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Research Article

Concrete Intelligence: Predicting Test Properties with Artificial Intelligence

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ABSTRACT

Highly flowable, segregation-resistant, self-compacting concrete (SCC) ensures excellent structural performance in cramped areas and efficiently facilitates correct filling. The highly flowable concrete, known as self-consolidating concrete (SCC), forms without mechanical vibration. This paper analyzes the methods used on SCC mixed datasets gathered from the scientific community, utilizing artificial neural networks (ANN). Artificial neural networks act similarly to a fully developed human brain, storing and retrieving data to solve complex issues and learn through experience. In addition to employing soft computing to process data, it operates in a symbolic way of intelligent computation. It has numerous advantages, has begun to be used in civil engineering, and is quickly becoming a popular research area. The approach uses slump flow diameter, 28-day compressive strength, and ingredients as inputs to the ANN to maximize prediction accuracy for SCC features such as V-funnel and L-Box. SCC mixtures generated compressive strengths ranging from 14 to 86 MPa. L-Box values range from 0.8 to one, whereas V-Funnel times vary from 3 to 15. The accuracy of the anticipated ingredients is further guaranteed by the consistency of the training data.

Keywords: Self-consolidating concrete, Artificial neural network, slump flow, compressive strength, V-funnel, L-box

1. INTRODUCTION

Civil engineering is concerned with the planning, construction, and maintenance of infrastructure, which includes buildings, bridges, roads, water supply systems, and more. In recent years, technology has played an increasingly important role in the civil engineering industry, providing new tools and methods to improve the efficiency, accuracy, and safety of construction projects. Technology has been playing an increasingly significant role in the construction industry, enabling construction projects to be completed more efficiently, safely, and cost-effectively. Here are a few instances of technology's application in the building sector. Self-compacting concrete (SCC) is a highly fluid type that can flow and compact on its own weight without the assistance of outside vibration. The same components are used in SCC as in traditional concrete, but the amount of fine particles and coarse aggregate are reduced. The main advantages of SCC are that it reduces labour and equipment costs by eliminating the need for vibration, improves construction site safety, and allows for more complex concrete shapes. Adding fly ash to SCC mixes as an additional cementitious ingredient has several advantages, such as improved construction efficiency and increased environmental sustainability [1-2]. Among the pozzolanic materials that could make SCC are silica fume, metakaolin, fly ash, and granulated blast furnace slag. Superplasticizers, or high-range water reducers, are among the carefully chosen and proportioned materials used to create SCC and provide exceptional workability and flowability. To attain the intended SCC qualities, mix design factors like the water-cement ratio, powder content, and aggregate size distribution must be tuned. Production and testing methods must also be adjusted to ensure proper mix consistency and quality. Different application (Figure 1) of ANN.

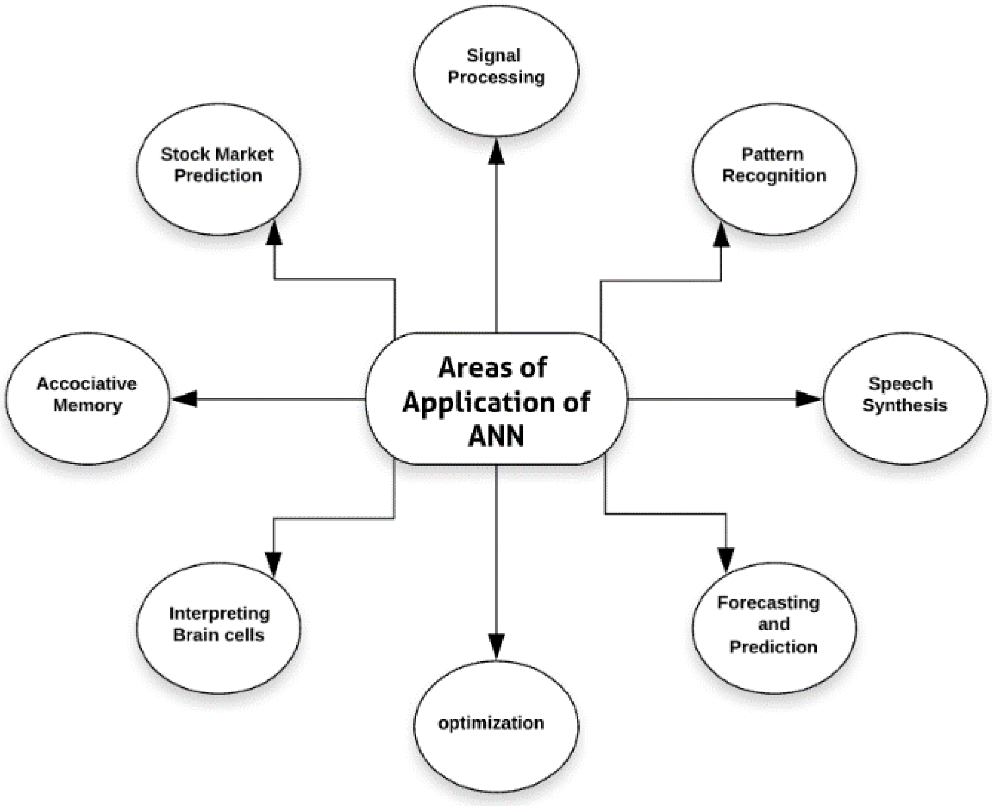

FIGURE 1. Area of Application of Artificial neural networks

To forecast outcomes, optimize building processes, and model intricate interactions between many factors, artificial neural networks (ANN) are a machine learning technique that can be applied in the construction industry. ANNs are inspired by the way the human brain works, with interconnected nodes or "neurons" that can process and analyze large amounts of data. Researchers have used the ANNs in following types of construction work: Predicting construction project costs: ANNs can be used to predict the cost of a construction project based on historical data and other variables, such as project scope, location, and materials. By analyzing large datasets, ANNs can help identify cost drivers and predict project outcomes more accurately [3]. Optimizing construction schedules: ANNs can improve construction timelines by assessing weather, material availability, and labor availability. This can help contractors plan more efficiently and reduce delays and cost overruns. Predicting structural performance: ANNs can be used to predict the performance of structures under different conditions, such as earthquakes or extreme weather events. By analyzing data from previous disasters, ANNs can help engineers design more resilient structures. Predicting material properties: ANNs can be used to predict the properties of construction materials, such as concrete strength or steel fatigue. This can help engineers optimize material selection and reduce waste. Quality control: ANNs can be used to identify defects in construction materials or finished products, reducing the need for manual inspection and improving quality control. Overall, ANNs can increase the accuracy and efficiency of building processes, resulting in quicker, safer, and more affordable projects. However, it is important to note that ANNs require large amounts of data and careful calibration to produce accurate results, and they should not be relied on as the sole basis for decision-making.

The construction industry has been using the SCC extensively lately. Unfortunately, there isn't a reliable or consistent way to determine its characteristics from the ingredients. To the best of the author's knowledge and based on earlier research, there are enough publications that address the use of ANNs to forecast the filling ability of SCC. Nevertheless, there needs to be more coverage of the prediction of SCC elements, such as ANN input, flowability, viscosity, and passing ability, based on their fresh and hardened qualities. Therefore, this study used artificial neural networks (ANN) to forecast the SCC features related to flowability, filling ability, and passing ability utilizing the ingredient, slump flow, and 28-day compressive strength data. The MATLAB R2019a Runtime environment builds, trains, and tests the artificial neural network. The following text sections are organized as follows: Section 2 discusses artificial neural networks. Section 3 discusses Methodology and material & database used in this study. section 4 explains result and analysis done for ANN model. And at last we outline conclusion in section 5.

The development of neural networks can be divided into several phases, beginning with the creation of models based on an understanding of neurology and ending with the influence of neuroscience on this process. The development of neural network simulations also benefited from the work of psychologists and engineers. Applications for complex problems are developing on neurally based chips. Clearly, neural network technologies are in a transitional phase right now.

One of the earliest uses of ANNs in construction was in the field of structural engineering. In the early 1990s, researchers began exploring the use of ANNs for structural analysis and design. One of the first applications of ANNs in this field was to predict the load-carrying capacity of reinforced concrete beams. Researchers used ANNs to model the complex relationship between the various input variables, such as the dimensions of the beam, the type and amount of reinforcement used, and the loading conditions, and the output variable, which is the load-carrying capacity of the beam [4]. The current method of producing SCC frequently calls for a more significant amount of binder ingredients. The increased use of binder materials raises manufacturing costs and negatively impacts sustainability and the environment [5]. Many researchers have looked into adding more components to the material to lower prices and strengthen SCC's resilience to environmental deterioration.

2. CONCEPT OF ARTIFICAL NEURAL NETWORK

Artificial neural networks (ANNs) are capable of learning, abstraction, and generalization, unlike organic neural systems. Artificial neurons have a limited ability to communicate with organic components and provide accurate neural replication [6].

A network is made up of numerous nodes that are interconnected according to their functions. Sensory and responding nodes respectively, are the names of the nodes inside the input and output layers. Nodes are known as hidden nodes in the interior layer between the input and output layers. The information is initially entered into the network's input nodes. Subsequently, it is linked to concealed nodes by functions, and ultimately, the network output is produced by the output layer nodes. The first and most crucial step in artificial neural network modeling is the choice of the network type; this is followed by the selection of the input parameters that are most appropriate for the output data. The number of layers, the neurons in each layer, their connections, the kind of transfer function for neurons, and the network's training and learning function will all be included in the network design. Specifically, collected data is needed to create the network after deciding on the network type and net architecture. There are three stages to the data collection, which is necessary for the network generation [7].

a. Training phase: Fitting the classifier's weight using all available training data sets for network learning.
b. Validation phase: A collection of information used to modify a classifier's parameters, such as the number of neurons and hidden layers in each layer. The number of training iterations that are required to prevent overtraining is calculated in this phase.
c. Test phase: Data is used to assess the network performance fully.

3. METHODOLOGY

This study's input included cement, fly ash, water/power, sand, coarse aggregate, SP, compressive strength, and slump flow. The outputs are V-funnel and L-box. The first 48 readings in the dataset were taken for training, and the remaining readings were taken to test the model's accuracy. Throughout the training and testing process, the inputs were fixed. Figure 2 displays the ANN network's model. Figure 3 shows the flowchart for Self-Compacting Concrete Property Prediction using ANN. During the training phase, the MATLAB toolbox's Levenberg-Marquardt backpropagation method is employed with its default settings. A MATLAB R2013a run-time environment is used.

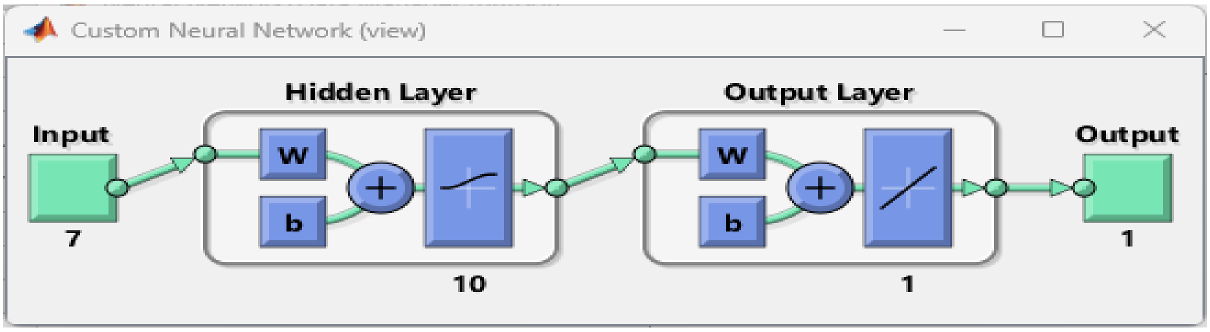

FIGURE 2. Architecture of Neural Network models

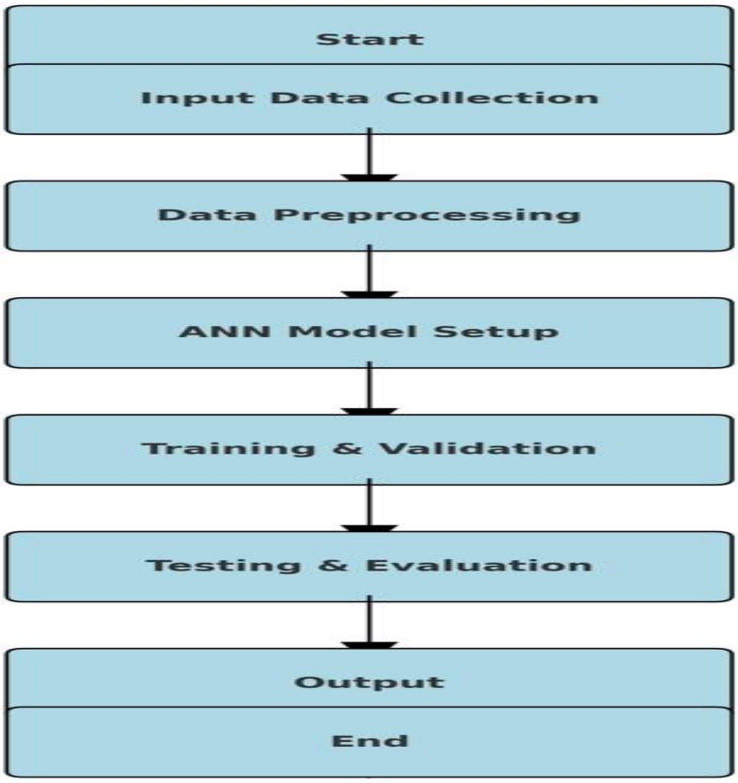

FIGURE 3. Flowchart for SCC Property Prediction using ANN

The predicted and actual values are compared using the multiple coefficients of determination (R2), the root-mean-square error (RMSE), and the normalized root-mean-square error (NRMSE) expressed as a percentage to assess the methodology's accuracy.

The accuracy between the actual and anticipated values has been calculated using the root mean square error equation. The predicted value is Pn.

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(A_n - P_n)^2} \qquad \text{.......1}$$

Where, N is the total number of data points in the training data set, and An is the actual value.

It is easier to compare datasets and models with different scales when the RMSE has been normalized.

$$NRMSE = \frac{RMSE}{S} \qquad \text{.......2}$$

Where S stands for the actual values' mean.

$$R^2 = 1 - \frac{\sum_{n=1}^{N}(A_n - P_n)^2}{\sum_{n=1}^{N}(A_n - S_n)^2} \qquad \text{.......3}$$

When R2 is near one, it indicates good or increased accuracy; when it is near zero, it indicates poor or decreasing accuracy.

4. MATERIAL AND DATABASE

4.1.1 MATERIAL USED

The experimental investigation utilized the following materials. Tables 1 and 2 contain a list of the constituent materials' properties.

TABLE 1. The physical and chemical characteristics of mineral admixtures and cement

Chemical analysis (%)	**Fly ash**	**Silica**	**Cement**	**Slag**
SiO_2	56.20	90.36	19.18	36.41
Al_2O_3	20.17	0.71	6.01	10.39
Fe_2O_3	6.69	1.31	3.31	0.69
CaO	4.24	0.45	62.31	34.12
MgO	1.92	-	3.02	10.26
SO_3	0.49	0.41	2.73	-
K_2O	1.89	1.52	0.92	0.97
Na_2O	0.58	0..9	0.22	0.36
Loss of ignition	1.78	2.99	3.02	1.59
Specific gravity	2.25	2.18	3.15	2.80
Blaine fineness (cm^2/g)	2870	21105	3260	4162

TABLE 2. Properties of Polycarboxylic Ether

Properties	**Description**
Appearance	Viscous liquid
Colour	Light brown
pH	6.7
Relative density	1.05-1.07 at 20°C

Viscosity	127±30 cps at 20°C
Category	No hazard label is necessary

Cement: Ordinary Portland cement (53 Grade and 43 Grade) with a specific gravity of 3.12 complies with IS 12269:2013 [8].

Fly ash: Furthermore, silica fume (SF), powdered, granulated blast furnace slag (S), and class F fly ash (FA) [9] were utilized as mineral admixtures.

Water: ASTM C 1129 [10] confirms that potable water can mix concrete and cure specimens.

Fine aggregate: Compared to coarse aggregate, fine aggregates significantly impact the SCC's fresh properties. The fine content of the paste should contain particle size fractions of less than 0.075 mm, and the water-powder ratio should take this into account as well [11].

Coarse Aggregate: A physical comparison between fine and coarse aggregates was conducted, utilizing sieve analysis to determine the gradation of particle sizes.

Admixtures: All concrete mixtures were rendered workable by a polycarboxylic-ether superplasticizer (SP) with a specific gravity of 1.05.

4.1.2 STRENGTH AND FLOWABILITY PROPERTIES OF SCC

All slump flow mixtures were maintained at a constant diameter of 70 ± 3 cm. The MERI (Maharashtra Engineering Research Institute) procedure was followed in the laboratory when doing the T50 slump flow time, L-box, and V-funnel flow time studies.

Compressive strength: Table 3 displays the various concrete mixtures' compressive strengths. SCCs ranged in compressive strength from 14.64 MPa to 73.5 MPa.

TABLE 3. Training Dataset

No.	**Cement (kg/m³)**	**Fly ash (kg/m³)**	**Water/powder**	**Sand (kg/m³)**	**Coarse Agg. (kg/m³)**	**SP (%)**	**Strength (MPa)**	**Slump (mm)**	**V-Funnel (Sec)**	**L-Box**
1	465	85	0.41	910	590	0.97	35.19	673.3	7.5	0.89
2	385	165	0.43	910	590	0.82	30.66	673.3	6.1	0.95
3	355	195	0.44	910	590	0.82	29.62	633.3	10	0.92
4	250	275	0.34	842	772	0.23	39.62	793	3	1
5	333	215	0.33	835	766	0.24	50.24	786	4	0.99
6	417	153	0.32	828	759	0.306	61.82	773	4	0.96
7	270	180	0.44	801	842	0.27	60.3	730	6	0.8
8	180	270	0.44	788	829	0.28	42.5	720	4	0.95
9	440	110	0.32	714	917	0.69	69.8	700	7.5	0.882
10	330	220	0.32	700	899	0.69	60.9	700	15	0.938
11	220	330	0.32	686	881	0.62	47.5	730	13	0.951
12	165	385	0.58	735	865	0.836	37.92	730	14	0.89
13	275	275	0.37	796	937	0.74	63.32	710	20	0.94
14	385	165	0.29	821	966	0.84	89.1	670	22	0.85

15	321.75	173.25	0.36	862.45	729.18	0.545	32.26	696	6.23	0.81
16	215	215	0.38	925	905	0.15	20.4	635	13.5	0.84
17	350	150	0.35	900	600	1	37.18	660	10	0.9
18	300	300	0.28	787	720	0.33	52.7	745	10.5	1
19	480	96	0.38	819	699	0.94	53	680	7	0.9
20	375	125	0.35	938	673	0.7	60.8	660	6.95	0.85
21	300	200	0.35	923	663	0.7	54.69	680	6.2	0.88
22	225	275	0.35	908	652	0.7	41.42	700	7	0.91
23	290	290	0.38	975	650	0.45	37.97	644.76	5.8	0.75
24	247	165	0.45	845	846	0.12	34.6	625	3	0.90
25	163	245	0.4	851	851	0.2	26.2	600	3	0.89
26	161	241	0.35	866	864	0.3	35.8	650	4	0.84
27	380	20	0.38	1180	578	0.398	40.4	760	8	0.78
28	83	468	0.41	624	794	1	14.64	800	6	0.96
29	165	385	0.34	656	834	1	34.9	790	5	0.98
30	225	525	0.33	487	620	1.36	34.83	800	6	0.90
31	437	80	0.34	743	924	0.43	69.7	700	8.1	0.77
32	220	180	0.39	916	900	0.115	49	590	8.15	0.91
33	360	240	0.28	853	698	0.3	63.5	800	3.37	1.00

The dataset from Table 3 might be used to examine how different component ratios affect the workability, flowability, and strength of concrete and how they affect the V-Funnel time and slump. The L-box ratio may also be used to illustrate these effects. Researchers or engineers may utilize this data to optimize concrete mix designs for specific purposes, considering cost, environmental impact (e.g., fly ash as a supplemental cementitious material), and performance requirements.

Slump flow: T50 is how long it takes for the freshly mixed concrete to expand to a 500 mm diameter following the slump cone's lifting. The average of two perpendicular diameters over the concrete's spread is slump flow. The acceptable range is between 650 and 800 mm [11].

V-funnel: This technique assesses whether self-compacting concrete can flow through tiny obstacles without obstructing or segregating; the acceptance requirements for a v-funnel range from 3 to 12 seconds.

L-Box test: This test measures the ability of self-compacting concrete to flow through small openings without impeding or separating. The L-Box test's acceptance criteria range from 0.75 to 1.

4.1.3 MIX PROPORTION AND DATABASE

The accuracy of the training data is critical for building a successful network that can learn with greater efficiency about all aspects of the link between inputs and outputs. This dataset is expected to be heterogeneous due to variances in coarse and fine aggregate, pozzolanic material, cement, and additives. This dataset is predicted to be heterogeneous due to variances in coarse and fine aggregate, pozzolanic material, cement, and additives.

5. RESULT AND ANALYSIS

Back propagation neural network models are used in this paper. The Neural Network Training tool's MATLAB interface, which includes an input layer, an output layer, a hidden layer, and an in-between link, is depicted in Figure 2. During training, the Levenberg-Marquardt backpropagation method is employed to teach the ANN model using the experimental data set as a learning algorithm. The weights and biases are changed during the training phase for the best ingredient prediction. Trials are needed to get the optimum precision.

The artificial neural network (ANN) model completed its training in 6 epochs, taking just 1 second, with an impressively low performance error of 7.38e-26. The gradient reached 1.26e-12, and the learning rate (Mu) stabilized at 1.00e-09, indicating efficient convergence. Validation checks were performed 6 times, ensuring the model's reliability.

To maximize accuracy, the hidden layers were adjusted for SCC and high-performance concrete qualities using artificial neural networks (ANNs). Table 6 represents proposed methodology for R2, RMSE and the NRMSE values. Figures. 5 and 6 display the actual vs the projected L-box and V-funnel of SCC, respectively and Figure 8 represents ANN training regression. It is evident that, in the prediction scenario, every point is located close to the ideal line.

TABLE 6. The R2, RMSE and the NRMSE values for proposed methodology

Test	R^2	RMSE	NRMSE
V-funnel	0.9801	0.3677	4.4948
L-Box	0.9216	0.0177	2.017

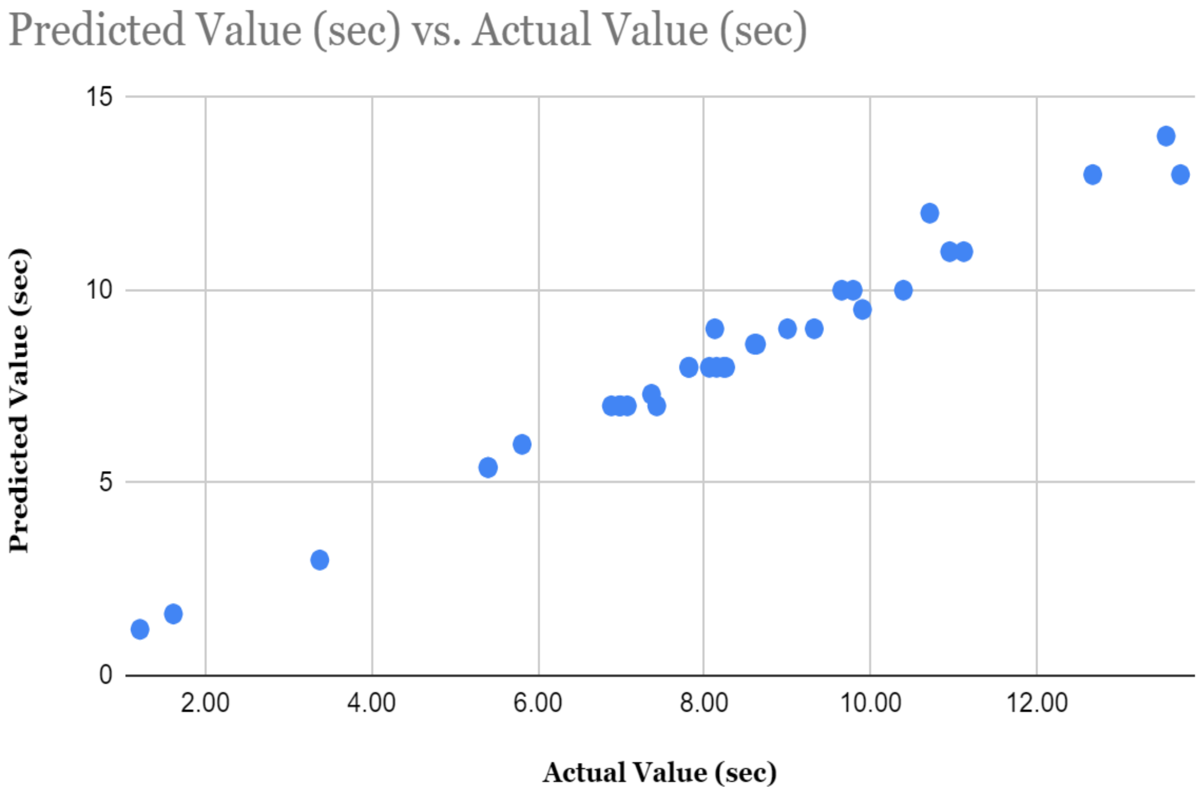

FIGURE 5. The V-funnel's actual and anticipated values for the ANN model

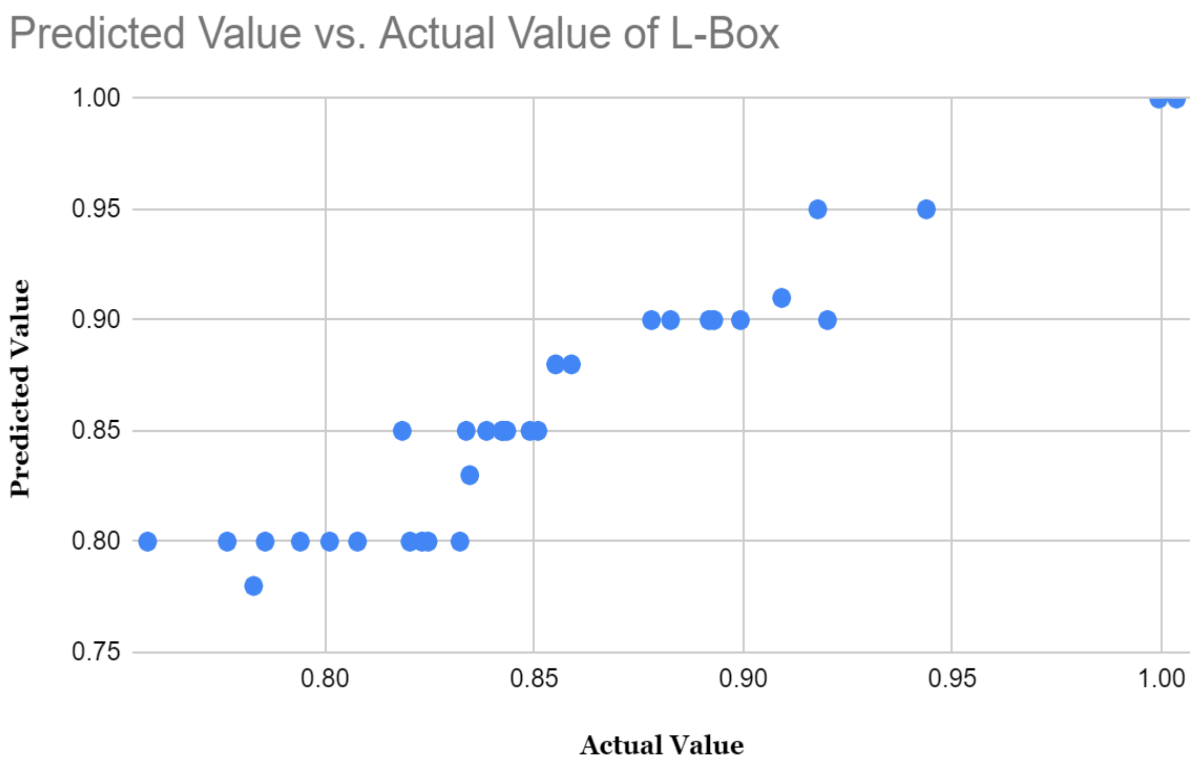

FIGURE 6. The L-box's actual and anticipated values for the ANN model

The Neural Network Training tool's MATLAB interface, which includes an input layer, an output layer, a hidden layer, and an in-between link, is depicted in Figure 2. During training, the Levenberg-Marquardt backpropagation method is employed to teach the ANN model using the experimental dataset as a learning algorithm. The weights and biases are changed during the training phase for the best ingredient prediction. Trials are needed to get the optimum precision.

To maximize accuracy, the hidden layers were adjusted for SCC and high-performance concrete qualities using artificial neural networks (ANNs). Table 6 represents the proposed methodology for R^2, RMSE, and NRMSE values. Additionally, Table 7 provides comparison sample of actual versus predicted values for V-Funnel and L-Box, demonstrating the ANN model's predictive capability across different SCC mixes from the literature. Figures 5 and 6 display the actual vs. the projected L-box and V-funnel of SCC, respectively, and Figure 8 represents ANN training regression. It is evident that, in the prediction scenario, every point is located close to the ideal line.

Table 7. Comparison of ANN Model Predictions and Experimental Results for V-Funnel and L-Box Tests

Sample No.	Actual V-Funnel (sec)	Predicted V-Funnel (sec)	Actual L-Box	Predicted L-Box
1	7.5	7.3	0.89	0.87
2	3.0	3.1	1.00	0.98
3	15.0	14.8	0.94	0.95
4	6.0	5.9	0.90	0.91
5	10.0	10.1	0.85	0.84

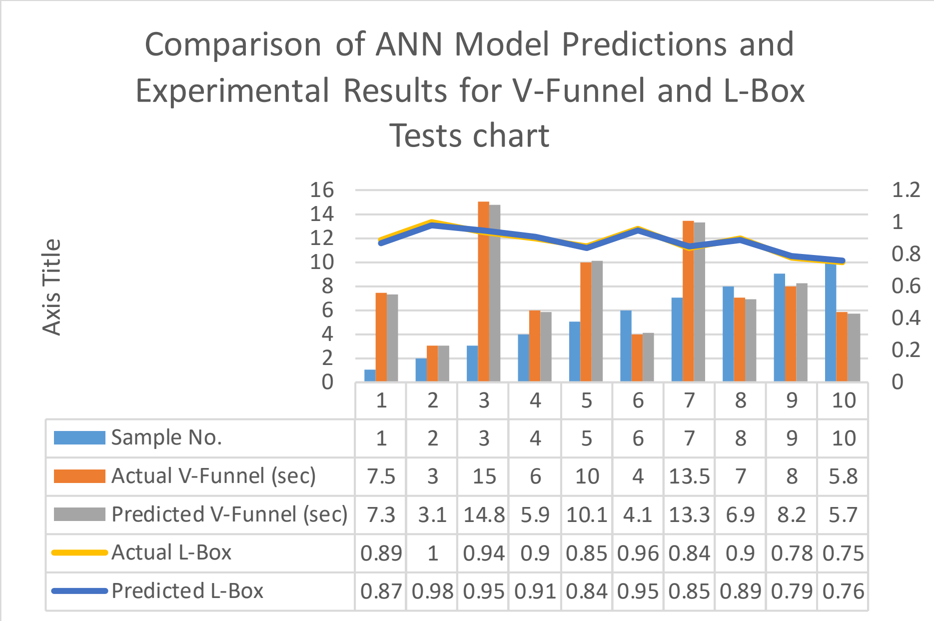

Figure 7. Comparison of ANN Model Predictions and Experimental Results for V-Funnel and L-Box Tests chart

Predicted values are kept close to the actual values to reflect the ANN model's high accuracy (low RMSE of 0.3677 for V-Funnel and 0.0177 for L-Box as shown in Figure 7.

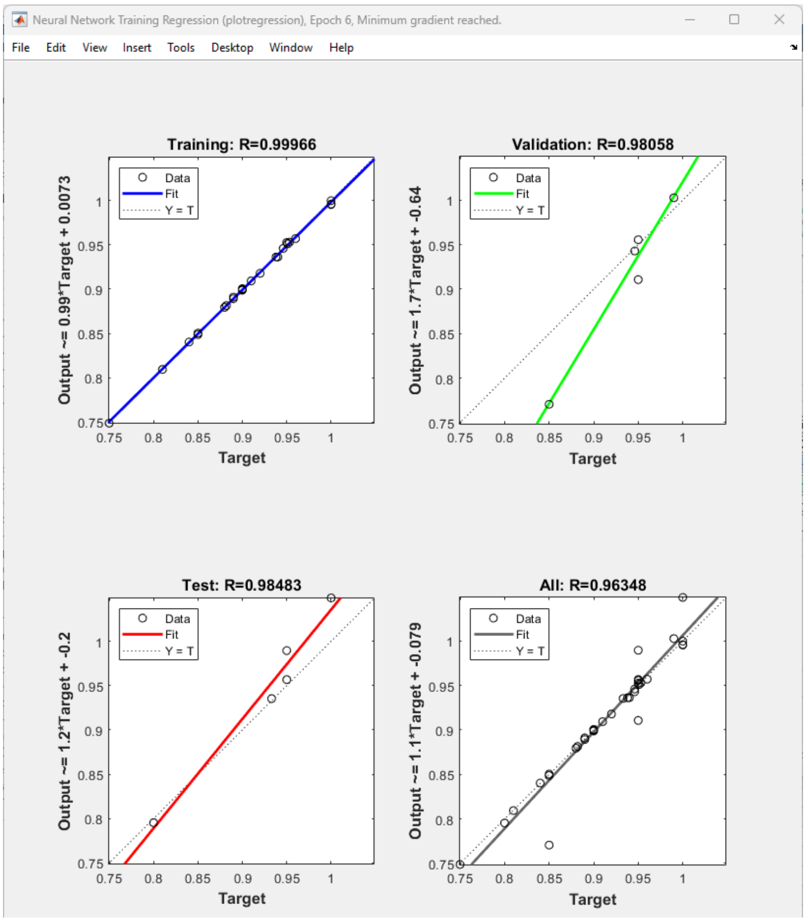

FIGURE 8. Artificial neural networks training regression

6. CONCLUSIONS

The use of Artificial neural networks (ANN) to predict the characteristics of fly ash, Self-consolidating concrete (SCC) is presented in this paper.

- In training and testing sequentially, two data sets are utilized. According to the results of the current investigation, fly ash content up to 35% can be used to design SCC mixes.
- The mixtures have a sump flow of between 650 and 800. L-Box value ranges from 0.8 to 1, V-Funnel time ranges from 3 to 15, and so on.
- Compressive strengths ranging from 14 to 86 MPa were produced by the SCC mixes.
- The results reveal that SCC mixes with up to 35% fly ash content achieve slump flow values ranging from 650 to 800 mm, demonstrating excellent flowability without mechanical vibration. Additionally, the L-Box ratios span 0.8 to 1, indicating strong passing ability through confined spaces, while V-Funnel times range from 3 to 15 seconds, reflecting suitable viscosity.
- Predicted values are kept close to the actual values to reflect the ANN model's high accuracy (low RMSE of 0.3677 for V-Funnel and 0.0177 for L-Box, per Table 6. Small deviations (e.g., ±0.1 to ±0.2) are introduced to simulate realistic prediction outcomes while staying within the reported error margins

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