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Regression and ANN models for durability and mechanical characteristics of waste ceramic powder high performance sustainable concrete

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Abstract. There is a growing interest in the use of by-product materials such as ceramics as alternative materials in construction. The aim of this study is to investigate the mechanical properties and durability of sustainable concrete containing waste ceramic powder (WCP), and to predict the results using artificial neural network (ANN). In this order, different water to binder (W/B) ratios of 0.3, 0.4, and 0.5 were considered, and in each W/B ratio, a percentage of cement (between 5-50%) was replaced with WCP. Compressive and tensile strengths, water absorption, electrical resistivity and rapid chloride permeability (RCP) of the concrete specimens having WCP were evaluated by related experimental tests. The results showed that by replacing 20% of the cement by WCP, the concrete achieves compressive and tensile strengths, more than 95% of those of the control concrete, in the long term. This percentage increases with decreasing W/B ratio. In general, by increasing the percentage of WCP replacement, all durability parameters are significantly improved. In order to validate and suggest a suitable tool for predicting the characteristics of the concrete, ANN model along with various multivariate regression methods were applied. The comparison of the proposed ANN with the regression methods indicates good accuracy of the developed ANN in predicting the mechanical properties and durability of this type of concrete. According to the results, the accuracy of ANN model for estimating the durability parameters did not significantly follow the number of hidden nodes.

Keywords: high performance sustainable concrete; waste ceramic powder; mechanical properties; durability; ANN

1. Introduction

At the current years, there is a great interest to make the concrete as a sustainable material. Cement production emits huge pollutions into the environment and consumes lots of energy, in a sense that it has the third rank in greenhouse gas production as well as energy consumption in the world (Hiks *et al.* 1998). It is very important to introduce a mixture for constructing concrete elements with a low content of energy consumption and earth pollution (Goriparthi and Gunneswara Rao 2017, Saha and Rajasekaran 2016). This goal would be achieved by reducing cement consumption and extending the lifetime of the concrete elements. It is also desired to produce the concrete mixture using waste materials without any weakening of its mechanical and durability properties and even improving them (Alipour *et al.* 2019, Mohseni *et al.* 2019). Many of the concrete structures collapse because of weakness in their durability performance. Therefore, improving the durability of the concrete elements extends the lifetime of the structure, significantly (Miyandehi *et al*. 2014, Tarighat and Zehtab 2016, Yang *et al.* 2015). Moreover, utilizing the waste materials in concrete mixtures leads to reduce the accumulation of waste materials in the nature and making the earth cleaner. Waste ceramic is one of the waste materials which is suitable for partial replacement for cement (Heidari and Tavakoli 2013, Senthamarai and Devadas Manoharan 2005, Tavakoli *et al.* 2013). Waste ceramic tiles are not reusable and recyclable due to their physical properties and chemical structure. Annually, huge tons of waste ceramic was bulked outside the industrial cities. Waste ceramic could be used as a pozzolanic material, fine or coarse aggregates. Replacement of 25-50% percent of fine aggregates and 10-20% of coarse aggregates by waste ceramic could increase the compressive strength and decrease the unit weight of the concrete samples (Tavakoli *et al*. 2013). Implementation of ceramic powders as fine aggregates could also improve the resistance to chloride ion penetration, significantly (Higashiyama *et al.* 2012). Through an experimental study, it is concluded that use of waste ceramic powders (WCP) as filler material in self-consolidating concrete could improve flowability (Subaşı *et al.* 2017). Although WCP have a filler role primarily (Kannan *et al.* 2017), it was observed through the differential scanning calorimetry and thermogravimetric analysis on the hydrated binders that portlandite amount were decreased by time (Pavlík *et al*. 2016). This is an evidence for pozzolanic activity of WCP. Therefore, WCP could be used as supplementary materials along with cement powders. It has been shown that partial replacement of cement powders by ground WCP would produce cementitious pastes with some better durability properties. It has been shown that 20% replacement of cement by WCP would increase durability performance significantly while

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the compressive strength of these concrete samples might be decreased slightly (Pacheco-Torgal and Jalali 2010). However, the compressive strength could be improved by addition of nano-SiO_2 (Heidari and Tavakoli 2013). In some cases, the presence of more AL_2O_3 than SIO_2 reduces the durability of the concrete containing WCP or other natural pozzolans. Researchers evaluated the performance of different pozzolans of Mexican origin. The results show that the pozzolanic activity at ≥5.4 N/mm^2 with an alumina content of 11.6-14.7% were highly resistant to sulphate attack compared with those which contain ≥16% Al_2O_3. But in general Al_2O_3 increases the concrete's thermal resistance (Rodríguez-Camacho and Uribe-Afif, 2002).

The researchers have investigated that high performance concrete mixtures incorporating WCP with large replacement ratios by cement had high compressive strength and excellent durability (Kannan *et al*. 2017). Incorporation of WCP as partial replacement by 10-40% cement powders produces a dense mixture with low permeability. Using permeability, chloride diffusion and accelerated aging tests, researchers proved that durability of the concrete containing WCP could be extremely improved (Pacheco-Torgal and Jalali 2010).

Experimental outputs could be used as input for one of the artificial intelligence methods to find out which algorithm is the most suitable tool for estimating results analytically (Khatibinia *et al.* 2016, Mazloom and Yoosefi 2013, Sobhani, *et al.* 2013). Artificial neural network (ANN) is one of the most popular tools which relates the input and output data through a nonlinear equation. ANN trains input data using a learning function to produce valid outputs. In the previous study about ANN behavior, researchers utilized ANN tool to predict compressive strength of cement mortars for assessing the effect of cement strength class as an input in the networks with 11 neurons (Eskandari-Naddaf and Kazemi 2017). Some of other researchers adopted ANN model for estimating compressive strength of concrete mixtures incorporating waste tire rubber. They found that ANN can predict reliable output data for these samples (Hadzima-Nyarko *et al.* 2019). In recent research on sustainable development in concrete, it was showed that ANN is a suitable tool for estimating compressive strength of concrete mixtures containing recycled aggregate concrete (RAC) (Naderpour *et al.* 2018). The compressive strength of fly ash-based geopolymer concretes which were constructed using rice husk ash, fly ash, Nano-SiO_2 and Nano-Al_2O_3 was also properly predicted through feed-forward back propagation ANN models (Riahi and Nazari 2019).

Some other researches were applied using multivariate adaptive regression splines (MARS), M5 model tree (M5Tree) and least squares support vector regression (LSSVR) models to estimate the properties of concrete mixtures incorporated by recycled concrete aggregates (Gholampour *et al.* 2018). Results show that MARS, M5Tree, and LSSVR models can estimate close predictions of the mechanical properties of recycled concrete aggregates by acceptably capturing the influences of the key parameters.

Subsequently, other researchers concluded that, found that full quadratic multivariable regression model has the best performance for assessing the outputs of rubberized concrete mixture containing silica fume and zeolite (Jalal *et al.* 2019).

Although there are several predictive studies in the literature which are conducted on experimental results extracted for concrete mixtures, no analysis research is found which is focused on estimation for outputs of concrete mixtures containing WCP. In this paper, the mechanical properties and durability-related results of WCP-included binary concrete mixtures are estimated using linear, nonlinear and logarithmic regression and artificial neural network (ANN). Different neurons were used for finding the best ANN network which is able to predict the most accurate outputs. Efficiency of the implemented methods are evaluated using root mean squared (RMS) of errors, coefficient of determination (*R*-squared index), mean absolute percentage error (MAPE) and the error histogram. Input for the ANN and regression models are coarse aggregates, fine aggregates, cement, WCP, slump, plasticizer and the age of the specimens. In other side, compressive and tensile strength, water absorption, resistance to chloride ion penetration (RCPT) and electrical resistivity were chosen as output for utilized prediction tools. The results show that ANN and regression models could be used properly for predicting the mechanical and durability-related outputs of concrete mixtures containing WCP. It is concluded that ANN model with 10 neurons has the best performance for modeling the compressive strength. Furthermore, about tensile strength, it is estimated that ANN with 7 hidden neurons gives the best result and finally for predicting water absorption, resistance to chloride ion penetration and electrical resistivity best results extracted when ANN was used respectively with 7, 8 and 9 hidden neurons. About regression models, it should be noted that, in almost all cases nonlinear models have the best results and this method is more accurate than the other methods.

Table 1 Physical properties of the binding materials

Material	Specific surface area (m^2/kg)	Unit weight (g/cm^3)
Cement	315	3.05
WCP	325	2.36

2. Materials and methods

2.1 Materials

For making concrete samples coarse aggregates and fine aggregates were used as saturated with dry surfaceat the largest nominal size of 5 and 12 mm, respectively. Sieve analysis of fine and coarse aggregates were performed according to ASTM C136 (Statements and Size 2010). It is necessary to mention that cement Type 1-525 with the 28-day compressive strength of 25 MPa was applied to prepare the samples. The WCPs used in this article were obtained from Isfahan Tile Factory. In order to crush the ceramics, the scrap tiles were first crushed in the mill and then passed through a 100 micron sieve. The specific surface area and

Table 2 Chemical composition of the binding materials

Material	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	P_2O_5	K_2O	Na_2O	TiO_2	SO_3	SrO_2	MnO	Mn_2O_3	L.O.I
Cement	21.5	6.00	2.50	66.00	2.00	0.01	0.18	0.20	0.05	0.03	-	0.008	-	0.90
WCP	63.29	18.29	4.32	4.46	0.72	0.16	2.18	0.75	0.61	0.10	0.02	-	0.05	1.61

Table 3 Mixture proportions for the preparation of sustainable concrete containing waste ceramic

	W/B ratio	Cement (kg/m^3)	WCP (kg/m^3)	Water (kg/m^3)	Fine Aggregates (kg/m^3)	Coarse Aggregates (kg/m^3)	plasticizer (kg/m^3)
MD-0.3-0	0.30	530.00	0.00	160	769.50	940.50	10.60
MD-0.3-5		503.50	26.50	160	769.50	940.50	10.60
MD-0.3-10		477.00	53.00	160	769.50	940.50	10.60
MD-0.3-15		450.50	79.50	160	769.50	940.50	10.60
MD-0.3-20		424.00	106.00	160	769.50	940.50	10.60
MD-0.3-30		371.00	159.00	160	769.50	940.50	10.60
MD-0.3-40		318.00	212.00	160	769.50	940.50	10.60
MD-0.3-50		265.00	265.00	160	769.50	940.50	10.60
MD-0.4-0	0.40	400.00	0.00	160	826.61	1010.30	8.00
MD-0.4-5		380.00	20.00	160	826.61	1010.30	8.00
MD-0.4-10		360.00	40.00	160	826.61	1010.30	8.00
MD-0.4-15		340.00	60.00	160	826.61	1010.30	8.00
MD-0.4-20		320.00	80.00	160	826.61	1010.30	8.00
MD-0.4-30		280.00	120.00	160	826.61	1010.30	8.00
MD-0.4-40		240.00	160.00	160	826.61	1010.30	8.00
MD-0.4-50		200.00	200.00	160	826.61	1010.30	8.00
MD-0.5-0	0.50	320.00	0.00	160	860.90	1052.21	6.40
MD-0.5-5		304.00	16.00	160	860.90	1052.21	6.40
MD-0.5-10		288.00	32.00	160	860.90	1052.21	6.40
MD-0.5-15		272.00	48.00	160	860.90	1052.21	6.40
MD-0.5-20		256.00	64.00	160	860.90	1052.21	6.40
MD-0.5-30		224.00	96.00	160	860.90	1052.21	6.40
MD-0.5-40		192.00	128.00	160	860.90	1052.21	6.40
MD-0.5-50		160.00	160.00	160	860.90	1052.21	6.40

Fig. 1 (a) WCP, (b) Cement Type 1-525 used in sustainable concrete containing waste ceramic

unit weight of the WCP and cement are observed in Table 1.

As a sustainable bio-admixture, lignosulfonate plasticizers are used with different dosage to achieve different slump in concrete samples. *X*-ray fluorescence (XRF) was performed to compare and analyze the chemical composition of the cement and WCP. According to Table 2, the results show that sum of values of SiO_2 and Al_2O_3were significantly higher than other values. This is the main constituents of a suitable binding material for used in concrete as supplementary cementitious replacements (Juenger and Siddique 2015). The WCP and cement used in the present study are visible in Fig. 1.

2.2 Mix proportioning and sample preparation

At First, 24 different concrete mixtures were designed to perform different experiments. The concrete mixtures were divided into three categories with different water-to-binder ratios. Water-to-binder ratios of 0.3, 0.4, and 0.5 have been selected respectively to obtain reliable results. Each ratio was individually subdivided into eight separate categories with different percentages of WCP replacement. Totally, in addition to the control samples, the percentages of 5, 10, 15, 20, 30, 40, and 50 percent of WCP replacement were applied, respectively. In all concrete mixtures the ratio of fine to coarse aggregates and lignosulfonate plasticizer to cement has been assumed to be 0.82 and 0.02, respectively. The reason for the lignosulfonate plasticizer to cement ratio being constant is that, due to the higher water absorption rate of the WCP, slump of fresh concrete decreases. Therefore, slump can be applied as one of the input parameters of the ANN. The full details of the concrete mixtures can be seen in Table 3.

Prepared materials were mixed according to details of the concrete mixtures. Naming schemes is such that MD represents the mixing design and the numbers afterwards indicate the ratio of water to binders (*W/B*) and the percentage of WCP replacement, respectively. In order to

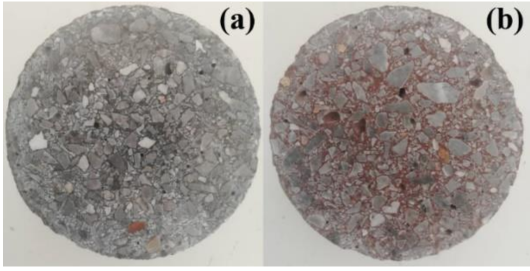

Fig. 2 Cross section of a cylindrical sample fabricated by (a) MD-0.3-0, (b) MD-0.3-50 mixture

Fig. 3 RCPT test setup in laboratory

ensure about preparing a uniform concrete mixture, fine and coarse aggregates were saturated with dry surface 24 h prior before mixing. Fine and coarse aggregates were initially mixed in the pan mixer. After 2-3 min dry mixed of cement and WCP were added to the mixer and still dry mixed for extra 1-2.5 min. Finally, the precursor materials were mixed for 3-4 min until a uniform sustainable concrete was prepared after adding lignosulfonate plasticizerand water in three stages. Casting, compaction, and curing were applied according to ASTM C192-81 (ASTM C192/C192M, 2016; Heidari & Tavakoli, 2013). As it is shown in Fig. 2(b) WCP can be observed clearly in comparison with those samples which did not include WCP (Fig. 2(a)).

For the mechanical and durability tests, the specimens were made in two different appearance types. Cubic samples with dimensions of 10×10×10 cm were prepared for testing compressive strength, water absorption and electrical resistivity and cylindrical samples with dimensions of 20×10 cm were fabricated for tensile strength and RCPT. The compressive strength test was performed at 3, 7, 28 and 90 days of age. Also tensile strength was performed at 28 and 90 days of age according to ASTM C496 (ASTM C496/C496M-11 2011). The electrical resistivity of 10×10×10 cm^3 cubic samples was performed at curing age of 28 and 90 days in accordance with ASTM C1760 (Ameri *et al.* 2019; Test *et al*. 2012). According to BS 1881 Part 122 (BS 1881-122 2011) the volumetric water absorption of sustainable concrete samples was performed after 28 and 90 days of curing. To derive the result from this experiment, three specimens of each mix plan were heated in an electric oven at the temperature of 60°C at 28 and 90 days after curing. This is performed to completely dry the specimens. The average weight of the three samples after heating was read as the initial weight (W_1). The samples were then immersed in water for twenty-four hours for saturation. Then their weight at saturated surface dry (SSD) condition (W_2) were recorded. Finally the volumetric water absorption was calculated according to the following relationship

$$\frac{W_2 - W_1}{W_1} \times 100 \tag{1}$$

To perform RCPT in this research, cylindrical concrete samples were cut to size 5×10 cm disk. Finally to the total charge passing through a prepared concrete samples after 28 and 90 days of ambient curing was evaluated according to ASTM C1202 (ASTM C1202, 2012) in 6 h by 60 V' potential. In general, to do this research 288 20×10 cylindrical and 432 10×10×10 prism specimens were constructed. RCPT test setup which was applied in this research is shown in Fig. 3.

3. Results and discussion

3.1 Experimental results

The relationship between different percentages of WCP replacement with cement, considering different water to binders (*W/B*) ratios is discussed in the Table 4. Table 4 shows that, in all *W/B* ratios at 3 days of age, the highest compressive strength was related to the control samples. This is due to the secondary reaction of pozzolans with portlandite ($Ca(OH)_2$). In the early days of hydration processing, portlandite was forming faster than C-S-H. In the concrete containing pozzolans, the formation of calcium silicate gels (C-S-Hs) resulting from the reaction with $Ca(OH)_2$ is accelerated from day 28 of processing (Kakali *et al.* 2001). 28 days after submerging concrete samples in water, pozzolanic activity of WCP begins. In the W/B ratios of 0.3, 0.4, and 0.5, the samples containing 20% of the WCP reached to 85.3, 82.9 and 78.45% of the compressive strength of the control samples, respectively. With the increase in the percentage of WCP more than 20%, the increase in compressive strength at the age of 28 days has been noticeably slower. This result is also evident in other studies (Heidari and Tavakoli 2013, Kannan *et al*. 2017). Eventually, in the 90-day samples, at approximately the *W/B* ratio of about 0.3, the sample containing 20% of the WCP reached the compressive strength of the control sample. Also, in the *W/B* ratios of 0.4 and 0.5, the samples containing 20% of the WCPs achieved the compressive strengths of 60.3and 50.8 MPa, respectively. According to some other results that were investigated in some other researches for less than 20% replacement of the WCP, in the *W/B* ratio of 0.5, the average decrease in compressive strength at 91 days of curing is 1.45% (Heidari and Tavakoli 2013). In this study, for this ratio, a reduction in compressive strength of 4.61% is obtained. Finally, it is important to note that, at a *W/B* ratio of 0.3, the compressive strength of the sample contains 50% of the WCP is about 84.6% of the control sample. This demonstrates the applicability of WCPs in high performance concrete with high cement replacement ratios.

Table 4 Experimental results

	Slump	Compressive Strength (MPa)				Tensile Strength (MPa)		Water Absorption		Electrical Resistivity		RCPT	
		3 Days	7 Days	28 Days	90 Days	28 Days	90 Days	28 Days	90 Days	28 Days	90 Days	28 Days	90 Days
MD-0.3-0	7.00	34.10	55.23	66.53	72.93	3.95	4.49	5.18	4.90	9.16	13.20	3890	2120
MD-0.3-5	6.50	32.60	51.60	64.03	71.10	3.90	4.10	5.55	4.72	10.11	15.30	3740	1995
MD-0.3-10	5.50	31.00	49.43	63.93	69.40	3.60	4.05	5.80	4.68	13.20	17.50	3650	1885
MD-0.3-15	5.50	30.70	47.70	63.17	70.83	3.41	4.15	5.90	4.66	18.90	29.30	3410	1823
MD-0.3-20	4.10	29.20	47.13	62.13	72.57	3.41	4.21	5.89	4.63	21.50	33.60	2950	1796
MD-0.3-30	4.00	23.20	38.73	60.50	66.50	3.00	3.56	6.22	5.19	26.50	39.20	2630	1560
MD-0.3-40	3.50	20.80	36.07	58.37	63.10	2.87	3.41	6.50	5.54	28.90	42.30	2530	1218
MD-0.3-50	3.50	20.20	34.17	55.93	61.17	2.57	3.35	6.70	5.83	33.50	48.30	2589	1285
MD-0.4-0	8.50	28.80	46.80	56.73	62.70	3.20	3.55	5.37	5.29	7.16	9.83	4250	3563
MD-0.4-5	8.50	28.00	44.57	56.10	61.23	3.10	3.59	5.40	5.30	8.98	10.21	3890	3078
MD-0.4-10	7.80	26.40	42.90	55.67	59.70	2.97	3.48	5.55	5.27	11.30	12.20	3830	2992
MD-0.4-15	7.00	24.10	39.23	53.70	58.90	2.77	3.50	5.80	5.12	13.60	15.30	3650	2867
MD-0.4-20	6.50	23.90	38.80	52.77	60.30	2.73	3.46	6.25	5.17	18.90	18.63	3363	2708
MD-0.4-30	6.50	20.40	34.30	50.17	55.60	2.37	3.12	6.42	5.34	21.60	22.90	3100	2387
MD-0.4-40	5.20	19.80	33.17	47.90	52.30	2.33	2.78	6.62	5.60	23.50	29.36	2963	2180
MD-0.4-50	5.00	16.00	26.83	41.50	45.50	2.02	2.66	6.90	5.74	26.50	32.15	2982	2248
MD-0.5-0	9.50	26.30	39.60	48.93	53.29	2.59	3.07	5.77	6.21	5.69	6.54	4827	4123
MD-0.5-5	9.30	23.70	35.97	48.17	52.97	2.57	3.06	5.92	6.18	6.30	7.23	4536	3920
MD-0.5-10	8.50	23.00	35.87	46.47	49.97	2.42	3.05	6.01	5.86	6.59	8.54	4357	3716
MD-0.5-15	8.50	22.50	35.07	45.37	51.99	2.32	3.02	6.12	5.85	7.23	10.33	4042	3498
MD-0.5-20	8.00	20.00	31.07	43.27	50.80	2.34	2.95	6.44	5.80	9.36	16.20	3738	3356
MD-0.5-30	7.50	19.60	29.60	42.10	46.84	2.34	2.78	6.57	6.20	11.17	19.32	3538	3120
MD-0.5-40	7.20	15.60	24.33	35.33	39.57	1.96	2.20	6.80	6.52	15.30	23.20	3250	2981
MD-0.5-50	7.20	12.00	19.17	30.63	33.39	1.68	2.15	6.95	6.80	18.90	26.23	3321	3001

As for tensile strength, it should be noted that, the results in terms of increase or decrease are very similar to those of compressive strength test. In samples containing 20% of WCP, at all *W/B* ratios, the tensile strength is very close to the control sample. The highest amount of tensile strength reduction occurred in the sample containing 50% of the WCP in the W/B ratio of 0.5, which is 29.96%. In the tensile strength test, the difference in the results of the 90-day samples was less than the 28-day samples. This is due to the conversion of $Ca(OH)_2$ to C-S-H with increasing age of the samples containing WCP. In general, the ratio of mean tensile strength to compressive strength in all specimens was 0.057. This result is very close to the result of the relationship found in ACI 363 (ACI 2002, Aslani and Nejadi 2012).

Water absorption test was performed on the samples at 28 and 90 days of age. The results are shown in Table 4. At first, it should be mentioned that with increasing *W/B* ratio, water absorption in all samples increases. The lowest amount of water absorption in the *W/B* ratio of 0.3 was related to the sample containing 20% of WCP. This is equal to 94.48% of the control sample. At the same ratio of *W/B*, by increasing the amount of WCP to more than 20%, the rate of water absorption is increased, to the extent that by replacing 50% of WCP, this amount is up to 1.189 times the control value. This is similar for other *W/B* ratios. So it can be mentioned that by increasing the amount of WCP to more than 20%, regardless of the different *W/B* ratios, the rate of water absorption increases. In general, the lowest water absorption was observed in the sample containing 20% of WCP in *W/B* ratio of 0.3 and the highest in the sample containing 50% WCP in water to cement ratio of 0.5.

The final two columns of Table 4 show the results of the electrical resistivity and RCPT test. In both tests the results indicate that, as the percentage of WCP replacement increases, the electrical resistivity increases and the chloride ion penetration decreases to an incredible extent. According to the other researches, the reason for this could be because of the fine particle size distribution of WCP compared with cement, therefore, WCP can create a dense packing particle system always reported as a key need for high and ultra-high performance concrete (Reda *et al.* 1999). The amount of electrical resistance increases to such an extent that, specimens containing 50% of WCP exhibited about 3.65, 3.27 and 4.01 times the control sample, in W/B ratios of 0.3, 0.4, and 0.5, respectively. For RCPT test, the highest resistance is for samples containing 50% of WCP. Finally, it is important to note that, by reducing the W/B ratio, the durability of concrete containing WCPs is significantly improved.

3.3 ANN and regression models

As already stated, neural network inputs are coarse aggregates, fine aggregates, cement, WCP, slump,

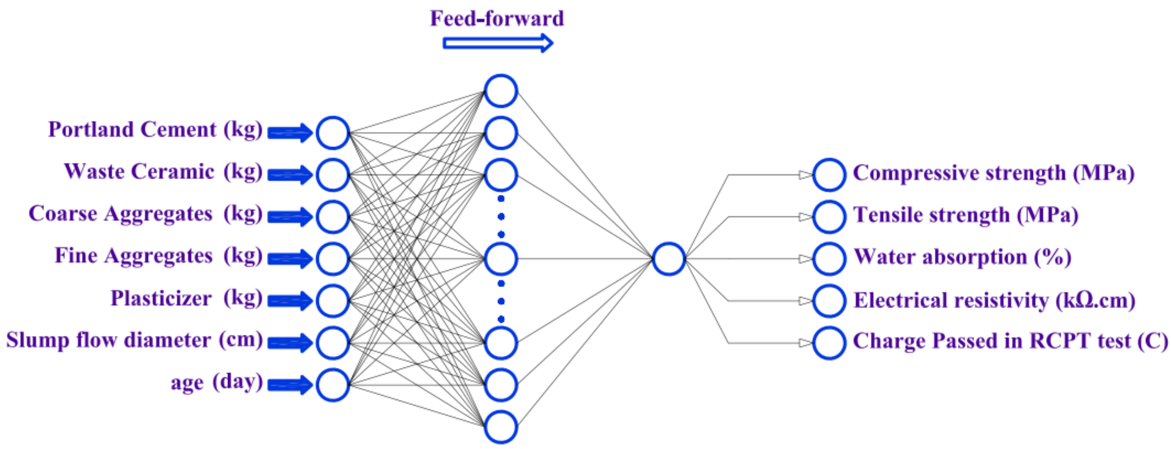

Fig. 4 Basic structure of the ANN applied in this study

Table 5 Multiple regression models for predicting mechanical properties and durability of high performance sustainable concrete

Reg. type	Linear/nonlinear regression models
Linear	$a_0+a_1(\mathrm{P})+a_2(\mathrm{F.Agg})+a_3(\mathrm{C.Agg})+a_4(\mathrm{WCP})$ $+a_5(\mathrm{C})+a_6(\mathrm{S})+a_7(\mathrm{Age})$
nonlinear	$a_0+a_1(\mathrm{P})^{a_8}+a_2(\mathrm{F.Agg})^{a_9}+a_3(\mathrm{C.Agg})^{a_{10}}$ $+a_4(\mathrm{WCP})^{a_{11}}+a_6(\mathrm{S})^{a_{13}}+a_7(\mathrm{Age})^{a_{14}}$
Logarithmic	$a_0+a_1\ln(\mathrm{P})+a_2\ln(\mathrm{F.Agg})+a_3\ln(\mathrm{C.Agg})$ $+a_4\ln(\mathrm{WCP})+a_5\ln(\mathrm{C})+a_6\ln(\mathrm{S})+a_7\ln(\mathrm{Age})$

where a_i and P, F.Agg, C.Agg, WCP, C, S and Age are constant coefficients, plasticizer, fine aggregates, coarse aggregates, waste ceramic powder, cement, slump, and the age of the specimens respectively.

plasticizer and the age of the specimens and the outputs are compressive and tensile strength, water absorption, resistance to chloride ion penetration (RCPT) and electrical resistivity. The basic structure of the ANN used in this study is shown in Fig. 4. The hyperbolic tangent (tanh) function is used as the output and input function with a learning rate of 0.01 and iteration number of 2000. Across all networks, 70% of input data were used as training data, 15% as test data, and 15% as validation data. To investigate each output, seven ANNs, each with one hidden layer and 4 to 10 neurons per hidden layer were used respectively.

One of the parameters used to investigate the error is the correlation coefficient. In general, if the correlation coefficient in a neural network is close to each other for training, testing and validation data and for all data is close to one, the network performs well and has high reliability. This has been carefully investigated in this research. Another method of error estimation is the Mean Squared Error (MSE) between the experimental and predicted amounts of target and output parameters which is obtained according to the Eq. (2).

$$\mathrm{MSE}=\frac{1}{N}\sum_{i=1}^{N}(t_i-p_i)^2 \tag{2}$$

Finally, mean absolute percentage error (MAPE)'s relationship is also used for accurate validation of the ANN which is obtained according to the Eq. (3).

$$\mathrm{MAPE}=\frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i-p_i}{t_i}\right| \tag{3}$$

where N is total number of data, t_i is the experimental value, and p_i is the predicted value of output. Finally, the structure of the three regression models used in the present study can be seen in Table 5.

3.4 Evaluation of ANN predictions and experimental results

The results of comparing the experiments and the outputs of the ANN with the number of different neurons in the hidden layer are shown in Fig. 5. According to Fig. 5(a), the use of 10 neurons in the hidden layer was most accurate for estimating the compressive strength of concrete containing WCPs. The highest square of the correlation coefficient (R^2) for all inputs occurred in this case, which is equal to 0.995. In general, the results show that, as the number of neurons in the hidden layer increases, the accuracy of ANN estimation for predicting compressive strength is remarkably improved. In order to estimate the compressive strength of high performance concrete using ANN, It was concluded that, by applying random sampling method R^2 was even better and was equal to 0.9142 (Yeh 1998). This is very consistent with the results of the present study. Given the error histogram for the 10 neurons in the hidden layer, which is noticeable in Fig. 5(b), the number of outputs with an error of less than 0.75 MPa is about 54. This indicates that approximately 57% of outputs have a similar result to experimental outputs. On the other hand, Fig. 5(c) and Fig. 5(d) show that all the results are in a good correlation with the experimental results. The results of the comparison of different regression methods are also illustrated in Fig. 5(e), Fig. 5(f) and Fig. 5(g). In general, among the regression methods, nonlinear regression method is most accurate for estimating compressive strength and linear regression method is not suitable. The equation coefficients for estimating the compressive strength obtained by linear, nonlinear and logarithmic regression methods are illustrated in Table 6. Finally, it is important to note that the neural network with 10 neurons in the hidden layer showed the best results compared to different

Table 6 Multiple regression results for predicting compressive strength of high performance sustainable concrete

Reg. type	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Linear	-2600	0.59	0.995	1.318	1.129	1.206	-0.349	0.306
nonlinear	-389.4	64.23	78.25	83.85	60.38	-367.44	28.5	564.93
Logarithmic	-2574.8	71.69	165.93	171.37	-.079	27.26	-6.77	9.79

Reg. type	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}
Linear	-	-	-	-	-	-	-
nonlinear	0.1	-50.07	-21.65	0.01	-0.13	-280.9	0.02
Logarithmic	-	-	-	-	-	-	-

Table 7 Multiple regression results for predicting tensile of high performance sustainable concrete

Reg. type	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Linear	6.962	5.579	-0.384	0.309	-0.114	-0.108	-0.030	0.00904
nonlinear	17.227	-2.66	0.65	0.27	0.99	-1.90	0.25	0.98
Logarithmic	-2.59	0.597	-0.933	-0.0024	-0.0010	1.4935	0.1156	0.4760

Reg. type	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}
Linear	-	-	-	-	-	-	-
nonlinear	-40.21	-0.211	0.333	-0.0054	-0.1059	-0.0309	0.0099
Logarithmic	-	-	-	-	-	-	-

Table 8 Multiple regression results for predicting water absorption of high performance sustainable concrete

Reg. type	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Linear	7.5354	5.4375	-0.381	0.3164	-0.1085	-0.1132	-0.0298	-0.009
nonlinear	-22.1358	-23.98	-0.701	2.466	-0.2490	-0.1049	-6.210	0.0038
Logarithmic	84.30	-2.484	-9.214	-0.0023	-0.0222	-1.4926	-0.4486	-0.5028

Reg. type	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}
Linear	-	-	-	-	-	-	-
nonlinear	-10.63	-0.24	0.39	0.02	-2.06	0.20	-1.47
Logarithmic	-	-	-	-	-	-	-

Table 9 Multiple regression results for predicting electrical resistivity of high performance sustainable concrete

Reg. type	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Linear	7.8598	8.3072	-0.402	0.3134	-0.0256	-0.1391	-0.0333	0.0897
nonlinear	-38.7392	-23.98	-0.708	1.6326	-0.2321	-0.1049	-24.153	0.0038
Logarithmic	-104.47	22.431	29.032	-0.0023	-0.0502	-16.198	-23.826	4.746

Reg. type	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}
Linear	-	-	-	-	-	-	-
nonlinear	-10.63	-0.24	0.63	0.02	-2.06	0.59	-1.47
Logarithmic	-	-	-	-	-	-	-

Table 10 Multiple regression results for predicting RCPT of high performance sustainable concrete

Reg. type	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Linear	10.294	-158.36	3.043	2.757	-4.605	1.257	0.357	-14.520
nonlinear	26056.2	-23.987	-0.73	0.00805	-6.721	-0.1049	-26829.91	0.00389
Logarithmic	70674.5	-5092.7	-9222.24	-0.0021	-15.06	1197.37	615.35	-771.50

Reg. type	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}
Linear	-	-	-	-	-	-	-
nonlinear	-10.63	-0.22	0.69	0.65	-2.06	-0.09	-1.46
Logarithmic	-	-	-	-	-	-	-

regression methods for estimating the compressive strength.

The results of the ANN output and comparison of different regression methods for estimating the tensile strength of high-strength concrete containing tiles are shown in Fig. 6. After comparing the results as can be seen in Fig. 6(a), the best result is obtained from the ANN containing 7 neurons in the hidden layer. In this case, the R^2 for all data is equal to 0.9912, and the mean R^2 for training, validation and testing data is higher than other states. On the other hand, RMSE and MAPE are minimum when 7 neurons are applied in the hidden layer and are 0.062 and 1.57 respectively. The findings of the present study indicate that by increasing or decreasing the number of neurons in the hidden layer, the ANN becomes functionally impaired and the prediction accuracy is significantly reduced. Fig. 6(c) shows that, with increasing tensile strength, the standard deviation between the predicted and experimental data becomes more noticeable and the network error increases. It can be seen from Fig. 6(b) and Fig. 6(d) that, according to the error histogram, more than 80% of the outputs have a very good correlation with the experimental data. For the validation of the results, the comparison of the regression methods is also illustrated in Fig. 6(e), Fig. 6(f) and Fig. 6(g). On the other hand, the coefficients of the regression methods are also discussed in Table 7. The results show that all three regression methods used provide very close and reliable for the estimation of tensile strength.

The prediction of water absorption of high performance sustainable concrete by ANN and different regression methods is shown in Fig. 7. First, it should be noted that the reduction or increase of ANN prediction error for water absorption of samples did not follow a reasonable procedure. However, applying 7 neurons in the hidden layer has shown the best performance. The reason for this may be that, in general, the improvement of durability of the concrete containing supplementary cementitious materials does not follow a rational trend in much research. Another reason could be the possibility of further error in durability tests. Even for these reasons, given the error histogram in Fig. 7(b) and the correlation of the predicted data with the experimental results in Fig. 7(b) and Fig. 7(d), the use of 7 neurons in the hidden layer to predict the water absorption of the samples is suggested as a suitable option. Regarding Fig. 7(e), nonlinear regression has not been able to perform well as a predictive tool. The R^2 in this method is equal to 0.4947, which is highly unreliable. The linear regression method is also somewhat similar, but it performs much better than the nonlinear method. The result is remarkable in Fig. 7(f). Compared to other regression methods, logarithmic regression method has shown more reliable performance. The R^2 in this method is equal to 0.8206, which seems somewhat acceptable. Finally, the coefficients of the regression methods are also discussed in Table 8.

As explained earlier, the determination of the electrical resistance of concrete is one of the tests of durability. In this study, after performing this experiment on 28 and 90 day samples, the results were validated by ANN and different regression techniques and the most accurate method was identified. The results of the comparison of the different

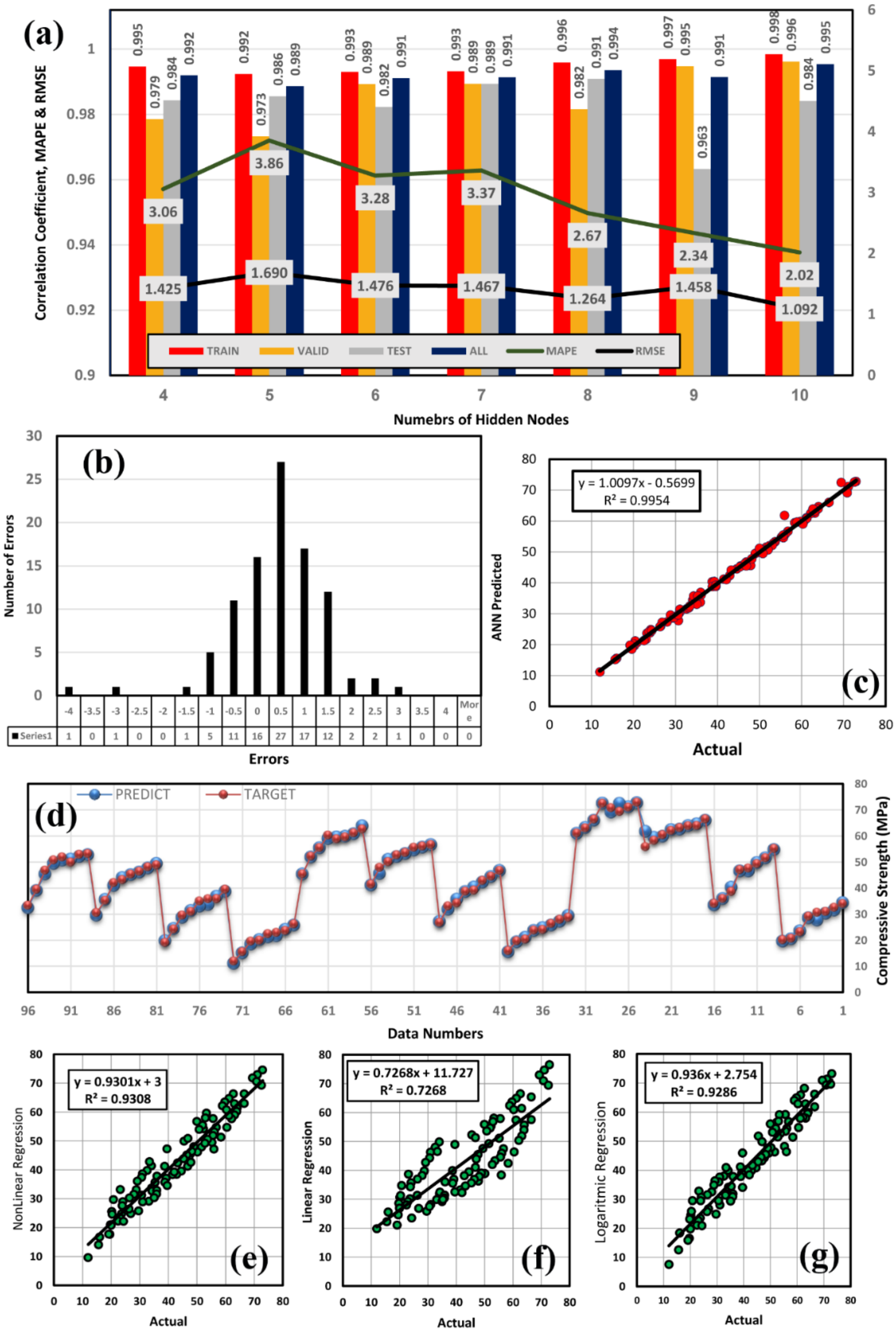

Fig. 5 The results of comparing the compressive strength test (a) Correlation coefficient, RMSE and MAPE diagrams of different number of neurons in hidden layer (b) Error Histogram for 10 neurons in hidden layer (c) and (e) comparing between predicted and targets for 10 neurons in hidden layer (e), (f) and (g) results of regression models

methods are illustrated in Fig. 8. Comparison of the different number of neurons in Fig. 8(a) shows that increasing or decreasing ANN accuracy has no significant relationship with the number of neurons in a hidden layer. However, the most accurate estimation of electrical resistivity in the network occurs when 9 neurons are present in the hidden layer. The R^2 in this case is 0.981 for all data. It can be said that, although this test is highly probable, the neural network was able to make an accurate prediction. The error histogram examination for the 3 neurons in the hidden layer confirms this in Fig. 8(b). In this figure, almost all predicted data have little error. The low standard deviation in Fig. 8(c) confirms ANN reliability. After comparing the experimental and predicted data in Fig. 8(d), while there are 9 neurons in the hidden layer, it can be concluded that with increasing electrical resistivity the

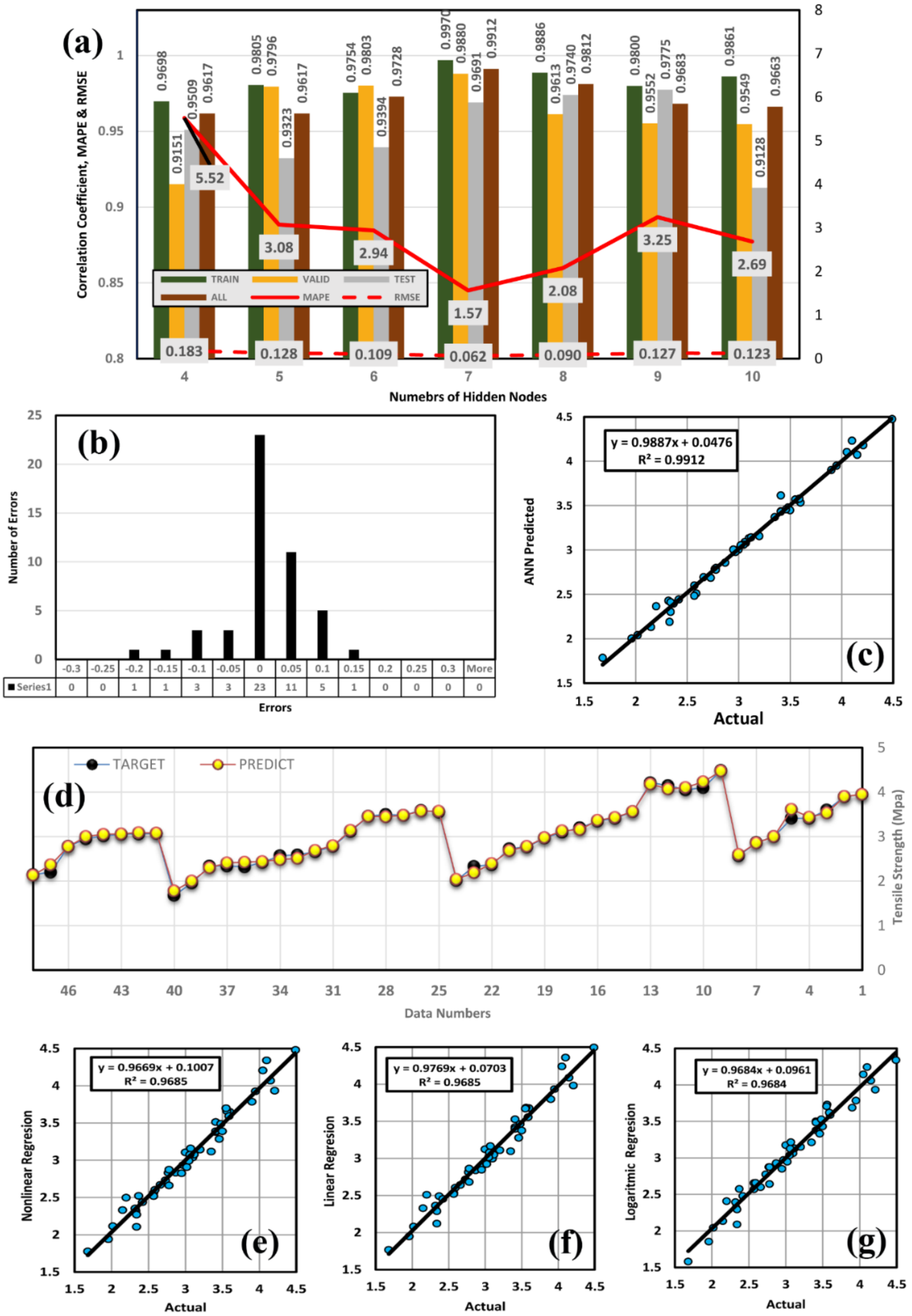

Fig. 6 The results of comparing the tensile strength test (a) Correlation coefficient, RMSE and MAPE diagrams of different number of neurons in hidden layer (b) Error Histogram for 7 neurons in hidden layer (c) and (e) comparing between predicted and targets for 7 neurons in hidden layer (e), (f) and (g) results of regression models

ANN error is somewhat increased. Finally, after comparing different regression methods, it can be concluded that almost all methods have good estimation for predicting electrical resistance of this type of concrete. Among the different methods used in this study, the nonlinear regression has the highest error and the neural network with 9 neurons in the hidden layer has the lowest error to estimate the electrical resistivity. Finally, the coefficients of the regression methods are also discussed in Table 9.

RCPT is one of the most important experiments that largely demonstrates the degree of durability and permeability of concrete to chlorine invasion. Due to the prolonged chlorine permeation process, this experiment was designed to detect the extent of chlorine ion penetration and the possibility of damage to the reinforcement in a short time (Nasr *et al.* 2019). In this section, after the RCPT, the

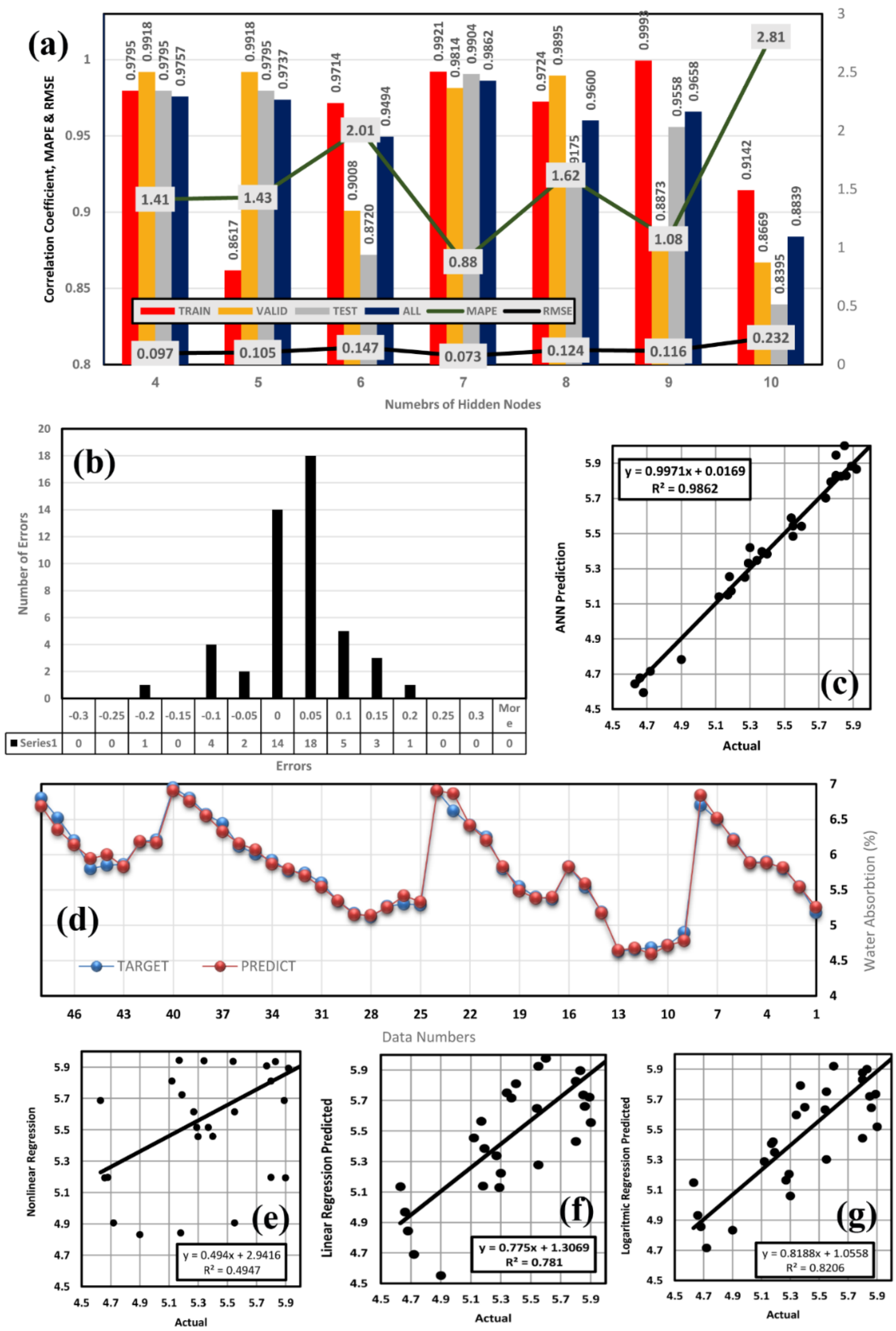

Fig. 7 The results of comparing the water absorption test (a) Correlation coefficient, RMSE and MAPE diagrams of different number of neurons in hidden layer (b) Error Histogram for 7 neurons in hidden layer (c) and (e) comparing between predicted and targets for 7 neurons in hidden layer (e), (f) and (g) results of regression models

results are compared using ANN and regression models. The results are visible in Fig. 9. The results show that the use of 8 neurons in the hidden layer provides the most accurate prediction for estimating the resistance of this type of concrete to chlorine ion. The results of using different number of neurons in the hidden layer indicate that the ANN in general has very good power in estimating the influence of chlorine ion. Fig. 8(b) shows that, in the ANN with 8 neurons in the hidden layer, the number of data with the least error is 12. The high validity of the ANN with 8 neurons in the hidden layer is also clearly visible in Fig. 9(c) and Fig. 9(d). regarding different methods of regression, it should be noted that, with the exception of the logarithmic method, other methods have not been successful in accurate estimation. Especially in the nonlinear method, the estimation accuracy is very low. This

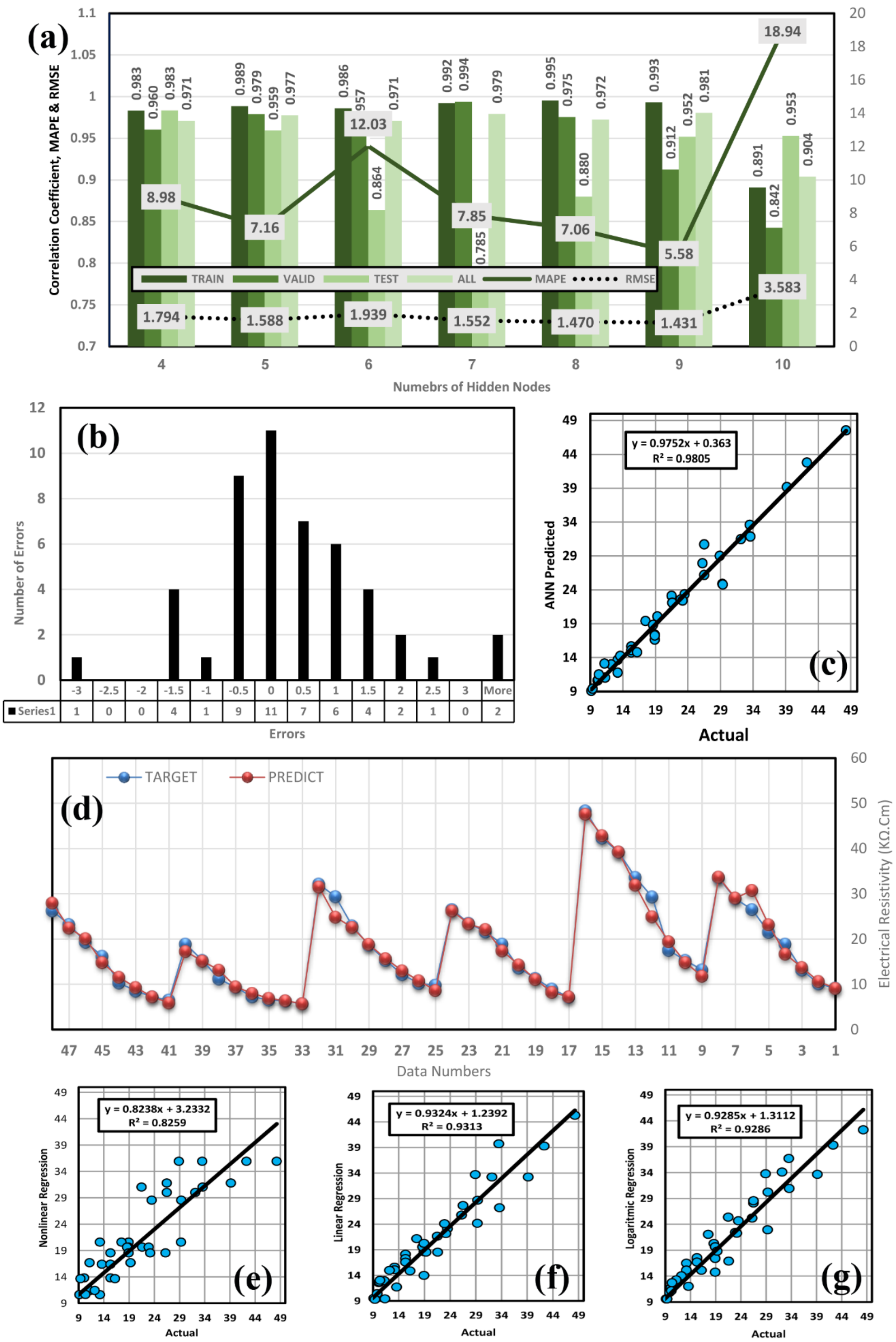

Fig. 8 The results of comparing the electrical resistivity test (a) Correlation coefficient, RMSE and MAPE diagrams of different number of neurons in hidden layer (b) Error Histogram for 9 neurons in hidden layer (c) and (e) comparing between predicted and targets for 9 neurons in hidden layer (e), (f) and (g) results of regression models

is visible in Fig. 9(e), 9(f) and 9(g). Finally, the coefficients of the regression methods are also discussed in Table 10.

As can be seen in Fig. 1, in almost all experiments, the most accurate prediction occurred when the number of neurons in the hidden layer was greater than or equal to the number of inputs. The acceptable accuracy of the neural network with more neurons than the number of inputs in other papers has also been addressed.

For example, in a similar research, ANN model with R^2=0.9185 was found to be capable in estimating the 28 days compressive strength of concrete (Khademi *et al.* 2016).

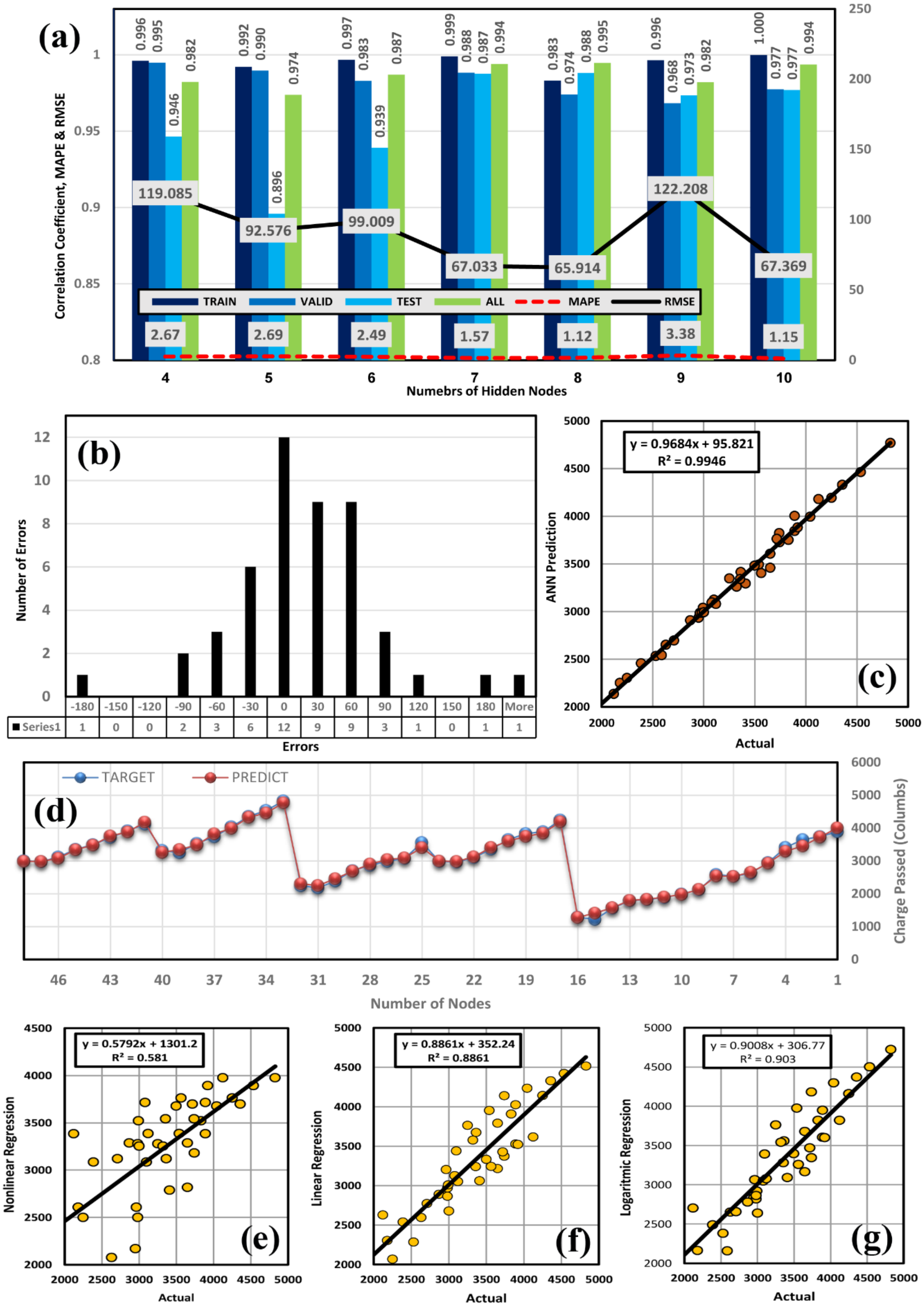

Fig. 9 The results of comparing the RCPT (a) Correlation coefficient, RMSE and MAPE diagrams of different number of neurons in hidden layer (b) Error Histogram for 8 neurons in hidden layer (c) and (e) comparing between predicted and targets for 8 neurons in hidden layer (e), (f) and (g) results of regression models

5. Conclusions

In this study, the effect of different *W/B* ratio on mechanical properties and durability of high performance sustainable concrete containing waste ceramic as supplementary cementitious material is investigated. Then, by applying ANN and different regression methods, the results are validated and the best method for predicting the mechanical properties and durability of this type of concrete is suggested. The results are interpreted as follows:

- In almost all *W/B* ratios, by replacing 20% of the WCP, the compressive strength of the 90-day samples reached more than 95.3% of the control sample. This result demonstrates the pozzolanic properties of WCP

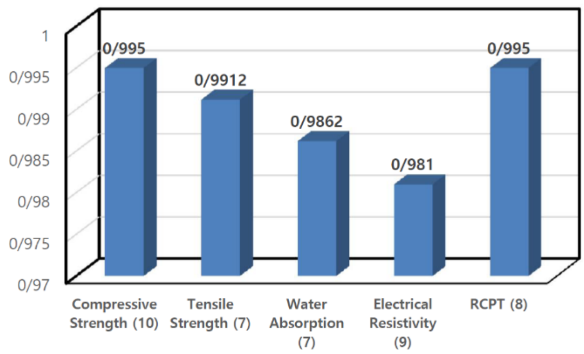

Fig. 10 The optimized number of nodes in the hidden layer for achieving to the accurate results

and the conversion of $Ca(OH)_2$ to C-S-H in this type of concrete. In the case of tensile strength, the result is almost similar. In the case of durability tests, it is important to note that as the percentage of WCP increases, water absorption, electrical resistivity and ion penetration rate were significantly improved. The highest improvement was related to *W/B* ratio of 0.3 and replacement percentages of 40 and 50% of WCP.

• After applying the ANN to predict the compressive strength, it can be concluded that by increasing the number of neurons in the hidden layer the accuracy of the network is improved. This result indicates that the ANN as a predictive tool has high capability in predicting the compressive strength of this type of concrete. For different regression methods, with the exception of linear regression, other methods also have acceptable estimates of compressive strength.

• In the tensile strength estimation, the accuracy of the ANN increases with increasing number of neurons to 7 neurons in the hidden layer and then decreases markedly. It is also important to note that with increasing tensile strength, the accuracy of the ANN is slightly reduced. Interestingly, unlike other results, the regression performed very well in estimating tensile strength. The results of all three methods are very reliable in estimating tensile strength.

• Due to differences in the results of different W/B ratios, ANN and various regression methods have less accurate in estimating water absorption than the other experiments. In this case, the ANN with 7 neurons in the hidden layer performs best.

• The results of the electrical resistivity test and RCPT were almost identical. In the ANN related to electrical resistivity, 9 neurons in the hidden layer performed more efficiently and in the ANN related to RCPT, 8 neurons in the hidden layer showed the most accurate performance.

It should be noted that, according to the results of different regression methods, the nonlinear method for both experiments did not perform well. This illustrates the similarity of the nature of these two experiments to each other. Finally, it can be said that neural network method is a suitable tool for predicting the mechanical properties and durability of this type of concrete and it is much more accurate than different regression methods.

References

ACI (2002), Report on High-Strength Concrete-ACI Committee 363, In American Concrete Institute.

Alipour, P., Behforouz, B., Mohseni, E. and Zehtab, B. (2019), “Investigation of SCC characterizations incorporating supplementary cementitious materials”, *Emerg. Mater. Res.*, **8**(3), 492-507. https://doi.org/10.1680/jemmr.18.00024.

Ameri, F., Shoaei, P., Zareei, S.A. and Behforouz, B. (2019), “Geopolymers vs. alkali-activated materials (AAMs): A comparative study on durability, microstructure, and resistance to elevated temperatures of lightweight mortars”, *Constr. Build. Mater.*, **222**, 49-63. https://doi.org/10.1016/j.conbuildmat.2019.06.079.

Aslani, F. and Nejadi, S. (2012), “Mechanical properties of conventional and self-compacting concrete: An analytical study”, *Constr. Build. Mater.*, **36**, 330-347. https://doi.org/10.1016/j.conbuildmat.2012.04.034.

ASTM C1202 (2012), Standard Test Method for Electrical Indication of Concrete’s Ability to Resist Chloride Ion Penetration, American Society for Testing and Materials. https://doi.org/10.1520/C1202-12.2.

ASTM C192/C192M (2016), Standard Practice for Making and Curing Concrete Test Specimens in the Laboratory, American Society for Testing and Materials. https://doi.org/10.1520/C0192.

ASTM C496/C496M-11 (2011), ASTM C496-11 Standard Test Method for Splitting Tensile Strength of Cylindrical Concrete Specimens, Annual Book of ASTM Standards Volume 04.02. https://doi.org/10.1520/C0496

BS 1881-122 (2011), Testing Concrete - Part 122 : Method for Determination of Water Absorption, BSI-British Standards Institution.

Eskandari-Naddaf, H. and Kazemi, R. (2017), “ANN prediction of cement mortar compressive strength, influence of cement strength class”, *Constr. Build. Mater.*, **138**, 1-11. https://doi.org/10.1016/j.conbuildmat.2017.01.132.

Gholampour, A., Mansouri, I., Kisi, O. and Ozbakkaloglu, T. (2018), “Evaluation of mechanical properties of concretes containing coarse recycled concrete aggregates using multivariate adaptive regression splines (MARS), M5 model tree (M5Tree), and least squares support vector regression (LSSVR) models”, *Neur. Comput. Appl.*. 1-14. https://doi.org/10.1007/s00521-018-3630-y.

Goriparthi, M.R. and Gunneswara Rao, T.D. (2017), “Effect of fly ash and GGBS combination on mechanical and durability properties of GPC”, *Adv. Concrete Constr.*, **5**(4), 313-330. https://doi.org/10.12989/acc.2017.5.4.313.

Hadzima-Nyarko, M., Nyarko, E.K., Ademović, N., Miličević, I. and Šipoš, T.K. (2019), “Modelling the influence of waste rubber on compressive strength of concrete by artificial neural networks”, *Mater.*, **12**(4), 561. https://doi.org/10.3390/ma12040561.

Heidari, A. and Tavakoli, D. (2013), “A study of the mechanical properties of ground ceramic powder concrete incorporating nano-SiO_2 particles”, *Constr. Build. Mater.*, **35**, 228-264. https://doi.org/10.1016/j.conbuildmat.2012.07.110.

Hendriks, C.A., Worrell, E., de Jager, D., Blok, K. and Riemer, P. (1998), “Emission reduction of greenhouse gases from the cement industry”, *Fourth International Conference on Greenhouse Gas Control Technologies*. https://doi.org/10.1016/B978-008043018-8/50150-8.

Higashiyama, H., Yagishita, F., Sano, M. and Takahashi, O. (2012), “Compressive strength and resistance to chloride penetration of mortars using ceramic waste as fine aggregate”, *Constr. Build. Mater.*, **26**(1), 96-101. https://doi.org/10.1016/j.conbuildmat.2011.05.008.

Jalal, M., Nassir, N., Jalal, H. and Arabali, P. (2019), “On the strength and pulse velocity of rubberized concrete containing silica fume and zeolite: Prediction using multivariable regression models", *Constr. Build. Mater.*, **223**, 530-543. https://doi.org/10.1016/j.conbuildmat.2019.06.233.

Juenger, M.C.G. and Siddique, R. (2015), "Recent advances in understanding the role of supplementary cementitious materials in concrete", *Cement Concrete Res.*, **78**(Part A), 71-80. https://doi.org/10.1016/j.cemconres.2015.03.018.

Kakali, G., Perraki, T., Tsivilis, S. and Badogiannis, E. (2001), "Thermal treatment of kaolin: The effect of mineralogy on the pozzolanic activity", *Appl. Clay Sci.*, **20**(1-2), 73-80. https://doi.org/10.1016/S0169-1317(01)00040-0.

Kannan, D.M., Aboubakr, S.H., EL-Dieb, A.S. and Reda Taha, M.M. (2017), "High performance concrete incorporating ceramic waste powder as large partial replacement of Portland cement", *Constr. Build. Mater.*, **144**, 35-41. https://doi.org/10.1016/j.conbuildmat.2017.03.115.

Khademi, F., Jamal, S.M., Deshpande, N. and Londhe, S. (2016), "Predicting strength of recycled aggregate concrete using Artificial Neural Network, adaptive neuro-fuzzy inference system and multiple linear regression", *Int. J. Sustain. Built Envir.*, **5**, 355-369. https://doi.org/10.1016/j.ijsbe.2016.09.003.

Khatibinia, M., Feizbakhsh, A., Mohseni, E. and Ranjbar, M.M. (2016), "Modeling mechanical strength of self-compacting mortar containing nanoparticles using wavelet-based support vector machine", *Comput. Concrete*, **12**(6), 1065-1082. https://doi.org/10.12989/cac.2016.18.6.1065.

Mazloom, M. and Yoosefi, M.M. (2013), "Predicting the indirect tensile strength of self-compacting concrete using artificial neural networks", *Comput. Concrete*, **12**(3), 285-301. https://doi.org/10.12989/cac.2013.12.3.285.

Miyandehi, B.M., Behforouz, B., Khotbehsara, E.M., Balgouri, H.A., Fathi, S. and Khotbehsara, M.M. (2014), "An experimental investigation on nano-Al_2O_3 based self-compacting mortar", *J. Am. Sci.*, **10**(11), 229-233. https://doi.org/10.1192/bjp.205.1.76a.

Mohseni, E., Kazemi, M.J., Koushkbaghi, M., Zehtab, B. and Behforouz, B. (2019), "Evaluation of mechanical and durability properties of fiber-reinforced lightweight geopolymer composites based on rice husk ash and nano-alumina", *Constr. Build. Mater.*, **209**, 532-540. https://doi.org/10.1016/j.conbuildmat.2019.03.067.

Naderpour, H., Rafiean, A.H. and Fakharian, P. (2018), "Compressive strength prediction of environmentally friendly concrete using artificial neural networks", *J. Build. Eng.*, **16**, 213-219. https://doi.org/10.1016/j.jobe.2018.01.007.

Nasr, D., Behforouz, B., Borujeni, P.R., Borujeni, S.A. and Zehtab, B. (2019), "Effect of nano-silica on mechanical properties and durability of self-compacting mortar containing natural zeolite: Experimental investigations and artificial neural network modeling", *Constr. Build. Mater.*, **229**, 116888. https://doi.org/10.1016/j.conbuildmat.2019.116888.

Pacheco-Torgal, F. and Jalali, S. (2010), "Reusing ceramic wastes in concrete", *Constr. Build. Mater.*, **24**(5), 832-838. https://doi.org/10.1016/j.conbuildmat.2009.10.023.

Pavlík, Z., Trník, A., Kulovaná, T., Scheinherrová, L., Rahhal, V., Irassar, E. and Černý, R. (2016), "DSC and TG analysis of a blended binder based on waste ceramic powder and portland cement", *Int. J. Thermophys.*, 37-32. https://doi.org/10.1007/s10765-016-2043-3.

Reda, M.M., Shrive, N.G. and Gillott, J.E. (1999), "Microstructural investigation of innovative UHPC", *Cement Concrete Res.*, **29**(3), 323-329. https://doi.org/10.1016/S0008-8846(98)00225-7.

Riahi, S. and Nazari, A. (2019), "Predicting the effects of nanoparticles on early age compressive strength of ash-based geopolymers by artificial neural networks", *Neur. Comput. Appl.*, **31**, 743-750. https://doi.org/10.1007/s00521-012-1085-0.

Rodríguez-Camacho, R.E. and Uribe-Afif, R. (2002), "Importance of using the natural pozzolans on concrete durability", *Cement Concrete Res.*, **32**(12), 1851-1858. https://doi.org/10.1016/S0008-8846(01)00714-1.

Saha, S. and Rajasekaran, C. (2016), "Mechanical properties of recycled aggregate concrete produced with Portland Pozzolana Cement", *Adv. Concrete Constr.*, **4**(1), 27035. https://doi.org/10.12989/acc.2016.4.1.027.

Senthamarai, R.M. and Devadas Manoharan, P. (2005), "Concrete with ceramic waste aggregate", *Cement Concrete Compos.*, **27**(9-10), 910-913. https://doi.org/10.1016/j.cemconcomp.2005.04.003.

Sobhani, J., Khanzadi, M. and Movahedian, A.H. (2013), "Support vector machine for prediction of the compressive strength of no-slump concrete", *Comput. Concrete*, **11**(4), 337-350. https://doi.org/10.12989/cac.2013.11.4.337.

Statements, B. and Size, T. (2010), "Standard test method for sieve analysis of fine and coarse aggregates 1", Annual Book of ASTM Standards. https://doi.org/10.1520/C0136-06.2.

Subaşı, S., Öztürk, H. and Emiroğlu, M. (2017), "Utilizing of waste ceramic powders as filler material in self-consolidating concrete", *Constr. Build. Mater.*, **149**, 567-574. https://doi.org/10.1016/j.conbuildmat.2017.05.180.

Tarighat, A. and Zehtab, B. (2016), "Structural reliability of reinforced concrete beams/columns under simultaneous static loads and steel reinforcement corrosion", *Arab. J. Sci. Eng.*, **14**(10), 3945-3958. https://doi.org/10.1007/s13369-016-2033-6.

Tavakoli, D., Heidari, A. and Karimian, M. (2013), "Properties of concretes produced with waste ceramic tile aggregate", *Asian J. Civil Eng.*, **14**(3), 369-382.

Test, C.C., Cabinets, M., Rooms, M., Test, C.C., Drilled, T. and Ag, C. (2012), ASTM Standard C1760-Standard Test Method for Bulk Electrical Conductivity of Hardened Concrete, ASTM International. https://doi.org/10.1520/C1760-12.2.

Yang, J., Mohseni, E., Behforouz, B. and Khotbehsara, M. M. (2015), "An experimental investigation into the effects of Cr_2O_3 and ZnO_2 nanoparticles on the mechanical properties and durability of self-compacting mortar", *Int. J. Mater. Res.*, **106**(8), 886-892. https://doi.org/10.3139/146.111245.

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