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Bond strength of corroded reinforcement in concrete: Neural and tree based approaches

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Abstract. Reinforcement corrosion affects the existing concrete structures, particularly in the coastal regions. One of the effects of corrosion of reinforcement is degradation of the bond stress that can be developed between the reinforcement and the surrounding concrete and this in turn affects the capacity of the reinforced concrete member. Prediction of the bond stress applicable for the corroded reinforcement has been attempted using analytical, empirical and soft computing methods. This article presents the comparative performance of two data-driven tools, artificial neural network (ANN) and decision tree (DT) for the task of prediction of bond stress from the corrosion level, the compressive strength of concrete and the ratio of cover and diameter of reinforcement bar. From the extensive evaluation of performance with both quantitative and graphical methods, it was concluded that the ANN approach would be better suited for the application, with the available data. For development of the models 8-fold cross validation scheme was adopted due to the limitations of data. The ANN models trained with pull-out test data, when employed with ensemble approach in predictive mode for a different experiment setup and bond strength test (flexural) data, could produce results comparable to ANN models trained with flexural test data (reported in literature). The inclusion of the additional factors (compressive strength of concrete and the ratio of cover and diameter of reinforcement bar), 8-fold cross validation approach, and ensemble prediction could be the possible reasons for achieving such portability of pull-out test based model for prediction of flexural test data.

Keywords: artificial neural network; decision tree; bond strength; concrete; corrosion; reinforcement

1. Introduction

Many concrete structures across the world constructed during 1970-80s are reaching the end of their postulated design life (generally 50 years). For continued performance, it becomes necessary to evaluate the structure for the present day strength according to the present design standards and codes. Many of these structures would be affected by one form of distress or the other and the present day strength estimation becomes particularly important in such scenarios. Given the explosion of cities and associated development of coastal infrastructure all over the world, corrosion of reinforcement and associated loss of structural capacity remain a prime concern for extending the life of such facilities. In concrete the cover to reinforcement has been traditionally provided for

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reduction of the probability of corrosion. Present day improvements in construction techniques include use of corrosion inhibiting paints, fusion bonded epoxy coated reinforcement, corrosion inhibitors in concrete, sacrificial anodes, high performance (dense) concrete, and in extreme cases stainless steel reinforcement has also been suggested for prevention of corrosion of steel.

Acknowledging the corrosion concern, the cover required for reinforcement has undergone upward revision in Indian design standard for concrete structures (BIS 2000) since 1970s and similar revisions would have happened in many other countries as well. However, for the constructed facilities, the issue of corrosion remains a concern and therefore the effects of corrosion on the load carrying capacity of the structure remain an active research topic. The various effects of corrosion on the coastal structures were discussed by Dauji (2018a). Estimation of probability of corrosion is possible by partially destructive test such as half-cell potential test. The degree of corrosion can be indirectly estimated by resistivity of the concrete using empirical models (Ahmad 2014, Dauji 2016a) or ANN (Sadowski 2013, Dauji 2019a).

Once the degree of corrosion is estimated for an existing structure, the effect of the same on the capacity of the structure needs to be ascertained. The effects of corrosion in reduction of structural capacity would include loss of steel area, loss of the bond strength between steel and concrete (crucial for the composite action of reinforced concrete), expansion of the corrosion products would lead to development of cracks, thereby resulting in intrusion of more corrosion agents and aggravating the corrosion (may even induce local pitting action) issue, and could finally lead to spalling of the cover concrete resulting in loss of confinement and loss of protection to the steel from environmental aggressive agents and fire. All these effects reduce the capacity of the member and thereby of the structure as a whole as well. Though the alkalinity of concrete provides inherent protection against corrosion, the carbonation and the chloride action, aggravated by the salt spray in coastal and alternate wetting and drying spells in tidal zones invariably result in loss of the alkalinity of concrete required for the corrosion protection. Therefore, addressing the effects of already occurred corrosion in existing structures for reduction in capacity is an essential part of health assessment of such facilities.

The bond characteristics for non-uniform corrosion would be different from uniform corrosion and this was studied by Fu *et al*. (2021). The stochastic character of the reinforcement corrosion, particularly under sustained load conditions has received attention of researchers (Huang *et al*. 2020). The corrosion induced bond degradation is very useful in fatigue life or service life prediction of reinforced concrete structures (Guo *et al*. 2020, Ito *et al*. 2021). Bending capacity of concrete members with corroded reinforcement has been studied with experiments (Nasser *et al*. 2021) or meso-scale models (Jiradilok *et al*. 2020). The influence of specimen dimension on the bond of corrosion affected steel bars has been examined (Zhang *et al*. 2020). The bond behaviour has been studied for post-fire concrete (Cai *et al*. 2020) and fibre-reinforced concrete (Wu *et al*. 2020) as well.

This article addresses one of the effects of corrosion, namely reduction in bond stress, with the machine learning tools: artificial neural network (ANN) and decision tree (DT). The effect of corrosion level (expressed in percentage) on the bond stress would be dependent on several factors such as: the grade of concrete (compressive strength), the nature of the reinforcement (plain bars or deformed bars), the cover provided to the reinforcement, the diameter of the reinforcement bar, the dimensions of the member, the ingredients of concrete, the water-cement ratio, the density of the concrete, the environmental exposure conditions, and stress levels among others. Incorporating so many factors into predictive models is a daunting task and therefore researchers over the years have tried to provide analytical, empirical (Cabrera 1996, Stanish *et al*. 1999, Auyeung *et al*. 2000, Lee *et al*. 2002, Chung *et al*. 2004, 2008, Bhargava *et al*. 2008, Yalciner *et al*. 2012, Lin and Zhao 2016) and soft computing models (Dauji and Bhargava 2016, 2018) for the same, and these models could consider only a few factors among so many. In literature different models have been generally reported for pull-out and flexural tests (Cabrera 1996, Stanish *et al*. 1999, Auyeung *et al*. 2000, Lee *et al*. 2002, Chung *et al*. 2004, 2008, Bhargava *et al*. 2008, Dauji and Bhargava 2016, 2018), but most of these expressions predicted normalized bond strength values from corrosion level only and few considered other factors such as the concrete grade or ratio of the cover and diameter of reinforcement. Considering the normalized bond stress indirectly incorporates the compressive strength of concrete in the formulation, but the important aspect of the provided cover to reinforcement is missing in most formulations available in literature.

Among the studies, Yalciner *et al*. (2012) developed empirical equations incorporating the compressive strength of concrete and the ratio of cover to the reinforcement diameter into the formulation. However, for higher levels of corrosion (typically > 4%) the formulation required the measured crack width for prediction of the bond stress of the corroded bar. It is recognized that whereas the crack width can be used as a very good input for understanding the corrosion effects on bond stress, measurement of the crack width with accuracy for the real-life projects could be a severe limitation for the practical implementation of such formulations.

The application of machine learning tools in concrete technology, and particularly the corrosion studies have increased in the recent times. ANN has been the universally popular and most applied tool and has been utilized for: prediction of potential characteristics of steel (Parthiban *et al*. 2005); prediction of temporal variation of corrosion current in reinforced concrete (Topcu *et al*. 2009); estimation of corrosion current from resistivity (Sadowski 2013, Dauji 2019a); prediction of the time to initiation of corrosion in concrete (Hodhod and Ahmed 2014); prediction of normalized bond stress of corroded reinforcement from the corrosion levels (Dauji and Bhargava 2016, 2018); prediction of concrete compressive strength (Dauji 2018c, Ramachandra and Mandal 2020); bridge scour evaluation based on vibration using support vector machine, a variant of ANN (Zhang *et al*. 2019); prediction of blast induced spalling in concrete members (Dauji 2020a); recovery of compressed images for automatic crack detection (Huang *et al*. 2021). In recent times another variant of ANN, namely, deep learning neural network, has found applications in civil domain for: automatic detection of pavement cracks (Zhang *et al*. 2016); structural damage detection (Lin *et al*. 2017); prediction of compressive strength of recycled concrete (Deng *et al*. 2018); estimation of missing structural temperature data (Liu *et al*. 2020).

The tree based methods have found relatively less application and this study attempts to introduce decision tree for prediction of bond stress of corroded reinforcement. However, DT has been successfully applied in many civil engineering applications such as: prediction of ocean currents (Dauji and Deo 2020); prediction of concrete strength from its ingredients (Dauji 2016b); estimation of capacity of single angle struts (Dauji 2019b); prediction of blast induced ground vibrations (Dauji 2020b). From the previous success of the model-based approach of DT and the model-free approach of ANN, these two tools are used for prediction of the bond stress of corroded reinforcement in this study and the performances of the two approaches are compared exhaustively using qualitative and quantitative tools.

Research significance

- In literature, different empirical models have been provided for prediction of bond strength of corroded reinforcement in concrete, for various ranges of concrete compressive strength or corrosion level. In this study, general purpose soft computing models are developed which would be applicable for any given compressive strength or corrosion level, within the ranges of variables of the basic data.

- ANN has been reportedly used for prediction of normalized bond strength from corrosion level, but the factors of concrete compressive strength or cover were not considered. In this study, ANN model is developed to predict bond strength corresponding to three variables: cover to reinforcement diameter ratio, concrete compressive strength and corrosion level.
- A new machine learning tool, namely, decision tree is introduced and its performance is compared to that of ANN model in providing prediction of bond strength between corroded reinforcement and concrete.
- Portability of ANN model developed for prediction of bond stress for corroded bars from pull-out test data applied in predictive mode for flexural test data has been investigated.

2. Data and methodology

2.1 Data

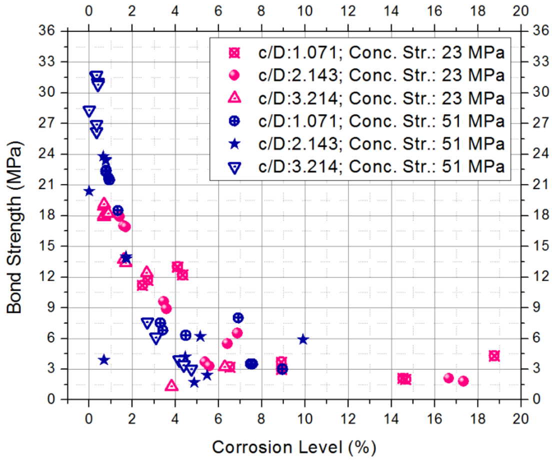
The present study is based on data obtained from literature (Yalciner *et al*. 2012, Lin and Zhao 2016). The study by Yalciner *et al*. (2012) was based on pull-out experiments conducted for two concrete compressive strengths (23 MPa and 51 MPa), the cover to reinforcement (deformed bars, 14 mm diameter) was varied as 15 mm, 30 mm, and 45 mm to obtain the ultimate bond strength of bars corresponding to various levels of corrosion.

The cover on the orthogonal direction was 68 mm for all specimens. The yield strength of steel was 458 MPa. The experiment was based on accelerated corrosion achieved by electrochemical method. The maximum bond strength was calculated based on the pull-out strength results based on 50 mm bond length and original bar diameter. During the accelerated corrosion test, continuous current of 60 V constant potential at 0 A to 5 A was maintained across the specimen. For further details of the experimental program readers are directed to the original article (Yalciner *et al*. 2012).

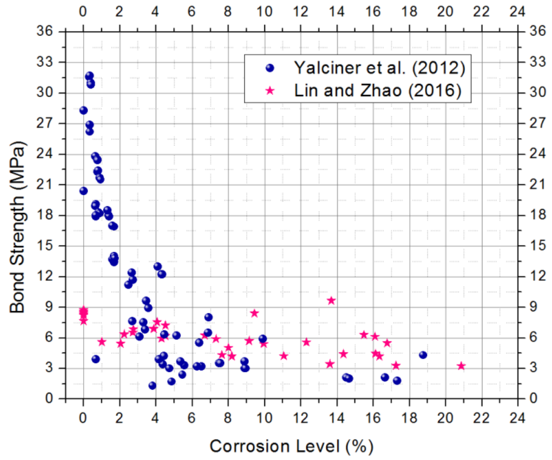
The data used for development of the ANN and DT models is presented in Fig. 1(a) in pictorial form. In the figure, the ratio of cover (c) to the diameter of reinforcement (D), and the compressive strength of concrete (Conc. Str.) are indicated by different symbols and the bond strength observed are plotted against the varying corrosion levels. In Fig. 1(b), the data from Lin and Zhao (2016) are plotted along with the data from Yalciner *et al.* (2012) to depict the entire data employed in this study.

Here it must be mentioned that the article (Yalciner *et al*. 2012) reported a total of 90 bond strength test results. Out of the 90, 18 were control specimens that were not exposed to the corrosion environment; and 72 were the specimens actually subjected to corrosion tests. Inclusion of the results (20% of 90: 18) from specimens which had not been subjected to corrosion environment could be spurious data and compromise the generalization capability of the data driven model for prediction of bond strength of corroded reinforcement. Hence, for the development of ANN and DT models in this study, the data from the specimens (72 nos.) actually subjected to corrosive environment were only selected.

It needs mention here that among the 72 specimens subjected to accelerated corrosion test, two specimens (Yalciner *et al*. 2012: $R_{14}SP_1$ and $R_{15}SP_1$) did not undergo corrosion (can also be seen in Fig. 1(a)), but these have been included in the database for present study, as they had been exposed to the corrosion environment.



(a) Data from Yalciner *et al*. (2012) (Pull-out test) – used for model development and testing



(b) Data from Yalciner *et al*. (2012) (Pull-out test) and Lin and Zhao (2016) (Flexural test)

Fig. 1 Data used in this study

Data from a later study by Lin and Zhao (2016) was selected for which the targeted input variables were available, for the purpose of examining the portability of the ANN model developed on the basis of the earlier set of data. This was a flexural test experiment with 20 mm diameter deformed bars, in beam specimens of 150 mm × 250 mm cross-section and 1200 mm length, with cover values as 40 mm at bottom and 65 mm at sides. The accelerated corrosion was achieved through electrochemical method, augmented by wetting (4 days) and drying (3 days) cycles. The current density was maintained at 400 μA/cm^2 across the specimen during the wetting cycle whereas no current was applied during drying phase. This was targeted towards achieving the corrosion environment for the reinforcement as close as possible to the natural environment, even while conducting accelerated corrosion test.

The high current density generally encountered in accelerated corrosion testing results in corrosion characteristics quite different from that occurring naturally in atmosphere (Lin and Zhao 2016, Vanama and Ramakrishnan 2020). The bond length was 150 mm in this study. For further

Table 1 Details of data used in the present study

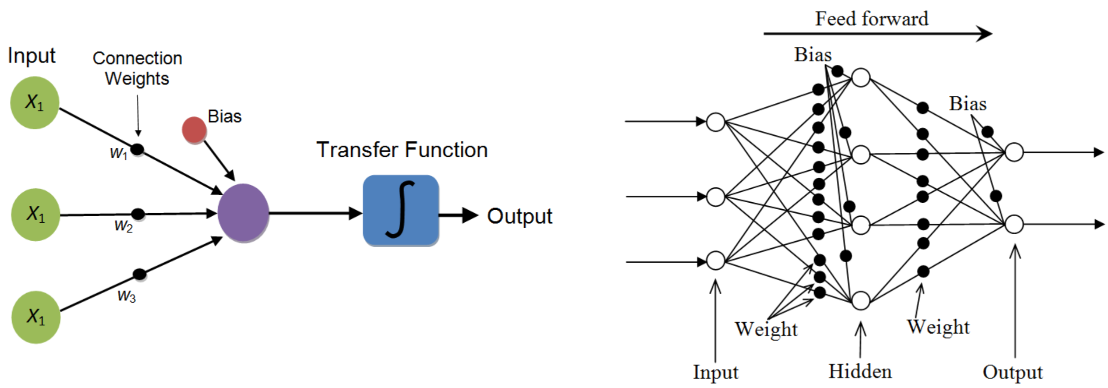
Variable	Details/Statistic	Yalciner *et al*. (2012)	Lin and Zhao (2016)
Number of data	-	72	36
Concrete strength (MPa)/ Water-cement ratio	-	23 / 0.750 51 / 0.400	30 / 0.695
Reinforcement yield strength (Mpa)	-	458	540
Reinforcement diameter (mm)	-	14	20
Bond length (mm)	-	50	150
Concrete cover (mm)	Bottom	15, 30, 45	40
	Side	68	65
Corrosion level (%)	Minimum	0	1.17
	Maximum	18.75	20.86
	Mean	4.08	7.84
	Median	3.19	7.48
	Standard deviation	4.24	6.22
Bond strength (MPa)	Minimum	1.30	3.24
	Maximum	31.70	9.64
	Mean	12.18	6.11
	Median	11.45	6.03
	Standard deviation	8.95	1.68

details of the experiment, the original article (Lin and Zhao 2016) might be referred. Concrete compressive strength was 30 MPa and steel yield strength was 540 MPa. However, it might be mentioned here that due to the differences in the material properties, experimental set-up (wetting-drying cycle and low current density in the latter), bond estimation method (pull-out in former and flexural in latter) between the two experimental studies, the accuracy of the testing performance might be less than that obtained for the pull-out test. Salient features of the two testing methods (pull-out test and flexural test for bond strength) have been compared and the differences have been highlighted in literature (Arslan and Pul 2020). The salient details of the data used in this study are presented in Table 1.

It can be appreciated from Table 1 that the range of corrosion level matches more or less for the two experiments, though for the latter, the upper limit is higher. The mean and median, however is almost double in the second study, when compared to the former, whereas the standard deviation is around 50% higher. In case of the bond strength, the range of the latter study is encompassed by the range in the previous study. But in this case, for the latter study, the mean and median is almost half of those of the former, and the standard deviation is one-fifth of the former. Therefore, the data characteristics are quite different for the two experiments.

2.2 *Artificial Neural Network* (*ANN*)

ANN is a versatile machine learning tool based on the concept of biological neural network or the brain. Just as the intelligence of a person is attributed to the complexity of the brain, the ANN modeling derives its' success from the high degree of complexity that can be achieved by using



(a) Basic Structure (b) Feed Forward Network

Fig. 2 Artificial Neural Network

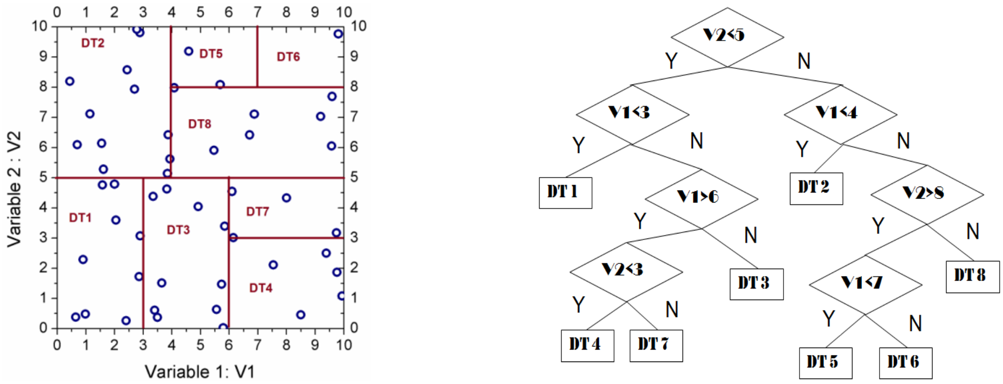
simple building blocks: the artificial neurons (Fig. 2(a)). The artificial neurons are arranged in layers: one input layer, one or more hidden layer and one output layers (Fig. 2(b)).

The input layer contains the number of neurons equal to the number of inputs. The output layer has that many numbers of neurons as there are outputs. The number of hidden layers and number of neuron in each hidden layer actually imparts the complexity to ANN architecture. In general, for regression models (as the present case) a single hidden layer would be sufficient and the number of neurons in hidden layer is often chosen by trial and error approach, targeted towards best accuracy with minimum complexity. Another thumb-rule is that the maximum trainable parameters of the ANN should be one-fourth to one-fifth of the number of data sets available for training the network (Dauji 2019a), in order to attain good generalization capabilities. Interested readers would find the details of structure and functioning of variety of ANN in textbooks (Wasserman 1993, Bose and Liang 1993, Haykin 2008).

The neurons are connected to one another between adjacent layers, though weights. An artificial neuron aggregates the weighted inputs, adds a bias and passes the result through an activation function, which fires the next neuron(s) if it is above a threshold value. The procedure of optimizing the weights and biases is generally referred to as the training of the network. In this study, feed-forward (inputs are passed forward) backward propagation (errors are propagated back to adjust the weights and biases) network was used and Levenberg-Marquardt algorithm was employed for training for the associated speed of convergence. The inputs and outputs for the ANN as well as DT would be jointly explained in the sub-section: Methodology. Compared to regression equations, the main advantage in ANN approach is that with only data of the dependent variables, the independent variable is estimated without a-priori assumptions about the complex non-linear dependencies between them.

2.3 Decision Tree (DT)

Another soft computing tool that is well adapted for development of regression type of models is decision tree (DT). This method is also known as model tree or regression tree and works on the principle of dividing the (multidimensional) model space into sub-domains and thereafter formulating separate regression models for each sub-domain. This method becomes especially suitable for non-linearly related data with high scatter, wherein a single model often falls short of



(a) Model domain split (b) Tree structure resulting from sub-division of model space into sub-domains shown in (a)

Fig. 3 Decision tree

the acceptable performance. There have been few applications of decision trees in civil engineering domain and ocean engineering applications as discussed in Introduction. In this study, it was therefore decided to explore this method and compare its performance with that of the universally popular and successful ANN.

In development of decision tree, the sub-division of the model space is performed according to some pre-decided criterion that may be: collecting highest number of samples in one class, attaining lowest entropy in each sub-domain, or some different algorithm. In decision tree research, the M5 algorithm, in which the sub-division is achieved by minimizing the standard deviation of the class value reaching a node, is very popular and the same is employed in this study. As the name implies, the DT has a tree-like architecture, in which the first decision box is the root, and from there, the branching is performed to reach other decision boxes (nodes) or leaves (models).

Based on the domain splitting criterion adopted, the progression of the branching beyond a node or termination of the branch in a leaf (model) would be decided. There are issues that have to be addressed in development of DT models, such as numerous domain splits or broad discontinuities between adjacent models and there are algorithms available in the literature for the same (Rokach and Maimon 2015, Jekabsons 2016). For the underlying principles of the structure and functioning of DT models, textbooks on the subject (Quinlan 1992, Witten and Frank 2000, Rokach and Maimon 2015) would provide ample information. Fig. 3(a) depicts a sample DT with the corresponding domain splitting (Fig. 3(b)) for two variables. In the present study, there are three input variables, and the model space would be a three-dimensional cube in which sub-domains (volumes) would be created and individual simple models would be developed for each of them.

2.4 Methodology

In this study, the input variables are chosen so that the salient factors affecting the bond strength of reinforcement bar may be incorporated in the ANN / DT model, similar to the empirical models reported by Yalciner *et al*. (2012). Therefore, the concrete compressive strength, the cover to reinforcement diameter ratio, and the corrosion level are chosen as input variables. The output of the ANN / DT models would be the bond strength of corroded reinforcement. In order to provide necessary trainable parameters to the ANN models for capturing the non-linear dependencies between the variables, the number of training data would have been insufficient for training-testing division in ratio 70:30 (which would amount to around 50 data for training purposes) and using higher proportion for training would severely reduce number of testing data for desired confidence in the testing performance. This issue is particularly encountered when developing data driven model for non-linear relationship between multiple input variables and output variables, from limited availability of datasets.

An elegant solution to this problem is n-fold cross validation exercise, wherein n models are developed, each with (N/n) number of testing data and the remaining as training data (N is total number of data). This facilitates development of ANN models with $\{(n\text{-}1) \times N\} / n$ data in each case, and combining the testing results of all the n ANN models, the total testing data becomes N in number. The beauty of cross validation approach is that each of the N testing data is 'new' for the particular ANN, and was not used in training of that particular model. Therefore, it can be appreciated that the n-fold cross validation approach would be useful particularly for development of data-driven models from limited data.

In the present study, 8-fold cross validation was implemented for ANN. Considering 63 training datasets and number of trainable parameters as given in literature (Dauji 2019a), the number of neurons in the hidden layer would be limited to 3, for training each model (63 / 4 ~ 16). Thus, the architectures explored in this study were 3-1-1, 3-2-1, and 3-3-1 with the trainable parameters as 6, 11 and 16 respectively. As a further check, two additional architectures with higher number of neuron in hidden layers were also considered for ANN models: 3-4-1 and 3-6-1 with the respective number of trainable parameters of 21 and 31.

As explained for the ANN model, similar cross validation scheme was adopted for the DT model development as well. Pertinent parameters of the DT model implemented in this study are: training algorithm: M5 algorithm (explained earlier): minimum number of training data to belong to a leaf (decision rule) is two; the minimum number of data belonging to a node for splitting to occur would be therefore, four; pruning option was implemented to reduce number of models, if that improved the estimated error of the respective sub-tree; split threshold is 0.05 (node considered for split if the standard deviation of response variable is higher than the split threshold at the node).

Evaluation of the developed prediction models is generally performed using a few selected performance measures (Dauji 2018b, 2020b, Ray and Dauji 2019) and the importance of using carefully selected multiple metrics have been highlighted in literature (Dauji 2021). The study by Yalciner *et al*. (2012) reported only the correlation coefficient for the proposed models. However, in this study, multiple performance metrics are selected for comprehensive evaluation of the model performance. The selected metrics include the correlation coefficient (which indicates the degree of linear association of the experimental and predicted values); root mean squared error (RMSE: larger errors are penalized more); mean absolute error (MAE: error measure on absolute values); mean absolute relative error (MARE: absolute error measure on relative scale); and root mean square relative error (RMSRE: relative error measure penalizing larger deviations more). These error metrics are self-explanatory and detailed formulations can be found in a basic statistics textbook. In addition to these quantitative measures, scatter plot of experimental and predicted values, variable plots, and residual plots would be studied for visual appreciation of the accuracy of the developed models. The points which lie nearest to the 1:1 diagonal in the scatter plot would indicate the better fit. As adopted in literature (Rafi *et al*. 2020), points falling within one standard deviation on either side of scatter plot is taken as acceptable result for this study, and the number of points outside these bounds are also reported. In residual plots, random and small values of residuals with the mean / median closest to zero would indicate the better model.

Comparison of all these qualitative (visual) and quantitative metrics, the better suited method for this application would be identified. Thereafter, the better suited model would be subjected to test using data from a different experiment (Lin and Zhao 2016) to check whether such portability could be possible for the chosen model.

3. Results and discussion

3.1 Performance metrics for ANN Model

The study (Yalciner *et al*. 2012) from which the basic data for development of the ANN (and later DT) models was taken established the suitability of the proposed equations with a single quantitative metric: correlation coefficient. As mentioned earlier, correlation coefficient is a good indicator of the linear association between the experimental and predicted values of a variable, but fails to capture proportional errors and therefore, models with same correlation coefficient might end up with a wide variation of prediction errors. Yalciner *et al*. (2012) proposed three equations for prediction of the bond strength of corroded reinforcement, to be selected based on the compressive strength of concrete, ratio of cover to diameter of bar, and degree of corrosion. The variables in the equations included the ratio of cover to diameter of bar, corrosion level and concrete compressive strength. For higher corrosion level, the equation had another variable in the form of the crack width. The correlation coefficients were reported as 0.98, 0.94 and 0.96 for the three equations, for which the average works out as 0.96.

It has to be noted that though whether the evaluation of the developed model was performed with fresh data or not – has not been mentioned in the study (Yalciner *et al*. 2012). If the other similar empirical studies are any indication, then the performance evaluation was performed with same data as was used for development of the regression model. This would be considered a serious limitation for proper evaluation of performance, as highlighted in literature for other studies (Dauji 2018b, 2021). In this study, the ANN (and DT) models were developed with three variables as inputs and hence were independent of crack width for prediction purpose.

As explained in the sub-section: Methodology, 8-fold cross validation was performed thereby ensuring that the model performance was always evaluated by data not used for development of the model. The results are summarised in Table 2 for all the ANN models developed with different numbers of neurons (1 to 4, and 6) in the hidden layer. The performance of ANN model with three neurons in hidden layer is adjudged the best (in boldface) considering all performance measures. In Table 2, it can be seen that the correlation coefficient of the best ANN model (3-3-1) is equal to the

Table 2 Prediction performance of ANN model: 8-fold cross validation

Performance metric	Number of neurons in hidden layer of ANN				
	1	2	**3**	4	6
Correlation coefficient (r)	0.89	0.91	**0.96**	0.91	0.88
RMSE (MPa)	4.02	3.78	**2.43**	3.73	4.20
MAE (MPa)	2.81	2.57	**1.67**	2.53	2.67
RMSRE	1.05	1.11	**0.60**	0.95	0.91
MARE	0.49	0.48	**0.30**	0.44	0.46

Table 3 Prediction performance of DT model: 8-fold cross validation

Performance metric	DT
Correlation coefficient (r)	0.88
RMSE (MPa)	4.40
MAE (MPa)	2.82
RMSRE	1.02
MARE	0.45

average value reported in literature (Yalciner *et al*. 2012) with associated errors between 1.5 MPa and 2.5 MPa, which would be between 30% and 60% of the bond strength. The graphical evaluation of the ANN model would be presented along with the DT model in subsequent sub-section.

3.2 Performance metrics for DT Model

The same five performance metrics are evaluated for the DT models, developed based on the 8-fold cross validation approach, and are presented in Table 3, wherein it is observed that the correlation of the DT model is less than that of the ANN model reported in Section 3.1, as well as the empirical equations in literature (average correlation coefficient: 0.96, Yalciner *et al*. 2012).

It is however mentioned that the model evaluation was presumably conducted in literature (Yalciner *et al*. 2012) with same data as used for model development, whereas for the DT models, the data for evaluation was fresh. The associated errors for this prediction performance of DT are noted to be higher, around 1.5 to 2 times compared to the best ANN model (this study). The comparison of performance of ANN and DT would be further examined graphically in Section 3.3 with scatter plots, variable plots and residual plots. However, from the quantitative metrics (Table 2 and Table 3) it can be appreciated that development of DT based model has not been able to efficiently capture the non-linear relationship between the three input variables and the bond strength, when compared to the prediction performance of model-free ANN.

3.3 Comparison of ANN and DT Model Performance: Plots

As mentioned in the earlier section, the performance of the DT models was relatively less accurate when compared to the ANN models. Presently, the performance comparison is undertaken with plots for pictorial representation. The scatter plot of the experimental and predicted bond strength for the entire data set (Yalciner *et al*. 2012) is shown in Fig. 4 which clearly indicates the relative closeness of the ANN points (circles) to the 1:1 diagonal line, compared to the DT points (triangles). Whereas there are three points on lower and two points on higher sides for DT prediction beyond the $\pm\sigma$ lines, there is only one ANN point on the higher side falling outside the $\pm\sigma$ lines.

Hence from the scatter plot also, it is concluded that in this case, the DT models would have less accurate performance compared to ANN. This could be due to the smaller number of data points for each of the six sets of input variable combination (12 data in each: refer Fig. 1), which restricted the formulation of sufficiently accurate regression models in the sub-domains for DT. The variable plot for the experimental data points (Yalciner *et al*. 2012) and the ANN as well as DT predictions are plotted against the corrosion levels in Fig. 5. The points are not differentiated for the concrete compressive strength or the ratio of cover and bar diameter in Fig. 5 to avoid confusion with that

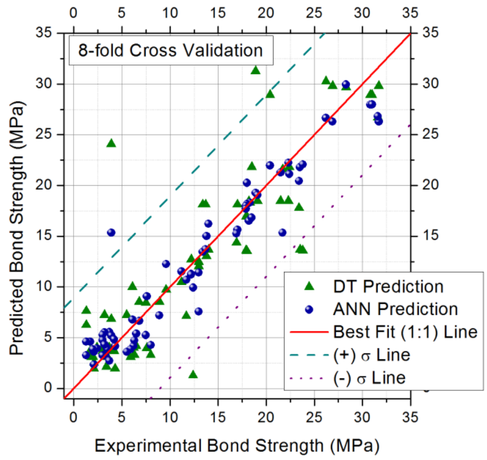


Fig. 4 Scatter plot of experimental bond strength (Yalciner *et al*. 2012) and model (ANN, DT) predictions

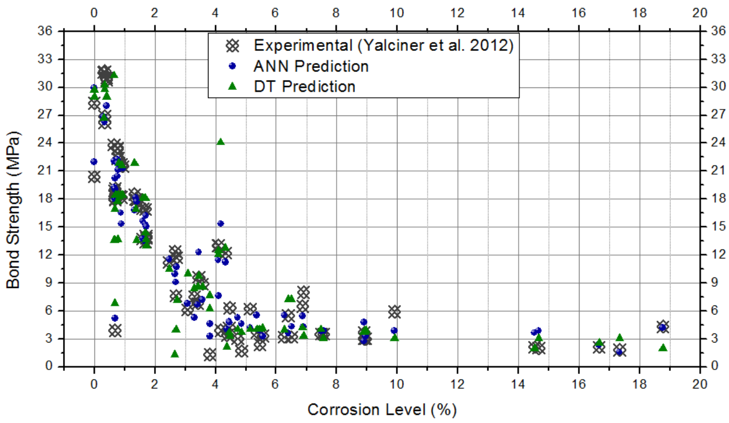


Fig. 5 Variable plot of experimental bond strength (Yalciner *et al*. 2012) and model (ANN, DT) predictions

many number of symbols and overlaps. In Fig. 5 also, the ANN points (circles) are closer to the experimental points (rhombus), compared to the DT points (triangles). An aspect important for corrosion modeling would be the accuracy of the developed models for un-corroded specimens. In Fig. 5 it can be seen that for the zero-corrosion data (2 nos.), there is marginal over-prediction by the ANN / DT model and therefore the accuracy of the models for zero-corrosion data is acceptable.

The box-and-whisker plots for the experimental bond strength and the predictions from ANN as well as DT models are depicted in Fig. 6 wherein it can be appreciated that though the mean value (circle) are almost similar for the three data sets, the median (line across the box) is closer to the observations for the ANN model predictions. The other percentiles (box ends, lower whisker) from the two models (ANN and DT) developed in this study almost match the experimental values, though the maximum value (top whisker) is slightly reduced for the ANN model.

The residual of the prediction model is another important aspect which should be examined for prediction models, and this was missing for most of the models (empirical as well as data-driven) in literature for bond strength prediction. The residuals of the model predictions for ANN and DT

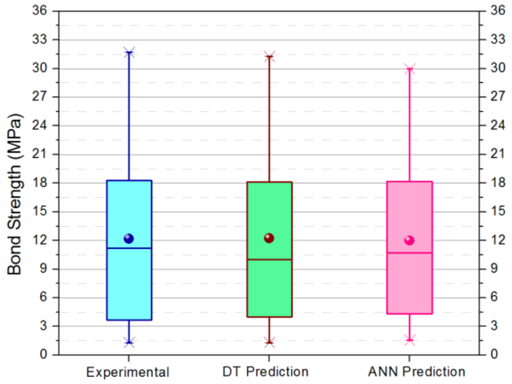


Fig. 6 Box-and-whisker plot of experimental bond strength (Yalciner *et al*. 2012) and model (ANN, DT) predictions

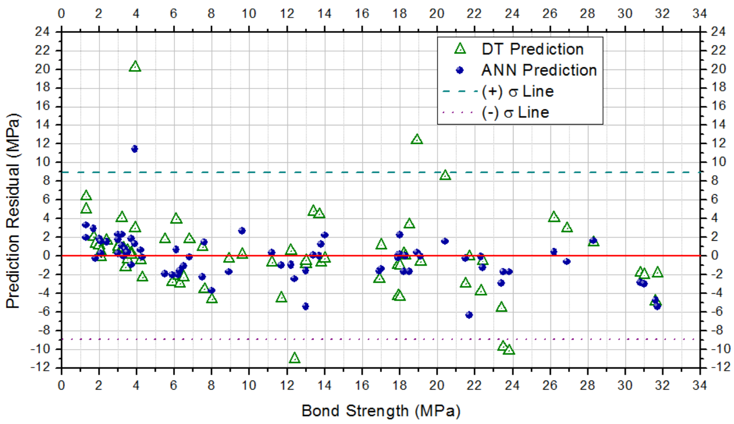


Fig. 7 Residual plot of the model (ANN, DT) predictions

are plotted against the respective experimental bond strength in Fig. 7 wherein it is clear that the residuals are not proportional to the bond strength values, but are random in nature. This observation confirms that the errors in the model predictions are random in nature.

As a final check, the box-and-whisker plot of the relative residuals for the two models (ANN and DT) developed in this study are presented in Fig. 8, wherein it is highlighted that the median (line across the box) relative residual is almost on zero and the mean (circle) is very close to zero for both ANN and DT, closer to zero for ANN.

The maximum residuals of the DT predictions err more on the positive side as compared to the negative side (cross and horizontal line) whereas the other percentiles are more or less balanced (box extents, and whiskers). For the ANN model predictions, the percentile values (box extents and whiskers) as well as the maximum relative residuals (cross and horizontal line) are more balanced, and the percentile values are much less than those of DT model. These also indicate that the ANN model is better in prediction for this application compared to DT, when developed with the present set of experimental data.

It is mentioned here that the time taken for developing or running the models was typically 2-3

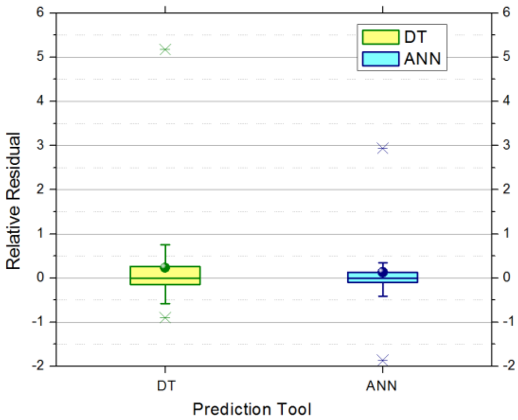


Fig. 8 Box-and-whisker plot of relative residuals of model (ANN, DT) predictions

seconds for ANN and 1 second for DT on an i3-3220 @ 3.3 GHz Desktop, 64 bit OS, 8 GB RAM. Thus the time for development or implementation of the ANN / DT models is very small and would not be a significant consideration for this application.

3.4 Testing performance of ANN model with different experimental data

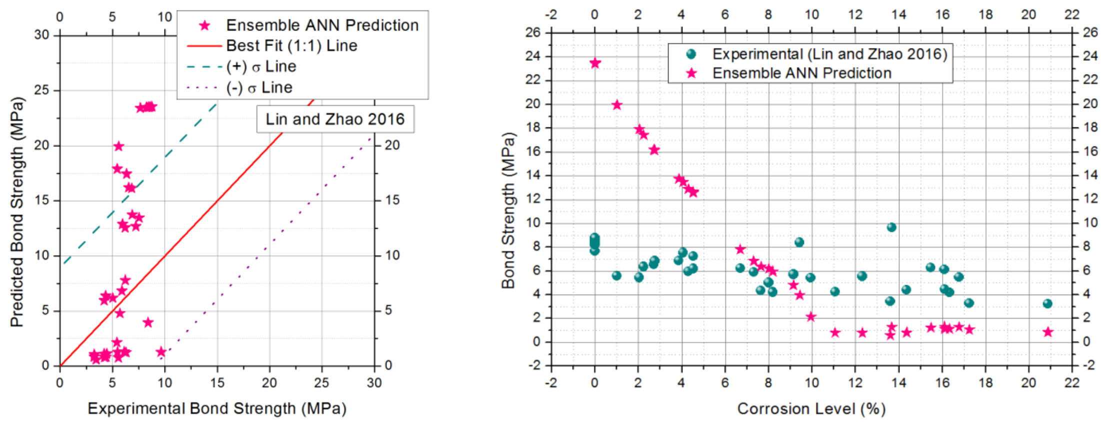
As explained in the section: Data, due to scarcity of suitable data from pull-out bond strength tests for corroded reinforcements from a different experimental set-up, the portability of the developed (ANN) model, which has been adjudged the better between ANN and DT approaches, has been examined with requisite data which was available from flexural test (Lin and Zhao 2016). For the purposes of this testing performance with fresh data set, all the eight ANN models developed earlier were used in ensemble approach wherein the final output of the ANN model is taken as the weighted combination of the predictions for that data set from all the models, and equal weights were assigned to all the models. Thereafter the same model performance metrics were evaluated and presently those are listed in Table 4, wherein it is observed that the correlation has dropped to 0.63 from 0.96; the error measures have increased over the ANN model reported in Section 3.1 by factors of two to five. These differences could be attributed to a variety of reasons, which will be discussed shortly.

The performance of the ensemble ANN model for the fresh data is examined with the scatter and variable plots in Figs. 9(a) and 9(b) respectively, wherein it is noted that almost 25% of the points (8 nos. out of 36 nos.) are falling outside the acceptable range of ± σ lines, which occurs between corrosion level of 5% to 10% and all the errors are on the higher side, thereby could yield non-conservative results. The reason for the difference jumps up to the eye in Fig. 9(b) – the variation of the bond strength with various levels of corrosion of the reinforcement bar in the experiment (Lin and Zhao 2016) is appearing to be random – thereby a pattern is not clearly discernable. On the other hand, the predictions by ensemble ANN approach, when tested with the fresh data (Lin and Zhao 2016) the results follow a defined (exponential decay, with some fluctuations) pattern, same as that could be seen in the experimental data (Yalciner *et al*. 2012) in Fig. 1 presented earlier.

Similar variation between the predicted bond strength (normalized) of corroded reinforcement bars obtained from ANN model developed for flexural test data and the experimental results of Lin and Zhao (2016) has been reported in literature (Fig. 14 of Dauji and Bhargava 2018). For this same

Table 4 Prediction performance of ANN model in ensemble mode: Testing with fresh data (Lin and Zhao 2016)

Performance metric	ANN
Correlation coefficient (r)	0.63
RMSE (MPa)	8.35
MAE (MPa)	6.77
RMSRE	1.20
MARE	1.04



(a) Scatter Plot (b) Variable Plot

Fig. 4 Scatter plot of experimental bond strength (Yalciner *et al*. 2012) and model (ANN, DT) predictions

dataset, the correlation coefficient reported there was 0.62 for best ANN model (developed for flexural test results) as against 0.63 obtained in this study (ANN model developed for pull-out test results). The drop in correlation (0.94 to 0.62) reported by Dauji and Bhargava (2018) was similar to this study (0.96 to 0.63) and the doubling of the error measures (RMSE: 0.25 from 0.13 and MAE: 0.22 from 0.12) was also reported.

From the aforementioned discussions, it is the contention of the author that inclusion of the two new independent variables, namely, ratio of cover to bar diameter and the grade of concrete, in addition to the corrosion level, for prediction of bond strength has improved the performance of the ANN model developed for pull-out tests such that it can predict the bond strength for flexural tests with similar error metrics as ANN model developed for flexural tests (Dauji and Bhargava 2018). The development of the ANN models using the 8-fold cross validation approach and thereafter using the eight ANN models in ensemble mode for prediction could also have contributed towards achieving the portability of ANN developed for pull-out test results for predictive application in case of flexural test data.

However, there is still ample scope of improving the accuracy of the predictions by reduction of the errors, and that can be attempted by: development of models from a larger database or with more sophisticated machine learning algorithms. The errors could be attributed to the variations in the input and output data statistics, which is always a limitation of the data driven models. The other aspects which could have influenced the reduction in accuracy would include the difference in material properties, mix proportions, specimen sizes, bond lengths, impressed currents and wetting-drying conditions, presence of stirrups (including diameter and spacing) and other experimental details.

Particularly, for the data driven models such as ANN, the relationship between the chosen variables is defined by the training data and thereby such variations are not explicitly addressed by the models developed. In order to capture such effects effectively, the database has to include all these factors and the length of database would also have to be long enough for developing ANN models of sufficient trainable parameters to represent all the pertinent factors in the prediction phase. Nonetheless, the ANN models similar to the one developed with *n*-fold cross validation approach as performed in this study, when used for prediction in ensemble mode, would be more effective than the empirical equations available in literature, for reasons discussed earlier. The promise of this approach is hereby established, though the model performance might not be as accurate for data with different statistics compared to the data used to develop the ANN model.

3.5 Implementation of developed ANN Models for bond strength prediction

It has to be appreciated that the reported performance originated from 8-fold cross validation exercise carried out for both the ANN and the DT models. This modeling strategy resulted in eight models for ANN as well as DT. The ANN model has been found to be superior in performance compared to that of the DT in this study. Therefore, in this section the implementation aspect of these ANN models for bond strength prediction is discussed. Many of the empirical equations (Cabrera 1996, Stanish *et al*. 1999, Auyeung *et al*. 2000, Lee *et al*. 2002, Chung *et al*. 2004, 2008, Bhargava *et al*. 2008) or the ANN models (Dauji and Bhargava 2018) available in literature ignores the cover to the concrete and the reinforcement diameter, while incorporating the compressive strength of concrete indirectly in use of the normalized bond strength.

As was mentioned earlier, the measurement of the crack width in the actual structures would be difficult to execute on operational level, thereby limiting the application options for the empirical equations (Yalciner *et al*. 2012) for prediction of bond strength based on corrosion levels, concrete compressive strength, the ratio of concrete cover to reinforcement diameter, and crack width required for the higher levels of corrosion or higher values of ratio of concrete cover to reinforcement diameter. The ANN models developed in this study precluded the inclusion of crack width in predictions and achieved similar accuracy in predictions (correlation coefficient of 0.96) as the equations (Yalciner *et al*. 2012), which require crack width for prediction of bond strength of corroded bars. Thus, the ANN models work on less data and provide equally good predictions and therefore can be considered superior to the empirical equations in literature (Yalciner *et al*. 2012).

The implementation strategy would also be quite simple, and this was implemented for the predictions executed for the data from Lin and Zhao (2016) in Section 3.4 earlier. The predicted bond strength is to be taken equal to the value obtained from the weighted predictions of the eight ANN models in ensemble mode, and given the fact that assigning equal weights to all the eight models worked well in this study (Section 3.4), same can be adopted for future predictions as well. It is highlighted here that the accuracy of the predicted bond strength would be good (with errors around the values reported in Table 2) for the ranges of input variables listed in Table 1 – and this would be for pull-out bond strength.

When applied outside the ranges of the variables (Table 1) the accuracy would possibly reduce, as it would when these models are applied for the flexural bond strength prediction (as seen in Table

4). It is hereby suggested that the data base be expanded with more experimental studies and/or inclusion of more pertinent variables, and thereafter more generalized models can be developed. There can be a possibility of inclusion of the type of bond strength test (pull-out or flexural) as a variable in the machine learning (ANN) model for an all-purpose prediction tool. Comparison of such all-purpose prediction tool with the modular tools (specific to the type of test) could enlighten further of the limitations of the developed models.

4. Conclusions

In this article, ANN and DT models have been developed for prediction of bond strength of corroded reinforcement in concrete, based on three input variables: the corrosion level (expressed as percentage), the compressive strength of concrete, and the ratio of the cover to the diameter of the reinforcement. As the database was relatively small, 8-fold cross validation approach was adopted in order to achieve sufficient complexity of the models and at the same time properly evaluate the performance of the model with a larger set of data. The salient findings of the study can be summarized as:

- A new modelling tool (DT) was introduced for prediction of bond strength of corroded reinforcement and the performance was compared to ANN model. Within the limitations of this study, the ANN modelling was adjudged superior to that of the DT approach.
- The adopted 8-fold cross validation approach was effective in development of ANN models with less data but comparable performance as the empirical equations reported earlier (Yalciner *et al*. 2012).
- A comprehensive performance evaluation was presented for the models (ANN and DT) developed in this study, and such evaluation was missing in literature (Yalciner *et al*. 2012, Lin and Zhao 2016). The improvements would include: use of different data for model development and performance evaluation; use of multiple error metrics for examining all aspects of the performance; examining the residuals in prediction mode; comparison of the data statistics of the experimental values and the predicted ones.
- Whereas the aspects (compressive strength of concrete and ratio of the cover to the diameter of reinforcement) missing in many models (empirical equations as well as ANN models) were included in the (ANN and DT) models developed in this study, these models were free from requirement of measurement of crack width. It is highlighted that the requirement of crack width for prediction of bond strength (Yalciner *et al*. 2012) would be a limitation for practical implementation for real-life projects.
- The ANN models, developed from pull-out test data, when employed in ensemble mode for prediction of flexural test data, could provide comparable accuracy as the ANN models (developed from flexural test data) reported in literature (Dauji and Bhargava 2018).

This study definitely reinforces the promise of the ANN modeling approach for prediction of bond strength of corroded reinforcement from various pertinent factors (three employed as inputs in this study) and introduced the n-fold cross validation approach for development of ANN of sufficient complexity from limited data and demonstrated an ensemble approach for use of the 'n' models in predictive mode. In conclusion, the scope of future research experimentation for expanding the database with inclusion of more numbers of pertinent factors for development of more generalized models is highlighted.

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Conflict of interest

The author declares that there was no known conflict of interest.

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