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Original scientific paper

Predicting Concrete Slump using Fly Ash and Stone Powder in Central Vietnam

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Abstract: Fly ash and stone powder, which are abundant wastes in Central Vietnam, are viable alternatives to cement and sand in concrete production. However, this replacement may worsen the compressive strength and slump of concrete. This study deals with the prediction of the slump and compressive strength of concrete using fly ash and stone powder in Central Vietnam as cement and sand substitute materials, respectively. First, the Ishikawa diagram was used to analyze the factors affecting the concrete workability and compressive strength, in combination with the method of design of experiment to determine the required number of testing specimens. A total of 72 concrete mixtures with slump of 3 - 12 cm and compressive strengths 10 MPa - 60 MPa were designed. Subsequently, regression and artificial neural network methods were used to predict the concrete slump and compressive strength. The results demonstrated the high accuracy of the artificial neural network model. In addition, the above models allowed us to determine the proportion of concrete ingredients that met the slump and compressive strength requirements.

Keywords: artificial neural network; concrete; design of experiment; fly ash; multivariable linear regression; slump; stone powder

1 INTRODUCTION

Concrete is a commonly used construction material in Vietnam, and the traditional materials used for making concrete are derived from nature, such as sand, gravel, cement, and water. The current overexploitation of these materials, especially sand mining in rivers and quarrying in quarries Fig. 1, causes severe natural disasters such as floods and landslides in the area Fig. 2. Therefore, finding alternatives to traditional materials is an urgent problem.

Figure 1 Mining of stone for construction in Danang, Vietnam

Figure 2 Landslides due to environmental destruction in Vietnam

As for alternative materials, many works have confirmed that fly ash waste from thermal power plants can partially replace cement while still assuring the required properties of concrete [1-6]. Several studies have investigated the use of waste products originating from Vietnam, such as fly ash, rice husk ash to replace cement partially [7-9], broken concrete, brick, and recyclable waste medical glass for sand [10, 11]. In Central Vietnam, fly ash is obtained from the Vung Ang Thermal Power Plant, which generates millions of tons of fly ash annually. In this location and its neighboring provinces, many quarries exploit stone for construction work and generate massive amounts of stone powder during the quarrying process. Therefore, this study proposes the use of fly ash and stone powder to partially replace cement and sand.

Concrete must possess several properties. Among these, compressive strength and slump (workability) are the two main characteristics that are regularly tested during concrete manufacturing. Depending on the type of fabricated structure (floors, beams, columns, foundations, etc.), the slump value requirements of concrete may vary. However, the commonly required slump values for concrete workability range from 3 cm to 12 cm. Most construction works in Vietnam require concrete compressive strength from 10 MPa to 60 MPa. This study aimed to predict concrete slumps from 3 to 12 cm with compressive strengths in the range of 10 - 60 MPa.

In recent years, multivariate regression and artificial neural models have been used to predict concrete slump and compressive strength. Although regression models are widely used, they do not provide high accuracy in cases where it is necessary to predict many input variables or the variables interact with each other in a complex manner [12]. Artificial neural networks have become dominant with the development of computational tools and can solve highly nonlinear problems [13]. Many studies have confirmed that artificial neural networks can help predict the slump value [12, 14-16] and compressive strength of concrete [17-23].

This study aimed to build a multivariable regression model and an artificial neural network to predict both the slump and compressive strength of concrete, with the compressive strength reaching 10 - 60 MPa, while ensuring a slump in the range of 3 - 12 cm. In addition, the two models help determine the concrete mixture that satisfies the required compressive strength and slump. The reuse of waste products, fly ash, and stone powder to partially replace cement and sand is one of the highlights of this study.

2 METHODOLOGY

2.1 Research Content

First, the Ishikawa diagram was used to analyze the main parameters affecting the slump and compressive strength of concrete to choose suitable parameters to be investigated. The design of experiments (full factorial method) helped select the required number of testing specimens to ensure an even distribution of the statistical data. Subsequently, the specimens were manufactured in the laboratory, and their slump and 28 day compressive strength were measured. A regression model and an artificial neural network (ANN) were built using these experimental data to predict the concrete slump and compressive strength Fig. 3.

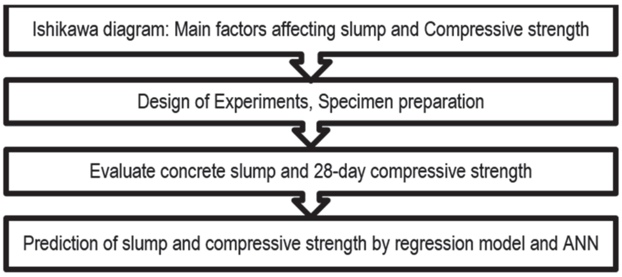


Figure 3 Research routing

2.2 Ishikawa Diagram

The concrete slump and compressive strength are influenced by many factors, such as the concrete materials, environment, mixing method, test specimens, and additives, as shown in the Ishikawa diagram Fig. 4. However, if all these factors are considered, the problem becomes complicated. Only concrete ingredient parameters were considered as the input of the predictive model for investigating the reuse of the two waste products (fly ash and stone powder). Other influencing parameters remained unchanged, and their values were in accordance with Vietnamese standards. Thus, the four investigated parameters for the predictive models were the concrete components: fine aggregate, coarse aggregate, binder, and water. The model outputs were the slump and compressive strength.

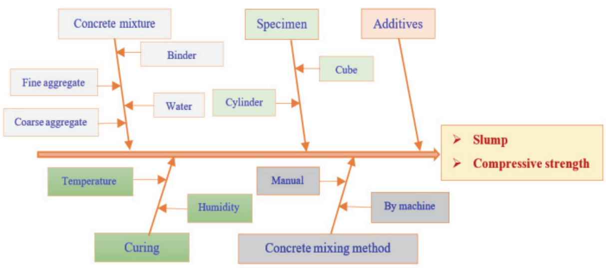


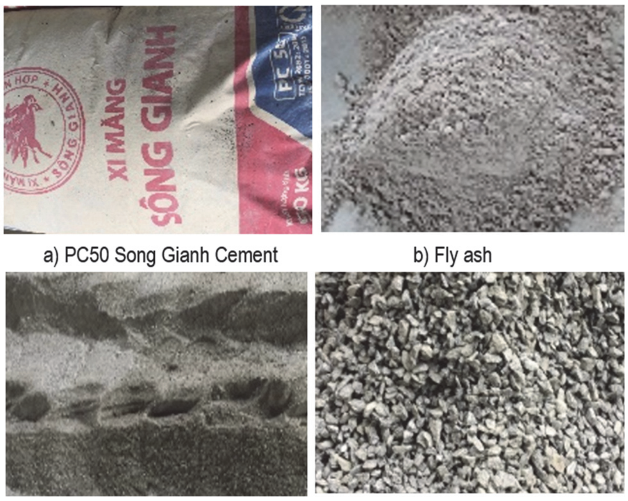
Figure 4 Ishikawa diagram showing the main parameters affecting the slump and compressive strength

2.3 Methods of Design of Experiments

The materials used to make the concrete are sand, gravel, cement, and water. Referring to actual data from concrete batching plants in Vietnam, this study chose the amounts of fly ash and stone powder to replace 20% cement and 20% stone powder, respectively. Fig. 5 shows some of the essential materials used to manufacture concrete.

The preliminary and precise design of concrete mixtures for a particular concrete with corresponding compressive strength using conventional materials like sand, gravel, cement, and water has been addressed in previous studies [24, 25]. However, there has been limited research on designing concrete with a specific slump and compressive strength when incorporating a significant amount of fly ash and stone powder to replace cement.

To address this gap, the current paper adopts a design of experiments approach to identify an appropriate concrete mixture for producing concrete with a slump ranging from 3 to 12 cm and a compressive strength between 10 and 60 MPa. The goal is to explore how these alternative materials impact the concrete's properties and find the most suitable combination for the desired performance. Tab. 1 illustrates the changes in the content of concrete components. The results show that the content ranges of the material ingredients vary, with the binder having the most considerable variation range of 58.9% compared to the full content of this material, followed by the fine aggregate of 32.2%, water of 17.4%, and coarse aggregate of 8.3%. Because of the different variation intervals, the number of levels of each ingredient in the method of design of experiments is different. The levels of each ingredient, such as fine aggregate, coarse aggregate, binder, and water, were three, two, four, and three, respectively, as listed in Tab. 2.



a) PC50 Song Gianh Cement b) Fly ash
c) Stone powder d) Gravel (Crushed stone)

Figure 5 Materials used in the experiments

Table 1 Materials for making concrete and their content range in specimens

Material		Unit	Content range
Fine aggregate	Sand (80%)	kg	512 - 755.2
	Stone powder (20%)	kg	128 - 188.8
	Total	kg	640 - 944
Coarse aggregate (gravel)		kg	1100 - 1200
Binder	Cement (80%)	kg	172.8 - 409.6
	Fly ash (20%)	kg	43.2 - 102.4
	Total	kg	216 - 512
Water		l	190 - 230

The required number of experimental specimens was determined using the full factorial design method, as follows: Number of specimens $= 2^1 \times 3^2 \times 4^1 = 72$.

The details of the 72 concrete mixtures are shown in Tab. 3.

Table 2 Material ingredients at their variation levels in the method of Design of Experiments

Label	Material - Unit		Level of variation								Number of levels
			1		2		3		4		
A	Fine aggregate	Sand (80%) / kg	512	640	633.6	792	755.2	944	*		3
		Stone powder (20%) / kg	128		158.4		188.8				
B	Coarse aggregate	Gravel / kg	1100		1200		*		*		2
C	Binder	Cement (80%) / kg	172.8	216	255.2	319	337.6	422	420	525	4
		Fly ash (20%) / kg	43.2		63.8		84.4		105		
D	Water - liter		190		210		230		*		3

Table 3 Material content of 72 concrete mixtures

Mixture	Designation of mixture	Fine aggregate (A) / kg			Gravel (B) / kg	Binder (C) / kg			Water (D) (l)
		Sand (80%)	Stone powder (20%)	Total (100%)		Cement (80%)	Fly ash (20%)	Total (100%)	
1	A1B1C1D1	512	128	640	1100	172.8	43.2	216	190
2	A1B1C1D2	512	128	640	1100	172.8	43.2	216	210
3	A1B1C1D3	512	128	640	1100	172.8	43.2	216	230
…	…	…	…	…	…	…	…	…	…
71	A3B2C4D2	755.2	188.8	944	1200	420	105	525	210
72	A3B2C4D3	755.2	188.8	944	1200	420	105	525	230

2.4 Evaluating the Concrete Slump and Compressive Strength

The slump measuring procedure for the 72 specimens was conducted according to the instructions in the Vietnamese Standard on Slump Test Fig. 6. The slump values of all 72 concrete mixtures used in this study were distributed in the range of 3 - 12 cm Tab. 4.

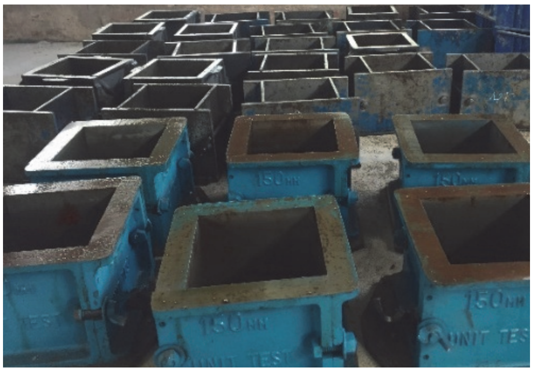
Figure 6 Measuring concrete slump

The Vietnamese standard stipulates that the test specimen for determining the concrete compressive strength should have a cubic shape of 15 cm × 15 cm × 15 cm. After being fabricated, the specimen was cured at the laboratory temperature of about 25 ± 25 °C and with a humidity of 80 ± 7% Fig. 7.Two concrete specimens were fabricated for each concrete mixture as shown in Tab. 3 in order to ensure the reproducibility and accuracy of the experiment. The slump and compressive strength measurements were taken from these two samples. The values presented in Tab. 4 represent the average measurements obtained from these two samples.

A hydraulic compressor (SYE-2000A) with a maximum compressive force of 200 t was used to press the concrete specimens Fig. 8. The specimens were compressed at 28 d of age to determine their compressive strength. The compressive strength of the specimen is determined according to the following expression:

$$f_C = \frac{P}{A} \tag{1}$$

where f_C is the compressive strength of the concrete (MPa), P is the compressive force (N), and A is the area of the specimen cross-section (mm^2). The compressive strengths of the 72 concrete mixtures are presented in Tab. 4.



a) Mold manufacture

b) Curing concrete specimens in water

Figure 7 Manufacturing molds and curing concrete specimens

Figure 8 Compression of specimens for determining compressive strength of concret

Table 4 Slump and compressive strength of 72 concrete mixtures

Mixture	Slump	f_c	Mixture	Slump	f_c	Mixture	Slump	f_c	Mixture	Slump	f_c
	x / cm	MPa		x / cm	MPa		x / cm	MPa		x / cm	MPa
1	6	14.5	19	3.1	35.4	37	4.2	18.0	55	3.1	46.7
2	8.5	10.8	20	3.5	41.7	38	10.3	10.6	56	5	41.8
3	11.7	9.0	21	5.5	36.4	39	3.2	10.8	57	7.3	39.5
4	4.1	31.6	22	3	59.2	40	3.3	30.5	58	3	36.6
5	11	21.5	23	3.7	50.9	41	6	24.3	59	4.5	51.5
6	11.9	19.4	24	3.6	46.9	42	11.2	18.4	60	6.1	39.2
7	3.1	44.8	25	3.2	15.7	43	3	48.8	61	3.3	15.3
8	3.7	40.3	26	9.2	12.0	44	5	38.8	62	5.3	11.8
9	11.6	31.8	27	9.8	9.6	45	7	33.3	63	7.1	8.7
10	3	54.6	28	4	30.6	46	3.1	46.2	64	3.1	31.3
11	4	55.3	29	5.3	24.3	47	5	32.2	65	5.6	26.1
12	7.4	46.7	30	10	19.7	48	7	48.3	66	7.2	22.8
13	11.1	15.2	31	3.4	44.4	49	3.4	16.7	67	3.1	47.8
14	10.5	10.3	32	3.6	37.4	50	5.5	12.1	68	5.1	47.7
15	11.8	9.5	33	4.3	37.0	51	7.5	9.4	69	7.2	38.3
16	4	12.1	34	3.1	53.9	52	3.3	29.5	70	3.1	62.1
17	5	24.6	35	4	47.6	53	5.6	27.0	71	4	46.7
18	11.1	22.0	36	4.3	45.7	54	7	22.0	72	5.1	52.0

2.5 Model for Predicting Concrete Slump and Compressive Strength

2.5.1 Structures of Prediction Models

The objective of this study was to predict the concrete slump and compressive strength in the range of 10 - 60 MPa, depending on the concrete mixtures. Therefore, the predictive model had four input parameters: fine aggregate, coarse aggregate, binder, and water. The model outputs were concrete slump and compressive strength Fig. 9.

Two prediction models were used: multivariate linear regression and an artificial neural network with two output parameters, as shown in Fig. 9. As for the multivariate linear regression model, Minitab 19 software supports the derivation of the predictive linear equations between the outputs and input parameters.

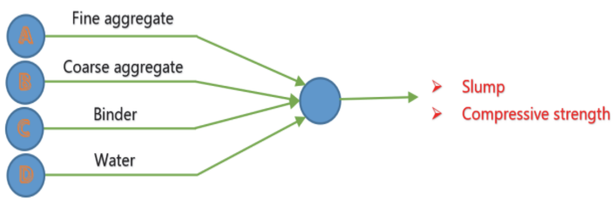


Figure 9 Concrete slump and compressive strength prediction model

The structure of an ANN considerably affects the prediction results; therefore, soa trial-and-error method was used to determine the most suitable network structure. The neural network with backward propagation used in this study consists of three layers: an input layer with four material parameters (fine aggregate, coarse aggregate, binder, and water), a hidden layer with 12 neurons, and one output layer with two parameters (concrete slump and compressive strength), as shown in Fig. 10. The nntool tool in MATLAB 2017b software was used to analyze the data. The training function was Levenberg Marquardt (TRAINLM), and the activation function (transfer function) wasTANSIG.

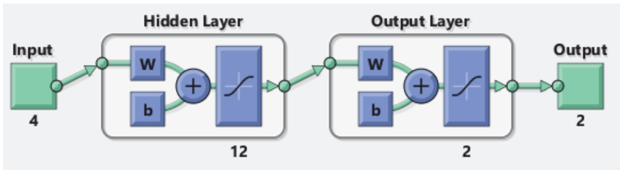


Figure 10 Structure of ANN network

After establishing the suitable architecture of the ANN network, we will utilize data from 72 concrete mixtures for both training and testing purposes. In general practice, data for training and testing is commonly divided in an 80% - 20% ratio. However, due to the limited size of the experimental dataset, which comprises only 72 data points, this paper suggests a novel approach to partition the data into training, testing, and validation sets with a distribution of 70% - 15%, respectively.

These 72 data points will be randomly divided into three sub-datasets using nntool function in Matlab, each comprising 70%, 15%, and 15% of the total data, respectively. The sub-dataset with 70% of the test samples will be employed for training, while the remaining two subsets will be used for testing and validation.

2.5.2 Performance Indicators

Several coefficients are used to evaluate the prediction accuracy of the models. In this study, the determination coefficient (R) was used to evaluate the fitness of the experimental and predicted data, which was determined using the following expressions:

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2}} \qquad (2)$$

where y_i is the output value of the ith experimental datum, $\hat{y}_i$ is the predictive value of the ith experimental datum, $\overline{y}$ is the mean output value of all the experimental data, and n is the number of specimens.

3 RESULTS AND DISCUSSIONS

3.1 Prediction of Concrete Slump and Compression Strength

Using Minitab 19 software, the linear multivariate regression equations to predict the slump and concrete compressive strength were derived as shown in Eq. (3) and Eq. (4), where Sp (cm) and f_c (MPa) denote the concrete slump and compressive strength, respectively. A, B, C, and D represent the amounts of fine aggregate (kg), coarse aggregate (kg), binder (kg), and water (l), respectively.

$$Sp = -5.49 - 0.00566A - 0.00118B - 0.01049C + 0.0999D \quad (3)$$

$$f_c = 23.7 + 0.00528A - 0.0049B + 0.122C - 0.1712D \quad (4)$$

The determination coefficient (R) of Eq. (3) was only 0.7736, whereas that of Eq. (4) was 0.949. These results indicate that the accuracy of slump prediction using the regression model is lower than that of the ANN model. The slump residual analysis plots Fig. 11 also show that the residual values of the slump are relatively large, revealing that multivariate linear regression is an unsuitable model for the concrete slump prediction problem.

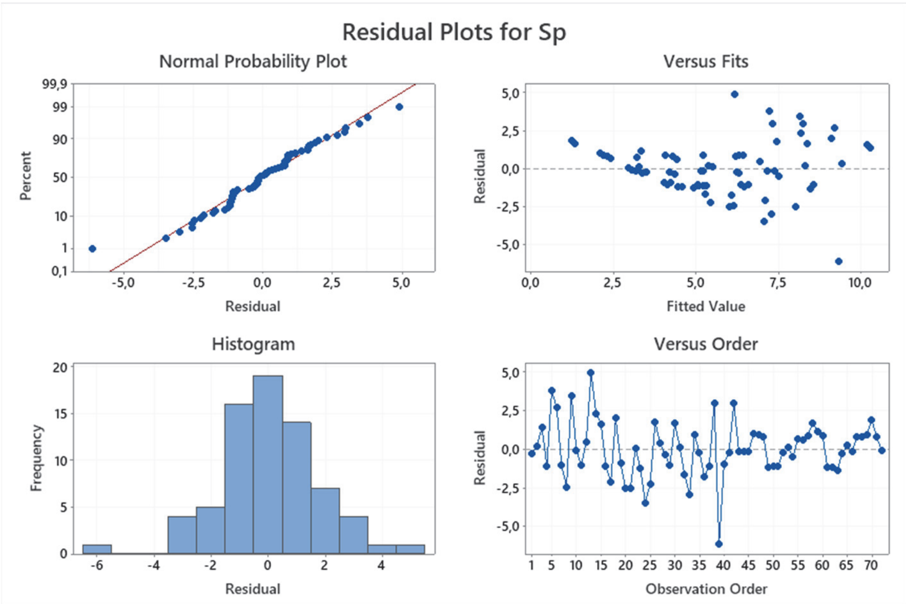


Figure 11 Results of residual analysis of slump

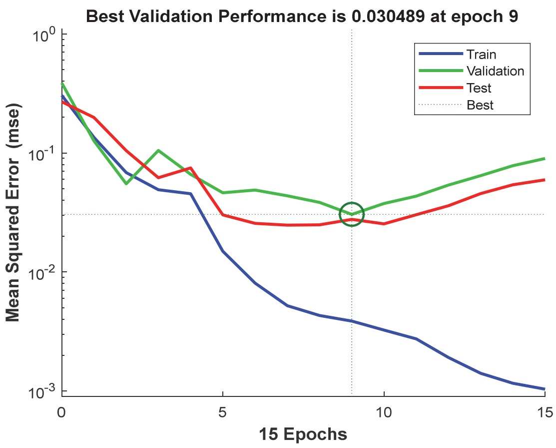


Figure 12 The training process to predict concrete slump and compressive strength by ANN network

For the artificial neural network model, the training process and results for predicting the concrete slump and compressive strength are shown in Fig. 12 and Fig. 13, respectively. The training process Fig. 12 shows that the best validation performance is 0.030489 at the 9th iteration. The determination coefficient (R) is 0.9355 Fig. 13, which was considerably better than that of Eq. (3) in predicting the concrete slump, whose coefficient (R) value is only 0.7736. This shows that the artificial neural network is a suitable model to predict the slump from 3 cm to 12 cm for concrete meeting the compressive strength from 10 MPa to 60 MPa.

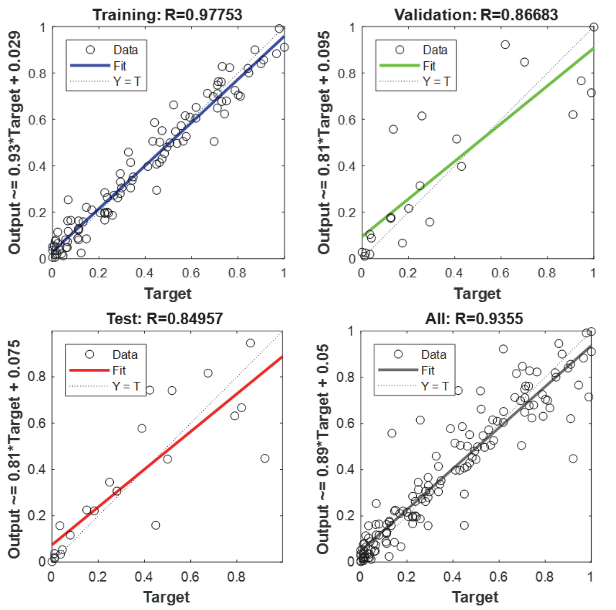


Figure 13 Prediction results of the concrete slump and compressive strength by ANN network

3.2 Prediction of Material Ingredient Content Meeting Required Slump and Compressive Strength

Several steps must be implemented to evaluate concrete mixtures to satisfy the required slump and compressive strength, from the preliminary design of the initial mixture to the fabrication of specimens and testing of the slump and compressive strength. However, these methods are time-consuming and costly. The proposed multivariate regression and artificial neural network can help identify concrete mixtures that satisfy concrete quality requirements without requiring sophisticated experiments.

With the regression model, the contour plots Fig. 14 and Fig. 15 derived from Minitab 19 supported the estimation of the content range of the material ingredients required to ensure the desired compressive strength and slump. For example, the contour plots in Fig. 14 revealed that to achieve the compressive strength of concrete (f_c) superior to 30 MPa, the required amount of binder (C) must be greater than 350 kg. For the concrete slump, to ensure that the slump is greater than 6 cm, the amount of water must be at least 210 l Fig. 15.

In addition, the regression model can be used to determine suitable concrete mixtures from statistical data. Fig. 16 illustrates the optimal concrete mixture analysis to achieve a slump Sp of 6 cm and compressive strength f_c of 30 MPa, and the corresponding optimal mixture obtained: Sand:636.6 kg, stone powder:158.4 kg, gravel:1100 kg, cement:337.6 kg, fly ash:84.4 kg, water:230 l. Tab. 5 presents five cases of optimal concrete mixtures that satisfied the desired slump and compressive strength.

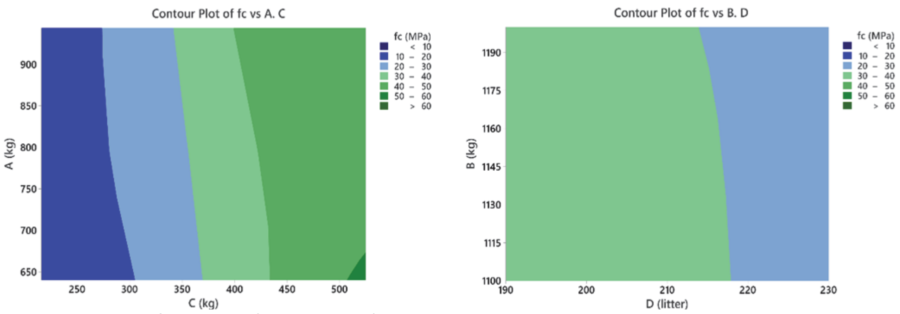


Figure 14 Contour plot for prediction of concrete mixtures assuring required compressive strength

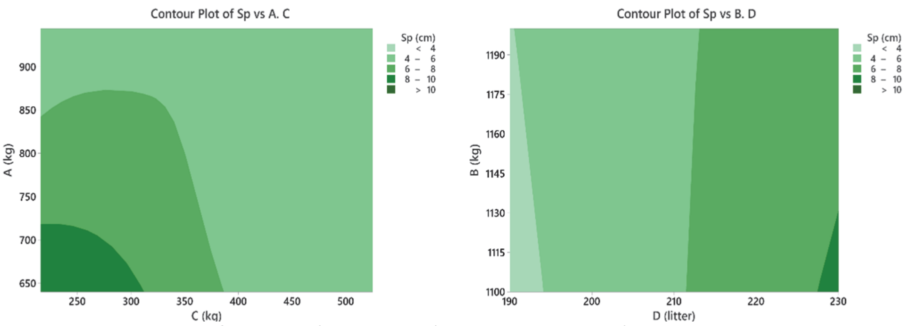


Figure 15 Contour plot for prediction of concrete mixtures satisfying required slump

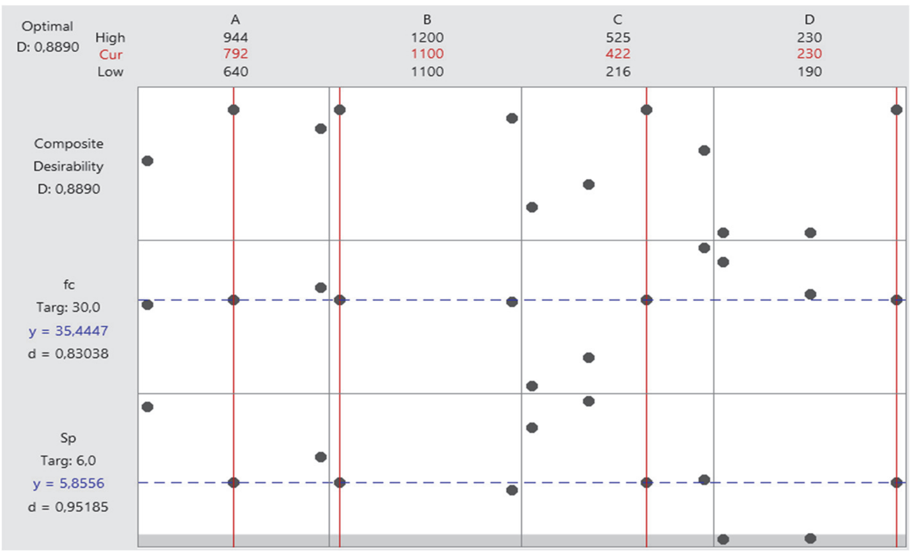


Figure 16 Optimal concrete mixture analysis to achieve a slump of 6cm and compressive strength of 30MPa

Table 5 Optimal concrete mixture prediction by regression model and artificial neural network

Mixture	Required slump *Sp* / cm	Required compressive strength f_c / MPa	Predictive models	Fine aggregate *A* / kg			Coarse aggregate *B* / kg	Binder *C* / kg			Water *D* [l]
				Sand (80%)	Stone powder (20%)	Total	Gravel	Cement (80%)	Fly ash (20%)	Total	
CP1	3	20	Regression	633.6	158.4	792	1200	172.8	43.2	216	190
			ANN	751.4	187.8	939.2	1153	174.2	43.6	217.8	192.1
CP2	6	30	Regression	633.6	158.4	792	1100	337.6	84.4	422	230
			ANN	752.6	188.1	940.7	1166.4	303.9	76	379.9	220.5
CP3	10	40	Regression	512	128	640	1100	337.6	84.4	422	230
			ANN	578.4	144.6	723	1141.3	337.5	84.4	421.9	226.7
CP4	8	50	Regression	512	128	640	1200	420	105	525	230
			ANN	512.1	128	640.1	1120.5	414.4	103.6	518	229.5
CP5	6	60	Regression	633.6	158.4	792	1100	420	105	525	230
			ANN	525.5	131.4	656.9	1182.8	419	104.8	523.8	195

Similar to the regression model, the artificial neural network can predict the concrete ingredient content to satisfy the required slump and compressive strengths. A suitable network structure was determined by trial-and-error. The artificial neural network with backward propagation Fig. 17 was composed of three layers: an input layer of two parameters (slump and compressive strength), one hidden layer with ten neurons, and an output layer of four parameters (four concrete ingredient amounts: fine aggregate, coarse aggregate, binder, and water). The Levenberg-Marquardt (TRAINLM) and TANSIG training and activation functions were used. The nntool tool of the MATLAB 2017b software was used to analyze the data.

The training results of the network Fig. 18 reveal that the blue (training), green (validation), and red (testing) lines all have good convergence and achieve the best validation performance at the 7th iteration. Fig. 19 illustrates the concrete mixture prediction results and again shows the accuracy of the prediction by the artificial neural network. The performance coefficients of the prediction process are as follows: training process, R = 0.98471; validation, R = 0.98362; testing, R = 0.97199; and overall, R = 0.98253.

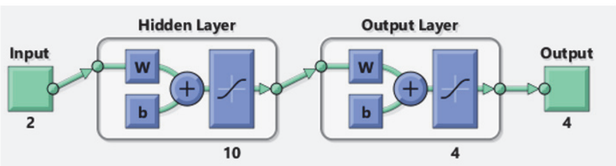


Figure 17 Structure of ANN network to predict concrete mixtures

The prediction results for the concrete mixtures with the five investigated cases are listed in Tab. 5. According to the above analysis of the performance indicators, when predicting the compressive strength using the regression model, the fitness of this model is relatively good (R = 0.949), whereas a modest accuracy is obtained for the slump evaluation (R = 0.7736). The results show that the amount of binder increases with the compressive strength, while at various levels of slump (3, 6, 8, and 10 cm), the amount of water only changes by two levels of 190 l and 230 l.

For the artificial neural network, when predicting concrete mixtures according to the desired slump and compressive strength, the prediction accuracy is more appropriate (R = 0.98253). The concrete mixture prediction for binder content (A) by either the regression model or ANN yielded similar results Tab. 5. However, the water-content prediction results of the two models varied significantly. For cases CP2 - CP4, although the slump and compressive strength differed, the predicted results were 230 l of water. The prediction results from the ANN varied from 195 l to 229.5 l. This means that the regression model only selects the optimal concrete mixture from the 72 mixture datasets introduced into the model, whereas the ANN evaluates the optimal concrete mixture. The above analysis reveals that the ANN provides more accurate prediction results than the regression model, making it the most suitable model for concrete mixture prediction.

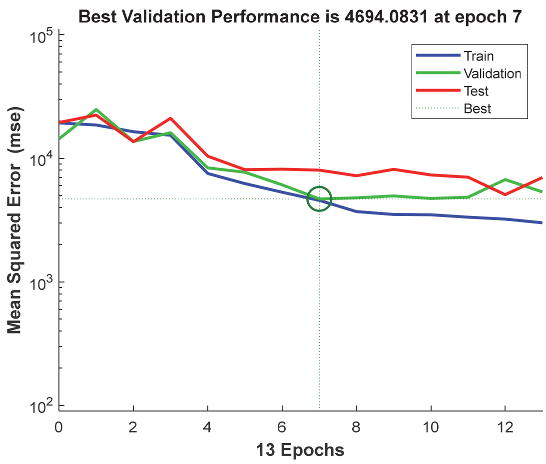


Figure 18 Training process of the ANN network to predict concrete mixtures

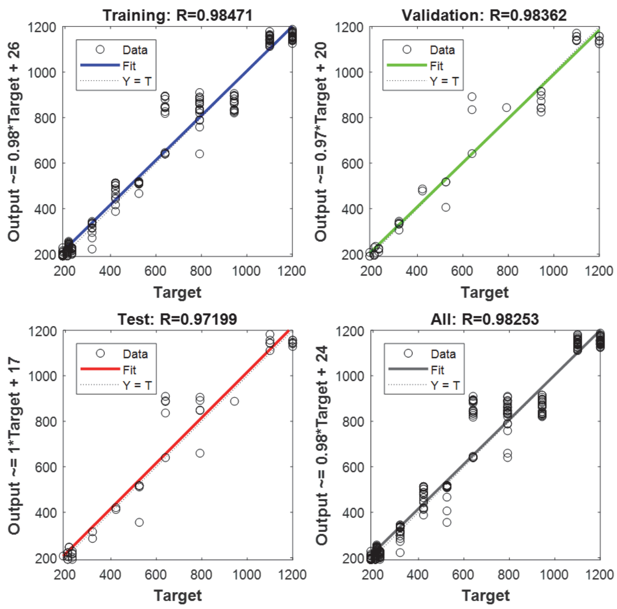


Figure 19 Prediction results of concrete mixtures by ANN

4 CONCLUSIONS

In this study, a total of 72 concrete mixtures of slump concrete between 3 cm and 12 cm with compressive strength in the range 10 - 60 MPa were used. Waste products in Central Vietnam, such as fly ash and stone powder, were used to substitute 20% of the cement and 20% of sand content, respectively. Two models for predicting concrete slump and compressive strength were proposed: linear multivariate regression and artificial neural networks. Based on the results, the following conclusions were drawn.

- Fly ash and stone powder can be used as alternative materials for manufacturing concrete that satisfies the widely used compressive strength and slump requirements by replacing cement.
- Both the proposed multivariate regression and artificial neural network models can be used to predict the concrete slump and compression strength. However, the analysis results revealed that the ANN network provided a more accurate prediction than the regression model ($R = 0.98253$ when predicting the slump and compressive strength, compared with $R = 0.7736$ for predicting the slump by the regression model).

In the future, in order to deploy this model for predicting concrete slump using fly ash in concrete manufacturing companies, we will enhance its performance by leveraging larger sets of experimental data collected from various concrete manufacturing companies.

Furthermore, there are plans to explore the utilization of chemical activators, plasticizers, and superplasticizers in the future. These investigations aim to enhance the compressive strength of concrete by using recycled materials like fly ash and stone powder as substitutes for cement.

Acknowledgements

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