Ridge Regression Analysis Application on Iterative FR-SCC Mix Design to Predict Compressive Strength and Slump Flow Parameters

Cemal Agaoglu[a], Ozgur Eren[b]

[a]Ph.D. Student, Dept. of Civil Engineering, Eastern Mediterranean University, Famagusta, Mersin 10, Turkey. (E-mail: agaoglucemal@hotmail.com)

[b]Professor, Dept. of Civil Engineering, Eastern Mediterranean University, Famagusta, Mersin 10, Turkey. (E-mail: ozgur.eren@emu.edu.tr)

CORRESPONDENCE Cemal Agaoglu agaoglucemal@hotmail.com Dept. of Civil Engineering, Eastern Mediterranean University, Famagusta, Mersin 10, Turkey.

Abstract

This study addresses the development and predictive modeling of polypropylene fiber-reinforced self-compacting concrete (FR-SCC) as a strengthening material for reinforced concrete structures. In jacketing applications, compatibility between the existing substrate and the new layer is critical: concretes with similar compressive strength and modulus of elasticity transfer load more uniformly and reduce the risk of delamination. At the same time, SCC must achieve adequate flow since vibration cannot be applied during placement; poor workability may compromise compaction, bonding, and durability. Thus, proportioning SCC with both target compressive strength and sufficient workability is essential. A total of 29 SCC trial iterations were performed, systematically adjusting binder content, water-to-binder ratio, superplasticizer dosage, and aggregate proportions to achieve self-compaction and target strengths with and without 6mm polypropylene fibers. In parallel, a transparent predictive framework was implemented in Excel. The model employs z-score standardization, a physics-guided polynomial expansion, ridge regression, and guideline systems to avoid extrapolations. It achieved high accuracy for compressive strength ($R^2 \approx 0.90$) and reasonable performance for slump flow ($R^2 \approx 0.66$). These findings confirm that the proposed ridge regression approach can effectively capture both strength and workability trends, offering a practical tool for optimizing FR-SCC mix design.

Keywords: Fiber-reinforced self-compacting concrete (FR-SCC); Ridge regression; Polypropylene fibers; Mix-design optimization; Compressive strength prediction; Slump-flow modeling; Data-driven materials design

1. Introduction

By definition Self-compacting concrete (SCC) can consolidate under its own weight without the need for vibration or tamping [1, 2]. The superior flowability of the SCC enables the concrete to be used in even highly reinforcing bar congested elements while reducing the labor during the placement process [3]. This superior workability properties of the SCC makes it a phenomenal option to be used in the strengthening and rehabilitation applications on the existing concrete elements, particularly in the jacketing applications where the additional reinforcement jacket might need to be kept slender and highly congested with reinforcing rebars [4, 5].

During a strengthening/protection jacketing application, one of the most important aspects is the placement of the new concrete element to form a uniform distribution and proper bonding with the substrate. Concrete with low workability and segregation issues may cause poor bonding to the substrate and improper protection abilities [6, 7]. Therefore, high workability of the SCC is an excellent parameter for the jacketing applications to form a reliable interface and durable protection of the substrate existing concrete element. Consequently, achieving an optimal balance between compressive strength and workability is critical for SCC when used as a strengthening material.

During a jacketing application, the compatibility between the existing and the new layer is one of the most crucial parameters for a successful strengthening/protection application. If the two layers has distinct elasticity and compressive strength parameters, delamination and debonding between the interface might occur during loading and deformation of the strengthened element [8, 9]. Therefore, similar mechanical properties between the two layers ensures an efficient strengthening application.

Moreover, one of the most challenging aspects of the use of SCC during a jacketing application is to be able to keep the mixture highly flowable while also providing the required compressive strength parameters. High-flowability of the SCC ensures the formation of a highly durable layer with low permeability [4, 5]. Otherwise, poor compaction of the jacketing layer might cause poor performance in long-term use.

The bonding between the existing and the new concrete layers is one of the most important parameters in a jacketing or any strengthening application. As [10] and [11] suggests that the use of SCC can perform significantly well in bond-critical applications due to the development of a reliable bar-concrete bonding to provide a sufficient load transfer between the faces.

One of the most challenging part of the SCC for jacketing application is the adjustment period of the compressive strength and the flowability of the concrete without segregation where guidelines like BRE (British Research Establishment) [12] and EFNARC [2] specifications provide an initial ground work for the mix designs, they can't really provide a direct approach for the compressive strength and workability parameters due to having many variables in the SCC matrix. Cement replacement materials, modern admixtures and use of fibers in the mix design effect the workability of the self-compacting concrete immensely. Therefore, it's a common practice for SCC applications to do extensive iterative work to adjust the compressive strength and workability parameters [1, 3]. This time-consuming process reportedly becomes more challenging especially when the fibers are introduced to the mix design, as the increase of the fibers reduces the workability, hence higher fines content and superplasticizer dosages are required to achieve a self-consolidating concrete without affecting the compressive strength parameter significantly [6, 7].

Generally, the high workability of the self-compacting concrete and fiber reinforced concrete can be kept as two completely different concrete types where even a slight addition of the fibers into SCC can lead to significant reduction on the flowability of the mixture [13, 14]. Therefore, completely eliminating the main characteristic of the SCC without significantly altering the mix design. So, it's safe to assume that the incorporation of the fibers into the SCC matrix extends the iterative adjustment period even more to achieve a FR-SCC mix designs.

While the iterative method can be acceptable in a laboratory scale project, it is costly and time-consuming, and it offers limited guidance for practitioners who must design SCC under project constraints. Hence, a predictive model that can estimate the effects of different variations in the FR-SCC mix design is required to be able to efficiently adjust variations and capture the required mechanical and physical properties.

As the trial-and-error approach is the most challenging part of the SCC jacketing applications, many approaches have been made to predict the fresh and hardened properties of SCC by using multiple linear regression (MLR) and polynomial regression analysis. These prediction approaches use the mix design parameters of the SCC in interaction with its compressive strength and workability of the mixes to provide interpolate models [3, 15, 16]. Main issue with these approaches is the lack of adaptation of the models on nonlinear behaviour of the mix variation outcomes.

Due to the limitations of the multiple linear regression (MLR) and polynomial regression analysis methods, recent studies mostly focused the applications on machine learning (ML) techniques like random forest, artificial neural networks (ANN) and support vector machines (SVM) to predict the SCC mix design proportioning in regards to its compressive strength and workability [17, 18, 19]. While these techniques yield high accuracy on the predictions of the compressive strength and workability performance of the SCC, due to only running the analysis in a "black-box" nature they are usually accepted as limited to perform accurately on the analysed iterations and lack the adaptation on individual materials influence on the SCC performance [20].

The lack of accurate prediction of the SCC performance on practical adoption in engineering applications highlighted a demand for a reliable and transparent prediction model that can adapt and be influenced by each individual parameter of a self-compacting concrete mix matrix to predict the compressive strength and workability without iterative approach.

To be able to achieve this desire, this study combines the iterative approach with z-score standardization, a physics guided polynomial expansion and ridge regression with calibration guardrails to form a transparent predictive modelling approach. As the raw data 29 iterations of SCC mix designs with their workability and compressive strength parameters were used with distinctive binder contents, water/binder ratios, fiber contents and aggregate proportions. The iterations have carried out until 3 compressive strength classes have achieved (C16/20, C25/30 and C30/37) while keeping the SCC workability levels within EFNARC [2] standards. In parallel with this application, a predictive framework was implemented in Excel to estimate SCC performance directly from mix design parameters to create a calculator like easy to apply framework for ease of use.

In general, most studies on the FR-SCC mixes focused on the steel fibre reinforced systems, with limited attention to the polypropylene fibers. In comparison with the steel fibers, its more challenging to achieve a self-compacting concrete parameters when the polypropylene fibers are introduced to the mix matrix due to the hydrophilic nature of the polypropylene fibers. High water absorption behaviour of the polypropylene fibers reduces the workability of the SCC immensely and may cause segregation and fiber balling effects that prevents achieving a reliable mix design when excessive amount of fibers are introduced. Therefore, in comparison with the steel fibers the content of the polypropylene fibers may be much lower to maintain the required workability parameters of the SCC. However, one of the most important aspect of the use of polypropylene fibers is the ability to resist corrosion and to be able to use the polypropylene fiber reinforced self-compacting concrete as a rehabilitation material on the corroded reinforced concrete elements.

In this study, three strength classes of C16/20, C25/35 and C30/37 were established with both SCC and FR-SCC mixtures where 29 iterations were produced in total to acquire these strength classes. Using these iterations, a transparent ridge-regression analysis have been conducted to predict both compressive strength and slump flow parameters by using only the mix design constituents. In comparison with the other black-box approaches, the proposed method provides direct physical interpretability of each variable, enabling practical proportioning adjustments without extensive iterative process. The combined use of a hydrophilic fiber system and an interpretable prediction model establishes the novelty of this work as a materials-oriented contribution to sustainable SCC mix design for rehabilitation and jacketing applications.

2. Methodology

2.1. Materials

CEM II 42.5N Ordinary Portland Cement with a specific gravity of 3.15 g/cm³ (conforming to EN 197-1) was used for all the iterations. As a cement replacement material and additional filler in the SCC matrix, silica fume (SF) is used in most of the iterations to adjust the SCC parameters generically to enhance the workability and to reduce the segregation.

As for the aggregates for all the mixes, locally available crushed limestone was used for both fine and coarse aggregates. 10mm, 14mm and 20mm coarse aggregates were used for all the iterations with distinctive proportions. Where with initial iterations, BS 882:1992 limits were used for grading the sizes of aggregates. The specific gravities were 2.65 g/cm³ for sand and 2.70 g/cm³ for coarse aggregates.

One of the most important ingredients in a SCC mix design is the additives that are used to increase the workability without affecting the compressive strength of the self-compacting concrete [1, 3]. In this study for all the iterations Sikaplast 180 has been used as a superplasticizer and no additional viscosity-modifying agents (VMA) was used to keep the variables lower within the iterations. The superplasticizer was used in rate of binder content of the mix design.

Even though, the workability of the mixes affected significantly with the introduction of the fibers into a SCC mix design [4, 21] polypropylene fibers were used in most of the iterations to improve the crack resistance, reduce the permeability and to achieve a better strengthening/rehabilitation material for jacketing applications. 6mm polypropylene fibers were used with 30 μm diameters and density of 910 kg/m³. In general, due to fiber balling and high-water absorption parameters of the polypropylene fibers, low fiber contents between 0% and 0.75% was used as with increasing fiber contents, reduction in the workability and compressive strength performances were observed.

All materials were stored in laboratory conditions prior to mixing, and potable water was used in all batches.

2.2. Conventional Concrete Mixes (BRE Method)

As discussed above, C16/20, C25/30 and C30/37 strength classes are chosen for the conventional concrete reference mixes for the comparison with the self-compacting concrete (SCC) iterations. These strength classes were chosen as initially C25/30, C30/37 and C35/45 classes were decided however, to represent a structure in need of a strengthening/rehabilitation jacketing, lower strength classes were also introduced to the study such as C16/20. Throughout the SCC iterations, C35/45 strength class was not obtained with the FR-SCC mixes. Therefore, only 3 strength levels that are stated on the Table 1 below are implemented into this study. For the conventional concrete mixes, British research establishment (BRE) method [12] was utilized.

Mix designs for the final conventional concrete mixes are represented on the Table 1 below. These mixes shaped the initial iterations of SCC trials.

Table 1. BRE-designed conventional concretes

Mix ID	Cement (kg/m³)	Water (kg/m³)	Fine Agg. (kg/m³)	Coarse 10 mm (kg/m³)	Coarse 14 mm (kg/m³)	Coarse 20 mm (kg/m³)	w/c
C16/20	195	170	859	247	432	557	**0.87**
C25/30	275	190	782	235	410	528	**0.69**
C30/37	320	190	725	237	415	533	**0.59**

2.3. SCC Trial Mixes (iterations and targets)

Throughout this study 29 trial iterations for SCC have conducted to obtain the desired similar compressive strength to the conventional concrete mixes discussed above in section 2.2. Iterations were adjusted with the components described below;

- **Binder content (powder, P)** and **water-to-binder ratio (w/b)** to steer compressive strength.
- **Fiber Content (Fr%)** to develop a gap bridging and more ductile concrete.
- **Superplasticizer dosage (SP%)** to recover/maintain flow.
- **Sand ratio (S_r)** and **coarse aggregate gradation (10/14/20 mm)** to control viscosity and blocking;

Paste ratio (R_p) to balance filling and segregation risk.

Since the workability of the SCC is the most important parameter and without the validation of the workability tests in guidance with the EFNARC, self-compacting concrete cannot be defined as "self-compacting". Therefore, slump-flow, V-funnel and L-box tests are conducted for all the iterations to check the flowability, segregation resistance and passing ability of the mixes in respect to the limitations provided by EFNARC [2].

The iterative approach was continued until the desired 3 strength classes were achieved for both SCC and FR-SCC (0.5%) combinations with EFNARC approved workability levels.

2.4. Fresh Property Tests

Expanding upon the earlier section, the workability parameters were determined with EFNARC classifications as 600-800mm slump flow, 6-12 s with the V-funnel and ≥ 0.8 for the L-Box test was aimed for all the SCC iterations.

Within some of the iterations there were apparent segregation or excessive bleeding, although the slump flow performances were within the EFNARC limits. Consequently, within the predictive model those mixes recorded as censored data for accurate guidance.

This testing regime ensured that all SCC mixes were benchmarked against established international criteria for self-compaction, enabling direct comparison of trial results and predictive model outputs.

2.5. Predictive Modeling Framework

By using the iterative SCC mix designs a prediction model was developed to simulate the workability (slump flow) and 28-day compressive strength parameters in Microsoft Excel based framework for high usability. In the sections below, more information about the work process for these calculations are represented.

2.5.1 Input variables and derived parameters

The predictor is based on eight mix-design variables that govern both fresh and hardened behaviour of SCC. Unless noted otherwise, all quantities are computed from **kg/m³** inputs; ratios are **dimensionless** (units cancel).

In the SCC iterations, the variables have been quantified into 8 divisions that influence both the fresh and hardened behaviour of SCC. In the sub-sections below, all the divisions are presented.

2.5.1.1 Water-to-binder ratio, w/b

$$\frac{w}{b} = \frac{m_{water}}{m_{binder}} \qquad (1)$$

with $m_{binder} = m_{cement} + m_{silica\ fume} + m_{fly\ ash} + m_{slag} = P$

This ratio primarily controls compressive strength and influences flow.

2.5.1.2 Powder (binder) content, P [kg/m³]

$$P = m_{cement} + m_{silica\ fume} + m_{fly\ ash} + m_{slag} \qquad (2)$$

Powder governs paste viscosity and segregation resistance.

2.5.1.3 Superplasticizer dosage, SP% [% of binder]

$$SP\% = 100 \times \frac{m_{SP}}{m_{binder}} \qquad (3)$$

Regulates flowability without increasing w/b.

2.5.1.4 Polypropylene fiber content, Fib% [% by volume]

$$Fib\,\% = 100 \times \frac{V_{fibers}}{V_{concrete}} \qquad (4)$$

Included explicitly to capture fiber-induced changes in rheology/workability.

2.5.1.5 Sand ratio, Sr [-] (mass basis)

$$S_r = \frac{m_{fine}}{m_{fine} + m_{coarse}} \qquad (5)$$

Balances viscosity and blocking through the fine-to-coarse aggregate proportion.

Here $m_{coarse} = m_{10\,mm} + m_{14\,mm} + m_{20\,mm} = Gc$

2.5.1.6 Maximum aggregate size, Dmax [mm]

Entered directly as the nominal maximum size.

2.5.1.7 Paste ratio, Rp [-] (mass basis)

$$R_p = \frac{m_{water} + P}{m_{water} + P + m_{fine} + m_{coarse}} \qquad (6)$$

Controls deformability and filling capacity while guarding against segregation. *(Note: mass-proportional form is used in the Excel tool.)*

2.5.1.8 *Total coarse aggregate content, Gc [kg/m³]*

$$Gc = m_{10\,mm} + m_{14\,mm} + m_{20\,mm} \qquad (7)$$

Represents the skeleton stiffness and its interaction with paste volume.

To keep the prediction model as responsive to each component as possible sand (Sr) and paste (Rp) ratios are derived by combining raw material proportions. The statements that are defined per each coefficient was consistent with the established SCC design literature [22, 23, 24].

2.5.2 Data preparation and standardization

Prior the regression analysis application to the prediction model, numerical stability of the coefficients was calibrated using the mean and standard deviation of the variables derived from the 29 iterations. Each raw variable x_k was converted into a standardized score (z_k):

$$z_k = \frac{x_k - \mu_k}{\sigma_k} \qquad (8)$$

Where;

μ_k = Mean value of the individual variable from the iterations

σ_k = Standard deviation of the individual variable from the iterations

x_k = Individual raw variable

Standardization method clears irregularities in measurement units (e.g., kilograms, percentages, millimetres) and prevents variables with larger numerical ranges from disproportionately influencing the regression [25, 24]. This application also separates the coefficients from each other which enables comparability across studies.

Table 2 below summarizes the descriptive statistics of the eight input variables derived from the 29 SCC trial mixes conducted in this study in comparison with other studies from the literature review.

Table 2. Descriptive statistics (mean ± SD) of SCC input variables compared with literature ranges

Variable	Symbol	Unit	This study (μ ± σ, n=29)	Reported ranges in literature	Key references
Water-to-binder ratio	w/b	–	0.751 ± 0.100	0.30–0.85	[22, 26],
Powder content	P	kg/m³	620.83 ± 58.82	350–600	[27, 23],
Superplasticizer dosage	SP%	% binder	1.927 ± 0.451	0.5–3.0	[7, 21],
Fiber volume fraction	Fib%	%	0.813 ± 0.306	0–1.0	[21]
Sand ratio	Sr	–	0.573 ± 0.028	0.40–0.55	[22, 27],
Maximum aggregate size	Dmax	mm	13.667 ± 3.422	10–25	[23]
Paste ratio	Rp	–	0.344 ± 0.022	0.30–0.38	[27, 24],
Coarse aggregate content	Gc	kg/m³	881.21 ± 54.35	800–1200	[22, 27],

Generally, the determined mean and standard deviation values for the variables determined from the iterations represents similar results in comparison with the reported ranges from the literature. Most apparent difference between this study and reported ranges in the literature are the higher binder and sand content in this study. This characteristic may be expected due to the addition of the fibers in this study in contrary to the literature data to optimize the viscosity and passing ability of the FR-SCC matrix. These observations confirm that the 29 iterations represent a realistic but challenging dataset, making standardization a critical step for robust regression modeling.

2.5.3 Feature expansion (polynomial and interactions)

Prediction model cannot be derived from a linear relationship and be calculated via simple formula as the compressive strength does not improve linearly by increasing the binder or reducing the w/b content and the workability of the concrete matrix is influenced by many variables in the mix design. To be able to overcome these effects, standardized input variables were expanded into a reduced quadratic feature set.

The general regression structure was defined as:

$$\hat{y} = \beta_0 + \sum_{i=1}^{8} \beta_i z_i + \sum_{i=1}^{8} \beta_{ii} z_i^2 + \sum_{(i,j)\in I} \beta_{ij} z_i z_j \qquad (9)$$

where z_i are the standardized input variables, β are regression coefficients, and I denote the set of physically motivated interaction terms.

The final specification consisted of **23 terms**, grouped as follows:

8 linear terms: one for each standardized input (Z_k) (w/b, P, SP%, Fib%, Sr, Dmax, Rp, Gc).

8 squared terms: allowing curvature effects to be represented, such as diminishing returns of increasing powder content or superplasticizer dosage (Z_k^2).

7 interaction terms: selected based on physical reasoning and prior SCC research, including:

1. $Z_{w/b}$ x Z_P → reflects the combined effect of water content and powder fineness on strength and segregation resistance.
2. $Z_{w/b}$ x Z_{SP}→ capture the joint role of superplasticizer and binder in flowability.
3. Z_{SP} x Z_P → captures the balance between superplasticizer dosage and powder content in controlling flowability and segregation resistance.
4. Z_{Fib} x Z_{Rp} → accounts for the balance between fiber presence and paste volume in preventing balling.
5. Z_{Sr} x Z_{Dmax} → links sand proportion and maximum aggregate size, known to influence blocking.
6. Z_{Rp} x Z_{Gc} → represents paste–aggregate skeleton interaction.
7. $Z_{w/b}$ x Z_{Sr} → reflects the dependency of passing ability on both fluidity and fine content.

These 7 interaction terms above are derived from **quadratic response surface methodology (RSM)** rather than using a full polynomial expansion which would complicate the prediction tool and may lead to overestimated values.

Few recent studies have also applied response surface methodology (RSM) to optimize the SCC mix design with effective results for high-volume fly ash as cement replacement and additional filler [24] and by fuzzy classification for the predictions of the material properties [28]. More current studies like [29] use the RSM with Analysis of Variance (ANOVA) method to predict the SCC properties with the cement replacement and filler materials like the marble dust and glass powders. Also, [30] applied Box-Behnken RSM designs to predict the SCC performance with accuracies up to 95%. Mutually, these studies laid the groundwork for the application of RSM model with the compressive strength and slump flow predictions of the FR-SCC in this study.

2.5.4 Regression method: ridge regression

Due to the unstable predictor variables like the powder content which is both correlated by the paste and sand ratio, ridge regression is therefore introduced to the regression analysis system to shrink the coefficient magnitudes and provide stability.

The optimization problem was formulated as:

$$\min_{\beta} ||y-(\beta_0\cdot 1+\Phi\beta||^2+\lambda||\beta||^2 \qquad (10)$$

Where;

y is the target vector (either compressive strength f_{28} or log-transformed slump flow ln(s))

Φ is the feature matrix (23 terms)

β are regression coefficients

λ is the ridge penalty parameter.

There are few methods that the ridge regression applies to the RSM, initially the large coefficients are restricted to avoid the instability. Additionally, coefficients with lower values are favoured to generate more robust predictions from even a limited value data set (only 29 iterations). Finally, the penalty parameter (λ) that is defined above was selected using k-fold cross-validation to minimize prediction error.

By the implication of the ridge regression analysis rather than just ordinary RSM, more stable and comprehensive predictions were achieved. For example, increases in w/b consistently decreased predicted strength, while higher powder content and superplasticizer dosage improved flowability.

The most important aspect of the ridge regression analysis on the prediction accuracy is the transparency and the susceptibility of the model to individual mix parameters. This approach maintains balance between the "black box" SCC strength prediction methods where neural networks, ensemble learning and support vector regression have been applied [31, 32, 25, 33, 34, 35]. Even though "black box" practices might estimate more accurate predictions in some cases, ridge regression analysis is more practical for engineering adoptions as its less susceptible to significant variable changes.

2.5.5 Calibration of model outputs

After estimating the reduced quadratic model on standardized inputs, the raw outputs from each prediction head are mapped to laboratory measurement scales using a **two-parameter affine calibration**. In this mapping, **a** is a global **offset** and **b** is a global **scale** that align each head's raw output to the lab measurements on this dataset.

2.5.5.1 Compressive strength (MPa).

Let f_{28}, raw denote the raw strength output. The reported prediction is

$$\boldsymbol{f_{28,final} = a_f + b_f f_{28,raw}} \qquad (\mathbf{11})$$

with constants estimated on this study's iterations:

$$a_f = -0.739463 \quad b_f = 1.025898$$

2.5.5.2 Slump flow (mm).

Slump is modeled on the logarithmic scale. Let t_{raw} denote the raw log-slump output. The final mapping is

$$\boldsymbol{t_{final} = a_s + b_s t_{raw}} \qquad (\mathbf{12})$$

$$\boldsymbol{Slump_{mm} = \exp(t_{final})} \qquad (\mathbf{13})$$

with dataset-specific constants:

$$a_s = -2.821421 \quad b_s = 1.453333$$

These constants were obtained through ordinary least squares for the strength constants (a_f and b_f) with the iterative mixes where 28 iterations were used for the strength values as one of the iterations was not tested for compressive strength due to significant segregation. And the slump constants (a_s and b_s) were determined by robust two-parameter fit method on the log-slump head.

For completeness: the internal head intercepts used to form the raw outputs are;

$$Intercept\ f_{28} = 22.257292$$

$$Intercept\ \log_{slump} = 6.313932.$$

2.5.6 Guardrails and validity domain

As there were only 29 iterations, the prediction model may generate unrealistic results when the input of the variables is outside the range of iterations that was used to create the ridge regression analysis. Therefore, guardrail system is incorporated to the prediction model to restrict the unrealistic outputs.

2.5.6.1 Standardization range check:

Initially, the standardization derivatives were assessed to avoid generating high, unrealistic factors that would create a snowball effect during the generation of the final results. So, the z_k factors were limited to be generated up to 2.5 ($z_k < 2.5$) to be acceptable. If the z_k factor exceeds 2.5 ($z_k > 2.5$) the standardization range check function recorded the prediction model as OUT-OF-RANGE.

2.5.6.2 Physical limits on outputs:

Predicted values were constrained to lie within ranges consistent with both the experimental program and SCC guidelines [2]:

$$f_{28} \in [5, 100] MPa, \qquad s \in [300, 850] mm$$

The upper and lower levels for the 28-day strength and slump flow measurements were used to check the validity of the parameters where the prediction outcomes out of these ranges are assumed to be invalid. Even though the EFNARC [2] states that the slump flow should be above 550 mm to be in the lowest class of SF1 the prediction models' lowest level was kept at 300 mm to assist the user for deciding on the mix design parameters.

The integration of these control boundaries to the framework of the prediction model ensured that the produced outputs support validity of the data which distinguishes this model from machine learning algorithms.

2.5.7 Practical implementation in Excel

As mentioned before, the prediction model is implemented in Microsoft Excel to generate the 28-day strength and slump flow parameters by using the described ridge regression model and calibrations that has described above as straightforward as possible. All the precautions, guardrails and established factors are baked into the Excel sheet to calculate the predictions by using simple formulas.

The creation of the prediction tool in a well accessible platform like the Microsoft Excel establishes a very practical tool while preserving full interpretability of how each parameter contributes to the predicted compressive strength and slump flow [10, 11].

The described Excel based prediction tool is provided as a supplementary material to this article to facilitate practical application of the proposed regression model.

3. Results and Discussion

3.1. Experimental Outcomes

A total of 29 SCC trial mixes were produced across the three strength classes (C16/20, C25/30, C30/37) and two fiber contents (0% and 0.5%). Table 3 below summarized the final optimized SCC mixes, while the complete set of iterations was used to train the predictive model.

Table 3 – SCC and FR-SCC Mix designs for C16/20, C25/30 and C30/37 strength classes

SCC #2 - C16/20 – 0% Fibers							Notes
Cement (Kg/m3)	Water (Kg/m3)	Fine Aggregate (Kg/m3)	Coarse Aggregate (Kg/m3)	Silica Fume (Kg/m3	Super Plasticizer (Kg/m3)	Polypropylene Fiber (Kg/m3)	-50% 10mm and 50% 14mm as Coarse Aggragates
290.076	250.92	1115.10	901.35	27.58	6.35	0	
SCC #1 – C25/30 – 0% Fibers							Notes
Cement (Kg/m3)	Water (Kg/m3)	Fine Aggregate (Kg/m3)	Coarse Aggregate (Kg/m3)	Silica Fume (Kg/m3	Super Plasticizer (Kg/m3)	Polypropylene Fiber (Kg/m3)	-50% 10mm and 50% 14mm as Coarse Aggragates
335.36	283.2	1115.10	901.35	37.26	5.8	0	
SCC #4 – C30/37 – 0% Fibers							Notes
Cement (Kg/m3)	Water (Kg/m3)	Fine Aggregate (Kg/m3)	Coarse Aggregate (Kg/m3)	Silica Fume (Kg/m3	Super Plasticizer (Kg/m3)	Polypropylene Fiber (Kg/m3)	-50% 10mm and 50% 14mm as Coarse Aggragates
405	270	1115.1	901.3548	45	9	0	
SCC #13 – C16/20 – 0.5% Fibers							Notes
Cement (Kg/m3)	Water (Kg/m3)	Fine Aggregate (Kg/m3)	Coarse Aggregate (Kg/m3)	Silica Fume (Kg/m3	Super Plasticizer (Kg/m3)	Polypropylene Fiber (Kg/m3)	-50% 10mm and 50% 14mm as Coarse Aggragates
585	520	1115.1	874.85	65	9.75	4.55	
SCC #18 – C25/30 – 0.5% Fibers							Notes
Cement (Kg/m3)	Water (Kg/m3)	Fine Aggregate (Kg/m3)	Coarse Aggregate (Kg/m3)	Silica Fume (Kg/m3	Super Plasticizer (Kg/m3)	Polypropylene Fiber (Kg/m3)	-20% 10mm, 35% 14mm and 45% 20mm as Coarse Aggragates
552.5	428.9286	1293.52	738.68	97.5	9.75	4.55	
SCC #25 – C30/37 – 0.5% Fibers							Notes
Cement (Kg/m3)	Water (Kg/m3)	Fine Aggregate (Kg/m3)	Coarse Aggregate (Kg/m3)	Silica Fume (Kg/m3	Super Plasticizer (Kg/m3)	Polypropylene Fiber (Kg/m3)	-100% 10mm as Coarse Aggragates
585	422.5	1115.1	907.63	65	16.25	4.55	

3.1.1. Workability

All classes of Slump flow (SF1, SF2 and SF3) was obtained throughout the iterations where some trials did not manage to pass 550 mm flow and some iterations passed the 850mm when the w/b ratio was above 80% and excessive amount of superplasticizer was used (>2.5%) hence segregation was observed. Those cases were recorded but flagged in the prediction dataset to comply with the EFNARC boundaries. The majority of the mixes were within the 550mm and 850mm slump flow range and were consistently above 0.8 with the L-Box passing ability test and 2-5 seconds V-funnel segregation test.

3.1.2. Compressive strength

Throughout the iterations it was apparent that the compressive strength of the mixes reduced when the w/b ratio was high and the binder content was low. This effect can also be overserved on the Table 3 above where the lowest compressive strength values were obtained when the binder content was around low 300 kg/m^3 and highest was observed when it's around 650 kg/m^3. Between 16-42 MPa of 28 days compressive strength was obtained throughout all the iterations.

3.1.3. Effect of fibers

Initially, higher fiber contents were desired to be used within the SCC mix designs (up to 2%) however due to hydrophilic property of the polypropylene fibers, the workability of the mixes reduced immensely. Therefore, only 0.5% of polypropylene fibers were used in most of the iterations and even when the reduced amount of fiber is used, segregation of the mixes was observed and significant reduction on the slump flow and passing ability was also substantial. Therefore, once the fibers were introduced to the mix design, the filler content inside the mixture including the binder content was increased to avoid segregation and bleeding. Reduction in the flow rate and segregation resistance was also consistent with the literature for FR-SCC [21, 4].

Ultimately, all the iterations have been used to create the predictive framework covering both plain and fiber reinforced mixes and provided a sufficient and representative dataset. Model accuracy was evaluated using root-mean-square error (RMSE) and coefficient of determination (R^2).

3.2 Model Accuracy Outcomes

3.2.1 Compressive strength

As the most accurate predicted parameter of this study, the model has achieved 90% accuracy between 28 trial mixes for the compressive strength values with RMSE = 3.23MPa, MAE 2.73MPa and $R^2 = 0.9$ where N=24. This demonstrates that the prediction model reliably be used in engineering applications. Figure 1 below represents the scatter diagram of the prediction model against the results from the iterations.

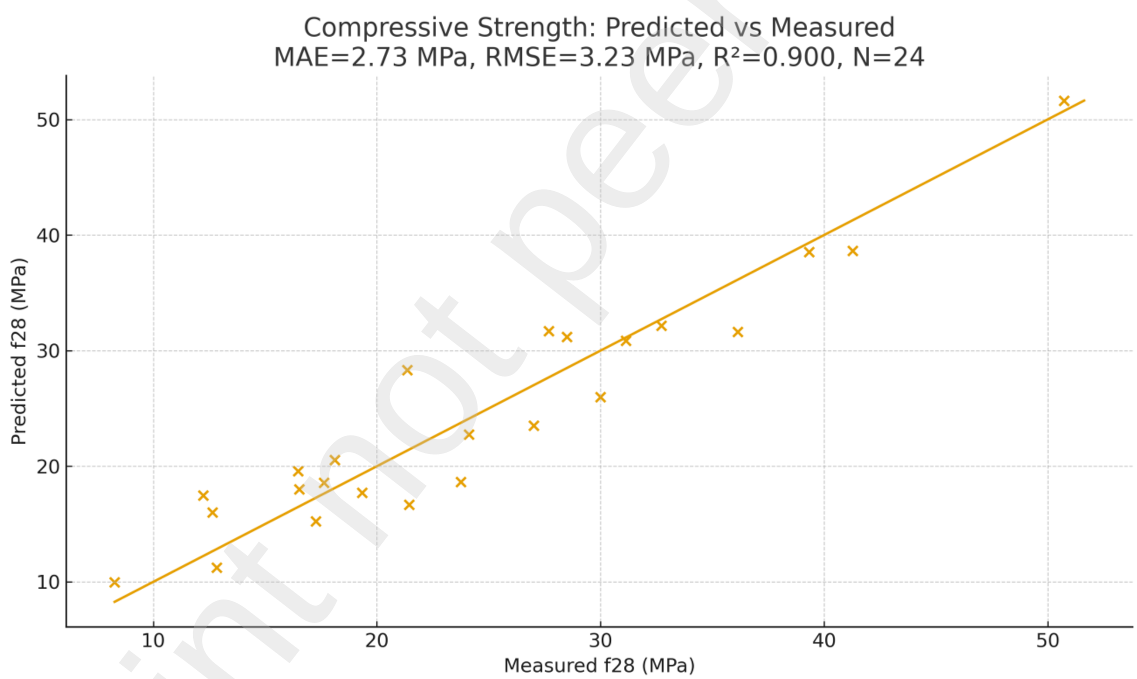

Figure 1 - Predicted vs Measured Compressive Strength diagram

Alt-text: Scatter plot comparing predicted 28-day compressive strength values with laboratory-measured results. Points cluster around the 1:1 line, indicating strong agreement between predictions and experiments.

3.2.2 Slump flow

A more modest prediction accuracy was obtained for the slump flow parameter. There are many reasons for this slight reduction as the RMSE = 78.94 mm, MAE = 58.46 and $R^2 = 0.66$ was achieved. As can be seen from the scatter diagram below in Figure 2, the accuracy of the model reduced at high fluidity cases

(>800 mm) as the model was adopted in respect to [2] recommendations. Nevertheless, 80% of predictions fell within ±100 mm of the measured slump flow values therefore still a valid guidance can be achieved by the application of this model.

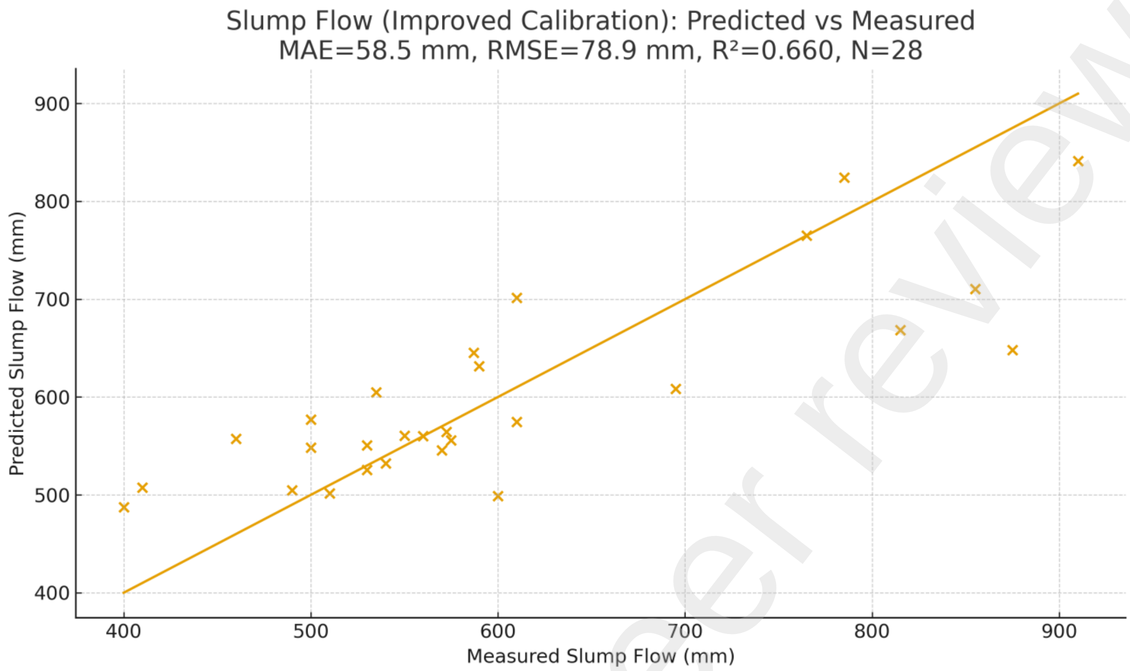

Figure 2 - Predicted vs Measured Slump Flow Diagram

Alt-text: Scatter plot comparing predicted slump-flow values with measured slump-flow data. Points show wider dispersion at high flow levels, reflecting reduced accuracy at high fluidity.

3.2.3 Model accuracy and validation

The ridge regression analysis model within this study obtained R^2 value of 0.9 for compressive strength with an RMSE of 3.23 MPa. In comparison with the literature, the accomplished prediction tool is better or similar to the previously reported regression-based SCC models. Where [15] has used recycled aggregates and achieved R^2 value of 0.8-0.9 by using multiple linear regression analysis. Also, [16] has used machine-learning-based regression method to achieve R^2 of 0.88.

The Table 4 below represents the comparison between the literature and this study including important notes about which materials and methods each study applied to achieve the reported accuracies. Even though the current study may be slightly more accurate than the other regression analysis approaches, it is clear that the black-box techniques may offer slightly more accurate results in comparison with the ridge regression method. However, only a slightly lower accuracy doesn't represents that the proposed model is not competitive with the ANN-based accuracies obtained through the studies of [17, 18] or Machine Learning methods which topped the scale by also including hybrid methods to ensure top notch accuracies of R^2 of 0.96 [19, 20].

Table 4 summarizes representative accuracy results:

Study	Method	Reported accuracy	Notes
[15]	MLR/ANFIS/ANN	R2 ≈ 0.85–0.90	Recycled aggregate SCC

Study	Method	Reported accuracy	Notes
[16]	ML regression	R2 ≈ 0.88	SCC, multiple variables
[17]	ANN	R2 ≈ 0.91	Slump & strength
[18]	ANN ensemble	R2 ≈ 0.92–0.95	High-performance concrete
[19]	ML ensemble	R2 up to 0.96	SCC compressive strength
[20]	Hybrid ML	R2 ≈ 0.94–0.96	Fly ash SCC
[33]	SVR	R2 ≈ 0.91	SCC fresh & hardened props.
[36]	Random forest	R2 ≈ 0.93	Lightweight SCC
Present study	Ridge regression	R2 = 0.90 (RMSE ≈ 3.23 MPa)	Transparent, Excel-based

The achieved accuracy values demonstrate the robustness of the proposed ridge-regression model. Further comparison with recent literature is provided in Section 3.2.4 to contextualize these outcomes.

3.2.4. Comparison with literature

In comparison with the corresponding reported ridge regression-based SCC prediction models the proposed model demonstrated excellent accuracy for the compressive strength with R^2 value of 0.90 and root-mean-square error (RMSE) of 3.23 MPa for the 28-day predictions. Whereas, the accuracy of the proposed model was marginally lower than the performance of advanced machine-learning techniques especially for the slump-flow estimations.

More comprehensively, the studies on the machine learning based or neural-network models (Black-box algorithms) achieved R^2 values of 0.92-0.96 [17, 18, 19, 20] which are more accurate than the previous studies that applied multiple linear or polynomial regression typically reported R^2 values between 0.80 and 0.88 for the compressive strength predictions [15, 16]. The present model therefore achieves comparable predictive reliability while requiring substantially fewer data points and maintaining complete mathematical transparency.

Unlike the non-interpretable ML algorithms the proposed method does not limit the interpretability of each standardized coefficient. Therefore, the availability of the interpolation between the coefficients enables the users of the model to observe the influence of each parameter within the mix design on the compressive strength and slump flow characteristics even without any iterative process.

Hence, the contribution of this study lies not only in achieving high predictive accuracy but also in establishing a materials-oriented, interpretable, and readily implementable prediction tool. The model can be applied in spreadsheet environments to guide the proportioning of FR-SCC mixtures without extensive experimental iteration, thereby supporting more efficient and sustainable materials development practices.

3.3. Novelty and contribution

The most novel part of this study is the interpretability of each coefficient into the ridge regression analysis to directly affect the standardized variables to enable practitioners to understand how changes in the mix design variable influence both strength and slump flow. The applicability of this framework in a simple Microsoft Excel based infrastructure is also very practical for easily following the calculator and observing the effects of each variable within the prediction tool. The achieved high accuracy of the model also demonstrates that the model can reliably serve as a “pre-screening tool” for SCC and FR-SCC mix designs.

Additionally, one of the most distinctive aspects of this study is the use of 6mm polypropylene fiber as the fiber reinforcement for the self-compacting concrete. Use of polypropylene fibers are more challenging than most of the other fiber types in the case of self-compacting concrete applications due to excessive water absorption and fiber balling effects. So, one of the main contribution of this study is the achievement of controllable compressive strength parameters with the workability characteristics of a self-compacting concrete while introducing polypropylene fibers to the concrete matrix.

4. Conclusions

This study combined iterative SCC mix development with a regression-based predictive framework to enable proportioning of fiber-reinforced self-compacting concretes for strengthening applications. Based on the findings, the following conclusions are drawn:

1. **Iterative dataset production:** Mix proportions of the Self Compacting Concrete is adjusted systematically to achieve the desired compressive strength (C16/20, C25/30 and C30/37) and workability parameters with respect to EFNARC qualifications. The experimental program confirmed that systematic adjustment of the binder, water-to-binder ratio, and superplasticizer dosage provides a reliable basis for developing data-driven SCC models.
2. **Fiber inclusion:** The introduction of the fibers to the SCC mix design required a significant increase in the binder and w/b content within the mix design to accommodate the increased plastic viscosity of the concrete matrix and decreased segregation resistance. Among the trials, up to 1.5% 6mm polypropylene fibers were used but couldn’t reached the required workability levels. Therefore, the desired strength classes were only obtained by using 0.5% polypropylene fibers while maintaining EFNARC-compliant workability.
3. **Prediction model performance:** The created ridge regression model with guardrails and correction factors has achieved R^2 value of 0.9 with RMSE of only 3.23 MPa for compressive strength and R^2 value of 0.66 with RMSE of 78.94 mm for the slump flow predictions. These accuracies represented comparable results with the existing prediction models like the black-box models or other regression models while keeping the interpretable framework.
4. **Practical applicability:** The prediction model is implemented in Microsoft Excel to be easily accessible to serve as a pre-screening tool while minimizing the trial-and-error process to obtain the desired SCC mix parameters. This parameter may be crucial to use the SCC in a strengthening/rehabilitation application where strength capability and reliable flow are the most crucial parameters.
5. **Overall contribution:** In contrast to the previous research, the main advancement of this study is the inclusion and achieving essential workability parameters with 6mm polypropylene fibers. Additionally, the transparent and interpretable, spreadsheet-based model is demonstrated that optimised mix designs can be achieved even when the fibers were incorporated with desired compressive strength and workability parameters which is essential for rehabilitation and jacketing applications.

4.1 Limitations and future work

Within this research two main limitations are recognized, to begin with, the number of iterations is limited to claim that the prediction model would work on any given mix design range, even though it was sufficient enough to work with ridge regression analysis. Expanding the dataset with more iterations with viscosity modifying agents, different cement replacement and filler materials like fly ash or GGBS, or different kinds of fibers would enrich the capabilities of the model and could be used in wider range of applications.

Furthermore, during the iterative process, the aggregates were stored outdoors under varying humidity and weather conditions it was observed numerous times that the saturation condition of the aggregates exerted considerable effect on both the compressive strength and workability parameters of the SCC mix designs. Consequently, variations in actual moisture content may have altered the effective water-to-binder ratio, producing small deviations between measured and predicted properties. As aggregate moisture content could not be measured or controlled reliably and immediately during the pouring process, the proposed model should be able to interpret the estimated saturation conditions of the aggregates to estimate the material characteristics more accurately. Future studies should incorporate controlled aggregate-moisture measurements to reduce uncertainty in slump-flow predictions.

Finally, the model is only calibrated to predict the compressive strength and slump flow parameters, where it could be enhanced further to estimate the permeability, modulus of elasticity or shrinkage parameters of the mix design to illustrate the possible behavior of the SCC matrix before applying any iterative work.

4.2 Data Availability

The dataset of self-compacting concrete trial mixes generated and analysed during this study, together with the Excel-based prediction tool implementing the regression framework, is openly available at the following Google Drive link:
https://docs.google.com/spreadsheets/d/1dVDHh71ZGhu94mnFrE_5hgKxubcfALOb/

The files may be accessed and downloaded for non-commercial academic use.

6. References

[1] H. &. O. M. Okamura, "Self-compacting concrete," *Journal of Advanced Concrete Technology,* vol. 1, no. DOI: 10.3151/jact.1.5, pp. 5-15, 2003.

[2] EFNARC, "The European Guidelines for Self-Compacting Concrete: Specification, Production and Use," EFNARC, Surrey, UK, 2005.

[3] P. L. Domone, "Self-compacting concrete: An analysis of 11 years of case studies," *Cement and Concrete Composites,* vol. 28, no. DOI: 10.1016/j.cemconcomp.2005.10.003, pp. 197-208, 2006.

[4] P. G. K. G. Asteris, "Self-compacting concrete strength prediction using surrogate models," *Neural Computing and Applications,* vol. 31, no. DOI:10.1007/s00521-017-3007-7, pp. 409-424, 2019.

[5] Z. J. D. I. M. &. T.-Ć. G. A. Grdić, "Properties of self-compacting concrete with different types of additives," *Facta Universitatis, Series: Architecture and Civil Engineering,* vol. 6, no. DOI: 10.2298/FUACE0802173G, pp. 173-177, 2008.

[6] M. Sonebi, "Medium strength self-compacting concrete containing fly ash: Modelling using factorial experimental plans," *Cement and Concrete Research,* vol. 34, no. DOI: 10.1016/j.cemconres.2003.12.022, pp. 1199-1208, 2004.

[7] O. K. S. K. E. H. &. R. F. Boukendakdji, "Effects of granulated blast furnace slag and superplasticizer type on the fresh properties and compressive strength of self-compacting concrete," *Cement and Concrete Composites,* vol. 34, no. DOI: 10.1016/j.cemconcomp.2011.08.013, pp. 583-590, 2012.

[8] S. L. G. &. N. A. Babaeidarabad, "Flexural strengthening of RC beams with an externally bonded fabric-reinforced cementitious matrix.," *Journal of Composites for Construction,* vol. 18, no. DOI: 10.1061/(ASCE)CC.1943-5614.0000473, p. No.5, 2014.

[9] A. &. F. F. D'Ambrisi, "Flexural strengthening of RC beams with cement-based composites.," *Journal of Composites for Construction,* vol. 15, no. DOI: 10.1061/(ASCE)CC.1943-5614.0000218, pp. 707-720, 2011.

[10] M. &. M. G. Asaad, "Bond strength of reinforcing steel bars in self-consolidating concrete," *Buildings,* vol. 13, no. DOI: 10.3390/buildings13123009, p. 3009, 2023.

[11] H. E. B. &. N. A. Hadad, "Flexural analysis and design of FRCM-strengthened RC beams.," *Construction and Building Materials,* vol. 244, no. DOI: 10.1016/j.conbuildmat.2020.118371., p. 118371, 2020.

[12] Building Research Establishment, "Design of normal concrete mixes (2nd ed.)," BRE, Watford, UK, 1997.

[13] A. &. E. O. Alrawashdeh, "Mechanical and physical characterisation of steel fibre reinforced self-compacting concrete: Different aspect ratios and volume fractions of fibres," *Results in Engineering,* vol. 13, no. DOI: 10.1016/j.rineng.2022.100335, p. 100335, 2022.

[14] S. &. E. Ö. Kamkar, "Evaluation of maturity method for steel fiber reinforced concrete.," *KSCE Journal of Civil Engineering,* vol. 22, no. https://doi.org/10.1007/s12205-017-1761-9, pp. 213-221, 2018.

[15] F. J. S. M. D. N. &. L. S. Khademi, "Predicting strength of recycled aggregate concrete using ANN, ANFIS and MLR," *International Journal of Sustainable Built Environment,* vol. 5, no. DOI: 10.1016/j.ijsbe.2016.09.003, pp. 355-369, 2016.

[16] A. S. M. &. G. R. Kumar, "Prediction of strength and analysis in self-compacting concrete using machine learning based regression techniques," *Advances in Engineering Software,* vol. 173, no. https://doi.org/10.1016/j.advengsoft.2022.103267, p. 103267, 2022.

[17] I.-C. Yeh, "Modeling slump flow of concrete using second-order regressions and artificial neural networks," *Cement and Concrete Composites,* vol. 29, no. DOI: 10.1016/j.cemconcomp.2007.02.001, pp. 474-480, 2007.

[18] J.-S. &. P. A.-D. Chou, "Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength," *Construction and Building Materials,* vol. 49, no. DOI: 10.1016/j.conbuildmat.2013.08.078, pp. 554-563, 2013.

[19] N.-D. &. B. D. T. Hoang, "Machine learning-based estimation of the compressive strength of self-compacting concrete: A comparative study," *Mathematics,* vol. 10, no. https://doi.org/10.3390/math10203771, p. 3771, 2022.

[20] F. N. M. N. S. M. I. e. a. Farooq, "A Comparative Study for the Prediction of the Compressive Strength of Self-Compacting Concrete Modified with Fly Ash," *Materials,* vol. 14, no. https://doi.org/10.3390/ma14174934, p. 4934, 2021.

[21] L. P. Y.-D. &. S. S. P. Ferrara, "A method for mix-design of fiber-reinforced self-compacting concrete," *Cement and Concrete Research,* vol. 37, no. DOI: 10.1016/j.cemconres.2007.03.014, pp. 957-971, 2007.

[22] V. A. K. D. S. G. &. D. H. G. Boel, "Transport properties of self-compacting concrete with limestone filler or fly ash," *Materials and Structures,* vol. 40, no. DOI:10.1617/s11527-006-9159-z, pp. 507-516, 2007.

[23] V. K. A. Y. &. S. S. P. Bui, "Rheological model for self-consolidating concrete," *ACI Materials Journal,* vol. 99, no. DOI: 10.14359/12364, pp. 549-559, 2002.

[24] R. H. K. M. A. S. M. B. N. &. L. M. Patel, "Development of Statistical Models for Mixture Design of High-Volume Fly Ash Self-Consolidating Concrete," *ACI Materials Journal,* vol. 101, pp. 294-302, 2004.

[25] M. E. C. H. &. E. N. M. H. Nehdi, "Predicting performance of self-compacting concrete mixtures using artificial neural networks," *ACI Materials Journal,* vol. 98, pp. 394-401, 2001.

[26] B. T. S. &. B. B. Felekoğlu, "Effect of water/cement ratio on the fresh and hardened properties of self-compacting concrete," *Building and Environment,* vol. 42, no. DOI: 10.1016/j.buildenv.2006.01.012, pp. 1795-1802, 2007.

[27] H. J. H. &. R. H. J. Brouwers, "Self-compacting concrete: Theoretical and experimental study," *Cement and Concrete Research,* vol. 35, no. https://doi.org/10.1016/j.cemconres.2005.06.002, pp. 2116-2136, 2005.

[28] S. &. S. S. Selvaraj, "Prediction model for optimized SCC with fly ash using response surface method with fuzzy classification," *Neural Computing and Applications,* vol. 31, no. DOI:10.1007/s00521-018-3575-1, pp. 1365-1373, 2018.

[29] A. L. H. &. A. A. Aidjouli, "Modeling the Properties of Sustainable Self-Compacting Concrete Containing Marble and Glass Powder Wastes Using Response Surface Methodology.," *Sustainability,* vol. 16, no. https://doi.org/10.3390/su16051972, p. 1972, 2024.

[30] M. M. e. a. Zumba, "Forecasting the Rheological State Properties of Self-Compacting Concrete Mixes Using the Response Surface Methodology Technique for Sustainable Structural Concreting.," *PLOS ONE,* vol. 19, no. https://doi.org/10.1371/journal.pone.0302202, 2024.

[31] P. G. K. K. G. D. M. G. R. K. Asteris, "Prediction of self-compacting concrete strength using artificial neural networks," *European Journal of Environmental and Civil Engineering,* vol. 20, no. DOI: 10.1080/19648189.2016.1246693, pp. S102-S122, 2016.

[32] M. E.-N. H. &. P. A. Azimi-Pour, "Linear and nonlinear SVM prediction for fresh properties and compressive strength of HVFA-SCC," *Construction and Building Materials,* vol. 230, no. https://doi.org/10.1016/j.conbuildmat.2019.117021, p. 117021, 2020.

[33] P. D. P. &. T. P. Saha, "Prediction of fresh and hardened properties of SCC using support vector regression," *Neural Computing and Applications,* vol. 32, no. https://doi.org/10.1007/s00521-019-04267-w, pp. 7995-8010, 2020.

[34] R. A. P. &. A. Y. Siddique, "Prediction of compressive strength of SCC containing bottom ash using ANN," *Advances in Engineering Software,* vol. 42, no. DOI: 10.1016/j.advengsoft.2011.05.016, pp. 780-786, 2011.

[35] A. R. M. K. D. &. S. K. Gogineni, "Prediction of compressive strength of glass fiber-reinforced self-compacting concrete interpretable by machine learning algorithms," *Asian Journal of Civil Engineering,* vol. 25, no. https://doi.org/10.1007/s42107-023-00891-z, pp. 2015-2032, 2024.

[36] J. M. G. H. Y. S. J. A. F. &. N. B. Zhang, "Modelling uniaxial compressive strength of lightweight self-compacting concrete using random forest regression," *Construction and Building Materials,* vol. 210, no. https://doi.org/10.1016/j.conbuildmat.2019.03.189, pp. 713-719, 2019.

[37] "EN 206:2013+A2:2021. Concrete — Specification, performance, production and conformity," Brussels, 2021.

[38] "EN 12390-3:2019. Testing hardened concrete — Part 3: Compressive strength of test specimens," Brussels, 2019.

[39] "EN 12390-1:2012. Testing hardened concrete — Part 1: Shape, dimensions and other requirements for specimens and moulds," Brussels, 2012.

[40] S. O. M. E. &. O. F. O. Terlumun, "Predicting the compressive strength of self-compacting concrete using artificial intelligence techniques: a review.," *AI Civil Engineering,* vol. article 14, no. DOI: 10.1007/s43503-024-00029-3, p. 3, 2024.

[41] I.-C. Yeh, "Modeling of strength of high-performance concrete using artificial neural networks," *Cement and Concrete Research,* vol. 28, no. DOI: 10.1016/S0008-8846(98)00165-3, pp. 1797-1808, 1998.

[42] B. K. R. E. H. &. R. B. V. V. Prasad, "Prediction of compressive strength of SCC and HPC with high-volume fly ash using ANN," *Construction and Building Materials,* vol. 23, no. DOI: 10.1016/j.conbuildmat.2008.01.014, pp. 117-128, 2009.

[43] T. T. R. &. F. J. Hastie, The Elements of Statistical Learning (2nd ed.), Springer, 2009.

Author Contributions

Cemal Agaoglu conceived and designed the study, performed the experimental program, developed the prediction model and prepared the manuscript. Özgür Eren supervised the research and contributed to the interpretation of results and manuscript revision.

Funding

No external funding was received for this research.

Competing Interests

The authors declare no competing financial or personal interests.

Ethical Approval

Not applicable.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT 5 (OpenAI) to improve clarity, grammar and structure. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.