Review

Advances in Modeling Surface Chloride Concentrations in Concrete Serving in the Marine Environment: A Mini Review

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Abstract: Chloride corrosion is a key factor affecting the life of marine concrete, and surface chloride concentration is the main parameter for analyzing its durability. In this paper, we first introduce six erosion mechanism models for surface chloride ion concentration, reveal the convection effect in the diffusion behavior of chloride ions, and then introduce the corrosion mechanisms that occur in different marine exposure environments. On this basis, the analysis is carried out using empirical formulations and machine learning methods, which provides a clearer understanding of the research characteristics and differences between empirical formulas and emerging machine learning techniques. This paper summarizes the time-varying model and multifactor coupling model on the basis of empirical analysis. It is found that the exponential function and the reciprocal function are more consistent with the distribution law of chloride ion concentration, the multifactor model containing the time-varying law is the most effective, and the Chen model is the most reliable. Machine learning, as an emerging method, has been widely used in concrete durability research. It can make up for the shortcomings of the empirical formula method and solve the multifactor coupling problem of surface chloride ion concentration with strong prediction ability. In addition, the difficulty of data acquisition is also a major problem that restricts the development of machine learning and incorporating concrete maintenance conditions into machine learning is a future development direction. Through this study, researchers can systematically understand the characteristics and differences of different research methods and their respective models and choose appropriate techniques to explore the durability of concrete structures. Moreover, intelligent computing will certainly occupy an increasingly important position in marine concrete research.

Keywords: surface chloride concentration; concrete corrosion; marine environment; machine learning

1. Introduction

Abundant marine resources have attracted the attention of countries all over the world. The European Union has been continuously updating marine development documents since 2007 to promote the development of marine industry [1]. China put forward the major deployments of a “developing ocean economy” and “strengthening a strong marine country” at the 19th and 20th National Congresses of the Communist Party of China [2,3]. In 2017, the EU’s gross value added (GVA) reached EUR 184 billion, and the total turnover reached EUR 665 billion [4]. In 2021, China’s total marine economy exceeded CNY 9 trillion, accounting for 8% of the growth of the national economy [5]. With the rapid development of the marine industry, concrete has become the main material for the construction of marine infrastructures, such as deep-sea exploration and ship engineering, due to its advantages of low price, high strength, and high plasticity [6,7].

However, marine concrete often suffers from severe erosion, requiring large amounts of materials and funds to maintain the infrastructure and repair the damage. The annual cost of repair and replacement of chloride corrosion of marine concrete in the United States is reported to be approximately USD 1 billion [8]. In 2014, the cost of marine corrosion in...
China was RMB 700 billion, accounting for one-third of China’s total corrosion costs [9]. Marine corrosion can even cause human casualties. In 2021, a 12-story beachfront condominium in Miami, USA, collapsed due to seawater back-up corrosion, killing 97 people [10]. It is clear that exploring the corrosion mechanisms of marine concrete structures and accurately assessing their service life are important long-term issues for the global engineering industry [11,12].

Marine concrete faces an extremely complex environment [13]. Huang [14] reported that each kilogram of seawater contains about 19.345 g chloride ions, which is the highest chemical composition of seawater. Damage to marine concrete structures mainly comes from chloride salt erosion [15,16]. It is the most lethal factor leading to the degradation of reinforced concrete structures [17]. Tang [18] investigated the resistance of calcium sulfoaluminate cements to chloride ions under dry and wet cycling conditions. Al Sodani [19] developed five short-term empirical models for predicting the diffusion coefficients of chloride ions in the actual exposure environment. Most of the current studies on chloride ions are based on Fick’s second law, which explores the erosion process from the perspective of quantitative analysis. Among the most important parameters of Fick’s second theorem, the surface chloride concentration is the boundary condition for quantitatively analyzing the life of concrete and predicting the resistance of concrete to chloride ion erosion [20]. And it has been shown that the differences in chloride ion concentration in concrete will cause the change of concrete surface shape; when the chloride concentration exceeds a certain limit, it will cause the corrosion of the passivation film of concrete reinforcement, leading to cracks and accelerating the corrosion of concrete [21,22]. Wang [23] investigated coral aggregate concrete under alternating wet and dry conditions using the finite element software, and the chloride ion concentration was used as a key indicator. Bao [24] studied the relationship between factors such as the water-cement ratio and drew conclusions by measuring the chloride concentration under different exposure durations. It shows that the study of surface chloride ion concentration in concrete is of great engineering value for the design, maintenance, and service life assessment of marine concrete [25–27].

The influence of surface chloride ion concentration is intricate and affected by factors such as environment, material, concrete composition ratio, and application time [28], and researchers often neglect the influence of coupling factors. The different mechanisms of surface chloride concentration in different exposure environments lead to the convection phenomenon of chloride concentration, which is often neglected in numerical simulations. In addition, despite the rise of machine learning, its application in chloride erosion studies lacks uniform generalization. Compared with the traditional empirical formula methods, the characteristics of machine learning are not yet clear. It remains a challenge to utilize and translate existing research results into practical outcomes.

Marine structures include many regions where stress contours may be severely perturbed, which in turn lead to severe stress concentrations [29]. These regions are known as disturbed regions [30]. Pile caps, beam column joints, loading points, Corbels, deep beams, dapped ends, openings, T-shaped deep beams, and joints between piers and cross beams are other examples of these severely disturbed regions [31,32]. These regions are considered to be the most likely places for failure and the first cracks to occur. Therefore, improving the performance of these regions can improve the overall performance of the structure. It is worth mentioning that FE methods [33] (including ABAQUS 2022 R2/ANSYS 2022/SAP84) are considered to be powerful tools for dealing with such regions.

With the maturity of chloride erosion studies and the emergence of sulphate ions as another key factor in concrete durability problems [34], researchers have also begun to focus on the coupled erosion of chloride and sulphate ions [35]. Currently, the coupling of sulphate ions with chloride ions is mainly focused on elucidating their erosion mechanisms [36,37]. It is generally believed that chloride ions from Friedel’s salt together with hydration products refine the pore space and limit the diffusion of sulphate. Subsequently, sulphate triggers concrete damage and pore dilation, facilitating chloride ion diffusion [38,39]. However, calcium leaching by sulphate ions also hinders chloride ion
migration [40]. The mechanism by which chloride and sulfate ions couple to produce erosion is currently unknown. Numerical analysis is a common method of studying the interaction between these ions [41,42]. Zhuang [43] developed a numerical model of the diffusion response of their coupled erosion and investigated the effects of porosity and diffusion coefficient on the ion distribution and service life of concrete under dry and wet cycling and calcium leaching conditions. The researchers also focused on protective measures against coupled ion erosion. Liu [44] found that modified barium chloride–silica fume composite admixtures could improve the resistance of concrete to internal sulphate attack. Although some progress has been made, the coupled erosion mechanism is still unclear, and there are relatively few research tools. The coupling effect of chloride and sulfate ions still needs to be vigorously studied in the future. The present paper does not deal with this subject.

Here, this paper summarizes the erosion mechanism and diffusion behavior of surface chloride ion concentration. Considering various exposure environments and influencing factors, the current research status of the empirical formula method and the machine learning method are highlighted, and the shortcomings of different research methods are analyzed. Meanwhile, the advantages and future development of the machine learning method are revealed to provide reference for researchers’ studies.

2. Deterioration Mechanisms of Chloride Erosion of Concrete

2.1. Chloride Ion Migration Mechanism

The diffusion of chloride ions in concrete is fixed on the concentration gradient of chloride ions [45]; in general, the larger the gradient, the faster the diffusion of chloride ions [46]. In order to characterize the migration of chloride ions in concrete, Fick suggested in 1855 that diffusion can be expressed in terms of the amount of ions diffusing perpendicularly to the direction of diffusion through a unit of cross-sectional area per unit of time, i.e., the diffusion flux (J, mol/m²·s). The diffusion flux is calculated as follows [47]:

\[
J = -D \frac{\partial C(x,t)}{\partial x}
\]

where \( D \) is the diffusion coefficient, reflecting the permeability of chloride ions in concrete or the corrosion resistance of concrete; \( C(x,t) \) is the concentration of chloride ions; \( x \) is the distance from the surface of concrete; \( \frac{\partial C}{\partial x} \) represents the concentration gradient.

The diffusion flux in practical situations is highly dependent on diffusion time, exposure conditions, porosity, etc. In order to describe the chloride migration in practical situations, several prerequisites are proposed; for example, the concrete is considered as a homogeneous phase: there is no physical or chemical interaction between chloride ions and concrete, and the diffusion coefficient of chloride ions is a constant [48]. Based on these preconditions, Fick’s second law [49] can be expressed as follows:

\[
\frac{\partial C(x,t)}{\partial t} = \frac{\partial}{\partial x} \left( D \frac{\partial C(x,t)}{\partial x} \right) = D_s \frac{\partial^2 C(x,t)}{\partial x^2}
\]

where \( x \) is the distance from the concrete surface, i.e., diffusion depth (mm); \( t \) is the diffusion time (year, a); \( D_s \) is the diffusion coefficient of chloride ions.

Due to the difficulty of obtaining \( C(x,t) \) directly, a Gaussian error function \( \text{erf}() \) is generally used instead of \( C(x,t) \). In addition, it contains many artificial preconditions in Fick’s second law, which leads to difficulties in describing the diffusion of chloride ions in complex situations such as nonsaturated conditions [50]. In order to describe the diffusion process more accurately, different boundary conditions were introduced, and
analytical solutions were derived from them. Diffusion models were eventually developed. Collepardi et al. [51,52] proposed the following:

\[
C(x,t) = C_s \left(1 - \text{erf} \left( \frac{x}{2\sqrt{D_s t}} \right) \right)
\]  

(3)

\[
C(x>0,0) = 0
\]

\[
C(0,t\geq0) = C_s
\]

where \(C(x,t)\) denotes the chloride ion concentration at depth \(x\) and time \(t\), and \(C_s\) denotes the surface chloride concentration. The inclusion of the error function \(\text{erf}()\) can better describe the dynamic process of chloride ion diffusion from the region of high concentration to the region of low concentration, reflecting the temporal change and nonlinear characteristics of chloride ion diffusion.

Yao et al. [53–55] introduced the initial chloride ion concentration \(C_i\) in concrete:

\[
C(x,t) = C_i + (C_s - C_i) \left(1 - \text{erf} \left( \frac{x}{2\sqrt{D_s t}} \right) \right)
\]  

(4)

By incorporating \(C_i\) and \(C_s\), the model takes into account the gradient change in chloride concentration from the surface to the interior, which allows for a better understanding of the initial stages of chloride intrusion as well as the distribution and accumulation of chloride ions in the concrete.

The Federal Bureau of Investigation [56–58] introduced the convection phenomenon and modified the model as:

\[
C(x,t) = C_i + (C_s - C_i) \left(1 - \text{erf} \left( \frac{x - \Delta x}{2\sqrt{D_s t}} \right) \right)
\]  

(5)

\[
C(0,t) = C_s
\]

\[
C(\infty,t) = C_i
\]

where \(\Delta x\) is the convection depth (mm), \(D_s\) is the diffusion coefficient of chloride ions in the unsteady state, and \(D_s\) can also be obtained from the measured chloride ion concentration \(C(x,t)\). The diffusion coefficient of chloride ions decreases with increasing exposure time [59–62]. By introducing the offset \(\Delta x\), the model can more accurately describe the actual diffusion process of chloride ions in concrete by taking into account the nonhomogeneity and boundary effects of chloride ion diffusion in marine concrete.

The main difference between the various models is that they take into account different factors. It is worth noting that the last model has a higher agreement with the experimental results due to the comprehensive consideration of the various influencing factors. This enables more accurate prediction of the temporal distribution, accumulation rate, and concentration threshold of chloride ions in concrete. Thus, it plays a key role in facilitating the development of more effective strategies to mitigate chloride-induced corrosion, thereby improving the durability of concrete structures.

Then, it can be seen that \(C_s\) is crucial for concrete durability studies and concrete life prediction [63–65], and is therefore a key parameter for quantitatively characterizing the strength of corrosion effects.

2.2. Diffusion Behavior of Chloride Ions

Chloride ions are the main cause of concrete corrosion in marine environments [66]. It involves various processes such as diffusion, convection, capillary adsorption, infiltration, and chemical binding of chloride ions [67–69], with diffusion playing the largest role [70–72]. The corrosion depth, \(d\), is defined as the distance that chloride ions diffuse from the surface to the interior (see Figure 1a). The corrosion zone consists of two parts, the convection zone (CZ) and the diffusion zone (DZ) [73], which depend on the variation of chloride
ion concentration. In the CZ, the adsorption of chloride ions is realized by capillary adsorption of seawater or salt spray. The coupling of diffusion and capillary adsorption effects produces a zone of maximum concentration [74]. This zone is called the ‘convection zone’ (see Figure 1b) and its distance is called the convection zone depth (Δx) [75,76]. In this region, the chloride concentration increases with depth [77]. The diffusion behavior of chlorine ions in this zone cannot be explained by Fick’s second law [78,79]. Chan [80] reported that after 36 days of exposure to cyclic dry/wet environments, all samples showed peak concentrations at a certain depth, which proved the existence of the convection zone. In the diffusion zone, chloride concentrations decrease with depth and increase with exposure time. Chloride diffusion in this region can be well explained by Fick’s law.

The depth of the CZ and the peak chloride concentration are important predictors of the service life of concrete [81]. It is critical to obtain the depth of the CZ [82–87]. In practice, the depth is affected by a number of factors. In general, the depth of the convection zone moves forward, and the maximum chloride ion concentration increases with exposure time. Convection zone depth also increases with the number of dry/wet cycles. In addition, the higher the dry/wet ratio, the earlier the convective zone appears [88]. Balestra [89] proposed obtaining the depth of the CZ by using the maximum value of the chloride concentration and a linear approximation of the two neighboring points. Pang [90] numerically analyzed the depth of the CZ to be 20 mm. Gao [91] reported that the depth conforms to a normal distribution with a mean value of 4 mm by comparing artificial simulations with the natural environment. Based on the results of 270 experiments, the mean value of the convective zone depth is 3.99 mm [76]. Zhang [92] derived a mean convection zone depth of 2–5 mm from experiments and simulations based on data from Zhejiang province, China. Li [93] obtained a convection zone depth of 3–5 mm under alternating dry/wet conditions. Cai [94] reported a value of 10 mm. Cui [95] reported peak concentrations in the range of 10–15 mm by simulating the service of a splash zone. Duracrete [96] categorized convection zones into three series based on maintenance costs: high-cost zones (Δx around 20 mm), average-cost zones (Δx around 14 mm), and low-cost zones (Δx around 8 mm). Figure 2 summarizes the depth distribution of Δx between 2 mm and 20 mm.

Thus, it is clear that the depth of the convection zone is not a constant due to the heterogeneity of concrete composition and the different exposure conditions [51,76,97]. The presence of the convection phenomenon will greatly affect the distribution and value of chloride ion concentration in concrete, so the depth of convection zone must be considered in the study of concrete durability using Fick’s second law.
of chloride ion concentration in concrete, so the depth of convection zone must be considered. During ebbing, the concrete surface dries out and the water in the pores evaporates, leading to the migration and accumulation of chloride ions into the concrete.

Figure 2. Depth of convection zone reported in the literature. Rhombus, circle, green line, purple line, upper triangle, blue line, lower triangle are Pang [90], Gao [76,91], Zhang [92], Li [93], Cai [94], Cui [95], Duracrete [96].

2.3. Corrosion Mechanisms of Concrete under Different Exposure Conditions

The corrosion mechanism of chloride under different exposure conditions varies [98,99]. Depending on the exposure conditions, concrete can be categorized into four parts, i.e., atmospheric, splash, tidal, and underwater zones (see Figure 3 for details) [100].

Figure 3. Subdivision of concrete under different exposure conditions: atmospheric, splash, tidal, and underwater zones. The red triangular line shows the direction of chloride ions into the concrete. The blue line is the water level line.

In the underwater zone, the corrosion of concrete depends on the diffusion of chloride ions through the body, the incidence of which is relatively low. Convection is generally considered to be absent. However, Cai [81] reported that convection was also present by comparing several tests. This suggests that convection in the underwater zone is not well defined, and more work is needed in the future.

Chloride erosion in the tidal and splash zones is mainly driven by capillarity and diffusion [101]. In the tidal zone, it is most affected by the wetting–drying cycle. At high tide, the internal diffusion rate is significantly slower than the surface capillary adsorption rate [102], leading to a sharp increase in surface chloride ion concentration and the formation of concentration peaks at the boundary between the convection and diffusion zones [80,103]. During ebbing, the concrete surface dries out and the water in the pores evaporates, leading to the migration and accumulation of chloride ions into the concrete interior. The continuous wetting–drying cycle exacerbates the accumulation of chloride ions within the concrete, which ultimately leads to concrete cracking. In contrast, the splash zone is less affected by the wet–dry cycle, but more physically affected by seawater, with
more prominent physical effects. As a result, the two zones have different chloride ion concentrations \[104,105\] and the splash zone is more corrosive \[106\]. Apparently, some studies have simplified the tidal and splash zones as having similar corrosion mechanisms and combined the two in a study, ignoring their unique erosion mechanisms, which is not rigorous enough.

Corrosion processes in atmospheric zones exhibit a complex diversity and are usually divided into two stages \[107\]. In the first stage, the degree of corrosion is significantly influenced by environmental factors such as salt spray deposition, wind speed, humidity, temperature, rainfall, coastal distance, and building orientation. Specifically, variations in chloride content in the sea area and the influence of wave impact effects lead to different chloride ion concentrations in the salt spray environment, which directly affects the corrosion rate of concrete structures. Song \[108\] demonstrated, through the same sampling, that the chloride ion concentration in the coastal areas of the UK is lower than that of Japan and Venezuela, which further confirms the key role of environmental factors in chloride ion induced corrosion. Alcalá’s \[109\] research also showed significant differences in chloride deposition rates in different regions of the Iberian Peninsula. In the second stage, after chloride ions are deposited on the concrete surface, the corrosion process shifts to inward diffusion. This stage is more influenced by the internal properties of the concrete, such as the type and content of mineral admixtures. These properties determine the ability of concrete to absorb and diffuse chloride ions, which in turn affects the depth and rate of corrosion. It is therefore necessary to consider the influences of both stages together when assessing the corrosion risk of concrete structures in atmospheric zones.

It can be seen that the complexity of the environment in which concrete is used dictates that the chloride surface concentration is no longer a constant; therefore, the corrosion effects in different environments need to be analyzed differently when studying the chloride surface concentration.

3. Commonly Used Research Tools
3.1. Empirical Formulas

Current research on chloride erosion is mainly based on experimental methods, empirical formulas, and numerical calculations. Given that all studies are based on specific experimental data, numerical simulation methods may affect the accuracy of analysis by simplifying the actual problem. In addition, as shown in Figure 4, the chloride ion concentration on the surface of concrete is affected by the coupling of time, internal material, environment and transmission mode \[110,111\]. Therefore, in this paper, an empirical formula approach is used to explore the relevant model that integrates these factors.

![Figure 4. Main factors affecting the surface chloride ion concentration, C_s.](image-url)
3.2. Machine Learning

In the field of concrete science, the complexity of the cement system results in the surface chloride concentration being influenced by a number of factors, which may result in a ‘$1 + 1 > 2$’ superposition effect [112]. Nguyen [113] showed that the synergistic effect of the chloride ion concentration gradient and the two-layer effect in the migration process significantly increased the rate of mobility and the rate of concentration increase. In describing the performance of concrete, traditional empirical models are not able to cover all parameters, and their prediction accuracy is often limited by the scope of application of specific parameters, and thus have certain limitations. With the rise of artificial intelligence, machine learning shows great potential in the field of concrete science. It can not only well describe the complex properties of concrete and the nonlinear relationship between various properties, but also accurately describe the relationship between independent variables with higher fitting effect and accuracy [114,115].

It was found that the application of machine learning in concrete research focuses on two main areas:

1. Concrete performance prediction and material preparation optimization [116]. Peng [117] conducted an in-depth study on the compressive strength of recycled aggregate using traditional algorithms such as artificial neural network (ANN), support vector machine (SVM), and hybrid algorithms such as particle swarm optimization, grey wolf optimizer, and genetic algorithm (GA), in which uniaxial stress conditions can be used for concrete mechanical properties with accurate prediction.

2. Structural health monitoring of concrete infrastructure. Li [118] used convolutional neural networks (CNN) to accurately locate damage coordinates from data provided by acoustic emission sensors (AE). Laxman [119] used CNN to automatically detect crack depths.

The wide application of machine learning in concrete science provides a basis for further research on surface chloride ion concentration in marine concrete.

Figure 5. The general process of studying chloride erosion with machine learning.

The general process of studying chloride erosion using machine learning is shown in Figure 5. It consists of three main components:

1. Creation of a database.
   Collecting data from experiments and the literature.

2. Modeling.
   Clear and usable data are collected through data preprocessing and feature transformation. The obtained data are used to construct computational models such as SVM, random forest (RF), and ANN. The outputs of the models are then evaluated. The optimal
model will be used for later prediction and analysis, and the model will be iterated with the database to filter out appropriate target values.

(3) Analysis the physical significance of the data.

4. Advances in Research Based on the Empirical Formula Approach

4.1. Time-Varying Modeling Studies

Scholars usually consider the surface chloride concentration \( C_s \) as a constant based on the analytical solution of the chloride diffusion equation. Due to the variability of the marine environment and the mode of propagation, \( C_s \) in the real environment is the result of the coupling of many factors, and is characterized by time-varying and stochastic processes. With the extension of time, the degree of hydration of concrete becomes higher and the density of concrete increases, which leads to a larger growth rate in the early stage. The growth rate slows and levels off in later stages. The peak chloride concentration increases with time, as does the depth at which the peak occurs. The growth rate of the maximum concentration decreases with time as shown in Figure 6 [120]. Concentration variations in concrete can result in \( C_s \) values measured at the concrete surface being unequal to the numerical \( C_s \) values derived from diffusion modeling. Therefore, obtaining more accurate \( C_s \) is important for studying the durability of concrete.

![Figure 6. Chloride concentrations at different depths in the tidal zone. Reprinted/adapted with permission from Ref. [111]: blue, 2 a; orange, 10 a; purple, 25 a (year/a). Solid and dashed lines represent experimental and fitted data, respectively.](attachment:image)

Thus, as shown in Table 1, there are three methods for obtaining \( C_s \). One is to use the measured surface concentration as \( C_s \). This method is clearly time independent. The second method is to use the maximum concentration as \( C_s \). Although Moradllo [74] showed that this method best matches the actual chloride concentration distribution in the tidal zone, it does not take into account the time-varying nature of the maximum concentration. Thirdly, the time-varying properties of \( C_s \) were considered and removed from the convective zone for fitting. Using this approach, Bao [24] directly excluded the chloride distribution in the convection zone from 0 to 5 mm and used the initial concentration of the remaining portion as \( C_s \), achieving more accurate results for both splash zone and tidal zone data. This approach was further supported by Da [121], who excluded the initial concentration to mitigate the effects of the large chloride inherent in all-coral aggregate concrete. It is clear that taking into account the time-varying characteristics of \( C_s \) and excluding the convection zone for fitting has proven to be the most accurate approach.
Table 1. Calculations of surface chloride ion concentration.

<table>
<thead>
<tr>
<th>Way</th>
<th>Author</th>
<th>Values of Cs</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Tan [122]</td>
<td>Direct measurement of surface concentration</td>
</tr>
<tr>
<td>II</td>
<td>Moradillo [74]</td>
<td>Maximal concentration</td>
</tr>
<tr>
<td>III</td>
<td>Bao [24] Da [121]</td>
<td>Fitting results after removing the depth of the convective zone by considering the time-varying characteristics of Cs</td>
</tr>
</tbody>
</table>

In order to more accurately characterize the time-varying properties of surface chloride ion concentration, scholars have proposed a variety of functional models, including exponential, inverse function, logarithmic function, power function, and linear function, as shown in Table 2. Yu [123], in his study on the time-varying surface chloride concentration in the salt-lake area, found that, compared with the power function, the exponential function yielded the highest correlation between predicted and measured values, with a correlation coefficient of more than 0.96. Zhou [124] also proved that the exponential function could better characterize the chloride diffusion characteristics in the wet–dry alternating zone and salt spray zone through a simulation study based on similarity theory. Yang [125] compared several time-varying models based on natural exposure tests and found that the inverse-type model had a higher accuracy in describing the variation of the chloride ion concentration in the splash zone. Therefore, the exponential and inverse function models are more consistent with the time-varying distribution of chloride ion concentration and are more reliable.

Table 2. Common time-varying models describing surface chloride ion concentrations.

<table>
<thead>
<tr>
<th>Models</th>
<th>Expressions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential type [107,123,126,127]</td>
<td>$C_s(t) = C_a (1 - \exp (-at))$</td>
</tr>
<tr>
<td>Inverse type [125,128]</td>
<td>$C_s(t) = C_a (1/(t + a))$</td>
</tr>
<tr>
<td>Logarithmic type [129,130]</td>
<td>$C_s(t) = a \ln t + b$</td>
</tr>
<tr>
<td>Power function type [70,131–134]</td>
<td>$C_s(t) = a t^b$</td>
</tr>
<tr>
<td>Linear type [135]</td>
<td>$C_s(t) = at$</td>
</tr>
</tbody>
</table>

Notes: $C_s(t)$ denotes surface chloride ion concentration (%), $t$ denotes corrosion time (year/a), a and b denote fitting coefficients, and $C_a$ denotes chloride concentration in stable diffusion.

4.2. Multifactor Coupled Studies

Due to the large number and complexity of factors affecting $C_s$, a model containing only time-varying features is not sufficient to present the variation of surface chloride concentrations. Therefore, it is necessary to establish a multifactor coupling model to quantitatively describe the variation of surface chloride concentration of marine concrete.

The water–cement ratio (w/c) is an important index for evaluating the performance of concrete. Generally, the smaller the w/c is, the higher the compactness of the concrete, thus hindering the migration of chloride ions. The European DuraCrete standard [96] gives correction coefficients corresponding to the w/c of concrete in four regions. Wang [136] proposed a relationship between w/c and surface chloride concentration by taking 0.53 as a criterion, and integrating the time-varying properties, w/c, and the effect of sulfate ions. This treatment provides the possibility to study the effects of multiple ions.

Cementitious materials are another key component affecting chloride ion exchange due to the different chemical and physical binding capacities of cement pastes with chloride ions. Studies [137–139] have shown that the incorporation of auxiliary cementitious materials such as fly ash, slag, silica fume, volcanic ash, and rice husk ash can help to improve the densification and meet the requirements of sustainable development strategies. According to Da [121], the accumulation factor of surface chloride ion content in all-coral concrete was reduced by about 26.4–88.5% compared to ordinary Portland cement. The change of chloride ion concentration in concrete changed from linear to exponential growth after the incorporation of coral, indicating that all-coral concrete has a stronger ability to adsorb...
and immobilize chloride ions. Xue [140] found experimentally that, when the fly ash content was 15%, the surface chloride ion concentration was reduced by 0.12% compared to concrete with a fly ash content of 30%. When the mineral powder content was 30%, the surface chloride ion concentration of concrete was reduced to 0.63%, which was the lowest concentration. Tan [122] further explored the coupling effect of gangue and fly ash, and found that the coupling of these two mineral admixtures could improve the compactness and durability of concrete.

Scholars usually divide concrete into different zones based on the complex marine environment. Bao [24] developed a time-varying model of the splash zone that included both materials and environmental factors, and the simulation results matched the results of actual marine exposure tests. The Chinese standard “JTS 153-2015” [141] introduced the sub-component factors and provided correction factors for the water–binder ratio in the tidal, splash, and atmospheric zones. Based on the European DuraCrete model, Cai [94] proposed a multifactor model for the tidal and splash zones, including water–cement ratio, cementitious material, and time (called Cai I), which showed good utility in fitting large samples. However, the model was unable to describe the effect of different cementitious materials on the surface chloride concentration. Later, they corrected it separately for different materials (OPC, fly ash, slag, and silica fume) (called Cai II [142]).

There are many factors affecting the atmospheric zone. Researchers [143,144] collected actual samples from different areas and found that the amount of chloride ions deposited on the surface of concrete decreased with increasing distance from the coast. Yang [126] used an exponential function to determine the relationship between $C_s$ and distance from the coast. However, the model mainly focused on environmental factors and did not consider other factors such as material properties sufficiently. Later, Yang [107] improved and provided a more comprehensive model including exposure time, cementitious materials, water–cement ratio, wind speed, and near-shore distance by considering the effect of cementitious material type on the correction factor, but it still needs to be strengthened in evaluating the direct effect of the cementitious material type on the $C_s$. The Portuguese Technical Specification (LNEC E465) [145], on the other hand, considers more parameters and improves the prediction accuracy. Chen [111,146] further considered the type of gelling material, water–cement ratio, exposure time, offshore distance, and mean wind speed to develop an inverse-type model, which has gained wider acceptance in terms of practicality.

Multifactor models with time-varying properties take into account the initial material and environmental conditions of concrete and accurately reflect the degradation of its properties over time and the accumulation of chloride ion concentrations. They are able to predict the trend of $C_s$ more accurately through the processing of long-term tracking data and complex mathematical techniques. Among them, Wang’s model is the most practical due to the large number of factors included, the wide range of data sources (17 countries, 1385 sets of field data), and the best prediction results. In contrast, models without time-varying properties focus only on concrete performance and the environment at a specific point in time, making it difficult to demonstrate long-term performance changes. These models tend to emphasize static data analysis and simplified modeling process. Multifactor models without time-varying properties (Table 3) and with time-varying properties (Table 4) are summarized below.

Therefore, in order to more accurately predict the changes of chloride ion concentration on the surface of marine concrete, it is necessary to establish an all-around multifactor coupling model by region. At the same time, attention should also be paid to the optimization of model parameters and the effect of practical application in order to continuously improve the accuracy and practicality of the model.
### Table 3. Multifactor models without time-varying characteristics.

<table>
<thead>
<tr>
<th>Literature</th>
<th>Models</th>
<th>Parameters</th>
<th>Area of Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Akiyama [147]</td>
<td>( C_s = 0.988 \left[ 1.29T_{2.35}^{0.366} \left( \frac{d}{1000} \right) \right]^{-0.967} )</td>
<td>( y ), the ratio of sea wind.</td>
<td>Atmospheric zone.</td>
</tr>
<tr>
<td>DuraCrete [96]</td>
<td>( C_s = A_d R_{w/b} / T )</td>
<td>( y ), sub-factor, equals to 1.7, 1.4, and 1.2 for durability costs higher than, equal to, or lower than later maintenance costs.</td>
<td>Tidal and splash zones, atmospheric zone.</td>
</tr>
<tr>
<td>JTS153-2015 [141]</td>
<td>( C_s = m R_{w/b} / T )</td>
<td>( y ), effect of randomness on ( C_s ), taken as 1.1.</td>
<td>Tidal zones, splash zones, atmospheric zone.</td>
</tr>
<tr>
<td>LNEC-E465 [145]</td>
<td>( C_s = 2.5 R_{w/b} / A_d )</td>
<td>( A_d, A_b, ) and ( A_T ) refer to correction coefficients for the nearshore distance, sea level, and temperature of concrete surface.</td>
<td>Tidal zones, splash zones.</td>
</tr>
</tbody>
</table>

Notes: \( A_b \) is the corrected coefficient of different cementitious materials for \( C_s \), \( R_{w/b} \) is the ratio of water to binder, and \( v \) is the wind speed.

### Table 4. Multifactor models with time-varying characteristics.

<table>
<thead>
<tr>
<th>Literature</th>
<th>Models</th>
<th>Parameters</th>
<th>Area of Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chalee [148]</td>
<td>( C_s = (-0.379 R_{w/b} + 2.064) \ln(t) + (4.078 R_{w/b} + 1.011) )</td>
<td>--</td>
<td>Tidal zone.</td>
</tr>
<tr>
<td>Petcherdchoo [149]</td>
<td>( C_s = 10^{(0.018 R_{w/b} - 0.213)} + 2.11 \sqrt{T} )</td>
<td>--</td>
<td>Tidal zone.</td>
</tr>
<tr>
<td>Muthulingam [150]</td>
<td>( C_s = 2.0 \ln(1.9122 + 1) + 2.365 R_{w/b} )</td>
<td>--</td>
<td>Tidal zone.</td>
</tr>
<tr>
<td>Li [128]</td>
<td>( C_s = n R_{w/b} / A_a )</td>
<td>( n ), the environmental coefficient.</td>
<td>Tidal and splash zone.</td>
</tr>
<tr>
<td>Yang [107,151]</td>
<td>( C_s = 1.03 A_e^{0.120} (0.85 R_{w/b} (1 - e^{-1.811}) + 1) )</td>
<td>( C_w ), the concentration of chloride ions in seawater.</td>
<td>Atmospheric zone.</td>
</tr>
<tr>
<td>Wang [136]</td>
<td>( C_s = 1.25 A_e R_{w/b}^{0.13735} R_{w/b}^{0.8064} e^{-0.084 d^{0.74}} )</td>
<td>( G ), the effect on sulphate.</td>
<td>Underwater zone.</td>
</tr>
<tr>
<td>Chen [120,125,146]</td>
<td>( C_s = 9.44 A_e R_{w/b}^{0.15} )</td>
<td>( A_b ), the correction factor for the type of cementitious material to the time-varying law.</td>
<td>Atmospheric zone.</td>
</tr>
<tr>
<td>Cai Model I [94]</td>
<td>( C_s = 1.46 A_e (1 - e^{-0.0809 R_{w/b}}) )</td>
<td>( A_b ) using the DuraCrete’s coefficient.</td>
<td>Tidal zone.</td>
</tr>
<tr>
<td>Cai Model II [142]</td>
<td>( C_s = 10.01 A_e (1 - e^{-0.065 R_{w/b}}) )</td>
<td>( A_b ) is corrected.</td>
<td>Tidal and splash zone.</td>
</tr>
<tr>
<td>Wang Lu [152]</td>
<td>( C_s = 9.77 A_e R_{w/b}^{0.1286} )</td>
<td>( C_w ), the concentration of chloride ions in seawater.</td>
<td>Atmospheric zone.</td>
</tr>
<tr>
<td></td>
<td>( C_s = 1.26 A_e R_{w/b}^{1.65} )</td>
<td>( C_w ), the concentration of chloride ions in seawater.</td>
<td>Underwater zone.</td>
</tr>
</tbody>
</table>

Note: \( A_b \) is the corrected coefficient of different cementitious materials for \( C_s \), \( v \) is wind speed. \( d \) is the nearshore distance, \( R_{w/b} \) is the ratio of water to binder.

### 4.3. Analyses and Shortcomings of Existing Models

In summary, as research has progressed, multifactorial models describing surface chloride concentration have shown their comprehensiveness and completeness, including not only time-varying characteristics but also material and environmental factors. However, from a quantitative point of view, these models still face serious challenges and limitations.

First, most of these models focus on a single cementitious material and do not adequately consider the coupling effect of multiple mineral admixtures, limiting their applicability in complex real-world environments. The effect of concrete curing conditions is often neglected, resulting in model predictions that do not match the actual situation. In addition, capturing environmental factors, e. g., wet–dry ratio and rainfall, remains challenging, thus reducing authenticity. Second, scholars usually simulate real environments based on similarity theory; although they are very similar to actual environments [153,154], discrepancies still exist between artificial accelerated experiments and field measurements [124]. Some uncontrollable factors in laboratory environments may result in the absence of convective zones in the prepared concrete. Dou’s [155] research showed that actual surface
chloride concentration near an island in the South China Sea were 60–90% higher than laboratory data.

Thus, despite the progress made by current multifactor models in characterizing surface chloride concentration, many issues and challenges remain to be addressed. Future research should further explore the mechanisms of these factors and incorporate them into the model to improve the accuracy and reliability of the model.

5. Advances in Research Based on Novel Machine Learning

5.1. Machine Learning Research Updates

In order to demonstrate the progress of machine learning in the field of concrete chloride erosion research and to provide a comprehensive overview of the general development trend, the search terms set in Web of Science were ‘TS = (‘chloride ion’ OR ‘chloride’) and TS = (‘machine learning’ OR ‘artificial intelligence’ OR ‘ML’) and TS = (concrete) and Time = ‘1 January 2003–31 June 2023’. A total of 154 papers in the fields of materials science, engineering and building technology were screened. The keywords in the titles and abstracts of the papers were processed using the VOSviewer 1.6.19 [156], such as merging the synonyms of the keywords, recording the number of recurring keywords in each paper as 1, and singling out the keywords that appeared more than two times to obtain the similarity matrices of the three clustered families. As shown in Figure 7a, different colors represent different clustering groups (or themes). It can be seen that there are three distinct clusters in the figure. The core keywords “Compressive strength”, “Corrosion”, and “ML” occupy a prominent position in the network, which indicates that the compressive strength of concrete, the corrosion behavior of concrete, and the integration of machine learning methods with concrete are the focus of the study. The size of the nodes in each cluster is proportional to the frequency of the occurrence of the corresponding keyword. The larger the node, the more frequently the keyword appears in the literature. In the green cluster, the larger the nodes for “Corrosion” and “Reinforced concrete” are, the higher the frequency of occurrence. This indicates that corrosion research is usually centered on reinforced concrete. In the red cluster, “ML”, “Prediction”, and “Durability” have larger nodes, indicating that machine learning mainly focuses on studying the durability of concrete from the perspective of model prediction. The connecting lines in the graph indicate the co-occurrence relationship between the keywords. The denser the connecting line is, the more frequently the keywords appear in the literature, indicating a closer relationship between them. The high number and dense distribution of the connecting lines between the keywords “durability” and “silica fume” and between “compressive strength” and “fly ash” indicate that these terms are highly correlated in the literature. The high correlation between them suggests that research on concrete durability has focused on strength and the incorporation of supplementary cementitious materials. Figure 7b overlays time into the keyword co-occurrence network, showing the application of AI in different research fields. The dark color represents the time of keyword occurrence. The darker color represents the time of keyword occurrence. The time frame here is January 2003–August 2023. The following can be seen:

(1) Research on concrete strength is weakening, while research on ML is becoming more important, e.g., ‘RF’ and ‘genetic algorithm’.
(2) Research on chloride corrosion of concrete is transitioning from durability to model prediction.
(3) Emphasis is placed on the use of other auxiliary materials to obtain better performing concrete, such as the use of bacterial cultures to make concrete.

Based on the fact that machine learning is starting to play an important role in specific research areas and further exploring the changes in research hotspots over the last 10 years. Figure 7 shows the variation of keywords from 1 January 2012 to 31 August 2023 for different time periods. It can also be seen from the figure that the research on chloride corrosion of concrete mainly focuses on the durability and impermeability of concrete, and the mechanical properties of concrete (e.g., compressive strength) have been receiving
attention, but with a gradually decreasing proportion. The emergence of machine learning (Figure 8b), finite elements, and safety monitoring (Figure 8c) suggests that numerical simulation methods have gradually entered the relevant research field, and the frequency of use of machine learning has been increasing rapidly over time (Figure 8c,d), becoming an important tool for the study of chloride erosion of concrete. In addition, there is an increasing variety of machine learning models, ranging from a single ANN model to multiple models such as RF and ensemble learners (EL).

![Network co-occurrence diagram of keyword for machine learning application in concrete chloride erosion: (a) clustered view and (b) time-stacked view, where ML, RCP, RF, GEP, GA, ANN, and CS are abbreviations for machine learning, rapid chloride permeability, random forest, gene expression programming, genetic algorithms, artificial neural networks, and surface chloride ion concentration, respectively.](image-url)
The significant increase in the number of keywords suggests a broader field of research permeability and diffusion. These algorithms can accurately predict the permeability and (environment corrosion, and marine environment. variations” suggests that the multifactorial coupling of chloride erosion is receiving more attention. Meanwhile, the simultaneous appearance of the keywords “auxiliary cementitious materials” (slag and fly ash in Figure 8d), “environmental factors”, and “time variations” suggests that the multifactorial coupling of chloride erosion is receiving more attention. The significant increase in the number of keywords suggests a broader field of research in applying machine learning to chloride ion eroded concrete. It can also be seen from Figures 7 and 8 that early studies focused on concrete performance and chloride corrosion mechanisms. With the advent of machine learning techniques, researchers have begun to utilize this methodology to predict the diffusion of chloride ions in concrete, to study changes in concrete performance, and to assess the durability of structures. Currently, research efforts are increasingly geared towards reducing maintenance costs, developing novel materials and manufacturing protective coatings to further extend the service life of concrete and promote environmental sustainability.

5.2. Application of Machine Learning to Chloride Penetrations

Studies [157–161] have found that a large amount of machine-learning-based work has focused on concrete permeability resistance and the diffusion coefficient. Supervised machine learning approaches, such as SVM, RF, and ANN, are mainly used for chloride permeability and diffusion. These algorithms can accurately predict the permeability and diffusion of concrete by learning and analyzing large datasets. Micha [162] used a clas-
sification rule of a decision tree to select 158 kg/m$^3$ as the cut-off between the high and low water content of concrete and selected high-calcium fly ash (HCFA) to replace cement by 15% or 30%. It was found that the addition of HCFA improved the impermeability at high and low water contents, while cement was better at low water contents. Yu [163] conducted endogenous measurements of chloride diffusion coefficients using five models (back-propagation neural network (BPNN), decision tree (DT), linear regression (LR), ridge regression, and RF) and found that the water-cement ratio, thickness of concrete specimens, coarse aggregate gradation volume, and the ratio of ambient humidity to relative humidity were the main factors affecting chloride diffusion, while BPNN had a higher predictive ability. Taffese [164] predicted the distribution of chloride ions using an integrated model based on bagging and regression tree. They used 33 input variables, including site conditions, freshness, and hardening characteristics. Comparative experiments verified the superiority of the model in predicting chloride ion distribution and analyzed the effect input variables over time, providing a scientific basis for the long-term monitoring of concrete durability. In two other studies, Taffese used a similar approach to investigate the relationship between concrete mix and chloride ion penetration levels by considering all influencing factors and significant influencing factors, respectively [165]. In addition, the input factors were categorized into four cases and the extreme gradient boosting (XGBoost) method was used to predict the unstable migration coefficients of chloride ions in different types of concrete [166]. In this study, the authors considered the effects of fresh concrete, compressive strength, and age, which ensures richer characterization results. These two studies not only demonstrate the wide application of machine learning in concrete durability assessment, but also provide valuable lessons for subsequent studies.

It is worth noting that, since redundant information may exist in highly complex data, thus potentially interfering with the model learning process, Taffese employed data reduction techniques to reduce data complexity and improve the accuracy of the learned model [167]. Similarly, Verónica [168] utilized feature selection methods to process large amounts of image data, reducing data complexity and effectively improving accuracy.

Machine learning shows great potential in concrete durability assessment and provides new ideas for subsequent research. Future research can further explore the combination and optimization of different machine learning algorithms while considering the complexity of feature engineering to improve prediction accuracy and model performance.

5.3. Application of Machine Learning in Determining Surface Chloride Ion Concentrations

Diffusion and penetration of chloride ions have been extensively studied in concrete durability research, and prediction of surface chloride concentration is equally critical. Machine learning techniques provide new perspectives and methods for this research area. Cai [169] developed an ensemble machine learning model based on weighted voting (Cai Mode III), which considers 12 influencing factors. The model exhibited higher prediction accuracy in tidal, splash, and submerged zones compared to traditional models (e.g., LR, GPR, SVM, MLP, RF), demonstrating the significant advantages of machine learning in dealing with complex multifactor influence prediction problems. Similarly, Ahmad [170] predicted the surface chloride ion concentration of marine structural concrete in different exposure zones (tidal, splash, and submerged zones) using single supervised machine learning methods such as genetic expression programming (GEP), decision tree (DT), and artificial neural network (ANN), and found that GEP is an effective model that accurately captures the variations in the concentration of surface chloride ions. Guo [171] further demonstrated the potential of machine learning in concrete durability assessment. He developed a hybrid model combining a random forest approach and a fuzzy logic systems approach to solve the problem of low accuracy in single models. The model visually expresses the stabilization time of the surface chloride concentration in different exposure zones (2.75, 3, and 3.5 years for submerged, splash, and tidal zones, respectively). In addition, the model considered the independent effects of fly ash and SG on the surface.
chloride concentration, with a critical water–binder ratio of 0.6 in the non-submerged zone and 0.7 in the submerged zone, which is consistent with previous studies.

To address the challenges posed by the diversity of concrete compositions in predictive models, Ashrafian [20] designed a model with a mixture of variable mixing ratios to optimize the GEP using nonlinear multivariate adaptive regression spline (MARS) and a classified M5P model tree. This innovative approach not only improves the prediction accuracy of Cs but also provides new insights into the modeling of the service life of concrete in different exposure environments.

It can be seen that machine learning has great potential and advantages in predicting the surface chloride ion concentration of concrete. By integrating various influencing factors, machine learning models can more accurately capture the changes in surface chloride ion concentration and provide more reliable and comprehensive support for concrete durability assessments.

5.4. Challenges and Future of Machine Learning for Marine Concrete Corrosion

5.4.1. Challenges for Machine Learning for Marine Concrete Corrosion

The application of machine learning to marine concrete corrosion has made great progress, but still faces the following challenges:

(1) Difficulty in data collection.

The key to machine learning model training is sufficient data. Concrete structures in marine environments face problems such as high detection difficulty, high detection cost, and long detection period. The complex external environment leads to a very low repetition rate of experiments. The data obtained are limited, and the quality of some data needs to be improved. In addition, some of the data are not open to users, and these factors in turn affect the reliability of the model.

(2) Poor portability of the model.

Although many scholars have studied surface chloride concentration in the marine environment, the variability of different regions in turn makes the data unrepresentative and incomparable; the poor portability of most models limits scholars from utilizing the existing data to make improvements. In 2022, Hafez [172] introduced the Pre-bcc regression model for predicting the performance of resistance to chloride intrusion to users for the first time. This provides a great opportunity to share and improve the success of the applications.

(3) Inadequate interpretation of data.

The modeling process of machine learning is like a ‘black box’ that is unable to generate expressions and lacks a clear interpretation of the physical meaning, thus making it difficult to gain insights into the performance of a particular structure. In order to address these issues, attention has been given to interpretable artificial intelligence [173], such as feature importance methods, locally interpretable model-agnostic explanations, Shapley addition interpretation, and post hoc local interpretation. Utilizing physically meaningful and interpretable data is also an option when identifying influencing factors (i.e., descriptors). Duan [174] integrated a priori knowledge into a machine learning model and proposed a deep neural network model with explicit physical constraints to effectively identify the properties of the material and explore the intrinsic patterns of the data.

(4) Challenges in incorporating concrete curing conditions into machine learning models.

The effect of curing conditions on the chloride concentration on the concrete surface is critical. Current artificial intelligence models often ignore this factor, affecting the accuracy and usefulness of predictions. Models that consider curing conditions can more accurately simulate concrete aging, leading to targeted curing schedules that extend the service life of concrete. However, curing conditions involve a variety of complex factors such as humidity, and the slow process of concrete aging makes data collection time-consuming and labor-intensive.
Researchers in the computational field have recognized these developments to some extent. However, experimentalists still have questions about the veracity of these computational models and data, and there is still a long way to go in terms of the reliability of the computational results and how they can be applied to practical engineering and accepted by most researchers.

5.4.2. Future Development of Machine Learning for Marine Concrete Corrosion

Machine learning can make full use of experimental data to learn the complex relation between multiple factors, maximize the coupling problem, and perform data analysis, which can be applied to the research of new concrete materials and structures to avoid repeated experiments. The machine learning model can also automatically adjust the parameters to continuously optimize the prediction performance, which provides strong support for predicting concrete durability and chloride ion erosion. In addition, the literature data provide valuable historical experience and supplementary knowledge for the models. In the future, we can focus on the development of machine learning method to comprehensively consider the coupling effects of multiple factors, such as materials, environment, and maintenance conditions, and optimize them in the following aspects.

(1) Data and model sharing and standardization.

To address the problems of difficult data collection and poor model portability, the establishment of an integrated large-scale database and model sharing platform will greatly improve data collection and analysis capabilities, facilitate researchers’ sharing of relevant data, optimize models, expand databases, and promote scientific research and social development. Meanwhile, in order to avoid data abuse and other behaviors that undermine the overall data quality, methods and guidelines for data standardization should be developed. It should be noted that there are still some subtle differences between experimental and computational data, and computational data do not fully represent experimental data, which should be supplemented by experimental data in real environments. Actively dismantling “knowledge fences” and “data islands”, accelerating the flow of knowledge, and forming a developed model with legal basis, universal participation, and epochal sharing should be the goals of future universal efforts.

(2) Optimization and extension of models.

Many machine learning models have been applied to study the surface chloride concentration in concrete. Firstly, scholars chose appropriate models according to different applicability or combined several given models using their respective advantages for more comprehensive and accurate prediction and analysis. In this regard, although there has been better development, there is still room for improvement and more appropriate models need to be carefully considered. Secondly, the accuracy of the model is directly related to the optimization method, and model optimization is the key to improving the model, e.g., by establishing a more rational and comprehensive feature engineering approach, which improves the accuracy and robustness of the modeling and reduces the dependence on the amount of data.

(3) Optimizing curing conditions.

To address the challenges associated with concrete curing conditions, real-time monitoring and data collection of concrete curing conditions can be realized using advanced sensors and Internet of Things technology. This approach improves data accuracy and real-time performance while reducing data collection costs. In addition, techniques such as transfer learning and domain adaptation can be used to introduce knowledge and experience from other related fields into the modeling of concrete curing conditions, thereby improving the performance and generalization of the model.
6. Summary and Outlook

Corrosion by chloride ions is the main cause of degradation of marine concrete, and this paper focuses on the current research status of the surface chloride concentration in the marine concrete. By adopting different research methods, this paper reviewed the research hotspots and models of the two methods, including the empirical formula method and the machine learning method, and clearly put forward the characteristics and differences of the two methods. In addition, this paper presented the challenges faced by the two methods and filled the gap of other studies lacking research methods. Furthermore, this paper reorganized the mechanism and evolution of chloride ion migration, revealing the diffusion phenomenon of chloride ions inside concrete and the corrosion mechanism in various marine exposure environments, and thus providing a more comprehensive analysis. See the following points:

(1) The paper summarized six diffusion models for chloride ions and mainly focused on the convection phenomenon, in which the chloride ion concentration at a certain distance from the concrete surface does not conform to the diffusion law. The introduction of the concretion zone depth can most accurately reflect the diffusion of chloride ions in concrete.

(2) The current status of time-varying and multifactorial models for studying the surface chloride concentration of marine concrete was presented through empirical analysis based on different influencing factors. There is a lack of coupled studies on mineral admixtures. In addition, the existence of “relative theory” may require modification of the model when applied to different conditions or scenarios.

(3) The application of machine learning models in concrete engineering allows for deep learning of nonlinear relationships between multiple factors with good fitting, high accuracy, and high predictive ability, thus compensating for the limitations of empirical models and avoiding repetitive experiments. With new iterations of artificial intelligence and scientific paradigms, machine learning can also make better use of the discovered knowledge to study the corrosion conditions of concrete, extend the study of surface chloride concentration, and optimize the performance of marine concrete. Therefore, future work in machine learning, including the combination and optimization of different algorithms, should receive more attention.

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Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Parameters</th>
</tr>
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<tbody>
<tr>
<td>C</td>
<td>concentration of chloride ions</td>
</tr>
<tr>
<td>C_s</td>
<td>surface chloride ion concentration</td>
</tr>
<tr>
<td>D</td>
<td>diffusion coefficient</td>
</tr>
<tr>
<td>D_s</td>
<td>diffusion coefficient of chloride ions</td>
</tr>
<tr>
<td>t</td>
<td>diffusion time</td>
</tr>
</tbody>
</table>
\( x \) distance from the concrete surface
\( \Delta x \) convection depth
\( C(x,t) \) chloride ion concentration at depth \( x \) and time \( t \)
DZ diffusion zone
CZ convection zone
OPC Ordinary Portland Cement
\( w/c \) water–cement ratio
\( \partial C/\partial x \) concentration gradient
ML machine learning
RCP rapid chloride permeability
DT decision tree
RF random forest
GA genetic algorithm
BPNN back-propagation neural network
DCL chloride diffusion coefficient
LR linear regression
EL ensemble learning
ANN artificial neural network
SVM support vector machine
CNN convolutional neural network
HCFA high-calcium fly ash
Xgboost extreme gradient boosting

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