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Evaluation Of Compressive Strength Of Concrete Using Ndt And Artificial Intelligence Methods

Dr K Ramadevi[1*], Sonal Banchhor[2], P Sudheer Kumar[3], Riyaz Syed[4], B Naga Kiran[5], Amruta Jagadish Killol[6]

[1]Professor, Department of Civil Engineering, Kumaraguru College of Technology, Coimbatore, Tamil Nadu, India. Email: ramadevi.k.ce@kct.ac.in*
[2]Assistant Professor, Department of Civil Engineering, Guru Ghasidas Vishwavidyalaya Bilaspur Chhattisgarh, India
[3]Assistant Professor, Department of Civil Engineering, Balaji Institute of Technology and Science (Autonomous), Narsampet, Warangal, Telangana, India.
[4]Assistant Professor, Department of Civil Engineering, Vaagdevi College of Engineering, Bollikunta, Warangal, Telangana-506005, India.
[5]Associate Professor, Department of Civil Engineering, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal District, Andhra Pradesh, India.
[6]PhD scholar, Department of Civil Engineering, G.H. Raisoni College of Engineering, Nagpur, Maharashtra, India.

***Corresponding Author:** Dr K Ramadevi*
Email: ramadevi.k.ce@kct.ac.in

Abstract

Non-destructive testing (NDT) techniques are frequently applied in the field to evaluate the compressive strength of concrete in the construction sector. NDT techniques are comparatively inexpensive and do not harm the current structure. The ultrasonic pulse velocity (UPV) test and the rebound hammer (RH) test are two common NDT techniques. The concrete compressive strength estimates are not particularly precise when compared to the outcomes of the destructive tests, which is one of the main disadvantages of the RH and UPV tests. The researchers used artificial intelligence prediction models to examine the correlations between the input values—the outcomes of the two NDT tests—and the output values—concrete strength—in order to enhance the estimation of concrete strength. In cooperation with a material testing facility and the Professional Civil Engineer Association, in-situ NDT data from 98 samples were gathered. Both conventional statistical and artificial intelligence (AI) prediction models were developed and validated using in-situ NDT data. The analysis's findings demonstrated that, in comparison to statistical regression models, artificial intelligence prediction models yield more accurate estimations. When AI methods (ANNs, SVM, and ANFIS) are used to predict concrete compressive strength in RH and UPV tests, the study findings demonstrate a considerable improvement.

	Keywords: adaptive neural fuzzy inference system; artificial intelligence; support vector machine; artificial neural network; concrete strength; non–destructive testing; rebound hammer test; ultrasonic pulse velocity

1. Introduction

These days, a wide range of artificial intelligence (AI) techniques, such as support vector machines (SVM), adaptive neural fuzzy inference systems (ANFIS), and artificial neural networks (ANNs), find extensive use in research across numerous domains. Notably, a number of study findings [1–5] show that ANNs, SVMs, and ANFIS are successful AI prediction techniques. Non-destructive testing (NDT) techniques are essential for determining the compressive strength of concrete in the construction sector. These approaches, which are quite simple to use and reasonably priced, are crucial substitutes for destructive testing. The quality of in-situ cast concrete may differ from that of destructive testing in a lab environment for a variety of reasons, including installation, transporting, tamping, and curing. As a result, examining core samples from existing structures becomes the preferable choice, despite the fact that it is occasionally unfeasible or might cause structural damage during drilling. For non-destructive evaluation, NDT techniques including Ultrasonic Pulse Velocity (UPV) testing and Rebound Hammer (RH) testing are therefore recommended [6]. In order to perform the RH test, the rebound hammer's plunger must be pressed up against the concrete surface. The mass rebound is then measured using a graduated scale, and the rebound value is then converted to a rebound number or rebound index. Next, using a conversion table that the manufacturer provides, the compressive strength is computed [7, 8]. Conversely, ultrasonic pulse wave (UPV) tests measure the time it takes for an ultrasonic pulse wave to propagate through concrete samples; higher velocities of the wave indicate higher quality samples [9, 10]. In order to improve concrete compressive strength predictions, this study analyzes Silver Schmidt RH and UPV test results using artificial intelligence approaches. The ultimate objective is to create more accurate prediction models using both artificial intelligence models and conventional statistical techniques [11,12]. To create prediction models, this study uses ANNs, SVMs, and ANFIS. Comparing the estimation findings to more conventional estimating techniques, there is a noticeable improvement. For the purpose of the investigation, 98 in-situ test samples were gathered. Of them, 28 samples were utilized for model validation, and 70 were selected at random to serve as the training dataset. Using the sample data, conventional statistical models and artificial intelligence models were created and evaluated. The analysis's findings demonstrated that the AI models may produce more accurate predictions of concrete's compressive strength.

2. Research Significance

While lab concrete samples were utilized in the majority of earlier studies to evaluate the compressive strength of concrete, this study employs drilled samples from actual structures for its NDT. The use of artificial intelligence and conventional statistical analysis techniques is utilized to examine the correlation between the SONREB (UPV + RH) test results and the compressive strength of the concrete samples. Additional samples from other currently-existing buildings might be gathered for additional investigation in future studies. Other non-destructive techniques can also be included for additional research.

3. Literature Review

Destructive procedures are often avoided when evaluating concrete structures because of the possible harm they might cause. Non-destructive testing (NDT) techniques are becoming more and more popular as alternatives since they use very basic test equipment and need little sample preparation [13]. Due to limitations in laboratory equipment, these nondestructive testing (NDT) methods—which are preferred for forecasting concrete compressive strength—involve assessing the empirical connection between material strength and NDT parameters [14]. The link between the two is explained in detail by the manufacturers, and different types of concrete require calibration [15, 16].

Two popular NDT techniques for evaluating concrete qualities are the Ultrasonic Pulse Velocity (UPV) test and the Rebound Hammer (RH) test. In the RH test, an elastic mass is used to strike the concrete surface. The rebound is measured, and the rebound number is interpreted as a measure of the concrete's strength. Nonetheless, a variety of variables, including surface smoothness and moisture content, might affect the rebound number. It varies for different concrete compositions, despite attempts to develop a general connection [17].

Ultrasonic pulse wave velocity (UPV) is used in the test to assess material strength. Variations in this velocity might be indicative of internal faults, changes in material condition, and more. Nevertheless, not all types of concrete can benefit from the UPV process, particularly those with uneven surfaces or water-filled fissures. Coupling gels are employed, taking into account variables such as moisture content, water/cement ratio, and aggregate size, to improve accuracy. The intricacy of these variables influences the irregularity of ultrasonic waves and, in turn, impacts the estimation of concrete compressive strength in non-destructive testing. Neural networks have been the main focus of current study when utilizing AI to forecast concrete strength. These studies have employed databases that were gathered from earlier research projects. Asteris and Mokos' usage of ANNs, Gholamreza and Arash's hybrid AI technique, and Bonagura and Bobile's verification of artificial neural techniques are a few noteworthy instances. To create and evaluate concrete compressive strength prediction models, other AI techniques like Support Vector Machines (SVMs) and Adaptive Neural Fuzzy Inference Systems (ANFIS) have been used.

4. Experiment Methodology

Together with a material testing facility in Taiwan, the data was gathered. The raw data material is secret according to a non-disclosure agreement signed by the authors of this study. As a result, only a restricted amount of data may be made public. For this study, data from 98 samples in total were gathered. The prediction model in this work was created using three AI techniques: ANNs, SVM, and ANFIS. Using AI was predicted to increase the model's performance in predicting concrete compressive strength, especially when compared to traditional methods. Khademi [18] states that while the prediction models' generalizability can be improved, further research is necessary to determine how useful they are.

4.1. Artificial Intelligence Prediction Methods

The concrete compressive strength prediction models for the RH and UPV tests are created using ANNs, SVM, and ANFIS. These models are created and utilized for a wide range of non-linear issues. This research develops prediction models to evaluate concrete compressive strength using these three methodologies in an effort to look for more accurate prediction outcomes.

4.1.1. Multilayer-Feedforward Neural Network

Neurons in the networks are grouped in layers for multi-layer ANNs. The outputs of one layer become the inputs of the next in a multilayered feed-forward neural network (FFNN). Hidden layers are those that lie between the input and output layers. An increased number of hidden layers suggests that the network's approximation function is more sophisticated. Within a finite collection of patterns, one or two hidden layers can approximate an arbitrarily complicated mapping.

4.1.2. Overview of Artificial Neural Networks

Two key functions of the human brain are simulated by artificial neural networks: learning and adapting. Artificial Neural Networks (ANNs) have found widespread use in several engineering domains, including pattern recognition, system identification, system model and control, and classification tasks. According to earlier studies, ANNs perform better than more conventional techniques like multivariate analysis and multiple regression analysis. A highly linked system with basic processing components may understand the intricate connection between independent and dependent variables in artificial neural networks (ANNs). An information processing system unit called a neuron is described as having an activation function and a connecting connection, which is a summation with or without bias.

4.1.3. General Linear Regression

General linear regression (GLR) estimates the correlation between inputs and outputs to ascertain the reaction of a dependent variable, or response variable, to the independent variables, or predictors. Both linear and non-linear regression fall within the GLR category. In linear regression, the optimal hyperplane is used to maximize the margin of the input training data. The training sample with the smallest distance to the hyperplane inside the interval $\{-1, +1\}$ is considered the hyperplane boundary. A mapping function Φ is used in non-linear regression to convert the data into a high dimension feature space.

4.1.4. Radial Basis Function Neural Network

Samarasinghe [19] suggested the radial basis function neuron network (RBFNN) as an alternative multilayered feed-forward neural network. The input layer, one hidden layer, and the output layer make up an RBFNN's three layers. RBFNN offers various advantages to FFNN, including a faster training rate and a lower susceptibility to issues with non-stationary inputs. The two kinds of neural networks are distinguished by the hidden neurons. RBFNN employs the Gaussian radial basis function, whereas FFNN utilizes the S-shaped sigmoid activation function. Vector linking weights, or w, exist in RBFNN between the hidden layer and the output layer. But between the input layer and the hidden layer, there are no weights.

4.2. In-Situ NDT Test and Lab Destructive Test

A qualified material testing facility with expertise in both destructive and nondestructive testing on building materials was partnered with this study. Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV), two nondestructive tests (NDT), were performed on 98 non-structural beams in the basement of a sizable apartment building. The width and depth of the beams were 50 and 70 cm, respectively. Ten RH measurements were obtained for every beam using the Silver Schmidt N-Type electronic rebound hammer manufactured by PROCEQ. UPV tests were conducted using the TICO concrete ultrasonic detector from PROCEQ Company in Zurich, Switzerland, in accordance with the protocols described in the research by Tharmaratnam and Tan [20] and the ASTMC59716 standard. For every test site, four UPV measurements were taken.Core samples were taken from the same sites after the RH and UPV testing. To ensure uniformity, one person performed the RH and UPV measurements, whereas a different, more skilled person took the core samples. The models of artificial intelligence (AI) were developed and tested using the collected data. Destructive tests were carried out in compliance with the Taiwan National CNS1232 standard, especially the "Compressive Strength of Concrete Specimens," in order to ascertain the concrete samples' true compressive strength. For testing, the HT-8391 compressing machine—which can apply pressure of up to 200 tons on the surface of a concrete sample—was utilized. The upper surface of the concrete beams was cleaned with a moist tissue before testing.

4.3. Prediction Model Development

4.3.1. Artificial Neural Networks

In this study, Neuro Solutions 7.0 software coupled with Excel was used to build the artificial neural networks (ANNs) model for forecasting concrete compressive strength. For the prediction procedure, a back-propagation network (BPN) was used, and data from 98 samples—all taken from non-structural beams in a big residential building's basement—were used. Of these samples, 28 were used as the testing dataset for model validation, while 70 were chosen at random to serve as the training dataset. The average ultrasonic pulse velocity and average rebound number from in-situ trials served as the model's input variables, while the model's output was the compressive strength of concrete.

After loading the training data to train the ANNs model, the model training procedure identified the optimal prediction model. The actual concrete compressive strength discovered through destructive testing on core samples was then contrasted with the prediction findings. Metrics including root mean square error (RMSE), mean absolute error (MAE), mean forecast error (MFE), error to signal ratio (ESR), and mean absolute percentage error (MAPE) were used to assess the accuracy of the predictions.

Numerous modes with varying configurations were investigated in order to optimize the ANNs model. The majority of non-linear regression problems may be solved with one or two hidden layers, according to prior research; both configurations were examined in this work. The parameters used for the ANNs models created in this study are compiled in Table 1.

Table 1. Network model parameter settings.

Network Parameters of the Project	**Explanation**	
Internet usage examples model	Back-propagation neural network	
Sample selection (Exemplars)	Total Data	100
	Training Data	75
	Testing Data	32
The number (Hidden Layers)	One Layer and Two Layer	
Transfer	Tanh Axon	
Learning Rule	Levenberg Marqua	
Maximum Epochs	The default value is 200, and gradually increased	
Termination	1. The minimum tolerable range (MSE) 2. The maximum training period (Epochs)	
Cumulative weights update method	Batch	

4.3.2. Support Vector Machine setting

In this work, the support vector machine (SVM) prediction model was created using MATLAB's LS-SVM tool. Metrics including root mean square error (RMSE), mean absolute error (MAE), mean forecast error (MFE), error to signal ratio (ESR), and mean absolute percentage error (MAPE) were used to evaluate the performance of SVM models, much like ANN models. For the SVM model, the literature-recommended Gaussian Radial Basis Function (RBF) kernel was used.

To create the prediction model for the RBF kernel SVMs, two parameters, σ and γ, had to be found. Similar to how the ANNs model was developed, the training dataset consisted of 70 randomly chosen samples out of 98, while the testing dataset consisted of the remaining 28 examples. Concrete compressive strength was the model's output, and the average rebound number and average ultrasonic pulse velocity from in-situ studies served as its input variables. A bigger number in RBF kernel SVMs suggests stronger smoothing. σ measures how smooth the decision surface is. The regularization parameter, gamma, affects how complicated the model is and how well the training data points are fitted. Because σ and γ values vary depending on the task, it was necessary to select them via trial and error. Using RMSE, MAE, MFE, ESR, and MAPE, the SVM prediction models' performance was assessed.

4.3.3. Setting for an Adaptive Neural Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) models used in this study's training and testing of prediction models were created using MATLAB. The neuron-based fuzzy inference system was trained using seventy of the ninety-eight experimental data points; the other twenty-eight samples were used for testing. Concrete compressive strengths were predicted using the ANFIS models, and the results were compared to the actual compressive values found by destructive testing. To measure prediction accuracy, evaluation measures such as RMSE, MAE, MFE, ESR, and MAPE were used.

Excel files were used to import training and testing data for the ANFIS model building process. The MATLAB program "anfisedit" was utilized to develop the ANFIS prediction model. It examined eight distinct kinds of fuzzy membership functions and changed the quantity of input membership functions from two to five. The type of output membership function was set to constant, and a hybrid FIS training approach was used. Convergence conditions were first established with a learning period of 10 and a default value of 5000 times, progressively increasing, in order to manage training time. A network error tolerance of 0.2 was set.

Testing datasets were used to evaluate the model following the training phase. The "evalfis" function was used to export the prediction findings, which were then compared to the concrete's actual compressive strength. By using RMSE, MAE, MFE, ESR, and MAPE as metrics to assess how well the ANFIS models predicted the compressive strength of concrete, assessment consistency was preserved.

5. Prediction Results

5.1. Implications for Research

The average and standard deviation of in-situ non-destructive testing (NDT) data were computed during the creation and validation of prediction models. Ten measurements were made at each test location for the Rebound Hammer (RH) test, and four measurements were made at each location for the Ultrasonic Pulse Velocity (UPV) test. The corresponding formulae were used to get the average and standard deviation. Of the 98 test samples that were gathered, 70 were selected at random to serve as the training dataset and the remaining 28 as the testing dataset. Core samples were taken at each place and subjected to destructive testing in the laboratory to ascertain the true compressive strength of the concrete. Metrics including root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), mean forecast error (MFE), and error to signal ratio (ESR) were used to evaluate the quality of the model prediction. Three different artificial intelligence (AI)-based prediction models were used in the study: an adaptive neural fuzzy inference system (c), a support vector machine (b), and an artificial neural network (a). Concrete compressive strength was chosen as the output variable in these models, which used RH and UPV test results as input factors. The best model and parameter configurations were investigated in order to identify the best setting for each AI technique. The testing dataset was then used to validate the training models.

5.2. ANNs Model Prediction Results

The ultrasonic pulse velocity and the rebound number were the two input variables for the ANNs model. The compressive strength of the concrete served as the output variable.

- First input: the mean of ten RH readings
- Second input: the mean of the four UPV readings

- Concrete's compressive strength is the result.

The ANNs employed a multilayer perceptron, a generalized regression network, a radial basic function network (RBFN) trained using Bayesian regularization, and linear regression as their functions.

5.3. ANFIS Model Forecasted Outcomes

Users can select various membership function kinds and numbers throughout the ANFIS model construction process in the MATLAB environment. In order to investigate the prediction performance of various model configurations, ANFIS models with two, three, four, and five membership functions were developed for this study. Meanwhile, the ANFIS models were also used to investigate eight distinct categories of attribution functions: trimf, trapmf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, and psigmf. A total of 32 distinct ANFIS models (eight types of attribute function x four types of function number) were created for this study. The models using the trapezoid membership function (tramf) and the triangular membership function (trimf) among the 32 ANFIS models had the best training outcomes.

6. Conclusions

To enhance the accuracy of in-situ non-destructive concrete compressive strength tests, artificial intelligence (AI) methods were employed to analyze experimental data from rebound hammer and ultrasonic pulse velocity tests. The study utilized three AI techniques, namely artificial neural networks (ANNs), support vector machines (SVMs), and adaptive neural fuzzy inference system (ANFIS), to develop prediction models. Experimental data from 98 samples in a residential complex were collected, with both rebound hammer (RH) and ultrasonic pulse velocity (UPV) tests conducted. Core samples were extracted to determine the actual concrete compressive strength. Of the 98 samples, 70 were randomly chosen as training data, and the remaining 28 were designated as testing data for model evaluation. Different model setups were explored during the development process, utilizing the average rebound hammer number and average ultrasonic pulse velocity as input variables and concrete compressive strength as the output. The training models were identified, and their performance was validated using the testing data.
Traditional concrete compressive strength estimations often exhibit a mean absolute percentage error (MAPE) exceeding 20% compared to actual strengths obtained through destructive tests. Most previous research relied on laboratory samples rather than those from actual structures. In this study, in-situ non-destructive tests were conducted, and core samples were taken for accurate strength identification. Applying AI techniques to data analysis yielded satisfactory results, with MAPEs of 14.69%, 10.23%, and 10.01% for ANNs, SVMs, and ANFIS prediction models, respectively. This represents a significant improvement over prior research outcomes. The study's findings offer valuable insights for researchers and industry practitioners assessing in-situ concrete compressive strength using non-destructive testing methods.

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