# International Journal of Engineering

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

V. L. Thang, L. Cung*, D. S. Nguyen

*University of Science and Technology, The University of Danang, Vietnam*

## PAPER INFO

## 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.

## 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

---

*Corresponding Author Institutional Email: lcung@dut.udn.vn* (L. Cung)
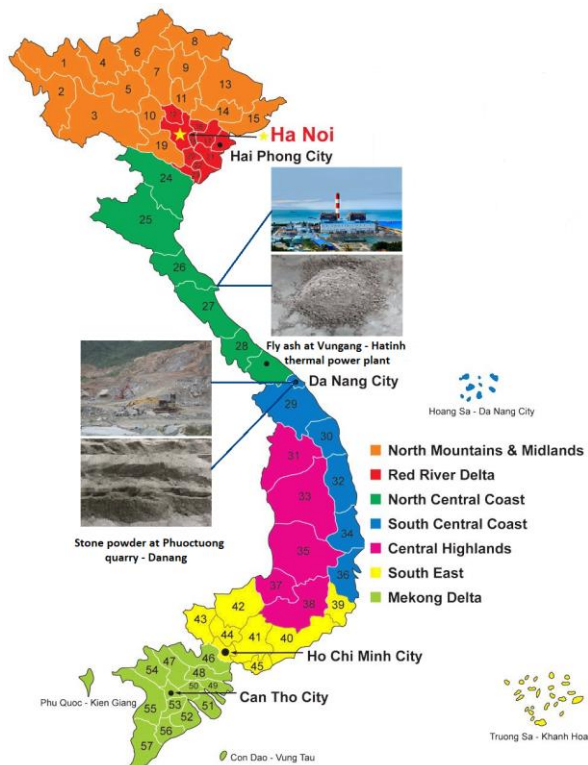
**Figure 1.** Origin of fly ash and stone powder in Central Vietnam

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].
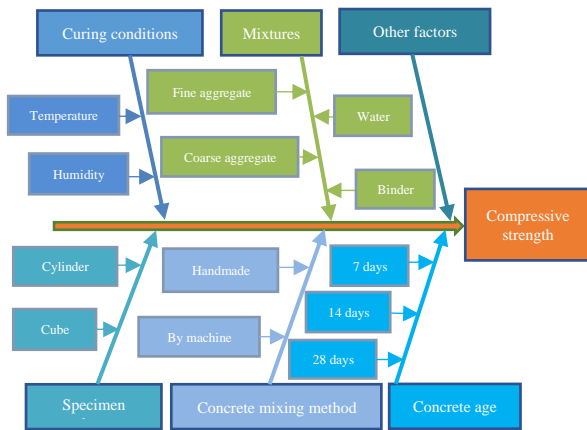
Each year, about one million tons of fly ash are generated at Vung-Ang thermal power plants. At Phuoc-Tuong quarry, there is a large amount of waste stone powder (as shown in Figure 1). The paper proposes to reuse fly ash and stone powder to replace cement and sand partially. At construction sites in 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

**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 |

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:

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

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

**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 |

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 i$^{th}$ observed response value; $\bar{y}$ is the mean response; $\hat{y}_i$ is the i$^{th}$ fitted response and $n$ is the number of observations.

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

## 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 $25\pm2^0$C and relative humidity of $80\pm7\%$ 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



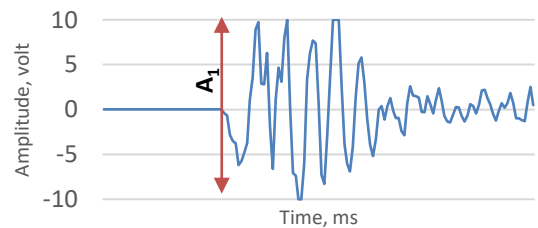Direct      Semi-indirect      Indirect
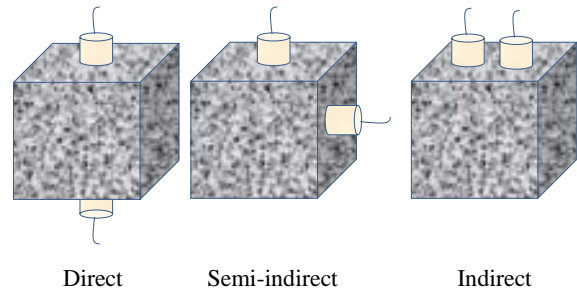
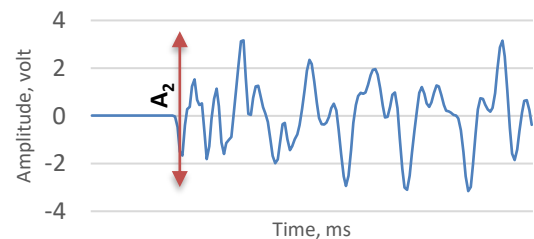**Figure 5.** Positions of ultrasonic transducers



**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).

$$f_c = \frac{P}{A} \qquad (3)$$

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).
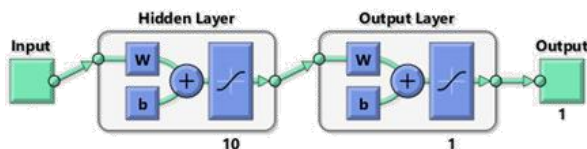


**Figure 10.** ANN network structure

**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

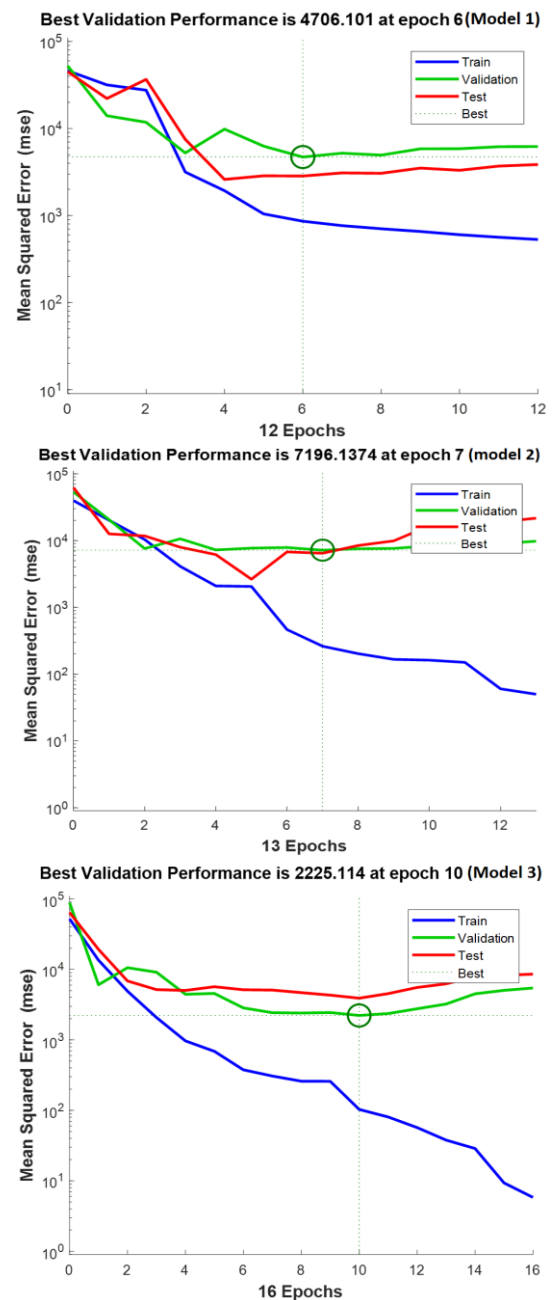have occurred. The results show that the validation and test curves are similar in all three prediction models. In which model 3 has the minor mean squared error (MSE). Therefore, model 3 has the best training among the three predictive models.

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.
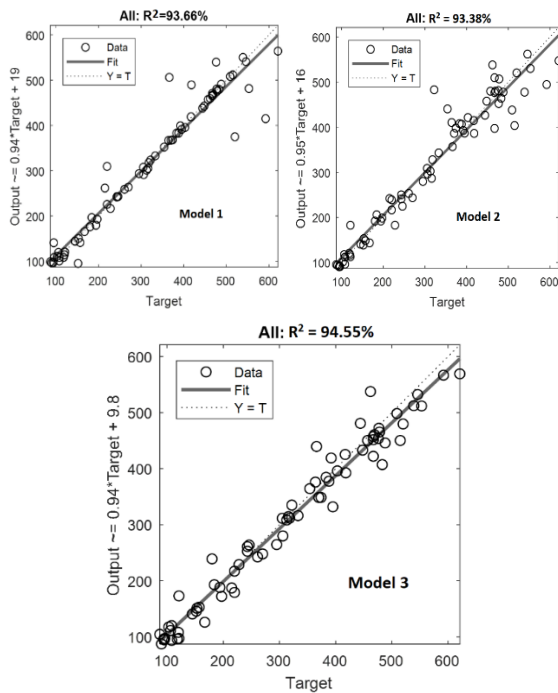


**Figure 12.** Prediction results of compressive strength of three ANN models

**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 | | |
| | Stone powder | 129 | | |
| Coarse aggregate (kg) | | 1200 | 4395 | 0.277 | 227.26 |
| 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

## 7. REFERENCES

1. Nguyen Ngoc, L., "Recycling of aac waste in the manufacture of autoclaved aerated concrete in vietnam", *GEOMATE Journal*, Vol. 20, No. 78, (2021), 128-134, doi: 10.21660/2021.78.j2048.

2. Van Nguyen, C., Lambert, P. and Hung Tran, Q., "Effect of vietnamese fly ash on selected physical properties, durability and probability of corrosion of steel in concrete", *Materials*, Vol. 12, No. 4, (2019), doi: 10.3390/ma12040593.

3. Tran, H.-B., Le, V.-B. and Phan, V.T., "Mechanical properties of high strength concrete containing nano $SiO_2$ made from rice husk ash in southern vietnam", *Crystals*, Vol. 11, No. 8, (2021), doi: 10.3390/cryst11080932.

4. Teixeira, E.R., Camões, A., Branco, F.G., Aguiar, J.B. and Fangueiro, R., "Recycling of biomass and coal fly ash as cement replacement material and its effect on hydration and carbonation of concrete", *Waste Management*, Vol. 94, (2019), 39-48, doi: 10.1016/j.wasman.2019.05.044.

5. Hafez, H., Kurda, R., Cheung, W.M. and Nagaratnam, B., "Comparative life cycle assessment between imported and recovered fly ash for blended cement concrete in the uk", *Journal of Cleaner Production*, Vol. 244, (2020), 118722, doi: 10.1016/j.jclepro.2019.118722.

6. Kanthe, V., Deo, S. and Murmu, M., "Combine use of fly ash and rice husk ash in concrete to improve its properties (research note)", *International Journal of Engineering, Transctions A: Basics*, Vol. 31, No. 7, (2018), 1012-1019, doi: 10.5829/ije.2018.31.07a.02.

7. Sadowski, Ł., Piechówka-Mielnik, M., Widziszowski, T., Gardynik, A. and Mackiewicz, S., "Hybrid ultrasonic-neural prediction of the compressive strength of environmentally friendly concrete screeds with high volume of waste quartz mineral dust", *Journal of Cleaner Production*, Vol. 212, No., (2019), 727-740, doi: 10.1016/j.jclepro.2018.12.059.

8. Shariq, M., Prasad, J. and Masood, A., "Studies in ultrasonic pulse velocity of concrete containing ggbfs", *Construction and Building Materials*, Vol. 40, (2013), 944-950, doi: 10.1016/j.conbuildmat.2012.11.070.

9. Jin, R., Yan, L., Soboyejo, A.B.O., Huang, L. and Kasal, B., "Multivariate regression models in estimating the behavior of frp tube encased recycled aggregate concrete", *Construction and Building Materials*, Vol. 191, (2018), 216-227, doi: 10.1016/j.conbuildmat.2018.10.012.

10. Trtnik, G., Kavčič, F. and Turk, G., "Prediction of concrete strength using ultrasonic pulse velocity and artificial neural networks", *Ultrasonics*, Vol. 49, No. 1, (2009), 53-60, doi: 10.1016/j.ultras.2008.05.001.

11. Bogas, J.A., Gomes, M.G. and Gomes, A., "Compressive strength evaluation of structural lightweight concrete by non-destructive ultrasonic pulse velocity method", *Ultrasonics*, Vol. 53, No. 5, (2013), 962-972, doi: 10.1016/j.ultras.2012.12.012.

12. Ashrafian, A., Taheri Amiri, M.J., Rezaie-Balf, M., Ozbakkaloglu, T. and Lotfi-Omran, O., "Prediction of compressive strength and ultrasonic pulse velocity of fiber reinforced concrete incorporating nano silica using heuristic regression methods", *Construction and Building Materials*, Vol. 190, (2018), 479-494, doi: 10.1016/j.conbuildmat.2018.09.047.

13. Shahmansouri, A.A., Yazdani, M., Ghanbari, S., Akbarzadeh Bengar, H., Jafari, A. and Farrokh Ghatte, H., "Artificial neural network model to predict the compressive strength of eco-friendly geopolymer concrete incorporating silica fume and natural zeolite", *Journal of Cleaner Production*, Vol. 279, (2021), 123697, doi: 10.1016/j.jclepro.2020.123697.

14. Vuong, L.T., Le, C. and Nguyen, D.S., "Prediction of compressive strength of concrete using recycled materials from fly ash based on ultrasonic pulse velocity and design of experiment", in Computational Intelligence Methods for Green Technology and Sustainable Development, Cham, Springer International Publishing., (2021), 600-612.

15. Zhang, Y., Aslani, F. and Lehane, B., "Compressive strength of rubberized concrete: Regression and ga-bpnn approaches using ultrasonic pulse velocity", *Construction and Building Materials*, Vol. 307, (2021), 124951, doi: 10.1016/j.conbuildmat.2021.124951.

16. Tenza-Abril, A.J., Villacampa, Y., Solak, A.M. and Baeza-Brotons, F., "Prediction and sensitivity analysis of compressive strength in segregated lightweight concrete based on artificial neural network using ultrasonic pulse velocity", *Construction and Building Materials*, Vol. 189, (2018), 1173-1183, doi: 10.1016/j.conbuildmat.2018.09.096.

17. Ranjbar, A., Barahmand, N. and Ghanbari, A., "Hybrid artificial intelligence model development for roller-compacted concrete compressive strength estimation", *International Journal of Engineering, Transctions A: Basics*, Vol. 33, No. 10, (2020), 1852-1863, doi: 10.5829/ije.2020.33.10a.04.

18. Heidari, A. and Hashempour, M., "Investigation of mechanical properties of self compacting polymeric concrete with backpropagation network", *International Journal of Engineering, Transctions C: Aspects*, Vol. 31, No. 6, (2018), 903-909, doi: 10.5829/ije.2018.31.06c.06.

**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/m³ | | | Gravel (B) kg/m³ | Binder (C) (kg/m³) | | | 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/cm²) |
| 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/m³ | | | Gravel (B) kg/m³ | Binder (C) (kg/m³) | | | Water (D) liter | UPV (m/s) | Amplitude attenuation ratio | Compressive strength |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Sand (80%) | Stone (20%) | Total (100%) | | Cement (80%) | Fly ash (20%) | Total (100%) | | | A₂/A₁ | f_c(daN/cm²) |
| 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 ٧٢ 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 ٢٨ روزه بتن را در محدوده (90-620daN/cm2) MPa ٩-٦٢ 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.