditional fatigue *S-N* curves by incorporating corrosion acceleration factors[66] and use the Palmgren-Miner linear accumulation criterion[67–69] to predict life under random loading conditions. However, despite its engineering practicality, this approach exhibits significant limitations. It is restricted to the crack initiation stage and cannot effectively characterize propagation behavior. Furthermore, it relies excessively on specific operational data, resulting in poor extrapolation to complex environments. Critically, the method lacks a fundamental physical explanation for the coupled corrosion-fatigue mechanisms, which generally confines its application to preliminary design phases.



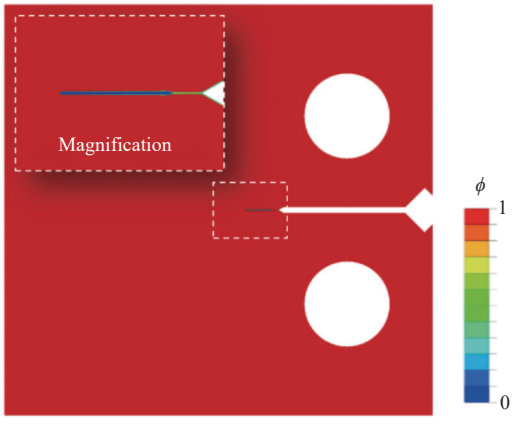
(a) *S-N* curve



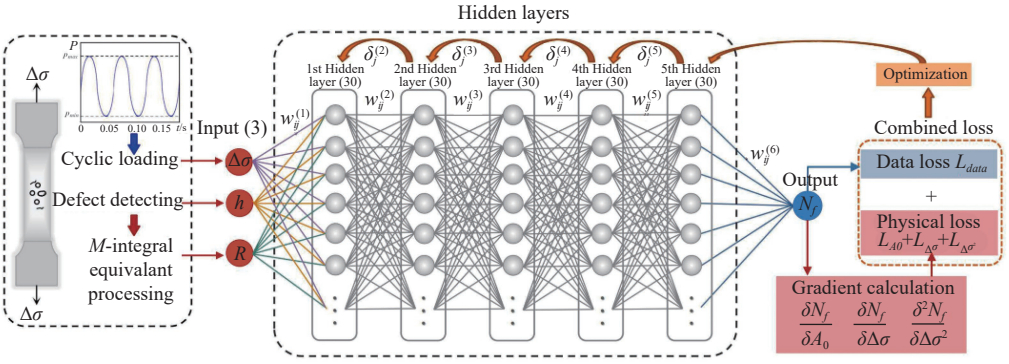
(b) Fracture mechanics[29] (Copyright 2015 Elsevier)



(c) CDM[71] (Copyright 2020 Elsevier)



(d) Phase field approach[72] (Copyright 2025 Elsevier)



(e) Physics-informed neural networks[73] (Copyright 2025 Elsevier)

Fig.5 Models for corrosion fatigue crack propagation

Fracture mechanics-based models primarily rely on the Paris formula[74–76], with extensions that consider stress ratio corrections (Walker model[75]), crack closure effects (Forman model[76]), or adjustments for corrosion sensitivity thresholds (McEvily classification[77]). These models frequently simplify 3D pits into two-dimensional (2D) semi-elliptical cracks and employ long crack propagation thresholds and competing growth criteria for crack initiation. Classical linear elastic fracture mechanics (LEFM), however, does not address the "short crack anomaly", a phenomenon characteristic of early-stage propagation. Rokhlin's two-stage model[25] partially mitigates this limitation by employing equivalent angular cracks and differentiated stress intensity factor calculations. Cumulative models[51,78–80] decompose crack growth rates into linearly superimposed contributions from mechanical fatigue, corrosion fatigue, and stress corrosion cracking. Nonetheless, they struggle with quantifying the competing mechanisms of anodic dissolution and hydrogen embrittlement[81]. Key limitations arise from geometric simplifications of pits, which introduce deviations in stress intensity factor, and from empirically derived corrosion correction terms[82–84] that lack explicit characterization of electrochemical-mechanical coupling processes.

CDM-based methods introduce damage variables to characterize the progressive degradation of materials, enabling a unified description of microdefect evolution and macroscale crack propagation. Nevertheless, these methods face inherent limitations in characterizing discrete fracture surfaces and are often susceptible to mesh-induced artifacts and spurious stress transfer[85]. To overcome these constraints, Peerlings et al[86] proposed a fatigue damage law integrated with a gradient-enhanced nonlocal method, thereby coupling CDM with finite element analysis to simulate fatigue crack growth. Subsequent studies[87–90] developed alternative fatigue damage criteria for similar simulations. While these approaches achieved improved crack propagation modeling, they incurred substantial computational costs. Consequently, mesh-independent fracture simulation methods—including the crack particle method (CPM)[91–92], extended finite element method (XFEM)[93–95], extended isogeometric analysis (XIGA)[96–97], and peridynamics (PD)[98]—have gained prominence. Though effective for crack propagation analysis, such methods remain limited in full-life cycle modeling. Recent efforts have aimed to couple CDM with XFEM to enable comprehensive life simulation[85,99–100]. However, multi-physics studies of corrosion fatigue remain scarce, with minimal exploration of the regulatory role of pitting morphology in damage evolution.

The phase-field model epitomizes an emerging paradigm that implicitly tracks crack interfaces through phase-field variables, circumventing complexities associated with explicit geometric tracking. Wang et al[72] developed a displacement-electrochemical-phase-field coupled framework incorporating a strain energy

degradation function to simulate corrosion fatigue damage, successfully capturing corrosion-accelerated crack propagation. Although this model was validated on carbon steel compact tension specimens, its ability to simulate complex pitting morphology evolution and its regulatory effects on fatigue damage mechanisms—ranging from initiation through propagation—remains unverified. Research in this domain is still in the early stage.

Data-driven models utilize algorithms, such as neural networks, to establish nonlinear mappings between environmental parameters (like temperature, pH, and stress amplitude) and crack propagation behavior[3], addressing mechanistically complex scenarios with strong multi-parameter coupling. For instance, Cavanaugh et al[101] employed artificial neural networks to predict the influence of Cl^- concentration and pH on pitting morphology parameters (depth and diameter distribution). Similarly, Ji et al[102] integrated a grey wolf optimization algorithm to enhance neural network accuracy in predicting aluminum alloy corrosion fatigue life. Although these methods are highly effective for high-dimensional nonlinear problems, they exhibit two critical limitations: heavy reliance on extensive training datasets and inherently limited interpretability, which obstructs elucidation of underlying physical mechanisms.

Hybrid enhanced models, exemplified by Physics-Informed Neural Networks (PINNs), have emerged as a potent approach to integrate physical interpretability with data adaptability, effectively addressing the limitations of single-method strategies in corrosion fatigue crack propagation modeling. Specifically, Dourado et al[103] proposed a dual-pathway framework tailored for corrosion fatigue crack propagation prediction of Al 2024-T3 aluminum alloy aircraft wing panels, which are typically subjected to cyclic loading and saline corrosion. This framework comprises two complementary branches: a physics-driven branch embedding the governing equations of fracture mechanics (i.e., Walker model) to characterize the mechanical fatigue crack growth baseline, and a data-driven branch trained to learn corrections to crack growth rates based on the corrosion environment that reflects the NaCl concentration of airport environments. Unlike traditional data-driven models[101] and the conventional BP neural network[102] that rely heavily on extensive training datasets, this PINNs architecture retains strong generalization capability even with limited samples. Validation on a synthetic fleet dataset demonstrated that the PINNs model achieved a prediction deviation of $\leqslant$15% between the predicted crack length and actual inspection results, and its generalization ability was improved by approximately 28% compared to traditional Artificial Neural Networks (ANNs) as discussed by Cavanaugh et al[101]. Its core value lies in the synergistic optimization of physical constraints (ensuring mechanistic interpretability by embedding the Walker model) and empirical data (compensating for missing corrosion physics that is difficult to characterize by pure mechanism-driven models). Current applications, however, remain constrained by the fidelity of mathematical representations for corrosion-fatigue coupling mechanisms—particularly in their inadequate quantitative characterization of electrochemical-mechanical interactions. Additionally, the model construction complexity is higher than that of optimized data-driven models[102], requiring careful balance between the rationality of physical constraints and the accuracy of data fitting.

A comprehensive comparison of the three types of corrosion fatigue crack propagation models is summarized in Tab.2. All models exhibit distinct advantages and limitations, with mechanism-driven models excelling in physical interpretability, data-driven models in computational efficiency, and hybrid-enhanced models in balancing data dependency and mechanistic clarity. This comparison provides a reference for selecting appropriate models based on specific engineering scenarios (e.g., data availability, corrosion environment complexity, and prediction accuracy requirements).

Tab.2 Comparison of fatigue crack growth models in corrosive environments

Model type	Theoretical basis	Applicable scope	Advantages	Disadvantages	Typical application cases
Mechanism-driven models[29,70–72]	Corrosion kinetics, fracture mechanics, CDM theory or phase field model	Materials: Al 2024-T3 aluminum alloy, AA7075 aluminum alloy, carbon steel; Environment: seawater, Cl^--containing corrosive media, alternating load conditions, partially applicable to complex fatigue crack propagation simulation in corrosive media;	Clear physical mechanism, able to explain the intrinsic law of fatigue crack propagation in corrosive media; Phase field model does not require explicit tracking of crack geometry; CDM can uniformly describe the evolution of microdefects and macroscale fatigue cracks;	Ignoring complex coupling factors such as medium flow and load fluctuation; Geometric simplification introduces deviations in stress intensity factor; CDM has mesh-induced artifacts; phase field model is still in the early stage and difficult to characterize the influence of complex pitting morphology on fatigue crack propagation;	Predicting fatigue crack initiation-propagation and life under cyclic loading.
Data-driven models[101,102]	Machine learning algorithm and nonlinear mapping theory	Material: AA7075 aluminum alloy; Environment: Cl^--containing, different pH corrosive media, fixed/variable load corrosion-fatigue conditions, requiring matching with the coverage of training data for fatigue crack propagation prediction;	No need for clear physical mechanism, high prediction efficiency, able to handle high-dimensional nonlinear coupling problems in fatigue crack propagation under corrosion conditions;	Highly dependent on the quantity/quality of training data; lack of physical interpretability; difficulty in clarifying the intrinsic mechanism of corrosion-fatigue coupling in crack propagation;	Fatigue life of 7050 aluminum alloy in corrosive media
Hybrid-enhanced models[103]	Fusion theory of fracture mechanics physical constraints and data-driven fitting	Material: Al 2024-T3 aluminum alloy; Environment: Complex corrosion-fatigue conditions (variable load, multi-medium switching, airport corrosive environment), limited sample scenarios (only partial fleet inspection data) for fatigue crack propagation prediction;	Prediction deviation ⩽15% under limited samples for fatigue crack propagation in corrosive media, generalization ability improved by approximately 28% compared with traditional ANN; balancing physical interpretability and data adaptability;	Complex model construction, requiring balance between the rationality of physical constraints and the accuracy of data fitting; higher computational cost than traditional data-driven models; difficulty in quantifying the details of electrochemical-mechanical interaction in fatigue crack propagation;	Prediction of fatigue crack propagation in Al 2024-T3 aluminum alloy aircraft wing panels and fleet inspection priority planning in corrosive environments

1.2.3 Critical review of theoretical limitations

The theoretical framework for corrosion-fatigue coupling has evolved along two primary trajectories: pitting evolution modeling under cyclic loading (incorporating mechano-electrochemical interactions, empirical formulations, and thermodynamic principles), and crack propagation modeling in corrosive environments (encompassing fracture mechanics corrections, damage mechanics approaches, and multiscale methodologies). Collectively, these studies establish foundational frameworks for predicting crack initiation life (notably pitting-to-crack transition criteria) and quantifying propagation behavior. However, extant theoretical models exhibit three fundamental limitations:

(1) Morphological oversimplification: Pitting evolution models typically simplify actual morphologies to idealized semi-ellipsoidal geometries, while crack propagation models approximate pits as 2D semi-elliptical cracks. Crucially, both approaches characterize pits solely through unidimensional parameters (i.e., depth or aspect ratio), neglecting multidimensional features including shape complexity, spatial clustering, and surface irregularity.

(2) Inadequate representation of coupling mechanism: Pitting growth models disregard mechanically induced anisotropic morphology evolution, whereas crack propagation models, despite incorporating empirical corrosion corrections, neglect explicit physical modeling of electrochemical-mechanical coupling within crack-tip microdomains.

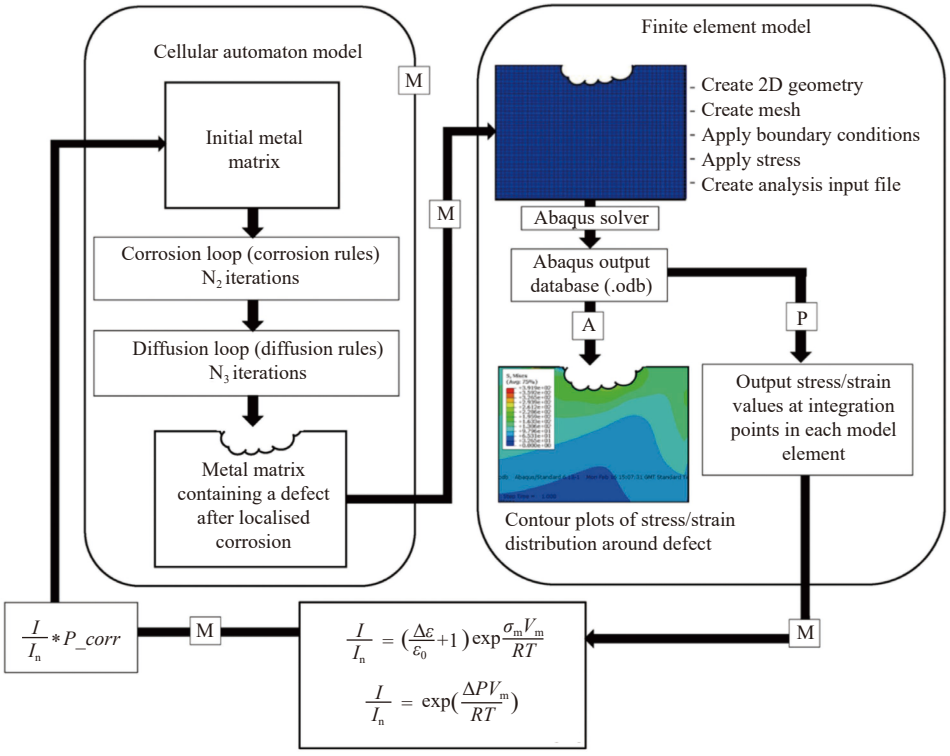
(3) Absence of cross-scale transition criteria: Current pitting-to-crack transition frameworks fail to incorporate spatiotemporal heterogeneity in morphological evolution, leading to erroneous identification of critical transition states between microscale pitting and macroscale cracking.

The core limitation stems from the insufficient characterization of pitting morphology's high-dimensional complexity within existing frameworks. While regularization assumptions enhance computational tractability, they compromise physical fidelity—particularly undermining model predictive accuracy in practical scenarios. To comprehensively quantify corrosion-fatigue interactions, future work must establish time-variant characterization systems that integrate multidimensional morphology parameters (size, shape, distribution, irregularity) and develop coupled models that relate these parameters to mechanical-environmental field interactions.

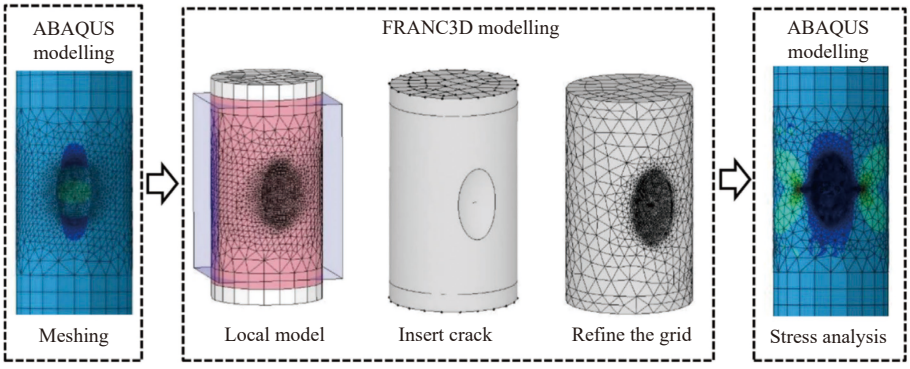
1.3 Computational approaches to corrosion-fatigue

Current methodologies for simulating corrosion fatigue face shared bottlenecks in the evolution of pitting and crack propagation. A key issue is that the assumption of regular geometries severely compromises the physical accuracy of these models. In pitting simulations, CDM frameworks, such as those presented by Amiri et al[53−54,65], predict crack initiation life by coupling Faraday's corrosion law with high-cycle fatigue damage models[104]. Yet these approaches consistently ignore the acceleration of the corrosion rate by local plastic strain. Hu et al[54] improved the characterization of local stress fields by utilizing an octahedral shear stress criterion, but the empirical nature of this model requires further validation for broader applicability. The Cellular Automaton Finite Element (CAFE) approach[105−106] has revealed the effects of electrochemical and stress parameters on pit aspect ratios, with the logic diagram of the CAFE model displayed in Fig.6(a). Nevertheless, this methodology remains confined to 2D constant-load scenarios and fails to capture 3D morphological anisotropy induced by alternating loads. While other researchers, such as Li et al[71,107–110], have incorporated corrosion stochasticity, they have not adequately addressed the dynamics of fatigue-driven pit morphology. Crucially, all aforementioned methods artificially reduce complex pit morphologies to regular geometries, such as ellipsoids or cylinders. This simplification distorts local stress field computations and precludes quantification of pit clustering effects.

In the simulation of crack propagation, fracture mechanics approaches achieve engineering applicability by approximating pits as semi-elliptical cracks. This simplification can lead to significant deviations in the calculations of the stress intensity factor. Although the integration of FRANC3D with ABAQUS improves the capabilities to predict dynamic crack paths[111] (see Fig.6(b)), it is still limited by assumptions related to geometric idealization. Emerging phase-field models[72] quantitatively resolve the mechanisms at the crack tip by coupling electrochemo-mechanical processes with phase field dynamics. These models effectively characterize growth dominated by anodic dissolution. However, their high computational costs restrict their practical application in engineering, and they fail to incorporate parameters related to pitting morphology. Furthermore, PINNs[103] (see Fig.5(e)) can achieve reliable predictions under limited data conditions, thanks to the incorporation of embedded physical constraints like Paris law. Nonetheless, these models currently lack a dynamic framework that connects crack growth behavior with changes in pitting morphology, environmental factors, and loading conditions.



(a) The CAFE model[105] (Copyright 2018 Elsevier)



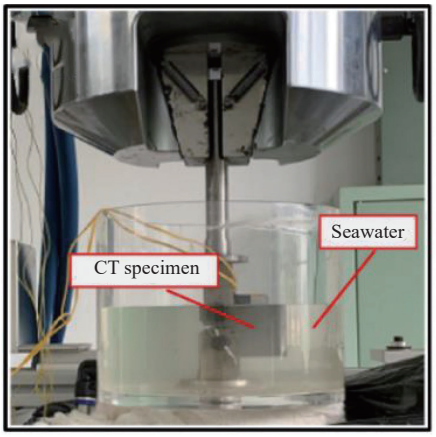
(b) The combined simulation by ABAQUS and FRANC3D[111] (Copyright 2023 Elsevier)

Fig.6 Schematic of the CAFE model[105] and the combined simulation by ABAQUS and FRANC3D[111]

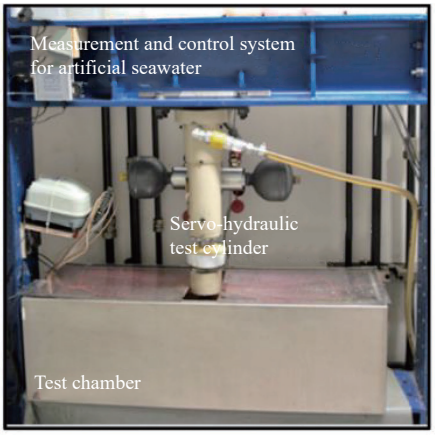
The fundamental limitation across various methodologies originates from the universal regularization of pit geometry (e.g., hemispherical or conical shapes), which disregards the multidimensional features of realistic morphologies, particularly the initiation of cracks at multiple sites due to irregular boundaries. This shortcoming is evident in several ways: (i) It ignores the stress concentrations and local plastic strain caused by irregularities, which can accelerate corrosion rates during the pitting stages; (ii) There is a lack of morphology-sensitive equivalence methods for calculating the stress intensity factors during the propagation of microcracks; and (iii) There is a fragmented approach to understanding microscale pitting evolution and macroscale crack propagation due to inadequate mechanisms for cross-scale coupling. These gaps are epitomized by the absence of integrated criteria for the transition from pitting to crack that account for changes in morphology, signifying an unmet research challenge.

1.4 Experimental methodologies for corrosion-fatigue

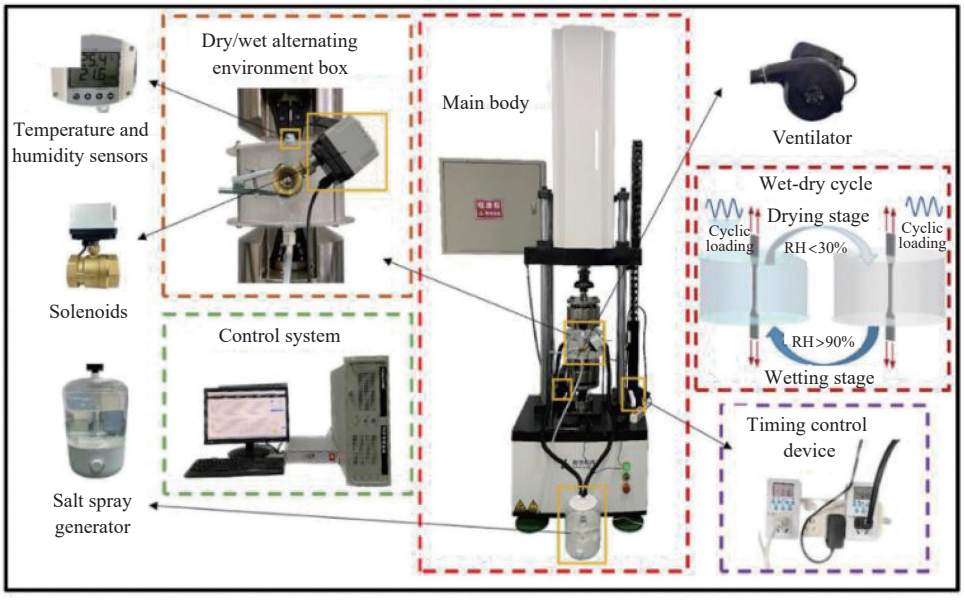
Corrosion fatigue testing is a direct method for quantifying the coupled effects of environmental and mechanical factors; however, it encounters three persistent challenges: temporal scale mismatch, insufficient monitoring of dynamic surface morphologies, and size effects in structure. Corrosion-fatigue testing systems (see Fig.7) simulate fundamental mechanochemical coupling but face a critical limitation: actual service



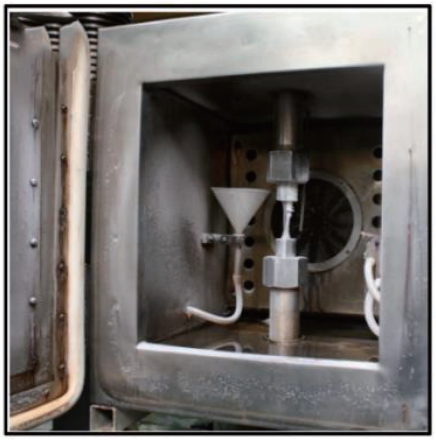
(a) Seawater[121] (Copyright 2022 Elsevier)



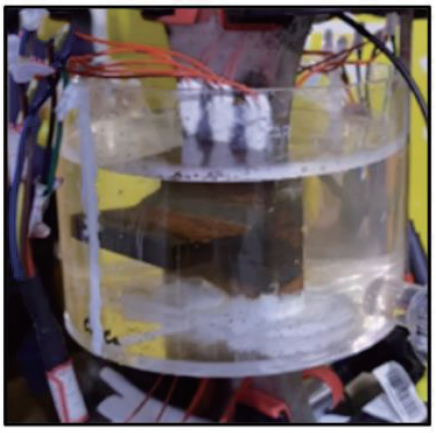
(b) Artificial seawater[112] (Copyright 2019 Elsevier)



(c) Dry/wet alternating environment[122] (Copyright 2025 Elsevier)



(d) Distilled water-spray and 5% NaCl salt-spray[123] (Copyright 2017 Elsevier)



(e) Synthetic water[124] (Copyright 2023 Elsevier)

Fig.7 Schematic diagram of corrosion-fatigue coupling systems

environments can involve corrosion processes over years, while laboratory tests often require acceleration through high-frequency loading within much shorter timeframes (e.g., days). This temporal compression compromises the fidelity of accelerated media —such as salt spray[112–114], artificial solutions[42,115–118], and electrolysis[112]—in replicating the intensity of long-term service coupling, as shown in Fig.8.

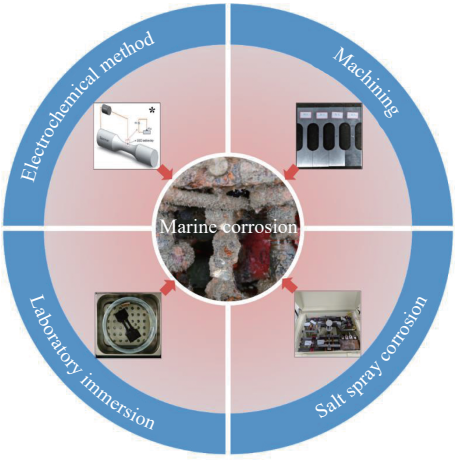


Fig.8 Schematic diagram of common techniques used to accelerate corrosion

A pivotal unresolved issue in these accelerated corrosion strategies lies in reconciling test efficiency with the authenticity of simulated corrosion behavior. On the one hand, enhancing the concentration of corrosive media (e.g., the 3.5% NaCl solution commonly used in laboratory experiments), increasing environmental temperature, or reducing wet-dry cycle periods can effectively boost test efficiency, thereby mitigating the temporal scale mismatch between laboratory tests and actual service. On the other hand, such acceleration strategies deviate substantially from real marine service conditions, primarily due to notable differences in ion composition, temperature stability, and biofouling effects—factors that are often simplified or overlooked in laboratory settings. These discrepancies can lead to distorted corrosion mechanisms and inaccurate evaluations of corrosion-fatigue coupling behavior.

Although constant-temperature cyclic systems, as presented by Liao et al[119], enable precise control over environmental parameters (like ion concentration, pH, and temperature), and LeBozec's joint plate apparatus[120] enhances the accuracy of environmental simulations, both methodologies are fundamentally constrained by temporal scale distortion effects on corrosion kinetics and the lack of biofouling simulation, which further complicates the reconciliation of test efficiency and simulated authenticity.

Crack propagation monitoring typically relies on optical observations during pause tests, as demonstrated by Zhang et al[126], which have limited accuracy and can disrupt the damage process. While Shao et al[121] have validated an indirect monitoring method based on the relationship between back stress and

crack length in compact tension specimens, this approach struggles to capture micrometer-scale deformations at the initiation stage. More critically, no in situ monitoring methods are currently available for tracking the dynamic evolution of pitting morphology, with inherent bottlenecks in existing high-precision characterization techniques: scanning electron microscopy (SEM) requires a high-vacuum environment that prevents real-time observation under actual corrosive conditions, while confocal laser scanning microscopy (CLSM) exhibits insufficient resolution on rough corroded surfaces and requires complex sample preparation, limiting its application in dynamic morphology monitoring[127]. To address these limitations, environmental scanning electron microscopy (ESEM)[128] has emerged as a practical improvement, enabling real-time non-contact observation of corrosion initiation and evolution in humid or liquid environments without high vacuum—a feature that has been widely applied in corrosion morphology observation. Beyond ESEM, in-situ X-ray computed tomography (X-ray CT) is another emerging characterization technique for dynamic tracking of the pit-to-crack transition process: it offers the advantage of non-destructive 3D imaging to quantify pit and crack evolution, yet its application is constrained by relatively slow detection speed and limited resolution for micro-scale cracks. Additionally, the test systems primarily target small specimens[129], complicating efforts to scale findings to large engineering structures and neglecting the variations in boundary conditions due to size effects.

In summary, existing testing technologies suffer from temporal scale distortion, morphological monitoring blind spots, and size constraints—with the latter two further exacerbated by the bottlenecks in conventional in-situ characterization techniques and the limited application of emerging technologies (ESEM and in-situ X-ray CT). These limitations severely hinder the acquisition of high-fidelity dynamic data on pitting evolution and crack propagation, impeding elucidation of the intrinsic correlation between pitting features and corrosion-fatigue coupling behavior. This urgent need for high-precision, multi-dimensional pitting morphology characterization drives the development of in-situ, multi-scale monitoring technology, which is essential for establishing real-time correlations between environmental factors, loading conditions, and morphological changes to advance understanding of corrosion-fatigue coupling mechanisms. Specifically, this demand creates a strong impetus for exploring pitting morphology quantification methods and multi-scale detection technologies—the core contents of Chapter 2, which align with the development trend of multi-scale integration and in-situ dynamic monitoring in pitting morphology characterization.

2 Multiscale characterization and quantification of pitting morphology

As a core factor governing corrosion-fatigue failure, pitting morphology is both the failure initiation site and a key indicator of structural degradation. However, existing testing limitations (elaborated in Section 1.4) prevent capturing complex pitting geometric features and evolutionary laws during corrosion-fatigue, directly leading to discrepancies between traditional coupling models and physical reality (e.g., oversimplified ellipsoidal pit assumptions). To fill this gap, precise multi-scale characterization and quantification of pitting morphology are essential to overcome experimental drawbacks, assess structural durability, and improve corrosion-fatigue life prediction accuracy. This chapter focuses on these aspects, exploring feasible methods and strategies to support subsequent corrosion-fatigue coupling mechanism research.

Importantly, morphological characteristics, including pit depth, aspect ratio, and irregularity, play a direct role in stress concentration effects and crack initiation behavior. To advance quantification of corrosion-fatigue interactions, establishing a multidimensional parameter system capturing complex

geometric features and evolutionary patterns is imperative. Recent progress in multiscale detection technologies and quantitative modeling provides the foundational framework for developing such comprehensive characterization systems.

2.1 Multiscale detection techniques for pitting morphology

The precise quantification of pitting corrosion morphology necessitates the coordinated advancement of multi-scale detection methodologies. Existing techniques are categorized by observation scale and resolution: macro-scale (>100 μm), meso-scale (1–100 μm), micro-scale (0.1–1 μm), and nano-scale (<0.1 μm), as shown in Fig.9. Macroscale approaches, such as digital image correlation (DIC)[125,130], 3D optical profilometry[17], and gravimetric methods, primarily measure bulk corrosion damage characteristics, including maximum pit depth, degree of pitting corrosion (DOP), average corrosion rate, and cross-sectional loss. Meso-scale techniques focus on the detailed morphology within localized corrosion regions. Technologies like CLSM[127] and X-CT[131] enable precise characterization of individual pit or localized area geometric features (e.g., depth, diameter, pit shape, volume, surface area) and surface roughness. Microscopic and nanoscopic techniques, such as SEM[119], combined with energy dispersive spectroscopy (EDS), electron backscatter diffraction (EBSD)[132], scanning electrochemical microscopy (SECM)[133], and transmission electron microscopy (TEM)[132], probe the material's microstructure. These techniques reveal local strain distributions, crystallographic orientations, compositional variations in micro-regions, and mechanisms of corrosion initiation at the submicron and nanoscale levels.

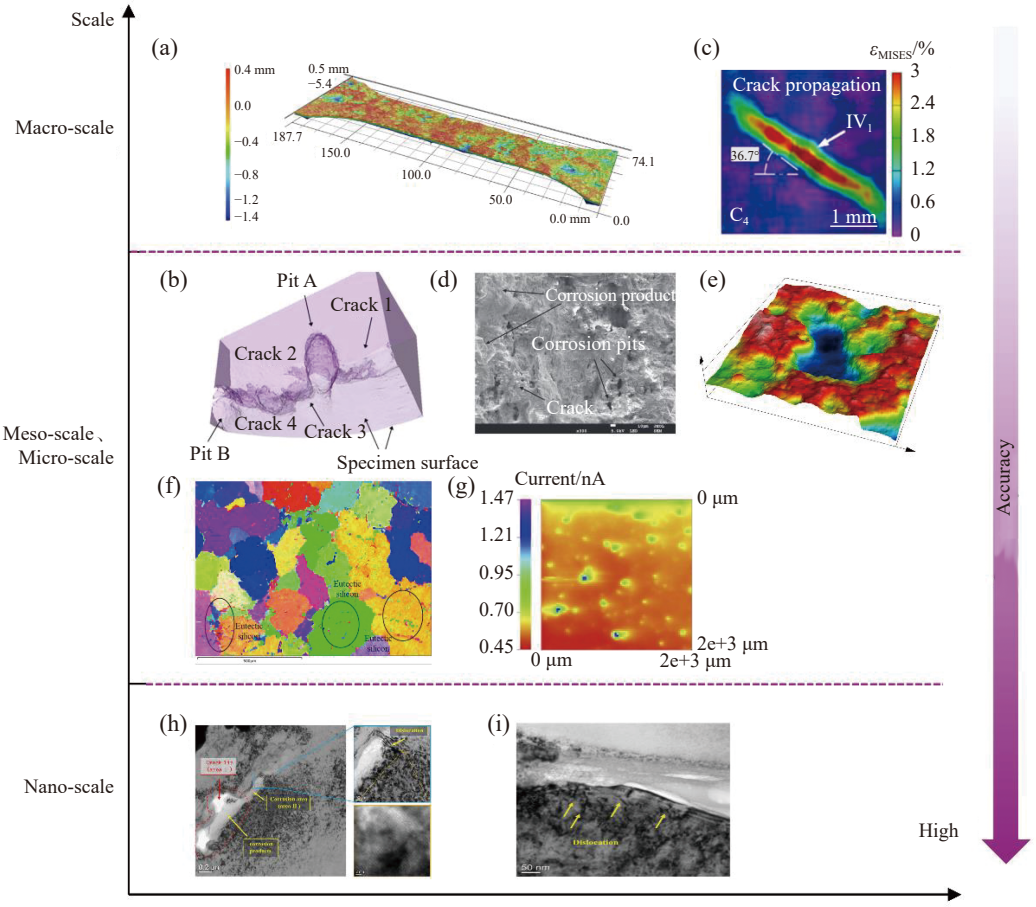


Fig.9 Schematic diagram of multiscale detection techniques

Current research emphasizes the integration of multi-scale detection with in-situ monitoring. For

instance, Song et al[125] combined macroscale 3D-DIC for full-field strain monitoring with micro- or meso-scale optical microscopy (OM), SEM, and EBSD analysis to investigate fatigue in pre-corroded aluminum alloys. This approach facilitated damage analysis spanning macro-scale phenomena (such as strain field evolution and crack initiation/propagation) to micro-scale mechanisms (like microcrack nucleation and grain deformation). Similarly, Xiao et al[134] employed a micro-electrochemical cell technique (MECT) alongside SECM to study corrosion in duplex stainless steel. MECT quantifies electrochemical responses within individual microstructural phases, while SECM maps the in-situ pH distributions. This combination directly correlates localized electrochemical activity with spatiotemporal changes in the chemical microenvironment, yielding phase-resolved data on corrosion kinetics.

In light of recent advancements, the characterization of pitting morphology is progressing towards multi-scale integration, in-situ dynamic monitoring, and 3D spatial quantification. The aforementioned multi-scale strategies effectively enable cross-scale correlation analysis, linking macroscale damage manifestations (such as localized strain concentrations and crack initiation) with underlying microscale mechanisms, like disparities in micro-region electrochemical activity, the evolution of local chemical microenvironments, and grain-scale deformation. These comprehensive, cross-scale, multi-physics field data provide a robust technical framework for elucidating pitting initiation mechanisms, pit-to-crack transition processes, and interactions within corrosion-fatigue processes.

2.2 Evolution of pitting morphology characterization

Pitting corrosion, a prominent form of localized degradation, significantly compromises the mechanical properties of structures, especially under conditions of corrosion-fatigue coupling. Traditional metrics for assessing damage, such as maximum pit depth and DOP, often overlook the complexity of pit geometry and surface irregularities. Importantly, in corrosion-fatigue mechanisms that involve cyclic loading in corrosive environments, local stress concentration induced by pit morphology becomes critical. Specific morphological features, such as sharp discontinuities and high aspect ratios, increase stress concentration, which directly affects the locations and rates of fatigue crack initiation while altering the electrochemical activity at the pit sites. This combination accelerates synergistic corrosion-fatigue damage, ultimately leading to significant deviations in the predictions of component lifespan.

Current corrosion-fatigue research employs two primary methodologies for characterizing pitting morphology:

(1) Regular geometric simplification: In this approach, complex pits are reduced to idealized geometries, such as semi-ellipsoids[41,54,65,135–137], hemispheres[62], cones[36,138], or cylinders[36] (see Fig.10(a)). The semi-ellipsoidal model is favored due to its parametric flexibility, allowing adjustments to the major axes, minor axes, and depth. Researchers conduct theoretical analyses, such as Faraday's law-based calculations, and simulations under the assumption of a single defect[52–54,65,105] to investigate the impact of corrosion-fatigue on the evolution of pit size (depth and radius) and its implications for lifetime. This line of research has produced significant findings, including Ma et al's[41] work on pitting growth anisotropy, Huang et al's[60–62,139–140] exploration of thermodynamic transitions, as well as studies by Amiri[65] and Hu et al[54] on pit evolution under uniaxial/multiaxial stress conditions, and Cui et al's[137] confirmation of reduced fatigue life in steel cables related to increasing depth/radius ratios.

(2) Stochastic morphology simulation: To address the inherent randomness of pitting, studies implement numerical methods based on statistical distributions or electrochemical principles. Techniques like cellular automata[141–142], neural networks[101,143], and Monte Carlo simulations[144–145] are employed. For instance,

Fatoba et al[105] integrated the Gutman model into a cellular automaton-FEM framework to simulate stress-accelerated corrosion, while Valor et al[146] utilized non-homogeneous Markov chains to replicate pit evolution. These approaches geometrically simulate the initiation, growth, and interaction of pits while examining how stress affects corrosion kinetics and how irregularities contribute to stress concentration during fatigue crack nucleation.

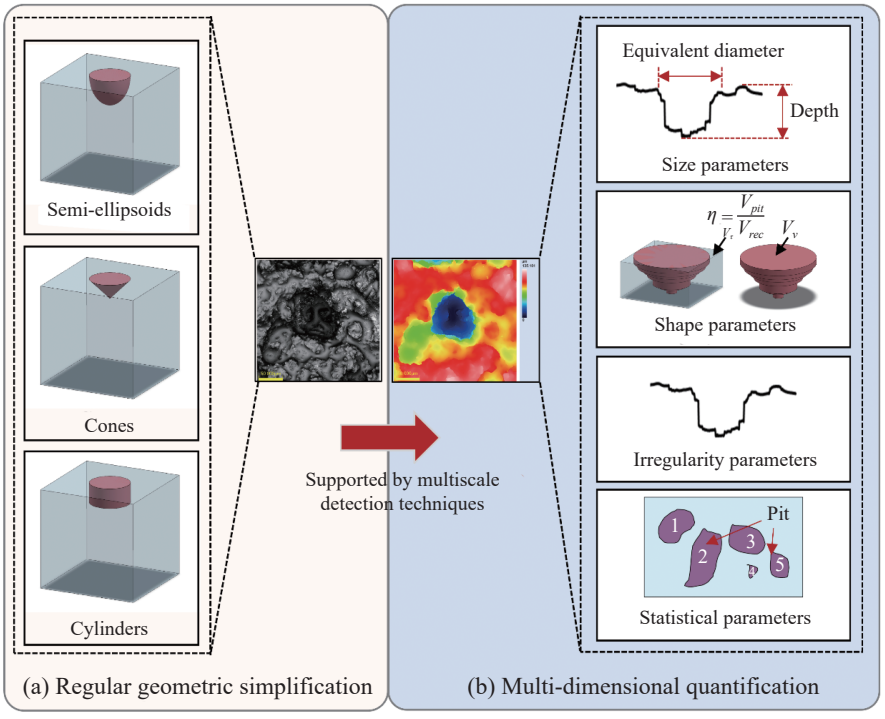


Fig.10 Schematic of the strategy for multidimensional morphology quantification

The two aforementioned characterization methodologies are not mutually exclusive but exhibit distinct applicable scenarios and inherent complementarity, and together form the theoretical and numerical foundation of pitting morphology characterization in corrosion-fatigue research. Regular geometric simplification is well-suited for fundamental theoretical modeling and single-defect corrosion-fatigue mechanism analysis: its advantage lies in the simplification of complex geometric features into adjustable parametric models, which facilitates the establishment of analytical equations between pitting parameters and stress concentration, and the quantitative exploration of the intrinsic influence of a single pitting feature on corrosion-fatigue evolution without excessive computational cost. Stochastic morphology simulation, by contrast, is more applicable to the analysis of multi-pit interaction effects and the prediction of corrosion-fatigue behavior of actual engineering structures: it can accurately capture the randomness of pitting initiation, spatial distribution, and geometric irregularity in real service environments, and reflect the synergistic damage effect of multiple pitting defects on structural performance. In practical research, the two methods are highly complementary: the parametric laws and mechanism conclusions derived from regular geometric simplification can provide theoretical guidance and validation criteria for stochastic morphology simulation, while the numerical results of stochastic morphology simulation can further optimize and revise the idealized assumptions of regular geometric models, making the theoretical models more consistent with the actual corrosion-fatigue process.

Despite advancements, current corrosion-fatigue research faces three main limitations in pitting morphology characterization. Firstly, geometric oversimplification through regular models, such as

hemispheres or cones, tends to underestimate stress concentration because they do not accurately capture the sharp discontinuities and irregular contours of actual pits, thereby compromising the accuracy of the local stress field. Secondly, many statistical simulation methods focus primarily on size distributions and often neglect to systematically integrate multidimensional features, such as shape complexity and surface roughness. Thirdly, the collective quantitative influence of various morphological parameters on corrosion-fatigue life remains poorly characterized. Existing descriptors include size (depth/diameter), shape (aspect ratio), and statistical features (density/distribution), but their interactions require further investigation.

To address these challenges, future research should consider four categories of morphology features: size parameters (e.g., pit depth, equivalent diameter), shape parameters (e.g., aspect ratio, contour geometry), irregularity parameters (e.g., fractal dimension, surface roughness), and statistical parameters (e.g., pit density, spatial distribution), as depicted in Fig.10(b). A key challenge is to establish synergistic relationships across these dimensions to develop representative parameters that capture the effects of corrosion-fatigue coupling. Advances in machine learning aid in mapping these data-driven complex parameter interactions, leading to the development of high-precision life prediction models that reflect realistic morphology quantification.

Future research priorities should include:

(1) Establishing a consensus on multidimensional feature parameter systems;

(2) Quantifying the relative influence of morphological parameters on damage evolution;

(3) Developing cross-scale in situ time-resolved monitoring techniques.

The shift from single-parameter analysis (e.g., depth) to multidimensional evaluation, complemented by physics-informed machine learning and cross-scale validation, will enhance fundamental understanding of corrosion-fatigue mechanisms and improve the reliability of lifespan predictions.

3 Conclusions

This paper systematically analyzed the research progress in characterizing pitting morphology under the influence of corrosion-fatigue coupling. It demonstrated the essential role of multidimensional quantitative methods in addressing current characterization challenges. By thoroughly reviewing theoretical models, simulation techniques, and experimental approaches, the following conclusions can be drawn:

(1) Theoretical Aspects: Models for analyzing pitting evolution primarily depend on mechano-electrochemical effects, thermodynamic laws, or empirical fitting. They establish criteria for the transition from pits to cracks using principles from fracture mechanics and damage mechanics. However, many of these models disproportionately rely on assumptions regarding regular pit geometry and single-defect scenarios, often neglecting the complexity of actual pit morphology and interactions between multiple pits.

(2) Simulation: Integrated approaches, particularly PINNs, are beginning to bridge the gap between deterministic physical models and data-driven methods. This offers a new paradigm for analyzing coupled mechanisms.

(3) Experimental Aspects: Current techniques are limited by the inherent mismatch in timescales between corrosion and fatigue processes, alongside challenges in in-situ monitoring. This makes it challenging to obtain high-fidelity data on dynamic pit evolution and crack initiation.

These limitations significantly undermine the predictive reliability of existing models under complex operational conditions, highlighting the need for a more comprehensive framework for characterizing

morphology. To address these bottlenecks and enhance mechanistic understanding, future research should prioritize three key directions:

(1) Develop a multidimensional morphological quantification Framework: An integrated characterization system can be established that combines geometric dimensions, shape parameters, irregularity metrics, and distribution parameters of corrosion pits. This system should incorporate machine learning, guided by physical laws and validated through cross-scale experiments, to establish quantitative mappings between morphological parameters and corrosion-fatigue life, moving beyond traditional simplified assumptions.

(2) Develop in-situ dynamic monitoring technology: A synergistic platform needs to be designed that integrates micro-area electrochemical response monitoring with high-resolution morphology scanning. Such a system will enable real-time tracking of the entire process from pit initiation to crack propagation. A critical breakthrough involves developing models that align the timescales of accelerated corrosion tests with real-service conditions, addressing the experimental and operational timescale mismatch.

(3) Advanced physics-data fusion modeling: The focus of the research should be on enhancing the application of PINNs. The predictive interpretability can be improved by directly embedding fracture mechanics criteria and corrosion kinetics equations into the model architecture. This advancement relies on creating a multi-material corrosion-fatigue database to provide robust data for training models under complex morphological conditions. Ultimately, it is important to conduct closed-loop validation tests on representative engineering structural components to translate theoretical advancements into engineering practice.

This study represents the first systematic demonstration of the critical role that multidimensional pitting morphology quantification plays in understanding corrosion-fatigue coupling mechanisms. It proposes an innovative pathway from in-situ dynamic monitoring to physics-data fusion modeling, thereby establishing a comprehensive theoretical foundation for the precise and rapid assessment of the service life of major equipment.

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腐蚀-疲劳耦合损伤中点蚀形貌表征研究进展

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摘要: 腐蚀-疲劳耦合作用所带来的风险远高于单一损伤机制。本文综述了该领域在理论框架、数值模拟与实验方法方面的最新研究进展, 重点关注点蚀演化与裂纹扩展两个关键过程。当前点蚀形貌模型受限于单一缺陷假设与蚀坑形状规则化简化, 难以实现对点蚀特征的多维全面表征。在裂纹扩展建模方面, 主要有机理驱动型模型、数据驱动型模型以及混合增强型模型三大范式, 其中物理信息神经网络在处理腐蚀-疲劳耦合作用方面展现出极大的潜力。研究表明, 当前点蚀表征中蚀坑形状过度简化问题突出, 几何规则化假设已成为量化腐蚀-疲劳协同效应的瓶颈。突破这一局限需提出综合尺寸、形状、不规则性与统计分布特性的多维量化方法。该领域的进展将深化对耦合机制的理解, 并有助于工程结构安全性评估, 从而推动高精度腐蚀-疲劳寿命预测模型的发展, 为基础设施安全保障提供支撑。

关键词: 腐蚀-疲劳耦合作用; 多维形貌表征; 点蚀; 原位监测

中图分类号: U663.1　　**文献标识码:** A

基金项目: 湖北省自然科学基金资助项目(2025AFB870); 国家自然科学基金资助项目(52201388); 稳定支持项目基金(WDZX70202030207)

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