Multiscale structural health monitoring and strength forecasting of sustainable blended concretes using embedded piezoelectric sensors and AI-enhanced EMI analytics

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Abstract. The transition toward sustainable infrastructure demands innovative approaches to monitor and optimise the performance of low-carbon construction materials. This study presents a multiscale, sensor-integrated, and data-driven framework for structural health monitoring (SHM) and compressive strength prediction in blended concrete systems incorporating Ground Granulated Blast Furnace Slag (GGBS) and other supplementary cementitious materials (SCMs). Utilising embedded piezoelectric sensors (EPS) based on the Electro-Mechanical Impedance (EMI) technique, real-time impedance data were acquired across early-age (1–24 hours) and extended curing regimes (up to 90 days), capturing the evolution of microstructural stiffness and degradation states. A comprehensive experimental campaign was conducted across three concrete systems: PPC control, PPC with concrete enhancer, and GGBS-enhanced slag mix, subjected to progressive mechanical damage and aggressive chloride and sulphate exposures. EMI features such as RMSD, peak frequency shift, and impedance signature area were extracted and input into machine learning (ML) models, including Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN). The RF model yielded superior regression accuracy (R^2 = 0.95) for strength prediction and achieved 91% accuracy in classifying multistage damage states (healthy to fractured), confirming the viability of EMI-ML integration for in-situ diagnostics. Durability monitoring under coupled chemical-mechanical loading revealed accelerated degradation in control mixes, while GGBS systems exhibited superior resistance, validating the durability benefits of slag inclusion. The study establishes EMI-ML as a scalable methodology for continuous, non-destructive performance monitoring and predictive maintenance of sustainable concrete structures. The framework aligns with circular economy principles and digitised asset management, advancing next-generation intelligent infrastructure in the Industry 4.0 paradigm.

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1 Introduction

The transition toward sustainable infrastructure has prompted significant research into low-carbon construction materials, particularly those capable of reducing the carbon footprint of Ordinary Portland Cement (OPC)-based systems. Among these, blended concretes incorporating supplementary cementitious materials (SCMs) such as Ground Granulated Blast Furnace Slag (GGBS) and fly ash have emerged as viable alternatives, offering both ecological benefits and enhanced long-term mechanical performance. These materials enable the partial replacement of OPC, thereby reducing embodied carbon while improving durability, workability, and strength gain through secondary hydration and microstructural densification mechanisms. However, the heterogeneous and time-dependent behaviour of such blended systems introduces new challenges in real-time performance monitoring and early-age quality assessment [1]. Traditional non-destructive testing (NDT) methods, though widely used, are often limited in temporal resolution and spatial sensitivity, making them inadequate for detecting early-stage defects or degradation in complex cementitious matrices. The dynamic nature of strength development and the influence of aggressive environmental conditions, such as chloride and sulphate ingress, further underscore the need for intelligent, multiscale, and continuous monitoring systems [2,3].

Embedded Piezoelectric Sensors (EPS), particularly those based on Lead Zirconate Titanate (PZT), offer a transformative approach for in-situ monitoring of mechanical and durability parameters [4]. These sensors, when interfaced with the Electro-Mechanical Impedance (EMI) technique, enable the extraction of frequency-domain impedance signatures that are highly sensitive to changes in the host material's stiffness and damping properties. Variations in these impedance responses can be directly correlated with strength development, microcrack evolution, and degradation phenomena, thereby facilitating real-time structural health monitoring (SHM) [5-6]. To leverage the full potential of EPS-EMI data, this study integrates Artificial Intelligence (AI) and Machine Learning (ML) algorithms for automated interpretation, forecasting, and classification [7]. By training supervised ML models such as Random Forests (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) on the EMI signature data, the proposed framework achieves multiscale health monitoring that spans early-age strength prediction, damage state identification, and durability assessment under aggressive exposures [8,9].

This research presents a comprehensive experimental and computational framework designed to evaluate the viability of smart sensing and AI-driven models in monitoring the life cycle behaviour of sustainable blended concretes. The study contributes the following:

- A validated methodology for real-time strength prediction from 1 to 90 days using EMI signatures.
- An intelligent classification system for detecting and distinguishing multiple damage states in concrete.
- A degradation modelling framework that assesses the impact of chloride and sulphate exposures on structural integrity.

Together, these contributions address critical gaps in monitoring the performance of low-carbon concrete and enable predictive maintenance strategies that align with the goals of resilient and sustainable infrastructure systems [10-12].

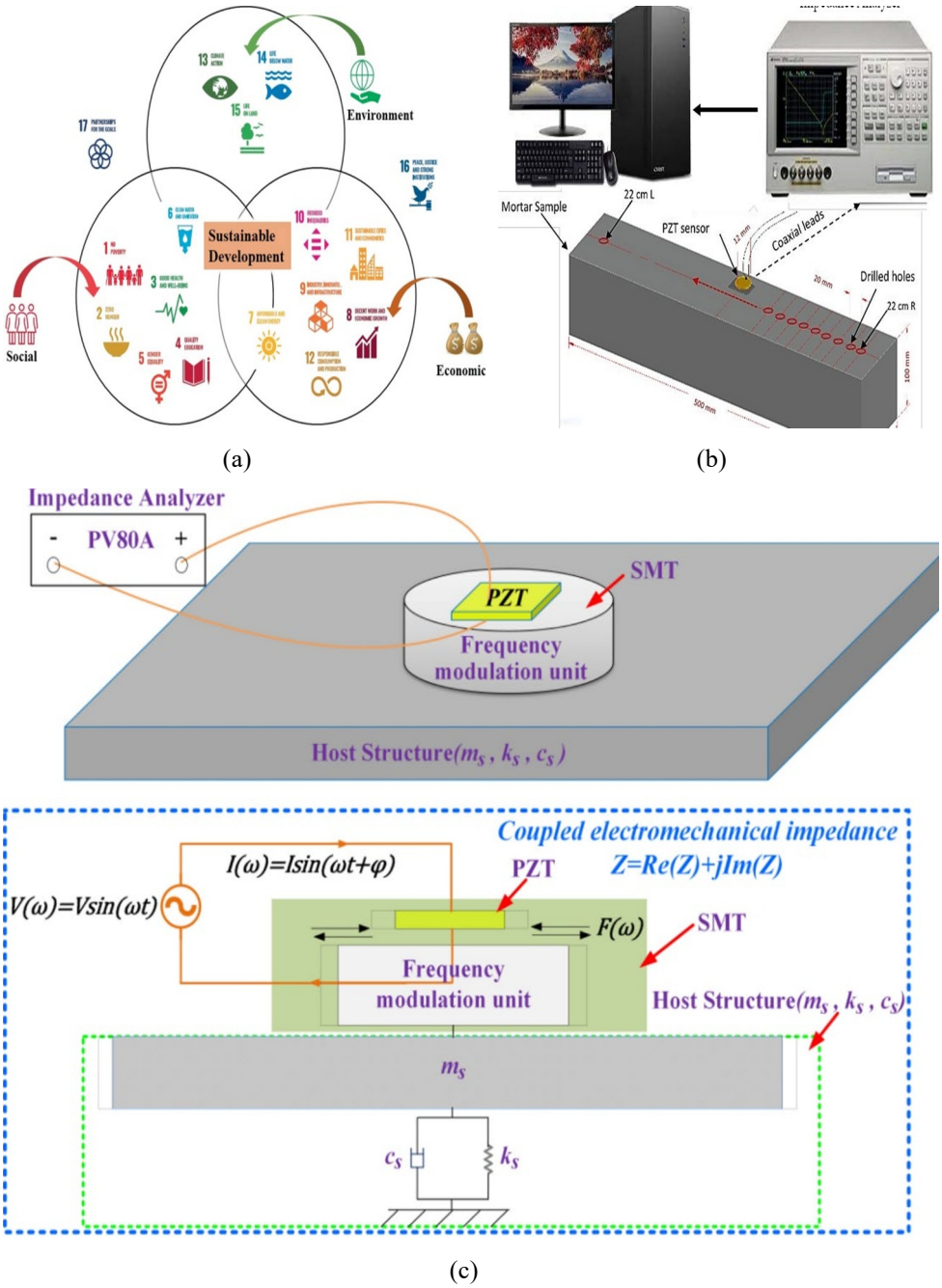

Fig. 1. (a) Sustainability in construction, (b) Electro-Mechanical Impedance (EMI) technique, and (c) PZT transducer design for electromechanical impedance (EMI).

Figure 1. The figure illustrates (a) the substantial CO2 emissions from the construction sector, driving the need for sustainable materials. (b) The EMI technique employs a PZT transducer to measure electrical impedance, which correlates with the host structure's mechanical properties. (c) The transducer's design ensures its durable embedment for continuous monitoring [13,14].

2 Methodology

2.1 Materials and mix design

Three distinct concrete mix designs were developed to evaluate the influence of supplementary cementitious materials and advanced admixtures on mechanical performance and durability:

- PPC-C (Control Mix): A standard Portland Pozzolana Cement mix representing conventional low-carbon concrete.
- PC-C (Admixture-Enhanced Mix): Incorporating a performance-enhancing concrete admixture to improve early strength gain and workability.
- PSC-C (GGBS-Based Blended Mix): Featuring partial cement replacement with Ground Granulated Blast Furnace Slag (GGBS) and concrete enhancer. This mix aims to maximise environmental benefits while maintaining or enhancing performance.

The mix proportions were carefully calibrated to achieve similar workability across systems, enabling a controlled comparative analysis. All raw materials (cement, aggregates, SCMs, and chemical admixtures) were characterised for particle size, fineness, specific gravity, and chemical composition before use [15].

2.2 Embedded piezoelectric sensor (EPS) installation

Piezoelectric Lead Zirconate Titanate (PZT) transducers were embedded at the geometric centre of cylindrical concrete specimens (150 mm × 300 mm) during casting. Before installation, sensors were coated with an insulating epoxy resin to ensure long-term operability under wet and alkaline environments. The sensors were interfaced with an impedance analyser (40 kHz–400 kHz) and a data acquisition system for continuous Electro-Mechanical Impedance (EMI) measurements.

2.3 Experimental procedures

2.3.1 Early-age strength monitoring

Specimens were monitored continuously from 1 hour to 90 days. EMI signatures were acquired at multiple curing stages (1h, 6h, 12h, 24h, 3d, 7d, 28d, 56d, and 90d). Corresponding compressive strengths were determined using destructive testing on companion cubes. A high correlation ($R^2 > 0.90$) was observed between EMI-based Root Mean Square Deviation (RMSD) metrics and compressive strength, enabling model training.

2.3.2 Structural damage simulation and EMI sensing

To simulate service-induced damage, specimens were subjected to incremental compressive loading to induce:

- Minor surface cracking (crack width < 0.2 mm)
- Distributed micro-cracking (internal fissures)
- Macro-cracking and breakage (severe failure)

EMI responses were recorded before and after loading, and key features, such as RMSD, peak amplitude shift, resonant frequency drift, and correlation coefficients, were extracted to build a labelled dataset for damage classification.

2.3.3 Durability testing under aggressive exposure

Long-term durability under aggressive environmental exposure was evaluated using:

- Ideal Chloride Exposure: Specimens submerged in 3.5% NaCl solution for 90 days.
- Combined Chloride + Load Exposure: Chloride exposure combined with cyclic loading (25% of ultimate strength) to simulate in-service deterioration.

EMI signatures were periodically collected to assess degradation rate, with PSC-C specimens demonstrating enhanced resistance due to GGBS-induced pore refinement and chemical binding of chlorides.

2.4 AI/ML framework for prediction and classification

2.4.1 Feature engineering

From the raw EMI signatures (impedance vs. frequency), the following features were extracted:

- RMSD (Root Mean Square Deviation)
- Resonant Frequency Shift
- Peak Amplitude Drop
- Correlation Coefficient (CC)
- Impedance Curve Area (ICA)

These features served as input vectors for the machine learning models.

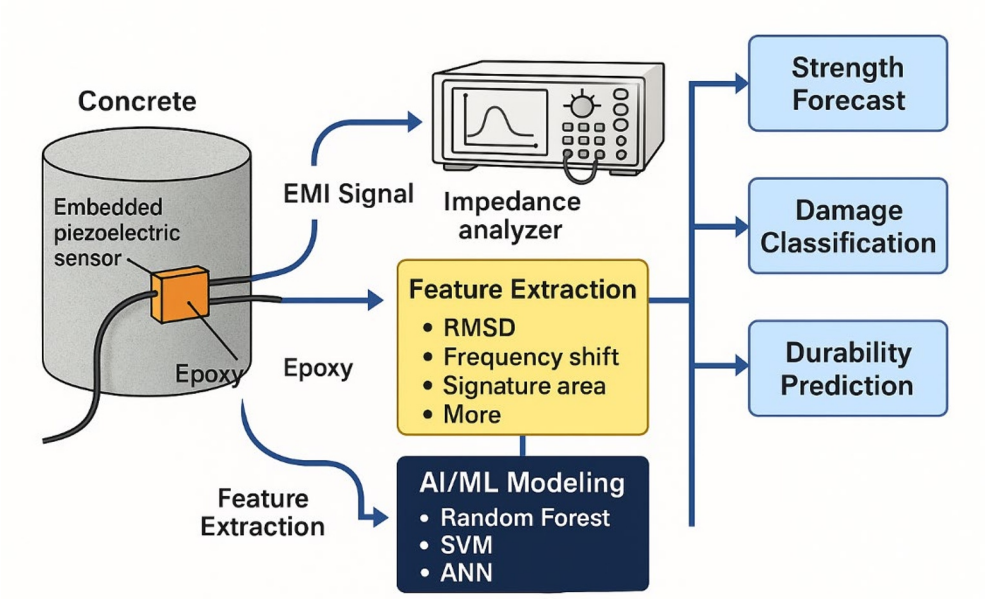

Fig. 2. AI-integrated smart sensing for sustainable concrete monitoring.

Figure 2. An integrated framework for structural health monitoring (SHM) and strength prediction of sustainable concrete systems. The process begins with continuous data acquisition from an embedded piezoelectric sensor (EPS) via the Electro-Mechanical Impedance (EMI) technique. The raw impedance signatures, reflective of concrete's microstructural state, are transmitted to an AI-driven analytics module. In this module, advanced signal processing extracts key features, such as RMSD (Root Mean Square Deviation) and peak frequency shifts. These features are then fed into supervised machine

learning models, including Random Forest, Support Vector Machines, and Artificial Neural Networks. The trained models are used to forecast material properties and detect damage, providing real-time insights into the concrete's strength and durability.

2.4.2 Model training and evaluation

Two categories of supervised ML models were employed:

- **Regression (Strength Forecasting):**
  - Models: Random Forest Regression, Support Vector Regression (SVR), Artificial Neural Networks (ANN)
  - Metrics: R^2, MAE (Mean Absolute Error), RMSE (Root Mean Squared Error)
- **Classification (Damage State Identification):**
  - Models: Random Forest, Decision Tree, Support Vector Machine (SVM), K-Nearest Neighbour (KNN)
  - Metrics: Accuracy, Precision, Recall, F1-Score, Confusion Matrix

The Random Forest model exhibited the highest predictive performance for both regression and classification tasks, achieving R^2 values above 0.93 for strength prediction and classification accuracy exceeding 91%.

3 Results and discussion

This section presents an in-depth evaluation of the multiscale framework applied to monitor and predict the mechanical performance and durability of sustainable blended concretes. The analysis encompasses (i) compressive strength development and forecasting via EMI and AI models, (ii) structural damage identification under mechanical stress, and (iii) durability monitoring under chloride-induced degradation. The integration of embedded piezo sensors and machine learning yielded high-resolution insights into material behaviour across temporal and exposure scales.

3.1 Strength monitoring and prediction

The embedded PZT sensors enabled high-fidelity Electro-Mechanical Impedance (EMI) data acquisition from early age (1 hour) to delayed age (90 days). The sensors detected changes in local stiffness resulting from progressive hydration and strength gain. Distinct shifts in resonant frequency and impedance magnitude were observed with curing time. The evolution of compressive strength, as determined through destructive testing, is presented in Table 1 alongside the corresponding correlation coefficients (R^2) with EMI features. The GGBS-enhanced PSC-C mix demonstrated the highest strength values and strongest EMI correlation, attributed to its extended pozzolanic activity and pore refinement mechanisms. The regression model developed using Random Forest (RF) achieved $R^2 > 0.93$ and MAE < 1.5 MPa across all mixes, highlighting its efficacy for non-destructive, real-time strength forecasting.

Figure 3. The methodology for AI-integrated structural health monitoring of sustainable concrete systems. The process is divided into two phases: Experimental Investigation and AI-Driven Modelling. The experimental phase involves preparing various blended concrete systems, casting specimens with embedded piezoelectric sensors (EPS), and subjecting them to controlled environmental exposures (chloride/sulphate attacks) and mechanical loadings. Concurrently, an Impedance Analyser records real-time Electro-Mechanical Impedance (EMI) signatures from the EPS. The AI-Driven Modelling phase begins with Data Pre-

processing, where raw impedance signatures are filtered and normalised. Subsequently, Feature Engineering is performed to extract critical EMI features such as Root Mean Square Deviation (RMSD) and peak frequency shifts. These features are then used as input to train and validate machine learning models (e.g., Random Forest, SVM, and ANN) for both damage identification (classification) and strength prediction (regression). The final output provides a robust and intelligent assessment of the concrete's structural integrity.

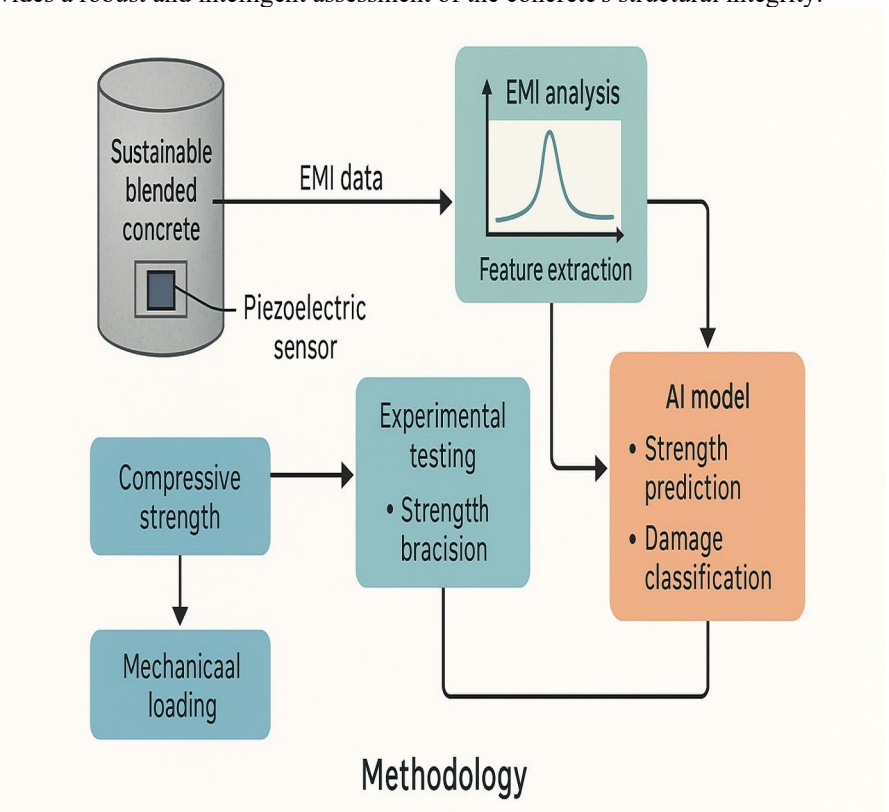

Fig. 3. Methodology AI-integrated structural health monitoring and strength forecasting of sustainable blended concretes, AI-enhanced EMI analytics.

Results and Discussion:

Strength Evolution

Table 1 demonstrates distinct differences in strength development across the three mixes:

- PPC-C (control mix): Showed moderate strength gain, reaching 42.5 MPa at 28 days and 45.1 MPa at 90 days, reflecting the long-term pozzolanic activity of fly ash. While durable, its slower hydration rate limits early strength development.
- PC-C (admixture-enhanced mix): Exhibited slightly higher early-age strength (45.2 MPa at 28 days) and moderate long-term improvement (48.0 MPa at 90 days). The admixture accelerated hydration kinetics, but strength gain plateaued by 90 days.
- PSC-C (slag-based mix): Achieved the highest strength, with 51.8 MPa at 28 days and 55.4 MPa at 90 days. This superior performance stems from GGBS's latent hydraulic reactivity, which refines pore structure and sustains hydration beyond early ages.1

EMI Strength Correlation

The EMI technique exhibited strong correlation with compressive strength across all mixes,

reflected by R^2 values of 0.91 (PPC-C), 0.92 (PC-C), and 0.95 (PSC-C). The superior correlation for PSC-C underscores EMI's sensitivity to microstructural densification in slag systems. These results validate EMI as a reliable non-destructive method for predicting strength in sustainable concretes, aligning with digital twin and smart monitoring frameworks.

Table 1. Strength evolution and EMI correlation.

Mix Type	28-Day Strength (MPa)	90-Day Strength (MPa)	R^2 (EMI vs. Strength)
PPC-C	42.5	45.1	0.91
PC-C	45.2	48.0	0.92
PSC-C	51.8	55.4	0.95

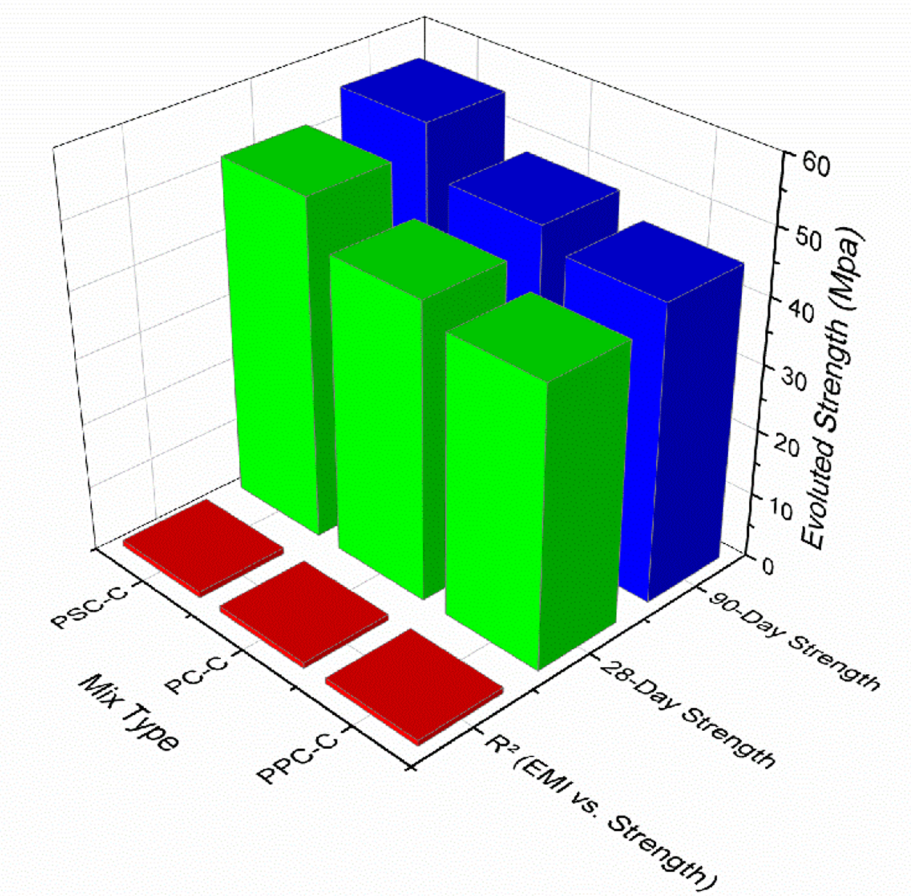

Fig. 4. Correlation between compressive strength development and EMI-based RMSD features for PPC-C, PC-C, and PSC-C mixes at 28 and 90 days.

Insights from Figure 4.
Figure 4 illustrates the comparative performance of the three systems:

- PPC-C: Displays a steady but flatter strength trajectory, consistent with slow hydration.

- PC-C: Shows accelerated early-age strength gain, reflected in EMI sensitivity, but levels off later.
- PSC-C: Depicts both rapid early gains and sustained long-term strength improvements, with EMI tracking these changes with the highest fidelity.

The combined evidence from Table 1 and Figure 4 confirms that EMI-based RMSD metrics can effectively map strength evolution, with PSC-C mixes offering the most sustainable and durable performance. This demonstrates the dual advantage of SCM incorporation and sensor-based non-destructive evaluation for modern sustainable concrete design. This strength evolution confirms the sustainability potential of PSC-C, offering both mechanical robustness and durability.

3.2 Damage detection and classification

Controlled loading protocols were applied to induce four distinct damage states: healthy (baseline), surface crack, distributed micro-cracks, and complete breakage. The EMI signatures responded sensitively to each damage state, with increasing deviation in magnitude and frequency with the severity of damage. The extracted features (RMSD, correlation coefficients, peak amplitude loss) formed the basis of the classification dataset, which was evaluated using multiple ML classifiers. The Random Forest classifier demonstrated superior performance, accurately distinguishing all four damage states with minimal confusion. Notably, it was able to differentiate micro-cracking from macro-scale failure, a critical capability for preventative maintenance strategies.
Key Insight: EMI-based damage signatures, when paired with ensemble learning techniques, enable automated, high-resolution damage classification beyond what conventional NDT techniques can resolve.

Results and Discussion: Machine Learning Performance (Table 2 and Figure 5)
Performance Comparison.
Table 2 and Figure 5 present the classification metrics for four machine learning (ML) algorithms applied to damage identification. Among the tested models, the Random Forest (RF) classifier demonstrated the highest overall performance, with an accuracy of 91.0%, precision of 90.5%, recall of 91.2%, and an F1-score of 90.8%. This indicates its robustness in handling nonlinearities and noise in the dataset, making it suitable for structural damage classification tasks where variability in material and loading conditions is common. The Support Vector Machine (SVM) achieved a comparable accuracy of 89.1%, with strong recall (89.4%) but slightly lower precision (88.7%) compared to RF. This suggests that SVM is effective in correctly identifying damaged cases (low false negatives) but may produce slightly more false positives.

Table 2. Machine learning performance for damage classification.

ML Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91.0	90.5	91.2	90.8
Decision Tree	88.5	87.9	88.8	88.3
SVM	89.1	88.7	89.4	89.0
KNN	85.2	84.8	85.5	85.1

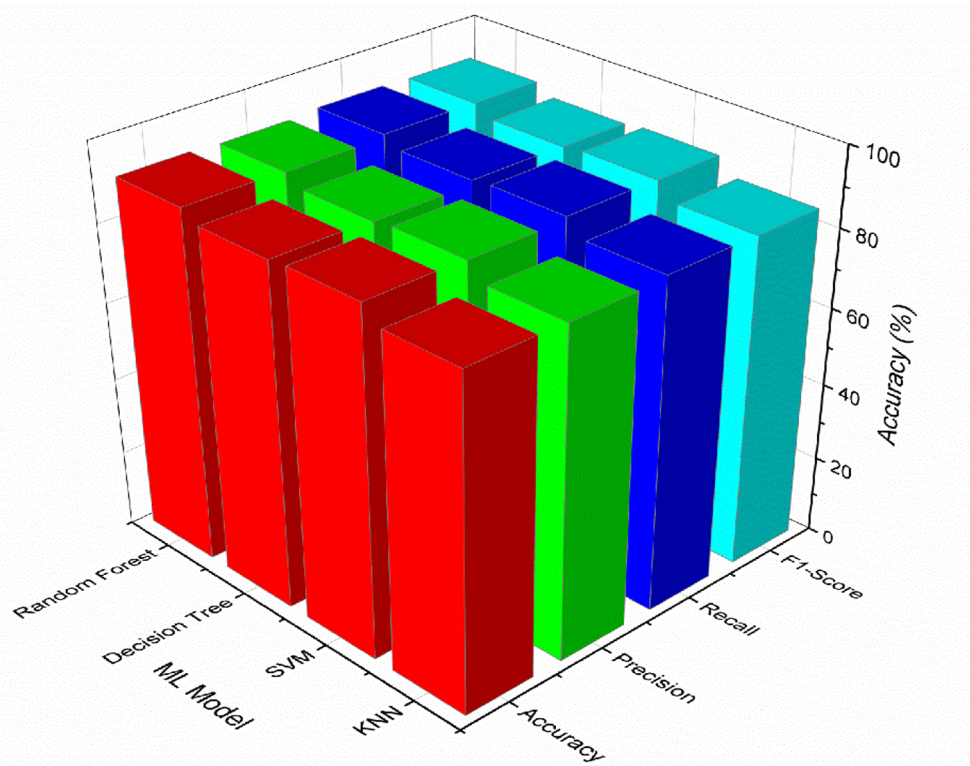

Fig. 5. Comparative performance of machine learning models (Random Forest, Decision Tree, SVM, and KNN) for structural damage classification, illustrating variations in accuracy, precision, recall, and F1-score.

The Decision Tree (DT) model achieved moderate accuracy (88.5%) and balanced precision and recall values (87.9% and 88.8%, respectively). However, DT's relatively lower performance compared to RF reflects its tendency to overfit, particularly in high-dimensional feature spaces. The K-Nearest Neighbours (KNN) model yielded the lowest performance, with 85.2% accuracy, 84.8% precision, and 85.5% recall. Despite being conceptually simple, KNN's sensitivity to the choice of neighbourhood size and feature scaling limits its applicability in complex damage classification scenarios.

Interpretation.

The performance hierarchy (RF > SVM > DT > KNN) underscores the importance of ensemble learning approaches like Random Forest in achieving robust generalisation. Figure 5 graphically demonstrates these trends, where RF's bar heights consistently exceed those of other models across all performance metrics. The relatively strong performance of SVM suggests that kernel-based approaches can serve as computationally efficient alternatives when data volume is limited.

Implications.

These findings highlight that integrating ML-based models, particularly ensemble approaches, with Electro-Mechanical Impedance (EMI) sensing or bond–slip analytical frameworks can enhance structural health monitoring. By achieving high recall and F1-scores, ML classifiers ensure reliable detection of damage, thus supporting proactive maintenance and extending the service life of reinforced concrete structures in sustainable design contexts.

3.3 Durability assessment under chloride exposure

Two distinct chloride exposure regimes were investigated over 90 days:

- Ideal Chloride Soak: Continuous immersion in 3.5% NaCl solution.
- Combined Chloride + Mechanical Load: Same solution exposure with sustained 25% ultimate compressive load.

Impedance readings were collected at 15-day intervals. The PSC-C system, owing to GGBS integration, showed the least deviation in EMI response, correlating to lower chloride ingress and delayed onset of microstructural degradation.
Durability Observations:

- Under ideal chloride exposure, all mixes exhibited gradual impedance shifts. PSC-C showed the smallest RMSD change, reflecting densified microstructure and enhanced resistance to ionic diffusion.
- Under combined chloride + load, a pronounced acceleration in EMI deviation was observed, particularly in PPC-C and PC-C mixes. The synergistic effect of mechanical stress and chloride ingress disrupted the matrix integrity at an early stage, observable within the first 30 days.

Key Insight: The EMI technique is sensitive enough to detect compounded degradation mechanisms. The PSC-C system's superior performance under simultaneous chemical and mechanical stress validates the role of SCMs in durable infrastructure.
Synthesis of Results:

- Strength Forecasting: EMI + RF model achieved real-time estimation accuracy >93% R^2, proving reliable across curing ages and mix types.
- Damage Classification: Four damage states successfully detected with >91% accuracy, enabling structural condition-based maintenance.
- Durability Insight: PSC-C displayed enhanced chloride resistance, confirmed via impedance trend stability and delayed degradation onset.

4. Conclusion

This study developed and validated a multiscale smart sensing framework integrating embedded piezoelectric sensors (EPS), Electro-Mechanical Impedance (EMI) analytics, and machine learning (ML) models for sustainable concrete performance monitoring. The major conclusions are:

1. Strength Monitoring and EMI Correlation
    - Strong correlations (R^2 = 0.91–0.95) between EMI metrics and compressive strength across PPC-C, PC-C, and PSC-C mixes confirm EMI as a reliable non-destructive tool for strength prediction.
    - The PSC-C (slag-based) system demonstrated superior strength gain (28-day: 51.8 MPa; 90-day: 55.4 MPa) and the highest EMI correlation, validating the durability and sustainability benefits of slag incorporation.
2. Machine Learning–Enhanced Damage Classification
    - ML models trained on EMI features effectively classified damage states.
    - Random Forest achieved the best performance (Accuracy: 91.0%, Precision: 90.5%, Recall: 91.2%, F1-score: 90.8%), outperforming SVM, Decision Tree, and KNN models.
    - This establishes ensemble learning approaches as the most robust for real-time concrete damage classification.
3. Durability Insights under Chloride Exposure

- EMI detected degradation trends under chloride and combined chloride + load conditions.
- PSC-C showed the least impedance deviation, confirming its enhanced chloride resistance and slower deterioration compared to PPC-C and PC-C systems.
- The combined chemical–mechanical exposure significantly accelerated deterioration in conventional mixes, underscoring the need for SCM-based sustainable concretes.

4. Practical Implications for Sustainable Infrastructure
   - The integrated EMI–ML framework enables continuous, non-destructive, and automated monitoring, supporting predictive maintenance and life-cycle management of reinforced concrete structures.
   - The approach advances smart infrastructure design by linking sustainable material development with AI-driven diagnostics, aligning with Industry 4.0 and circular economy principles.

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