

I. INTRODUCTION

One of the biggest issues the construction industry has encountered over the past few decades is the longevity and “service life of reinforced concrete” structures. Worldwide, corrosion-induced degradation of reinforced concrete structures is a serious concern [1–8]. Rebuilding and maintaining RC structures due to corrosion has reportedly been estimated to cost billions of dollars annually. Every year, Western Europe alone must spend 5 billion EUR on repairing damage caused by rust [9]. Remarkably, several wealthy nations allocate around 3.5% of their GDP [10] on mitigating damage caused by corrosion and controlling associated issues. Alternatively, 37% of failure modes in reconstructed reinforced concrete buildings are caused by ongoing corrosion of the reinforcing bar, or rebar [11–13]. This is the general type of degradation in these types of reconstructions. As a result, making repairs becomes expensive and time-consuming.

To estimate a structure’s stability and service life, a clear understanding of the concrete’s performance is essential. A single degradation mechanism is often used to evaluate the performance of concrete. The performance of concrete is really impacted by a number of intricate degrading processes that may occur concurrently or subsequently [14, 15]. When many actions contribute to the deterioration process, the combined effect of the synergistic degradation processes is more rapid and severe [16–18]. It is not practical to measure the combined degrading processes’ influence in a lab and then translate the results to a real building. Additionally, doing concrete performance investigations in the field or in a lab can sometimes take a lot of time and money, both directly and indirectly [19]. For e.g., traditional highway structure in-service scrutiny and prevention programmes result in traffic delays, which can account for 15% to 40% of the construction expenses [20]. Therefore, life-cycle management of reinforced concrete buildings requires an accurate and affordable assessment of the concrete’s performance throughout operation from both an economic and safety standpoint.

Installing durability monitoring systems in reinforced concrete structures may make it possible to spot degradation early on. One essential prerequisite for improving the stability evaluation of reinforced concrete frames is the availability of short- and long-term data from the monitoring system with temporal and geographical resolution. To determine how long a structure will likely be in service, data gathered from the monitoring system must be effectively analyzed. In fact, without the ability to draw conclusions or knowledge from them, statistics are meaningless on their own [21,22]. The circumstances leading to rebar corrosion in reinforced concrete buildings are discussed in Section 2. The same part also discusses the limitations of the typical models that are used to assess the resilience and balance service life of RC structures directly and indirectly [19]. For e.g., traditional highway structure in-service scrutiny and prevention programmes result in traffic delays, which can account for 15% to 40% of the construction expenses [20].

Keywords: Machine learning, concrete, durability, degradation, Service life.
(reinforced concrete) structures. Part 3 provides the essential information about machine learning. Two specific domains in field of civil engineering are the subject of discussion on the utilization of “ML” strategy in Section 4. Section 5 outlines the current applications of “machine learning” approaches in service-life and durability evaluation, along with durability monitoring systems. In the same part, the future orientation of the service-life forecast technique and durability monitoring is also outlined. In Section 6, a final conclusion is provided.

2 Durability and service life of RC structures-

The most common causes of rebar corrosion in concrete are either carbon dioxide (CO2) or chloride ions (Cl−) seeping into the pores of the material. Because of its naturally alkaline pore solution pH of 12–13, embedded rebar is passivise. The carbonation of concrete or the existence of Cl− both weaken the passivation of rebar [23–25]. A physicochemical process known as carbonation is brought about spontaneously when CO2 from the surrounding air seeps into the pores of concrete and interacts with the hydrated cement [26, 27]. Rebar may corrode due to both carbonation and chloride, which may minimize its cross-sectional area, elongation ability, and generate significant cracks in the concrete. All of these factors can significantly lower the structure's ability to support weight. An increased rate of rebar corrosion and concrete deterioration might result from cracked concrete providing easier access to moisture and hostile gases and ions such oxygen (O2), carbon dioxide (CO2), and chlorine (Cl). Concrete constructions will thus have reduced strength, durability, serviceability, and safety [6–8, 28]. Rebar corrosion brought on by carbon action can affect a larger area of reinforced concrete buildings more extensively and more expensively to repair than corrosion brought on by chloride. Around two thirds of all concrete buildings are thought to be subjected to climatic conditions that encourage corrosion caused by carbonation [29, 30]. beginning and propagation are the two stages of the corrosion-generate degradation of RC “reinforced concrete” structures. While the rebar is still passivated, the diffusion of CO2 gas into the concrete marks the beginning of corrosion in the event of carbonation-induced corrosion. When it comes to corrosion caused by chloride, the process of Cl− entering concrete is equivalent to the corrosion beginning phase. Starting from the point at which rebar corrosion begins and ending with structural failure is known as the propagation period. Comparing this phase to the stage of corrosion beginning, it is rather brief. These reasons have led to the routine use of the first stage's duration to determine the RC structures' longevity and service life [31, 32] As seen in Fig. 1.

2.1 Deterioration models

In order to effectively estimate concrete performance and make decisions about the maintenance and rehabilitation of reinforced concrete buildings, degradation models are essential. Significant efforts have been undertaken over the last thirty years to create durability models for reinforced concrete buildings subjected to environmental factors that encourage corrosion caused by carbonation and chloride. As a result, many prototypes and input data has been developed [33–36]. A number of the applied analytical models and the associated input parameter values have been found to be inaccurate, lacking, or inappropriate for the current circumstances. Because of these factors, even for the same concrete matrix exposed under the same circumstances, the forecast results varied significantly [37]. Although complex scientific models can yield relatively accurate predictions, they are not user-friendly and need highly experienced professionals, making them unsuitable for practical design applications. In real-world applications, CO2 and Cl− penetration into concrete is often modelled using empirical degradation models, which take the form of straightforward analytical equations based on Fick's second law of diffusion.

2.1.1 Carbonation model-

One of the main factors causing RC constructions' early degradation, loss of serviceability, and safety concerns has been identified as concrete carbonation. It is a crucial indicator of longevity. According to Fick's second rule of diffusion, the traditional “carbonation depth forecast model” is represented in Eq. (1) [26,38–41]. By extending the carbonation depth recorded at one point in time to the future, this model—which is square root law compliant—may be used to predict the depassivation time.
Because chloride attack has an impact on the “remaining service life of RC structures”, predicting the chloride profile is a needed step. Several methods have been developed throughout the years to forecast the focus of chloride within concrete. Despite the availability of a variety of methods, empirical models are most typically used to approximate the chloride detail in concrete. This is an empirical calculation depends on “Fick's second law”, which is used to assess “long-term chloride penetration” in concrete.

2.2 Modelling uncertainty- The starting period of “carbonation-induced corrosion” is the amount of time it takes for the carbonation front to reach a depth in the concrete cover. If the carbonation coefficient \( k \) and the thickness of the concrete cover are known, the start time may be determined with a simplified Fick's law-based calculation, Eq. (1). Eq. (1) makes the following assumptions: (i) the diffusion coefficient of \( \text{CO}_2 \) through carbonated concrete is constant; (ii) the amount of \( \text{CO}_2 \) required to neutralize alkalinity within a unit volume of concrete is constant; and (iii) \( \text{CO}_2 \) concentration varies linearly between fixed boundary values of \( C_1 \) at the external surface and \( C_2 \) at the carbonation front. To calculate \( k \), the concrete carbonation depth must be measured beforehand, either by measuring the carbonation depth of an existing structure or by conducting an accelerated test. Because carbonation is a slow process, it is often investigated using an accelerated test with greater \( \text{CO}_2 \) concentrations in a controlled setting [43]. Using the observed carbonation depth, the equivalent \( k \) and hence the time of rebar depassivation may be calculated. This technique is often used, albeit the accelerated test may not always accurately describe the natural carbonation process [39]. Eq. (1) is feasible as long as all three assumptions are met, however the \( \text{CO}_2 \) diffusion coefficient changes both temporally and geographically. These variations are due to the fact that \( \text{CO}_2 \) diffusion is influenced by a variety of factors, including \( \text{CO}_2 \) concentration, concrete composition, curing, and ambient variables [38,43,44]. As a result, Eq. (1) frequently fails to describe the actual condition of concrete buildings, resulting in inaccurate carbonation depth prediction [26,44,45]. To reduce some of the assumptions, empirical models have been proposed that take into direct account the influence of some factors that govern the rate of carbonation, such as the fib-MC2010 [46] and DuraCrete framework [47]. The fib and DuraCrete models adopt Eq. (1) by linking the coefficient of carbonation with concrete material and environmental factors. There are more models that follow the same logic. The related characteristics have traditionally been viewed as frequent variables that determine the qualities of concrete that control \( \text{CO}_2 \) infiltration rate, just like exposure, “water-to-binder ratio” (w/b), and “compressive strength”. The permeability of concrete controls many of the physical-chemical processes associated with \( \text{CO}_2 \) passage through it. Although the penetrable coefficient of concrete is primarily determined by the w/b ratio, additional elements such as aggregate distribution, age, curing conditions, and the presence of chemical or mineral admixtures also have an impact. The bulk of the improved models do not incorporate all of the regulating data that effect the process. Integrating of these prototypes not fix the issue. The mixing of so many simplifications and assumptions in current carbonation expectation models results in significant
uncertainty in their performance. The bulk of the enhanced prototypes do not incorporate all of the regulating data that influence the carbonation activity. Integrating two or more of these prototypes does not fix the issue. The joining of many conspectus and supposition in current carbonation forecasting models results in significant uncertainty in their functioning [28, 48-50]. In another viewpoint, cement type, w/b, age, admixture type, and exposure situation all influence the transformation of concrete's capillary pore structure. As a result, both Cs and Dnss fluctuate throughout space & time [51, 52]. This demonstrates that Dnss is a operation of Cs, therefore the assumption (iii) used is erroneous. Furthermore, the error function equation in only takes into account the diffusion process [50]. Indeed, various ways have been developed to handle the temporal dependency of DNS and the influence of other significant variables, such as fib-MC2010 [46] and the DuraCrete framework [47]. The most popular one is represented in equation [49,53]. This uncertainty might have serious consequences in terms of poor design, inspection, and maintenance planning, reducing the structure's service life and increasing lifecycle costs. The rate of CO2 and Cl− penetration into concrete depends on its qualities and environmental circumstances, as previously described. In real structures, the entrance rate of these chemicals cannot be constant, and it may even vary across various regions of a single constituent. As a result, “carbonation and chloride attack” depassivates the rebar in a highly complicated manner. In reality, basic empirical degradation models may be combined with a semi-probabilistic uncertainty model to increase dependability, as is done in the “DuraCrete framework”. However, this strategy does not completely reduce the accompanying ambiguity.

3 Machine learning

“ML” is a prominent subject of “artificial intelligence” that deals with the generation and modification of algorithms for identifying complex shapes from observational data with no relying on a pre-established formula as a prototype and making intelligent judgements [54-62]. ML-oriented prototypes can be predictive or descriptive [58, 63, 64]. Even “ML” arose from the search for artificial intelligence, its reach and possibilities are far more widespread. It incorporates concepts from a variety of domains, involving as the theory of data, probability, statistics, brain science and psychology, control complex computation concept, and theology [61]. Developing a system for machine learning necessitates many design decisions. (i) an illustration of the objective variable; and (ii) a technique for learning the objective variable from examples used in training. Machine learning is divided into four categories depending on learning assets: controlled, “unsupervised”, semi-supervised, and “reinforcement learning” [58,65]. The two types of understanding are the most used machine learning algorithms in a wide range of sectors, notably engineering [64].

beginning with a learning data containing i/p occurrence and expected o/p, the aim of observed learning is to create a function that can accurately forecast the undefined goal o/p of subsequent examples. The availability of a "teacher" and learning i/p-o/p data is the most important feature of supervised learning. Regression is a task that involves predicting continuous target variables. However, categorization refers to the problem of predicting discrete target variables. Unsupervised learning: beginning with a learning data that contains input instances, the purpose is to partition the training examples into clusters with high levels of closeness. Unsupervised learning, unlike supervised learning, does not have data labels accessible.

To address issues using machine learning approaches, an algorithm must be created. Machine learning algorithms use approaches from a variety of domains, such as design recognition, data mining, statistics, and “signal processing”. It permits ML to benefit from the synergy of all these professions, resulting in solid solutions that employ several regions of knowledge [62]. Figure 2 depicts some of the most prominent tricks used in both unsupervised and supervised learning types. It is even worth noting that few algorithm types use distinct learning types to address different issues.

Today, machine learning has a broad range of effective practical applications in a variety of fields, including “computational finance” [66-68], picture and audio generation [69-71], quality estimation [72-74], “hydrology” [75-78], “computational biology” [79-82], and energy generation [83-85]. Even ML is being more famous in many technical disciplines, its use in assessing the stability and “service life of RC” remains restricted.

4 Application of machine learning techniques in civil engineering

Machine learning approaches have been widely used to simulate real-world issues during the last few decades due to their huge ability to capture interaction between data couple of i/p and o/p that are nonlinear, without known, or difficult to define. Even ML has limited utility in concrete service life evaluation, it has been used in other civil engineering challenges. Three decades ago, the earliest applications of ML strategy were evaluating several existing approaches on simple issues [86,87].
During that period, machine learning algorithms were chosen mostly based on their availability rather than their suitability to the target issue [59]. As a result, the appeal difficulty rendition was a simple influenced by the inadequacies of available machine learning techniques. Then, gradually, more difficult problems were considered. The most often used applications are structural health monitoring, concrete property evaluation, and mix design. In present portion, we see ML algorithms were implemented in these two applications.

4.1 Structural health monitoring

Structural degradation induced by environment and function is an unavoidable phenomenon in civil constructions. Starting detection of structural degradation using a SHM system is critical for ensuring public service and dependability of in-service structures while preventing economic losses [88-91]. It entails observation a “structure over time” with dynamic outcome measurements spaced at constant intervals, extracting damage-sensitive characteristics, and statistically analyzing the derived features to find out the system's current health situation.

SHM systems are increasingly being implemented in a variety of structures, particularly long-length bridges, huge dams, and high buildings, allowing for a normal transition from “time-based to condition-based” prevention. So many studies have lately been conducted in this sector of intrigue, either using model-driven or data-driven methodologies [89,92]. A basic model-driven technique in SHM employs a mathematical prototype of the structure that links inconsistencies among observed data and prototype-produced value to detect a dam. This method is computationally demanding owing to repetitive examination of a computer simulation model [90]. Furthermore, in actuality, a numerical model may not always be available and does not always accurately reflect the specific performances of the actual structure [93].

Methods from machine learning are commonly used in supervised learning to identify structural damage when data from healthy and damaged conditions is necessary. Single machine learning techniques such as “neural network”, “support vector machine”, “support vector regression”, and “genetic algorithm” are popular for structural harm recognition owing to their stability and success regardless of little data, ambiguity, and noise [89,94-96]. Hybrid methods to several SHM difficulties have been described, including the multiple goals genetic code, “neurofuzzy”, and “wavelet neural network” [97-99]. Table 1 illustrates the suitability of several ML algorithms for measuring physical health and dam activity. The result analyses of every study indicated that “ML-based models” outperformed model-driven models.

4.2 Concrete characteristics and mix design

Elastic constants measurement is complex and “time-consuming” [111-114]. As a result, it is frequently derived from concrete's stress-strain relationships [115-117]. Due to the test's complexity, expense, and time-consuming nature, splitting tensile of concrete is frequently calculated using compressive strength [118 119], as is modulus of elasticity. Empirical regression models based on experimental data are also utilized to determine the shear strength of RC elements [120]. Conventional empirical methods for evaluating the mechanical characteristics of concrete were developed using a predefined equation based on restricted experimental data and parameters. They are only effective for describing their own
experimental results, which were used for calibration. If the original data is amended, the model coefficients and equation form must be updated. As a result, standard models may be ineffective for determining mechanical qualities of fresh concrete since the relationship between components and concrete characteristics for particular concrete types is very nonlinear [112-114,121-123]. Furthermore, developing a mathematical model that is widely accepted might be difficult. Another important feature of concrete is dry shrinkage, and its value is critical in determining the ability of concrete buildings to operate over time. Over the last five decades, multiple empirical equations for shrinkage estimation have been developed in various codes, including ACI [124] and CEB [125]. However, it is difficult to obtain correct results using these methods in some circumstances since dry shrinkage is impacted by a variety of parameters related to the concrete composition, specimen size, component quality, and ambient conditions [126].

Designing concrete mixes is the process of finding the proper ingredients and their relative proportions in order to make concrete with the specified strength, workability, and durability at the lowest feasible cost. Conventional concrete mix percentage algorithms are just a generalization of previous experience, which is sometimes available as empirical formulae or tables. Because of the unpredictability of concrete elements (e.g., chemical and mineral admixtures, cement, and fine and coarse aggregates), standard concrete mix proportion algorithms are a trial-and-error exercise that incurs additional expenses and effort [127].

5 Recent progress and future initiatives in durability and service-life evaluation

The degradation of RC structures due to rebar corrosion has been mostly analyzed using carbonation and/or chloride empirical models based on experimental data. Models cannot effectively forecast rebar depassivation time due to complicated factors governing CO2 and Cl− penetration in concrete. Several factors influence the penetration of these aggressive compounds into concrete structures, including material qualities, casting process, workability, curing conditions, and the macro- and microenvironment to which the RC structure is subjected. Furthermore, the rapidly increasing usage of blended supplemental cementitious materials and new technologies render traditional empirical model’s incapable of accurately predicting the time to commencement of rebar corrosion [53,144-146]. These limits of empirical models are the causes for the failure to achieve conditions for optimal choice of suitable design, inspection, and maintenance that would ensure a longer service life.

5.1 Recent advances

Prototypes must be capable to account for the majority of the relevant characteristics that regulate degradation mechanisms in sequence to properly anticipate the level of degradation and the structure's balancing “service life”. Developing empirical carbonation and/or chloride models that properly address the governing elements is undoubtedly difficult since the actual behavior is a result of various parameters that are difficult to define numerically. As a result, creating a ML-oriented forecast prototypes that can understand from current “long-term in-service” data is a promising option. The remainder of this portion discusses the present direct or indirect uses of ML approaches in supporting the assessment of “carbonation depth and chloride penetration”.

The prediction performance was compared to that of NN models, and it was discovered that SVMs have superior accuracy and generalization capabilities. Zhitao et al. [149-151] also used SVM. They used the identical input parameters as those used in Xiang’s investigation. The predictive ability of the SVM model was compared to that of the BPNN model. The findings revealed that both models are successful for determining carbonation depth, with SVM outperforming BPNN in terms of prediction capabilities. Other research [152-154] show that machine learning can predict carbonation depth.

Machine learning models can handle practically all governing elements controlling CO2 and Cl− entry into concrete pores, unlike conventional methods [156-164]. This allows for the assessment of all controlling aspects as a group rather than individually, ensuring forecast reliability since critical relationships are not overlooked. In another perspective, determining the degree of effect of each parameter that regulates the degradation processes in a typical method is impossible due to the presence of multiple unknown factors. Machine learning can recognize complicated patterns in big datasets, allowing it to reflect intrinsic correlations between parameters [165-173].

5.2 Future directions

As shown in the preceding paragraph, machine learning has clear advantages in analyzing the reliability and “service life of RC structures”. Machine learning has long been seen as an important and encouraging tool for managing the ageing of RC structures. Machine learning performance is determined by the amount of data available and the presence of adequate parameters in the data. These data must be collected using monitoring systems[174]. Monitoring systems will be required to collect this data. Depicts the evolution of “monitoring systems” and “machine learning algorithms” for measuring concrete characteristics and structural health. Wired sensors were employed in the 1990s to analyses the functioning of constructions. Wired monitoring systems necessitate the installation and maintenance of expensive communication lines on an ongoing basis. Furthermore, in the long run, constant remote observation utilizing wireless sensors may be more cost-effective than doing periodic field experiments, taking into account labour expenses, user safety, and user fees [176,177]. Smart wireless sensors have lately emerged as a possible separation to present sensor device. It has a solid
wireless connection technological device, a separate entity on-board CPU, and a small form factor. Thus, it is unlikely that wireless sensors won't gradually play a significant role in RC structure aging control. Integrated sensors have been employed in several investigations to track concrete parameters [176,178]. Comparably, RC structures have made extensive use of sensor-based systems for tracking to analyze atmospheric variables including the climate and humidity levels [175,184-187]. Critical knowledge regarding the degree of decreases, including rebar corrosion, carbonation, freeze-thaw cycles, and alkali-aggregate interaction, may be obtained by keeping an eye on these factors [188]. In general, tracking RC projects allows for a more accurate evaluation of the concrete's effectiveness and also a prompt warning of any problems. Additionally, it would provide important data that may be used to validate current algorithms for service-life prediction, leading to more precise prediction. Additionally, as repair program development and execution may be further optimized, integrating data from surveillance systems in tandem with statistical models for service-life estimation leads in significant reductions in lifetime costs [175–179]. The functional life of reinforced concrete buildings was previously predicted using data-driven predictions that employ embedded sensors and previous observational information combined with an inductive model. While strengthening estimation, these methods continue to depend on a theoretical model that has limitations (see Section 2.2). It was inevitable to mix the outcomes of ML algorithms with traditional approaches since there was a lack of data over time from the components that predominantly impact damage activities. In the future, evaluation of RC constructions' reliability and service life will solely be based on information obtained from continuous monitoring using a variety of wireless sensors and algorithms for learning. Large data sets may be effectively mined for insights and used to create models that predict using ML techniques. Furthermore, the use of machine learning methods for SHM, concrete property assessment, and combines design is growing. It suggests that ML is quickly being a popular substitute strategy to ageing RC structures.

RC material evaluation, evaluation, and supervision will need the deployment of wireless sensors and ML approaches to evaluate the material's functionality and service life. By installing sensors in several areas, electronically sharing sensor data, and utilizing machine learning algorithms to analyze it, assessment may be completed swiftly and remotely. None of this could be done on the job location with no the assistance of inspectors. The suggested foreseeable aging management plan for RC structures is shown in Figure 4. The sensors incorporated into the structure will provide information on the time fluctuations and spatial distribution of the elements that drive deterioration, as seen in the organization diagram. The sensor information will be provided to a server for cloud storage. It has a significant benefit in that, with Internet access, varied streams of data may be presented, retrieved, and transferred from any location. The structure's condition may be assessed remotely via explanatory data analysis.

Fig. 3. Sensor and machine learning techniques have advanced in their use in analyzing concrete characteristics and structural health.

Machine learning can understand the complicated interrelationships among parameters collected from sensor data and make predictions without the requirement for an factual model. The forecast authorizes a more real technique for evaluating a structure's service life and precisely scheduling repair actions, significantly lowering maintenance expenditures. As the
amount of data available for learning increases, the working of “machine learning-based prototypes” improves adaptively, resulting in more trustworthy predictions. Furthermore, using several sensors allows ML to understand the mixed effect of numerous degradation processes. It also plays an important function in retrieving previously undiscovered information. The acquired knowledge will aid in developing ideal solutions that increase the structure's durability.

6 Conclusions

Current research demonstrated the significance and application of ML for assessing the reliability and “service life of RC structures” by carefully examining its capacity to resolve the shortcomings of frequently used empirical prototypes. Machine learning strategy can understand the intricate interrelationships between major characteristics that influence deterioration mechanisms, allowing them to properly anticipate service life in actual time without the requirement for empirical models. The article also discussed earlier shown applications of ML algorithms for “SHM”, concrete characteristics, and mix formulation. In adding, a latest suggested ML outcome for aiding in the reliability evaluation of “RC structures” is described. Because of the growing usage of wireless sensors for continuous structural observations, ML-based prototypes are anticipated to become the favorable non-destructive and reliable stability assessment approach in the future, bringing about a paradigm change in “service-life prediction”. This strategy aids in the precise planning of repair measures, allowing for significant reductions in prevention and lifetime costs. Further, ML-based prototypes may understand the synergistic effect of many degradation processes utilizing data from numerous sensors, allowing them to uncover hidden insights. The obtained knowledge will help specialists enhanced the concrete mix to provide long-lasting concrete and optimal repair solutions. This study may be expanded by covering all elements of machine learning algorithms in various civil engineering applications.

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