Case Studies in Construction Materials 13 (2020) e00414

Contents lists available at ScienceDirect

Case Studies in Construction Materials

journal homepage: www.elsevier.com/locate/cscm

Case study

Predicting the contribution of recycled aggregate concrete to the shear capacity of beams without transverse reinforcement using artificial neural networks

Ayman Ababneh[a,*], Mohammad Alhassan[a,b], Mohammad Abu-Haifa[a]

[a] *Department of Civil Engineering, Jordan University of Science and Technology, Irbid, Jordan*
[b] *Civil Engineering Program, Al Ain University, P.O. Box 64141, Al Ain, United Arab Emirates*

A R T I C L E I N F O

Article history:
Received 8 May 2020
Received in revised form 25 June 2020
Accepted 6 August 2020

Keywords:
Recycled aggregate concrete
Shear strength
Shear span-depth ratio
Artificial neural networks
Building codes and standards

A B S T R A C T

Although many researchers have studied the shear and flexural behavior of recycled aggregate concrete (RAC) beams, code provisions have not been modified yet to take RAC into account. Therefore, the slow development of code provisions to govern RAC usage limited their widespread use as a construction material for concrete structures. Several factors control the shear behavior for RAC beams and make it different from conventional concrete (CC) beams, such as recycled aggregate content and properties of parent concrete. The main objective of this study is to demonstrate the efficiency of using Artificial Neural Networks (ANNs) in predicting concrete contribution in the shear capacity of RAC beams. The study presents an appropriate model that can predict the experimental value of concrete contribution in shear resistance for RAC beams without transverse reinforcement when knowing the values of 6 inputs (recycled aggregate content, shear span-depth ratio, beam width, beam depth, longitudinal tensile steel ratio, and compressive strength at 28-days) using the intelligent adaptive ANNs based on a database comprised of 231 data points collected exclusively from structural literature. It is found that the proposed ANNs model showed satisfactory results when verified against the calculated values of the concrete shear strength calculated using common-used models existed in literature and code provisions, where the maximum variation for the present ANN model was about 8%. In particular, a comprehensive parametric study was conducted and discussed in detail to investigate the effect of various key parameters on the value of the concrete shear strength and the shape of the behavior. The results demonstrated that ANNs are capable of predicting the shear strength for beams cast with RAC without transverse reinforcement. A sensitivity analysis for the predicted concrete shear strength was conducted to give a better understanding of the effect of the key parameters (inputs).

1. Introduction

The demolition of many concrete structures due to the end of their actual service period or early deterioration produced significant amounts of construction wastes. Also, intensive wars and conflicts spread in many countries around the world cause destruction in concrete buildings and infrastructure and produce huge amounts of debris. In general, most of the

* Corresponding author.
E-mail address: anababneh@just.edu.jo (A. Ababneh).

https://doi.org/10.1016/j.cscm.2020.e00414
2214-5095/

construction wastes and debris are considered as landfill material. The environmental and economic impact of waste concrete and debris is considered to be significant. Consequently, concrete recycling became an alternative solution utilizing the concrete rubble instead of transporting to landfills for disposal. Concrete waste recycling can reduce the money spent on rubbles transportation, reduce consumption of natural aggregate that is consumed by the construction industry, save the landfill areas, and reduce the environmental impacts associated with transportation.

Nowadays, the employment of construction and demolition (C&D) waste, known as recycled aggregate in concrete, is permitted in several countries by simplifying their infrastructural laws. This material is obtained from recycling the existing concrete structures and rigid pavements that have reached the end of their design life. Recycled concrete aggregate (RCA) is the type of aggregate obtained by processing C&D wastes. When RCA or unsorted C&D is used as a replacement to natural aggregate (NA) in concrete, the term recycled aggregate concrete (RAC) is used to describe the resulting concrete.

To get a better understanding of the behavior of RAC and its properties, many researchers have studied the physical and mechanical properties of recycled aggregate (RA) used in recycled concrete. In comparison with natural aggregate (NA), most studies showed that RCA has lower quality, lower bulk and saturated-surface-dry (SSD) density, lower resistance to impact and crushing actions, lower specific gravity, higher porosity, and higher water absorption [1–4].

According to Yehia et al. [5], the loading condition of demolished structures and condition of exposure affect the strength and quality of RCA. It is worth mentioning that concrete waste contains two phases: natural aggregates and old attached mortar (AM). The content of AM is responsible for the changes in water absorption, bulk density, and the most engineering properties of RCAs. This explains why RCA properties are highly dependent on the properties of parent concrete [6].

In comparison with conventional concrete (CC), using RAs in concrete mix causes reducing in the compressive strength [7–9], modulus of elasticity [9,10], modulus of rupture [11], splitting tensile strength but with lesser reduction than that observed in compressive strength [12], and workability of the recycled concrete mix due to their remarkable absorption capacity particularly if RAs are employed in dry conditions [13]. The level of this decrease mainly depends on recycled aggregates' type, size, and origin [14] and the recycled aggregates content [15].

The shear behavior (including load deflection, deflection shape, shear deformation, failure mode, and shear strength) of beams composed of recycled aggregate is similar to that of reinforced concrete beams with natural coarse aggregate [16]. Knaack and Kurama [17] showed that the crack pattern of RAC beams and failure mode are similar to those of CC beams. However, most researchers found that the value of the shear strength of RAC beams is smaller than the shear strength of CC beams and it decreases as the RA replacement ratio increased [17–25]. Also, the shear strength of RAC beams, like CC beams, decreases with increasing the shear span-depth ratio when other parameters remain fixed [17,26,27].

Choi et al. [18] studied the effects of recycled aggregate on concrete shear strength experimentally by performing flexural tests on 20 RAC beams with various span-to-depth ratios (1.50, 2.50, 3.25). Their test results indicated that the concrete shear strength reduced by up to 30 % at a 100 % replacement ratio in comparison with the normal aggregate concrete. Arezoumandi et al. [20] conducted an experimental investigation on the shear strength of full-scale beams made with 100 % recycled concrete aggregate. The experimental shear strengths of the beams were compared with the shear provisions of several international design codes including ACI-318 code. Their results show that the 100 % RCA beams have approximately 12 % lower shear strength compared with the conventional concrete beams and the current design standards do not apply to RAC beams and require modifications to reflect the reduction in the shear capacity of this type of concrete. Katkhuda and Shatarat [21] constructed ten full-scale reinforced concrete beams using natural aggregate, recycled aggregate and treated recycled aggregate to study the shear behavior experimentally and analytically. All beams were constructed with 50 % and 100 % recycled aggregate, without stirrups, and shear span-depth ratio equal to 2.0 and 3.0. The experimental results showed that using treated RA usually improves slightly the shear capacity of the beams in comparison with NA and untreated RA. Also, the treated RAC beams were considered more conservative compared to the CC and untreated RAC beams regardless of the shear span-depth ratio. Choi and Yun [16] have found that the current ACI code equations can conservatively predict the shear strength of RAC beams and can be applied for recycled aggregate in structural elements. Rahal and Alrefaei [22] suggested that the shear strength equations of reinforced beams are reduced by 20 % when RCA is used in the concrete. Tabsh and Yehia [28] showed that the elastic stiffness, residual strength, and ultimate shear capacity of longitudinally reinforced beams made with 50 % and 100 % RCA can be approximately predicted by the equations of ACI-318 code. Etman et al. [29] showed that increasing the replacement ratio of the RCA resulted in decrease the shear capacity proportionally. Also, it was shown that providing internal short fibers enabled the RC beams made of recycled coarse aggregate to compensate for the decreases in the shear capacities and to increase their shear capacities compared to the control beams. Recently, Chaboki et al. [30] tested 27 concrete beams to study the shear characteristics of RC beams manufactured by introducing coarse RA and steel fibers. The variables were the coarse aggregate replacement ratio (0, 50, and 100 %), and the steel fibers ratio (0%, 1%, and 2%). The results showed that that steel fibers improved the beams' maximum strain and their use improved the shear behavior of RA concrete beams relative to control beams.

Like other engineering systems, civil engineering is considered as a complex field that is associated with a variety of problems. Analyzing such problems using traditional tools is a tedious task. Accordingly, artificial intelligence techniques have increasingly been used to model various applications related to civil engineering. Structural behavior prediction is included in those applications. Recently, artificial neural networks (ANNs), an important technique to solve artificial intelligence problems, has become popular and has also been an accepted technique in predicting different parameters in civil engineering applications [31,32] such as the compressive strength of concrete, strength of recycled aggregate concrete, elastic modulus, strength and slump of high strength concrete and ready mixed concrete when mineral additives and/or chemical admixtures were used, and the slump flow of concrete [33–36]. Also, using different machine learning techniques to predict the mechanical properties of RAC has recently become popular and widespread. Modulus of elasticity was predicted using different machine learning techniques; such as artificial bee colony programming, genetic programming, biogeography-based programming [55], M5′ model tree algorithm [56], fuzzy TSK, support vector regression, and radial basis function neural network [57]. Also, grey theory and multiple nonlinear regression were used to model the mechanical properties of normal and high strength RAC [58], and both multivariable regression and genetic programming were used to predict the mechanical properties of RAC [59].

Many equations and models for predicting concrete contribution in shear resistance (V_c) are proposed in literature and building design codes. Such models were derived from theoretical studies based on experimental results. A summary of some common-used empirical formulas which exist in literature and various codes for V_c prediction of RC beams is presented in Table 1, where V_c is the concrete contribution to the shear resistance of beam (N), b is the width of the beam (mm), d is the effective depth of beam (mm), f'_c is the cylinder concrete compressive strength (MPa), λ is the lightweight aggregate correction factor, ρ is the longitudinal tensile reinforcement ratio, V_u and M_u are the shear and moment at the critical section, respectively, a/d is the shear span-depth ratio, a_g is the nominal maximum size of coarse aggregate (mm), β is the shear resistance of cracked concrete of the beam factor, d_a is the maximum aggregate size (mm), and R is the recycled aggregate replacement ratio.

Up to our knowledge, no ANNs model predicts the shear strength of RAC beams taking into account the variation in RA content, compressive strength, beam dimensions, steel ratio, and shear span-depth ratio. This study investigates the application of ANNs to predict the concrete shear strengths of RAC beams in terms of different key parameters. This paper aims to provide precise predictions of concrete contribution for the shear strength of RAC beams without transverse reinforcement with the aid of ANNs; especially with existing recommendations from many researchers, that equations in the current standards can not be generalized for predicting the value of V_c for RAC beams. This study presents a foundation for future studies to propose design equations for RAC beams using ANNs. The results of ANNs modeling papers are usually presented as mathematical models or design charts. The relationships between V_c and different input parameters are investigated in this paper. An ANNs model is built and tested using a total of 231 data points collected from the technical literature, representing a wide range of experimental data arranged in a format of six input parameters. The ANNs model is validated by comparing ANNs' predictions with those generated using published different literature analytical models. Furthermore, the ANNs model was used to show that it could make parametric studies to investigate the impact of some of the inputs parameters on the chosen output (V_c). Also, the importance of this paper appears by studying the coupling effect of some parameters on the value of V_c strength using ANNs.

2. Artificial neural networks

The work on ANNs, referred to as "neural networks", has been motivated right from its beginning by biological neural networks that constitute the brain. The brain is highly nonlinear and complex. It has the potential to organize its structural constituents (neurons) to perform certain computations (e.g., perception, and motor control) much faster than the fastest digital computer in real today. ANNs are composed of multiple nodes, mimicking the biological neurons of the human brain. ANNs are used to solve problems in the same way that a human brain would. It can provide powerful solutions to problems in a very wide range of disciplines, particularly in problems that need classification, prediction, filtering, optimization, pattern recognition, and function approximation [38].

There are many advantages to using artificial intelligence techniques. The most important ones are; 1) requiring less formal statistical training, 2) detect implicitly complex nonlinear relationships between independent and dependent

Table 1
Summary of some existing equations to predict concrete shear strength (V_c) of RC beams.

Codes/Authors	Expression
ACI-318 [37]	$V_c = \frac{1}{6}\lambda\sqrt{f'_c}\,bd$ $V_c = (0.16\lambda\sqrt{f'c} + 17\rho\,\frac{Vu\,d}{Mu})bd \leq 0.29\lambda\sqrt{f'c}\,b$
New Zealand code (NZS-3101) [51]	$V_c = (0.07 + 10\rho)\sqrt{f'_c}\,bd$
Canadian Standards Association (CSA) [52]	$V_c = \lambda\beta\sqrt{f'_c}\,bd$ $\beta = \frac{230}{1000+d_v}$; without transverse reinforcement and a_g >20 mm $\beta = \frac{230}{1000+d_v}$; without transverse reinforcement and $a_g \leq$20 mm
Zsutty [53]	$V_c = 2.21(f'_c\rho\frac{d}{a})^{\frac{1}{3}}\,\frac{2.5d}{a}\,bd$ $\frac{2.5d}{a} \geq 1$
Bazˇant and Yu [54]	$V_c = 3.5\sqrt{f'_c\frac{7\rho^{2/3}}{d}}\,bd \leq 3.5\sqrt{f'_c}\,bd$
Pradhan et al. [25]	$V_c = 1.6R^{-0.1}{f'_c}^{0.6}\rho^{0.45}\left(\frac{d_a}{d}\right)^{0.48}(\frac{a}{d})^{-0.91}\,bd$

variables, 3) ANNs are capable to detect all probable interactions between predictor variables, and 4) the availability of multiple training algorithms [62].

The ANNs architecture consists of three main parts: an input layer which is a vector of the inputs, middle (hidden) layer/s which is the main part of the ANNs architecture, and each hidden layer contains a collection of neurons, and the final part is the output layer which is responsible for producing the outcome. A neural network must have only one input layer and one output layer. The neurons, inside each layer, accomplish the same role. The neuron in ANNs is an information-processing unit, which forms the basis for designing a large family of neural networks [60]. Neurons calculate the weighted sum of inputs in the input layer and weights, add the bias, and execute an activation function to provide the output. The neurons are connected by links by which they interact, and each link is associated with a weight that will be modified depending on the results. The results are passed to other neurons and the sent values differ from the received depending on these weights. The weight is the value that is multiplied by the carried value before passing the result to the next neuron. The weight value is highly dependent on the intended task; its value is decided by learning and memorizing doing that task. The neuron weights are design variables to be modified. Another parameter that can enhance the neural network performance is a bias term that is included in every neuron in hidden and output layers [38].

In general, two main types of ANNs are used for solving input-output problems: feed-forward (FFNN) and radial basis (RBNN) networks. A feed-forward neural network is the fundamental neural network that allows the information to be transferred forward and hierarchically. This network has no loops; neurons are organized into layers that have one-direction connections between them. Therefore, they are static; they produce one set of output values rather than a sequence, the feed-forward network can be classified according to the existence on the hidden layer into “Single-layer” or “Multilayer”. The input layer is not accounted for in this classification as no computation is performed there. The term “hidden” refers to the fact that this part of the neural network is not recognized from the input or output layer of the network. By adding one or more hidden layers, the network is enabled to interfere between the input and the output in a more useful manner [38,61]. Another type of ANN that lies under the Feed-forward networks is the radial basis neural networks (RBNN). This network consists of one hidden layer and one output layer as well as the input and output vector. Inside each hidden neuron, there is a radial transfer function that produces an output, which is multiplied with a weight vector to produce a hidden output vector. The output layer has several neurons equal to the number of outputs. Inside each output neuron, the output is calculated by taking the sum of the received output vector. Backpropagation neural networks (BPNN) are one of the supervised learning algorithms, for training multi-layer perceptrons. The backpropagation algorithm looks for the minimum error function in weight space using the method of gradient descent. The gradient descent method involves calculating the derivative of the squared error function for the weights of the network. Gradient descent with backpropagation is not guaranteed to find the global minimum of the error function, but only a local minimum; as it has a "Zig-Zagging" nature to find a solution. The weights combination, which minimizes the error function, is considered as the solution to the learning problem. Backpropagation networks require three layers to work correctly at least as well the most used activation functions for them is the sigmoid activation function [38]. There are four basic types of learning rules: error correction, Boltzmann, Hebbian, and competitive learning [39].

3. Experimental data sets

The collected data consists of 231 input-output sets, which are collected from publications of experimental researches [16–27,29,30,40,41,43–47,49] about the shear strength of RAC beams. The most important properties and test conditions for the database selected from the previous test results are given in Table 2. Data mainly contained the most important parameters that are thought to affect the concrete shear strength of RAC beams based on the previous research studies. These parameters are the dimensions of beams, longitudinal tension-steel ratio, shear span-depth ratio (a/d), replacement ratio (R), properties of both parent concrete and produced RAC, and proportions of materials used for making CC and RAC. Data that contradict the physical quantity that is supposed to be measured were excluded. Also, most specimens were tested in cylinders. However, when specimens were not cylindrical, the conversion factor of 0.7 was used to convert the compressive strength of cube to cylinder [50]. In the ANN model, there are 6 inputs to be considered, and there is one targeted output as shown in Table 3. Beamwidth (b), effective beam depth (d), longitudinal tension reinforcement ratio (ρ), replacement ratio

Table 2
Conditions and properties for the selecting test results for the database.

Parameter	Value range and test conditions
f'_{cy} at 28-days	20–49.83 (MPa)
R	5–100 (%)
Source of recycled aggregates	Demolished concrete/laboratory-cast concrete/airport pavement/rejected structural precast element
Cure method	Standard/water/cement slurry/ compound SBR
Bulk density	1270–1941 (kg/m^3)
Water/cement ratio	0.40–0.596
Cement content	293–593 (kg/m^3)
Absorption of NAs (%)	0.17–1.76
Absorption of RAs (%)	1.185–9.44

Table 3
The factors considered in ANN.

Name	Description	Use	Unit
B	Width of beam	Input	Mm
D	The effective depth of the beam	Input	Mm
a/d	Shear span-depth ratio	Input	–
R	Replacement ratio of natural aggregate by recycled aggregate	Input	%
P	Longitudinal tension reinforcement ratio.	Input	–
f'_{cy}	Specified concrete cylinder compressive strength	Input	MPa
V_c	Nominal shear strength provided by concrete	Target	kN

(R), shear span-depth ratio (a/d), and concrete cylinder compressive strength (f'_{cy}) are the significant parameters which influence the concrete contribution on the shear capacity of reinforced RAC beams. Therefore, these parameters were chosen to form the input layer for the BPNN model. The experimental value of concrete shear strength of reinforced RAC beams was used as the output layer.

All factors considered in the ANNs model exist originally in building codes' empirical equations in addition to the RA replacement ratio. The shear strength (V_u) of an RC beam strongly depends on stirrups distributions and characteristics (V_s). However, the contribution of steel yield strength on the value of V_c of RC beams and the dowel effect of the longitudinal reinforcement is almost negligible. So, the effect of these factors was not considered in the ANN model to simplify the proposed ANN model especially that the output of the proposed model is V_c (not V_u). It is worth mentioning that the RA replacement ratio strongly affects the value of f'cy for RAC, and f'cy is the principal parameter that affects the value of concrete shear strength. However, the decrease in f'_{cy} for RAC is not enough to attain the same safety factor in comparison with CC when using the original code equations. Also, some researchers have used improved mix design procedures to compensate for the decrease in the compressive strength due to increasing RA content like equivalent mortar volume (EMV) [43].

Table 4 shows the inputs and output ranges by numbers and their statistical parameters (maximum value, minimum value, arithmetic mean, and standard deviation) related to the collected data.

4. Results and discussion

4.1. Proposed network properties and training results

In this paper, a backpropagation feed-forward neural network is chosen as an optimal network type for input-output fitting problems. Normalized squared error method was used for training with applying regularization, which updates the weight and bias values according to Quasi-Newton optimization as a training algorithm. It is based on Newton's method. The hyperbolic tangent was used as an activation function in the hidden layer. The data were divided into training and selection data at about 80 % and for testing at 20 %. The size of the scaling layer (inputs) is 6. The scaling method for this layer is the minimum-maximum approach. In this approach, the data is scaled to a fixed range usually (from 0 to 1). The strong point of having this bounded range in contrast to standardization is that getting smaller standard deviations, this leads to suppress the effect of outliers. The size of the unscaling layer (outputs) is 1 which is V_c. Also, the unscaling method for this layer is the minimum-maximum approach. The performance of the selected ANN is evaluated through the mean relative error (MRE), the mean absolute error (MAE), and the squared value of Pearson's correlation coefficient (R^2), as shown in the following equations, where x_i is the computed value, and y_i is the target output.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |x_i - y_i| \tag{1}$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N} \frac{|x_i - y_i|}{y_i} \tag{2}$$

Table 4
Parameters Ranges; minimum, maximum, mean and standard deviation.

Parameter	Minimum	Maximum	Mean	Deviation
b (mm)	100	400	195.83	61.92
d (mm)	180	525	322.16	81.32
ρ	0.0053	0.0297	0.0165	0.0060
a/d	1	5	2.933	0.851
R (%)	0	100	52.81	40.63
f'_{cy} (MPa)	20	49.83	35.11	6.70
V_c (kN)	18	256.69	86.35	53.42

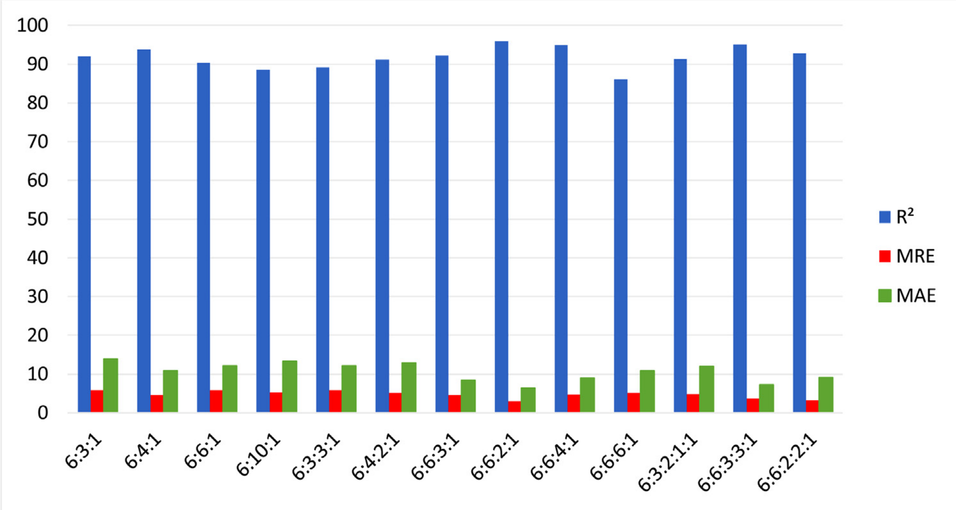

Fig. 1. MAE, MRE, and R^2 for different network architectures.

The selected network architecture was determined based on a trial and error approach. This approach stands on obtaining the best scheme with low or acceptable errors and a high correlation coefficient. A varying number of hidden layers and neurons for each layer were considered to get the best architecture. Some iterations for selecting the best architecture are shown in Fig. 1. The optimal architecture is represented by 6:6:2:1, which means that the optimal number of hidden layers is 2, and the optimal number of hidden neurons, which represent the network complexity, was 8; 6 at the first layer and 2 at the second layer, with MRE and R^2 about 2.91 % and 0.96, respectively.

The ANNs toolbox of Neural Designer software was used to develop a program with optimum architecture. A graphical representation of the optimal architecture used in this study is depicted in Fig. 2. The network convergence into a solution when 386 Epochs are used to produce the network is illustrated in Fig. 3. The MRE for training data and testing data is found at 2.91 % and 3.77 %, respectively. Fig. 3 illustrates that the convergence for both training and testing phases happened very quickly at about epoch 70, and then remain flat with almost no change in the value of MRE.

Fig. 4(a)–(c) show the experimental versus predicted curves of the concrete contribution on shear capacities of RAC beams for the selected parameters per each set. It was observed that the R^2 values for the training, testing, and all data sets were recorded as 0.96, 0.95, and 0.96, respectively. Therefore, it is observed that the ANNs model with the selected inputs performs the model with the selected parameters and predicts well the training and testing data.

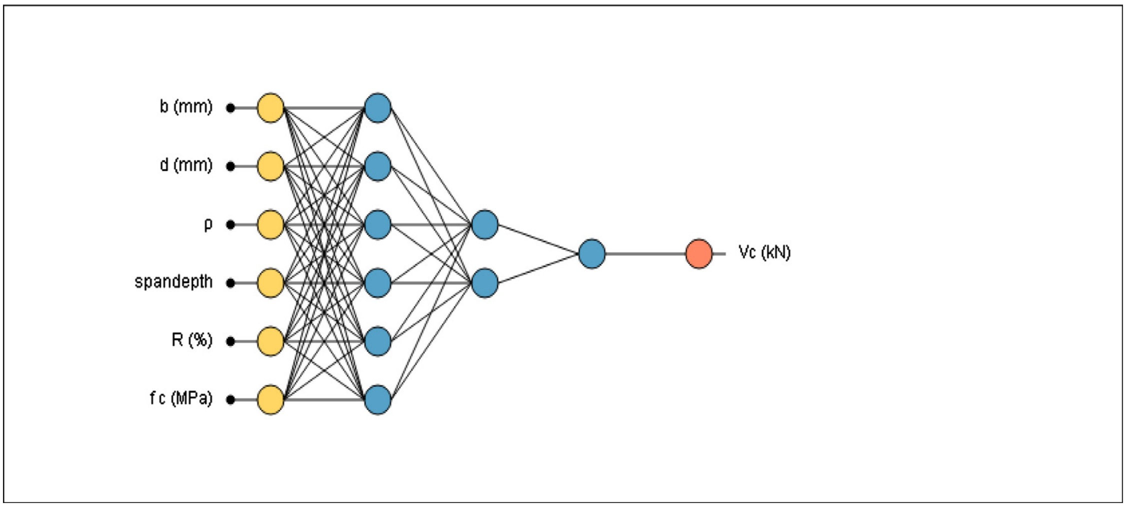

Fig. 2. Proposed neural network Architecture.

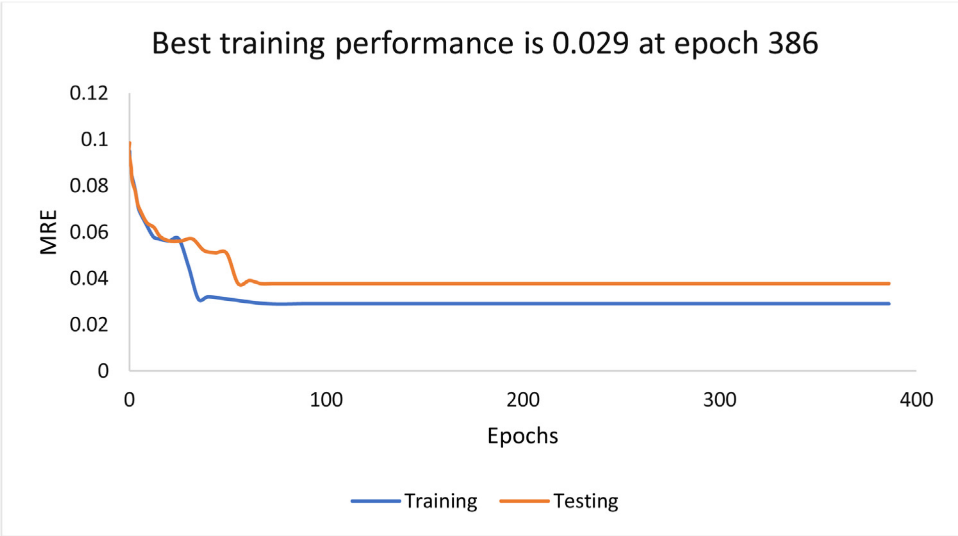

Fig. 3. Convergence performance for training and testing stages.

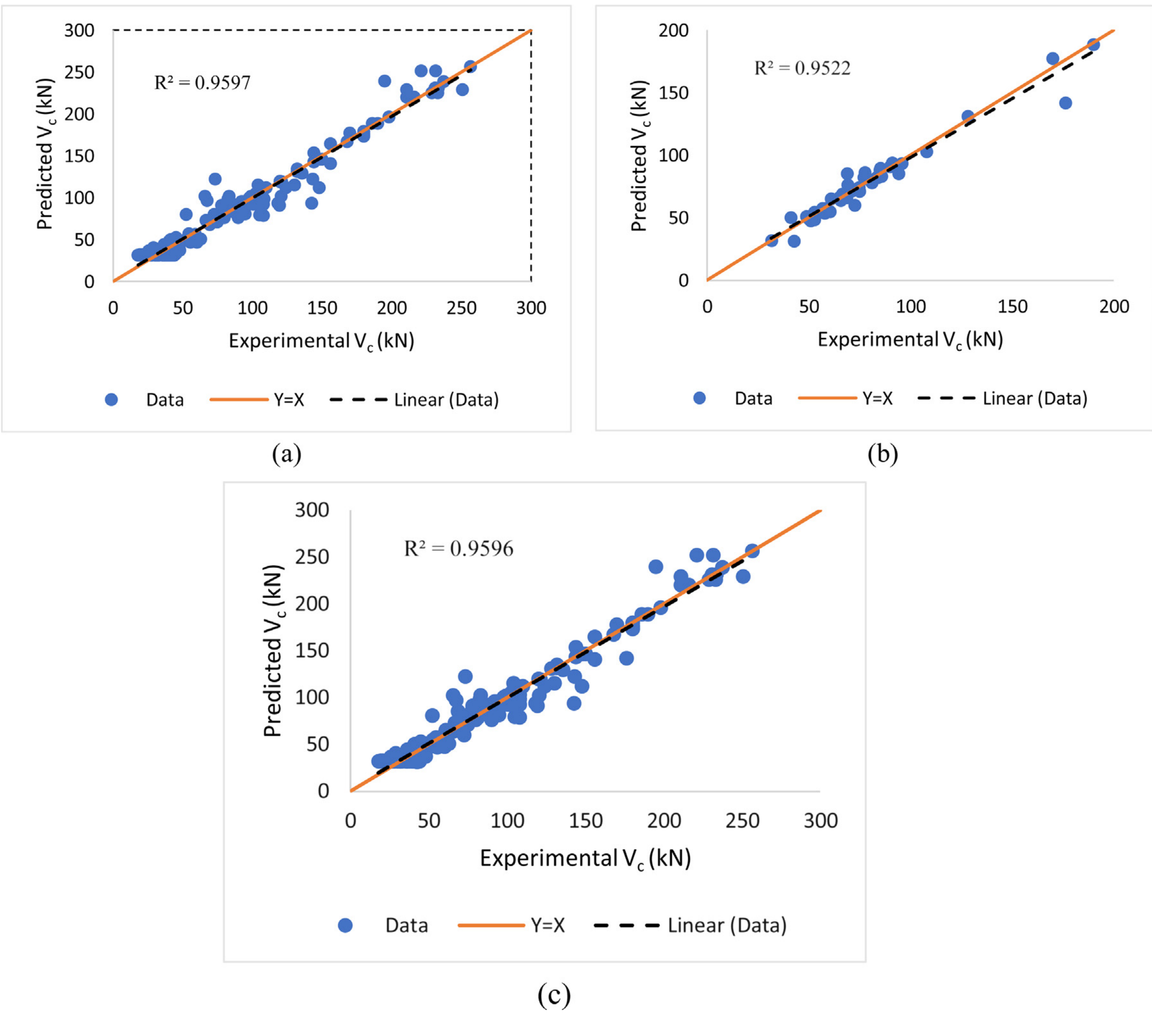

Fig. 4. Predicted outputs from the proposed model versus experimental values of V_c (a) training data, (b) testing data, and (c) training and testing data.

4.2. Validation and comparison of the proposed network

To investigate the accuracy of the proposed model, validation was done manually using 34 known experimental points from the references [28,42,48], which were not used in training and testing phases. The predicted V_c results using the present ANNs model and those calculated by literature models versus the experimental V_c for the 34 beams are shown in Fig. 5(a)–(g). The mean and coefficient of variation (COV) values are calculated based on the ratio of experimental to

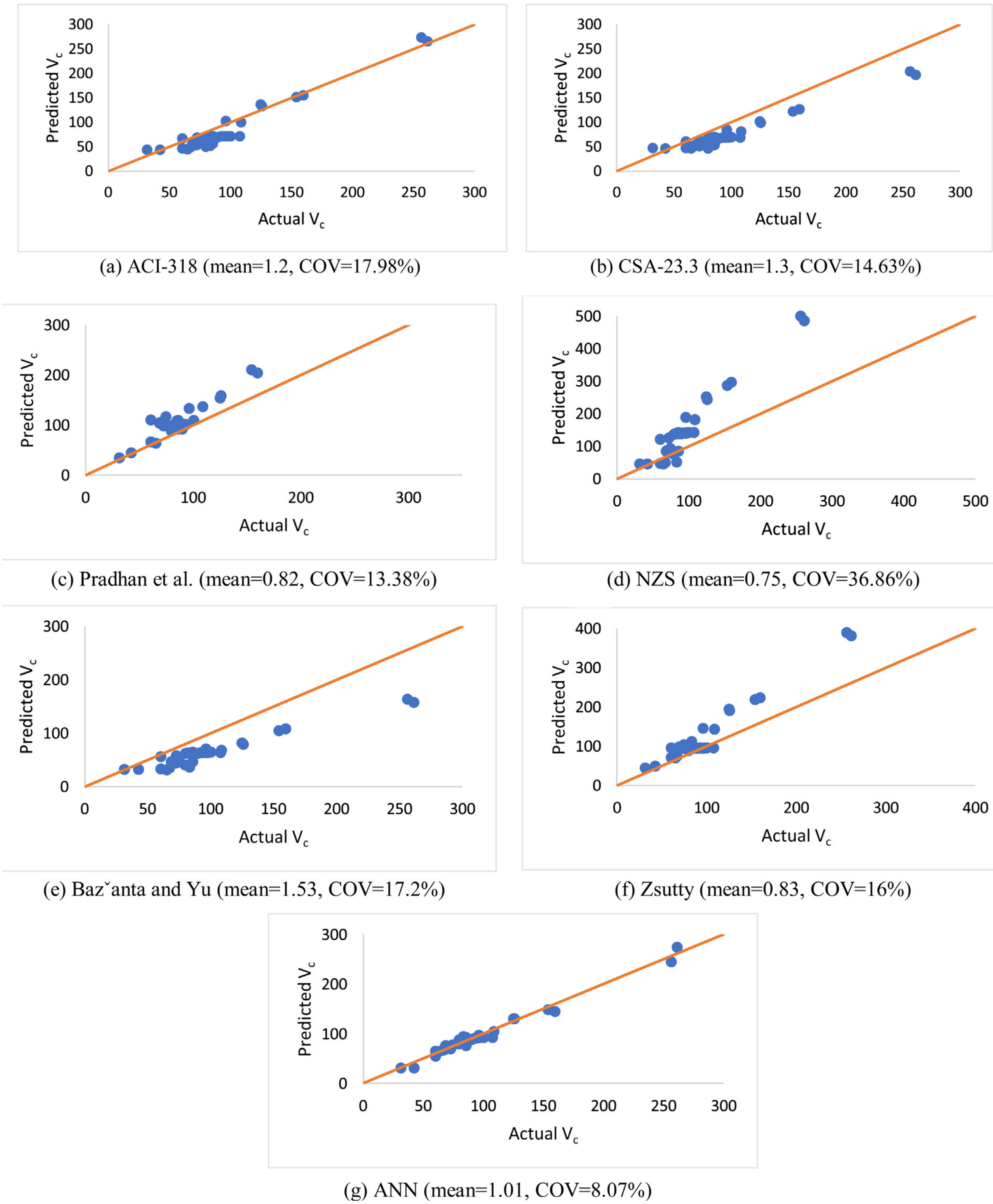

Fig. 5. Comparison between the predicted and experimental outputs using different models.

predicted V_c and given for comparison purposes. From the figure, it is observed that the average ratio of experimental to predicted V_c is very close to 1 for the proposed ANNs model with the lowest variation around the average at a standard deviation value of 0.0815 and COV at about 8.07 %. So, the proposed ANN model can give an accurate prediction for the value of V_c for different RAC beams without transverse reinforcement within the parameter ranges. On the other hand, the other literature models either show higher variation around the average value or show an average value with more deviation from one. The results obtained by (ACI-318, CSA-23.3, and Pradhan et al.) models are closer to the actual values than NZS, Zsutty, and Bazˇant and Yu for RAC beams. Furthermore, CSA-23.3 and Bazˇant and Yu underestimate the actual V_c and yield scattered and conservative results for the range of input parameters being investigated, while the predicted V_c results of the RAC beams using the NZS and Zsutty display overestimation and yield scattered and unconservative prediction for the actual V_c.

4.3. Parametric study

It is very useful to see how the outputs vary as a function of a single input when all the others are fixed to examine the prediction of the proposed ANNs model with respect to other various literature models. The directional relationships between normalized concrete contribution on shear strength ($v_c = \frac{V_c}{bd}$) and shear span-depth ratio, RA replacement ratio, tensile steel ratio, and compressive strength using the present ANNs model, and various literature models are plotted as depicted in Fig. 6(a–d). This can be seen as the cut of the proposed model along some input direction and through some reference points which are taken typically as values that conform to the ranges of the collected database shown in Table 4. The values of the reference points (b, d, ρ, a/d, R, and f'_c) are (200 mm, 300 mm, 0.0165, 3, 65 %, and 30 MPa), respectively.

Fig. 6(a) shows the relation between concrete contribution to shear stress and the tensile steel ratio in RAC beams. As shown, increasing the steel ratio increased the shear stress proportionally. Crack width and depth in tension surface decrease with the increase in steel ratio, with a slight spread of cracks into the compression zone, and this reduction in the crack depth causes an increase in the shear capacity of the uncracked concrete block. Also, the large tensile steel ratio means a large effective moment of inertia, which contributes to determining the value of shear strength. The trending behavior of the shear stress as found from the present ANNs model is very close to that predicted by Bazˇant and Yu, Zsutty, and Pradhan et al., models. However, the literature models tend to give almost steady sensitivity towards the steel ratio. The trending behavior, which predicted using the present ANNs model, seems more realistic than that predicted using those models. Fig. 6(b) indicates that rates of change in shear strength versus the compressive strength, as predicted by the Pradhan et al., NZS, and the present ANNs model, are highly dependent on the value of compressive strength. However, Pradhan et al. and the present ANNs models are strongly influenced by the compressive strength for values higher than 40 MPa and 30 MPa, respectively. This behavior can be explained by the fact that when the compressive strength becomes greater, then the resulting concrete stress distribution becomes more symmetrical.

Fig. 6(c) demonstrates the relationship between the shear strength and the shear span-depth ratio using ANNs and various literature models. The impact of the shear span-depth ratio is considered exaggeratedly in Zsutty model especially at low ratios, well in both Pradhan et al. and ANNs models, and slightly in the ACI-318 model. It is observed that shear strength decreases with increasing shear span-depth ratio. However, for short beams ($a/d \le 2.5$), the impact is significant due to the propensity of long beams ($a/d > 2.5$) to work as a flexure-critical member, while short beams work as a shear-critical member. Arch action is responsible for the transferring of the applied loads to the supports. In short beams, RC beyond the formation of a first diagonal crack resists additional loading before total failure occurs. This redistribution of stresses plays an essential role in increasing the shear capacity of short beams due to the short distance between the applied loads and the supports. In short beams, the critical diagonal crack is considered approximately by a straight line between the applied load and the support with many finer cracks nearby. On the other hand, the critical diagonal crack for long beams is characterized usually by S-shaped, resulting from the more impact of normal stress formed by flexural moment. Thus, a long beam fails suddenly, directly after the formation of a first diagonal cracking. The relationship between RA replacement ratio and shear stress is shown in Fig. 6(d). The curves show that the effect of RA content was considered only in Pradhan et al. and the present ANNs models, while other literature models didn't take RA content into account. As shown in the figure, using RAs in the concrete mix causes a reduction in the shear strength of RAC beams. The present ANNs model suggests that the impact of RA is small at a low replacement ratio and then significantly increases with increasing replacement ratio. This behavior is attributed to the appearance of microcracks in the RA due to the crushing process. Also, the old attached mortar contains several pores due to the crushing process. So, the appearance of both shear and flexural cracks of RAC beams accelerates with increasing the RA content.

4.4. Coupling effect

The contribution of concrete in the shear strength for RC beams is mainly resisted by dowel action of longitudinal reinforcement intersecting the inclined cracks, aggregate interlocking action across tension-shear cracks which mainly depends on crack surface roughness and crack kinematics, the bond between concrete and reinforcement, and residual diagonal tensile strength of cracked concrete. The transfer of shear forces across diagonal cracks is allowed by the dowel

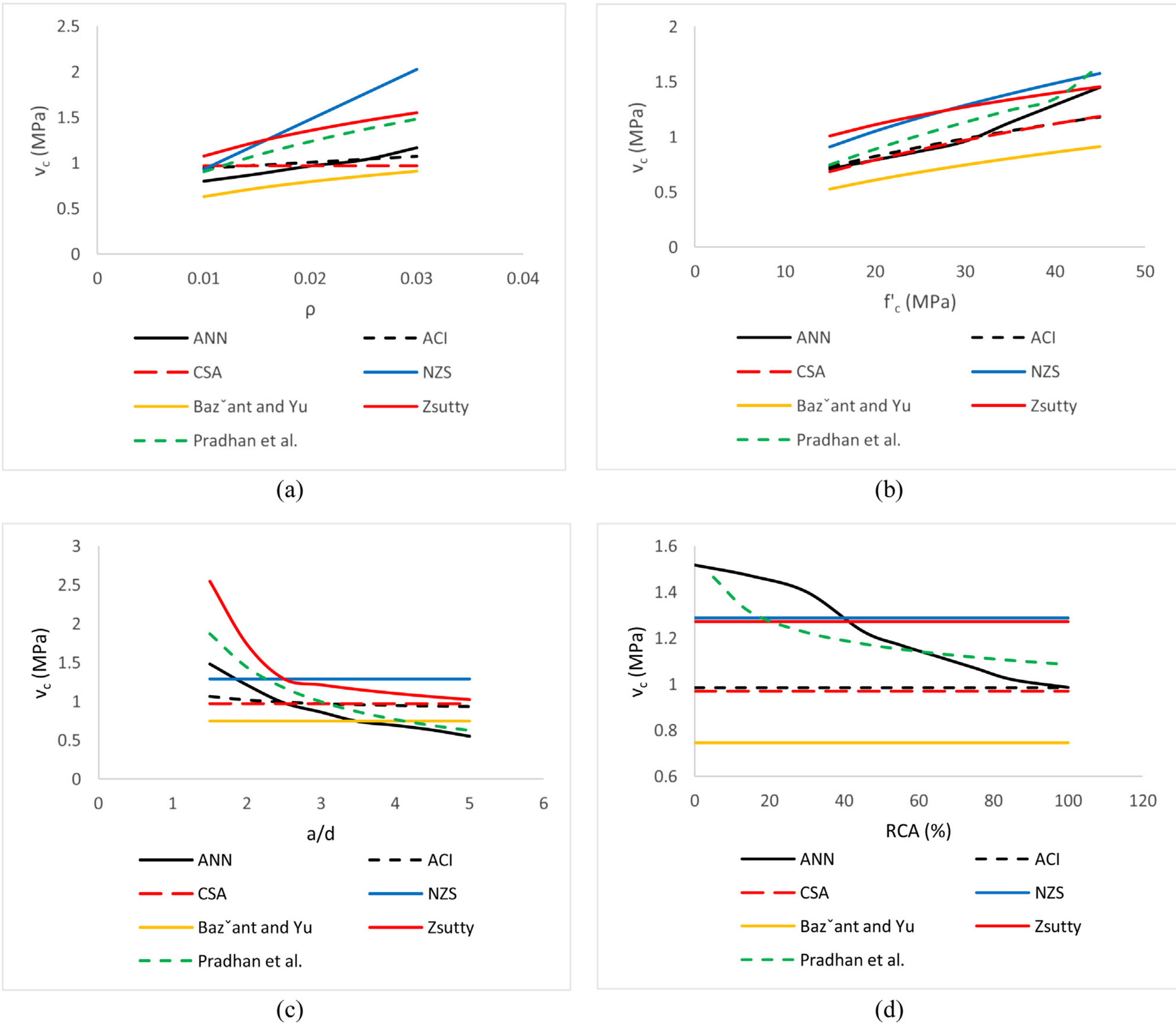

Fig. 6. Directional line charts for v_c as a function of different parameters using various models.

action of the main steel that locks the beam segments together. Loss of dowel stiffness permits the diagonal crack to increase quickly and lose its interface shear strength.

To investigate the coupling effect of the input parameters on the cracking shear strength, the sensitivity analysis is conducted on the input parameters as illustrated in Fig. 7(a–d). Fig. 7(a and b) shows that the concrete shear strength is highly influenced by a/d and f'_c, respectively. However, the rate of change of shear strength with a/d for low strength RAC beams is smaller than that for high strength RAC beams. In other words, the increase in shear strength with increasing f'_c for short beams is more pronounced than long beams. This is understandable because of the increase in f'_c results with increasing the modulus of elasticity. Therefore, beams with higher f'_c are, at least initially, stiffer than beams with lower f'_c. Thus, beam with lower f'_c value has greater deflection and lower shear strength than the beam with higher f'_c value for a given applied load. This makes the impact of a/d lesser in the beam with higher compressive strength.

The relationship between shear strength and a/d with different replacement ratios is constructed in Fig. 7(c). The figure indicates that the impact of RA content at low a/d (short beams) on shear strength is almost more than that at high a/d (long beams). Also, the reduction of shear strength with increasing a/d at low RA content is slightly larger than the reduction at high replacement ratio. This behavior is explained by the mechanical properties of RA itself. RA has a lower mass density and higher water absorption than natural aggregate due to the existence of old attached mortar, this results in high porosity and low compressive strength for the produced RAC. Therefore, it is very clear that the shear strength of RAC beams with high replacement ratio is smaller than that with small replacement ratio at same a/d. However, at high a/d, the effect of RA content is observed to be less than low a/d, resulting from the significant impact of normal stress formed by flexural moment. This normal stress affects the shape of the critical diagonal crack and the load-deflection response, and then the value of the concrete shear strength. Also, the strength of aggregates becomes a limiting factor at higher shear strength, and it is well known that shear resistance increases with decreasing a/d. Therefore, the strength of the aggregate may also be a reason for increasing the impact of RA content at long beams.

Fig. 7(d) shows the relationship between shear strength and longitudinal reinforcement ratio with different a/d. For a given applied load, the longitudinal steel promotes the aggregate interlock mechanism, so the shear strength increases with increasing the steel ratio. However, the impact of the tensile steel ratio on the concrete shear strength in the case of short beams is smaller than long beams. This behavior can be explained by the basic shear transfer mechanisms. As mentioned above, long beams tend to work as flexural-critical members, and the tensile steel ratio has a pronounced effect on the penetration of the flexural cracks; the penetration decrease with increasing the value of steel ratio. The depth of this penetration directly affects the intensity of stresses above the flexural cracks. These stresses affect the rate of developing a flexural crack into an inclined crack. Accordingly, the greater the steel ratio, the lesser intense stresses which will result in diagonal tension cracking.

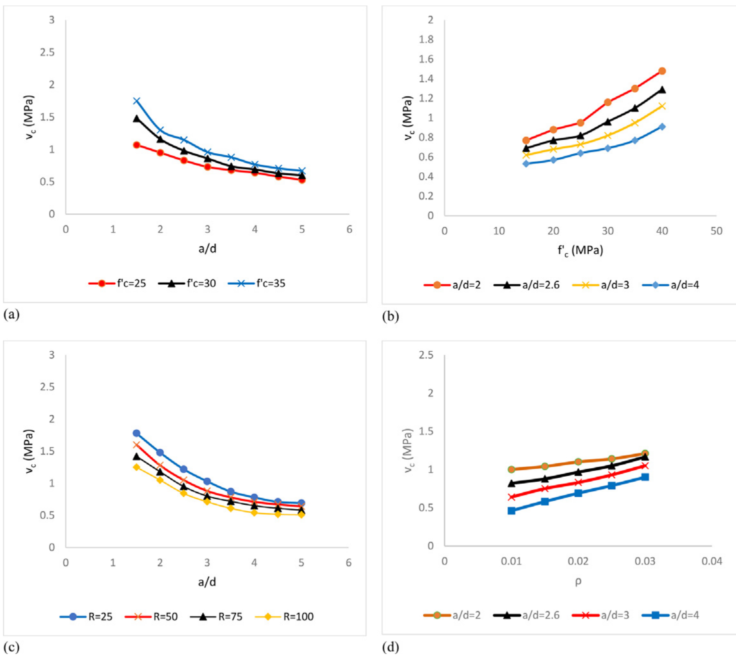

Fig. 7. The effect of the key parameters on each other for the predicted v_c using ANN model.

5. Conclusions

Based on this study, the following conclusions can be drawn:

1 The complexity of predicting shear strength for RAC beams is referred to as multiple factors that have a substantial impact on the V_c. the proposed network agrees with findings by other researchers and can predict properly the experimental value of concrete shear strength for beams cast with RAC when knowing the values of the input parameters, with a linear regression correlation equals to 0.9596.
2 The parametric study using the proposed ANN model investigates the impact of the input parameters on the concrete contribution in shear strength for RAC beams. The trending behavior of the studied RAC beams using the present model confirms very well with the available experimental results (concrete shear strength increases as ρ increases, f'_c increases, a/d decreases, and RA replacement ratio decreases).
3 When the present ANN model compared to common-used models in code provisions and literature, the proposed ANN model shows satisfactory results with an average value for the experimental to predicted shear strength equals to 1.01 with a low COV at about 8.07 %. On the other hand, the average values of the experimental to predicted shear strength using other literature models are to some extent far from 1 with large COV values as a result of not taking the RA incorporation into account.
4 RAC beams with low compressive strength have a smaller reduction in the concrete shear strength due to increasing a/d is smaller than RAC beams with high compressive strength.
5 The impact of the shear span-depth ratio is more pronounced at high RA content than the low replacement ratio for RAC beams.
6 In comparison with long beams, the impact of the longitudinal tensile reinforcement ratio on the concrete contribution to the shear strength is very small in the case of short beams.

Declaration of Competing Interest

The authors report no declarations of interest.

References

[1] N.K. Bairagi, H.S. Vidyadhara, K. Ravande, Mix design procedure for recycled aggregate concrete, Constr. Build. Mater. 4 (4) (1990) 188–193.
[2] A.M. Wagih, H.Z. El-Karmoty, M. Ebid, S.H. Okba, Recycled construction and demolition concrete waste as aggregate for structural concrete, HBRC J. 9 (3) (2013) 193–200.
[3] S. Kabir, A. Al-Shayeb, I.M. Khan, Recycled construction debris as concrete aggregate for sustainable construction materials, Procedia Eng. 145 (2016) 1518–1525.
[4] S. Shahidan, M.A.M. Azmi, K. Kupusamy, S.S.M. Zuki, N. Ali, Utilizing construction and demolition (C&D) waste as recycled aggregates (RA) in concrete, Procedia Eng. 174 (2017) 1028–1035.
[5] S. Yehia, K. Helal, A. Abusharkh, A. Zaher, H. Istaitiyeh, Strength and durability evaluation of recycled aggregate concrete, Int. J. Concr. Struct. Mater. 9 (2) (2015) 219–239.
[6] L. Butler, Evaluation of Recycled Concrete Aggregate Performance in Structural Concrete, (2012) .
[7] J.R. dos Santos, F. Branco, J. De Brito, Mechanical properties of concrete with coarse recycled aggregates, Struct. Eng. Int. 14 (3) (2004) 213–215.
[8] J.M. Gómez-Soberón, Porosity of recycled concrete with substitution of recycled concrete aggregate: an experimental study, Cem. Concr. Res. 32 (8) (2002) 1301–1311.
[9] J.Z. Xiao, J.B. Li, C. Zhang, On relationships between the mechanical properties of recycled aggregate concrete: an overview, Mater. Struct. 39 (6) (2006) 655–664.
[10] S.C. Kou, C.S. Poon, D. Chan, Influence of fly ash as a cement addition on the hardened properties of recycled aggregate concrete, Mater. Struct. 41 (7) (2008) 1191–1201.
[11] K. McNeil, T.H.K. Kang, Recycled concrete aggregates: a review, Int. J. Concr. Struct. Mater. 7 (1) (2013) 61–69.
[12] J.D. Brito, R. Robles, Recycled Aggregate Concrete (RAC) Methodology for Estimating Its Long-Term Properties, (2010) .
[13] M. Etxeberria, E. Vázquez, A. Marí, M. Barra, Influence of amount of recycled coarse aggregates and production process on properties of recycled aggregate concrete, Cem. Concr. Res. 37 (5) (2007) 735–742.
[14] M.C. Rao, Properties of recycled aggregate and recycled aggregate concrete: effect of parent concrete, Asian J. Civ. Eng. 19 (1) (2018) 103–110.
[15] I. González-Taboada, B. González-Fonteboa, F. Martínez-Abella, J.L. Pérez-Ordóñez, Prediction of the mechanical properties of structural recycled concrete using multivariable regression and genetic programming, Constr. Build. Mater. 106 (2016) 480–499.
[16] W.C. Choi, H.D. Yun, Shear strength of reinforced recycled aggregate concrete beams without shear reinforcements, J. Civ. Eng. Manag. 23 (1) (2017) 76–84.
[17] A.M. Knaack, Y.C. Kurama, Behavior of reinforced concrete beams with recycled concrete coarse aggregates, J. Struct. Eng. 141 (3) (2015) p.B4014009.
[18] H.B. Choi, C. Yi, H.H. Cho, K.I. Kang, Experimental study on the shear strength of recycled aggregate concrete beams, Mag. Concr. Res. 62 (2) (2010) 103–114.
[19] F. Al-Zahraa, M.T. El-Mihilmy, T. Bahaa, Experimental investigation of shear strength of concrete beams with recycled concrete aggregates, Int. J. Mater. Struct. Integr. 5 (4) (2011) 291–310.
[20] M. Arezoumandi, A. Smith, J.S. Volz, K.H. Khayat, An experimental study on shear strength of reinforced concrete beams with 100% recycled concrete aggregate, Constr. Build. Mater. 53 (2014) 612–620.
[21] H. Katkhuda, N. Shatarat, Shear behavior of reinforced concrete beams using treated recycled concrete aggregate, Constr. Build. Mater. 125 (2016) 63–71.
[22] K.N. Rahal, Y.T. Alrefaei, Shear strength of longitudinally reinforced recycled aggregate concrete beams, Eng. Struct. 145 (2017) 273–282.
[23] K.N. Rahal, Y.T. Alrefaei, Shear strength of recycled aggregate concrete beams containing stirrups, Constr. Build. Mater. 191 (2018) 866–876.
[24] S.W. Tabash, S. Yehia, Shear strength of reinforced concrete beams made with recycled aggregate, 3rd World Congress on Civil, Structural, and Environmental Engineering (CSEE'18), ICSENM 130, Budapest, Hungary, 2018.

[25] S. Pradhan, S. Kumar, S.V. Barai, Shear performance of recycled aggregate concrete beams: an insight for design aspects, Constr. Build. Mater. 178 (2018) 593–611.
[26] C.Y. Li, G.X. Li, W.J. Shao, Q. Guo, R. Liu, Shear-crack behaviors of reinforced full-recycled aggregate concrete beams, Applied Mechanics and Materials, 438, Trans Tech Publications Ltd., 2013, pp. 794–799.
[27] G. Fathifazl, A.G. Razaqpur, O.B. Isgor, A. Abbas, B. Fournier, S. Foo, Shear capacity evaluation of steel reinforced recycled concrete (RRC) beams, Eng. Struct. 33 (3) (2011) 1025–1033.
[28] S.W. Kim, C.Y. Jeong, J.S. Lee, K.H. Kim, Size effect in shear failure of reinforced concrete beams with recycled aggregate, J. Asian Archit. Build. Eng. 12 (2) (2013) 323–330.
[29] E.E. Etman, H.M. Afefy, A.T. Baraghith, S.A. Khedr, Improving the shear performance of reinforced concrete beams made of recycled coarse aggregate, Constr. Build. Mater. 185 (2018) 310–324.
[30] H.R. Chaboki, M. Ghalehnovi, A. Karimipour, J. de Brito, M. Khatibinia, Shear behaviour of concrete beams with recycled aggregate and steel fibres, Constr. Build. Mater. 204 (2019) 809–827.
[31] M.Y. Mansour, M. Dicleli, J.Y. Lee, J. Zhang, Predicting the shear strength of reinforced concrete beams using artificial neural networks, Eng. Struct. 26 (6) (2004) 781–799.
[32] S.C. Lee, Prediction of concrete strength using artificial neural networks, Eng. Struct. 25 (7) (2003) 849–857.
[33] N. Deshpande, S. Londhe, S.S. Kulkarni, Modeling compressive strength of recycled aggregate concrete using neural networks and regression analysis, Concr. Res. Lett. 4 (2) (2013) 580–590.
[34] W.P.S. Dias, S.P. Pooliyadda, Neural networks for predicting properties of concretes with admixtures, Constr. Build. Mater. 15 (7) (2001) 371–379.
[35] İ.B. Topçu, M. Sarıdemir, Prediction of mechanical properties of recycled aggregate concretes containing silica fume using artificial neural networks and fuzzy logic, Comput. Mater. Sci. 42 (1) (2008) 74–82.
[36] Z.H. Duan, S.C. Kou, C.S. Poon, Using artificial neural networks for predicting the elastic modulus of recycled aggregate concrete, Constr. Build. Mater. 44 (2013) 524–532.
[37] ACI Committee, Building Code Requirements for Structural Concrete (ACI 318-08) and Commentary, American Concrete Institute, 2008.
[38] S.S. Haykin, Neural Networks and Learning Machines/Simon Haykin, (2009) .
[39] M.A. Mashrei, R. Seracino, M.S. Rahman, Application of artificial neural networks to predict the bond strength of FRP-to-concrete joints, Constr. Build. Mater. 40 (2013) 812–821.
[40] Shear Strength of Self-Compacting Concrete and Recycled Aggregate Concrete Beams: An Appraisal of Design Codes, (2020) .
[41] W. Alnahhal, O. Aljidda, Flexural behavior of basalt fiber reinforced concrete beams with recycled concrete coarse aggregates, Constr. Build. Mater. 169 (2018) 165–178.
[42] M. Etxeberria, A.R. Marí, E. Vázquez, Recycled aggregate concrete as structural material, Mater. Struct. 40 (5) (2007) 529–541.
[43] G. Fathifazl, A.G. Razaqpur, O.B. Isgor, A. Abbas, B. Fournier, S. Foo, Shear strength of reinforced recycled concrete beams without stirrups, Mag. Concr. Res. 61 (7) (2009) 477–490.
[44] B. Gonzalez-Fonteboa, F. Martinez-Abella, Shear strength of recycled concrete beams, Constr. Build. Mater. 21 (4) (2007) 887–893.
[45] I.S. Ignjatović, S.B. Marinković, N. Tošić, Shear behaviour of recycled aggregate concrete beams with and without shear reinforcement, Eng. Struct. 141 (2017) 386–401.
[46] M. Adom-Asamoah, J. Wiafe Ampofo, R. Owusu Afrifa, Flexural and shear behaviour of reinforced concrete beams made from recycled materials, J. Ghana Inst. Eng. 6 (1) (2009) 57–66.
[47] A.B. Ajdukiewicz, A.T. Kliszczewicz, Comparative tests of beams and columns made of recycled aggregate concrete and natural aggregate concrete, J. Adv. Concr. Technol. 5 (2) (2007) 259–273.
[48] B.C. Han, H.D. Yun, S.Y. Chung, Shear capacity of reinforced concrete beams made with recycled-aggregate, Special Publication 200 (2001) 503–516.
[49] T. Ikegawa, H. Saito, H. Ohuchi, H. Kitoh, H. Tsunokake, Flexural and shear failure tests of reinforced concrete beams with low grade recycled aggregate, Int. J. Civil Eng. Technol. 50 (12) (2009) 29–36.
[50] A.H. Buller, M. Oad, B.A. Memon, Relationship between cubical and cylindrical compressive strength of recycled aggregate concrete, IJIRMPS-Int. J. Innov. Res. Eng. Multidisc. Phys. Sci. 7 (2) (2019).
[51] Standards Association of New Zealand, New Zealand Standard Code of Practice for General Structural Design and Design Loadings for Buildings, Standards Association of New Zealand, 1984.
[52] Canadian Standards Association, Design of Concrete Structures, Canadian Standard Association, 2004 CSA23.3.
[53] T. Zsutty, Shear strength prediction for separate catagories of simple beam tests, J. Proc. 68 (2) (1971) 138–143.
[54] Z.P. Bažant, Q. Yu, Designing against size effect on shear strength of reinforced concrete beams without stirrups: I. Formulation, J. Struct. Eng. 131 (12) (2005) 1877–1885.
[55] E.M. Golafshani, A. Behnood, Automatic regression methods for formulation of elastic modulus of recycled aggregate concrete, Appl. Soft Comput. 64 (2018) 377–400.
[56] A. Behnood, J. Olek, M.A. Glinicki, Predicting modulus elasticity of recycled aggregate concrete using M5′ model tree algorithm, Constr. Build. Mater. 94 (2015) 137–147.
[57] E.M. Golafshani, A. Behnood, Application of soft computing methods for predicting the elastic modulus of recycled aggregate concrete, J. Clean. Prod. 176 (2018) 1163–1176.
[58] J. Xu, X. Zhao, Y. Yu, T. Xie, G. Yang, J. Xue, Parametric sensitivity analysis and modelling of mechanical properties of normal-and high-strength recycled aggregate concrete using grey theory, multiple nonlinear regression and artificial neural networks, Constr. Build. Mater. 211 (2019) 479–491.
[59] I. González-Taboada, B. González-Fonteboa, F. Martínez-Abella, J.L. Pérez-Ordóñez, Prediction of the mechanical properties of structural recycled concrete using multivariable regression and genetic programming, Constr. Build. Mater. 106 (2016) 480–499.
[60] M. Ishikawa, K. Doya, H. Miyamoto, T. Yamakawa, Neural Information Processing: 14th International Confernce, ICONIP 2007, (2008) Kitakyushu, Japan, November 13-16, 2007, Revised Selec..
[61] J.J. Jenq, W. Li, Feedforward backpropagation artificial neural networks on reconfigurable meshes, Future Gener. Comput. Syst. 14 (5-6) (1998) 313–319.
[62] J.V. Tu, Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes, J. Clin. Epidemiol. 49 (11) (1996) 1225–1231.