Health Monitoring of Concrete Structure with Nondestructive Testing using ANN Technique

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***Abstract*—The prediction of concrete compressive strength using Non-Destructive Testing (NDT) methods, such as the Rebound Hammer Test, has become increasingly popular in the construction industry due to their efficiency and non-invasive nature for Structural Health Monitoring (SHM) However, the accuracy of these traditional methods remains a concern, due to the higher percentage of error in the prediction of strength of concrete structures. This study proposes the application of Artificial Neural Networks (ANN) to enhance the accuracy of concrete strength predictions based on rebound hammer data. Using a dataset of Rebound Hammer Test samples, which is the rebound number, an ANN model was developed, trained, and validated. The results demonstrate a significant improvement, reducing the Mean Absolute Percentage Error (MAPE) to 8.27%. This research highlights the potential of ANNs in improving the reliability of NDT methods and recommends further exploration of artificial intelligence techniques for enhanced prediction accuracy in structural health assessments.**

Keywords*— Structural Health Monitoring, Concrete Structures, Non-destructive Testing, Rebound Hammer, Artificial Neural Network

I. INTRODUCTION

Concrete is one of the most widely used construction materials due to its strength, durability, and versatility. However, over time, concrete structures can suffer from deterioration due to environmental conditions, material fatigue, and other factors. As a result, many of the important structures have collapsed in recent years all over the world. Therefore, early detection of such deterioration is crucial for maintaining the safety and longevity of concrete structures. Traditional methods of Structural Health Monitoring (SHM) often involve time-consuming and labor-intensive processes. In the industry, to ensure structural health conditions, non-destructive testing (NDT) methods are becoming increasingly popular due to their ability to assess the properties of in-situ components without causing damage. NDTs are generally faster and more cost-effective compared to traditional destructive testing methods. This is particularly beneficial when estimating the strength of concrete on site, as it preserves the structural integrity. Among these methods, the rebound hammer test is a common non-destructive technique used to estimate the surface hardness of concrete, which can indicate its strength and overall condition [1]. By utilizing the rebound value generated from the test hammer, the compressive strength can easily be estimated using the conversion chart provided by the manufacturer [2].

The rebound hammer test, developed by Schmidt in the 1950s, measures the hardness of concrete by assessing the rebound of a spring-loaded hammer. This test provides a quick and easy method to estimate the compressive strength of concrete and evaluate its quality [3]. The rebound number obtained from the test is influenced by concrete mix, age, and surface conditions. The rebound hammer test provides a quick and efficient means to estimate the surface hardness and, by extension, the compressive strength of concrete. Several studies have explored the correlation between rebound hammer readings and concrete strength, highlighting the test's utility in quality control and evaluation of existing structures [4]. Despite its advantages, the rebound hammer test has limitations. The accuracy of rebound measurements can be affected by surface roughness, moisture content, and carbonation. Additionally, the rebound hammer provides only a superficial assessment of concrete strength, which may not reflect the internal condition of the material [5]. Despite its wide application, the rebound hammer test can produce estimations with significant variability, often resulting in a high mean absolute percentage error when compared to results from destructive compressive strength tests. These challenges necessitate the development of more sophisticated methods to interpret rebound hammer data accurately. To address these issues and improve the reliability of concrete health assessments, researchers have turned to advanced computational techniques, such as Artificial Neural Networks (ANNs) [2]. ANNs offer the ability to model complex, non-linear relationships between input data and target variables, making them ideal for processing noisy, multidimensional data, such as rebound hammer readings.

Recent advancements in artificial intelligence (AI) and machine learning (ML) techniques have opened new avenues for enhancing the accuracy and efficiency of concrete health monitoring. Artificial Neural Networks (ANNs), in particular, have demonstrated significant potential in predicting concrete properties and detecting anomalies based on various input data. By integrating ANN techniques with rebound hammer data, researchers aim to improve the precision of concrete health assessments and provide actionable insights for maintenance and repair strategies [6,7]. Artificial Neural Networks (ANNs) are computational models inspired by the human brain's neural structure. ANNs are capable of learning complex patterns and relationships from data, making them suitable for predictive modeling and classification tasks. In the context of concrete health monitoring, ANNs have been employed to predict various concrete properties, including compressive strength and durability, based on experimental data. Recent studies have demonstrated the effectiveness of ANNs in analyzing and interpreting rebound hammer data [8-10]. For instance, researchers have developed ANN models that incorporate rebound hammer readings, along with other parameters, to predict concrete strength more accurately [11-12]. These models leverage the ability of ANNs to process large datasets and capture non-linear relationships, leading to improved prediction accuracy compared to traditional methods [13-14].

A typical neural network consists of an input layer, an output layer, and one or more hidden layers, all of which are connected by neurons to create a parallel distributed processing system (Fig. 1). Each neuron acts as a Processing Element (PE) that receives inputs and generates outputs through an activation function, with the connections between neurons having assigned weights (Fig. 2).

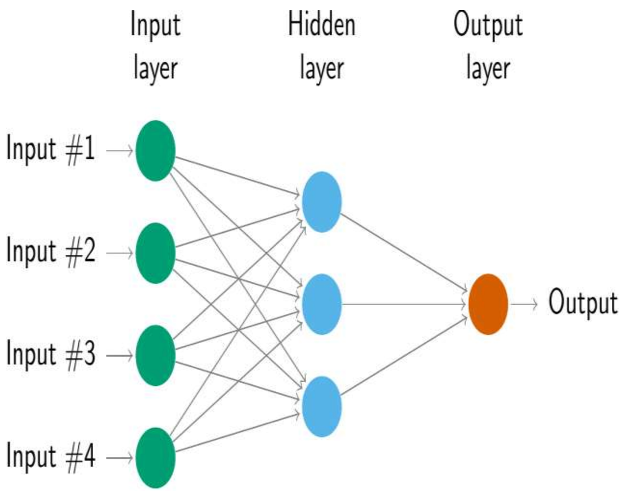

Fig. 1: Typical three-layer ANN Model

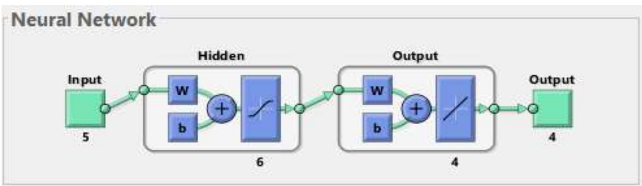

Fig. 2: Architecture of ANN Model

In the hidden layer, each neuron receives an activation signal, which is the weighted sum of all the signals entering the neuron, as described in Equation 1. In this equation, x_j represents the activation signal received by neuron j in the hidden layer,I_i is the input from the input layer, and W_{ij} is the weight of the connection between input $I_i$and neuron j. The neuron then produces an output through an activation function, which can be either linear or non-linear. One of the most used activation functions is the sigmoid function, whose general form is shown in Equation 2, where h_j is the output of neuron$j$ andx_j is its input. As described in Equation 3, the neurons in the output layer receive activation signals, which are the weighted sum of inputs from the hidden layer neurons. In this equation, y_k represents the input to neuron k in the output layer, and W_{jk} is the weight of the connection between neurons j (in the hidden layer) and$k$ (in the output layer). Once these activation signals reach the output layer, they are processed through an activation function to generate the network's output, as shown in Equation 4, where O_k is the predicted output value. The expected outputs are then compared to the desired or actual values,d_k, and the error, which is the difference between the predicted and actual values, is calculated (as shown in Equation 5). Optimal neural network performance is achieved when this error is minimized.

$$x_j = \sum_i I_i W_{ij} \quad (1)$$

$$h_j = f(x_j) = \frac{1}{1+e^{-x_j}} \quad (2)$$

$$y_k = \sum_j h_j W_{jk} \quad (3)$$

$$O_k = f(y_k) = \frac{1}{1+e^{-y_k}} \quad (4)$$

$$E(W) = \frac{1}{2}\sum_k (d_k - o_k)^2 \quad (5)$$

In supervised neural networks, where models have specific target outputs, one of the most effective and widely used methods to minimize the error function $E(W)$ is the back-propagation (BP) algorithm. In back-propagation networks, the error calculated at the output layer is propagated backward through the hidden layer to the input layer, adjusting the weights of the connections in the network. This forward process (from the input layer to the hidden layer to the output layer) and backward process (from the output layer back through the hidden and input layers) are repeated to minimize the error.

These repeated iterations form the learning or training process, during which the system learns the relationships between inputs and outputs by updating the connection weights. Before the learning process begins, small random numbers (e.g., between -0.1 and 0.1) are assigned as initial weights to the connections between neurons. This step prevents the network from becoming saturated with large weights and helps avoid certain training issues. Additionally, data normalization is often performed beforehand to ensure the model converges within a reasonable number of cycles.

Integrating ANN techniques with rebound hammer data presents a promising approach to enhancing concrete health monitoring. By training ANNs on rebound hammer data and corresponding concrete strength measurements, researchers can develop models that offer more reliable assessments of concrete conditions. Furthermore, combining ANN models with other non-destructive testing methods and environmental factors can provide a comprehensive view of concrete health [15-16]. The current paper explores the application of ANN techniques in analyzing rebound hammer data for concrete health monitoring. The authors have tried to develop and validate an ANN-based model using the rebound hammer data collected from concrete slabs that can accurately predict concrete conditions and highlight potential areas of concern, thus offering a more effective approach to concrete health assessment.

II. METHODOLOGY

For casting the concrete slabs, tests were performed on the cement, sand, and aggregates (12.5 mm passing, 10 mm retaining), followed by the mix design in the laboratory. Adhering to grade specifications, the mix was carefully measured and prepared in appropriate ratios to ensure consistency. Plain cement concrete (PCC) slabs measuring 600 mm × 600 mm were cast with three different thicknesses (25 mm, 37 mm, and 50 mm) for testing. Similarly, for the compression strength measurement, three cubes of size 150 cu. mm were cast. After adequate curing for 28 days to ensure the gain of proper strength, cubes were tested with the destructive testing instrument, the compressive strength testing machine (Fig.3). The values are recorded in table 1. Non-destructive tests were then performed using a rebound hammer (RH) positioned at a 90-degree angle to the slab surface. The hammer's impact produced rebound numbers, which indicated the surface hardness and indirectly estimated the concrete's strength. The slabs were marked on the surfaces to identify the points of rebound hammer testing (Fig. 4). The authors collected data from concrete slab samples; some sample values are shown in Table 2. The rebound numbers were recorded from various test points across the slab surfaces and subsequently converted into strength values in MPa from the conversion table provided by the manufacturer along with the instrument (Fig. 5). It is visible that the values obtained from the destructive testing are higher as compared to the nondestructive testing. Hence, the ANN model is required to achieve better results.

Fig. 3: Compression strength test of cube

TABLE I: COMPRESSIVE STRENGTH TEST RESULT OF ALL THREE CUBE AFTER 28 DAYS

Sample for Slab	Average Compressive Strength (Megapascal)
Set 1	30.26
Set 2	31.33
Set 3	30.73

TABLE II: REBOUND HAMMER TEST DATA

Observation	Rebound Number	Strength (Megapascal)
1	25	25.75
2	26	26.5
3	25	25.75
4	30	29.5
5	29	28.75
6	26	26.5
7	25	25.75
8	31	30.25
9	30	29.5
10	25	25.75
11	24	25
12	27	27.25
13	24	32.5
14	24	31
15	24	25
16	25	25.75

Fig. 4: Rebound hammer and the concrete slab

Fig. 5: Rebound number to strength conversion table

For the development of the ANN model, a few samples were randomly selected to form the training dataset, while a few data were used to test the model's performance. The ANN model employed a backpropagation network, and various configurations were tested to optimize its predictive accuracy. The model parameters included the number of hidden layers, the number of processing elements, the type of transfer function, and the learning rule. After training, the model was evaluated using the Mean Absolute Percentage Error as the primary metric for prediction accuracy.

III. Results and Discussion

The model was trained on data from concrete with samples used for training and a few samples for testing. Figure 6 provided a visual representation of the results, showcasing the ANN model's consistent attainment of an exceptional regression value near 1. Several ANN configurations were tested, including models with varying numbers of hidden layers and processing elements (Table 3). The model using only two input variables (average and standard deviation of the RH measurements) outperformed models that used all ten RH measurements as input variables. The Artificial Neural Networks (ANNs) model significantly improved the prediction of concrete compressive strength based on Rebound Hammer (RH) test data. In comparison, the mean absolute percentage error of the test samples using the rebound hammer alone was more than 20%, indicating a substantial improvement in accuracy with the ANNs model. The best mean absolute percentage error achieved by the ANNs model was 8.37% as described in Table4. The authors have used the Levenberg-Marquardt method for minimizing the error. This was obtained using a 2-2-1 network (2 inputs, 1 hidden layer with 2 processing elements, and 1 output). Hence, the use of ANN outperformed traditional statistical methods, demonstrating the effectiveness of AI for non-linear data regression and prediction. The findings suggest that ANNs can be a reliable tool in the construction industry, not just for improving RH predictions but potentially for other NDT methods as well .The developed model has been used for the prediction in real-life structures in a building site, where the rebound hammer test was performed and the results were validated using the values provided by the site engineers. The model showed accuracy around 9% in this case study.

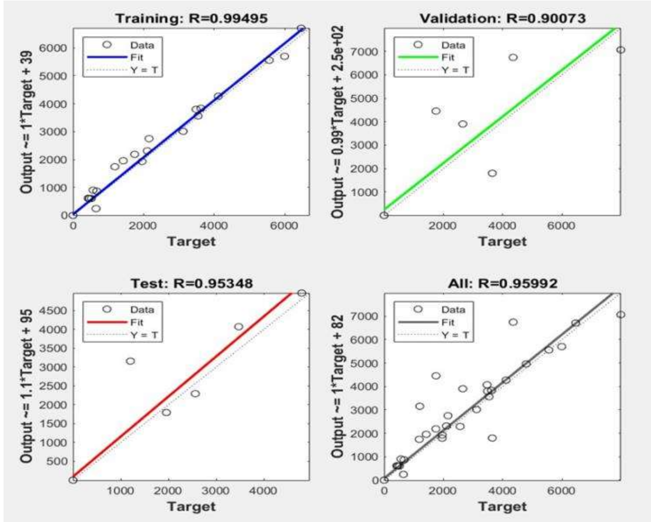

Fig. 6: Regression plot of trained RH values

TABLE III: ANNs Model Parameter

Model Parameter	Contents
ANNs Model	Backpropagation Network
No. of Hidden Layer	1 and 2
No. of Processing Elements	Constructive Algorithm
Learning Rule	Levenberg-Marquardt
Maximum Epochs	Default: 5000
Termination	1.Minimum MSE 2.Maximum Epochs

TABLE IV: ANNs Model Prediction Result

Network Type	No. of Hidden Layer	Epochs	MAPE (%)
2-2-1	1	5000	8.37
2-2-2-1	2	5000	8.20

IV. Conclusion

The results demonstrated that the ANNs model provided more reliable compressive strength predictions than the standard rebound hammer method, reducing the error significantly. The findings suggest that ANNs can effectively enhance non-destructive testing (NDT) methods like the rebound hammer test, making them more accurate for concrete strength estimation. The paper recommends that other artificial intelligence techniques could also be explored to further improve the accuracy of NDT methods like the rebound hammer test. Future research in this area should focus on refining ANN models to handle diverse concrete conditions and testing environments. Additionally, exploring hybrid approaches that integrate ANN with other AI techniques, such as support vector machines or deep learning, could further enhance the accuracy and robustness of concrete health monitoring systems. Using the rebound numbers, the quality of the concrete prediction is challenging. Hence, for further research, non-destructive testing facilities like an ultrasonic pulse velocity meter (UPV), acoustic emission (AE) technique, which are basically sensor based techniques, could also be used and integrated with the ANN model to improve the accuracy of the results. Moreover, a few more techniques, which involve the concept of machine learning, could similarly be used for improved health monitoring of concrete structures.

V. Acknowledgement

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