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QUANTITATIVE APPROACHES FOR DEVELOPING PITTING CORROSION MODELS FOR STEEL REINFORCING BARS

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ABSTRACT

Corrosion-induced deterioration of steel reinforcing bars (rebar) in reinforced concrete (RC) structures poses a significant challenge that threatens the service life and structural integrity of essential infrastructures, particularly in critical environments such as nuclear facilities. Among various forms of corrosion, pitting corrosion causes localized damage on rebar in RC structures exposed to deleterious ions. To ensure an accurate assessment of the extent of corrosion damage and to develop effective repair and maintenance strategies for corroding facilities, the utilization of reliable corrosion propagation models is imperative. However, the complexity of pitting corrosion, coupled with limited data availability and the constraints of existing models, currently presents a lack of a universally accepted optimal methodology for predicting pit growth in metals. This research investigates concepts, performance, and applicability of existing pitting initiation and propagation corrosion models for RC structures, reporting their strengths, weaknesses, and limitations. This finding will aid the on-going effort to develop corrosion model applicable to RC structures in nuclear industry and beyond, as well as provide infrastructure stakeholders with robust tools to proactively combat pitting corrosion, safeguard the durability of existing nuclear structures and the development of new resilient and sustainable infrastructure.

Keywords: pitting corrosion, corrosion modelling, reinforced concrete, rebar, chloride, nuclear facilities

INTRODUCTION

Corrosion of steel reinforcing bars (rebar) in reinforced concrete (RC) structures is a major durability challenge on a global scale. Exposure of marine and inland RC structures to chloride ions is a key contributing factor to corrosion attack (Finozzi, et al., 2018). This deterioration process commences with the diffusion of chloride ions into concrete, moving towards the surface of the embedded rebar until it reaches a specific concentration threshold that triggers active corrosion. Active corrosion is preceded by a localized breakdown of a protective oxide layer, known as passive film, formed on the rebar surface due to alkaline environment in concrete (pH ≈ 13.7) (Ogunsanya and Hansson, 2020). This localized breakdown of the passive film, known as depassivation, exposes the rebar to deleterious species that initiate pitting corrosion (Lollini *et al.*, 2019) and cause a substantial reduction in the cross-sectional area of the rebar, thereby negatively impacting structural load-bearing capacity and safety (Zhang *et al.*, 2022).

The implications of corrosion in RC structures take on heightened significance when considering their use in nuclear facilities. These structures serve not only as load-bearing elements but also as critical barriers for isolating and confining radioactive materials, making their long-term integrity paramount (Ding *et al.*, 2023). Nuclear power plants, face a unique set of challenges from both external and internal environments that can accelerate corrosion, including exposure to deleterious chemical species, elevated temperatures, and radiation. The potential for structural weakening due to corrosion directly impacts the safety and operational lifespan of these facilities, increasing the risk of economic losses, radiation exposure, leakage of hazardous chemicals and environmental hazards (Ouda, 2024). This is particularly true for facilities near coastal regions where chloride-induced corrosion is a significant concern, as well as in reprocessing plants – industrial sites that chemically treat used fuel to recover valuable materials and manage nuclear waste – where acidic conditions can arise (Nishimura and Raman, 2010). Given the critical safety functions and the extended operational lifespan, ranging from decades for power plants to millennia for waste repositories, understanding and managing corrosion in these structures is of utmost importance (Tri Phung *et al.*, 2018).

Accurate quantification of metal loss resulting from corrosion damage, calculation of a structure's residual life, and development of effective rehabilitation strategies for corroding structures begin with and rely on precise prediction of time-dependent pitting corrosion damage, incorporating both initiation process and propagation rate (Li *et al.*, 2019; Tran *et al.*, 2023). Therefore, pitting corrosion propagation (i.e., tracking pit growth over time) model plays a key role in assessing future/subsequent structural performance and advising management strategies by providing scientific guidance for reliability analysis, determining inspection intervals, and prioritizing repair activities. Predicting and modelling the time evolution of the pitting corrosion process is a complex task due to its stochastic nature, influenced by several factors, including the heterogeneity around the circumference and along the length of rebar in concrete, which leads to varying extents and rates of pitting corrosion in different localized regions (Klapper *et al.*, 2014). Moreover, pitting corrosion damage can take numerous forms and morphologies influenced by various factors, such as steel type (composition and microstructure), surface finishes, surrounding media, and exposure conditions (Coelho *et al.*, 2020; Ogunsanya *et al.*, 2021; Ogunsanya and Hansson, 2018, 2019). Overall, factors such as variability in environmental and exposure conditions (e.g., temperature, humidity, corrosive agents), differences in material properties, variation in experimental setups and corrosion detection techniques, and measurement errors from various techniques are sources of uncertainty in corrosion detection process, increasing complexity in model's prediction accuracy (Abdolhosseini and Ogunsanya, 2024; Gorla Nogueira *et al.*, 2023). Therefore, there is a need for a unique pitting corrosion propagation model possessing: (i) ability to represent data variety and accuracy, (ii) a robust corrosion mechanism that minimizes model uncertainties, and (iii) robustness and computational efficiency (Guo *et al.*, 2020).

Extensive research has been devoted to assessing and modelling chloride-induced rebar corrosion with various studies employing statistical analysis to understand corrosion initiation, pit distribution, and pit characteristics in various exposure environments (Darowicki *et al.*, n.d.; Faroz, 2016; Hou *et al.*, 2016; Kashani *et al.*, 2013; Shibata, 1990; Strutr *et al.*, 1985; Tang *et al.*, 2014; Wang and Cheng, 2016). Available pitting corrosion models can be classified into three types: (i) mechanism-based model – developed based on mechanisms of corrosion reactions on metal surfaces using electrochemical equations to explain the initiation and growth of corrosion pits, (ii) empirical models – either deterministic (developed using prior knowledge of known metal degradation mechanisms) or probabilistic (developed using probability theory or stochastic processes), and (iii) data-driven models – developed from datasets and can learn the complex relationships between influencing factors and corrosion propagation patterns (Ma *et al.*, 2023).

The primary focus of this research is to explore existing pitting corrosion propagation models across engineering fields to highlight their concepts, advantages, and drawbacks and assess their fit for use in the field of RC structure corrosion. By analyzing and comparing various models, this work will highlight their effectiveness in capturing corrosion behavior of nuclear structures which is influenced by different factors discussed earlier. Only empirical models were discussed in the present work. Ultimately, this research findings contributes to the development of reliable predictive models for RC structures, aiding design and maintenance of resilient and durable engineering structures in corrosive environments.

PREDICTION METHODS FOR CORROSION PROPAGATION

Empirical Models: Deterministic Approach

Various deterministic approaches have been employed to model pitting corrosion propagation over time, including the estimation of pit depth and area to calculate the residual diameter and area of steel rebar. Three common types of deterministic models have been used Single-value corrosion model, linear corrosion depth model, and power function corrosion depth model are three common types of deterministic models have been used.

(i) *The single-value corrosion model* assumes a constant non-time-dependent corrosion rate with a conservative value, which is then used to estimate the time for repair and remaining service life of the structure. According to Stewart (Stewart, 2009), corrosion rates of RC structures typically range from 0.1 to 10 μA/cm^2 (~1.16 – 116 μm/year) depending on the environmental aggressiveness. Corrosion rates in the range of 1 to 3 μA/cm^2 (11 – 33 μm/year) are frequently observed during active corrosion, below which rebar corrosion state is assumed to be in the passive (Gonzalez *et al.*, 1995). However, this rate can vary for RC nuclear facilities due to their specific exposure conditions. These rate values are used to determine metal loss rate per year and plan maintenance and repair accordingly. However, the limitation of this approach is that corrosion rate is not the same yearly.

(ii) *The linear corrosion depth model* predicts that pit depth increases linearly over time. Valor et al. (Valor *et al.*, 2012) illustrated the model's relatively simple structure using Eq. 1.

$$D(t) = D_0 + \dot{D}t \tag{1}$$

where, D(t) is pit depth (mm) over time, t is time interval (year), D_0 is corrosion depth (mm) at initial time and $\dot{D}$ is constant corrosion rate (mm/year).

This approach allows pit depth to be monitored over time and can be done for several pits, allowing for severity of some pits to be captured. However, information on the initial pit depth must be known and the model assumes a linear increase in the pit depth over time, which may not necessarily be the case since condition of exposure environment may change.

(iii) *The power function corrosion model* is a commonly used empirical model, originally developed by Romanoff (Romanoff, 1957), and is based on Power law which depicts a non-linear relationship between two quantities, shown as D(t) and t in Eq. 2, indicating that pit depth increases nonlinearly over time.

$$D(t) = kt^n \tag{2}$$

where D(t) and t have the same definition as mentioned above. Also, k and n are constants, with parameters related to the material-environment system that can be fitted using statistical methods with field or laboratory corrosion data. This model enables to solve the limitations associated with two previous empirical models such as capturing non-linearity in corrosion behavior and fit to more complex corrosion patterns; however, has its own limitations. One significant limitation is that this model often relies on empirical data and may not fully capture the complex electrochemical processes involved in corrosion, such as repassivation of pits. Alos, corrosion is influenced by a multitude of factors that may not be adequately represented by a simple power function with often large inherent uncertainties as well as relies on an assumed homogeneity that contrasts with localized corrosion variations and offers limited spatial consideration of the corrosion process. In the past decades, several attempts were made to enhance this model relating to Eq. 2. By incorporating initial time of corrosion, t_0, Velázquez et al. (Velazquez *et al.*, 2009) proposed a more accurate version of the Romanoff model as:

$$D(t) = k(t - t_0)^n \tag{3}$$

(iv) *The semi-spherical model* is one of the widely adopted approaches in civil engineering to calculate residual area of steel rebar subjected to pitting corrosion using Faraday's laws and assume that the pit area has a semi-spherical shape as shown in Fig. 1 (Ayazian *et al.*, 2021).

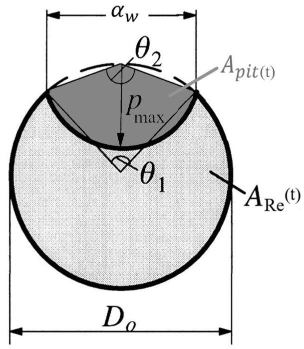

Figure 1. Schematic illustration of the geometry of a semi-spherical pit configuration, showing the pit area (A_{pit}), pit width (a_w), pit depth (p_{max})(Val and Melchers, 1997).

Given the original bar diameter, D_0, pit area, $A_{pit}(t)$, can be estimated using an equation developed by Val and Melchers (Val and Melchers, 1997):

$$A_{pit}(t) = \begin{cases} A_1 + A_2 & p_{max}(t) \leq \frac{D_0}{\sqrt{2}} \\ \frac{\pi D_0^2}{4} - A_1 + A_2 & \frac{D_0}{\sqrt{2}} \leq p_{max}(t) \leq D_0 \\ \frac{\pi D_0^2}{4} & p_{max}(t) \geq \frac{D_0}{\sqrt{2}} \end{cases} \tag{4}$$

$$A_1 = \frac{1}{2}\left[\theta_1\left(\frac{D_0}{2}\right)^2 - a\left|\frac{D_0}{2} - \frac{(p_{max(t)})^2}{D_0}\right|\right], A_2 = \frac{1}{2}\left[\theta_2 p_{max}(t)^2 - a\frac{p_{max}(t)^2}{D_0}\right] \tag{5, 6}$$

$$a_w = 2\, p_{max}(t)\sqrt{1 - \left(\frac{p_{max}(t)}{D_0}\right)^2}, \quad \theta_1 = 2\, arc\, sin\left(\frac{a}{D_0}\right), \theta_2 = 2\, arc\, sin\left(\frac{a}{2p_{max}(t)}\right) \tag{7-9}$$

where $p_{max}(t)$ is maximum pit depth (mm) over time, a_w is pit width (mm), and other variables are similar to the one mentioned above. It is worth mentioning that the statistical parameter of $p_{max}(t)$ distribution, representing the likely location of critical section of corroded rebar, is not known for this model (Darmawan, 2010). While this model enhances geometric realism by approximating pit morphology and links structural degradation to corrosion-induced reduction in load-bearing capacity (by considering the reduction in rebar's cross-sectional area), its limitations include simplified pit shape, dependance on accurate geometry and depth, neglecting pit interactions and metal heterogeneity, assuming uniform corrosion rates, and a potential lack of detailed mechanistic understanding.

Empirical Models: Statistical (Probabilistic) Approach

Common statistical-based (probabilistic) pitting corrosion models can be random-variable-based models (Caleyo *et al.*, 2009; Pandey *et al.*, n.d.; Stewart and Al-Harthy, 2008) or stochastic-process-based models (Valor *et al.*, 2006a, 2010, 2014). Random-variable-based models focus on characterizing uncertainty in specific parameters (e.g. chloride diffusion or concrete permeability), while stochastic process-based models take a broader approach by modelling the event (e.g. corrosion process) itself as a random phenomenon. Pitting corrosion has been recognized to be a highly stochastic process posing challenges in accurately predicting the initiation time of pits and their exact location. Therefore, researchers have focused on analyzing distribution data from pit nucleation events (Valor *et al.*, 2010) to develop stochastic models such as Gamma process, Markov chain, inverse Gaussian process, and Brownian motion process that are used to understand corrosion behavior of pits (Valor *et al.*, 2006b).

(i) *The Gamma process*, one of the most common stochastic processes in civil engineering applications, has been successfully employed since its introduction in 1975 for modelling stochastic deterioration to optimize maintenance strategy (Van Noortwijk, 2009). Applying the Gamma process, Baji

(Baji, 2020) effectively modelled the temporal variability of steel mass loss, with the steel mass loss at time t, $\delta_s(t)$, following a Gamma density function as follows:

$$f_{\delta_s(t)}(\delta) = Ga[\delta|\lambda(t).\beta] = \frac{\beta^{\lambda(t)}}{\Gamma[\lambda(t)]}\delta^{\lambda(t)-1}e^{-\beta\delta} \tag{10}$$

where δ is a random variable representing steel mass loss, λ(t) is shape function of Gamma process (which can be represented with any monotonically function of time and determines whether the rate of growth over time is increasing, constant or decreasing), β is scale parameter (generally taken as temporally invariant parameter), and Γ is Gamma function defined for λ(t)>0. A visual progression of steel mass loss using the Gamma process is illustrated in Fig. 2, revealing that at distinct time points, t_1 and t_2, two separate Gamma density functions can be observed in relation to rebar mass loss, indicating varying mass loss patterns over time. Parameters for the Gamma process can be established from gathered time-dependent data through standard statistical techniques such as Maximum Likelihood Estimation or Method of Moments (Van Noortwijk, 2009).

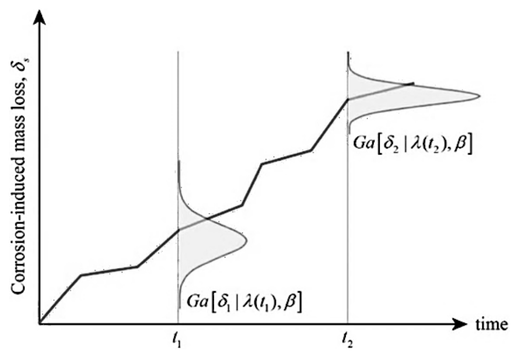

Figure 2. Evolution of steel mass loss based on the Gamma process, where t_1 and t_2 are two different time spots (adapted from (Baji, 2020)).

To incorporate spatial variability in corrosion analysis, multivariate probability density functions are required, and copulas (linking dots) are used to account for spatial correlation in the corrosion process (Baji, 2020). Elements of these functions represent a mass loss on different points on the rebar surface, as shown in Fig. 3. Perimeter of the rebar is discretized into small segments.

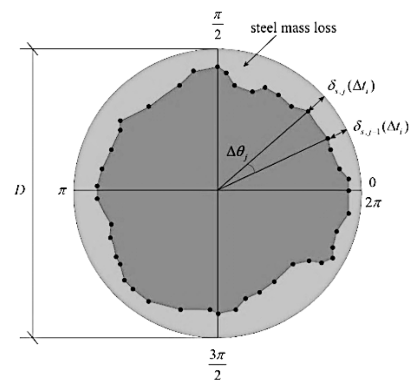

Figure 3. Spatial variation of steel mass loss at a typical time interval (adapted from (Baji, 2020)).

At each time interval, Δt_i, random variables $\Delta\delta_{(s,j)}$, with identical probability density functions and parameters, describe the steel mass loss at different points on the rebar surface. More details can be found in (Baji, 2020). For large-scale engineering structures, measuring pit depth and frequency can both be time-consuming and expensive. As a result, only the deepest pits are studied since they are more likely to be potential cause of structural failure (Bhandari *et al.*, 2015; Valor *et al.*, 2010, 2014; Velázquez *et al.*, 2014). Statistics of extreme values (EV) are usually applied to such pitting corrosion results, where the maximum pit depth in a given area is measured (Valor *et al.*, 2014) and have been extensively used to characterize pitting in steel plates and pipes, and more recently for prestressing strands (Darmawan and Stewart, 2007; Hawn, 1997; Sheikh *et al.*, 1990). In most cases, Gumbel (EV-Type I) distribution function, given by Eq. (11), is used to model the deepest pit depth and is fitted to extreme data (Valor *et al.*, 2010).

$$G(x) = \exp\left\{-exp\left[-\left(\frac{x-\mu}{\sigma}\right)\right]\right\}, \qquad -\infty < x < \infty \tag{11}$$

where x is a random variable representing the maximum pit depth (mm) and μ and σ are the location and scale parameters of Gamma function, respectively, that can be obtained from experimental data.

(ii) *The Markov process*, which was initially explored by Proven and Rodriguez in 1989 (Provan and Rodriguez, 1989), is another approach to modelling pit depth growth over time. In recent decades, there has been notable progress in Markov chain modelling of pitting corrosion, particularly in the gas pipelines sector (Valor *et al.*, 2013). However, the approach put forward by Valor et al. (Valor *et al.*, 2013) has gained substantial adoption (e.g., (McCallum *et al.*, 2014; Ossai *et al.*, 2015)) due to their extensive investigation of Markov chain models to stochastically simulate pitting corrosion.

One of the Markov chain models Valor et al. developed describes time evolution of pit depths that corresponds to the general population of pits in underground pipelines. This model utilizes a continuous-time, non-homogeneous linear growth Markov process that allows prediction of pit depth value and distribution at any future moment in time, $p_n(t)$, using the following expression:

$$p_n(t) = \sum_{m=1}^{n} p_m(t_0)\binom{n-1}{n-m}\left(\frac{t_0-t_{sd}}{t-t_{sd}}\right)^{\nu m}\left[1-\left(\frac{t_0-t_{sd}}{t-t_{sd}}\right)^{\nu}\right]^{n-m} \tag{12}$$

where $p_m(t_0)$ is initial probability distribution of corrosion depth (mm) at t_0, t_0 is time of first inspection (or first time of data collection) and t_{sd} is starting time of the pitting corrosion process in years. ν is estimated pitting parameters as a typical pitting exponent (year) associated with the typical values of the surrounding media-metal system (e.g., pipe-soil environment in clay soil class = 0.839). Also, metal thickness (along which pits propagate) is divided into N discrete non-overlapping Markov states, so that pitting damage is represented through Markov chains with states ranging from m=1 to n=N.

In Fig. 4, the Markov chain-predicted pit depth distribution for time t is represented with a line. Inspection data collected at time t_0 were utilized as initial distribution for deriving the predicted Markov pit depth distribution $p_n(t)$ using Eq. (12) at time t. Subsequently, empirical inspection data at time t were used to assess the accuracy of prediction model.

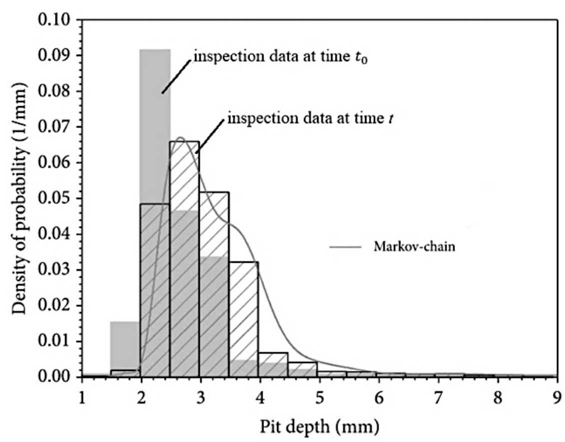

Figure 4. Histograms of the pit depth distribution in time t_0 (grey) and t (hatched). The line is the Markov-estimated pit depth distribution for time t (adapted from (Valor *et al.*, 2013)).

Another Markov chain model, also developed by Valour et al. (Valor *et al.*, 2013) for pitting corrosion, addresses the maximum pit depths. It combines two independent processes, pit initiation and pit growth, using appropriate physical and statistical techniques such as extreme value statistics. Pit initiation is represented by a Poisson process, allowing multiple pit nucleation events to be modelled as a Weibull process. Pit growth is described by a Markov process, with its intensity related to corrosion rate and derived from experimental results. The novelty in this second stochastic model is the consideration of multiple pits in a given corrosion area. The authors claim that the model's parameters and assumptions do not depend on the corroded materials or corrosion environment, making it suitable for various corrosion systems.

The aforementioned models have limitations in that they primarily focus on characterizing the growth of corrosion depth while neglecting the growth of corrosion pit volume. This oversight could potentially lead to inaccurate predictions of RC structure's service life. Wang and Elsayed (Wang and Elsayed, 2020) introduced a pioneering general model that addresses both corrosion pit depth and pit volume growth over time in carbon steel. To aim this, they treated pit growth in both radial and depth dimensions as independent state Gamma processes. As shown in Fig. 5(a), the pit is divided into n_s sectors. Also, it has been assumed that the pit consists of many small pixels, as shown in Fig. 5(b), with pixel depths varying across different locations. Detailed insights into the modelling process and equations are available in (Wang and Elsayed, 2020).

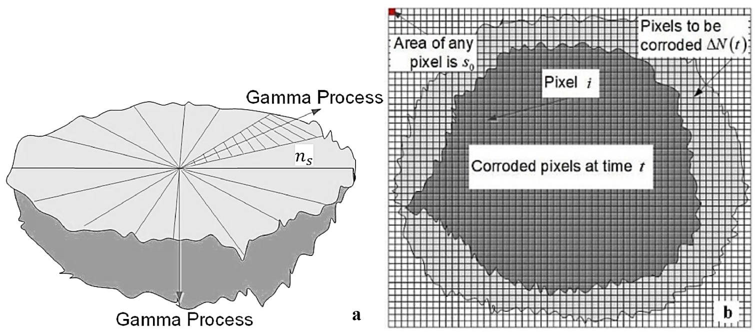

Figure 5. (a) A simplified schematic diagram of the corrosion pit growth, (b) Projected view of the area growth of a corrosion pit (adopted from (Wang and Elsayed, 2020)).

It is worth mentioning that recent efforts have been directed toward updating and enhancing existing models. For instance, Velázquez et al. (Velazquez *et al.*, 2009) employed Poisson process (a special case of Gamma process) to develop a pit initiation and growth model. Moreover, Inverse Gaussian processes, has been used by multiple researchers to ensure traceability and interpretability of results (Guida and Pulcini, 2013). Additionally, Brownian Motion process model and its expansions have been devised to effectively represent the degradation mechanism (Elsayed and Liao, 2003).

SUMMARY AND CONCLUSIONS

This study provides a review of existing pitting corrosion propagation models in carbon steel, summarizing the fundamentals of empirical modelling techniques among other modelling approaches. Table 1 summarizes the underlying concept of these techniques, assessing their strength and potential implications.

Table 1. Summaries of empirical corrosion models investigated in this review study.

Model	Type	Strengths	Limitations
Deterministic models	Single value	- Simplicity - Minimal data requirement (applicable to scarce data)	- Conservative estimation - Lack of time-dependent/spatial accuracy
	Linear	- Simplicity - Efficient computational efforts - Provides time relationship - Good for preliminary analysis	- Simplistic assumption of constant corrosion rate over time - Limited predictive accuracy (due to dependency on data quality) - Lack of spatial accuracy
	Power function	- Capture non-linear corrosion behavior - Fits complex corrosion patterns - Long-term predictions considering evolution over time - Mechanistic insight (using k and n factors)	- Validation challenges when practical data collection is limited - Assumed homogeneity (in contrast with localized corrosion variations)

		- Application to various materials and systems	- Limited spatial/time-dependent consideration
	Semi-spherical	- Geometric realism by approximating pit shape - Physical interpretation using pit depth - Applicability to critical area analysis - Link to structural degradation and corrosion-induced reduction in load-bearing capacity - Incorporation of environmental factors	- Simplification of pit shape - Dependence on pit geometry and pit depth - Neglect of interaction between pits - Assumption of uniform corrosion rates - Neglect of material heterogeneity - Lack of mechanistic understanding
Probabilistic models	Gamma process	- Incorporation of temporal/time-dependent variability - Statistical foundation (fittable to experimental data) - Capturing the stochastic nature of corrosion - Ability to model initiation and growth - Integration of environmental factors - Accurate predictive capabilities - Handling limited data	- Complexity of parameter estimation - Sensitive to initial conditions - Corrosion depth increment is independent of time - Data requirement to estimate parameters - Limited ability to capture spatial variability - Computational demands in calibrating large data
	Gumble process	- Less mathematical complexity - Ability to fit corrosion data - Simple implementation - Limited data requirement, suitable for large datasets - Statistical accuracy, predicting worst-case scenario - Inherently incorporates uncertainty	- Extrapolation challenges - Assumption of stationarity of properties of extreme pit depths - Dependency on statistical assumption - Computational demands - Data requirement to estimate parameters
	Markov process	- Obtains pit depth and density variation and distribution at each time - Incorporate pit initiation - Probabilistic predictions - Flexible parameter estimation from experimental data - Applicability to various materials and systems - Incorporating mechanistic insights - Capture sudden changes in corrosion behavior	- Model accuracy is sensitive to the number of discrete states - Dependency on initial conditions - Finite state space assumption - Sensitive to transition probabilities - Assumption of Markov property (corrosion behavior depends solely on the present state and not on previous states)
	Multivariate radial	- Incorporation of spatial variation of pitting behavior - Realistic representation - Improved accuracy for localized corrosion - Applicability to complex geometries	- Complex parameterization - Increased computational demand - Calibration challenges - Require copulas to account for spatial correlation in the corrosion process - Validation challenges for both radial and depth directions over time
	Pit volume growth	- Incorporation of stochasticity using Gamma process - Physical meaningful parameters (shape and scale in Gamma process) - Integration with experimental data - Incorporating environmental affecting factors - Higher accuracy in predicting remaining service life and reliability of corroded systems - Can be extended to account for pit interactions	- Need 3D scan tools to validate results - Computational demands - Pits overlap and coalescence process is not thoroughly discussed or quantitively validated

The simplicity of deterministic models has led to their widespread use in describing corrosion pit growth. However, since underlying corrosion process is inherently random, exhibiting temporal and spatial variability (Wang and Elsayed, 2020), deterministic models lack the capability to account for uncertainties tied to factors like pit location, shape, size, and morphology. Furthermore, they only provide single estimates at specific points in time (Ma *et al.*, 2023). Therefore, the probabilistic models have gained momentum. They offer a framework to predict the remaining service life of infrastructure and plan maintenance strategies under uncertainties (Wang and Elsayed, 2020).

It is important to note that the majority of these models find application in the oil and gas sector, particularly for carbon steel. As the construction industry shifts towards more sustainable and durable materials, and as the nuclear sector seeks safe, long-term performance under conditions of acidic and elevated temperatures exposures of metals in different regions of the plant, investigating the applicability of these models becomes essential. Assessing their validity and feasibility in RC systems with diverse compositions requires attention. Similarly, the adaptation and verification of these models for different grades of stainless steel, a potential solution to corrosion durability challenges of RC structures in corrosive environments, remains relatively unexplored and demands further investigation. Furthermore, the implementation and suitability of these models in large-scale RC structures in nuclear facilities and beyond to study reliability-based service life predictions stay unexplored areas. Therefore, the overarching aim should be to develop more accurate, realistic, and comprehensive models while accounting for uncertainty, enabling precise estimation of the degradation process in RC structures to facilitate optimal repair strategies. These require collaboration between researchers, industry, and policymakers to address these challenges and to ensure that the models are reliable in practice.

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