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A Computational Framework for Risk Assessment of RC Structures Using Indicators

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Abstract: *The present article starts out by proposing a framework for risk assessment of RC structures utilizing condition indicators. Thereafter, the various building stones of the suggested framework are described. This description includes a summary of the basis for the probabilistic modeling of the initiation phases of chloride-induced corrosion of concrete structures. Furthermore, a probabilistic modeling of condition indicators regarding the condition state of concrete structures is proposed whereby information available at the design stage of concrete structures as well as information obtained through in-service inspections may be utilized for the purpose of reliability updating. Finally, it is described how the probability of localized and spatially distributed degradation of different degrees can be assessed and examples are given on how the various indicators may be used for the purpose of updating the statistical characteristics of the future degradation of RC structures. The presented framework forms a consistent basis for risk assessment of concrete structures subject to chloride-induced corrosion. It can easily be adopted to other degradation phenomena such as carbonation-induced corrosion and it forms a good basis for the development of efficient approaches to Asset Integrity Management of RC structures.*

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1 INTRODUCTION

Degradation of the built environment constitutes a significant economical burden to society. As an example hereof Alsalam et al. (1998) reports that the costs of maintaining the infrastructure in the USA amounts to around 10% of the GDP. As the GDP constitutes the basis for maintaining and improving the standard of living for the individuals in society it is of utmost importance that the fixed costs of maintaining the necessary infrastructure are kept to a minimum. Due to the fact that a high proportion of infrastructure facilities are built at least partly of concrete it is evident that efficient design and maintenance of such structures has great societal significance.

Especially during the last two decades significant efforts have been allocated by the engineering profession to improve the basis for decision making in regard to design, construction, and maintenance of concrete structures. Cornerstones in an Asset Integrity Management (AIM) framework include a decision theoretical framework for the identification of optimal maintenance actions (Faber, 1997), a consistent treatment of uncertainties (Faber, 2003), together with a set of probabilistic models for the assessment of the statistical characteristics of the future degradation and performance of the structures.

Important contributions in regard to the modeling of degradation are provided in Hetek et al. (1996) and

DuraCrete (2000) (whereas the Hetek project was an industrial project initiated by the Danish roadway authorities, the DuraCrete project was an EU-funded project with a broad European participation). In the work described there the main effort has been devoted to the modeling of the degradation of localized areas of concrete structures. The modeling takes into account the effect of the concrete mix, the quality control applied during the manufacturing and construction of the structures, the specifics of the environmental exposure as well as the various uncertainties associated with these factors. Later developments have aimed to also model the aspects of the spatial variability of the degradation of concrete structures as discussed in Stewart et al. (2003). In Hergenröder (1992), Sterrit et al. (2001), Faber and Rostam (2001), Faber and Sorensen (2002), Maes (2003), Faber and Gehlen (2002), Lentz et al. (2002), and Malioka and Faber (2004) the spatial characteristics of the initial phases of degradation of concrete structures, such as chloride ingress and carbonation is modeled by means of a subdivision of the structures into elements of a size governed by the spatial variability of the most important factors for the degradation. In the recent works by Vu and Stewart (2002) the spatial variability associated with the propagation phases is investigated.

The present article starts out by proposing a framework for risk assessment of RC structures utilizing condition indicators. Thereafter, the various building stones of the suggested framework are described. This description includes a summary of the basis for the probabilistic modeling of the initiation phases of chloride-induced corrosion of concrete structures. Furthermore, a probabilistic modeling of condition indicators regarding the condition state of concrete structures is proposed whereby information available at the design stage of concrete structures as well as information obtained through in-service inspections may be utilized for the purpose of reliability updating. Finally, it is described how the probability of localized and spatially distributed degradation of different degrees can be assessed and examples are given on how the various indicators may be used for the purpose of updating the statistical characteristics of the future degradation of RC structures. The present framework forms a consistent basis for risk assessment of concrete structures subject to chloride-induced corrosion. It can easily be adopted to other degradation phenomena such as carbonation-induced corrosion and it forms a good basis for the development of efficient approaches to AIM.

2 RISK ASSESSMENT FRAMEWORK

The integrity management of a portfolio of facilities or structures may be enhanced through a logical organization of the objects in the portfolio together with an efficient utilization of available information concerning the condition of the objects. Considering in the present context a portfolio of concrete facilities or structures and limiting the scope of the AIM to consider the effect of degradation due to corrosion, a framework as illustrated in Figure 1 can be utilized.

In Figure 1 a hierarchical representation of the portfolio is suggested. At the top level the portfolio of facilities is organized according to the networks or regions. At subsequent levels the individual facilities are arranged

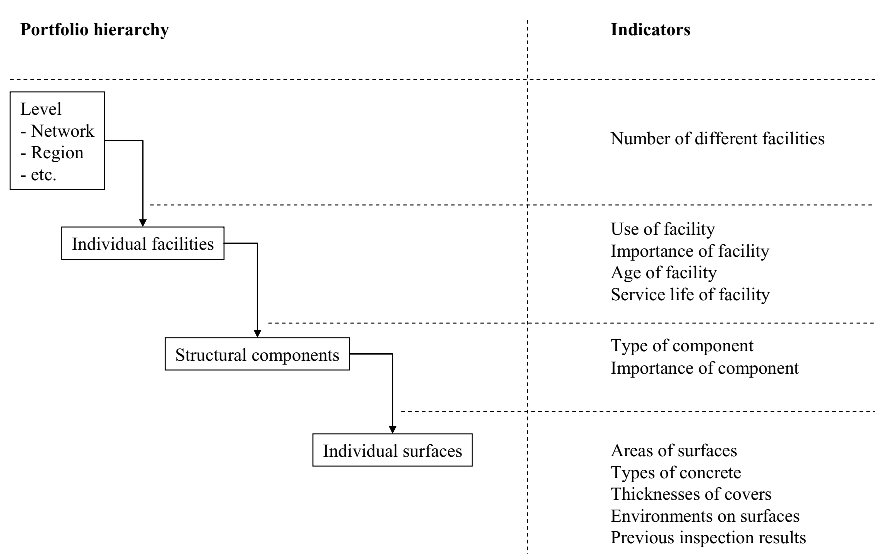

Fig. 1. Illustration of hierarchical organization and condition indicators in AIM.

into components and finally into surfaces. The reason for splitting up the portfolio into surfaces of structural components is that the surfaces of the concrete structures constitute the focal point in any AIM strategy. It might be imagined that a portfolio of facilities in this way can be represented by a set of concrete surfaces corresponding to different classes of concretes, cover thicknesses, environmental exposures, etc.

Here, the specifics of the organization of data for the purpose of AIM will not be treated in detail, but instead the important aspect of utilization of available information will be addressed. At the level of concrete surfaces, the condition and future need for inspections and repairs depend on the parameters governing the degradation processes. These are, for example, the thickness of the concrete cover, the characteristics of the concrete, the age of the concrete, the environmental exposure acting on the surfaces, and the anticipated residual service life. Furthermore, the results of previous inspections will also provide important information about the future performance of the concrete surfaces. Finally, the life cycle costs for a given surface depend on the area of the surface and the consequence associated with excessive degradation which in turn depends on the use of the structure. In an AIM framework, these different types of information can be utilized to enhance a cost-efficient allocation of activities and resources. In the following, the computational basis for such a framework is described with special emphasis on the use of indicators for the purpose of updating the probabilistic modeling of the degradation both for localized and distributed degradation.

3 MODELING OF DETERIORATION PHASES

Deterioration of concrete structures in the context of inspection and maintenance planning can appropriately be described in terms of the different phases of the deterioration, which are associated with different consequences and which may be observed and differentiated by means of inspection.

Considering deterioration due to corrosion, see Figure 2, the first phase is the initiation phase at the end of which the outer layer of reinforcement is de-passivated and corrosion initiates.

NDE inspections such as half-cell potential measurements may be applied to indicate whether or not corrosion has initiated at a given location and thus serve as a decision support tool in the planning of protective and corrective maintenance measures.

Simultaneously with the de-passivation of the next layers of reinforcement the propagation phase follows in various steps. The characteristics and duration of these steps depend in general on the specifics of the concrete, the reinforcement, the concrete cover thickness, the humidity, and the exposure conditions. At first the corrosion is initiated and corrosion products build up on the surface of the reinforcement. After a certain increase of the volume of the corrosion materials small cracks of the concrete cover will occur and again after some time the corrosion products may disperse through the cracks and become visible on the surface of the structure. Visible corrosion is a strong indication that deterioration not only has initiated but also progressed significantly. In practice the extent of visible corrosion is one of the important factors considered when making decisions in regard to corrective maintenance.

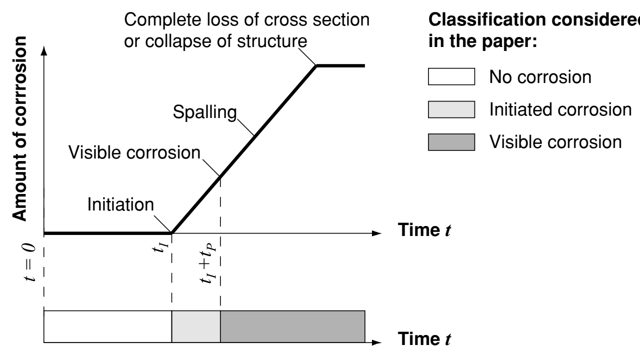

Fig. 2. Degradation phases of concrete structures.

If the corrosion products continue to build up on the surface of the reinforcement the concrete cover may eventually spall, leaving the structure even more exposed to the environment and thus accelerating the deterioration processes for the next layer of reinforcement. Ultimately, the deterioration may proceed until the load carrying capacity or the serviceability of the structure is reduced beyond acceptability.

Due to the characteristics of the different phases of the degradation process the cost efficiency of maintenance and repair activities will be highly dependent on when and how these are implemented. If the progress of deterioration is detected at an early stage it may be possible by means of minor and relatively inexpensive repairs to reduce the risk of major and expensive future repair works.

For normal reinforced concrete structures the ultimate load carrying capacity may be reduced by corrosion degradation due to mainly two effects, namely, loss of reinforcement cross-sectional area due to homogeneous and/or localized (e.g., pitting) corrosion, and loss of bond of reinforcement caused by spalling. Some models have been proposed for the description of the temporal and spatial evolution of corrosion of reinforcement (Stewart, 2004), however, a realistic model of loss of bond has yet to be developed. Furthermore, as spalling for most infrastructure facilities implies the risk of fatalities due to chunks of concrete falling and potentially hitting by-passers or vehicles, it may generally be viewed as an ultimate limit state.

For concrete structures where the likely location of deterioration is known, as in the case of structures with identifiable "hot spots," the criteria for implementing a repair can simply be the indication of initiated corrosion. Similarly for concrete structures with spatially distributed deterioration, that is, where in principle "all spots are hot," the criteria for implementing a preventive maintenance action can be the indication of initiated corrosion exceeding a critical percentage of the surface of the structure.

4 PROBABILISTIC MODELING OF CONDITION STATES

Only quantitative deterioration models allow for the integration of the different condition indicators in a consistent manner. Such quantitative models describe the physical properties of the deterioration as a function of the most influencing parameters. Quantitative deterioration models are available for the most common mechanisms such as chloride-induced corrosion or corrosion caused by carbonation of the concrete. To facilitate the use of the quantitative deterioration models in an AIM framework it is required to relate the models to specific condition states.

As outlined in Stewart et al. (2003) there is great variation in assessed temporal and spatial variability of degradation of concrete structures depending on the applied models and corresponding parameters. Partly motivated by these findings, recently a workshop (LCC03, 2003) was set out to investigate if a generally acceptable basis could be identified and agreed upon by the research community for the modeling of degradation of concrete structures. In short, it was found at the workshop (LCC03, 2003) that at present no such basis can be agreed upon for the propagation phases. However, in regard to the initiation phases a consensus was achieved at the workshop that the models summarized and developed in DuraCrete (2000) provide a sound basis for the assessment of the early stages of degradation. Specifically, the probabilistic modeling of chloride-induced corrosion is thus considered below.

According to DuraCrete (2000) the ingress of chlorides may be appropriately described by Fick's second law of diffusion. The chloride concentration at the cover depth d is calculated as:

$$C_{x=d} = C_S\left[1 - \mathrm{erf}\left(\frac{d}{2\sqrt{t \cdot D_a(t)}}\right)\right] \tag{1}$$

where C_S (percentage by weight of binder) is the concentration of chlorides on the surface of the concrete and $D_a(t)$ is the time dependent diffusion (or transportation) coefficient; erf(.) denotes the error function. The model assumes that corrosion starts when the chloride concentration at the reinforcement, $C_{x=d}$, has reached the critical chloride concentration C_{cr}.

$D_a(t)$ may be calculated as (DuraCrete, 2000):

$$D_a(t) = k_e \cdot k_t \cdot k_c \cdot D_0 \cdot \left(\frac{t_0}{t}\right)^n \tag{2}$$

with the additional parameters t_0 is the reference period, n is the age factor, k_e is the environmental factor, k_t is a parameter which considers the influence of the test method on the measured D_0, k_c is a parameter that accounts for the influence of curing, and D_0 is the empirical diffusion coefficient, see the Appendix.

Based on the above, the random variable T_I representing the time until initiation may be written as:

$$T_I = \left(\frac{d^2}{4k_e k_t k_c D_0 (t_0)^n}\left[\mathrm{erf}^{-1}\left(1 - \frac{C_{cr}}{C_s}\right)\right]^{-2}\right)^{\frac{1}{1-n}} \tag{3}$$

Equation (3) shows the empirical chloride diffusion model in its complete form.

Correspondingly the event of corrosion initiation can be represented by the limit state function $g_1(t)$:

$$g_1(t) = X_I T_I - t \tag{4}$$

where X_I is a model uncertainty taking into account that Fick's second law is an idealization of reality.

The time till visible corrosion corresponding to minor cracking and coloring of the concrete surface can be determined based on experience, see also Engelund et al. (1999). By adding the propagation time T_P to the initiation time T_I, the limit state function $g_2(t)$ for visible corrosion can be written as:

$$g_2(t) = X_I T_I + T_P - t \tag{5}$$

The values of the distribution parameters of the random variables in Equations (3)–(5) can in general be given as functions of the indicators defined in the next section. The prior values (i.e., the values of the distribution parameters before any in-service inspections or tests are performed) may be obtained as a function of what will be presented as "initial condition indicators."

In the Appendix the probabilistic models from the DuraCrete (2000) project are presented for ordinary Portland cement (OPC or PC). In DuraCrete (2000), values representative for other binders are also available.

Based on the probabilistic models given previously and the distribution parameter values given in the Appendix, the a priori probability of a particular element falling into different condition states can be calculated by using FORM/SORM methods, see Madsen et al. (1986), or by simulation methods. This is illustrated in Figure 3

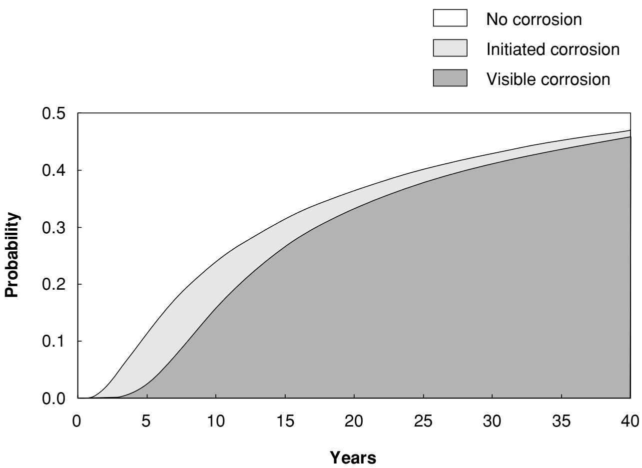

Fig. 3. Probability of being in one of three condition states (no corrosion, initiated corrosion and visible corrosion).

considering the events of corrosion initiation and visible corrosion, applying the distribution parameter values shown in Table 1 together with the dimensions and distribution types given in the Appendix. Note that the chloride surface concentration C_S is modeled as a function of the water/binder ratio by a linear model including the two parameters A_{C_S} and ε_{C_S}, as described in the Appendix.

The distribution parameter values are representative for a structural element with nominal cover thickness 45 mm, PC with *w/c* ratio = 0.40 and tidal exposure. For the example, T_P is modeled as LN (3.5 yr, 1.5 yr). The resulting probabilities of the different degradation states as illustrated in Figure 3 are obtained using Monte Carlo simulation. It should be mentioned that FORM/SORM techniques would have been more elegant and less time-consuming for this particular type of calculation, however, in general, when computation time is no problem and for example, sensitivity studies or code calibration is not in question, Monte Carlo simulation often provides a more robust computation scheme especially when the probability of intersections of events is of interest. In the present article, all probability calculations have been performed using Monte Carlo simulations with in-house software especially developed for the considered types of assessments.

Table 1
Parameter values for the example (see also Appendix)

	d	k_e	k_c	D_0	n	C_{cr}	A_{C_S}	ε_{C_S}
μ	45	0.924	0.8	220.9	0.362	0.8	7.758	0
σ	13.5	0.155	0.1	25.4	0.245	0.1	1.36	1.105

When specific indicators of the considered deterioration mechanism are available, the probability of being in the different states may be updated accordingly. The next section therefore identifies the possible condition indicators that can be considered in an AIM framework.

5 IDENTIFICATION AND DESCRIPTION OF CONDITION INDICATORS

Condition indicators are defined as (qualitative and quantitative) descriptors that provide information regarding the state of the structure with respect to the considered deterioration mechanism. The condition indicators influence the probabilistic deterioration model and consequently affect our knowledge regarding the actual state of the structural component. Based on the concept described in Faber and Sorensen (2002), the condition indicators for corrosion of the reinforcement can generally be modeled by the following two probabilities:

1. $P(S_i|D_j)$, the probability that the inspected component is in any condition state S_i $(i = 1, 2, \ldots, n,$ where n is the total number of possible different condition states) given the indication D_j.
2. $P(S_i|\bar{D}_j)$, the probability that the inspected component is in any condition state S_i, $i = 1, 2, \ldots, n$, given the nonindication $\bar{D}_j$.

For the case of chloride-induced corrosion of reinforcement, the following condition indicators may be applied in an AIM framework:

1. Initial condition indicators:
   - Construction year.
   - Cover thickness according to design specifications.
   - Concrete properties such as the *w/c* ratio of the cement and the type of binder.
   - Environmental exposure of the considered structural component (a combination of the location of the structure, the local environment and exposure of the considered structural surface).
2. In-service condition indicators:
   - Different tests and inspection results. Typical tests and inspections include:
     - visual inspection;
     - half-cell potential measurement;
     - cover depth measurements; and
     - chloride profiles.

Note that most of these indicators are also relevant for other deterioration mechanisms.

In the following, the quantitative modeling of selected condition indicators is demonstrated. The modeling of other indicators, however, follows the same principles. Specific quantitative models for different inspection techniques are provided in Malioka and Faber (2003) and Wicki et al. (2003).

5.1 Construction year

The construction year influences the probability of corrosion in different ways. First of all, it determines the age of the structure, that is, the parameter t in the limit state functions describing the different condition states. Secondly, the construction year also provides some information on the applied construction techniques, qualities, materials, and relevant design codes. It is proposed that this indirect information is accounted for when modeling the parameters. For instance, when no specific information is available about the concrete material and quality (including the *w/c* ratio), then the corresponding parameters in the limit state functions should be assessed as a function of the construction year. The consideration of the structure's age through the parameter t is straightforward. In accordance with Figure 3 the probability of belonging to different condition states is a function of the age t.

5.2 Environmental exposure

The corrosion of a structural element depends to a considerable extent on the environmental exposure. For instance, when modeling chloride-induced corrosion, typically the humidity and the salinity are considered. Whereas the salinity directly influences the chloride concentration on the surface C_S, the humidity influences both C_S as well as the diffusion coefficient D; furthermore the propagation time T_P is also dependent on the environmental exposure. To model condition indicators for the representation of the exposure it is thus required to build different exposure classes and to assess the parameters (C_S, D, and T_P) accordingly. Following DuraCrete (2000), the following exposure classes are differentiated for chloride-induced corrosion in marine environments:

- atmospheric zone,
- splash zone,
- tidal zone, and
- submerged.

Clearly the values of C_S and D which are representative for a specific building class are uncertain themselves. Therefore, it is possible to update these values based on the results from prior tests and inspections. In other words, existing inspection results can be used to improve the model of this condition indicator. This aspect is considered more closely in subsequent sections.

As an illustration of the influence of the condition indicator exposure, the example presented in Section 4 is now recalculated assuming that the environmental exposure class corresponds to a splash zone environment:

- The environmental factor k_e: Gamma (0.265, 0.045).
- The corrosion propagation period T_P: LN (7.5, 1.9).

All other parameters are as given in Table 1. The resulting probabilities for the different states are illustrated in Figure 4.

It is observed that the exposure class has a significant influence on the probability of the condition states.

5.3 Visual inspections

For structural components with surfaces which can be inspected visually, a visual inspection can provide highly accurate information about the visible condition states (e.g., stains of corrosion on the surface of the concrete, longitudinal cracks, and spalling). Although it should be borne in mind that these inspections also are not perfect (human errors can occur at the inspection or the documentation of the results), it is a first reasonable approximation to assume that the visual inspection is perfect. Consequently

- $P(S_i \mid D_{VI}) = 1$, when S_i is the condition state *visible corrosion* or any more advanced state, $P(S_i \mid D_{VI}) = 0$ for any other condition state; D_{VI} denotes indication of visible corrosion.
- $P(S_i \mid \overline{D_{VI}}) = 0$, when S_i is the condition state *visible corrosion* or any more advanced state.

If the condition states *visible corrosion* and *spalling* are distinguished, then additional considerations are

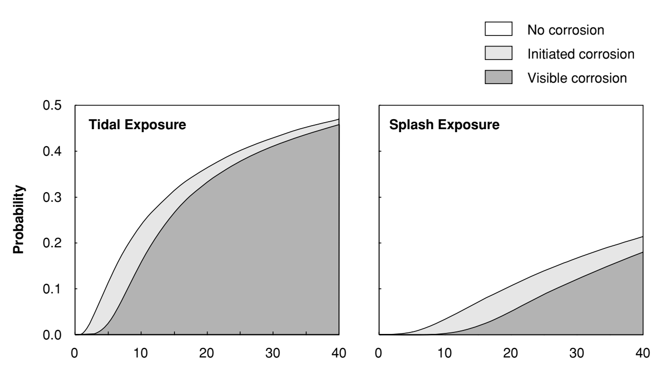

Fig. 4. Differences in initial probabilities of the different condition states for the same structure assuming two different exposure classes. The left figure corresponds to Figure 3.

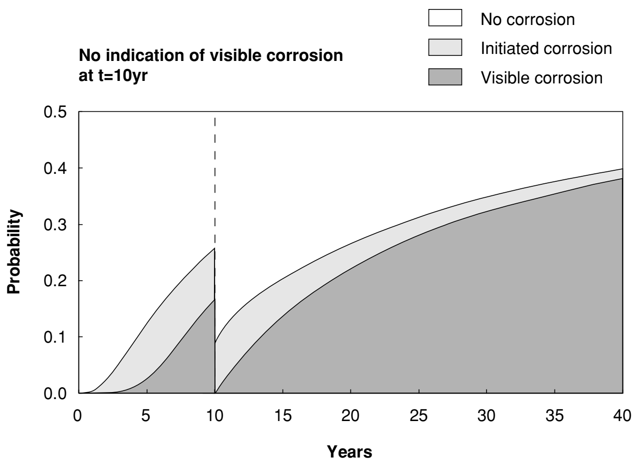

Fig. 5. The influence of no indication of visible corrosion in year 10 on the probability of occurrence of the different condition states.

possible. When the inspection result indicates only visible corrosion, this signifies that visible corrosion has initiated, but also that spalling has not yet started. These events can be described by checking that the limit state function given by Equation (5) is less than 0 and that the limit state function for spalling, $g_3(t)$, as presented in Equation (6), is greater than 0.

$$g_3(t) = t - X_{\mathrm{I}} T_{\mathrm{I}} + T_{\mathrm{P}} + T_{\mathrm{SP}} \tag{6}$$

In Equation (6) the event of spalling is modeled by the random variable T_{SP}, the time period from the first occurrence of visible corrosion to the occurrence of spalling.

Figure 5 illustrates the effect of a visual inspection indicating *no* visible corrosion of a structural component in year $t = 10$ year. If visible corrosion is observed during the inspection, then the probability of having corrosion is equal to 1 for all t after the inspection. By the same token it follows from Equation (6) that the observation of *no* visible corrosion has no influence on the probability of being in the condition state "initiated corrosion."

5.4 Half-cell potential measurements

Half-cell potential measurements only provide information about the state of corrosion initiation, denoted S_{CI}. The quality of this condition indicator D_{HC} may thus be given by the following probabilistic descriptors:

- $P(D_{\mathrm{HC}}|S_{\mathrm{CI}})$, the probability of an indication of corrosion given that the corrosion has initiated (correct indication).
- $P(D_{\mathrm{HC}}|\overline{S_{\mathrm{CI}}})$, the probability of an indication of corrosion given that corrosion has not yet initiated (spurious indication).

These two descriptors depend on the evaluation of the test results, as the measurements result in a potential which is subject to interpretation. The limiting potential U_{lim}, which differentiates between indication and no-indication, determines the two quantities. Furthermore, the effect of humidity must be taken into account (Lentz et al., 2002). However, based on recent research projects (Lentz, 2001; Johnsen et al., 2003) the half-cell potential measurements can be interpreted quantitatively. For a given probability ($P(D_{\mathrm{HC}}|S_{\mathrm{CI}}) = 90\%$) that initiated corrosion is correctly indicated by a half-cell measurement, one can easily determine the corresponding limit potential (U_{lim}) and the probability of initiated corrosion being wrongly indicated ($P(D_{\mathrm{HC}}|\overline{S_{\mathrm{CI}}})$) (spurious indications). This is done in terms of the conditional probability density function for the measured potential given that corrosion has and has not initiated, respectively, see also Faber and Sorensen (2002). In Table 2, recently derived quantitative models are given based on Lentz et al. (2002) and Johnsen et al. (2003). The data are classified according to the type of structural component but not in accordance with their orientation relative to the nearby passing traffic. The main classes are bridge decks, arcs from RC arch bridges of which there exist quite a number in Switzerland and columns that are situated next to streets and thus exposed to sideway spray. The class "bridge archs" includes the columns between the arch and the bridge deck. For structural components with surfaces not included in Table 2, the parameters from the collective Swiss data may be relevant provided that engineering traditions and climatic conditions are comparable to those of Switzerland.

Figure 6 shows the reliability of the tidal zone exposure example when, in addition to the visual inspection, a half-cell potential measurement is performed after $t = 10$ years resulting in an indication of corrosion.

Due to the effect that if visible corrosion is observed, there is no need for a half-cell potential measurement, the probability of visible corrosion becomes 0 immediately after the inspection.

Table 2
Limit potentials and probabilities of spurious corrosion indications given $P(D_{\mathrm{HC}}|S_{\mathrm{CI}}) = 90\%$

Distribution	U_{lim}	$P(D_{\mathrm{HC}}|\overline{S_{\mathrm{CI}}})$
Collective Swiss data	207 mVCSE	24.0%
Bridge arcs (Swiss)	238 mVCSE	1.3%
Bridge decks (Swiss)	259 mVCSE	18.1%
Columns next to streets (Swiss)	193 mVCSE	33.1%
Columns next to streets (Danish)	201 mVSSC	29.0%

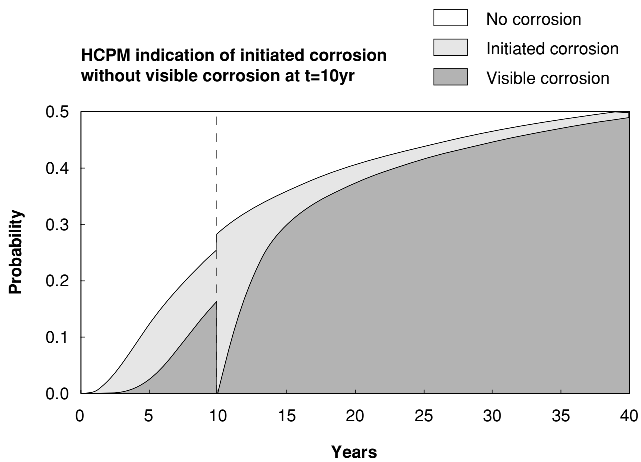

Fig. 6. The influence of an indication from a half-cell potential measurement at $t = 10$ year.

6 MODELING OF SPATIALLY DISTRIBUTED DETERIORATION

As previously mentioned, it is proposed to represent the concrete structures by means of concrete surfaces belonging on different categories. A brief overview of the state-of-the-art in modeling spatial variability of the initial phases of degradation of concrete structures is provided in Malioka and Faber (2004).

The individual concrete surfaces are divided into zones. Zones are defined as areas which can be described by similar initial condition indicators; that is, prior to inspections and tests no area within a zone can be distinguished and all are represented by the same probabilistic model and carry the same risks. Zones are further subdivided into elements to take into account the spatial variation of the deterioration process. The idea behind the model is to divide each concrete surface zone into a number of individual elements which in terms of degradation may be assumed to behave statistically independently, as illustrated in Figure 7. This model allows the use of highly efficient tools for the statistical analysis of the degree of spatial degradation of a structure as will be seen later.

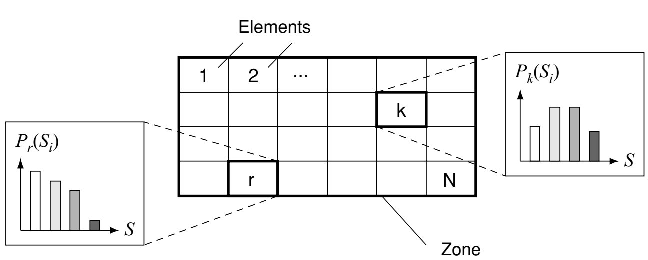

Fig. 7. Illustration of the system model: subdivision of a concrete surface. S_i indicate the different condition states.

Considering the permeability of concrete, Malioka and Faber (2004) suggest that the size of the individual elements should be 0.5 m × 0.5 m based on the (reasonable) assumption of an isotropic random field. The same element size is also recommended in Sterritt et al. (2001) for the parameters "cover depth" and "diffusivity" and it is also supported by studies reported in Hergenröder (1992). At the edges of the considered surface zones, it may be necessary to identify smaller elements.

6.1 Probabilistic modeling of spatial degradation

Based on the above-introduced spatial representation of concrete structures each element is represented by a probabilistic model with initial parameter values based on its initial condition indicators, including exposure type, design cover thickness, etc. The random variables in each element within one zone are initially independent and identically distributed. Using information regarding the in-service condition indicators, the models for the individual elements are updated and start varying from element to element, depending on the individual inspection outcomes. The models proposed in Faber and Sorensen (2002) and Maes (2003) utilize hyper-parameters $\boldsymbol{\omega}$ to ensure that some of the parameters describing the probabilistic deterioration model for the individual elements are themselves uncertain. As the realizations of these hyper-parameters $\boldsymbol{\omega}$ are identical for all elements in one zone, the statistical characteristics of the degradation of elements within one zone are conditionally independent, given $\boldsymbol{\omega}$.

For the parameters of the chloride penetration model given in Section 4 and the Appendix, the hyper-parameters $\boldsymbol{\omega}$ may include the mean value of the diffusion coefficient μ_{D} and the mean value of the chloride surface concentration $\mu_{C_{\mathrm{S}}}$. Note that realizations of the hyper-parameters, in principle, are also the same for identical zones in different structures; identical zones being zones with the same initial condition indicators. Information obtained on one structure thus also influences the reliability of other structures. On the other hand, different zones within the same structure are considered fully independent.

Based on the above-introduced spatial model, it is possible to assess the characteristics of spatially distributed corrosion. The probability that a certain surface percentage of a zone, $\Delta(t)$, exhibits a critical degree of deterioration may then be expressed as:

$$P(\Delta(t) \geq n/N) = P\left(\bigcup_{i=1}^{K_{N,n}} \bigcap_{j=1}^{m_i} \{g_j(\mathbf{X}, t) \leq 0\}\right) \tag{7}$$

where n is the number of elements that exhibit critical degradation, N is the total number of elements, $K_{N,n}$ is the number of combinations of elements of the critical percentage of the zone and m_i is the number of elements in the ith combination. The limit state function describing critical degradation (e.g., initiated or visible corrosion) for element j is expressed by $g_j(\mathbf{X}, t)$. As the elements constituting a certain zone of the structure can be assumed conditionally independent, given the hyper-parameters $\boldsymbol{\omega}$, (7) simplifies into:

$$P(\Delta(t) \geq n/N) = 1 - E_\omega\left[B(n-1, N, \theta(t|\boldsymbol{\omega}))\right] \quad (8)$$

where $E_\omega[\cdot]$ denotes the expected value operator in regard to the hyper-parameters $\boldsymbol{\omega}$, $B(n-1, N, \theta(t \mid \boldsymbol{\omega}))$ is the cumulative binomial distribution with sample size N, argument $n-1$, and probability $\theta(t \mid \boldsymbol{\omega})$, which is the probability of an individual element at time t belonging to a specific condition state. This value can be determined by simulation or FORM/SORM analysis. If the prior probability distribution of the probability of failure, $f_{\theta(t)}(\theta(t))$, is known, then the probability that visible corrosion is present over a critical fraction ψ_{CRIT} of the zone under consideration may be obtained by:

$$\begin{aligned} &P(\Delta(t) \geq \psi_{\mathrm{CRIT}}) \\ &\quad = 1 - \int_0^1 B(\psi_{\mathrm{CRIT}} \cdot N - 1, N, \theta(t))\, f''_{\theta(t)}(\theta(t))\, d\theta(t) \end{aligned} \quad (9)$$

where the posterior probability density $f''_{\theta(t)}(\theta(t))$ may be determined as discussed in Faber and Sorensen (2002) for a given outcome of an inspection, for example, the number of positive and negative indications of initiated corrosion. In other words, Equation (9) accounts for the fact that the assumption of independence between the states of the individual elements is only valid for a given realization of the statistical uncertainty.

For the previously described example representing a concrete surface in a "splash zone" environmental exposure category, it is now assumed that this surface is discretized as explained in the foregoing into 50 elements, all with the parameters as given previously with the exception of the nominal cover thickness which is now set to $d_{\mathrm{nom}} = 35$ mm. When $\theta(t)$ is assumed to represent the probability of corrosion initiation, then Figure 8 shows the distribution of $\theta(t)$ for different points in time when no inspection is performed. The results in Figure 8 are calculated using Monte Carlo simulation with a nested FORM routine.

Based on the distributions illustrated in Figure 8 it is possible to assess the distribution of the number of elements exhibiting initiated corrosion at any point in time based on Equation (9). Such a distribution is shown in Figure 9 for the 50 elements considered and $t = 30$ years.

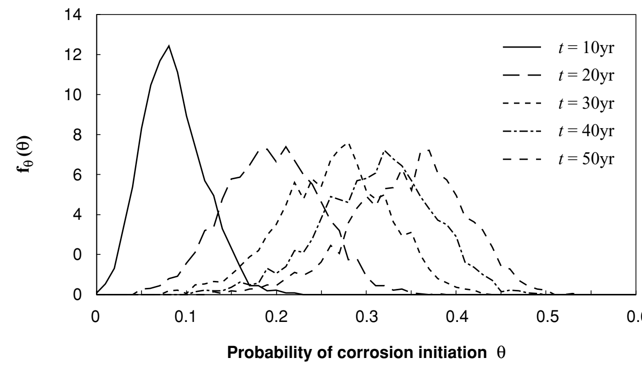

Fig. 8. Distribution of $\theta(t)$ (the probability of corrosion initiation) at different points in time.

7 RISK ASSESSMENT OF CONCRETE SURFACES USING INDICATORS

Based on the characterization of the state of the various zones and elements within a structure, the residual service life and the various condition states can be described in probabilistic terms. It is illustrated how this description can be used to assess the risk in terms of the expected cost or damage, taking into account the spatial distribution of the damages and the cost-consequences associated with repairs.

The structure is represented in terms of its zones which consist of individual elements of the size 0.5 m × 0.5 m or smaller. As an example a bridge structure is considered, in particular one column of the bridge. The bridge consists of various zones, two of which are situated in the considered column. This is illustrated in Figure 10.

Zone A is located in the splash zone, zone B is located on top of it.[1] In the following, the considerations are directed toward the splash zone. There are several

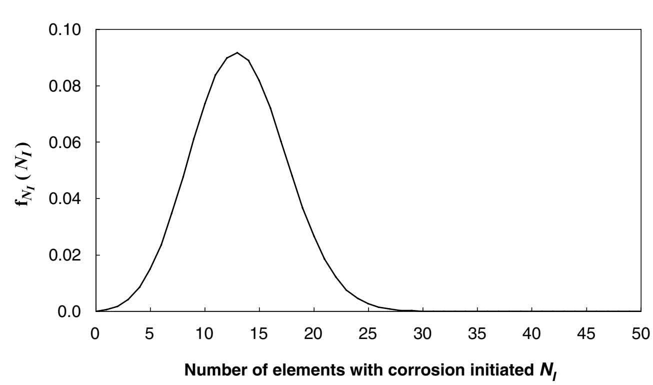

Fig. 9. Probability mass of the number of elements with initiated corrosion at time $t = 30$ years in a group of 50 elements.

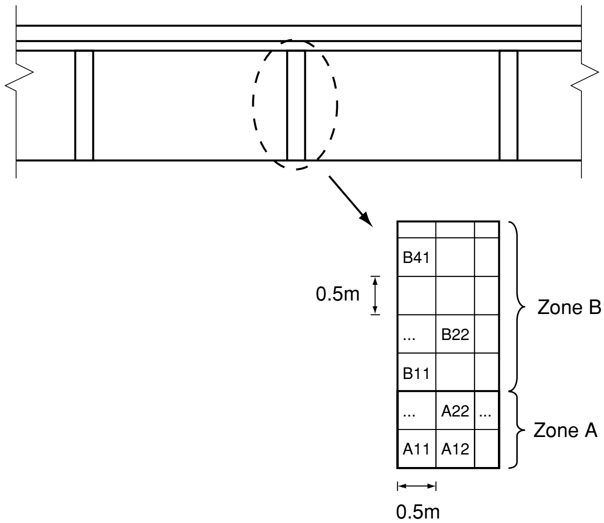

Fig. 10. Example of a structure: bridge column.

columns on this bridge and it is assumed that there are in total 50 elements in zone A.

The probabilistic model of the 50 elements in zone A is taken as the one introduced previously. The prior probability of the different condition states is thus as (partly) shown in Figure 4. Figure 11 shows the distribution of the number of elements exhibiting initiated corrosion and visible corrosion after 20 years in service, before any inspection is performed.

It should be noted that prior to an inspection the evaluated risk of degradation is uniform for all elements within one zone. This is because all individual elements are represented by the same probabilistic deterioration model.

When a critical fraction of elements with visible corrosion, ψ_{CRIT}, is specified, the probability of having a critical condition of the system can be calculated as a function of time following Equation (9). This is illustrated in Figure 12 for the considered example.

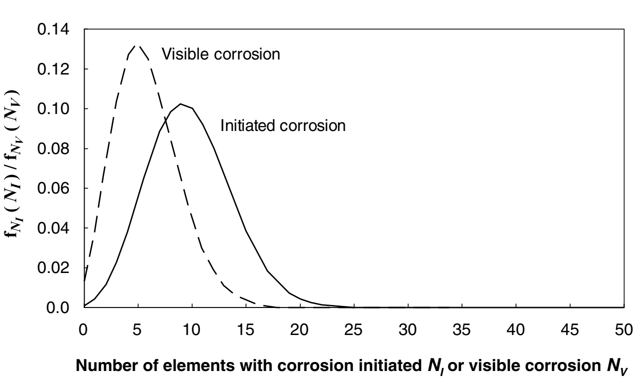

Fig. 11. Distribution of the number of elements in the different condition states at $t = 20$ year before any inspection.

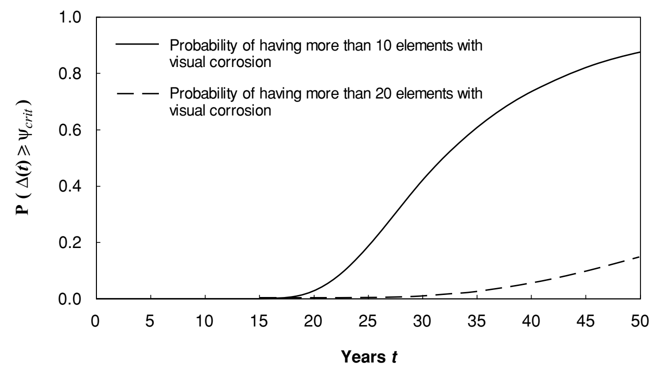

Fig. 12. Probability of exceeding a critical amount of elements with visible corrosion in accordance with Equation (9).

Assume now that, based on a prior assessment, it is decided that an inspection must be performed at $t = 20$ year. It is assumed that 40% of the columns (and thus all zones) are inspected using half-cell potential measurements; this results in 20 elements being subject to inspection. After these inspections, the risk is no longer uniform within one zone; it is different for the inspected elements and for the noninspected elements and again different for those elements where the half-cell potential measurement indicates initiated corrosion. For the individual elements subject to inspection, the updated probabilities can be approximated with those shown in Figures 5 and 6. For the noninspected elements, it is the model of θ (the probability of corrosion initiation or propagation) which is updated. For given hyper-parameters, the updated model of $f_\theta(\theta)$ is obtained as follows:

$$f''_\theta(\theta \mid z) = L(z \mid \theta)\, f_\theta(\theta) c_1 \tag{10}$$

where z is the observed inspection result, $L(z \mid \theta)$ is the likelihood function describing the inspection quality and c_1 is a constant determined by the condition that (10) must integrate to 1 over the entire domain of θ.

To determine $L(z \mid \theta)$, the likelihood of the individual inspection results (indication or nonindication at each element) are assessed: $L(D \mid \theta)$ and $L(\bar{D} \mid \theta)$. The full likelihood function is then calculated using:

$$L(z \mid \theta) \propto L(D \mid \theta)^{n_D}\, L\left(\bar{D} \mid \theta\right)^{n_{\bar{D}}} \tag{11}$$

where n_D is the number of elements with an indication and $n_{\bar{D}}$ is the number of elements without an indication.

It is in the following assumed that out of the 20 inspected elements, only 5 have an indication of corrosion initiation at the half-cell potential measurement ($n_D = 5$, $n_{\bar{D}} = 15$). For the considered bridge columns it is furthermore assumed that the concrete surface is visible and a half-cell potential measurement is thus only carried out if there is no visual evidence of corrosion. There are thus three different inspection outcomes:

1. visual indication of corrosion and no half-cell potential measurement,
2. half-cell potential measurement resulting in an indication (and no indication of corrosion following a visual inspection), and
3. half-cell potential measurement resulting in no indication (and no indication of corrosion following a visual inspection).

When Figure 13 is interpreted, it is of importance to remember that the likelihood function is only conditional on the values of the probability of indication in the system, but not on the actual state of the inspected element. The inspected element can still be in each of the three states. Note also that the likelihood functions must be computed only once for all different combinations of inspection outcomes.

Based on Equations (10) and (11) together with Figure 13 the posterior probability of θ (the probability of corrosion initiation or propagation) is now calculated for the event of no visible corrosion at any of the 20 inspected elements and 5 indications using the half-cell potential measurement. The resulting posterior pdf is shown in Figure 14.

From Figure 14, it is observed that the assumed inspection outcomes provide evidence that the reliability of the structure against corrosion is greater than initially expected.

Based on Figure 14 it is now possible to model the updated probabilities of the different condition states for all elements, subsequent to the inspection. This is summarized in Figure 15. Although they are situated within the same zone, the elements with a positive indication following the half-cell potential inspection, the elements with a negative indication, and the noninspected elements, all behave in distinct ways.

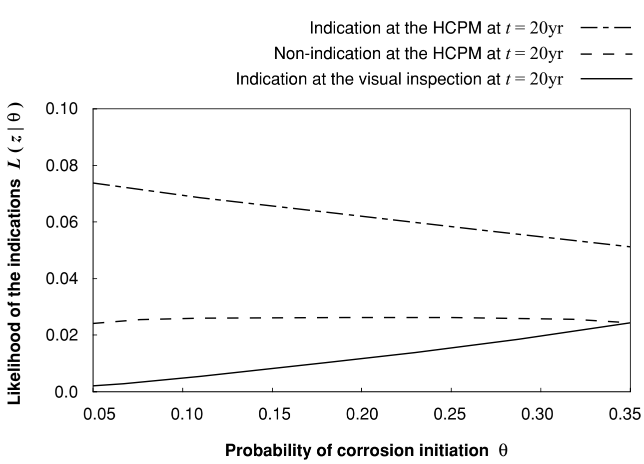

Fig. 13. Likelihood functions for the three possible inspection outcomes at $t = 20$.

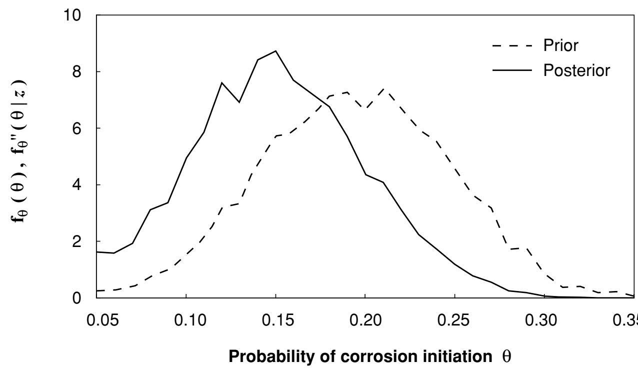

Fig. 14. Updated probability of corrosion initiation in the system.

Based on Figure 15 it is possible to calculate the probability that the number of elements with visible corrosion exceeds a critical value, similar to Figure 12.

8 CONCLUSIONS

The present article is concerned about the computational framework for risk assessment of RC structures utilizing condition indicators. First, a hierarchical representation of portfolios of RC structures is proposed and it is suggested how condition indicators can be identified at the various levels for the purpose of improved risk assessment. Thereafter, the various building stones of the suggested framework are described. This description includes the basis for the probabilistic modeling of the initiation phases of chloride-induced corrosion of concrete structures. Furthermore, a probabilistic modeling of condition indicators regarding the condition state of RC structures is proposed whereby information available at the design stage as well as information obtained through in-service inspections may be utilized for the purpose of reliability updating. Finally, it is described how the probability of localized and spatially distributed degradation of different degrees can be assessed and examples are given on how the various indicators may be used for the purpose of updating the statistical characteristics of the future degradation of RC structures. The presented framework forms a sound basis for risk assessment of concrete structures subject to chloride-induced corrosion, and it can easily be adapted to other degradation phenomena such as carbonation-induced corrosion

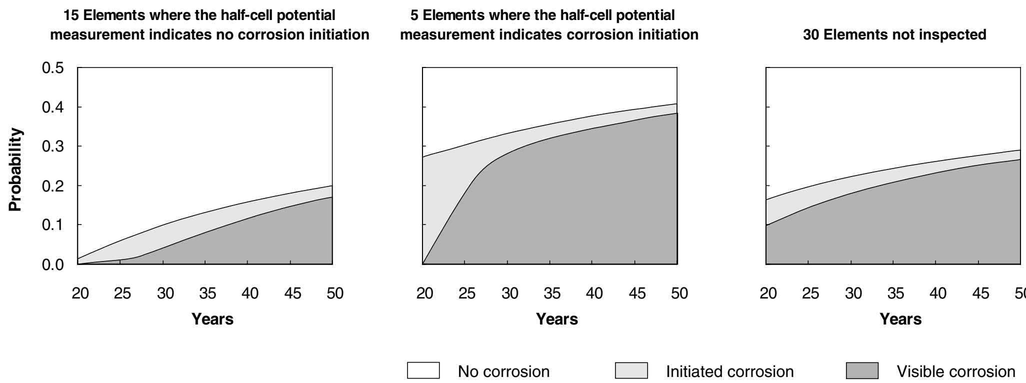

Fig. 15. Summarized state of the considered zone with 50 elements after the inspection of 20 elements.

and forms a basis for the development of efficient approaches to AIM.

The handling of the statistical characteristics of future deterioration of RC structures may appear computationally demanding. The use of the framework as a decision support tool in AIM in practice thus necessitates the development of computational approaches which are efficient and at the same time applicable also for engineers without expertise in probabilistic modeling and analysis. However, the application of the so-called generic approaches used successfully in risk-based inspection and maintenance planning for offshore steel structures (Faber et al., 2000) is a feasible solution to this problem. The main idea behind the generic approach to risk assessments is the preanalysis of the probabilities which are required for the risk assessments. This includes prior probabilities and updated probabilities of the performance of concrete structures for a generic representation of the considered type of structures and inspection results. The specific probabilistic characteristics of different states of degradation for the individual zones and elements within a structure can then be interpolated from within a library including the results of the preanalysis based on the values of the generic parameters. All elements (respectively, zones or locations) for which the model is valid are fully described by the condition indicators (termed generic parameters). Because the condition indicators are formulated in terms of common engineering characteristics of the structures and their exposure conditions, the risk assessment can be performed without any specialist input.

ACKNOWLEDGMENTS

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NOTE

1. Here it is assumed that the orientation is not relevant for corrosion.

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APPENDIX: PROBABILISTIC MODELS FOR CHLORIDE-INDUCED CORROSION

Cover thickness

With d_{nom} denoting the nominal value of the cover thickness, the probabilistic model for the cover thickness d is given as in Table A.1.

Table A.1
Cover thickness model

Distribution	*Mean value* μ_d *(mm)*	*Standard deviation* σ_d *(mm)*
Lognormal	d_{nom}	$0.3 \cdot \mu_{\text{d}}$

Diffusion coefficient

The “empirical” diffusion coefficient D_0 is not a physical parameter but a parameter obtained from a regression analysis using the empirical diffusion model. The time dependent diffusion coefficient $D_a(t)$ is obtained by multiplying the material parameter D_0 with different correction factors in accordance with Equation (2). D_0 is provided in Table A.2 as a function of the *w/c* ratio:

Table A.2
Probabilistic model of the material parameter D_0 (valid for PC)

w/c Ratio	*Distribution*	μ_{D_0} *(mm²/year)*	σ_{D_0} *(10^{-12} m²/s)*
0.40	Normal	220.9	25.4
0.45	Normal	315.6	32.5
0.50	Normal	473.0	43.24

Age factor

The age factor n is quantified for different marine environments in DuraCrete (2000). For other structures it is recommended to apply the parameter values for the marine splash zone. Here the value given in DuraCrete (2000) is used, Table A.3.

Table A.3
Probabilistic model of the age factor n

Distribution	μ_n *(–)*	σ_n *(–)*	*A*	*b*
Beta	0.362	0.245	0	0.98

Reference period

The reference period t_0 is 28 days = 0.077 year.

Environmental factor

This factor accounts for the differences of the diffusion in the different environments. The environmental factors in accordance with DuraCrete (2000) are given as a function of the binder type and the environment. For PC-concrete the values are as given in Table A.4.

Table A.4
Probabilistic model of the environmental factor k_e (valid for ordinary PC)

Environment	*Distribution*	μ_{k_e} (–)	σ_{k_e} (–)
Submerged	Gamma	1.325	0.223
Tidal	Gamma	0.924	0.155
Splash	Gamma	0.265	0.045
Atmospheric	Gamma	0.676	0.114

Curing time correction factor

This factor accounts for the influence of the curing time (DuraCrete, 2000): The parameter values for k_c can be used as given in Table A.5.

Table A.5
Probabilistic model of the curing time factor k_c

Curing time (d)	*Distribution*	μ_{k_c} (–)	σ_{k_c} (–)	a_{k_c}	b_{k_c}
1	Beta	2.4	0.7	1.0	4.0
3	Beta	1.5	0.3	1.0	4.0
7	Deterministic	1	–	–	–
28	Beta	0.8	0.1	0.4	1.0

Correction factor for tests

The correction factor k_t accounts for the differences in the measured D if a test method other than rapide chloride migration method (RCM) is used. If the chloride profiling method (CPM) is used, k_t is given as shown in Table A.6.

Table A.6
Probabilistic model of the correction factor k_t for the CPM method

Distribution	μ_{k_t} (–)	σ_{k_t} (–)
Normal	0.832	0.024

If the models given herein are used, without additional measurements, it is $k_t = 1$.

Chloride surface concentration

The chloride surface concentration C_S is dependent on the environment. The two major sources of chloride are de-icing salts and marine environments. Furthermore, following DuraCrete (2000) it is also dependent on the applied binder and in particular the water-to-binder-ratio w/b. C_S is modeled as a linear function of w/b:

$$C_S = A_{C_S} \cdot (w/b) + \varepsilon_{C_S} \tag{A.1}$$

The two regression parameters are given for PC in marine environments as shown in Table A.7.

Table A.7
Probabilistic model of the chloride surface concentration regression parameters (valid for ordinary PC). The values here are given in percentage by weight of binder

Environment	*Distribution*	$\mu_{A_{C_S}}$	$\sigma_{A_{C_S}}$	$\mu_{\varepsilon_{C_S}}$	$\sigma_{\varepsilon_{C_S}}$
Submerged	Normal	10.348	0.714	0	0.580
Tidal & Splash	Normal	7.758	1.360	0	1.105
Atmospheric	Normal	2.565	0.356	0	0.405

Critical chloride content

The critical chloride content C_{cr} is defined as the concentration of chlorides on the surface of the reinforcement that leads to damage of the surrounding concrete structure (small cracks) (Wicki et al., 2003). Using this definition C_{cr} is dependent on environmental parameters such as oxygen supply and humidity. The values in Table A.8 are thus representative:

Table A.8
Probabilistic model of the critical chloride content C_{cr}

	w/c ratio	*Distribution*	$\mu_{C_{cr}}$ *(mass–percentage of binder)*	$\sigma_{C_{cr}}$ *(mass–percentage of binder)*
Constantly saturated	0.30	Normal	2.30	0.20
	0.40	Normal	2.10	0.20
	0.50	Normal	1.60	0.20
Constantly humid or many humid-dry cycles	0.30	Normal	0.50	0.10
	0.40	Normal	0.80	0.10
	0.50	Normal	0.90	0.15

Model uncertainty

The model uncertainty X_I is modeled in accordance with Faber and Sorensen (2002) as shown in Table A.9.

Table A.9
Probabilistic model of the model uncertainty

Distribution	$\mu_{X_{\rm I}}$ (–)	$\sigma_{X_{\rm I}}$ (–)
Lognormal	1.0	0.05

Visible corrosion

The time period from the initiation of corrosion at the reinforcement until visible corrosion at the concrete surface can be modeled by limit state functions, based on a general corrosion rate $V_{\rm corr}$ and a model describing the cracking of the concrete cover. Input to these limit state functions is provided in DuraCrete (2000).

For the sake of demonstration, the examples presented in this article are calculated with a highly simplified model. Visible corrosion is accounted for by modeling directly the time between corrosion initiation and visible corrosion, $T_{\rm P}$, in accordance with Equation (5). It is assumed that $T_{\rm P}$ can be modeled by a Lognormal distribution with the parameter values given in Table A.10.

Table A.10
Probabilistic model for the corrosion propagation period $T_{\rm P}$

Environment	*Distribution*	$\mu_{T_{\rm P}}$	$\sigma_{T_{\rm P}}$
Submerged	Not expected, if not for low cover/bad concrete		
Tidal zone	Lognormal	3.5	1.5
Splash	Lognormal	7.5	1.9
Atmospheric	Lognormal	12	2