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Review Article

A Comprehensive Review on Strength Prediction and Self-Healing Properties of Bacterial Concrete using Machine Learning and Optimization Algorithms

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Abstract - *Bacterial concrete is an innovative self-healing material that deals with durability challenges in traditional concrete using Microbial Induced Calcium Carbonate Precipitation (MICP). Recent advances in optimization and ML algorithms have enabled accurate prediction of healing and strength efficiency, decreasing reliance on costly trial-and-error experimentation. This review offers present research on predictive modelling approaches, including ensemble methods, hybrid ANN, regression models, and ensemble methods optimized with PSO. A comparative study has been performed and emphasized the better performance of ANN-PSO in identifying non-linearities and mix design parameters optimization. PSO-like optimization algorithms improve sustainability and predictive accuracy. The key challenges may include variability, limited interpretability, and data scarcity of black box models. Future directions highlight the integration of recent technologies. This review emphasized the transformative potential of ML-driven optimization in advancing bacterial concrete as a sustainable and durable construction material.*

Keywords -*Bacterial Concrete, Machine Learning, Optimization Algorithms, Self-Healing Properties, Crack Healing.*

1. Introduction

Globally, the most widely used construction material is concrete; however, its exposure to durability and microcracking loss exhibits major challenges. Conventional repair approaches are expensive and usually ineffective in extending service life. Bacterial concrete integrating self-healing microorganisms accomplished in calcium carbonate precipitation provides a sustainable solution in repairing cracks autonomously and improving mechanical properties. Experimental studies have verified improvements in tensile, flexural, and compressive strength with decreased permeability and improved durability.

Even though bacterial concrete is an evolutionary solution toward sustainable infrastructures, the actual implementation of such an approach is still limited due to the complex mechanisms of MICP. The effectiveness of this self-healing process is largely dictated by stochastically varied parameters, which, according to MICP characteristics, consist of microbial population, nutrient concentration, variations in pH, ambient temperature, and others. Standard empirical models usually do not take into account these non-linear correlations, and as such, a large prediction discrepancy occurs. This randomness is essentially the barrier against its industrial applications, requiring innovative computing frameworks that ensure a reliable performance on large-scale structures. Recently, researchers began leveraging Computational Intelligence for this purpose. ML algorithms, like ANN and ensembles, are used to reveal complex trends within experimental data that could not otherwise be seen.

Moreover, tuning of metaheuristic optimization techniques like PSO and GAs will yield more robust mix designs and significantly more accurate strength prediction of bacterial concrete. Despite the significant amount of research carried out on bio-cementitious composites, the integration of computational optimization with microbial kinetics has been relatively less studied; hence, this review serves to fill this void by integrating the biochemistry involved in MICP and characterizing the environmental conditions causing non-linearity in the structural behavior. Furthermore, this review also highlights the evolution of modeling strategies from conventional empirical analysis to the latest ML architectures (i.e., individual and hybrid metaheuristics approaches) and identifies future steps and directions to overcoming issues such as 'black-box' prediction, data insufficiency, by taking advantage of

Explainable AI (XAI) and digitalization. This review attempts to define a unified paradigm that merges material science, microbiology, and computational intelligence to bring bacterial concrete to the forefront as an advanced and environmentally conscious choice for next-generation structures, by summarizing the most recent findings in the area of self-healing performance evaluation and strength prediction of bacterial concrete.

2. Bacterial Concrete: An Overview

To give a background on the present work, a survey of technology used for ureolytic feasibility studies development will be presented to show the present state of the art for application on cementitious composites. In contrast to the few early relevant papers that have analyzed the survival of Sporosarcinapasteurii on conventional mortars [1], recent research has studied non-Ureolytic Alkaliphilic bacteria (e.g., Bacillus cohnii) and novel methods of spore encapsulating [2]. Ensuring that the spores are not affected by the alkaline environment in the cement matrix will contribute to spore viability using expanded clay, hydrogel, etc. In recent literature, the research seems to focus again on UHPC and Fiber-Reinforced Composites [3]. The challenge in these cases lies in prediction, due to the complex, non-linear interaction between the fiber-bridging mechanism and bacterial mineralization. As this research has accounted for the interaction effects of the different modes, it provides a wider perspective than studies that may have ignored the interaction effects of advanced materials and microorganisms' behavior [4]. Table 1 briefly summarizes some common biochemical mechanisms in the bacterial concrete, which shows a trade-off between healing efficiency and environmental impact or application engineering purpose.

Table 1. Comparison of microbial metabolic pathways in self-healing concrete

Mechanism	Biochemical Pathway	Strengths (Pros)	Weaknesses (Cons)	Applicability
Ureolytic	Urea Hydrolysis $(CO(NH_2)_2 \rightarrow NH_3 + CO_2)$	Rapid CaCO3 precipitation; high healing efficiency for cracks up to 0.5 mm.	Produces ammonia (NH3) as a byproduct; high urea consumption costs.	General civil infrastructure requiring rapid repair.
Non-Ureolytic	Organic Acid Oxidation (e.g., Calcium Lactate)	Environmentally friendly; no harmful byproducts; significantly enhances matrix durability.	Slower healing rates necessitate specific alkaliphilic bacterial strains.	Eco-friendly urban construction and green buildings.
Denitrification	Nitrate Reduction $(NO_3^- \rightarrow N_2)$	Highly effective in oxygen-deprived environments (e.g., saturated soil or deep concrete).	Potential for nitrite accumulation; requires complex gas release management.	Marine structures and underground deep-foundation works.

The technical differences between various types of self-healing have been compiled in Table 2, with the greater potential for bridging cracks attributed to a biological system. Autogenous healing is an inherent mechanism whose efficacy is only guaranteed for very fine hairline cracks[5]. Chemical methods offer a wider crack-bridging capability than Autogenous, but most techniques offer a non-rechargeable system; once the capsule breaks, the healing agent is consumed. The Biological category, which is the focus of this review, is capable of healing much wider structural cracks (up to 1.0 mm), hence the need for sophisticated computational modeling [6].

Table 2. Classification of self-healing mechanisms in cementitious materials

Category	Mechanism Type	Process Description	Healing Limit (Crack Width)
Autogenous	Physical/Chemical	Continued hydration of unhydrated cement particles and carbonation of Ca(OH)2 within the matrix.	<0.1 mm
Chemical	Autonomous	Activation of encapsulated polymers, epoxies, or mineral admixtures (e.g., crystalline additives) upon crack formation.	0.1−0.3 mm
Biological	Autonomous (Active)	Microbial Induced Calcite Precipitation (MICP) triggered by moisture/oxygen ingress via ureolytic or non-ureolytic pathways.	Up to 1.0 mm

Several Kinds of bacteria are utilized in concrete, such as Bacilluscohnii, Bacillus pseudofirmus, Bacillus subtilis, Bacillus sphaericus, etc. The bacteria above are able to tolerate environments with a high alkaline pH value. An example of the metabolic processes utilized by these bacteria is that urea hydrolysis, photosynthesis, and sulphate reduction, where a product of the reaction process creates calcium carbonate as a byproduct. There is a reaction process where the pH changes from neutral to alkaline, therefore producing carbonate and bicarbonate ions. These ions precipitate with calcium ions, which are present in the concrete, to produce calcium carbonate reserves. Historically, the field of self-healing cementitious materials has evolved from slow autogenous healing with its limited capability for crack widths below 0.2 mm [7], towards active bio-mineralization. Studies carried out in the early investigations have primarily been about the metabolism of ureolytic bacteria, e.g.,Sporosarcinapasteurii; however, the conditions of concrete are highly alkaline (pH 12-13), and survival of ureolytic bacteria may prove a challenge. Therefore, literature has moved from proof of concept through to computational optimization, max CaCO3 yield using a controlled mix design, and on to extremophilic spore-forming Bacillus species that will not be metabolized until spore germination by water in the crack.

The bacteria-induced self-healing has demonstrated its effectiveness for a 0.5mm crack width. In the external part of the control, concrete $CaCO_3$is formed through the reaction of $CO_2$with $Ca(OH)_2$ contained in the concrete structure.

$$CO_2 + Ca\,(OH)_2 \rightarrow CaCO_3 + H_2O \tag{1}$$

From Equation 1, we can infer that the production of calcium carbonate is because of restriction limited amount of CO_2. Since Ca $(OH)_2$ is a mineral that is soluble in water, it can be dissolved readily and diffuse to the outer region of the crack. The self-healing reaction in bacteria in concrete is efficient because the bacteria are metabolizing and absorbing nutrients:

$$Ca(C_3H_5O_2)_2 + 7O_2 CaCO_3 + 5CO_2 + 5H_2O \tag{2}$$

In Equation 2, it is clearly visible that $CaCO_3$ is produced not directly due to bacteria but indirectly from the mechanism of autogenous healing. Hence, a practical way of closing cracks by bacteria is achieved. It catalyzes urea to carbon and ammonium [8]. The urea initially undergoes hydrolysis to ammonia and carbonate ions. These carbonate ions undergo further hydrolysis to yield additional ammonia and carbonic acid ions. These molecules yield hydroxide, ammonium, and bicarbonate ions. The bicarbonate equilibrium is shifted by the addition of ammonia and forms calcium carbonate ions. Since the bacterial cell membrane is negatively charged, the cations on the cell surface are attracted to the bacterial cell, for instance, Ca^{2+} ions. Later, the Ca^{2+} ions get aggregated and react with CO_3^{2-} ions to form a precipitate of $CaCO_3$on the bacteria cell surface, which acts as a nucleation center:

$$Ca_2^{++}Cell \rightarrow Cell\text{-}Ca_2^{+} + Cell\text{-}Ca^{2+} + CO_3^{2-} + Cell\text{-} \rightarrow CaCO_3 \tag{3}$$

Although urea hydrolysis and organic acid oxidation explain, in theory, how self-healing happens, the real engineering value of bacterial concrete shows up in its large-scale performance. Calcium carbonate precipitation inside the cement pores not only seals cracks. More importantly, it changes the internal microstructure of the composite, mainly by lowering porosity and tortuosity. That distinction makes a real difference, as structural performance is not really defined at the crack surface. We must analyze the test results of compressive, tensile, and flexural strength to relate the reactions on a micro-biochemical level to the structural performance on a macroscopic level. It has also been suggested that it is the bio-densification that is occurring within the ITZ that is largely responsible for this improvement in mechanical properties [9]. However, the degree of improvement is not necessarily consistent across all bacterial densities and precursors. Still, it is instead sensitive to the former in particular [10], thus highlighting the importance of data-based prediction of performance in such systems.

The corrosive nature of the marine environment also tends to attack and degrade the concrete structures in that environment. Though the potential of bacterial concrete is enormous, it has its own disadvantages when placed in the marine environment due to high concentrations of chlorides and variable pH, seawater, etc. These factors could have an effect on bacterial growth and performance in healing the cracks. This review is designed to provide insight into the same and identify how the performance could be maintained with the optimized bacteria and parameters.

Even though strength improvement is reported due to MICP in numerous papers, the actual reasons are still debated quite seriously. [11] makes quite a convincing case against MICP being solely responsible for the strength enhancement. According to their study, even adding bacterial growth medium and inactive bacterial biomass was responsible for mechanical strength, not metabolic calcification. In some cases, the reported gains may come from organic materials filling pores or altering the hydration process, not from bio-cementation itself, which is often treated as the obvious cause

3. Strength Prediction of Bacterial Concrete

Some of the observations made in the past ten years have revealed that bacteria are often used to improve cementitious materials. It is widely known as MICP. However, the ability of bacteria to survive, multiply, and sustain their metabolic process in the concrete is debatable. Therefore, in the investigation, the different processes will be examined for the improvement in strength in the bacteria-based cementation material. Incorporation of live and dead cells of Bacillus cohnii in varied concentrations of cement mortar gave an increase in compressive strength and flexural strength. Also, it is seen that concrete strength can be obtained through filling or as microbiologically mediated exceptional growth in [12, 13] with the inclusion of Bacillus megaterium. The split tensile and tensile strength were determined in the prisms and concrete cylinders, both without bacteria and with bacteria. Both split flexural and tensile strength were improved upon inclusion of bacteria. Also, it can be noted from the Scanning Electron Micrograph that after colonization by bacteria, the pores were found to be partly plugged with growth.

A previous study [14] mentioned that a major weakness of concrete is its reduced splitting tensile strength, which is attributable to microcracks. For self-healing concrete, bacteria have recently been used. Concrete mechanical properties testing is highly time-consuming, involves destructive approaches, is labor-intensive, and results in wastage of materials.

Accordingly, [15] evaluated the design of microbiological concrete in plain water using Optical Density (OD_{600}) 0.5±0.1, one culture density. Compared with traditional concrete 100:0, two water-to-bacteria mix proportions, 50:50 and 75:25, have been used. For the capacity of water absorption, compressive strength, SEM-Scanning Electron Microscopy analysis, and UPV-Ultrasonic Pulse Velocity have been performed on the samples at usual intervals.

However, the experimental data presented in the previous section show considerable variability, mainly because microbial systems are inherently stochastic and the concrete mix reacts sharply to environmental changes. The problem with the traditional empirical models used in practice is that they generally cannot account for the non-linear and multi-level nature of these interactions. When this happens, the model generates outputs that are not accurate or consistent enough for industrial applications. Thus, there is a need for Computational Intelligence (CI), more specifically Machine Learning (ML), to infer such intricate relationships that are often too complex for deterministic methods. Similarly, for understanding the self-healing concrete mechanical properties prediction, the intelligent learning abilities of MVO- Multi-Verse Optimization, MFO- Moth Fly optimization, GWO- Grey Wolf Optimization, meta-heuristic approaches, RSM- Response Surface Methodology, WOA- Whale Optimization Algorithm, and PSO- Particle Swarm Optimization are considered. Here, the GWO model outperformed the other methods in concrete slump prediction, 0.989 for testing and 0.998 for training, respectively, whereas PSO outperformed in predicting flexural strength with 0.989 R^2.[16] Recent studies have demonstrated that machine learning approaches such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) can transform complex experimental datasets into robust predictive frameworks by simultaneously accounting for bacterial cell concentration, nutrient concentration, calcium concentration, urea concentration, and curing time, thereby facilitating the optimization of bacterial concrete performance. [17].

Previous study [17] assessed the robustness of Random Tree, Random Forest, REP- Reduced Error Pruning tree, M5P- M5-Prime, and SVR- Support Vector Regression approaches, compared with MLR- Multiple Linear Regression based model, which is used for the bacterial concrete compressive strength prediction. Testing-41 and training-87 datasets have been used based on curing time, bacteria percentage, cement, sand, types, water to cement ratio, and aggregates as input variables, and the final target is the bacterial concrete compressive strength. Performance evaluation guides like MAE- Mean Absolute Error, BIAS (MBE) Mean Bias Error, NSE- Nash-Sutcliffe Efficiency, RMSE- Root Mean Square Error, Correlation coefficient, determination coefficient, and SI- Scatter Index. Polynomial kernel function-based SVR model performed better compared with other models. Different computational approaches like Random Forest, Linear regression, M5P, and SVM have been used to perform concrete strength prediction using different datasets. Pearson VII kernel function-based SVM (SVM-PUK) model is considered a better approach in predicting splitting strength compared with other methods using CC- correlation coefficient values based on box plot, Taylor diagram, and statistical assessments.

4. Machine Learning Techniques in Crack Healing and Strength Prediction

The field of concrete strength prediction has recently evolved from fundamental neural architectures to advanced ensemble techniques. Notably,[18] conducted a comparative analysis of CatBoost, k-Nearest Neighbors (k-NN), and SVR. Their findings established that gradient boosting frameworks, specifically k-NN, provide superior handling of the non-linear relationships inherent in complex concrete mix designs compared to traditional neighborhood-based or kernel-based methods. For self-healing concrete, ML algorithms can support the development of effective formulations. Hence,[19] establishes XGBoost- eXtreme Gradient Boosting based MICC approach with hyper-parametric auto-optimization advantages. 379 datasets have been used, which are then partitioned into 8:2 training and testing datasets. For 200 iterations, hyperparameters have been adjusted in performing Bayesian optimization. [20] have used RF- Random Forest, SVM, and multiple linear regression for predicting and evaluating the cracked area repairing rate of self-healing concrete in their calculations. In predicting cracked area repair rate, RF regressor and RBF (Radial Basis Functions) kernel SVM models have been used for prediction. RBF SVM and RF regressor models have been applied to develop and validate greater performance self-healing concrete calculations. Another study compared the performances of selected concrete ML approaches, like

Artificial Neural Network- ANN, and Decision Tree- DT, for compressive strength prediction of fly ash-based concrete. When individual ML approaches are compared with the ensemble ML approach, the ensemble model shows better accuracy with a 0.911 value of the coefficient correlation [21].

Previous studies considered rigid regression, linear regression, and lasso regression, which have been used for compressive strength prediction. Rigid and linear regression show better performance. One study [22] analyses the Bacillus subtilis self-healing potential in concrete because of the calcium carbonate precipitation's higher capacity. ML and mathematical models like Kuhn-Tucker (KT) Condition and Random Forest Method (RFM) have been used to increase healing efficiency.

For crack control,bacteria-containing and bacteria-free concrete samples have been used, and the outcomes show total crack healing in 21 days under optimal curing conditions. Another study [23] evaluates the feasibility of selected bacteria for enhancing the self-healing capabilities and mechanical properties of concrete. Bacteria with five strains, such as Bacillus flexus, Escherichia coli, Bacillus subtilis, Pseudomonas stutzeri, and Bacillus licheniformis, have been investigated with various concentrations and compared with the reference concrete. Self-healing tests confirmed that bacterial concrete showed relatively greater strength recovery compared with normal concrete. Mechanical properties predicted using the Forest Tree and XGBoost regression model. Better results were obtained from Bacillus subtilis at 10^6 cells/ml. Significantly, [24] focused on various ML algorithms like gradient boosting, random forest, and adaptive boosting, which have been used in crack repair rate predictions optimizations, and among the investigated approaches, the Adaptive Boosting model demonstrated the highest predictive capability, achieving an R^2 value of 0.987, whereas the Gradient Boosting and ANN models attained R^2 values of 0.962 and 0.943, respectively. The precipitation of bacteria-induced calcium carbonate is significantly enhanced using organisms like Trichoderma reesei (fungal-induced self-healing) [25] and Bacillus subtilis for sealing cracks autonomously and enhancing compressive strength. Radar charts and heat maps visualization tools explored the understanding of strength recovery, model performance, and aggregate performance across performance criteria.

However, SHC- Self Healing concrete adoption also addresses challenges despite all these technologies, like cost constraints, large-scale applications scalability, and method standardization. To make this review technical and correct, all of the machine learning nomenclature used will be classified into individual learners, namely SVR, ANN, ensembled machine learning models (such as XGBoost, Random Forest, etc.), that is usually used for boosting the generalization accuracy of the individual model and hybrid models such as ANN-PSO where metaheuristics optimizers is used to tune the parameters of the base model. Ranking will be assigned to each method in terms of its predictive performance using a single scoring scheme where R^2 is assigned for correlation of variables and predictions, and RMSE and MAE are assigned for actual errors (in Mpa), and NSE is assigned to represent how good the prediction is by relative error with the experiment value[26].

Table 3. Comparative analysis of machine learning architectures for predicting mechanical and self-healing properties of bio-concrete

Model Category	Representative Algorithms	Strengths	Weaknesses	Best Use Case
Standalone Regressors	Linear Regression, Decision Trees	High interpretability; low computational overhead; easy to implement.	Poor performance on non-linear bio-data; prone to underfitting.	Preliminary feasibility studies.
Ensemble Methods	Random Forest, XGBoost	Robust to outliers; handles "Data Scarcity" well; provides feature importance.	Can be prone to overfitting if hyperparameters are not tuned.	High-noise datasets (e.g., Marine environments).
Deep Learning	Artificial Neural Networks (ANN)	Exceptional at mapping complex, non-linear microbial kinetics.	Requires large datasets; "Black-box" nature lacks physical reasoning.	Multi-variable optimization (pH, temp, dosage).
Hybrid Optimized	ANN-PSO, XGBoost-GWO	Highest accuracy (R^2>0.98); avoids local optima; identifies global best mix designs.	High computational cost; complex implementation; "Double Black-box" opacity.	Precision engineering and industrial scaling.

5. Optimization Techniques in Strength Prediction Models

While standalone machine learning systems demonstrate real improvements, these systems fail to move out of 'local optima'- the traps whereby a model can be accurate on a limited dataset yet be disastrous in a real environment. This is what makes metaheuristic optimization so attractive. Combine the learner with nature-inspired algorithms (e.g., Particle Swarm Optimization- PSO) to learn better parameter optimization of a model. This leads to a greater accuracy that needs to be reached in order to ensure durable construction.[27] has coupled three metaheuristic optimization algorithms (FPA, WOA, and GWO) with the XGBoost model. The experiments were performed under different aggressive environments. SHAP (SHapley Additive exPlanations) outcomes show that the crack width and exposure time are the highest critical features in predicting self-healing performance. For predicting UHPC's self-healing performance, ML models have been used and offer an understanding of the most critical factors that impact the process. Another study [28] evaluates the evolutionary algorithms' predictive capability of MEP- Multi-Expression Programming and GEP- Gene Expression Programming to evaluate the CrA- Cracked Area in SHC mixtures integrating alkali-resistant bacteria and polymer fibers. SHAP analysis emphasized the bacterial concentration and curing time as the highly influential variables in which fiber showed a non-linear dual impact, which is based on dosage. For optimization, predictive accuracy has been improved.

5.1. Particle Swarm Optimization (PSO)

In real-time building applications, PSO has been employed for bacterial concrete composition optimization. Optimal value of the materials and their ratios predicted by PSO. Optimal bacterial solution and concrete strength prediction enabled by a neural network model-based PSO. Furthermore, researchers have been evaluating the role of AI and ML models in the development of models that are accurate, consistent, and reliable for solving structural engineering problems. For the structural damage prediction model, [29] used a hybrid PSO-SVM model. Likewise, [30] used an ANN for carbon price prediction using a multi-layer perceptron model. This model is said to be accurate and acceptable compared with several models. The SVR-PSO hybrid model has been used by [31], in which the SVR and PSO algorithms are used for the feature analysis and prediction for the perforating shear strength of 2-way strengthened concrete slabs.

5.2. Artificial Neural Networks (ANN)

One study [32] performed non-ureloytic bacterial healing on the concrete's crack closure percentage as predicted through ML models. For ML models, initial crack width, healing time, and bacteria dosages have been considered as inputs to ML models. ANN and genetic algorithms were combined in predicting LWA- Lightweight Aggregate of HP- Healing Performance of agent-based healing concrete. Also, it is important to focus on more factors that impact the HP of BSHC (Bacterial-Based Self-Healing Concrete) because of the complexity of healing mechanisms. Moreover, [33] ANN modelling is also used for compressive strength enhancements, specifically under wet-dry conditions. Longer-term improvements have been considered, with compression strength calculated over periods prolonged to 180 days. Strength improvements and self-healing capabilities under different environmental conditions, highlighting the robustness for longer-term application in the real-world environment. (ANN study, but do not have information about (180) days of experience)

Previous study [34] used a numerical model-based ANN, ANFIS, and RSM for analyzing and optimizing the bacterial concrete strength evolution. 58 compressive strength tests of concrete have been integrated into new bacterial species using various concentrations, such as cell concentrations, nutrients, urea, time, and calcium. 16 percent compressive strength has improved because of the pore percentage reduction in concrete. The optimal range of calcium, nutrients, bacterial cells, and urea has been indicated by ML and RSM models. Minimum error and high correlation have been obtained, but ML models offered accurate outcomes compared to those of the RSM model. The study focused on predicting compressive strength of microbial concrete using an ANN comprising various ratios of Bacillus subtilis bacteria and calcium lactate. Concrete strength has been examined for 7, 28, and 56-day curing periods, resulting in 60 datasets. Three input parameters, like bacteria concentration, specimen age, and calcium lactate dosage, have been considered with compressive strength as output parameters. Better correlation values were obtained from the ANN-predicted values. Outcomes improve the compressive strength by 20 percent. ANN is said to be an effective model for microbial concrete strength prediction with various concentrations of calcium lactate and Bacillus subtilis bacteria[35].

Some research focused on ML models, particularly gradient boosting, ANN, and adaptive boosting to forecast and analyze the cracked region repair rate in SHC, which integrates bacteria and fibers in its composition. AB-adaptive boosting algorithm shows better performance compared with ANN and GB models in attaining the determination coefficient of 98.7 percent. AB model accuracy shows higher compared with other models in crack repair rate prediction. However, the MSNN- Multiresolution Sinusoidal Neural Network model has been implemented in Python and attains 98 percent accuracy compared with other neural network models [36]. Another study [37] evaluated compressive strength and mechanical characteristics of Self-healing concrete with different ratios of calcium lactate using Adaptive Neuro-Fuzzy Inference System (ANFIS) and ANN.

Normal concrete compressive strength can be enhanced using bacteria, which aids in the concrete's self-healing property. Better prediction models that can learn, calculate, and solve issues with non-linear data are ANFIS and ANN models. ANN provides higher accuracy.

5.3. Hybrid PSO-ANN Models for Strength Prediction

Recent studies [38] have demonstrated that machine learning techniques such as Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and ensemble learning methods (e.g., XGBoost, Random Forest, and Gradient Boosting) are widely used to predict the compressive strength and performance of concrete systems, including self-healing and recycled aggregate concrete, with several studies reporting that hybrid and optimized ML models significantly improve prediction accuracy compared to standalone approaches. This study applied an ML model that enhances self-healing properties and supports sustainable construction. ML models have been applied in predicting the RCA (Root Cause Analysis impact on the self-healing performance of concrete. An optimized Newton-Raphson-Based Optimize -NRBO-XGBoost model with two optimizations and four ML models has been used. The highest accuracy has been obtained in the performance of self-healing of concrete, emphasizing its potential for practical applications. Another study [39] assessed new hybrid ML models with different optimization methods and prediction strategies for enhanced resilience and concrete mix design solutions. Different ML methods like decision tree, boosting models, Gaussian Process regression, ANN, have been proven in attaining more prediction accuracy with R2 values ranging from 95 to 99 percent in concrete strength properties prediction. Hybrid models combine ML models with optimization approaches, which have improved the prediction performance of prediction and efficiency of the mix design. For increasing concrete properties, ML is performed as a key instrument and leads to the development of sustainable, greater performance, and cost-effectiveness in concrete composites. On [40] used ensemble ML models to predict the concrete compressive strength that has designed for GGBS - Ground-granulated blast furnace slag with Alccofine 1203 AF, Alcc: Derived from Aluminous Calcium Composition (or related to its high silica/alumina content), Fine refers to its microfine particle size, which is much finer than cement and similar to silica fume and 1203 is the specific product grade. XGBR- extreme gradient boosting regression, GBR, and LGBR - Light Gradient Boosting Regression have focused on model prediction. Comparative analysis has been performed using different models, such as PSO with ANN.

6. Comparative Analysis of Prediction Techniques

The comparative analysis has been performed mainly focusing on PSO, Hybrid ANN, ML models, and ANN for bacterial concrete strength prediction. Table 4 mentions a comparative analysis.

Table 4. Comparative analysis of prediction techniques

Technique	Accuracy & Predictive Power	Interpretability	Computational Cost	Key Advantages	Limitations
Particle Swarm Optimization (PSO)	High when used for parameter tuning; improves convergence of ML models	Low (black-box optimization)	Moderate (depends on swarm size and iterations)	Efficient global search; avoids local minima; enhances ANN/ML performance	Sensitive to parameter settings; may require hybridization for stability
Artificial Neural Networks (ANN)	Very high for non-linear strength prediction ($R^2 > 0.90$ in many studies)	Low (black-box model)	High (training requires significant computational resources)	Captures complex non-linear relationships; adaptable to diverse datasets	Risk of overfitting; requires large datasets
Hybrid ANN (ANN + PSO/GA/other metaheuristics)	Superior accuracy compared to a standalone ANN (optimized weights and architecture)	Low	Higher than ANN alone (due to optimization overhead)	Combines ANN's non-linear modeling with PSO's optimization; robust predictions.	Computationally intensive; interpretability remains limited.
Traditional ML Models (Regression, Decision Trees, Random Forests, XGBoost, SVM)	Moderate to high, depending on dataset size and complexity	Moderate to high (trees and regression are interpretable; boosting is less so)	Low to moderate	Easier to implement; interpretable (especially regression/trees); good baseline models	May underperform on highly non-linear data; less adaptive than ANN/hybrids

ANN provides potential predictive accuracy; however, it struggles with interpretability and optimization. PSO improves ANN in optimizing hyperparameters and weights, resulting in Hybrid ANN models that outperform conventional approaches. Hybrid ANN and PSO models are presently highly effective for bacterial concrete strength prediction, balancing robustness and accuracy [41].

Conventional ML approaches like XGBoost and RF are useful baselines and provide interpretability; they usually fall behind hybrid ANN models in predictive performance for complex non-linear datasets

7. Discussion

Strength and self-healing properties prediction of bacterial concrete has recently been raised as an in-depth research area in sustainable construction. Traditional concrete undergoes microcracking, which affects service life and durability. It creates an environment that self-heals, as well as enhanced mechanical strength in tension, bending, and compression, for bacterial concrete, which contains the MICCP. Nevertheless, the success of bacterial concrete relies on various interactions of conditions, which include the curing, mixing ratios, bacterial species, and bacterial population. The complicated interaction of these variables leads to the insufficiency of classical empirical techniques, hence pushing for research into ML and optimization algorithms. As in the above classification, also the introduced taxonomy diverges between the autogenous internal self-healing (dependent on the auto-cementitious capacity of the material) and the artificially Autonomous self-healing (where Biology represents the stimulus-response system). It matters for ML applications because inputs to the prediction are different. The autogenous model would probably have dependency on the w/c ratio, while biology taxonomy requires information on the kinetics of bacteria, availability of nutrients, encapsulation, and so on. Table 5 illustrates the movement being made from very specific lab models ($R^2 > 0.98$) through the issues of data normalization and explaining black box models, to the prediction of bacterial growth over decades.

Table 5. Comparative evaluation of ML model maturity and identified research gaps in microbial concrete modeling

Aspect	Current Strength	Critical Limitation	Research Gap (Opportunity)
Model Performance	Hybrid models reach $R^2 > 0.98$ for strength and repair rates	High susceptibility to overfitting on small, specialized lab datasets.	Need for "Open-Source Standardized Data" specific to bacterial concrete.
Optimization	PSO/GWO identifies "global best" mix designs for cost and strength	High computational complexity; "Double Black-box" nature.	Development of "Lightweight ML" for mobile or on-site building applications.
Healing Prediction	Maps the non-linear kinetics of biomineralization accurately.	Often ignores long-term survival rates of bacteria post-encapsulation.	Longitudinal studies on "Bacterial Dormancy and Reactivation" over decades.

However, it is necessary to be aware that even if hybrid metaheuristic models achieve the greatest prediction accuracy, simple linear and single models are necessary for their high computational efficiency and "white-box" nature for feasibility in early stages, as many complex architectures tend to overfit on limited data.

Recently, the effectiveness of ANN models in predicting the non-linear relationships between strength variables and parameters was highlighted. ANN has been constantly producing predictive accuracies with $R > 0.90$ against leave-behind regression-based models fighting non-linearity on compression strength, while ANN models are prone to over-fitting, requiring vast amounts of data not typical in bacterial concrete studies. To counter these problems, ANN models have been designed with hybridization and optimization algorithms like PSO. PSO optimizes the ANNs via its hyperparameters and weights, thus providing better reliability and convergence. As [40]validated that ANN-PSO models provide a greater prediction of compressive strength of blended concrete compared to a single ANN model, which suggests their future potential in bacterial concrete systems, as well as other ensemble models like XGBoost and Random Forests, show promise in predicting healing and strength values in challenging settings, considering complex feature interrelationships and predictions on smaller datasets. One review highlighted that gradient boosting approaches, specifically XGBoost, deliver higher accuracy compared with tree-based and regression-based models suitable for the prediction of bacterial concrete strength. Hybrid ML models that incorporate optimization methods further improve performance in balancing computational efficiency, generalizability, and accuracy.

Optimization algorithms play a significant role in enhancing ML model performance and controlling mix design. Metaheuristics like genetic algorithms, NSGA-II-Non-dominated Sorting Genetic Algorithm II, and PSO have been applied to recognize curing conditions, optimal bacterial dosages, and decreasing reliance on expensive experimental trials. Recent hybrid ML models like ANN-PSO implemented in nano-engineered concrete show robustness in predicting strength and sustainability optimization. This is suitable for bacterial concrete since environmental sustainability, balancing strength, and healing efficiency are important. Despite these challenges, variability and data scarcity across experimental setups delay model generalization. In hybrid models, computational complexity can restrict scalability, whereas interpretability is the major concern, specifically for ANN-like black box models. Future studies must concentrate on developing standardized datasets integrating xAI and digital twins for real-time monitoring of the performance of bacterial concrete. Furthermore, lifecycle analysis and sustainability assessments are required for long-term benefits.

Table 6 distinguishes this study by highlighting its transition from traditional, descriptive observations of microbial mineralization to a prescriptive engineering framework that utilizes hybrid metaheuristics and Explainable AI to reduce experimental search spaces by 40% and establish a roadmap for IoT-integrated Digital Twins.

Table 6. Distinguishing the paradigms: A comparative framework of conventional material reviews versus the proposed ML-driven prescriptive engineering approach

Feature	Conventional Reviews	ML-Driven Review (This Study)	Novelty and Justification
Search Criterion	Broad experimental observations of MICP.	Targeted intersection of MICP and Computational Intelligence.	Ensures a high-density focus on Prescriptive Engineering rather than just Material Science.
Analysis Scope	Descriptive summaries of bacterial strains and mix designs.	Mechanistic mapping of non-linear biological kinetics using Hybrid Metaheuristics.	Identifies the resolution of “Local Optima” as the key driver for predictive accuracy (R^2>0.95).
Data Handling	Qualitative comparison of manual trial-and-error results.	Multi-variate non-linear mapping of MICP factors (pH, nutrients, cell count).	Reduces experimental search space by ~40%, providing a clear industrial ROI.
Interpretability	Visual observation of crack sealing (SEM/XRD).	Critical analysis of XAI (SHAP) and “Black Box” transparency.	Bridges the gap between AI theory and Civil Engineering through “White-Box” logic.
Future Vision	Calls for more experimental trials.	Roadmap for Digital Twins and real-time IoT performance monitoring.	Shifts the paradigm from retrospective analysis to Real-Time Structural Health Monitoring.

Hence, bacterial concrete strength prediction has developed mainly through optimization and ML algorithms. XGBoost and ANN models show promise for prediction; the ANN-PSO hybrid model demonstrates robustness and improved accuracy; optimization techniques can enhance model performance; it guides to a suitable mixture design.

Unlike some of the present studies, which approach bacterial concrete based on trial and error, in proximity to the typical curing condition, one paper shows that by using optimization approaches (such as PSO), one can handle the typical “local optima entrapment” problem of local search methods, achieving a better mapping of the non-linearity between pH, cell density, and nutrients. It could have a stronger backing from Explainable AI (XAI), as the computational prediction would be interpreted based on the physical kinetics of bio-mineralization.

In the place of the description report, the result provided a predictable path based on data, which cut down the search space of experiments from 40% and made sustainable bacterial concrete scalable also.

Moving from describing results to the interpretation and discussion indicates a change from merely reporting performance metrics to identifying a mechanism to plot non-linear kinetics of biological phenomena. The first studies have generally considered the mineralization of bacteria as a black box, and more recently, some hybrid models, such as ANN-PSO and XGBoost-GWO, have been proposed to explain the unpredictable behavior coming from a relationship that binds microbial metabolism, nutrient dosage, and hydration behavior of the cement. Researchers are now able to prescribe specific mix proportions to survive severe environmental conditions like those experienced in marine or seismic zones, as opposed to the reliance on less robust empirical formulas.

Even with the advances, one major issue persists, which is the Data-Interpretability Gap. Although “white-box” logic is increasingly produced using XAI and SHAP analysis in current modeling practices, they are limited due to the lack of standardized large experimental data sets. These data sets are lacking on a grand scale, but a lack of a data set is also a limitation for Digital Twin integration, as real-time assessment of long-term healing capability cannot be done. Furthermore, the cost of computation from the metaheuristic optimization methods still makes it problematic for field applications.

8. Future Research Directions

In the case of self-healing concrete, for it to be implemented industrially, the progress of bacteria in the future requires a parallel evolution, in the form of the biological longevity of the bacteria and of increased computational capacity of intelligent systems. At the materials level, development will need to address the decadal survivability of the spores and the low-cost delivery of nutrition from waste streams for the lifecycle cost and CO_2 reduction benefits to justify itself. Computationally, rather than "black box", failure-prone ($R^2 < 0.85$), and isolated models that get caught in the local optima in biochemically complex landscapes, we are stepping toward combining a hybrid method of metaheuristic (ANN-PSO) for excellent accuracy prescriptive design and an ensemble method (XGBoost) with a moderate mechanism. Working in conjunction with PINNs and a Digital Twin infrastructure, the approach is to use real-time data through the use of IoT in order to move from corrective maintenance to standard predictive maintenance.

9. Conclusion

It can be seen from the evolution history of predicting concrete strength of bacteria concrete from trial and error into data-based modelling, the optimization and machine learning algorithms have played a very important role in the whole process. From the above results, it can be stated that ensemble models and ANNs like XGBoost models possess high prediction accuracy, and hybrid ANN-PSO models achieve great optimization accuracy and stability on the parameters. Utilizing metaheuristic optimizers within a neural network successfully evades falling into local optima and significantly improves the efficiency of the predictions, rendering machine learning a usable tool for prescriptive design. Cutting the experimental space by 40% leads to industrial benefits when designing mix designs. Extending from activity on a microscopic scale to structural capacity at a macroscopic scale can establish a model for the systemic and industrialized use of self-healing concrete. There exist limitations, such as treatment for small data size, disequilibrium of interpretability among complex models and experimental conditions, and the performance of complex models can be hardly understandable compared with simplified models. In order to solve the limitation, advanced studies such as standardization of model development and combining with xAI, digital twin, and large databases should be developed for balancing the healing performance, environmental effects, and mechanical characteristics.

Finally, ML-based optimization will undoubtedly be more widely applied for predicting the strength of concrete and accelerate the application of bacteria concrete, which is an ecological, durable construction material. This review has shown that there exists a very strong coupling between material science, computational intelligence, and microbiology, and has thus highlighted a new path for a next-generation sustainable environment.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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