Journal of Industrial Technology, Kangwon Natl. Univ., Korea, No. 41:1 (2021) 1~6
ISSN 1229-9588
eISSN 1598-1371
https://doi.org/10.22805/JIT.2021.41.1.001

인공신경망을 이용한 플라이애시 및 실리카 흄 복합 콘크리트의 압축강도 예측

Prediction of strength development of fly ash and silica fume ternary composite concrete using artificial neural network

번위결[a], 최영지[b], 왕소용[c*]
Wei-Jie Fan[a], Young-Ji Choi[b], Xiao-Yong Wang[c*]

[a] NingboTech University, Assistant Professor, Ningbo 315100, China
[b] Department of Architectural Engineering, Kangwon National University, Associate Professor, 1, Kangwondaehak-gil, Chuncheon-si, Gangwon-do, 24341, Republic of Korea
[c] Department of Integrated Energy and Infra System, Department of Architectural Engineering, Kangwon National University, Professor, 1, Kangwondaehak-gil, Chuncheon-Si, Gangwon-do, 24341, Republic of Korea

Received 2 September 2021; Revised 19 October 2021; Accepted 19 October 2021

Abstract

Fly ash and silica fume belong to industry by-products that can be used to produce concrete. This study shows the model of a neural network to evaluate the strength development of blended concrete containing fly ash and silica fume. The neural network model has four input parameters, such as fly ash replacement content, silica fume replacement content, water/binder ratio, and ages. Strength is the output variable of neural network. Based on the backpropagation algorithm, the values of elements in the hidden layer of neural network are determined. The number of neurons in the hidden layer is confirmed based on trial calculations. We find (1) neural network can give a reasonable evaluation of the strength development of composite concrete. Neural network can reflect the improvement of strength due to silica fume additions and can consider the reductions of strength as water/binder increases. (2) When the number of neurons in the hidden layer is five, the prediction results show more accuracy than four neurons in the hidden layer. Moreover, five neurons in the hidden layer can reproduce the strength crossover between fly ash concrete and plain concrete. Summarily, the neural network-based model is valuable for design sustainable composite concrete containing silica fume and fly ash.

Keywords: Fly as, Silica fume, Strength, Prediction, Neural network

1. Introduction

Fly ash is a coal combustion product and shows pozzolanic reactivity. Fly ash can be used as a mineral admixture in concrete productions. Fly ash blended concrete has some advantages, such as low hydration heat, high workability, and good durability for chloride ingress[1, 2]. However, the early-age strength of fly ash blended concrete is low because of the low reactivity of fly ash. To enhance the early-age strength of concrete, silica fume, which is a high reactive pozzolanic material, can be used[3, 4]. Ternary concrete with fly ash and silica fume can overcome the weak points of binary concrete. Moreover, the aims of sustainable development can be achieved using environmentally friendly composite concrete[5-7].

Strength is an essential property of concrete. The evaluation of strength development is critical of a cement-based material. Some models have been proposed for properties evaluations. Regarding fly ash blended concrete, Yaman *et al.*[8]evaluated the components of concrete using a neural network. The contents of cement, fly ash, fine aggregate, and coarse aggregate was predicted. Pazouki *et*

* Corresponding author. Tel.: +82-33-250-6229
fax: +82-33-259-5542
E-mail address: wxbrave@kangwon.ac.kr (Xiao-Young Wang).

al.[9] predicted the strength of class F fly ash blended concrete using radial basis function neural network. After being combined with the firefly optimization algorithm, the neural network showed more accurate analysis results. Nguyen *et al*.[10] made experimental studies and theoretical analyses of the strength of fly ash-based geopolymer using machine learning techniques. Regarding silica fume blended concrete, Behnood and Golafshani[11] evaluated the strength of concrete with silica fume using a hybrid neural network. The multi-objective grey wolves optimization method was used to find the neural network model. Serraye *et al*.[12] evaluated the strength of self-compacting concrete with silica fume based on neural network models. Paulson *et al*.[13] conducted experimental studies about the strength of silica fume blended concrete. Moreover, they evaluated the strength using a neural network. García *et al*.[14] evaluated the strength of ultra-high-performance concrete using an artificial neural network. Olden algorithm was used to analyze the dependence of strength on components.

Based on the literature study, we can find although many studies have been performed about strength evaluations, these previous studies show some weak points. First, previous studies mainly focused on binary concrete, i.e., concrete containing fly ash or silica fume. The strength evaluations of ternary concrete containing fly ash and slag together are seldom considered. Second, the neural network model consists of the input layer, output layer, and hidden layer. The number of neurons in the hidden layer has a significant impact on the performance of neural network. Previous studies pay marginal attention to the number of neurons in the hidden layer.

To conquer the weak points of previous studies, this study proposed the model of a neural network to evaluate the strength development of blended concrete containing fly ash and silica fume. The effect of the number of neurons in the hidden layer on the prediction results is discussed. The fly ash and silica fume replacement content and the benefit of fly ash and silica fume combinations are clarified based on parameter analysis.

2. Neural network model

2.1 Experimental data collections

Lam *et al*.[15] made a systematical study about the strength development of composite concrete containing fly ash and silica fume. The mixtures and results of strength are shown in Table 1. Three water/binder ratios, such as 0.3, 0.4, and 0.5, were used. The fly ash replacement contents ranged from low replacement (15%) to high replacement (55%). To improve the early age strength of fly ash concrete, 5% silica fume was used. The strength of concrete was measured from early age three days to late age 180 days. The long-term strength can reflect the pozzolanic reaction of fly ash. Summarily, the experimental data covers ordinary-strength (water/binder ratio 0.5) and high strength (water/binder ratio 0.3), low fly ash content(15%) and high fly ash content (55%), early-age (3 days) and late age (180 days).

Table 1 Mixtures and strength of specimens

Water/binder ratio	Fly ash/binder ratio	Silica fume/binder ratio	3 days strength (MPa)	7 days strength (MPa)	28 days strength (MPa)	56 days strength (MPa)	90 days strength (MPa)	180 days strength (MPa)
0.3	0	0	64.9	75.5	86.8	87.2	95.7	97.7
0.3	0.15	0	52.1	66.4	86	94.8	99.6	106.3
0.3	0.25	0	48	65.7	85.4	90.4	95.4	107.8
0.3	0.45	0	34.1	49.2	71.8	85.4	87.7	97.7
0.3	0.55	0	22.3	36.4	57.4	66.6	72.8	79.9
0.3	0	0.05	58.3	75.5	87.8	93.1	93.6	99.3
0.3	0.2	0.05	46.3	65.6	78.5	85.8	90.3	95.9
0.3	0.4	0.05	30.5	48.6	71.1	80	83.4	88.3
0.4	0	0	35	48.4	60.7	67.1	70.5	70.6
0.4	0.15	0	29.3	39.9	56	63.4	68.5	72.1
0.4	0.25	0	24.7	33.7	49.3	60.8	66.2	70.2
0.4	0.45	0	14.5	20.3	43.9	54.1	61.2	63.7
0.4	0.55	0	13.6	19.8	37.3	47.1	52.9	63.2
0.4	0	0.05	37.3	53	69.4	72.1	73.7	74.5
0.4	0.2	0.05	28.9	42.1	62.3	69.9	72.4	76
0.4	0.4	0.05	14.5	20.5	44.6	55.3	59.1	68.4
0.5	0	0	26.1	36.9	50.8	57.1	58.1	60.6
0.5	0.15	0	23.3	32.3	48.9	55.7	62.6	64.8
0.5	0.25	0	18.4	26.2	41.7	49.1	53.7	57.9
0.5	0.45	0	13.4	18.4	35.6	47	54.1	56.6
0.5	0.55	0	7.8	11.3	24	33.7	41.4	48.3
0.5	0	0.05	27.4	39.2	57.3	59.6	67.3	66.3
0.5	0.2	0.05	20.1	30.6	52.9	60.7	63.7	68
0.5	0.4	0.05	11.4	16.8	38.7	45.9	48.7	58.4

2.2 Neural network with four neurons in the hidden layer

The experimental data in section 2.1 can be used to make neural network model. The Neural network consist of three layers, i.e., input layer, hidden layer, and output layer. In this study, the input layer includes four variables, such as fly ash content, silica fume content, water/binder ratio, and ages. The output layer is compressive strength. The hidden layer consists of some neurons. The number of neurons in the hidden layer has a significant impact on the prediction results. In this study, the number of neurons in the hidden layer is confirmed based on trial calculations. Section 2.2 firstly sets the number of neurons in the hidden layer as 4 (shown in Figure 1).

In the training process, all the experimental data are divided into three groups, i.e., training group, validation group, and test group. The ratios of the training group, validation group, and testing group to total data are 70%, 15%, and 15%. Based on thebackpropagation algorithm, the values of the matrix in the hidden layer can be found. Figure 2 shows analysis results versus experimental results. The correlation coefficients of the training group, validation group, and test group are 0.993, 0.983, and 0.985, respectively. The integral correlation coefficient between analysis results and experimental results is 0.991. Generally, the analysis results show good agreement with experimental results.

Figure 3 shows the trend of parameter analysis. As shown in the Figure 3-a and Figure 3-b, at early ages, as the fly ash content increases, the strength of concrete decreases. This is because fly ash reacts much slower than cement. Moreover, at late ages, the strength difference becomes not obvious due to the contributions of fly ash pozzolanic reaction. In addition, when the water/binder ratio increases, the strength of concrete decreases due to more pore space. Figure 3-c shows when silica fume is used to replace partial fly ash, the strength of concrete increases because silica fume has higher reactivity than fly ash.

Lam *et al*.'s test found the strength crossover between fly ash blended concrete and plain concrete[15]. However, four neurons hidden layer neural network can not reflect the strength crossover between fly ash blended concrete and plain concrete. In other words, to improve the prediction accuracy, the structures of neural network should be modified.

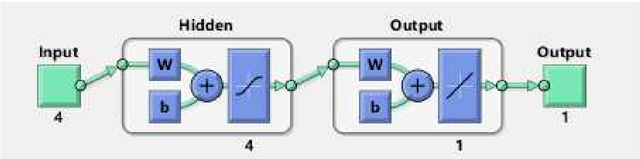


Fig. 1 Set up of 4 neurons hidden layer neural network

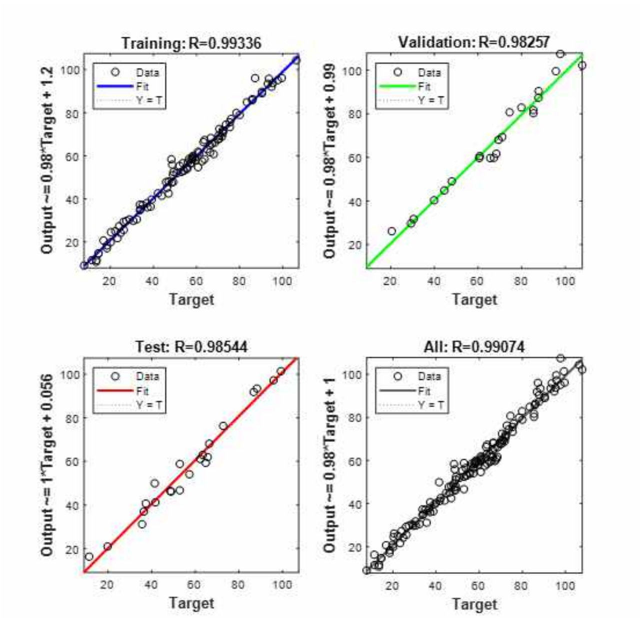
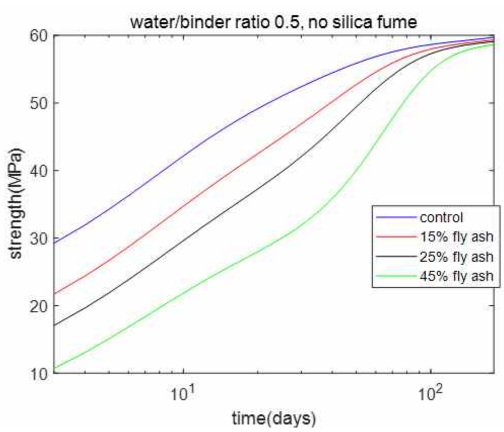
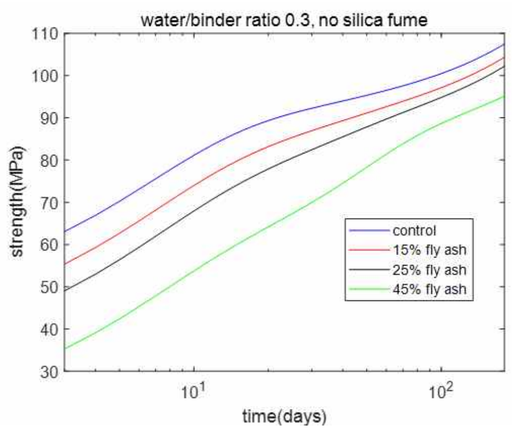


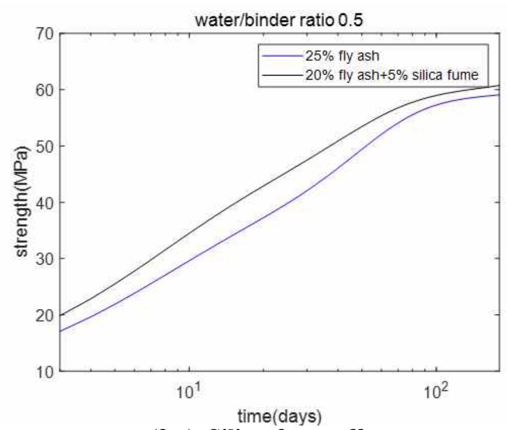
Fig. 2 Analysis results of 4 neurons hidden layer neural network



(3-a) Different fly ash contents of water/binder ratio 0.5



(3-b) Different fly ash contents of water/binder ratio 0.3



(3-c) Silica fume effect

Fig. 3 Trends of analysis results of 4 neurons hidden layer neural network

2.3 Neural network with 5 neurons in the hidden layer

Section 2.2 shows when the number of neurons in the hidden layer is 4, the neural network can not reflect the strength crossover between fly ash blended concrete and plain concrete. To improve the prediction accuracy, this section improves the number of neurons in the hidden layer from 4 to 5(shown in Figure 4).

Based on the backpropagation algorithm, the values of the matrix in the hidden layer are determined. Figure 5 shows analysis results versus experimental results. The correlation coefficients of the training group, validation group, and test group are 0.994, 0.986, and 0.986, respectively. The integral correlation coefficient between analysis results and experimental results is 0.991. Based on the comparisons of results shown in Figure 5 and Figure 2, we can find five neurons hidden layer neural network shows more accurate evaluation than four neurons hidden layer neural network.

Figure 6 shows the trend of parameter analysis. As shown in Figure 6-a, when the water/binder ratio is 0.5, fly ash blended concrete shows lower strength than plain concrete. Strength crossover does not occur for concrete with a water/binder ratio is 0.5. Moreover, As shown in Figure 6-b, when the water/binder ratio is 0.3, at early-ages, fly ash blended concrete shows lower strength than plain concrete, while at late ages, fly ash blended concrete shows higher strength than plain concrete. In other words, strength crossover occurs for concrete with a water/binder ratio is 0.3. In addition, as the replacement content of fly ash increases, the time of strength crossover retards. This is because the degree of reaction of fly ash decreases as the replacement of fly ash increases. Based on the comparisons of results shown in Figure 6 and Figure 3, we can find five neurons hidden layer neural network shows a more reasonable trend than four neurons hidden layer neural network.

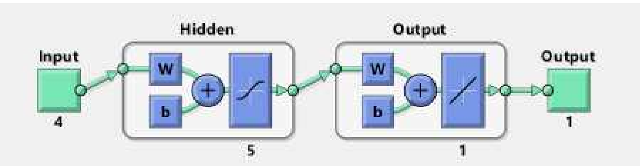


Fig. 4 Set up of 5 neurons hidden layer neural network

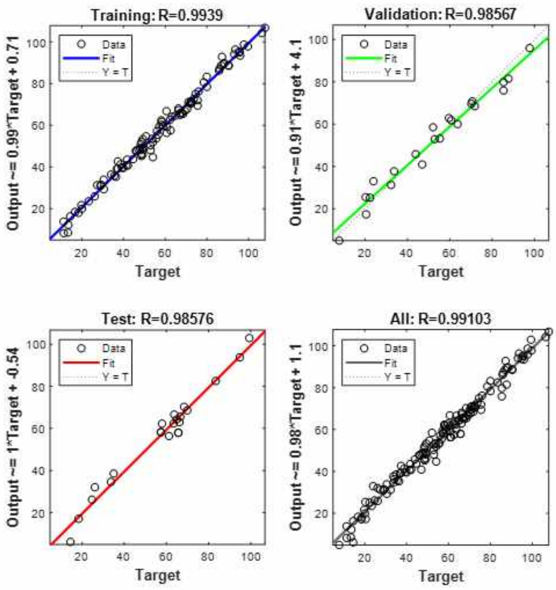
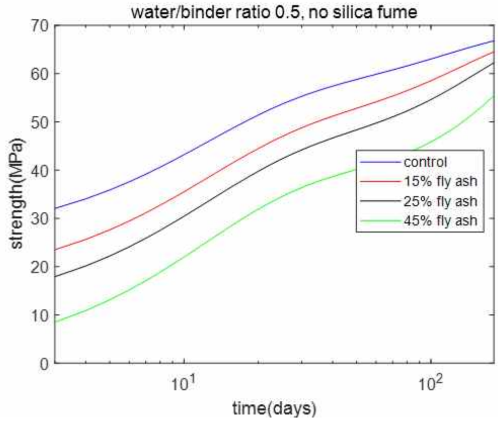
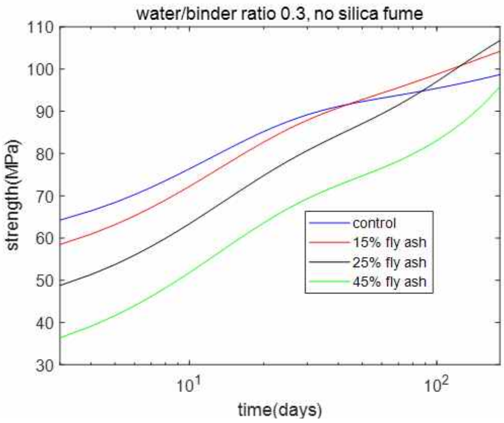


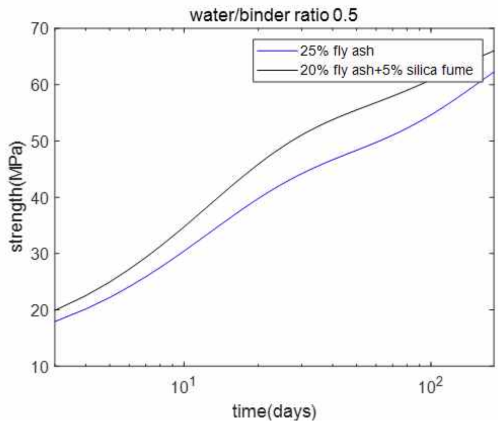
Fig. 5 Analysis results of 5 neurons hidden layer neural network



(6-a) Different fly ash contents of water/binder ratio 0.5



(6-b) Different fly ash contents of water/binder ratio 0.3



(6-c) Silica fume effect

Fig. 6 Trends of analysis results of 5 neurons hidden layer neural network

3. Conclusions

This study shows neural network models for the predictions of the strength of fly ash and silica fume composite concrete. Two models with different neurons in the hidden layer are proposed. The main findings are shown as follows:

First, when the number of neurons in the hidden layer is set as 4, the correlation coefficients of the training group, validation group, and test group are 0.993, 0.983, and 0.985, respectively. The integral correlation coefficient between analysis results and experimental results is 0.991. Generally, the analysis results show good agreement with experimental results. However, the strength crossover between fly ash blended concrete and plain concrete can not be reflected.

Second, when the number of neurons in the hidden layer is set as 5, the correlation coefficients of the training group, validation group, and test group are 0.994, 0.986, and 0.986, respectively. The integral correlation coefficient between analysis results and experimental results is 0.991. Moreover, strength crossover does not occur for concrete with a water/binder ratio is 0.5. Strength crossover occurs for concrete with a water/binder ratio is 0.3. In addition, as the replacement content of fly ash increases, the time of strength crossover retards.

Summarily, the neural network-based model is valuable for design sustainable composite concrete containing silica fume and fly ash. Five neurons hidden layer neural network shows more reasonable trend than four neurons hidden layer neural network.

References

[1] X.-Y. Wang, 2021, Evaluation of the Phase Assemblage and Strength Progress of Hybrid Blends of Cement and Fly Ash Using Kinetic and Thermodynamic Hydration Model, Ceramics – Silikaty 1-9.

[2] E. Harrison, *et al*., 2020, Recycling of waste glass as aggregate in cement-based materials, Environmental Science and Ecotechnology 4 100064.

[3] X.-Y. Wang, 2021, Evaluation of the properties of cement–calcined Hwangtoh clay–limestone ternary blends using a kinetic hydration model, Construction and Building Materials 303 124596.

[4] M.Y. Xuan, *et al*., 2021, Effect of Cement Types and Superabsorbent Polymers on the Properties of Sustainable Ultra-High-Performance Paste, Materials (Basel) 14(6) 1497-1517.

[5] S. Tian, *et al*., 2021, Global patterns and changes of carbon emissions from land use during 1992–2015, Environmental Science and Ecotechnology 7 100108.

[6] X. Zhao, *et al*., 2021, On the applicability of the 'humic acids' nomenclature from natural ecosystems to engineering sciences, Environmental Science and Ecotechnology 6 100082.

[7] Y. Han, *et al*., 2021, Performance and sustainability of quaternary composite paste comprising limestone, calcined Hwangtoh clay, and granulated blast furnace slag, Journal of Building Engineering 43 102655.

[8] M. Abu Yaman, *et al*., 2017, Predicting the ingredients of self compacting concrete using artificial neural network, Alexandria Engineering Journal 56(4) 523-532.

[9] G. Pazouki, *et al*., 2021, Predicting the compressive strength of self-compacting concrete containing Class F fly ash using metaheuristic radial basis function neural network, Structural Concrete 1-23.

[10] K.T. Nguyen, *et al*., 2020, Analyzing the compressive strength of green fly ash based geopolymer concrete using experiment and machine learning approaches, Construction and Building Materials 247 118581.

[11] A. Behnood, E.M. Golafshani, 2018, Predicting the compressive strength of silica fume concrete using hybrid artificial neural network with multi-objective grey wolves, Journal of Cleaner Production 202 54-64.

[12] M. Serraye, *et al*., 2021, Prediction of Compressive Strength of Self-Compacting Concrete (SCC) with Silica Fume Using Neural Networks Models, Civil Engineering Journal 7(1) 118-139.

[13] A.J. Paulson, *et al*., 2019, APPLICATION OF NEURAL NETWORK FOR PREDICTION OF COMPRESSIVE STRENGTH OF SILICA FUME CONCRETE, International Journal of Civil Engineering and Technology 10 1859–1867.

[14] J. Abellán-García, 2021, Artificial Neural Network Model for Strength Prediction of Ultra-High-Performance Concrete, ACI Materials Journal 118(4) 1-12.

[15] L. Lam, *et al*., 1998, EFFECT OF FLY ASH AND SILICA FUME ON COMPRESSIVE AND FRACTURE BEHAVIORS OF CONCRETE, Cement and Concrete Research 28(2) 271-283.