Application of Neural Networks for the Estimation of the Shear Strength of Circular RC Columns

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Abstract-This study aims to develop Artificial Neural Networks (ANNs) for predicting the shear strength of circular Reinforced Concrete (RC) columns. A set of 156 experimental data samples of various circular RC columns were utilized to establish the ANN model. The performance results of the ANN model show that it predicts the shear strength of circular RC columns accurately with a high coefficient of determination (0.99) and a small root-mean-square error (4.6kN). The result comparison reveals that the proposed ANN model can predict the shear strength of the columns more accurately than the existing equations. Moreover, an ANN-based formula is proposed to explicitly calculate the shear strength of the columns. Additionally, a practical Graphical User Interface (GUI) tool is developed for facilitating the practical design process of the circular RC columns.

Keywords-artificial neural networks; circular reinforced concrete column; graphical user interface; shear strength

I. INTRODUCTION

Circular Reinforced Concrete (RC) columns have been widely used in civil engineering structures. Shear strength is one of the most critical values considered in the design process. Estimation of this parameter can be performed by experiments or design code provisions. However, experimental tests require time-consuming implementations and are costly. Moreover, many studies pointed out that the current design code equations in calculating the shear strength of RC columns may give a large dispersion compared to the experimental results [1-4]. Therefore, it is necessary to develop soft-computing models, which ensure the accuracy demands and have less modeling effort and cost. Machine Learning (ML) models have been extensively applied for various engineering problems since they possess great advantages such as computational efficiency and sufficient consideration of uncertainties [5-14]. Numerous studies utilized ML techniques to estimate the responses of RC structures and elements [15-22]. Specifically, ML models have been used to predict the shear strength of rectangular RC columns in [4, 23]. Additionally, several studies have carried out data-driven models to estimate the shear strength of circular RC columns [1-3, 23]. Authors in [1] collected 47 experimental datasets to develop ANNs for calculating the shear strength of RC columns. They highlighted that the ANN model obtained better results compared to the design codes. Authors in [2] developed the Gene Expression Programming (GEP) and Particle Swarm Optimization (PSO) models to predict the shear strength of short circular RC columns with 200 numerical data sets. The results revealed that those ML techniques outperformed other design code formulas. Recently, a set of linear and nonlinear equations, based on regression analysis, were proposed in [23] for the estimation of the maximum shear strength of circular RC columns.

Previous studies mostly proposed ML models for calculating the shear strength of circular RC columns. However, the previous models were not transferred to practical tools, which can be used in design problems. Designers and analysts have difficulty in applying those soft-computing models. Additionally, the influence of the input variables on the predicted shear strength was not investigated. So far, only the proposed equation of [23] can be practical in the design purpose. In this study, we aim to develop a GUI to simplify the calculation procedure of the shear strength of circular RC columns. For that, ANNs are constructed based on 156 experimental data samples of RC columns. Moreover, an ANN-based formula for shear strength calculation of the column is proposed in the present study.

II. DATASET

To construct the neural network model, 156 experimental data samples of circular RC columns were collected from the literature [24]. Nine input parameters, including geometric dimensions, reinforcing bar details, material properties, and axial load, need to be provided to predict the shear strength of

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the columns. Geometric dimensions comprise the height of the column (L), the diameter of the cross − section (D). Reinforcement details include the longitudinal reinforcement ratio (ρ_l), the transversal reinforcing bar ratio (ρ_s), and the spacing of the transversal reinforcements (s). Material properties are the yield strength of the longitudinal (f_{yl}) and transversal (f_{ys}) reinforcing bars and the compressive strength of concrete (f'_c). The axial load (P) is also considered.

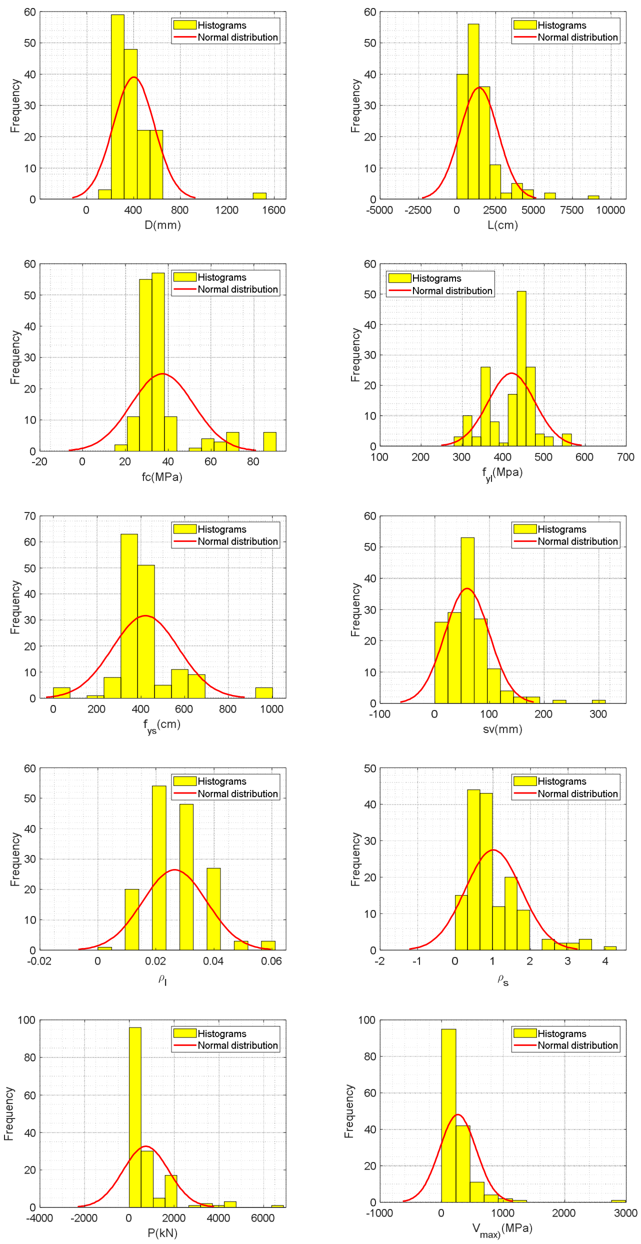

Fig. 1. Distributions of the dataset.

The distributions of input parameters of the dataset are shown in Figure 1. The statistical properties of the experimental results are described in Table I. In this table, the 9 input variables to consider in performing ANN models are numbered from X_1 to X_9.

III. EXISTING EQUATIONS FOR SHEAR STRENGTH OF CIRCULAR RC COLUMNS

In this study, we employed 5 typical equations, which were proposed in [25-29] for calculating the shear strength of circular RC columns, as expressed in Table II.

TABLE I. STATISTICAL PROPERTIES OF INPUT VARIABLES OF THE DATASET

Input variable	D (mm) (X_1)	L (mm) (X_2)	ρ_l (%) (X_3)	ρ_s (%) (X_4)	s (mm) (X_5)	f'_c (MPa) (X_6)	f_{yl} (MPa) (X_7)	f_{ys} (MPa) (X_8)	P (kN) (X_9)
Min	152	250	0.46	0.10	9	19	294	207	0.0
Mean	402	1429	2.69	1.03	61	37	420	430	736
Max	1520	9140	5.58	4.27	305	90	565	1000	6770
SD	175	1234	1.03	0.73	40	15	57	135	1010
COV	0.44	0.86	0.38	0.70	0.65	0.39	0.14	0.31	1.37

SD: standard deviation; COV: coefficient of variation

TABLE II. CIRCULAR RC COLUMNS SHEAR STRENGTH EQUATIONS

No.	Reference	Expression	Eq.
1	ACI 318 [25]	$V_1 = V_c + V_s$ $V_c = 0.166\left(1 + \frac{P}{13.8A_g}\right)Dd\sqrt{f'_c}$ $V_s = \frac{A_{st}f_{ys}d}{s}$; d is the effective depth of cross section; $d = 0.8D$ A_g is the gross section of the columns. A_{st} is the transversal reinforcement area	(1)
2	Ascheim and Moehle [26]	$V_2 = V_c + V_s$ $V_c = 0.3\left(k + \frac{P}{13.8A_g}\right)0.8A_g\sqrt{f'_c}$ $k = \frac{4-\mu}{3}$, μ is the displacement ductility $V_s = \frac{A_{st}f_{ys}d}{s\tan(30^0)}$; $d = 0.8D$	(2)
3	Biskinis et al. [27]	$V_3 = V_p + k(V_c + V_s)$ $V_c = 0.16max(0.5; 100\rho_l)\cdot$ $\left(1 - 0.16min\left(5; \frac{a}{d}\right)\right)A_c\sqrt{f'_c}$ $V_s = \frac{A_{st}}{s}(d - d')f_{ys}$ $V_p = \frac{D-x}{2a}\min(P; 0.55A_cf'_c)$ x is the neutral axis depth, d' is the depth of the compression reinforcement layer; $k = 1{\sim}0.75\ for\ \mu < 1{\sim}6$ A_c is the concrete area of cross section.	(3)
4	Moehle et al. [28]	$V_4 = k(V_c + V_s)$ $k = 0.7 \leq 1.15 - 0.075\mu \leq 1.0$ $V_c = 0.5\sqrt{f'_c}\left(\sqrt{1 + \frac{P}{0.5\sqrt{f'_c}A_g}}\right)\left(A_g\frac{D}{L}\right)$ $V_s = \frac{\pi}{2}\frac{A_{st}f_{yd}D'}{s}\cot(45^0)$; $D' = D - 2\times cover$	(4)
5	Priestley et al. [29]	$V_5 = V_c + V_s + V_p$ $V_c = 0.8A_gk\sqrt{f'_c}$ $k = 0.29$ for $\mu < 2$ $k = 0.29 - 0.12(\mu - 2)$ for $2 < \mu < 4$ $k = 0.10$ for $\mu > 4$ $V_s = \frac{\pi}{2}\frac{A_{st}f_{ys}D'}{s}\cot(30^0)$; $V_p = \frac{D-c}{2a}P$	(5)

IV. PERFORMANCE OF THE NEURAL NETWORK MODEL

The ANN model was used for predicting the shear strength of circular RC columns. An ANN model contains three layers:

- The input layer, where input parameters are entered.
- Hidden layer(s).
- The utput layer, where the predicting result is obtained.

To perform the ANN algorithm, the following processes are required.

- Firstly, the input data are provided to the input layer, the signals are transferred through the connections, from one node (neuron) to another in the network. This procedure is called the forward pass.
- Secondly, after obtaining the output from the forward pass, it is required to evaluate this output by comparing it with the target using the Mean Squared Error (*MSE*).
- Thirdly, the network adjusts its weighted values according to a learning rule and using the error. Successively iterative adjustments will cause the network to produce the output, which is increasingly close to the target. After enough iterations, the training can be stopped based upon certain criteria.

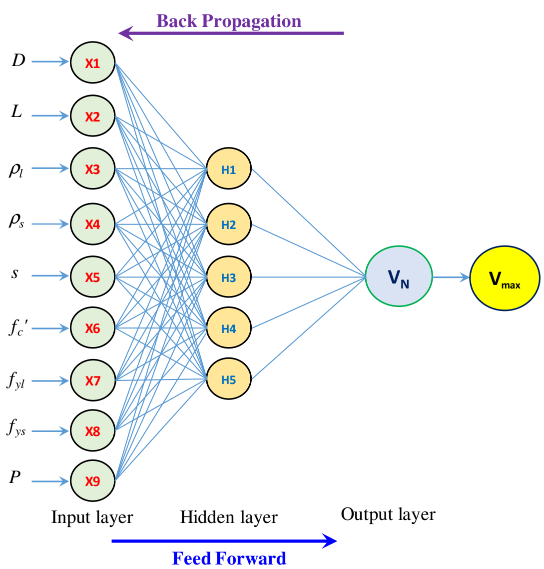

Fig. 2. Structure of the proposed neural network.

Figure 2 shows the structure of the ANN model, in which 9 variables are defined for the input layer, while 5 neurons are selected for the hidden layer. The predicted shear strength is the output variable of the network. The iteration for optimizing the network and choosing the optimal model is shown in Figure 3. It demonstrates that after 9 epochs the process is converged and the *MSE* value is 0.0003462, highlighting a very small error. Figure 4 shows the performance of the ANN model with all data used. The difference between the test data and the predicted values is trivial, mostly less than 2%. This result implies that the ANN model predicted well the shear strength of the circular RC column.

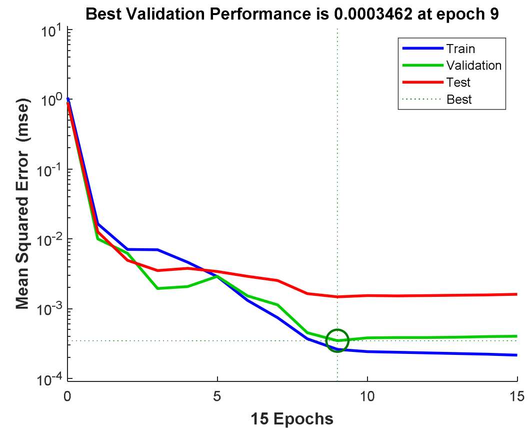

Fig. 3. Selection of the best ANN model.

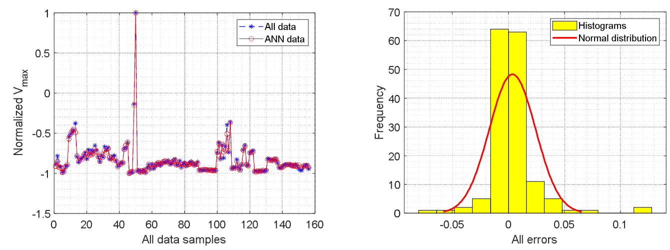

Fig. 4. Performance of all data.

Various architectures were tried, in which the training ratio changed from 0.6 to 0.85 and the number of hidden layers varied from 1 to 20. As a result, the best ANN architecture with the highest value of coefficient of determination (R^2) and the lowest value of Root-Mean-Square Error (*RMSE*) in training, testing, and validating phase was chosen. This ANN model comprises training ratio of 0.75, testing and validating ratios of 0.125, and 5 neurons in the hidden layer.

In the current study, we used 3 statistical parameters, which are R^2, $RMSE$, and $a20-index$, to evaluate the performance of ANN model. The definitions of these indicators are expressed by following equations:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=1}^{N}(t_i - \bar{o})^2}\right) \quad (6)$$

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(t_i - o_i)^2} \quad (7)$$

$$a20 - index = \frac{n20}{N} \quad (8)$$

where t_i and o_i represent the target and output of i^{th} data point, respectively, $\bar{o}$ is the mean of output data samples, N is the total number of the dataset, and $n20$ is the number of data statisfying $0.8 \leq \left|\frac{V_{exp}}{V_{predict}}\right| \leq 1.2$, in which V_{exp} and $V_{predict}$ are the shear strengths obtained from experiments and predictions respectively.

Table III shows the statistical parameters of the performance of the ANN model. It is found that the R^2 values are very high (i.e. 0.99) and the *RMSE* is very small. Additionally, the $a20-index$, which represents whether the samples fit the predicted values considering a deviation of ±20% compared with the test results, are close to unity. These results emphasize that the ANN model performed very well.

A comparison of shear strength between the predicted models (i.e. the 5 existing equations and the ANN model) is illustrated in Figure 5. It can be observed that the scattering of the regression obtained from the ANN model is significantly smaller than that from the other models. This highlights that the developed ANN model outperformed the other existing models which were based on design codes and previous studies.

TABLE III. ANN PERFORMANCE STATISTICAL PROPERTIES

Phase	R^2	*RMSE* (kN)	*a20-index*
Training	0.9980	5.490	0.9828
Testing	0.9917	6.026	1.0000
Validation	0.9807	1.862	1.0000
All data	0.9949	4.596	0.9872

We also developed a GUI in Matlab to facilitate the prediction of the shear strength of circular RC columns, as shown in Figure 6. Nine input parameters need to be provided. The shear strength of the column is readily obtained by clicking the Start Predict button after filling the inputs. It spends a few seconds to achieve the predictive results. The GUI tool is provided freely at https://github.com/duyduan1304/GUI_cirRC columns.

V. ANN-BASED FORMULA AND GUI FOR CALCULATING SHEAR STRENGTH OF CIRCULAR RC COLUMNS

To apply the proposed ANN model in the design practice, a convenient tool needs to be established. An ANN-based formula is proposed, in which the 9 input parameters are considered, as shown in (9) and (10).

$$V_{\max}^{\text{Predict}} = 263.10\times(V_{\max}^{N}+1)+14.00 \quad (9)$$

$$V_{\max}^{N} = h_0 + \sum_{i=1}^{5} h_i H_i \quad (10)$$

where $H_i = tanh(c_{i0} + c_{i1}X_1 + c_{i2}X_2 + \ldots + c_{i9}X_9)$, and h_0, h_i, and c_{ij} (j = 1÷9) are coefficients. Since the equation is based on the ANN model, the accuracy is already verified in the previous section. The coefficients of (10) are provided in Table IV.

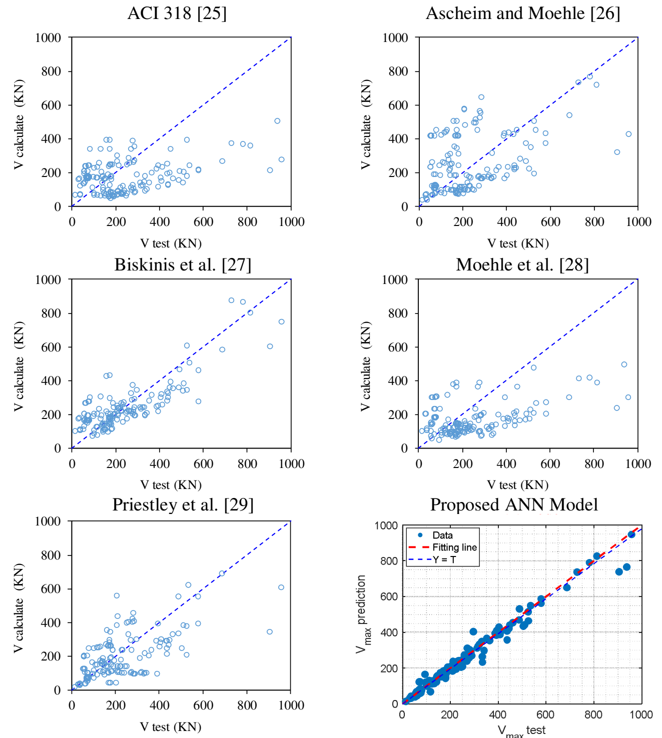

Fig. 5. Comparison between the predictive models and the test results.

TABLE IV. COEFFICIENTS OF (10)

i	h_i	c_{io}	c_{i1}	c_{i2}	c_{i3}	c_{i4}	c_{i5}	c_{i6}	c_{i7}	c_{i8}	c_{i9}
0	-0.4004										
1	-2.0669	-0.5781	1.6751	1.6594	-0.1383	-0.3201	-0.3521	0.4429	-0.0890	-0.2107	0.8183
2	0.7730	0.0411	4.5936	-3.0741	0.4458	-0.4895	0.5590	1.0053	-1.0579	-1.5919	-0.6568
3	1.2947	-0.4285	-2.9629	3.2788	0.0685	-0.3139	0.7816	0.7325	-0.1291	-0.2473	-1.0247
4	0.2651	0.9082	4.1902	0.1640	0.4885	0.6303	0.1474	0.7892	1.3074	-0.6409	-0.4272
5	-3.4530	-0.1804	1.6534	-2.3002	-0.6223	0.5371	-2.2544	-2.1388	-1.3028	-0.3572	1.6519

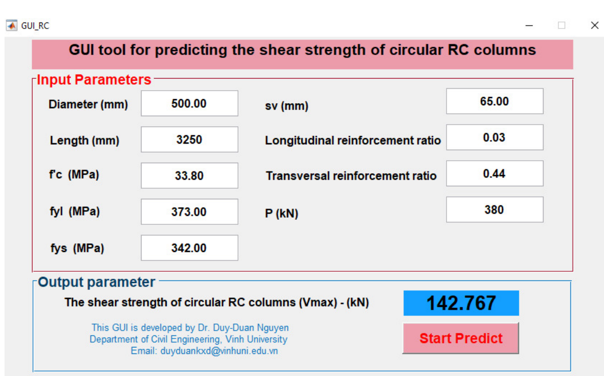

Fig. 6. GUI for calculating the shear strength of circular RC columns.

VI. CONCLUSIONS

A practical ANN model was developed to calculate the shear strength of circular RC columns using 156 experiment data samples. The performance result of the proposed model was compared to that of 5 published models. The main conclusions of this study are.

- The proposed ANN model outperforms the existing equations in calculating the shear strength of circular RC columns. The performance of the model is verified using R^2, $RMSE$, and $a20-index$ values with respect to the predict-to-test strength ratio.

- An ANN-based formula, which accounts for 9 input variables, is proposed for the estimation the shear strength of the RC column.
- A practical GUI tool is developed for using in the design practice of circular RC columns.

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