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TECHNICAL PAPER

Comparison of artificial neural network and hierarchical regression in prediction compressive strength of self-compacting concrete with fly ash

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Abstract
This study aims to predict and model the compressive strength of self-compacting concrete (SCC) across various fly ash content ranges. The research utilized two approaches: hierarchical regression (HR) and artificial neural networks (ANN) for modeling six variables influencing the process (cement content, fly ash content, water-to-binder ratio (W/B), coarse aggregate, fine aggregate, and superplasticizer). The fly ash content varied from 0 to 60% of the total weight of cement. The findings emphasize that the compressive strength of SCC is significantly affected by all the independent variables studied, except for superplasticizer. The statistical evaluation using the Pearson correlation (R), determination coefficient (R^2), Adjusted R^2, Predicted R^2, root mean square error (RMSE), mean square error (MSE) and mean absolute percentage error (MAPE) demonstrate that both ANN and HR are robust tools for predicting compressive strength of SCC. Additionally, the ANN and HR models show strong correlations with experimental data, with the ANN model displaying superior accuracy. As the performance indices showed, the ANN model had a higher predictive accuracy than HR. The ANN model had a higher determination coefficient (R^2) of 98.51%, compared to 95.25% for HR, indicating a higher accuracy.

Keywords Self-compacting concrete · ANN · Hierarchical regression · Statistical analysis · Fly ash

Introduction

Concrete is a prevalent construction material worldwide, with much of the existing knowledge in concrete technology originating from highly developed regions [1]. Over recent years, special concrete types like self-compacting concrete (SCC) have gained popularity. SCC, which originated in Japan during the late 1980s, is capable of flowing under its self-weight. This feature permits for effortless placement of concrete without the need for extra consolidation in intricate formwork, densely reinforced structural components, or areas that are difficult to reach. This not only conserves time and lowers overall expenses, but it also improves the work environment and sets the stage for automation in concrete construction. SCC is an innovative, consistent, and compact concrete when hardened, exhibiting mechanical properties and durability akin to conventional consolidated concrete. Numerous scholars have set forth principles for the composition of SCC mixtures. These include decreasing the volume ratio of aggregate to cementitious material, augmenting the volume of paste and the water-to-cement ratio (w/c), meticulously managing the maximum size of coarse aggregate particles and their total volume, and making use of admixtures that enhance viscosity [2].

Superplasticizers are typically necessary to achieve high workability in SCC, while viscosity-modifying admixtures help eliminate segregation. However, chemical admixtures can be expensive, potentially increasing material costs. Offsetting this, the use of mineral additions, known as supplementary cementing materials, can improve concrete slump without escalating costs. These SCMs, such as fly ash, silica fume, blast furnace slag, or limestone filler, are by-products of various manufacturing processes. When used as partial replacements for Portland cement, they reduce the quantity of cement required, thus lowering the energy and CO_2 footprint of concrete, while also enhancing workability and

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Table 1 The parameters utilized in the creation of ANN and HR models

No.	Parameters	Symbol of parameters	Minimum	Maximum	Mean	Deviation
1	Cement (kg/m^3)	C	160	670	311.04	109.88
2	Fly ash (kg/m^3)	F	0	330	156.59	69.02
3	Water-to-binder ratio	W/B	0.26	0.87	0.432	0.118
4	Fine aggregate (kg/m^3)	S	478	1079	858.73	91.94
5	Coarse aggregate (kg/m^3)	G	590	926	802	115.72
6	Superplasticizer (kg/m^3)	SP	0.4	21.8	4.682	4.69
7	Compressive strength (MPa)	CS	13.3	85	43.22	15.01

long-term concrete properties [3, 4]. Fly ash (FA), a residue from coal combustion transported by flue gases, is widely utilized in diverse concrete applications. Incorporating FA in concrete develops strength and durability depending on its reactivity, particle size distribution, and carbon content. Typically, FA is used to partially replace cement or fine aggregates, aiming to attain desired concrete properties. Studies have shown that using FA in SCC reduces the required superplasticizer dosage to achieve a similar slump flow compared to concrete made solely with Portland cement [5, 6].

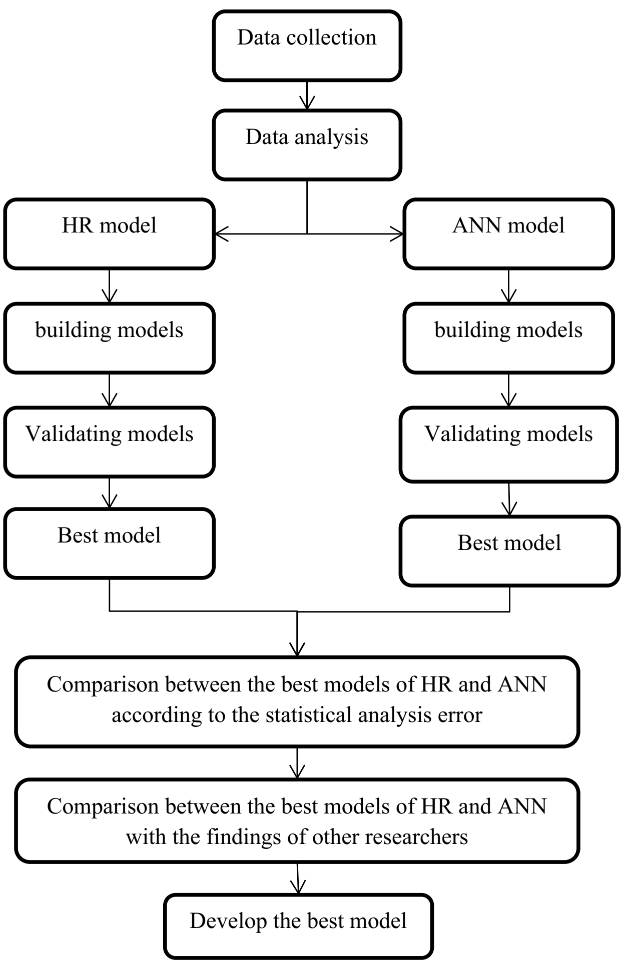

Fig. 1 Flow chart of the steps of the both HR and ANN models

Several studies have attempted to optimize SCC mix proportions by incorporating FA, suggesting that around 30% cement replacement with FA results in exceptional workability [7]. Though, due to variations in material constituents' quality and quantity, coupled with different design specifications, founding a universal relationship between fly ash and cement ratio, plasticizer, and w/c ratio presents a challenge. Different properties of SCC have been predicted using AI and ML methods in the last few decades [8, 9]. The output and input variables in a data set have a nonlinear relationship that can be modeled with high accuracy by these algorithms. Engineering problems have been solved successfully using various ML algorithms such as support vector machines (SVMs), artificial neural networks (ANNs), response surface method (RSM), genetic programming (GP), and others [8–10].

In civil engineering, these techniques have been employed to develop models predicting concrete properties [11]. In the context of SCC, researchers have utilized these techniques to propose predictive models. For instance, Asteris et al. [12] developed a back propagation neural network prediction model for compressive of SCC containing different mineral admixture. Silva and Štemberk [13] created shrinkage prediction models for SCC using a combination of fuzzy logic and genetic algorithms. Using RSM and ANN, Ofuyatan et al. [14] created models to estimate the compressive, tensile and impact strength of SCC with silica fume and polyethylene terephthalate waste as partial replacements of cement and sand. The RSM model had a good accuracy ($R^2 \geq 0.92$) for the mechanical properties. The ANN model performed better as it captured the data variability with a high R^2 value ($R^2 > 0.93$) for training, testing and validation. However, most of studies primarily rely on experimental data from their environments, limiting the generalizability of results. In contrast, our study compiles a comprehensive database from diverse data sources, including international literature, enabling broader applicability.

In this study, a comparison was made between a hierarchical regression analysis and an ANN-based model to predict the compressive strength of SCC, considering factors like cement content, fly ash content, W/B ratio, fine aggregate, coarse aggregate and superplasticizer. The evaluation of each method's efficiency was based on comparing metrics such as the coefficient of variation (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE), mean square error (MSE), and Pearson correlation (R) for both models. Significant data was collected to construct a comprehensive database including various mixtures of fly ash SCC. Notably, this study marks the first comparison of HR and ANN in predicting the compressive strength of SCC with fly ash.

Data collection

The dataset for this study was compiled from diverse sources and used to train and test both the ANN and HR models. A total of 165 (Appendix A) distinct experimental data points were collected from various literature sources [15, 16]. In the suggested models, the data is structured into six input factors that comprise cement content, fly ash content, W/B ratio, coarse aggregate, fine aggregate and superplasticizer. The output parameters forecasted by both the ANN and HR models relate to the compressive strength of SCC. The limit values for the input and output factors utilized in the ANN and HR models are provided in Table 1

The models underwent evaluation through a process involving statistical analysis and comparison with other experimental findings. The process of feature engineering for the models involves common steps:

(1) *Data collection* Gather the raw data that will be used to train the model.
(2) *Data cleaning* Handle missing values, remove duplicates, and deal with outliers. This step ensures that the quality of data fed into the model is good.

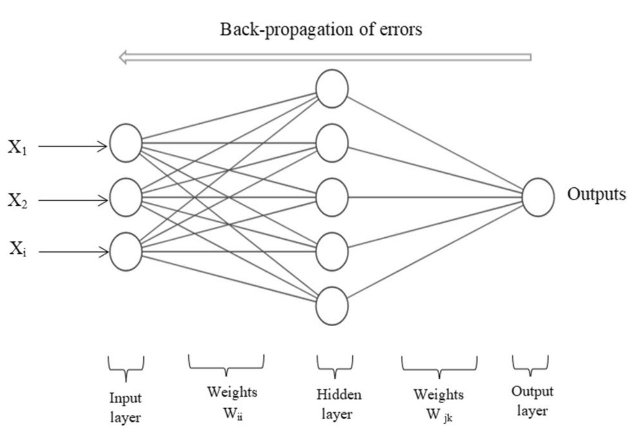

Fig. 2 Typical architecture of a back-propagation ANN

(3) *Feature selection* Identify and select the most relevant features to use in the model. This can reduce overfitting, improve accuracy, and reduce training time.
(4) *Data splitting* Split the data into training, validation, and test sets to evaluate the performance and generalizability of the ANN model. Figure 1 provides a more comprehensive overview of the study's methodology.

Mathematical models

Hierarchical regression (HR)

Hierarchical regression Analysis is a statistical technique used to predict the relationship between a dependent variable (Y) and an independent variable (x) by employing a polynomial equation of nth degree. Essentially, it's a specific application of multiple linear regression within the realm of machine learning. The process involves integrating polynomial terms into the multiple linear regression equation, effectively transforming it into polynomial regression. In this methodology, the original features are modified into polynomial features up to the desired degree (2, 3, …, n), which are then utilized in a linear framework. This approach provides several advantages, including the ability to estimate the quadratic impact of the variables being examined and identify potential interactions among various variables. The standard formula for a quadratic polynomial model is outlined as follows [17]:

$$\mathrm{Y} = \alpha_0 + \sum \alpha_i \mathrm{X}_i + \sum \alpha_{ij} \mathrm{X}_i \mathrm{X}_j + \sum \alpha_{ii} \mathrm{X}_i^2 \tag{1}$$

In this quadratic polynomial model, Y represents the predicted response, where α_0 is the constant term (intercept), α_i represents the linear coefficients, α_{ij} corresponds to the coefficients for interactions, and α_{ii} represents the quadratic coefficients. The variables x_i and x_j are used to denote the selected independent variables.

For predicting the compressive strength (CS) of SCC, CS is considered as the dependent parameter. The amounts of cement, fly ash, water-to-binder ratio (W/B), fine aggregate, coarse aggregate, and superplasticizer are regarded as independent variables (Table 1).

To assess the significance of the model, various metrics were employed, including Pearson correlation (R), the determination coefficient (R^2), Adj. R^2, Pred. R^2, root mean square error (RMSE), mean squared error (MSE) and mean absolute percentage error (MAPE). The equations of statistical error analysis were presented as follow [18]:

$$\mathrm{MSE} = \left(\frac{1}{N}\right) * \sum_{1}^{N} \left(O_{\mathrm{pred}} - O_{\mathrm{exp}}\right)^2 \tag{2}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} \left(O_{\text{pred}} - O_{\text{exp}} \right)^2}{\sum_{i=1}^{N} \left(O_{\text{pred}} - O_{\text{ave}} \right)^2} \right) \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \left(O_{\text{pred}} - O_{\text{exp}} \right)^2}{N}} \tag{4}$$

$$\text{MAPE} = \frac{1}{N} \sum_{j} \left(\left| \frac{O_{\text{pred}} - O_{\text{exp}}}{O_{\text{pred}}} \right| * 100 \right) \tag{5}$$

where N represents the overall number of inputs, and O_{pred}, O_{exp} and O_{ave} represent the predicted value, target value and average of predicted values, respectively.

One possible approach to assessing the predictive ability of the model for the value out of the limitation is by using the predicted R^2. Higher values of predicted R^2 indicate better predictive capability. If the predicted R^2 is significantly lower than the R^2, it may suggest overfitting.

Artificial neural network (ANN)

An Artificial Neural Network is a flexible assembly of extensively parallel structures, engineered to address complex issues by leveraging the collective strength of simple computing units, often known as artificial neurons [19]. The principle of ANNs is that an interrelated network of straightforward processing units can understand the complex relationships between input and output factors. In ANN modeling, there's no requirement for prior understanding of the functional relations between the parameters [20], and the ANN methodology has been successfully applied to resolve reverse problems [21]. As depicted in Fig. 2, an ANN is consisted from an input layer, an output layer, and one or more hidden layers.

Each neuron functions as a processing unit, receiving one or multiple inputs and generating an output signal by means of a transfer function. Each connection is associated with a weight that indicates the influence on the present processing unit from a set of inputs or another processing unit in the prior layer. At the outset, linking weights and bias values are allocated randomly, and then they are fine-tuned according to the results of the training procedure.

Numerous training methods are at one's disposal, such as back propagation and cascade correlation schemes. The back-propagation algorithm, a widely used gradient descent technique, was employed for minimizing the error in each training pattern by adjusting the weighting incrementally [22]. The assessment of this effectiveness, or generality, is done by testing the network with new data sets. A successful learning procedure entails choosing a suitable network setup, which includes determining the number of hidden layers and their corresponding neurons. The function of the neurons in these hidden layers is to discern the connection between the inputs and outputs of the network [23].

Deciding on the size of the hidden layer can be complex and is somewhat reliant on the quantity and quality of training arrays. There's no one-size-fits-all rule for choosing the

Table 2 Analysis of variance for statistical HR model

No.	Term	Coef	P value
1.	Constant	−728.3	0.000
2.	SP	0.302	0.121
3.	Coarse aggregate (G)	0.948	0.000
4.	Fine aggregate (S)	0.1387	0.001
5.	W/B	165.1	0.001
6.	fly ash (F)	0.457	0.007
7.	Cement (C)	0.942	0.000
8.	G*G	−0.000533	0.000
9.	F*F	−0.000346	0.009
10.	C*C	−0.000570	0.000
11.	W/B*S	−0.0864	0.011
12.	F*S	−0.000168	0.036
13.	C*S	−0.000075	0.262
14.	F*W/B	−0.0328	0.617
15.	C*W/B	−0.3983	0.000
16.	C*F	−0.000883	0.000
Statically error analysis			
17.	R^2		95.25%
18.	Adj. R^2		94.77%
19.	Pred. R^2		94.28%
20.	Difference between adjusted R^2 and Predicted R^2		0.49%
21.	F-value		199.18
22.	Model P value		0.000

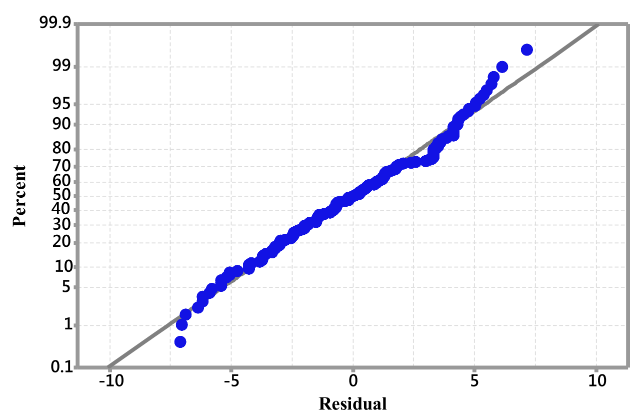

Fig. 3 Normal probability plot of residuals for compressive strength of HR model

number of neurons in the hidden layer. The neuron count in an ANN should be appropriate for precise modeling of the particular problem, however also limited to promote the network's ability to generalize. Past research has tried to connect the number of neurons to the input and output variables, as well as the training patterns [23]. Nonetheless, these rules cannot be universally applied [24]. Some researchers have proposed an upper bound for the necessary number of neurons in the hidden layer, suggesting it should be one more than twice the number of input points; however, even this rule does not guarantee optimal generalization of the network.

In order to develop a robust back propagation network, it's often beneficial to perform a parametric analysis by adjusting the number of neurons in the hidden layer and assessing the subsequent stability of the ANN. The construction of ANN typically involves two or three key stages, often known as 'training,' 'validation,' and 'testing.' During the training phase, the network is exposed to training data and modifications are made based on the errors observed. Both input and desired output data are used to fine-tune the ANN's output and reduce discrepancies.Validation is used to assess the ANN ability to generalize and to stop training when generalization improvements stop. Testing does not influence training but provides an independent evaluation of ANN performance through and after training [25].

The statistical significance of the ANN model was assessed using several measures, including the R^2, adj. R^2, pred. R^2, Pearson R, MSE, MAPE and RMSE. Moreover, it's crucial to verify the predictive capability of the proposed ANN and HR models for the compressive strength of SCC, using new data derived from extra experimental findings provided by other researchers, which were not included in the training data.

Results and discussion

Derivative HR statistical model

The modeling process consisted of two primary stages: initially identifying an appropriate model and subsequently checking its efficacy. The process commenced by employing a second-order polynomial model, as depicted in Eq. (1). Following this, parameters with P-values exceeding 0.05 were systematically removed, refining the model iteratively until only significant parameters ($P < 0.05$) remained [26–28].

The initial analysis emphasized the relationship between compressive strength and six independent variables (cement C, fly ash F, water-binder-ratio W/B, fine aggregate S, coarse aggregate G, superplasticizer SP). Numerous trials were

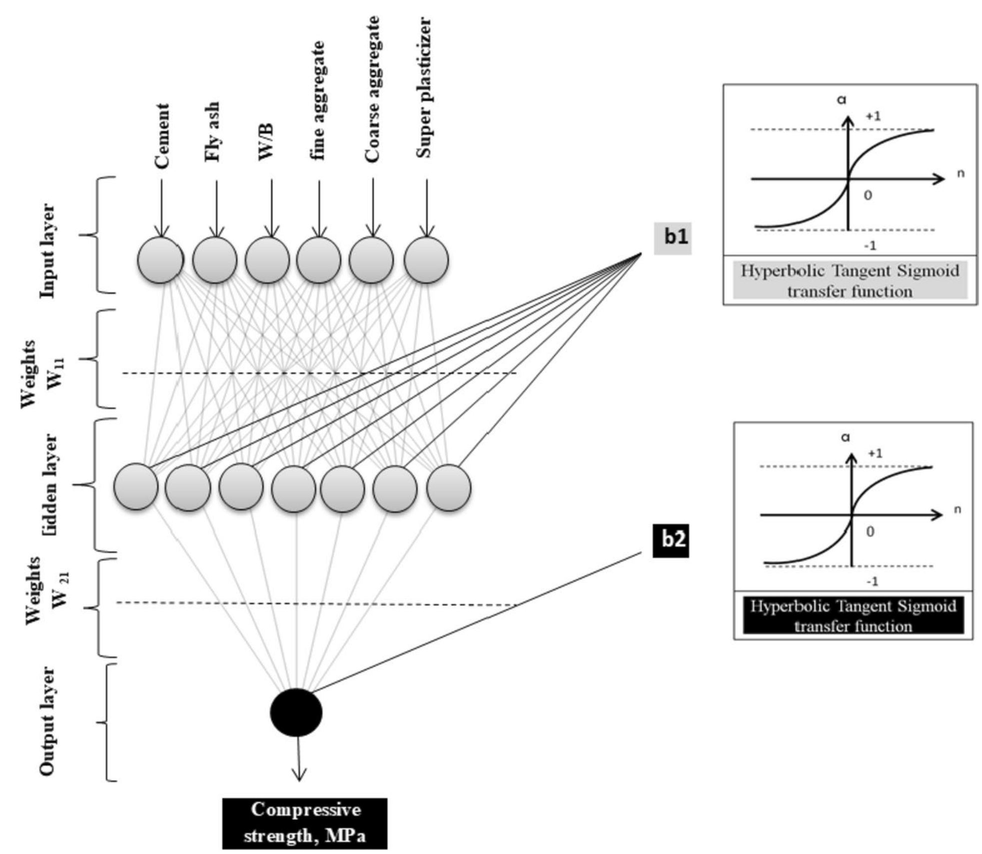

Fig. 4 The architecture of the (6-7-1) ANN

Table 3 Training parameters of (6-7-1) ANN

Parameter	Value
Training algorithm	Levenberg–Marquardt algorithm
Number of hidden layers	1; 2
Number of neurons per hidden layer	1–30
Training goal	0
Epochs	1000
Performance functions	MSE; RMSE
Hidden layers activation function	Hyperbolic tangent sigmoid
Transfer functions	Hyperbolic tangent sigmoid

adopted to investigate the impact of the number of terms and the span of exponents on the predictive accuracy of the model.

Subsequently, the most optimal model derived from multivariable HR regression was presented in Eq. (6), encompassing the six independent variables. After establishing this model, the subsequent step involved evaluating its adequacy through residual plots [29, 30]. Using the gathered experimental data, a second-order polynomial model was formulated, following Eq. (1). The regression model fitting the response is expressed in Eq. (6).

$$
\begin{aligned}
CS = &-728.3 + 0.302\ SP + 0.9480\ G \\
&+ 0.1387\ S + 165.1\ W/B + 0.457F + 0.942\ C \\
&- 0.000533\ G*G - 0.000346\ F*F \\
&- 0.000570\ C*C - 0.0864\ S*W/B \\
&+ 0.000168\ S*F - 0.000075\ S*C \\
&- 0.0328\ W/B*F - 0.3983\ W/B*C \\
&- 0.000883\ F*C
\end{aligned}
\tag{6}
$$

The model described by Eq. (6) reveals that all the independent variables investigated significantly influenced compressive strength, except for superplasticizer. Notably, cement and fly ash had a primary impact on compressive strength, appearing in multiple terms within the derivative model. Table 2 further substantiates the significance of the linear terms of cement and fly ash for compressive strength, as indicated by their P-values being below 0.05%. The interaction among most variables significantly impacted the response within Eq. (6).

To ensure the efficiency of the model, the residuals plot should display a structureless pattern. The normal plot of residuals for the response, illustrated in Fig. 3, exhibits residuals closely aligning with a straight line, implying a normal scattering of errors. This suggests that the terms incorporated in the model hold significance.

The significance of the model was assessed using the F test and P-value. The P-values for the model were below 0.05, underscoring their significance. Typically, a model is considered significant if the F value is higher [31]. As shown in Table 2, the F value of 199.18 emphasizes the model's substantial significance.

Table 5 Evaluation of the proposed models

Type of statistical function	Model	
	(6-7-1) ANN	HR
Pearson R	99.254%	97.595%
R^2	98.51%	95.25%
Adj. R^2,%	98.51%	94.77%
Pred. R^2,%	98.48%	94.28%
RMSE	1.83	3.26
MAPE	3.69	7.06
MSE	3.35	10.63

Table 4 Final values of weights and bias of the (6-7-1) ANN model

iw{1,1}—Weight to layer 1 from input 1(Weight matrix 1)						b{1}—Bias to layer 1 (Weight vector 1)
[− 1.1246	0.24562	− 3.318	− 3.3203	− 0.096463	1.4877;	[4.3348;
0.93421	0.17504	− 1.5406	0.99145	− 0.79537	− 1.3757;	− 1.0468;
2.7772	− 3.1259	− 0.92321	2.6508	− 0.83352	0.47695;	0.3175;
− 1.9313	− 1.1375	− 1.0786	− 0.39878	− 0.20483	− 1.42;	− 1.8306;
2.954	− 0.1202	− 1.3571	1.9111	− 0.036802	0.076187;	− 0.21;
5.9347	8.5414	8.1762	8.0606	− 5.5303	− 2.8943;	− 2.7053;
− 0.25051	0.66952	2.5754	− 1.7783	0.73305	1.6311]	1.3208;]
lw{2,1}—Weight to layer (Bias vector)						b{2}—Bias to layer 2 (Out scalar bais)
[− 4.2667	− 0.62216	− 0.76551	1.6497	− 0.25615	− 2.0131]	[2.0921-]

The accuracy of the statistical models can be confirmed by analyzing the variance proportions (R^2), making sure that the discrepancy between the adjusted R^2 and the pred. R^2 is less than 20% [32]. In this study, the model demonstrated a notably high determination coefficient, R^2, at 95.25%, signifying that only 4.75% of the variation couldn't be accounted for this model. This underscores the robust statistical significance of the model and its suitable fit, suggesting a significant relation between the actual values and those predicted by the model.

Table 2 further confirms that the difference between the adjusted R^2 and predicted R^2 was less than 20%, validating the model's practicality for response. Additionally, the adjusted R^2 values closely aligned with the R^2, suggesting the absence of unnecessary terms in the model. All the P-values in Table 2, established through ANOVA, demonstrated that the lack of fit had an insignificant relationship with pure error.

Artificial neural network ANN

In this study, the MATLAB program's ANN toolbox (nftool) was utilized for the necessary computations. A feed-forward network with one hidden layer was trained

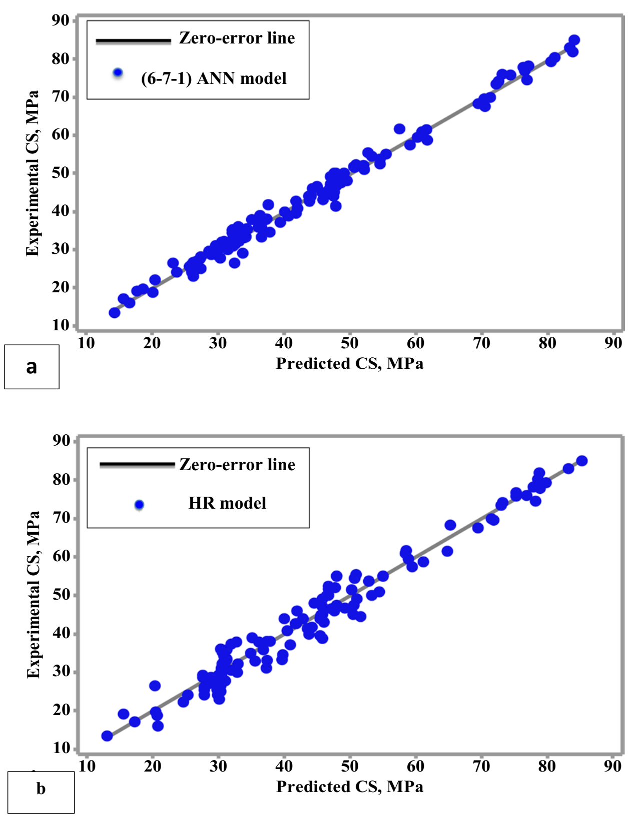

Fig. 5 Experimental versus predicted values for compressive strength **a** (6-7-1) ANN model and **b** HR model

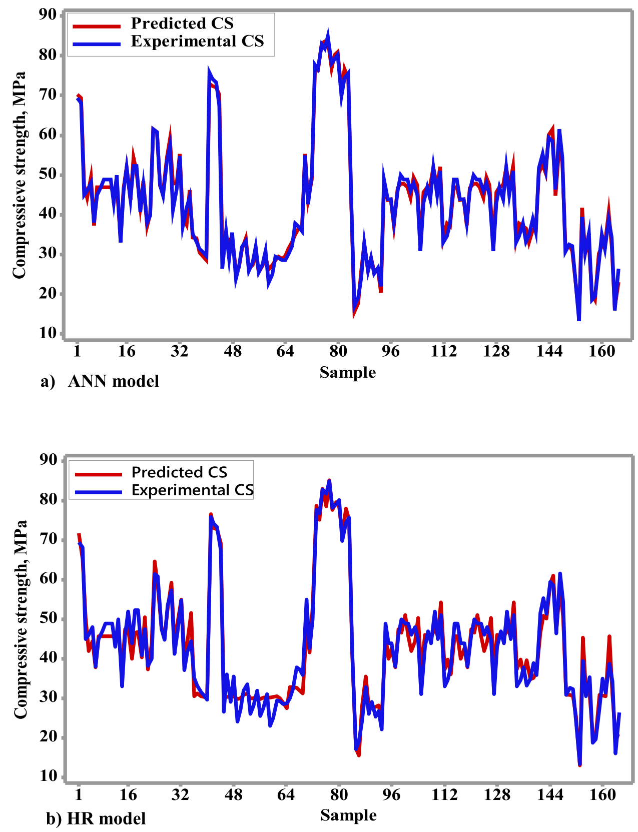

Fig. 6 Time series plots for experimental and predicted CS for the two models **a** ANN (6-7-1) model and **b** HR model

using a back-propagation training algorithm with the Levenberg–Marquardt back propagation algorithm.

If the trust-region algorithm failed to provide a satisfactory fit and suitably limit the coefficients, the Levenberg–Marquardt algorithm was selected [33]. As it is presented in Fig. 4, the transfer functions are the hyperbolic tangent sigmoid for both hidden and output layer.

The training, validation, and testing sets for an ANN can have different percentages depending on the project or data size. A common way is to use 70% for training, 15% for validation, and 15% for testing [34]. The aim is to have enough data in the training set to build a good model, enough data in the validation set to adjust hyperparameters and select the best model during training, and enough data in the test set to measure the final model's performance [35]. These percentages are not fixed and can be changed based on factors such as the total data amount and the model complexity [34, 35]. For instance, if there are a lot of data, you might use a smaller percentage for training and give more to the validation and test sets. On the other hand, with less data, you might need a larger training set to prevent underfitting [34]. In this study, 91 out of 131 specimens (70% of the total data) were used to train the ANN model in this set. To check the reliability of the results, 20 out of 131 specimens (15%

Table 6 Comparison of (6-7-1) ANN and HR models with other researcher's results

N	References	Fly ash %	Compressive strength, MPa				
			Experimental	(6-7-1) ANN	E%	HR	E%
1.	Leung et al. [37]	10	61	62.89	3.11	59.02	3.25
2.		20	54.4	59.55	9.48	59.13	8.74
3.		30	52.6	55.51	5.54	58.67	11.54
4.	Naik, et al. [38]	0	60	67.48	12.48	69.27	15.44
5.		35	62	68.72	10.85	61.04	1.55
6.		45	60	68.62	14.37	66.86	11.43
7.	Zhu and Bartos [39]	0	68.5	57.71	15.75	56.83	17.04
8.		20	71.3	64.93	8.93	66.67	6.49
9.		30	49.9	50.94	2.08	55.53	11.27
10.	Liu [5]	0	73.3	69.81	4.74	71.99	1.78
11.		20	69.7	61.12	12.31	63.19	9.33
12.		40	58.5	54.27	7.21	53.26	8.95
13.		60	37.2	44.69	20.16	41.84	12.48
14.	Kazim et al. [18]	25	53.5	57.56	7.59	59.61	11.42
15.		30	55	61.69	12.16	60.14	9.34
16.		35	58	61.43	5.91	59.95	3.37
17.		40	59	60.15	1.96	59.74	1.25
18.	Dinakar, et al. [36]	10	79	74.07	6.23	82.54	4.53
19.		30	88.1	71.88	18.41	76.67	12.93
20.		50	60.8	68.50	12.67	68.49	12.59

of the total data) were used for validation. The remaining 20 specimens (15% of the total data) were used for testing.

The number of neurons in the hidden layer was ascertained by training various ANN with varying numbers of neurons and matching the forecast outcomes with the anticipated response. The ideal number of hidden neurons was found to be 7 for a single hidden layer of the (6-7-1) ANN, as depicted in Fig. 4. Table 3 summarizes the parameters used for ANN training.

The ANN models' predictions were not affected by the number of neurons in the input layer or the input data expressions in practical scenarios, according to the ANN models analysis. However, the results contradicted the common belief and showed that the lowest standard deviation values were obtained by normalizing within the [min–max] range. The ANN models were trained for epochs ranging from 6 to 20. Training usually stops before reaching the maximum number of epochs to avoid overfitting the data. This improves the network's generalization. Training also stops if the cross-validation results do not improve beyond a certain tolerance. This shows that the advanced multilayer feed-forward neural network models can predict the compressive strength with high accuracy and low computational effort. It is important to know that the optimal architecture of a neural network model provided by the authors may not be very helpful to other researchers and engineers in practice without the specific values of the ANN weights. However, if the suggested ANN structure also includes the specific numerical values of the weights, it can be very useful. This allows the ANN model to be easily implemented in an MS-Excel file, making it accessible to anyone interested in modeling. Therefore, Table 4 shows the final weights for both hidden layers and bias. By using the properties specified in Table 1 and applying the assigned weights and bias values across the layers of an ANN according to Fig. 4, it is possible to estimate the expected compressive strength.

Remarkably high Pearson *R*-values of 0.99374, 0.98507, 0.99386, and 0.99254 were attained for training, validation, testing, and overall, respectively.

The calculation of CS using (6-7-1) ANN is less common compared to HR analysis due to the advantages of HR, including not requiring specialized software, generating easily interpretable regression constants, and assessing the importance of various input factors.

Validation and comparison of HR and (6-7-1) ANN models by

Statistical analysis error

In this study, both HR and ANN models were employed to predict the compressive strength of SCC incorporating fly ash. The correlation between the experimental and computed values was used to validate the effectiveness of these mathematical models. The high correlation confirmed that the mathematical models accurately reflected the predicted results. The statistical analysis in Table 5 showed the high-quality predictions made by both HR and (6-7-1) ANN models. However, the (6-7-1) ANN model had a clear advantage in data fitting and estimation capabilities over HR. The (6-7-1) ANN model had a higher determination coefficient (R^2) of 98.51%, compared to 95.25% for HR, indicating a higher accuracy. The statistical analysis in Table 5 supported the accuracy and quality of predictions obtained by both HR and (6-7-1) ANN models. The actual and predicted values of compressive strength for both models were plotted in Fig. 5a, b. It was observed that the deviations of the residuals were notably smaller and more regular for (6-7-1) ANN compared to HR. The HR model exhibited higher variation than the ANN model as presented in Fig. 6a, b. It's important to note that while HR provides a regression equation for prediction and demonstrates the effects of experimental parameters and their interactions on the response, ANN offers flexibility in adapting to any experimental plan to construct the model. The ANN allows for incorporating new experimental data, contributing to a reliable and adaptable model. Thus, interpreting the compressive strength of SCC data through an ANN architecture is more rational and consistent.

Comparison with the findings of other researchers

The effectiveness of the trained (6-7-1) ANN and HR models is determined by their capacity to extrapolate predictions from the training data and to handle new, unfamiliar data effectively in the range of input factors used during training. Thus, it was crucial to validate the capability of the proposed (6-7-1) ANN and HR models to predict SCC compressive strength for new data attained from further results from other researchers. The models were represented with a total of 20 unseen records and were tasked with predicting SCC compressive strength for each set of values within the six prominent factors [5, 18, 36–39]. Table 6 presents a comparison among the values computed by the proposed models and the new data records used for validation. This accurately depicts the calculated relative error in each calculation, as defined by Eq. (4).

$$E(\%) = ABS\left(\frac{O_{\text{exp}} - O_{\text{pred}}}{O_{\text{exp}}}\right) \times 100 \tag{4}$$

where O_{exp} is the experimental output and O_{pred} is the output estimated by the ANN and HR models.

The evaluation of the (6-7-1) ANN model and the HR models were expressed through the total relative error. This measurement demonstrates that employing the suggested models enables accurate prediction of the 28-day compressive strength of SCC with varying proportions of fly ash.

Limitations

The ANN model can be used when the experimental values for (cement, fly ash, W/B, fine aggregate, coarse aggregate and SP) tests are available to the researcher or practitioner. It is important to note that the HR and ANN models can only give reliable predictions within the parameter values range shown in Table 1. If the parameter values are outside this range, the prediction may not be trustworthy.

Conclusions

In the current study, an analysis was carried out to examine the impact of modifying the quantities of cement, fly ash, water-to-binder ratio, fine aggregate, coarse aggregate, and superplasticizer on the compressive strength of self-compacting concrete. The hierarchical regression and artificial neural network models were utilized to assess and predict the compressive strength, drawing upon experimental data from prior literature.

Key conclusions from this study include:

- Both ANN and HR models, built on prior experimental outcomes, proved to be effective and efficient in forecasting compressive strength. Leveraging these models allowed us to gather valuable insights with fewer trial mixtures.
- In terms of predictive accuracy, the tested ANN models outperformed HR, as evidenced by superior performance indices. The comparison highlighted that ANN models yielded a high Pearson R, approaching 1 (0.99254). The results underscored ANN's efficacy in predicting compressive strength for SCC with diverse fly ash proportions. However, to enhance the ANN model's versatility, a more extensive and diverse training database would be beneficial.
- The utilization of ANN for compressive strength prediction is less common compared to HR, primarily because the latter offers advantages such as not requiring specific software, producing easily applicable regression constants, and evaluating the importance of different input factors. However, employing ANN for predicting compressive strength in SCC at 28 days is particularly advantageous when dealing with nonlinear functional relationships, where traditional methods may fall short.

Appendix A: Experimental database of self-compacting concrete

See Table 7.

Table 7 Inputs and output parameters of (6-7-1) ANN and HR models

No	Inputs						Output	(6-7-1) ANN model		HR model	
	Cement (kg/m^3)	Fly ash (kg/m^3)	W/B (kg/m^3)	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	SP (kg/m^3)	Experimental CS, MPa	Predicted CS, MPa	Exp. CS/ pred. CS	Predicted CS, MPa	Exp. CS/ pred. CS
1.	441.63	259.37	0.27	774	723	8.1000	69.5	70.2788	0.9889	71.7633	0.9685
2.	461.79	271.21	0.26	748	698	8.4000	68.2	69.3849	0.9829	65.2309	1.0455
3.	280.00	120.00	0.39	946	900	1.4000	45.0	47.5693	0.946	50.4382	0.8922
4.	236.80	133.20	0.43	960	900	1.8500	46.0	44.2248	1.0401	41.8931	1.098
5.	275.20	154.80	0.43	827	900	2.1500	48.0	49.4712	0.9703	44.5160	1.0783
6.	220.00	180.00	0.45	850	900	1.4000	38.0	37.3067	1.0186	37.7762	1.0059
7.	220.00	180.00	0.39	916	900	1.4000	45.0	46.9935	0.9576	45.7172	0.9843
8.	220.00	180.00	0.39	916	900	1.4000	47.0	46.9935	1.0001	45.7172	1.0281
9.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
10.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
11.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
12.	220.00	180.00	0.39	916	900	2.4000	43.0	45.7995	0.9389	46.0190	0.9344
13.	247.50	202.50	0.39	808	900	1.5800	50.0	47.6120	1.0502	46.3673	1.0783
14.	170.20	199.80	0.43	928	900	1.8500	33.0	33.9070	0.9733	37.3088	0.8845
15.	197.80	232.20	0.34	874	900	0.8600	46.0	46.8340	0.9822	47.5143	0.9681
16.	197.80	232.20	0.36	872	900	2.1500	52.0	51.9872	1.0002	47.7050	1.09
17.	160.00	240.00	0.39	886	900	1.4000	44.0	43.7158	1.0065	39.8895	1.103
18.	350.00	150.00	0.34	1006	620	6.7500	52.4	54.5164	0.9612	46.6302	1.1237
19.	300.00	200.00	0.32	1004	618	6.7500	52.3	50.8810	1.0279	46.8144	1.1172
20.	250.00	250.00	0.35	988	608	6.7500	40.8	41.9970	0.9715	40.3820	1.0104
21.	250.00	250.00	0.30	1010	628	6.7500	47.5	48.5930	0.9775	50.5496	0.9397
22.	200.00	300.00	0.35	979	603	6.7500	38.1	37.1300	1.0261	37.2664	1.0224
23.	200.00	300.00	0.30	997	614	6.7500	39.9	40.1117	0.9947	43.6675	0.9137
24.	550.00	0.00	0.44	826	868	3.5000	61.5	61.5523	0.9992	64.7197	0.9503
25.	330.00	220.00	0.32	700	899	7.4300	60.9	60.8620	1.0006	58.3298	1.0441
26.	220.00	330.00	0.32	686	881	6.6700	47.5	47.3169	1.0039	47.8481	0.9927
27.	315.00	135.00	0.43	789	926	2.7700	44.8	45.7623	0.979	45.5523	0.9835
28.	350.00	150.00	0.39	731	862	6.1500	53.6	54.4443	0.9845	52.7602	1.0159
29.	385.00	165.00	0.35	711	835	4.7400	57.3	59.0467	0.9704	59.3726	0.9651
30.	270.00	180.00	0.43	780	917	2.7700	41.3	47.7782	0.8644	43.4878	0.9497
31.	300.00	200.00	0.39	724	850	6.1500	46.7	47.9527	0.9739	49.1488	0.9502
32.	330.00	220.00	0.35	701	823	6.7700	54.9	55.3647	0.9916	54.9684	0.9988
33.	225.00	225.00	0.43	770	907	2.5000	37.1	39.3591	0.9426	40.8255	0.9087
34.	250.00	250.00	0.39	714	836	4.9200	41.8	37.5435	1.1134	44.1861	0.946

Table 7 (continued)

No	Inputs						Output	(6-7-1) ANN model		HR model	
	Cement (kg/m^3)	Fly ash (kg/m^3)	W/B (kg/m^3)	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	SP (kg/m^3)	Experimental CS, MPa	Predicted CS, MPa	Exp. CS/ pred. CS	Predicted CS, MPa	Exp. CS/ pred. CS
35.	275.00	275.00	0.35	703	824	5.4100	44.4	46.1974	0.9611	51.5219	0.8618
36.	467.50	82.50	0.41	910	590	10.7300	35.2	34.3470	1.0248	30.4871	1.1546
37.	440.00	110.00	0.41	910	590	11.0100	33.2	34.1382	0.9725	31.1522	1.0657
38.	412.50	137.50	0.42	910	590	9.9100	31.5	30.5973	1.0295	30.5291	1.0318
39.	385.00	165.00	0.43	910	590	9.9100	30.7	29.6099	1.0368	30.3904	1.0102
40.	357.50	192.50	0.44	910	590	9.9100	29.6	28.5900	1.0353	30.4039	0.9736
41.	550.00	0.00	0.33	869	778	8.8000	75.9	72.9764	1.0401	76.7354	0.9891
42.	467.50	82.50	0.33	865	762	8.8000	74.2	72.4189	1.0246	73.1514	1.0143
43.	412.50	137.50	0.33	887	752	8.8000	73.4	72.1206	1.0177	72.8967	1.0069
44.	357.50	192.50	0.33	878	742	8.8000	67.5	70.3646	0.9593	69.3447	0.9734
45.	467.50	82.50	0.41	910	590	9.9000	26.5	32.4903	0.8156	30.2365	0.8764
46.	467.50	82.50	0.41	910	590	10.1700	36.0	33.0610	1.0889	30.3180	1.1874
47.	467.50	82.50	0.41	910	590	10.4500	29.0	33.6841	0.8609	30.4025	0.9539
48.	467.50	82.50	0.41	910	590	10.7200	35.5	34.3226	1.0343	30.4840	1.1645
49.	440.00	110.00	0.41	910	590	6.6000	24.0	26.2080	0.9158	29.8209	0.8048
50.	440.00	110.00	0.41	910	590	7.1500	27.0	26.8204	1.0067	29.9870	0.9004
51.	440.00	110.00	0.41	910	590	9.9000	32.0	31.5051	1.0157	30.8171	1.0384
52.	440.00	110.00	0.41	910	590	11.0000	33.5	34.1112	0.9821	31.1492	1.0755
53.	412.50	137.50	0.42	910	590	7.7000	26.0	26.5496	0.9793	29.8620	0.8707
54.	412.50	137.50	0.42	910	590	8.2500	28.0	27.3719	1.0229	30.0280	0.9325
55.	412.50	137.50	0.42	910	590	9.9000	32.0	30.5745	1.0466	30.5261	1.0483
56.	385.00	165.00	0.43	910	590	7.7000	25.5	25.5957	0.9963	29.7232	0.8579
57.	385.00	165.00	0.43	910	590	8.8000	27.5	27.2726	1.0083	30.0553	0.915
58.	385.00	165.00	0.43	910	590	9.9000	31.0	29.5858	1.0478	30.3874	1.0202
59.	357.50	192.50	0.44	910	590	8.8000	23.0	26.2570	0.876	30.0688	0.7649
60.	357.50	192.50	0.44	910	590	9.3500	25.0	27.3095	0.9154	30.2348	0.8269
61.	357.50	192.50	0.44	910	590	9.9000	29.5	28.5651	1.0327	30.4009	0.9704
62.	350.00	150.00	0.35	900	600	11.0000	29.2	29.4781	0.9906	29.9292	0.9756
63.	300.00	200.00	0.35	900	600	10.7500	28.6	28.9225	0.9888	28.7968	0.9932
64.	250.00	250.00	0.35	900	600	10.5000	28.7	29.6476	0.968	27.5032	1.0435
65.	530.00	0.00	0.45	768	668	4.5500	30.0	31.4045	0.9553	32.8147	0.9142
66.	477.00	53.00	0.45	768	668	4.5500	32.2	33.1809	0.9704	32.8476	0.9803
67.	424.00	106.00	0.45	768	668	4.5500	37.9	35.1137	1.0794	32.6993	1.159

Table 7 (continued)

No	Inputs						Output	(6-7-1) ANN model		HR model	
	Cement (kg/m^3)	Fly ash (kg/m^3)	W/B (kg/m^3)	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	SP (kg/m^3)	Experimental CS, MPa	Predicted CS, MPa	Exp. CS/ pred. CS	Predicted CS, MPa	Exp. CS/ pred. CS
68.	318.00	212.00	0.45	768	668	4.5500	37.2	36.5422	1.018	31.8592	1.1676
69.	265.00	265.00	0.45	768	668	4.5500	35.9	36.5490	0.9822	31.1673	1.1518
70.	300.00	200.00	0.35	923	663	7.5000	55.0	55.3450	0.9938	47.8577	1.1492
71.	225.00	275.00	0.35	908	652	7.5000	42.7	43.8492	0.9738	41.6093	1.0262
72.	450.00	0.00	0.45	890	810	9.2500	50.0	49.0112	1.0202	53.2798	0.9384
73.	575.00	0.00	0.31	794	772	17.2200	77.8	76.2126	1.0208	78.7744	0.9876
74.	589.00	0.00	0.31	813	729	17.6400	76.8	76.3696	1.0056	75.1730	1.0216
75.	628.00	0.00	0.29	744	772	19.5300	82.9	83.1849	0.9966	83.0957	0.9976
76.	643.00	0.00	0.29	761	729	19.9500	81.9	83.6292	0.9793	78.6759	1.041
77.	670.00	0.00	0.27	695	772	21.8400	85.0	83.9507	1.0125	85.2168	0.9975
78.	465.88	147.12	0.26	685	875	15.3300	78.2	76.9318	1.0165	77.8172	1.0049
79.	481.08	151.92	0.26	706	820	15.8600	79.2	80.3780	0.9853	79.7133	0.9936
80.	493.24	155.76	0.26	726	772	16.2800	80.3	80.9333	0.9922	78.4487	1.0236
81.	425.25	141.75	0.30	846	729	13.8600	69.9	71.1860	0.9819	71.4301	0.9786
82.	455.25	151.75	0.27	774	772	15.1200	74.5	76.7899	0.9702	78.1182	0.9537
83.	465.00	155.00	0.27	792	729	15.5400	75.7	74.2955	1.0189	75.1585	1.0072
84.	290.00	100.00	0.45	913	837	3.1200	42.7	41.7246	1.0234	41.7626	1.0224
85.	250.00	261.00	0.55	478	837	2.5600	17.0	15.6351	1.0873	17.1980	0.9885
86.	210.00	100.00	0.65	910	837	2.4800	19.1	17.6734	1.0807	15.5363	1.2294
87.	250.00	160.00	0.55	742	837	2.0500	24.1	25.9709	0.928	27.7927	0.8671
88.	290.00	220.00	0.45	625	837	1.0200	32.9	32.6248	1.0084	35.4833	0.9272
89.	250.00	160.00	0.55	742	837	2.0500	26.0	25.9709	1.0011	27.7927	0.9355
90.	317.00	160.00	0.55	594	837	2.3850	29.1	29.1543	0.9981	27.5189	1.0575
91.	250.00	160.00	0.55	742	837	2.0500	25.3	25.9709	0.9742	27.7927	0.9103
92.	250.00	160.00	0.55	746	837	2.0500	26.7	26.2375	1.0176	28.1896	0.9472
93.	183.00	160.00	0.55	891	837	1.7200	22.1	20.4011	1.0833	24.5479	0.9003
94.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
95.	160.00	240.00	0.39	886	900	1.4000	44.0	43.7158	1.0065	39.8895	1.103
96.	193.00	158.00	0.39	1024	900	1.2300	44.0	44.0165	0.9996	42.7402	1.0295
97.	220.00	180.00	0.45	850	900	1.4000	38.0	37.3067	1.0186	37.7762	1.0059
98.	198.00	232.00	0.34	874	900	0.8600	46.0	46.8579	0.9817	47.5248	0.9679
99.	248.00	203.00	0.39	808	900	1.5800	50.0	47.7866	1.0463	46.6099	1.0727
100.	237.00	133.00	0.36	1034	900	0.7400	49.0	47.9195	1.0225	51.0132	0.9605

Table 7 (continued)

No	Inputs						Output	(6-7-1) ANN model		HR model	
	Cement (kg/m^3)	Fly ash (kg/m^3)	W/B (kg/m^3)	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	SP (kg/m^3)	Experimental CS, MPa	Predicted CS, MPa	Exp. CS/ pred. CS	Predicted CS, MPa	Exp. CS/ pred. CS
101.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
102.	237.00	133.00	0.43	960	900	1.8500	46.0	44.2431	1.0397	41.8946	1.098
103.	275.00	155.00	0.43	827	900	2.1500	48.0	49.4724	0.9702	44.5107	1.0784
104.	280.00	120.00	0.39	946	900	1.4000	45.0	47.5693	0.946	50.4382	0.8922
105.	170.00	200.00	0.43	930	900	0.7400	31.0	32.2492	0.9613	37.2144	0.833
106.	220.00	180.00	0.39	916	900	2.4000	43.0	45.7995	0.9389	46.0190	0.9344
107.	220.00	180.00	0.39	916	900	1.4000	47.0	46.9935	1.0001	45.7172	1.0281
108.	220.00	180.00	0.39	916	900	0.4000	44.0	47.4767	0.9268	45.4153	0.9688
109.	198.00	232.00	0.36	872	900	2.1500	52.0	52.0111	0.9998	47.7142	1.0898
110.	220.00	180.00	0.39	916	900	1.4000	45.0	46.9935	0.9576	45.7172	0.9843
111.	220.00	180.00	0.33	982	900	1.4000	51.0	52.0817	0.9792	54.3421	0.9385
112.	170.00	200.00	0.43	928	900	1.8500	33.0	33.8928	0.9737	37.3048	0.8846
113.	247.00	165.00	0.45	845	846	0.4900	34.6	37.8271	0.9147	39.7113	0.8713
114.	238.00	159.00	0.40	844	844	1.1500	37.8	37.2183	1.0156	36.0345	1.049
115.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
116.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
117.	160.00	240.00	0.39	886	900	1.4000	44.0	43.7158	1.0065	39.8895	1.103
118.	193.00	158.00	0.39	1024	900	1.2285	44.0	44.0110	0.9997	42.7398	1.0295
119.	220.00	180.00	0.45	850	900	1.4000	38.0	37.3067	1.0186	37.7762	1.0059
120.	198.00	232.00	0.34	874	900	0.8600	46.0	46.8579	0.9817	47.5248	0.9679
121.	248.00	203.00	0.39	808	900	1.5785	50.0	47.7815	1.0464	46.6094	1.0727
122.	237.00	133.00	0.36	1034	900	0.7400	49.0	47.9195	1.0225	51.0132	0.9605
123.	220.00	180.00	0.39	916	900	1.4000	49.0	46.9935	1.0427	45.7172	1.0718
124.	237.00	133.00	0.43	960	900	1.8500	46.0	44.2431	1.0397	41.8946	1.098
125.	275.00	155.00	0.43	827	900	2.1500	48.0	49.4724	0.9702	44.5107	1.0784
126.	280.00	120.00	0.39	946	900	1.4000	45.0	47.5693	0.946	50.4382	0.8922
127.	170.00	200.00	0.43	930	900	0.7400	31.0	32.2492	0.9613	37.2144	0.833
128.	220.00	180.00	0.39	916	900	2.4000	43.0	45.7995	0.9389	46.0190	0.9344
129.	220.00	180.00	0.39	916	900	1.4000	47.0	46.9935	1.0001	45.7172	1.0281
130.	220.00	180.00	0.39	916	900	0.4000	44.0	47.4767	0.9268	45.4153	0.9688
131.	198.00	232.00	0.36	872	900	2.1500	52.0	52.0111	0.9998	47.7142	1.0898
132.	220.00	180.00	0.39	916	900	1.4000	45.0	46.9935	0.9576	45.7172	0.9843
133.	220.00	180.00	0.33	982	900	1.4000	51.0	52.0817	0.9792	54.3421	0.9385

Table 7 (continued)

No	Inputs						Output	(6-7-1) ANN model		HR model	
	Cement (kg/m^3)	Fly ash (kg/m^3)	W/B (kg/m^3)	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	SP (kg/m^3)	Experimental CS, MPa	Predicted CS, MPa	Exp. CS/ pred. CS	Predicted CS, MPa	Exp. CS/ pred. CS
134.	170.00	200.00	0.43	928	900	1.8500	33.0	33.8928	0.9737	37.3048	0.8846
135.	247.00	165.00	0.45	845	846	0.4944	34.6	37.8382	0.9144	39.7126	0.8713
136.	238.00	159.00	0.40	844	844	1.1513	37.8	37.2215	1.0155	36.0349	1.049
137.	207.00	207.00	0.45	845	843	1.6560	33.2	36.5832	0.9075	39.5934	0.8385
138.	200.00	200.00	0.40	842	843	0.6800	34.9	33.0139	1.0571	34.7781	1.0035
139.	197.00	197.00	0.35	856	856	1.1032	38.9	36.3500	1.0702	35.0819	1.1088
140.	161.00	241.00	0.35	866	864	1.2060	35.8	36.1248	0.991	36.7765	0.9734
141.	350.00	162.00	0.59	768	840	0.4608	51.7	50.4658	1.0245	46.6825	1.1075
142.	350.00	133.00	0.52	815	883	0.7728	55.3	52.6580	1.0502	50.8928	1.0866
143.	250.00	257.00	0.77	787	853	0.5577	51.5	50.5688	1.0184	50.1641	1.0266
144.	427.00	115.00	0.45	779	844	0.6504	59.4	60.1884	0.9869	58.8644	1.0091
145.	348.00	224.00	0.50	783	848	2.4596	58.6	61.6226	0.951	61.1006	0.9591
146.	350.00	90.00	0.48	852	923	0.6160	46.5	44.9066	1.0355	47.1383	0.9865
147.	327.00	173.00	0.53	902	803	1.0000	61.6	57.4464	1.0723	58.4762	1.0534
148.	275.00	250.00	0.67	775	840	0.4725	54.5	53.2299	1.0239	50.6063	1.0769
149.	325.00	60.00	0.65	899	850	1.6555	30.8	32.2748	0.9543	30.7654	1.0011
150.	325.00	60.00	0.65	899	850	1.6555	32.6	32.2748	1.0101	30.7654	1.0596
151.	325.00	120.00	0.75	755	850	1.9135	32.2	30.9026	1.042	30.4691	1.0568
152.	249.00	60.00	0.68	1079	850	1.3287	24.0	23.7253	1.0116	25.2187	0.9517
153.	325.00	60.00	0.85	722	850	1.6555	13.3	14.3204	0.9287	12.9636	1.0259
154.	370.00	96.00	0.57	833	850	1.1650	39.5	41.7197	0.9468	45.4230	0.8696
155.	400.00	60.00	0.63	718	850	1.9780	30.4	30.5185	0.9961	31.8911	0.9532
156.	325.00	60.00	0.65	899	850	1.6555	35.3	32.2748	1.0937	30.7654	1.1474
157.	370.00	24.00	0.69	770	850	2.4428	18.7	20.0727	0.9316	20.6117	0.9073
158.	280.00	96.00	0.87	820	850	0.9400	19.6	18.6044	1.0535	20.4208	0.9598
159.	325.00	60.00	0.65	896	850	2.8875	27.7	30.2968	0.9143	30.9327	0.8955
160.	325.00	60.00	0.65	898	850	1.6555	35.0	32.1229	1.0896	30.6972	1.1402
161.	325.00	60.00	0.65	900	850	0.4620	31.4	32.5171	0.9656	30.4733	1.0304
162.	370.00	96.00	0.57	830	850	2.8892	38.8	40.6251	0.9551	45.7103	0.8488
163.	325.00	60.00	0.65	898	850	1.6555	34.3	32.1229	1.0678	30.6972	1.1174
164.	280.00	96.00	0.87	817	850	2.3312	15.9	16.6025	0.9577	20.6649	0.7694
165.	370.00	24.00	0.69	772	850	0.9850	26.4	23.1446	1.1407	20.2822	1.3016

Declarations

Conflict of interest The authors declare that they have no confict of interest.

Human and animal rights This study does not contain any studies with human participants or animals performed by any of the authors.

Informed consent For this type of study, formal consent is not required.

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