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An Application of Artificial Neural Network to Predict the Compressive Strength of Concrete using Fly Ash and Stone Powder Waste Products in Central Vietnam

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ABSTRACT

In Central Vietnam, the traditional materials for making concrete are usually of natural origin. The overexploitation of these materials causes many adverse effects on the natural environment. Local industrial plants and quarries generate millions of tons of waste products such as fly ash and stone powder. However, when used for the partial replacement of cement and sand, these waste products can affect the compressive strength of concrete. Therefore, it is necessary to build models to predict compressive strength for this type of concrete. The paper aimed to apply artificial neural network models to predict the compressive strength of concrete using fly ash and stone powder waste products. The input of the ANN model includes six parameters: ultrasonic pulse velocity, wave amplitude attenuation ratio, and 4 parameters of concrete materials. Experimental data were obtained from 72 cubic specimens of different mixtures using available materials in Central Vietnam. These models allow predicting the 28-day compressive strength of concrete within the range of 9-62MPa (90-620daN/cm^2). Furthermore, these models can predict compressive strength with any mixture. It is significant when re-evaluating whether the actual compressive strength value is as reliable as the one provided by the manufacturer.

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NOMENCLATURE

ANN	Artificial neural network	C	Binder
f_c	Concrete compressive strength	D	Water
A	Fine aggregate	UPV	Ultrasonic pulse velocity
B	Coarse aggregate	A_2/A_1	Amplitude attenuation ratio

1. INTRODUCTION

In Central Vietnam, as shown in Figure 1, the traditional materials for making concrete are sand, gravel, Portland cement, and water. The sources of these materials are often natural, such as sand mined from rivers, stone powder from quarries, cement formed by fine grinding clinker, natural gypsum, shells, and clay. The over-exploitation of these materials causes adverse effects on nature. Especially sand mining in rivers causes landslides and floods in this area. Therefore, it is necessary to find alternative sources of materials for those traditional ones. Some studies in Vietnam use waste products to partially replace traditional materials such as autoclaved aerated concrete after the autoclaving process to replace 25% of natural sand [1], rice husk ash, and fly ash, partially replacing cement [2, 3]. This research axis of using waste products has received significant attention in many countries. The mechanical properties of the concrete using these materials have been considered in literature [4, 5] and the compressive strength was also studied by Kanthe et al. [6] and Sadowski et al. [7]. Therefore, it helps to benefit waste products and limit the use of traditional materials, helping to reduce adverse effects on the natural environment [8, 9].

One problem arises: waste products can affect compressive strength, an essential parameter of concrete quality. Therefore, it is necessary to study the

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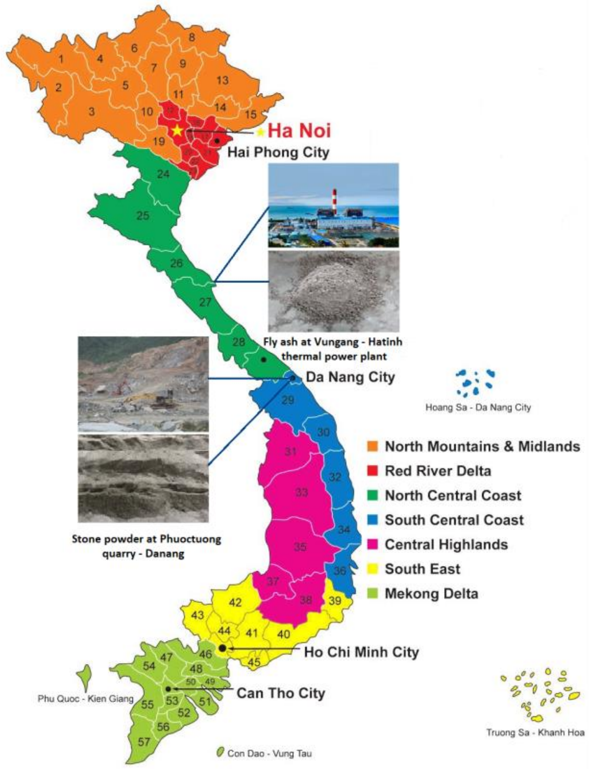

Figure 1. Origin of fly ash and stone powder in Central Vietnam

compressive strength of concrete using these new alternative materials. Scientists have examined the application of ultrasonic pulse velocity (UPV) to evaluate concrete compressive strength for decades due to its distinct advantages over conventional compression measurements. The widely used relationship between concrete compressive strength and UPV is expressed in the exponential formulation. However, examining the performance coefficients of these models shows that the single nonlinear regression with exponential formulation provides bad fitting curves since some concrete ingredients affect much on compressive strength but at a low rate on UPV [10, 11]. The multivariable model with many input parameters, including UPV and other parameters such as concrete ingredient materials, age, and temperature is recommended to enhance the situation. Regression models and artificial neural network models are commonly used to predict the compressive strength of concrete [12, 13]. The accuracy of the regression model depends on the selection of input parameters and the amount of input data of the model [14, 15]. For the artificial neural network model, the choice of the artificial neural network structure determines the prediction results [16, 17]. The sensitivity analysis to predict the compressive strength of concrete based on the artificial neural network has been mentioned by Heidari and Hashempour [18].

Each year, about one million tons of fly ash are generated at Vung-Ang thermal power plants. At Phuoc-Tuong quarry, there is a large amount of waste stone powder (as shown in Figure 1). The paper proposes to reuse fly ash and stone powder to replace cement and sand partially. At construction sites in the area, the required compressive strength for concrete is from 20-50MPa (200-500daN/cm^2). Some studies have predicted the compressive strength of concrete in this range. However, no studies have been available for predicting compressive strength in such a wide range as above using fly ash and stone powder to replace cement and sand. This paper aimed to build an artificial neural network model to predict the compressive strength of concrete using two waste products, fly ash and stone powder. The input of the ANN model will be the concrete mixtures, UPV, and wave amplitude attenuation ratio. The number of specimens for the experiment is determined by the design of the experiment method. Many different structures of artificial neural networks are elaborated to choose the most optimal one. The model allows predicting compressive strength in the range of 8.65-62.13MPa (86.5-621.3daN/cm^2). The research results help concrete manufacturers evaluate the concrete mixtures and determine the optimal mix to ensure the design compressive strength requirements. In addition, the model allows the supervision consultant to re-evaluate the compressive strength provided by the concrete manufacturer.

2. MATERIALS AND METHODS

2. 1. Materials Compressive strength value is influenced by many factors such as mixtures, concrete mixing method, curing conditions, specimen shape, concrete age. Therefore, the Ishikawa diagram was used to analyze the effect of the affecting factors as shown in Figure 2. Because the concrete using fly ash and stone powder waste is the object of study, the concrete mixture will be a factor to be included in the research model. Other factors are assumed to be in standard conditions according to Vietnamese standards.

The traditional local material for making concrete are sand, gravel, cement, and water. Based on actual data at concrete factories in the area, the study uses fly ash and stone powder waste products to replace 20% cement and sand.

2. 2. Design of Experiments Based on the analysis of the Ishikawa diagram as shown in Figure 2, the concrete mixture is the input parameter of the artificial neural network model to predict the compressive strength. By consulting the Vietnamese Ministry of Construction, for concrete of compressive strength from 20 to 50MPa (200-500daN/cm^2), the essential material

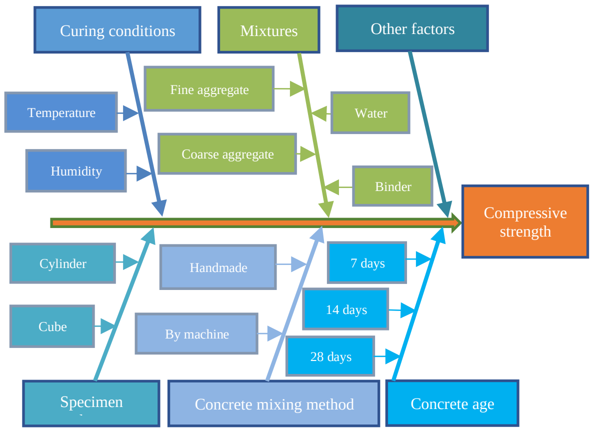

Figure 2. Ishikawa diagram: Main factors affecting the compressive strength

components for making concrete are shown in Table 1. The result indicates that the binder has the most considerable variation with 58.9% compared to the full content of this material. The remaining parameters such as fine aggregates, water, and coarse aggregates (a mixture of aggregate particles with sizes from 10-20mm) are changed by 32.2, 17.4, and 8.3%, respectively.

The study uses the design of experiments method to determine the number of specimens to be taken. The number of levels of each parameter such as fine aggregate, coarse aggregate, binder, and water is 3, 2, 4 and 3, respectively, as given in Table 2. The number of experimental specimens was determined according to the full factorial experiment design method as follows:

$$\text{Experimental mixture number} = 2^1 \times 3^2 \times 4^1 = 72 \qquad (1)$$

All component materials of 72 concrete mixtures are shown in Table A1 in the appendix.

2. 3. Artificial Neural Network

Using fly ash and stone powder with different mixtures can change the compressive strength of concrete. Therefore, it is necessary to predict the compressive strength of concrete using these waste products. The paper proposes to use an artificial neural network to predict the compressive strength of concrete using waste products in central Vietnam. The model inputs are four concrete materials such as fine aggregate, coarse aggregate, binder, and water and two ultrasonic wave characteristics such as ultrasonic pulse velocity and wave amplitude attenuation ratio measured at 28 days . Three prediction models with different inputs are elaborated to compare their performances in order to find the best model.

Model 1: There are five input parameters including fine aggregate (A) [kg], coarse aggregate (B) [kg], binder (C) [kg], water (D) [liter] and ultrasonic pulse velocity (UPV) [m/s]. The output is the compressive strength at 28 days (f_c) [daN/cm^2].

Model 2: There are five input parameters including fine aggregate (A) [kg], coarse aggregate (B) [kg], binder (C) [kg], water (D) [liter] and amplitude attenuation ratio (A_2/A_1). The output is the compressive strength at 28 days (f_c) [daN/cm^2].

Model 3: There are six input parameters including fine aggregate (A) [kg], coarse aggregate (B) [kg], binder (C) [kg], water (D) [liter], UPV [m/s] and amplitude attenuation ratio (A_2/A_1). The output is the compressive strength at 28 days (f_c) [daN/cm^2].

The neural network is a backward propagation consisting of 3 layers including one input layer, one hidden layer, and one output layer. A total of 72 experimental datasets is randomly split into training, validation, and testing datasets by MATLAB software. The training data has 50 samples accounting for 70% of the total dataset. The validation and testing data have 11 samples respectively.

Three coefficients such as standard deviation (S), coefficient of determination (R^2), and mean squared error are used to evaluate the prediction model accuracy, as given in Equation (2). Where y_i is the ith observed response value; $\bar{y}$ is the mean response; $\hat{y}_i$ is the ith fitted response and n is the number of observations.

$$S = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y} - y_i)^2} \qquad (2)$$
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

TABLE 1. Content range of specimen concrete components

Concrete components		Unit	Content range	Total
Fine aggregate	Sand (80%)	kg	512-755.2	640-944
	Stone powder (20%)	kg	128-188.8	
Coarse aggregate (gravel)		kg	1100-1200	1100-1200
Binder	Cement (80%)	kg	172.8-420	216-525
	Fly ash (20%)	kg	43.2-105	
Water		liter	190-230	190-230

TABLE 2. Content level of each specimen component

Label	Concrete components	Level of variation				Number of levels
		1	2	3	4	
A	Fine aggregate (kg)	640	792	944	*	3
B	Coarse aggregate (kg)	1100	1200	*	*	2
C	Binder (kg)	216	319	422	525	4
D	Water (liter)	190	210	230	*	3

3. EXPERIMENTS AND RESULTS

3. 1. Specimen Preparation According to Vietnam Standard TCVN 5574:2018, the concrete specimen is a cube with an edge of 15cm as given in Figure 3. The specimen is fabricated and cured at the University of Science and Technology Laboratory, The University of Da Nang in Vietnam. Specimen curing in the laboratory at a temperature of 25±2^{0}C and relative humidity of 80±7% as shown in Figure 4.

Figure 3. Mold for making concrete samples

Figure 4. Curing concrete samples

3. 2. Experiment Results At the age of 28 days, ultrasonic pulse velocity (UPV), wave amplitude attenuation ratio (A_2/A_1), and compressive strength of the specimen are measured. There are three ways to determine the ultrasonic pulse velocity based on the propagation of ultrasonic waves as shown in Figure 5. The paper uses direct transmission through the sample using the Tico Proceq ultrasound device.

Waves emitted from the Tico Proceq ultrasound device with a frequency of 54kHz and connected to a digital signal acquisition as shown in Figure 6. Figure 7 shows the device connection diagram to receive wave signals. The amplitudes of the emitted wave (A_1) and received wave (A_2) are illustrated in Figures 8 and 9. The amplitude attenuation ratio when propagating through the

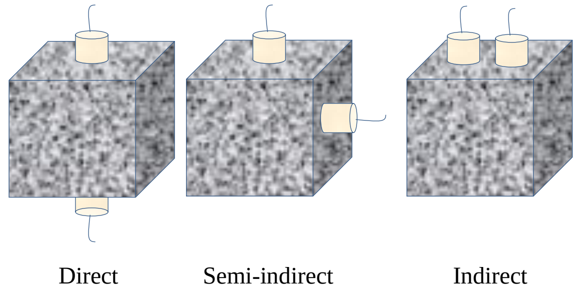

Figure 5. Positions of ultrasonic transducers

Figure 6. Tico Proceq ultrasound and SYSAM-SP5 signal acquisition

Figure 7. Device connection diagram to receive wave signal

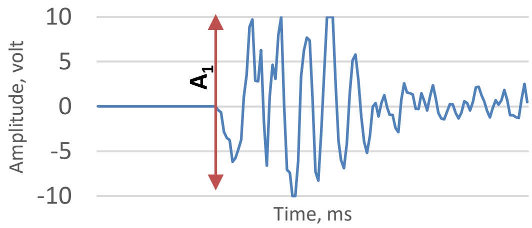

Figure 8. Wave signal from the emitting source

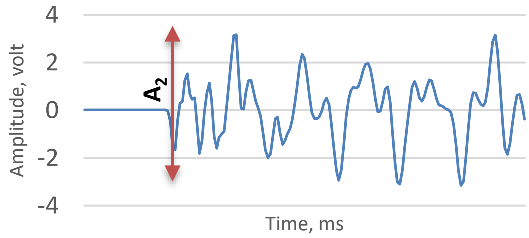

Figure 9. Wave signal from the receiving source

concrete specimen is determined. The concrete compressor used for measuring the compressive strength is a hydraulic compressor SYE-2000A with a maximum compressive force of 200 tons. Then, the characteristic compressive strength is calculated by Equation (3).

$$f_c = \frac{P}{A} \tag{3}$$

where P is the destructive compressive force, and A is the cross-sectional area of the specimen. The ultrasonic pulse velocity (UPV), wave amplitude attenuation ratio (A_2/A_1), and compressive strength of 72 mixtures are shown in Table A1 in the appendix.

3. 3. Results of the Artificial Neural Network The artificial neural network structure proposed in the paper to predict the compressive strength consists of three layers including the input, hidden, and output layer, as given in Figure 10. In order to determine the appropriate number of neurons in the hidden layer, the trial-and-error method is proposed to use for many cases with different hidden neuron numbers. Table 3 illustrates the results of three prediction models with different numbers of neurons in the hidden layer. The results show that the ANN model with ten hidden neurons gives the highest accuracy of compressive strength prediction. Therefore, the three most suitable models to predict compressive strength are selected including model 1 (5x10x1), model 2 (5x10x1), and model 3 (6x10x1).

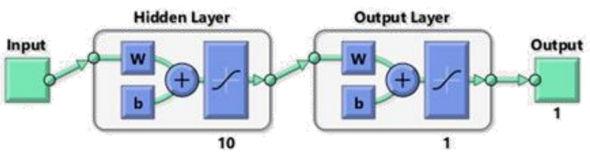

Figure 10. ANN network structure

TABLE 3. Coefficients of determination of ANN networks

Networks ANN	The structure of layers	The coefficient (R^2)
Model 1	5x8x1	88.36%
	5x10x1	93.66%
	5x15x1	91.7%
	5x20x1	90.6%
Model 2	5x8x1	86.89%
	5x10x1	93.38%
	5x15x1	92.7%
	5x20x1	90.7%
Model 3	6x8x1	89.31%
	6x10x1	94.55%
	6x15x1	93.07%
	6x20x1	92.87%

The training procedure of the three ANN models is shown in Figure 11. In this figure, the vertical axis is the mean squared error (MSE), and the horizontal axis is the number of training iterations. The meaning of Figure 11 is to evaluate the training process of the artificial neural network model. The best validation performance indicates the iteration at which the validation performance reached a minimum. The training work continues for six more iterations and then stops. If the test curve increased significantly before the validation curve has increased, it is possible that some overfitting may

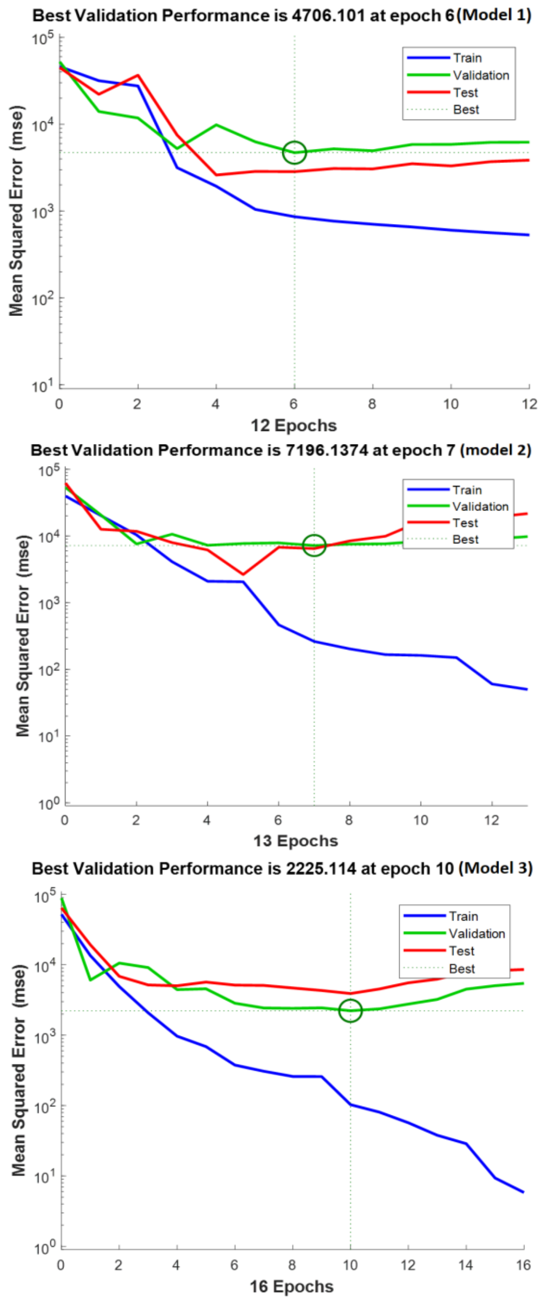

Figure 11. Training procedure of three ANN models

have occurred. The results show that the validation and test curves are similar in all three prediction models. In which model 3 has the minor mean squared error (MSE). Therefore, model 3 has the best training among the three predictive models.

Figure 12 shows the relationship between the outputs of the network and the targets. The three graphs represent training, validation, and testing data. The dashed line in each graph represents the perfect result as the output equals the target. The solid line represents the best-fit linear regression line between the output and the target. The predicted compressive strength (output) compared with the experimental results (target) of all three models has a good agreement. At the same time, the line approximating the predicted compressive strength for both cases above coincides with the straight-line Y=T of the graphs. However, the evaluation parameters of model 3 are the best of the three models, as given in Table 4.

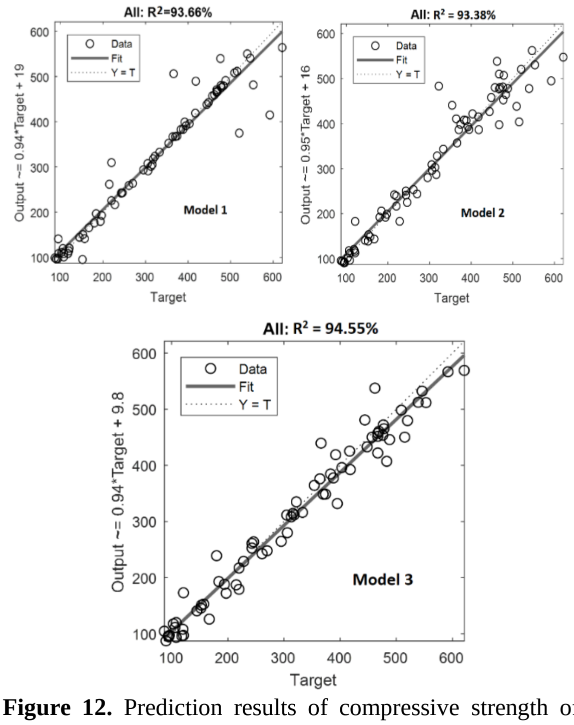

Figure 12. Prediction results of compressive strength of three ANN models

TABLE 4. Performance parameters of models 1, 2, and 3

Performance coefficients		Deviation (S), daN/cm^2	Determination coefficient (R^2), %
ANN model	Model 1	38.05	93.66
	Model 2	38.89	93.38
	Model 3	35.26	94.55

4. DISCUSSIONS

The results of the training process and the prediction of compressive strength, as given in Figures 11 and 12, show that the artificial neural network models have high accuracy. Model 3 is the most accurate predictor and the most suitable model to predict the compressive strength of concrete using fly ash and stone powder. However, model 1 and 2 can be very suitable for predicting the compressive strength for manufacturers corresponding to selected concrete ingredients using fly ash and stone powder.

In addition to predicting the compressive strength for 72 existing grades, the ANN can predict the compressive strength for any mix when the model's input parameters are known. For example, it is necessary to check whether the supplier's actual compressive strength value of concrete ensures the designed one or not. Then, with the known concrete mix provided by the concrete manufacturer, while the UPV values and the amplitude attenuation ratio were measured experimentally, with an established ANN network (model 3), it is facilitated to predict the compressive strength of concrete. For illustration, Table 5 shows the expected compressive strength value based on the given mixtures, known UPV, and amplitude attenuation ratio values.

TABLE 5. Predicting compressive strength of concrete according to model 3 by ANN

Concrete components			UPV (m/s)	A_2/A_1	Predicted results (daN/cm^2)
Fine aggregate (kg)	Sand	515	4395	0.277	227.26
	Stone powder	129			
Coarse aggregate (kg)		1200			
Binder (kg)	Cement	224			
	Fly ash	56			
Water (liter)		195			

5. CONCLUSIONS

The paper proposes three artificial neural network models that allow predicting the compressive strength of concrete using ingredient materials in Central Vietnam. The highlight is the reuse of fly ash and stone powder waste products. The inputs of ANN models are concrete mixtures, ultrasonic pulse velocity (UPV), and amplitude attenuation ratio. These models allow predicting the compressive strength of concrete at 28 days within the range of 8.65-62.13MPa (86.5- 621.3daN/cm^2).

The outstanding advantage of the built neural network model is that it can predict the compressive strength for any concrete mixture. It is significant when it is necessary to evaluate the compressive strength provided by the concrete supplier. Then, with the concrete manufacturer's known concrete mix, while ultrasonic pulse velocity and amplitude attenuation ratio were experimentally measured, using the built ANN model, it is easy to predict the compressive strength of concrete.

6. ACKNOWLEDGEMENTS

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APPENDIX

TABLE A1. Designation of mixture, ultrasonic pulse velocity (UPV), amplitude attenuation ratio (A_1/A_1), and compressive strength (f_c)

Mixture	Designation of mixture	Fine aggregate (A), kg/m^3			Gravel (B) kg/m^3	Binder (C) (kg/m^3)			Water (D) liter	UPV (m/s)	Amplitude attenuation ratio	Compressive strength
		Sand (80%)	Stone (20%)	Total (100%)		Cement (80%)	Fly ash (20%)	Total (100%)			A_2/A_1	f_c(daN/cm^2)
1	A1B1C1D1	512	128	640	1100	172.8	43.2	216	190	4250	0.074	144.7
2	A1B1C1D2	512	128	640	1100	172.8	43.2	216	210	4055	0.112	108.1
3	A1B1C1D3	512	128	640	1100	172.8	43.2	216	230	3935	0.093	90.4
4	A1B1C2D1	512	128	640	1100	255.2	63.8	319	190	4495	0.472	315.8
5	A1B1C2D2	512	128	640	1100	255.2	63.8	319	210	4360	0.347	215.4
6	A1B1C2D3	512	128	640	1100	255.2	63.8	319	230	4355	0.128	193.9
7	A1B1C3D1	512	128	640	1100	337.6	84.4	422	190	4695	0.390	447.5
8	A1B1C3D2	512	128	640	1100	337.6	84.4	422	210	4560	0.309	403.3
9	A1B1C3D3	512	128	640	1100	337.6	84.4	422	230	4515	0.453	317.7
10	A1B1C4D1	512	128	640	1100	420	105	525	190	4715	0.618	545.7
11	A1B1C4D2	512	128	640	1100	420	105	525	210	4675	0.194	553.3
12	A1B1C4D3	512	128	640	1100	420	105	525	230	4520	0.308	467.0
13	A1B2C1D1	512	128	640	1200	172.8	43.2	216	190	4440	0.051	152.3
14	A1B2C1D2	512	128	640	1200	172.8	43.2	216	210	4215	0.016	103.3
15	A1B2C1D3	512	128	640	1200	172.8	43.2	216	230	4185	0.034	95.2
16	A1B2C2D1	512	128	640	1200	255.2	63.8	319	190	4690	0.021	121.4
17	A1B2C2D2	512	128	640	1200	255.2	63.8	319	210	4525	0.088	246.1
18	A1B2C2D3	512	128	640	1200	255.2	63.8	319	230	4465	0.054	220.4
19	A1B2C3D1	512	128	640	1200	337.6	84.4	422	190	4760	0.027	354.1
20	A1B2C3D2	512	128	640	1200	337.6	84.4	422	210	4745	0.110	417.0
21	A1B2C3D3	512	128	640	1200	337.6	84.4	422	230	4715	0.205	364.3
22	A1B2C4D1	512	128	640	1200	420	105	525	190	4900	0.097	592.2
23	A1B2C4D2	512	128	640	1200	420	105	525	210	4705	0.408	509.3
24	A1B2C4D3	512	128	640	1200	420	105	525	230	4680	0.499	469.1
25	A2B1C1D1	633.6	158.4	792	1100	172.8	43.2	216	190	4410	0.037	157.1
26	A2B1C1D2	633.6	158.4	792	1100	172.8	43.2	216	210	4120	0.040	120.0
27	A2B1C1D3	633.6	158.4	792	1100	172.8	43.2	216	230	4080	0.062	96.5
28	A2B1C2D1	633.6	158.4	792	1100	255.2	63.8	319	190	4560	0.049	306.2
29	A2B1C2D2	633.6	158.4	792	1100	255.2	63.8	319	210	4485	0.065	242.9
30	A2B1C2D3	633.6	158.4	792	1100	255.2	63.8	319	230	4330	0.025	196.8
31	A2B1C3D1	633.6	158.4	792	1100	337.6	84.4	422	190	4705	0.058	443.9
32	A2B1C3D2	633.6	158.4	792	1100	337.6	84.4	422	210	4680	0.092	373.6
33	A2B1C3D3	633.6	158.4	792	1100	337.6	84.4	422	230	4540	0.050	369.9
34	A2B1C4D1	633.6	158.4	792	1100	420	105	525	190	4775	0.249	539.3
35	A2B1C4D2	633.6	158.4	792	1100	420	105	525	210	4625	0.057	475.6

Mixture	Designation of mixture	Fine aggregate (A), kg/m^3			Gravel (B) kg/m^3	Binder (C) (kg/m^3)			Water (D) liter	UPV (m/s)	Amplitude attenuation ratio	Compressive strength
		Sand (80%)	Stone (20%)	Total (100%)		Cement (80%)	Fly ash (20%)	Total (100%)			A_2/A_1	$f_c(daN/cm^2)$
36	A2B1C4D3	633.6	158.4	792	1100	420	105	525	230	4445	0.235	457.0
37	A2B2C1D1	633.6	158.4	792	1200	172.8	43.2	216	190	4245	0.076	179.6
38	A2B2C1D2	633.6	158.4	792	1200	172.8	43.2	216	210	3945	0.070	106.2
39	A2B2C1D3	633.6	158.4	792	1200	172.8	43.2	216	230	3905	0.102	107.6
40	A2B2C2D1	633.6	158.4	792	1200	255.2	63.8	319	190	4490	0.144	304.8
41	A2B2C2D2	633.6	158.4	792	1200	255.2	63.8	319	210	4310	0.036	243.2
42	A2B2C2D3	633.6	158.4	792	1200	255.2	63.8	319	230	4260	0.143	184.5
43	A2B2C3D1	633.6	158.4	792	1200	337.6	84.4	422	190	4630	0.195	487.7
44	A2B2C3D2	633.6	158.4	792	1200	337.6	84.4	422	210	4500	0.109	387.6
45	A2B2C3D3	633.6	158.4	792	1200	337.6	84.4	422	230	4510	0.083	333.4
46	A2B2C4D1	633.6	158.4	792	1200	420	105	525	190	4650	0.189	461.7
47	A2B2C4D2	633.6	158.4	792	1200	420	105	525	210	4550	0.116	322.1
48	A2B2C4D3	633.6	158.4	792	1200	420	105	525	230	4505	0.161	483.4
49	A3B1C1D1	755.2	188.8	944	1100	172.8	43.2	216	190	4105	0.084	166.8
50	A3B1C1D2	755.2	188.8	944	1100	172.8	43.2	216	210	3975	0.082	120.8
51	A3B1C1D3	755.2	188.8	944	1100	172.8	43.2	216	230	3720	0.082	93.8
52	A3B1C2D1	755.2	188.8	944	1100	255.2	63.8	319	190	4445	0.119	294.7
53	A3B1C2D2	755.2	188.8	944	1100	255.2	63.8	319	210	4285	0.097	269.7
54	A3B1C2D3	755.2	188.8	944	1100	255.2	63.8	319	230	4175	0.137	219.9
55	A3B1C3D1	755.2	188.8	944	1100	337.6	84.4	422	190	4580	0.084	467.3
56	A3B1C3D2	755.2	188.8	944	1100	337.6	84.4	422	210	4620	0.100	417.8
57	A3B1C3D3	755.2	188.8	944	1100	337.6	84.4	422	230	4495	0.113	394.5
58	A3B1C4D1	755.2	188.8	944	1100	420	105	525	190	4645	0.143	365.8
59	A3B1C4D2	755.2	188.8	944	1100	420	105	525	210	4555	0.118	514.9
60	A3B1C4D3	755.2	188.8	944	1100	420	105	525	230	4455	0.045	392.2
61	A3B2C1D1	755.2	188.8	944	1200	172.8	43.2	216	190	4135	0.028	152.9
62	A3B2C1D2	755.2	188.8	944	1200	172.8	43.2	216	210	3965	0.033	118.2
63	A3B2C1D3	755.2	188.8	944	1200	172.8	43.2	216	230	3765	0.010	86.5
64	A3B2C2D1	755.2	188.8	944	1200	255.2	63.8	319	190	4415	0.016	313.0
65	A3B2C2D2	755.2	188.8	944	1200	255.2	63.8	319	210	4370	0.012	261.4
66	A3B2C2D3	755.2	188.8	944	1200	255.2	63.8	319	230	4215	0.042	228.0
67	A3B2C3D1	755.2	188.8	944	1200	337.6	84.4	422	190	4540	0.194	478.1
68	A3B2C3D2	755.2	188.8	944	1200	337.6	84.4	422	210	4460	0.105	477.2
69	A3B2C3D3	755.2	188.8	944	1200	337.6	84.4	422	230	4400	0.032	383.4
70	A3B2C4D1	755.2	188.8	944	1200	420	105	525	190	4555	0.175	621.3
71	A3B2C4D2	755.2	188.8	944	1200	420	105	525	210	4525	0.057	466.8
72	A3B2C4D3	755.2	188.8	944	1200	420	105	525	230	4520	0.039	519.6

Persian Abstract

چکیده

در مرکز ویتنام، مواد سنتی برای ساخت بتن معمولا منشاء طبیعی دارند. بهره برداری بیش از حد از این مواد اثرات نامطلوب زیادی بر محیط طبیعی ایجاد می کند. کارخانه ها و معادن صنعتی محلی میلیون ها تن مواد زائد مانند خاکستر بادی و پودر سنگ تولید می کنند. با این حال، هنگامی که برای جایگزینی جزئی سیمان و ماسه استفاده می شود، این مواد زائد می توانند بر مقاومت فشاری بتن تأثیر بگذارند. بنابراین ساخت مدل هایی برای پیش بینی مقاومت فشاری این نوع بتن ضروری است. هدف این مقاله استفاده از مدل‌های شبکه عصبی مصنوعی برای پیش‌بینی مقاومت فشاری بتن با استفاده از خاکستر بادی و مواد زائد پودر سنگ بود. ورودی مدل ANN شامل شش پارامتر است: سرعت پالس اولتراسونیک، نسبت تضعیف دامنه موج و ٤ پارامتر مصالح بتن. داده های تجربی از ۷۲ نمونه مکعبی از مخلوط های مختلف با استفاده از مواد موجود در ویتنام مرکزی به دست آمد. این مدل ها امکان پیش بینی مقاومت فشاری ۲۸ روزه بتن را در محدوده (90-620daN/cm2) MPa ۹-٦٢ فراهم می کنند. علاوه بر این، این مدل ها می توانند مقاومت فشاری را با هر مخلوطی پیش بینی کنند. هنگام ارزیابی مجدد اینکه آیا مقدار مقاومت فشاری واقعی به اندازه مقدار ارائه شده توسط سازنده قابل اعتماد است یا خیر، مهم است.