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Probabilistic modelling of deterioration of reinforced concrete structures

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A B S T R A C T

Reinforced concrete (RC) structures deteriorate over time which affects their strength and serviceability. To develop measures for protecting new RC structures against deterioration and assess the condition of existing RC structures subjected to deterioration an understanding of the deterioration processes and the ability to predict their development, including structural consequences, are essential. This problem has attracted significant attention from researchers, including those working in the area of structural reliability (in particular within the JCSS) since there are major uncertainties associated with the deterioration processes and their structural effects. The paper presents an overview of the probabilistic modelling of various deterioration processes affecting RC structures such as corrosion of reinforcing steel, freezing-thawing, alkali-aggregate reaction, sulphate attack and fatigue, and their structural implications, including the historical perspective and current state-of-the-art. It also addresses the issues related to the inspection/monitoring of deteriorating RC structures and the analysis of collected data taking into account relevant uncertainties. Examples illustrating the application of the presented probabilistic models are provided. Finally, the current gaps in the knowledge related to the problem, which require further attention, are discussed.

1. Introduction

Concrete has been used industrially since the beginning of the 20th century, allowing time to gain significant experience in its performance and durability. While the structural analysis of reinforced concrete (RC) structures has developed relatively quickly, understanding of different natural and man-made influences/factors which can affect the durability of such structures over their lifetime has progressed much slower. Since RC is a composite material, consisting of concrete and reinforcing steel, relevant deterioration processes can be broadly divided into those occurring only in concrete, those affecting reinforcing steel, or both constituents.

The processes that can cause concrete deterioration include freeze/thaw action, alkali-aggregate reaction, internal and external sulphate attack, erosion, and leaching of alkalinity which ends in the disintegration and dissolution of the hydrated cement phases. Generally, these processes result in concrete cracking, distributed or localised, that affects the concrete volumetric integrity and strength [1–3]. These deterioration processes can be prevented or their harmful effects can be considerably reduced with a proper selection of the cement type, mix proportions and incorporation of appropriate mineral additions.

Another process that may lead to the deterioration of a RC structure is fatigue, which occurs when such a structure or its member is subject to multi-cycle loading and damages both concrete and reinforcing steel. Recently, with the introduction of high-strength concretes, the problem attracted renewed attention because RC structures became more slender, permanent loads decreased, and such structures as bridges and towers of wind turbines experience multiple wide-range variations of variable loads over their service life [4].

The main deterioration process affecting reinforcing steel is corrosion [5–7]. It takes place when the passive film formed on the steel surface in a highly alkaline environment of the concrete pore solution is

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damaged. This can be caused by either carbonation, i.e., a reaction between carbon dioxide from the atmosphere and calcium and alkali hydroxides present in the concrete pore solution, or chloride ions which penetrate into concrete from the environment, e.g., in marine environments or environments containing de-icing salts. Corrosion starts when the carbonation front reaches reinforcing steel or the concentration of chloride ions near reinforcing steel exceeds a certain threshold value. It should be noted that by themselves, carbonation and chloride ingress do not cause damage to concrete. However, the iron oxides, which form after the corrosion initiation, occupy a larger volume than the original steel and that creates pressure on the surrounding concrete. The latter leads to cracking and eventual spalling of the concrete cover that impairs the protection provided by concrete to reinforcing steel and may accelerate the deterioration process. Thus, corrosion damages reinforcing steel - due to the loss of its cross-sectional area, concrete - due to cracking, and bond between them. As a result, both the strength and serviceability of the structure degrade, e.g., [8–11].

The current approach in the design standards to mitigate the risk to RC structures posed by various deterioration processes is prescriptive, i.e., it specifies the requirements which need to be satisfied to ensure adequate durability of a RC structure in particular environmental conditions. However, there are still multiple cases of the deterioration of RC structures within their design life, especially due to corrosion, which damages the structure's reliability and result in costly repairs or even more severe consequences. As an attempt to cost-effectively improve the durability of RC structures and also to facilitate the use of new concretes a performance-based approach was proposed. The development of the prescriptive requirements, as well as the application of the performance-based approach, requires predicting the durability performance of a RC structure over its design life. For that, models describing the deterioration of RC structures over time due to the processes listed above are needed.

Models of the deterioration of RC structures are needed not only for the design of new structures but also for the assessment of existing structures, as well as for planning their inspection and maintenance, e.g., [12–14]. Uncertainties affecting the assessment of existing RC structures (or at least some of them) are different from those associated with the new design. In contrast to the latter, an existing structure can be monitored and/or inspected and new information about its properties and deterioration can be collected. Usually, there are uncertainties associated with this new information; in particular, due to inaccuracies of measurements, a limited amount of collected data, and the inability to measure directly the property of interest (e.g., remaining cross-sectional area of corroded reinforcing bars). This new information can also be combined with previously available data. Thus, probabilistic modelling of the deterioration processes for the design of new structures and the assessment of existing RC structures has attracted the attention of researchers, e.g., [6,15–17].

After repair the structure will probably be subjected to the same deterioration process. This means that it is necessary to be able to assess/predict the performance of repaired RC structures suffering from deterioration. However, probabilistic modelling of deterioration processes for repaired RC structures differs from that for the original ones due to uncertainties associated with repairs and because of that has become a separate topic of research [18].

The Joint Committee on Structural Safety (JCSS) and its members have made major contributions to modelling the deterioration processes in RC structures, especially within a probabilistic framework. In the following, the main developments in this area are presented and illustrated by case studies, with emphasis on the JCSS-related contributions. Section 2 provides a brief overview of past research on the deterioration of RC structures and its probabilistic modelling. In Section 3, probabilistic models of RC deterioration are presented, with the main focus on corrosion. Section 4 includes several case studies illustrating the application of the models described in the previous section. Section 5 discusses the remaining challenges and gaps in knowledge. Finally, Section 6 contains a brief summary and concluding remarks.

2. Overview of past research

2.1. Corrosion in RC structures

2.1.1. Initial developments from the 1960s to 2000

Over the last half-century, numerous models of different levels of complexity aimed to predict/describe the deterioration of RC structures have been developed, with the main focus on carbonation- and chloride-induced corrosion. In 1967, Hausmann experimentally investigated the initiation of chloride-induced corrosion in steel in an environment simulating concrete pores and derived a probabilistic model of the chloride threshold concentration [19]. In the 1970s and 1980s, the emphasis was on modelling the processes which cause the initiation of corrosion of reinforcing steel in concrete, i.e., the penetration of chloride ions and carbonation, and relatively simple deterministic models of these processes based on Fick's laws of diffusion were proposed, e.g., [5,20]. It should be noted that the seminal report by Tuutti [5] also covered many other factors related to the corrosion of reinforcing steel in concrete such as the effect of cement type, the influence of concrete cracking, the rate of corrosion after it started, and relevant laboratory studies. Thus, the report presented a methodology for the assessment of the service life of RC structures subjected to corrosion. In particular, it was suggested to divide this assessment into two stages – a corrosion initiation stage and a corrosion propagation stage, since the key parameters controlling these stages were essentially different. The report was a major step in developing the models for the prediction of corrosion-induced deterioration of RC structures, but this was done within a deterministic framework. At the same time, research also started on non-destructive techniques for measuring the corrosion rate on-site, with the laboratory study by Andrade and Gonzalez [21] on the polarization resistance method. Along with these theoretical and laboratory studies, research on the assessment of the condition/performance of existing RC structures, mainly bridges, subjected to reinforcement corrosion was also conducted [22]. The latter work paid special attention to two types of corrosion – general (or uniform) and localised (or pitting), which were observed in RC elements.

Research in the area was further expanded in the 1990s. The difference between general and pitting corrosion of reinforcing steel was studied experimentally [23]. More attention was also given to monitoring the condition of existing RC structures with corroding reinforcement, especially measuring the corrosion rate on-site and relating it to localised corrosion [24]. The propagation stage of corrosion was further studied, in particular, corrosion-caused cracking of the concrete cover [25]. Since there are significant uncertainties associated with the key parameters affecting the deterioration of RC structures (e.g., material properties, environmental conditions, loads), as well as with the models themselves, deterministic application of such models may produce misleading results. As a reflection of that, based on the outcomes of the previous experimental and theoretical studies, probabilistic models for predicting the effect of corrosion on RC structures, mainly bridges, started to be developed [8–10,26]. Most of these models [8,10,26] took into account both the initiation and propagation stages of corrosion, but for the latter stage pitting corrosion was only considered by Stewart and Rosowsky [10]. While omitting the initiation stage from their analysis, Val and Melchers [9] included modelling of pitting corrosion and reduction of bond strength between corroding reinforcement and concrete.

The probabilistic modelling of the initiation and propagation stages of chloride-induced corrosion was further addressed in [15]. All the above models did not account for spatial variability of corrosion, i.e., the reliability of a corroding RC member was assessed for its most critical section/location. One of the first probabilistic models which addressed the issue of spatial variability was a stochastic model of chloride ingress into concrete [27]. The model took into account spatial variability of the surface chloride concentration, the chloride diffusion coefficient, the thickness of the concrete cover, and the critical chloride threshold. It was also shown how the model could be applied to optimise the repair and maintenance strategy for a RC member in a marine environment.

Several major European projects dealing with the deterioration of RC structures were funded by the European Commission at the end of the 1990s – beginning 2000s. CONTECVET [28] concentrated on the assessment of existing RC structures suffering from corrosion of reinforcing steel. The project addressed mainly inspections of RC structures, modelling the structural effects of corrosion and checking the members of the structures subjected to deterioration for the ultimate and serviceability limit states. The results were presented in a deterministic format. Another project, DuraCrete, was dedicated to the probabilistic modelling of deterioration and durability design of RC structures [6] and benefited from the contributions of several JCSS members. The project primarily concentrated on probabilistic modelling of the initiation and propagation of corrosion, both due to carbonation and chloride ingress. Probabilistic models describing the corrosion initiation and propagation were formulated, and their parameters were quantified using available data and new experimental results. Some consideration was also given to other deterioration processes such as freeze/thaw attack, alkali-aggregate reaction and fatigue of pavements. The work done in DuraCrete was further continued in LIFECON [16], which integrated the probabilistic models of deterioration (once again with the main emphasis on corrosion of reinforcing steel) with the life-cycle management of RC structures. Later, the probabilistic models of carbonation- and chloride-induced corrosion (initiation stage only) and freeze–thaw attack, which were based on results of DuraCrete and LIFECON, were included in the *fib* Model Code for Service Life Design [29] and then in *fib* Model Code for Concrete Structures 2010 [30].

2.1.2. Further research in 2000–2010

An important event in the development of probabilistic models of RC deterioration was a workshop jointly organised by the JCSS and IABMAS in 2003 [7]. Although the workshop primarily aimed at establishing a common basis for the probabilistic modelling of RC structures' deterioration (i.e., summing up the results of previous research), several papers contributed to further advancements in the area. Progress was made in modelling the spatial variability of deterioration, updating the probabilistic models using inspection/monitoring data, and the use of probabilistic deterioration modelling for the life-cycle management of RC structures. The discussion of future research needs in the area was summarised in the workshop proceedings [7]. This makes it possible to compare the current research needs and gaps in knowledge with the situation 20 years ago which is presented in Section 5 of this paper.

To a large degree, research in the 2000s followed the directions identified at the workshop. A significant amount of work was done on modelling the spatial variability of deterioration, mainly in connection to chloride-induced corrosion [13,14,32–35]. Several of these papers addressed serviceability failures related to corrosion-caused damage (e.g., cracking of the concrete cover) in RC components with relatively large surface areas (e.g., bridge decks, tunnel walls) [11,13,14,34]. To account for the spatial variability of the parameters which affect corrosion in RC structures (e.g., surface chloride concentration, thickness of the concrete cover, chloride diffusion coefficient) these parameters were represented by homogeneous, usually normal (Gaussian) random fields with the exponential autocorrelation function. Due to the lack of data about the spatial correlation of such parameters in real RC structures, boundary cases such as no correlation and full correlation were usually considered. The dependence between corrosion levels at different locations across a RC component was also caused by modelling other important parameters (e.g., threshold chloride concentration) as random variables (i.e., each of such parameters had the same value across the entire component or its part under consideration). In addition to the spatial correlation, Frier and Sørensen [32] also modelled the temporal correlation of such parameters as the surface chloride concentration and chloride diffusion coefficient; however, their work dealt only with corrosion initiation. Sudret [36] showed that the expected extent of damage did not depend on how the spatial correlation was modelled, and the standard deviation of the damage extent was relatively insensitive to that.

Other papers considered the effect of spatial variability on the resistance and the ultimate state reliability of corroding RC members [31,33,35]. The papers focused on the corrosion propagation stage, especially on the spatial variability of pitting corrosion and its influence on failures of RC members in flexure [31] or in both flexure and shear [33]. Due to the lack of actual data, similar to the previously mentioned papers on spatial variability in the context of serviceability failures, only boundary cases of the spatial correlation of pitting corrosion, namely no correlation and full correlation, were analysed. Results of the analyses indicated that accounting for spatial variability of pitting corrosion led to higher probabilities of failure compared to those from non-spatial analyses. Spatial and temporal variability of corrosion, both general and pitting, was taken into account in [35] via the corresponding variations of the assumed corrosion rate to show how structural health monitoring (SHM) data on corrosion rate could be incorporated into structural reliability analysis.

Research was carried out on the quantification of uncertainties associated with the key parameters controlling the corrosion initiation such as the chloride threshold concentration. Breit [37] and later Alonso et al. [38] and Izquierdo et al. [39] derived probabilistic models for this parameter by statistical analysis of their experimental results, while Markeset [40] used measurements in real structures.

The use of inspection and/or SHM data for the reliability assessment of deteriorating RC structures was also addressed in several other papers published in the 2000s, including a couple of papers mentioned previously [11,14]. In these papers, a Bayesian approach to updating the probabilistic predictions of damage (cracking and spalling of the concrete cover) caused by chloride-induced corrosion in RC structures was presented. The updating was carried out using data collected by on-site inspections (visual and half-cell potential measurements). In [11], it was applied to assess relevant probabilities (e.g., of corrosion initiation, extent of damage), while in [14] it was incorporated into a framework for planning inspections and repairs of RC structures. The use of SHM data to update the probabilities of initiation of chloride-induced corrosion in RC bridges was considered in [41]. Data related to the ingress of chlorides – half-cell potential measurements, were to be collected with the help of sensors embedded at different depths in the structure and integrated with results provided by a predictive model via a Bayesian approach.

One of the main applications of the probabilistic deterioration models is the life-cycle management of RC structures, in particular, maintenance planning. Two papers published in the 2000s [13,14] dealt with maintenance planning in the context of serviceability failures due to cracking and spalling of the concrete cover caused by chloride-induced corrosion of reinforcing steel. Another approach to the life-cycle management of RC structures in chloride-contaminated environments involving the probabilistic deterioration modelling was presented in [12]. Only serviceability failures due to corrosion-induced damage to the concrete cover were considered. The approach was based on life-cycle costing and as such took into account both the initial and maintenance costs of the structure. The optimisation of the maintenance planning of corroding RC structures was also addressed in [42]. The main novel aspect of the paper was the use of cellular automata – a computational technique for simulations of the evolution of spatially distributed phenomena over time. It was applied to modelling the deterioration of the bending resistance of such structures due to chloride-induced corrosion. The model was then employed in probabilistic analyses to estimate the reliability of a RC structure and identify its optimal inspection/repair intervals.

To model the corrosion initiation stage all previously mentioned publications treated chloride ingress into concrete as a pure diffusion process which followed Fick's 2nd law of diffusion. This approach would be completely correct if chlorides are non-charged particles which diffuse due to concentration differences through fully saturated concrete pores without any interaction with the concrete. However, the reality is more complicated. First, chlorides bind with concrete, while only free chlorides can diffuse. Second, concrete pores are usually only partially saturated. Third, chlorides are ions and their interaction with other charged particles in the concrete pore solution may need to be taken into account. In the 2000s, the probabilistic models of corrosion initiation which accounted for some of these factors were published. Kong et al. [43] took into account chloride binding with concrete, while the concrete was assumed to be fully saturated; only a one-dimensional (1-D) formulation was implemented. Val and Trapper [17] also considered chloride binding but it was done for partially saturated concrete that required joint modelling of moisture and chloride transport in concrete; the problem was solved both for 1-D and 2-D formulations. Finally, at the beginning of the 2010s, Bastidas-Arteaga et al. [44] presented a probabilistic model of chloride ingress into concrete which covered chloride binding, moisture transport and heat transfer, both for 1-D and 2-D formulations.

The research was also initiated on the interaction between different deterioration processes and their combined effect on RC structures. Bastidas-Arteaga et al. [45] developed a probabilistic model which accounted for chloride-induced corrosion, caused by it cracking of the concrete cover and biodeterioration; the latter term referred to actions of living organisms which led to the reduction of the concrete cover thickness. The model was applied to evaluate the combined effect of these deterioration processes on the ductility and associated with it reliability of a RC pile in a marine environment. In another paper [46], a probabilistic model of the interaction between two deterioration processes – chloride-induced corrosion and fatigue, was proposed and then used to estimate the probability of failure of a RC bridge girder due to fracture of its reinforcing bars. The effect of corrosion of reinforcing steel on the performance, reliability and life-cycle cost of RC structures subjected to natural hazards such as earthquakes was also studied [47,48]. Corrosion can also affect prestressing steel in prestressed concrete structures that is potentially more dangerous since it can lead to sudden brittle failure of such structures. A probabilistic model of the resistance of post-tensioning strands subjected to corrosion was developed by Gardoni et al. [49] based on extensive experimental data.

2.1.3. *Recent developments from 2010*

In the 2010s and early 2020s, research was mainly conducted on the same topics as in the past, one of which was the reliability assessment of corroding RC structures. Akiyama et al. [50] presented a method based on sequential Monte Carlo simulation (MCS) for the time-variant reliability assessment of RC structures in marine environments. The method included several empirical models/relationships in which parameters were estimated/updated using observational (i.e., on-site inspection) data. It was illustrated by the calculation of the time-variant probabilities of failure in flexure of RC slabs with corroding reinforcement. Hackl and Köhler [51] proposed to use dynamic Bayesian networks to combine information provided by existing probabilistic models of corrosion initiation and propagation (adopted primarily from DuraCrete [6]) with inspection/SHM data to evaluate the probabilities of corrosion initiation and failure of RC beams. A probabilistic framework for assessing the time-variant flexural reliability of post-tensioned concrete bridges in corrosive environments was presented in [52].

The issue of spatial variability also continued to attract research attention. The effects of the spatial variability of material/structural properties and environmental factors on the probabilities of chloride-induced corrosion initiation [53] and cracking of the concrete cover caused by such corrosion [54] were investigated. In both papers, special attention was given to the generation of the random fields, both Gaussian and non-Gaussian, for modelling the spatial variation of relevant parameters (e.g., surface chloride concentration, chloride diffusion coefficient, critical/threshold chloride concentration, thickness of the concrete cover). The spectral representation method was employed for this purpose. It was noted in both papers that there was no sufficient actual data for determining the scale of fluctuation (or the correlation distance) for the above parameters. The latter issue was addressed in [55,56], where data on the spatial variation of the surface chloride concentration and chloride diffusion coefficient were collected on two road bridges – one in Ireland [55] and the other in Norway [56], and then analysed to determine the scales of fluctuation and autocorrelation functions for these parameters. Pedrosa and Andrade [57] conducted a laboratory study to obtain data on the spatial variability of the corrosion rate. Another study to collect information on the statistical properties of the corrosion rate in real structures was undertaken in [58].

The research was also carried out on the spatial variation of localised (pitting) corrosion of reinforcing steel and its influence on the ultimate limit state reliability of RC beams. Kioumarsi et al. [59] proposed a probabilistic model for the distribution of pits of random sizes along the length of a reinforcing bar and then investigated how the spatial variation of pits on two bottom longitudinal rebars of a simply supported RC beam affected the failure probability of beams in flexure when uniform corrosion was also present. Based on the results of accelerated corrosion tests, Srivaranun et al. [60] derived a multi-variate random field model to simulate a non-uniform distribution of the steel weight losses due to both uniform and pitting corrosion across several parallel rebars, i.e., along the length of each rebar and between the rebars. The model was then employed to estimate the probabilities of failure in flexure of RC girders with different numbers of corroded tensile rebars. Spatial variability of the parameters controlling chloride-induced corrosion was also considered in [61,62] in the context of its effect on the probability of failure of RC beams in flexure. In [61], it was done to more realistically model the performance of RC structures subjected to corrosion, while the main aim of that paper was to present a framework for the optimisation of inspection and repair strategies for such structures; in particular, that included the estimation of the value of information (VoI) of different inspection options. The other paper specifically concentrated on modelling the spatial variation (or correlation) of the parameters controlling the corrosion initiation and propagation such as the time to corrosion initiation and corrosion rate, and how this modelling could affect the estimated probability of failure [62].

More work has also been done on the combined effect of corrosion and other deterioration processes. For example, a coupled probabilistic model of corrosion and load-induced flexural cracking was proposed and then applied to assess the time-variant reliability of simply supported RC beams made from different types of concrete [63].

A new research topic, which emerged in the 2010s, was related to climate change, i.e., how an increase in the atmospheric CO_2 concentration and associated climatic changes could affect the corrosion-caused deterioration of RC structures. Probabilistic models of chloride- and carbonation-induced corrosion, which took into account future changes in the atmospheric CO_2 concentration, temperature and relative humidity, were proposed and then applied to investigate this phenomenon, e.g., [64–66]. It was shown that for certain climatic conditions climate change could accelerate the deterioration of RC structures due to corrosion and that adaptation measures improving the resistance of such structures to corrosion would need to be undertaken.

2.2. *Other deterioration processes in RC structures*

2.2.1. *Freeze-thaw action*

Freeze/thaw (F/T) (or frost) action is one of the major causes of deterioration of RC structures in cold climates. In simple terms, it is often explained as follows: water in the concrete pores when freezes increases its volume by about 9 % that creates hydrostatic pressure on the surrounding concrete leading to its damage, which accumulates over F/T cycles. In reality, this is a complex combination of physico-chemical processes which may lead to two types of concrete deterioration: (i) internal damage/cracking that degrades the properties of bulk concrete (e.g., modulus of elasticity, compressive and tensile strength); and (ii) surface (or salt) scaling, when flakes of concrete split from its surface if the latter is in contact with cyclically freezing/thawing saline water. Several theories associated with different mechanisms have been introduced to explain the development of these two deterioration types. Powers [67] explained the internal damage to concrete by hydraulic pressure generated during pore water freezing. A few years later, Powers and Helmuth [68] showed that freezing of saline water led to osmotic pressure that partially explained surface scaling. Scherer [69] suggested that internal damage to concrete could also be caused by the growth of ice crystals in the pores, i.e., crystallization pressure. Further observations and experiments demonstrated that not all characteristics of surface scaling could be explained by the previously mentioned mechanisms, and to address that the glue spall theory was proposed [70]. A review of theories and modelling methods of concrete deterioration due to F/T action can be found in [3,71].

The deterioration due to F/T action depends on the concrete air content, degree of pore saturation, pore structure, presence of salt, concrete properties and environmental conditions. In particular, it was observed that if the degree of pore saturation is below a certain critical level then damage due to F/T action does not occur [72]. One of the main protective measures against F/T action is the use of air-entrained admixtures; other measures include the use of supplementary cementitious materials (SCM), hydrophobic coating, etc. [73].

There are many uncertainties associated with this type of concrete deterioration and its modelling because of the complexity of the process and the large number of factors affecting it. However, limited work has been done on its probabilistic modelling. Fagerlund [74] suggested estimating the probability of frost damage as the probability of the actual degree of pore saturation exceeding its critical value when both these parameters were treated as random variables. Probabilistic modelling of the internal concrete damage due to F/T cycles was considered in [75]. The damage was expressed in terms of accumulated residual tensile strain; the water-cement ratio, the entrained air content and the number of F/T cycles were treated as normal random variables with arbitrarily selected parameters, and the response surface method was employed for the calculation of the probability of failure. A probabilistic model relating the internal damage to concrete (in terms of the relative reduction of its fracture energy) with the number of F/T cycles was derived in [76]. The model parameters were estimated using the results of cohesive fracture tests of concrete specimens made with low-degradation aggregates. A similar approach was employed in [77], but the internal damage was expressed in terms of the reduction of relative dynamic modulus of elasticity and only non-air-entrained concretes were considered. An analytical approach to modelling the probability of internal concrete damage due to F/T cycles was adopted in [78]. The limit state function was expressed as the difference between the tensile strength of hardened cement paste and the internal hydraulic pressure, which was calculated using Powers' theory [67]. The compressive strength of the paste, total entrained air content and spacing factor were considered as random variables.

2.2.2. Alkali-aggregate reaction

Alkali-aggregate reaction (AAR) refers to chemical reactions between alkali hydroxides (K^+, Na^+, OH^-) in the concrete pore solution with certain minerals contained in the concrete aggregates. Depending on the type of the minerals it is common to distinguish: (i) alkali-carbonate reaction (ACR); and (ii) alkali-silica reaction (ASR). In the case of ACR, the mineral is dolomite ($CaMg(CO_3)_2$), which is contained in dolomitic limestone. The second type, ASR, is more widespread and occurs when the aggregates are rocks with inclusions of metastable silica minerals (e.g., opal, tridymite), volcanic and artificial glass, or very fine-grained quartz [1]. Although the mechanisms of ACR and ASR are different, they lead to similar consequences – the products of the reactions expand causing concrete cracking and internal damage that, like F/T action, degrades the concrete mechanical properties such as strength and modulus of elasticity. Moreover, when ASR deterioration reaches a certain level it can damage the bond between concrete and reinforcing steel [79] and even cause fracture of reinforcing steel bars [80].

Three conditions need to be in place for AAR to occur: (i) aggregates should contain reactive minerals; (ii) the alkalinity of the concrete pore solution should be high; and (iii) enough moisture should be in the concrete. The mechanisms involved in AAR are complex and, in addition to the factors controlling the above conditions, depend on many other factors such as the concrete mix composition (e.g., presence of SCM), pore structure, environmental (e.g., temperature, humidity) and load (e.g., confinement, stress levels) conditions, and reinforcement. Therefore, modelling of AAR and its structural consequences is a very challenging problem. Numerous analytical and numerical models at different scales and levels of complexity have been proposed to solve it [81,82].

The complexity of AAR and the large number of factors controlling it indicate that there are many uncertainties associated with this deterioration process and its modelling. In such a case, the use of probabilistic modelling is beneficial but also complicated, and so far, very few studies addressed this issue. Capra and Sellier [83] noted that modelling of AAR was strongly affected by the randomness of the location of reactive mineral inclusions and the imperfect knowledge of the reaction mechanisms. In their AAR model, they used elements of probabilistic damage mechanics; in particular, introduced the probabilities of cracking (defined by a Weibull distribution) due to AAR and mechanical loading and then included these probabilities in the calculations of the damage coefficients and strains. However, the results of their analyses were in a deterministic format. A probabilistic model taking into account the ASR effect on the reinforcing steel–concrete bond behaviour was presented in [79]. A model which described the deterioration of RC structures due to the combined effect of corrosion and earthquakes and accounted for the influence of ASR on the initiation of chloride-induced corrosion was developed in [84]. So far, there is no fully probabilistic model covering all aspects of the deterioration of RC structures due to AAR. This lack of modelling is mainly due to the problem's complexity and, as a result of that, the emphasis on preventing AAR (e.g., the use of non-reactive aggregates, limiting the concrete alkalinity, use of SCM [1]) rather than accounting for it in design.

2.2.3. Sulphate attack, calcium leaching and sulphate corrosion

Sulphate attack refers to a series of chemical reactions between sulphate salts (e.g., Na_2SO_4, K_2SO_4, $MgSO_4$) and compounds of the hardened cement paste such as portlandite ($Ca(OH)_2$), calcium silicate hydrate (C – S – H) and calcium aluminates (e.g., tricalcium aluminate C_3A). As a result of these reactions, precipitates – gypsum, ettringite and, under certain conditions, thaumasite, or their mixtures, are formed. Their formation can lead to concrete deterioration due to expansion, cracking, loss of strength and spalling [2,85]. It is common to distinguish between external and internal sulphate attack. In the first case, sulphates ingress from an environment (e.g., underground – from ground waters, offshore – from seawater); in the second, sulphates are contained in the components used for the concrete mix production. External sulphate attack is of most concern and, as such, has attracted more research interest.

Calcium leaching occurs when the concrete surface is in contact with pure or acidic water; the latter means that it can take place concurrently with sulphate attack. The process is initiated by the concentration gradient for calcium ions at the contact between such external water and the concrete pore solution, which leads to the diffusion of calcium ions from the concrete pores to the surrounding environment. As a result of that, the calcium concentration in the pore solution decreases causing the dissolution of portlandite and the decalcification of C – S – H. The decalcification front gradually progresses inside the concrete reducing its alkalinity, changing microstructure (e.g., increasing the pore volume) and degrading mechanical properties (e.g., reducing the compressive strength) [2].

The term “sulphate corrosion” is often used interchangeably with sulphate attack but technically this is not correct because they refer to two different mechanisms. Microbiologically induced sulphate (or sulphide) corrosion is a common problem for RC sewers [86]. Initially, bacteria reduce sulphate (SO_4^{2-}), which is always present in wastewater, into sulphide (S^{2-}). The latter is then chemically converted into hydrogen sulphide gas (H_2S), and after that other bacteria convert H_2S into sulphuric acid (H_2SO_4), which attacks the inner surface of sewage pipes. The chemical reactions caused by this attack are similar to those of sulphate attack and lead mainly to the formation of gypsum (i.e., calcium sulphate), which does not have any binding capacity and is easily washed off from the pipe surface. This results in the loss of concrete on the inner surface of the pipes.

Modelling the above deterioration processes is a complicated task because it should account for three phenomena – (i) diffusion of ions, (ii) chemical reactions, and (iii) mechanical damage to concrete. This usually requires the use of numerical methods, e.g., finite element analysis [85,87,88]. Hence, similar to AAR, rather than relying on modelling these deterioration processes, especially sulphate attack and leaching, it is common practice to concentrate on prescriptive preventive methods (e.g., using special concrete mix design, application of surface coatings, etc.) to mitigate any potential damage. As a result of that, very few probabilistic models of sulphate attack and leaching have been proposed so far [89,90]. Modelling of the deterioration processes (i.e., sulphate attack and leaching) in both works takes into account all three phenomena and is implemented using a finite-element method. Uncertainties associated with environmental conditions, material properties and available data are taken into account. MCS-based probabilistic analysis was coupled with a special vector regression algorithm to accelerate the calculation process in [90].

Since sulphate corrosion of RC sewers is difficult to prevent, it needs to be considered in their design and assessment. For this purpose, simple empirical models/formulas for estimating the loss of concrete over time are often employed, e.g., [91–93]. Based on these empirical formulas, simple probabilistic models have been proposed for estimating the probability of failure of RC sewers due to sulphate corrosion [94,95].

2.2.4. Fatigue

The issue of fatigue of RC structures has been around for a long time, mainly in the context of the design and assessment of RC bridges. There are currently provisions for the fatigue design of RC structures in relevant standards, e.g., [96]. One of the first publications on probabilistic modelling of fatigue in RC structures in the context of their reliability-based design was by Warner [97]. Several possible design formats were considered and the format in terms of the number of cycles to failure (or design fatigue life) was recommended. The code calibration procedure was described, including the selection of the target safety level and the evaluation of the safety factor. Crespo-Mingullion and Casas [98] presented a probabilistic model for the reliability analysis of prestressed concrete bridges based on the S-N curves and the Palmgren-Miner linear damage accumulation rule. A probabilistic fatigue damage model for the reliability analysis of RC structures deteriorating under high-cycling loading was presented in [99], combining a non-linear finite element modelling with the response surface method to calculate the time-dependent probability of failure.

More recently, a novel probabilistic method for the evaluation of concrete fatigue life was proposed in [100]. The method included a stochastic damage model of concrete, which was calibrated using available experimental data. Mankar et al. [101] presented a probabilistic framework for the reliability assessment of an existing RC bridge deck for the fatigue limit state when new data obtained by monitoring were available. The data included weight-in-motion (WIM) data on traffic and temperature and strain measurements and were used to update a stochastic traffic load model, modify existing S-N curves for concrete, and accurately estimate load effects (i.e., stresses). Results of the reliability analysis were employed to calibrate the partial safety factor for material (i.e., concrete compression strength). The reliability assessment of reinforcement of RC bridge girders in terms of fatigue was considered in [102]. It was assumed that WIM data were available for the analysis. The reliability indices for longitudinal reinforcement and stirrups were calculated for different bridge dimensions.

Fatigue is an important problem for RC components of wind turbines. Velarde et al. [4] carried out the reliability-based calibration of the partial safety material factor for the fatigue design of RC gravity-based foundations of such turbines. A probabilistic load model was specifically developed for offshore wind turbines; model uncertainties associated with fatigue resistance were considered according to the DNV standard [103].

3. Probabilistic deterioration models

3.1. Probabilistic modelling of corrosion of reinforcing steel and its effects

Established probabilistic models of corrosion initiation and propagation, which are currently used in practice, are briefly described in this section.

3.1.1. Corrosion initiation: Chloride-induced corrosion

For practical applications, it is usually assumed that chloride ingress into concrete is described by Fick’s 2nd law of diffusion, which in a 1-D formulation can be expressed by the following differential equation:

$$\frac{\partial C}{\partial t} = \frac{\partial}{\partial x}\left[D(x,t)\frac{\partial C}{\partial x}\right] \quad (1)$$

where C is the chloride concentration at distance x from the concrete surface at time t, and $D(x,t)$ the chloride diffusion coefficient, which in general can change with x and t. To solve Eq. (1) the boundary and initial conditions must be defined:

$$C(0,t) = C_s(t)$$

$$C(x,0) = C_i(x) \quad (2)$$

where $C_s(t)$ is the surface chloride concentration which may vary with time, and $C_i(x)$ the initial chloride concentration which can change with the distance from the surface. The solution of Eq. (1) depends on the formulations of the $D(x,t)$, $C_s(t)$ and $C_i(x)$ functions.

It is common to assume that C_s and C_i are constants, while the chloride diffusion coefficient decreases over time [30]. If temperature is taken into account then the chloride diffusion coefficient can be estimated as

$$D_{app} = D_{ref}\left(\frac{t_{ref}}{t}\right)^{m_c}\exp\left[b_T\left(\frac{1}{T_{ref}} - \frac{1}{T}\right)\right] \quad (3)$$

where t_{ref} and T_{ref} are the reference time and temperature, respectively; D_{ref} the value of D_{app} at the reference conditions; m_c the age factor; and $b_T = U_c/R$, in which U_c is the activation energy of the chloride diffusion process and R the gas constant. It needs to be explained that D_{app} denotes the apparent chloride diffusion coefficient because it represents its average value over the time interval t. Under these assumptions, the solution of Eq. (1) becomes [30]

$$C(x,t) = \left\{C_0 + (C_s - C_0)\left[1 - \mathrm{erf}\left(\frac{x}{2\sqrt{D_{app}t}}\right)\right]\right\} \quad (4)$$

where C_0 is the constant initial chloride concentration, and erf(.) the error function. It is worth noting that the solution (i.e., Eq. (4)) looks slightly different to the one in [29,30] because in the latter it is taken into account that in a relatively thin surface concrete layer (of the thickness Δx) the chloride ingress is controlled by convection and not diffusion.

The problem becomes significantly more complex when dealing with a repaired RC structure, where the outer concrete layer (slightly thicker than the cover thickness) has been replaced with fresh concrete. In this case, the concrete medium should be divided into two domains – one representing the new concrete and the other one the original concrete. The initial and boundary conditions (Eq. (2)) will be different for each domain, as well as the values of the chloride diffusion coefficient [18]. A simple analytical solution, like Eq. (4), does not exist and a numerical solution, e.g., by a finite element method, is required.

Corrosion starts when the chloride concentration near reinforcing steel reaches its threshold value, C_{crit}, i.e., $C(c,t) \geq C_{crit}$, where c is the thickness of the concrete cover. To account for uncertainties associated with the time of corrosion initiation, the parameters in Eqs. (3) and (4) such as D_{ref}, m_c, b_T (or U_c), C_s, along with C_{crit} and c are usually treated as random variables, which probabilistic description can be found in [29] and other relevant publications (e.g., [37–40] with data on C_{crit}). The probability of corrosion initiation, P_{ini}, is then time-dependent and can be calculated as $P_{ini}(t) = \Pr[C(c,t)) \geq C_{crit}]$.

3.1.2. Corrosion initiation: carbonation-induced corrosion

The penetration of carbon dioxide into concrete is usually modelled by Fick's 1st law of diffusion which in a 1-D formulation can be written as

$$J_{CO_2} = D_{CO_2}\frac{\partial C_{CO_2}}{\partial x} \tag{5}$$

where J_{CO2} is the flux of CO_2, C_{CO2} the concentration of CO_2, and D_{CO2} the diffusion coefficient of CO_2 in concrete. Since the flux can be expressed as $J_{CO_2} = A_c \times dQ_{CO_2}/dt$, Eq. (5) can be re-written as

$$dQ_{CO_2} = A_c D_{CO_2}\frac{\Delta C_{CO_2}}{x}dt \tag{6}$$

where Q_{CO2} is the mass of diffusing CO_2, A_c the surface area of concrete, ΔC_{CO2} the difference in the CO_2 concentration in the atmosphere and at the carbonation front, and x the distance from the concrete surface to the carbonation front. Since $dQ_{CO_2} = bA_c dx$, where b is the CO_2-binding capacity of concrete, the solution of Eq. (6) is

$$x_c(t) = \sqrt{\frac{2D_{CO_2}\Delta C_{CO_2}}{b}}\sqrt{t} \tag{7}$$

where $x_c(t)$ is the carbonation depth at time t. Often, it is written in a simpler form as $x_c(t) = A\sqrt{t}$, where A represents the carbonation rate.

In [29,30], Eq. (7) is expressed in a different form, to account for some other factors, which affect the carbonation rate

$$x_c(t) = \sqrt{2k_e k_c R_{NAC,0}^{-1} C_{CO_2,s}}\sqrt{t}W(t) \tag{8}$$

where k_e is the so-called environmental function which takes into account the influence of the concrete relative humidity (RH), k_c accounts for the duration of curing, $R_{NAC,0}^{-1}(=D_{CO_2}/b)$ the inverse effective carbonation resistance of concrete at RH = 65 %, $C_{CO_2,s}$ the atmospheric concentration of CO_2, and $W(t)$ the weather function which accounts for the exposure of the concrete surface to rain.

Corrosion starts when the carbonation depth, $x_c(t)$, becomes equal to the thickness of the concrete cover, c. To account for uncertainties associated with the CO_2 ingress into concrete several parameters in Eq. (8), e.g., $R_{NAC,0}^{-1}$, $C_{CO_2,s}$, are treated as random variables. Their probabilistic description, as well as the description of the functions k_e, k_c and $W(t)$, can be found in [29]. The probability of corrosion initiation due to carbonation is time-dependent and can be calculated as $P_{ini}(t) = \Pr[x_c(t)) \geq c]$.

3.1.3. Corrosion propagation

The key parameter controlling corrosion propagation and damage is the corrosion rate. When an existing RC structure is assessed, the corrosion rate can be measured on-site in terms of the corrosion current density, i_{corr}; however, electrochemical techniques available for that need to be applied and interpreted by specialists [104,105]. As with all measuring methods, uncertainties associated with the measurement technique should be taken into account in the assessment of the structure.

When such measurements are not possible, an empirical model relating the corrosion rate, V_{corr}, with the concrete resistivity, $\rho(t)$, is often employed [6,16]

$$V_{corr}(t) = \frac{m_0}{\rho(t)}F_{Cl}[\mu\text{m/year}] \tag{9}$$

where m_0 is a constant regression parameter equal to 882 μm·Ωm/year, and F_{Cl} the chloride content factor (accounts for the influence of chlorides on the corrosion rate). The corrosion penetration at time t, $p_{corr}(t)$, can then be found as $p_{corr}(t) = \int_{t_{ini}}^{t} V_{corr}(\tau)d\tau$, where t_{ini} is the time of corrosion initiation The concrete resistivity depends on several factors and is expressed as

$$\rho(t) = \rho_0 k_{R,T} k_{R,RH} k_{R,Cl}\left(\frac{t}{t_0}\right)^n \tag{10}$$

where ρ_0 is the specific electrical concrete resistivity in (Ωm) at time t_0, $k_{R,T} = \exp[b_{R,T}(1/T_{real}\text{-}1/T_0)]$ the temperature factor, $k_{R,RH}$ the relative humidity factor, $k_{R,Cl}$ the chloride factor (accounts for the influence of chlorides on the resistivity, t (≤365 days) the age of concrete, and n the ageing factor for resistivity. Uncertainties associated with the prediction of the corrosion rate are taken into account by treating ρ_0, $b_{R,T}$, $k_{R,RH}$ and n as random variables. Their probabilistic description is available in [6,16]. More recent data on the variability of V_{corr}, especially its spatial variability, can be found in [57,58].

There are models relating various deterioration effects of corrosion with V_{corr}. The calculation of the remaining cross-sectional area of a corroding reinforcing bar depends on the type of corrosion. In the case of uniform corrosion, the remaining diameter of the bar at time t is easily found as its original diameter minus $2p_{corr}(t)$. In the case of pitting corrosion, the pit depth can be assessed as $p_{corr}(t)$ times the pitting factor [23], whose maximum value can be described by a Gumbel distribution [106]. After the pit depth has been found, the remaining cross-sectional area of the bar can be calculated as, e.g., the area of a circle with a diameter equal to the original diameter minus the pit depth [23,28], or the original area minus the area of the hemispherically shaped pit [9].

Corrosion causes cracking of the concrete cover which can lead to serviceability failure. There are many relatively simple empirical and analytical models relating the corrosion rate with the time of crack initiation, or this time can be estimated numerically by finite element analysis [107,108]. There are also models relating the crack growth (or width) with the corrosion rate, e.g., [109,110]. Corrosion can cause damage to the bond between reinforcing steel and concrete; this can also be modelled when the corrosion rate and, subsequently, the corrosion penetration into the steel are known, e.g., [28,111,112]. The loss of the cross-sectional area of reinforcing steel and damage to the bond can then be taken into account to assess the effect of corrosion on the strength and subsequently, reliability of RC structures, using either simple empirical/analytical models, e.g., [8,10,26,31,33] or finite element analysis, e.g., [9,113]. As noted above, serviceability failure can be caused by excessive cracking and its probability, $P_{f,s}$, can be calculated as $P_{f,s}(t) = \Pr[a(t) \geq a_{lim}]$, where $a(t)$ is the width of a corrosion-induced crack and a_{lim} the limit crack width (e.g., $a_{lim} = 0.3$ mm). In terms of ultimate limit state, the probability of failure, $P_{f,u}$, can be defined as $P_{f,u}(t) = \Pr[R(t) \leq S(t)]$, where $R(t)$ is the resistance (e.g., bending strength, shear strength) which deteriorates over time and $S(t)$ the corresponding load effect which, in general, is also time-dependent.

3.2. Probabilistic modelling of other deterioration processes

Probabilistic modelling of other deterioration processes (except for fatigue) is much less developed compared to corrosion of reinforcing steel. In this section, more or less commonly accepted elements of existing models for these deterioration processes are presented.

3.2.1. Freeze/thaw (F/T) action

There are two types of deterioration due to F/T action: internal damage and surface scaling. It has mainly been agreed that no internal damage occurs when the actual degree of pore saturation, S_{act}, is less than its critical value, S_{cr}. The latter can be considered as a random material property and determined experimentally [74], while S_{act} can be treated as either a stochastic function or a time-variant function of random variable(s), i.e., $S_{act}(t)$. The probability of internal damage initiation is then $P_{F/T,ini}(t) = \Pr[S_{act}(t) \geq S_{cr}]$. The unresolved issue is how to model $S_{act}(t)$, although some suggestions in this respect have been made [74].

After its initiation, internal damage to concrete accumulates with an increasing number of F/T cycles. It is common to present the damage, D, in terms of the dynamic modulus of elasticity of concrete, E_d, or more exactly, its relative value – relative dynamic modulus (RDM), i.e., $D(N) = 1 - E_d(N)/E_{d,0}$, where $E_{d,0}$ is the initial value of this modulus and N the number of F/T cycles. Various relationships between D and N (i.e., D – N curves) for E_d and some other mechanical characteristics of concrete have been proposed [71]. Significant uncertainties associated with the D – N curves can be described by assigning probabilities to these curves based on experimental results by analogy with S – N – P curves in fatigue [76,77].

Currently, there is no proper probabilistic model describing surface scaling.

3.2.2. Alkali-aggregate reaction (AAR)

There are no probabilistic models of concrete deterioration due to AAR. It can be suggested that similar to F/T action uncertainties associated with the deterioration caused by AAR are taken into account by relating the AAR expansion (%) – D curves with probabilities using experimental data.

3.2.3. Sulphate attack, calcium leaching and sulphate corrosion

Sulphate attack and calcium leaching are complex chemo-physical–mechanical processes. The probabilistic models, which have been proposed for their simulation, strive to address this complexity by considering all relevant mechanisms (i.e., diffusion of ions, chemical reactions and mechanical damage) [89,90]. However, because the models are complicated, they have not been independently verified and sufficiently tested.

Available probabilistic models of sulphate corrosion are based on simple empirical formulas for predicting the loss of concrete over time [94,95]. However, the probabilistic description of the random variables appearing in these models has not been properly justified and looks rather arbitrary.

3.2.4. Fatigue

Probabilistic modelling of fatigue for RC structures is typically based on the S – N – P curves and the Palmgren-Miner linear damage accumulation rule with some possible modifications and adjustments, e.g., [97,100–102]. Generally, the probability of failure due to fatigue can be expressed as $P_f = \Pr\left[\sum_i n_i/N_i \geq DM\right]$, where N_i is the number of cycles to failure for the stress range $\Delta\sigma_i$, n_i the actual number of cycles for this stress range, DM the so-called variable damage of Miner which represents the fatigue resistance.

4. Case studies

4.1. Improving the prediction of carbonation in cooling towers using inspection data

Usually, uncertainties related to the prediction of the carbonation depth in a RC structure are large so the assessment of the structure condition and planning its maintenance may significantly benefit from new information collected during on-site inspections. However, this new information is also associated with uncertainties (e.g., due to inaccuracies and/or a limited number of measurements) and often combined with previously available data (i.e., prior information). This case study aims to demonstrate how uncertainties related to prior information about the carbonation depth can be quantified and how collecting structure-specific data through an on-site inspection can improve this depth prediction.

The probabilistic analysis of carbonation is focused on the outer surface of the shell of a cooling tower (hereafter simply '*shell*') located in the Czech Republic, in an area with negligible chloride exposure. The *shell* was cast in 1970 with concrete of the strength class equivalent to C20/25, with improved resistance against bleeding, freeze–thaw attacks and chemical degradation. Based on limited information, it is judged that the cement in the concrete mix was similar to CEM I with a strength of about 40 MPa, and its content was about 350–375 kg/m^3. The water-cement (w/c) ratio was about 0.55. From the level + 23 m to the top (+100 m) of the *shell*, its thickness is 130 mm and the nominal concrete cover is 20 mm.

Assuming that initially no measurements of time-dependent carbonation depth, $x_c(t)$, in the *shell* are available, the carbonation progress can be modelled based on prior information. According to [114], $x_c(t)$ can be estimated as

$$x_c(t) = A\, t^{0.5-\eta} \tag{11}$$

where A [mm/year$^{0.5-\eta}$] denotes the carbonation rate primarily reflecting the diffusion properties of concrete and the model uncertainty accounting for deliberately ignored effects (e.g., due to coating, freeze–thaw cycles, thermal actions, stresses and microcracks), other simplifications of the model (e.g., considering concrete diffusion properties time-invariant, representing fluctuating relative humidity by a long-term average value), and unknown effects; η is the exponent reflecting local climatic conditions.

Prior information on the depth of carbonation is based on the large dataset [115], containing about 2200 measurements of the carbonation depth in 31 cooling towers (age 10–40 years). The cooling towers are located in the Czech Republic, so it is assumed that they were all built from similar materials, using similar technologies and exposed to similar environmental conditions as the *shell*. The dataset does not contain a time series of measurements of x_c and provides an insufficient basis for inferring statistical characteristics of the exponent η. According to [114], the exponent is equal to 0 for indoor conditions and 0.3 for unsheltered outdoor conditions. The detailed analysis presented in [116], which was based on the carbonation model from *fib* MC 2010 [30] (including its weather function; see Eq. (8)), yielded $\eta = 0.15$. Using data from the meteorological station nearest to the *shell*, the probability of driving rain of 50 % and the relative time of wetness of 13 % are considered. When the product of the probability of driving rain and the relative time of wetness is doubled (for windy regions with wet climates), η increases up to 0.2. Following the recommendations of [30] regarding the weather function, the coefficient of variation of η is about 0.45, and a normal distribution might be considered for η in the absence of other information.

The dataset in [115] can now be utilised to infer prior statistical characteristics of the carbonation rate A, namely, its mean, μ_A', and standard deviation, σ_A', which values are shown in Fig. 1, and where "'" denotes prior information. The analysis yields the expected value of μ_A',

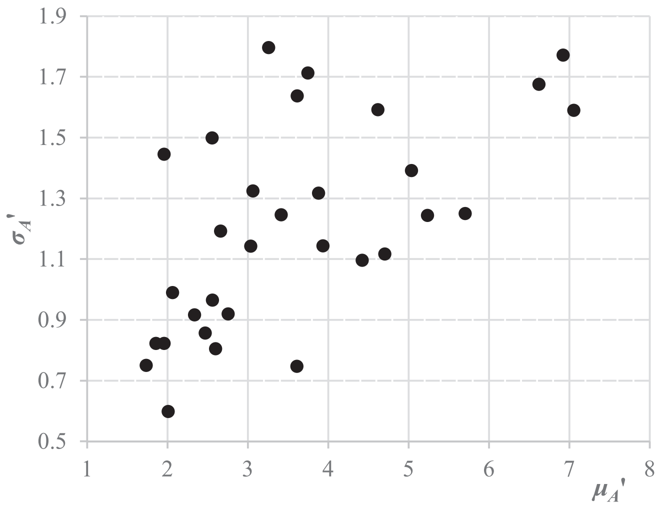

Fig. 1. Variability of the prior mean and standard deviation of the carbonation rate A (in mm/year$^{0.35}$).

$E(\mu_A') = 3.59$ mm/year$^{0.35}$ with the coefficient of variation $CoV(\mu_A') = 0.42$, and the expected value of σ_A', $E(\sigma_A') = 1.25$ mm/year$^{0.35}$ with $CoV(\sigma_A') = 0.28$, with a significant degree of statistical dependence between them (correlation coefficient of 0.6).

Following ISO 2394:2015 [117], these characteristics may be recalculated to:

- a hypothetical number of observations for the prior mean $n'_A \approx \{E(\sigma_A')\,/\,[E(\mu_A')CoV(\mu_A')]\}^2 = 0.7$;
- a hypothetical number of the degrees of freedom for the prior standard deviation $\nu'_A \approx 1/[2CoV(\sigma'_A)^2] = 6.4$.

Fig. 2 illustrates how the carbonation depth changes with the time since construction, t, based on the prior information (the effects of a changing climate are ignored); the best estimates and 80 % confidence intervals are shown until $t = 37$ years when measurements of the carbonation depth were made during an on-site inspection. The prior confidence interval is wide and its upper bound exceeds the nominal concrete cover of 20 mm at $t = 25$ years, i.e., it is expected that at that time the carbonation front reaches reinforcing steel on about 10 % of the area of the *shell*.

Using the results of a single on-site inspection of the *shell* at $t = 37$ years, it is checked whether combining the prior information with available limited measurements reduces statistical uncertainty. The measurements were taken at ten locations representative of the

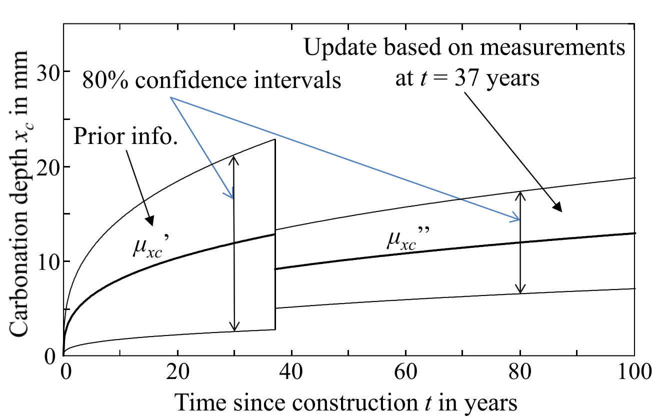

Fig. 2. Prediction of carbonation depth based on prior and updated models (mean estimates and 80% confidence intervals).

conditions of the whole *shell*. Their statistical analysis yielded the following results:

- Carbonation depth: mean $\mu_{xc} = 8.7$ mm and standard deviation $\sigma_{xc} = 6.3$ mm corresponding to $\mu_A = 2.46$ mm/year$^{0.35}$, $\sigma_A = 1.78$ mm/year$^{0.35}$ for $\eta = 0.15$, with $n = 10$ and $\nu = n - 1 = 9$.
- Concrete cover: $\mu_c = 21.6$ mm and $CoV_c = 0.13$.
- In-situ concrete compressive strength: $\mu_{fc} = 31.8$ MPa and $CoV_{fc} = 0.15$.

Bayesian updating of carbonation rate A is based on a simplified approach provided in [117]. The parameters of the posterior distribution of A are:

$$n'' = n' + n - 1 = 6.4 + 9 - 1 = 14.4$$

$$n'' = n' + n = 0.7 + 10 = 10.7$$

$$\mu''_A = \frac{(n'\mu'_A + n\mu_A)}{n''} = \frac{(0.7\times 3.59 + 10\times 2.46)}{10.7} = 2.56\,\frac{mm}{year^{0.35}}$$

$$\sigma''_A = \sqrt{\frac{\left[\nu'\sigma'^2_A + \nu\sigma^2_A + \frac{n'n}{n''}(\mu'_A - \mu_A)^2\right]}{\nu''}}$$

$$= \sqrt{\frac{\left[6.4\times 1.25^2 + 9\times 1.78^2 + \frac{0.7\times 10}{10.7}(3.59 - 2.46)^2\right]}{14.4}} = 0.95\,\frac{mm}{year^{0.35}}$$

which leads to the posterior $CoV''_A = 0.37$. Fig. 2 shows the updated trend of carbonation depth based on the updated model, the one after 37 years. It demonstrates the benefit of updating using new measurements – the updated trend reflects better the structure-specific conditions and both mean values and scatter of the distribution parameters were significantly reduced. The decrease of the mean values may be attributed to a higher quality of the *shell* concrete compared to the average represented by the dataset in [115], as well as to a significantly smaller scatter of the measured properties since they represent a single structure versus multiple structures in the dataset. The case study indicates that on-site inspections with in-situ measurements of the carbonation depth are useful for the assessment of cooling towers and more efficient planning of their maintenance.

4.2. Impact of climate change on carbonation-induced corrosion

As noted above, the degradation of RC structures is often a direct result of environmental exposure – atmospheric CO_2 level, temperature, relative humidity (RH), rainfall, sea spray, etc. In the past, these climate variables have been assumed as stationary, however, they become non-stationary in a changing climate. For example, atmospheric CO_2 is projected to increase by 45 % by 2100 for the medium RCP4.5 climate scenario. Structural degradation due to carbonation-induced corrosion is an electrochemical process, so increases in temperature will tend to accelerate the process at both the initiation and propagation stages. For example, in certain relatively humid climatic conditions, a 2 °C temperature increase may increase the CO_2 diffusion coefficient and corrosion rate by 12 % each, and a 5 % reduction in RH can increase the CO_2 diffusion coefficient by 11 % [118]. It is important to appreciate that climate change will not always lead to more severe deterioration. For drier climatic conditions considered by Breysse et al. [119], a reduction in RH by 5 % will reduce corrosion rates by 15 %.

Peng and Stewart [118] and Peng [120] conducted a spatial and time-dependent reliability analysis of the carbonation-induced deterioration of concrete structures constructed in coastal cities of Australia (Sydney) and China (Xiamen) under a changing climate. Two emissions scenarios were considered – RCP 8.5 and RCP 4.5, representing high and medium greenhouse gas emissions scenarios, respectively. The spatial time-dependent reliability analysis included time-dependent climate variables (temperature and RH) and degradation processes, as well as a large number of random variables and spatial random fields of material properties and dimensions. The surface of RC structures was discretised into a large number of elements of size $\Delta = 0.5$ m and the likelihood and extent of corrosion damage were calculated by tracking the evolution of the corrosion process of each element using MCS.

Six Atmosphere-Ocean General Circulation Models or GCMs (BCC-CSM1.1, MIROC5, IPSL-CM5A-LR, CSIRO-MK3.6.0, CNRMCM5, AC-CESS1.0) were used to project future temperature and RH. Fig. 3 shows the temperature and RH projections for Sydney for the RCP4.5 medium greenhouse gas emissions scenario (similar to the latest Intergovernmental Panel on Climate Change SSP2-4.5 scenario). Temperature is projected to increase, whereas RH is projected to slightly reduce. It is noted there is some variability between CGMs. However, this has reduced the impact on deterioration rates, and so in the following, it is reasonable to present the average of the simulation results of six GCMs. Note that the RCP8.5 emission scenario assumes a worst-case scenario of unabated climate change with CO_2 emissions doubled by 2050 with a 2 °C temperature increase. Hence, the following discussion is mainly focused on the more realistic RCP4.5 scenario.

A 10 m × 10 m RC slab, which represents a bridge deck, is analysed. It is assumed that it was built in 2010, and both sheltered (e.g., sheltered pedestrian bridge or soffit of the bridge), and unsheltered microclimate conditions are considered. Fig. 4 shows for RCP4.5 the mean carbonation depth is predicted to increase by up to 15 % by 2100. Fig. 5 shows that the mean extent of a bridge deck with corrosion initiation (d_{ini}) is projected to be 1.5 % by 2100 in the absence of maintenance or repair strategies. However, this will increase to 2.4 % for RCP4.5. Corrosion damage is defined to occur when corrosion-induced cover crack widths exceed 1 mm. In this case, the mean proportion of bridge deck damage (d_{crack}) is also shown in Fig. 5 and is projected to be only 0.95 % by 2100, and this will increase by 26 % to 1.2 % for RCP4.5. For unsheltered conditions, carbonation rates are much lower and although corrosion rates are higher (when corrosion starts) damage risks are noticeably reduced. However, climate change can also affect rainfall patterns which may alter damage risks for unsheltered structures.

The durability design requirements for Australian RC structures are higher than those for Chinese RC structures [118]. Hence, RC structures in China are more likely to be influenced by the adverse effects of climate change. Though the climates of Sydney and Xiamen are characterised by similar temperatures and RH, Peng and Stewart [121] show that damage risks for sheltered bridge decks in Xiamen increase from 4 % to 7.5 % by 2100 for RCP4.5. For a Chinese inland city such as Kunming, the damage risk can reach 20 % by 2100 [121]. Since climate change is highly spatial, some regions may well experience reduced

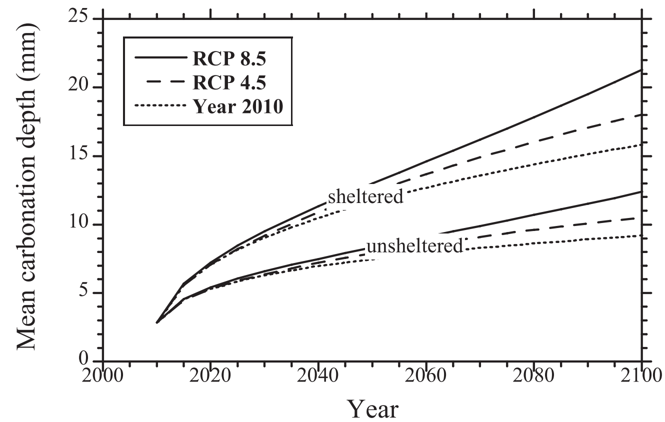

Fig. 4. Predicted mean carbonation depths for bridges in Sydney ().
adapted from [120]

deterioration due to more favourable changes in temperature, RH, rainfall, etc. (e.g., [65]). Nonetheless, climate change can increase damage risks considerably for some/many regions, therefore, it should be taken into account in the durability design requirements.

4.3. *Probabilistic maintenance planning of repairable RC structures subjected to chloride-induced corrosion*

As noted in Section 3.1.1, modelling the chloride ingress into a repaired RC structure is a complex problem because it involves the redistribution of chloride ions between the new chloride-free concrete layer cast during the repair and old chloride-contaminated concrete. This case study aims to show how this problem can be solved in a probabilistic format with a limited computational effort using the numerical model proposed in [18,122] in 1-D and 2-D formulations, respectively, in combination with polynomial chaos expansion (PCE). For this purpose, planning the maintenance of repairable RC structures in chloride-contaminated environments is considered. The structure under consideration has a service life of 70 years; its concrete has a water/cement ratio of 0.5 and a Portland cement content of 400 kg/m^3 with 8 % C_3A. The average ambient temperature and RH are 15 °C and 0.70, respectively. The chosen repair method is to replace the chloride-contaminated concrete cover with a new concrete layer of thickness c_p, which is on average 10 mm thicker than the original cover thickness, c; i.e., $c_p = c + c_r$, where c_r is the extra cover thickness added during the repair. It is assumed that the quality and properties of the new concrete are identical to those of the original one. The statistical characteristics and probabilistic models of the independent basic random variables are listed in Table 1 (see [18]).

The parameter of interest is the chloride concentration in concrete

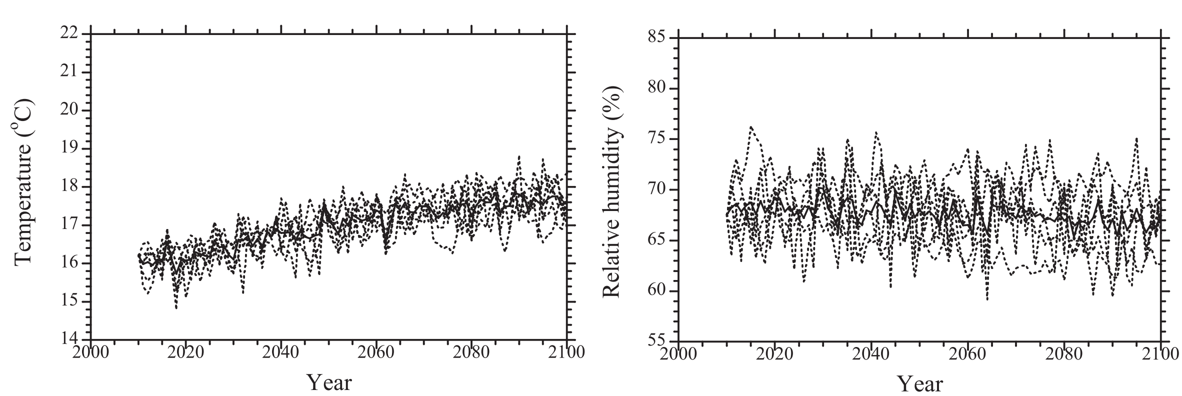

Fig. 3. Projected annual average temperature and RH for the six GCM projections for the RCP 4.5 emissions scenario for Sydney ().
adapted from [118]

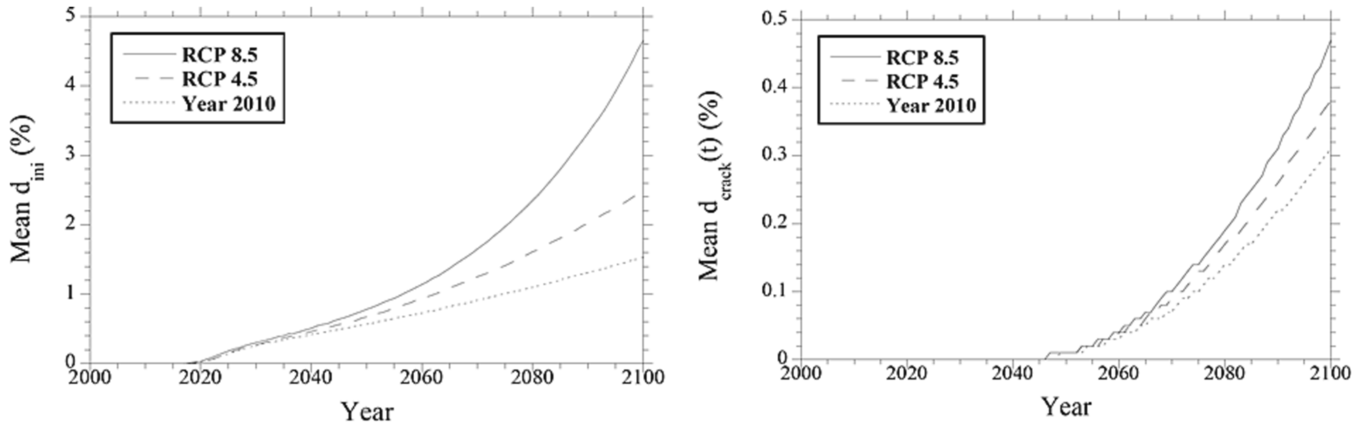

Fig. 5. Predicted mean extents of corrosion initiation (d_{ini}) and corrosion damage (d_{crack}) for sheltered bridge decks in Sydney (). adapted from [120]

Table 1
Probabilistic models of random variables.

Variables	Mean	COV	Distribution
Reference chloride diffusion coefficient, D_{ref}	3 x 10^{-11} m^2/s	0.20	Log-normal
Activation energy of the chloride diffusion process, U_c	41.8 kJ/mol	0.10	Beta on [32.,44.6]
Age reduction factor, m_c	0.15	0.30	Beta on [0,1]
Threshold chloride concentration, C_{crit}	2 kg/m^3	0.20	Normal (trunc. at 0)
Surface chloride concentration, C_s	7.35 kg/m^3	0.7	Log-normal
Concrete cover thickness, c	40 mm	0.25	Normal (trunc. at 10 mm)
Extra concrete cover thickness after repair, c_r	10 mm	0.1	Normal (trunc. at 0 mm)

near reinforcing steel, C_{fc}, which depends on the vector of the basic random variables $\mathbf{X} = \{D_{ref}, U_c, m_c, C_s, c, c_r\}^T$. It can be written that $C_{fc} = \mathscr{M}(\mathbf{X})$, where $\mathscr{M}$ is the numerical model employed for the calculation of chloride ingress into concrete based on the solution of Eq. (1). As explained in Section 3.1.1, to model the chloride diffusion after a repair, the concrete medium is divided into two domains – one representing the new concrete layer of thickness c_p (domain 1) and the other one the remaining original concrete (domain 2). The boundary condition on the surface remains the same as in Eq. (2) but the initial conditions are different. The initial chloride concentration in domain 1 is set equal to zero, while in domain 2 it equals the chloride content calculated before the repair. The chloride diffusion coefficients are also different for domains 1 and 2. The chloride diffusion is then a combination of the chloride ingress from the surface and the redistribution of chlorides between the domains. The problem is solved by the finite element method; see [18] for more details. Since C_{fc} depends on $\mathbf{X}$, it is also a random variable. Corrosion starts when C_{fc} exceeds C_{crit}.

A direct probabilistic analysis of chloride ingress into a repaired RC structure is computationally expensive. For that reason, PCE, which is one of the most popular methods for surrogate modelling, is employed because it enables to capture nonlinear relationships between input variables and output responses without excessive model evaluations [123]. A surrogate model based on PCE is created; i.e., C_{fc} is approximated by $\widehat{C_{fc}} = \mathscr{M}^{PCE}(\mathbf{X}) = \sum_{\alpha\in\mathscr{A}} \mathbf{y}_\alpha \Psi_\alpha(\mathbf{X})$, where $\alpha \in \mathscr{A}$ are multi-indices identifying the components of the multivariate polynomials, $\mathbf{y}_\alpha \in \mathbb{R}$ are the unknown expansion coefficients to be determined and $\Psi_\alpha(\mathbf{X})$ are multivariate polynomials. The set of unknown coefficients y_α can be obtained by minimising the mean-square error of the polynomial expansion over a set of N realizations of the input vector $\mathbf{X}$, which is called the experimental design (ED). Since $\widehat{C_{fc}}$ values can be easily calculated, the probability of corrosion initiation, $P_{ini} = \Pr\{C_{crit} - \widehat{C_{fc}} \le 0\}$, can be estimated by crude MCS within a short computational time.

This PCE model of C_{fc} can be employed for modelling and planning the preventive and corrective maintenance of RC structures in chloride-contaminated environments. Preventive maintenance strategies which aim to repair the structure approximately at the expected times of corrosion initiation will be considered herein. Of course, using the proposed model other repair strategies can also be analysed. It is initially assumed that the first repair is made in 15 years (Y15) after the end of construction; the subsequent repairs are then made every 10 years until year 65 (Y65). The application of the PCE metamodel allows us to evaluate the corresponding corrosion initiation probabilities. Note that from economical and operational points of view, it may not be practicable to repair the structure every 10–15 years. For extreme environmental conditions as in this case study, it would be more appropriate to use a better concrete type and/or increase the thickness of the cover depth. However, the above-described combination of the exposure conditions and material/structural properties is intentionally considered herein to obtain large corrosion initiation probabilities leading to multiple repairs over the structure's service life. This helps to illustrate the benefit of the proposed PCE model - without it, the problem solution would become excessively computationally demanding.

The PCE metamodel is first calibrated for the previously mentioned maintenance schedule (repair strategy 1) to obtain the optimal size of the experimental design, N_{ED}, which could similarly be used to construct surrogate models for other maintenance schedules. The model outputs, which are the chloride concentrations at the cover depth at the planned repair times, are used to compute PCEs. Eventually, for each scheduled repair time (from Y15 through Y65), a PCE model of the chloride concentration at the cover depth is obtained. A set of ED points of the size $N_{ED} = 100$ was generated PCE model was constructed. To assess PCE quality, a measure of accuracy – the leave-one-out error, ϵ_{LOO} [123], is evaluated. After increasing N_{ED} to 200, $\epsilon_{LOO} = 5 \times 10^{-3} < 10^{-2}$ is achieved, satisfying the criterion for non-linear problems according to [124]. It can be shown that the PCE model provides a high accuracy at a low computational cost.

The surrogate PCE models are then employed to calculate the probability of corrosion initiation, P_{ini}, using a crude MCS with 10^6 simulation trials; the results are shown in Fig. 6. As can be seen, P_{ini} is equal to 0.51 at the first repair time and below 0.5 (0.45–0.46) at all other repair times. It should be noted that in the considered example the probabilities of corrosion initiation are high, e.g., in about 10 % of the structures corrosion starts within 3 years after the completion of their construction or repair – see Fig. 6. After the corrosion starts, the

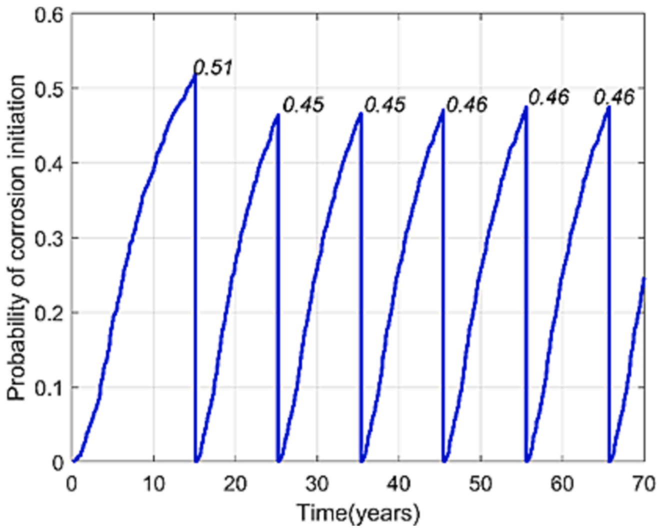

Fig. 6. Probability of corrosion initiation (repair strategy 1).

structures may deteriorate quickly and need to be repaired earlier compared to the repair times assumed in the example.

The PCE-based surrogate model can be applied to other repair strategies which involve different repair times and/or additional repair methods to reduce the risk of corrosion initiation, such as early repairs and/or deeper replacement depth. Two other repair strategies are then examined:

- Repair strategy 2, with 10-year repair intervals and the same extra cover thickness as in repair strategy 1; and
- Repair strategy 3, with the same repair intervals as in repair strategy 1 and the mean extra concrete thickness of 20 mm.

As for repair strategy 1, 200 ED points were used to build the PCE metamodels for each of the new strategies. After that, MCS was employed to calculate the probabilities of corrosion initiation like it was done for repair strategy 1. Table 2 shows the probabilities of corrosion initiation at each repair time for the three repair strategies. In the case of repair strategy 2, the shorter first repair interval led to lower corrosion initiation probabilities than repair strategy 1; the maximum P_{ini} is 0.45 and corresponds to the last repair. In the case of repair strategy 3, as expected, P_{ini} at the first repair is the same (=0.51) as in repair strategy 1; however, the thicker concrete cover after the repairs reduces the probability of corrosion initiation at all subsequent repairs – P_{ini} = 0.40–0.41 vs. 0.45–0.46 for repair strategy 1.

The results confirm that the proposed approach to the estimation of the probability of corrosion initiation in repaired RC structures, based on the combination of the numerical model from [18,122] with PCE, is computationally efficient. Several assumptions which were made (e.g., the identical properties of the new and old concrete, the repair strategies involving frequent repairs) do not affect this outcome. The approach can be employed to analyse other repair strategies (e.g., different repair materials, repair times, etc.). In addition, it can be used for life-cycle cost analysis, focusing on the structural maintenance process. Optimised maintenance planning can also be carried out by minimising the combined costs of inspections, repairs and failure, with a relatively small computational effort.

5. Discussion

The discussion concentrates on the remaining challenges and gaps in knowledge, which need to be addressed in relation to the probabilistic modelling of deteriorating RC structures. In particular, the current situation is compared with that 20 years ago; the latter was described in the concluding statements of the joint JCSS and IABMAS workshop held in 2003 [7].

5.1. Corrosion-induced deterioration

The deterioration process which attracted the most attention at and after the workshop was the corrosion of reinforcing steel in concrete. First, it was noted at the workshop that predictive models of deterioration processes needed to be improved. This has been achieved not only for corrosion but all deterioration processes considered in this paper. Is it necessary to further improve currently available predictive models? The answer is ‘yes’ as progress is always welcome, but this is probably not the most important ‘need’ because the gap between the most advanced available models and those used in practice has only increased in the last 20 years.

The next three research needs formulated at the workshop were: (i) establish a generally acceptable and consistent basis for probabilistic modelling of a relevant deterioration process; (ii) clarify how parameters of both deterministic and probabilistic models be assessed and quantified; (iii) incorporate probabilistic deterioration models into the design and assessment of safety and serviceability of RC structures. Since the first two needs are prerequisites for the third one it is convenient to consider them all together. The probabilistic models for corrosion presented in Section 3.1 are the closest to being generally accepted. They seem well established after being around for more than 20 years and included in many relevant guidelines, in particular, they will be in the next edition of the fib Model Code for concrete structures (MC2020) which should be published shortly.

However, more detailed insight reveals noticeable differences between the models for corrosion initiation and corrosion propagation. The models for corrosion initiation were previously included in MC2010 [30] (and before that in [29]) and there are reasonably clear guidelines on how to assess/quantify their parameters. Out of the two models, the one for chloride-induced corrosion causes more concerns. One of them is related to the estimation of the chloride ingress into concrete, i.e., Eqs. (3) and (4). It has been noted that the connection between the values of the chloride diffusion coefficient measured in short-term tests (e.g., Rapid Chloride Migration test) and D_{ref} in Eq. (3) is not straightforward and depends on the age factor, m_c; moreover, the predictions by Eq. (4) are very sensitive to the values of m_c when they are larger than 0.3 (which is the case for concretes with SCM [16]) [125]. Hence, the statistical characteristics of m_c given in [29] should be treated with care and may require reassessment for different concrete compositions. The other concern is about the quantification of C_{crit}, i.e., the critical chloride concentration near reinforcing steel which triggers the corrosion initiation. The spread of the reported values of C_{crit} is very wide and it may be

Table 2
Probabilities of corrosion initiation at the repair times for the three repair strategies.

Repair strategy 1	Repair times	1st_Y15	2nd_Y25	3rd_Y35	4th_Y45	5th_Y55	6th_Y65
	P_{ini}	0.51	0.45	0.45	0.46	0.46	0.46
Repair strategy 2	Repair times	1st_Y10	2nd_Y20	3rd_Y30	4th_Y40	5th_Y50	6th_Y60
	P_{ini}	0.37	0.41	0.43	0.44	0.44	0.45
Repair strategy 3	Repair times	1st_Y15	2nd_Y25	3rd_Y35	4th_Y45	5th_Y55	6th_Y65
	P_{ini}	0.51	0.40	0.40	0.40	0.41	0.41

problematic to sufficiently accurately quantify its mean and coefficient of variation without additional site-specific tests [126]. These issues require further clarification and, if necessary, further research, but in general it looks like the three 'needs' have mostly been achieved for corrosion initiation.

Any prediction of the effects of corrosion on the strength or serviceability of a RC structure depends on the corrosion rate, V_{corr}. Hence, its evaluation is of utmost importance for modelling the corrosion propagation. The empirical model relating V_{corr} with the concrete resistivity, Eq. (9), was proposed a long time ago and is now to be included in MC2020 (but without F_{Cl}). However, the information available for the quantification of the probabilistic model parameters is incomplete and based on limited data [6,16]. Moreover, there is some evidence that the model may be misleading for carbonated concrete [127]. Thus, while the model will soon (with the publication of MC2020) be incorporated into the design/assessment of RC structures, the other two 'needs' – general acceptability and clarity of how the model parameters should be quantified, have yet to be achieved and, hence, further research on probabilistic modelling of the corrosion rate is required.

Another research 'need' highlighted at the workshop was the development of deterioration models which considered spatial variability. In the context of corrosion, this problem has attracted plenty of attention and in terms of modelling itself, it has been mainly resolved. There is still a lack of (or very limited) data on the spatial correlation in real structures of the key parameters which control corrosion-induced deterioration (e.g., chloride diffusion coefficient, corrosion rate). In addition, most of the studies related to spatial variability have been carried out at the component level (i.e., on RC beams, slabs or columns), e.g., [54–57]. However, it may be essential to account for corrosion effects, including spatial variability, at the structural system level, e.g., to assess the seismic performance of corroded RC structures. While this has been done for relatively small RC structures like frames [128], for large-scale structures such as multi-span highway bridges this remains a challenge [129].

The importance of on-site inspections and monitoring for collecting new data, which could be used for updating the probabilistic deterioration models, was also discussed at the workshop. Two research 'needs' were identified in this respect – determine the ability to use existing monitoring systems for updating deterioration models, and develop models to quantify uncertainties of on-site testing methods. There have been many publications which demonstrate how the data provided by on-site inspections and monitoring systems can be used to update probabilistic models of corrosion initiation and propagation, e.g., [14,35,41,51,61]. However, there are still no probabilistic models, which have been quantified using real data, to represent uncertainties associated with on-site inspection techniques. Such models are especially important for electrochemical techniques, which are used for on-site measuring of the corrosion current density. It is known that these techniques are rather inaccurate, while the parameter which they measure is essential for the assessment of the condition of corroding RC structures. Further research in this area is needed.

The last two research needs, which were discussed at the workshop, were related to repaired structures – develop models to predict the behaviour of repaired structures, and determine the effects of repairs on deterioration processes. In the context of probabilistic modelling, these issues have attracted attention only recently, see for example Section 4.3. Thus, it is necessary to continue research in this area.

5.2. Other deterioration processes

The lack of attention to other deterioration processes such as F/T action, AAR, sulphate attack and fatigue was highlighted in the workshop conclusions. As can be seen from the state-of-the-art overview presented in this paper, the situation has not changed much since then. The main reason for that is the complexity of modelling F/T action, AAR and sulphate attack and, as a result of that, the reliance on protective measures, which have been developed using experimental studies and field observations, to avoid/limit damage due to these processes. Recent publications show that advances have been made in understanding the mechanisms behind the processes through experimental work and transferring this understanding into sophisticated numerical models, e.g., for F/T action – [67], AAR – [81,82], sulphate attack and leaching – [85,88]. Thus, the 'need' to improve existing predictive models has been fulfilled for F/T action, AAR and sulphate attack. The rest of the research 'needs' identified at the workshop have received very limited attention in the context of these deterioration processes.

To use the advances in deterministic modelling of F/T action, AAR and sulphate attack for the development of their probabilistic models two challenges need to be overcome. First, the deterministic models include a large number of parameters and consistent quantification of their uncertainties is a very challenging task, which requires extensive experimental and fieldwork. Second, deterministic analysis with these models is relatively time-consuming; hence, simple techniques for probabilistic analysis such as crude MCS cannot be employed. Although, with recent developments in probabilistic analysis techniques, the second challenge can be overcome easier than the first one, it still adds complexity to probabilistic modelling. It also seems that there has been no strong demand for such probabilistic models from practice and only a few probabilistic models, which are based on rigorous deterministic modelling of these deterioration processes, have been proposed so far [89,90]. It may take a long time, especially the part on the uncertainty quantification of the model parameters, but the models can be useful research tools for better understanding of the deterioration processes, improving methods for their prevention/mitigation and predicting/assessing the performance of existing RC structures damaged by these processes.

The situation with probabilistic modelling of fatigue of RC structures is significantly different from that of the deterioration processes considered above. First, there are provisions for the fatigue design of RC structures in the standards, e.g., [96]. Second, the main framework for fatigue probabilistic modelling is well established and based on the combination of the S – N (or S – N – P) curves, which are obtained using results of relatively standard fatigue tests, with a damage accumulation rule (usually, this is the Palmgren-Miner linear rule). Thus, new research in this area may deal with modifications of various elements of this framework such as the S – N curves (e.g., for new concrete types), fatigue load model (e.g., for different structural applications), damage accumulation rule, and random variables and their probabilistic description. Apart from that, a couple of stochastic constitutive fatigue damage models for concrete have been proposed, to be used in numerical simulations which replace physical fatigue tests [99,100]. The development of such fatigue damage models is another possible direction of future research.

Returning to probabilistic modelling of F/T action, there is another approach, which is very similar to the one used for fatigue. This approach relates the damage variable D, which represents the deterioration of one of the concrete mechanical properties, with the number of F/T cycles. All data for that are obtained experimentally. Since there are uncertainties associated with the test results, for each number of F/T cycles the probability of reaching a certain damage level can be estimated [76,77]. This allows constructing the so-called D – N – P curves, which are similar to S – N – P curves in fatigue. The approach can further be developed since it is relatively easy to implement in practice and can provide useful information for the design of RC structures against F/T action and the selection of efficient protective measures. It can also be extended to surface scaling, i.e., determining experimentally the relationship between the loss of surface concrete with the number of F/T cycles, while taking into account uncertainties associated with the experimental data. Moreover, a similar approach can be developed for AAR, in which experiments are used to establish the relationship between the AAR expansion (in %) and the damage level in terms of the damage variable *D*.

Sulphate corrosion of sewers is a practical problem which should be addressed in their design and maintenance planning. For this purpose, simple deterministic empirical models have been developed, which predict the rate of concrete loss over time. Based on these empirical models, probabilistic models have been proposed. The main issue here is that uncertainties associated with these empirical models and their parameters have not been properly quantified. This issue needs to be addressed, i.e., the relevant uncertainties need to be quantified.

6. Conclusions

The paper presented an overview of the development of probabilistic deterioration models for RC structures over time, with emphasis on the contributions of the JCSS members. Well-accepted models for corrosion of reinforcing steel in concrete were briefly described, and an overview of other deterioration processes such as F/T action, AAR, sulphate attack, leaching and fatigue was provided. Case studies illustrated the application of probabilistic deterioration models for corrosion. Finally, the progress in the area over the last twenty years was discussed, the research needs twenty years ago and at present were compared, and directions for further research were suggested. New research topics which have emerged (or become more urgent) recently include the development of probabilistic deterioration models which can: (i) account for the effects of climate change, (ii) deal with more sustainable materials including low carbon concretes with a very low Portland cement content (or without it as alkali-activated concrete), and (iii) take into account the combined effect of several deterioration processes (e.g., corrosion and sulphate attack, corrosion and AAR).

CRediT authorship contribution statement

Dimitri V. Val: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization. **Carmen Andrade:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization. **Miroslav Sykora:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Formal analysis, Data curation. **Mark G. Stewart:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Emilio Bastidas-Arteaga:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Jan Mlcoch:** Writing – original draft, Formal analysis, Data curation. **Quynh Chau Truong:** Writing – original draft, Formal analysis, Data curation. **Charbel-Pierre El Soueidy:** Writing – original draft, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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