



SHEAR STRENGTH ASSESSMENT OF SELF-COMPACTING CONCRETE BEAMS USING LASSO REGRESSION TECHNIQUE

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ABSTRACT

Existing code provisions for shear strength prediction of self-compacting concrete (SCC) beams have often fallen short of its degree of predictability in relation to experimental responses. The research study seeks to develop a model that better predicts the shear capacity of self-compacted concrete beams without shear reinforcement. In addition, the critical parameters that influence the shear strength of an SCC beam was also investigated by using varying regression techniques (Linear, Stepwise, Lasso, Ridge and Elastic Net regressions). A pooled database having a total of 179 SCC beams without shear reinforcement was compiled for the analysis. The Lasso regression was the most effective from statistical analysis having the least relative and mean squared errors. In comparison with existing codes: ACI 318-08, AASHTO LRFD Bridge Design Specification-2007, Eurocode 2 and BS8110, the Lasso model performed better with least mean percentage error (12.23%), least average safety factor (1.1012) and the least coefficient of variation (0.159). The Lasso model also showed that compressive strength, height, breadth, depth of beam, shear span to depth ratio, longitudinal reinforcement ratio, maximum aggregate size and fine to coarse aggregate ratio were all relevant parameters in shear strength prediction of SCC beams without stirrups.

Keywords: RC beams, self-compacting concrete beams, shear strength, Lasso regression and error measures.

INTRODUCTION

Concrete which is the most widely used construction material has been studied extensively in terms of aggregate and reinforcement behaviour [31-35]. Self-compacting concrete (SCC) is a self-flowing concrete that consolidates on its own weight without any form of vibration [23, 28-30]. Following the diminution in skilled labor in Japan, the need to develop a concrete technology that requires less labor was of dire need. Its development since its inception has helped solve many issues associated with conventional vibrated concrete to the construction and design industry. Eliminating the problems associated with vibration, SCC also permits for greater freedom and flexibility in design without fear of reduced quality and durability. Its flow ability allows for a faster construction process meaning lesser time period and ease of placement resulting in lesser equipment and labor offering lowered cost. Time and cost, essentials in construction to that effect is curtailed not leaving the added benefit of reduced noise pollution often associated with the conventional vibrated concrete.

With such many benefits, the use of SCC concrete is disadvantaged with respect to shear strength owing from the fact that SCC concrete often have less coarse aggregate resulting in reduced aggregate interlock and ultimately reduced shear resistance [13]. Just as in conventionally vibrated concrete, the accurate prediction of the shear strength of a beam is a bit problematic mainly due to the reservations associated with shear transfer mechanism and unidentifiable parameters, which may have significant influence. Unlike the flexural behavior of concrete, prediction of the shear strength capacity of concrete has been one to which no common grounds has been reached. This unsettled grounds gives need for the development of a model that can adequately predict the

shear capacity of concrete, specifically self-consolidated beams.

Methodological approaches like Bayesian and regression techniques can be used model the shear strength of such members. In an attempt to develop a better prediction model, this research study also seeks to identify variables that have the strongest influence on the shear strength of SCC beams thus providing those parameters to which prediction errors would be most minimized. To this reason, the various regression models which would achieve such objectives that is the Linear regression, Stepwise regression, Lasso regression, the Elastic Net regressions and Ridge regressions were employed.

DATABASE

In total, 179 simply supported beams were compiled from various sources ([3], [9], [20], [10], [16], [7], [12], [27], [16], [11], [17], [25], [5], [19], [2], [4], [12], [1], [18], [26], [22], [14], [15], [24]). Parameters that were commonly provided in the literature sources include the width of beam (b), height of depth (h), effective depth (d), shear-span to depth ratio (a/d), compressive strength (f_c), longitudinal reinforcement ratio (ρ_w), coarse to fine aggregate ratio, max aggregate size and their corresponding ultimate shear force (V_u). Table-1 provides the summary of the data ranges of the various parameters under consideration.

The least compressive strength of beams considered was 24.81MPa, the highest being 119MPa with a greater majority below 66kN, as seen in the box plot representation in Figure-3. Depths of beams ranged from 150-750mm, with predominate depths lying between 150-250mm, the latter being the median value as shown in Figure-1. Effective depths ranged from 100-668mm. Beam widths from the data sources compiled largely fell within



100-250mm, a width of 400mm as the highest. Longitudinal reinforcement ratios mostly fell within 1-2%. Shear span to depth ratio ranged from 1.05-5.84 and 2.5 as the median value (Figure-2). The least maximum aggregate size in the database was 10mm with a large

chunk of aggregate sizes being either 19 or 20mm and an aggregate index lying between 0.33 and 0.92. The database showed that the parameters were negatively skewed hence a log-normal distribution seemed preferable.

Table-1. Distribution of the various parameters under consideration for the beam database.

f_c	Range	20-40	41-60	61-80	81-100	101-120	Total
MPa	Beams	40	62	69	6	2	179
h	Range	100-200	201-300	300-400	401-500	501-750	
mm	Beams	80	82	3	12	2	179
b	Range	75-100	101-150	151-200	201-250	>250	
mm	Beams	96	10	25	28	20	179
d	Range	100-200	201-300	301-400	401-500	501-750	
mm	Beams	90	72	12	3	2	179
ρ_w	Range	<1	1-1.5	1.51-2	2.1-2.5	> 2.5	
%	Beams	14	58	73	21	13	179
I_a	Range	1-2	2.1-3	3.1-4	4.1-5	5-6	

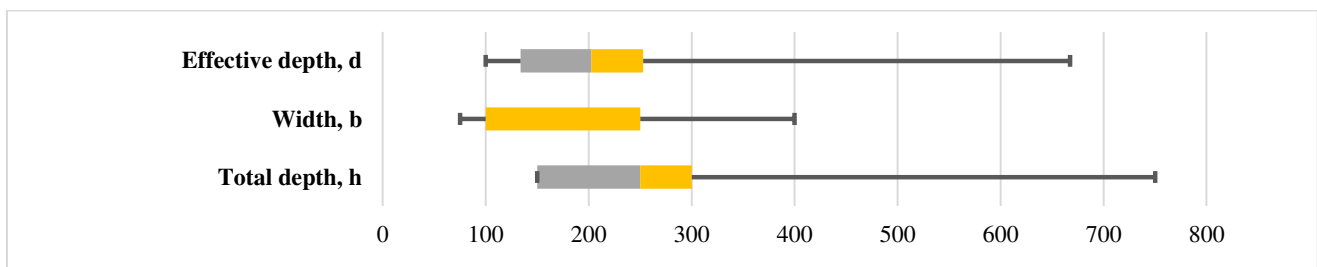


Figure-1. A box plot representation of the total depth, width and effective depth parameters.

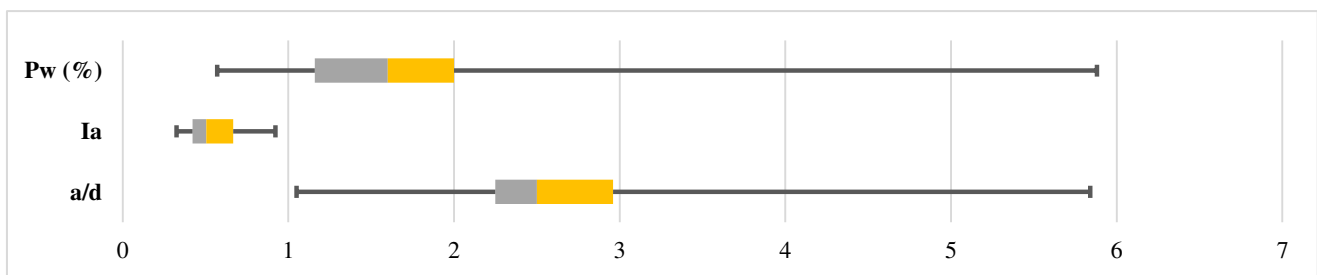


Figure-2. A box plot representation of the longitudinal reinforcement, aggregate index and shear-span to depth.

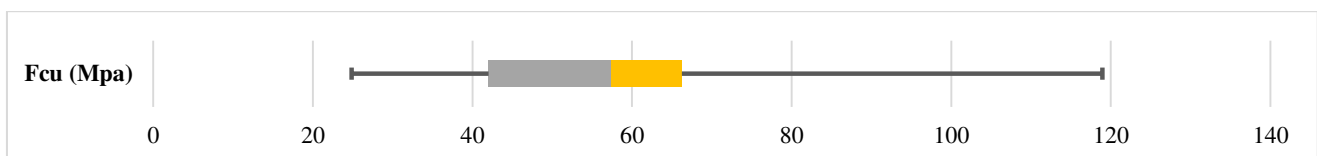


Figure-3. Box plot representation of compressive strengths of data.



Figure-4. Box plot representation of shear force (output).

REGRESSION MODELS

From a database of 179, seventy-five percent was randomly sampled and used as training data, with the remaining twenty-five percent for the test/validation data. The regression models used for the analysis of the training data are linear regression, stepwise regression, Lasso regression, the elastic net regressions and Ridge regression model.

Linear regression

The linear regression model is the simplest and most widely used of all regression techniques. It is also called the least square fitting in that it provides a line of best fit through a set of points. In the shear strength prediction model, V , the output function of linear regression model used in this assumes the equation,

$$V = c + \sum_{j=1}^p X_j \beta_j \quad (1)$$

where V = shear strength; X_j = input variables or predictors; p = number of input predictors; c = intercept and β_j = uncertain parameters.

With a set of training data $(x_1, v_1), \dots, (x_n, v_n)$, the estimates of the coefficients β are given by minimizing the residual sum of squares (RSS), as seen in Equation 2.

$$RSS(\beta) = \sum_{i=1}^N [v_i - f(x_i)]^2 = \sum_{i=1}^N [v_i - c - \sum_{j=1}^p x_{ij} \beta_j]^2 \quad (2)$$

Stepwise regression

Despite the simplicity of linear regression, its low bias and high variance often results in inaccurate prediction. Secondly the linear regression model includes all predictors (there is no variable selection) that result in the output. This may not be desirable. Sometimes not all parameters may be readily available to the analyst and as such a parsimonious model, which is interpretable with large predictability is preferred. In this study, the forward stepwise approach was used, which starts with the intercept, c , and sequentially adds a parameter that most improves the fit. By using this approach an expected lower variance can be achieved. The better fit is based on the F statistic of Equation 3 where variables are added one after the other till the largest value of F is reached.

$$F = \frac{RSS(\hat{\beta}) - RSS(\tilde{\beta})}{RSS(\tilde{\beta}) / (N - k - 2)} \quad (3)$$

Where the estimate $\hat{\beta}$ is with k inputs and the estimate $\tilde{\beta}$ is with the addition of a predictor.

Ridge regression

As with all shrinkage (regularization) methods, the ridge model addresses the issue of high variability that arise from the discrete process of the stepwise method with a process that is continuous. The model shrinks coefficients by imposing a penalty on their size. The ridge coefficients minimize a penalized residual sum of squares, RSS (Friedman *et al* 2008). The Ridge estimate in its Lagrangian form is defined as,

$$\hat{\beta}^{Ridge} = \underset{\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^N (y_i - \beta_0 - \sum_{j=1}^p x_{ij} \beta_j)^2 + \lambda \sum_{j=1}^p \beta_j^2 \right\} \quad (4)$$

where λ corresponds to the shrinkage parameter; a larger value resulting in greater shrinkage of coefficients (approaching zero), x_{ij} = input variables or predictors; p = number of input predictors; c = intercept and β_j = uncertain parameters.

Lasso regression

The Lasso as a shrinkage method transforms by translating each coefficient by a constant factor, λ trimming at zero, a process known as “soft thresholding”. Comparing with the ridge regression technique, the lasso differs with a replaced penalty of $\sum_{j=1}^p |\beta_j| \leq t$ making its solutions nonlinear. The Lasso regression model does variable selection eliminating the least significant parameters. The Lasso estimate in Lagrangian form is Equation. 5 where λ corresponds to the shrinkage parameter; a larger value resulting in greater shrinkage of coefficients (approaching zero), x_{ij} = input variables or predictors; p = number of input predictors; c = intercept and β_j = uncertain parameters.

$$\hat{\beta}^{Lasso} = \underset{\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^N (y_i - \beta_0 - \sum_{j=1}^p x_{ij} \beta_j)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\} \quad (5)$$

Elastic net

The elastic net is a compromise between the Lasso and the Ridge regression techniques. The parameter, determines the mix of the penalties, and is often pre-chosen on qualitative grounds. The elastic net can yield more N non-zero coefficients when $p > N$, a potential advantage over the Lasso [8]. The elastic net model is defined by



$$\hat{\beta}^{Lasso} = \operatorname{argmin} \left\{ \sum_{i=1}^N (y_i - \beta_0 - \sum_{j=1}^p x_{ij} \beta_j)^2 + \lambda \sum_{j=1}^p (\alpha \beta_j^2 + (1 - \alpha) |\beta_j|) \right\} \quad (6)$$

where α corresponds to parameter that determines mix of the penalties.

PERFORMANCE MEASURES

Mean squared error and root mean squared error. Mean-squared error is the primary and most often used measure. Where outliers (instances when the prediction error is larger than the others) exist, the mean squared error tends to overstate its effect. The mean squared error is equal to

$$M.S.E = \frac{1}{n} \sum_{i=1}^p (p_i - a_i)^2 \quad (7)$$

where M.S.E is the mean squared error, n is the number of predictors, p_i is the predicted value and a_i is the actual value. In order for dimensional equality to be achieved, the relative mean squared error which is the root of the mean squared error is found. It is defined as

$$R.M.S.E = \sqrt{\frac{1}{n} \sum_{i=1}^p (p_i - a_i)^2} \quad (8)$$

Relative squared error

Though the mean square error is often used, it tends to exaggerate the effect of outliers especially when prediction error is large, the relative squared error can be used relating the error to the average of the actual values of the data. The relative squared error is represented in Eqn. 9 where R.S.E is the relative squared error, p_i is the predicted value and a_i is the actual value, \bar{a} is the mean value of the actual values of number.

$$R.S.E = \sqrt{\frac{\sum_{i=1}^p (p_i - a_i)^2}{\sum_{i=1}^p (a_i - \bar{a})^2}} \quad (9)$$

NUMERICAL MODELLING AND DEMAND PARAMETERS

In finding a model to predict the shear capacity of self-compacting concrete a multiple linear regression model in the logarithmic space was used. The functional form of the regression model is given in Eqn. (10) where Y is the output (shear capacity) of vector dimension $N \times 1$, β_0 is the intercept, X is the input predictor of vector dimension $N \times 1$ and β_n is the uncertain parameter.

$$\ln(Y) = \beta_0 + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + \beta_3 \ln(X_3) + \dots + \beta_n \ln(X_n) \quad (10)$$

In the parameter selection, different uncertainties in geometric, material properties and test set-up orientation were considered. Table-2 gives the standard deviations (σ), the mean value (μ), and the probability distribution input variables of the database used.

COMPARISON OF REGRESSION MODELS

Multiple regression models implies multiple outputs. In the best model selection, factors considered include accuracy in predicting outputs (shear capacity of beams), simplicity and ease in output prediction (interpretability). To adequately do that, certain error measures were used to selecting the best choice of regression technique. Table. 3 gives the coefficients of the different regression models in predicting shear capacity of self-consolidating concrete beams. The error measures used in this model were the mean squared error and the relative squared error. In checking the performance accuracy of models, prediction errors were calculated based on the test data instead of the trained data.

Table-2. Uncertain parameters considered in the model.

Parameter	Unit	Distribution		
		Type	μ	σ
f_c	MPa	Lognormal	0.286	3.983
h	mm	Lognormal	0.373	5.391
b	mm	Lognormal	0.467	4.976
d	mm	Lognormal	0.365	5.241
ρ_w	%	Lognormal	0.423	0.445
a/d	-	Lognormal	0.286	0.901
I_a	-	Lognormal	0.288	-0.636

The numeric analysis software used was the Math laboratory software with Monte-Carlo replications for the Lasso and Elastic net models, in order to identify the shrinkage parameter, λ with the least error rate. The mean squared error and the relative squared error were the performance measures used to evaluate the predictability of the regression techniques. For Lasso regression technique, the optimal lambda (shrinkage parameter) used was 0.002, largest value that would result in the greatest shrinkage of coefficients. For the Elastic net regression technique the optimal lambda was 0.2 with the optimal alpha being 0.13. Using the test data, assessing the various regression models by mean squared error, relative squared error and root mean squared error, the Lasso regression model was the best.

The Lasso model equation of the shear capacity of a self - compacted beam is given in Eqn. 11 where V_c = Shear capacity(N); f_c = compressive strength of concrete(MPa); h = the total height of beam(mm); b = breadth of beam(mm); d = effective depth of beam(mm); ρ_w = longitudinal reinforcement ratio expressed as a percentage(%); a/d = shear span to depth ratio; I_a is the aggregate index = $(d_a/12.5)(1 - f/t)$ where d_a = the maximum aggregate size; f/t = fine aggregate to total aggregate ratio.

$$V_c = 4.1745 f_c^{0.1888} h^{-0.0794} b^{0.7899} d^{0.9894} \rho_w^{0.3564} \times \left(\frac{a}{d}\right)^{-0.4246} I_a^{-0.1856} \quad (11)$$



For the equivalent shear stress, v_c is the shear stress of the self-compacting beam in Equation. 12

$$v_c = 4.1745 f_c^{0.1888} h^{-0.0794} b^{-0.2101} d^{-0.0106} \rho_w^{0.3564} \left(\frac{a}{d}\right)^{-0.4246} I_a^{-0.1856} \quad (12)$$

Table-3. Estimated coefficients and test errors of the various regression techniques.

Parameters	Linear	Stepwise	Ridge	Lasso	Elastic net
Intercept	1.361	1.361	1.361	1.429	1.554
f_c	0.189	0.189	0.189	0.189	0.160
h	-0.091	-0.091	-0.091	-0.079	0.263
b	0.790	0.790	0.790	0.790	0.755
d	1.001	1.001	1.001	0.989	0.655
ρ_w	0.356	0.356	0.356	0.356	0.349
a/d	-0.425	-0.425	-0.425	-0.425	-0.398
I_a	-0.186	-0.186	-0.186	-0.186	-0.162
MSE(test error)	92159244	92159244	92159243.95	86133737	4182745023
RMSE(test error)	9599.961	9599.961	9599.961	9280.826	64674.145
RSE(test error)	0.057	0.057	0.057	0.053	2.593

EXISTING CODE BASED PREDICTIONS

ACI 318-08

As per the ACI, in members without shear reinforcement, the shear stress is carried by the concrete cross section and longitudinal reinforcement within the web. The predicted ultimate shear force, V_u of beams without stirrups is evaluated in Equation. 13 by,

$$V_u = 0.158\lambda\sqrt{f_c}bd + 17.24\rho_w\frac{V_f}{M_f}bd \leq 0.29\sqrt{f_c}bd \quad (13)$$

where λ is the concrete modification factor, f_c is the concrete compressive strength, b and d as beam width and effective depth of beam cross section, respectively. V_f is the factored shear force at section, M_f the factored moment at section, ρ_w is the ratio of longitudinal reinforcement, $\frac{A_s}{bd}$. A_s equals the area of non-prestressed tension reinforcement in the beam.

AASHTO-LRFD Bridge Design Specification -2007

As stated in the AASHTO-LRFD, the shear force of a beam without stirrups is given in Equation. 14 by

$$V_u = 0.083\beta\sqrt{f_c}b_vd_v \quad (14)$$

where b_v is the effective web width taken as the minimum web width within the depth d_v . β is the factor indicative of the ability of diagonally cracked concrete to transmit tension. For lightweight concrete, if the average splitting tensile strength is lacking, the term shall be replaced by $0.75\sqrt{f_c}$ for all lightweight concrete and $0.85\sqrt{f_c}$ for sand-lightweight concrete.

Eurocode 2

The shear force of a beam in the Eurocode 2 is given in Equation. 15 by,

$$V_{rd,c} = \left[(0.18/\gamma) K (100\rho_w\eta\sqrt{f_c})^{1/3} \right] b_w d \geq (v_{min} + k_1\sigma_{cp})b_w d \quad (15)$$

where γ = the concrete partial safety factor and equals 1.5; K = the size effect factor ($K = 1 + \sqrt{200/d} \leq 2$); ρ_w = the longitudinal reinforcement ratio, η = the factor to account for lightweight concrete ($\eta = 0.4 + 0.6\rho/2,200$); ρ = concrete density; f_c = compressive strength; b_w = beam width and d = effective depth of the beam; v_{min} = minimum shear stress equal to $0.035k^{3/2}\sqrt{f_c}$; $k_1 = 0.15$; σ_{cp} = axial stress on the stress on the cross section equal to N_{ed}/A_c where N_{ed} is the axial force due to loading or prestressing. Due to the data under consideration $k_1\sigma_{cp} = 0$, reducing the minimum value to $v_{min}b_w d$ and η for the purposes of the research was taken to be 1.

BS 8110

The ultimate shear resistances of concrete beams without shear reinforcement per BS 8110 is given in Equation. 16 by

$$V_c = \left[0.79(100\rho_w)^{1/2}(400/d)^{1/4}/\gamma_{mc} \right] \left[f_c/25 \right]^{1/3} b_v d \quad (16)$$

*If f_c is more than 40MPa then denominator to which f_c is divided is 40 instead of 25.



Where ρ_w is the longitudinal reinforcement ratio ($\rho_w = A_s/b_v d$); where A_s = area of steel reinforcement; b_v = effective breadth; d is the effective depth; γ_{mc} is the partial safety factor of concrete in shear strength without shear reinforcement which equals 1.25; f_c is the concrete compressive strength. For beams without shear reinforcement $(400/d)^{0.25} \geq 0.67$ and $0.15 \leq 100\rho_w \leq 3$.

COMPARISON OF EXPERIMENTAL SHEAR CAPACITY WITH CODE PREDICTIONS AND PROPOSED MODEL

To contrast experimentally measured shear strength capacities, V_{EXP} with code based predictions V_{Code} a relation known as the safety factor or margin of safety is defined in Equation. 17, where γ_{Cs} is the safety factor.

$$\gamma_{Cs} = V_{EXP}/V_{Code} \quad (17)$$

The safety factor can then be used to predict the accuracy and safety of a model. In shear strength prediction, a $\gamma_{Cs} < 1$ implies a more conservative prediction which is safer for design. To further assess the prediction performance, the average safety factor and the coefficient of variation are stated in figures 5, 6, 7, 8 and 9 representing a graphical representation of the safety factors of the ACI 318-08, AASHTO LRFD Bridge Design Specification -2007, Eurocode 2, BS8110 and the Lasso based model developed respectively. A scatter plot of the shear strength capacities of the various models is illustrated in Figure-10.

The charts indicatively show that AASHTO was the most conservative with average safety factor of 2.796 standard deviation of 2.482 and a coefficient of variation of 0.314. Among the existent codes the ACI was the least conservative with an average safety factor of 1.311, standard deviation of 1.041 and a coefficient of variation of 0.271. The lasso based strength formula gave an average safety factor of 1.009, standard deviation of 0.846 and a coefficient of variation of 0.162.

As seen in Figure-11 the Lasso model showed that the shear strength prediction tended to be more un-conservative when the compressive strength was less than 60MPa with effective depths lesser than 200mm. Figure-12 shows that the prediction tends to be conservative when greater than 60MPa for shear span-to-depth ratio greater than 3. The same also showed that for compressive strengths greater than 60MPa and shear span to depth ratios between 2 and 3, predictions were more un-conservative.

This implies that for high strength SCC beams, shear strength capacity is more likely to be conservative if shear span to depth ratios were greater than 3. Similarly a very low strength SCC beam of low depth (< 200mm) would be un-conservative.

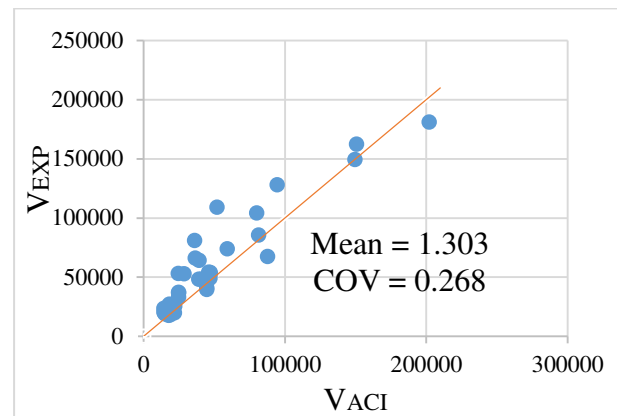


Figure-5. Margin of safety-ACI 318-08.

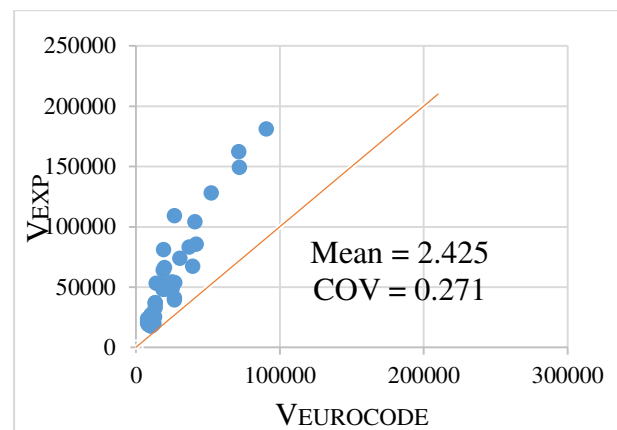


Figure-6. Margin of safety -Eurocode 2.

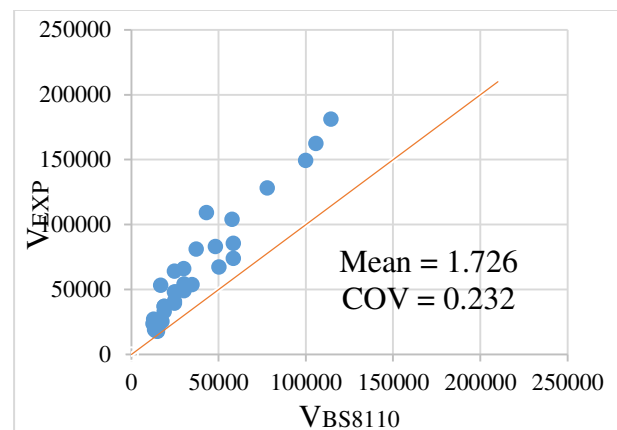


Figure-7. Margin of safety-BS 8110.

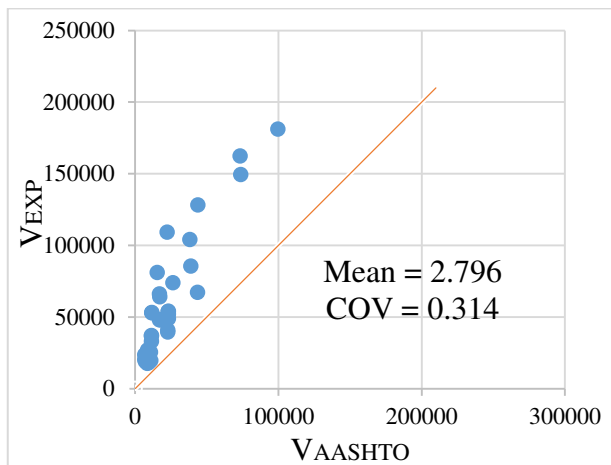


Figure-8. Margin of safety - AASHTO LRFD bridge design specification -2007.

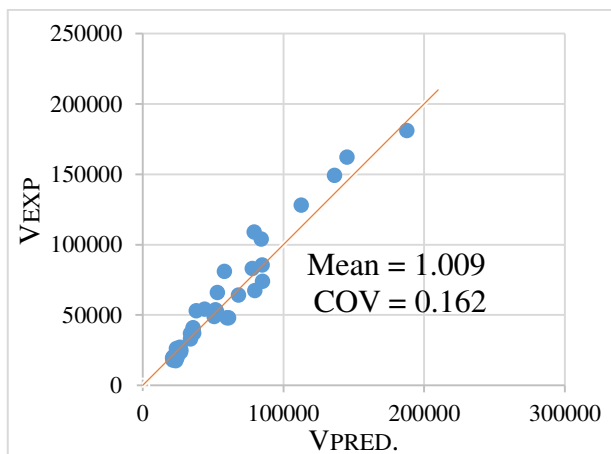


Figure-9. Margin of safety - Lasso prediction model.

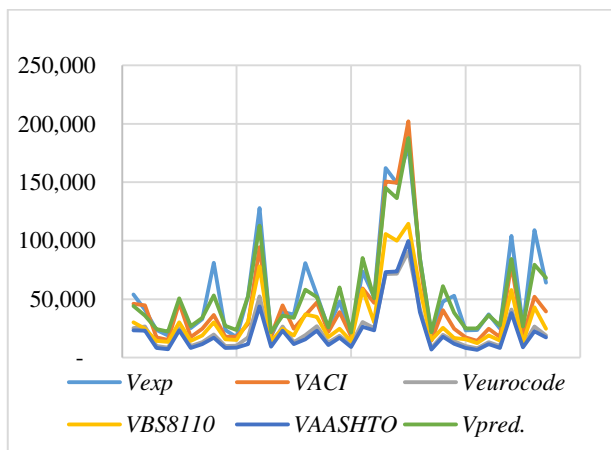


Figure-10. Scatter plot of shear strength capacities of the various models.

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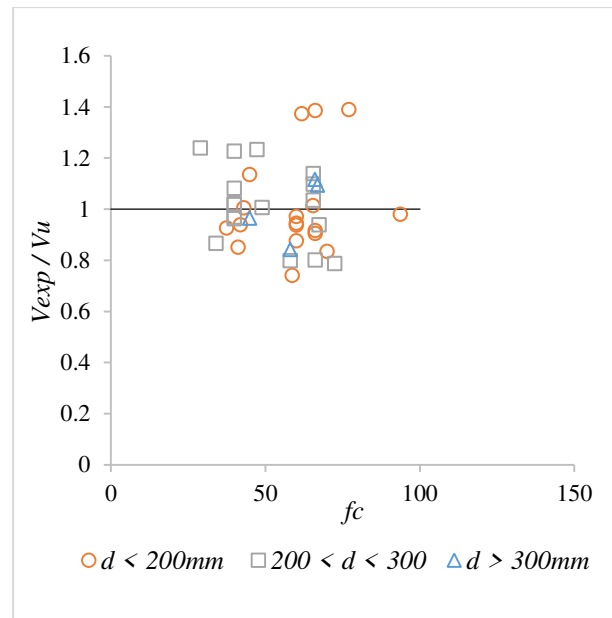


Figure11. Influence of f_c on V_{exp} / V_u with varying depths.

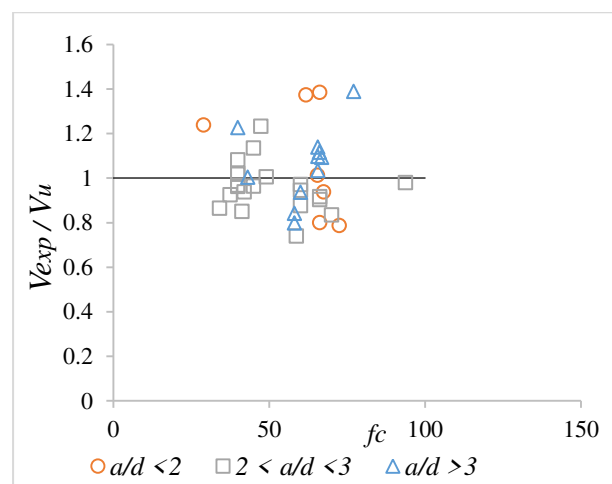


Figure12. Influence of f_c on V_{exp} / V_u with varying depths.

CONCLUSIONS

Considering that existing code provisions for shear strength prediction SCC beams have often fallen short of its degree of predictability in relation to experimental responses, the need for a more accurate predictive model arises. 179 test specimens carried on SCC beams without shear reinforcement were compiled



with various uncertain parameters. Various regression techniques (Linear, Stepwise, Ridge, Lasso, and Elastic Net regressions) used in developing an equation that more accurately predicts the shear strength of SCC beams were analyzed. Existing code based equations for shear strength prediction and the most preferred model equation were compared, analyzed and discussed. Based on the results obtained, the following conclusions can be drawn.

- a) All parameters: compressive strength, height, breadth, depth of beam, shear to depth ratio, longitudinal reinforcement ratio, maximum aggregate size and fine to coarse aggregate ratio considered for the purposes of the research were relevant. The parameters that were of stronger influence on the shear strength include the compressive strength, breadth, effective depth, shear span to depth ratio and the longitudinal reinforcement ratio. The compressive strength, effective depth, breadth and the longitudinal reinforcement ratio all had a positive association to the shear strength capacity. A negative correlation however existed between the shear span to depth ratio and the shear strength.
- b) The Lasso modelled equation performed better compared to code based equations with the least average margin of safety (1.009) and coefficient of variation (0.162) and can be used to determine the shear capacity of SCC beams. In ascending order the average safety margin for the ACI, BS 8110, Eurocode 2 and AASHTO were 1.303, 1.726, 2.425 and 2.76 respectively, a lower average safety margin implying a higher prediction accuracy. Although an increasing margin safety means an increasing conservativeness, prediction tendency decreases also with increasing safety margins. With the proposed model producing the highest prediction tendency and a fairly satisfactory average safety margin, the model in effect becomes most preferable.
- c) The proposed model tends to be conservative when compressive strength exceeds 60MPa and beams are tested at a shear span-to-depth ratio greater than 3, indicating that the model would perform best for high strength SCC beams. The proposed model on the other hand, tends to be un-conservative for compressive strengths lesser than 60MPa having effective depths lower than 200mm. The proposed model prediction would be unsafe for low and normal strength concrete of very low depths.

REFERENCES

- [1] Ahmed A. A., Assem A. A. H. & Hossam S. A. A. 2013. Influence of pouring techniques and mixtures fresh properties on the structural performance of self-consolidating concrete beams. *Scientific Research and Essays*. 8(42): 2108-2119. <https://doi.org/10.5897/SRE2013.5642>
- [2] Alghazali H. H. & Myers J. J. 2017. Shear behavior of full-scale high volume fly ash-self consolidating concrete (HVFA-SCC) beams. *Construction and Building Materials*. 157, 161-171. <https://doi.org/10.1016/j.conbuildmat.2017.09.061>
- [3] Aoude H. & Cohen M. 2014. Shear Response of SFRC Beams Constructed with SCC and Steel Fibers.
- [4] Biolzi L., Cattaneo S. & Mola F. 2014. Bending-shear response of self-consolidating and high-performance reinforced concrete beams. *Engineering Structures*. 59, 399-410. <https://doi.org/10.1016/j.engstruct.2013.10.043>
- [5] Boel V., Helincks P., Desnerck P. & De Schutter G. 2010. Bond Behaviour and Shear Capacity of Self-Compacting Concrete, 343-353. https://doi.org/10.1007/978-90-481-9664-7_29
- [6] Ding Y., You Z. & Jalali S. 2011. The composite effect of steel fibres and stirrups on the shear behaviour of beams using self-consolidating concrete. *Engineering Structures*. 33(1): 107-117. <https://doi.org/10.1016/j.engstruct.2010.09.023>
- [7] Ding Y., Zhang F., Torgal F. & Zhang Y. 2012. Shear behaviour of steel fibre reinforced self-consolidating concrete beams based on the modified compression field theory. *Composite Structures*. 94(8): 2440-2449. <https://doi.org/10.1016/j.compstruct.2012.02.025>
- [8] Friedman J., Hastie T. & Tibshirani R. 2008. *The Elements of Statistical Learning*.
- [9] Fritih Y., Vidal T., Turatsinze A. & Pons G. 2013. Flexural and shear behavior of steel fiber reinforced SCC beams. *KSCE Journal of Civil Engineering*. 17(6): 1383-1393. <https://doi.org/10.1007/s12205-013-1115-1>
- [10] Greenough T. & Nehdi M. 2009. Shear Behavior of Fiber-Reinforced Self-Consolidating Concrete Slender Beams. *ACI Materials Journal*. (105): 468-477.
- [11] Hanoon A., Jaafar M. & Abed H. 2014. Experimental Investigations Into The Shear Behavior Of Self-Compacting RC Beams With And Without Shear. (2): 15-23.



- [12] Hassan A. A. A., Hossain K. M. A. & Lachemi M. 2008. Behavior of full-scale self-consolidating concrete beams in shear. *Cement and Concrete Composites*, 30(7): 588-596. <https://doi.org/10.1016/j.cemconcomp.2008.03.005>
- [13] Hassan A. A. A., Hossain K. M. A. & Lachemi M. 2010. Structural assessment of corroded self-consolidating concrete beams. *Engineering Structures*. 32(3): 874-885. <https://doi.org/10.1016/j.engstruct.2009.12.013>
- [14] Hassan A. A. A., Ph D., Ismail M. K. & Mayo J. 2012. Shear Behavior of SCC Beams with Different Coarse-to-Fine Aggregate Ratios and Coarse Aggregate Types, (Dymond 2007): 1-11. [https://doi.org/10.1061/\(ASCE\)MT.1943-5533.0001276](https://doi.org/10.1061/(ASCE)MT.1943-5533.0001276).
- [15] Helincks P., Boel V., Corte W. De, Schutter G. De & Desnerck P. 2013. Structural behaviour of powder-type self-compacting concrete: Bond performance and shear capacity. *Engineering Structures*. 48, 121-132. <https://doi.org/10.1016/j.engstruct.2012.08.035>
- [16] Helincks P., De Corte W., Boel V. & De Schutter G. 2010. Influence of Steel Fibre Reinforcement on the Shear Resistance and Crack Pattern Formation of Self-Compacting Concrete Beams. *Key Engineering Materials*, 452-453, 669-672. <https://doi.org/10.4028/www.scientific.net/KEM.452-453.669>
- [17] Huber P., Huber T. & Kollegger J. 2016. Investigation of the shear behavior of RC beams on the basis of measured crack kinematics. *Engineering Structures*. 113, 41-58. <https://doi.org/10.1016/j.engstruct.2016.01.025>
- [18] Itterbeeck P. Van, Cauberg N., Parmentier B., Gysel A. Van & Vandewalle L. 2013. Shear Capacity of Self-Compacting Concrete. *Proceedings of the Fifth North American Conference on the Design and Use of Self-Consolidating Concrete*, Chicago, Illinois, USA. May 12- 15, 2013, 1-10.
- [19] Jum O. 2015. Shear Behavior of Steel-Fiber Reinforced Ultra- High-Strength Self-Compacted Concrete Beams. United Arab Emirates University.
- [20] Khudair J. A. & Atea R. S. 2015. Shear Behavior of self Compacting Concrete Slender Beams Strengthened with Carbon Fiber Reinforced Polymer Sheets. *International Journal of Advanced Research* (2015), 3(1), 706-713.
- [21] Lachemi M., Al-Bayati N., Sahmaran M. & Anil O. 2014. The effect of corrosion on shear behavior of reinforced self-consolidating concrete beams. *Engineering Structures*, 79, 1-12. <https://doi.org/10.1016/j.engstruct.2014.07.044>
- [22] Lachemi M., Hossain K. & Lambros V. 2005. Shear resistance of self-consolidating concrete beams - experimental investigations. *Canadian Journal of Civil Engineering*. 32(6): 1103-1113. <https://doi.org/10.1139/105-066>
- [23] Okamura, H., Ozawa, K., & Ouchi, M. (2000). Self-compacting concrete. *Structural Concrete*, 2(1), 3-17.
- [24] Safan M. A. 2012. Shear strength of concrete beams cast with self-compacting concrete containing different fillers and coarse aggregates. *Canadian Journal of Civil Engineering*. 39(7): 760-770. <https://doi.org/10.1139/12012-062>
- [25] Sathiyamoorthy K., Hossain K. & Lotfy A. 2016. Shear resistance of light weight self- consolidating concrete beams. (2015): 1-11.
- [26] Savaris G. & Pinto R. C. A. 2017. Influence of coarse aggregate on shear resistance of self-consolidating concrete beams. *Ibracon Structures and Materials Journal*. 10(1): 30-40.
- [27] Waleed Z., Mahmoud K. & Abdul Salam L. 2016. Shear Strength Of Self Compacted Concrete With And Without Stirrups At Different Shapes. *Diyala Journal of Engineering Sciences* Vol. 09, No. 01, -p. 67-85, March 2016 ISSN 1999-8716, 09(01): 67-85.
- [28] Adom-Asamoah M., Osei J.B., Obeng J. & Antwi B.E. 2017. Bamboo-reinforced self-compacting concrete beams for sustainable construction in rural areas. *Structural Concrete*, 1103-1113. <https://doi.org/10.1139/105-066>
- [29] Adom-Asamoah M., Osei B.J. 2018. Shear behaviour of bamboo reinforced self-compacting concrete beams without stirrups. *ARPN Journal of Engineering and Applied Sciences*. 13(10): 3312-3324.
- [30] Adom-Asamoah M., Osei J.B. & Afrifa R.O. 2012. Bamboo reinforced self-compacting one-way slabs for sustainable construction in rural areas. *Cogent Engineering*. 5: 1477464.



- [31] Acheampong A., Adom-Asamoah M., Ayarkwa J. & Afrifa R.O. 2015. Code compliant behaviour of palm kernel shell reinforced concrete (RC) beams in shear, *Journal of Civil Engineering and Construction Technology*. 6(4): 59-70.
- [32] Afrifa R.O., Adom-Asamoah M. & Owusu-Ansah E. 2012. Artificial neural network model for low strength RC beam shear capacity. *Journal of Science and Technology*. 32(2): 119-132.
- [33] Adom-Asamoah M., Kankam C.K. 2009. Flexural behaviour of one-way concrete slabs reinforced with steel bars milled from scrap metals. *Materials & Design*. 30(5): 1737-1742.
- [34] Yaw L.T., Osei J.B. & Adom-Asamoah M. 2017. On the non-linear modelling of self-compacting concrete beams. *Journal of Structural and Transportation Studies*. 2(2): 1-18.
- [35] Adom-Asamoah M., Wiafe-Ampofo J. & Owusu R.A. 2009. Flexural and shear behaviour of reinforced concrete beams made from recycled materials, *Journal of Ghana Institution of Engineers*. 57-66.