CONVENTIONAL EMPIRICAL AND MACHINE LEARNING MODELS: A REVIEW OF CHLORIDE CONCENTRATION IN MARINE CONCRETE

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Abstract- The measurement of chloride concentration (Cs) on the surface of the concrete is a crucial parameter for durable design and predicting concrete buildings' longevity in aquatic habitats. As a result of the effects of chloride, numerous reinforced concrete structures cannot achieve their intended or planned lifespan and undergo premature degradation. This study reviews both independent and ensemble machine learning methods applied previously, along with standard empirical provisions now in practice in the design industry. However, the empirical models have some uncertain calculation fallouts in some areas with different onsite constraints, which results in the diversion from experimental onsite measured chloride content. On the other hand, the machine learning model, which utilizes experimental data rather than an empirical calculation foundation, yields much better results but cannot be practiced in design fields due to its reliability on a small set of experimental data. Additionally, the statistical quality of experimental data and onsite experimental and environmental setup constraints are another chapter that needs to be addressed carefully. The overfitting issue is another drawback of machine learning models, though evolutionary models can derive the most superficial and complex empirical equations from surpassing the classical work in this field. The most recent machine learning model, trained on an extensive dataset, successfully incorporated 13 essential features that present a way to confront traditional model limitations. In Swift, all the findings suggest that the predicted accuracy of standard models could be enhanced by incorporating more varied datasets and considering novel variables. It is recommended that a more extensive dataset using applied Physics Informed Neural Networks (PINNs) be employed to reduce overfitting and increase the application of ML models in design disciplines.

Keywords- Conventional Models; Diffusion constraints; LNEC model; PINNs

1 Introduction

Marine concrete's surface chloride content (Cs) is crucial in designing and considering durability. The growing importance of coastal infrastructure is giving rise to an increased focus on studying chloride-induced corrosion in reinforced concrete (RC) structures. Extensive and long-term investigations are currently conducted by researchers on the endurance of concrete when exposed to marine environments, resulting in a significant amount of test data [1]. Ahmad et al. [2] investigated the machine learning (ML) model application for calculating Cs in marine concrete containing waste. The durability design for marine concrete categorizes exposure circumstances into the air, splash, tidal, and submerged zones based on specific standards and recommendations [3], [4]. The benefits and suitability of the ML approach have been confirmed by comparisons with traditional experimental data based quantitative Cs models [5]. The forecast performances of ensemble ML model, standalone ML models, and traditional approaches are compared to determine if, considering domain restriction and applicability while normalizing the experimental data yielding, the best model for predicting concrete Cs. By comparing traditional and ML methods, this study proposes using a novel method, PINNs, that may help with C_s Prediction and, hence, the durable design of RC structures in coastal settings.

2 Empirical and Conventional Models

Fick's second law of diffusion is often employed to characterize the total entrance of chloride into concrete, regardless of the zone [6]. Eq (1) provides the analytical solution for Fick's second law, commonly used in the service life design of reinforced concrete buildings in marine settings [7].

$$\frac{d\varphi}{dt} = D\,\frac{d_{\varphi}^{2}}{dt^{2}} \tag{1}$$

More specifically, from the perspective of marine concrete, we have simplified this to Eq (2)

$$C(x,T) = C_o + (C_C - C_o)\left[1 - \; ERF * \left(\frac{x}{(4 * D_L * T)^{\frac{1}{2}}}\right)\right] \tag{2}$$

Where C (x, t) is the chloride concentration after exposure time t, measured at distance x from the surface; C_o represents initial chloride concentration in concrete, C_c represents apparent surface chloride concentration, apparent chloride diffusion coefficient is represented by D_L, and the error function is represented by erf (•). Since C_o is a constant, Cc and D_L define the amount of chloride intrusion. A time-dependent material attribute, the chloride diffusion coefficient D may be calculated or predicted using data related to the microstructure and composition of the material. Cc is a more complex variable than D_L since it varies on time, environmental factors, and material qualities. A convection zone is often seen in many concrete fields. In this scenario, the region of the chloride profile that involves the movement of particles in large quantities is adjusted to determine the value of Cs. Convection zones may not be visible in some laboratory experiments. Hence, the whole profile might be analyzed to determine Cs. Consequently, the vacant applicability space is created while calculating the ingress chloride when compared to the experimental results of the same marine site. Alongside empirical equations, we analyzed many conventional quantitative models of Cs, selecting only a few to substantiate their reliability and applicability compared to other options in the design industry, as represented in Table 1.

Table 1 Ingress Chloride Conventional Models

S.No	Conventional Model (Applicability)	Equation and Description	Ref.
1.	Cai-Yang (Submerged Zone)	$C_{s-ts} = 4.12 * A_c * \left(\frac{w}{b}\right) * C_{sw} * (1 - e^{-0.56*t})$	[8]
2.	DuraCrete (All Zones)	$C_s = A_c\left(\frac{W}{b}\right)$	[9]
3.	Song's (All Zones)	$C_s = 1.52 * ln(3.77t + 1)$	[10]
4.	Chalee's (Tidal Zones)	$C_s = \left[-0.379\left(\frac{W}{b}\right) + 2.064\right]\ln(t) + \left[4.078\left(\frac{W}{b}\right) + 1.01\right]$	[11]
5.	Petcherdchoo's (Tidal Zones)	$C_s = 10^{(0.814\left(\frac{W}{b}\right)*0.213} + 2.11 * t^{0.5}$	[12]
6.	Costa's (Tidal Zones)	$C_s = 0.38 * t^{0.37}$	[13]
7.	LNEC (All Zones)	$C_s = 2.5\left({}^{w}/_{b}\right)k_T C_b$	[14]
8.	Cai's (Tidal and Splash Zones)	$C_{s-ts} = 10.01 * A_c * \left(\frac{W}{b}\right) * (1 - e^{-0.96*t})$	[15]
***C$_{sw}$**: Seawater Chloride Concentration (%), ***A$_c$**: binder type correction factor (%) , ***t**: exposure time (years), ***k$_T$**: coefficient accounting for the concrete temperature and ***C$_b$**: Cs in the conditions of the specific coastal (%),			

The Root-Mean Square Error (δ) and the μ (projected to the experimental values mean ratio) are used to assess each model's prediction accuracy and determine their usefulness. Among the eight standard C_s models, the Cai-Yang model possesses the best fitting accuracy, with δ being 1.71% and μ being 1.17 applicable to only submerged zones. The empirical equation of this model relies on the water-to-binder ratio (w/b) and A_c (a correction factor representing the binder type). The performance of the Song's and DuraCrete models is inferior to that of the Yang model. The DuraCrete, like the Cai-Yang model, relies on identical parameters but can be implemented throughout all zones. Furthermore, Song's model [10], unlike the other two models, relies on the duration of exposure and suggests a logarithmic relationship between C_s and t. Costa's, Petcherdchoo's, and Chalee's models provide accurate forecasts but are limited in their applicability to the tidal zone. A thorough comparison of traditional models reveals that a model that incorporates a broader range of data sources and considers more influential elements has the potential to achieve superior performance in forecasting Cs. Costa et al. [13]

demonstrated that the Cs in concrete exposed to all climates except submerged zones consistently rise over time, irrespective of the concrete compositions used. Power functions were used to fit time-dependent models of Cs based on long-term exposure field data for concrete. The LNEC Model suggests that the Cs model is a folded-linear equation, where Cs increases linearly during the initial exposure stage and then reaches and maintains a constant value during the stable stage following prolonged exposure. Petcherdchoo et al. [12] proposed the Cs model as a n^{th} root function. However, the model's projected values were found to overestimate the Cs during the steady period of concrete weathering.

Some investigators also offered exponential time-dependent Cs models. Time-dependent Cs models in the literature contain exponential, logarithmic, linear, folded-linear, and square root functions. These models were not developed entirely from field test data but with several expedited lab tests.

3 Machine Learning Models

While using Eq. (2), recommendations often assume that C_o remains constant in specific surroundings. However, this assumption might result in a substantial margin of error. Several previous studies have shown a wide range of field values for C_o and have also presented quantitative frameworks for this significant parameter [8], [15], [16]. Nevertheless, the models could have performed better in accurately predicting or describing Cs. This is due to the intricate nature of Cs, which is influenced by numerous factors, including environmental conditions (such as chloride levels in seawater, zonation, carbonizing effects, climate, and relative the level of humidity), material properties (such as content of binder, composition of binder, ratio of water and binder(w/b)), and the period of contact. Cia et al. [17] applied the ensemble ML technique to forecast the chloride content in marine concrete with the highest correlation factor up till now in the literature. However, these models fail to adequately capture the pattern of fast initial growth followed by eventual stabilization of Cs levels [11], [18]. In addition, several models failed to include other crucial elements, namely, the composition of materials and the classifications of environmental actions. Previous studies [12], [16], [19] have developed predictive models for Cs concentrations based on the (w/b) and exposure duration (t). However, these models did not include the influence of binder type and environmental conditions. The models presented in [9] and Costa et al. [14] include variables related to materials and environmental action classes in the context of Cs. However, these models fail to include the significant influence of exposure duration. These typical quantitative Cs models are limited in addressing all significant elements due to insufficient experimental data and a robust flow to account for many variables. The empirical equations, conventional models, and ML models had flaws due to reliability, limited applicability, and overfitting. ML experts often recommend an extensive dataset with more reliable parameters. This often leads to synthetic and experimental data in a controlled environment with different site conditions and climate catalysts. However, taking in-depth data trends from such a diverse dataset, Artificial Neural Networks (ANN) is insufficient. This review study recommends that the Physic Informed Neural Networks (PINNs) forecast the marine concrete chloride content. A PINN is a network that integrates physical rules or principles into its structure and training methodology. Incorporating physics into the neural network makes it more adept at accurately representing and following the fundamental equations regulating a given system. Fig. 1 illustrates that data taken by PINNs will result in a prediction later compared with experimental values and onward fed back to the same loop, reinforcing the accuracy and making the loop dynamic.

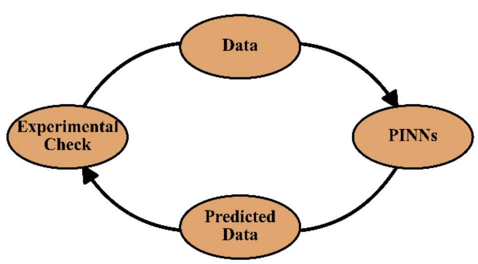

Fig. 1 PINNs Workflow Loop

They are engineered specifically to adhere to and integrate established physical rules or equations that govern a particular system. This is accomplished by integrating words into the neural network design that embodies these fundamental physical laws. PINNs seek to integrate the advantages of data-driven machine learning by explicitly incorporating physics rules. This enables the model to provide precise forecasts using the existing data while staying in line with the underlying rules governing the system. They are significant when a limited amount of data is available or when acquiring data is costly. These networks may provide precise forecasts using the constraints even when training data has low dimensions.

4 Conclusion

This study reviews the employed ensemble and independent ML prediction techniques in contrast with the empirical equations for chloride content in marine space while considering the experimental data as standard. Fick's law is the most practiced empirical equation, but it has flaws due to parameter representations and inclusive relationships. Some conventional quantitative models addressed all zones of the marinated environment but still lag experimental data due to missing critical parameters. In contrast, others are limited to specific zones and yield good results in local environments. ML Models considerably have more accurate results than conventional models and design practical equations. The most diverse dataset considered till now consists of 642 data points from different zones, but due to the data clustering, linearization, and symmetry, the issue of overfitting arises, which suggests that Physics-Informed Neural Networks (PINNs) should be used instead of Artificial Neural networks (ANNs) while tackling the experimental setup discrepancies across laboratory research. To improve proposed model's endurance and dependability, future research should concentrate on controlled experimental testing with PINNs, a reliable source for data collection in the same setting from different environmental conditions with more diverse parameters taken into account.

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