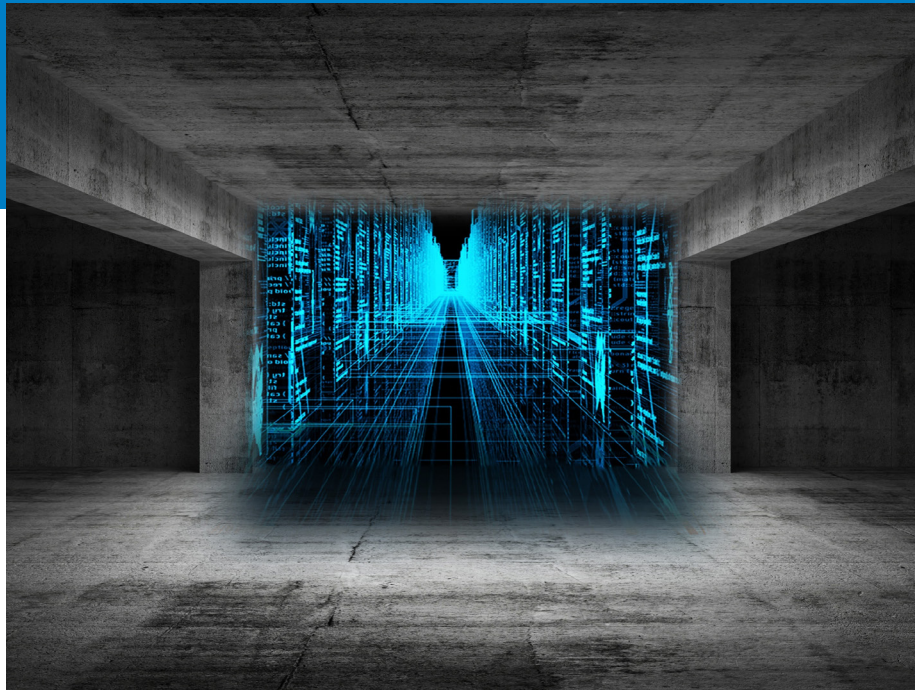


An ACI Technical Publication

SYMPOSIUM VOLUME



The Concrete Industry in the Era of Artificial Intelligence

SP-350

Editors:
M.Z. Naser and Kevin Mueller



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The Concrete Industry in the Era of Artificial Intelligence

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March 29-April 2, 2020

Editors:
M.Z. Naser and
Kevin Mueller



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PREFACE

The Concrete Industry in the Era of Artificial Intelligence

This special publication draws inspiration from the Technical Session entitled “The Concrete Industry in the Era of Artificial Intelligence,” held during the ACI Virtual Concrete Convention in spring 2020. To parallel the Technical Session, this special publication is also tailored to showcase the unprecedented potential of leveraging artificial intelligence (AI) methods—including its derivatives of machine learning (ML) and deep learning (DL)—in the concrete industry as a whole.

The idea behind this effort started as a thought during an ACI Committee 216 meeting. From there, both ACI Committees 444 (Chair: Thomas Schumacher) and 554 (Chair: Liberato Ferrara) displayed interest in co-sponsoring this special publication. This special publication comprises fifteen papers (five from our panelists and ten received from authors representing academia and the concrete industry). This collection of papers covers the use of various AI techniques at the material level (i.e., concrete performance and mass-scale testing, property predictions, and optimization, etc.), elemental level (e.g., behavioral and capacity prediction of slabs, walls, beams, and anchorages, etc.), as well as system level (viz. damage and crack detection of concrete bridges and concrete composite structures).

We are very thankful to ACI, the ACI Technical Activities Committee, as well as all three technical committees. Your kind support and commitment have not only allowed us to explore a new realm of possibilities but have also enabled us to set the stage towards a new and modern future to our industry. Special thanks go to our panelists and contributors who were very kind to share their most recent research and unique ideas pertaining to infusing AI solutions to various problems within our domain. In addition, we send our warm regards to our reviewers, ACI staff, and Ms. Barbara A. Coleman for her help in setting up and editing this effort.

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Damage Detection in Concrete Bridge T girders using 3D Finite Element Simulations Trained by Artificial Neural Network

AlaaEldin Abouelleil, Hayder A. Rasheed, and Eric Fletcher

Synopsis: The structural deterioration of aging infrastructure systems is becoming an increasingly important issue worldwide. To compound the problem, economic strains limit the resources available for repair or replacement of such systems. Over the past several decades, structural health monitoring (SHM) has proven to be a cost-effective method for the detection and evaluation of damage in structures. Visual inspection and condition rating is one of the most commonly applied SHM techniques, but the effectiveness of SHM varies depending on the availability and experience of qualified personnel and largely qualitative damage evaluations. Simply supported three-dimensional reinforced concrete T-beams with varying geometric, material, and cracking properties were modeled using Abaqus finite element (FE) analysis software. Up to five cracks were considered in each beam, and the ratios of stiffness between cracked and healthy beams with the same geometric and material parameters were measured at nine equidistant nodes along the beam. A feedforward ANN utilizing backpropagation learning algorithms was then trained on the FE model database with beam properties and nodal stiffness ratios serving as inputs for the neural network model. The outputs consisted of the predicted parameters of location, depth and width of up to five cracks. This inverse problem is very difficult or impossible to solve with the training done by the Artificial Neural Network. One ANN was trained to predict the parameters of the cracks using the full database of FE simulations. The damage prediction ANN achieved fair prediction accuracies, with coefficients of determination (R^2) equal to 0.42. This result was the outcome of the no uniqueness in the prediction of this inverse analysis. Nevertheless, this ANN model provides a rough estimate of the cracking type and damage content in bridge girders once the nodal stiffness ratios are measured by applying a field vehicle loading and measuring the deflection using a theodolite. A touch-enabled user interface was developed to allow the ANN model to predict the crack configurations. The application was given the acronym DRY BEAM, for Damage Recognition Yielding Bridge Evaluation After Monitoring.

Keywords: artificial neural network, finite element, damage detection, girders

INTRODUCTION

A significant amount of Structural Health Monitoring (SHM) research has been conducted in the recent past. The majority of researchers agree on relying on reference parameters extracted from healthy beams for comparison. However, they differ in defining these parameters, which could be categorized into dynamic and static parameters.

Ndambi et al. (2002) investigated the potential for use of Eigen frequencies and mode shape-derived properties to detect the location and estimate the severity of damage in reinforced concrete beams. The results of their tests suggest that Eigen frequencies of reinforced concrete members can be numerically correlated to changes in stiffness, allowing damage to be quantified with non-destructive test methods.

Teughels et al. (2002) presented an approach to damage quantification using FE model updating. Results of this research demonstrated that modal properties can be used with processing and analysis techniques, such as FE model updating, to reliably quantify damage in reinforced concrete structures.

Ghods and Esfahani (2009) conducted static loading tests and dynamic modal analyses on eight reinforced concrete beams with varying compressive strengths and reinforcement ratios. This experiment highlighted the ability of modal analyses to characterize the specific damage level in reinforced concrete beams.

Reynders and De Roeck (2009) applied modal analysis parameters to develop a flexibility-based damage assessment method for beam members. The conclusion was made that the modal data-based flexibility method shows promise as a nondestructive method for quantifying damage in concrete beams.

Tan et al. (2020) developed and applied a procedure for detecting damage in a composite slab-on-girder bridge structure comprising of a reinforced concrete slab and three steel I beams, using vibration characteristics and Artificial Neural Network (ANN). The procedure is applied across a range of damage scenarios and the results confirm its feasibility to detect and quantify damage in composite concrete slab on steel girder bridges.

Researchers have also used wave response methods to localize and quantify damage in reinforced concrete structures. One such method, acoustic emission (AE), uses mechanical loading to cause damaged material sections to emit elastic waves that are read by surface sensors.

Sagar et al. (2012) utilized the AE technique to assess damage in three experimental reinforced concrete beams subjected to cyclic loading stages. Four AE sensors were attached to each beam in order to gather wave response data during each loading cycle to evaluate damage severity in the beams. Although the experiment was limited to three experimental beams, the researchers proposed that AE techniques display significant potential for structural damage assessment applications.

Shiotani et al. (2012) utilized AE and elastic wave tomography techniques to assess the structural health of an experimental reinforced concrete bridge deck subjected to fatigue damage. Fatigue loading was simulated by load stages of 0, 10,000, and 20,000 passes of a 100 kN moving wheel load, and wave data was recorded for the bridge deck under incremental static load steps after each fatigue loading stage. Elastic wave tomography and AE analyses of two in-situ bridge decks substantiated their findings, and wave velocities and natural frequencies again showed great promise as damage quantification parameters.

Ongpeng et al. (2019) monitored the damage in 18 reinforced concrete beams with varying water cement ratios and reinforcements tested under four-point bending test. Repeated step loads were designed and at each step load acoustic emission (AE) signals were recorded and processed to obtain the acoustic emission source location (AESL). The computed convex hull volume (CHV) showed good relation to the damage encountered until 60% of the ultimate load at the midspan was reached.

Researchers have also utilized digital imaging techniques such as digital image correlation (DIC), light detection and ranging (LiDAR), and fractal analysis to evaluate damage in reinforced concrete structures. DIC relies on algorithms that process data from high resolution images to measure surface displacements and strains.

Li et al. (2008) used DIC to detect cracks and assess damage for several experimental reinforced concrete beams. Loland's model was selected to quantify damage and damage evolution, and data recorded through DIC was applied

in FE model updating to define the initial damage and material parameters in the damage model. The results of this experiment suggested that DIC combined with techniques such as FE model updating can effectively quantify structural damage.

Applications of 3D LiDAR technology in damage detection and quantification were investigated in three case studies summarized by Chen et al. (2012). One case study of a bridge in Iowa highlighted the ability of LiDAR to not only detect cracks, but also to describe their precise location and dimensions.

Researchers have also investigated fusion of ANNs and the FE model updating approach. Jeyasehar and Sumangala (2006) investigated the ability of ANNs to quantitatively predict damage in an experiment involving five post-tensioned prestressed concrete beams. Damage in the beams was introduced by snapping a variable percentage of the wires through inducing localized pitting corrosion at a crack former placed at the center of the beams, and the beams were subjected to static loading stages of increasing magnitude. The results showed that the damage level assessment error could be reduced with the introduction of static test data to the ANN instead of dynamic test data.

Hasançebi and Dumlupinar (2013) discussed the potential of using ANNs to perform FE model updating operations for reinforced concrete T-beam bridges. The researchers developed analytical FE bridge models with various boundary stiffnesses, elastic moduli, and deck masses. Changes in these properties from an initial state were used to characterize damage and assess structural health. The researchers concluded that ANNs can be successfully used in conjunction with FE model updating to quantitatively evaluate damage, provided they utilize both static and dynamic test results.

Al-Rahmani (2012) conducted research involving the application of a feedforward ANN utilizing a backpropagation learning algorithm to develop both structural health prediction and damage detection models. Databases composed of material, geometric, and cracking properties of simply-supported two-dimensional concrete beams were constructed by modeling healthy and damaged beams with Abaqus FE analysis software. Al-Rahmani's work demonstrated the effectiveness of ANNs as SHM tools for both damage prediction and evaluation. This work was summarized in two publications. The first paper focused on damage detection in simple beams with a single crack (Al-Rahmani et al. 2013). The second paper addressed damage quantification and damage detection in simple beams with dual cracks (Al-Rahmani et al. 2014).

Generation of 3D Reinforced Concrete T Beam Database

Reinforced concrete beams were modeled using the FE analysis software program ABAQUS, version 6.13 (ABAQUS 2013). The FE models in this study represent concrete T-beams reinforced in tension with mild steel bars in order to accurately emulate real-world bridge girders. 3D reinforced concrete T-beams were modeled using ABAQUS. These beam models were composed of 3D solid parts and were meshed with 10-node quadratic tetrahedral (C3D10) elements utilizing an automatic meshing technique. Reinforcement was modeled using 3D wire parts meshed with 3-node truss elements (T3D3), and three equally spaced reinforcing bars were embedded in all concrete beam models with a perfect non-slip bond between the concrete and the reinforcing bars. Figures 1 and 2 display 3D ABAQUS views of a sample reinforced concrete T-beam. Reinforcement was present in the sample beam, but is not depicted.

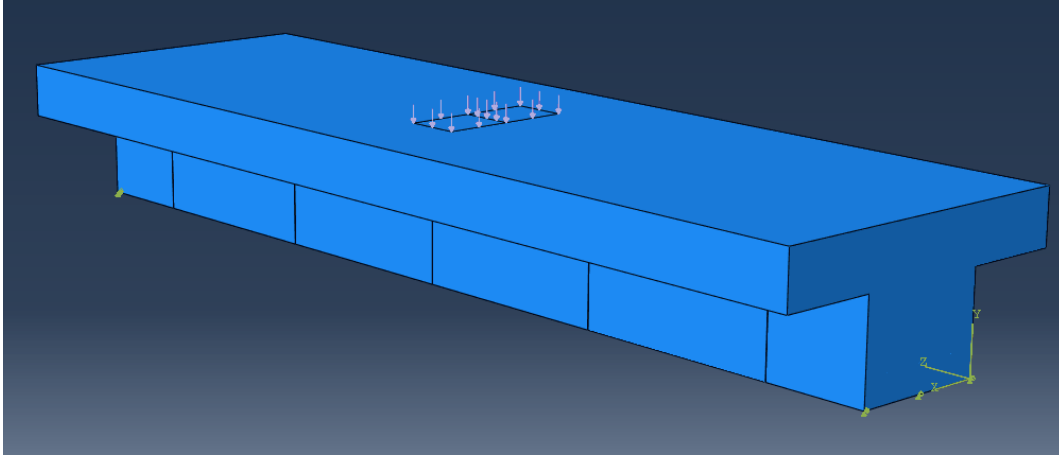


Figure 1 — ABAQUS view of 3D reinforced concrete T-beam showing five cracks along span, support conditions and applied load.

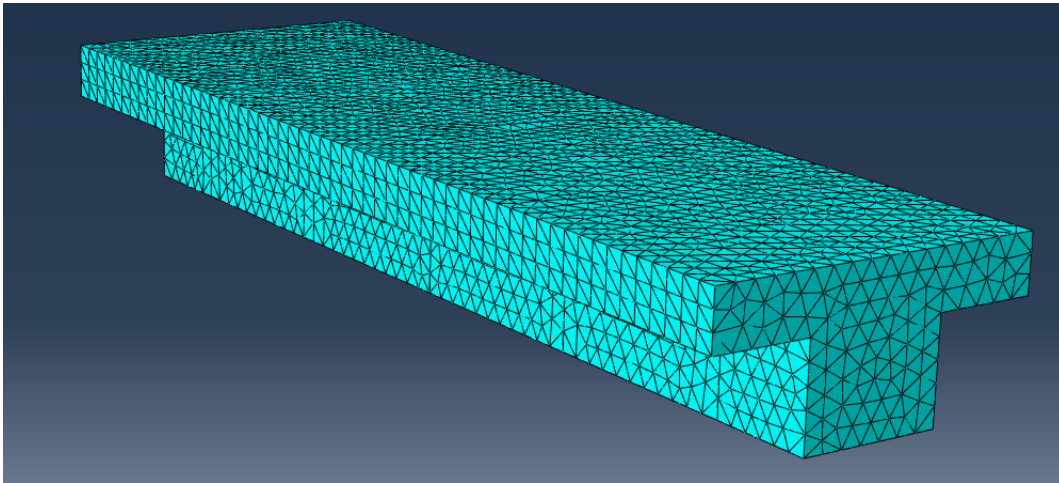


Figure 2 — FE mesh of the 3D reinforced T-beam example in Figure 1.

Material models were held constant throughout the study, and both concrete and steel were modeled as linear elastic. Poisson's ratios (ν) for concrete and steel were set at 0.2 and 0.3, respectively, and the modulus of elasticity of steel (E_s) was taken to be 200,000 MPa (29000 ksi). Table 1 shows the parameter variability of the geometry, material and stiffness inputs. The modulus of elasticity of concrete was set according to the ACI equation below:

$$E_c = 4,700\sqrt{f'_c} \text{ (MPa)} \quad (57\sqrt{f'_c} \text{ (ksi)}) \quad 1$$

where:

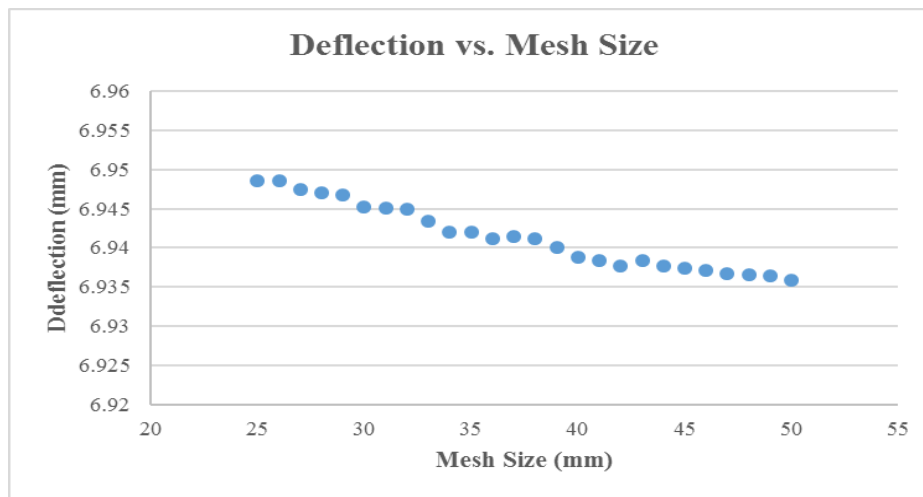
E_c = modulus of elasticity of concrete MPa (ksi)

f'_c = 28-day compressive strength of concrete MPa (ksi)

Table 1—Parameter variability for Inputs

Parameters	Values								
b_w/h	0.5	0.7	0.9						
L/h	7	10	13						
ρ	0.005	0.01							
f'_c MPa (ksi)	20 (2.9)	30 (4.35)		40 (5.8)		50 (7.25)			
$K\%_{0n}$	$K\%_{01}$	$K\%_{02}$	$K\%_{03}$	$K\%_{04}$	$K\%_{05}$	$K\%_{06}$	$K\%_{07}$	$K\%_{08}$	$K\%_{09}$

Other properties standardized between all models in this study included the concrete cover dimension and the FE mesh size. The concrete cover was set at 50mm to the center of steel for both vertical and horizontal cover values. The mesh size refers to the size of each element used in the construction of the FE model and is entered in linear units for the applied measurement system (mm, in, etc.). The mesh size was initially established by attempting to achieve a balance between the precision of results afforded by a reduced mesh size, and the significantly increased ABAQUS analysis time resulting from the use of small mesh sizes. The midspan deflection results for an uncracked sample 3D T-beam under a constant load with mesh sizes ranging from 50 mm (1.97 in) – 25 mm (0.98 in) are plotted in Figure 3. Sample ABAQUS analysis times for the beam with mesh sizes of 48 mm (1.9 in), 35 mm (1.4 in), and 26 mm (1.02 in) were 0:40, 1:00, and 2:13 hours:minutes, respectively. From Figure 3, it can be seen that the variation in the deflection results is insignificant with respect to the variation in ABAQUS analysis time. However, mesh attachment errors were noted for beams with small cracks having mesh sizes of 50 mm (1.97 in). Testing revealed that the frequency of mesh attachment errors reduced with decreasing mesh size. Therefore, the mesh size was set at 35 mm for both the concrete and steel elements in the beam models.

**Figure 3 — Variation in beam deflection with reduction of mesh size**

For all FE models, nine stiffness nodes were inserted along the top face of the beam at equidistant spacing. The number of stiffness nodes was set according to Al-Rahmani's work (2012), in which beams with nine stiffness nodes provided optimal results. Each stiffness node was subjected to a static load of 100 kN (22480 lb.) in turn, and deflection results at the stiffness nodes were extracted from the ABAQUS analysis. The load was applied as an area load over a small section of the top face of the beam, centered on the stiffness node, for the 3D analyses. This scheme of loading configurations was necessary because the application of a point load for 3D beam models resulted in very high relative deflections at the stiffness node, suggesting that localized deformation was significant. For all models, the stiffness at a given node was found by dividing the total applied force by the deflection at that node according to the following formula:

$$k_n = \frac{P_n}{\Delta_n}$$

2

where:

k_n = stiffness at node n

P_n = applied load at node n

Δ_n = deflection at node n

Nodal stiffness ratios were used to quantitatively describe the damage level, or residual structural health, of the reinforced concrete beams. In general, beams with low nodal stiffness ratios have deep, wide, or an extensive number of cracks. Nodal stiffness ratios were also found to indicate damage locations within a beam; stiffness ratios of nodes near existing cracks are typically lower than stiffness ratios of nodes far from damage locations. It was observed that cracks placed very close to the beam supports resulted in unreasonably low nodal stiffness ratios. This was thought to be due in part to a failure to meet Saint-Venant's principle, which suggests that the stress distribution in a material may be assumed to be independent of the manner of load application, except in the immediate vicinity of the applied loads (Beer et al. 2012). The presence of both an applied load and a discontinuity (crack) in the beam close to the supports likely introduced stress and strain concentrations that contributed to the unexpected deflection of the beam. Therefore, crack placement was limited to 0.06–0.94 of the beam span length; a range in which the nodal stiffness ratios were generally observed to stabilize to reasonable values.

The 3D reinforced concrete T-beam database was established by variation of the geometric and material parameters for all beams as well as cracking parameters for cracked beams. Geometric parameters included the width of the beam web cross-section (b_w), the depth of the entire beam cross-section (h), the height of the beam flange, or slab (h_s), and the beam span length (L). The beam flange was modeled according to the provisions of American Concrete Institute (ACI 318-14) Section 8.4.1.8 for two-way slabs, which indicates that the total width of the T-beam flange should be equal to the sum of the web width and twice the depth of the beam extending below the flange as shown in Figure 4 (ACI Committee 318 2014).

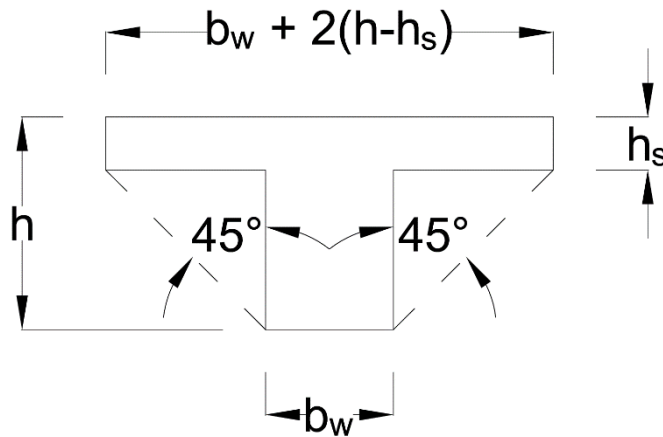


Figure 4 — T-beam flange dimension

The size of the reinforcing bars in each beam depended upon the steel ratio (ρ) and the beam's cross-sectional area according to the relationship $A_s = \rho b_w d$, where A_s is the total cross-sectional area of steel reinforcement and d is the effective depth of the beam section, taken as the beam depth minus the cover. The 28-day concrete compressive strength (f'_c) was the only variable material parameter. Cracking parameters included the location (b_{cr}), depth (d_{cr}), and width (w_{cr}) of each crack, and all crack locations were measured from a constant (left) edge of the beam. With the exception of f'_c , ρ , and w_{cr} , all parameters were directly normalized with respect to a beam web width of $b_w = 250$ mm (9.8 in), resulting in the normalized parameters b_w/h , h_s/h , L/h , b_{cr}/L , and d_{cr}/h . This normalization was performed so that the results of this study could be applied to beams of various sizes. The slab height was also set to remain constant at $h_s = 100$ mm (3.9 in) in order to limit the number of beams created through parametric variation, although the

normalized parameter h_s/h fluctuated due to variability in the beam depth. Figure 5 displays an elevation view of a beam with two cracks and highlights several geometric property dimensions and all stiffness node locations.

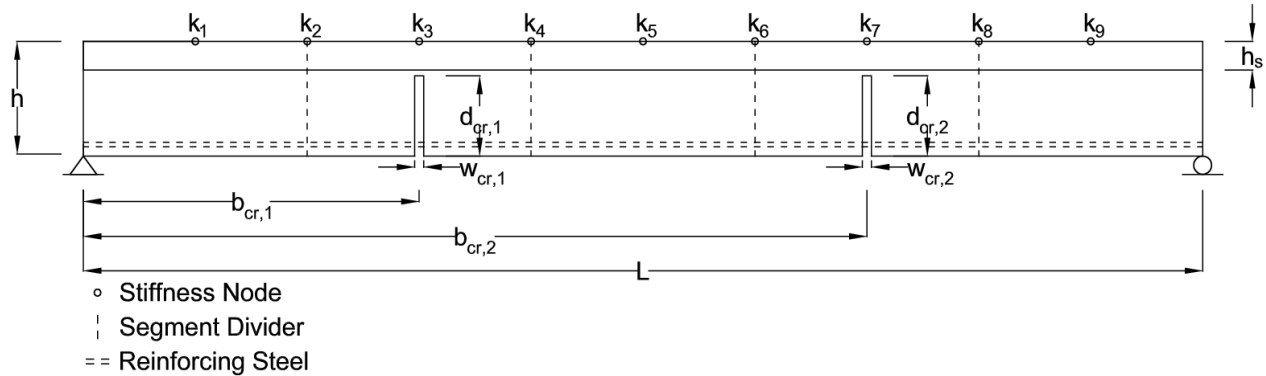


Figure 5— 3D reinforced concrete T-beam elevation view.

All beams were divided into five equal segments that could each contain up to one crack. Seventy-two healthy beams were first created to provide reference results for computation of the nodal stiffness ratios for cracked beams. A majority of the beam database was composed of beams with a single crack; a total of 6,624 singly-cracked beams were modeled. These beams were allowed to have a crack in any segment, and crack locations were varied between the beginning, middle, and end of each segment. Significantly fewer beams (3,600) with five cracks were generated. Two crack location configurations were allowed for these beams, and crack locations were set at the center of each segment. Crack location configurations are defined as a unique combination of cracked segments and b_{cr}/L values. Only 384 beams with two cracks, 448 beams with three cracks and 320 beams with four cracks were created and a crack existed in or was missing from each of the five segments. By exposing the ANNs to a large amount of data for singly-cracked beams with sample data for beams with two and five cracks, the neural networks were anticipated to provide reasonably accurate damage predictions for beams with 0–5 cracks in any configuration.

ANN Modeling for Structural Damage Detection

One ANN was trained in order to develop a structural damage detection model for 3D reinforced concrete T-beams. The network was trained with the geometric, material, and stiffness parameters (b_w/h , h_s/h , L/h , ρ , f'_c , $k\%$, where n is the n^{th} stiffness node at the nine equidistant stiffness nodes) as inputs and the crack parameters ($b_{cr,m}/L$, $d_{cr,m}/h$, and $w_{cr,m}$, where m denotes the m^{th} crack) as outputs.

Microsoft Excel spreadsheets were used to maintain the beam database and format the datasets for ANN analyses. In addition to the 14 geometric, material, and nodal stiffness input parameters and the fifteen crack parameters, the spreadsheets also contained an identification number (*ID*) and a set identifier (*Set*). The identification number served as a term by which beams were referenced between the spreadsheets and ANNs. The set identifiers had values of one, two, or three, and indicated whether the beam data was used for training, testing, or validation of the ANN, respectively. These identifiers were assigned manually in a semi-random fashion, but some beams with parameters having extreme values were assigned to the training dataset. Also, according to this procedure, 50%, 25%, and 25% of the original unique beam datasets were assigned to the training, testing, and validation sets, respectively. Table 2 displays a sample header for the Microsoft Excel spreadsheets where “I” indicates an input parameter, “O” indicates an output parameter, “m” indicates the m^{th} crack, and “n” indicates the n^{th} stiffness node.

Table 2 — Sample Microsoft Excel database header for damage detection problem

<i>ID</i>	b_w/h	h_s/h	L/h	ρ	f'_c (MPa)	$k\%$	$b_{cr,m}/L$	$d_{cr,m}/h$	$w_{cr,m}$ (mm)	<i>Set</i>
#	I	I	I	I	I	I	O	O	O	1, 2, or 3

The final reinforced concrete beam database contained data for 42,804 beams. A total of 37,116 beams (5,688 original and 31,428 duplicated by mirroring the location, depth and width of cracks) were used for training. On the other hand, one half of the original number of beams (2,844 beams) were employed in each of the testing and validating of the ANNs. Minimum and maximum parameter value ranges supplied to the ANNs were expanded to keep the actual parameter values in the sensitive region of the sigmoidal activation function of the network. The input parameter range was expanded to allow the input parameters to fit within 10%–90% of the expanded range. Nodal stiffness ratios were limited to those of a healthy beam (≤ 1.0), so the output parameter range was expanded so that only the minimum values were modified and the output parameters fit within 20%–100% of the expanded range. The expanded parameter ranges are displayed in Table 3.

Table 3 — ANN expanded parameter ranges for the damage detection problem

Inputs			Outputs		
Parameter	Minimum	Maximum	Parameter	Minimum	Maximum
b_w/h	0.45	0.95	b_{cr1}/L	0.013333	0.24667
h_s/h	0.18	0.38	d_{cr1}/h	0	0.852
L/h	6.25	13.75	w_{cr1}	0	6.6667
ρ	0.004375	0.010625	b_{cr2}/L	0.13333	0.46667
f_c MPa (ksi)	16.25 (2.35)	53.75 (7.79)	d_{cr2}/h	0	0.852
$k\%_1$	0.63539	1	w_{cr2}	0	6.6667
$k\%_2$	0.50907	1	b_{cr3}/L	0.33333	0.66667
$k\%_3$	0.47686	1	d_{cr3}/h	0	0.852
$k\%_4$	0.43376	1	w_{cr3}	0	6.6667
$k\%_5$	0.41189	1	b_{cr4}/L	0.53333	0.86667
$k\%_6$	0.43176	1	d_{cr4}/h	0	0.852
$k\%_7$	0.48287	1	w_{cr4}	0	6.6667
$k\%_8$	0.51158	1	b_{cr5}/L	0.75333	0.98667
$k\%_9$	0.63937	1	d_{cr5}/h	0	0.852
			w_{cr5}	0	6.6667

RESULTS

An ANN program with a single hidden layer was utilized in this study, and the initial number of hidden nodes was set to vary between 2 and 10. Although the maximum number of hidden nodes calculated exceeded 270, the use of 20 hidden nodes as a maximum was found to sufficiently facilitate learning within the neural network. In addition to reducing program run time, using fewer than the calculated maximum number of hidden nodes helped the ANNs avoid memorization. The training and testing datasets were used to train nine network architectures, each corresponding to a different number of initial hidden nodes. The ANNs were first evaluated by their ASE (average squared errors) and

R^2 (coefficient of correlation). The optimal initial and final numbers of hidden nodes and the number of iterations at the final hidden node were recorded for the most effective three networks in terms of their statistical measure performance. These optimal networks were then tested using the validation datasets and trained on the entire reinforced concrete T-beam database in order to expose them to all available data and establish a robust structural damage detection model. Table 4 presents the statistical results for these optimum models used during the selection of the final network structures for damage detection prediction applications.

Similarly, the artificial neural network (ANN) training process and optimal model selection procedure was applied to the finite element (FE) reinforced concrete beam model database to establish the damage detection prediction model. Model identification was based on the following nomenclature: (initial number of hidden nodes-final number of hidden nodes-iterations at the final number of hidden nodes). Statistical results from the initial training and testing phase revealed the best-performing network architectures to be models 4-15-2000, 8-10-2000, and 9-16-18900. These ANN's were then tested on the validation sets and trained on the entire database (All Data). Detailed statistical results for these optimal networks are displayed in Table 4.

Table 4 — Statistical results for optimal ANN crack prediction parameters.

		Model 1 (4-15-2000)	Model 2 (8-10-2000)	Model 3 (9-16-18900)
Training	R^2	0.40529	0.36465	0.42176
	ASE	0.045959	0.050298	0.04065
Testing	R^2	0.37743	0.2887	0.42179
	ASE	0.042688	0.04356	0.031652
Validation	R^2	0.36535	0.29846	0.40444
	ASE	0.046458	0.048582	0.035467
All Data	R^2	0.39081	0.35084	0.42564
	ASE	0.045105	0.049255	0.040025

Several general observations and trends are evident in Table 4. First and foremost, the networks displayed weak prediction accuracies with high squared errors (ASE) in all phases and coefficients of determination (R^2) in excess of 0.42 for all data analysis. As expected, the damage detection network, which predicts 15 unknowns, performed modestly according to the statistical measures due to the non-uniqueness nature of the problem, Figures 6-10. In addition, the voids in the dataset established in terms of the beams with missing two, three and four cracks are expected to contribute to slightly lowering the statistical measures of the ANN model. Enriching the database with additional information, which is very time consuming, is expected to boost the resulting statistical measures marginally. Nevertheless, these measures are expected to remain relatively modest due to the lack of uniqueness of the damage prediction process.

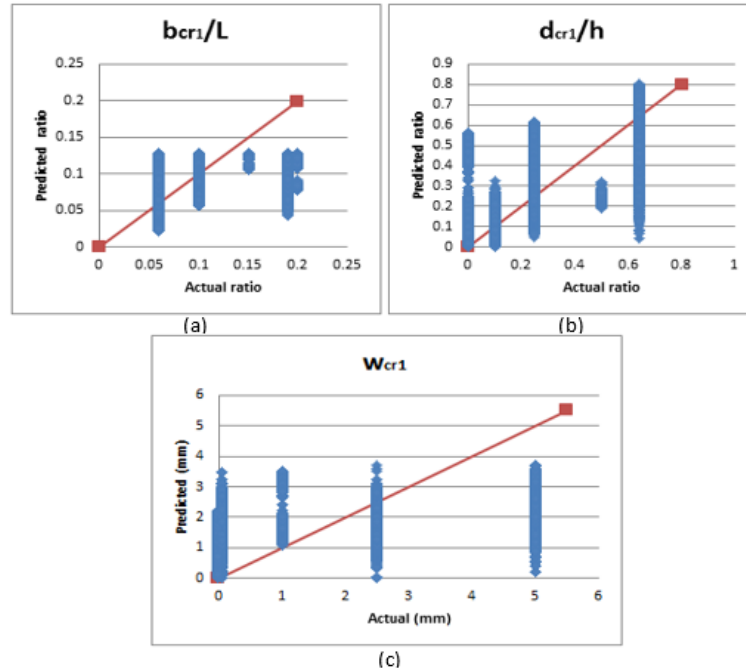


Figure 6 — Actual vs. predicted parameters of the first crack. (a) crack location-length ratio, (b) crack depth-height ratio, (c) crack width.

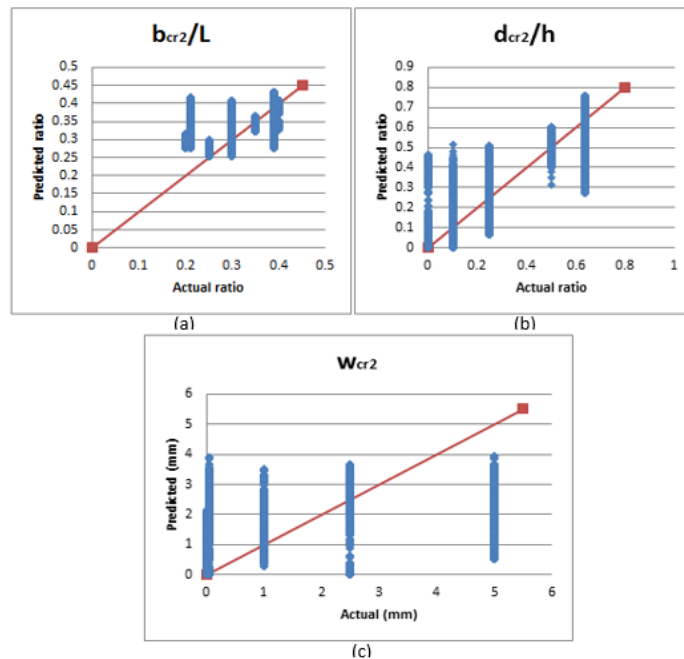


Figure 7 — Actual vs. predicted parameters of the second crack. (a) crack location-length ratio, (b) crack depth-height ratio, (c) crack width.

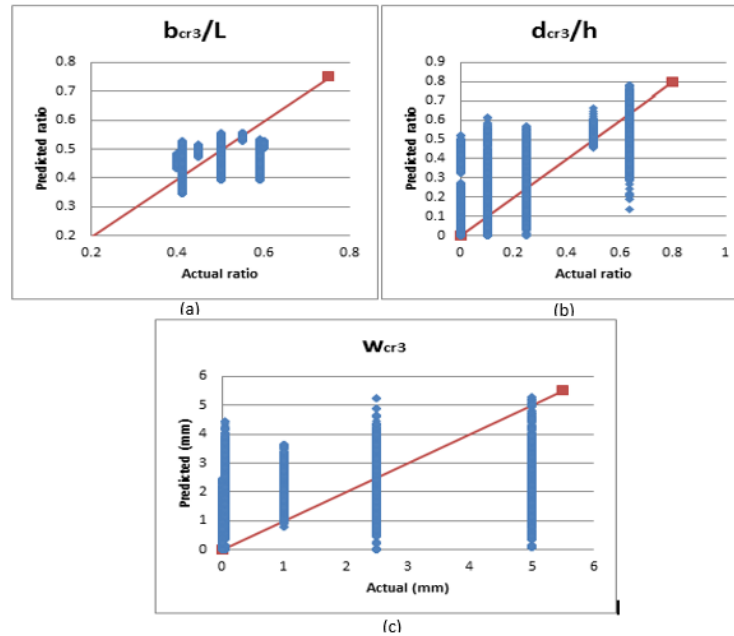


Figure 8 — Actual vs. predicted parameters of the third crack. (a) crack location-length ratio, (b) crack depth-height ratio, (c) crack width.

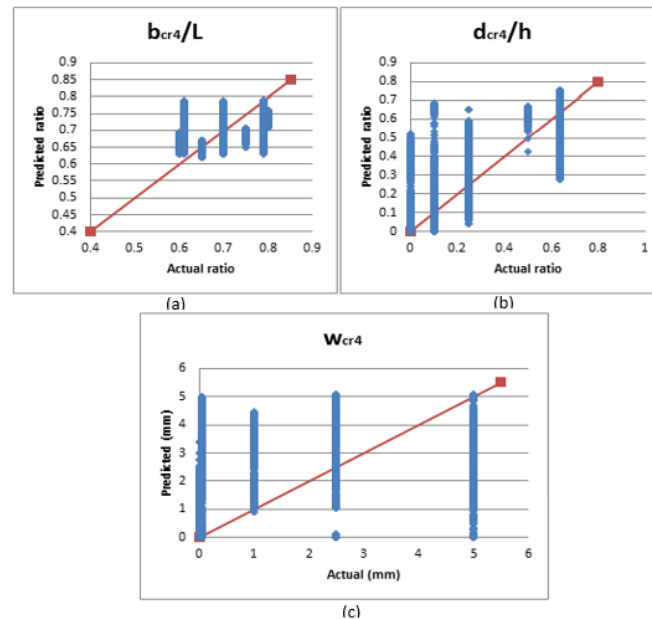


Figure 9 — Actual vs. predicted parameters of the fourth crack. (a) crack location-length ratio, (b) crack depth-height ratio, (c) crack width.

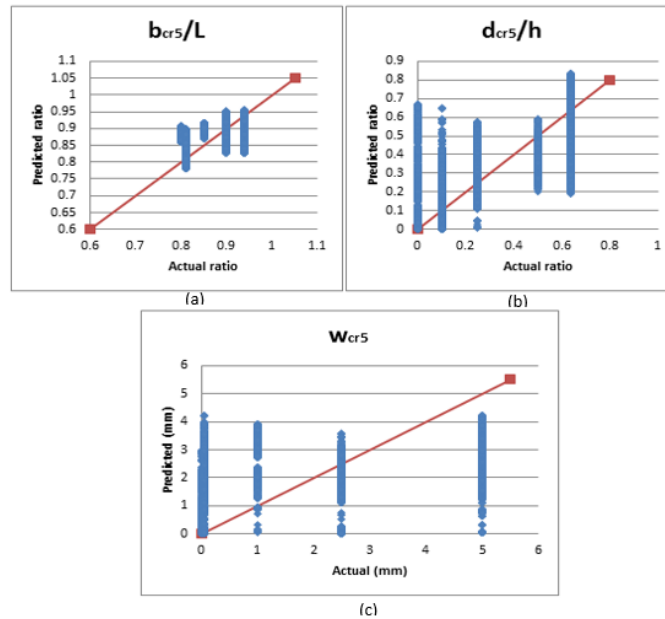


Figure 10 — Actual vs. predicted parameters of the fifth crack. (a) crack location-length ratio, (b) crack depth-height ratio, (c) crack width.

The ANN predictions are more accurate for points near the 45° fit line in Figures 6-10. These figures highlight the prediction performance of the optimal networks trained on all the data. For all figures, data points for the crack parameters prediction model were not close to the 45° fit line except for b_{cr_m}/L ratios indicating the ANN models are capable of locating the cracks with a very good accuracy. On the other hand, the presently collected and trained database was not successful in predicting the depth and width of the cracks. The overall parametric statistical study showed a modest agreement against the actual crack configurations which was indicated previously with an R^2 equal to 0.42.

ANN user interface application

After applying the artificial neural network (ANN) training process and optimum model selection procedure and evaluating the top-performing models' prediction accuracies on additional testing datasets, the optimal ANN architectures for cracking parameters prediction application were established. Biases and connection weights for the input layer-hidden layer and hidden layer-output layer were retrieved after these network structures were trained on all the data in the main database. Application of these biases and connection weights to the summation and activation functions described allowed for calculation of the ANN-predicted cracking parameters for any simply-supported reinforced concrete T-beam having parameters within the range of those used to create the finite element (FE) model database. In order to automate these calculations and facilitate on-site damage evaluation using the optimal ANN models, a touch user-interface driven electronic application was developed.

The application was developed with Visual Studio 2015 using .net framework version 4.5 on a desktop running PC Windows operating system. Figure 11 displays the final version of the graphical user interface that may be loaded on a tablet PC and used for field prediction.

Figure 11 — Cracks damage prediction graphical user interface (DRY BEAM).

As shown in Figure 11, the user interface accepts geometric and material parameters (b_w , h , h_s , L , ρ , and f'_c) in the “Beam Data” section and the nodal stiffness ratios (K_n %) in the “Nodal Stiffness” section as inputs. Upon activation of the “Solve” button, the input parameters are normalized to function as input nodes for the ANN calculations. The biases and connection weights from the optimum cracks parameters ANN models are applied to pass the input parameters to the hidden nodes and ultimately to the output nodes. The output parameters are then de-normalized, and the predicted cracks parameters are displayed in the “Results” section at the lower half of the user interface. Also after pressing the “Solve” button, the “Beam Profile” is updated to display the location of the flange of the T-beam and the location and depth of each crack. The height and length labels are also changed to reflect the user-input height and length of the beam.

Practical implementation of the field mobile app—In order to implement this mobile app into practical field applications, the user needs to evaluate and input the nodal stiffness ratios (K_n %). These could be easily determined by loading the bridge girder directly with a vehicle load with its centroid placed on the stiffness nodes while measuring the relative deflections at the stiffness nodes using theodolite readings. This will establish the stiffness values of the damaged beams at the stiffness nodes. When normalizing these stiffness values by their healthy beam counterparts through FE analysis, the nodal stiffness ratios (K_n %) are furnished. These nodal stiffness ratios, along with the geometric and material parameters of the girder, are input into the field mobile app to predict the fifteen cracking parameters. So long as the crack locations are predicted accurately, the crack depths and widths are not as critical to be recovered very accurately but rather estimates of these values may be used.

Conclusion

This paper investigates the potential for application of the finite element (FE) method and artificial neural networks (ANN) to create a damage detection model for 3D reinforced concrete bridge T-girders that could be utilized with nodal stiffness ratios as inputs. A three-dimensional reinforced concrete T-beam FE model database was constructed using ABAQUS FE software. Geometric (b_w/h , h_s/h , L/h , and ρ), material (f'_c) parameters, and nine equidistant nodes along the beams (k_n %) were varied between the models. Damage detection measures were then computed, including the cracking ($b_{cr,m}/L$, $d_{cr,m}/h$, and $w_{cr,m}$) parameters. One ANN was employed to predict the damage configurations of beams up to five cracks. The predicted damage parameters define the location, the depth, and the width of each crack. The ANN accepted the geometric, material, and the nodal stiffness ratios as inputs and predicted the crack parameters as outputs. Upon determining the optimum model for crack configuration prediction, the statistical results for this optimum model were modest with R^2 value equal to 0.42 in the training, testing, and validation phases due to the non-uniqueness of these cracking predictions and missing cases from the two, three and four cracks in the database.

Utilizing this network architecture, a touch-enabled mobile application was developed to serve as an on-site damage prediction tool. This application has been given the acronym DRY BEAM, which stands for Damage Recognition Yielding Bridge Evaluation After Monitoring. The low R^2 for the damage detection ANN indicates the effect of the non-uniqueness of this problem due to the high number of unknowns.

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AlaaEldin Abouelleil is Senior Structural Software Developer with Advanced Engineering Design Apps (AEDA, LLC). He received his BS and MS in civil engineering and his PhD in structural engineering from Kansas State University, Manhattan, KS. His research interests are in the areas of shear behavior of reinforced concrete beams and columns.

ACI Fellow **Hayder A. Rasheed** is Professor of structural engineering at Kansas State University. He received his BS and MS from the University of Baghdad, Baghdad, Iraq, and his PhD from The University of Texas at Austin, Austin, TX. He is a member of ACI Committees 369, Seismic Repair and Rehabilitation; 440, Fiber-Reinforced Polymer Reinforcement; and Joint ACI-ASCE Committee 441, Reinforced Concrete Columns. His research interests include reinforced concrete and composite behavior.

Eric Fletcher is a professional engineer at BSE Structural Engineers LLC in Lenexa, KS. He received his BS and MS in civil engineering from Kansas State University, Manhattan, KS. His research interests are in the areas of Artificial Intelligence (AI) and health monitoring of concrete structures.

References

- ABAQUS (2013). Abaqus 6.13 [computer software]. Providence, RI: Dassault Systèmes Simulia Corp.
- Al-Rahmani, A. (2012). *A combined soft computing-mechanics approach to damage evaluation and detection in reinforced concrete beams* (Master's thesis). Kansas State University, Manhattan, Kansas.
- Al-Rahmani, A., Rasheed, H., & Najjar, Y. (2013). Intelligent damage detection in bridge girders: Hybrid approach. *Journal of Engineering Mechanics*, 139(3), 296-304. doi: 10.1061/(ASCE)EM.1943-7889.0000536.
- Al-Rahmani, A., Rasheed, H., & Najjar, Y. (2014). An artificial intelligence approach to objective health monitoring and damage detection in concrete bridge girders. *American Concrete Institute Special Publication*, 298(6), 73-89.
- American Concrete Institute Committee 318. (2014). *Building code requirements for structural concrete and commentary*. (ACI 318-14). Farmington Hills, MI: American Concrete Institute.
- Beer, F. P., Johnston, E. R., Dewolf, J. T., & Mazurek, D. F. (2012). *Mechanics of Materials* (6th ed.). New York, NY: McGraw-Hill Companies, Inc.
- Chen, S., Liu, W., Bian, H., & Smith, B. (2012). *3D LiDAR scans for bridge damage evaluation*. Paper presented at the 6th Congress on Forensic Engineering: Gateway to a Better Tomorrow. San Francisco, CA, United States. doi:10.1061/9780784412640.052.
- Ghods, A. S., & Esfahani, M. R. (2009, July 22–24). *Damage assessment of reinforced concrete beams by modal test*. Paper presented at the 4th International Conference on Structural Health Monitoring of Intelligent Infrastructure. Zurich, Switzerland. Retrieved from Compendex database.
- Hasançebi, O., & Dumlupinar, T. (2013). Linear and nonlinear model updating of reinforced concrete T-beam bridges using artificial neural networks. *Computers & Structures*, 119, 1–11. doi:10.1016/j.compstruc.2012.12.017.

- Jeyasehar, C. A., & Sumangala, K. (2006). Damage assessment of prestressed concrete beams using artificial neural network (ANN) approach. *Computers & Structures*, 84(26), 1709–1718. doi:10.1016/j.compstruc.2006.03.005.
- Li, L., Ghrib, S., & Lee, S. (2008, Jun 10-13). *Damage identification of reinforced concrete beams by digital image correlation and FE-updating*. Paper presented at the Canadian Society for Civil Engineering Annual Conference: Partnership for Innovation. Quebec City, QC, Canada. Retrieved from Compendex database.
- Ndambi, J., Vantomme, J., & Harri, K. (2002). Damage assessment in reinforced concrete beams using eigenfrequencies and mode shape derivatives. *Engineering Structures*, 24(4), 501–515. doi:10.1016/S0141-0296(01)00117-1.
- Ongpeng, J. M. C., Oreta, A. W. C., & Hirose, S. (2018). Monitoring damage using acoustic emission source location and computational geometry in reinforced concrete beams. *Applied Sciences*, 8(2), 189.
- Reynders, E., & De Roeck, G. (2009). A local flexibility method for vibration-based damage localization and quantification. *Journal of Sound and Vibration*, 329(12), 2367–2383. doi:10.1016/j.jsv.2009.04.026.
- Sagar, R. V., Prasad, B. K. R., & Sharma, R. (2012). Evaluation of damage in reinforced concrete bridge beams using acoustic emission technique. *Nondestructive Testing and Evaluation*, 27(2), 95–108. doi:10.1080/10589759.2011.610452.
- Shiotani, T., Ohtsu, H., Momoki, S., Chai, H. K., Onishi, H., & Kamada, T. (2012). Damage evaluation for concrete bridge deck by means of stress wave techniques. *Journal of Bridge Engineering*, 17(6), 847–856. doi:10.1061/(ASCE)BE.1943-5592.0000373.
- Tan, Z. X., Thambiratnam, D. P., Chan, T. H., Gordan, M., & Abdul Razak, H. (2020). Damage detection in steel-concrete composite bridge using vibration characteristics and artificial neural network. *Structure and Infrastructure Engineering*, 16(9), 1247-1261.
- Teughels, A., Maeck, J., & De Roeck, G. (2002). Damage assessment by FE model updating using damage functions. *Computers & Structures*, 80(25), 1869–1879. doi:10.1016/S0045-7949(02)00217-1.

Machine Learning Driven Drift Capacity Model for Reinforced Concrete Walls

Muneera Aladsani, Henry Burton, Ph.D., S.E., Saman Abdullah, Ph.D.,
and John Wallace, Ph.D., P.E.

Synopsis: Many modeling approaches in engineering are based on physical principles. The input and output relationships are developed using physical laws (e.g., Newton's laws of motion and conservation of mass and energy). However, in many situations, the development of physically-based models requires simplifying assumptions due to the complicated nature of the systems, which could lead to a large degree of uncertainty. In these situations, data can be used to formulate models by detecting relationships between the system's variables (inputs and outputs) without explicitly knowing the physical behavior of the system. Therefore, there is a paradigm shift from physically-based models to data-driven models. The objective of this study is to develop a drift capacity prediction model for structural walls with special boundary elements using the extreme gradient boosting (XGBoost) machine learning algorithm. The resulting prediction model is compared with the recently developed empirical model presented in literature i.e., the Abdullah & Wallace (2019) model. The results reveal the proposed model's superior predictive capabilities relative to the empirical model.

Keywords: reinforced concrete walls, special boundary elements, drift capacity, machine learning, extreme gradient boosting, artificial intelligence

INTRODUCTION

Background on Machine Learning

Machine Learning (ML) can be defined as methods and techniques that are utilized to improve performance and produce accurate results using past experience (training data). It allows computers to learn from data to be able to make predictions or conclusions without being explicitly programmed. ML is a branch of Artificial Intelligence (AI). A system is considered intelligent if it has the ability to learn in a changing environment. The system learns and adapts to changes so that it would be able to predict solutions for all possible situations (Alpaydin, 2009).

ML algorithms can be placed in one of the following three categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning algorithms are used when labeled training data are available. The aim of supervised learning is to map between input examples and the target variable. It starts with analyzing the training dataset to produce an inferred function to make predictions for any new input variable. The two main supervised learning methods are regression and classification which involves predicting continuous and discrete target variables, respectively.

Unsupervised learning is used when there is no prior information about the labels i.e., the training data are not labeled. Data-exploration is used to draw inferences and help find previously unknown patterns. The most common unsupervised learning method is cluster analysis. Clustering is the task of identifying similarities between the observations (input) so that they are grouped together.

Reinforcement learning lies between supervised learning and unsupervised learning. It is learning by interacting with an environment. This method enables an agent to learn by trial and error using feedback. The agent gets either rewards or penalties for the actions performed. The goal is to determine the ideal sequence of actions to maximize the total cumulative reward.

Machine Learning for Structural Reinforced Concrete Applications

Over the last decade, the field of ML has moved from theoretical studies to real-world applications. Especially within the last few years, the application of ML techniques in the field of structural engineering is considered as an intensive area of research. This interest in ML methods grew out of their ability to capture nonlinear and complex relations between the different variables represented in the data and provide more accurate predictions of the system behavior. In this section, the focus is placed on studies that utilized ML techniques in predicting behavior and capacities of different reinforced concrete (RC) structural elements.

Luo and Paal (2018) proposed a ML-based backbone curve model for RC rectangular columns exhibiting different failure modes due to reversed cyclic loading. They developed a multioutput least-squares support vector machine regression procedure (MLS-SVMR) to predict the four parameters that define the backbone curve. The same authors (Luo and Paal, 2019) later proposed a ML model called locally weighted least squares support vector machines for regression (LWLS-SVMR), which integrates LS-SVMR with locally weighted training criteria to enhance and generalize the prediction of the drift capacity of RC columns, regardless of the failure mode or column features.

Inel (2007) used artificial neural networks (ANN) to estimate the ultimate deformation of RC columns whose behavior is dominated by flexure. The considered experimental data, which were obtained from literature, consists of 237 rectangular columns. The input parameters included aspect ratio, longitudinal reinforcement ratio, yield strength of longitudinal and transverse reinforcement, uniaxial concrete compressive strength, transverse reinforcement spacing, ratio of transverse reinforcement parallel to the direction of loading, axial load ratio, and confinement effectiveness factor.

Mangalathu and Jeon (2019) investigated the ability of ML techniques such as quadratic discriminant analysis (QDA), K-nearest neighbors (KNN), decision trees (DT), random forests (RF), naïve Bayes (NB), and ANN in identifying the failure mode of RC bridge columns with circular cross-section. An experimental database, which included reported failure modes of bridge columns under different geometries, material properties, and axial load ratios, was assembled. The comparison of various ML techniques confirmed that ANN and QDA perform the best among the considered ML techniques.

Feng et al. (2020) presented an approach for failure mode (FM) classification and bearing capacity prediction of RC columns using adaptive boosting (AdaBoost), which is an ensemble ML algorithm. A dataset of 254 cyclic loading tests of RC columns was gathered from the Pacific Earthquake Engineering Research Center (PEER) website. The

geometric dimensions, material properties, and reinforcing details were used as the input features. Different learning algorithms were employed and their results were compared to those of the AdaBoost algorithm.

Vu and Hoang (2016) established a hybrid ML model for predicting the punching shear capacity of FRP-reinforced concrete slabs. The proposed model is constructed by hybridizing the LS-SVM, which is used to learn the nonlinear mapping between the input variables and the punching shear strength with the firefly algorithm. The performance of the proposed model is compared to those of ANN and several analytical equations.

Almustafa and Nehdi (2020) developed a ML model to predict the maximum displacement of RC slabs subjected to blast loading by implementing a hybrid classification-regression Random Forests algorithm. They utilized a dataset of 150 points retrieved from the results of physical testing programs and experimentally validated numerical models. The performance of the proposed model in predicting maximum slab displacement under blast loading was satisfactory and more effective than existing numerical approaches.

Pham et al. (2020) proposed an ML model for predicting long-term deflections in cracked RC flexural members such as beams and slabs. The model's efficacy was evaluated by comparing its predictive accuracy among single, ensemble ML models, and empirical methods using a large set of long-term tests on RC flexural members. The experimental dataset consisted of 181 tests on RC simply supported beams and slabs. The study identified the most important parameters for forecasting long-term deflections in RC members.

Many researchers have attempted to predict shear strength of RC beams. Pal and Deswal (2011) proposed an SVR-based approach to predict the shear strength of RC deep beams. A hybrid model that combines a smart artificial firefly colony algorithm (SFA) and least squares support vector regression (LS-SVR) was also used to predict the shear strength of RC deep beams reported by Chou et al. (2016). The hyperparameters of the LS-SVR were optimized via the SFA to generate an optimal LS-SVR model. A dataset, which contains experimental results from 214 RC deep beam tests, was collected to establish and confirm the proposed prediction model's applicability and efficiency. Fiore et al. (2016) adopted a hybrid computational technique called evolutionary polynomial regression to estimate shear capacity of rectangular RC beams without stirrups. Additionally, Linear genetic programming has been applied to predict shear strength of RC beams without stirrups (Gandomi et al., 2014). Zhang et al. (2020) constructed a random forest model to predict shear strength of RC beams with and without stirrups. They utilized two datasets, one for beams with stirrups and one without stirrups, and the developed model resulted in high prediction accuracy for both datasets. They were able to conclude through the calculated variable importance that the geometry and reinforcement ratio have significant influence on shear strength of RC beams with and without stirrups. Finally, Prayogo et al. (2020) introduced an inference model, called optimized support vector machines with adaptive ensemble weighting, to predict shear strength of RC deep beams. This technique combines the support vector machine (SVM) and least-squares support vector machine (LS-SVM) with the SOS optimization algorithm as the optimizer.

Focus and Scope of the Current Study

Abdullah and Wallace (2019) assembled an RC wall database with detailed information on more than 1000 tests (called UCLA-RCWalls database, see Abdullah, 2019) and filtered it to obtain a subset of ACI 318-14 code-, or nearly code-, compliant walls with special boundary elements (SBE). Using the filtered dataset, they first studied the impact of multiple parameters on the lateral drift capacity of walls with SBEs. They suggested that the most influential parameters are the combined slenderness parameter ($\lambda_b = l_w c / b^2$) which accounts for the slenderness of both the entire cross section and the compression zone, the shear stress demand, and the configuration of boundary transverse reinforcement. Furthermore, they applied linear regression analysis considering the aforementioned parameters and developed a model to predict the lateral drift capacity of structural walls with SBEs. Their model was adopted in ACI 318-19, Equation (18.10.6.2b). Nonetheless, due to the nonlinearity that exists between different influencing variables, a model that considers this complexity is necessary to provide more accurate predictions of the wall drift capacity, which is the focus of this study.

OVERVIEW OF METHDOLOGY

A schematic overview of the methodology used to develop a drift capacity prediction model for structural walls with SBEs using the XGBoost algorithm and assess its performance is shown in Figure 1. As shown, the first step is the feature selection. The variables that impact wall drift capacity are investigated and, using statistical methods, the most influential features are chosen as input variables for the model. Next, using cross-validation, the data is split to tune the hyperparameters and evaluate the model performance. The performance metrics used in this study are explained, and an easy-to-interpret and -adapt metric is proposed.

After developing the proposed model, its performance is compared with that developed by Abdullah and Wallace (2019) by: a) developing two separated models based on the configuration of boundary transverse reinforcement, and b) including the configuration of boundary transverse reinforcement as an input feature. The model is constructed using the same dataset used by Abdullah and Wallace (2019), i.e., the results from the 164 test specimens.

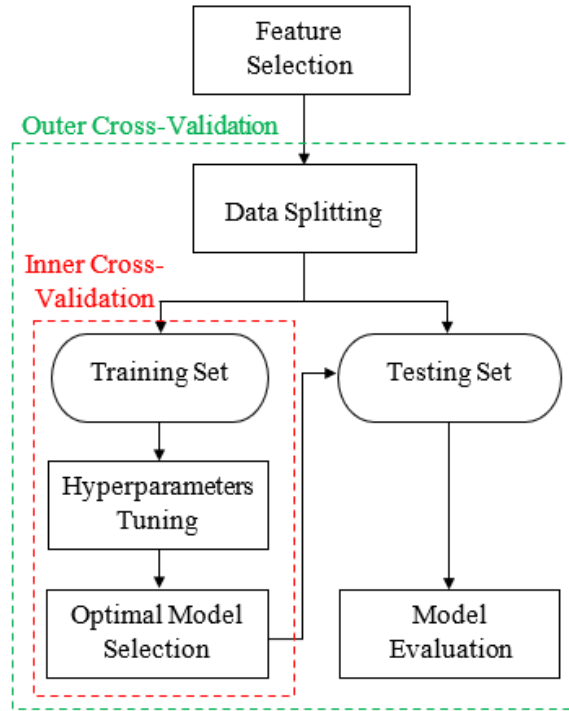


Figure 1— Development of the machine learning model

FEATURE SELECTION

Feature or variable selection is the process of selecting a subset of inputs that contribute most to the target variable. The objective is to retain relevant features and remove the irrelevant and/or redundant ones as they can negatively impact the model performance. Therefore, it should be the first step in designing the model. Furthermore, effective feature selection can also reduce the computation time associated with training, avoid unnecessarily complex models, improve prediction performance, and lead to a better understanding of the data.

The considered features, which are selected based on the Abdullah and Wallace study, include the impact of the slenderness of the cross-section (l_w/b), slenderness of the compression zone of the cross-section (c/b), the shear stress demand ($v_{max}/\sqrt{f'_c}$), the axial load ratio ($P/A_g f'_c$), the ratio of provided-to-required (by ACI 318-19) area of boundary transverse reinforcement ($A_{sh,prov}/A_{sh,req}$), the ratio of transverse reinforcement spacing to longitudinal bar diameter (s/d_b), the ratio of centerline distance between laterally supported boundary longitudinal bars to the width of the compression zone (h_x/b), the boundary longitudinal reinforcement ratio ($\rho_{long,BE}$), the web transverse reinforcement ratio ($\rho_{t,web}$), the ratio of neutral axis depth to wall length (c/l_w), the length of the confined boundary normalized by wall length (l_{BE}/l_w), the ratio of tested tensile-to-yield strength of the boundary longitudinal reinforcement (f_u/f_y), and the configuration of boundary transverse reinforcement.

To quantitatively assess the relationship between each feature and the drift capacity, Spearman's correlation coefficient is used. Spearman's correlation coefficient is a statistical measure of the strength and direction of a monotonic relationship between two variables. Unlike Pearson's correlation coefficient, it does not require the assumption of a linear association between variables. Like other correlation coefficients, Spearman's correlation coefficient varies between -1 and +1 with 0 implying no correlation. Table 1 reports the Spearman's correlation coefficient (r_s) between the individual features and drift capacity. It is observed that λ_b , $v_{max}/\sqrt{f'_c}$, $A_{sh,prov}/A_{sh,req}$, $\rho_{long,BE}$, $\rho_{t,web}$, h_x/b , and c/l_w have measurable association with the drift capacity.

Table 1— Spearman's correlation coefficient between each feature and the drift capacity

Variable	Correlation Coefficient
λ_b	-0.659
$v_{max}/\sqrt{f'_c}$	-0.356
$P/A_g f'_c$	-0.106
$A_{sh,prov}/A_{sh,req}$	0.220
s/d_b	0.044
$\rho_{long,BE}$	-0.367
$\rho_{t,web}$	-0.212
c/l_w	-0.352
h_x/b	-0.168
l_{BE}/l_w	0.059
f_u/f_y	-0.127

The Spearman's correlation evaluates the relationship between each feature and the drift capacity without considering the effect of others. This can be deceptive because having two features that are highly correlated with the output and with each other might negatively impact the model. Therefore, the second technique used for the feature selection is importance score quantification. Scores assigned to each input feature indicate its relative importance in predicting the target variable. The type of feature importance used is the average gain of the feature when it is used in trees. For gradient boosted trees, there is no need to check for multicollinearity because of its robustness (Chen et al. 2018). However, it is good practice to remove highly correlated or redundant features before training regardless of the model's algorithm. Thus, before applying the importance score technique, only one feature is retained for each pair of highly correlated features ($|r_s| > 0.5$). From the Spearman's correlation matrix, we observe that $v_{max}/\sqrt{f'_c}$ is correlated with $\rho_{t,web}$, c/l_w is correlated with $P/A_g f'_c$, and $\rho_{long,BE}$ is correlated with s/d_b . Since $v_{max}/\sqrt{f'_c}$, c/l_w , and $\rho_{long,BE}$ have higher correlation coefficients with the drift capacity, $\rho_{t,web}$, s/d_b , and $P/f'_c A_g$ are eliminated before implementing the importance score technique.

As can be seen from Figure 2, λ_b and $v_{max}/\sqrt{f'_c}$ have the highest feature importance values which are equal to 0.491 and 0.188, respectively. The rest of the features have feature importance scores ranging between 0.071 and 0.039. A higher importance value implies that the corresponding feature is more important for generating a prediction when compared with a feature with a lower importance value. It can, therefore, be concluded that the two most important features used in the model are λ_b and $v_{max}/\sqrt{f'_c}$. To test the association between the drift capacity and the configuration of the boundary transverse reinforcement, the ANOVA (analysis of variance) test was performed, and it was concluded that there are significant differences among the configuration of boundary transverse reinforcement.

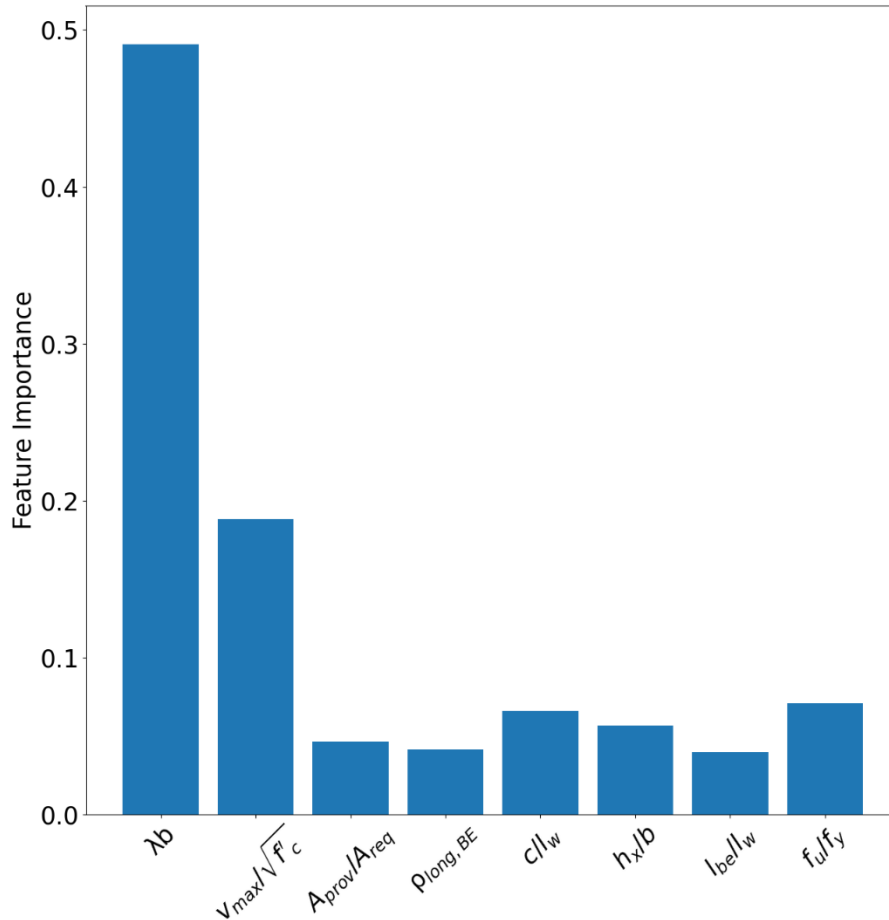


Figure 2— Feature importance score for each input parameter

EXTREME GRADIENT BOOSTING ALGORITHM

Extreme Gradient Boosting (XGBoost) is a scalable ML algorithm for tree boosting proposed by Chen and Guestrin (2016). It is a tree-based method which builds decision trees sequentially. A decision tree, as illustrated in Figure 3, is a supervised learning approach that implements a sequential decision process. It consists of decision nodes and terminal leaves. Each decision node represents a test on a feature, which forms the basis for splitting the tree into branches. This procedure starts from the root node and is repeated recursively until a leaf node is reached, which represents the output. “Gradient Boosting”, which originates from the paper by Friedman (2001), iteratively combines weak learners into a single stronger ML model. As shown in Figure 4, the residual, which is the difference between the observed and the predicted value, is used to correct the previous predictor at each iteration of gradient boosting. Readers are referred to Chen and Guestrin (2016) for the details of the mathematical formulation of the XGBoost algorithm.

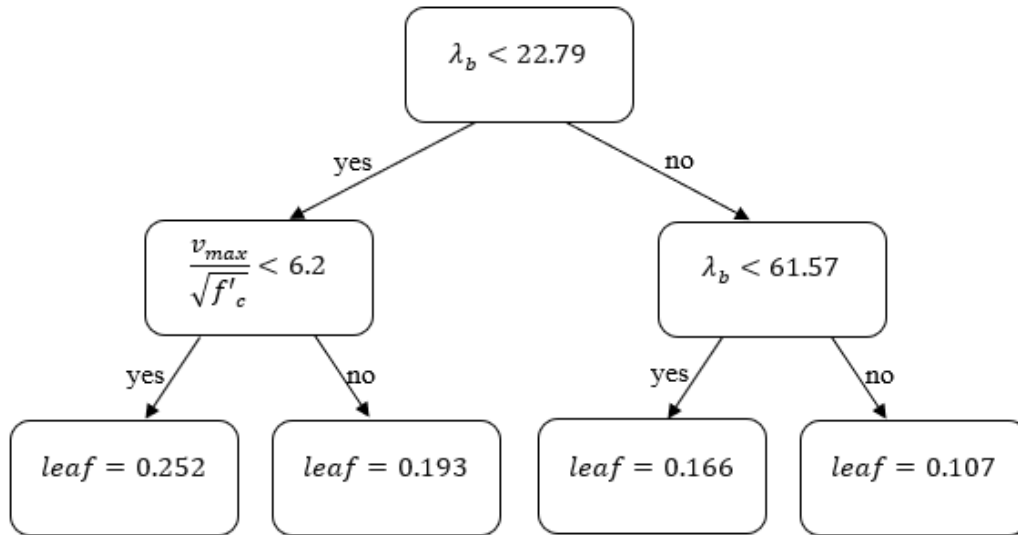


Figure 3— Graphical illustration of decision tree model

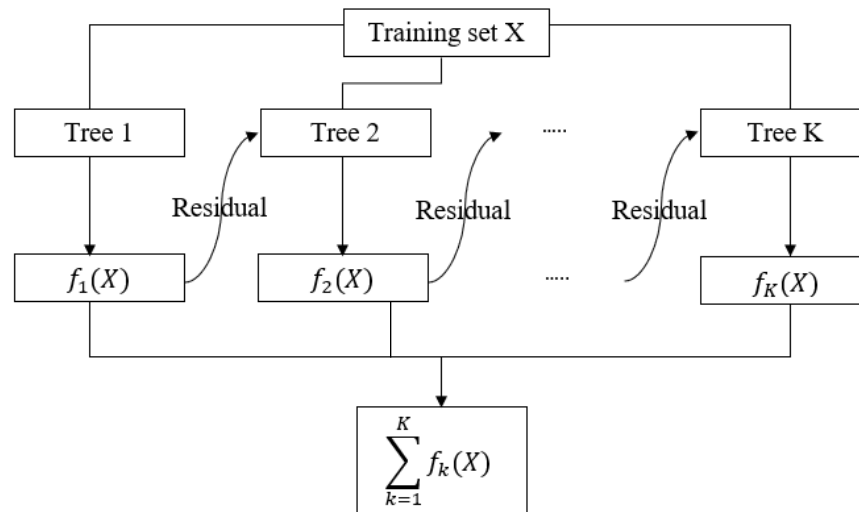


Figure 4— Flowchart of gradient boosting

STATISTICAL PERFORMANCE EVALUATION

The performance of prediction models is evaluated using three metrics that incorporate the predicted and observed drift capacity: the root mean square error ($RMSE$), the coefficient of determination (R^2), and D_{X_u, X_o} , which is a new performance metric introduced in this study. $RMSE$ is computed as the square root of the average of squared differences between the predicted and observed values. This metric gives a relatively high weight to large errors; therefore, it efficiently identifies undesirably large differences. However, while $RMSE$ is useful for comparing the performance of different models, it is less useful for evaluating the adequacy of a single model. The second metric, coefficient of determination, which indicates the fraction of the data variance that is captured in the model. The third metric, which is proposed as part of the current study, is much easier to interpret and adapt (compared to $RMSE$ and R^2). This is especially true when evaluating the effectiveness of a single model. It is similar to the accuracy that is used to evaluate classification tasks, which is calculated as the number of correct predictions ($\hat{y}_i = y_i$) divided by the total number of predictions. Instead of using the true value (i.e., $\hat{y}_i = y_i$), which is not applicable in regression tasks, the “acceptable” predictions are defined as those that satisfy the following equation:

$$(1 - X_u) \leq \left(\frac{\hat{y}_i}{y_i} \right) \leq (1 + X_o) \quad (1)$$

Where X_u and X_o are predefined lower- and upper-bound thresholds, respectively, which are defined as fractions or percentages, y_i is the actual value for observation i , and $\hat{y}_i$ is the predicted value for observation i . One of the advantages of this approach is that different thresholds can be specified to evaluate the performance based on underestimating and overestimating the results. For example, if there is a need to be more lenient towards underestimation, the value of X_u would be larger than X_o and vice versa.

The performance metric is mathematically defined as:

$$D_{X_u, X_o} = \frac{N_{(1-X_u) \leq \left(\frac{\hat{y}_i}{y_i} \right) \leq (1+X_o)}}{N_T} \quad (2)$$

Where $N_{(1-X_u) \leq \left(\frac{\hat{y}_i}{y_i} \right) \leq (1+X_o)}$ is the number of predictions that satisfy the inequality in Equation 1 and N_T is the total number of predictions.

RESULTS AND DISCUSSION

The XGBoost model is compared with the predictive equation (Equation 3) for the mean drift capacity of walls with SBEs presented in Abdullah and Wallace (2019):

$$\frac{\delta_c}{h_w} (\%) = 3.85 - \frac{\lambda_b}{\alpha} - \frac{v_{max}}{10\sqrt{f'_c} \text{ psi}} \quad (3)$$

Where $\alpha = \begin{cases} 60 & \text{for overlapping hoops} \\ 45 & \text{for single perimeter hoop with crossties} \end{cases}$

To ensure a fair comparison, two models are trained using the XGBoost algorithm, one for walls with overlapping hoops and the other for walls with single perimeter hoop with crossties. Also, the same data is used for both training and testing. Table 2 shows values of $RMSE$, R^2 , $D_{25\%,25\%}$, $D_{10\%,10\%}$, and the mean and coefficient of variation of the ratio of predicted-to-experimental drift capacity for both models. The latter two metrics were used in the Abdullah and Wallace study. Note that XGBoost1 represents two different models based on the configuration of boundary transverse reinforcement (as was done in the Abdullah & Wallace study). However, using the target encoding approach, a single model that includes the configuration of boundary transverse reinforcement as a feature (XGBoost2) is also developed. It should be noted that the same dataset (164 wall tests) is used for both models.

Table 2— Comparing the performance of the XGBoost and Abdullah & Wallace (2019) models

Model	RMSE (%)	R^2	$D_{25\%,25\%}$	$D_{10\%,10\%}$	Predicted/experimental ratio	
					Mean	COV
XGBoost1	0.200	0.910	0.987	0.800	1.000	0.074
XGBoost2	0.233	0.870	0.988	0.756	0.999	0.085
Abdullah & Wallace (2019)	0.403	0.612	0.848	0.518	0.983	0.151

Figure 5 presents the experimental versus the predicted drift capacities of the RC walls using XGBoost and the model proposed in Abdullah and Wallace (2019). Both Figure 5 and Table 2 show that the proposed ML model can predict

the drift capacity of RC walls much better than the model presented in Abdullah and Wallace (2019). Additionally, a model is trained using XGBoost algorithm that includes the configuration of boundary transverse reinforcement as an input feature to compare its results with that of the two XGBoost separated models. The results demonstrate that the ML model can include different types of configuration of boundary transverse reinforcement (i.e., no need to have multiple models), and it produces similar results to the separated models.

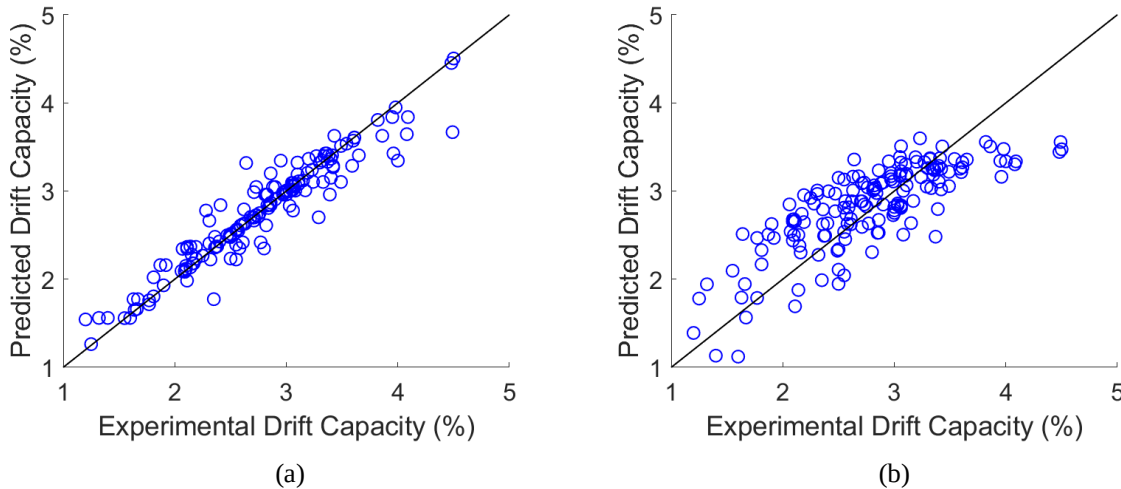


Figure 5— Measured versus predicted drift capacity: (a) XGBoost model; (b) Abdullah and Wallace (2019) model

CONCLUSION

Geometrical and mechanical characteristics have complex nonlinear effects on the drift capacity of RC walls. This study employed a ML algorithm called XGBoost to predict drift capacity of RC walls with SBEs. The UCLA-RCWall database was utilized in this study. First, a set of preliminary features were investigated, and the most influential ones based on correlation and feature importance were selected for the prediction model. The results showed that the most important features are λ_b , $v_{max}/\sqrt{f'_c}$, and the configuration of boundary transverse reinforcement. To confirm the proposed model's reliability and efficiency, its predictive performance was compared with that of an empirical model presented in literature. The results revealed that the XGBoost is more accurate in terms of estimating drift capacity for RC walls due to its ability to capture the nonlinearity that exists between the drift capacity and the different influencing variables.

REFERENCES

- Abdullah, S., & Wallace, J. (2019). Drift capacity of reinforced concrete structural walls with special boundary elements. *ACI Structural Journal*, 116(1), 183-194.
- ACI Committee 318, (2014) Building Code Requirements for Structural Concrete (ACI 318-14) and Commentary (ACI 318R-14), American Concrete Institute, Farmington Hills, MI, 519 pp.
- Almustafa, M., & Nehdi, M. (2020). Machine learning model for predicting structural response of RC slabs exposed to blast loading. *Engineering Structures*, 221.
- Alpaydin, E. (2009). *Introduction to Machine Learning* (2nd ed.). The MIT Press.
- Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 13-17-August-2016, pp. 785-794. Association for Computing Machinery.
- Chen, T., He, T., Benesty, M., & Tang, Y. (2018). Understand your dataset with Xgboost. Retrieved from <https://cran.r-project.org/web/packages/xgboost/vignettes/discoverYourData.html>.

- Chou, J., Ngo, N., & Pham, A. (2016). Shear Strength Prediction in Reinforced Concrete Deep Beams Using Nature-Inspired Metaheuristic Support Vector Regression. *Journal of Computing in Civil Engineering*, 30(1).
- Feng, D., Liu, Z., Wang, X., Jiang, Z., & Liang, S. (2020). Failure mode classification and bearing capacity prediction for reinforced concrete columns based on ensemble machine learning algorithm. *Advanced Engineering Informatics*, 45.
- Fiore, A., Quaranta, G., Marano, G., & Monti, G. (2016). Evolutionary Polynomial Regression-Based Statistical Determination of the Shear Capacity Equation for Reinforced Concrete Beams without Stirrups. *Journal of Computing in Civil Engineering*, 30(1).
- Friedman, J. (2001). Greedy function approximation: a gradient boosting machine. *Annals of Statistics*, 29(5), 1189–1232.
- Gandomi, A., Mohammadzadeh S., D., Pérez-Ordóñez, J., & Alavi, A. (2014). Linear genetic programming for shear strength prediction of reinforced concrete beams without stirrups. *Applied Soft Computing Journal*, 19, 112-120.
- Inel, M. (2007). Modeling ultimate deformation capacity of RC columns using artificial neural networks. *Engineering Structures*, 29(3), 329-335.
- Luo, H., & Paal, S. (2018). Machine Learning-Based Backbone Curve Model of Reinforced Concrete Columns Subjected to Cyclic Loading Reversals. *Journal of Computing in Civil Engineering*, 32(5).
- Luo, H., & Paal, S. (2019). A locally weighted machine learning model for generalized prediction of drift capacity in seismic vulnerability assessments. *Computer-Aided Civil and Infrastructure Engineering*, 34(11), 935-950.
- Mangalathu, S., & Jeon, J. (2019). Machine Learning-Based Failure Mode Recognition of Circular Reinforced Concrete Bridge Columns: Comparative Study. *Journal of Structural Engineering (United States)*, 145(10).
- Pal, M., & Deswal, S. (2011). Support vector regression based shear strength modelling of deep beams. *Computers and Structures*, 89(13-14), 1430-1439.
- Pham, A.-D., Ngo, N.-T., & Nguyen, T.-K. (2020). Machine learning for predicting long-term deflections in reinforced concrete flexural structures. *Journal of Computational Design and Engineering*, 7(1), 95-106.
- Pradhan, A., & Bouwkamp, J. (1992). *Shear Walls in Hybrid construction for aseismic design*. Rotterdam: Balkema.
- Prayogo, D., Cheng, M., Wu, Y., & Tran, D. (2020). Combining machine learning models via adaptive ensemble weighting for prediction of shear capacity of reinforced-concrete deep beams. *Engineering with Computers*, 36(3), 1135-1153.
- Vu, D., & Hoang, N. (2016). Punching shear capacity estimation of FRP-reinforced concrete slabs using a hybrid machine learning approach. *Structure and Infrastructure Engineering*, 12(9), 1153-1161.
- Zhang, J., Sun, Y., Li, G., Wang, Y., Sun, J., & Li, J. (2020). Machine-learning-assisted shear strength prediction of reinforced concrete beams with and without stirrups. *Engineering with Computers*.

AUTHOR BIOS

Muneera Aladsani is a PhD candidate in the Department of Civil and Environmental Engineering at UCLA. Her research is focused on the application of machine learning techniques to better understand and predict the structural behavior (local and global) of seismic systems.

Henry Burton is an Associate Professor and the Englekirk Presidential Chair in Structural Engineering in the Department of Civil and Environmental Engineering at UCLA. He teaches the Advanced Structural Analysis, Structural Reliability, Nonlinear Structural Analysis and Structural Testing and Design courses at UCLA.

Saman Abdullah is currently a Research Scholar in the Department of Civil and Environmental Engineering at UCLA, and a Lecturer in the Department of Civil Engineering, University of Sulaimani, Kurdistan Region, Iraq. Saman does research on the behavior and performance of RC structural walls and coupling beams subjected to seismic and wind demands.

John Wallace is a Professor of civil engineering at UCLA. He is an internationally recognized expert on the seismic behavior of reinforced concrete structures. His research contributions focus on assessing the behavior of structures subjected to earthquake loading, laboratory and field testing of structural components and systems, developing and validating models for structural analysis and design, and applying sensors and sensor networks to measure responses and interactions between complex structural systems.

State of the Art on Self-Healing Capacity of Cementitious Materials Based on Data Mining Strategies

Shashank Gupta, Salam Al-Obaidi, and Liberato Ferrara

Synopsis: Concrete and cement-based materials inherently possess an autogenous self-healing capacity, which is even higher in High and Ultra-High-Performance Concretes (HPC, UHPC) because of the high content of cement and supplementary cementitious materials (SCM) and low water/binder ratios. In this study, quantitative correlation through statistical models have been investigated based on the meta-data analysis. The employed approaches aim at establishing a correlation between the mix proportions, exposure type, and time and width of the initial crack against suitably defined self-healing indices. This study provides a holistic investigation of the autogenous self-healing capacity of cement-based materials based on extensive literature data mining. This is also intended to pave the way towards consistent incorporation of self-healing concepts into durability-based design approaches for reinforced concrete structures. The study has shown that the exposure type and duration, crack width size, and chemical admixtures have the most significant promotion on self-healing indices. However, other parameters, such as fibres and mineral admixtures have less impact on the autogenous self-healing of UHPC. The study also propose suitably built design charts to quickly predict and evaluate the self-healing efficiency of cement-based materials which can significantly reduce, in the design stage, the time and efforts of laboratory investigation.

Keywords: Durability Based Design; Meta-Analysis; Self-healing concrete

ACI student member Shashank Gupta is a Graduate Student in the Department of Civil and Environmental Engineering at Politecnico di Milano, Italy.

ACI student member Salam Al-Obaidi is a PhD student in the Department of Civil and Environmental Engineering at Politecnico di Milano, Italy. He is also a lecturer at Roads and Transportations Engineering Department ,University of Al-Qadisiyah ,Diwaniyah,Iraq.

ACI member Liberato Ferrara is associate professor in the Department of Civil and Environmental Engineering at Politecnico di Milano, Italy. He is currently chair of the ACI TC 544-Fiber Reinforced Concrete and Italian representative in the COST Action 15020 SARCOS- Self healing as preventive repair in concrete structures. The coordinator of the project RESHEALIENCE funded by the Horizon H2020 European Union Funding for Research & Innovation His research interests include material concept and structural applications of advanced cementitious composites, self-healing concrete, 3D printing with cementitious materials and sustainability of cement-based structures.

INTRODUCTION

Cementitious materials undergo the natural process of autogenous healing that is total or partial self-closure of cracks. The closure of these cracks subsequently results in partial regaining of concrete initial strength as well as improving the durability performance. In 1973, tests were performed on cement mortars used for the lining of iron water pipes, to study the autogenous self-healing under the pipe service water as well as non-service water conditions ^[1]. The study reported substantial self-healing in both cases whereas the latter mentioned exposure condition showed a slightly better rate of healing. Correspondingly, several old structures, bridges, as well as buildings have shown exceptional durability, resulting in unpredicted longevity ^[2-3]. This behaviour can have been contributed by the autogenous self-healing property of concrete.

Several self-healing mechanisms and their efficacy have been investigated to promote the self-healing properties of concrete. Some of these mechanisms are continuing hydration, dissolution & crystallization, particle clogging, and carbonation ^[4]. The process of continuing hydration in autogenous healing is a principal step in recovering the mechanical properties as the newly formed hydrated products have similar strength properties as the Calcium silicate hydrate (CSH) gel. The microstructural characterization of healed concrete through SEM-EDX analysis shows the presence of CSH, Ettringite, and Calcium Hydroxide ($\text{Ca}(\text{OH})_2$) in healed cracks ^[5].

Based on the mechanism of autogenous self-healing of cementitious material, several parameters have been determined that influence the rate of self-healing. Crack width, mix design, fibre content, together with treatment duration, and environmental exposure conditions are the most significant variables that affect the self-healing of concrete ^[6]. However, many studies have been done to determine the relationship between performance recovery rate and initial crack width for different types of concrete. For HPC with fly ash, micro-silica, and water-reducing agent, a logarithmic relation was obtained between the normalized flow rate recovery and time of exposure. It was observed that for larger cracks, the permeability was increasing at a higher rate. The experimental results were also in close agreement with the law of Hagen-Poiseuille ^[7].

The addition of mineral and crystalline admixture (CA) can additionally improve the rate and efficiency of self-healing as a “stimulated-autogenous healing” approach. The partial substitution of cement with fly ash as well as the addition of crystalline admixture can recover both compressive strength and electrical resistivity of concrete up to 94% ^[8]. It was observed that after 30 days of water curing, a sample containing a high volume of fly ash regained 74% of the loss of the compressive strength, whereas samples without fly ash regained only 68%. Furthermore, more pronounced improvements were observed in permeability analysis ^[9]. Similarly, a crack healing rate of around 81% to 93% was reported for concrete containing CA. On the other hand, the specimens without CA exhibited the crack healing rate of 80-86%. Cracks with a width up to 0.25 mm were healed in the specimens containing CA ^[10].

Polymers are widely used to enhance the self-healing of concrete either by encapsulation method, or vascular method, or by directly injecting the polymers into the crack. Some of these polymers are polyurethane, SAP, acrylamide, acrylate, epoxy, poly styrene-divinylbenzene, styrene-butadiene rubber, etc. The inclusion of these polymers improves the regain ratio of mechanical properties and increases the surface crack healing ^[11].

Numerous experiments, as well as studies, have been also conducted on the concrete reinforced with synthetic fibres and steel fibres. The fibres control the opening of the cracks that make self-healing products easily attach to the surface of the crack and fill them. Permeability tests and microstructural characterization of the Engineered Cementitious Composite (ECC) containing different synthetic fibres, like polypropylene (PP), ethylene vinyl alcohol (EVA), and poly-vinyl acrylate (PVA) have been performed. The study concluded that the precipitation of calcium carbonate potentially increases with the inclusion of synthetic fibres ^[12]. A similar result was obtained by a study dealing with concrete containing PVA microfibres and superabsorbent polymers (SAP) ^[13]. The environment and the time of exposure have been varied by different researchers to either optimize the treatment condition for concrete under investigation or to investigate the effect of the intended field of investigation. Some of these treatment conditions are tap/distilled water curing at a different temperature, air chambers with controlled relative humidity (RH) and temperature, wet/dry cycle, freeze/thaw cycles, etc ^[14].

The experimental tests have been carried out to evaluate the self-healing of ECC containing supplementary cementitious material (SCM) by varying the healing conditioning and aging. The samples were either submerged in water, exposed to natural weathering, or kept in moderate humidity controlled in a lab setup. The mechanical analysis of samples showed that water submersion for 90 days resulted in a 60% and 70% regain of stiffness and tensile strength, respectively ^[15]. The results show that the presence of water or high humidity is essential for the rapid and effective healing of the concrete. In addition to the conditioning environment, the duration of treatment is also an essential parameter. The autogenous healing of concrete can continue for up to two years, whereas concrete with encapsulated cyanoacrylate can heal within less than a minute ^[14].

Similarly, UHPC/UHPFRC materials, because of their mix composition featuring a high binder content and a low water/binder ratio ^[16-18], have been identified as highly conducive to exhibit autogenous self-healing capacity, also thanks to their ability to spread and control the damage through small crack width, which will be an excellent parameter for self-healing in water emersion and with presence of the seal healing promoters as well ^[19-25].

From the above summary review, it appears that several factors influence the efficiency of self-healing which makes the systematic review of research the best supporting evidence. This form of reviews has anyway to be supported by statistical mathematical tools like meta-data analysis. This form of analysis is quite common in evidence-based healthcare research. Multiple clinical trials are performed by different labs and the results are publicly filed. The systematic reviews summarize the results of different labs with several statistical parameters. The first systematic review was performed in 1747 by James Lind to find the optimum treatment of scurvy ^[26].

In the field of cement-based construction materials; a few systematic reviews have been performed. Moreover, meta-data analyses are rarer in the same field. A recent systematic review has been done to study the effect of fly-ash replacement in high volume fly-ash concrete (HVFAC) ^[27]. In this study, the mechanical and durability properties of HVFAC of different mix-designs were numerically compared. However, the study was limited to the numerical presentation of the values of flexural strength, compressive strength, splitting tensile strength, and elasticity modulus. The meta-data analysis was not carried out. Similarly, the effects of recycled fibres of different types on the mechanical, durability, and physical properties of concrete have been investigated using a systematic review. The effect of plastic, metal, and natural fibres on the performance of different cementitious matrices was analysed. The effect of variables on self-healing was qualitatively compared but the correlation of data was not developed by any mathematical model ^[28].

A meta-analysis study has been done, where the parameters of mix-design of self-consolidating concrete have been related to fresh state parameters of concrete ^[29]. In this study, the meta-analysis has been performed by determining the collected variables as input and output data. The amount of cement, water content, amount of SCM, and aggregate size was taken as input data. On the other hand, the results from slump-flow tests were taken as output data. The multiple linear regression was performed to study the impact of input variables on the output variables.

It is evident from the discussion that substantial research and review have been carried out on autogenous healing of different cement-based materials. The construction industry is interested in concrete that does not decay; however, further research is needed to perform the standardization and codification of the existing findings. One way of supporting this activity is to carry out a state-of-the-art quantitative study that unifies the observations of numerous studies on an individual scale. Hence, this study will determine the effect of several factors on the self-healing of cementitious material using data-based statistical tools, it will lay down a comparison and present in a quantitative way the effect of every parameter on the autogenous self-healing of UHPC.

METHODOLOGY

The relevant data has been collected from numerous peer-reviewed articles. "ScienceDirect" was a major scientific data-base to collect the relevant articles, journals, and book chapters. In the initial survey, more than 236 papers related to the self-healing capacity of concrete were analysed. However, based on the required data, several papers were later removed because of inadequacy or incompleteness of data provided. The total number of relevant papers collected for both meta-analyses is 100. More recent publications were focused to get more results from more recent studies. The distribution of the timeline of publications is presented in Figure 1. It can be observed that half of the papers have been published between 2018 and 2021.

The input parameters collected from each of these studies are the dosage of cement (kg/m^3) and of supplementary cementitious materials (SCM) (kg/m^3), fibre type and content (%Vol), water/cement ratio, crack width (μm), age of treatment (days), and self-healing environment. The parameters collected as output are relevant results of the self-healing characterization test and geometrical closure of crack. The relevant results are then converted into "Self-Healing Indices" (SHI) to maintain the consistency of results. These parameters for different tests are determined according to the experiment and the initial data. The values are being normalized to 1.0 by simple mathematical manipulations. The formulas of self-healing indices for several experiments are presented in Table 1.

The self-healing indices are then used to develop forest plots. A Forest plot is a graph that displays results from several studies. The inference of the forest plot is a diamond that represents the result of a meta-analysis of the considered studies.

The position of the diamond represents Cohen's d-value (effect size) and its width represents the 95% Confidence Interval (CI). The mean and standard deviations of SHI values are used to calculate the Margin of Error (MoE) (Eq. 1) and Cohen's d-value (Eq. 2 & 3) [30]. The Cohen's d value is used to represent the magnitude of the effect of the certain parameter under analysis. The meta-analysis results of the various comparison will be shown in terms of Cohen's d-value and MoE.

$$MoE = 0.5 * (SHI_{mean} + z \frac{SHI_{sd}}{\sqrt{N}}) \quad (1)$$

Where, SHI_{mean} is mean, SHI_{sd} is the standard deviation, z is Z-value (i.e., 1.96 for 95% CI), and N is the sample size.

$$d = (SHI_{1,mean} - SHI_{2,mean})/SHI_{sd,p} \quad (2)$$

where 'd' is Cohen's d, $SHI_{1,mean}$ and $SHI_{2,mean}$ are mean of SHI of two data-sets, and $SHI_{sd,p}$ is pooled standard deviation.

$$SHI_{sd,p} = \sqrt{\frac{(N_1 - 1)SHI_{1,sd}^2 + (N_2 - 1)SHI_{2,sd}^2}{(N_1 - 1) + (N_2 - 1)}} \quad (3)$$

Where, $SHI_{1,sd}$ & $SHI_{2,sd}$ are standard deviations of two data-sets and N_1 & N_2 are a sample size of two data-sets.

The relative importance analysis is carried out from the collected dataset to calculate the importance percentage of total cementitious material, water to cement content, crack width, age of healing, and fibre content in determining the self-healing index of concrete. Tonidandel and LeBreton method has been used to calculate the relative weight percentage [31]. The technique is an alternative to multi-regression analysis and considers the problem of multicollinearity. The method helps to lay out the importance rank of the variable based on their contribution to R-squared [32].

RESULTS AND DISCUSSIONS

Based on the literature review, most of the researchers have investigated the effects of different parameters on the self-healing efficiency and since the data mining analysis is based on the accumulations of the existing study parameters and their effects, the focus has been kept on the effect of the most common studied parameters including crack size, healing time and environment, presence of admixture, and presence of fibres.

Crack Size

A multitude of research has been carried out on the effect of crack size on the self-healing efficiency of concrete. Following the gathering of relevant data and preliminary inspection, the whole range of crack sizes is distributed in a certain range. The argument in this study is self-healing efficiency of cracks "less than equal to 'X' µm" and "greater than 'X' µm". The ACI 224R-01 suggests the maximum allowable crack in the range of 100-250 micron for a different type of environment [33]. Hence, the three values of 'X' are considered in the given range provided by ACI 224R-01, i.e., 75 µm, 150 µm, and 225 µm. The three ranges assist to analyse the rate of healing with the size of the crack.

The meta-analyses of three different arguments are shown in Figures 2-4. It should be noted that the "negative d-value" on scale presents "less than equal to 'X' µm" and "positive d-value" represents "greater than 'X' µm" case. Furthermore, the meta-data parameters of the three analyses are presented in Table 2. The total number of relevant studies considered are 16, 13, and 11, for the 'X' value of 75 µm, 150 µm, and 225 µm, respectively.

It is visually clear from the forest plots that the self-healing efficiency of smaller cracks is better than the bigger cracks. The average d-value is -0.2203 which shows the faster rate of healing for the smaller crack in all the cases. It is also evident that the absolute value of Cohen's d is increasing with the increase in the value of 'X'. The d-coefficient, as defined earlier, is proportional to the difference in mean values from two opposing arguments. Therefore, it is evident that the difference between SHI increases with the increase in crack size with the difference between average SHI for cracks "less than equal to 225 µm" and "greater than 225 µm" being largest. Furthermore, it can be noticed that the difference in d value is also increasing with the crack size. Therefore, this result quantitatively infers that the SHI value decreases at a faster rate with the increase in crack size.

The MoE values are of the same order for all three studies showing the equal similar variance in data for three analyses. The average value of the diamond ratio is calculated as 2.61 which shows the presence of heterogeneity in data collected from different studies. This can be attributed to the variation of other parameters, that aspect the self-healing efficiency of concrete, among multiple studies.

Healing Period

The effect of the healing period on self-healing is the most researched parameter on the self-healing efficiency of cement-based materials. The self-healing time has been varied from few hours to 1 year. However, most studies focus on the healing period of 3 days to 90 days. Imitating the same steps as in the case of cracks, the overall range of healing time has been divided by three values based on the observations from multiple studies. The opposing arguments will be the self-healing capacity of concrete treated for "less than or equal to 'X' days" and "greater than 'X' days". The three values of 'X' chosen are 7 days, 28 days, and 56 days. The meta-analyses of three different arguments are shown in Figures 5-7. It should be noted that the "negative d-value" on the scale presents "less than equal to 'X' days" and "positive d-value" represents "greater than 'X' days" case. Furthermore, the meta-data parameters of the three analyses are presented in Table 3.3. The total number of relevant studies considered are 28, 25, and 18, for 'X' value of 7 days, 28 days, and 56 days, respectively.

It can be observed in the forest plots that the self-healing efficiency for longer healing time is better than for shorter periods. The average d-value is 0.2068 which shows the faster rate of healing for a longer amount of treatment time. It is also evident that the d value is decreasing with the increase in the value of 'X'. It is inferred that the difference between SHI decreases with the increase in the healing period with the difference between average SHI for the period of "less than equal to 7 days" and "greater than 7 days" being largest. Furthermore, it can be noticed that the difference in d-value is also increasing with the healing period. Therefore, this result quantitatively suggests that the rate of healing decreases with an increase in the healing period. The healing rate is higher in the early stage, as autogenous healing happens predominantly in the first 28 days.

The average value of the diamond ratio is calculated as 3.11 which shows the presence of heterogeneity in data collected from different studies. The reasons have been explained in the latter section. It is also evident from the average d-value that the significance of the effect of crack size is like the effect of the healing period on the self-healing capacity of concrete.

Admixtures

In this study, the effect of mineral admixtures, and the effect of chemical admixtures have been studied separately. The mineral admixtures and chemical admixture considered are SCM and crystalline admixture, respectively. In both the studies, the opposing arguments is the self-healing capacity of concrete "without admixture" and with admixture". The meta-analysis of two different admixtures are shown in Figures 8-9. It should be noted that the "negative d-value" on scale presents "without admixture" and "positive d-value" represents "with admixture" case. Furthermore, the meta-data parameters of the two analyses are presented in Table 4. The total number of relevant studies considered are 14 and 15, for mineral and chemical admixture, respectively.

The forest plots show that the self-healing efficiency of concrete containing the admixtures is higher than for concrete without the presence of admixtures. The d-value for analysis with mineral admixture and chemical admixture are 0.0811 and 0.2275, respectively. This striking difference between these two values shows the upper hand of chemical admixtures on improving the self-healing capacity of concrete. The presence of chemical admixture in the concrete mix-design is a significant factor equivalent to, if not more than, the crack size and healing period. A very low d-value infers the improvement of SHI with the inclusion of mineral admixtures; however, its effect is not as significant compared to the presence of chemical admixture. The average value of the diamond ratio is calculated as 2.22 which shows the presence of heterogeneity in data collected from different studies. The reasons have been explained in the previous sections.

Healing Environment

The healing environment significantly influences the self-healing efficiency of concrete. The studies have been carried out with different treatment conditions, such as complete water immersion, wet/dry cycles, sea-water exposure, humid chamber, air curing, natural weathering, etc. However, two of the most common methods are water immersion and wet/dry cycles. The analyses of all the treatment conditions have not been possible due to the lack of multiple studies. Therefore, the meta-data analysis is carried out to compare the effect of water curing with the effect of the wet/dry cycle on the self-healing capacity of concrete.

The two arguments in this study are "Water immersion" and "Wet/Dry cycle". The meta-analysis has been presented in Figure 10. The positive d value supports the wet/dry cycles, and the negative value supports the

complete water immersion. The total number of studies considered is limited to 8. Furthermore, Table 5 shows the meta-data parameters of the study. The forest plots show that the self-healing efficiency of concrete incomplete water immersion is far greater than the wet-dry cycles. The d value for analysis is -0.2736. This is a relevant value compared to all the other values obtained in the analysis. This shows the high significance of the healing environment on the self-healing capacity of the cementitious system, more importantly, the time of exposure to water.

The MoE value is 0.1234, which shows high variance in the errors. This is mainly because of a smaller number of relevant studies on the same topics. The average value of the diamond ratio is calculated as 2.91 which shows the presence of heterogeneity in data collected from different studies. The reasons have been explained in the previous sections.

Presence of fibres

The effect of the presence of fibres on autogenous self-healing of concrete has been explored by several researchers. The type of fibres has been varied, including PVA fibres, PP fibres, steel fibres of different shapes, acrylic fibres, etc. However, there are not a significant number of studies with the variation of fibre content and type. Therefore, all the types of fibre have been grouped in a single category of fibre. The meta-analysis is carried out to study the effect of the presence of any fibre on the SHI of concrete.

The two arguments in this study are "Without fibre" and "With fibre". The meta-analysis has been presented in Figure 11. The positive d value supports the presence of fibre and the negative value supports the absence of fibres. The total number of studies considered is limited to 5. Furthermore, Table 6 shows the meta-data parameters of the study.

The forest plots show that the self-healing efficiency of concrete with the presence of fibre is slightly better than the concrete without fibre. The d value for analysis is 0.1185. This is a small value compared to all the other values obtained in the analysis. This shows the low significance of fibre on the self-healing capacity of the cementitious system. The MoE value is 0.0957, which shows high variance in the errors. This is mainly because of a smaller number of relevant studies on the same topics. The average value of the diamond ratio is calculated as 2.02 which shows the presence of heterogeneity in data collected from different studies. The reasons have been explained in the previous sections.

Relative Importance Analysis:

The relative weight analysis is an effective method to evaluate the relative importance of correlated parameters. Figure 12 represents the results obtained from the analysis. It is observed that total cementitious material in concrete has the greatest influence on the improvement of SHI, with an importance percentage of 32.7%. The crack width has a similar influence on SHI as the amount of cementitious material with an importance factor of 30.5%. It has also been shown through the meta-analysis that the crack width has a high influence on the self-healing capacity of the concrete. Hence, this analysis corroborates the result of the meta-analysis.

The age of healing and water to cement content has also a significant effect on determining the SHI with an importance percentage of around 20% and 13%, respectively. The results validate the statements made based on the meta-analysis regarding the healing period in the previous sections of the study. Similarly, the relative importance percentage of fibre content is lowest with a percentage of 4.1%, confirming the low d -value result from the meta-analysis hence the low influence of the fibre content on the self-healing capacity of concrete.

Optimization Charts

Based on the collected data, optimization charts are developed for optimized design concerning the self-healing capacity of cementitious material. The Delaunay triangulation has been implemented to evaluate the interpolated values of SHI to generate the contours lines. Delaunay triangulation is used as an optimal method to generate a linear interpolation function that can be used to reconstruct the functional approximation in 3-dimensional space. The Delaunay triangulation is applied to the pair of chosen parameters (like cement content, crack width, etc.) and linear interpolation functions are constructed based on the value of response (SHI) ^[34].

The optimization charts of some of the design parameters are shown in Figure 13-15. The SHI contours for the w/c ratio and the dosage of cement (kg/m^3) in concrete is presented in Figure 13. The results obtained evidently depend on the composition of concrete, generally having high w/c ratio for low-cement concrete (low quality concrete) and vice-versa (high performance concrete). The SHI also get significantly influenced by other factors like period of healing and width of cracks. It is notable from the chart that SHI increases with cement content even with low w/c ratios, which is reasonable because this will correspond to higher availability of un-hydrated cement for further hydration reactions.

The effect of supplementary cementitious material on the SHI is presented in Figure 14 using cement content and the amount of total cementitious material. As anticipated, the SHI increases with the amount of total cementitious material in concrete. However, it can be noted that there is peak range for SCM content for the given amount of total cementitious material for optimum SHI. Following the peak, the increase in cement content in total cementitious constituent is preferred for improved SHI. This can be attributed to the thermo-chemistry of hydration reaction of the cement-fly ash blend in concrete. The hydration reaction of fly-ash utilizes the hydration products of cement, namely the calcium hydroxide to produce new calcium silicate hydrates ^[35]. Hence, the low amount of cement in the blend results in lack of activation of hydration reaction of fly-ash. This can be overcome with the addition of activators like sodium hydroxide and sodium silicate in the mix-design ^[36].

The influence of crack width and period of healing (immersed in water) on the SHI is finally shown in Figure 15. The cracks smaller than 100 microns heal almost completely, even after short period of treatment as anticipated by several studies ^[37]. Furthermore, it is observed that the rate of healing decreases notably after 14 days of treatment.

It has anyway to be remarked that, since the optimization charts are based on the available reliable literature, they only cover specific range of parameters. Therefore, more range of parameters should be included and an effort from the scientific community being implemented in documenting in the papers as many of them as possible to enable meta-analysis to cover wider range of applicability, thus also paving the way for the construction of a vigorous database which could foster standardization of healing test methods and design-oriented healing efficacy assessment procedures. Furthermore, in addition of estimating SHI using the Delaunay triangulation, a multi-input-output neural network model is being developed and optimized using the collected data. This further investigation would yield a robust mechanism that would provide more accurate approximation of SHI based on all the input parameters involved.

SUMMARY AND CONCLUSIONS

A systematic review has been carried out to study the effect of several factors on the self-healing capacity of cementitious systems. A preliminary literature review has been primarily carried out to investigate the factors that influence the autogenous self-healing efficiency of concrete. The total number of articles analysed was 236. However, the relevant and quality data suitable for the review study were 100. The numerical values of these factors and corresponding self-healing indices (calculated) are obtained from the selected 100 articles are used to carry on quantitative analysis. Meta-analysis has been carried out using statistical tools, like effect size, the margin of error, and diamond ratio. The results of meta-analysis are validated using relative importance analysis. The important findings are as below.

1. The crack size has a significant effect on the self-healing of concrete: smaller cracks have high healing capacity and with the increase in the size of the cracks, the rate of self-healing decreases.
2. The healing period is also a significant factor as confirmed by the high d-value. Furthermore, the difference in d-value indicates that the rate of healing decreases with the increase in the healing period. This corroborates the evidence that autogenous healing happens at the early age of exposure.
3. The addition of crystalline admixtures, favours the healing. The various studies show the dramatic increase in recovery when they are added into concrete. On the other hand, the impact of mineral admixtures and supplementary cementitious materials is quite low compare to crystalline ones.
4. The healing environment of complete water immersion has been hugely favoured over wet-dry cycles in this study. This comparison yielded the highest d-value in the whole study. This result can be assisted with the fact that water is required for the hydration as well as carbonation reaction in concrete.
5. The presence of fibres, thanks to their crack width control, favours the healing, though their relative importance, as compared to other parameters, being actually an indirect one, remains quite limited.
6. The relative importance analysis shows the importance percentage of several parameters influencing the self-healing of concrete. The amount of cementitious material and crack width have the highest influence over the self-healing capacity followed by healing age, w/c ratio, and fibre content. The results validate the claims made by the meta-analysis study regarding the crack width, healing age, and fibre content.

The design charts based on Delaunay's triangulation, examples of which has been herein shown, can be the final output of this kind of meta-analysis, which, besides confirming qualitatively known facts on the influences of the different mix-composition and structural service scenario parameters on the healing efficacy, will also provide a tool to quantitatively govern the same composition of the material, as a function of its structural service scenario to exploit at their best the self-healing capacities. This with the goal of quantifying, as a design parameter, a "scenario dependant" healable crack width which could easily be incorporated into current structural design approaches for reinforced concrete structures paving the way towards consistent exploitation of the benefits of self-healing concretes into a "truly" durability performance -based structural design (not merely limited to

prescriptions). The further goal is to develop more advanced estimation models based on artificial neural networks to improve the accuracy of the estimated SHI values. The multiple correlated design charts based on the estimated values from neural network would be developed and compared to the current charts developed using Delaunay triangulation algorithm.

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REFERENCES

- [1] Wagner, E.F., 1974, "Autogenous healing of cracks in cement-mortar linings for gray-iron and ductile-iron water pipe.", *Journal of American Water Works Association*, pp.358-360.
- [2] Ghosh, S., Biswas, M., Chattopadhyay, B.D. and Mandal, S., 2009, "Microbial activity on the microstructure of bacteria modified mortar", *Cement and Concrete Composites*, 31(2), pp.93-98.
- [3] Westerbeek, T., 2005. "Self-healing Materials Radio Netherlands".
- [4] Hearn, N. and Morley, C.T., 1997, "Self-sealing property of concrete—Experimental evidence", *Materials and structures*, 30(7), pp.404-411.
- [5] Jacobsen, S., Marchand, J. and Hornain, H., 1995, "SEM observations of the microstructure of frost deteriorated and self-healed concretes", *Cement and Concrete Research*, 25(8), pp.1781-1790.
- [6] De Belie, N., Gruyaert, E., Al-Tabbaa, A., Antonaci, P., Baera, C., Bajare, D., Darquennes, A., Davies, R., Ferrara, L., Jefferson, T. and Litina, C., 2018, "A review of self-healing concrete for damage management of structures", *Advanced Materials Interfaces*, 5(17), p.1800074.
- [7] Reinhardt, H.W. and Jooss, M., 2003, "Permeability and self-healing of cracked concrete as a function of temperature and crack width", *Cement and concrete research*, 33(7), pp.981-985.
- [8] Li, G., Liu, S., Niu, M., Liu, Q., Yang, X. and Deng, M., 2020, "Effect of granulated blast furnace slag on the self-healing capability of mortar incorporating crystalline admixture", *Construction and Building Materials*, 239, p.117818.
- [9] Litina, C. and Al-Tabbaa, A., 2020, "First generation microcapsule-based self-healing cementitious construction repair materials", *Construction and Building Materials*, 255, p.119389.
- [10] Roig-Flores, M., Moscato, S., Serna, P. and Ferrara, L., 2015, "Self-healing capability of concrete with crystalline admixtures in different environments", *Construction and Building Materials*, 86, pp.1-11.
- [11] Medjigbodo, S., Bendimerad, A.Z., Rozière, E. and Loukili, A., 2018, "How do recycled concrete aggregates modify the shrinkage and self-healing properties?", *Cement and Concrete Composites*, 86, pp.72-86.
- [12] Nishikawa, T., Yoshida, J., Sugiyama, T. and Fujino, Y., 2012, "Concrete crack detection by multiple sequential image filtering", *Computer-Aided Civil and Infrastructure Engineering*, 27(1), pp.29-47.
- [13] Snoeck, D., Van Tittelboom, K., Steuperaert, S., Dubruel, P. and De Belie, N., 2014, "Self-healing cementitious materials by the combination of microfibres and superabsorbent polymers", *Journal of Intelligent Material Systems and Structures*, 25(1), pp.13-24.
- [14] Ferrara, L., Van Mullem, T., Alonso, M.C., Antonaci, P., Borg, R.P., Cuenca, E., Jefferson, A., Ng, P.L., Peled, A., Roig-Flores, M. and Sanchez, M., 2018, "Experimental characterization of the self-healing capacity of cement based materials and its effects on the material performance: A state of the art report by COST Action SARCOS WG2", *Construction and Building Materials*, 167, pp.115-142.
- [15] Hung, C.C. and Su, Y.F., 2016, "Medium-term self-healing evaluation of Engineered Cementitious Composites with varying amounts of fly ash and exposure durations", *Construction and Building Materials*, 118, pp.194-203.
- [16] Di Prisco, M., Ferrara, L. and Lamperti, M.G., 2013, "Double edge wedge splitting (DEWS): an indirect

tension test to identify post-cracking behaviour of fibre reinforced cementitious composites”, *Materials and structures*, 46(11), pp.1893-1918.

[17] Ferrara, L., Ozyurt, N. and Di Prisco, M., 2011, “High mechanical performance of fibre reinforced cementitious composites: the role of “casting-flow induced” fibre orientation”, *Materials and Structures*, 44(1), pp.109-128.

[18] Monte, F.L. and Ferrara, L., 2020, “Tensile behaviour identification in Ultra-High Performance Fibre Reinforced Cementitious Composites: indirect tension tests and back analysis of flexural test results”, *Materials and Structures*, 53(6), pp.1-12.

[19] Ferrara, L., Krelani, V. and Moretti, F., 2016, “Autogenous healing on the recovery of mechanical performance of High Performance Fibre Reinforced Cementitious Composites (HPFRCCs): Part 2–Correlation between healing of mechanical performance and crack sealing”, *Cement and Concrete Composites*, 73, pp.299-315.

[20] Droval, G., Feller, J.F., Salagnac, P. and Glouannec, P., 2008, “Conductive polymer composites with double percolated architecture of carbon nanoparticles and ceramic microparticles for high heat dissipation and sharp PTC switching”, *Smart materials and structures*, 17(2), p.025011.

[21] Ferrara, L., Krelani, V., Moretti, F., Flores, M.R. and Ros, P.S., 2017, “Effects of autogenous healing on the recovery of mechanical performance of High Performance Fibre Reinforced Cementitious Composites (HPFRCCs): Part 1”, *Cement and Concrete Composites*, 83, pp.76-100.

[22] Cuenca, E., Tejedor, A. and Ferrara, L., 2018, “A methodology to assess crack-sealing effectiveness of crystalline admixtures under repeated cracking-healing cycles”, *Construction and Building Materials*, 179, pp.619-632.

[23] Cuenca, E., Mezzena, A. and Ferrara, L., 2021, “Synergy between crystalline admixtures and nano-constituents in enhancing autogenous healing capacity of cementitious composites under cracking and healing cycles in aggressive waters”, *Construction and Building Materials*, 266, p.121447.

[24] Cuenca, E., D'Ambrosio, L., Lizunov, D., Tretjakov, A., Volobujeva, O. and Ferrara, L., 2021, “Mechanical properties and self-healing capacity of ultra high performance Fibre Reinforced Concrete with alumina nano-fibres: Tailoring Ultra High Durability Concrete for aggressive exposure scenarios”, *Cement and Concrete Composites*, p.103956.

[25] Monte, F.L. and Ferrara, L., 2021, “Self-Healing Characterization of UHPFRCC with Crystalline Admixture: Experimental Assessment via Multi-Test/Multi-Parameter Approach”, accepted for publication in *Construction and Building Materials*.

[26] Askie, L. and Offringa, M., 2015, “Systematic reviews and meta-analysis”, In *Seminars in Fetal and Neonatal Medicine* (Vol. 20, No. 6, pp. 403-409). WB Saunders.

[27] Herath, C., Gunasekara, C., Law, D.W. and Setunge, S., 2020, “Performance of high volume fly ash concrete incorporating additives: A systematic literature review”, *Construction and Building Materials*, 258, p.120606.

[28] Merli, R., Preziosi, M., Acampora, A., Lucchetti, M.C. and Petrucci, E., 2020, “Recycled fibres in reinforced concrete: A systematic literature review”, *Journal of Cleaner Production*, 248, p.119207.

[29] Garcia-Taengua, E., 2018. “Fundamental fresh state properties of self-consolidating concrete: a meta-analysis of mix designs”, *Advances in Civil Engineering*, 2018.

[30] Borenstein, M., Hedges, L.V., Higgins, J.P. and Rothstein, H.R., 2010, “A basic introduction to fixed-effect and random-effects models for meta-analysis”, *Research synthesis methods*, 1(2), pp.97-111.

[31] Tonidandel, S. and LeBreton, J.M., 2015, “RWA web: A free, comprehensive, web-based, and user-friendly tool for relative weight analyses”, *Journal of Business and Psychology*, 30(2), pp.207-216.

[32] Shen, Z. and Chen, A., 2020, “Comprehensive relative importance analysis and its applications to high dimensional gene expression data analysis”, *Knowledge-Based Systems*, 203, p.106-120.

[33] Abou-Zeid, M., Fowler, D.W., Nawy, E.G., Allen, J.H., Halvorsen, G.T., Poston, R.W., Barlow, J.P., Hansen, W., Rhoads, R.J., Brander, M.E. and Hassoun, M.N., 2001, “Control of cracking in concrete structures”, Report, ACI Committee, 224, pp.12-16.

[34] Amidror, I., 2002, “Scattered data interpolation methods for electronic imaging systems: a survey. Journal of electronic imaging”, 11(2), pp.157-176.

[35] Moghaddam, F., Sirivivatnanon, V. and Vessalas, K., 2019, “The effect of fly ash fineness on heat of hydration, microstructure, flow and compressive strength of blended cement pastes”, Case Studies in Construction Materials, 10, p.e00218.

[36] Ramagiri, K.K., Chauhan, D.R., Gupta, S., Kar, A., Adak, D. and Mukherjee, A., 2021, “High-temperature performance of ambient-cured alkali-activated binder concrete”, Innovative Infrastructure Solutions, 6(2), pp.1-11.

[37] Cuenca, E., Rigamonti, S., Gastaldo Brac, E. and Ferrara, L., 2021, “Crystalline Admixture as Healing Promoter in Concrete Exposed to Chloride-Rich Environments: Experimental Study”, Journal of Materials in Civil Engineering, 33(3), p.04020491.

Table 1 — Formulas for Self-Healing Indices (SHI) of cementitious material for different experiments

S. No.	Experiment	Parameters	Formula
1	Crack Size	w_i = initial width & w_f = final width	$(w_i - w_f)/w_i$
2	Permeability Test	Q_i = initial flow & Q_f = final flow	$(Q_i - Q_f)/Q_i$
3	Ultrasonic Pulse Velocity (UPV) Test	U_h = UPV of healed sample & U_c = UPV of cracked sample	$(U_h - U_c)/U_h$
4	Electrical Resistivity/Impedance	E_h = Reading of healed sample & E_c = Reading of cracked sample	(E_h/E_c)
5	Mechanical Strength	M_h = Strength of healed sample & M_c = Strength of cracked sample	$(M_h - M_c)/M_h$

Table 2 — Meta-data Parameters for Crack width

	75 μ m	150 μ m	225 μ m	Average
d-value	-0.2047	-0.2158	-0.2406	-0.2203
MoE	0.0862	0.0805	0.0788	0.0818
Diamond Ratio	3.37	2.19	2.26	2.61

Table 3 — Meta-data Parameters for the healing period

	7 days	28 days	56 days	Average
d-value	0.2187	0.2109	0.1909	0.2068
MoE	0.0499	0.0636	0.0703	0.0613
Diamond Ratio	3.05	3.08	3.2	3.11

Table 4 — Meta-data Parameters for admixtures

	Mineral Admix	Chemical Admix	Average
d-value	0.0811	0.2275	0.1543
MoE	0.0391	0.0831	0.0611
Diamond Ratio	1.63	2.81	2.22

Table 5 — Meta-data Parameters for treatment condition

d value	-0.2736
MoE	0.1234
Diamond Ratio	2.91

Table 6 — Meta-data Parameters for the effect of fibres.

d value	0.1185
MoE	0.0957
Diamond Ratio	2.02

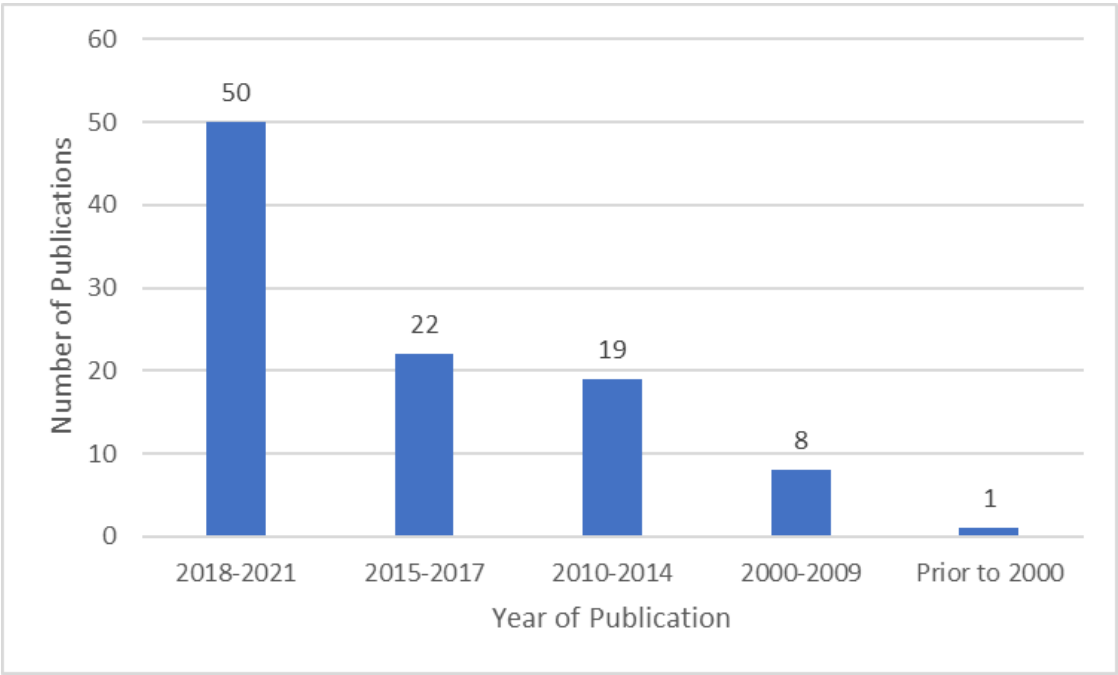


Figure 1 — Distribution of timeline of publication of relevant publications

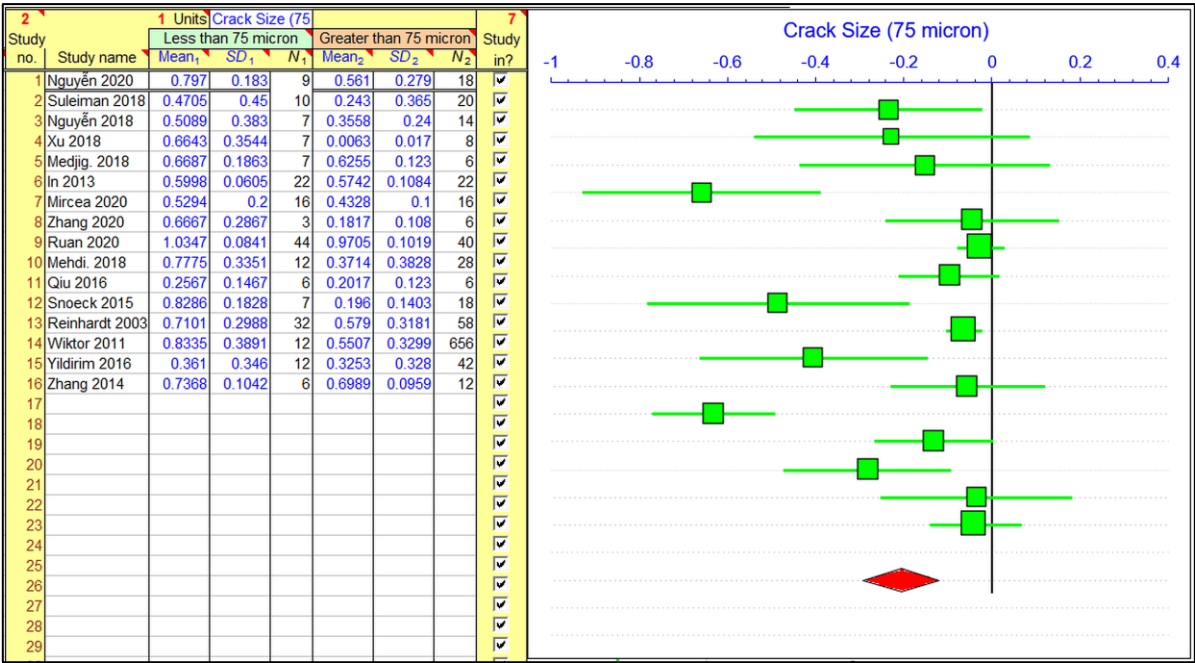


Figure 2 — The comparison of self-healing of cracks less than and greater than 75 microns.

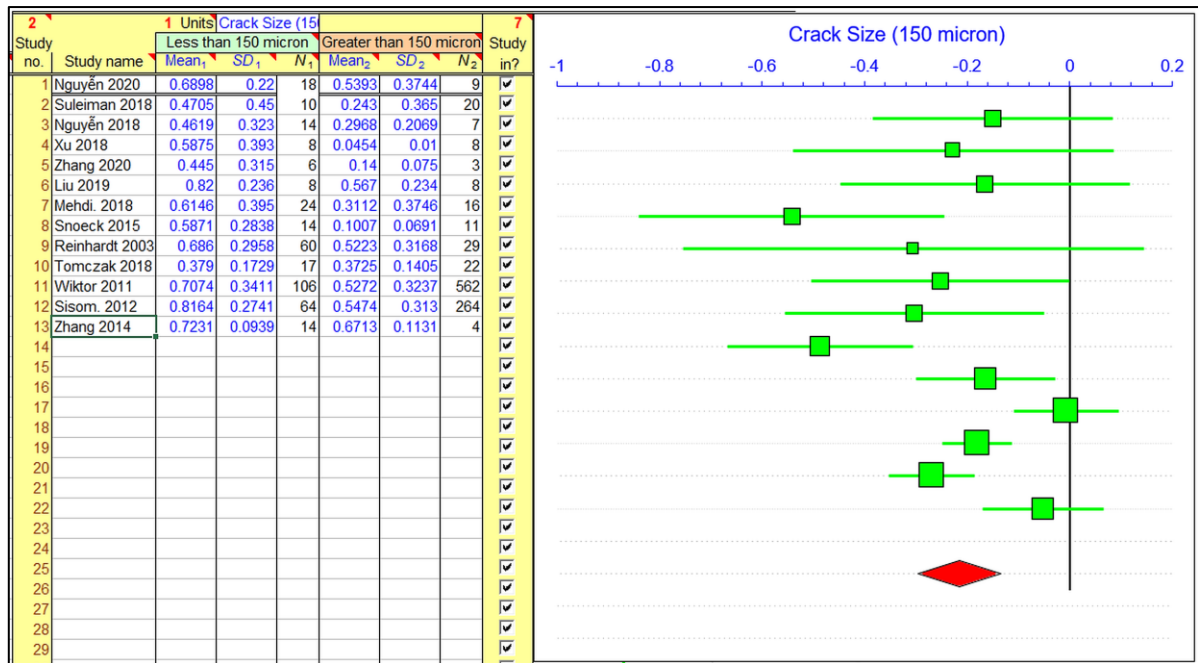


Figure 3 —The comparison of self-healing of cracks less than and greater than 150 microns.

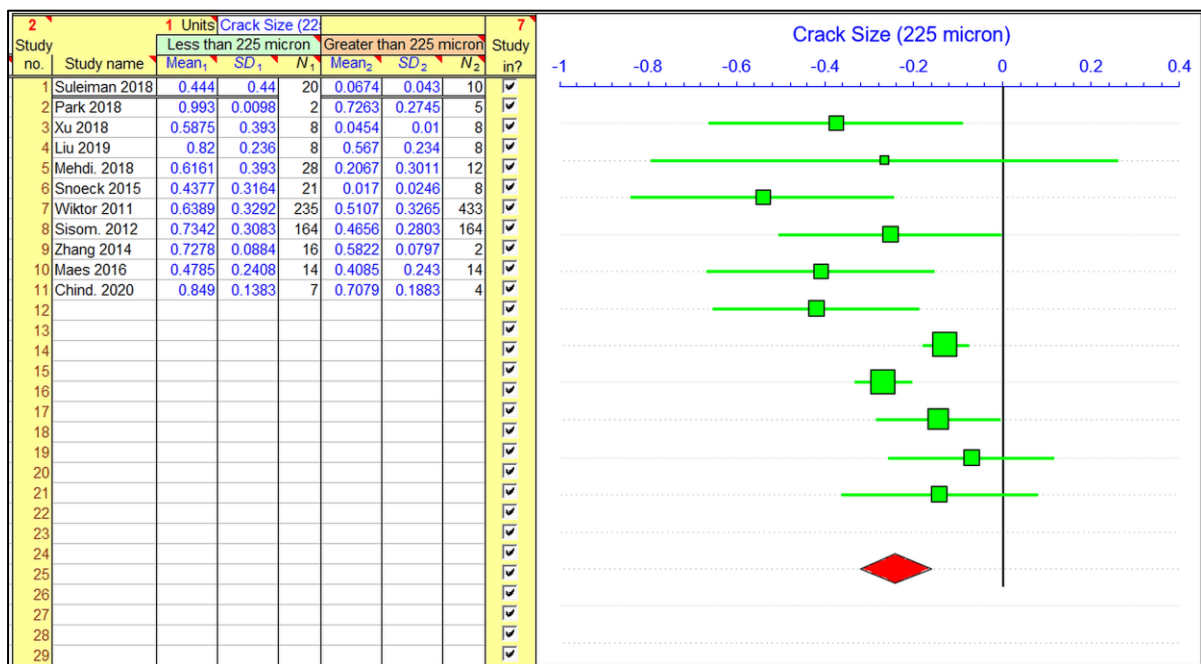


Figure 4 —The comparison of self-healing of cracks less than and greater than 225 microns.

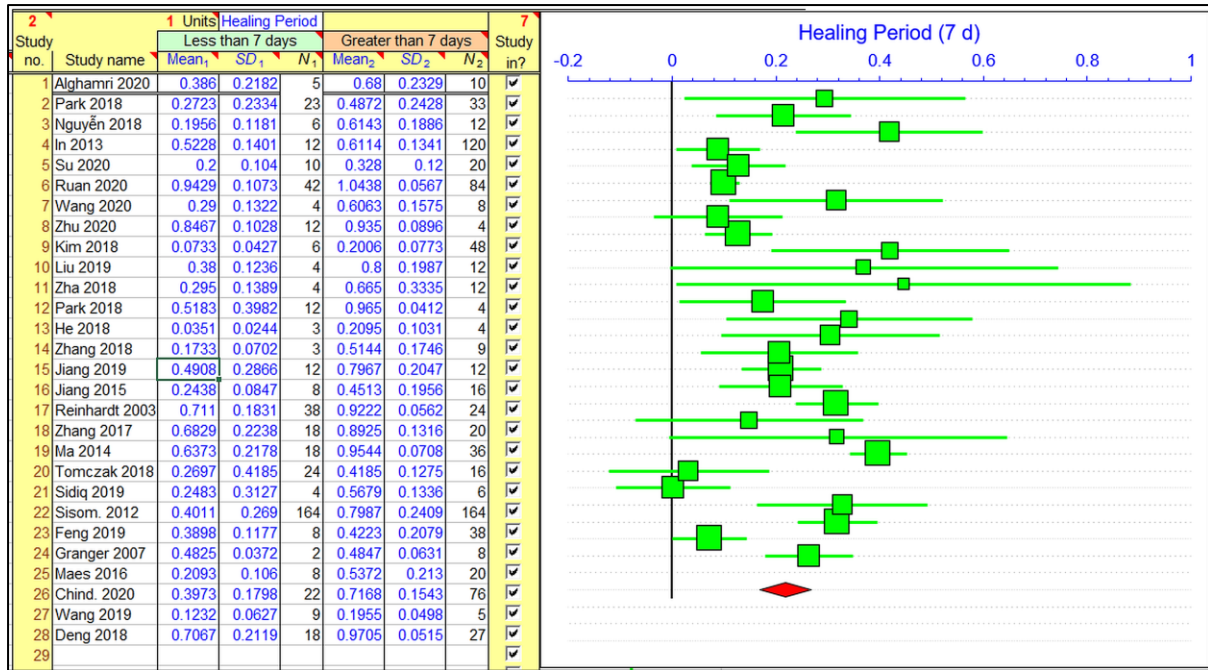


Figure 5 — The comparison of self-healing of cracks less than and greater than 7 days.

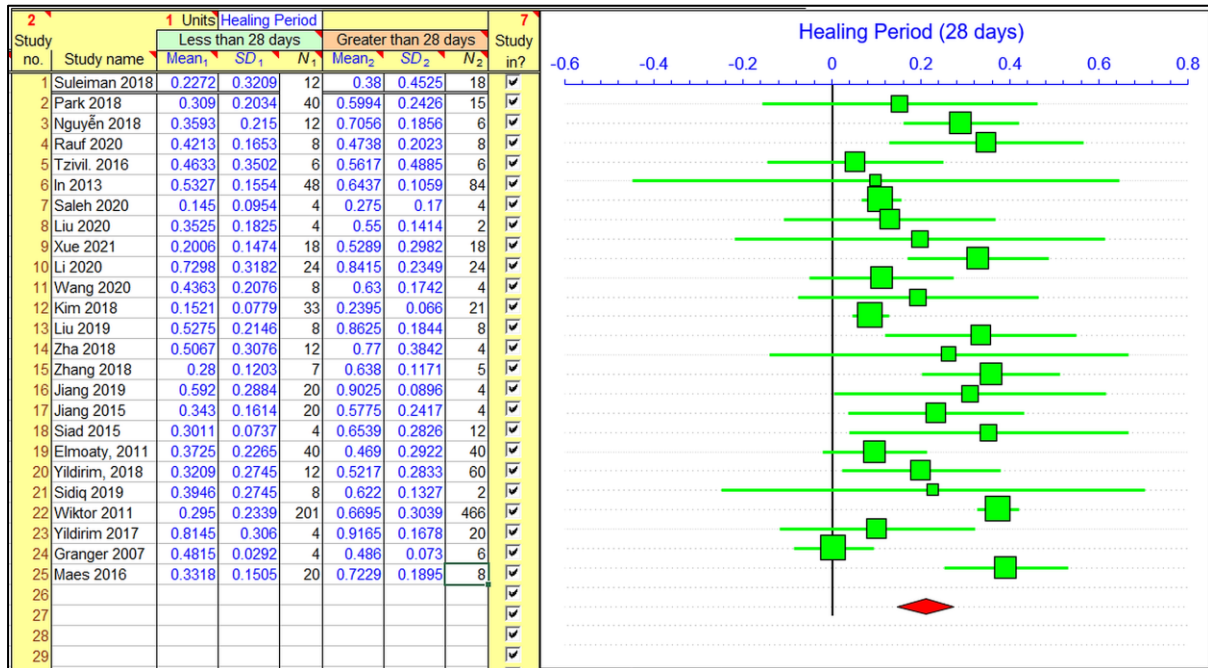


Figure 6 — The comparison of self-healing of concrete less than and greater than 28 days.

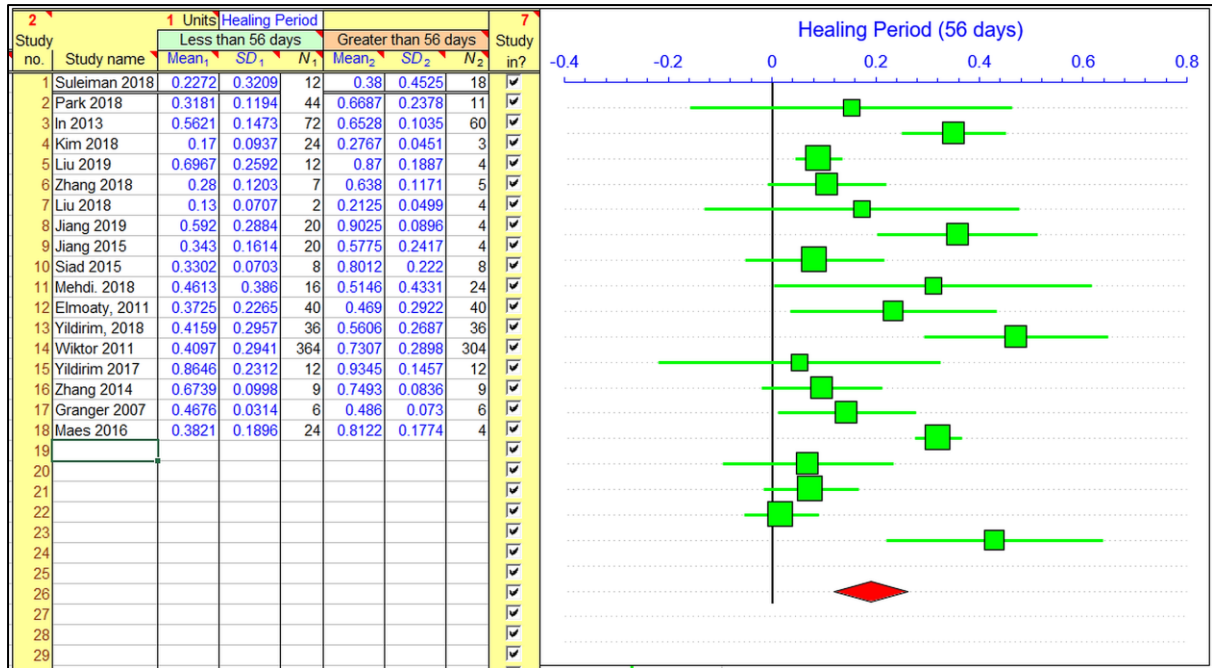


Figure 7 — The comparison of self-healing of concrete less than and greater than 56 days.

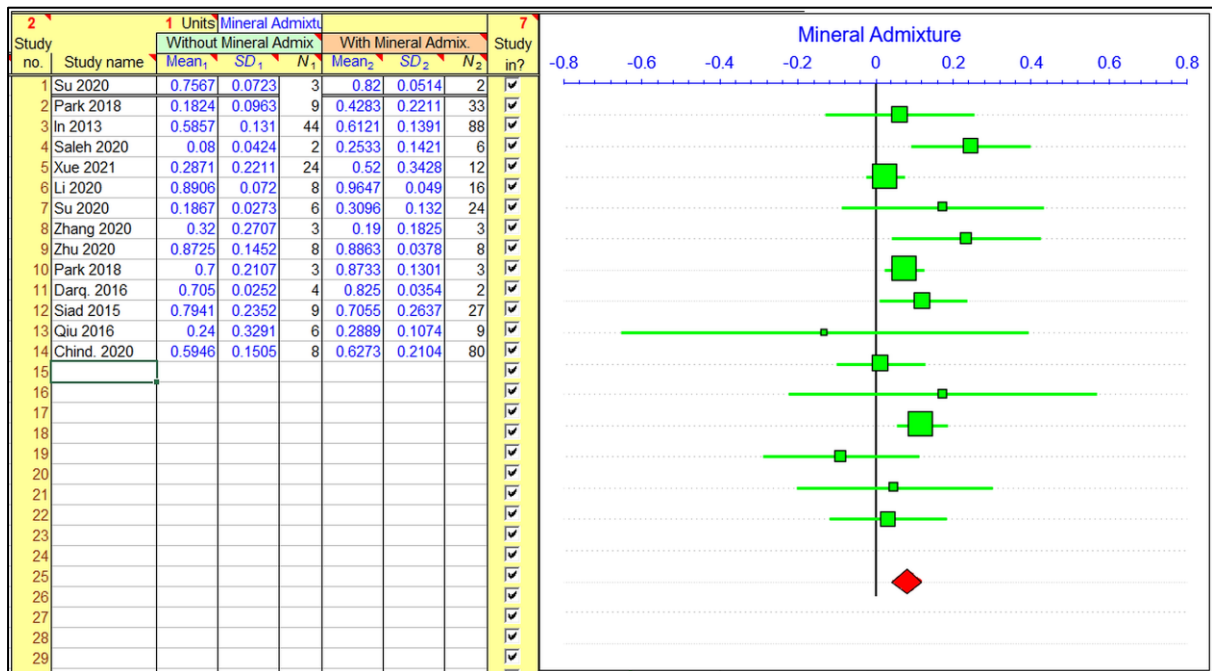


Figure 8 — The effect of mineral admixture on the self-healing capacity of concrete.

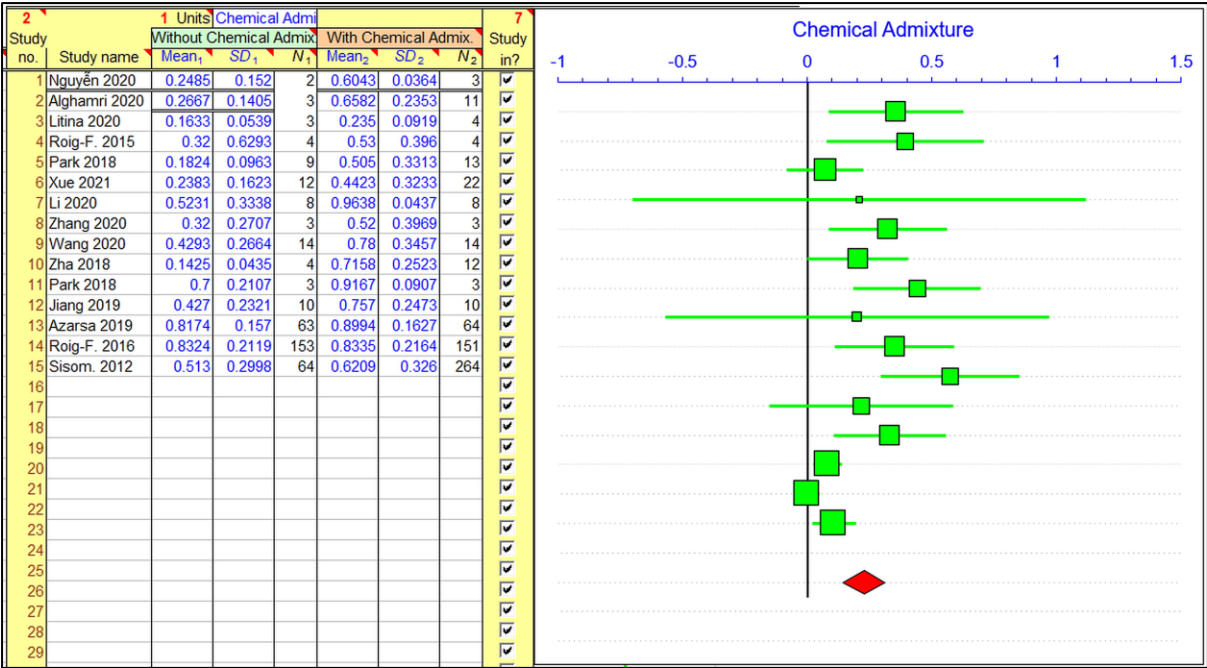


Figure 9 — The effect of chemical admixture on the self-healing capacity of concrete.

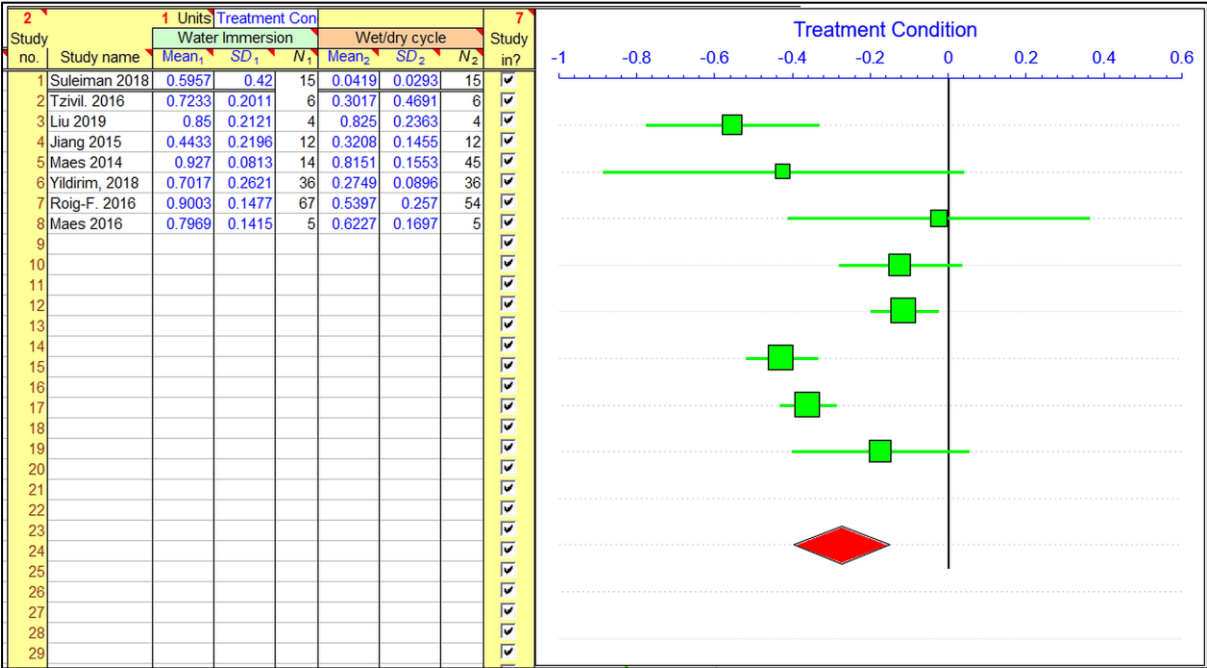


Figure 10 — The effect of treatment environment on the self-healing capacity of concrete

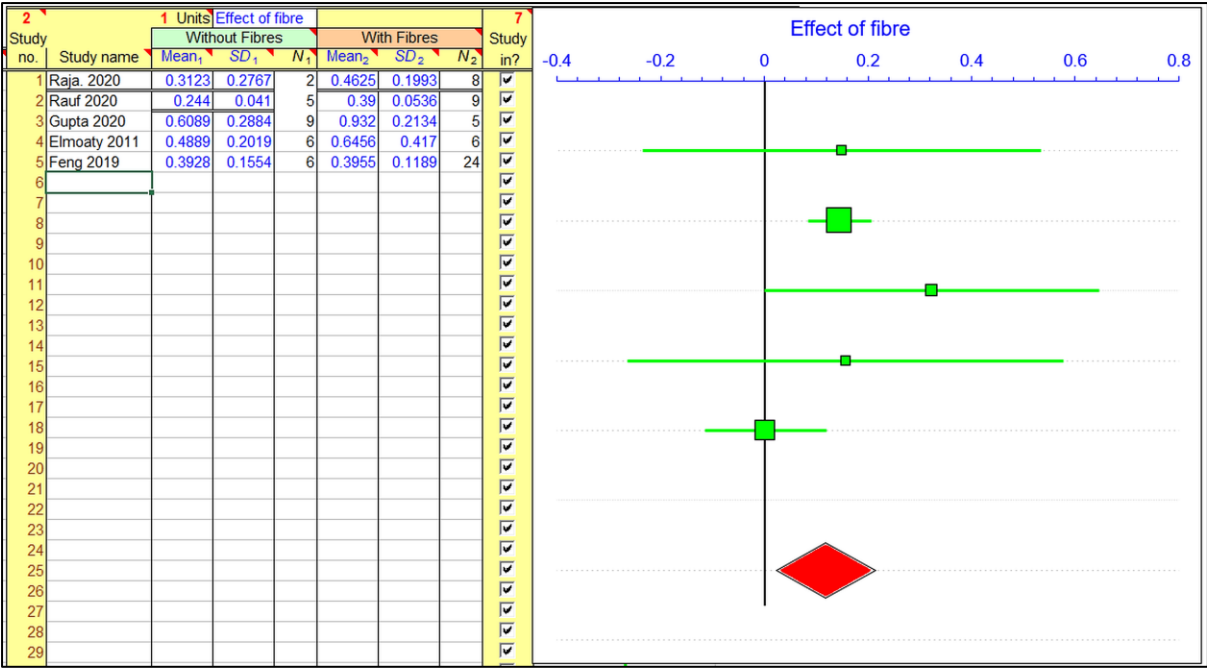


Figure 11 — The effect fibre’s presence on the self-healing capacity of concrete

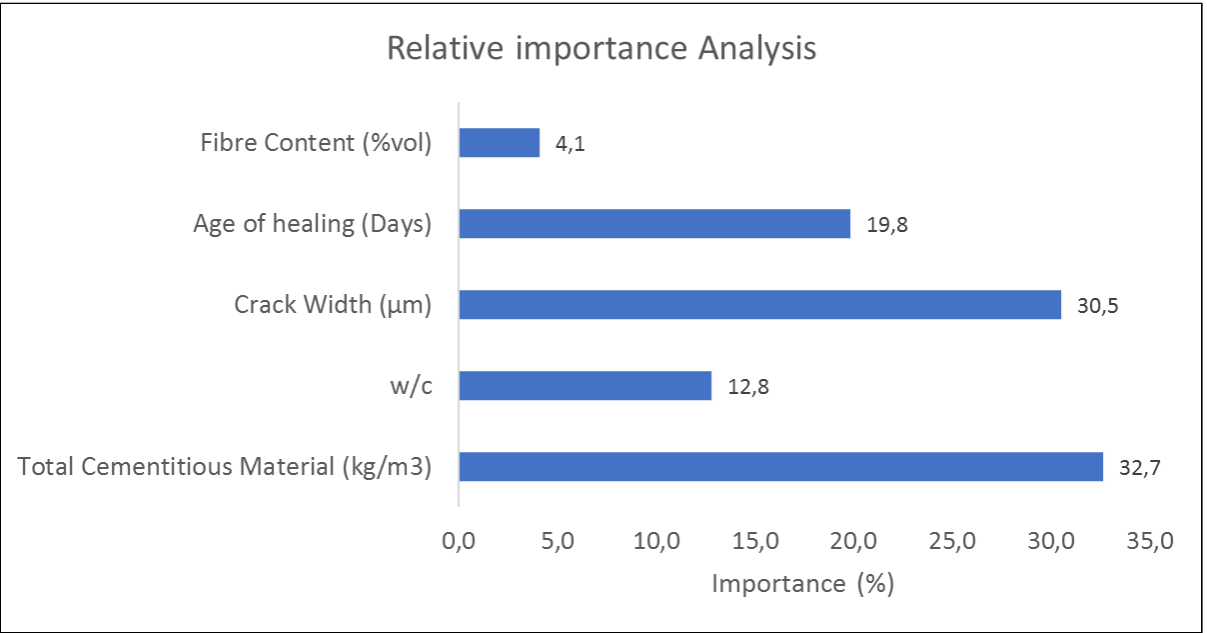


Figure 12 — Relative Importance Analysis