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Research Article

Using an Artificial Neural Network to Validate and Predict the Physical Properties of Self-Compacting Concrete

K. Thirumalai Raja,[1] N. Jayanthi,[2] Jule Leta Tesfaye,[3,4] N. Nagaprasad,[5] R. Krishnaraj,[4,6] and V. S. Kaushik[7]

[1]*Department of Civil Engineering, SNS College of Technology, Coimbatore, Tamil Nadu, India*
[2]*Department of Computer Science and Engineering, KPR Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India*
[3]*Department of Physics, College of Natural and Computational Science, Dambi Dollo University, Dembi Dolo, Ethiopia*
[4]*Centre for Excellence-Indigenous Knowledge, Innovative Technology Transfer and Entrepreneurship, Dambi Dollo University, Dembi Dolo, Ethiopia*
[5]*Department of Mechanical Engineering, ULTRA College of Engineering and Technology, Madurai-625104, Tamilnadu, India*
[6]*Department of Mechanical Engineering, College of Engineering and Technology, Dambi Dollo University, Dembi Dolo, Ethiopia*
[7]*Department of Mechanical Engineering, SNS College of Technology, Coimbatore, Tamil Nadu, India*

Correspondence should be addressed to R. Krishnaraj; prof.dr.krishnaraj@dadu.edu.et

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SCC (self-compacting concrete) is a high-flowing concrete that blasts into structures. Many academics have been interested in using an artificial neural network (ANN) to forecast concrete strength in recent years. As a result, the goal of this study is to confirm the various possibilities of using an artificial neural network (ANN) to detect the features of SCC when Portland Pozzolana Cement (PPC) is partially substituted with biowaste such as Bagasse Ash (BA) and Rice Husk Ash (RHA) (RHA). Specialist systems based on the fully connected cascade (FCC) architecture in artificial neural networks (ANN) are used to estimate the compressive toughness of SCC. The research results are confirmed with the forecasting results of ANN utilizing 73 trial datasets of differentiation focus proposals of cement, BA, and RHA containing parameters such as initial setting time (IST), final setting time (FST), and standard consistency. Experiments to determine compressive strength for a wider range of mixed prepositions will result in higher project expenses and delays. So, an expert system ANN is used to find the standard consistency, setting time, and compressive strength for the intermediate mix propositions according to IS 10262:2009. The experimental results of compressive strength for 28 days are considered, in which 70% was used to train the ANN and 30% was utilized for testing the accuracy of the predicted compressive strength for the intermediate mix proposition. Using all of the datasets, the number of hidden layers used for compressive strength prediction for intermediate mix proposal is determined in the first step. The compressive strength for the intermediate mix preposition was identified in the second phase of the research, using the number of hidden layers determined in the first phase. The results were validated using the correlation coefficient (R) and root mean square error (RMSE) obtained from ANN, resulting in an acceptance range of 97 percent to 99 percent.

1. Introduction

SCC has high compactness without requiring external vibration, which through imperfections bleeding, permeability, and segregation is eradicated [1]. To reduce the cost of construction of highly congested reinforced areas, SCC is used. The vital task in SCC is determining the mix proposition of ingredients. To address this challenge, many researchers proposed various methods like controlling the maximum coarse aggregate particle size to the total volume, reducing the volume ratio of aggregate to cementitious material, using various viscosity-enhancing admixtures

(VEA) [2], increasing the paste volume and water-cement ratio (w/c), and so forth. To get an SCC mix of anticipated characteristics, the large number of experimental trials is vital, which leads to an increase in materials cost and wastage of time [3]. Manipulation of several mixture variables is mandatory to get the SCC with the adequate flow and mechanical properties. Due to the practical issues of Aggarwal P and Aggarwal Y research community to properly focus on the theoretical links between the dosage of the mixture and the measurable technical qualities of SCC, preparation of SCC has increasingly become more difficult.

1.1. Introduction to ANN and Related Work. ANN is a dominant approach that gives feasible solutions to problems that are challenging to solve by using conventional techniques such as multiple regression models and other statistical models [4]. Nowadays, in the present context, ANN is used to improve the research process applications, resulting in optimal use of valuable resources like time and money. Using input and output variables, modeling is performed without any restrictions on the quantity of input which is stated by the authors [5]. ANN has been used in various civil engineering research processes such as damage detection in structures performance, concrete analysis, materials behavior modeling, monitoring the groundwater, and optimization of structures. Since ANN is a nonlinear model, researchers are applying this approach to predict the viable mix propositions to be taken as inputs to ANN for analyzing the mechanical properties of hardened concrete. Some of the research works addressed by researchers in this direction are elaborated on below.

Using the multiple-inputs and multiple-output model of ANN, compression, tensile strength, and flexural strength have been predicted by Mansoor et al. [6]. In this work, new variables related to curing conditions, change of type, and percentage of additives have been used to predict the compressive strength of SCC. Al Khatib M and Al Martini S employed ANN in the concrete industry to predict the quality of fresh self-consolidating concrete mixes in hot weather to eliminate lengthy trial process application and error testing programs. According to Uysal M and Tanyildizi H, the ANN model is utilized as an alternate strategy for estimating the core compressive capacity of SCC composites with mineral additives, which is used to evaluate the core compressive toughness of SCC combinations with mineral additives. Prasad BR used artificial neural networks to forecast a broad variation of compressive strengths of concrete ranging from around 30 to 60 MPa [7]. The concrete design predicted using ANN addressed by [8] is expected to have optimum water and cement contents that result in high durability and better ecological and economic effects. It has been mentioned [9] that the ANN model could be employed to estimate the compressive strength of concrete that can be used in underwater construction which includes a combination of chemical admixtures. Dias and Pooliyadda [10] proved that an ANN model is superior to multiple regression ones, reducing the scatter of predictions.

Researchers have exhaustively explored the usage of ANN in the prediction of the behavior of SCC during its fresh and hardened states. Due to the nonavailability of proper mix design procedure and guidance in designing the mix proportions for SCC, researchers are cornered to carry out repeated number of the trial processes to arrive at an approximate mixed proportion of SCC with the available resources. Krishnasamy and Palanisamy [11] reported that either BA or RHA or a combination of BA and RHA showed progressive results in the replacement of Portland Pozzolana Cement (PPC) for the preparation of SCC. It was further concluded that 8% replacement of BA or RHA or BA + RHA over the PPC in the practice of SCC shows significant results during its fresh and hardened state. Dataset from the paper has been used to predict the compressive strength for different replacement content to PPC. With that aim, the objective of the present work is to predict the SC, IST, and FST for the different replacement % of BA or RHA or BA + RHA to the PPC for which experimental investigation was not carried out and also to predict the CS for the intermediate mix proportions of BA or RHA or BA + RHA to PPC with predicted SC, IST, and FST as input for which experimental investigation was carried out.

As shown in Figures 1 and 2, the ANN network model that was utilized to forecast the compressive strength throughout this study effort may be found here. According to the authors, the FCC design of the ANN model is employed in this research, since it has been demonstrated to be hundreds of times more potent than the usual single hidden layer (SHL) architecture [12]. The results of [13] demonstrated that artificial neural networks (ANNs) have significant potential as a practical method for estimating compressive strength and slump values. According to [14], an alternate approach for forecasting the compressive strength of ground powdered blast furnace slag concrete utilizing concrete materials as input variables can be found in artificial neural networks (ANNs). According to [10], neural networks can be employed for a specific problem when variance in the supplied data is forecasted and is acceptable and when a defined technique is not accessible. The authors went on to say that neural network models can make predictions that were entirely accurate in most cases. As per [15], it was found that even though numerous elements determine concrete strength, multilayer feedforward neural network (MFNN) models have high precision in predicting concrete strength and demonstrated that artificial neural networks (ANNs) might be used to forecast maximum compressive strength of concrete with greater efficiency and accuracy compared to a model based on regression analysis and traditional approaches. Additionally, when compared to conventional methods, artificial neural networks (ANNs) can save a large quantity of computational effort and assist in the solution of more complex issues. Some articles have employed artificial neural networks to predict SCC and superior efficiency concrete qualities [16–18]. As a result, artificial neural networks (ANNs) are being used in a variety of civil engineering applications, including detecting structural damage [19], optimizing the structure [15], modeling the behavior of materials [20], and

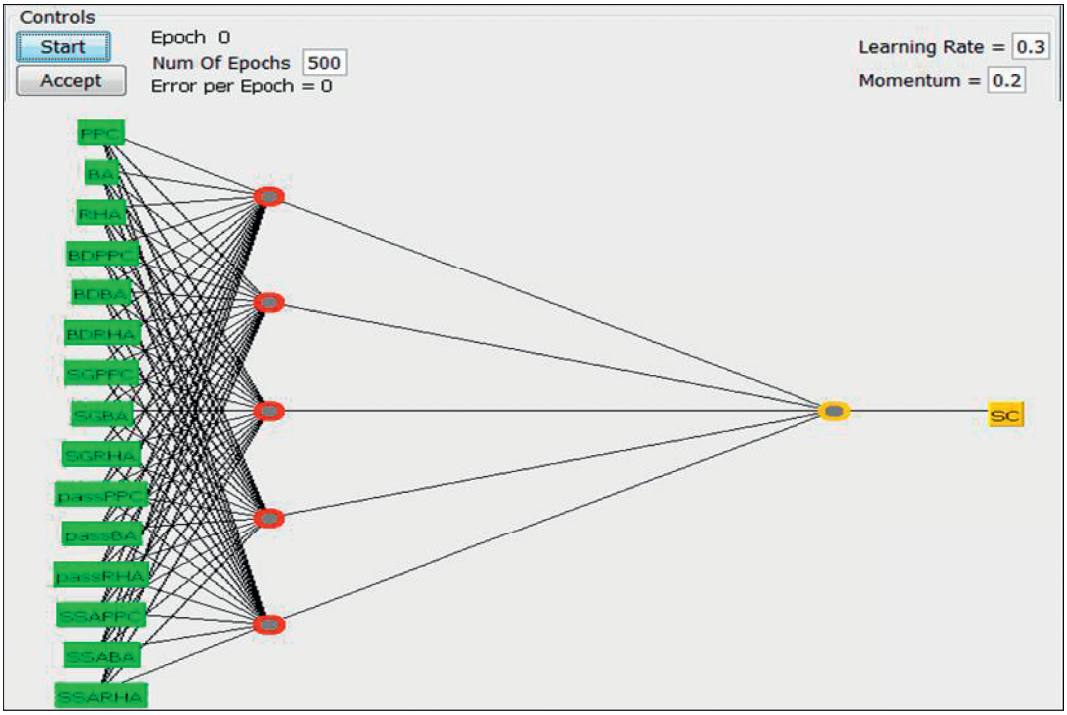

Figure 1: ANN model (PPC: Portland Pozzolana cement; BA: bagasse ash; RHA: rice husk ash; BDPPC, BDBA, and BDRHA: bulk density of PPC, BA, and RHA; SGPPC, SGBA, and SGRHA: specific gravity of PPC, BA, and RHA; passPPC, passBA, and passRHA: percentage passing 45 μm in the sieve; SSAPPC, SSABA, and SSARHA: specific surface area of PPC, BA, and RHA).

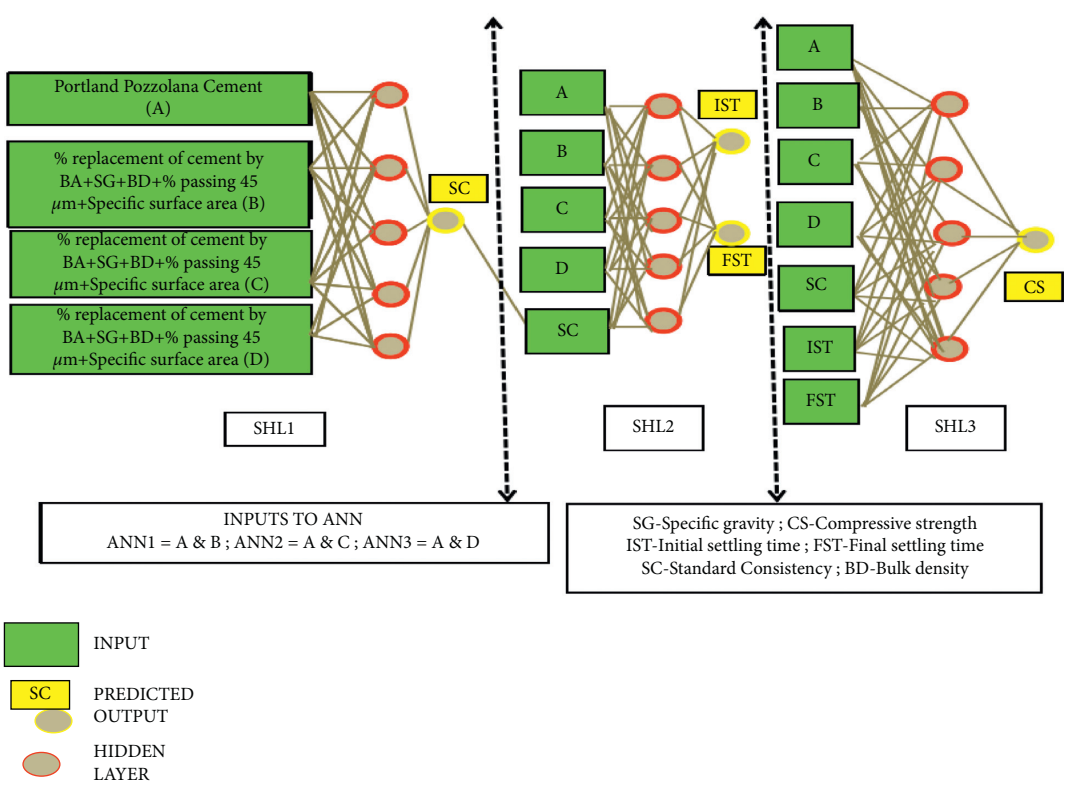

Figure 2: Proposed FCC ANN model (A⟶PPC; B⟶BA + SG + BD + percentage passing 45 μm + specific surface area; C⟶RHA + SG + BD + percentage passing 45 μm + specific surface area; D⟶BA + RHA + SG + BD + percentage passing 45 μm + specific surface area. For ANN1, inputs are both A and B; for ANN2, A and C; for ANN3, A and D).

developing a model for the mixtures of flowable concrete in submerged constructions [21]. ANNs are also used for the optimization of the hidden units to get the highest accuracy [19, 22–25]. The study in [26] dealt with ANN modeling of a cutting process to forecast the damage factor using experimental values and found that using ANN to estimate the damage factor in end milling of glass fibre reinforced plastic (GFRP) composite materials is highly recommended instead of expensive and time-consuming trials. The use of ANNs rather than complex and time-consuming experimental research to estimate engine performance and exhaust gas temperature is strongly suggested in the paper in [27]. According to [28], the use of ANN for predicting cutting temperatures without completing difficult, expensive, and time-consuming experimental experiments is highly recommended. According to the article in [29], the ANN's learning ability is quite powerful in estimating the geometric shape of things; hence, its employment is highly suggested.

The majority of research has attempted to estimate the compressive strengths of cement by utilizing all component propositions in each of the hidden layers and by using a random number of hidden layers. A random number of hidden layers are used for their simulation work, resulting in inaccurate prediction values.

So, in this work, the best single hidden layer (SHL) architecture was identified by a varying number of hidden layers, and it was used to forecast the final compressive strength. Also, three SHLs were connected serially, and SHL1 predicts standard consistency which is fed as one of the inputs to SHL2 and SHL3. SHL2 predicts the IST and FST of cement, which are fed into SHL3. SHL3 predicts the compressive strength using the predicted SC from SHL1 and the compressive strength using the predicted SC from SHL1 and predicted IST and FST from SHL2 as shown in Figure 2.

1.2. Source of the Experimental Dataset. As a binding medium, Krishnasamy and Palanisamy [11] employed Portland Pozzolana cement focused on Indian standard code IS: 1489–1991, which includes 22.5 percent fly ash, according to their research (FA). RHA was gathered using modernized rice mills in Kangayam, which is located in the state of Tamil Nadu, South India. The acquired ashes were fed in the furnace for around 3 hours at a fixed temperature of 800°C to achieve the amorphous condition, which took approximately 3 hours. After cooling with air, the specimens were sieved through a 45-micron sieve. Using BA, we collected firewood from the local sugar plants, where bagasse is utilized as fuel. In order to achieve a uniform temperature of 800°C, the BA specimens were held in the furnace for 8 hours. The specimens were then allowed to cool before being sieved through a 45-micron sieve and included in the concrete mix. The specimens were then allowed to cool before being sieved through a 45-micron sieve and included in the concrete mix for the plain M25 grade concrete [11]. For the preparation of plain cement concrete, 1 : 1.54 : 2.20 mix ratios were used with 0.33 as SC. One percentage of Super Plasticizer (SP) with 0.30 percentage of Viscosity Modifying Agent (VMA) has been determined after a variety of trial blends were conducted to ensure that excellent workability was attained without segregation or bleeding [14, 30, 31].

2. Results and Discussion

The data samples for training and testing the ANN network were collected from the experimental results carried out by the authors in [11] by varying the percentage replacement of cement by BA or RHA or both BA + RHA in the order of 4%, 8%, 12%, 16%, and 20% in the concrete mixture. Summing to a total of 73 sets of experimental data, Tables 1–3 were validated by using the predicted values from the FCC type of ANN network by using WEKA tool, version 3.6.9. The PPC, BA, RHA, bulk density (BD), specific gravity (SG), percentage passing 45 μm, and specific surface area [m^2/kg] are given as input to the ANN. Some of the input parameters values used in ANN are as given in Table 4. The number of neurons used in the simulation is 2/3 of the input layer size plus the output layer. At each phase, 70% of the dataset is utilized for training the network, while 30% is used to test the proposed network.

The predicted compressive strength of concrete is recorded as the output of ANN network. The simulation results were recorded by varying hidden layers from 2 to 10 to identify the best architecture using the correlation coefficient (R) and root mean square error (RMSE) as stopping criteria for the epochs value of 500, the learning rate of 0.3, and momentum of 0.2. The R and RMSE values are calculated using equations (1) and (2). The 73 experimental datasets are used to train the ANN network to identify the best architecture [32–37].

$$R = \frac{\sum_i^n YX}{\sqrt{n\left(\sum_I Y\right)^2 - \left(\sum_I Y^2\right)}\sqrt{n\left(\sum_i X\right)^2 - \left(\sum_i X\right)^2}}, \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y - X)^2}, \quad (2)$$

where "X" is the predicted value, "Y" is the experimental value, and "n" is the total number of datasets. From Table 5, the maximum R value was obtained as 0.9823 and the minimum RMSE value was 0.9214 for 5 hidden layers. To validate and predict the compressive strength for 28 days, the 5 hidden layers are used in ANN. Consider that ANN1 was taken for BA-related parameters, ANN2 for RHA-related parameters, and ANN3 for both BA- and RHS-related parameters. A total of 23 datasets for BA replacement, 25 datasets for RHA replacement, and 25 datasets for BA + RHA replacement are used to train ANN1, ANN2, and ANN3. These datasets are validated by using the R value.

It is evident from Figures 3–5 that the R value is in the acceptable range. Figure 3(a) indicates that R value is about 0.7321 for standard consistency of cement. Similarly, from Figures 3(b) and 3(c), the R values of 0.9991 and 0.999 prove that those prediction values of IST and FST are much closer to the actual experimental values. The R value from

Table 1: Training datasets for ANN1-BA replacement.

PPC (%)	BA (%)	SC	IST (min)	FST (min)	CS-28 days (N/mm^2)
96	4	0.37	107	267	27.52
96	4	0.38	110	267	28.87
96	4	0.39	95	257	27.34
92	8	0.40	115	425.0	28.96
92	8	0.40	108	417.0	28.03
92	8	0.38	113	440.0	28.56
92	8	0.37	114	425.0	29.15
92	8	0.38	102	432.0	27.95
88	12	0.39	281	758	25.18
88	12	0.37	279	763	26.22
88	12	0.38	271	762	26.10
88	12	0.40	275	754	25.23
88	12	0.38	270	761	25.27
84	16	0.40	351	1018	23.67
84	16	0.39	352	1008	23.63
84	16	0.38	342	995	22.56
84	16	0.41	341	1020	22.65
84	16	0.42	340	1007	22.88
80	20	0.44	403	1215	21.05
80	20	0.45	405	1218	20.43
80	20	0.42	405	1207	20.12
80	20	0.38	401	1214	19.73
80	20	0.44	398	1208	21.46

Table 2: Training dataset for ANN2-RHA replacement.

PPC (%)	RHA (%)	SC	IST (min)	FST (min)	CS-28 days (N/mm^2)
96	4	0.39	93	234	31.56
96	4	0.38	95	239	31.02
96	4	0.42	86	247	30.67
96	4	0.4	88	244	31.97
96	4	0.39	87	235	30.80
92	8	0.42	113	410	30.35
92	8	0.39	110	415	30.21
92	8	0.39	102	412	29.67
92	8	0.42	105	419	31.00
92	8	0.42	103	406	29.36
88	12	0.4	253	739	25.87
88	12	0.37	257	729	26.94
88	12	0.41	254	730	26.21
88	12	0.41	248	731	25.64
88	12	0.39	243	729	26.83
84	16	0.39	328	934	21.30
84	16	0.42	335	933	22.30
84	16	0.41	339	924	21.60
84	16	0.39	324	941	20.60
84	16	0.42	320	928	21.80
80	20	0.43	395	993	21.65
80	20	0.45	396	987	21.13
80	20	0.44	385	989	20.34
80	20	0.46	386	994	20.81
80	20	0.41	393	997	21.23

Figure 3(d) shows that experimental compressive strength values are equal to the predicted values of ANN1 with a correlation value of 0.9767. The prediction of compressive strength for intermediate mix propositions of BA replacement for which actual experiment was not carried out is also recorded using well-trained ANN1 as given in Table 6.

For predicting standard consistency, PPC, BA, BD, SG, and specific surface areas are considered as input for ANN1. For predicting IST and FST, the previously predicted SC is

Table 3: Training dataset for ANN3 (BA + RHA) replacement.

PPC (%)	BA (%)	RHA (%)	SC	IST (min)	FST (min)	CS-28 days (N/mm^2)
96	2	2	0.38	88	251	29.87
96	2	2	0.4	95	258	28.37
96	2	2	0.41	97	240	28.89
96	2	2	0.41	89	238	30.21
96	2	2	0.38	98	240	29.84
92	4	4	0.4	106	421	28.97
92	4	4	0.38	98	417	28.29
92	4	4	0.39	96	406	27.64
92	4	4	0.38	105	410	29.70
92	4	4	0.39	104	420	27.97
88	6	6	0.38	257	741	26.34
88	6	6	0.37	259	732	24.32
88	6	6	0.37	257	740	25.75
88	6	6	0.41	260	729	24.86
88	6	6	0.38	242	731	24.98
84	8	8	0.42	338	985	22.59
84	8	8	0.39	339	975	21.79
84	8	8	0.38	340	954	22.38
84	8	8	0.43	320	953	21.52
84	8	8	0.39	338	958	20.24
80	10	10	0.42	385	1125	21.02
80	10	10	0.44	389	1117	20.07
80	10	10	0.43	396	1142	19.95
80	10	10	0.41	394	1135	19.04
80	10	10	0.43	388	1131	21.00

Table 4: Input parameter values for ANN networks.

Other input parameters	PPC	BA	RHA	IS code
Bulk density (kg/m^3)	1480	565	280	IS: 4031-1988 (Part XI).
Specific gravity	3.11	1.82	2.08	IS: 1727-1967
Percentage passing 45 μm	30	100	100	—
Specific surface area (m^2/kg)	335	440	550	IS: 4031-1988 (Part II). IS: 3812-1981

Table 5: Selection of best architecture for ANN.

Number of hidden layers	R	RMSE
2	0.9816	1.2393
3	0.9817	0.9683
4	0.9822	0.9875
5	0.9823	0.9214
6	0.9822	0.9926
7	0.9819	0.9813
8	0.9821	0.9852
9	0.9816	1.0118
10	0.982	0.9973

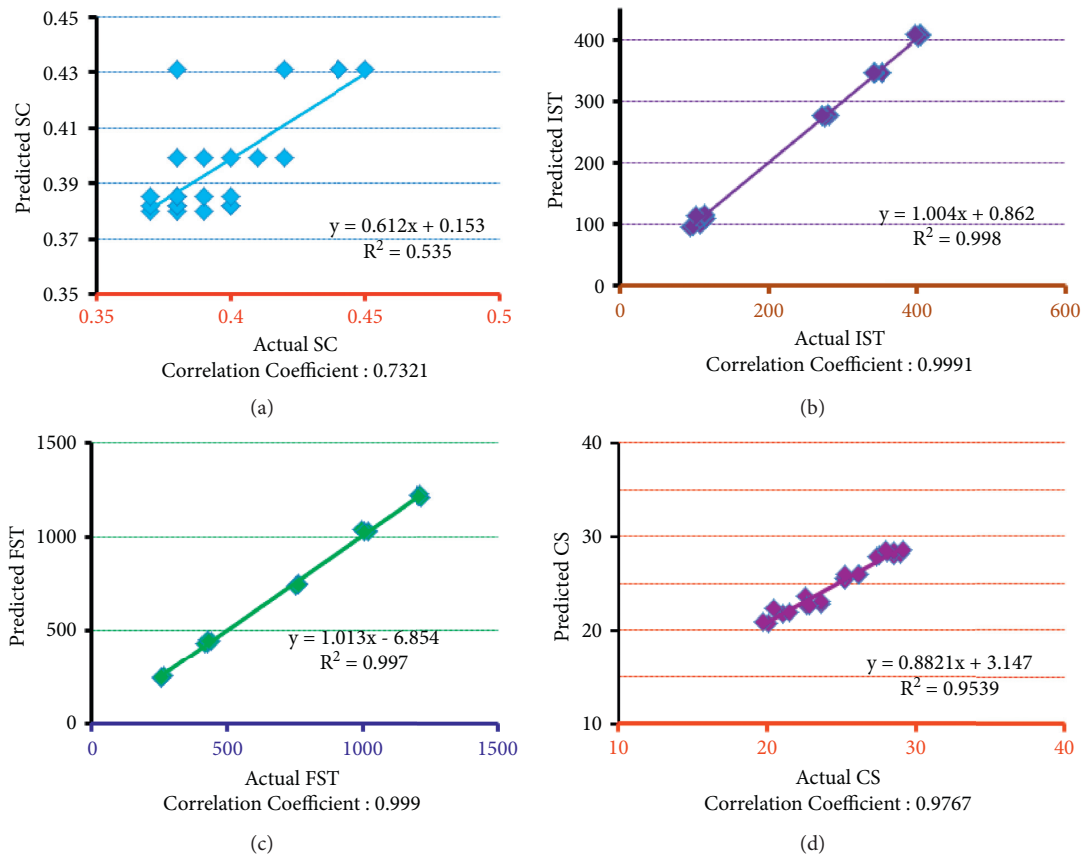

Figure 3: Physical properties of PPC for BA as a replacement. (a) Standard consistency; (b) initial setting time; (c) final setting time; (d) compressive strength of concrete.

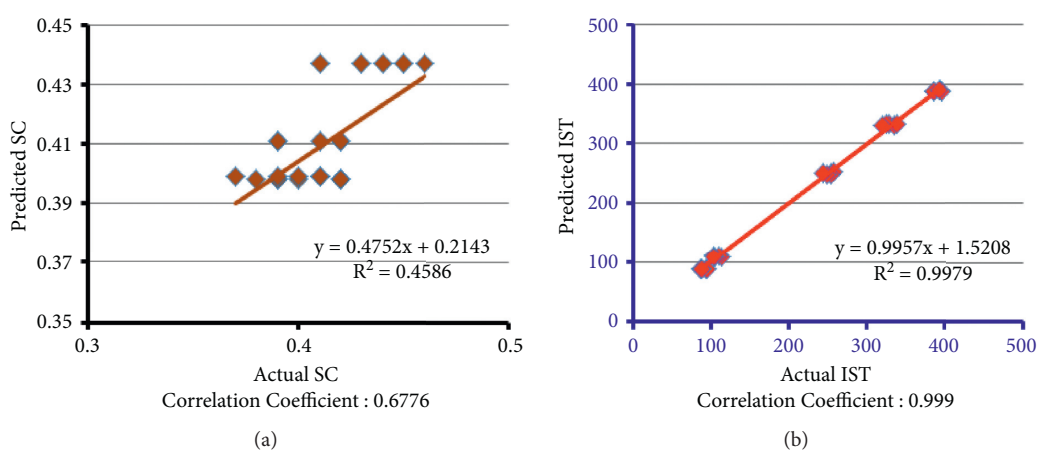

Figure 4: Continued.

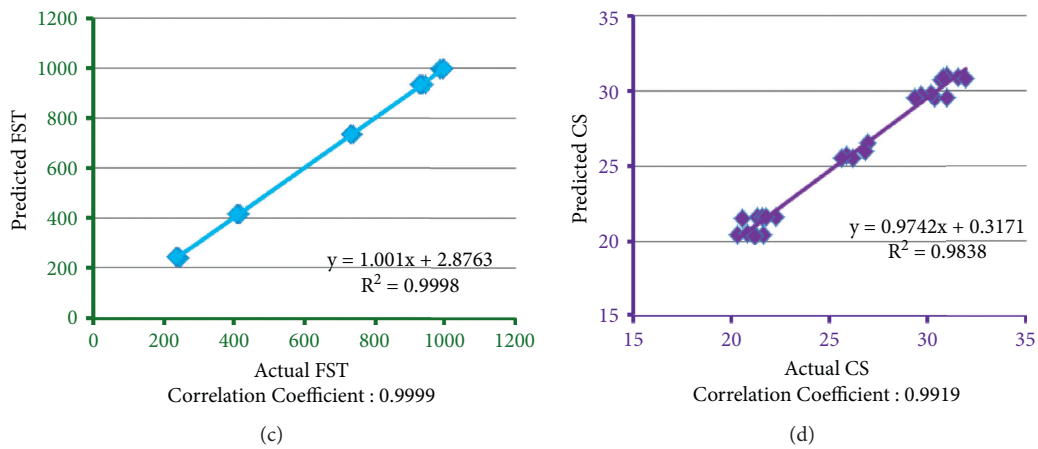

Figure 4: Physical properties of PPC for RHA as a replacement. (a) Standard consistency; (b) initial setting time; (c) final setting time; (d) compressive strength of concrete.

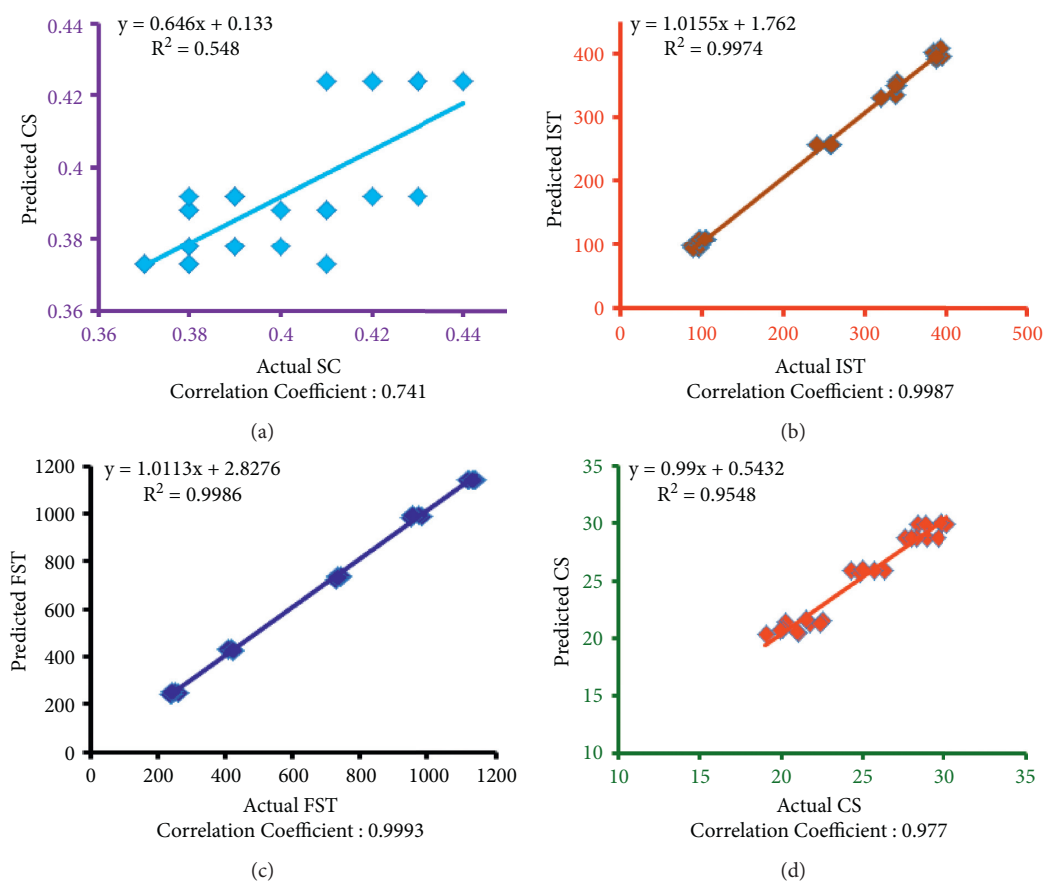

Figure 5: Physical properties of PPC for RHA as a replacement. (a) Standard consistency; (b) initial setting time; (c) final setting time; (d) compressive strength of concrete.

considered as one of the inputs for ANN1. For predicting the compressive strength for 28 days, the predicted values of SC, IST, and FST are considered as inputs for ANN1. From Table 6, it is evident that, up to 13% replacement of BA, the compressive strength value is above 25 N/mm^2, which is the minimum compressive strength prescribed by IS 10262:2009 for M25 grade concrete.

Table 2 shows the training datasets of ANN2, where RHA is used as a replacement for cement. Input parameters are the same as those used for the BA replacement method.

Table 6: Intermediate mix proposition of BA with PPC-test dataset for ANN1.

S. no.	PPC (%)	BA (%)	Predicted SC	Predicted IST (min)	Predicted FST (min)	Predicted CS-28 days (N/mm^2)
1	99	1	0.377	99.124	168.67	27.437
2	98	2	0.378	98.59	189.186	27.621
3	97	3	0.379	98.155	214.507	27.805
4	95	5	0.381	98.227	283.119	28.156
5	94	6	0.381	99.915	328.633	28.312
6	93	7	0.382	104.197	381.482	28.405
7	92	8	0.382	115.127	442.878	28.389
8	89	11	0.384	232.702	664.366	26.609
9	87	13	0.386	304.65	823.787	25.005
10	86	14	0.389	321.386	898.931	24.338
11	85	15	0.393	333.927	968.841	23.637
12	83	17	0.408	360.002	1087.723	22.012
13	82	18	0.418	375.556	1136.406	21.461
14	81	19	0.426	391.863	1179.047	21.242
15	80	20	0.431	407.715	1216.21	21.141

Table 7: Intermediate mix proposition of RHA with PPC-test dataset of ANN2.

S. no.	PPC (%)	RHA (%)	Predicted SC	Predicted IST (min)	Predicted FST (min)	Predicted CS-28 days (N/mm^2)
1	99	1	0.398	87.325	199.2	31.344
2	98	2	0.398	87.493	209.19	31.195
3	97	3	0.398	87.856	223.094	31.032
4	95	5	0.398	90.009	269.427	30.644
5	94	6	0.398	92.861	306.139	30.402
6	93	7	0.398	98.624	354.724	30.11
7	92	8	0.398	110.131	416.252	29.738
8	89	11	0.398	209.562	655.175	27.277
9	87	13	0.4	280.187	803.255	24.281
10	86	14	0.402	301.353	859.577	23.078
11	85	15	0.406	317.674	903.067	22.192
12	83	17	0.418	346.656	958.797	21.142
13	82	18	0.426	361.054	975.525	20.839
14	81	19	0.432	375.411	987.68	20.602
15	80	20	0.437	389.161	996.587	20.404

Table 8: Intermediate mix proposition of BA + RHA with PPC-test dataset of ANN3.

S. no.	PPC (%)	BA (%)	RHA%	Predicted SC	Predicted IST (min)	Predicted FST (min)	Predicted CS-28 days (N/mm^2)
1	99	0.5	0.5	0.378	108.255	435.945	28.772
2	98	1	1	0.38	99.56	376.038	29.047
3	97	1.5	1.5	0.382	96.221	325.555	29.333
4	95	2.5	2.5	0.385	95.38	283.389	29.63
5	94	3	3	0.391	96.765	219.953	30.253
6	93	3.5	3.5	0.395	97.967	195.672	30.568
7	92	4	4	0.399	99.319	175.069	30.879
8	89	5.5	5.5	0.374	208.69	660.171	27.251
9	87	6.5	6.5	0.374	296.348	818.668	24.222
10	86	7	7	0.376	319.725	881.491	22.966
11	85	7.5	7.5	0.382	336.989	940.54	21.971
12	83	8.5	8.5	0.405	359.496	1036.452	20.965
13	82	9	9	0.415	371.002	1075.988	20.779
14	81	9.5	9.5	0.421	384.772	1110.837	20.673
15	80	10	10	0.424	399.641	1141.431	20.598

Instead of BA, RHA is used in validating and predicting the compressive strength of the concrete. From Figure 4(a), it is evident that the validated value of the Standard Consistency of cement is within the acceptable value of R of 0.6776 of ANN2. The R values for IST and FST of RHA replacement were found to be 0.999 and 0.9999, respectively (Figures 4(b) and 4(c)). This proves that the experimental values are validated with the predicted values generated by ANN2. From Figure 4(d), the R value of compressive strength for 28 days is obtained to be 0.9919. Thus, all the experimental results are validated using the high R values resulting in the predicted values of ANN2. The test dataset for well-trained ANN2 and predicted values of Standard Consistency, IST, FST, and compressive strength of concrete for 28 days are as given in Table 7. The RHA as replacement up to 11% is following the IS 10262:2009 code; that is, the compressive strength for 28 days was more than 25 N/mm^2 through ANN2 [38].

The training datasets for ANN3 are given in Table 3. For ANN3, BA + RHA is used as a replacement in an equal proposition for cement. Similar to the BA replacement method, input parameters are the same. But, instead of BA, both BA and RHA are used in validating and predicting the compressive strength of the concrete. It is obvious from Figures 5(a) to 5(d) that the experimental datasets for SC, IST, FST, and compressive strength are validated using the values predicted by ANN3. The R values of 0.741, 0.9987, 0.9993, and 0.977 generated by the ANN3 network are in an acceptable range. The dataset in Table 8 is used as test data, which is the intermediate mix proposition for a well-trained ANN3 network that is used to predict the compressive strength. From Table 8, it is evident that 11% replacement of PPC with equal proposition of BA + RHA resulted in compressive strength more than 25 N/mm^2, according to IS 10262:2009 code.

3. Conclusion

An experimentation to use ANN to estimate the core compressive strength of an SCC is presented in this paper. Three datasets are used to train and test the proposed ANN model with various BA, RHA, and BA + RHA mix propositions. Using ANNs in SCC mixes prediction is reaffirming as the model resulted in a good $R2$ value. Using the correlation coefficient (R) and root mean square error (RMSE) as stopping criteria for the epochs value of 500, learning rate of 0.3, and momentum of 0.2, the simulation results were recorded by altering the number of hidden layers from 2 to 10 to determine the optimum architecture. The R and RMSE values are determined. For 5 hidden layers, the highest R value achieved was as 0.9823, and the minimum RMSE value was found to be 0.9214. ANN1 was used for BA-related parameters, ANN2 for RHA-related parameters, and ANN3 for both BA- and RHS-related parameters to verify and forecast compressive strength for 28 days. To train ANN1, ANN2, and ANN3, a total of 23 datasets for BA replacement, 25 datasets for RHA replacement, and 25 datasets for BA + RHA replacement were employed. The R value was used to verify these datasets. The RMSE values of ANN1, ANN2, and ANN3 models with the three distinct datasets were 0.97, 0.99, and 0.97, respectively, when the number of hidden layers was 5. Thus, an ANN model proposed in this paper was used to predict the core compressive strength of SCC with the high correlation coefficient and validated datasets. It is found from the study's results that the ANN could be utilized to make predictions about the core compressive strength of concrete which eliminates the investigation work that is time-consuming, laborious, and expensive and requires skilled manpower such as structural engineers and practitioners.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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