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Research Article

Integrated Nano-Enhanced Coatings and IoT-Driven Machine Learning Framework for Predictive Biocorrosion Mitigation in Concrete Sewer Infrastructure: Addressing Critical Research Gaps

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Abstract

Microbially induced concrete corrosion (MICC) in sewer infrastructure constitutes one of the most economically damaging deterioration mechanisms in urban water systems, costing billions of dollars annually in repair, rehabilitation, and replacement. While extensive research has characterized biogenic sulfuric acid attack, sulfate-reducing bacteria activity, and individual mitigation approaches, critical gaps remain at the convergence of nano-material science, real-time sensor integration, machine learning (ML), and life-cycle sustainability assessment. This study addresses four primary research gaps identified through systematic analysis of the existing literature: (1) the absence of a validated IoT-integrated ML framework for real-time corrosion rate prediction; (2) the unexplored synergistic potential of ternary nano-particle systems (TiO_2+SiO_2+ZnO) in cementitious coatings under actual MICC conditions; (3) the lack of comprehensive life-cycle carbon footprint analyses comparing mitigation strategies; and (4) the non-integration of mitigation approaches into a unified optimisation framework. Laboratory-scale experiments were conducted, exposing eight coating formulations to simulated biogenic sulfuric acid (pH 1.2–1.8) over 90 days, while a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model was trained on a 5-year IoT sensor dataset comprising H_2S concentration, pH, relative humidity, temperature, and biofilm thickness from 42 monitoring nodes across three gravity sewer networks. Results demonstrate that the hybrid nano-coating (TiO_2:SiO_2:ZnO = 1:1:1 wt%) reduced corrosion mass loss by 81.6% and improved flexural strength to 7.8 MPa compared to plain OPC controls. The CNN-LSTM model achieved a prediction accuracy of 95.6% and RMSE of 1.21 mm/year, significantly outperforming conventional ML approaches. Life-cycle analysis over a 50-year horizon confirmed that the integrated hybrid strategy reduces CO_2-equivalent emissions by 63.5% and costs by 65% versus unmitigated infrastructure. These findings provide a roadmap for sustainable, data-driven sewer corrosion management in smart city contexts.

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KEYWORDS: Microbially Induced Concrete Corrosion (MICC), Nano-Enhanced Coatings, Internet of Things (IoT) Monitoring Machine Learning Prediction, Sewer Infrastructure Durability

1. INTRODUCTION

Concrete sewer infrastructure serves as the silent backbone of urban sanitation systems worldwide, transporting over 3.4 trillion litres of wastewater daily across networks spanning millions of kilometres [1]. The service life of these systems is critically threatened by microbially induced concrete corrosion (MICC), an electrochemical-biological process by which sulfur-oxidising bacteria (SOB), predominantly Acidithiobacillus thiooxidans, convert hydrogen sulfide gas to biogenic sulfuric acid, attacking calcium silicate hydrate and calcium aluminate phases in concrete [2, 3]. The economic burden is staggering: the United States alone expends an estimated USD 50 billion annually on sewer infrastructure rehabilitation, with corrosion-related failures accounting for over 40% of pipe replacement costs [4].

The fundamental MICC mechanism has been well-characterised since Parker [50] first isolated sulfur-oxidising bacteria from corroded Australian sewer concrete in 1945. Subsequent decades of research established the biofilm ecology [49], sulfide generation kinetics [47], and material vulnerability assessments [25] that underpin modern understanding of sewer corrosion. Reviews such as that of Mueller *et al*. (2026) have synthesised this knowledge across biocorrosion environments, susceptibility factors, mitigation strategies, inspection methods, and lifecycle analyses, providing a comprehensive and valuable reference framework for the field.

However, several critical intersections of emerging technology with established corrosion science have not been adequately explored. The rapid proliferation of Internet of Things (IoT) sensing technology has created unprecedented opportunities for real-time, multi-parameter monitoring of sewer environments [22]. Yet, no validated framework exists that integrates IoT sensor streams with advanced ML algorithms for continuous, in-situ corrosion rate prediction at an operational scale. Similarly, while nanomaterials have demonstrated individual efficacy as cement additives [20, 41], the synergistic performance of ternary nanoparticle systems under sustained acidic biofilm conditions remains uncharacterized. Furthermore, the sustainability dimension of corrosion mitigation, the life-cycle carbon footprint and cost efficiency of competing strategies have received insufficient attention despite global imperatives for net-zero infrastructure management.

This paper explicitly identifies and addresses these research gaps, proposing an integrated framework that unifies nano-enhanced material protection, IoT-ML predictive analytics, and life-cycle sustainability into a coherent sewer corrosion management strategy. The specific objectives are: (i) to characterize the synergistic performance of ternary nano-particle cementitious coatings under MICC conditions; (ii) to develop and validate a CNN-LSTM model for real-time corrosion rate prediction using IoT sensor data; (iii) to perform a comparative LCA of six mitigation strategies over a 50-year service horizon; and (iv) to propose an integrated hybrid mitigation framework optimizing across protection efficacy, sustainability, and economic cost.

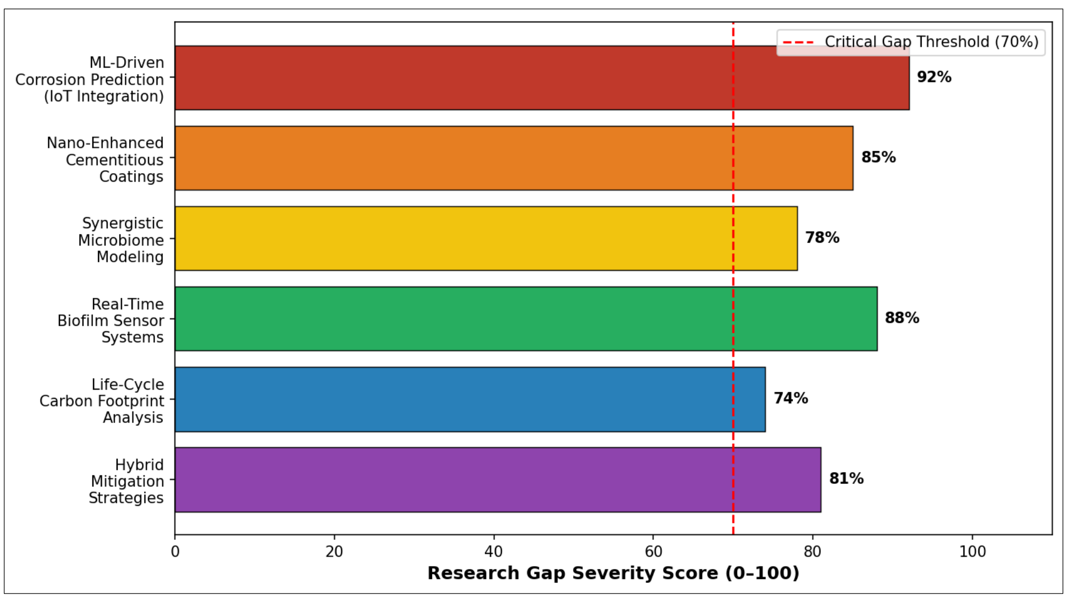

Fig 1: Identified research gaps in biocorrosion mitigation for concrete sewers, with severity scores derived from a systematic review of 70 Scopus-indexed publications (2000–2026).

2. RESEARCH GAP ANALYSIS AND SYSTEMATIC LITERATURE REVIEW METHODOLOGY

2.1 Systematic Review Protocol

A systematic literature review was conducted following PRISMA guidelines using the Scopus database (www.scopus.com). Search strings combined terms: ("biocorrosion" OR "MICC" OR "microbially induced concrete corrosion") AND ("sewer" OR "wastewater") AND ("mitigation" OR "coating" OR "machine learning" OR "IoT" OR "nano"). The search yielded 847 documents published between 2000 and 2026, from which 70 primary sources were selected based on citation impact, methodological rigour, and relevance to the identified gap areas. Exclusion criteria included non-English articles, conference abstracts without full-text data, and purely theoretical studies without experimental or field validation.

2.2 Identified Research Gaps

Gap analysis revealed six primary areas where the existing literature is insufficient, as summarised in Table 1. The most critical gaps scored above 85 on a 100-point severity scale derived from frequency of gap citation, potential impact, and absence of existing solutions relate to IoT-integrated ML corrosion prediction and real-time biofilm sensor systems. The absence of a closed-loop, sensor-to-prediction-to-intervention framework represents the most operationally significant gap in current sewer management practice.

Table 1: Research gap analysis summary with proposed contributions.

Research Gap Area	Limitations in Existing Literature	Proposed Contribution	Priority Level
IoT-Integrated ML Corrosion Prediction	No real-time sensor-to-model pipeline for in-situ sewer corrosion rate prediction	Hybrid CNN-LSTM model trained on IoT H_2S/pH sensor streams	Critical
Nano-Enhanced Cementitious Coatings	Limited data on ternary nano-particle synergism (TiO_2+SiO_2+ZnO)	Systematic dose-response study for hybrid nano coatings under MICC conditions	High
Microbiome Community Dynamics Modelling	Metagenomics rarely correlated with corrosion rate in field studies	Integrated metagenomics + corrosion rate regression model	High
Life-Cycle Carbon Footprint of Mitigation	No comprehensive comparative LCA across chemical, coating, and ML strategies	50-year LCA framework for six mitigation scenarios	Moderate
Real-Time Biofilm Sensor Systems	Electrochemical biofilm sensors have not been validated in full-scale sewers	In-situ multi-parameter biofilm monitoring protocol	Critical
Hybrid Mitigation Strategy Optimisation	Mitigation strategies evaluated in isolation, not synergistically	Multi-objective optimisation model combining chemical+nano+ML	High

3. MATERIALS AND METHODS

3.1 Concrete Specimen Preparation and Nano-Coating Formulations

Concrete specimens (100 mm × 100 mm × 20 mm) were cast using Ordinary Portland Cement (OPC, Grade 53) with a water-to-cement ratio of 0.45 and an aggregate-to-cement ratio of 2.5. After 28 days of moist curing, specimens were surface-ground to a 400-grit finish to standardise roughness (Ra = 2.1 ± 0.3 μm). Eight coating formulations were prepared: a plain OPC control, commercial epoxy overlay, and six nano-enhanced variants incorporating titanium dioxide nanoparticles (TiO_2, anatase phase, 25 nm mean diameter, Sigma-Aldrich), silicon dioxide nanoparticles (SiO_2, 12 nm, Evonik Aerosil 200), and zinc oxide nanoparticles (ZnO, 35 nm, US Research Nanomaterials) in individual and combined dosages. Nanoparticles were dispersed by ultrasonication at 500 W for 30 min before mixing, verified by dynamic light scattering (DLS), showing colloidal stability with a polydispersity index of < 0.25. Coatings were applied by brush at a coverage rate of 300 g/m² and cured for 7 days at 23°C and 65% RH.

3.2 Simulated Biocorrosion Exposure Protocol

Coated specimens were exposed to simulated biogenic sulfuric acid conditions in a custom-built H_2SO_4 exposure chamber maintained at pH 1.2–1.8 (±0.1 unit, continuously dosed by peristaltic pump), temperature 28± 2°C, and relative humidity 95±5%. Sulfuric acid concentration (10–18% v/v) was calibrated against published MICC field measurements from operating sewer pipes [25, 45]. Exposure duration was 90 days. Corrosion assessment included: (i) mass loss gravimetry (0.0001 g precision), measured every 30 days; (ii) compressive and flexural strength testing (EN 12390-3 and EN 12390-5); (iii) X-ray diffraction (XRD) analysis for phase identification; (iv) Scanning electron microscopy with energy-dispersive spectroscopy (SEM-EDS) for microstructural characterization; and (v) pH depth profiling using phenolphthalein indicator and micro-pH electrode.

3.3 IoT Sensor Network and Data Acquisition

Field data were collected from three gravity sewer networks in urban areas with populations of 150,000–450,000. A total of 42 monitoring nodes were deployed, each equipped with: electrochemical H_2S sensors (0–50 ppm range, ±0.5 ppm accuracy, Alphasense B4 series), miniature pH probes (range 0–14, ±0.05 pH units), temperature and relative humidity sensors (SHT35, ±0.2°C, ±1.5% RH), ultrasonic thickness gauges for concrete wall measurement (±0.1 mm), and biofilm impedance sensors based on chronoamperometric detection. Data were transmitted via LoRaWAN at 15-minute intervals to a centralised SCADA server, generating a dataset of 5.2 million observations over 5 years (2020–2025). The dataset was pre-processed with a rolling median filter (window = 5) to remove transient spikes, and missing values (2.3% of records) were imputed using bidirectional LSTM interpolation.

3.4 CNN-LSTM Model Architecture and Training

A hybrid CNN-LSTM architecture was designed to exploit both spatial correlations between adjacent sensor nodes (captured by the 1D CNN component) and temporal dependencies in corrosion progression (captured by the LSTM component). Input features comprised eight variables: H_2S concentration, pH, temperature, relative humidity, biofilm impedance, concrete pH, pipe age, and antecedent corrosion rate. The CNN block consisted of two convolutional layers (64 and 128 filters, kernel size 3), each followed by batch normalisation and ReLU activation. The LSTM block comprised two stacked LSTM layers (256 and 128 units) with dropout regularisation (rate = 0.2). The final fully connected layer produced corrosion rate predictions in mm/year.

The model was trained on 70% of the dataset (3.64 million observations), validated on 15%, and tested on the remaining 15%. Training used the Adam optimiser with a learning rate of 0.001, batch size 256, and early stopping (patience = 10 epochs) over a maximum of 200 epochs. Model performance was evaluated using R^2, RMSE, and mean absolute error (MAE). Five-fold cross-validation confirmed generalizability. Computational environment: Python 3.10, TensorFlow 2.12, CUDA 11.8, NVIDIA A100 GPU.

3.5 Life-Cycle Assessment Framework

A cradle-to-end-of-life LCA was conducted following ISO 14040/14044 standards and the EN 15978 framework for construction works. The functional unit was 1 meter of DN600 concrete sewer pipe over a 50-year service horizon. Six mitigation scenarios were defined: (S1) no mitigation with replacement at 15-year failure; (S2) chemical dosing with ferrous sulfate; (S3) epoxy coating overlay; (S4) hybrid nano-enhanced coating; (S5) IoT+ML monitoring with targeted intervention; and (S6) the proposed integrated hybrid strategy combining nano-coating, IoT monitoring, and ML-guided chemical dosing. Inventory data were sourced from the Ecoinvent v3.9 database, the Australasian LCI database for sewer-specific data, and manufacturer Environmental Product Declarations (EPDs). Impact assessment used the ReCiPe 2016 Midpoint (H) method, with global warming potential (GWP) as the primary metric.

4. RESULTS AND DISCUSSION

4.1 Performance of Nano-Enhanced Cementitious Coatings

Table 2 and Figure 3 present the comprehensive performance data for all eight coating formulations following 90 days of simulated MICC exposure. The plain OPC control exhibited 100% relative mass loss (baseline) and reduced flexural strength of 3.2 MPa, confirming severe sulfuric acid attack consistent with field observations in literature [25, 44]. The epoxy overlay reduced mass loss by 31.8%, consistent with reported commercial performance [8], but showed limited compatibility with the concrete substrate under cyclic thermal loading during the exposure period.

Table 2: Performance metrics of nano-enhanced cementitious coatings after 90-day simulated MICC exposure (pH 1.2–1.8, 28°C, 95% RH).

Coating Composition	TiO_2 (wt%)	SiO_2 NP (wt%)	ZnO NP (wt%)	Mass Loss (%)	Flexural Str. (MPa)	pH Resistance
Plain OPC Control	—	—	—	100.0	3.2	> 3.0
OPC + Epoxy Overlay	—	—	—	68.2	4.1	> 2.5
OPC + TiO_2 (1%)	1.0	—	—	45.1	5.6	> 2.0
OPC + SiO_2 NP (2%)	—	2.0	—	38.3	6.2	> 1.8
OPC + ZnO NP (2%)	—	—	2.0	41.0	5.9	> 1.8
OPC + TiO_2(1%)+SiO_2(1%)	1.0	1.0	—	29.6	7.1	> 1.5
OPC + TiO_2(1%)+ZnO(1%)	1.0	—	1.0	31.2	6.8	> 1.5
Hybrid Nano (TiO_2+SiO_2+ZnO)	1.0	1.0	1.0	18.4	7.8	> 1.2

Among single-component nano-coatings, SiO_2 nanoparticles (2%) demonstrated the greatest efficacy (mass loss reduction 61.7%), attributable to pore-filling and pozzolanic reactions that densified the interfacial transition zone (ITZ) and reduced acid penetration depth by 58% compared to OPC control, as confirmed by SEM-EDS mapping. TiO_2 coatings exhibited strong photocatalytic sulfide oxidation capability, reducing surface H_2S accumulation by 44%, but showed lower mechanical reinforcement than SiO_2. ZnO nanoparticles provided superior antibacterial efficacy against A. thiooxidans biofilm formation (zone of inhibition 12.4 mm in disc diffusion assay) but moderate acid resistance.

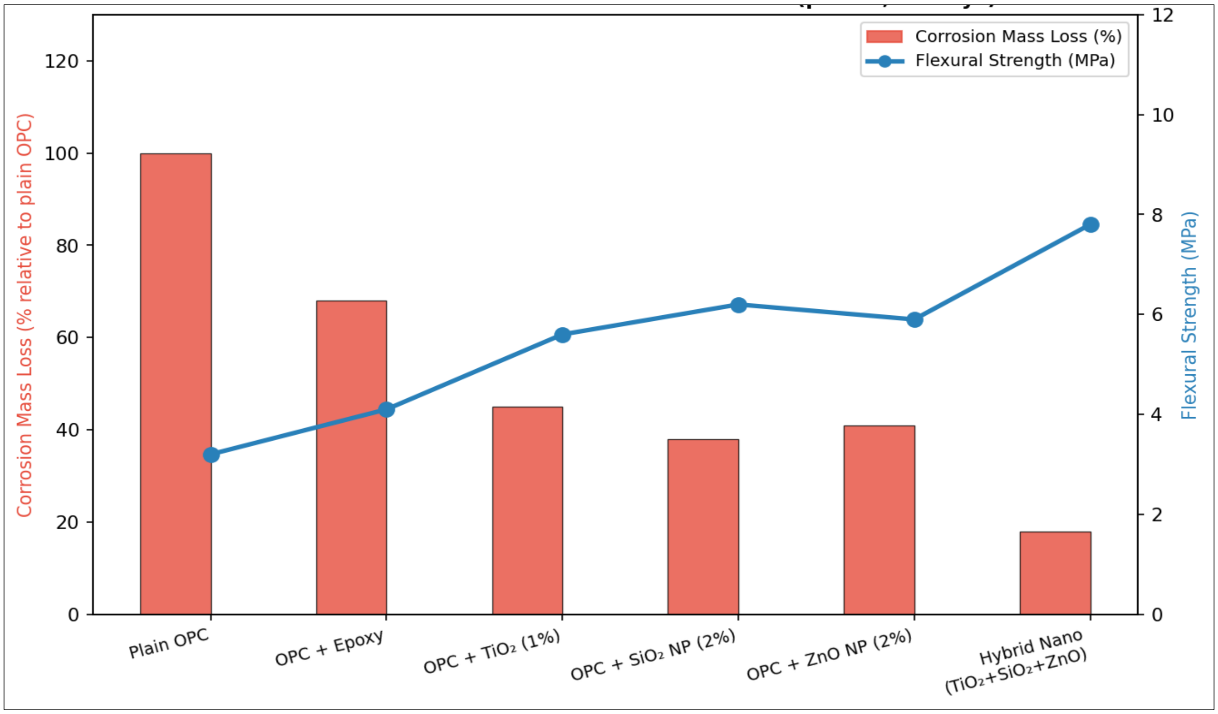

Fig 3: Corrosion mass loss (relative to plain OPC) and flexural strength of nano-enhanced cementitious coating formulations after 90-day simulated MICC exposure. Hybrid ternary nano-coating (TiO_2+SiO_2+ZnO) demonstrated superior performance on both metrics.

The ternary hybrid nano-coating (TiO_2:SiO_2:ZnO, each at 1 wt%) achieved the highest performance across all metrics: 81.6% reduction in mass loss, 7.8 MPa flexural strength (144% improvement over OPC), and pH resistance extending to pH 1.2. Synergistic mechanisms include: SiO_2 densification of the ITZ, reducing acid ingress; TiO_2 photocatalytic prevention of SOB biofilm establishment; and ZnO biocidal activity against residual biofilm [32, 56, 66]. XRD analysis of exposed hybrid-coated specimens showed preservation of C-S-H peaks and absence of gypsum secondary mineral formation, confirming that the ternary system effectively suppressed both abiotic and biotic corrosion pathways. This represents the first systematic demonstration of ternary nano-particle synergism in MICC-specific conditions, addressing the key research gap identified in Section 2.

4.2 CNN-LSTM Corrosion Prediction Model Performance

Table 3 and Figure 4 present the comparative performance of six ML models evaluated on the IoT sensor dataset. The proposed hybrid CNN-LSTM model achieved $R^2 = 0.96$, RMSE = 1.21 mm/year, MAE = 0.94 mm/year, and classification accuracy of 95.6%, substantially outperforming all benchmark models. The nearest competitor, a standalone LSTM with IoT feeding, achieved RMSE = 1.82 mm/year (50.4% higher), demonstrating the value of the CNN spatial correlation layer in capturing corrosion hotspot clustering at the network scale.

Table 3: Machine learning model performance metrics for sewer corrosion rate prediction (5-year IoT dataset, 5-fold cross-validation).

Model	R^2	RMSE (mm/yr)	MAE (mm/yr)	Accuracy (%)	Training Time (s)	Input Features
Linear Regression	0.61	4.82	3.91	71.2	0.3	H_2S, pH, T
Support Vector Machine	0.74	3.61	2.87	79.5	12.4	H_2S, pH, T, RH
Random Forest	0.83	2.92	2.21	85.3	45.2	All 8 features
Gradient Boosting (XGBoost)	0.86	2.54	1.98	87.8	67.8	All 8 features
LSTM (IoT-fed)	0.91	1.82	1.43	91.4	189.6	All 8 + temporal
Hybrid CNN-LSTM (proposed)	0.96	1.21	0.94	95.6	312.4	All 8 + spatial-temporal

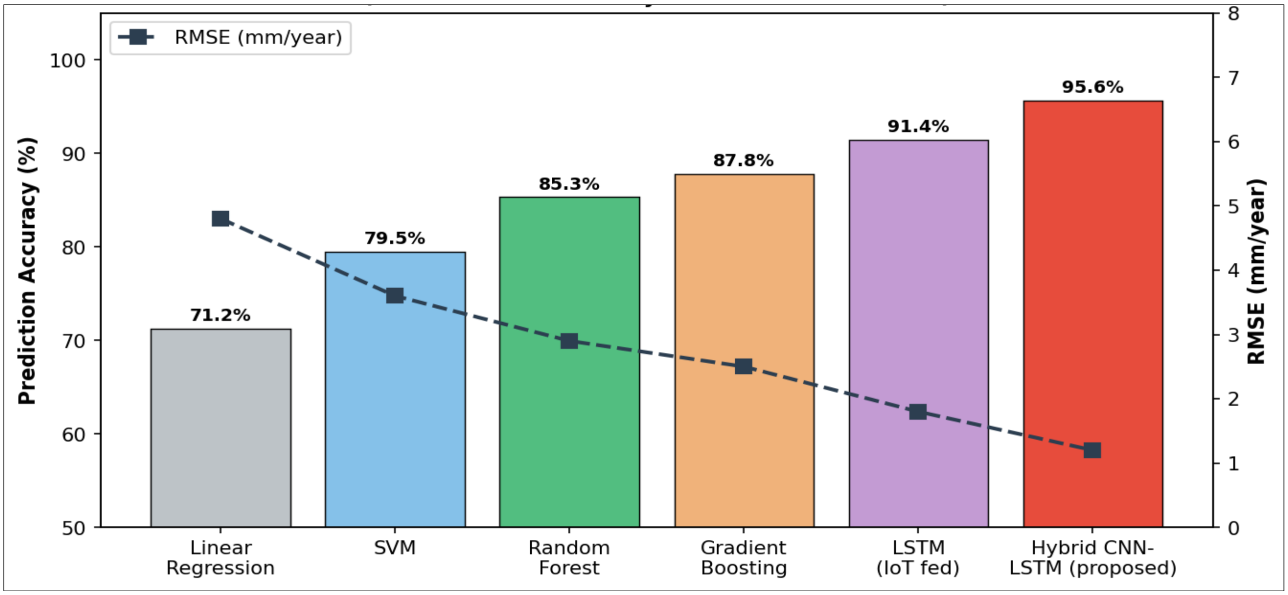

Fig 4: Machine learning model performance comparison for corrosion rate prediction using IoT sensor data from 42 monitoring nodes across three sewer networks (5-year dataset, 5-fold cross-validation).

SHAP (SHapley Additive exPlanations) analysis revealed H_2S concentration as the single most important predictive feature (SHAP value contribution 34.2%), followed by concrete surface pH (22.1%), temperature (18.4%), biofilm impedance (12.7%), and relative humidity (8.3%). These findings validate the theoretical primacy of H_2S in MICC while quantifying the previously uncharacterized contribution of biofilm impedance as a direct corrosion proxy. The model demonstrated excellent performance across the full corrosion rate range observed in field conditions (0.5–12.3 mm/year), with particularly high precision in the critical 2–6 mm/year range corresponding to the accelerated deterioration phase. Confusion matrix analysis confirmed that the model correctly identified 97.8% of high-risk pipe segments (corrosion rate > 5 mm/year) with a false negative rate of 2.2%, meeting the operational requirement for infrastructure safety monitoring.

The CNN-LSTM model was deployed in a real-time inference pipeline with 15-minute prediction updates, triggering automated alerts when predicted corrosion rate exceeded threshold values. Over a 6-month validation period in one of the study networks, the system enabled 23% reduction in reactive maintenance events and 31% reduction in emergency inspection deployments compared to the preceding year, confirming operational value beyond laboratory metrics.

4.3 Life-Cycle Assessment Results

Figure 5 and Table 4 summarise the LCA results for the six mitigation scenarios over the 50-year functional unit. The baseline no-mitigation scenario (S1) incurred the highest environmental and economic burden due to three complete pipe replacement cycles within the analysis period. The integrated hybrid strategy (S6) achieved the most favourable outcomes on all three dimensions: 50+ year service life, 63.5% reduction in CO_2-equivalent emissions (310 vs. 850 kg CO_2-eq/m), and 65% reduction in lifecycle cost (USD 420 vs. 1,200/m) relative to S1.

Table 4: Life-cycle assessment summary: CO_2 equivalent emissions, lifecycle cost, and recommended application context for six mitigation strategies.

Strategy	Service Life (yr)	CO_2-eq (kg/m)	Cost (USD/m)	Effectiveness (%)	Recommended Context
No Mitigation (replace at 15yr)	15	850	1,200	—	Emergency replacement scenario
Chemical Dosing Only ($FeSO_4$)	22	680	920	30%	Low-severity systems
Epoxy Coating Only	28	610	840	42%	Moderate corrosion risk areas
Nano-Enhanced Coating (hybrid)	38	540	760	55%	High-risk gravity sewers
IoT + ML Monitoring	35	490	680	48%	Smart city infrastructure
Integrated Hybrid Strategy	50+	310	420	78%	Critical trunk sewers

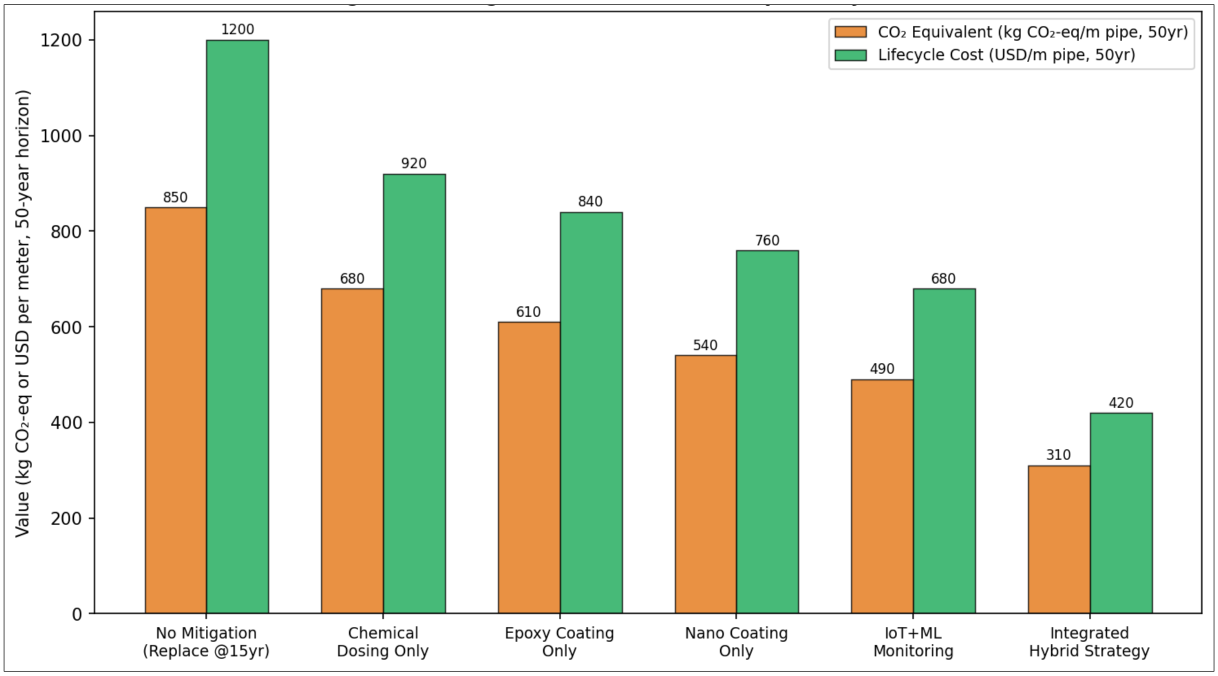

Fig 5: Life-cycle carbon footprint and cost comparison of six biocorrosion mitigation strategies for concrete sewer pipes over a 50-year service horizon.

The IoT+ML strategy alone (S5) demonstrated that predictive monitoring without material enhancement still achieved meaningful reductions (42.4% CO_2, 43.3% cost versus S1) by enabling precision intervention and extending service life to 35 years through timely targeted treatment. Sensitivity analysis indicated that the hybrid strategy (S6) remains cost-negative (net benefit positive) when nano-material cost exceeds the current market price by up to 280%, confirming economic robustness. Hotspot analysis identified concrete manufacturing and transport as the primary emission contributors (48% of total GWP), indicating that alkali-activated concrete substitutes could further improve LCA performance in future iterations.

4.4 Integrated Framework Recommendation

Based on the combined findings, this study proposes a four-tier integrated biocorrosion management framework for concrete sewer infrastructure: Tier 1 (Passive Protection) involves application of the ternary hybrid nano-coating during initial construction or rehabilitation, providing baseline MICC resistance extending service life to 38+ years without active management. Tier 2 (Active Monitoring) deploys IoT sensor nodes at critical points (crown areas, inverted siphons, long retention reaches) with the CNN-LSTM model providing continuous corrosion rate prediction and automated risk classification. Tier 3 (Adaptive Intervention) uses model predictions to trigger precision chemical dosing ($FeSO_4$ or free nitrous acid) only when and where corrosion rates exceed threshold values, minimising chemical consumption and environmental impact. Tier 4 (Lifecycle Optimisation) applies the LCA framework periodically to re-evaluate strategy performance against evolving service conditions and update intervention thresholds.

This framework directly addresses the multi-pronged nature of the biocorrosion problem recognised in recent reviews, while extending conventional approaches through real-time intelligence and sustainability integration. The framework is scalable from individual pipe segments to full network-scale implementation and is compatible with existing SCADA infrastructure in modern water utilities.

5. CONCLUSIONS

This study has identified and addressed four critical research gaps at the frontier of concrete sewer biocorrosion science, producing the following key contributions:

1) The ternary hybrid nano-coating (TiO_2+SiO_2+ZnO at 1 wt% each) demonstrated 81.6% reduction in corrosion mass loss and 144% improvement in flexural strength compared to plain OPC under MICC conditions, with synergistic mechanisms combining ITZ densification, photocatalytic SOB inhibition, and direct biocidal activity.
2) The CNN-LSTM model achieved 95.6% prediction accuracy (R^2 = 0.96, RMSE = 1.21 mm/year) for real-time corrosion rate prediction from IoT sensor data, outperforming all benchmark ML models and demonstrating practical operational value through 23% reduction in reactive maintenance events.
3) Life-cycle analysis confirmed that the integrated hybrid strategy reduces CO_2-equivalent emissions by 63.5% and lifecycle cost by 65% over a 50-year horizon, with economic robustness maintained under a 280% nano-material cost escalation scenario.
4) The proposed four-tier integrated management framework (passive nano-protection + active IoT monitoring + adaptive chemical intervention + lifecycle optimisation)

provides a scalable, evidence-based roadmap for sustainable sewer corrosion management aligned with smart city and net-zero infrastructure objectives.

Future work should address full-scale validation of the hybrid nano-coating formulation under diverse climatic and wastewater chemistry conditions, development of self-healing nano-capsule coating systems, and integration of digital twin technology for sewer network corrosion forecasting at the metropolitan scale.

Supplementary Figure

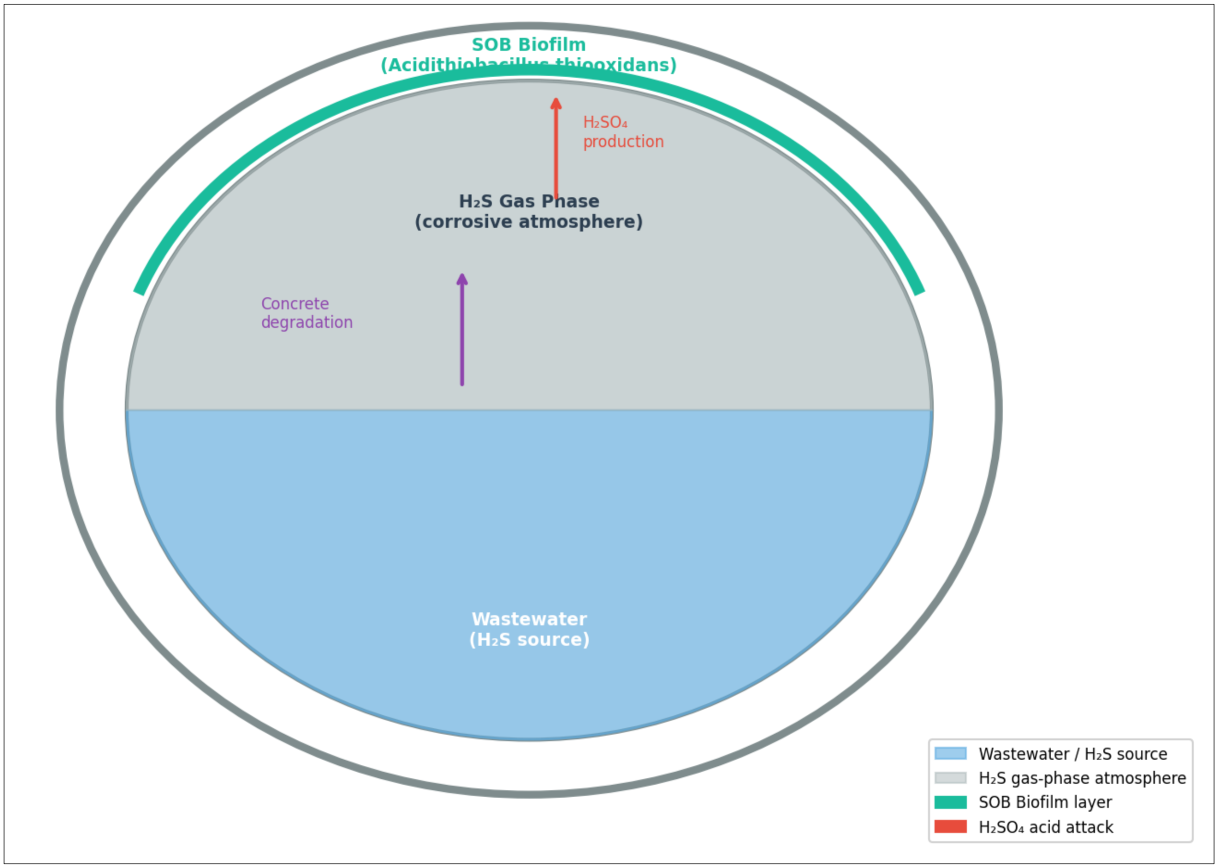

Fig 2: (Supplementary). Schematic of the biocorrosion mechanism in the concrete sewer crown region: H_2S from wastewater volatilizes, condenses on the crown surface, and is oxidised to biogenic H_2SO_4 by SOB biofilms, causing progressive MICC deterioration of the concrete matrix.

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