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RESEARCH PAPER

Predicting of Load Carrying Capacity of Reactive Powder Concrete and Normal Strength Concrete Column Specimens using Artificial Neural Network

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Abstract

In present work, prediction of the maximum loading carrying capacity of reactive powder concrete and normal strength concrete column specimens using artificial neural networks (ANNs), were studied experimentally. Twenty-three column specimens were cast and tested in the experimental work, five of which were cast using normal strength concrete (NSC). The other eighteen columns were cast using Reactive Powder Concrete (RPC) with different steel fibers volume fraction (1 and 2%) and four cases was taken from previous studies were used as final trained. The cross-sections of all column test specimens were (150×150 mm), (100×100 mm), (75×75 mm) and (50×50 mm) with a length of 900 mm. The column specimens were tested under concentric axial compression load up to failure. The result of experimental work demonstrated that the results obtained by ANN model are reasonably agree with the experimental results with higher coefficient of determination value (R^2 = 0.993). The distribution of the errors is well, around the zero axis and the uniform distribution of the extra four case study. The results showed that the residual values (experimental and predicted) for all column specimens are within acceptable range. Based on the reported results using ANN model, it can be revealed that the parameters (cross-section and compressive strength) of the column specimens are the greatest important factor affecting on the output parameter of the model. However, the other parameters such as percentage of steel fibers and the spacing between the lateral reinforcement, is unimportant with respect to the importance of the other parameters.

Keywords: Artificial neural networks; reactive powder concrete; normal strength concrete; coefficient of correlation

1. Introduction

Reactive Powder Concrete is synthetic with perfect mixture designs in order to satisfy the perfect industry principles and have greater ductility which makes it competitive with other structure member [7, 13]. Besides, RPC has a substantial cost advantage for many structural applications [2]. RPC is able to reach a greater quantity of the maximum load carrying capacity because of the principle of RPC that is depending on a material with a very low of weakness such as pore spaces and micro-crack [22, 15, 21]. Studying the properties of RPC mixture is one of the essential step for predesign and primary preparation for structure and material science [8, 1]. Among those properties investigations is the load carrying capacity [10, 5].

In last years, the computer aid technologies have been developed rapidly in the development of artificial intelligence (AI) and have been spread in all parts of life [9, 3]. They have been approved their potential in the domain of material and structural engineering [24, 25, 20, 27]. Among all the applied AI algorithms, ANN model is considered one of the most important algorithms because it is able to solve complex problems in a very short time, particularly for problems when the relationship between inputs and outputs cannot be clearly demonstrated [16]. ANN model has been evidenced its capacity in modeling different related issues of structural engineering and concrete sciences, e.g., beam shear strength [26], beam cracks detection [18], flexural strength [11], beam damage assessment [12], concrete compressive strength [14], and several others. Hence, the motivation of the current research was initiated to use the feasibility of ANN model with a large number of input parameters and to increase the accuracy in predicting the load-carrying capacity of the column specimens, the is to the best knowledge of the current research.

2. Experimental Work

2.1 The Experimental Work Program

During this research, the predicting of load carrying capacity of RPC and NSC column specimens by using artificial neural networks (ANNs) was based on twenty-three of experimental database (eighteen reactive powder concrete columns and five normal strengths reinforced concrete columns) that were cast and tested in laboratory, and four cases was taken from previous studies were used as final trained. To avoid or reduce the variation in the exposure conditions, all column specimens were cast at the same period. Each column with dimensions of 150×150×900 mm was strengthened with 4Ø10 mm as longitudinal reinforcement, and Ø5 mm bars were used for ties (lateral reinforcement) and other columns with dimensions of (100$\times$100$\times$900 mm, 75×75×900 mm and 50×50×900 mm) were cast without reinforcement. All column specimens were completely submerged in water for (2 weeks). After that the column specimens were tested after exposed the columns for a period of 60 days in the open air.

2.2 Materials

i. Cement:- Mass Iraq ASTM Type (I), ordinary portland cement (O.P.C) processed in Iraq was used for concrete mixes and taken from local markets.
ii. Fine Aggregate:- Natural fine aggregate was used for normal strength concrete mixes. In RPC, very fine sand passing (600μm) was used. The particle size distribution should fall into the range of (150-600)μm.
iii. Coarse Aggregate (Gravel):- Rounded gravel was used in normal concrete mixes, with maximum size of (14) mm.
iv. Micro Silica Fume (SF):- This material is really active pozzolanic material and is a by-product from the production and purification of Silicon metal or Ferro-silicon alloys in submerged-arc electric furnaces. The individual grains are very small, and may be reached to approximately (100 times) smaller than the particle of the cement.
v. Superplasticizer:- Glenium 54 (G54) from BASF COMPANY was used in this work. There are not possible to product RPC mixes without the use of superplasticizer, so that the benefit of using superplasticizer is reducing water with the rate above (32%).
vi. Micro Steel Fibers:- The greatest effect can be realized by using steel fibers to increase the ductility of the concrete. In addition, the best way to increase the mechanical properties is the adding of short plain steel fibers on condition of spreading of these fibers within the matrix.
vii. Mixing Water:- For both mixing and curing all the column specimens, clean tap water was used with room temperature about (23pm5)^{o}C.

3. The applied Artificial Neural Network Model

Artificial neural networks are defined as a computing systems, typically named neural networks (NNs) and caused by the biological neural networks that create animal brains [6]. Many nodes or units called artificial neurons are connected together to make an artificial neural network, which loosely model the neurons in a biological brain [4]. The signal can be transmitted to other neurons by the connection of the artificial neural network, like the synapses in a biological brain [23, 19]. An artificial neuron takes a signal, then processes it and can signal neurons connected to it. The (signal) at a connection is a real number, and the output of each neuron is calculated by some non-linear function of the sum of its inputs. The connections are termed edges. Neurons and edges usually have a weight that adjusts as learning proceeds. ANN can be used as there are flexible and complex relationships between inputs and outputs revealed by changing the model structure and the connection weights' [14]. So that the weight can be increased or decreased the strength of the signal at a connection. If the combined signal moves from threshold, neurons may have a threshold such that a signal is sent only. Normally, neurons are combined into layers (input, hidden and output layer). Different layers can perform different transformations on their inputs. Many signals travel from the input layer (first layer), to the output layer (last layer), possibly after traversing the layers multiple times [17]. In this research, ANN model was carried out. Various sets of combinations of available data were considered for prediction modeling. Many studies showed that the perfect mathematical model has input layer with four neurons, output layer with one neuron and one hidden layer with four neurons to provide maximum correlation values and minimum error. Artificial neural network modeling of the column specimens was performed using Program IBM SPSS Statistic program version [14]. The input layer treated the compressive strength (f_{cu}), percentage of steel fibers (V_f), spacing of lateral reinforcement (S_{st}) and cross–section of RPC column specimens (C_s). While the output layer characterized the predicted maximum load capacity of the column specimens (P_u). Figure 1 demonstrates the graphic of the inputs (independent variables), the output (the dependent variable) and threshold levels (Bias) along with the hidden layers neurons.

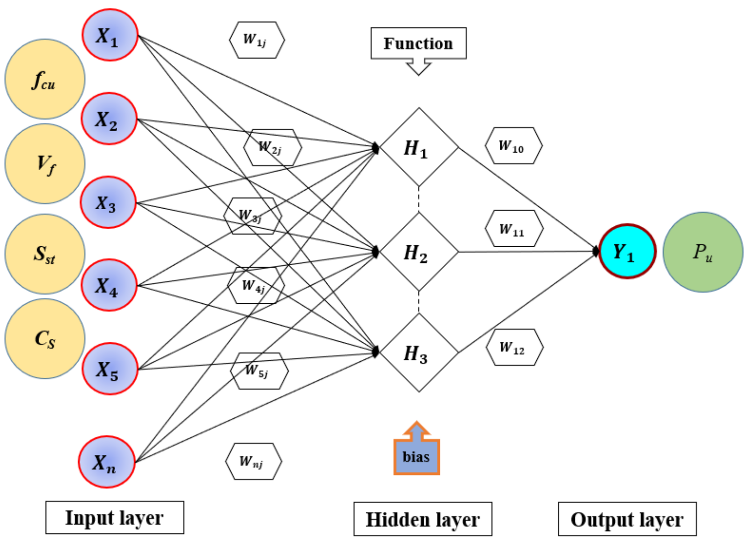

Figure 1: *The schematic of the input layer, hidden and output layer of the developed ANN model.*

4. Results and Discussion

The first step in the development of the analysis methods was the selection of the variables included in the model. The independent and dependent variables were selected as shown in Table 1. Table 2 presents adopted ANN model architecture information. In present work, twenty-three cases was carried for testing, training and building the ANN model and the other four cases from previous studies were used as final trained. Table 3 shows parameters and the values of database used in the present work to improve ANN model.

Table 1: *Dependent and independent variables.*

Dependent variable	Independent variables
P_u	f_{cu}, V_f, $C.S$, and S_{st}

Table 2: *Adopted artificial neural network architecture information.*

Information of the Network			
Details of Input Layer	Covariates	1	Tie spacing (cm)
		2	Cross-section (mm)
		3	V_f (%)
		4	f_{cu} (MPa)
	Number of the units		4
	Rescaling method for covariates		Standardized
Details of Hidden Layer	Number of the hidden layers		1
	Number of units in the hidden layer		4
	Activation function		Hyperbolic tangent
Details of Output Layer	Dependent variables	1	P_u
	Number of units		1
	Rescaling method for scale dependents		Standardized
	Activation function		Identity
	Error function		Sum of squares

The importance and normalize importance of independent variables (input) are summarized in Table 4. Figure 2 shows the importance of input parameters that can be predicted the column load capacity. From this figure, it can be revealed that the parameters (cross-section and compressive strength) of the column specimens are the greatest important factor affecting on the output parameter of the model. But the other parameters in input layer such as (percentage of steel fibers and the spacing between the lateral reinforcement) is unimportant with respect to the importance of the other parameters.

The experimental values, predicted values obtained by artificial neural network (ANN) model and residual values of load carrying capacity of column specimens shown in Table 5. From this table, it can be noted that the results obtained using ANN model are reasonably agree with the experimental results. The predicted and residual values of ANN model are shown in Figures 3 and 4, respectively, with respect to the experimental results of load carrying capacity. In Figure 4, it can be shown that the distribution of the errors is well, around the zero axis. Also, this figure presents uniform distribution of the extra four case study so that ANN-case study state the constant performance of ANN model.

R^2 (coefficient of correlation) is usually used to exam the trained network accuracy. This coefficient is also consider a measure of how well the independent variables considered account with respect to the measured dependent variable. Very high (R^2) value demonstrates a best relationship for prediction. From this results, the ANN technique had the ability of prediction load carrying capacity of column specimens with an accuracy of 0.993.

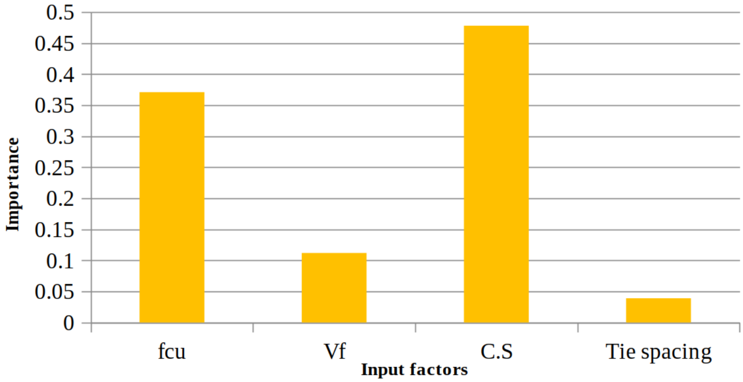

Figure 2: *Comparative importance of input parameters (independent variables).*

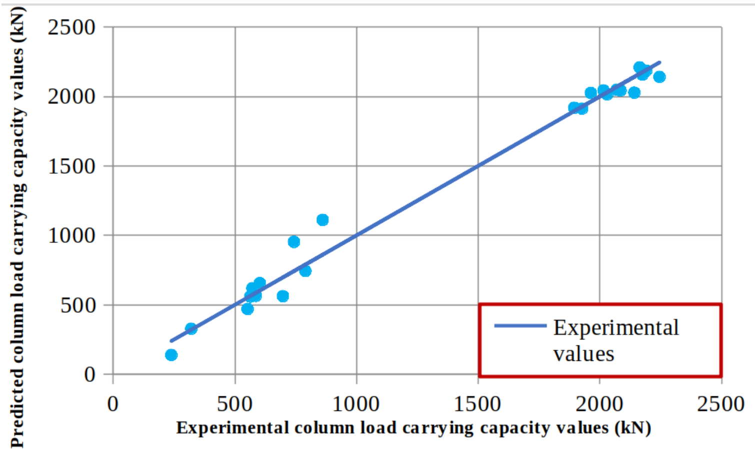

Figure 3: *Experimental versus predicted values of column load carrying capacity by using ANN model.*

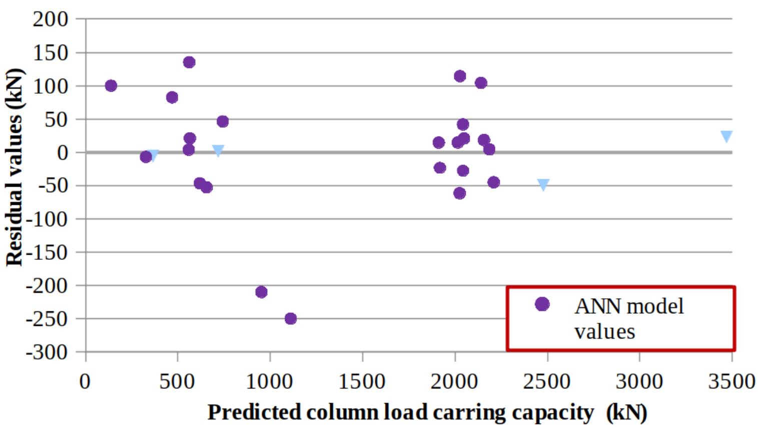

Figure 4: *Predicted versus residual values of column load carrying capacity by using ANN.*

Table 3: *Adopted artificial neural network architecture information.*

Data Type	No.	F_{cu} (MPa)	V_f %	Cross section (mm)	Main reinforcement	Lateral reinforcement	Experimental values (KN)
Data Used to Improve the Model	1	130.6	1	150×150	without	without	1895.0
	2	138.2	2	150×150	without	without	2070.0
	3	125.1	1	100×100	without	without	742.6
	4	134.5	2	100×100	without	without	860.8
	5	128.3	1	75×75	without	without	697.4
	6	139.2	2	75×75	without	without	789.6
	7	129.4	1	50×50	without	without	238.6
	8	140.8	2	50×50	without	without	320.5
	9	130.5	1	150×150	$4\emptyset10$	$\emptyset5@20$ cm	1963.2
	10	141.6	2	150×150	$4\emptyset10$	$\emptyset5@20$ cm	2164.0
	11	131.1	1	150×150	$4\emptyset10$	$\emptyset5@15$ cm	2015.6
	12	137.6	2	150×150	$4\emptyset10$	$\emptyset5@15$ cm	2175.4
	13	128.7	1	150×150	$4\emptyset10$	$\emptyset5@10$ cm	2030.3
	14	138.9	2	150×150	$4\emptyset10$	$\emptyset5@10$ cm	2190.6
	15	129.9	1	150×150	$4\emptyset10$	$\emptyset5@5$ cm	2085.0
	16	135.4	2	150×150	$4\emptyset10$	$\emptyset5@5$ cm	2245.5
	17	130.2	1	150×150	$4\emptyset10$	without	1927.2
	18	136.8	2	150×150	$4\emptyset10$	without	2142.0
	19	36.3	-	150×150	$4\emptyset10$	$\emptyset5@20$ cm	563.1
	20	39.6	-	150×150	$4\emptyset10$	$\emptyset5@15$ cm	571.9
	22	35.5	-	150×150	$4\emptyset10$	$\emptyset5@10$ cm	585.8
	22	40.8	-	150×150	$4\emptyset10$	$\emptyset5@5$ cm	602.4
	23	37.5	-	150×150	$4\emptyset10$	without	552.2
Case Study Data	24	154	2	150×150	$4\emptyset16$	without	3493.0
	25	154	2	150×150	$4\emptyset12$	without	2428.0
	26	132	2	100×100	$4\emptyset6$	$\emptyset4@60$ cm	720.0
	27	132	2	70×70	$4\emptyset4$	$\emptyset4@60$ cm	360.0

Table 4: *The importance of the independent variables.*

Inputs	Importance	Normalized importance (%)
f_{cu}	0.371	77.7
V_f	0.112 23.3	
$C.S$	0.478	100.0
S_{st}	0.039	8.2

Table 5: *The experimental values, predicted values obtained by ANN model and residual values of maximum load capacity of column specimens.*

Columns identification	Experimental values (kN)	Predicted values (kN)	Residual values (kN) (Experimental-Predicted)
RC1	1895.0	1918.5	-23.5
RC2	2070.0	2048.9	21.1
RC3	742.6	952.8	-210.2
RC4	860.8	1111.0	-250.2
RC5	697.4	561.7	135.7
RC6	789.6	743.0	46.6
RC7	238.6	138.3	100.3
RC8	320.5	327.3	-6.8
RC9-S_{20}	1963.2	2025.1	-61.9
RC10-S_{20}	2164.0	2209.5	-45.5
RC11-S_{15}	2015.6	2043.4	-27.8
RC12-S_{15}	2175.4	2156.8	18.6
RC13-S_{10}	2030.3	2015.4	14.9
RC14-S_{10}	2190.6	2185.9	4.7
RC15-S_5	2085.0	2042.9	42.1
RC16-S_5	2245.5	2140.9	104.6
RC17-S_0	1927.2	1912.3	14.9
RC18-S_0	2142.0	2027.3	114.7
NC1-S_{20}	563.1	559.0	4.1
NC2-S_{15}	571.9	619.0	-47.1
NC3-S_{10}	585.8	564.7	21.1
NC4-S_5	602.4	655.5	-53.1
NC5-S_0	552.2	469.3	82.9
Case Study Data	3493.0	3469.6	23.4
	2428.0	2478.0	-50
	720.0	718.2	1.8
	360.0	365.5	-5.5

5. Conclusions

The following research findings were achieved;

i. The use of RPC technology can considerably improve the behavior of the column specimens and their efficiency as compared to the behavior of normal strength concrete columns mixes because of the compressive strength and homogeneity of this type of concrete.
ii. As a result, the multilayer feed-forward neural network models were expected the maximum loading carrying capacity of (reactive powder concrete and normal strength concrete) column specimens in a comparatively short period of time with tiny error rates.
iii. An artificial neural network (ANN) was developed in this study as a mathematical model. This model obtained to provide expected load carrying capacity of the column specimens to an accuracy of 0.993.
iv. The parametric study presented that the parameters (cross-section and compressive strength) of the column specimens are the greatest important factor affecting on the output parameter of the model. But the other parameters in input layer such as (percentage of steel fibers and the spacing between the lateral reinforcement) is unimportant with respect to the importance of the other parameters.
v. The conclusions have confirmed that (ANN models) are practicable trained algorithm for predicting maximum load capacity of (reactive powder concrete and normal strength concrete column specimens) with minimum error % and maximum correlation values.

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Conflicts of Interest: The authors have no conflict of interest to any part.

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