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FATIGUE LIFE PREDICTION OF CEMENTITIOUS MATERIALS USING ARTIFICIAL NEURAL NETWORK

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Abstract: Concrete serves as a prevalent construction material in various infrastructure elements, including bridge decks, airfield and highway pavements, offshore structures, and machinery foundations. Many of these structures undergo fatigue loading, which is a process of gradually introducing permanent internal changes to the material, resulting in the reduction of remaining life of the structure. Despite its inherent heterogeneity, concrete is often treated as homogeneous, disregarding the influence of its variations. These disparities significantly influence the life concrete subjected to fatigue loading. Hence, it's prudent to adopt a probabilistic approach that accommodates these divergent effects when estimating the fatigue life of cementitious materials. Artificial Neural Networks (ANNs) have emerged as a promising computational tool for addressing this challenge. ANNs embrace a probabilistic framework to model the intricate relationships within cementitious composites. In this study, an ANN tool has been employed to predict the fatigue life of both plain concrete and reinforced concrete beams across varying sizes: small, medium, and large. The model is trained using experimental data corresponding to small and medium specimens and then validated using data from large specimens. By incorporating material and fracture mechanics properties associated with concrete's softening behavior as input, this model can forecast fatigue life in terms of crack length. Notably, this approach offers distinct advantages over alternative methods as it takes into account the stochastic nature of concrete characteristics under fatigue loading, consequently providing a reasonably accurate prediction of concrete's fatigue life.

1 INTRODUCTION

Despite the heterogeneous nature, concrete is one of the most commonly used construction material. Upon loading concrete structures, the innate imperfections due to its heterogeneities will develop into cracks. This cracking process adversely affects the life of concrete structures. The crack propagation occurs more rapidly when these structures are subjected to fatigue loading.

Fatigue is the process of gradual and permanent internal changes occurring within a material due to repetitive or cyclic loading [1]. This process triggers the development of cracks from existing flaws within the material, ultimately resulting in failure. Structures when subjected to fatigue loading can fail even before reaching its yield strength. As a result, evaluating the fatigue life of structures becomes crucial. Numerous structures, such as offshore support systems, bridge decks, machinery foundations, highways, and airfield pavements, are subject to repetitive loading. The intricate interaction of these heterogeneous constituents of concrete adds complexity to the analysis of fatigue failure in reinforced concrete. Predicting the fatigue life of reinforced concrete can be approached deterministically or probabilistically. The deterministic approach includes various methods like fatigue life models, fracture mechanics models, and fatigue damage models. However, relying solely on the fatigue life method to assess concrete's fatigue life is flawed due to its distinctive characteristics. This method is better suited for materials with both brittle and ductile properties [2]. On the other hand, fracture mechanics models offer relatively accurate predictions for the lifespan of metals. When compared to fatigue life models, fracture mechanics provides a better understanding on the fatigue behavior of concrete. However, utilizing the fracture mechanics approach to predict concrete behavior becomes more intricate due to the heterogeneous nature of concrete [3].Upon loading structures, the inherent micro cracks in the material merge to form larger cracks, eventually culminating in failure [2]. The deterministic models fall short of precision due to the uncertainties stemming from these inherent complexities.

Given the limitations of the fatigue models discussed above, the probabilistic method emerges as a suitable choice for predicting the fatigue life of reinforced concrete. The probabilistic approach considers a distributed value for a parameter rather than fixed ones, thereby encompassing fluctuations and uncertainties within the model. The prevalent probabilistic strategies are the Weibull distribution, Bayes' rule, and the application of Artificial Neural Networks (ANN). An Artificial Neural Network is a computational tool inspired by the structure of biological nervous systems. ANN can be utilized in predicting the fatigue life by analysing the input and output data [5].

2 ARTIFICIAL NEURAL NETWORK

As an element of artificial intelligence, the Artificial Neural Network (ANN) is created, comprising multiple interconnected artificial neurons. Each neuron functions as a nonlinear unit that takes in input signals and produces an output. The ANN consists of three layers of neurons: the Input layer, the Hidden layer, and the Output layer [6]. The Input layer acquires information, the Hidden layer processes and assesses information from the Input layer, and finally, the Output layer gives the output. The architecture of an ANN is categorized into two types: the Single-layer Neural Network and the Multilayer Neural Network. In Single-layer Neural Network, each neuron in the single layer processes the input independently and produces a corresponding output without any intermediate processing steps. A Multilayer Neural Network, in contrast to a single-layer neural network, is a more sophisticated artificial neural network architecture designed to handle complex and nonlinear relationships within data. This network type consists of multiple layers of interconnected neurons, which enable it to perform intricate feature extraction and transformation tasks. The selection of the type of layer depends on the type of problem that has to be addressed [7].

2.1 Neural Network Model development

This study focuses in developing the fatigue life of reinforced concrete in terms of relative crack depth. The model is developed by making use of experimental data gleaned from existing literature. The accuracy of the model depends on the number of data set used. The more the data set, the more accurate the results will be. Out of the total data set in Artificial Neural Network (ANN), 70% of the data is used for training, while 15% is used for testing and remaining 15% for validation [8]. This study considers a multilayer neural network, ie, input layer, hidden layer and output layer. Input features encompass fracture mechanics properties and material properties that account for softening behaviour of concrete.

The development and training of the model are carried out using the Neural Network Toolbox within MATLAB 2018a. The ANN model is developed by testing, training and validating the experimental and analytical data reported by Sonalisa and Kishen [9]. The ANN architecture employed a multilayer perceptron network (MLPN), also known as a multilayer feed-forward backpropagation network. To train the model, the Levenberg-Marquardt backpropagation algorithm was adopted due to its capacity to yield accurate results in a shorter timeframe and its reliability in addressing complex modelling challenges.

The neural network was created using datasets taken from the experiments conducted on reinforced concrete beams subjected to four-point bending. The specific geometric properties and material parameters of the chosen specimens can be found in Table 2.1. The fracture-related parameters, including fracture toughness and tensile strength, utilized in this study are detailed in the same table.

Table 2.1 Material and Geometric properties of specimen used

Sl no	Input Parameter	Input Range
1	Span *S* (mm)	1200
2	Depth *D* (mm)	250
3	Thickness *B* (mm)	150
4	Notch size *a* (mm)	30
5	Fracture Toughness G_f (N/mm)	0.3
6	Elastic Modulus *E* (MPa)	16500
7	Tensile Stress σ_t (MPa)	2.86

The selection of input parameters depends on both material properties and fracture mechanics properties that attributes towards the propagation of crack in concrete. The chosen input parameters, along with their corresponding explanations, are outlined in Table 2.2.

Table 2.2 Description details of Input Parameter

No	Input Parameter	Description
1	Number of Cycles to failure	Number of cycles required for crack development
2	Structural Size	Depth of the beam
3	Area of steel	Area of steel reinforcement in beam
4	Tensile stress	When tensile stress exceeds this value crack occur
5	Modulus of elasticity of concrete	Ratio of applied stress to corresponding strain
6	Energy release rate	Energy required by crack to propagate

In this study, the output data selected is the relative crack depth. The dataset was partitioned randomly, with 70% designated for training, 15% for validation, and the remaining 15% for testing purposes. Table 2.3 outlines the network configuration employed in developing the ANN model.

Table 2.3 Neural network configuration used for validation of Model

Parameter	Specification
No: of neurons in input layer	6
No: of neurons in hidden layer	2-10
No: of neurons in Output layer	1
Training Function	Levenberg-Marquardt (trainlm)
Activation Function	Tan-sigmoid
Performance Function	Mean squared error (MSE) Regression value

The neural network model was developed

using 100 dataset with 1000 iterations. To determine the optimal number of hidden neurons that yield the most effective performance of ANN model, evaluation criteria like Mean Squared Error (MSE) and regression value (R) were adopted. The neural network architecture that demonstrated the lowest MSE value and an R value approaching 1 was chosen as the most suitable. In this study, the neural network configuration featuring 7 neurons within the hidden layer as considered as the optimal neural network architecture, as it gave an MSE value of approximately 0.0000003 and an R value of 0.999. Thus, this optimal configuration corresponds to 6 input neurons, 7 hidden neurons, and 1 output neuron (6-7-1 architecture) as depicted in Figure 2.1 and Figure 2.2.

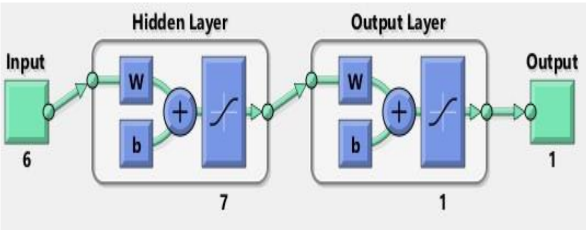

Fig 2.1: N 6-7-1 Neural Network architecture used in MATLAB R2018a

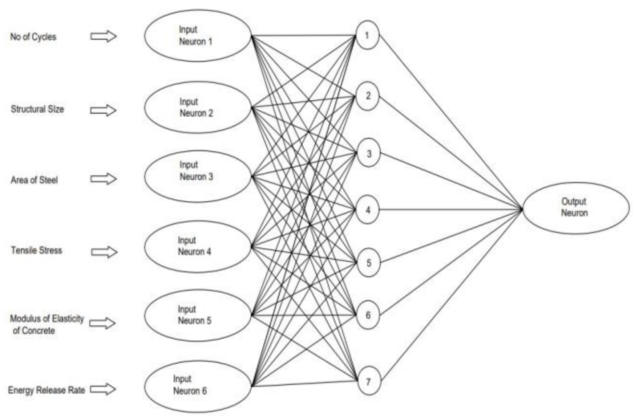

Fig 2.2: Neural Network Architecture Model

2.2 Evaluation of Neural Network Model

The performance of the neural network architecture can be assessed based on the Regression value (R).

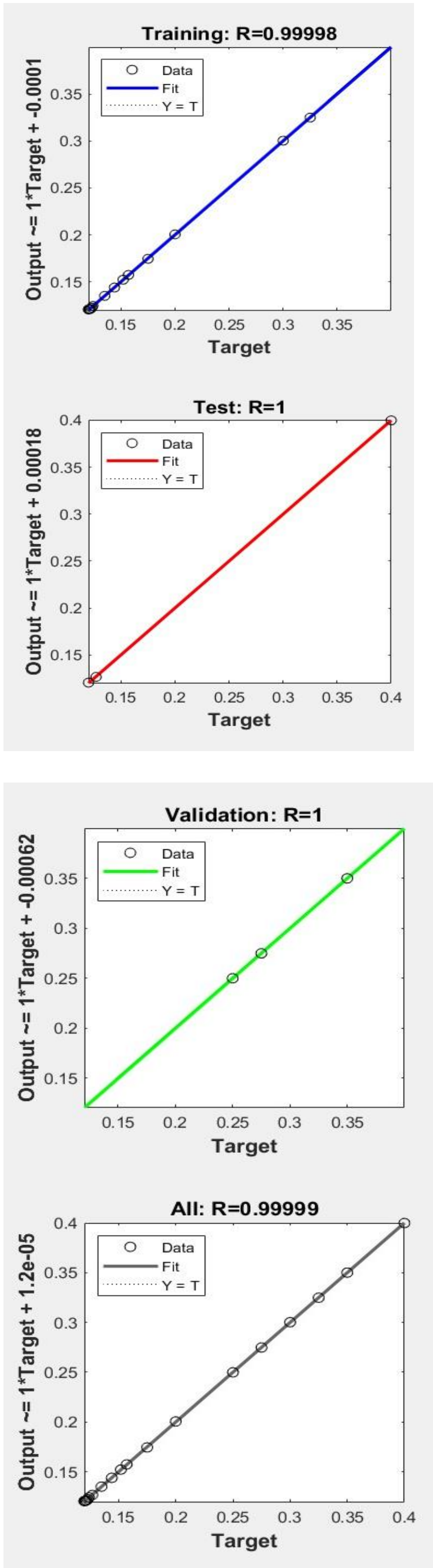

Fig 2.3: Regression plots for training, validation, testing, and overall data

A model with an R value approaching 1 signifies the accuracy of the model. Furthermore, determining the optimal number of neurons within the hidden layer plays a crucial role in achieving the best network configuration. Consequently, an optimal neural network structure can be achieved by considering the R value. The ANN model, possessing a reliability (R) value of 0.999, is adopted to predict the relative crack length of a reinforced concrete beam, as depicted in Figure 2.3. This underscores the accuracy of predictions using the ANN architecture. The output predicted using the ANN architecture in terms of relative crack length is plotted against the number of cycles and compared with experimental results taken from literature and is shown in Figure 2.4.

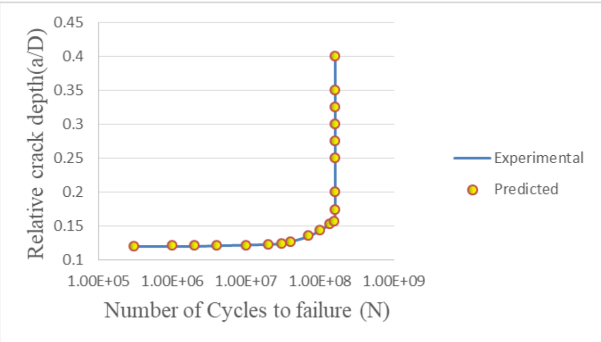

Fig 2.4: Comparison of predicted output with experimental results [8]

The experimental results and the predicted results exhibit a good agreement. The validation result shows a minimal error percentage, thus affirming the capability of the developed model to accurately predict the fatigue life of reinforced concrete beams.

3 CONCLUSIONS

In this study, ANN architecture is used to predict the fatigue life of reinforced concrete with reasonable accuracy. The accuracy can be further improved by considering other relevant parameters.

This study focuses on developing a model to predict the fatigue life of reinforced concrete using Artificial Neural Networks (ANN). ANN is a computational tool inspired by biological nervous systems. A novel model based on ANN is developed to predict the fatigue life of reinforced concrete, aimed at addressing the intricacies and time demands associated with alternative fatigue life prediction methods. A multilayer model was adopted to develop the ANN model to predict the fatigue life of reinforced concrete. Out of 100 dataset taken from the data reported by Sonalisa and Kishen [8], 70% of data was used to train the model, 15% to test the model and remaining 15% to validate the model. Training was done by considering 2-10 neurons in the hidden layer. The ANN architecture with 7 neurons in the hidden layer showed a low Mean Squared Error (MSE) of approximately 0.0000003 and 0.999 as the Regression (R) value. Thus, the optimum architecture was obtained while using 6 input neurons, 7 hidden layer neurons, and 1 output neuron. The relative crack depth thus obtained is plotted against the number of cycles and compared with the experimental data. The relative crack depth thus predicted using the suggested ANN architectures matches well with the experimental results.

Employing this ANN architecture offers a reasonable level of accuracy in predicting the fatigue life of reinforced concrete. This model can be further refined by considering additional pertinent parameters influencing the fatigue of reinforced concrete.

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