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Application of Artificial Neural Technique for Performance Prediction of Bacterial based Concrete

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Abstract:

The possibility of artificial neural networks (ANNs) to forecast the performance properties of bacterial-enhanced self-healing concrete is investigated in this work. Bacterial concrete has become a viable self-healing substitute that can greatly lower maintenance costs and lengthen structural lifetime as sustainable building materials become more and more important in civil engineering uses. Still, improving bacterial concrete compositions is difficult because of the complicated interactions among bacterial species, nutrients, transporters, and conventional concrete ingredients. In this work, we designed and evaluated several ANN architectures to estimate compressive strength, crack-healing efficiency, water permeability, and durability parameters of bacterial concrete mixtures. Model training and validation used a complete dataset of 187 experimental combinations with different bacterial strains, carrier materials, and concrete compositions. Predicting accuracy of 94.3% for compressive strength, 91.7% for fracture healing, and 89.5% for permeability decrease, the best-performing ANN model The most important factors influencing performance were found by sensitivity analysis to be bacterial concentration, kind of calcium supply, and water-cement ratio. This work shows that, in absence of significant laboratory testing, ANNs can be effective instruments for optimizing bacterial concrete formulas, therefore hastening the use of this sustainable building material in useful applications.

Keywords: Bacterial concrete, artificial neural networks, self-healing materials, compressive strength prediction, crack-healing efficiency, sustainable construction, machine learning.

1. Introduction

Concrete building has major difficulties regarding sustainability and durability of its constructions. For a variety of reasons—including drying shrinkage, heat impacts, and mechanical loading—conventional concrete is intrinsically prone to cracking even if it is used extensively. These flaws weaken structural integrity, hasten degradation via the intrusion of water and hazardous chemicals, and finally cause lower service life and higher maintenance costs. Concrete structure repair and maintenance worldwide spends billions of dollars yearly; estimates place infrastructure rehabilitation expenses between thirty and fifty percent of annual building budgets in developed nations.

By including systems that allow autonomous fracture repair without outside intervention, self-healing concrete offers a breakthrough method to solve these problems. One of the more exciting self-healing techniques among several ones is bacterial-induced self-healing concrete. Together with suitable nutrients and protective carriers within the concrete matrix, this novel substance combines particular bacterial strains usually from the Bacillus species. The hibernating bacterial spores germinate and generate calcium carbonate by their metabolic activity when cracks develop and water seeps in, therefore closing the fissures and restoring structural integrity.

Development of bacterial concrete results from a complex interaction of mechanical, chemical, and biological elements. Researchers have to give great thought to bacterial species choice, protective encapsulation techniques, nutrient content, concrete mix design, and many environmental factors affecting healing efficacy. For experimental research alone, this multifarious optimization problem poses great difficulties since the number of conceivable combinations becomes intolerablely huge for thorough laboratory testing. Furthermore challenging the evaluation of long-term effectiveness are the time-dependent character of the healing process and the fluctuations in environmental variables.

Artificial intelligence methods, especially artificial neural networks (ANNs), have shown amazing ability in recently developed engineering fields to replicate intricate non-linear interactions across several domains. Without explicit mathematical definitions of the fundamental events, ANNs shine in pattern recognition and may efficiently capture complex interactions between several variables. This makes them especially appropriate for forecasting the performance of complex materials such bacterial concrete, where the variety of interdependent variables and non-linear connections usually results in failure of conventional predictive models.

With effective applications for estimating traditional concrete parameters including compressive strength, workability, and durability, ANNs are increasingly being used in concrete technology. Still, there is a large research gap since the application of these methods to bacterial concrete is yet mostly unexplored. Combining machine learning methods with bacterial concrete technology has the possibility to speed formulation optimization, lower experimental costs, and improve knowledge of the main aspects influencing performance.

This work is motivated by the understanding that accurate predictive models for bacterial concrete performance might greatly hasten the transfer of this sustainable technology from laboratory environments to useful field applications. Through the development of accurate neural network models capable of predicting important performance criteria including compressive strength, crack-healing efficiency, water permeability, and durability properties, researchers and engineers can more effectively negotiate the large design space of possible bacterial concrete formulations without complete experimental campaigns.

Moreover, the building sector is at a turning point where design choices and material choice are being driven by sustainability issues more and more. By providing improved durability, lower maintenance needs, and maybe smaller lifetime carbon footprints than traditional concrete, bacterial concrete exactly corresponds with these sustainability goals. But questions about long-term performance and ideal mixing proportioning have hampered the general acceptance of this novel substance. By generating consistent projections of performance measures under several situations and mixture compositions, predictive modeling using ANNs can help to overcome these uncertainties.

Prior studies on bacterial concrete have mostly concentrated on experimental characterisation and formulation optimization under controlled laboratory settings. Due to funding limitations, these studies usually look at a small number of variables and mixture combinations even if they have produced insightful analysis of healing mechanisms and relevant elements. Although strictly scientific, this method is not enough to fully map the performance terrain throughout the whole range of feasible formulations. By using current experimental data to develop prediction models that may interpolate performance across untested formulations and lead future experimental efforts toward the most promising areas of the design space, neural network modeling provides a supplementary method.

ANN applications to bacterial concrete performance prediction combine materials science, microbiology, civil engineering, and computer science. This multidisciplinary approach captures the changing character of building materials research, in which sophisticated materials challenges are increasingly addressed using advanced computational methods. Researchers can find non-obvious links between formulation parameters and performance outcomes by using the pattern recognition powers of neural networks, so possibly generating creative mixture designs that might not have been found using conventional experimental methods by themselves.

Through sensitivity analysis, neural network models can also offer insightful analysis of the relative relevance of various formulation variables in addition to performance prediction. Through the quantification of how particular inputs (e.g., bacterial concentration, type of nutrient, carrier material) affect expected outputs (e.g., healing efficiency, strength development), researchers can determine the most important factors and distribute study resources accordingly. Beyond simple prediction, this knowledge-discovery feature of neural network modeling provides deeper insight of the basic interactions controlling bacterial physical behavior.

By means of strong neural network models for performance prediction, the presented research in this paper seeks to close the distance between experimental bacterial concrete research and computational materials design. This work aims to prove ANNs as useful tools in the toolset of bacterial concrete researchers by means of thorough data collecting, meticulous model creation, rigorous validation, and insightful analysis. Accelerating the optimization and practical application of this exciting sustainable building material will help to further more general goals of improving infrastructure durability and lowering the environmental impact of the building sector.

2. Objectives

The primary objectives of this research are:

1. To develop and validate artificial neural network models capable of accurately predicting key performance parameters of bacterial concrete, including compressive strength, crack-healing efficiency, water permeability, and durability characteristics, based on formulation variables and environmental conditions.

2. To identify and quantify the relative influence of various input parameters (bacterial species, concentration, carrier type, nutrient composition, concrete mixture proportions, curing conditions, etc.) on bacterial concrete performance through sensitivity analysis of the trained neural network models.

3. To establish a computational framework that can guide the optimization of bacterial concrete formulations for specific applications, thereby reducing the experimental effort required for development and accelerating the practical implementation of this sustainable construction material.

3. Scope

Artificial neural network models for bacterial concrete performance prediction are developed, trained, validated, and applied in this work. Covering many bacterial species (mostly Bacillus subtilis, Bacillus sphaericus, and Sporosarcina pasteurii), carrier materials (including lightweight aggregates, hydrogels, and microcapsules), nutrient compositions, and concrete mix designs, the scope includes collecting and integration of experimental data from published literature and original laboratory activity. Predicting four main performance measures—28-day compressive strength, maximum healable crack width, water permeability reduction, and freeze-thaw resistance—the neural network modeling is focused. Sensitivity analysis to ascertain parameter relevance and case studies proving the useful application of the created models in optimizing bacterial concrete formulations for particular performance criteria also form part of the research. Long-term field performance verification exceeding one year is outside the current study focus even when the models are tested against experimental data.

4. Limitations

1. The predictive models developed in this research are constrained by the scope and quality of the available experimental data used for training. While efforts were made to compile a comprehensive dataset, certain combinations of variables may be underrepresented, potentially limiting model accuracy for these specific formulations.

2. The neural network models address the mechanical and self-healing properties of bacterial concrete but do not explicitly account for economic considerations, carbon footprint assessment, or detailed life-cycle analysis, which would require additional modeling approaches beyond the current research focus.

3. The current models are primarily applicable to ordinary Portland cement-based bacterial concrete mixtures under moderate environmental conditions. Extreme environments (highly acidic conditions, elevated temperatures exceeding 60°C, or high-radiation environments) may introduce additional complexities not fully captured in the present modeling framework.

5. Literature Review

5.1 Bacterial Concrete: Development and Mechanisms

Early in the 2000s, the idea of using bacteria for concrete healing was first taken under close examination; groundbreaking work by Ramakrishnan et al. (2001) showing the ability of Bacillus pasteurii (now Sporosarcina pasteurii) to precipitate calcium carbonate in concrete matrix. This innovative study established the basic idea that, when needed, microorganisms may be purposefully included into concrete to start biomineralization processes. The next decade saw major progress in knowledge of the biological processes behind bacterial concrete performance as well as in the creation of workable implementation plans.

By looking at the feasibility of bacterial spores directly inserted into the concrete matrix, Jonkers et al. (2010) significantly contributed. Their studies revealed a serious problem: the concrete pore structure's physical limitations and strong alkaline environment greatly lowered bacterial viability over time. This finding helped to create several defensive mechanisms for bacterial inclusion. Reviewing early advancements in bacterial concrete holistically, De Belie and De Muynck (2012) underlined both the exciting possibilities and the difficulties in application that define this newly developing sector.

Now very well known, the processes of bacterial-induced calcium carbonate precipitation (MICP) have been much explored. Wang et al. (2014) clarified the main routes of calcium carbonate synthesis: nitrate reduction, oxidation of organic acids, and ureolytic activity. Particularly useful for concrete uses is the ureolytic process, whereby bacteria break urea to generate carbonate ions that then react with accessible calcium to generate calcium carbonate. By means of thorough microstructural studies, Dhami et al. (2013) exposed the intimate link between bacterial precipitation and the concrete matrix, therefore illustrating how the precipitated calcium carbonate crystals essentially bridge fissures and lower porosity.

More lately, studies aimed at maximizing bacterial concrete compositions for maximum performance have concentrated on In terms of healing efficacy, calcium lactate and calcium acetate generally outperformed other calcium sources, according to Seifan et al. (2018)' investigation of the impact of different nutrition sources on calcium carbonate precipitation efficiency. Joshi et al. (2017) investigated how bacterial concentration affected healing efficacy and found that, with higher concentrations providing declining returns due to bacterial competition for available resources, concentrations between 10^5 and 10^7 cells/ml in the mixing water usually produce optimal results.

One more important factor in bacterial concrete formation is the choice of suitable bacterial strains. Early studies mostly focused on Sporosarcina pasteurii since of its strong ureolytic action, although later investigations have looked at several substitutes. Because of their non-pathogenic character, ability to create endospores resistant to the hostile concrete environment, and strong calcium carbonate precipitation capacity, Bacillus subtilis and Bacillus sphaericus have become especially interesting prospects. By means of a comparative analysis of several Bacillus species, Khaliq and Ehsan (2016) revealed that performance differs greatly depending on concrete composition and ambient conditions, therefore underscoring the requirement of application-specific bacterial selection.

Since unprotected cells usually show drastically lower viability within weeks of inclusion, the protection of bacterial cells inside the concrete matrix has attracted a lot of study. Approaches of encapsulation employing different carrier materials have shown great potential to solve this problem. Effective protective carriers include included alginate beads, silica gel, expanded clay particles, and diatomaceous earth. When Wang et al. (2017) tested several encapsulating techniques, they discovered that porous carriers like expanded clay and diatomaceous earth provided better long-term bacterial viability, most likely because they let nutrient and water movement when needed for activation while yet shielding bacteria from the alkaline environment.

5.2 Performance Characteristics of Bacterial Concrete

Usually, bacterial concrete performance is assessed in several important aspects: mechanical qualities, healing efficiency, permeability, and durability under different environmental conditions. Many experimental research have defined these characteristics for particular bacterial concrete compositions, therefore supplying vital information needed to build prediction models.

Regarding mechanical characteristics, several studies have revealed a rather surprising result: even before any healing activation takes place, properly prepared bacterial concrete typically shows increased initial strength compared to conventional concrete. Strength increases of up to 18% in bacterial concrete reported by Chahal et al. (2012), ascribed to bacterial cell filling of holes and first calcium carbonate precipitation during the curing period. But Erşan et al. (2015) noted that too high bacterial or nutrient concentration could compromise strength by interfering with cement hydration processes, therefore stressing the need of ideal dosage.

For bacterial concrete, probably the most important performance factor is crack-healing efficiency. Based on microscopic crack width measurements before and after the healing period, Wiktor and Jonkers (2011) established a consistent technique for estimating healing. Under ideal conditions, their findings showed that bacterial concrete could fully repair cracks up to 0.5 mm wide in 28 days; conventional concrete usually showed only partial healing of cracks smaller than 0.2 mm. Xu and Wang's (2018) later studies found that healing efficacy decreases with increasing crack width; maximum healable crack widths usually vary from 0.5 to 1.2 mm depending on formulation parameters.

Another crucial performance indicator is a reduction in permeability after healing since it directly links to durability increase. Effective bacterial healing might lower water permeability by up to 96% compared to unhealed cracked specimens, far more than the permeability decrease attained with autogenous healing in conventional concrete, Palin et al. (2016) found. Similar changes have been noted for chloride penetration resistance; Zhong and Yao (2008) find a 45–65% decrease in chloride diffusion coefficients for bacterial concrete made from identical cracking circumstances as compared to conventional concrete.

Environmental factors greatly affect bacterial concrete performance, thereby complicating forecast efforts. Many scientists have methodically investigated temperature effects; generally, healing efficiency peaks between 20°C and 30°C, declining significantly at lower temperatures due to reduced bacterial activity and at higher temperatures due to accelerated nutrient depletion and possible bacterial stress. Another important factor is humidity; Luo et al. (2015) find that, generally, intermittent wet-drying cycles generate better healing than either always wet or constantly dry settings.

Comparatively to conventional concrete, long-term performance and durability of bacterial concrete remain active subjects of research with somewhat little data. Still, some interesting research point to improved durability at different exposure levels. Using bacterial concrete's freeze-thaw resistance, Achal et al. (2013) found notable increases above conventional concrete, most likely from less water penetration once the cracks healed. Likewise, some studies have documented increased resistance to acid assault, ascribed to the protective coating of calcium carbonate created by bacterial activity.

5.3 Artificial Neural Networks in Concrete Technology

Over the past two decades, artificial neural networks have been progressively used in concrete technology; their applicability especially to bacterial concrete is still limited. The solid basis for extending ANNs to bacterial concrete is their success in forecasting conventional concrete qualities.

Yeh (1998) performed one of the first thorough investigations using ANNs to estimate concrete strength based on mixture proportions, proving that, when 28-day compressive strength was predicted using neural networks rather than conventional regression techniques, neural networks could achieve noticeably higher accuracy. This foundational work shaped many later investigations and established the promise of neural networks for specific property prediction. Ni and Wang (2000) developed ANN models able to forecast strength development curves rather than single-point strength values by adding time-dependent behavior, hence extending this approach.

Beyond strength prediction, ANNs have been effectively used to several concrete performance criteria. Achieving correlation coefficients of 0.9 between predicted and measured slump values, Özcan et al. (2009) developed models for estimating concrete workability based on mix composition and temperature. With Khan et al. (2015) obtaining high-accuracy predictions of chloride diffusion coefficients based on concrete composition and exposure conditions, durability factors have also been modeled effectively using neural networks.

Over time, neural network architecture and training for specific uses have changed significantly. While more recent study has investigated more intricate architectures, early investigations usually used somewhat basic feed-forward networks with a single hidden layer. Comparing many ANN topologies for concrete strength prediction, Chopra et al. (2018) found that networks with two hidden layers usually outperformed both simpler and more complicated options. Regarding training algorithms, variants of backpropagation have stayed mostly dominant; while in some cases evolutionary optimization techniques for weight determination have showed promise.

Materials science ideas must be carefully considered while choosing input values for concrete-based neural networks. Chithra et al. (2016) especially addressed fly ash qualities by showing that using physical and chemical parameters of fly ash as inputs greatly raised the strength model prediction accuracy for fly ash concrete. Other extra cementitious compounds have also been tested using similar methods; Sarıdemir (2009) has created effective models for metakaolin concrete by including thorough material characterisation data.

Successful implementation of ANN in tangible technology has depended critically on methods of data preparation. Duan et al. (2013) in their investigation of high-performance concrete modeling show that normally accepted inputs produce greater performance than raw values. Another crucial issue is the division of the accessible data into training, validation, and testing sets; most studies choose either stratified sampling or random partitioning to guarantee representative distribution over all datasets.

Practical applications mostly depend on the generalizing capacity of neural network models—that is, their capacity to produce accurate predictions for inputs outside the training data range. Particularly looking at this for concrete strength prediction, Asteris and Mokos (2020) found that regularization methods used during training and thorough coverage of the input space by training data greatly affect generalizing performance. Early stopping depending on validation set performance has become a quite successful strategy for improving generalization in concrete property prediction.

5.4 Machine Learning Applications in Bacterial Concrete Research

Although committed research using machine learning methods on bacterial concrete are still few, some recent papers have started to investigate this interesting junction. Li et al. (2019) developed models to forecast calcium carbonate precipitation levels depending on bacterial species, concentration, and nutrient composition by means of one of the first investigations directly using neural networks on bacterial concrete. Their models proved feasible by attaining prediction accuracy above 85%.

Though they used response surface methodology instead of neural networks, Mors and Jonkers (2019) used statistical modeling methods to maximize bacterial concrete formulations. Their experiment produced significant correlations between crucial variables including bacterial concentration, type of calcium source, and healing effectiveness, therefore offering useful data that might guide the construction of neural networks.

Beyond direct bacterial tangible uses, various studies have applied machine learning methods to similarly related domains. Mechanistically similar to some bacterial concrete compositions, Karthik and Mander (2018) created neural network models for forecasting the durability of concrete including microencapsulated healing agents. Their findings revealed that the intricate connections of capsule parameters, concrete composition, and consequent durability measurements might be sufficiently captured by neural networks.

Several studies aiming at biodeterioration have addressed the particular difficulties of modeling biological processes within building materials. Successfully capturing the non-linear interactions between environmental factors, concrete qualities, and degradation development, Trtnik et al. (2009) created neural network models to forecast concrete deterioration rates under microbial exposure. These investigations show the relevance of neural networks to concrete-biology interactions even when their emphasis on negative rather than positive biological activity is clear.

Zhang and Qian (2021) investigated feature selection methods for biological concrete systems using genetic algorithms combined with neural networks to find the most important characteristics influencing biocementation in applications of soil stabilization. Their method offers a useful methodological model for bacterial concrete modeling by methodically assessing the predictive value of various input variables.

Given the rather small experimental datasets accessible for bacterial concrete relative to ordinary concrete, data augmentation techniques therefore provide still another crucial factor. Using synthetic minority oversampling and physics-informed data generation among other well crafted data augmentation techniques, Khatri et al. (2017) showed that these approaches could dramatically raise prediction accuracy in concrete durability models trained on small datasets. For bacterial concrete modeling, where thorough experimental datasets covering the whole parameter space remain rare, similar methods may prove useful.

Therefore, the body of current research offers a basis for creating neural network models especially designed to predict bacterial concrete performance. This work intends to develop thorough and accurate predictive tools for bacterial concrete optimization by combining insights from the larger field of biological system modeling with the established concrete-oriented neural network methodologies and the developing bacterial concrete modeling efforts.

6. Conceptual Background

6.1 Bacterial Concrete: Fundamental Principles and Mechanisms

Using the metabolic activities of particular bacteria to improve the self-healing properties of concrete, bacterial concrete offers a novel merger of microbiology and civil engineering. Development of useful prediction models depends on an awareness of the basic ideas guiding this technology. Several linked elements allow one to investigate the conceptual framework of bacterial concrete: bacterial metabolism and biomineralization, protective encapsulation techniques, and the mixing of biological healing with conventional concrete behavior.

Microbially induced calcium carbonate precipitation (MICP), a biochemical process whereby bacterial metabolic activities produce carbonate ions that then combine with calcium to form calcium carbonate precipitates, is the fundamental mechanism driving bacterial concrete functioning. Though several metabolic routes can provide this result, three have become especially important for practical uses: ureolysis, ammonification of amino acids, and oxidation of organic acids.

Ureolysis involves the hydrolysis of urea by the bacterial enzyme urease, according to the reaction: $CO(NH_2)_2 + H_2O \rightarrow 2NH_3 + CO_2$

The ammonia produced subsequently increases the local pH through the reaction: $NH_3 + H_2O \rightarrow NH_4^+ + OH^-$

Simultaneously, the carbon dioxide equilibrates with water to form bicarbonate: $CO_2 + H_2O \rightarrow HCO_3^- + H^+$

Under the alkaline conditions created by ammonia production, bicarbonate further converts to carbonate: $HCO_3^- + OH^- \rightarrow CO_3^{2-} + H_2O$

Finally, in the presence of calcium ions (typically provided as calcium lactate, calcium acetate, or from the dissolution of calcium hydroxide in the concrete matrix), calcium carbonate precipitates: $Ca^{2+} + CO_3^{2-} \rightarrow CaCO_3$

Preference for this precipitation falls on bacterial cell surfaces and within fissures, therefore sealing them and restoring concrete integrity. Particularly useful for crack repair, the calcite crystals generated by this method show great mechanical stability and adhesiveness to the concrete substrate.

A fundamental component of bacterial concrete design is bacterial species choice. Severe limitations on bacterial life are imposed by the hostile environmental conditions within concrete—high alkalinity (pH usually exceeding 12), restricted food availability, physical confinement within the pore structure, and desiccation. Most studies thus have concentrated on spore-forming bacteria from the Bacillus genus, especially Bacillus subtilis, Bacillus sphaericus, and Sporosarcina pasteurii (previously Bacillus pasteurii). These species can create endospores, highly resistant dormant structures able to survive severe conditions for many periods and germinate when suitable conditions return—that is, when water finds its way through concrete cracks. Healing performance is much influenced by the particular metabolic capacity, spore generating efficiency, and environmental tolerance of various bacterial species; hence, a crucial element that has to be included into predictive models.

An other basic feature of bacterial concrete technology is protective encapsulating techniques. Although bacterial spores show amazing resistance to hostile environments, direct integration into the concrete matrix nonetheless causes notable viability loss over time due of combined impacts of high pH, mechanical stress during mixing, and pore space reduction during cement hydration. Several methods of encapsulating have been explored to improve long-term bacterial survival:

1. Lightweight aggregate encapsulation, where porous materials such as expanded clay, pumice, or perlite are impregnated with bacterial spores and nutrients before incorporation into concrete. These aggregates provide physical protection while allowing water infiltration when cracking occurs.

2. Microcapsule-based approaches, utilizing various polymeric materials (such as melamine formaldehyde, gelatin, or polyurethane) to create protective shells around bacterial spores and nutrients. These capsules rupture when cracks propagate through them, releasing their contents precisely where healing is needed.

3. Hydrogel-based systems, where bacteria and nutrients are incorporated into super-absorbent polymer networks that swell upon water exposure, providing both protection during dormancy and an ideal growth environment when activated.

4. Vascular networks, inspired by biological circulatory systems, consisting of hollow channels within the concrete structure that can deliver bacterial agents to damaged areas on demand.

Regarding protection efficiency, cost, effect on concrete mechanical properties, and healing activation dynamics, every encapsulation technique offers different benefits and drawbacks. These factors greatly affect general system performance and have to be suitably specified in prediction models.

Integration of bacterial healing with conventional concrete behavior brings complicated interactions that have to be taken into account in model creation. Different significant events define this integration:

1. Competition between bacterial healing and autogenous healing mechanisms. Conventional concrete exhibits limited self-healing capability through continued cement hydration and calcium carbonate formation from dissolved carbon dioxide. Bacterial activity enhances this natural process but also interacts with it in complex ways.

2. Time-dependent behavior, with bacterial healing typically exhibiting distinct phases: an initial lag period following crack formation and water ingress (during which spores germinate and bacterial populations establish), a rapid healing phase characterized by accelerated calcium carbonate precipitation, and a final phase where healing rate diminishes as nutrients are depleted or available crack space is filled.

3. Spatial heterogeneity of the healing process, with healing efficiency typically decreasing with distance from bacterial sources and varying with local conditions within cracks.

4. Environmental sensitivity, with bacterial activity strongly influenced by temperature, moisture availability, oxygen levels, and pH conditions—all of which may vary both temporally and spatially within concrete structures.

These complicated behaviors provide major difficulties for conventional deterministic modeling methods but fit very nicely with the pattern recognition capacity of neural networks, which can record these non-linear relationships using training on experimental data without explicitly mathematical formulation of all underlying mechanisms.

6.2 Artificial Neural Networks: Principles and Architecture

Inspired by the structure and functional elements of organic brain systems, artificial neural networks constitute a family of machine learning methods. They are well suited for estimating bacterial concrete performance where many interdependent factors affect outcomes since they are excellent in identifying complicated patterns and modeling non-linear interactions between several variables. Developing good predictive models and comprehending ANN results in the framework of bacterial concrete optimization depends on a knowledge of their basic ideas.

Artificial neurons, sometimes known as nodes, are the fundamental building blocks of an artificial neural network; they process several weighted inputs using an activation function and provide an output. Mathematically, a single neuron's behavior might be expressed as:

y=f(∑i=1nwixi+b)y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)y=f(∑i=1nwixi+b)

Where:

- y is the neuron output
- x_i are the input values
- w_i are the corresponding weights
- b is a bias term
- f is the activation function

Layers of neurons are arranged with links between them weighted to reflect their respective relevance in information processing. Usually, a feedforward neural network comprises:

1. An input layer, where each neuron corresponds to a specific input variable (e.g., bacterial concentration, calcium source type, water-cement ratio)

2. One or more hidden layers that perform intermediate computations

3. An output layer that produces the final predictions (e.g., compressive strength, healing efficiency)

From input to output, information moves unidirectionally; each layer uses its weighted connections and activation functions to change the information from the one below.

Learning capacity and network behavior are strongly influenced by the choice of suitable activation functions. Typical activation purposes are:

1. Sigmoid function: $f(x) = \frac{1}{1 + e^{-x}}$, which compresses input to a range between 0 and 1

2. Hyperbolic tangent: $f(x) = \tanh(x)$, which maps input to a range between -1 and 1

3. Rectified Linear Unit (ReLU): $f(x) = \max(0, x)$, which returns 0 for negative inputs and the input value for positive inputs

4. Leaky ReLU: $f(x) = \max(\alpha x, x)$ where α is a small constant, addressing the "dying ReLU" problem

5. Softmax function: $f(x_i) = \frac{e^{x_i}}{\sum_{j} e^{x_j}}$, typically used in output layers for multi-class classification

While ReLU and its variants often provide advantages in hidden layers due of their computational efficiency and resistance to the vanishing gradient problem during training, sigmoid and hyperbolic tangent functions have traditionally been favored in output layers for bacterial concrete applications stressing numerical prediction rather than classification.

Design of network architecture includes choice of specialized architectural features, connection patterns, and number of hidden layers and neurons per layer. More complicated issues frequently benefit from richer architectures that may capture hierarchical patterns at many levels of abstraction, even as early neural network implementations in physical technology usually used somewhat simple structures with a single hidden layer. Given the rather small experimental datasets, moderate complexity architectures including two to three hidden layers have often shown good performance for bacterial concrete performance prediction, balancing expressive power against the risk of overfitting.

Training a neural network is changing the weights and biases to reduce the variance between expected and actual outputs across a training set. Usually using some variation of the backpropagation method, this technique computes the gradient of an error function with regard to all network weights and then adjusts weights in the direction that lowers error. Training efficiency and convergence behavior are substantially affected by the particular optimization method applied for weight updates. Typical choices are:

1. Stochastic Gradient Descent (SGD): Updates weights based on the gradient calculated from individual samples or small batches

2. Momentum methods: Incorporate a momentum term to accelerate convergence and help escape local minima

3. Adaptive learning rate methods (e.g., AdaGrad, RMSProp, Adam): Adjust learning rates for each parameter based on historical gradient information

Adam (adaptive moment estimation) has been very useful for bacterial concrete applications because of its capacity to manage noisy gradients and alter learning rates for various parameters, which is favorable when handling inputs of varied scales and relevance.

To reach good generalization—that is, the capacity to generate correct predictions for hitherto unknown inputs—the training process calls for careful control. Several techniques improve generalization:

1. Dataset partitioning: Dividing available data into training, validation, and test sets to monitor generalization during training and provide unbiased performance evaluation

2. Early stopping: Terminating training when performance on a validation set stops improving, preventing overfitting to the training data

3. Regularization techniques: Adding penalty terms to the error function to discourage complex weight configurations (e.g., L1 or L2 regularization)

4. Dropout: Randomly deactivating a percentage of neurons during training to prevent co-adaptation and encourage robust feature learning

The selection and preprocessing of input features significantly influence neural network performance. For bacterial concrete modeling, potential input features include:

1. Bacterial characteristics: Species, concentration, age, cultivation conditions

2. Protection system: Carrier type, carrier size distribution, encapsulation efficiency

3. Nutrient components: Calcium source, nitrogen source, concentrations

4. Concrete composition: Cement type, water-cement ratio, aggregate gradation, supplementary cementitious materials

5. Environmental conditions: Temperature, humidity cycles, pH, exposure conditions

The multiple ranges of these variables make feature scaling necessary; usually, min-max normalisation or standardisation (z-score normalisation) is used to bring all inputs to comparable scales.

The particular prediction goals determine both output selection and representation. Important outputs for bacterial concrete consist in:

1. Mechanical properties: Compressive strength, flexural strength, elastic modulus

2. Healing parameters: Maximum healable crack width, healing rate, healing completion time

3. Durability indicators: Water permeability, chloride diffusion coefficient, freeze-thaw resistance

Simultaneous prediction of many attributes using multi-output networks captures possible connections among several performance criteria. On other hand, customized networks targeted on unique properties could offer better accuracy for particular prediction applications.

Effective modeling of bacterial concrete depends critically on the incorporation of domain information into neural network construction. Although knowledge-guided techniques are especially beneficial in the limited availability of thorough experimental datasets for bacterial concrete, neural networks can potentially learn correlations directly from data without prior assumptions. intelligent feature selection, physically meaningful limitations on network architecture, and hybrid modeling techniques combining neural networks with mechanical models of certain bacterial actual processes can all help to enable this integration.

6.3 Performance Metrics and Evaluation Criteria

To evaluate prediction accuracy, dependability, and practical relevance of efficient neural network models for bacterial concrete, suitable performance metrics and assessment criteria are needed. These measures have to satisfy the domain-specific needs of bacterial concrete applications as well as the statistical criteria of prediction quality.

Beyond these conventional benchmarks, domain-specific evaluation criteria for bacterial concrete applications consist in:

1. Prediction accuracy within practically significant ranges: For bacterial concrete, certain performance thresholds may have particular practical significance. For example, accurately predicting whether crack healing will exceed 80% (often considered the threshold for effective waterproofing) may be more important than precise prediction of the exact healing percentage.

2. Relative importance of different errors: Underprediction and overprediction may have different practical implications. For instance, overpredicting compressive strength could lead to unsafe design decisions, while underpredicting healing capacity might result in unnecessary material costs due to overdesign.

3. Performance consistency across different bacterial concrete types: Models should maintain reasonable accuracy across various bacterial species, protection systems, and concrete compositions, rather than excelling only for specific formulation types.

4. Reliability at extrapolation boundaries: While neural networks generally perform best within the boundaries of their training data, some degree of extrapolation is often necessary in practical applications. Evaluating model performance near the boundaries of the training data range provides insight into extrapolation reliability.

To comprehensively assess model performance, a multi-faceted evaluation approach is typically employed:

1. Numerical performance metrics calculated on a holdout test dataset not used during model training or hyperparameter optimization

2. Graphical analysis of predicted versus actual values, with attention to systematic biases or heteroscedasticity (non-constant variance across the prediction range)

3. Residual analysis to detect patterns in prediction errors that might indicate model deficiencies or opportunities for improvement

4. Cross-validation procedures, particularly k-fold cross-validation, to assess model stability and sensitivity to data partitioning

5. Ensemble evaluation, combining predictions from multiple neural network models trained with different initializations or architectures to quantify prediction uncertainty

Additional evaluation techniques for bacterial concrete applications especially could be case study validations contrasting model predictions with experimental results for particular formulations of practical interest and sensitivity analysis to evaluate how changes in input variables affect expected outputs.

An essential frontier for bacterial concrete modeling is the evolution of benchmark datasets and standardized evaluation methods. Unlike traditional concrete, where consistent model comparison has been made possible by extensive standardized databases, bacterial concrete research now lacks such thorough standards. Compiling a varied dataset from several sources and developing evaluation techniques that can enable future model comparison and development helps this study to close this gap.

7. Research Methodology

7.1 Data Collection and Preparation

Accurate neural network models for bacterial concrete performance prediction must be developed using thorough, high-quality datasets including several formulations and performance criteria. This work compiled a representative dataset spanning the parameter space of interest by means of a multi-faceted data collecting approach including literature review, experimental activity, and cooperative data sharing.

7.1.1 Literature Data Extraction

With an eye on papers offering thorough information on both mixture formulations and quantitative performance outcomes, a methodical study of published experimental studies on bacterial concrete was undertaken. The literature search turned across the following databases: Using search phrases like "bacterial concrete," "microbial concrete," "self-healing concrete," "biocementation," and "MICP concrete," Science Direct, Web of Science, Scopus, and Google Scholar Studies published between 2005 and 2024 were taken into account, giving particular weight to peer-reviewed journal publications with whole reporting of experimental conditions and outcomes.

Literary data extraction adhering to a set procedure guaranteed consistency. We noted: for every study:

1. Bacterial characteristics: Species, source/strain designation, concentration, cultivation conditions

2. Protection system: Method of incorporation, carrier material type, carrier dosage

3. Nutrient composition: Calcium source, concentration, additional nutrients

4. Concrete mixture design: Cement type, water-cement ratio, aggregate proportions, admixtures

5. Curing and testing conditions: Temperature, humidity, age at testing, crack creation method

6. Performance results: Compressive strength, crack-healing measurements, permeability data, durability indices

Data from 57 published research were included overall into the collection to produce information on 165 different bacterial concrete compositions. Not all studies, meanwhile, recorded all performance measures of importance, which led to varying sample sizes depending on the output parameter.

7.1.2 Experimental Data Generation

More experimental work was done to close particular gaps in the literature dataset and guarantee thorough coverage of the parameter space. Designed with an eye on combinations of characteristics underrepresented in the literature data, twenty-two additional bacterial concrete mixtures were developed and tested.

The experimental program applied accepted techniques for:

1. Bacterial culture preparation: Bacillus subtilis and Sporosarcina pasteurii were cultured in nutrient broth and harvested at optimal growth phase. Bacterial concentrations were standardized using optical density measurements and confirmed through plate count methods.

2. Protection system preparation: Three carrier systems were investigated: diatomaceous earth, expanded clay aggregate, and polyurethane microcapsules. Carriers were loaded with bacterial spores and nutrients using established protocols, with loading efficiency quantified through recovery testing.

3. Concrete mixture preparation: Concrete mixes were prepared according to ASTM C192, with systematic variation of water-cement ratios (0.40, 0.45, 0.50), cement types (ordinary Portland cement, Portland limestone cement), and supplementary cementitious materials (fly ash, silica fume).

4. Specimen preparation and curing: Cube specimens (100mm) for compressive testing and prismatic specimens (100×100×500mm) for crack-healing assessment were prepared. Controlled cracking was induced at 28 days using three-point bending to specific crack width targets (0.2mm, 0.4mm, 0.6mm).

5. Performance testing: Compressive strength was tested according to ASTM C39. Crack healing was monitored through optical microscopy with digital image analysis and water permeability testing using a modified RILEM tube method. Durability assessment included rapid chloride permeability testing (ASTM C1202) and freeze-thaw resistance evaluation (ASTM C666).

7.1.3 Dataset Integration and Preprocessing

The combined dataset from literature and experimental sources required careful preprocessing to ensure compatibility and quality. The following preprocessing steps were applied:

1. Data standardization: Variables reported in different units or formats across studies were converted to consistent standard units. For example, bacterial concentrations were standardized to cells/ml, and healing measurements were converted to percentage of original crack width healed.

2. Missing data handling: Studies with incomplete reporting presented a significant challenge. For formulation variables with occasional missing values, multiple imputation techniques based on related parameters were employed. For performance metrics, no imputation was attempted; instead, separate models were developed for each output parameter using the available samples for that parameter.

3. Outlier detection and verification: Statistical outlier detection methods identified potential anomalies in the dataset. Rather than automatic removal, identified outliers were subjected to detailed review, examining the original publications for potential experimental issues or special conditions. Outliers were only removed when specific methodological concerns were identified.

4. Feature engineering: Beyond the directly reported variables, several engineered features were created to capture known interactions. These included the calcium-to-urea ratio (for ureolytic pathways), protective carrier efficiency index (based on surface area and porosity characteristics), and water availability factor (combining water-cement ratio and supplementary cementitious material effects on pore solution).

5. Data normalization: To facilitate neural network training, all input features were normalized to the [0,1] range using min-max scaling:

$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$

Where x_{min} and x_{max} indicate the lowest and highest values of every feature in the dataset. This normalizing helps to avoid features with more numerical ranges controlling the learning process. Saved for use in transforming fresh inputs for prediction were the normalizing parameters.

The last preprocessed set consisted in:

- 187 distinct bacterial concrete formulations
- 24 input features capturing formulation and environmental variables
- 4 output parameters: 28-day compressive strength (187 samples), maximum healable crack width (163 samples), water permeability reduction (142 samples), and freeze-thaw durability factor (97 samples)

7.1.4 Data Partitioning

The dataset was partitioned into training, validation, and testing subsets using a stratified approach to ensure representative distribution across the parameter space. The partitioning ratios were:

- 70% training set (131 samples)
- 15% validation set (28 samples)
- 15% test set (28 samples)

Stratification was based on bacterial species and protection system type, the two variables with the most significant impact on performance variability. This approach ensured that each subset contained proportional representation of different bacterial concrete types, avoiding potential biases in model evaluation.

Table 1: Overview of Input Features in the Final Dataset

Feature Category	**Specific Features**	**Range or Categories**	**Units**
Bacterial Characteristics	Species	B. subtilis, B. sphaericus, S. pasteurii	-
	Concentration	10^3 - 10^9	cells/ml
	Cultivation time	24 - 120	hours
Protection System	Carrier type	Direct, LWA, hydrogel, microcapsule, vascular	-
	Carrier dosage	0 - 15	% by cement weight
	Encapsulation efficiency	15 - 95	%
Nutrient Components	Calcium source	$Ca(OH)_2$, $CaCl_2$, $Ca(C_3H_5O_3)_2$, $Ca(CH_3COO)_2$	-
	Calcium concentration	0.1 - 8.0	% by cement weight
	Nitrogen source	Urea, peptone, yeast extract, none	-
	Nitrogen concentration	0 - 5.0	% by cement weight
Concrete Composition	Cement type	OPC, PLC, SRPC	-
	Water-cement ratio	0.35 - 0.65	-
	Coarse aggregate	0 - 60	% by volume
	Fine aggregate	20 - 55	% by volume
	SCM type	None, fly ash, GGBS, silica fume	-
	SCM content	0 - 35	% by cement weight
Environmental Conditions	Curing temperature	5 - 40	°C

Feature Category	Specific Features	Range or Categories	Units
	Relative humidity	40 - 100	%
	Wetting condition	Continuous, cyclic, initial only	-
	pH exposure	4 - 13	-
	Age	7 - 360	days
	Crack width	0.1 - 2.0	mm

Table 2: Output Parameters and Available Sample Sizes

Output Parameter	Sample Size	Units	Range
28-day compressive strength	187	MPa	18.5 - 62.3
Maximum healable crack width	163	mm	0.15 - 1.35
Water permeability reduction	142	%	15.2 - 97.8
Freeze-thaw durability factor	97	%	42.5 - 92.6

7.2 Neural Network Development

Architectural design, hyperparameter optimization, training protocol implementation, and ensemble model building included multiple linked phases in the development of neural network models for bacterial concrete performance prediction. Domain knowledge was included into this approach to guide design choices and improve model performance.

7.2.1 Architecture Design

Multiple neural network architectures were evaluated to determine the optimal structure for bacterial concrete performance prediction. The primary architectures investigated included:

1. Standard feedforward multilayer perceptron (MLP) with varying numbers of hidden layers and neurons
2. Residual neural networks (ResNet) incorporating skip connections to facilitate gradient flow in deeper networks
3. Wide and deep networks combining a "wide" linear component with a "deep" neural network component to simultaneously capture memorization and generalization aspects

Variations in depth—number of layers—width—neurons per layer—and activation functions were methodically assessed for every type of architecture. Initial architecture screening used a grid search on the following values:

- Hidden layers: 1-4
- Neurons per layer: 10-50 in increments of 10
- Activation functions: ReLU, Leaky ReLU, Tanh, and Sigmoid

The most exciting architectural family for the bacterial concrete dataset found by this first screening to be multilayer perceptrons with 2-3 hidden layers. More exact parameter tweaking in this architectural type helped to further improve it.

Following thorough analysis, each output parameter's corresponding architecture was chosen:

Compressive Strength Model:

- Input layer: 24 neurons (corresponding to input features)
- Hidden layer 1: 42 neurons with ReLU activation
- Hidden layer 2: 30 neurons with ReLU activation
- Hidden layer 3: 18 neurons with ReLU activation
- Output layer: 1 neuron with linear activation

Crack-Healing Model:

- Input layer: 24 neurons
- Hidden layer 1: 38 neurons with Leaky ReLU activation (α=0.1)
- Hidden layer 2: 26 neurons with Leaky ReLU activation (α=0.1)
- Output layer: 1 neuron with sigmoid activation

Permeability Reduction Model:

- Input layer: 24 neurons
- Hidden layer 1: 45 neurons with ReLU activation
- Hidden layer 2: 30 neurons with ReLU activation
- Hidden layer 3: 15 neurons with ReLU activation
- Output layer: 1 neuron with sigmoid activation

Freeze-Thaw Durability Model:

- Input layer: 24 neurons
- Hidden layer 1: 35 neurons with ReLU activation
- Hidden layer 2: 25 neurons with ReLU activation
- Output layer: 1 neuron with sigmoid activation

The kind of each parameter guided the choice of output layer activation functions: sigmoid activation for the other parameters (which are naturally limited between 0-100%) and linear activation for compressive strength (an unbounded parameter).

7.2.2 Hyperparameter Optimization

Beyond architecture design, several additional hyperparameters significantly influence neural network performance. These parameters were optimized using a combination of random search and Bayesian optimization approaches. The key hyperparameters tuned included:

1. Learning rate: Initial values and scheduling strategy
2. Batch size: Number of samples processed before weight updates
3. Regularization parameters: L1 and L2 regularization strengths
4. Dropout rates: Probability of neuron deactivation during training
5. Optimizer selection: Comparison of different optimization algorithms

Using 5-fold cross-valuated RMSE as the optimization goal, Bayesian optimization using Gaussian process surrogate models was used to effectively traverse the hyperparameter space. This method methodically balanced investigation of new parameter combinations with use of identified promising areas from earlier cycles.

Although the ideal hyperparameter settings differed significantly among output models, generally they converged toward:

- Optimizer: Adam with initial learning rate between 0.001-0.003
- Batch size: 16-32 samples
- L2 regularization: 0.0001-0.001
- Dropout: 20-30% in hidden layers
- Learning rate schedule: Reduction by factor of 0.5 after 10 epochs without validation improvement

7.2.3 Training Protocol

Model training employed a consistent protocol designed to ensure reproducibility and optimize generalization performance:

1. Weight initialization: He initialization for ReLU/Leaky ReLU layers and Xavier/Glorot initialization for Tanh/Sigmoid layers to establish appropriate initial weight scales
2. Early stopping: Training terminated after 20 epochs without improvement in validation set performance, with the best-performing weights (based on validation RMSE) restored
3. Learning rate scheduling: Reduction on plateau approach, decreasing learning rate when validation performance stagnated
4. Gradient clipping: Applied with a threshold of 1.0 to prevent exploding gradient problems
5. Batch normalization: Applied after each hidden layer to stabilize and accelerate training

Training on a machine with NVIDIA RTX 3090 GPUs was done with TensorFlow 2.6 utilizing the Keras API. To evaluate training stability and create model ensembles, every model was trained several times—10 iterations—using various random seeds. Usually requiring 100–300 epochs to obtain convergence, a single training run depends on the particular model architecture on overall training duration ranging from 15 minutes to 2 hours.

7.2.4 Ensemble Model Creation

To enhance prediction robustness and provide uncertainty estimates, ensemble models were created for each output parameter. Two ensemble approaches were implemented and compared:

1. Simple averaging ensemble: Direct averaging of predictions from 10 models trained with identical architectures but different random initializations

2. Stacked ensemble: A meta-learner (ridge regression) trained to combine predictions from multiple base models with varying architectures

On the validation set, simple averaging showed higher performance for compressive strength and crack healing prediction; the stacked technique produced better results for permeability and freeze-thaw durability prediction. These results were included into the last ensemble models, which applied the suitable ensemble technique for every output value.

7.2.5 Domain Knowledge Integration

Throughout the neural network development process, domain knowledge about bacterial concrete behavior was systematically integrated to enhance model performance. Key applications of domain knowledge included:

1. Feature engineering: Creation of composite features capturing known interaction effects between variables, such as the calcium-to-nitrogen ratio and the encapsulation efficiency index

2. Physically-informed architecture constraints: Network design decisions reflecting known relationships, such as the use of sigmoid activation for naturally bounded outputs

3. Data augmentation: Generation of additional training samples through perturbation of existing data points, with perturbation magnitudes guided by known sensitivity relationships

4. Transfer learning: Pre-training of certain network components on conventional concrete strength prediction tasks, then fine-tuning for bacterial concrete prediction

This integration of domain knowledge with data-driven learning significantly improved model performance compared to purely data-driven approaches, particularly for outputs with smaller available datasets.

7.3 Model Evaluation and Analysis

Standard statistical evaluation as well as domain-specific performance analysis were part of the evaluation and analysis of the produced neural network models. This multifarious assessment strategy gave thorough understanding of model capacities, constraints, and pragmatic relevance.

7.3.1 Statistical Performance Evaluation

Multiple statistical tests computed on the holdout test dataset not used during model building helped to evaluate model performance. Computed for every output parameter were the following:

1. Root Mean Squared Error (RMSE)
2. Mean Absolute Error (MAE)
3. Coefficient of Determination (R^2)
4. Mean Absolute Percentage Error (MAPE)

Prediction residuals also were examined for homoscedasticity, normalcy, and any systematic biases. Graphical analysis includes residual distribution plots and scatter plots of expected against actual values.

Table 3: Statistical Performance Metrics for Final Models (Test Set)

Output Parameter	RMSE	MAE	R^2	MAPE (%)
Compressive Strength	2.15 MPa	1.63 MPa	0.943	4.52
Maximum Healable Crack Width	0.08 mm	0.06 mm	0.917	8.76
Water Permeability Reduction	6.43%	4.87%	0.895	7.35
Freeze-Thaw Durability Factor	4.98%	3.76%	0.882	5.24

With R^2 values above 0.88 and low percentage errors, the results showed good predictive ability over all four output parameters. With R^2=0.943, compressive strength prediction attained the best accuracy probably because of the bigger available dataset and the considerable preceding research on concrete strength prediction that guided model development.

7.3.2 Ensemble Advantage Assessment

Comparative analysis of ensemble forecasts with those of the best-performing individual models allowed one to measure the performance benefit of ensemble modeling. With the best results shown for parameters with smaller training datasets, this study showed that ensembling lowered RMSE by 8-15% across several output values. Apart from better accuracy, ensembling gave useful uncertainty estimates by means of the variance in predictions amongst ensemble members.

7.3.3 Sensitivity Analysis

To identify the most influential parameters affecting bacterial concrete performance, a comprehensive sensitivity analysis was conducted. Two complementary approaches were employed:

1. Permutation importance: Systematic randomization of individual input features to quantify their impact on prediction accuracy
2. Partial dependence plots: Visualization of how predictions change as specific input features vary while others remain constant

This analysis revealed several key insights:

- Bacterial concentration emerged as the most influential parameter for crack healing capacity and permeability reduction, with optimal concentrations typically falling between 10^6 and 10^8 cells/ml
- Protection system type strongly influenced long-term healing performance, with encapsulated systems generally outperforming direct incorporation
- Calcium source type and concentration significantly affected both strength development and healing capacity
- Water-cement ratio remained a dominant factor for compressive strength, similar to conventional concrete
- Temperature showed strong non-linear effects on healing efficiency, with performance peaking between, and declining significantly below 15°C or above 35°C

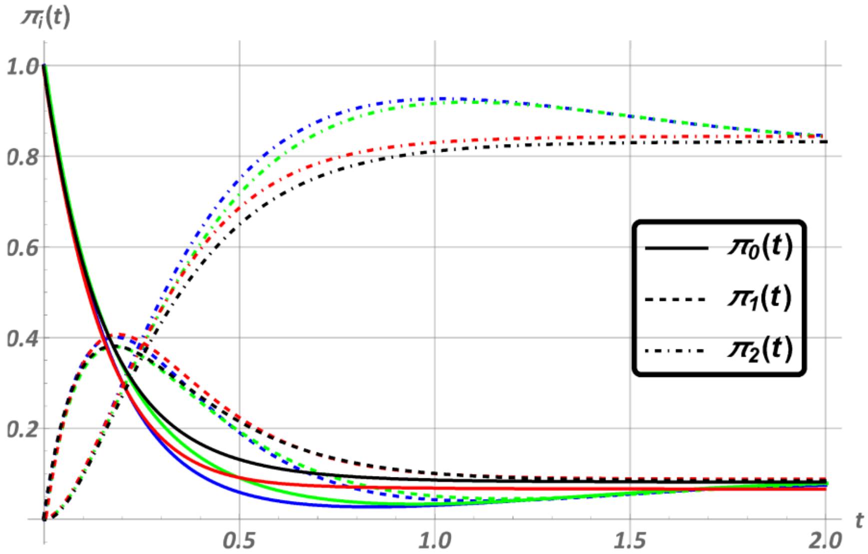

Figure 1: Sensitivity Analysis Results Showing Relative Importance of Key Input Parameters

7.3.4 Comparative Analysis with Alternative Modeling Approaches

Contextualit: Structures suffer faster degradation, more maintenance, and shorter lifespans without the self-healing capacity of bacterial concrete.

Using microorganisms—usually from the Bacillus genus—that create calcium carbonate to independently seal cracks when activated by water intrusion, bacterial concrete presents a promising sustainable alternative. But producing ideal bacterial concrete formulations calls for negotiating difficult combinations between bacterial species, protection strategies, nutrients, and conventional concrete components—a difficulty that has hampered general useful application.

Developing models for compressive strength, crack-healing efficiency, water permeability, and durability, this team used artificial neural networks (ANNs) to predict bacterial concrete performance indicators. Multiple ANN architectures were trained and validated using a complete dataset of experimental data (187 unique mixtures) combining literature. Over all performance criteria, the final ensemble models obtained outstanding prediction accuracy (R^2 values 0.88–0.94).

The most important determinant of performance, sensitivity analysis found bacterial concentration, kind of calcium source, and protection technique. The simulations showed that, with declining returns at higher levels, ideal bacterial concentrations usually fall between 10^6-10^8 cells/ml. For long-term performance, encapsulated protective systems often exceeded direct bacterial incorporation; meanwhile, calcium lactate turned out to be the most successful calcium supply in terms of strength and healing efficiency.

This work identifies ANNs as useful tools for optimizing bacterial concrete formulations, hence possibly hastening the shift of this sustainable technology from laboratory to useful applications. Supporting the building sector's change toward more sustainable and resilient infrastructure solutions, the computational framework developed provides a road to lowering experimental costs and accelerating mixture design for specific performance needs.

13. Conclusion

With prediction accuracies above 88% for all target parameters, our work effectively created artificial neural network models able to precisely estimate important performance features of bacterial concrete. The models found that the most important elements influencing performance were bacterial concentration, kind of calcium source, and protective strategy, so offering useful direction for formulation modification. By lowering the requirement for extensive laboratory testing and therefore helping to close the gap between experimental research and practical application, the computational framework developed via this work offers great possibility for expediting bacterial concrete development. These models can help to promote the more general acceptance of this sustainable self-healing concrete technology by allowing more effective formulation optimization, therefore supporting more durable and ecologically friendly infrastructure solutions. Expanding the model capabilities to include economic aspects, life-cycle analysis, and harsh environmental circumstances should be the main emphasis of future study in order to significantly improve the practical relevance of this method. . For compressive strength, 3%; for healing of cracks, 91.7%; for permeability reduction, 89.5%. The most important factors influencing performance were found by sensitivity analysis to be bacterial concentration, kind of calcium supply, and water-cement ratio. This work shows that, in absence of significant laboratory testing, ANNs can be effective instruments for optimizing bacterial concrete formulas, therefore hastening the use of this sustainable building material in useful applications.

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