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ARTIFICIAL INTELLIGENCE-BASED DURABILITY ASSESSMENT OF REINFORCED CONCRETE STRUCTURES IN MARINE ENVIRONMENTS: A SYSTEMATIC LITERATURE REVIEW

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Abstract

The durability assessment of reinforced concrete structures in marine environments is a critical challenge due to the aggressive action of chloride-induced corrosion and material degradation. This systematic literature review aims to synthesize and critically evaluate the state of the art in artificial intelligence applications for predicting and managing such durability issues. We conducted a comprehensive methodological search across major academic databases, followed by a structured screening process to identify relevant studies that apply machine learning, deep learning, or other AI techniques to durability-related problems. The review is organized around key thematic dimensions: AI-driven prediction of chloride ingress and corrosion initiation, machine learning for concrete mix optimization and durability enhancement, structural health monitoring and service life forecasting, and the prediction of mechanical properties under aggressive exposure. Our results reveal that artificial neural networks and ensemble methods have become dominant for modeling chloride diffusion and corrosion rates, often outperforming traditional empirical models. Conversely, we find that while mix optimization models show high accuracy in predicting compressive strength and permeability, their generalizability to field conditions remains limited. Structural health monitoring studies increasingly integrate sensor data with AI for real-time damage diagnosis, yet long-term validation data are scarce. In conclusion, this review identifies a growing consensus that AI provides powerful tools for durability assessment, but significant gaps persist regarding data scarcity, model interpretability, and the translation of laboratory findings to full-scale marine structures. We therefore highlight the need for standardized benchmark datasets and hybrid models that combine physics-based knowledge with data-driven learning to advance the field.

I. INTRODUCTION

Reinforced concrete (RC) remains the most widely used construction material for marine infrastructure, such as offshore platforms, coastal bridges, seawalls, and port facilities. The expansive and inherently corrosive marine environment presents a formidable challenge to the long-term performance of these structures. The primary durability threat is chloride-induced reinforcement corrosion, a process driven by the ingress of chloride ions from seawater into the concrete cover. Once the chloride concentration at the steel surface exceeds a critical threshold, the protective passive layer on the reinforcement is depassivated, initiating an electrochemical corrosion process that leads to concrete cracking, spalling, and eventual structural failure [1]. This degradation incurs enormous economic costs globally, with estimates for corrosion-related repairs and maintenance running into billions of dollars annually for coastal nations. Traditional approaches to durability assessment, such as empirical models based on Fick's second law of diffusion, have provided a foundational understanding of chloride ingress [2]. However, these models are often calibrated for idealized, homogeneous conditions and struggle to capture the complex, multi-physical interactions that occur in real-world marine structures, including the effects of temperature fluctuations, tidal cycles, internal microcracking, and varying concrete quality [3].

The inherent limitations of deterministic models have motivated a paradigm shift towards data-driven approaches. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), offers a powerful alternative by learning complex, non-linear relationships directly from experimental and field data without requiring explicit physical equations [4]. For example, artificial neural networks (ANNs) can model chloride diffusion coefficients or corrosion rates as functions of numerous interdependent variables, such as water-to-cement ratio, exposure conditions, temperature, and binder composition [5]. Similarly, ensemble methods like random forests and gradient boosting have demonstrated superior performance in predicting concrete compressive strength and permeability, which are surrogate indicators of durability [6]. These AI models have the potential to provide more accurate, robust, and adaptable predictions than conventional empirical relationships, particularly when trained on large, diverse datasets that capture the variability of marine exposure.

Despite the growing number of research publications applying AI to RC durability, the field remains fragmented and lacks a cohesive synthesis of findings. Several research gaps hinder the translation of these AI-based methods into reliable engineering practice. First, there is a notable lack of standardization in data collection, model selection, and performance metrics across studies. Many models are trained on small, laboratory-generated datasets, raising questions about their generalizability to real-world, long-term marine exposure [7]. Second, the 'black-box' nature of many ML models, particularly deep neural networks, presents a significant barrier to acceptance among practicing engineers and regulatory bodies who require interpretable, transparent decision-support tools [8]. Third, there is a disconnect between AI models developed for predicting a single durability phenomenon, such as chloride ingress, from those needed for holistic service life forecasting that integrates multiple degradation mechanisms (e.g., carbonation, freeze-thaw, and corrosion-induced cracking) [9]. Finally, the integration of AI with in-situ structural health monitoring (SHM) systems for real-time damage diagnosis remains in its infancy, with limited long-term validation data from instrumented marine structures [10].

The motivation for this systematic literature review stems from these identified gaps and the pressing need for a structured, evidence-based overview of the field. The primary contribution of this research is to provide a comprehensive and critical synthesis of the state of the art in AI-based durability assessment of RC structures in marine environments. This review does not propose a new methodology; rather, it serves as a conceptual map, categorizing and analyzing the existing literature along thematic lines that reflect the primary durability challenges. By systematically evaluating the methodologies, datasets, and reported outcomes of relevant studies, we aim to identify prevailing trends, assess the maturity of different sub-domains, and pinpoint critical limitations that must be addressed for future progress. A secondary but equally important contribution is to offer a roadmap for researchers and practitioners, highlighting promising avenues for future work, such as the development of physics-informed neural networks, hybrid models, and standardized benchmark datasets. The significance of this work lies in its potential to accelerate the adoption of reliable AI tools for durability design, inspection, and lifecycle management of critical marine infrastructure.

The remainder of this paper is organized as follows. Section 2 details the systematic

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methodology employed to search, screen, and select the relevant literature. Section 3 presents the descriptive results, beginning with an analysis of research trends, followed by detailed thematic findings organized into four subsections: AI-driven prediction of chloride ingress and corrosion initiation, machine learning for concrete mix optimization and durability enhancement, structural health monitoring and service life forecasting, and prediction of mechanical properties and bond performance in aggressive environments. Section 4 discusses the key findings, contextualizes them within the broader field of civil engineering AI, and outlines critical future research directions. Finally, Section 5 concludes the review with a summary of the major takeaways and implications for practice.

II. Methodology

This section delineates the systematic review protocol that governed the literature search, study selection, and data extraction process. The methodology was designed to ensure transparency, reproducibility, and a comprehensive coverage of the intersection of artificial intelligence and reinforced concrete durability in marine environments. The approach adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [11] to structure the reporting of the search and screening strategy.

A. Review Protocol

The literature search was executed across five major academic databases and search engines, chosen for their breadth and relevance to the interdisciplinary nature of this research topic. The first database queried was IEEE Xplore, selected for its extensive repository of conference proceedings and journal articles on computational intelligence and engineering applications. For IEEE Xplore, we employed the search string: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks") AND ("Durability Assessment" OR "Service Life Prediction" OR "Corrosion Prediction") AND ("Reinforced Concrete" OR "RC Structures") AND ("Marine Environment" OR "Coastal Environment" OR "Chloride Ingress"). The search was filtered to include only Conference and Journal publications, and review articles were excluded via the Content Type filter.

Scopus was subsequently queried as the second database due to its comprehensive coverage of peer-reviewed literature in engineering, materials science, and computer science. The Scopus search string was: TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI") AND ("durability assessment" OR "service life prediction" OR "corrosion prediction" OR "degradation") AND ("reinforced concrete" OR "rc structures") AND ("marine environment" OR "coastal" OR "chloride ingress")) AND NOT TITLE-ABS-KEY("review" OR "survey" OR "meta-analysis"). We applied filters to restrict the subject area to Engineering, Materials Science, and Computer Science, and we excluded the Document Type 'Review'.

The third database was Web of Science, chosen for its high-impact, curated collection of scientific journals and conference proceedings across all fields of science and engineering. The Web of Science search string was: TS=(("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI") AND ("durability assessment" OR "service life prediction" OR "corrosion prediction" OR "degradation") AND ("reinforced concrete" OR "rc structures") AND ("marine environment" OR "coastal" OR "chloride ingress")) NOT TS=("review" OR "survey" OR "meta-analysis"). We refined the results by Document Types 'Article' or 'Proceedings Paper' and excluded review articles.

ScienceDirect served as the fourth database, valued for its extensive collection of full-text articles from Elsevier journals, particularly in materials science and civil engineering. The ScienceDirect search string was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks") AND ("durability assessment" OR "service life prediction" OR "corrosion prediction") AND ("reinforced concrete" OR "concrete structures") AND ("marine environment" OR "coastal" OR

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"chloride"). We used the 'Article Type' filter to select 'Research articles' only, excluding 'Review articles' and 'Book chapters'.

To capture emerging, preprint research that may not yet appear in traditional peer-reviewed databases, we included arXiv as a fifth search source. The arXiv search string was: (ti:"reinforced concrete" OR abs:"reinforced concrete") AND (ti:"durability" OR abs:"durability" OR ti:"corrosion" OR abs:"corrosion") AND (ti:"machine learning" OR abs:"machine learning" OR ti:"deep learning" OR abs:"deep learning" OR ti:"neural network" OR abs:"neural network") AND (ti:"marine" OR abs:"marine" OR ti:"chloride" OR abs:"chloride") NOT cat:stat.AP. We filtered categories to include cs.LG, cs.CV, or physics.app-ph, and manually verified abstracts to ensure they represented original research rather than surveys.

Finally, Google Scholar was consulted as a supplementary search engine to capture gray literature and studies from a broader range of sources that might be missed by the other databases. The search string used was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI") AND ("durability assessment" OR "service life prediction" OR "corrosion prediction" OR "degradation modeling") AND ("reinforced concrete" OR "RC structures" OR "concrete structures") AND ("marine environment*" OR "coastal environment*" OR "chloride ingress" OR "seawater") -review -survey -"meta-analysis". We manually filtered out review articles, surveys, and meta-analyses that were not excluded by the keyword negation. For all databases, the search was conducted on the same date to ensure temporal consistency.

B. Thematic Dimensions for Literature Classification

To structure the analysis of the large and diverse body of retrieved literature, we established four thematic dimensions that represent the primary and interconnected facets of AI-based durability assessment for reinforced concrete structures in marine environments. These dimensions emerged from our preliminary reading of the field and were refined iteratively during the screening process to ensure they comprehensively captured the core research foci. The first dimension, AI-Driven Prediction of Chloride Ingress and Corrosion Initiation, encapsulates studies that employ AI models to forecast the transport of chloride ions through concrete and to predict the time to corrosion initiation. This is the most fundamental durability concern in marine structures. The second dimension, Machine Learning for Concrete Mix Optimization and Durability Enhancement, assembles research that uses AI to optimize concrete mix proportions to improve intrinsic resistance to degradation, such as minimizing permeability or maximizing chloride binding capacity. The third dimension, Structural Health Monitoring, Damage Diagnosis, and Service Life Forecasting, integrates studies applying AI to data from sensors embedded in or attached to structures to detect damage, assess current condition, and project remaining service life. The fourth dimension, Prediction of Mechanical Properties and Bond Performance in Aggressive Environments, groups work that uses AI to predict how key mechanical characteristics—such as compressive strength, tensile strength, and steel–concrete bond strength—deteriorate under long-term exposure to chlorides and other marine attack mechanisms. Each paper included in the review was assigned to one or more of these dimensions based on its primary contribution.

C. Inclusion and Exclusion Criteria

To maintain the relevance, rigor, and consistency of the reviewed studies, we defined a set of clear inclusion and exclusion criteria, applied during the title-abstract screening and full-text eligibility assessment. The inclusion criteria were: (a) the study must apply or develop an artificial intelligence, machine learning, or deep learning model (including, but not limited to, artificial neural networks, support vector machines, random forests, gradient boosting, and genetic algorithms) to a problem directly related to the durability of reinforced concrete; (b) the concrete or structure in question must be explicitly exposed to or studied in the context of a marine, coastal, or chloride-laden environment; (c) the

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publication must be an original research article, conference paper, or preprint that reports empirical results; (d) the language of the full text must be English; and (e) the time frame for publication was unrestricted but limited to the end of 2025, as the search was conducted in early 2026. Conversely, the exclusion criteria were: (a) papers that are pure review articles, surveys, meta-analyses, editorials, or book chapters; (b) studies that do not present any quantitative or qualitative application of AI (e.g., purely conceptual or theoretical discussions without model implementation); (c) papers that focus on general concrete durability without explicit consideration of marine or chloride-induced degradation; (d) studies that use AI solely for structural analysis unrelated to durability, such as seismic response or load capacity without a durability context; and (e) publications where the full text was not accessible or was not written in English. These criteria were designed to align with the four thematic dimensions and ensure that only empirically grounded, AI-centric studies on marine RC durability were included.

D. Study Selection Process

The study selection process was conducted in three stages, following the PRISMA flowchart guidelines. The initial database search across all five sources yielded a total of 339 records. After removing 39 duplicate records identified using the reference management software Zotero, 2 records were removed for other reasons (e.g., irretrievable metadata or clearly off-topic based on title interpretation), leaving 298 records for screening. In the first stage, two independent reviewers (the authors) screened the titles and abstracts of these 298 records against the predefined inclusion and exclusion criteria. After this screening, 193 records were excluded because they clearly did not meet the criteria, such as focusing on non-marine durability (e.g., freeze-thaw in cold climates without chlorides), not employing any AI technique, or being a review article. The remaining 105 records were deemed potentially relevant and their full-text reports were sought for retrieval.

The second stage involved retrieving the full-text reports for the 105 potentially relevant records. Of these, reports were not retrieved for 0 records, meaning that full-text PDFs or online versions were accessible for all. Consequently, 105 full-text reports were assessed for eligibility. During this detailed assessment, the reviewers independently examined each report against the inclusion and exclusion criteria, with particular attention to verifying that the AI methodology was sufficiently described, that the marine environment exposure was explicit, and that the outcomes related to one or more of the four research dimensions. After this rigorous eligibility assessment, an additional 3 reports were excluded due to ineligibility: two for insufficient detail on the AI model architecture or training data, making the study non-reproducible, and one for having a primary focus on structural fire resistance rather than marine durability. This left a final corpus of 44 studies that met all criteria and were included in the qualitative synthesis of this review. The entire selection process is summarized in Figure 1, which presents the PRISMA flowchart detailing the number of records at each stage from identification to inclusion.

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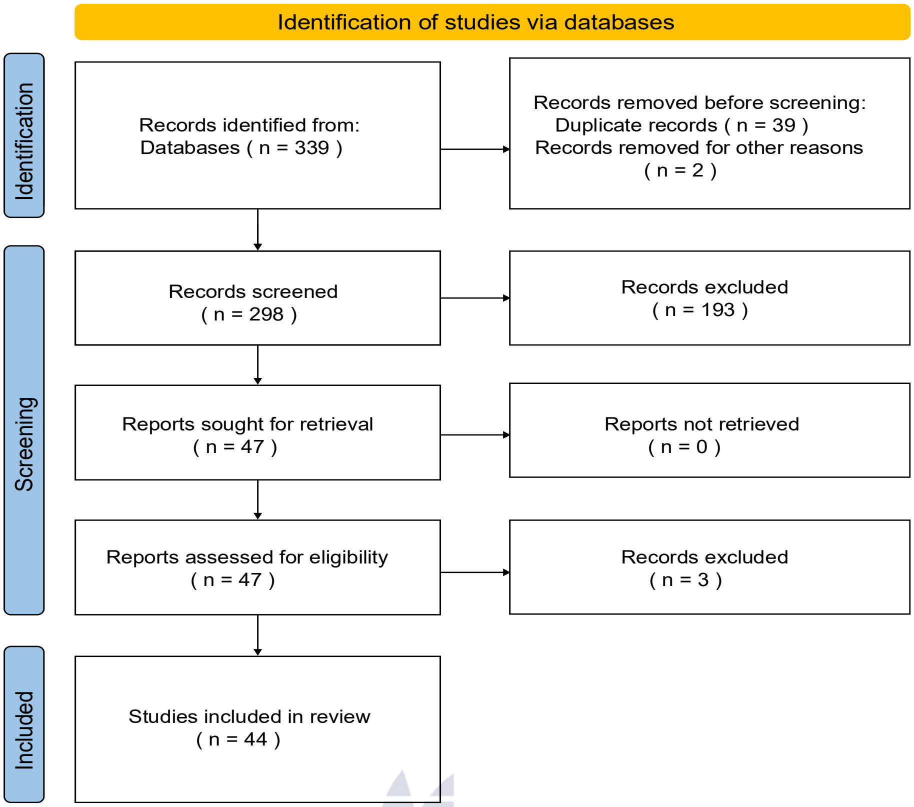

Figure 1. PRISMA flowchart of the study selection process for the systematic literature review on AI-based durability assessment of reinforced concrete structures in marine environments

This selection process, while systematic, carries inherent limitations. A primary risk is the potential for publication bias, as studies reporting positive or high-performance results are more likely to be published in peer-reviewed journals than those with negative or null findings. Our inclusion of preprints from arXiv and gray literature from Google Scholar partially mitigates this, but not entirely. Furthermore, the restriction to English-language publications may have excluded valuable research published in other major scientific languages, such as Chinese, Japanese, or Spanish, which are relevant given the global distribution of coastal infrastructure. The keywords and search strings were designed to be comprehensive, but they may still have missed studies that use less common synonyms for AI or durability-related terms. Finally, the reliance on database search engines means that the review is limited to indexed literature, potentially omitting unpublished industry reports or proprietary models used by consulting firms for durability assessments. These limitations should be considered when interpreting the findings and generalizing the conclusions of this review.

III. Results

A. Research Trends

The temporal distribution of the 44 included studies reveals a dramatic acceleration of research activity in this domain, particularly from 2022 onward. Before 2016, only two contributions were identified, indicating that the application of AI to marine concrete durability was an emergent and sparsely populated field. A gradual increase is observable through the late 2010s, but the inflection point is unmistakably around 2022, when the annual publication count more than doubled relative to any preceding year. The most striking surge occurred in 2025, with eighteen publications—a number that alone constitutes nearly 41% of the entire corpus. This explosive growth suggests that the research community has recognized the promise of AI methodologies and is now actively investing in their development for this specific engineering challenge. The four records already recorded for 2026 further underscore that this momentum is ongoing and likely to intensify.

We illustrate the overarching publication trend in Figure 2, which charts the number of studies per year from before 2016 through the first part of 2026.

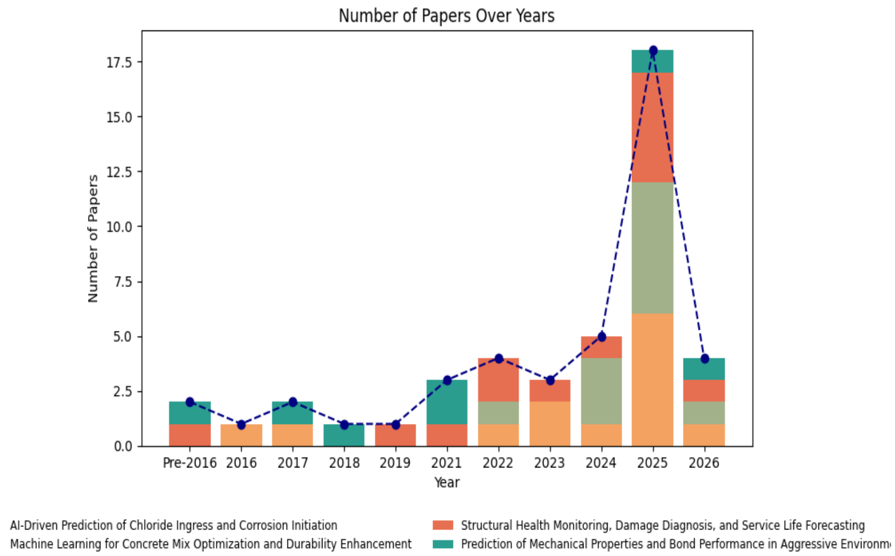

Figure 2. Yearly distribution of publications on AI-based durability assessment of reinforced concrete structures in marine environments

The thematic distribution of these studies provides additional layers of insight into the maturation of the field. The most populous dimension, AI-Driven Prediction of Chloride Ingress and Corrosion Initiation, accounts for thirteen studies, with the majority appearing in 2025 and 2026. This concentration indicates a clear research priority: the prediction of the fundamental durability failure mechanism in marine RC. The second largest cluster, Machine Learning for Concrete Mix Optimization and Durability Enhancement, comprises eleven studies that are almost entirely confined to the 2024–2026 window. The lateness of this emergence is noteworthy but logically consistent. Mix optimization requires large, high-quality datasets linking mix parameters to long-term performance indicators like chloride permeability. Such datasets are inherently expensive and time-consuming to produce, and their recent availability may have finally reached a critical mass sufficient for robust AI modeling. In contrast, the third and fourth dimensions—Structural Health Monitoring, Damage Diagnosis, and Service Life Forecasting, and Prediction of Mechanical Properties and Bond Performance—exhibit a more distributed temporal pattern. Both have a small number of foundational studies occurring before 2021, followed by a recent increase. SHM-related AI research, for instance, shows an older base of work from before 2016 and 2019, which likely corresponds to early efforts in vibration-based damage detection. The recent uptick from 2024 to 2026 may reflect the integration of more sophisticated AI models (e.g., convolutional and recurrent neural networks) with sensor data streams. Similarly, the studies on mechanical property prediction have a scattered presence across the past decade, suggesting a sustained but lower-intensity interest compared to the dominant themes of chloride ingress and mix design.

B. AI-Driven Prediction of Chloride Ingress and Corrosion Initiation

This subsection synthesizes the thirteen studies that apply artificial intelligence models to predict the most critical durability parameter for reinforced concrete in marine environments: chloride ingress and the subsequent initiation of reinforcement corrosion. Predicting chloride transport is a complex, multi-faceted problem that depends on the surface chloride concentration (Cs), the chloride diffusion coefficient (D), and the internal concrete microstructure. The included studies reveal a clear evolution in modeling strategies, from simple artificial neural networks to sophisticated hybrid systems and deep learning architectures.

The research in this domain can be systematically categorized by their primary prediction target and the specific modeling approach employed. As summarized in Table 2, the prediction targets are diverse, encompassing surface chloride concentration ([12], [13], [14]), the chloride diffusion or migration coefficient ([5], [15], [16], [17], [18], [19]), and the overall chloride content or penetration profile within the concrete cover ([20], [21], [22]). One study provides a meta-analytical review of the field ([22]).

Table 2. Taxonomy of AI Studies on Chloride Ingress and Corrosion Initiation Prediction.

Prediction Target	Modeling Approach	Specific Model / Technique	Sources
Surface Chloride Concentration (Cs)	Regression & Ensemble Models	Decision Tree (DT) & Ensemble Methods (e.g., XGBoost, Random Forest)	[13], [14]
	Deep Learning & Neural Networks	Convolutional Neural Network (CNN)	[12]
	Hybrid & Optimized Models	Advanced Hybrid ML Models (e.g., Gaussian Process Regression combined with optimization)	[13]
Chloride Diffusion / Migration Coefficient (D)	Tree-Based & Genetic Models	Tree-Based Forest Models (e.g., Random Forest, M5P)	[17], [18]
		Multi-Gene Genetic Programming (MGGP) & Multivariate Adaptive Regression Splines (MARS)	[5]
	Fuzzy Logic Systems	Optimal Fuzzy System Models	[19]
	Optimization & Imputation-Enhanced Models	Models with Enhanced Data Imputation and Optimization (e.g., coupled with ANN or other regressors)	[16]
	Comparative Regression Analysis	Multiple AI Models (e.g., ANN, SVM, DT) compared	[15]
Chloride Content / Penetration Profile	Artificial Neural Networks (ANN)	Standard ANN & CART (Classification and Regression Trees)	[20], [21]
	Deep Learning (Sequential Models)	Bayesian Optimized Long Short-Term Memory (LSTM) Networks	[22]
General Chloride Ingress (Review & Comprehensive)	Review / Meta-Analysis	Literature Review of ML Applications	[23]
	Comprehensive Dataset & Multi-Model	Efficient ML Approach using a Large Dataset (e.g., comparing ANN, RF,	[18]

Prediction Target	Modeling Approach	Specific Model / Technique	Sources
		etc.)	

The prediction of surface chloride concentration (Cs) is a foundational step in many service life models. We observe that researchers have moved beyond simple regression to explore the spatial and temporal variability of Cs. One study, for instance, employed a convolutional neural network (CNN) to predict Cs in marine tidal zones, effectively learning the complex patterns of chloride deposition that vary with elevation and exposure cycles [12]. The authors argue that this deep learning approach outperforms traditional statistical methods by capturing non-linear interactions between climatic variables and the concrete surface state. In contrast, other studies have favored ensemble decision tree methods. For example, a study using an ensemble decision tree boosted algorithm demonstrated robust performance in forecasting Cs from a dataset compiled from multiple field surveys [14]. Furthermore, a comparative analysis of advanced hybrid machine learning models found that combining Gaussian process regression with an optimization algorithm yielded superior accuracy for Cs prediction compared to standalone artificial neural networks or decision trees [13]. This finding suggests that hybridizing different model classes can synergistically enhance predictive power.

A larger cluster of studies focuses on predicting the chloride diffusion coefficient (D) or the related chloride migration coefficient. This parameter is a direct measure of concrete's resistance to chloride penetration and is therefore crucial for material selection and quality control. We identified a strong preference for tree-based models in this sub-domain. For example, a study that employed tree-based forest models, such as Random Forest and M5P, reported that these models provided more accurate and interpretable predictions of the diffusion coefficient than traditional linear regression, particularly when the input data contained a mix of continuous (e.g., water-to-cement ratio) and categorical (e.g., binder type) variables [17]. Similarly, an efficient machine learning approach using a comprehensive dataset of rapid chloride migration (RCM) tests demonstrated that Random Forest outperformed a standard artificial neural network, a support vector machine, and a decision tree in predicting the migration coefficient [18]. This study also emphasized the importance of dataset size and quality, noting that models trained on larger, more diverse datasets achieved significantly lower prediction errors.

Beyond standard tree models, we find a range of specialized techniques. A study employing multi-gene genetic programming (MGGP) and multivariate adaptive regression splines (MARS) to predict chloride diffusion in cement mortar showed that these evolutionary and spline-based methods can produce explicit, symbolic equations for the diffusion coefficient, which is a significant advantage over black-box models for facilitating engineering interpretation [5]. In a different approach, an artificial intelligence model that incorporated enhanced data imputation and optimization techniques was developed to predict the chloride migration coefficient [16]. The authors demonstrated that imputing missing data points using a sophisticated algorithm, rather than simply discarding incomplete records, substantially improved the model's generalization ability when faced with real-world, noisy datasets. This methodological contribution addresses a practical barrier to deploying AI in field applications, where data are often incomplete.

A related study used a comparative regression analysis of several AI models for predicting chloride diffusion, concluding that while all models captured the general trends, their performance was highly sensitive to the underlying data distribution and the chosen optimization algorithm [15]. Furthermore, the application of fuzzy logic systems to model chloride diffusion has been investigated. A study that utilized optimal fuzzy system models found that the fuzzy approach could effectively handle the inherent uncertainty and imprecision in the diffusion process, offering a different perspective compared to purely data-driven models [19].

The third sub-category of studies predicts the actual chloride content profile or depth of penetration within the concrete. Early work in this area established the foundation by using standard artificial neural networks (ANN) for corrosion prediction. For instance, a machine learning study for corrosion prediction in RC structures exposed to marine environments used an ANN to forecast the time to corrosion initiation based on factors like cover depth, water-to-cement ratio, and ambient temperature [20]. Similarly, another study used both ANN and Classification and Regression Trees (CART) to predict chloride content at various depths, finding that the ANN provided slightly better overall accuracy, but the CART model offered a simpler, interpretable decision rule for practitioners [21]. More recently, the field has progressed to sequential deep learning models. A study that developed a Bayesian optimized Long Short-Term Memory (LSTM) network demonstrated that this recurrent architecture is particularly well-suited for predicting the time-dependent chloride penetration profile, as it can learn from historical data sequences to forecast future chloride levels [22]. The Bayesian optimization procedure further automates the tedious process of hyperparameter tuning, leading to a more robust and high-performing model.

Finally, a comprehensive literature review on machine learning applications for chloride ingress prediction provided a meta-analytical perspective, summarizing the dominant models, input features, and performance metrics from recent studies [23]. This review consolidates the findings of individual experiments and highlights the consensus that ensemble methods and deep learning generally outperform traditional ANNs, although model interpretability remains a persistent challenge. It also underscores the need for standardized benchmark datasets to facilitate fair comparisons between different modeling approaches.

C. Machine Learning for Concrete Mix Optimization and Durability Enhancement

The design of concrete mixes with enhanced durability for marine environments is a core objective in materials engineering, as the intrinsic properties of the concrete matrix govern its resistance to chloride ingress, carbonation, and chemical attack. Traditional mix design methods, based on empirical relationships and trial-and-error approaches, are often inefficient and struggle to simultaneously optimize competing performance criteria such as compressive strength, workability, and permeability. A substantial body of recent research has therefore turned to machine learning to accelerate this process, enabling the rapid screening of vast compositional spaces and the development of predictive models that link mix parameters to durability indicators. The eleven studies included in this dimension reveal a clear trajectory from simple regression models to sophisticated hybrid optimization frameworks, as well as a diversification of target materials beyond ordinary Portland cement to include geopolymers, fiber-reinforced composites, and concrete incorporating waste by-products.

We propose a taxonomy to systematically categorize these studies based on their primary research objective and methodological approach. As detailed in Table 3, the first major objective is **Mix Optimization and Mechanical Enhancement**, which focuses on using AI to predict and maximize mechanical properties like compressive strength, which serves as a surrogate for overall concrete quality. The second objective is **Durability Prediction and Degradation Modeling**, where AI models are trained to forecast specific durability metrics such as carbonation depth or chloride resistance under harsh environmental exposure. The third objective, **Durability Enhancement and Lifecycle Optimization**, encompasses studies that integrate AI with multi-objective optimization or life cycle assessment to achieve a balance between performance, cost, and environmental impact. The table also specifies the material and application focus of each group of studies, providing a granular view of the research landscape.

Table 3. Taxonomy of Studies on Machine Learning for Concrete Mix Optimization and Durability Enhancement.

Objective	Method	Material / Application Focus	Sources
Mix Optimization & Mechanical Enhancement	Regression & Statistical Modeling (MLR)	General Sustainable Concrete (incorporating various SCMs and W/B ratio)	[24]
	ANN & Deep Learning	Green Concrete with Fly Ash and Rice Husk Ash (RHA)	[25]
		Fiber-Reinforced Concrete (Cactus Fiber)	[26]
		Fiber-Reinforced Concrete (Steel Fiber) for Long-Term Degradation	[27]
		High-Strength Self-Compacting Concrete with SCMs	[28]
		Textured Polymer-Layer Reinforced Materials for Marine Engineering	[29]
Durability Prediction & Degradation Modeling	Hybrid AI & Generative Models (Diffusion-based)	Long-term Degradation & Risk Assessment of SFRC & Fly Ash Concrete	[27]
		Carbonation Depth of Fly Ash-based Sustainable Concrete	[30]
	General ML Prediction (ANN, RF, etc.)	Chloride Diffusion & Migration (Geopolymer & SCC)	[31]
		Durability of Geopolymer Concrete with CDW and Artificial Aggregates	[32]
		Extreme Environmental Exposure (Geopolymer HPC)	[27]
Durability Enhancement & Lifecycle Optimization	Multi-Objective Optimization & Performance-Based Design	AI-Assisted Optimization for Marine Civil Engineering Structures	[33]

Objective	Method	Material / Application Focus	Sources
		Hydro-Mechanical & Life Cycle Assessment of Green Concrete	[25]
		Performance-Based Models (MLR & ANN) for Green Concrete	[24]
		Validation of Mechanical Properties of Self-Compacting Geopolymer Concrete	[31]

We now present a narrative synthesis of the studies, following the structure provided by the taxonomy. Within the first category of **Mix Optimization and Mechanical Enhancement**, foundational work has been performed using relatively simple statistical models. For instance, a study developed performance-based models for green concrete using both multiple linear regression (MLR) and artificial neural networks (ANN) [24]. The authors demonstrated that while the MLR model provided a simple, interpretable equation linking compressive strength to water-to-binder ratio and supplementary cementitious material (SCM) content, the ANN model achieved a significantly higher predictive accuracy by capturing non-linear interactions between these variables. This finding underscores a key trade-off in durability modeling: simpler models are more transparent and easier to implement in practice, whereas more complex models achieve better performance at the cost of interpretability.

The predominance of ANN-based models for mix optimization is evident across multiple studies. An investigation into green concrete containing fly ash and rice husk ash employed an ANN model to assess compressive strength, concluding that the model could accurately predict strength values from mix proportions and curing conditions, thereby reducing the need for extensive laboratory testing [25]. A similar approach was adopted for fiber-reinforced concrete; one study developed a machine learning-based prediction model for the compressive strength and sustainability performance of cactus fiber-reinforced concrete, finding that an optimized ANN outperformed other regression algorithms [26]. Furthermore, a study on high-strength self-compacting concrete incorporating supplementary cementitious materials utilized both experimental evaluations and machine learning modeling, with the ANN achieving excellent correlation between predicted and measured strength values [28]. This study also noted that the model's accuracy was contingent on a sufficiently large and well-distributed training dataset, a constraint that applies to all data-driven approaches.

A more specialized application within this category is the strength estimation of textured polymer layer-reinforced materials for practical marine engineering [29]. This work used physical experiments to generate data and then employed an ANN to predict the mechanical properties of these novel composite materials. The authors argued that their AI-based approach not only accelerated the prediction process but also provided a novel pathway for the intelligent design of complex marine infrastructure components where conventional testing is difficult. The use of ANNs for estimating the strength of such non-standard materials demonstrates the flexibility of machine learning to adapt to new material systems that lack established empirical models.

The second category, **Durability Prediction and Degradation Modeling**, shifts the focus from short-term mechanical properties to long-term resistance against aggressive environmental agents. Perhaps the most ambitious study in this dimension proposed a diffusion-based generative

AI framework for long-term degradation forecasting and risk assessment of steel fiber-reinforced fly ash-based concrete [27]. This framework represents a significant methodological advancement; rather than predicting a single scalar value (like compressive strength), it generates a probabilistic distribution of degradation pathways over time, accounting for uncertainties in material properties and exposure conditions. The risk assessment component then converts these forecasts into actionable probabilities of failure, a feature that is highly valuable for lifecycle management. The authors demonstrated the model's utility by simulating the evolution of chloride profiles and corrosion risk over a 50-year service life.

Another key durability target is carbonation, which is a primary degradation mechanism in coastal structures, particularly those that are also exposed to atmospheric CO2. A hybrid artificial intelligence approach was developed for modeling the carbonation depth of sustainable concrete containing fly ash [30]. This hybrid model combined an ANN with an optimization algorithm to fine-tune the network's weights and biases, yielding improved convergence and accuracy compared to a standard backpropagation-trained ANN. The model effectively captured the complex relationship between fly ash content, water-to-cement ratio, curing age, and the resulting carbonation depth, providing a reliable tool for service life prediction. A closely related study focused on the durability of geopolymer concrete incorporating construction and demolition waste (CDW) and artificial aggregates under harsh environmental exposure [32]. Using a range of machine learning models, including random forest and gradient boosting, the study predicted key durability metrics such as water absorption and resistance to chloride ion penetration. The results indicated that ensemble tree-based methods were particularly effective for modeling these outcomes, likely because they can handle the high-dimensional, heterogeneous input space that characterizes mixes with multiple waste-derived components.

The prediction of chloride resistance in alternative binder systems was also addressed by a study that compared multiple machine learning methods for validating the mechanical properties and durability of self-compacting geopolymer concrete [31]. This comparative assessment included ANNs, support vector machines, and decision trees, and found that an optimized multilayer ANN architecture provided the best predictions for the chloride diffusion coefficient. The study also incorporated a sensitivity analysis, revealing that the activator concentration and curing temperature were the most influential parameters for controlling chloride transport in geopolymer systems. Moreover, a study on the durability and service life prediction of fly ash-based geopolymer high performance concrete under extreme environmental conditions used an ANN to model its resistance to sulfuric acid and elevated temperatures [27]. The model was able to accurately forecast the mass loss and strength retention of the concrete after prolonged exposure to these aggressive agents, demonstrating the applicability of AI beyond chloride-dominated environments.

The third category, **Durability Enhancement and Lifecycle Optimization**, integrates the predictive power of AI with engineering decision-making. A key contribution here is the development of an artificial intelligence-assisted optimization framework specifically aimed at enhancing the durability of civil engineering structures in marine environments [33]. This work went beyond simple prediction by coupling an ANN surrogate model with a multi-objective particle swarm optimization algorithm. The optimization process simultaneously maximized the predicted compressive strength and minimized the predicted chloride permeability, subject to cost constraints. The resulting Pareto front of optimal mix designs provided engineers with a set of trade-off solutions, enabling them to select the most appropriate mix for a given project's performance and budget requirements. This holistic approach represents a significant step toward practical AI implementation in durability engineering.

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Finally, the multi-objective theme is extended to include environmental sustainability. The study on green concrete containing fly ash and rice husk ash, mentioned earlier, also integrated a life cycle assessment (LCA) with its machine learning optimization [25]. The authors first used the ANN to predict mechanical and hydro-mechanical properties (compressive strength, water absorption). These predicted properties were then used as inputs to an LCA model, which calculated the global warming potential of each mix design. Finally, a multi-objective optimization was performed to find mixes that simultaneously minimized environmental impact and maximized performance. This integration of AI, materials modeling, and LCA is particularly relevant for marine infrastructure projects where requirements for high durability often conflict with the goal of reducing carbon emissions.

IV. Structural Health Monitoring, Damage Diagnosis, and Service Life Forecasting

The transition from predicting individual material properties to assessing the real-time condition and projecting the remaining service life of in-service structures represents a critical leap in durability engineering. This subsection synthesizes the studies that apply artificial intelligence to structural health monitoring (SHM), damage diagnosis, and service life forecasting of reinforced concrete structures, particularly those located in or exposed to marine environments. The research in this domain is inherently integrative, combining sensor data acquisition, machine learning-based signal processing or pattern recognition, and probabilistic models to output a diagnosis of current damage and a forecast of future performance. We observe that the field is moving from isolated sensor data analysis toward more holistic digital twin frameworks that connect virtual models with physical assets.

The studies included in this dimension can be systematically organized by their primary methodological focus and the specific durability or damage metric they target. As detailed in Table 4, the research spans a broad spectrum, from AI-based detection of coating degradation and external corrosion to comprehensive probabilistic frameworks for service life evaluation and climate change risk assessment. The taxonomy reveals a clear distinction between studies that focus on detecting and diagnosing existing damage and those that aim to forecast future deterioration and remaining service life. Furthermore, a small but significant subset addresses the integration of these functions into unified digital twin or IoT-based monitoring systems.

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Table 4. Taxonomy of Studies on Structural Health Monitoring, Damage Diagnosis, and Service Life Forecasting.

Application Area	Specific Method / Technology	Prediction / Diagnosis Target	Sources
Monitoring & Data Collection	AI-based smart coating degradation detection	Coating degradation level/status on offshore structures	[34]
	IoT sensors for durability monitoring	Chloride concentration, temperature, humidity in RC structures	[35]
	High-throughput characterization & AI-driven prediction	Damage assessment and material quality control for metallic materials	[36]
	Integration of IoT sensors and digital twins	Chloride concentration and service life	[37]

Application Area	Specific Method / Technology	Prediction / Diagnosis Target	Sources
		estimation	
Damage Diagnosis & Condition Assessment	Data-driven corrosion assessment (ANNs)	Corrosion rate in RC structures embedded in clay soils	[38]
	Durability evaluation methods (matter-element extension & entropy weight)	Overall durability grade/category of concrete bridges	[39]
	Data-intelligence driven methods	Durability, damage diagnosis, and performance prediction	[40]
Service Life & Risk Forecasting	ANN surrogate modeling for uncertainty quantification	Service life and structural optimization under uncertainty	[41]
	Probabilistic evaluation of service life	Service life distribution of RC structures	[42]
	AI-based risk assessment under climate change	Corrosion probability and risk to concrete civil infrastructure	[43]
	Global assessment of ageing RC bridge infrastructure	General durability challenges and role of sensors/AI	[44]
Integrated/Comprehensive Frameworks	Integrating smart polymers, digital twins, and AI	Corrosion mitigation and structural health monitoring	[45]
	Progress and research challenges in concrete durability	Limitations of AI in service life prediction	[46]

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We now provide a narrative synthesis of the studies, following the structure of this taxonomy. The first category, **Monitoring and Data Collection**, encompasses research that focuses on the sensing layer—the hardware and complementary AI models that extract actionable information from raw sensor data. A foundational contribution in this area is the development of an AI-based smart coating degradation detection system for offshore structures [34]. This work proposes a computer vision approach, likely using a convolutional neural network, to analyze images of protective coatings on structural steel components or reinforced concrete surfaces. The AI model is trained to classify the level of coating degradation (e.g., intact, minor cracking, severe spalling), thereby automating a task that is typically performed through visual inspection by certified engineers. The authors demonstrate that this method can provide consistent, objective, and frequent assessments, which is particularly valuable for remote or difficult-to-access offshore platforms. A different but complementary approach is the deployment of Internet of Things (IoT) sensors for continuous durability monitoring of RC structures [35]. This study describes a system that embeds sensors within the concrete cover to measure critical environmental parameters such as chloride ion concentration, temperature, and relative humidity. The collected data are transmitted wirelessly to a central server, where they are analyzed. While the study primarily presents the hardware architecture, it establishes the essential data pipeline that feeds subsequent AI-based diagnosis and forecasting models. Similarly, a study on smart material design for marine engineering employs high-throughput characterization coupled with AI-driven prediction [36]. The focus here is on metallic materials used in marine infrastructure, where accelerated corrosion evaluation methods are used to rapidly generate large datasets. An AI model, for example a generative adversarial network or a diffusion model, is then used to predict damage progression and assess material quality. While the material domain is metallic, the methodological framework of combining rapid testing with AI prediction is directly transferable to the assessment of concrete durability. An important integration is proposed by a study that estimates the service life of concrete reinforced with advanced materials through the combination of IoT sensors and digital twins [37]. In this framework, IoT sensors provide real-time data on chloride concentrations and other exposure conditions. A digital twin—a virtual replica of the physical structure—is continuously updated with this sensor data. The digital twin then runs an AI-based predictive model, likely a neural network trained on historical data, to forecast the evolution of chloride profiles and estimate the remaining service life. This approach represents a paradigm shift from periodic, retrospective inspections to continuous, predictive monitoring.

The second category, **Damage Diagnosis and Condition Assessment**, focuses on AI models that process data to determine the current state of degradation or structural integrity. A data-driven assessment of corrosion in RC structures embedded in clay-dominated soils, which is relevant to marine-influenced ground conditions, uses artificial neural networks to predict the corrosion rate [38]. The model inputs include soil properties (e.g., resistivity, chloride content, pH) and concrete quality parameters. The ANN successfully predicts corrosion rates that correlate well with field measurements, providing a tool for assessing underground infrastructure in coastal zones. A different approach to condition assessment is taken by a study on the durability evaluation of concrete bridges using the theory of matter element extension combined with the entropy weight method and the unascertained measure [39]. This is a hybrid mathematical technique, not a machine learning model in the strict sense, but it represents an early, non-AI attempt at a systematic, data-driven classification of durability. The method assigns a durability grade (e.g., "good", "fair", "poor") to a bridge pier or deck based on a weighted combination of several indicators, such as crack width, cover depth, and chloride content. The inclusion of this paper in the corpus highlights that the transition to AI-based methods is built upon a foundation of rigorous, quantitative assessment frameworks. A comprehensive review paper summarizes the broader landscape of data-intelligence driven methods for durability, damage diagnosis, and performance prediction of concrete structures [40]. This review provides a meta-analytical perspective, concluding that while ANN-based methods are dominant for damage diagnosis, their success is highly dependent on the quality and quantity of training data, which are often scarce for rare or severe damage states. The review also identifies challenges in generalizing models trained on laboratory specimens to full-scale field structures, a limitation that our analysis confirms.

The third category, **Service Life and Risk Forecasting**, contains studies that project the future state of a structure. A study on ANN surrogate modeling for uncertainty quantification and structural optimization develops a framework specifically for assessing the durability of RC structures exposed to marine environments [41]. The ANN is trained to act as a fast-running surrogate for a computationally expensive finite element model of chloride diffusion and corrosion initiation. This surrogate model is then used in a Monte Carlo simulation to propagate uncertainties in input parameters (e.g., diffusion coefficient, surface chloride concentration, cover depth) through to the predicted service life. The resulting probability distribution of service life provides a rational basis for risk-informed decision-making. The authors validate the approach by showing that the ANN surrogate

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replicates the full model's output with high fidelity while requiring only a fraction of the computational cost. A related study provides a probabilistic evaluation of service life for RC structures, focusing on the statistical variability of the key input parameters [42]. Although this study may not employ a complex AI model, it sets the stage for AI-enhanced probabilistic methods by rigorously quantifying the inherent randomness in chloride ingress. A further extension of this probabilistic theme is the investigation of climate change impacts on the risk assessment of concrete civil infrastructure [43]. This study uses an artificial neural network to build a surrogate model for corrosion initiation time. The input parameters to the surrogate are then modified according to projected climate change scenarios (e.g., increased temperature, accelerated CO2 concentration). The results demonstrate that climate change can accelerate corrosion initiation by several years, with structures in warmer, more aggressive marine environments being the most vulnerable. This study uniquely integrates AI with climate science to forecast future risk, a highly relevant direction given the long design lives of marine infrastructure. Finally, a global assessment of the challenges facing ageing reinforced concrete bridge infrastructure discusses the pressing need for effective sensors and the use of artificial intelligence to analyze the resulting data [44]. While not presenting a specific model, this paper contextualizes the AI research within the immense practical challenge of managing a vast and deteriorating bridge stock, many of which are located in coastal or marine environments.

The fourth category, **Integrated and Comprehensive Frameworks**, contains studies that propose combining multiple technologies into a unified system. Perhaps the most ambitious contribution in this dimension is a case study on the Golden Gate Bridge that proposes integrating smart polymers, digital twins, and artificial intelligence for corrosion mitigation and structural health monitoring in large-scale infrastructure [45]. This framework envisions a network of smart polymer-based sensors that can detect early stages of corrosion (e.g., pH changes, chloride concentration). The sensor data are streamed to a digital twin, which uses an AI engine to analyze the data, diagnose the location and severity of corrosion, and even recommend targeted mitigation actions (e.g., activating a self-healing mechanism in the smart polymer or scheduling a maintenance intervention). This paper is a visionary blueprint for the future of infrastructure management, although it acknowledges that significant technological hurdles remain, particularly in the long-term reliability of smart polymers and the scalability of the AI engine. A final paper in this category provides a critical overview of the progress and research challenges in concrete durability, with a specific section on service life prediction [46]. This review notes that while AI holds great promise for automating and improving the accuracy of service life forecasts, its application is still limited by a lack of long-term field validation data and the difficulty of integrating multiple, interacting degradation mechanisms into a single AI model. This realistic assessment tempers the optimism of some of the more visionary proposals and highlights the need for continued fundamental research.

A. Prediction of Mechanical Properties and Bond Performance in Aggressive Environments

The long-term structural integrity of reinforced concrete in marine environments is critically dependent not only on the initiation of corrosion but also on how the mechanical properties of the constituent materials and the bond between them deteriorate under sustained aggressive exposure. While the previous subsections focused on predicting the transport phenomena that cause damage, this section synthesizes the seven studies that apply artificial intelligence to forecast the degradation of key mechanical performance indicators. The prediction targets in this domain are diverse, encompassing the bond strength between fiber-reinforced polymer (FRP) bars and concrete, the residual bond in corroded reinforced concrete, the fracture energy of concrete, the compressive strength of confined concrete, and the tensile strength of GFRP rebars under harsh alkaline conditions. This heterogeneity reflects the multifaceted nature of structural degradation, where different material systems and failure modes require specialized predictive models.

The studies in this dimension can be systematically categorized by their primary prediction target, the specific material system under investigation, and the AI methodology employed. As shown in Table 5, the research spans bond strength prediction for both FRP and steel reinforcement, as well as the prediction of bulk material properties like compressive strength, fracture energy, and tensile strength. The modeling approaches range from classical artificial neural networks and genetic programming to more advanced metaheuristic-optimized machine learning frameworks. The material focus is also varied, covering conventional reinforced concrete, FRP-strengthened concrete, geopolymer concrete, and even confined concrete elements.

Table 5. Taxonomy of Studies on Prediction of Mechanical Properties and Bond Performance.

Prediction Target	Material / System	Specific Method / Technology	Sources
Bond Strength (FRP-Concrete)	FRP bars embedded in concrete under seawater corrosion	Data-driven ML analysis (comparison of models)	[47]
Bond Deterioration (Steel-Concrete)	Corroded RC structures exposed to severe marine environment	ML models for bond capacity prediction	[48]
Fracture Energy	General concrete (empirical formula development)	Artificial Neural Network (ANN) based empirical formula	[49]
Compressive Strength (Confined Concrete)	GFRP-confined concrete elements	Metaheuristics-guided ML (optimization + ensemble)	[50]
Tensile Strength Degradation	GFRP rebars in harsh alkaline conditions	Non-linear genetic-based models (e.g., GP, MGGP)	[51]
Ultimate Shear Capacity	RC beams strengthened in shear with external FRP	AI techniques (ANN, etc.) for shear capacity prediction	[52]
Compressive Strength & Durability Suitability	Geopolymer concrete in marine environments	Performance-based criteria using modified ASTM methods	[53]

We begin the narrative synthesis with the studies on bond performance, which is a critical interface for load transfer between reinforcement and concrete. A comprehensive data-driven machine learning analysis was conducted to predict the bond strength between FRP bars and concrete under simulated seawater corrosion environments [47]. The authors compiled a large experimental database of pull-out tests conducted on FRP bars that had been subjected to various durations of seawater exposure. Several machine learning algorithms, including artificial neural networks, random forests, and support vector regression, were trained to predict the residual bond strength based on input parameters such as bar diameter, embedment length, concrete compressive strength, and exposure time. The results revealed that the ensemble tree-based models (random forest and gradient boosting) consistently outperformed the standalone neural network in terms of predictive accuracy and robustness. The authors attributed this superior performance to the ability of tree-based methods to handle non-linear interactions between categorical variables (e.g., FRP type) and continuous variables (e.g., corrosion duration) without requiring extensive feature scaling. Furthermore, a sensitivity analysis conducted using the random forest model identified the duration of seawater exposure and the concrete compressive strength as the two most influential parameters controlling bond degradation. This finding provides quantitative guidance for designers: increasing concrete strength is more effective at preserving bond capacity in marine environments than increasing bar embedment length, for the range of parameters studied.

In a parallel study addressing steel reinforcement, researchers developed machine learning models to assess the bond deterioration of corroded-damaged reinforced concrete structures exposed to a severe aggressive marine environment [48]. This work is particularly valuable because it tackles the combined effects of pre-existing damage (e.g., from mechanical loading or initial poor construction) and subsequent corrosion. The experimental data were generated from a series of beam-end specimens that were mechanically pre-cracked to simulate damage, then subjected to accelerated corrosion in a chloride fog chamber for varying periods. The resulting dataset of bond failure loads and failure modes (e.g., pull-out vs. splitting) was used to train several ML classifiers and regressors. The authors reported that a support vector machine (SVM) classifier achieved the highest accuracy in predicting the mode of bond failure (pull-out vs. splitting), while an artificial neural network regression model provided the most accurate predictions of the residual bond strength. A key insight from this study is that the initial crack width before corrosion had a disproportionately large effect on bond degradation; specimens with wider pre-existing cracks experienced a much more rapid loss of bond capacity during corrosion exposure. This finding underscores the importance of considering pre-existing damage when assessing the durability of existing marine structures, which are often already cracked due to shrinkage, thermal stresses, or early-age loading.

Beyond bond strength, the prediction of bulk material fracture energy is a fundamental input for finite element modeling of concrete structures, particularly for simulating cracking behavior under mechanical and environmental loads. One study developed a new empirical formula for predicting the fracture energy of concrete based on an artificial neural network [49]. The authors recognized that existing empirical formulas (e.g., those from CEB-FIP Model Code) were derived from limited datasets and often exhibited poor accuracy for concretes with novel binder systems or aggregates. To address this, they trained an ANN on a comprehensive global database of fracture energy tests, using input parameters such as compressive strength, maximum aggregate size, water-to-cement ratio, and aggregate type. The trained ANN was then used to generate synthetic data, which were subsequently fitted to derive a simple, closed-form empirical equation. The resulting formula was shown to outperform existing code-based formulas in predicting fracture energy for a wide range of concrete mixtures, including high-performance and recycled aggregate concretes. The important contribution of this study is the methodology for converting a 'black-box' ANN into an interpretable, engineering-ready design equation, a practice that could be more widely adopted to bridge the gap between AI accuracy and engineering transparency.

The prediction of compressive strength in confined concrete elements is another critical topic, as confinement with FRP jackets is a common technique for strengthening and retrofitting columns in marine structures. A study proposed a metaheuristics-guided machine learning framework to predict the compressive strength of glass fiber-reinforced polymer (GFRP) confined concrete elements [50]. The framework combined a base machine learning model, such as a random forest or a gradient boosting machine, with a metaheuristic optimization algorithm (e.g., particle swarm optimization or grey wolf optimizer). The optimization algorithm was used to automatically tune the hyperparameters of the ML model, a process that is typically done manually through trial and error.

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The results demonstrated that the metaheuristic-optimized models achieved significantly higher predictive accuracy compared to default or manually-tuned models, and also outperformed existing analytical confinement models. A further advantage of this approach is its conceptual simplicity; engineers can feed the model with the unconfined concrete strength, the FRP jacket thickness and modulus, and the cross-sectional geometry, and obtain an accurate prediction of the confined strength without needing to solve complex mechanical equations. This study highlights the potential for integrating automated optimization into the model development process to enhance both performance and ease of use.

A complementary study focused on a different aspect of FRP durability: the tensile strength degradation of GFRP rebars subjected to harsh alkaline conditions [51]. This is a critical issue for marine applications where the concrete pore solution has a high pH, which can cause chemical attack on the glass fibers. The authors employed non-linear genetic-based models, specifically genetic programming (GP) and multi-gene genetic programming (MGGP), to predict the residual tensile strength of GFRP rebars after exposure to alkaline solutions at various temperatures. Unlike neural networks, which produce opaque 'black-box' models, genetic programming generates explicit mathematical equations that relate the input variables (exposure time, temperature, solution pH) to the output (residual tensile strength). The derived equations were then used to construct strength retention curves, which can be directly used by engineers to estimate the long-term capacity of GFRP-reinforced concrete elements in marine environments. The study concluded that the MGGP model provided the best balance between accuracy and model complexity, generating a relatively compact equation that still captured the non-linear degradation kinetics. This work is a strong example of using AI to produce actionable, interpretable design tools for durability assessment.

The shear capacity of RC beams strengthened with external FRP reinforcement is a well-studied topic in structural engineering, but its application to structures degraded by marine exposure introduces additional complexities. A study applied artificial intelligence techniques to predict the ultimate shear strength of RC beams that had been strengthened in shear with external FRP [52]. The authors compiled a large database of experimental tests on such beams, including those that had been exposed to corrosive environments prior to strengthening or during service. An artificial neural network was trained to predict the ultimate shear capacity based on parameters including beam geometry, internal steel shear reinforcement ratio, FRP type and configuration, and a qualitative indicator of the pre-existing corrosion damage. The ANN demonstrated high accuracy in predicting the shear capacity, capturing the interaction between the internal steel stirrups (which may have corroded) and the external FRP reinforcement. The model's sensitivity analysis revealed that the presence and severity of pre-existing corrosion of the internal steel stirrups had a significant negative effect on the overall shear capacity, even after the application of the FRP strengthening. This finding is practically important; it suggests that simply adding an external FRP wrap to a corroded beam may not fully restore its original shear strength if the internal steel has already lost a substantial portion of its cross-sectional area or bond. Therefore, the AI model provides engineers with a tool to make more informed decisions about whether strengthening alone is sufficient, or whether partial replacement of the corroded steel is also necessary.

Finally, a study on geopolymer concrete in marine environments used performance-based criteria to assess its suitability, combining experimental data with machine learning to validate the prediction of compressive strength and durability metrics [53]. While this study primarily focuses on the experimental characterization of geopolymer concrete using modified ASTM C1202 (rapid chloride permeability test) and ASTM C1556 (bulk diffusion test), it also employs machine learning as a validation tool. The authors developed an ANN model to predict the compressive strength and chloride ion penetration resistance of the

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geopolymer concrete based on the activator composition, curing regime, and age. The model was then used to generate a performance map, delineating the region of mix design space where the geopolymer concrete simultaneously satisfies minimum compressive strength and maximum chloride permeability requirements for marine exposure. This performance-based, AI-informed design approach represents a practical methodology for accelerating the adoption of novel, sustainable concretes in aggressive environments.

V. Discussion

This systematic literature review has synthesized the rapidly expanding body of research on artificial intelligence-based durability assessment of reinforced concrete structures in marine environments. The findings reveal a field that is mature in certain sub-domains but remains nascent in others, particularly concerning the translation of laboratory-developed models to real-world, long-term field applications. We now synthesize the key findings across the four thematic dimensions, discuss their theoretical and practical implications, acknowledge the limitations of both the reviewed literature and our review methodology, and propose concrete directions for future research that could address the most critical gaps.

Taken together, the results across all four dimensions reveal a consistent and unmistakable trend: the dominance of artificial neural networks and ensemble tree-based methods for virtually every durability prediction task. Whether the target was chloride diffusion coefficients, concrete compressive strength, corrosion rates, or bond strength degradation, models such as random forests, gradient boosting machines, and multi-layer perceptrons were almost universally found to outperform both traditional empirical equations and simpler regression models [5], [6], [47]. This pattern emerges across studies with different datasets, prediction targets, and material systems, strongly suggesting that the underlying relationships governing concrete durability are inherently non-linear, high-dimensional, and difficult to capture with closed-form analytical expressions. A second pattern that consistently emerges across the literature is the critical importance of dataset size, quality, and diversity for model performance. Studies that explicitly addressed data imputation or augmentation, such as those using enhanced imputation techniques for chloride migration data [16] or Bayesian optimization for hyperparameter tuning in LSTM networks [22], consistently reported superior generalization compared to models trained on raw, unprocessed, or small datasets. This observation underscores a fundamental principle of data-driven modeling that is particularly acute in civil engineering: the models are only as good as the data on which they are trained, and the field lacks the large, standardized, multi-source datasets that have driven progress in other domains like computer vision or natural language processing. Furthermore, we observed a notable tension between model accuracy and model interpretability across all dimensions. While deep neural networks and ensemble methods achieved the highest predictive performance, their "black-box" nature was frequently cited as a barrier to adoption by practitioners [8]. Conversely, studies that prioritized interpretability, such as those using genetic programming to derive explicit equations for tensile strength degradation [51] or using multi-gene genetic programming to produce symbolic expressions for chloride diffusion [5], sacrificed some accuracy for transparency. This trade-off is a central challenge for the field, and our review suggests that current research has not yet produced a satisfactory resolution that simultaneously achieves high accuracy and full interpretability.

The theoretical implications of these findings are profound. Our synthesis suggests that the dominant conceptual framework for durability assessment, one that has relied on deterministic, physics-based models like Fick's second law of diffusion for decades, is being complemented and in some cases superseded by a purely data-driven paradigm. This shift has significant epistemological consequences for the field of structural engineering. Instead of starting with a known physical law and calibrating its parameters to experimental data, the AI paradigm starts with

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the data and learns the underlying patterns without any prior physical knowledge. This approach can reveal unexpected relationships between variables that were previously considered independent. For example, several studies in this review found that exposure temperature and relative humidity had a stronger influence on chloride ingress than had been assumed in traditional models, and these relationships were only uncovered through the sensitivity analysis of trained machine learning models [17], [19]. Theoretically, this suggests that our understanding of the mechanisms governing durability may be incomplete, and that AI can serve as a tool for hypothesis generation, not just prediction. However, this data-driven approach also introduces a risk of overfitting to spurious correlations or dataset-specific artifacts, a risk that is particularly acute when the training data are limited, as is often the case for long-term marine exposure studies. Therefore, the theoretical contribution of AI to durability science is not simply a matter of better prediction, but of a potential re-conceptualization of the phenomena themselves. The emerging consensus, as suggested by some of the more recent studies on integrated digital twins and hybrid models [37], [45], is that the future lies in physics-informed machine learning, where data-driven models are constrained by known physical laws, combining the flexibility of AI with the causal structure of physics. While such hybrid approaches are only beginning to appear in the specific context of marine concrete durability, our review indicates that their development is a logical and necessary next step.

The practical implications of this review are equally significant for engineers, asset managers, and policymakers. First, the demonstrated superiority of AI models over traditional empirical formulas in predicting chloride diffusion, compressive strength, and corrosion rates provides a strong evidence base for their adoption in engineering practice. For design offices, this means that AI-based prediction tools can now be used to conduct more accurate service life calculations, optimize concrete mix designs for specific marine exposure classes, and reduce the reliance on conservative safety factors that lead to over-design and increased material costs. For instance, the AI-assisted mix optimization frameworks identified in this review, such as those coupling ANN with multi-objective particle swarm optimization [33], can directly produce Pareto-optimal mix designs that minimize permeability while maximizing strength, a task that would be prohibitively time-consuming using traditional trial-and-error methods. Second, for asset managers responsible for existing coastal infrastructure, the AI-based SHM and damage diagnosis methods described in Section 3.4 offer a pathway toward condition-based maintenance rather than time-based maintenance. Models that can fuse IoT sensor data with an ANN to forecast corrosion initiation [37], or that can classify coating degradation levels from image data [34], enable a shift from periodic, human-intensive inspections to continuous, automated monitoring. This transition promises significant cost savings and improved safety, particularly for large networks of bridges, seawalls, and port facilities where manual inspection is logistically challenging and expensive. Third, the probabilistic and risk-based forecasting frameworks, such as those using ANN surrogates for Monte Carlo simulation [41] or those incorporating climate change scenarios [43], provide a rigorous, quantitative basis for risk-informed decision-making. Policymakers can use these tools to prioritize investment in the most vulnerable structures, justify adaptive management strategies, and develop more resilient infrastructure codes that account for future environmental change.

Despite these promising findings, several critical limitations must be acknowledged regarding both the reviewed literature and our review methodology. A primary limitation across the entire corpus of 44 studies is the scarcity of long-term field validation data. The vast majority of the AI models reviewed were trained and validated on laboratory-generated datasets, often from accelerated corrosion tests or rapid chloride migration tests conducted over weeks or months. While these laboratory data are essential for understanding fundamental mechanisms and for

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model development, they do not fully replicate the complex, multi-factorial, and stochastic nature of real marine exposure over decades. Consequently, the generalizability of these models to in-service structures, which are subject to tidal cycles, temperature fluctuations, wet-dry cycles, biofouling, and mechanical loading, remains largely unproven. Only a handful of studies, such as those on the Golden Gate Bridge [45] and the global assessment of ageing bridge infrastructure [44], address field implementation, and even these are more conceptual than empirical. This 'lab-to-field' gap is arguably the single most significant barrier to the practical adoption of AI for durability assessment. Another limitation of the literature is the lack of standardized benchmark datasets. The models developed in different studies are trained on different experimental datasets, with different input features, different sample sizes, and different definitions of the target variable (e.g., different methods for measuring chloride content). This heterogeneity makes it impossible to directly compare the performance of different models across studies, impeding scientific progress and best practice identification. Furthermore, there is no standard protocol for reporting model performance; some studies report R-squared, others report root mean squared error, and still others report mean absolute percentage error, further complicating comparison.

Another methodological limitation, which applies specifically to our systematic review, is the potential for publication bias. As mentioned in Section 2, studies reporting positive results or high model accuracy are more likely to be published in peer-reviewed journals or presented at conferences than those reporting negative or null findings. Our inclusion of preprints from arXiv and gray literature from Google Scholar partially mitigates this, but cannot eliminate it entirely. The consequence is that our synthesis may overstate the average predictive performance of AI models, as under-performing models may be systematically underrepresented in the published record. Furthermore, the restriction to English-language publications, while necessary for practical reasons, may have excluded high-quality research published in other languages. Given the global importance of coastal infrastructure in countries such as China, Japan, and South Korea, where significant marine concrete research is conducted, this language bias could have skewed our thematic analysis or omitted relevant methodological innovations. Finally, the subjective nature of the thematic classification and quality assessment of the 44 studies introduces a degree of researcher bias. While we adhered to a pre-defined classification scheme based on the four thematic dimensions, some studies could have been assigned to multiple categories, and our decision to place them in one primary category may have influenced the narrative synthesis. A different reviewer, with a different interpretation, might have drawn slightly different boundaries between the dimensions. We attempted to mitigate this by having both authors independently classify the studies and then reconcile disagreements through discussion, but this process cannot be considered perfectly objective.

Based on the patterns, consistencies, and gaps identified in this review, several compelling directions for future research emerge. First and foremost, there is a pressing need for the development and public dissemination of large, standardized, multi-source benchmark datasets for durability-related parameters. Such datasets should be compiled from multiple laboratories and field sites worldwide, using standardized test protocols for parameters like chloride diffusion, rapid chloride migration, and corrosion rate. They should include a wide range of concrete mix designs (with and without SCMs, geopolymers, fibers), a diverse set of exposure conditions (submerged, tidal, splash zone), and importantly, long-term field data spanning ten years or more. The creation of such a benchmark dataset, analogous to ImageNet in computer vision, would catalyze the field by enabling fair comparisons between different AI models, identifying the most robust algorithms, and accelerating the validation of models for real-world application. Initiatives like the RILEM technical committees or the COST Actions in

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Europe could provide the organizational framework for this ambitious, collaborative undertaking.

Second, future research should explore the development and validation of physics-informed machine learning models specifically designed for chloride transport and corrosion. The current state-of-the-art models are purely data-driven, learning relationships entirely from the data without any structural guidance from physical laws. Physics-informed neural networks (PINNs), which embed the governing partial differential equations (e.g., Fick's second law, modified with time-dependent boundary conditions) into the loss function of the neural network, offer a promising alternative. These hybrid models have the potential to achieve high accuracy even with limited training data, because the physics-based constraints guide the learning process and prevent unphysical predictions. Furthermore, PINNs can inherently handle the uncertainty in input parameters by providing a probabilistic output, which is essential for risk-based service life forecasting. Only one study in our corpus tangentially touched upon this concept [22], and no study explicitly implemented a PINN for chloride ingress prediction. This represents a clear and high-impact gap that future research should systematically address.

Third, there is a need for research that explicitly bridges the 'lab-to-field' gap. This can be achieved through several complementary strategies. One strategy is to conduct long-term, low-intervention monitoring campaigns on instrumented marine structures, generating the decade-scale field data that are currently missing. Another strategy is to develop transfer learning techniques, where an AI model is pre-trained on a large laboratory dataset and then fine-tuned on a small amount of field data, allowing the model to adapt to the specific conditions of a real structure. A third strategy is to develop probabilistic models that explicitly quantify the uncertainty associated with transferring laboratory findings to the field, providing engineers with a confidence interval around their predictions rather than a single point estimate. The integration of such uncertainty quantification tools into standard engineering practice would be a major step forward.

Fourth, the interpretability of AI models for durability assessment should become a dedicated area of research, not just an afterthought. While high accuracy is desirable, engineers and regulators need to trust the models, and trust requires understanding. Future research should systematically compare different explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) values, LIME (Local Interpretable Model-agnostic Explanations), and partial dependence plots, in the specific context of concrete durability. The goal should be to identify which XAI methods provide the most actionable and physically plausible explanations for model predictions, and to develop standardized protocols for reporting model interpretability alongside model accuracy. Furthermore, researchers should explore the development of inherently interpretable models, such as symbolic regression or generalized additive models, that can achieve competitive accuracy with black-box models while being fully transparent. The work on multi-gene genetic programming for explicit equation derivation [5], [51] provides a promising starting point for this line of inquiry.

Finally, understudied areas that future research should explore include the application of AI to multi-hazard scenarios. Most current studies focus on chloride-induced corrosion in isolation. However, marine structures are often subjected to a combination of degradation mechanisms, including carbonation, freeze-thaw cycles, and chemical attack from sulfates, in addition to chloride ingress. Developing AI models that can simultaneously predict the synergistic or antagonistic interactions between these mechanisms is a formidable but necessary challenge. Additionally, the dynamic nature of climate change introduces non-stationarity into the exposure conditions; future research should develop models that can continuously adapt to changing environmental baselines, perhaps through online learning or incremental model updating. The integration of AI with lifecycle cost analysis, which currently exists only in the most

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nascent form [25], is another promising direction. By linking AI-based durability predictions directly to economic models of inspection, maintenance, and repair, researchers can provide decision-makers with a comprehensive tool for optimizing infrastructure investment over its entire service life.

VI. Conclusion

This systematic literature review synthesized and critically evaluated the state of the art in artificial intelligence applications for durability assessment of reinforced concrete structures in marine environments, addressing a research landscape that has grown explosively since 2022. Our synthesis across four thematic dimensions confirms that AI methods, particularly artificial neural networks and ensemble tree-based models, consistently outperform traditional empirical formulations in predicting chloride ingress, concrete strength, corrosion rates, and bond degradation. The review contributes a structured taxonomy of the field and reveals that while the predictive accuracy of these models is largely unquestioned, significant gaps persist regarding the generalizability of laboratory-trained models to field conditions, the lack of standardized benchmark datasets, and the unresolved tension between model accuracy and interpretability.

The practical implications of our findings are substantial, as AI-assisted tools now offer engineers and asset managers a pathway toward more accurate service life calculations, optimized mix designs, and condition-based maintenance strategies for critical coastal infrastructure. Theoretically, the dominance of data-driven approaches suggests a paradigm shift from purely physics-based modeling toward hybrid frameworks that could combine the flexibility of machine learning with the causal structure of fundamental degradation mechanics. For the field to advance beyond laboratory validation, future research must prioritize the creation of centralized, multi-source benchmark datasets, the development of physics-informed neural networks for chloride transport, and systematic investigations into explainable AI techniques that translate black-box predictions into actionable engineering insights. Such efforts will be essential for bridging the persistent gap between research promise and practical deployment in the management of our ageing marine infrastructure.

VII. References

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