AI-guided Multi-objective Predicting and Evaluating of SCC Based on Random Forest

Boyuan Cheng [1, a], Wujian Long [1, b], Qiling Luo [1, c], Ganlin Feng [1, d], Junen Fu [3, e], Zhitang Li [4, f], Gang Dong [5, g], Fucheng Wu [2, h, *]

[1] Key Lab of Coastal Urban Resilient Infrastructure, MOE, Guangdong Provincial Key Laboratory of Durability for Marine Civil Engineering, College of Civil and Transportation Engineering, Shenzhen University, Shenzhen, 518060, Guangdong, PR China;

[2] Guangzhou Guangjian Construction Engineering Testing Center Co., Ltd, Guangzhou, 510405, Guangdong, PR China.

[3] China Railway Construction Bridge Engineering Bureau Group Co..Ltd, 300300, Tianjin, PR China;

[4] Poly Changda Engineering Co.Ltd, 510640, Guangdong, PR China;

[5] Shenzhen Yantiangang Construction Engineering Test Co., Ltd, 518101, Guangdong, PR China;

[a] chengboyuan2020@email.szu.edu.cn, [b] longwj@szu.edu.cn, [c] luoqiling@szu.edu.cn, [d] g-l.feng@szu.edu.cn, [e] 251580278@qq.com, [f] licareer@qq.com, [g] dg@ytgtest.com, [h] 2545504274@qq.com

Abstract. Self-compacting concrete (SCC) has unique properties that make it a promising alternative to traditional concrete. However, its prediction and design remain challenging due to the complex interaction of multiple factors. Traditional methods are limited in scope, and often inaccurate. This study presents a multi-objective predicting and evaluating model for SCC using machine learning techniques, particularly random forest algorithm. The model predicts flowability, mechanical property, and durability using nine critical features. The dataset used in this study consisted of 376 samples, and the model achieved high accuracy for predicting all three performance indicators, with R^2 values of 0.94 for compressive strength, 0.92 for slump flow, and 0.94 for rapid chloride permeability. The importance analysis results suggest that the weight of binder and sand are the two most critical factors that affect SCC properties. This approach provides a valuable tool for engineers and researchers in the field of concrete science and technology, improving the quality and durability of concrete structures.

Keywords: Self-compacting concrete; Machine learning; Random Forest; Workability; Mechanical strength; Durability.

1. Introduction

Self-compacting concrete (SCC) has emerged as a promising alternative to traditional concrete due to its unique properties, including high flowability, excellent homogeneity, and improved constructability [1,2]. SCC is particularly suitable for complex shapes and reinforced concrete structures where traditional concrete placement is challenging [3-5]. However, predicting and designing the performance of SCC remains a complex and challenging task due to the complex interaction of multiple factors, such as the properties of the materials, the mixing process, and the environmental conditions. Traditional methods of predicting the performance of SCC are based on empirical relationships that rely on limited data and are often inaccurate. Moreover, these models are often limited in scope, focusing on a single performance indicator, such as compressive strength, and do not take into account other critical factors, such as durability and workability. These limitations hinder the development of accurate and reliable SCC performance prediction models, which can lead to suboptimal designs, increased costs, and reduced durability of concrete structures.

In recent years, machine learning techniques have emerged as a promising approach for the development of accurate and reliable prediction models [6]. Machine learning algorithms have the ability to analyze large datasets and discover complex patterns that may not be evident using traditional methods. By leveraging the power of machine learning, it is possible to develop accurate and reliable models that can take into account multiple performance indicators and consider the complex interaction between various factors [6]. In the realm of concrete science, various researchers have investigated the use of machine learning algorithms for predicting the properties of different types of concrete. For instance, Naseri et al. [7] developed an intelligent mixture design method for sustainable concrete by using multiple algorithms, including artificial neural network (ANN) and support vector machine (SVM), to establish a compressive strength prediction model. Furqan et al. [8] developed ensemble models and individual models to predict the strength of high-performance concrete (HPC), with random forest (RF) demonstrating the most robust performance among the models, achieving a coefficient of determination (R^2) of 0.92. Despite the success of various machine learning models in predicting the properties of concrete, there has been limited research on the use of such models for SCC prediction. However, Mucteba et al. [9] developed an ANN model that efficiently predicted the compressive strength of SCC, with an R2 of up to 0.95. Similarly, Mohammed et al. [10] developed an SVM model that predicted the fresh properties of SCC with a low root mean square error (RMSE) of 26.9 mm. Prasenjit et al. [11] compared the accuracy of different models, including support vector regression (SVR), ANN, and multivariable regression analysis (MVR), for predicting the fresh and hardened properties of SCC and found that SVR outperformed the other models in terms of accuracy. However, prediction methods for the durability of SCC have not been reported, and critical factors such as cement strength grade, maximum aggregate particle size, and environmentally friendly alternative cementitious materials, such as limestone powder, have not been considered.

This study aimed to develop a multi-objective predicting and evaluating model for SCC using machine learning techniques. Specifically, this study used the RF algorithm, a popular machine learning algorithm, to predict three key performance indicators of SCC: flowability (characterized by slump flow (SF)), mechanical property (characterized by 28-day compressive strength (28-day SC)), and durability (characterized by 28-day rapid chloride permeability (28-day RCP)). The model considered nine features, including the cement grade (CG), the weight of cement (C), the weight of fly ash (FA), the weight of limestone powder (LP), the weight of sand (S), the weight of coarse aggregate (CA), the maximum diameter of aggregate (MAXD), the ratio of water to binder (W/B), and the ratio of superplasticizer to binder (SP/B). The proposed approach has several advantages over traditional methods of SCC performance prediction. Firstly, it can provide accurate and reliable predictions of multiple performance indicators, which can facilitate the design of SCC material that meet the required performance specifications. Secondly, the model can take into account the complex interaction between various factors, which can help to identify the optimal mix design and improve the durability of concrete structures. Finally, the model can be easily updated with new data, which can improve its accuracy and reliability over time.

The development of accurate and reliable SCC performance prediction models is critical to improving the quality and durability of concrete structures. This study presents a comprehensive approach to SCC performance prediction and evaluation using machine learning techniques, aiming to provide a valuable tool for engineers and researchers in the field of concrete science and technology.

2. Methods

2.1 Overview

The present study aimed to investigate the potential of using machine learning algorithms for predicting and evaluating the performance of SCC. To achieve this objective, this study employed the RF algorithm to develop an artificial intelligence (AI)-guided multi-objective prediction and evaluation model that takes into account nine different features and three key performance indicators of SCC, including flowability (characterized by SF), mechanical property (characterized by 28-day SC), and durability (characterized by 28-day RCP). The methodology for developing the model was divided into three main stages, starting with the data collection phase, followed by model training and model evaluation.

During the data collection phase, a large dataset of SCC properties and characteristics were gathered from different sources. This dataset was then preprocessed to eliminate any outliers or missing values, ensuring that the data was of high quality and suitable for use in model training. Subsequently, the preprocessed dataset was divided into training and testing sets, with the former used for training the model and the latter for evaluating its performance.

The model training stage involved developing an optimized RF algorithm-based model that could effectively predict and evaluate the performance of SCC. The RF algorithm was selected due to its ability to handle high-dimensional datasets with numerous features and its high accuracy in predicting complex relationships between variables. During model training, various parameters and hyperparameters of the algorithm were fine-tuned to obtain the best possible model performance.

Finally, the model evaluation stage was conducted to assess the accuracy and reliability of the developed model. The performance of the model was evaluated using various metrics, such as the R^2, mean squared error (MSE), RMSE, and mean absolute error (MAE). These metrics allowed us to compare the model's predictions with the actual experimental results and determine the model's overall accuracy in predicting SCC performance.

Overall, the developed AI-guided multi-objective prediction and evaluation model has the potential to become a valuable tool for the construction industry. By providing accurate and reliable predictions of SCC performance, this model can assist engineers and designers in developing more durable and sustainable concrete structures.

2.2 Random Forest

The RF algorithm is a popular machine learning technique that is well suited for regression and classification tasks. The algorithm works by constructing an ensemble of decision trees, each of which is trained on a random subset of the data. The final prediction is then made by averaging the predictions of all the decision trees in the ensemble. This approach helps to reduce overfitting and improve the accuracy and robustness of the model. In this study, we used the RF algorithm to predict the three key performance indicators of SCC [12, 13]. The Conceptual diagram of RF algorithm is shown in **Fig. 1**.

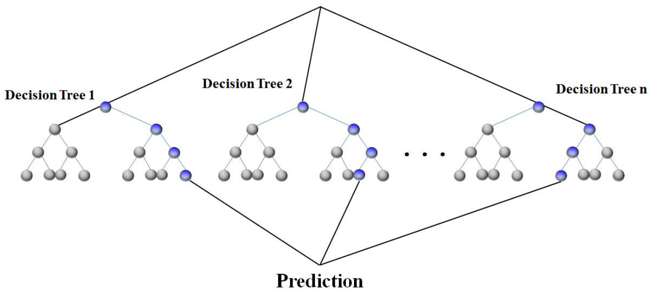


Fig. 1 Conceptual diagram of RF algorithm

2.3 Model evaluation

To evaluate the performance of the developed model, we used several metrics, including MAE, MSE, RMSE, and R^2. The MAE measures the average absolute difference between the predicted values and the actual values, while the MSE measures the average squared difference between the predicted values and the actual values. The R^2 measures the proportion of variance in the dependent variable that is explained by the independent variables. These metrics were used to assess the accuracy, precision, and reliability of the developed model. The equations for these parameters are shown as Eq. (1) ~ Eq. (4):

$$R^2 = \frac{\sum_{i=1}^{n} (y'_i - \bar{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y'_i - y_i| \quad (2)$$

$$MSE = \frac{\sum_{i=1}^{n}(y'_i - y_i)^2}{n} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y'_i - y_i)^2}{n}} \quad (4)$$

where n is the total number of instances; y'_i and y_i are the predicted and actual outputs; $\bar{y}_i$ is the mean values of the actual outputs.

3. Data collection

The data used in this study were collected from international journals [14-35] and databases related to SCC. The dataset consisted of 376 samples, with each sample representing a unique combination of the nine features and object. The features included cement grade (CG), the weight of cement (C), the weight of fly ash (FA), the weight of limestone powder (LP), the weight of sand (S), the weight of coarse aggregate (CA), the maximum diameter of aggregate (MAXD), the ratio of water to binder (W/B), and the ratio of superplasticizer to binder (SP/B). The performance indicators included SF, 28-day SC, and 28-day RCP. The Statistical values of the dataset for the three SCC properties prediction are shown in **Table 1** to **Table 3**.

The data were preprocessed to remove any outliers or missing values. The dataset was then randomly split into a training set (90%) and a testing set (10%) for model training and evaluation.

Table 1. Statistical values of the dataset for prediction of slum flow

Feature	C (Kg/m^3)	CG (MPa)	FA (Kg/m^3)	LP (Kg/m^3)	W/B	S (Kg/m^3)	CA (Kg/m^3)	MAXD (mm)	SP/B	SF (mm)
count	130	130	130	130	130	130	130	130	130	130
mean	314.35	43.27	122.72	33.49	0.39	846.43	779.95	17.75	0.0069	661.75
std	82.77	2.68	85.03	82.41	0.10	90.73	83.88	1.48	0.0053	60.16
min	150.00	42.50	0.00	0.00	0.23	562.00	500.00	16.00	0.0000	520.00
25%	250.00	42.50	66.00	0.00	0.31	808.50	773.00	16.00	0.0020	625.00
50%	312.50	42.50	130.00	0.00	0.35	866.50	800.00	19.00	0.0085	650.00
75%	380.00	42.50	168.75	0.00	0.45	899.75	836.50	19.00	0.0119	710.00
max	500.00	52.50	350.00	330.00	0.65	1050.00	914.90	19.00	0.0170	790.00

Table 2. Statistical values of the dataset for prediction of 28-day SC

Feature	C (Kg/m^3)	CG (MPa)	FA (Kg/m^3)	LP (Kg/m^3)	W/B	S (Kg/m^3)	CA (Kg/m^3)	MAXD (mm)	SP/B	28-day SC (MPa)
count	146	146	146	146	146	146	146	146	146	146
mean	277.25	44.28	135.10	32.25	0.47	844.33	805.51	18.78	0.0045	40.75
std	69.79	3.84	84.74	81.11	0.13	116.69	96.58	0.79	0.0033	14.71
min	150.00	42.50	0.00	0.00	0.23	478.00	500.00	16.00	0.0000	10.20

25%	220.00	42.50	60.00	0.00	0.36	772.75	773.00	19.00	0.0020	28.50
50%	255.00	42.50	160.00	0.00	0.45	854.50	837.00	19.00	0.0035	39.70
75%	325.00	42.50	184.50	0.00	0.55	916.00	850.00	19.00	0.0050	51.65
max	500.00	52.50	350.00	330.00	0.85	1079.00	923.00	19.00	0.0170	73.50

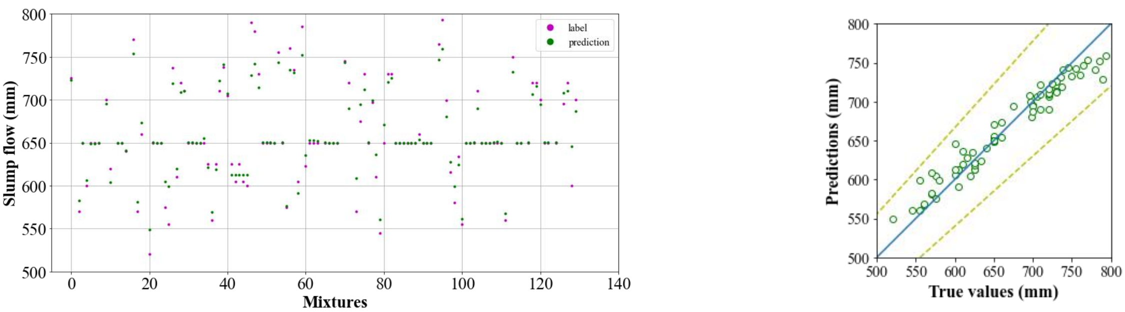
Table 3. Statistical values of the dataset for prediction of 28-day RCP

Feature	C (Kg/m^3)	CG (MPa)	FA (Kg/m^3)	LP (Kg/m^3)	W/B	S (Kg/m^3)	CA (Kg/m^3)	MAXD (mm)	SP/B	28-day RCP (Coulombs)
count	100	100	100	100	100	100	100	100	100	100
mean	372.02	48.60	78.85	13.92	0.40	810.25	809.72	14.85	0.0098	2319
std	92.39	4.90	96.87	41.44	0.09	146.93	105.36	3.65	0.0064	1572
min	135.00	42.50	0.00	0.00	0.08	375.20	526.20	10.00	0.0000	205
25%	325.00	42.50	0.00	0.00	0.35	722.30	761.75	12.50	0.0050	1141
50%	366.50	52.50	57.80	0.00	0.40	828.70	800.00	16.00	0.0080	2071
75%	436.79	52.50	129.00	0.00	0.45	912.25	862.93	16.75	0.0132	3146
max	600.00	52.50	350.00	175.00	0.57	1032.50	1062.00	20.00	0.0324	6900

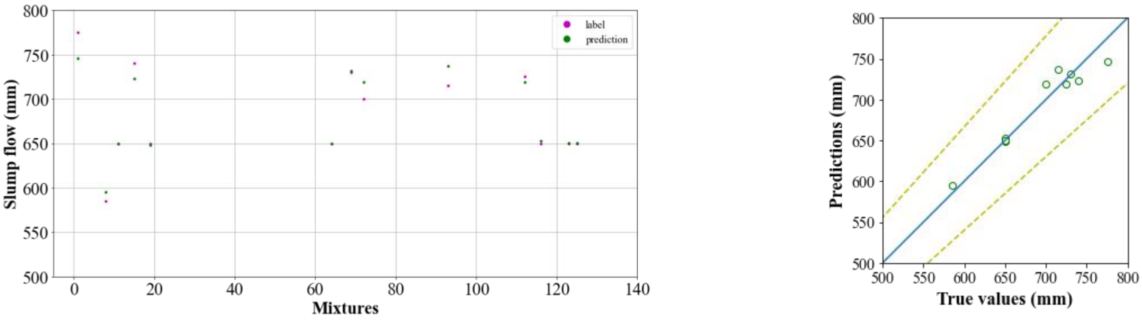
4. Results and discussions

4.1 Flowability prediction

The SF of SCC is a measure of its workability, or how easy it is to place and compact the concrete. It is an essential property of SCC, as it affects the ease of construction, transportation, and casting. Therefore, accurate prediction of SF is crucial in optimizing the mix design of SCC and ensuring its successful application.



(a) (b)



(c) (d)

Fig. 2 Model results vs. experimental observations for SF model: (a) – (b) training set; (c) – (d) test set

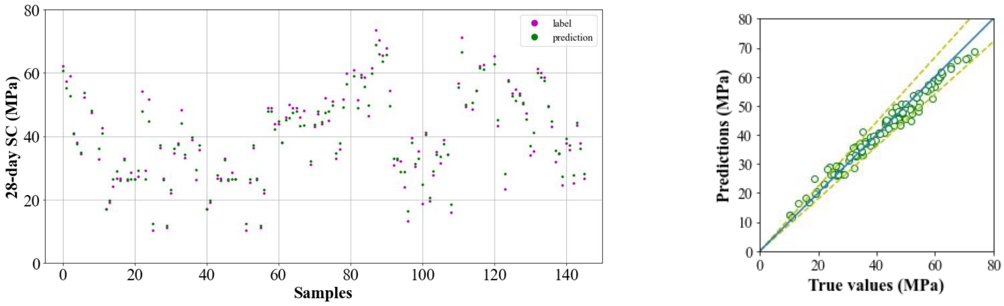
Following a comprehensive 10-fold cross-validation, the SF RF model's hyperparameters, namely n_estimators, max_features, and max_depth, were optimized to 610, 2, and 89, respectively. **Table 4** provides a summary of the statistical performance of the proposed SF RF model, while the comparison between the model's prediction results and experimental observation results are illustrated in **Fig. 2**. The results from both **Fig. 2** and **Table 4** demonstrate the model's high R^2 values for both the training data (0.93) and the testing data (0.94), which indicate the model's strong correlation with the experimental observations in both training and testing sets. Additionally, the satisfactory scores and similarity of the training and testing sets highlight the RF model's ability to capture the complex mapping relationship between the features and SF while demonstrating impressive generalization ability. The proposed SF RF model presents a promising approach to predicting SF and holds great potential for further development and practical applications in the field. Overall, the findings of this study contribute to the development of accurate and reliable predictive models for SF in various applications.

Table 4. Statistical performance of proposed SF RF model

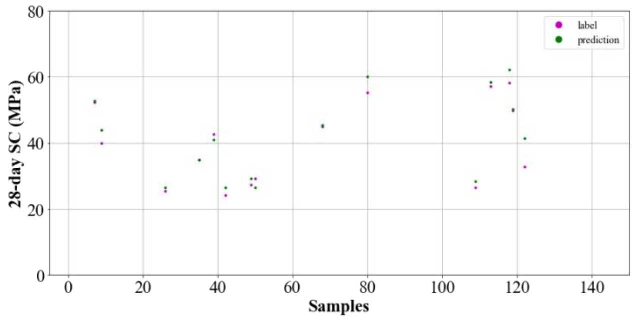
Items	R2	MAE (mm)	MSE (mm)	RMSE (mm)
Test set	0.94	8.4	151.8	12.3
Training set	0.93	9.0	249.5	15.8

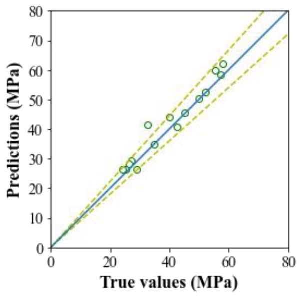
4.2 Strength prediction

The compressive strength of SCC is an important mechanical property that determines its load-bearing capacity and overall structural performance. Therefore, the accurate prediction of 28-day SC is crucial for assessing the quality and reliability of SCC in various applications.



(a) (b)





(c) (d)

Fig. 3 Model results vs. experimental observations for 28-day SC RF model: (a) – (b) training set; (c) – (d) test set

To evaluate the model's performance, a 10-fold cross-validation was conducted, which resulted in the determination of the optimal values for n_estimators, max_features, and max_depth as 580, 2, and 69, respectively. These values were used to train the 28-day SC RF model, which was then evaluated by comparing its prediction results with experimental observation results. **Fig. 3** displays the comparison between the model prediction results and the experimental observation results. **Table 5** provides a summary of the statistical performance of the proposed 28-day SC RF model. The data points are mainly distributed within their boundaries, indicating a high degree of accuracy for the model. Furthermore, the high R^2 for both the training data (0.97) and the testing data (0.92) confirmed the strong correlation between the model predictions and experimental observations. These results demonstrate the RF model's ability to effectively capture the complex mapping relationship between the nine features and the 28-day SC, as well as its satisfactory generalization ability across both the training and testing sets. The model's accuracy and generalization ability make it a valuable tool for predicting and evaluating the compressive strength of SCC, which can assist in optimizing its mix design and ensuring its long-term durability.

Table 5. Statistical performance of proposed 28-day SC RF model

Items	R2	MAE (MPa)	MSE (MPa)	RMSE (MPa)
Test set	0.92	2.6	11.7	3.4
Training set	0.97	1.8	5.6	2.4

4.3 Durability prediction

The durability of SCC is of paramount importance in construction, as it can have a significant impact on the longevity and safety of structures. The 28-day RCP of SCC is a key indicator of its durability, as it reflects the concrete's resistance to cracking and other forms of damage under various environmental conditions. Therefore, accurate prediction of the 28-day RCP is critical for ensuring the durability of SCC.

The proposed 28-day RCP RF model was evaluated for its durability prediction performance on both the training and test sets, with a focus on its generalization ability. **Fig. 4** presents a scatter plot comparing the model results to the experimental observations. It can be observed that the majority of the data points for both the training and test sets fall within the boundaries, indicating a high degree of accuracy of the model. This indicates that the model is able to effectively learn the complex mapping relationship between the input features and the 28-day RCP, and generalize well to unseen data. Furthermore, **Table 6** summarizes the statistical performance of the proposed 28-day RCP RF model. The R^2 value for the test set is 0.94, indicating a strong correlation between the model predictions and experimental observations. The MAE, MSE, and RMSE values for the test set are 172.0, 98903.5, and 314.5, respectively, demonstrating the model's ability to accurately predict the 28-day RCP of SCC. Similarly, for the training set, the R^2 value is 0.96, and the MAE, MSE, and RMSE values are 204.7, 92483.9, and 304.1, respectively. These results further validate the effectiveness of the proposed 28-day RCP RF model in predicting the durability of SCC. It can be concluded that the proposed model not only performs well on the training data, but also generalizes well to unseen data, indicating its strong potential for practical applications in the field of SCC durability prediction.

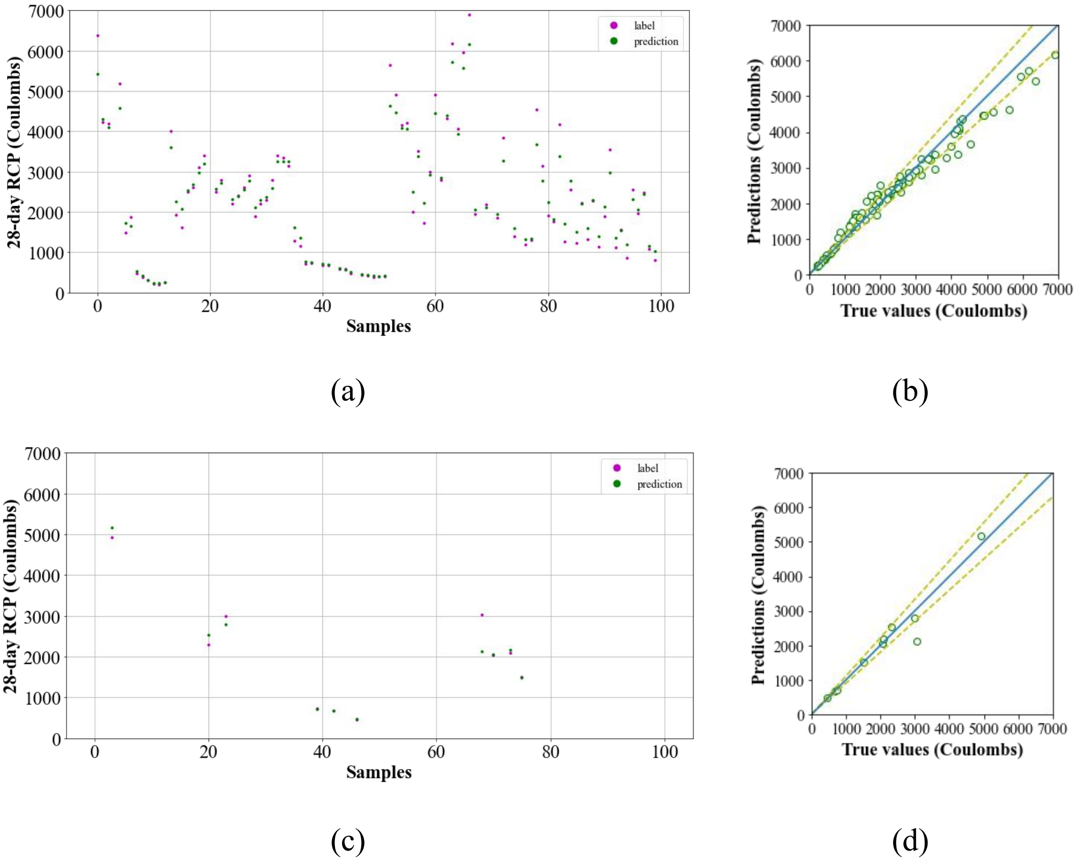


Fig. 4 Model results vs. experimental observations for 28-day RCP RF model: (a) – (b) training set; (c) – (d) test set

Table 6. Statistical performance of proposed 28-day RCP RF model

Items	R2	MAE (Coulombs)	MSE (Coulombs)	RMSE (Coulombs)
Test set	0.94	172.0	98903.5	314.5
Training set	0.96	204.7	92483.9	304.1

4.4 Importance analysis

Importance analysis is a technique used to identify and rank the most important factors that contribute to a particular outcome or result. In this study, importance analysis was performed to determine the factors that have the greatest impact on the SF, 28-day SC, and 28-day RCP of SCC. **Fig. 5** presents the feature importance for each outcome, with the most important factors listed first. For SF, the most important factor was W/B, followed by S and CA content. For 28-day SC, the most important factor was W/B, followed by S and CG. For 28-day RCP, the most important factor was S, followed by SP/B and CA.

The results of the importance analysis suggest that the W/B is the most critical factor that affects both SF and 28-day SC. This is because the W/B determines the amount of water needed to achieve the desired level of workability and strength, and has a significant impact on the porosity and hydration of the cementitious materials. For 28-day RCP, the sand content was the most important factor, as it has a direct impact on the packing density of the concrete mix and the interparticle bond strength. In summary, the importance analysis provides valuable insights into the factors that influence the performance of SCC, which can help optimize the mix design and enhance the overall quality and durability of SCC in practice.

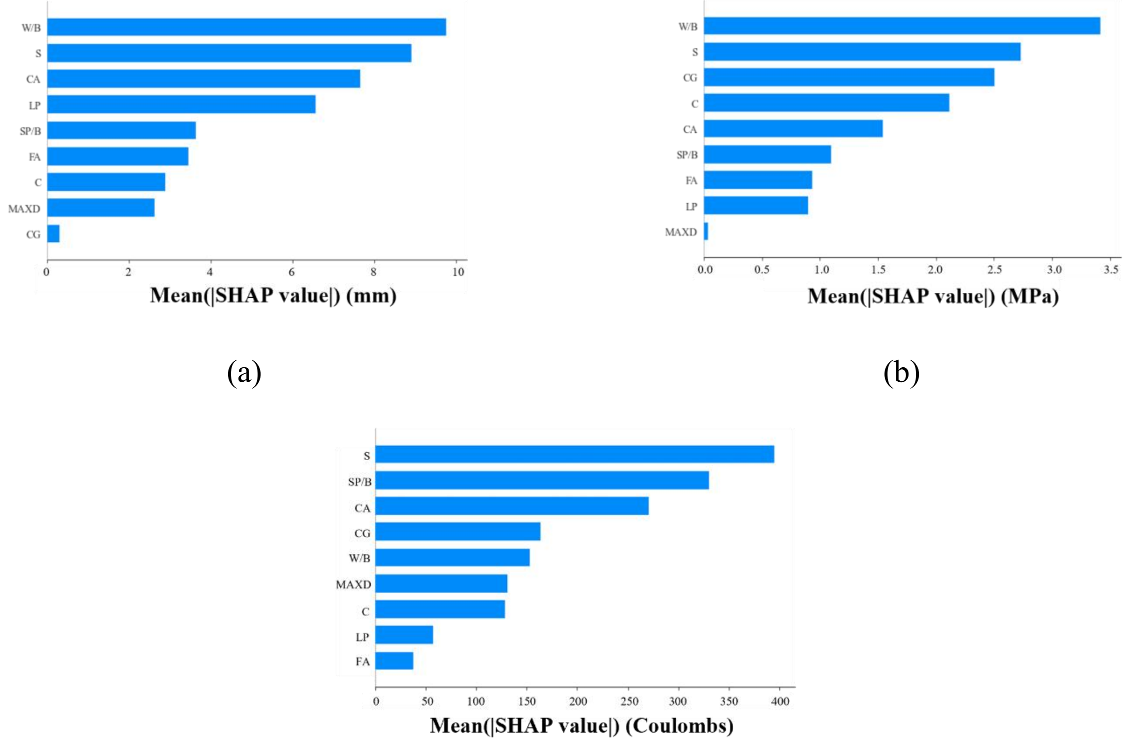


Fig. 5 Feature importance in terms of their contributions towards: (a) SF; (b) 28-day SC; (c) 28-day RCP

5. Conclusions

This study aimed to develop a multi-objective predicting and evaluating model for SCC using machine learning techniques. The proposed multi-objective predicting and evaluating model for SCC can predict multiple performance indicators, including flowability, mechanical property, and durability, using nine critical factors. This approach provides several advantages over traditional methods, including the ability to take into account the complex interaction between various factors, which can lead to the identification of optimal mix designs and improved durability of concrete structures.

The dataset used in this study consisted of 376 samples, and the model achieved high accuracy for predicting all three performance indicators, with R^2 values of 0.94 for 28-day SC, 0.92 for SF, and 0.94 for 28-day RCP.

The results of the importance analysis suggest that the W/B is the most critical factor that affects both SF and 28-day SC. For 28-day RCP, the sand content was the most important factor.

The proposed model is a valuable tool for engineers and researchers in the field of concrete science and technology, and it can be easily updated with new data, which can improve its accuracy and reliability over time.

Future work can focus on further improving the accuracy and reliability of the model by incorporating additional factors, such as temperature and humidity, and exploring the potential of other machine learning algorithms. Additionally, the model can be extended to predict the performance of SCC under different environmental conditions, such as freeze-thaw cycles and exposure to aggressive chemicals.

Overall, this study demonstrates the potential of machine learning in the development of accurate and reliable models for predicting the performance of SCC, which can lead to the improvement of the quality and durability of concrete structures.

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