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Reinforced Concrete Ultimate Bond Strength Model using Hybrid Neural Network-Genetic Algorithm

John Pepard M. Rinchon
Department of Civil Engineering
Technological Institute of the Philippines
Quezon City, Philippines
jprinchon27@gmail.com

Nolan C. Concha
Department of Civil Engineering
FEU – Institute of Technology
City of Manila, Philippines
Nolanconcha9183@yahoo.com

Mary Grace V. Calilung
Department of Civil Engineering
FEU – Institute of Technology
City of Manila, Philippines
mvcalilung@feutech.edu.com

***Abstract*—The bond strength in reinforced concrete is defined as resistance to slipping of the reinforcing steel bars from the concrete. This slipping resistance is one of the most important features in the performance of the reinforced concrete structure, particularly to its failure mode and mechanisms. In this study, a hybrid model using Artificial Neural Network (ANN) and Genetic Algorithm (GA) has been developed to predict and optimize the ultimate bond strength (τ_u) between the reinforcing bar and the concrete based on numerous variables that influence this property. These variables include 28-day cube compressive strength ($f'c$), concrete cover (c), the diameter of reinforcing bar (d_b), embedded length (L_m), rib height (h_r), and rib spacing (s_r). ANN was utilized into the prediction of bond property between the reinforcing bar and concrete based on the aforesaid input variables. The ultimate bond strength predicted by ANN model exhibited reasonably accurate and good agreement with the experimental values. On the other hand, GA was deployed in the search for the optimal combination of the input variables which resulted in high bond strength performance. Optimization results showed that smaller h_r and s_r developed high quality of the bond between the reinforcing steel bar and the concrete.**

Keywords—Bond Strength; Hybrid Model; Genetic Algorithm; Neural Network; Reinforced Concrete.

I. INTRODUCTION

One of the essential components of the durability based design in reinforced concrete is to ensure serviceability performance that is influenced by various parameters such as crack, deflection, bond, among others. In order to describe the complex interactions that involve in the system, development of analytical models using the neural network and genetic algorithm are generally utilized. This study focused on establishing prediction and optimization models of bond strength in reinforced concrete.

The bond strength in reinforced concrete is defined as the resistance to slipping of the reinforcing steel bars from the concrete. Insufficient amount of bond between the bars and concrete may destroy the composite action between the materials thus resulting in a brittle failure since the concrete will be subjected to an excessive amount of tensile forces [1]. This will result in poor performance of reinforced concrete structures [2]. The bond along the interface of the bars and the surrounding concrete is developed due to chemical reaction adhesion, bearing of the ribs of the bar against the concrete and the frictional forces [3]. Bond stresses must be developed along the boundary of the bar and the enveloping concrete if there is a change in the stress of a rebar from point to point along the length of the bar as shown in Fig. 1. If the stress on one end is greater than the stress on the other end, bond stress μ must be present on the rebar surface to maintain equilibrium.

Several studies were performed in order to study the influence of various factors in the bond strength of reinforcing bars in concrete. The bond quality is basically influenced by many factors such as concrete design, steel surface treatment, curing age, among others [4-6]. However, Robert and Thomas [7] suggested that mechanical interlock is the factor that greatly contribute to the development of bond strength. Several studies have been conducted to provide the best model of the bond strength using the different parameters and considering the mechanical interlock mechanism. Orangun et al. [8] and Hadi [9] utilized four independent variables namely the minimum concrete cover (c), compressive strength of concrete cylinder ($f'c$), diameter of reinforcing bar (d_b) and development length (L_d) while Darwin et al. [10] added variation on the concrete cover. Esfahani and Rangan [11] developed a simpler model with three input parameters (i.e. c, d_b and f_{ct}) in which in comparison with other equations, the tensile strength of concrete (f_{ct}) was used rather than the compressive strength. A more complicated expression was proposed by ACI Committee 408 [12] based on updated model of Zuo and Darwin [13] which considers 11 independent variables. Furthermore, a study conducted by Diab et al. [2] considers a large number of variables on bond behavior and ultimate design of bond stress of normal and high strength concrete. Single and double pull out tests were performed on samples with varying compressive strength, concrete cover, the size of the bar, embedded length (L_m), the length of pre-flexural crack and mechanical interlock parameters such as rib height (h_r) and rib spacing (s_r). Same with

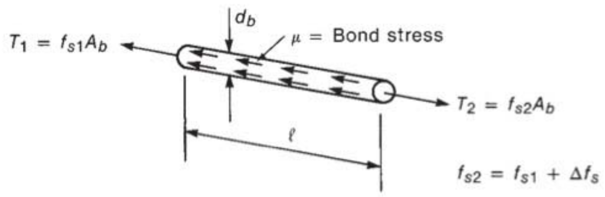


Fig. 1. Mechanics of Bond Stress. Image retrieved from Wight [16]

previously proposed models, two bond stress equations were also developed using multiple regression. The reliabilities of these equations were tested using results obtained from experiments and compared with estimated values given by other existing models. There was a good agreement of the proposed equations particularly to BSI [14] and EN [15] based on mean value ratios of 1.17 and 0.93 respectively.

On the other hand, Artificial Intelligence (AI) like Artificial Neural Network (ANN) and Genetic Algorithm (GA) became an emerging tool to a wide array of problems particularly in the field of civil engineering [17-20]. ANN was typically utilized as prediction model and proven to be successful in this application in recent years [5, 21-23]. It capable to solve engineering problems where analytical and numerical methods have difficulty to solve. However, application of GA in conjunction to ANN develops a more robust and hybrid AI model. Despite a small number of studies, this hybrid model became a promising tool in the field of civil engineering and construction materials in current years. It is used to establish the relationship between the properties and components of construction materials. Rinchon [24] deployed the Hybrid AI for prediction and optimization of two performance parameters of self-compacting concrete containing cementitious blend. Concha [25] and Concha and Dadios [26] utilized the Hybrid Model to establish the constitutive relationship of mineral admixtures along with self-compacting concrete components to slump flow, L-box ratio, and screen stability ratio and optimize the concrete mix proportion to derive high rheological performance.

Currently, the development of the analytical models of bond strength of reinforced concrete, several simplified ideal assumptions were adopted in the modeling process, thereby underestimating the underlying behavior of the bond performance of steel and concrete. In order to capture the dominant characteristics involved in the complex system of the ultimate bond strength, the study aims to employ the Hybrid AI model using ANN and GA.

II. Methods

A. Materials and Pull-Out Test

The data utilized in this study were retrieved from the study published by Diab et al. [2]. Consequently, forty-nine datasets from double tensile pull-out test results were summarized and prepared. Different input variables considered throughout the study were 28-day cube compressive strength test ($f'c$), concrete cover (c), the diameter of reinforcing bar (d_b), embedded length (L_m), rib height (h_r), and rib spacing (s_r) (Refer to Table 1). All specimens used in testing were prepared in accordance with guidelines and testing procedures set by American Society for Testing and Materials. The double tensile pull-out test was performed to determine the total bond load and later compute the bond strength using the following expression:

$$\tau = P/(\pi L_m d_b) \quad (1)$$

where τ is the bond strength (MPa), P is the ultimate load (N), L_m is the embedded length (mm), and d_b is the diameter of reinforcing bar (mm).

B. Artificial Neural Network (ANN)

In this study, the simplest and widely used ANN model known as feedforward multilayered supervised neural network with error back-propagation algorithm was selected. The topology of ANN is generally composed of artificial neurons similar to human brain natural neurons that are clumped into series of input, hidden, and output layers (See Fig. 2a). The design of ANN topology is based on the exploration of following internal parameters: 1) performance function, 2) learning function, 3) weights and biases, 4) hidden layers and neurons, 5) and transfer function (Refer to Table 2).

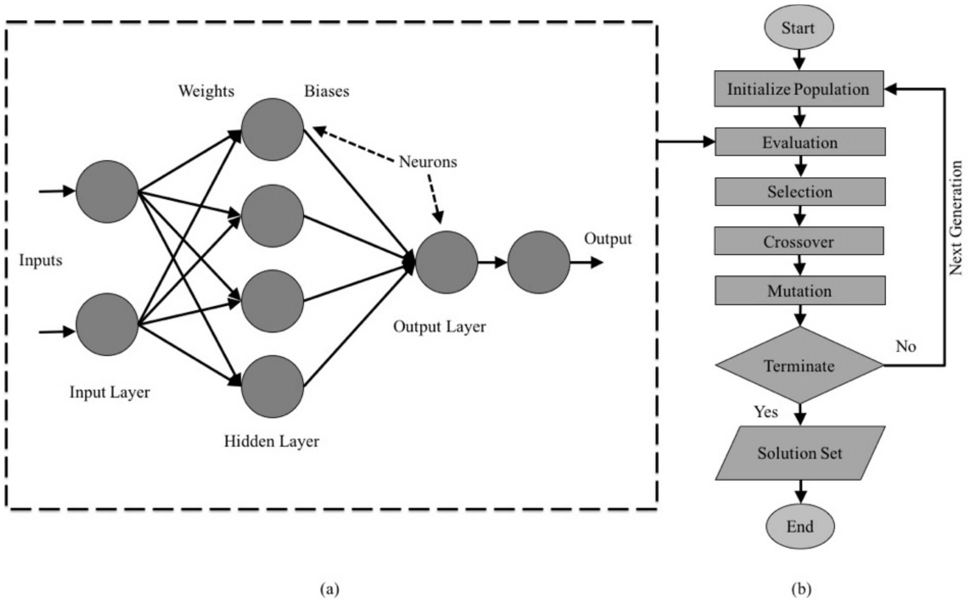


Fig. 2 The Hybrid Model (a) Artificial Neural Network Architecture (b) Genetic Algorithm Flow Chart [24]

Table 1. SUMMARY OF INPUT VARIABLES Diab et al. [2]

Variable	Details of Variable			
	Minimum	*Maximum*	*Range*	*Mean*
Input				
28-Day Cube Compressive Strength, $f'c$ (MPa)	18.0	96.8	78.8	50.7
Concrete Cover, c (mm)	42	67	25	65
Reinforcing Bar Diameter, d_b (mm)	16	18	2	16.2
Embedded Length, L_m (mm)	80	180	100	159.2
Rib Height, h_r (mm)	1	2.68	1.68	1.83
Rib Spacing, s_r (mm)	11.2	20.83	9.63	14.54
Output				
Bond Strength, τ_u (MPa)	4.68	14.32	9.64	7.82

Table 2. ANN INTERNAL PARAMETERS

Parameter	Value
Training algorithm	Levenberg-Marquardt Algorithm
Transfer function	Hyperbolic Tangent Sigmoid (Tansig)
Performance function	Mean Square Error (MSE), Pearson Correlation Coefficient (R)
Number of hidden layers	1
Number of neurons per hidden layer	$(nip - 1)$ [a]
Performance Goal	0.000001
Epochs	10,000

[a] nip corresponds to a number of input parameters; Asteris et al [27].

In this study, hyperbolic tangent sigmoid function or *tansig* function and Levernberg-Marquardt algorithm were utilized as transfer and training functions respectively. According to Asteris et al. [27] no clear reasons as to why the *tansig* function should always provide optimal decision borders while the choice of the transfer function has always a strong influence on the complexity and performance of the neural network. Transfer function serves as motivation function for the relationship between weights of a neuron and input element. Based on the general definition, the *tansig* function operates by returning outputs compressed between -1 and 1 in which it has an ability to learn the complex nonlinear relation between the input and output elements. According to previous studies [27, 28], Levernberg-Marquardt learning function is the most suitable algorithm for concrete related data and it is attributed to be significantly high-speed training method especially for moderately sized feedforward neural networks as well as nonlinear problems.

Previous studies suggested that more hidden layers can be used to handle complicated and erratic cases [29] however, Zhang et al. [30] recommended to use one or two hidden layers for modeling. In this investigation, the number of neurons in the hidden layer will be part of the experimental exploration. Consequently, the performance of ANN models was assessed using Pearson correlation coefficient (R) and mean square error (MSE), high performing ANN model has R and MSE values equal to one and zero respectively. Moreover, satisfactory values for R and MSE are used as stopping criteria for the series of training simulation in deriving the final weights and biases corresponding to high performing ANN models.

Furthermore, ANN modeling is divided into three stages (i.e. training, validation, and testing). The first part of the modeling is the training stage in which formulation of the initial structure of ANN is executed. Subsequently, validation is the stage where the final weights and biases were derived. While the testing stage is used to ensure the accuracy of the final model. In addition, the datasets are distributed to training, validation, and testing stages using 70, 15, and 15% proportion.

C. Genetic Algorithm (GA)

Genetic Algorithm originally proposed by Goldberg [31] was used in this study (See Fig. 2b). It is basically composed of three operators known as the selection, mutation and crossover. The objective function of the optimization problem in this study is express as follow:

$$\text{Maximize: } \tau_u = \mathrm{f}\,(f'c,\ c,\ d_b,\ L_m,\ h_r,\ s_r) \qquad (2)$$

where τ_u – ultimate bond strength (MPa); $f'c$ – 28-day cube compressive strength (MPa); c – concrete cover (mm); d_b – diameter of reinforcing bar (mm); L_m – embedded length (mm); h_r – rib height (mm); s_r – rib spacing (mm). τ_u is the prediction model developed through ANN modeling which was used as a function that establishes the relationship between input variables and ultimate bond strength of reinforced concrete.

In this research, single objective optimization problem was solved as expressed in Equation 2. The main objective is to determine the best combination of input variables that will yield a high bond quality between the reinforcing bar and the concrete. The ANN model developed from the first stage of hybrid model was used as the objective function in this GA stage. Consequently, to deploy GA, different available methods in MatLab® program for GA operators were assigned. Proper assignment of operators will influence the convergence rate and capability of GA model to search for the global solution of the optimization problem. A full discussion of each operator was presented in the succeeding paragraphs.

Commonly at the start of the optimization search, low selection pressure was specified in favor of a broad exploration of the search space while, at the latter part, high selection pressure was recommended in order to achieve the most promising regions in the search space. Driving force of GA search can achieve by appropriate method and pressure of selection operator [32]. Accordingly, the stochastic uniform or Stochastic Universal Sampling (SUS) [33] and tournament methods were utilized as selection operators in this study. SUS is one of the most popular selection methods particularly because of its capability in achieving a minimum spread of generated population and zero bias selection of individuals. In order to enhance the selection operator of the whole GA process, rank and top fitness scaling methods were combined to SUS. On the other hand, tournament selection generally operates by means of randomly chosen chromosomes and pick out high performing chromosome from the group and proceed to reproduction. This selected chromosome is inserted into a new population and the process is repeated until the population becomes full.

The mutation operator is a special feature of GA because of its mechanism of preserving specific characteristic of the initial population. This feature is vital in the search for promising regions of solution space. This special feature counterweighs the negative effect of crossover operator during the generation of the new set of chromosomes by losing specific characteristic. By definition, the mutation operates through mutation rate generally defined as percentages of new genes over a total number of genes in the population needed for trial. However, it is being noted that very slow mutation rate will yield to the local solution because of unexplored useful characteristics of other possible chromosomes. While high mutation rate will cause random perturbation of the new population losing resemblance to its parent population and later the algorithm loses its track of the search process. According to Libelli et al. [34], the adaptive feasible mutation has the capability to address the mutation rate issue, thus, this method was utilized in this study.

For the last operator, the crossover is based on the mechanism of sexual generation from two parent chromosomes to produce a new chromosome. The sexual mechanism operates by taking parts of the total characteristics of the two parent chromosomes and combine theme in order to generate a new chromosome. This mechanism is controlled by crossover rate that is defined as the ratio between the new chromosomes and population size that will undergo the operation. Lim et al. [32] reported that a high crossover rate allows the GA to explore the large region of search space thus reduces the probability of landing for a local optimal solution but if this rate is too high, this will yield to computationally intense while exploring the unpromising solution. In this investigation, four types of crossover operator were explored namely scattered, one-point, two-point, and intermediate crossover. These crossover models are all deployable in MatLab® program.

Another important part of the optimization procedure is to formulate constraints. This will help the algorithm to search for the global and realistic solution of the optimization problem. Thus, here are the following formulated constraints:

$$18 \le f'c \le 96.8 \tag{3}$$

$$42 \le c \le 67 \tag{4}$$

$$16 \le d_b \le 18 \tag{5}$$

$$80 \le L_m \le 180 \tag{6}$$

$$1.0 \le h_r \le 2.68 \tag{7}$$

$$11.2 \le s_r \le 20.83 \tag{8}$$

Table 3. GA OPERATORS FOR SINGLE OBJECTIVE PROBLEM

GA Operators	Method/s
Selection	Stochastic Uniform (SU), Tournament Method (TM)
Mutation	Adaptive Feasible (AF)
Crossover	Scattered (S), One-Point (OP), Two-Point (TP), Intermediate (I)

III. Results and Discussion

After series of training simulation and exploration of significant internal parameters, the final topology of ANN model for the ultimate bond strength was structured (i.e. BSNN1). Table 4 summarized the final internal parameters of final bond strength ANN model. This final architecture includes five hidden neurons with a single hidden layer. The *tansig* function was still proven to be the best performing transfer function that capable to handle input and output elements with different dimensions. Additionally, it is observed that Levenberg-Marquardt training algorithm is still efficient at high rate convergence for moderate-sized feedforward neural network with a nonlinear problem. Fig. 3 presented the performance of the BSNN1 model with Pearson correlation coefficient (R) of the training, validation, and testing greater than 0.99. An R value close to one describes a strong positive association between the dependent and independent variables. This remarked to be a high performing ANN model. This model has an overall R value of 0.992 providing a satisfactory prediction capability (Refer to Table 5).

Applicability of GA as optimization technique was tested in this study. GA was used to solve single objective optimization problem involving the bond strength between the reinforcing bar and concrete. Table 6 listed down the optimal solutions for the optimization problem which derived from different GA model configurations. In addition, stochastic uniform selection method combined to scattered or one-point crossover method proves to be efficient at high convergence rate in determining the optimal solution (See Fig. 4). Subsequently, intermediate crossover method shows low convergence with over 200 generations before the optimal value was derived.

It can be noted that all GA models agreed to a single best combination of input variables with a high bond quality of τ_u = 16 MPa. The optimization results show that each input variable has a large influence on the development of bond strength. It can be observed that smaller mechanical interlock parameters (i. e. h_r and s_r) and diameter of reinforcing bar will yield high bonding property. While larger embedded length and concrete cover with high concrete compressive strength will increase the bond strength of the reinforced concrete.

Table 4. FINAL INTERNAL PARAMETERS OF BSNN1 MODEL

ANN Model	BSNN1
Training algorithm	Levenberg-Marquardt Algorithm
Transfer function	Hyperbolic Tangent Sigmoid (Tansig)
Number of hidden layers	1
Number of neurons per hidden layer	5

Table 5. PERFORMANCE OF THE FINAL ANN MODEL (BSNN1)

Modeling Stages	ANN Performance	
	Pearson Correlation Coefficient, R	***Mean Square Error, MSE***
Training	0.993730	0.0578383
Validation	0.993735	0.1646320
Test	0.992267	0.1232380
All	0.992	-

Table 6. RESULTS OF SINGLE OBJECTIVE GENETIC ALGORITHM OPTIMIZATION

GA Model	***Input Variables***						***No. of Generation***	***Max: τ_u (MPa)***
	28-day cube compressive strength, f'c (MPa)	***Concrete cover, c (mm)***	***Rebar diameter, d_b (mm)***	***Embedded Length, L_m (mm)***	***Rib height, h_r (mm)***	***Rib spacing, s_r (mm)***		
SU-AF-S	96.8	67	16.156	180	1	11.2	146	15.8469
SU-AF-OP	96.8	67	16.157	180	1.002	11.2	121	15.8458
SU-AF-TP	96.8	67	16.158	180	1	11.202	142	15.8464
SU-AF-I	96.795	66.987	16.167	179.82	1.004	11.213	291	15.8283
TM-AF-S	96.8	67	16.158	180	1	11.2	129	15.8469
TM-AF-OP	96.8	67	16.159	180	1	11.2	134	15.8469
TM-AF-TP	96.8	67	16.158	180	1	11.2	146	15.8469
TM-AF-I	96.793	66.982	16.173	179.982	1.008	11.208	217	15.8374

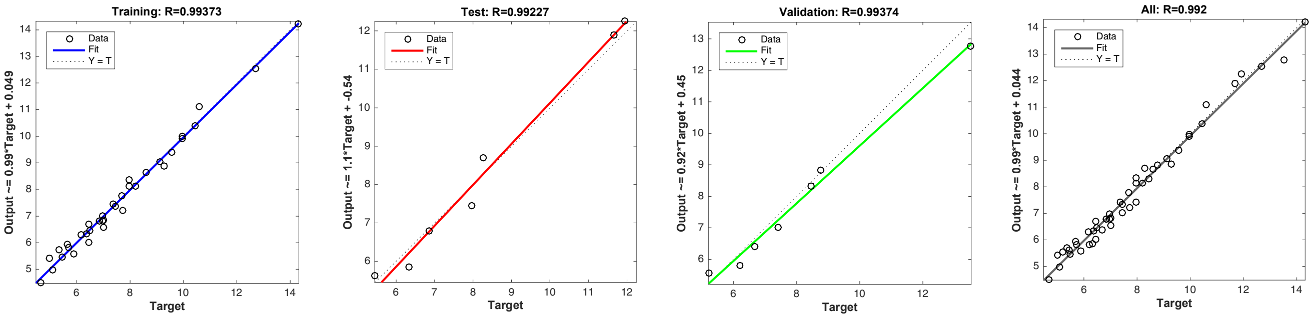
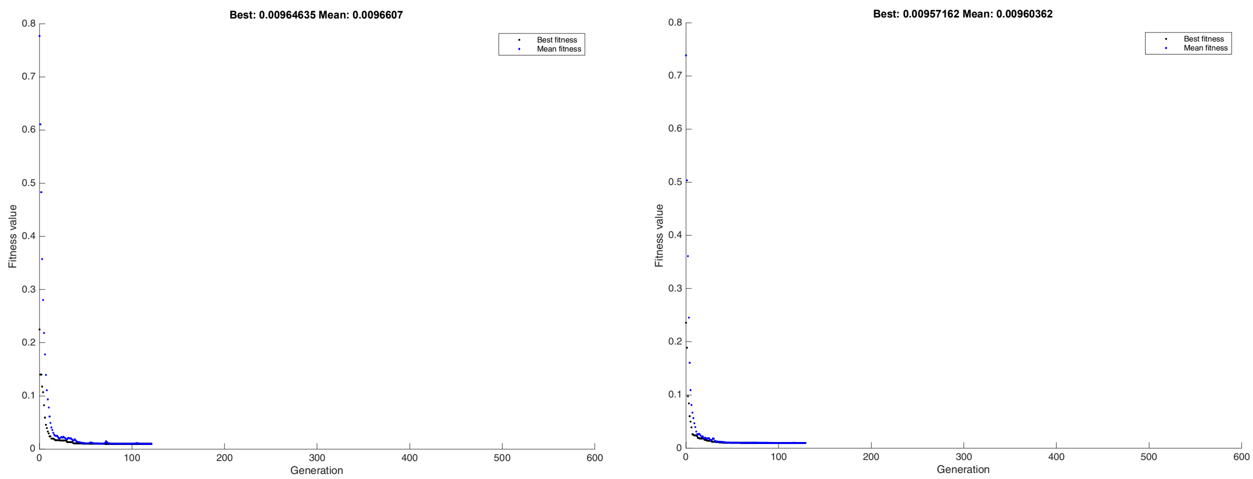


Fig. 4. Pearson correlation coefficient (R) values, for training, testing, validation, and overall



(a) (b)

Fig. 3. Results of genetic algorithm generation for bond strength optimization problem (a) SU-AF-OP (b) TM-AF-S

IV. Conclusion

After the computational experiment done through the use of hybrid AI model, twofold conclusions can be drawn. The developed Hybrid Neural Network-Genetic Algorithm model was able to provide satisfactory predicted results in good agreement with the experimental values as justified by high Pearson correlation coefficient (R) and minimal Mean Square Error (MSE) of 0.99 and 0.16 respectively. The influence of each input variables (i.e. $f'c$, c, d_b, L_m, h_r, and s_r) on the bond strength performance of the reinforcing bars and concrete was completely established as described by high Pearson correlation coefficients summarized in table 5. Furthermore, the optimal combination of the input variables was also derived achieving high bond quality (τ_u = 16 MPa) between the reinforcing bars and concrete under large constraints requirements. Different GA configurations agreed with one optimal combination of the input variables as reflected in table 6.

V. Recommendation

A full-scale sample and dynamic loading bond strength is recommended to capture the actual underlying behavior of bond performance of steel in the reinforced concrete structure subjected to dynamic loading. It is further recommended to incorporate the effect of other parameters such as bond-slip, mode of failure, corrosion, and carbonation of concrete.

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