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Modelling the spatial-temporal progression of corrosion with special emphasis on its influence on structural reliability

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Reinforced concrete (RC) structures constitute an essential part of the building infrastructure. This infrastructure is aging and a large number of structures will exceed the prescribed service period in the near future. The aging of concrete structures is often accompanied by corresponding deterioration mechanisms. One of the major deterioration mechanisms is the corrosion of the reinforcing steel, caused by chloride ions and carbon dioxide exposure. Corrosion is a complex physical, chemical and mechanical process. The modelling of this process is subjected to significant uncertainties, which originate from a simplistic representation of the actual physical process and limited information on material, environmental and loading characteristics. The present work proposes a probabilistic model for the assessment of spatial and temporal effects of corrosion for the estimation of structural reliability of a potentially corroded RC structure. The model is developed for the consideration of simply supported RC beams in flexure. In a case study various member spans, bar diameters and number of bars in a given cross-section are considered. The study concludes with an analysis of model results and a discussion on how the model can be extended to complex structural details and systems.

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I. INTRODUCTION

Reinforced concrete (RC) is a versatile and widely used building construction material. In many countries, RC is the dominant structural material in engineered structures. Under certain circumstances deterioration of a RC structure leads to a loss of structural functionality. One of the major deterioration mechanisms is corrosion of the reinforcing steel. This process causes effects such as cracking, spalling, or delamination of the concrete and it also leads not only to a reduction in the reinforcement cross-section but also to a loss of bond strength [1]. These changes are accompanied by a decrease of the load bearing capacity and the structural reliability of the corresponding structural elements.

A vast number of research has been done over the last decades and significant progress has been made on the development of stochastic models, which can be used to understand and characterize the corrosion process [2, 3]. These findings are adopted in many different engineering applications (e.g. [4–8]). Especially, pitting corrosion has been recognized as a significant degradation mechanism in engineering practice [9]. Pitting corrosion is a complex process in space and time. Current research has been mostly focused on the time-dependent aspect of pitting corrosion (eg. [10, 11]). Spatial properties of corrosion are treated mainly in a simplistic way or are often neglected. For instance, Stewart [6] assumes that the deepest pit occurs in the middle of an element with an element

length in the range between 100 *mm* to over 1000 *mm*. The spatial distribution of pitting corrosion can also be modelled by an extreme value distribution representing the maximum pit depth per length unit. This representation is already used for structural reliability analysis of concrete elements with corroded reinforcement bars (e.g. [12, 13]). Organ et al. [14] state that pitting events can lead to clustering of pit locations on the surface, where the initial pits are formed randomly. Consequently, reliability models should also consider clusters of pits, because in these spots the risk of failure is higher.

In this paper, a probabilistic model to assess spatial and temporal effects of corrosion for the estimation of structural reliability of a potentially corroded RC structure is presented. The model for the spatial-temporal description of the pits is an extension of the general extreme value (GEV) distribution. The spatial properties of the RC structure are described via random fields.

In the next section the degradation and reliability models for the analysis are described. In the next part, a brief review of the deterioration mechanism of RC structures, including the presentation of a chloride ingress model, is given. It follows a derivation of the GEV distribution in the context of a spatial-temporal probabilistic model for pitting corrosion. This section ends with the introduction of a spatial-temporal reliability model, based on the point-in-time probability of failure. After that, the proposed models are used to evaluate an application example. Beside a brief description of the used structural configuration, the computational method is explained. Finally, the results of the investigation are presented, followed by conclusions and recommendations for further research.

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II. DEGRADATION AND RELIABILITY MODELS

A. Chloride induced corrosion

A frequent cause of reinforcement steel corrosion is contamination by chloride [15]. To initiate the corrosion process, the chloride content at the surface of the reinforcement has to reach a certain threshold value [1]. However, the chloride transport in concrete is a rather complicated process, which involves, inter alia, ion diffusion and convection [16]. This complex transport mechanism can be simplified and estimated by use of Ficks second law of diffusion [17]. The solution of this partial differential equation is:

$$C_{cl}(x, t) = C_s \left(1 - \operatorname{erf} \frac{x}{2\sqrt{t \cdot D_{cl}}} \right) \quad (1)$$

where C_s is the surface concentration of chlorides, C_{cl} is the concentration of chloride ions at distance x from the concrete surface after time t of exposure to chlorides, and $D_{cl}(t)$ is the chloride diffusion coefficient. According to DuraCrete [18] $D_{cl}(t)$ can be calculated as:

$$D_{cl} = k_e \cdot k_t \cdot k_c \cdot D_o \cdot \left(\frac{t_o}{t} \right)^n \quad (2)$$

where k_e is the environmental parameter, k_t is a test method parameter, k_c is the execution parameter, D_o is the empirical diffusion coefficient, t_o is the reference time and, n is the age factor. Each parameter can be expressed as a random variable. The corresponding distributions and parameters that are used in this study are documented in Table I.

If the depth x is taken to be the depth of the reinforcement d_c , then equation (1) can be transformed to:

$$T_{cl} = \left(\frac{d_c^2}{4 \cdot k_e \cdot k_t \cdot k_c \cdot D_o(t_o)^n \left(\operatorname{erf}^{-1} \left(1 - \frac{C_{crit}}{C_s} \right) \right)^2} \right)^{\frac{1}{1-n}} \quad (3)$$

where T_{cl} represents the time until initiation. Correspondingly, the event of corrosion initiation can be represented by the limit state function $g_{cl}(t)$:

$$g_{cl}(t) = \theta_M T_{cl} - t \quad (4)$$

where θ_M is a model uncertainty, taking into account that equation (3) is an idealization of reality [8].

B. Spatial-temporal probabilistic model for pitting corrosion

After the depassivation of the reinforcement has occurred and the passive layer broke down, the so-called

propagation phase starts and the reinforcement steel starts to corrode. Local or pitting corrosion is only associated with chloride induced corrosion. The area of the anode (active zone) may be relatively small, but once corrosion has been initiated the resulting electrical field attracts negative chloride ions towards the pit. Hence, the corrosion rate can be relatively high, which leads to an extreme loss of steel cross section [19].

Therefore, a model for the depth of the deepest pits in an exposed surface area a of a reinforcement bar after an exposure time t_{ex} is needed. To model maxima a limiting extreme value distribution can be used [20]. Given a sample of independent identically distributed (iid) random variables X_1, \dots, X_n , the distribution of X_{\max} (i.e. the maximum pit depth) depends on n . If there exist location and scale factors a_n and b_n , such that $Y = a_n + b_n X_{\max}$ has a distribution that is independent of n , then the limiting distribution must satisfy the functional equation $F(x)_n = F(a_n + b_n x)$ [21]. The solution of this functional equation is the generalized extreme value (GEV) distribution, in the 3-parameter form [22]:

$$F(x; \mu, \sigma, \xi) = \exp \left\{ - \left[1 + \xi \left(\frac{x - \mu}{\sigma} \right) \right]^{-1/\xi} \right\} \quad (5)$$

for $1 + \xi(x - \mu)/\sigma > 0$, where μ is the location parameter, σ is the scale parameter and ξ is the shape parameter. The parameter values can be estimated by fitting the GEV to data observed from test specimens.

Hence, to use GEV for a larger area than the sample area equation (5) has to be extrapolated. Therefore, the distribution of the maximum over an area A is a multiple M of the specimen area a . Assuming a multiplier $M = A/a$, the parameters of GVE are given by:

$$\mu_M = \mu - \sigma(1 - M^\xi) \cdot \xi^{-1}, \quad \sigma_M = \sigma M^\xi, \quad \xi_M = \xi \quad (6)$$

Time-dependency is incorporated through pit growth. Therefore, a power-law growth for the mean maximum pit depth is assumed. In literature simple growth in mean pit depth is modelled as a power of t [23]. The parameters of equation (5), adopted for pit growth are:

$$\mu_t = \mu \cdot t^\gamma, \quad \sigma_t = \sigma \cdot t^\gamma, \quad \xi_t = \xi \quad (7)$$

According to the properties of GEV and considering an extrapolation in space and time, the expected extreme pit depths over time can be expressed as:

$$\mathbb{E}[X_{\max}] = \mu \cdot t^\gamma - \sigma \cdot t^\gamma (1 - M^\xi \Gamma(1 - \xi)) \cdot \xi^{-1} \quad (8)$$

The spatial proximity of pits can be described as a non-homogeneous Poisson point process (NH-PPP) [24, 25]. If X_{\max} follows the GEV distribution from equation (5)

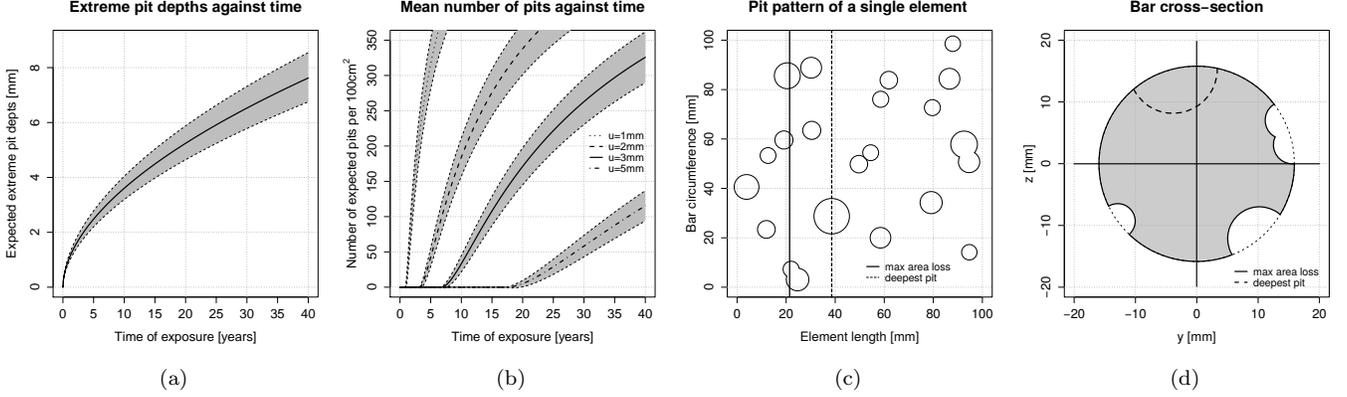


FIG. 1: Pitting

and the pit depths exceedances a certain threshold u per unit area, the intensity is given by [26]:

$$\lambda(t) = \left(1 + \frac{\xi(u - \mu_M \cdot t^\gamma)}{\sigma_M \cdot t^\gamma} \right)^{-1/\xi} \quad (9)$$

For structural reliability analysis the effects of pitting on reinforced cross-section are needed. Hence, the maximum steel loss along a reinforcing bar has to be found. Due to the fact that pits occur in a random pattern on the surface of the reinforcement bar, the maximum pit might be no decisive factor anymore. Instead a cluster of smaller pits in a certain configuration might affect the cross-section stronger. Therefore, the maximum loss of cross-section over the length of the reinforcing bar can be found by minimizing the remaining steel cross-section:

$$\min_{0 \leq x \leq L} (A_s(x, t)) \quad \text{with} \quad A_s(x, t) = \int_0^{2\pi} \int_0^R r(x, t, \varphi) dr d\varphi \quad (10)$$

where the cross-section depends on the location, time since the corrosion started and the random distribution of pits with varying depths (see Fig. 1).

C. Spatial-temporal reliability analysis

Using the approach proposed in section II A, modelling of pitting corrosion becomes a spatial-temporal problem. Hence, also the reliability analysis has to take spatial variability of the model parameters into account. This allows to characterize not only the probability of degradation, but also the extent of damage [27].

For this purpose is, according to Sudret [27], a point-in-space probability of failure defined. The model parameters are treated as random fields $\mathbf{Z}(\mathbf{x}) = \{Z_1(x), \dots, Z_N(x)\}$. This set describes the randomness of the model where \mathbf{x} is the spatial coordinate. For the

probabilistic descriptions of these fields the following assumptions are applied [27]:

i) Not all components of \mathbf{Z} have a spatial variability. Hence, they can be modelled as random variables, it has to be considered that this reduces the amount of random fields. ii) Random fields are treated as homogeneous fields, due to the fact that the size of the structure is rather small compared to the scale of the degradation parameters (e.g. environmental parameter, such as surface chloride concentration).

The failure criterion is represented by a limit state function $g(\mathbf{Z}(\mathbf{x}), t)$, which is defined in the space of spatial parameters at time instant $t \in [0, T]$. Furthermore, it is assumed that the input parameters $\mathbf{Z}(\mathbf{x})$ are not time-dependent, such that they can be modelled as random variables and not by random processes [27].

Taking this assumption into consideration, the point-in-space probability of failure is defined as followed:

$$P_f(\mathbf{x}, t) = \int_{g(\mathbf{Z}(\mathbf{x}), t) \leq 0} f_{\mathbf{Z}(\mathbf{x})}(\mathbf{z}) d\mathbf{z} = \mathbb{E} [\mathbf{1}_{g(\mathbf{Z}(\mathbf{x}), t) \leq 0}(\mathbf{z}, t)] \quad (11)$$

The probability of failure is computed by fixing \mathbf{x} and t , and by applying standard time-invariant reliability methods, such as Monte Carlo Simulation (MCS), FORM, SORM, etc. The point-in-time probability of failure is independent of \mathbf{x} [27]; therefore, the critical limit state for the structure is related to a series system where the load effect exceeds resistance at any element:

$$g(\mathbf{Z}(\mathbf{x}), t) = \min_{0 \leq x \leq L} (\mathbf{R}(\mathbf{x}, t) - \mathbf{S}(\mathbf{x}, t)) \quad (12)$$

III. APPLICATION EXAMPLE: BENDING BEAM

A. Structural configuration

In order to illustrate the concept of spatial-temporal progression of corrosion as described above, a RC beam of length $L = 5\text{ m}$ is considered. This beam is reinforced by $N = \{2, 3, 5\}$ reinforcing bars, which initial diameter d_s is modelled by a lognormal random variable. The beam length h and width b follow normal distributions. As univariate homogeneous random fields the concrete cover d_c , the chloride diffusion coefficient D_o , and the chloride surface concentration C_s are modelled. Dependencies between correlated random variables are described by Gaussian copulas. A complete overview of the used parameters, their distributions and values are given in Table I.

The beam is loaded with a uniform load composed of dead load g , long-term load q_{lt} , and short-term load q_{st} . The parameters of the long-term load correspond to the distribution of a 5 years maximum. Load combinations are done accordingly to the recommendations of JCSS [28]. The influence length e is in such a way assumed that the target reliability index can be described as $\beta(t = 0) = 4.2$, (without taking corrosion into account). The load effects can be written as:

$$S(x) = \theta_S(g + e(q_{lt} + q_{st}))\frac{x}{2}(L - x) \quad (13)$$

The resistance of a simply supported RC beams in flexure can be expressed as the ultimate flexural capacity [29]. Thereby it is assumed that the section strength and reinforcing bar capacity is directly proportional to yield capacity. This capacity also depends on the cross-sectional area of the reinforcement, which is affected by pitting corrosion [5, 6].

$$R(x, t) = M_u = \theta_R \cdot A_s(x, t) \cdot f_y \left(h - d_s - \frac{A_s(x, t) \cdot f_y}{1.7 \cdot f_c \cdot b} \right) \quad (14)$$

The minimal remaining steel cross-section $A_s(x, t)$ is calculated from equation (10); thereby, the GEV distribution and the NH-PPP have to be considered. Buxton et al. [30] have carried out experiments where fifteen rectangular test specimens with a distinct areas of 8.2 cm^2 were suspended in a deionized warm water bath under free corrosion. A GEV distribution was fitted to the observed pit depths, giving the specimens parameter values [31]: $\mu = 7.041$, $\sigma = 0.467$, and $\xi = -0.513$. A power-law dependence of $\gamma = 0.54$ was chosen, such that a long-term rate of pit development is considered [11, 23] but it is also satisfying the observations from Gonzalez et al. [32].

With the given data the expected extreme pit depth over time can be calculated from equation (8) as shown in figure 1a. The area of interest is assumed as $10\text{ cm} \times$

10 cm , i.e. a cylinder with the diameter 32 mm and the length 100 mm . Since the specimen size is 8.2 cm^2 the GEV parameters have to be extrapolated by $M = 100/8.2$. Figure 1b shows the mean number of pits per 100 cm^2 at time t . Only pits with a pit depth larger than $u = \{1, 2, 3, 5\}\text{ mm}$ are considered. For example, after 15 years of exposure, the mean number of pits are approximately 100. In figure 1c the unrolled lateral surface is plotted with a random pit pattern corresponding to the NH-PPP after several years of exposure. The loss of steel cross-section due to corrosion is shown in figure 1d. Here, it can be observed that the maximum pit depth is not determinative for the maximum steel area loss.

B. Computational method

The RC beam length is subdivided into 51 elements á 100 mm , allowing to evaluate a point-in-space probability of failure. Similarly, the beam width is subdivided into n sup parts, where n depends on the number of reinforcement bars. Equation (11) is computed using MCS. Therefore, a large number of samples are simulated for the set of random variables \mathbf{Z} . For every simulation the limit state function from equations (4) and (12) are evaluated. The load effects for equation (12) are described by equation (13) and the resistance is given in equation (14).

If $g_{cl}(t) \leq 0$, chloride induced corrosion has already started. The time since when the reinforcing bar is exposed to chloride ions can be estimated with equation (3). This time is used to generate a random pattern of pits for the affected element of the beam, as shown above. According to equation (10) the minimum remaining steel cross-section for the exposed element is calculated. This result is used to recalculate the steel cross-section in equation (14). It is to be noted that the reinforcing bars in an element are treated as a perfect parallel system, i.e. if one bar fails, the load will be redistributed to the remaining ones.

This process continues for successive annual time increments and elements until the service life is reached. The target service life of the RC beam is 50 years. This time horizon is discretized into 1-year time increments. Additional, it is assumed that the target reliability index decreases in time even without deterioration [33].

C. Results

The analyses presented herein will consider different member spans L , bar diameters d_s , number of bars N , and pitting thresholds u . A reference RC beam is considered with a length of 5 m , three reinforcement bars with 27 mm diameter, and a threshold of minimum pit depth larger than $u = 3\text{ mm}$.

Fig 2a shows the cumulative probability of failure for the RC beam. The 95%-confidence interval is obtained

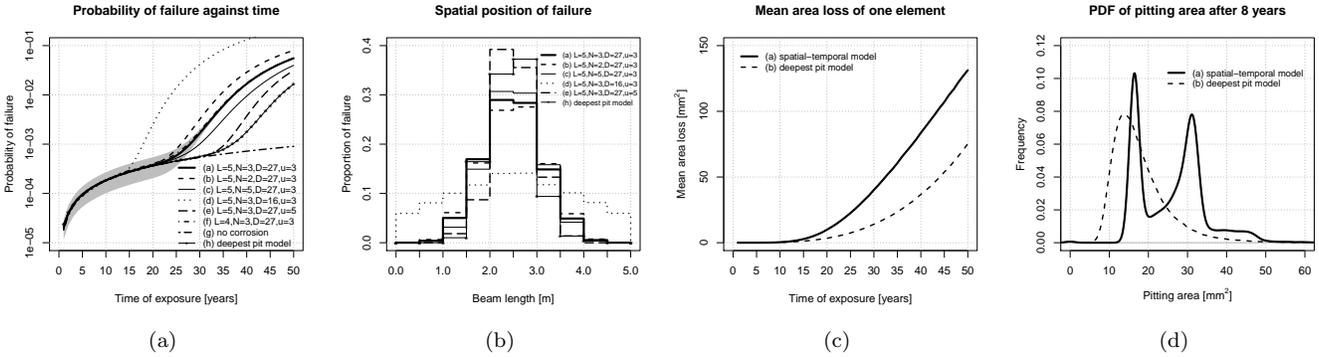


FIG. 2: Results

from the MCS for the reference beam. Since corrosion is considered as an additional deterioration mechanism, the probability of failure for all configurations (a-f) increases compared to the RC beam without corrosion (g).

The decrease of the reinforcement bars leads to an increase in the probability of failure (a-c). In this setup corrosion has a clear effect on the structural reliability after 20-25 years in service. The present analysis shows that also a reducing of the bar diameter (d) leads to a significant increase of the failure probability in flexure. If a higher thresholds of pitting depths (e) is assumed, it leads to the result that the effects of corrosion can only be observed in a later state of the service live. This corresponds to the fact that deeper pits occur in a late state of the corrosion process.

The results are compared with those from an analysis where only the deepest pit, in the center of an element, is considered (h). It can be observed that the probability of failure after 50 years is three times higher, if the spatial properties of the pits are taken into account.

Since spatial variability is considered, the simply supported RC beam can also fail beside the mid-span, especially when the pits occur randomly on the steel surface. Fig. 2b shows that the governing critical limit state for pitting corrosion is not always at the mid-span. However, if the diameter or the amount of rebars decrease, it becomes more likely that the failure is observed near the mid-span.

Fig. 2c shows the average corrosion loss of one element over time. By considering spatial and temporal effects of corrosion, higher expected values for the cross-section losses are observed, compared to the classical approach. This is due to the fact, that not only the deepest pit is considered, but also smaller pits and their spatial variations. This might cause a distribution of the pitting area A_{pit} as plotted in Fig. 2d. If no pit exceeds the threshold u , then there is no loss of steel. However, if pits occur the maximum loss might be a the deepest single pit or a combination of several pits.

IV. CONCLUSIONS

An improved method for the assessment of spatial and temporal effects of corrosion for the estimation of structural reliability of a potentially corroded RC structure has been presented. The analysis considers the spatial and time-dependent variability of pitting corrosion and structural resistance. This involves discretizing the RC beam in various elements and simulating, pit pattern for each reinforcing bar in each element. Since the randomly generated locations and sizes of the pits are taken into account, it could be shown that not only the maximum pit has an influence, but also clusters of several smaller pits can significantly influence the structural reliability.

Appendix A: Appendix

TABLE I: Probabilistic parameters

Name	Sym.	Type	Mean	CoV	Unit	A.c.f.	Ref.
age factor	n	Beta	0.37	0.19	-	-	[18]
bar diameter	d_s	Norm	27	0.01	mm	-	
beam height	h	Norm	500	0.02	mm	-	
beam length	L	Det.	5000	-	mm	-	
beam width	b	Norm	300	0.03	mm	-	
compressive strength	f_c	Lognorm	30	0.17	MPa	-	[28]
concrete cover	d_c	Lognorm	50	0.30	mm	ρ_{d_c}	[28]
concrete density	g_c	Norm	25	0.04	kN/m ³	-	[28]
critical concentration	C_{crit}	Norm	0.8	0.13	wb	-	[18]
critical threshold	u	Det.	3	-	mm	-	
diffusion coefficient	D_o	Norm	220.92	0.12	mm ² /year	ρ_{D_o}	[18]
environmental parameter	k_e	Gamma	0.924	0.17	-	-	[18]
execution parameter	k_c	Beta	0.8	0.13	-	-	[18]
extrapolation area	A	Det.	100	-	cm ²	-	
long-term load	q_{lt}	Gamma	0.5	1.34	kN/m ²	-	[28]
model uncertainty	θ_M	Lognorm	1	0.05	-	-	[8]
pit growth parameter	γ	Norm	0.54	0.01	-	-	
Short-term load	q_{st}	Gamma	0.2	2.00	kN/m ²	-	[28]
surface concentration	C_s	Norm	3.4911	0.34	wb	ρ_{C_s}	[18]
test method parameter	k_t	Norm	0.832	0.03	-	-	[18]
test specimen area	a	Det.	8.2	-	cm ²	-	[30]
uncertainty load	θ_S	Lognorm	1	0.20	-	-	[28]
uncertainty resistance	θ_R	Lognorm	1.1	0.07	-	-	[28]
yield strength	f_y	Lognorm	560	0.05	MPa	-	[28]

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