AI-Enabled Building Materials - Application of Self-Healing Concrete Technology

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Abstract

Concrete structures are inherently susceptible to cracking under combined mechanical, thermal, and environmental actions, leading to progressive deterioration of structural durability and significant increases in life-cycle maintenance costs. Conventional repair approaches, including manual patching, grouting injection, and surface coating, remain fundamentally reactive and are unable to achieve autonomous real-time microcrack remediation. Self-healing concrete, incorporating functional additives capable of autonomous crack repair, has emerged as a viable alternative. However, the integration of artificial intelligence (AI) with self-healing systems - enabling the transition from passive material response to active intelligent intervention through real-time monitoring, predictive analysis, and closed-loop repair control - remains insufficiently explored, particularly under harsh service environments.

This study systematically reviewed the current research landscape of AI-enabled self-healing concrete and experimentally investigated five mainstream self-healing technologies integrated with an AI monitoring and control platform. Comprehensive performance evaluation encompassed mechanical properties, crack repair efficiency, environmental adaptability under marine, polar, and high-temperature conditions, AI system responsiveness, and life-cycle economic benefits. The principal innovation of this work lay in the development of a composite self-healing agent system with AI-optimized dosage and activation parameters, and the systematic verification of its performance across multiple harsh exposure scenarios.

Results demonstrated that AI integration substantially enhanced monitoring accuracy, repair timeliness, and environmental adaptability of self-healing concrete systems. The composite self-healing agent system (6% microbial agent : 7% epoxy microcapsule : 1.5% vol Ni-Ti shape memory alloy fiber) in the AI-enabled group (G5) exhibited superior performance, achieving a 92.7% crack repair rate for 0.5 mm crack widths, a 25.6% extension in projected service life, and a 40.1% reduction in maintenance costs relative to the unmodified control group (G0), with a cost-benefit ratio of 5.57.

These findings provided both theoretical foundations and practical engineering guidance for the application of intelligent self-healing concrete in aggressive service environments, contributing to the advancement of intelligent and sustainable construction practices.

Keywords: AI-enabled self-healing concrete; microbial remediation; structural health monitoring; concrete durability

Introduction

Concrete structures have been widely used in civil engineering for their excellent mechanical properties and low cost, yet they are inherently brittle and prone to cracking under combined mechanical loads, thermal cycling, and environmental erosion such as chloride penetration and carbonation. Over 80% of concrete structural damage stems from crack propagation, which exposes reinforcement to corrosive agents, impairs durability, shortens service life, and incurs substantial maintenance costs. Traditional repair methods — manual patching, grouting, and surface coating — are fundamentally reactive and labor-intensive, unable to detect or repair microcracks in real time, thus failing to address progressive deterioration at its root.

Self-healing concrete, which autonomously repairs cracks via intrinsic properties or functional additives, offers a promising alternative. Four mainstream technologies have been developed: microbial remediation using bacterial calcium carbonate precipitation, capsule-based systems releasing repair agents upon rupture, fiber reinforcement for crack bridging, and nano-material modification accelerating hydration at crack surfaces. However, single-mechanism systems have inherent limitations — microbial remediation is sensitive to pH, temperature, and moisture; capsule self-healing lacks precise control over release timing; and fiber reinforcement struggles with targeted microcrack repair. These limitations have motivated the development of composite systems combining multiple mechanisms.

Integrating artificial intelligence (AI) further transforms self-healing concrete from passive response to active intelligent intervention, enabling real-time monitoring via embedded sensors, intelligent crack identification, propagation prediction through machine learning, and optimized repair agent release via closed-loop control. Shape Memory Alloy (SMA) Ni-Ti fiber was additionally incorporated in Group G4 for active crack closure through thermally triggered shape recovery.

Existing research, however, remains preliminary with critical gaps. Jonkers et al. (2010) verified microbial repair but did not explore AI integration; the China Academy of Building Research (2022) advanced material formulation without intelligent monitoring; the University of California, Berkeley (2022) applied machine learning to design but omitted harsh environment evaluation. Limited attention has been paid to AI-composite self-healing integration under challenging climates (Ding et al., 2022; Liu et al., 2022), and the optimal matching of agent dosage, AI parameters, and sensor configurations remains undefined (Wang et al., 2023; Zhou et al., 2024).

To address these gaps, this study: (1) assessed five mainstream self-healing technologies under standardized conditions; (2) explored AI's role in material optimization and repair control; (3) evaluated comprehensive performance across mechanical properties, crack repair efficiency, environmental adaptability, and economic viability; and (4) identified the optimal composite agent ratio and AI parameters. The research combined literature review, laboratory experiments, and life-cycle economic analysis to ensure scientific reliability and engineering value.

Materials and Methods

1. General

This study adopted a combination of literature review and laboratory experiment. The literature review systematically analyzed research progress on self-healing concrete and AI integration technology, identifying key research gaps — particularly the lack of systematic studies on AI-composite self-healing systems under harsh environmental conditions — and establishing the innovation direction for this work.

The laboratory experiment was designed following a comparative group approach, with one control group and five self-healing groups tested under standardized conditions. All mechanical property tests complied with the Chinese national standard GB/T 50081-2019 "Standard for Test Methods of Mechanical Properties of Ordinary Concrete" for specimen preparation, curing, and testing procedures, and the international standard ASTM C39/C39M-21 "Standard Test Method for Compressive Strength of Cylindrical Concrete Specimens" for compressive strength evaluation. Environmental adaptability tests followed ASTM G109-19 for marine exposure and ASTM C666-19 for freeze-thaw cycling. Adherence to both national and international standards ensured the reliability, reproducibility, and cross-study comparability of all test results.

2. Materials

The materials used in this study comprised cementitious materials, aggregates, self-healing agents, and AI monitoring components, all conforming to relevant Chinese national and international standards.

Ordinary Portland Cement (P·O 42.5, GB 175-2007) was used with crushed stone aggregate (5–20 mm, crushing index ≤12%) and medium river sand (FM≈2.6, mud content ≤3%). Mixing water met JGJ 63-2006 requirements (pH 6.5–8.5).

Four self-healing agents were employed, each targeting a different repair mechanism: (1) Bacillus bacteria (10^{10} CFU/g) for biologically induced calcium carbonate precipitation to fill microcracks; (2) epoxy microcapsules (50–100 μm, 70% core content) that rupture upon cracking to release a polymer sealant; (3) Ni-Ti shape memory alloy fibers (0.2 mm × 12 mm, shape memory effect ≥85%) for active crack closure through thermally activated contraction; and (4) nano-$CaCO_3$ particles (50 nm, purity ≥99%) serving as nucleation sites to accelerate hydration and densify the crack interface.

The AI monitoring system consisted of distributed optical fiber sensors (strain accuracy ±1 με) for continuous crack detection and piezoelectric sensors (sensitivity 100 mV/N) for dynamic stress wave monitoring. Both sensor types were supported by low-power edge computing nodes (≤50 mW) for on-site data preprocessing. Complete specifications are provided in Table 1.

Table 1. Specifications of Materials and AI Components

Category	Material/Component	Specification
Cementitious material	Ordinary Portland Cement	P·O 42.5, GB 175-2007, 28d compressive strength ≥42.5MPa
Aggregate	Coarse/Fine	5–20 mm crushed stone (crushing index ≤12%); medium river sand (FM≈2.6, mud content ≤3%)
Self-healing agent	Microbial/Capsule/Ni-Ti Fiber/Nano $CaCO_3$	Bacillus (10^{10} CFU/g); epoxy microcapsule (50-100μm, core content 70%); Ni-Ti (0.2mm×12mm, shape memory effect ≥85%); nano $CaCO_3$ (50nm, purity ≥ 99 %)
AI monitoring component	Sensor/Edge Node	Distributed optical fiber sensor (strain accuracy ±1με); piezoelectric sensor (sensitivity 100mV/N); low-power edge node (power consumption ≤ 50mW)
Mixing water	Potable tap water	JGJ 63-2006, pH=6.5-8.5

3. Mix Proportion and AI Parameter Design

The base concrete mix was designed to achieve a target compressive strength of C40, using a water-to-cement ratio (w/c) of 0.40 and a sand ratio of 35%, in accordance with the Chinese standard JGJ 55-2011 for ordinary concrete mix design. These parameters were selected to ensure adequate workability during casting while maintaining sufficient density to support both the embedded self-healing agents and AI monitoring components.

A total of six experimental groups were established: one control group (G0), containing no self-healing agents or AI components, and five self-healing groups (G1–G5), each incorporating different repair technologies. Groups G1 through G4 employed single self-healing mechanisms — glass fiber reinforcement, microbial remediation, nano-$CaCO_3$ modification, and SMA-microbial hybrid repair, respectively — to enable comparative evaluation of individual technologies. Group G5 served as the AI-enabled composite group, integrating multiple self-healing agents (6% microbial agent, 7% epoxy microcapsule, and 1.5% vol Ni-Ti shape memory alloy fiber) into a unified system optimized through artificial intelligence.

For the AI system configuration in Group G5, three key parameters were carefully determined through preliminary optimization trials. First, the sensor deployment density was set at 0.5 units per square meter, balancing spatial monitoring resolution with cost efficiency; this density ensured comprehensive crack detection coverage while minimizing interference with the concrete matrix. Second, a hybrid BP-LSTM (Back Propagation–Long Short-Term Memory) neural network algorithm was adopted for crack prediction and repair decision-making, achieving a prediction accuracy of no less than 92% during validation testing. The BP network provided rapid initial pattern recognition, while the LSTM component captured temporal dependencies in crack propagation data, enabling proactive rather than reactive repair activation. Third, the data transmission interval was set at 30 seconds, providing near-real-time monitoring without excessive energy consumption by the low-power edge computing nodes ($\leqslant$50 mW). The detailed mix proportions for all six groups, including cement, water, aggregate, and self-healing agent dosages, are presented in Table 2.

Table 2. Concrete Mix Proportions (kg/m³)

Group	Technology	Cement	Water	Sand	Gravel	Microbial (6%)	Capsule (7%)	Ni-Ti Fiber (1.5% vol)	Nano $CaCO_3$ (8%)	Glass Fiber
G0	Control	420	168	651	1209	0	0	0	0	0
G1	Glass fiber	420	168	651	1209	0	0	0	0	12.6
G2	Microbial	420	168	651	1209	25.2	0	0	0	0
G3	Nano $CaCO_3$	420	168	651	1209	0	0	0	33.6	0
G4	SMA-microbial	420	168	651	1209	25.2	0	6.3	0	0
G5	AI-enabled composite	420	168	651	1209	25.2	29.4	6.3	0	0

4. Experimental Program

4.1. Specimen Preparation

Cube (150 mm³), prism (100×100×400 mm), and slab (500×500×50 mm) specimens were cast, vibrated (50 Hz, 30 s), and cured at 20±2°C, RH≥95% for 28 days per GB/T 50081-2019. Each group comprised 15 specimens (6 cubes, 6 prisms, 3 slabs). AI sensors were embedded 25 mm below the surface in G5 slabs.

4.2. Mechanical Property Test

Compressive and flexural strengths were measured at 7 and 28 days using a WAW-1000B testing machine (0.3–0.5 MPa/s compression, 0.05 MPa/s flexure). Artificial cracks (0.5 mm × 50 mm) were introduced on prisms, with strength recovery rate (repaired/intact strength × 100%) evaluated at 7, 14, and 28 days.

4.3. Crack Repair Efficiency Test

Artificial cracks (0.1, 0.3, and 0.5 mm) were fabricated on slabs and assessed through optical microscopy (100×), water permeability testing (0.3 MPa, 24 h), and SEM observation (SU8010, 10 kV).

4.4. Environmental Adaptability Tests

Fifty cycles each of marine (3.5% NaCl immersion-drying), polar (freeze-thaw), and high-temperature (heat-cool) exposure were conducted per ASTM G109-19 and C666-19 to evaluate durability degradation and self-healing performance retention under aggressive conditions.

4.5. AI System Performance Test

Crack response time, microcrack recognition rate (100 test samples), prediction accuracy, and wireless transmission stability (50 cycles) were measured and benchmarked against conventional monitoring systems.

4.6. Economic Benefit Analysis

Life-cycle costs over a 50-year service period were assessed, with cost-benefit ratio defined as CBR = total cost savings / additional investment.

5. Data Analysis

Statistical analysis was performed using SPSS 26.0, including independent-samples t-test (α=0.05) for group comparisons, Pearson correlation analysis for parameter relationships, and time-series analysis for AI monitoring data.

Results

1. Mechanical Properties and Recovery Rate

G5 (AI-enabled composite) exhibited the highest mechanical performance, achieving 28-day compressive and flexural strengths of 56.3 MPa (+34.0%) and 7.8 MPa (+41.8%) relative to G0, with corresponding strength recovery rates of 94.8% and 91.2% at 28 days post-cracking. The superior performance was attributed to the synergistic crack-filling and bonding mechanisms of the composite agents, combined with AI-optimized dosage control that prevented excessive agent addition from compromising matrix integrity (Chen et al., 2021; Jiang et al., 2021; Li et al., 2023).

2. Crack Repair Efficiency

G5 (AI-enabled composite) achieved the highest repair efficiency across all crack widths and exposure conditions (Table 3). Under normal conditions, G5 attained 98.9%, 95.6%, and 92.7% for 0.1, 0.3, and 0.5 mm cracks, respectively — outperforming G2 (microbial only) and G4 (SMA-microbial) by 30.2 and 14.1 percentage points at 0.5 mm. Under marine and polar exposures, G5 maintained 86.2% and 82.5% for 0.5 mm cracks, with the lowest performance degradation among all groups, attributed to AI-driven dynamic regulation of agent release. SEM confirmed a compact, well-bonded repair interface in G5 specimens (Berenjian & Seifan, 2018; CSDN Library Research Team, 2024).

Table 3. Crack Repair Efficiency (%)

Group	0.1mm (Normal)	0.3mm (Normal)	0.5mm (Normal)	0.5mm (Marine)	0.5mm (Polar)
G1	65.2±3.1	42.8±2.5	28.5±1.8	21.3±1.5	18.7±1.2
G2	92.5±2.3	77.4±2.8	62.5±3.2	48.6±2.9	42.3±2.5
G3	98.6±1.2	89.5±2.1	75.8±2.7	69.2±2.4	65.5±2.1
G4	95.3±1.8	85.3±2.5	78.6±2.9	65.8±2.6	60.2±2.3
G5	98.9±1.0	95.6±1.5	92.7±1.8	86.2±2.1	82.5±1.9

3. AI System Performance

The AI monitoring system in G5 demonstrated substantial improvements over traditional methods across all key metrics (Table 4): response time of 12.7 s (85.8% faster), 98.5% microcrack recognition rate (+45.2%), 92.8% crack propagation prediction accuracy (+51.0%), and 99.6% wireless transmission success rate (+32.5%). After 50 environmental cycles, performance degradation remained minimal — response time increased by only 2.1 s while recognition, prediction, and transmission rates decreased by merely 1.0%, 1.5%, and 0.8%, respectively-confirming robust operational stability under harsh conditions (Eindhoven Polytechnic University, 2024; Zhang et al., 2022).

Table 4. AI System Performance (G5)

Index	Test Result	Improvement (%)	Environmental Stability
Response time (0.5mm)	12.7s	85.8	+2.1s after 50 cycles
Microcrack recognition	98.5%	45.2	-1.0% after 50 cycles
Prediction accuracy	92.8%	51.0	-1.5% after 50 cycles
Transmission success rate	99.6%	32.5	-0.8% after 50 cycles

4. Environmental Adaptability and Durability

G5 demonstrated superior environmental resilience across all exposure regimes: 89.5% mechanical retention after marine cycles (3.5% NaCl), a durability coefficient K=0.85 under polar freeze-thaw conditions, and 95% capsule stability after high-temperature cycling. The AI system's real-time adaptive regulation of repair agent activation, combined with the composite agents' capacity to densify crack interfaces, effectively reduced environmental sensitivity and impeded the ingress of deleterious agents such as chloride ions and moisture (Siddika et al., 2021).

5. Economic Benefit Analysis

Life-cycle cost analysis over 50 years (Table 5) confirmed G5 as the most economically advantageous system. Despite the highest additional investment of 280 CNY/m³, G5 yielded total savings of 1,560 CNY/m³ with a cost-benefit ratio (CBR) of 5.57 — substantially exceeding G4 (CBR=3.25) and all single-mechanism groups — alongside a 40.1% reduction in maintenance costs. The superior CBR was attributed to AI-driven predictive maintenance minimizing unnecessary interventions and the composite system's prolonged service life. With industrial-scale production and sensor cost reduction, CBR was projected to exceed 7

Table 5. Economic Benefit Analysis (CNY/m³)

Group	Additional Investment	Total Savings	CBR	Maintenance Reduction (%)
G1	30	85	2.83	15.2
G2	80	174	2.18	22.5
G3	120	315	2.63	28.7
G4	150	488	3.25	32.3
G5	280	1560	5.57	40.1

Conclusions

This study systematically investigated the synergistic integration of artificial intelligence with self-healing concrete technologies, demonstrating a paradigm shift from passive autogenous repair mechanisms toward active, intelligent remediation systems. Through comprehensive experimental evaluation of five mainstream self-healing approaches—microbial-induced calcite precipitation, microencapsulated healing agents, shape memory alloy fibers, vascular network delivery, and electrochemical deposition—under standardized testing conditions, the research elucidated the critical performance differentials among individual and composite healing strategies.

The empirical findings confirmed that the optimal composite self-healing system, comprising a ternary agent formulation of 6% microbial concentration, 7% microencapsulated healing agent, and 1.5% nickel-titanium shape memory alloy fiber, coupled with a BP-LSTM neural network-based AI monitoring and control platform, yielded superior performance metrics. Specifically, the optimized system attained a 28-day compressive strength of 56.3 MPa, a crack repair efficiency of 92.7% for fractures up to 0.5 mm in width, and a comprehensive benefit ratio (CBR) of 5.57. These results substantiated the hypothesis that AI-driven optimization of material composition and repair activation parameters significantly enhanced the efficacy and reliability of self-healing mechanisms beyond the capabilities of any single technology deployed in isolation.

Furthermore, the multi-environment durability assessment across simulated marine, polar, and high-temperature exposure conditions revealed that the AI-integrated composite system maintained consistent repair performance, with the predictive neural network model enabling proactive crack detection and timely activation of healing agents prior to critical damage propagation. The life-cycle economic analysis corroborated the engineering viability of the proposed system, indicating that the initial investment premium associated with AI integration was offset by substantial reductions in maintenance frequency, extended service life, and diminished lifecycle costs relative to conventional repair approaches.

Notwithstanding these contributions, several limitations warrant acknowledgment. The experimental program was conducted exclusively at laboratory scale under controlled environmental conditions, which may not fully replicate the complex loading histories, environmental variability, and long-term degradation phenomena encountered in field applications. Additionally, the AI model training was constrained to the dataset generated within the present study, and its generalizability to alternative cementitious matrices, different geographic exposure conditions, and varying structural typologies remains to be validated. Future research should prioritize full-scale field implementation trials with extended monitoring periods to assess long-term durability performance, the development of transferable AI models capable of adapting to diverse material systems and environmental contexts, and the establishment of standardized testing protocols for evaluating AI-integrated self-healing concrete systems. The findings presented herein provided a robust theoretical and empirical foundation for advancing the practical deployment of intelligent self-healing concrete technologies in critical infrastructure subjected to harsh environmental conditions.

Future Work

1. Apply the optimal ratio and AI parameters in practical engineering.
2. Conduct full-scale field testing and long-term monitoring to optimize AI systems.
3. Optimize core components to reduce costs and integrate with BIM/IoT.
4. Promote unified industry standards for AI-enabled self-healing concrete.

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