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Physics-trained Artificial Intelligence framework to detect chloride degradation

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ABSTRACT

Concrete structures undergo degradation throughout their service life, impacting their durability and load-carrying capacity. One prominent degradation agent is chloride ion, which leads to corrosion in reinforcement and subsequent cracking. Early detection of chloride-induced degradation is crucial for maintaining the safety of critical infrastructures. Structural health monitoring (SHM) frameworks using non-destructive testing (NDT) techniques can enable such detection, but interpreting complex NDT data poses challenges. Previous studies have employed artificial intelligence (AI) techniques for pattern recognition of NDT data, but the efficacy depends on the specific structures being monitored. Additionally, training AI algorithms for SHM necessitates data from degraded structures at different stages of degradation and lifespan, which is impractical to collect in real-time due to the gradual nature of degradation. To address these challenges, this research proposes an integrated SHM framework that employs a multi-step simulation process to generate data at various degradation stages. This approach allows insights into the structure's condition under different levels of chloride exposure. Considering the diverse information from multiple sources and formats in simulating chloride degradation, accounting for uncertainties becomes crucial. This research presents an innovative SHM framework that propagates uncertainties through a multi-step chloride degradation simulation. Forward uncertainty quantification (UQ) techniques are used to propagate individual uncertainties through different phases of the degradation process. The proposed physics-driven AI framework utilizes advanced finite element modeling, sensor data, and deep learning to detect non-uniform chloride degradation.

INTRODUCTION

The degradation of concrete in critical infrastructures, such as bridges, dams, and nuclear plants, poses a significant threat to their performance and integrity. However, the high costs associated with the monitoring and assessment of degraded structures have become a financial burden. One of the primary causes of degradation is chloride-induced corrosion, where chloride ions penetrate concrete, leading to reinforcement corrosion and subsequent damage. Detecting chloride degradation at early stages is crucial to ensure the reliability and extended service life of structures. Structural health monitoring (SHM) approaches using non-destructive testing (NDT) techniques have been proposed to detect chloride-induced corrosion. However, the lack of experimental data at different stages of the chloride degradation process hinders the development of effective detection methods. To overcome this limitation, a multi-step simulation process can be employed to generate data representing various stages of degradation. However, accurately capturing the behavior of concrete structures subjected to chloride degradation under uncertainty is essential (Mahadevan et al., 2014). Uncertainties arise from factors such as inaccurate structural data and natural variability in chloride ion concentrations over the lifespan of the structure. Forward uncertainty quantification (UQ) techniques are used to propagate these uncertainties through the multi-step chloride

degradation simulation (Bodda et al., 2020a,b, 2021; Sandhu et al., 2019). The interpretation of collected data from NDT techniques and the simulation process presents another challenge due to their complexity and lack of direct indication of degradation. In recent years, artificial intelligence (AI) has emerged as a powerful tool for interpreting complex data and making predictions in various applications, including structural health monitoring (Lei et al., 2021; Sandhu, 2021).

This research aims to propose a physics-trained AI framework for detecting chloride degradation to develop an integrated SHM framework. The framework incorporates uncertainty propagation through a multi-step chloride simulation and utilizes a physics-trained AI algorithm to detect non-uniform chloride degradation. Uncertainties in chloride concentration and concrete properties are considered in simulations, and a simulation-based NDT methodology using finite element models captures non-uniform degradation. An Artificial Neural Network (ANN) model learns from a repository of degraded-sensitive features to predict the severity of degradation at multiple zones. By addressing these challenges and integrating AI techniques, this research seeks to provide an effective and comprehensive framework for detecting and monitoring chloride degradation in concrete structures.

CHLORIDE DEGRADATION PROCESS

Concrete structures near chloride-rich soil are affected by chloride ions diffusing into the concrete cover, gradually spreading deeper within the structure. When the chloride ion concentration surpasses a threshold at the reinforcement, it corrodes the reinforcement bars, eliminating the protective cover (Figure 1). This weakens the bond between reinforcement and concrete, causing stress to increase. When stresses exceed the ultimate tensile stress limit, localized cracking occurs, propagating to form major cracks. The chloride degradation process comprises three phases (Ayinde et al., 2019; Chen and Mahadevan, 2008). The first phase involves diffusion analysis of chloride ions within the concrete. Once the chloride concentration reaches the reinforcement bar threshold, the second phase evaluates rust expansion. The final phase simulates the damage behavior of concrete, triggered when stresses from rust expansion reach the inelastic region.

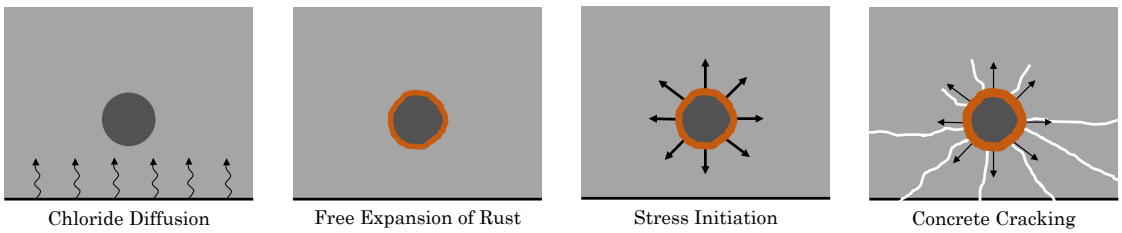


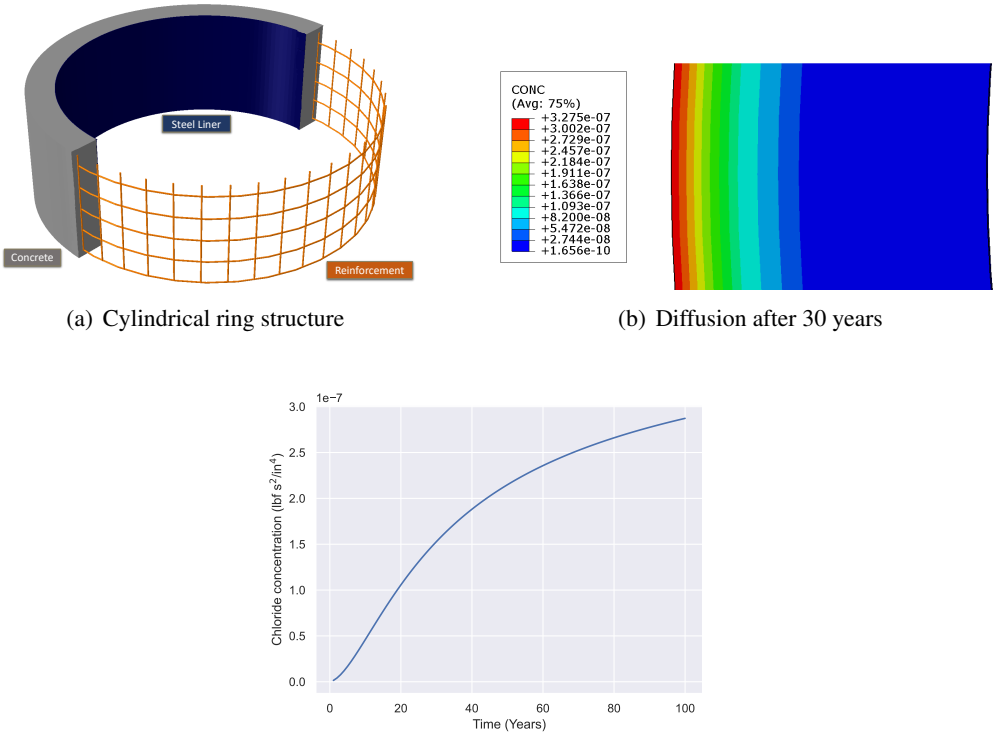
Figure 1. Chloride attack process

Stage 1: Chloride Ion Diffusion Analysis

In this study, a cylindrical concrete ring structure is utilized to simulate the chloride degradation process in three phases. The structure comprises a concrete ring (Figure 2a) with dimensions of 60 inches in height, 86.25 inches in outer radius, and 14 inches in thickness. The reinforcement consists of longitudinal and hoop bars with a diameter of 0.75 inches, with 44 longitudinal and 6 hoop bars evenly spaced. Additionally, the inner layer of the concrete ring features a 0.25-inch thick steel liner.

The initial phase involves conducting a diffusion analysis of chloride ions within the concrete structure, employing Fick's law (Zhang and Gjørv, 1996). Figure 2b illustrates the simulation of uniform chloride diffusion on a cylindrical concrete ring structure. A transient diffusion analysis is performed over a 100-year period and a constant and uniform chloride concentration of 4.70×10^{-7} lbf s^2/in^4 is applied as

a boundary condition on the outer surface of the concrete ring. The diffusion analysis reveals a gradual penetration of chloride ions into the concrete over time. The objective of this stage is to extract the chloride ion concentrations at the reinforcement bar locations as shown in Figure 2c, which are subsequently utilized in the subsequent stage.



(a) Cylindrical ring structure

(b) Diffusion after 30 years

(c) Chloride concentration at rebar location

Figure 2. Diffused chloride ion concentration

Stage 2: Corrosion Assessment

The chloride ion concentration at the reinforcement location serves as the basis for estimating corrosion in the second stage. When the chloride concentration surpasses a specific threshold, the protective layer of the reinforcement starts to degrade, leading to corrosion (Glass and Buenfeld, 1997). The corrosion rate (i_{corr}) is utilized in eq. (1) (Chen and Mahadevan, 2008) to determine the volumetric change in corrosion products and the loss in the reinforcement's cross-sectional area. This generates a reduction in the original mass of the reinforcing bar (M_{loss}) and applies pressure on the concrete (P_{corr}), which can be estimated using eq. (2) and eq. (3) (El Maaddawy and Soudki, 2007; Pantazopoulou and Papoulia, 2001), respectively. The corrosion-induced pressure is then transferred to the radial displacement (δ_c) of the concrete, as shown in eq. (4). Figure 3 illustrates the variation in corrosion-induced radial displacement over time.

$$i_{corr} = 0.926 \exp\left\{7.98 + 0.777 \ln(1.69 C_t) - \frac{3006}{T} - 0.000116 R_c + 2.24 t^{-0.215}\right\} \tag{1}$$

$$M_{Loss} = 2.8951 \times 10^{-7} \pi D_b \Delta t \cdot i_{corr} \tag{2}$$

$$P_{corr} = \frac{2E_{ef}}{(1+\mu+\nu)(D_b + 2\delta_0)} \left[\frac{M_{Loss}}{\pi D_b}\left(\frac{1}{0.622\rho_r} - \frac{1}{\rho_s}\right) - \delta_0\right] \tag{3}$$

$$\delta_c = kP_{corr} \tag{4}$$

where C_t is the total chloride concentration at the surface of the steel bar in kg/m^3, R_c is ohmic resistance of concrete cover in ohms, t is active corrosion time in years, and T is concrete temperature, D_b is the original diameter of the steel bar in meters, Δt is the difference between the exposure and corrosion times in years, ρ_r and ρ_s is the mass density of steel corrosion products and steel, respectively in kg/m^3, μ is concrete's Poisson's ratio, E_{ef} is the effective elastic modulus of concrete in Pa, δ_0 is porous zone thickness, and k is hole flexibility constant in m/Pa.

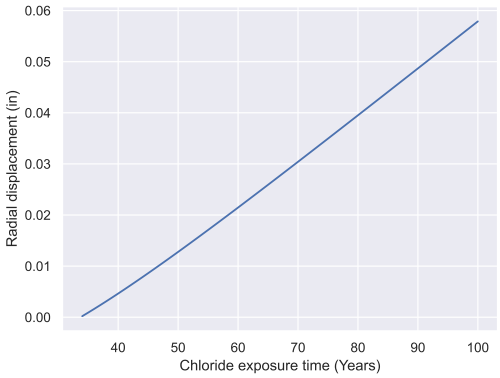


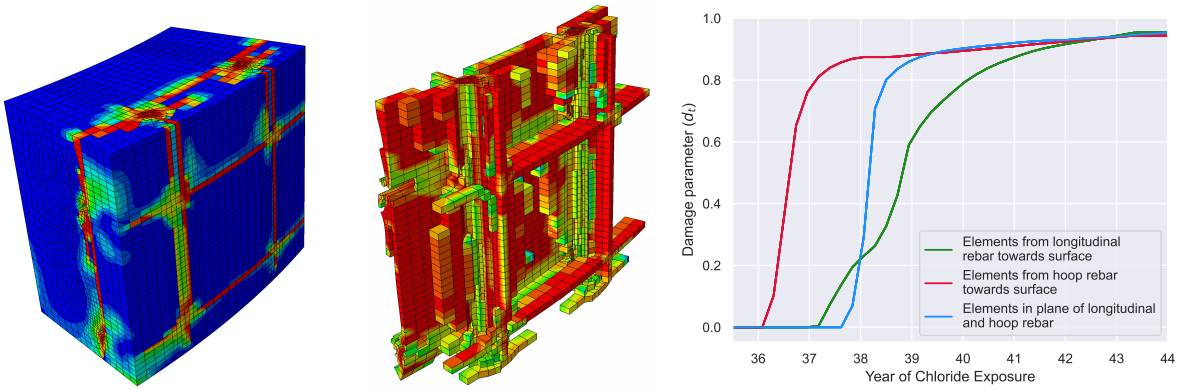
Figure 3. Change in corrosion induced radial displacement over time

Stage 3: Concrete Damage Analysis

In the final stage, the corrosion-induced radial displacement is utilized to simulate concrete damage through a reduced high-fidelity finite element (FE) model, benefiting from computational efficiency by leveraging symmetry. The concrete damage plasticity (CDP) model, known for capturing the nonlinear behavior of concrete, is employed (Patel et al., 2021, 2022a,b). The stress-strain response of the CDP model is defined for compression and tension using closed form equations (Patel, 2022). Additionally, the CDP model incorporates damage parameters, d_c for compression and d_t for tension, which define the unloading stiffness at each data point on the stress-strain curve. A radial displacement is applied to the reduced high-fidelity FE model at the hollow reinforcement locations over a duration of 68 years (Patel et al., 2023). The resulting damage due to the applied radial displacement is quantified in terms of d_t within this analysis.

MODELING NON-UNIFORM DAMAGE USING PATTERN RECOGNITION

Concrete damage resulting from chloride-induced radial displacement is investigated. Figure 4a illustrates the damaged state of concrete elements in tension based on d_t, where red represents maximum damage, and blue indicates no damage. To identify damage patterns, non-damaged elements are excluded from Figure 4a, as shown in Figure 4b. Simultaneous damage is observed in elements leading from the longitudinal reinforcement towards the outer surface, as well as in elements leading from the hoop reinforcement towards the surface. Similarly, elements in the plane of longitudinal and hoop reinforcement undergo damage simultaneously. Figure 4c displays the change in d_t over time at these three locations, demonstrating that they experience damage at different times and follow distinct paths towards complete degradation.



(a) Degradation in model (b) Degraded elements (c) Change in d_t over years

Figure 4. Identifying patterns in degradation

The damage simulation reveals patterns within these three element sets. Moreover, Figure 4c demonstrates the unique behavior of each element set based on d_t values over time. These identified patterns serve as the basis for defining a new finite element (FE) model representing the degraded structure. The three-element sets' patterns are modeled as separate zones in the new FE model. Zone 1 corresponds to a 1-inch thick strip of concrete elements extending from the longitudinal reinforcement to the outer surface. Similarly, zone 2 represents a 1-inch thick strip from the hoop reinforcement to the outer surface. Zone 3 consists of a cylindrical wall, 1 inch in thickness, within the plane of longitudinal and hoop reinforcement. The material behavior of these zones is governed by a degraded elastic modulus (E_{degraded}), calculated from the extracted d_t values obtained from the damage analysis (Figure 4c), as defined in eq. (5) (Abaqus, 2023). The elastic behavior of these three zones is characterized by E_{degraded} instead of the original elastic modulus (E_0). Elements outside these three zones retain the material behavior defined by E_0. This proposed FE model accurately represents the realistic degraded condition of the structure based on the identified patterns and serves as the basis for conducting non-destructive testing (NDT) simulations.

$$E_{degraded} = (1 - d_t)E_0 \tag{5}$$

UNCERTAINTY QUANTIFICATION

Uncertainty in the chloride degradation process can arise from various sources, including a lack of accurate structural data, natural variability in system properties, and the surrounding environment. The concentration of chloride ions and the elastic modulus of concrete are two parameters that contribute to this uncertainty. The propagation of these uncertainties through the three phases of the chloride degradation simulation is carried out. In the first phase, uncertainty in chloride concentration at the concrete surface is considered. The surface chloride concentration is characterized by a normal distribution of random values of surface chloride concentration generated using the Latin hypercube sampling method. The second phase involves diffusion, where transient diffusion analyses are conducted. The increase in surface chloride concentration leads to a higher radial displacement due to the accumulation of corrosion products, which leads to sooner occurrence of damage. The third phase focuses on the uncertainty in the original elastic modulus (E_0) of the concrete. Various combinations of uncertainty in E_0 and applied radial displacement resulting from propagated uncertainty in chloride concentration are used to conduct damage analysis. The variation of d_t with radial displacement is observed for different values of surface chloride concentration and constant E_0,

indicating that uncertainty in chloride concentration only delays or accelerates concrete damage. On the other hand, uncertainty in E_0 affects the damage behavior. Diverse sets of d_t values are obtained for Zones 1, 2, and 3, corresponding to distinct radial displacement values across various E_0 values. E_{degraded} values are determined based on d_t using eq. (5), representing the elastic behavior of the degraded zones in the FE model.

NDT SIMULATION

Non-destructive testing (NDT) based on a harmonic loading-based approach is utilized in this study to simulate NDT on a degraded concrete structure. The finite element (FE) model includes a concrete ring, steel liner, longitudinal, and hoop reinforcement. The harmonic loading applied to the structure is within the elastic zone due to its smaller magnitude compared to the concrete's ultimate capacity. The material properties for concrete, liner, and reinforcement are defined as elastic behavior. As shown in Figure 5, harmonic load with an amplitude of 10 lbs and frequency of 10 Hz is applied to the steel liner, with four defined accelerometer locations used to extract acceleration time-series responses. A linear time-history analysis is performed, extracting acceleration data from the accelerometer locations. Considering uncertainties, this analysis is repeated for a number of unique models having different E_{degraded} at each of the three zones.

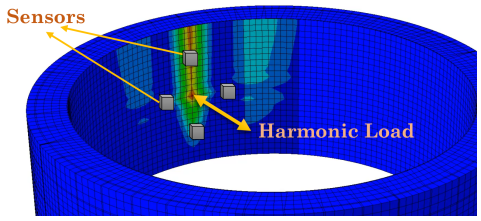


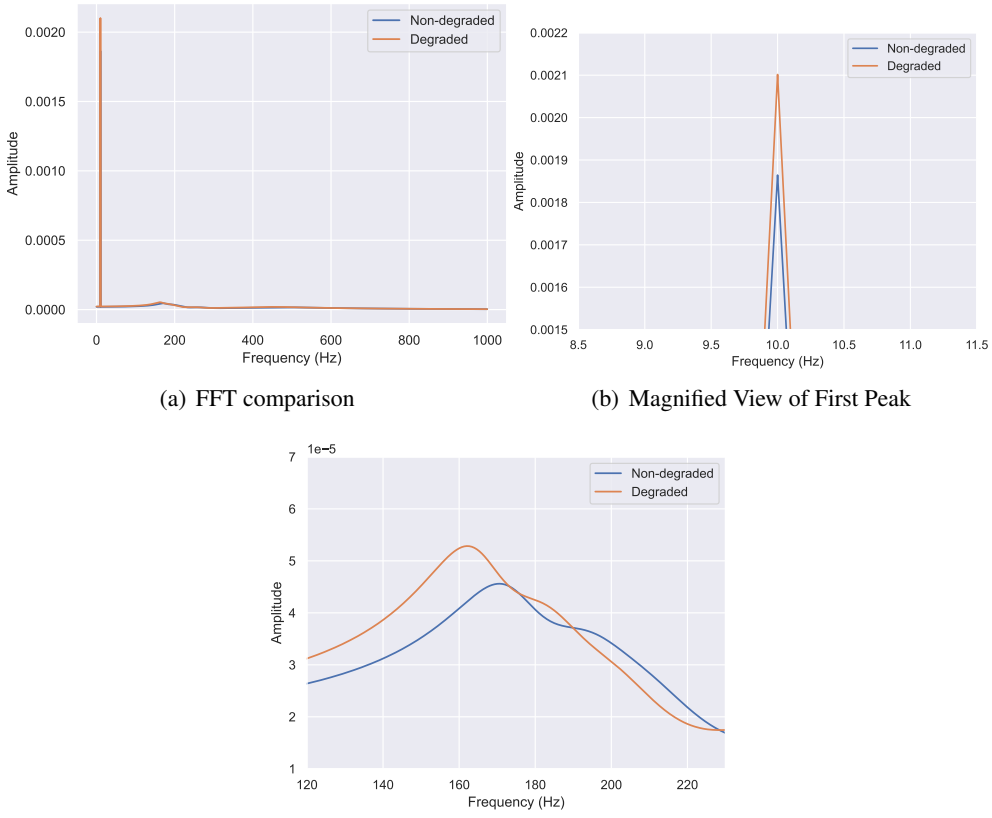
Figure 5. FE simulation of non-destructive testing using harmonic loading

AI FRAMEWORK

The NDT simulations yield sensor data in the form of acceleration time-series from four sensor locations in each case. In order to interpret and effectively utilize this data for detecting degradation, an investigation into a feature extraction strategy is conducted (Sandhu et al., 2023a,b, 2022, 2023c), followed by the development of an AI framework.

Feature Extraction

The time domain data collected from the sensors is converted to the frequency domain using the Fast Fourier Transform (FFT). The acceleration time-series data from NDT simulations yield FFT plots with two prominent peaks, as shown in the comparison between degraded and non-degraded models in Figure 6a. The first peak, at 10 Hz (the harmonic excitation frequency), experiences amplitude variation. Figure 6b highlights this change, while Figure 6c focuses on the second peak at around 165 Hz, noting changes in both amplitude and frequency. Extracting damage-sensitive features involves three Quantities of Interest (QoIs): (i) ΔFFT_1, the difference in first peak amplitude between degraded and non-degraded FFTs, (ii) ΔFFT_2, the amplitude difference at the second peak, and (iii) $\Delta\omega_2$, the frequency shift at the second peak. These features capture the impact of degradation on peak magnitudes and frequencies.



(a) FFT comparison

(b) Magnified View of First Peak

(c) Magnified View of Second Peak

Figure 6. Identifying the Quantities of Interest (QoIs)

Damage Classification

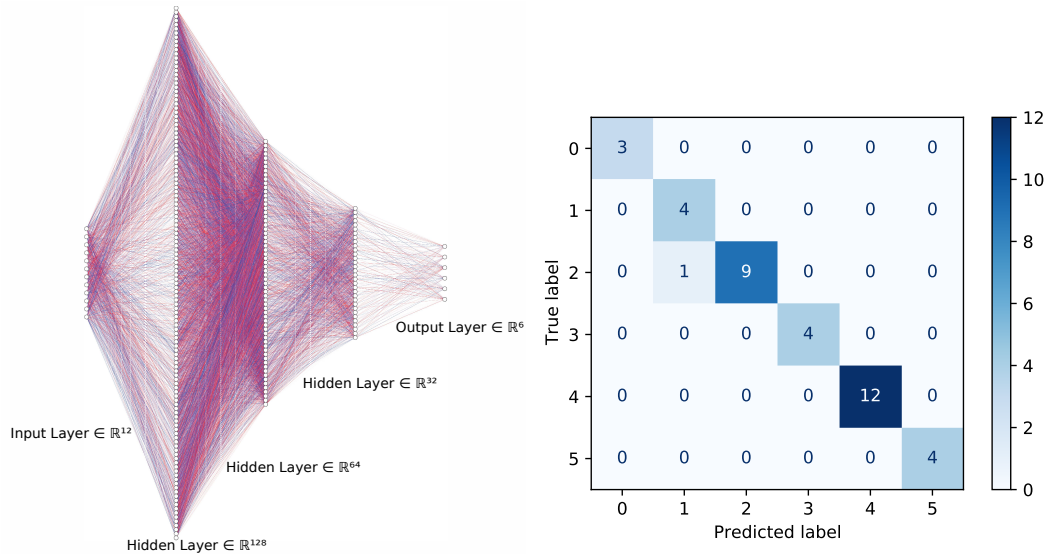
Damage behavior classification is crucial for designing the output layer of the AI framework. The E_{degraded} values, obtained from d_t in three degraded zones, are categorized into three severity levels: major degradation (66% to 100% decrease in E_0), moderate degradation (33% to 66% decrease in E_0), and minor degradation (less than 33% decrease in E_0). The classification of minor, moderate, and major degradation is based on the corresponding E_{degraded} values. With distinct cases of E_{degraded} values for the three degraded zones, each zone can exhibit degradation with different severity levels. Utilizing the data from **??**, six combinations of severity levels for the three zones are defined. Table 1 presents these combinations along with the corresponding pattern, relevant class numbers, and their utilization in predicting degradation scenarios within the deep learning algorithm.

Table 1: Degradation patterns in three degraded zones

Degradation level at three zones	**Class**
Minor - Minor - Minor	0
Moderate - Minor - Minor	1
Major - Minor - Minor	2
Major - Minor - Major	3
Major - Moderate - Major	4
Major - Major - Major	5

Neural Network Model

The feature extraction process resulted in 36 features for each FE model case, obtained from the acceleration time-series data collected from four sensors in X, Y, and Z directions. To streamline the training process and avoid overfitting, the input data was optimized by selecting only the X direction data, reducing the feature set from 36 to 12 features. This optimization helped to improve training time, reduce model complexity, and maintain high prediction accuracy. The dataset was split into 70% for training and validation, while the remaining 30% was reserved for testing. Hyperparameter tuning was performed to optimize the ANN model, exploring various parameter combinations and architectures. The final ANN model configuration, depicted in Figure 7a, comprised four hidden layers with 128, 64, and 32 neurons using 'ReLU' activation, and an output layer with six neurons using 'softmax' activation.



(a) ANN architecture (b) Confusion matrix

Figure 7. Artificial neural network model

During training, a batch size of 32 was used, and the model was compiled with a categorical cross-entropy loss function, the Adam optimizer with a learning rate of 0.001, and trained for 500 epochs. The trained ANN model achieved an accuracy of 96.43% for the training dataset and demonstrated the ability to detect degradation in the testing dataset with 93.33% accuracy. The confusion matrix shown in Figure 7b indicated that the model predominantly made correct predictions, with a majority of values aligning along the diagonal.

SUMMARY AND CONCLUSIONS

This paper presents a novel physics-trained AI-based approach for detecting degradation in concrete structures caused by chloride attack. The approach combines advanced finite element (FE) models, sensor data, and artificial intelligence techniques. The AI-based framework demonstrates its capability to predict the severity of degradation at multiple degraded zones, offering valuable insights for monitoring and managing chloride-induced degradation in concrete structures, thus enhancing their durability and safety. Some of the key conclusions from the current study are as follows:

- Through simulation of corrosion-induced concrete damage, distinct patterns are identified within

degraded concrete elements, leading to the categorization of three unique degradation zones.

- The propagation of uncertainties throughout the multi-phase chloride degradation process reveals that uncertainty in chloride concentration influences the rate of concrete damage progression.
- Quantifying uncertainty highlights the significant effect of uncertainty in the original elastic modulus on concrete damage behavior.
- The peak amplitude and frequency obtained from Fast Fourier Transform (FFT) analysis is identified as a damage-sensitive feature. The proposed physics-trained AI-based framework demonstrates the ability to accurately detect degradation severity at various degraded zones even in the presence of multiple uncertainties.

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