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Probabilistic modeling of chloride-induced corrosion in concrete structures using first- and second-order reliability methods

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A B S T R A C T

Concrete structures are subjected to chloride-induced corrosion that can lead to shortened service life. Reliable predictions of life cycle performance of concrete structures are critical to the optimization of their life cycle design and maintenance to minimize their life cycle costs. This paper presents two simplified semi-analytical probabilistic models based on the first- and second-order reliability methods to model the uncertainty of the key parameters including surface chloride concentration, chloride threshold, cover depth and diffusion coefficient, which govern the chloride ingress into concrete and corrosion of reinforcing steel. A case study of a reinforced concrete highway bridge deck is used to illustrate the capability and efficiency of these simplified probabilistic models in modeling the uncertainty and predicting the time-dependent probability of corrosion. The models enable to quantify the impact of the different governing parameters on probability of corrosion and service life, which can be used to develop cost-effective management strategies.

1. Introduction

The main cause of deterioration of different types of concrete structures (bridges, marine structures, off-shore platforms, parking garages, etc.) is due to chloride-induced corrosion of the steel reinforcement. The primary source of chlorides is from the external environment, either from deicing salts using during the winter months or from seawater. The rate of ingress or penetration of chlorides is dependent primarily on the quality of concrete and more particularly on the water–cement ratio of the concrete mix, the presence of supplementary cementing materials (e.g. silica fume, fly ash, or slag), and/or protective systems that delay or slow down chloride ingress (e.g. protective membrane). In porous media, such as concrete, chlorides can penetrate concrete via different physical mechanisms, such as diffusion, capillary absorption, electrical migration, presence of cracks and permeation due to hydraulic pressure heads [25]. Furthermore, the penetration process is also influenced by chemical reactions, such as chloride binding.

The corrosion of the steel reinforcement leads to concrete fracture through cracking, delamination and spalling of the concrete cover, reduction of concrete and reinforcement cross sections, loss of bond between the reinforcement and concrete, and reduction in strength and ductility. As a result, the serviceability, strength, safety and service life of concrete structures are reduced.

In the last three decades, chloride-induced corrosion has been extensively studied [43,39,8], particularly, as a result of the high costs of highway bridge repair in North America and Europe from the effects of chloride-induced corrosion and deterioration of concrete infrastructure. Most of these studies are based on the assumption of a process of diffusion for predicting the time and space variations of chloride content in concrete and on the concept of chloride threshold to define the corrosion resistance of reinforcing steel to chloride attack. Despite the large amount of research, the design of concrete structures for durability is mainly based on prescriptive rules, such as specifying minimum concrete cover depth (depending on the environmental exposure), maximum water-to-cement ratio (to achieve low chloride diffusivity), use of more corrosion resistant reinforcing steels (e.g. stainless steel), and use of protection systems. However, a considerable level of uncertainty may be associated with one or more of the above parameters. This is due to: (i) heterogeneity and aging of concrete with temporal and spatial variability of its chloride diffusivity; (ii) variability of concrete cover depth, which depends on quality control, workmanship and size of the structure; (iii) variability of surface chloride concentration, that depends on the severity of the environmental exposure, precipitation, washing of structure; and (iv) uncertainty in chloride threshold level that depends on the type of reinforcing steel, type of cementing materials, test methods, etc. [1]. It is clear that the combination of these uncertainties leads to a considerable uncertainty in the model output i.e. the time to corrosion initiation or service life. This uncertainty in the model output could have serious consequences in terms of inadequate design, planning of

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inspection and maintenance which in turn will shorten the service life of the structure and increase the life cycle cost [50,11]. Therefore, for an effective performance-based life cycle design that includes the use of mechanistic service life models will lead to a minimization of cost at the same time provides the level of service life required.

The objectives of this paper are threefold: (i) present a performance-based approach to durability or life cycle design based on mechanistic models for chloride ingress into concrete and onset of steel reinforcement corrosion; (ii) present simplified semi-analytical probabilistic models based on first-order and second-order reliability methods (FORM/SORM) that take into account the uncertainty and variability in the governing parameters and propagate it to predict the time-dependent probability of chloride contamination of concrete cover and probability of corrosion of steel reinforcement; and (iii) to assess the efficiency of the simplified analytical FORM and SORM methods by comparing their predictions to those obtained by using Monte Carlo simulation (MCS) with a large number of simulations on a typical highway concrete bridge deck exposed to deicing salts during winter.

2. Overview of mechanisms of chloride ingress into concrete structures

Since concrete is a porous medium, chlorides can penetrate concrete through a number of mechanisms. First, if the concrete is not fully saturated, the salt solution is absorbed into the unfilled spaces by capillary action [19]. As the chlorides migrate into the concrete, some chlorides are absorbed onto concrete and react with the cement hydrates [38], which slows down the rate of chloride migration [31]. When the surface dries, the salt crystallizes. With successive cycles, there may be a progressive build-up of salts at the surface and in the near surface layers until, after few cycles, a limiting value is reached [36]. The time it takes to achieve a stable surface level will, however, depend on the severity of exposure. In addition to this early absorption, the chloride ions migrate further into the concrete by diffusion through the pore water that is driven by the concentration gradient between the surface and the subsurface layers. As the chlorides migrate further, so the process of "binding" continues to remove chlorides from the pore solution [2]. In concrete, which is permanently submerged and saturated, this diffusion process is the only means of transport after the initial wetting. However, even without drying there may be a build-up of chlorides in the pores water to a level above that of the surrounding saline solution, due to a process defined as chloride "condensation" [35]. This is may be due to the physical adsorption of chlorides onto the pore surfaces by the electric double layer in cement and can result in chloride concentrations, which can be two to four times those of the solutions to which the concrete is exposed. These are commonly referred to as loosely-bound chlorides.

Therefore, in the absence of shrinkage phenomena, the main transport mechanisms of chlorides into concrete are diffusion and adsorption [25]. However, adsorption occurs in concrete surface layers that are subjected to wetting and drying cycles, and it only affects the exposed concrete surface down to 10–20 mm [44], so beyond this adsorption zone, the diffusion process will dominate [44,14].

Otherwise, if the concrete cover presents a considerable amount of cracking, two modeling options might be proposed:

- In a cracked concrete cover with relatively few and small cracks, the effect of cracks on the chloride ingress can be considered, by using the same diffusion model with a modified "apparent" diffusion coefficient that takes into account the effect of cracks on the diffusion as in [12,17,16,6].
- In a cracked concrete cover with several and large cracks, diffusion may not be the governing mechanism and the effect of cracks may lead to "permeability" as a mechanism for chloride transport that, by itself, needs to be modeled. This article does not take into account this case.

The chloride diffusion phenomena is a transfer of mass by random motion of free chloride ions in the pore solution, resulting in a net flow from regions of higher to regions of lower concentration [10]. The rate of chloride ingress is proportional to the concentration gradient and the diffusion coefficient of the concrete (Fick's first law of diffusion). Since in the field, chloride ingress occurs under transient conditions, Fick's second law of diffusion can be used to predict the time variation of chloride concentration for one-dimensional flow. This law can be expressed as a relationship between the diffusion coefficient and the gradients of concentration, by direct analogy with the equations of heat conduction [10], as follows:

$$\frac{\partial C_{x,t}}{\partial t} = \frac{\partial}{\partial x}\left(D\frac{\partial C_{x,t}}{\partial x}\right) \tag{1}$$

where $C_{x,\,t}$ is the concentration of chlorides at depth x and time t; D is the diffusion coefficient of chlorides, which is assumed to have a constant value, called "apparent" (or "effective") diffusion coefficient [2].

In fact, at early age, the diffusion coefficient presents a wide range of scatter (especially with respect to the 28-day value); however this scatter becomes less significant, especially after 5 years. All types of remaining uncertainties, such as time and space variation are supposed to be captured by the probabilistic model proposed. Therefore, the diffusion coefficient used is taken as a random variable having its characteristics based on, an "effective" time-invariant mean value, which is a good fit in the diffusion model, and varies in a narrow range of standard deviation to take into account the remaining uncertainties, that are induced by the effects of chloride binding and concrete aging.

Under the assumptions of a constant diffusion coefficient, a constant surface chloride concentration C_s as the boundary condition, and the initial condition specified as $C_{x,\,t} = 0$ for $x > 0$, $t = 0$, Crank's solution yields [10]:

$$C_{x,t} = C_s\left(1 - erf\frac{x}{2\sqrt{Dt}}\right) \tag{2}$$

where $erf(.)$ is the error function or Gauss error function, which is very similar to the standard normal (or Gaussian) cumulative distribution function [$\Phi(.)$]. $erf(.)$ and $\Phi(.)$ differ only by scaling and translation as follows:

$$erf(x) = 2\Phi(x\sqrt{2}) - 1 \tag{3}$$

In modeling the chloride ingress as a Fickian process, the following assumptions are made:

- Some phenomena (e.g. capillary flow, chloride binding, etc.) are not explicitly considered.
- Crank' solution for a plane sheet assumes dealing with plane isotropic concrete structures, i.e. one dimensional diffusion.
- The diffusion coefficient and surface chloride concentration are assumed time-invariant.
- Initial concentration of chlorides in the concrete is negligible.
- Interaction with other ions and with electrical double layer is ignored [9].

These conditions are not necessarily satisfied, for many reasons. For example, the diffusion coefficient is not constant because it is influenced by the following factors [25]: (i) concrete is not homogenous with some micro-cracks or some shrinkage-induced cracks; (ii) moisture is unlikely to be uniform, and its input can be considerable when the degree of saturation is high; (iii) some chlorides are bound by cement hydrates; (iv) D is influenced by concentration of chlorides content; and (v) chloride binding changes with time.

Therefore, to minimize the error in assuming time-invariant diffusion coefficient and surface chloride concentration, concrete cores are usually taken from the concrete structure to determine the “apparent” or ”effective” diffusion coefficient and “apparent” surface concentration by fitting the field data to Fick’s 2nd law of diffusion.

3. Overview of mechanism of corrosion of steel reinforcement in concrete structures

The corrosion of conventional carbon or “black” steel reinforcement embedded in concrete structures is an electrochemical process in which the steel is dissolved [46]. In the general corrosion process of steel in concrete, the steel loses its ions at the anode by the oxidation reaction ($Fe \rightarrow Fe^{++} + 2e^-$). The electrons are released and transported to the cathode for the reduction of oxygen ($O_2 + 2H_2O + 4e^- \rightarrow 4OH^-$). The flow of ions through the concrete pore solution and electrons form an electrical current for the reactions to proceed. As a result, the electrical resistivity of concrete, availability of oxygen, and chemistry of the pore solution are the determining factors for the corrosion kinetics of the carbon steel in a concrete medium [43,50]. The concrete pore solution is naturally alkaline with a pH level between 12.5 and 13.5. Embedded in such an environment, the steel is protected from corrosion by passivity, which is a condition for corrosion resistance of an active metal caused by the formation of a thin surface film of corrosion products [46]. The composition of the passive film is uncertain, it is either ferrous (Fe^{2+}) or ferric (Fe^{3+}) oxides.

The hydroxyl ions (OH^-) act as a corrosion inhibitor in concrete that is opposing the corrosive action of chloride ions, which destroy the protective passive film. Although, the interaction mechanism between the chlorides and passive film is not well understood, the mechanism can be analyzed from various viewpoints, including:

(i) *Disruption of the passive film*: The presence of chlorides changes the composition, thickness, and density of the passive film, and increases its water content [33]. This facilitates chloride penetration and consequently breaks down the passive film;

(ii) *Reduction of the pH level*: The pH level or concentration of OH^- and Cl^- are two competing forces in the corrosion process. The pH is reduced by an acid hydrolysis reaction as follows [23]:

$$Fe^{2+} + 2H_2O + 2Cl^- \rightarrow Fe(OH)_2 + 2HCl \quad (4)$$

(iii) *Catalyst of oxidation*: Chlorides act also as a catalyst for the oxidation of the steel by taking an active part in the reactions [46]:

$$2Fe + 6Cl^- \rightarrow 2(FeCl_3)^- + 4e^- \quad (5)$$

$$2(FeCl_3)^- + 2OH^- \rightarrow Fe(OH)_2 + 3Cl^- \quad (6)$$

The reactions consume OH^- ions and then release Cl^- ions back into the solution. It results in a concentration of Cl^- and a reduction of pH at the point of corrosion initiation, which accounts for pitting corrosion. The role of chlorides, more specifically free Cl^-, in inducing corrosion is generally thought to be a competing process with OH^- that stabilizes the passive film. Therefore, a relative high ratio of OH^-/Cl^- is critical to maintain the integrity of the passive film. The quantity of chloride ions that initiate corrosion is referred to as the “threshold chloride concentration” (C_{th}).

Corrosion in concrete structures can be described as a two stage process [43]: (i) corrosion initiation; and (ii) corrosion propagation. The corrosion initiation stage corresponds to the process of chloride ions (chlorides) ingress into concrete (and/or carbonation) while the steel remains passivated. The corrosion propagation stage starts after the initiation of active corrosion, and it often occurs after the chloride concentration on the steel surface reaches a certain threshold value (so-called “chloride threshold” C_{th} [43]) which depassivates the steel. Ideally, the corrosion initiates at time $\widetilde{T}_i$, which corresponds to an amount of chlorides (at the steel level), which is greater than or equal to the chloride threshold as follows:

$$C_{d,\widetilde{T}_i} \geqslant C_{th} \quad (7)$$

where d represents the concrete cover depth of the steel. From Eq. (7), the time to corrosion initiation can be deduced as follows:

$$\widetilde{T}_i = \frac{d^2}{4D\left[erf^{-1}\left(1 - \frac{C_{th}}{C_s}\right)\right]^2} \quad (8)$$

In this deterministic model, four parameters are assumed as well-defined independent design parameters that are critical for corrosion initiation: (i) structural parameter: concrete cover depth d; (ii) material parameters: chloride diffusion coefficient D, which is an indicator of the rate of chloride penetration into concrete, and chloride threshold value C_{th}, which is an indicator of the corrosion resistance of reinforcing steel; and (iii) environmental parameter: surface chloride concentration C_s, which is a measure of the corrosion load or exposure risk of concrete structures. Given the inherent complexity and heterogeneity of concrete as a corrosion medium, there exists large uncertainty in the above mentioned parameters and in the proposed model. The next section deals with the uncertainty in chloride ingress and corrosion initiation, and proposes efficient and practical methods of modeling it and predicting the probability of corrosion of concrete structures.

4. Uncertainty in mechanisms of chloride ingress into concrete and steel corrosion

4.1. Overview of epistemic and aleatory uncertainties

Many factors contribute to the uncertainty in predicting the chloride concentrations at different depths and times, as well as in predicting the time to initiation of steel corrosion, which can be grouped into the following two broad categories:

(a) *Aleatoric or statistical uncertainties*: The word aleatory is derived from the Latin word “alea”, which means the “rolling of dice”. Thus, aleatoric uncertainties are those presumed to be due to the intrinsic randomness in samples and parameters, such as variability in chloride diffusivity and concrete cover depth [22,37,13]. These uncertainties are inherent and cannot be eliminated by more accurate measurements.

(b) *Epistemic or systematic uncertainties*: The word epistemic derives from the Greek “episteme”, which means knowledge. Thus, an epistemic uncertainty is one that is presumed as being caused by lack of knowledge about fundamental phenomena, such as the lack of knowledge about the true mechanism of ingress of chlorides into concrete and the mechanism of corrosion initiation by chloride attack. This uncertainty can be reduced by improving the fundamental physical models, calibrating the measures or adding more explanatory variables to the model (more knowledge).

According to [22,37,13], the classification of the nature of uncertainty depends on the context of application. In other words, if the modeler can identify a way to reduce errors by collecting data or adding new explanatory variables, then these errors are epistemic. For example, more knowledge on the composition and structure of the passive film and its mechanism of deterioration may provide more reliable models to predict the chloride threshold or onset of corrosion, and then the error in prediction model can be categorized as epistemic. Another example about the distinction between the two categories is about a basic random variable describing a material property, such as the chloride diffusivity. Should the uncertainty in the chloride diffusivity be categorized as aleatory or epistemic? The answer depends on the circumstances. If the diffusivity is that of a concrete is in an existing structure, then the uncertainty should be categorized as epistemic if cores taken from the structure can be tested, yielding information about the diffusivity. The testing may, of course, involve random errors of measurement, particularly if non-destructive methods are used. This measurement uncertainty should also be categorized as epistemic, if there is possibility of considering alternative methods of measurement. On the other hand, the uncertainty in the chloride diffusivity should be categorized as aleatory, if there will be no attempts to make more detailed control of mix design and the control of the quality of workmanship in the construction of the structure. For the modeling of chloride ingress and corrosion initiation, the following sources of uncertainty can be identified:

(i) *Inherent uncertainty of the basic model variables*
   - *Chloride threshold* (C_{th}): It depends on the type of reinforcement, electrochemical environment in concrete, and testing method and consequently, a considerable variation is expected for this parameter. Recent studies of the chloride threshold show that, for every kind of reinforcement (stainless steel, galvanized, carbon fiber, etc.) that normally characterizes the chloride threshold there is considerable variability, and it's related to other external variables [49] (e.g. w/c ratio, humidity, aggregates, supplementary cementing materials like silica-fume (SF) and pulverized fuel ash (PFA)). Bamforth et al. report [2] presented some values of reduction of chloride threshold with respect to the percentage added of SF and PFA.

     The chloride threshold depends on the humidity of the concrete; this implies that for structures in a marine environment, the chloride threshold value is higher than for highway bridges. The chloride threshold level to cause initiation of corrosion is also lacking a standard test method to quantify it. Glass and Buenfeld suggest that a chloride threshold value for carbon steel can be expected to fall into a range of 0.03–0.07% of total chlorides by mass of concrete [4,18]. Bamforth et al. reported a variation, by weight of cement, from 0.06% to 2.2% for the chloride threshold for carbon steel [2]. Even though [4,18,2] acknowledge the variation and dependency of C_{th}, however they use a mean value ignoring all variability. In this paper, C_{th} is modeled as a random variable with a standard deviation based on the variability of data obtained.
   - *Concrete cover* (d): Its variability depends on the quality of workmanship and control during construction. For example, the associated variation of the concrete cover depth for bridge decks built in the sixties and seventies can vary from 10% to up to 50% [27].
   - *Chloride diffusion coefficient* (D): This material property is a measure of the rate of chloride penetration into concrete. The value of D depends on concrete mix design, such as water/cement ratio, quantity of mineral admixtures, aggregate fraction, and other parameters such as temperature and age of concrete [3,42]. The typical values of D for normal concrete (e.g. $w/c = 0.4$) were reported between 10^{-12} m^2/s and 10^{-11} m^2/s [42,5], e.g. $D = 4 \times 10^{-12}$ m^2/s for a normal concrete with $w/c = 0.4$ and $D = 10^{-11}$ m^2/s for $w/c = 0.55$ [5]. The incorporation of mineral admixtures (e.g. fly ash, slag, silica fume); however, can lead to orders of magnitude reduction of D in the long term [42]. Furthermore, D is time-independent and as such should be modeled using a more complex mathematical model such as a stochastic process.
   - *Surface chloride concentration* (C_s): there is a considerable variability in the surface chloride concentration between one region and another; it can vary from 0 kg/m^3 to 25 kg/m^3. Weyers et al. classified the corrosive environments surrounding bridge decks into four categories in terms of surface chloride concentration: Light, Moderate, Heavy, and Severe Exposures [48]. However, within the same structure, the variation can be also significant (variation coefficient of 30% [4]). Therefore, the study should be separated by regions or provinces by considering a case by case study (geographically, regulatory, etc.), then the variability in each region can be modeled.

(ii) *Uncertainty in the physical model*: resulting from selection of the physical sub-models used to describe the derived variables due to the assumption that chloride transport is the mainly diffusion process and ignoring other phenomena as the adsorption or the permeability due to cracks. Nevertheless, some of these phenomena are captured through the use of the so-called "apparent" or "effective" diffusion coefficient.

(iii) *Statistical uncertainty:* This results from the selection of the probabilistic sub-model (e.g. $f_X(C_{th}, d, D, C_s)$, such as the assumption of a random variable instead of a stochastic process or random field, and the estimation of its parameters (estimation of mean values), type of distribution to describe the basic variables.

(iv) *Uncertainty in measurement*: Resulting from errors in measuring the key parameters, based on which the parameters are estimated. These include errors involved in indirect measurement, e.g., the measurement of a quantity through a proxy, as in non-destructive testing of concrete cover depth.

4.2. Need for uncertainty modeling using probabilistic approaches

As mentioned above, the model and its associated parameters can exhibit a considerable level of uncertainty (e.g. chloride threshold), which may have coefficients of variation of 20% or higher, while some other variables (e.g. concrete cover depth, diffusion coefficient, etc.) may present a narrower scatter with coefficients of variation of 20% or lower [47,15,41,28]. The values of these parameters used in deterministic models are mainly based on the mean values or some conservative characteristic values of the variables (e.g. lower values for the "resistance" parameters such as the chloride threshold, and higher values for the "loading" parameters, such as C_s). The deterministic models can predict two states only for each performance measure or limit state investigated, i.e. failure or non-failure (e.g. corroded or non-corroded). A limit state is the border that separates the desired state of performance of a system from the "failed" state. For illustration purposes, an example of the limit state of corrosion of reinforcing steel is given. If after a period of time, the mean value ($c_{d,\ t}$) of the chloride concentration at the steel level ($C_{d,\ t}$) is found lower than the mean value (c_{th}) of chloride threshold level (C_{th}), as shown in Fig. 1, the deterministic model of Eq. (8) predicts no corrosion (i.e. the steel is in the passive state). Conversely, if $c_{d,\ t}$ is found higher than c_{th}, then the model predicts that the reinforcing steel is corroded. In actual field conditions, the measurements of chloride concentrations at the steel level can be represented by a scatter diagram or frequency distribution or probability density function (pdf); similarly, the chloride threshold concentration has also a scattered distribution with a pdf as shown in Fig. 1. From Fig. 1, it can be seen that the deterministic statements "corroded" or "non-corroded" are not anymore valid. Instead, there is a distinct zone or shaded area where $C_{d,\ t}$ and C_{th} overlap , where the chloride concentration at the steel level is higher than the chloride threshold value, which is then defined as the probability of corrosion. Hence, the extent of corrosion is neither zero nor 100%, as assumed in the deterministic prediction models, but is equal to a finite value, which starts at zero at the start of the chloride ingress stage and increases with time and ultimately can reach 100%.

It is therefore clear that the use of deterministic models cannot predict the actual chloride levels at different depths and times and cannot predict the level of corrosion. Hence, such models present serious shortcomings regarding the selection of appropriate design, maintenance and rehabilitation strategies that will ensure a long service life. A probabilistic modeling of the performance of RC structures has much to offer with regard to simplicity as compared to attempts to formulate purely deterministic models [34,15,26,28].

5. Probabilistic modeling of chloride-induced corrosion in concrete structures using semi-analytical first- and second-order reliability methods

5.1. Formulation of limit state function for corrosion initiation

As previously mentioned, a limit state is the border that separates the desired state from the failed state. The term "failure" is used, in this paper, in its general sense and refers to the violation of any specified performance requirement of the concrete structure at any stage during its service life. For example, failure can be defined as the event when "chloride concentration exceeds the threshold chloride level at the steel location", or "chloride concentration at a given depth exceeds some specified limit". Critical structural states or limit states otherwise are in principle divided into two categories: (i) ultimate limit states (ULSs) and (ii) serviceability limit states (SLSs).

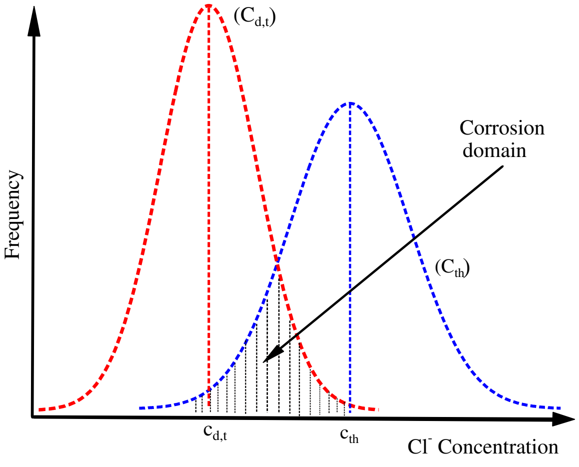

Fig. 1. Deterministic vs. probabilistic predictions of corrosion.

Ultimate limit states relate generally to the loss of static equilibrium and collapse and limit state functions may be formulated to express the boundary between a safe and unsafe condition for factors such as bending, tensile, shear and compressive strength. Serviceability limit states restrict the normal use of structure and can include excessive deformation, excessive vibration, excessive local damage (e.g. cracking, spalling, corrosion, etc.). Limit state functions for serviceability can be formulated to describe the different phases associated with damage initiation and accumulation in concrete structures, which can include corrosion initiation, cracking, spalling and delamination of the concrete. Other serviceability limit states can relate to phenomena which have an effect on durability such as deformations due to excessive loads. Events associated with serviceability limit states are often further distinguished into irreversible and reversible states [14,30]. Irreversible limit states refer to events after which the structure cannot recover or return to its condition before the event (e.g. corrosion). Reversible limit states, on the other hand, refer to events after which the structure may regain its previous condition (e.g. deformations that are not excessive i.e. before cracking) [30].

Depending on the variable of interest, the corresponding performance function can be formulated, generally, as the difference between a term that is equivalent to a "resistance" and a term that is equivalent to a "load or load effect". For example, the term "resistance" can be used to refer to the maximum permissible chloride concentration at the steel level, or chloride threshold level C_{th} which defines the resistance to corrosion of a given reinforcing steel type, or resistance of the concrete cover to corrosion-induced cracking, or spalling, or delamination. Similarly, the term "load effect" can be used to refer to the chloride concentration at the steel level $C_{d,\ t}$, or the corrosion-induced stresses that lead to cracking, spalling, etc. The values of both parameters C_{th} and $C_{d,\ t}$ can be functions of several variables (e.g. cover depth d, time t, diffusion coefficient D, water cement ratio, etc). Therefore, the limit state function for corrosion initiation can be formulated as follows:

$$g(C_s, d, D, C_{th}) = C_{th} - C_{d,t}(C_s, d, D, t) \tag{9}$$

Hence:

$g(C_s,\ d,\ D,\ C_{th}) = 0 =$ "limit state".
$g(C_s,\ d,\ D,\ C_{th}) > 0 =$ "desired state", or "un-corroded state".
$g(C_s,\ d,\ D,\ C_{th}) < 0 =$ "corrosion state", or "failure state".

The limit state equation $g(C_s,\ d,\ D,\ C_{th}) = 0$ can be represented geometrically by an n-dimensional surface, which is referred to as a "failure surface" or in this case "corrosion initiation surface". Using Fick's second law of diffusion of Eqs. (7) and (8), the limit state function for the corrosion initiation time can be formulated as a function of four variables, which include the concrete cover (d), diffusion coefficient (D), surface chloride concentration (C_s) and chloride threshold (C_{th}), and one parameter which is the time, as follows:

$$g(C_s, d, D, C_{th}) = C_{th} - C_s\left(1 - erf\,\frac{d}{2\sqrt{Dt}}\right) \tag{10}$$

For example, for the case of predicting the probability of corrosion after a specific time t_i,$g(X)$ can be written as follows:

$$g(C_s, C_{th}, t_i, D, d) = \frac{d^2}{4D\left[erf^{-1}\left(1 - \frac{C_{th}}{C_s}\right)\right]^2} - t_i \tag{11}$$

5.2. FORM and SORM methods for predicting corrosion probability

The probability of corrosion at time (t) as expressed in Eq. (11) corresponds to the integral of the probability density function $f_X(x)$ on the corrosion domain, as follows:

$$P_f = \int_{g(C_s,C_{th},t,d,D)<0} f_X(C_s,d,D,C_{th})dx \qquad (12)$$

For illustration purposes, Fig. 2 shows a model with two input variables that characterize the limit-state function $g(X_1, X_2)$ (two-dimensional representation). To calculate this integral (i.e. probability of corrosion P_f), several methods can be used. The most obvious and simple to implement is the Monte Carlo simulation (MCS). It consists of simulating outcomes of the limit state and counting the number of corrosion events obtained. In other words, random sampling of input variables [(C_s, d, D, C_{th}) or as in the example in Fig. 2 is represented by (X_1, X_2)] allows to collect a number of realizations for $g(X_1, X_2)$. If n is the number of simulations, the frequency of corrosion observation (represented by the ratio between the number of realizations verifying $g(X_1, X_2) < 0$ over the total number of simulations (n)), tends toward the probability of corrosion when n increases. This method attempts to characterize the whole domain of failure so it needs an important number of simulations (i.e. slow convergence rate). Advanced methods use an intelligent way to select simulations, also very efficient, which are based on two main concepts: (i) Approximation of the nonlinear state function and (ii) "smart" way of doing the simulations (e.g. experimental designs). Below are the most important features of these advanced methods:

- Approximate FORM/SORM methods: They are based on the Taylor's expansion series of the limit state function near the so-called "design point", which is explained in the next section. These methods allow the analyst to compute estimates of the probability of failure at a relative low computational cost compared to Monte Carlo simulation (MCS).

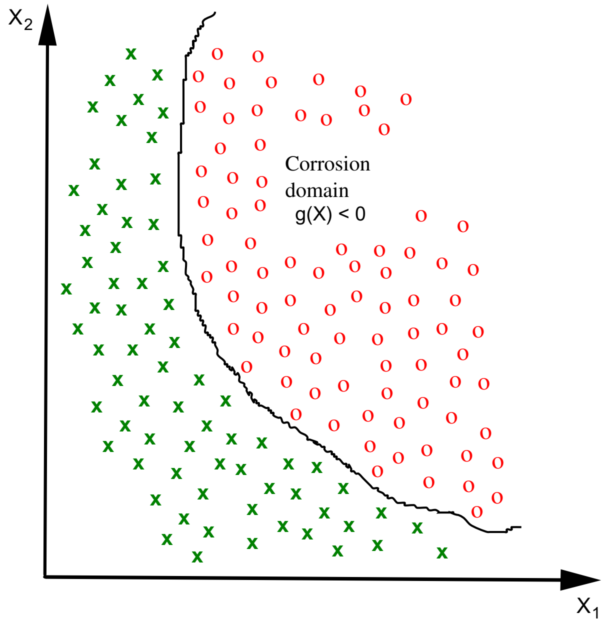

Fig. 2. Illustrative sketch of limit state of corrosion domain.

- Advanced simulation methods, including: *Importance Sampling* [20], *Directional Simulation, Latin Hypercube Sampling* [32] and *subset simulation method* and *Line Sampling technique* [24,40].

In this paper, the focus is on the two approximate semi-analytical methods of FORM and SORM, which are briefly presented. Their applicability and efficiency are illustrated in the illustrative example of the last section of the paper by comparing their accuracy and efficiency to that of MCS. In fact, the physical variables X_i (e.g. C_{th}, $C_{d,t}$,) cannot be represented by a multidimensional centered Gaussian density of probability with variance equal to 1 and without any correlation; therefore, the method presented above cannot be applied on physical variables. Hence, a transformation of the physical variable space into a new space of statistically independent Gaussian variables U_i called reduced variates [21,29], with zero mean and unit standard deviations. The mean value point in the physical space is mapped into the origin of the U_i space and the corrosion surface in the physical space is mapped onto its corresponding surface, as shown in Fig. 3.

For independent variables, the transformation T can be obtained using the equality of the distribution functions applied to their associated variables, which means:

$$F_{C_{th},C_{d,t}}(c_{th},c_{d,t}) = \Phi_{U_1,U_2}(u_1,u_2) \Rightarrow (u_1,u_2) = \Phi^{-1}_{U_1,U_2}(F_{C_{th},C_{d,t}}(c_{th},c_{d,t})) \qquad (13)$$

where $F_{C_{th},C_{d,t}}(.)$ represents the joint distribution function of the physical variables and Φ_{U_1,U_2} the independent standard Gaussian distribution. This transformation [i.e. $T(.) = \Phi^{-1}_{U_1,U_2} o F_{C_{th},C_{d,t}}(.)$], from the physical space [e.g. (c_{th}, $c_{d,\ t}$)] to the standard space [e.g. (u_1, u_2)], is called iso-probabilistic transformation. For the case where the variables are not independent, a general form of the transformation has been given by Rosenblatt [29].

The aim of the iso-probabilistic transformation is to "normalize" the input variables to get an invariant index. In other words, the input variables are transformed into multinormal Gaussian variables that have symmetry of revolution around the mean value point which represents the origin of the U space. The design point P^* represents the *most probable failure (corrosion) point* which is: (i) a point in the corrosion domain and (ii) the closest from the origin (i.e. means higher frequency) i.e. the point in the corrosion domain that has maximum density (see Fig. 4).

In Fig. 4, the distance (OP^*) separating it from the origin is called the Hasofer–Lind reliability index β_{HL} [21]. This index is determined by solving the following nonlinear optimization problem:

$$\text{Find } \beta_{HL} = \min\left(\sqrt{\sum_i u_i^2}\right) \qquad (14)$$

$$\text{Subject to}: h(u_1,u_2) \leqslant 0 \qquad (15)$$

where $h(u_1, u_2)$ is the transformed limit state function in the standard space (see Fig. 3).

(a) Prediction of corrosion probability using FORM
The first-order reliability method (FORM) method consists of the approximation of the limit-state function into a hyper plane using a first-order Taylor'series approximation of the limit state function in order to express the probability of failure as function of the reliability index (see Figs. 4 and 5). Using mathematical techniques (e.g. rotation of the U space in the direction of OP^*, and using Fubini's theorem to separate the integrals), the multiple integral of P_f can be reduced to a simple integral. Therefore, the probability of corrosion can be evaluated as follows:

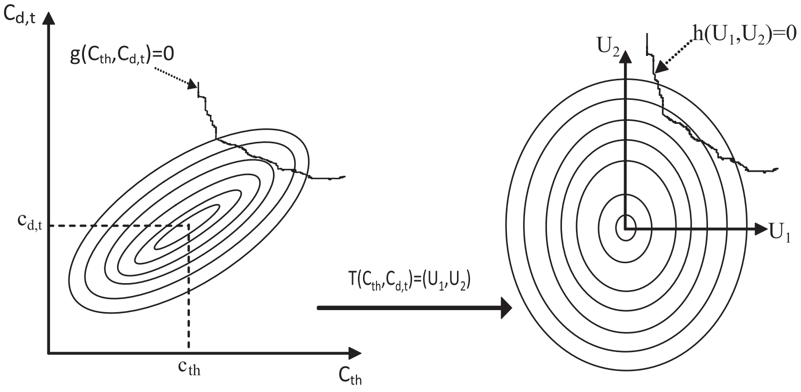

Fig. 3. Transformation of physical space into standard space.

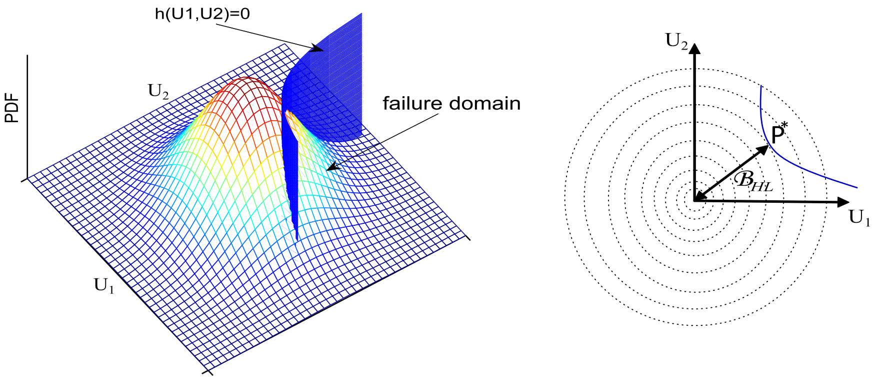

Fig. 4. Illustration of most probable point of corrosion.

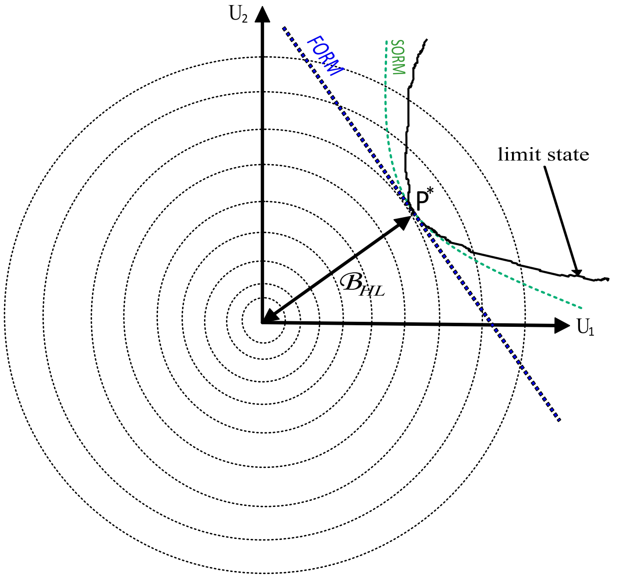

Fig. 5. FORM/SORM approximation of limit state function.

$$P_f = \int_{h(u_1,u_2)} f_{(U_1,U_2)}(u_1,u_2)du_1du_2 = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{-\beta} e^{-\frac{u_1^2}{2}}du_1 = \phi(-\beta) \quad (16)$$

with $\phi(.)$ is the cumulative distribution function of the Gaussian or normal distribution. In conclusion, the probability of corrosion calculated using FORM is:

$$P_{f,\text{FORM}} = \phi(-\beta) = 1 - \phi(\beta) \quad (17)$$

The advantage of this method is that it does not need a large number of iterations because it searches for one point (the design point) instead of characterizing the whole domain. Furthermore, it can be used with only two input data for each parameter, namely their mean value and coefficient of variation (assuming normal distribution), which is a major advantage over MCS that requires the probability distribution functions of all parameters. Such data are not readily available.

(b) Prediction of corrosion probability using SORM

The second-order reliability method (SORM) (also called curvature-fitting) consists of establishing a second order Taylor series of the series expansion of the limit state function around the design point. This requires the computation of the second order Taylor series at the design point. Similar to FORM, a suitable rotation allows the design point P^* to takes the coordinates: $P^* = (0, 0, \beta)$. Geometrically, the limit state hypersurface is approximated by a paraboloid at the design point (See Fig. 5). This approximation requires the calculation of the first $n-1$ curvatures of the limit state function denoted by:

$$\{\kappa_j, j = 1, ,n-1\} \quad (18)$$

Several approximations for the probability of failure using SORM, were proposed [7,45]. The asymptotic formula for the probability of failure derived by Breitung [7] is given by:

$$P_{f,\text{SORM}} \approx \Phi(-\beta)\Pi_{j=1}^{n-1}(1-\beta\kappa_j)^{-1/2} \quad (19)$$

hence, SORM uses the results found by FORM for the design point, and corrects the expression of the probability of failure obtained by FORM.

(c) Determination of importance factors

The importance factors associated with FORM can be seen as a specific technique for sensitivity analysis. The FORM importance factors offer a way to rank the importance of the input variables with respect to the probability of corrosion. They are often interpreted also as indicators of the impact of modeling the input components as random variables rather than fixed values. For the case proposed above, the importance factor of each parameter represents its contribution to the reliability index. In other words, the design point P^* is represented by the vector OP^* that defines the distance from the origin to the most probable corrosion point (P^*); OP^* can be written as: $OP^* = \sum_i u_i e_i$. Every parameter (e.g. C_s, d, D, C_{th}) has its transform in the standard space $(u_i)_i$. Therefore, the importance of the chloride surface value C_S, for example, can be written as follows:

$$\alpha_1^2 = \frac{u_1^2}{OP^{*2}} \tag{20}$$

Since $\sum_i \alpha_i^2 = 1$, the importance factor is expressed as a percentage value.

6. Illustrative example

6.1. Description of the structure

The proposed probabilistic approach for the uncertainty modeling and prediction of chloride concentration of concrete and reinforcement corrosion is illustrated on a reinforced concrete highway bridge deck structure that is subjected to the application of deicing salts during winter. The structure is a normal concrete bridge deck reinforced with conventional carbon steel. Reinforcement ratios of 0.3% are used for both top and bottom mats of reinforcement in the longitudinal and transverse directions.

The bridge deck is exposed to a corrosive environment with a surface chloride concentration of 6 kg/m^3 and a coefficient of variation (cov) of 30%. The concrete cover depth for the top reinforcement steel has a mean value of 70 mm and cov of 20%. The chloride diffusion coefficient in this concrete has a mean value of 0.4 cm^2/year and cov of 25%. The chloride threshold of this carbon steel is assumed to have a mean value of 0.7 kg/m^3 and cov of 20%.

The example is used to show the applicability, accuracy and efficiency of FORM and SORM to model the uncertainty in the parameters governing the probability of corrosion of reinforced concrete (RC) structures subjected to chloride attack. The main objectives of the example include also:

- Highlight the importance of taking into account the variability of different parameters and its impact on the probability of corrosion.
- Compare the predictions and efficiency of FORM and SORM to Monte Carlo simulations.
- Study the sensitivity of different parameters of the model and their influence on the service life of reinforced concrete structures.

The parameters values are based on data taken from field data and literature [27,28], and are listed in Table 1.

Table 1
Input data for illustrative example of RC bridge deck subjected to chlorides from deicing salts.

	C_s	d	D	C_{th}
Mean value	6 kg/m^3	70 mm	0.4 cm^2/year	0.7 kg/m^3
Coefficient of variation	30%	20%	25%	20%

By considering the parameters mean values, the prediction of deterministic time to corrosion initiation can easily be found by using the Fick's second law of Eq. (8). Fig. 6 shows the deterministic predictions (using mean values) of the chloride concentrations at the steel level at different points in time within the service life of the structure. As discussed earlier, corrosion initiates when the concentration of chlorides at the steel level becomes greater than the chloride threshold assumed as 0.7 kg/m^3, which in this case, occurs after 23 years and 10 months. When taking into account the variability of different parameters, the concept of time to corrosion becomes a probability of corrosion. The values obtained can be considered as more realistic estimates than the deterministic values. Fig. 7 shows the predictions of the time-varying probability of corrosion using Monte Carlo simulation (MCS) with 100,000 simulations for every interval of time and assuming lognormal random variables for all parameters. This figure shows that the probability of corrosion at the specific time determined in the previous section (after 23 years and 10 months) is around 45%. In this study, all the parameters assumed to be independent, i.e. correlation is not taken into consideration.

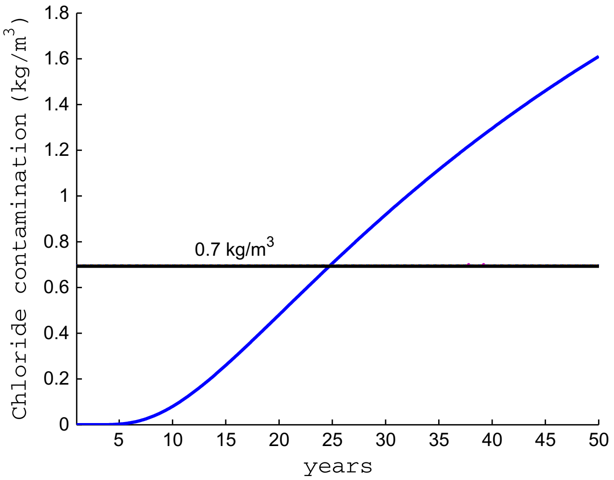

Fig. 6. Average time-varying chloride concentration at steel level.

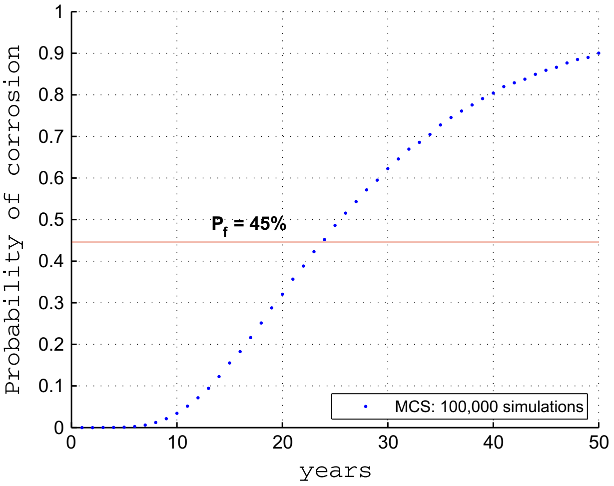

Fig. 7. Prediction of time-dependent probability of corrosion using Monte Carlo simulation.

6.2. Corrosion probability predictions using FORM

As it can be seen, the diffusion-based corrosion initiation model is a non-linear function of the four key parameters, which requires an important number of MC simulations to be characterized. In this section, the first order reliability method (FORM) is applied to the example presented above. The aim is to test its efficiency for this kind of highly nonlinear problems. The first one, taken as the reference solution, is performed using MCS with 100,000 simulations. Second, FORM was implemented. It requires only 300 iterations to provide satisfying results (smooth curve). The third analyses were done using MCS with the same number of simulations needed to determine the design point with the FORM method. Fig. 8 shows that FORM yields almost the same probability curve as the MCS with a negligible error that overestimates the probability of failure. Therefore, its error is on the conservative side.

6.3. Corrosion probability predictions using SORM

As mentioned above, SORM uses the curvature of the failure surface at the design point (second derivative), so it is more accurate than FORM and requires more iterations. In Fig. 9a, the two methods FORM and SORM are compared. By considering the interval 20–30 years, it can be seen that the difference between the two methods is not significant as shown in Fig. 9b.

6.4. Sensitivity of corrosion probability to governing parameters

To show the influence of the variability of the parameters on the probability of corrosion, the same example is considered at a specified time and by varying the precision of one or more of the parameters.

(a) *Impact of cover depth*: By varying the variation coefficient of the cover depth only (i.e. keeping everything else the same as in Table 1), its impact on the corrosion probability after 15 years is evaluated using FORM and MCS, which is shown on Fig. 10a. Fig. 10a shows that an increase of up to 25% in the probability of corrosion when the coefficient of variation of the cover depth is varied from 0% to 40%. By comparison with the previous analysis, this variation of 25% in the corrosion probability is equivalent to an uncertainty of 10 years (from 15 to 25 years in Fig. 9a).

(b) *Impact of chloride threshold*: A change in the variation coefficient of the chloride threshold has a much lower impact on the probability of corrosion than that of the cover depth. The same range of variation was noticed for the diffusion coefficient (D) and surface chloride concentration (C_s). In terms of the efficiency of FORM vs. MCS, the results are also satisfying in the case of change of the coefficient of variation (cov).

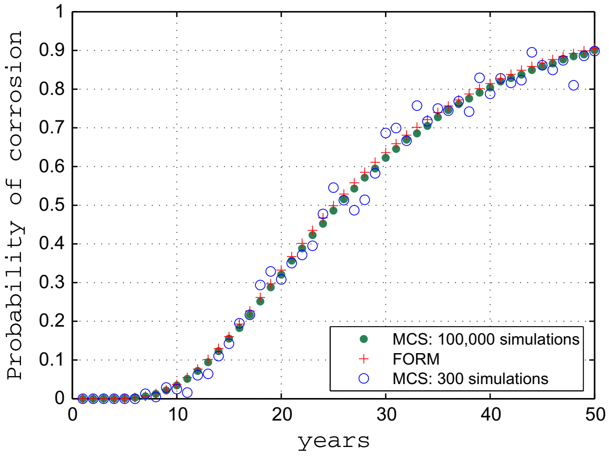

Fig. 8. Comparison of accuracy and efficiency of FORM and MCS in predicting corrosion probability.

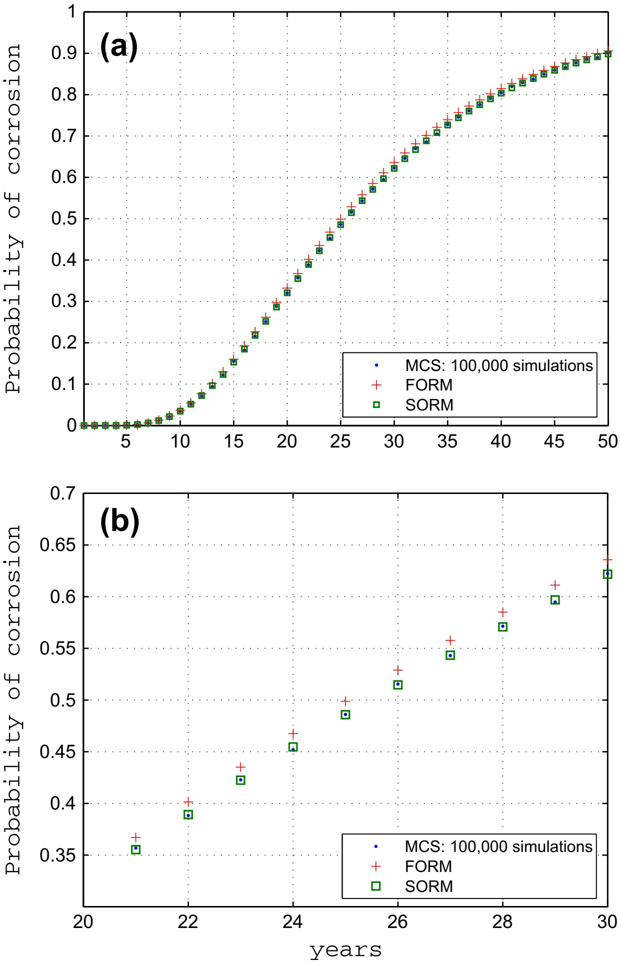

Fig. 9. Comparison of accuracy and efficiency of FORM and SORM with MCS.

6.5. Importance factors of different parameters

This section presents the study of the influence of every parameter and its contribution to the probability of corrosion or reliability index, by calculating the importance factors. First, an example of calculation of the importance factor for the above case is presented. The next paragraphs show how the influence of each parameter can change with time and how its importance depends also on its coefficient of variation even for similar mean values. The parameters (C_s, d, D, C_{th}) are assumed to be independent and follow lognormal distributions with the mean and coefficients of variation values presented in Table 1. Taking the example of $t = 20$ years, the corresponding Hasofer–Lind reliability index $\beta_{HL} = 0.43$ and associated probability of corrosion is 33%. The importance factor of each parameter is shown in Fig. 11. Fig. 11 shows the dominance of the cover depth on the other factors. In the major examples studied, this remains valid even if the probability law used is normal (or Gaussian) instead of lognormal and even for slightly different mean values of the parameters.

These importance factors are influenced by two key parameters; (i) time within the design life of the structure and (ii) the coefficient of variation of some parameters. In the next paragraphs these two cases are discussed.

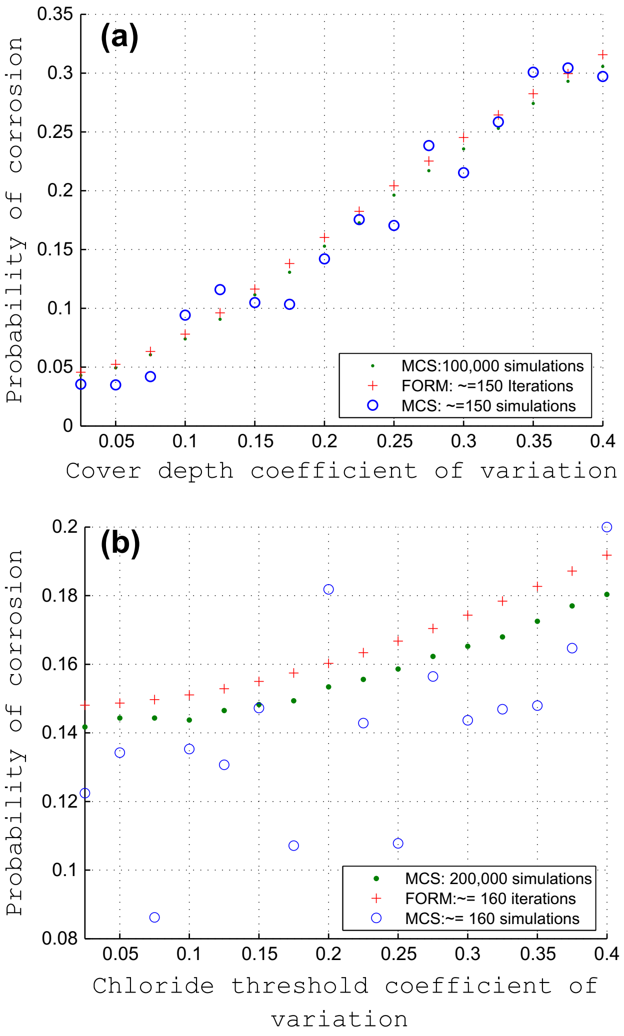

Fig. 10. Impacts of parameter variability on corrosion probability: (a) impact of cover depth; (b) impact of chloride threshold level.

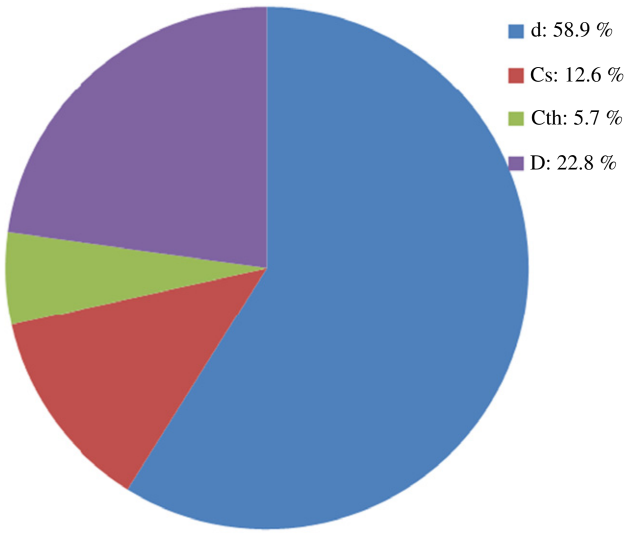

Fig. 11. Importance factors of governing parameters to corrosion probability.

(a) Sensitivity of importance factors to time

- The importance factors were calculated throughout the service life. For the reference case study (in Table 1), Fig. 12a shows that the importance factor of the cover depth remains slightly unchanged.
- In case of light exposure to chlorides (e.g. for $C_s \leqslant 2$ kg/m^3), the C_s importance factor becomes more significant with time. In other words, more attention should be given to obtain accurate estimates of the chloride surface in case of long service life design. For example, at 50 years, the importance factor of C_s is about 30% which becomes as important as the cover depth (Fig. 12b).
- In case of a more severe exposure (e.g. $C_s \geqslant 12$ kg/m^3), the use of stainless steel reinforcement (e.g. $C_{th} \approx 4$ kg/m^3) may be more appropriate to compensate for the severe exposure [same range of values for the probability of corrosion as in the case above ($C_{th} \approx 0.7$; $C_s \approx 2$ kg/m^3)], and the importance factors of the cover depth and C_s keep the same shapes with respect to the service life (see Fig. 13).

(b) Sensitivity of importance factor to coefficient of variation

At a given time, (e.g. 20 years), the influence of the coefficient of variation on the importance factors and the probability of corrosion can be evaluated. By assuming the mean values of the parameters as the same as in Table 1, and after varying the coefficient of variation of every parameter, three remarks can be made:

(i) An increase in the coefficient of variation (from 0% to 40%) of any parameter increases its importance factor, therefore increases its importance with respect to the other parameters, especially the importance

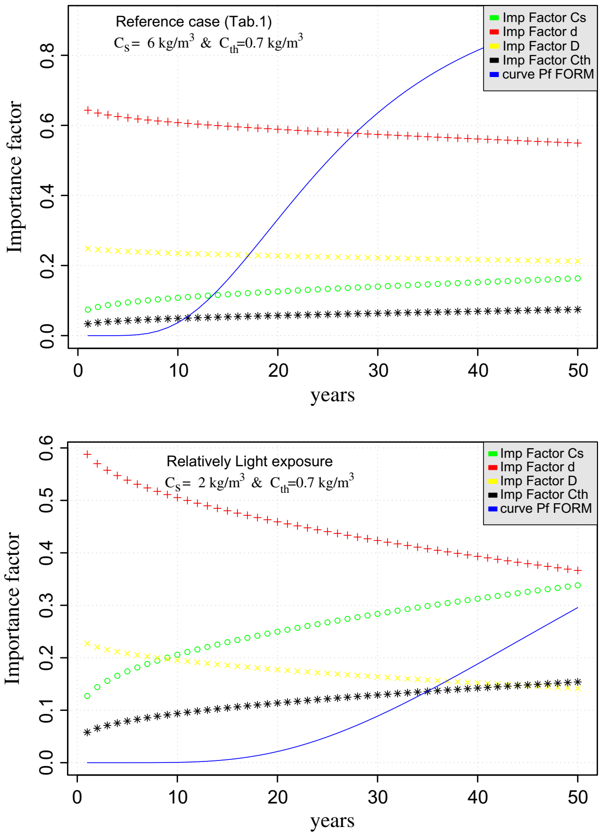

Fig. 12. Impact factors of model parameters on service life.

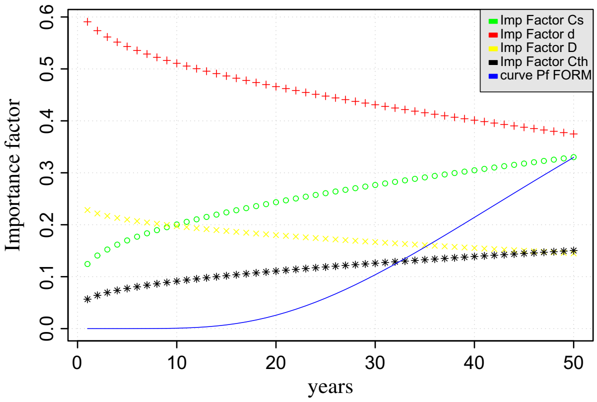

Fig. 13. Impact factors of model parameters on service life for cases of severe exposure and carbon steel reinforcement.

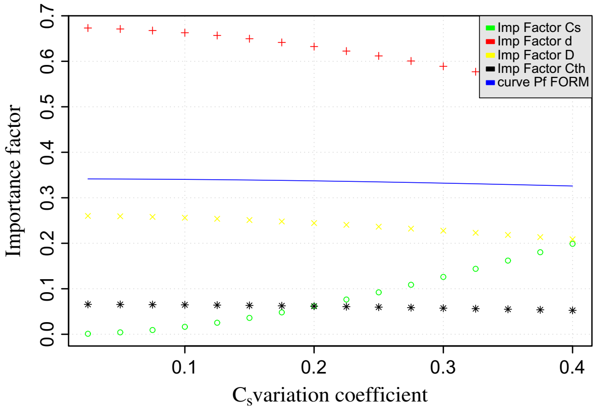

Fig. 14. Sensitivity of impact factor to variability of surface chloride concentration (kg/m^3).

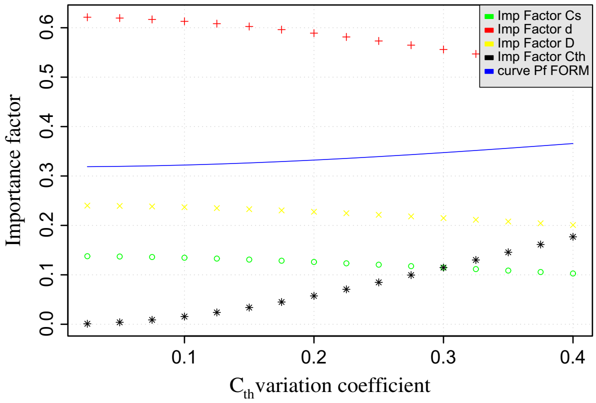

Fig. 15. Sensitivity of impact factor to variability of chloride threshold.

factor of the cover depth, which accounts for almost all the increase of the importance factor of interest (see Figs. 14–17).

(ii) The importance factor of the cover depth increases at a higher rate when its variation coefficient is increased (see Fig. 17). In other words, the increase in the importance factor for the parameters C_s and C_{th} remain in a range of 20%, for the diffusion coefficient D in the range of 40% (see Figs. 14–16), but for the cover depth, an 80% increase is noticed for 40% increase in its variation coefficient (Fig. 17).

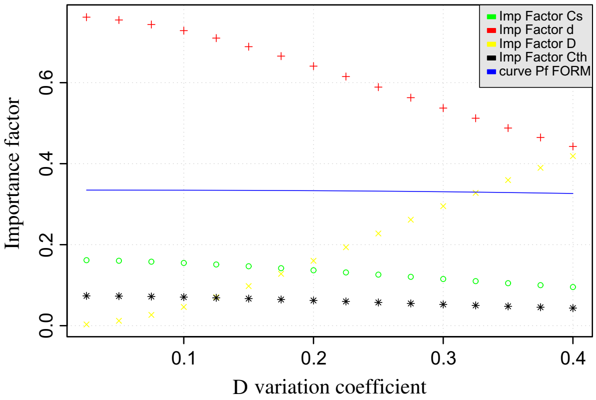

Fig. 16. Sensitivity of impact factor to variability of diffusion coefficient.

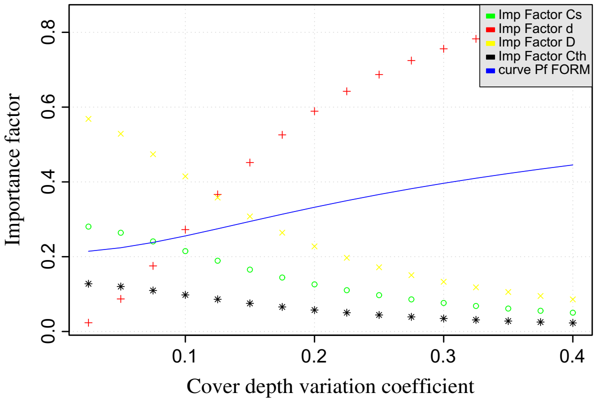

Fig. 17. Sensitivity of impact factor to variability of cover depth.

(iii) The probability of corrosion is affected marginally by a change in the variation coefficient of the three parameters C_s, D and C_{th}; its range of variation does not exceed the 5%; however exceeds 20% in case of change in the cover depth variation coefficient (see Fig. 17).

7. Summary and conclusions

This paper presented two simplified semi-analytical probabilistic methods based on the first- and second-order reliability methods (FORM/SORM) to model the uncertainty of the parameters that govern the chloride ingress into concrete and onset of corrosion of reinforcing steel in reinforced concrete structures subjected to chlorides from deicing salts. A case study illustrated the main capability and efficiency of the FORM & SORM models for the life cycle-based design and management of reinforced concrete structures. These models can be used to help designers quantify how changes to the structural design and maintenance will affect its probability of corrosion and service life.

The paper and the case study highlighted the benefits of probabilistic models to predict the service life of reinforced concrete structures when compared to deterministic models. The illustrative example showed that the simplified FORM and SORM methods can be applied even for highly non-linear problems, which is the case of the chloride ingress and corrosion problems. It illustrated the efficiency of FORM vs. Monte Carlo simulation especially when the coefficients of variations are relatively low (less than 50%).

The proposed methods enables also to study the sensitivity of the corrosion probability to different parameters, including their mean values and coefficients of variation. It is found that in order to achieve a low corrosion probability and durable design, the concrete cover depth is the most influencing parameter. More specifically, the variability of the cover depth makes it very important vs. the other parameters (importance factor increases of 80% for 40% increase in its coefficient of variation). In terms of probability of corrosion, an increase of 20% is noticed for a change in the coefficient of variation, which is relatively high with respect to other parameters (5%).

It is also found that it is important to identify the severity of the environment, type of concrete, and type of reinforcement to define different classes of durability designs of concrete structures built in chloride-laden environments. However, for effective life cycle design of structures, the life cycle costs associated with the changes in each design parameter should be evaluated in order to determine the optimum service life design of reinforced concrete structures.

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