Prediction of Mechanical Properties of Steel Fibre-Reinforced Self-compacting Concrete by Machine Learning Algorithms

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Abstract. With the development of big data processing technology and the continuous improvement of computer operation ability, machine learning has achieved remarkable results in recent years. Applying machine learning to solve engineering problems is gaining more attention from researchers. Steel fibre-reinforced self-compacting concrete (SFRSCC) is a new type of composite material prepared by combining the advantages of the high fluidity of self-compacting concrete (SCC) and the high toughness of steel fibre-reinforced concrete. However, the performance of SFRSCC is influenced by many factors such as water-binder ratio, mineral powder content and steel fibre content. This study aims to predict the mechanical properties of SFRSCC mixes based on datasets collected from the literature. In the presented work, the machine learning algorithms are employed to investigate the effect of SCC compositions and steel fibre on the performance of SFRSCC. The models used for the prediction are support vector regression (SVR) and artificial neural network (ANN). In both models, input variables are set to be water to binder ratio, sand to aggregate ratio, maximum size of coarse aggregate, amount of other mix components (e.g., superplasticizers, limestone powder, fly ash), volume fraction and aspect ratio of steel fibre, and curing age. The output variables are flexural strength and compressive strength of SFRSCC specimens. The performances of machine learning models are evaluated by comparing the predicted results with experimental results obtained from the literature. Furthermore, a comparative study is performed to select the best-proposed model with better accuracy.

Keywords: Machine Learning · Steel Fibre Reinforced Concrete · Self-compacting Concrete · Flexural Strength · Compressive Strength

1 Introduction

Concrete is the most widely used material in the civil engineering design of infrastructure and building construction industries. With the development of science and technology, numerous new buildings and structures have emerged, and the demand for better concrete performance has continued to increase. Steel fibre-reinforced self-compacting concrete (SFRSCC) combines the advantages of self-compacting concrete (SCC) and steel fibre-reinforced concrete (SFRC). On the one hand, as an improvement of SCC, it retains the

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advantages of high fluidity of SCC without the need for manual vibration; on the other hand, it has higher tensile strength, impact resistance and anti-penetration performance. It has been stated by Grunewald and Walraven [1] that the incorporation of steel fibres could expand the possible application scope of SCC. In addition, increasing the fibre volume fraction has been proven to improve the mechanical properties of SCC [2, 3].

The strength prediction of normal vibrated concrete (NVC) can be achieved with higher precision via numerical analysis. However, the compositions of SFRSCC are more complex because of the properties of fibres and mineral admixtures, and the traditional methods are not easily applicable to predict its strength. In recent years, machine learning (ML) predictions have been gradually used for evaluating some properties of concrete in the construction industry [4–7]. Many studies have been conducted to predict the mechanical properties of concrete based on machine learning techniques. Artificial neural networks (ANNs) were employed to forecast the compressive strength of high-performance concrete [8, 9]. Performance assessment showed that ANN prediction was remarkable in terms of accuracy. In addition, studies on the predictability of support vector machines (SVMs) have also been conducted in the past [10, 11]. Other supervised ML algorithms, such as decision trees, random forests, and evolutionary algorithms, were used for estimating concrete properties based on different sizes of datasets and input variables. However, there is lack of research on prediction of SFRSCC mechanical properties using ML models and performance comparison of such ML models. Therefore, this study proposes two ML algorithms to predict the compressive strength and flexural strength of SFRSCC, and presents a comparative analysis in the discussion section. In the presented study, ANN and SVM were applied to create ML models. To prevent overfitting, which can result in unreliable models, a five-fold cross-validation was used.

2 Data Processing

2.1 Dataset Description

To train a ML model effectively and accurately, a sufficient amount of data is essential. The dataset used in this study was collected from 15 published papers [12–26] and a total of 161 groups of data were employed to build ML models. To eliminate the influence of fibre type, the dataset was limited to the data from SCC reinforced with 2D hooked-end steel fibres only. Compositions of SFRSCC found to have considerable effect on mechanical properties were selected as input variables. Therefore, the dataset consists of nine input variables and two output variables. Input data included water to binder (W/B) ratio, sand to aggregate (S/A) ratio, maximum size of coarse aggregate, amount of other mix components (superplasticizers, limestone powder, fly ash), volume fraction and aspect ratio of steel fibre, and curing age. The output data were compressive strength and flexural strength. The basic information including mean and standard deviation (STD) values of all variables are listed in Table 1.

2.2 Data Scaling

The dataset was randomly divided into two groups before building the ML models. In this study, 80% data were used to train models and the rest 20% data were used as the

Table 1. Descriptive statistics of input and output variables

Category	Variable	Unit	Statistics			
			Min	Max	Average	STD
Input	Water to binder ratio	%	0.23	0.51	0.36	0.04
	Sand to aggregate ratio	%	0.40	0.71	0.56	0.06
	Coarse aggregate maximum size	mm	8.00	20.00	13.72	3.99
	Superplasticizers	kg	2.60	17.00	6.79	3.30
	Limestone powder	kg	0.00	288.90	57.42	78.59
	Fly ash	kg	0.00	250.00	67.47	80.92
	Volume fraction of fibre	%	0.00	2.00	0.65	0.54
	Aspect ratio of fibre	–	26.00	100.00	64.51	17.30
	Curing age	days	7.00	90.00	31.53	22.94
Output	Compressive strength	MPa	20.50	98.20	48.07	18.68
	Flexural strength	MPa	1.96	13.90	6.42	2.70

testing set. Due to the different units and range of variables, the data were standardized and converted into a standard normal distribution. To achieve this, the StandardScaler function in sklearn was employed.

3 Methodology

3.1 Evaluation Method

To evaluate the performance of ML models, correlation coefficient (R), coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RMSE) were used. The corresponding mathematical expressions are given in Eqs. (1)–(4).

$$R = \frac{\sum_{i=1}^{n}(P_i - P_A)(Y_i - Y_A)}{\sqrt{\sum_{i=1}^{n}(P_i - P_A)^2 \sum_{i=1}^{n}(Y_i - Y_A)^2}} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - Y_i)^2}{\sum_{i=1}^{n}(Y_i - Y_A)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - Y_i| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - Y_i)^2} \tag{4}$$

where P is the predicted result, Y is the actual result, and n is the total number of samples. P_A and Y_A are the average values of predicted and actual results, respectively.

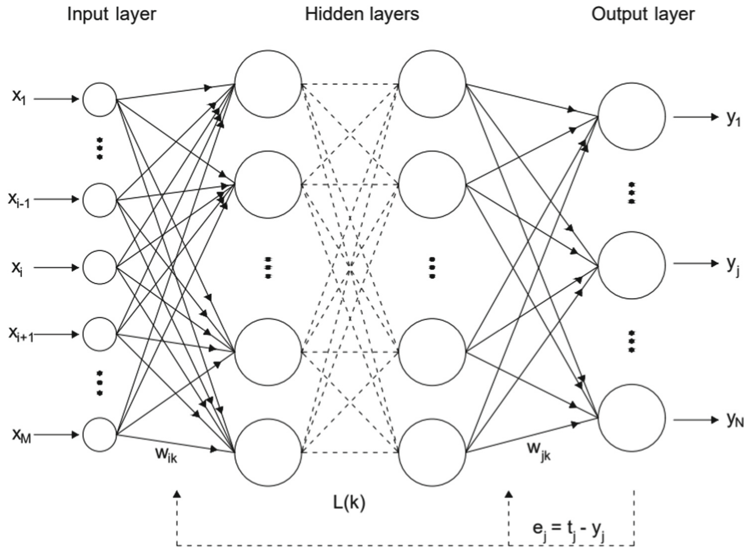


Fig. 1. The general structure of ANN

3.2 ML Algorithms

Artificial Neural Network (ANN). Artificial neural network (ANN) is a nonlinear model inspired by the framework of the real human brain. As a widely used feedforward neural network, Back Propagation neural network (BPNN) has excellent generalization ability, where the signal is propagated forward, and the error is propagated back. The learning rule of BPNN is the use of steepest descent method to continuously optimize the weights of the network by back-propagation, so that the corresponding evaluation indicators are optimal [27]. The BPNN is generally composed of three types of layers: an input layer, hidden layer(s), and an output layer. The parameters that affect the performance of the BP neural network mainly include the number of nodes in the hidden layer, the selection of the activation function and the learning rate, etc. A general structure of ANN is illustrated in Fig. 1.

Support Vector Regression (SVR). Support vector machine (SVM) is a small sample learning algorithm proposed by Vapnik et al. [28] based on statistical learning theory. Support vector regressor (SVR) was widely used to solve regression problems. By establishing a hyperplane or a set of hyperplanes in the high-dimensional space, the original limited-dimensional space is mapped to the high-dimensional space by kernel functions. Hence, the solution of the SVR is to minimize value of loss function and maximize the margin. Figure 2 shows the hyperplane classification of SVR. In this study, the adoption of different kernel functions was considered, and the models were optimized based on grid search.

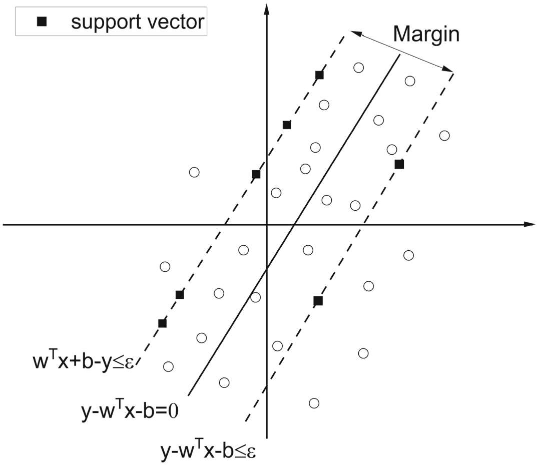


Fig. 2. The margin and hyperplane classification of SVR

4 Results and Discussion

In this section, the development of ML models is discussed. The compressive strength and flexural strength of SFRSCC are predicted based on optimized ANN and SVR models. To evaluate the efficiency of ML algorithms, the predicted results are compared with experimental results, and a comparison is made between proposed models.

4.1 ANN Model Development for SFRSCC

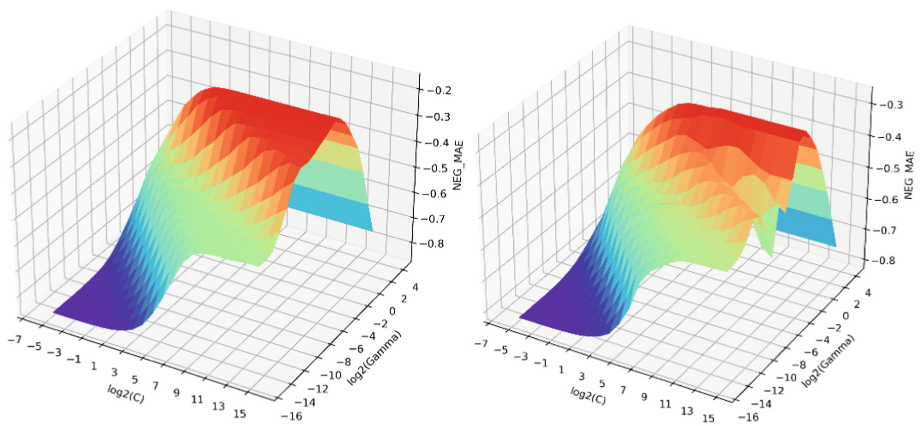
The ANN model was selected as containing nine neurons in the input layer, two neurons in the output layer and several neurons in one hidden layer. To build the network, Levenberg-Marquardt backpropagation was chosen as the training function. The maximum number of epochs in the training progress was 1000. By evaluating the ANN model containing different number of neurons in the hidden layer, the networks with best accuracy were selected as developed models. Additionally, to reduce the effect of randomness caused by training and testing dataset sampling, the splitting process has been repeated 5 times according to the cross-validation theory. The average outcome was computed to represent the performance of ANN models.

4.2 SVR Model Development for SFRSCC

Table 2 lists the performance of initial SVR models with different kernel functions. In terms of both compressive strength and flexural strength, the RBF function was found to be the best, with RMSE of 3.2223 and 0.8614, respectively. It should be emphasized that the value R^2 of Sigmoid SVR kernel function is negative only for the prediction of flexural strength. This is because the prediction error of Sigmoid SVR is greater than that of the mean error value of the function. Accordingly, the RBF SVR models were developed by five-fold cross-validation based grid search, where the main parameters C and gamma were chosen to be in the range of $\left[2^{-7}, 2^{15}\right]$ and $\left[2^{-16}, 2^{4}\right]$. Figure 3 shows the progress of optimizing SVR models, and the scores of the cross-validation were displayed in y-axis. Therefore, the best parameter pairs were found to be (32, 0.125) and (16, 0.125), respectively.

Table 2. Performance of SVR with different kernel functions

Output variable	Kernel function	Statistical parameters		
		R^2	RMSE	MAE
Compressive strength	Linear SVR	0.8311	7.8121	5.8957
	Poly SVR	0.9264	5.1548	3.7068
	RBF SVR	**0.9713**	**3.2223**	**2.2952**
	Sigmoid SVR	0.0765	18.2649	13.5662
Flexural strength	Linear SVR	0.7433	1.3360	0.9318
	Poly SVR	0.8740	0.9358	0.6940
	RBF SVR	**0.8933**	**0.8614**	**0.5951**
	Sigmoid SVR	−1.0733	3.7967	2.6231



(a) (b)

Fig. 3. Grid search of SVR models (a) compressive strength (b) flexural strength

4.3 Comparative Analysis

The performance of ML models on mechanical properties of SFRSCC is given in Table 3. It should be noticed that the prediction accuracy of optimized SVR models was improved due to the grid search, where correlation coefficients increased from 0.9713 and 0.8933 to 0.9802 and 0.9314. Additionally, the SVR algorithm exhibited better performance, with RMSE of 2.6749 and 0.6904, and MAE of 2.0388 and 0.5466, respectively.

Table 3. The prediction accuracy of ANN and SVR models

Output variable	Model	R^2	R	RMSE	MAE
Compressive strength	ANN	0.9261	0.9623	5.3720	3.2890
	SVR	0.9802	0.9900	2.6749	2.0388
Flexural strength	ANN	0.8453	0.9194	1.1890	0.7563
	SVR	0.9314	0.9651	0.6904	0.5466

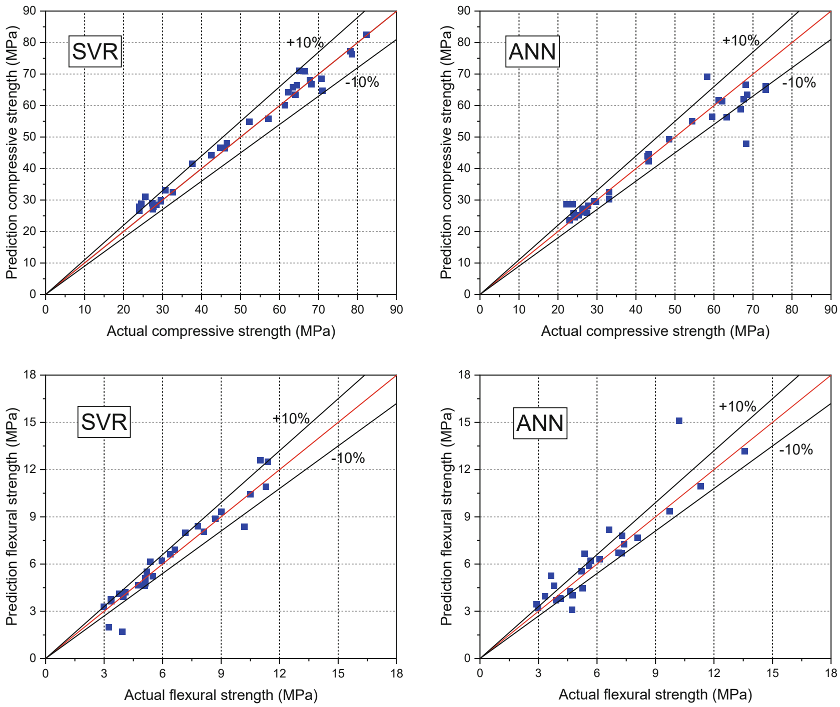


Fig. 4. The performance of SVR and ANN on SFRSCC mechanical properties

In Fig. 4, it can be seen that all models made with these two algorithms appeared to predict well the actual values of compressive strength and flexural strength. Most of the predicted points are lying within ±10% of the line of perfect agreement when predicting compressive strength of SFRSCC by SVR. Results suggest a better performance by SVR for this dataset in compressive strength prediction compared to ANN. For the prediction of flexural strength of SFRSCC, most of points are again lying within ±10% of the line of perfect agreement and correlation coefficients of 0.8453 and 0.9314 were obtained with ANN and SVR models respectively.

5 Conclusion

In this study, an attempt is made to estimate the compressive strength and flexural strength of SFRSCC using ML algorithms employing ANN and SVR. For this purpose, a reliable experimental dataset from literature that consists of 161 mixes was used. The performance of both models on these two mechanical properties were analysed and compared by using statistical methods. Meanwhile, the proposed SVR models were developed based on cross validation and grid search. The results show that SVR prediction is more accurate than ANN, and it has better generalization ability.

The proposed models may help to compensate the time-consuming and expensive laboratory tests for determining the mechanical properties of SFRSCC. However, the study is limited by the scale of datasets since it is not feasible to obtain a large amount of data with limited literature resource. Furthermore, the characteristics of materials, such as orientation of steel fibre and type of aggregates and cement, are rarely discussed in the current literature. Thus, a more extensive dataset with more parameters of interest can be generated in future research.

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