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Modeling slump flow of concrete using second-order regressions and artificial neural networks

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Abstract

High-performance concrete (HPC) is a highly complex material, which makes modeling its behavior a very difficult task. Several studies have independently shown that the slump flow of HPC is not only determined by the water content and maximum size of coarse aggregate, but that is also influenced by the contents of other concrete ingredients. In this paper, the methods for modeling the slump flow of concrete using second-order regression and artificial neural network (ANN) are described. This study led to the following conclusions: (1) The slump flow model based on ANN is much more accurate than that based on regression analysis. (2) It has become convenient and easy to use ANN models for numerical experiments to review the effects of mix proportions on concrete flow properties.

Keywords: Concrete; Workability; Modeling; Artificial neural network; Regression

1. Introduction

Workability of concrete is defined as the property determining the effort required to manipulate a freshly mixed quantity of concrete with minimum loss of homogeneity [1]. The term manipulate includes the early-age operations of placing, compacting, and finishing. The effort required to place a concrete mixture is determined largely by the overall work needed to initiate and maintain flow, which depends on the rheological property of the lubricant (the cement paste) and the internal friction between the aggregate particles on the one hand, and the external friction between the concrete and the surface of the framework on the other. Consistency, measured by slump-cone test, is used as a simple index for mobility or flowability of fresh concrete. In the slump-cone test, the slump can be deduced by measuring the drop from the top of the slumped fresh concrete, and the slump flow by measuring the diameter of it. The effort required to compact concrete is governed by the flow characteristics and the ease with which void reduction can be achieved without destroying the stability under pressure. Stability is an index of both the water-holding capacity (the opposite of bleeding) and the coarse-aggregate-holding capacity (the opposite of segregation) of a plastic concrete mixture. A qualitative measure of these characteristics is generally covered by the term cohesiveness [1].

The significance of workability in concrete technology is obvious. It is one of the key properties that must be satisfied. Regardless of the sophistication of the mix design procedure used and other considerations, such as cost, a concrete mixture that cannot be placed easily or compacted fully is not likely to yield the expected strength and durability characteristics [1].

High-performance concrete (HPC) has been used in the concrete construction industry after well-known high strength concrete (HSC) in recent years. Although, there are various definitions of HPC in many countries, the essence of HPC is emphasized on such characteristics as high strength, high workability with good consistency, dimensional stability and durability. It is generally accepted that a concrete having a high workability with

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good consistency at the fresh state and a high strength at the hardened state can exhibit properties of high dimensional stability and high durability [1].

In addition to four basic ingredients of the conventional concrete, i.e., Portland cement, fine and coarse aggregates and water, the making of HPC needs to incorporate the supplementary cementitious materials such as fly ash and blast furnace slag, and chemical admixture and superplasticizer. The use of fly ash and blast furnace slag plays an important role in contributing to a better workability and low slump loss rates of HPC, because of the mutual containment with surface lubrication and the ball-bearing effects among the fly ash and micro fine materials. In most cases there is also the economic benefit of the price differential between cement and the supplementary cementitious material. In addition, partial replacement of cement nearly always allows a significant reduction in the dosage of the superplasticizer, which is a particularly expensive ingredient [2,3]. Besides, partial replacement of cement by combined pozzolanic industrial byproducts may provide a more efficient use of cement, with less energy consumed and less hazardous emissions released in the air.

Most established material workability behavior models are based on extensive data and knowledge of materials existing in a particular region or country. Several studies have presented results from laboratory programs of modeling slump. These models are not adequate for modeling the many factors that need to be considered when designing HPC mixes. For example, advances in recent years have been assisted by the use and understanding of chemical admixtures, notably superplasticizers, and cement replacement materials, notably fly ash, blast furnace slag, etc. Modeling workability behavior for the concrete containing these materials is inherently more difficult than for the concrete without them.

In recent years, applying artificial neural networks (ANN) in modeling material behavior has received extensive attention [4–9]. A neural network model is a computer model, whose architecture essentially mimics the learning capability of the human brain. However, little research has been done on modeling workability of concrete using neural networks. Nehdi et al. [10] demonstrated that ANN methods can accurately predict the slump flow, filling capacity, and segregation test results of self-compacting concrete. Bai et al. [11] developed ANN models that provide effective predictive capability in respect of the workability of concrete. The results show that the models are reliable and accurate. Ji et al. [12] employed five parameters (nominal water–cement ratio, equivalent water–cement ratio, average paste thickness, fly ash-binder ratio, and grain volume fraction of fine aggregates) to build ANN models predicting strength and slump of concrete. Yeh [13] demonstrated the abilities of artificial neural networks to represent the effects of each material component on concrete slump.

In this paper, the slump flow is a function of the content of all concrete ingredients, including cement, fly ash, blast furnace slag, water, superplasticizer, coarse aggregate, and fine aggregate. We will compare ANN and second-order regressions in modeling concrete slump flow, and explore these models with response trace plots to observe the slump flow behavior.

2. Concrete ingredients and workability

For modeling workability behavior of HPC, an understanding of the characteristics of the primary concrete ingredients is necessary [1].

2.1. Water content

ACI 211.1 (Standard practice for selecting proportions for normal, heavyweight, and mass concrete) assumes that, for a given maximum size of coarse aggregate, the slump or consistency of concrete is a direct function of the water content; i.e., within limits it is independent of other factors such as aggregate grading and cement content.

2.2. Superplasticizer

When the water content of a concrete mixture is held constant, the addition of a superplasticizer will increase the consistency.

2.3. Pozzolanic admixtures

Pozzolanic admixtures tend to improve the cohesiveness of concrete. Fly ash, when used as a partial replacement for fine aggregate, generally increases the consistency at a given water content.

2.4. Cement content

Concretes containing a very high proportion of cement show excellent cohesiveness, but tend to be sticky. At a given water content, a considerable lowering of the cement content tends to produce harsh mixtures, with poor cohesiveness.

2.5. Aggregate characteristics

Very fine sands require more water for a given consistency; alternatively, they will produce harsh and unworkable mixtures at a water content that might have been adequate with coarser sands. Also, the particle size of coarse aggregate influences the water requirement for a given consistency.

3. Architecture of artificial neural networks

Artificial neural networks can learn complex input–output mappings. The mappings are not specified, but learned. The learning process is used to determine proper interconnection weights, and the network is trained to properly associate the inputs with their corresponding outputs. The basic strategy for developing a neural-based model of material behavior is to train a neural network on the results of a series of experiments on a material. If the experimental results contain the relevant information about the material behavior, then the trained neural network would contain sufficient information about the material behavior to quality as a material model. Such a trained neural network not only would be able to reproduce the experimental results it was trained on, but through its generalization capability it should be able to approximate the results of other experiments [4].

Most research that used ANN to model material behavior is based on back-propagation networks (BPN). The BPN learns by comparing its output of each input pattern with a target output of that pattern, then calculating the error and propagating an error function backward through the net. A thorough treatment of BPN is beyond the scope of this paper. The basic algorithms of back-propagation have been covered widely [14,15].

To run the network after it is trained, the values for the input parameters for the project are presented to the network. The network then calculates the node outputs by using the existing weight values and thresholds developed in the training process. To test the accuracy of the trained network, the coefficient of determination R^2 is adopted. The coefficient is a measure of how well the independent variables considered accounts for the measured dependent variable, and denotes the strength of the linear association between x and y. It is the ratio of the explained variation to the total variation, and such that $0 < R^2 < 1$; the higher the value of R^2, the better the prediction relation. It is useful, because it gives the proportion of the variance (fluctuation) of one variable that is predictable from the other variable.

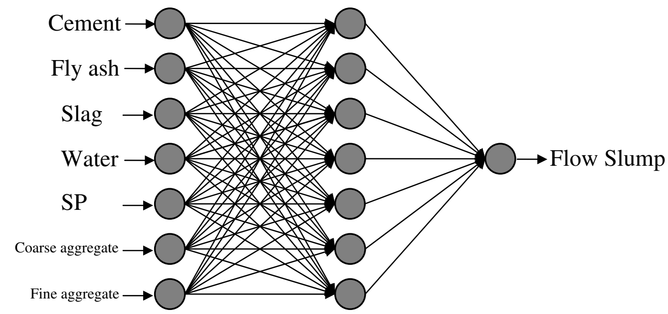

Fig. 1. The architecture of the system based on BPN.

Table 1
Ranges of components of data sets

Component content	Specific weight	Minimum weight (kg/m^3)	Maximum weight (kg/m^3)
Cement	3.15	137	374
Fly ash	2.22	0	193
Slag	2.85	0	260
Water	1.00	160	240
Superplasticizer	1.20	4.6	18.8
Coarse aggregate	2.65	708	1049
Fine aggregate	2.66	650	902

Table 2
Ranges of ratio of data sets

Ratio	Minimum	Maximum
Water/cement	0.37	1.46
Water/binder	0.25	0.70
Water/solid	0.12	0.54
SP/binder	0.01	0.03
Fly ash/binder	0.00	0.55
Slag/binder	0.00	0.61
(Fly ash + slag)/binder	0.00	0.68
Aggregate/ binder	2.72	6.86
Fine aggregate/coarse aggregate	0.39	0.51

4. System models and data sets

4.1. System models

In this approach, the workability of concrete is a function of the following seven input features: cement (kg/m^3), fly ash (kg/m^3), blast furnace slag (kg/m^3), water (kg/m^3), superplasticizer (kg/m^3), coarse aggregate (kg/m^3), and fine aggregate (kg/m^3). The output of the system is slump flow (cm) of the fresh concrete. The architecture of the system based on BPN is shown in Fig. 1.

4.2. Data sets

Because superplasticizer has a significant effect on workability while its chemical composition is various, the data for modeling workability were collected from the same lab by the author. Seventy-eight various mix proportions were performed to collect the data. These data were used to build the workability model. Tables 1 and 2 present the general details of the concretes evaluated in this study. The database of 78 records, each containing seven components of the input vector, one output value, and a slump flow (from 20 to 70 cm). As in the slump-cone test the slump flow can be deduced by measuring the diameter of the slumped fresh concrete, the minimum slump flow is the bottom diameter (20 cm) of the slump-cone.

The database was split in such a way that all the records were simply shuffled using a random sampling, dividing them into four data groups, i.e., A, B, C, and D group. Four models (Model A, Model B, Model C, and Model D) were developed based on these groups. For example, in Model A, data group A was assigned as the testing set, and the rest three data groups (B, C, and D) were assigned as the training set. The numbers of training example and testing example for these models are listed in Table 3. The four models have the same architecture, but different regression coefficients for regression analysis and connection weightings for neural networks since each was trained using a partially different set of data.

Table 3
The results of slump flow model of second-order regressions

Model	Training set				Testing set			
	Data group	Number of data	R^2	RMSE	Data group	Number of data	R^2	RMSE (cm)
Model A	B, C, D	58	0.8219	9.88	A	20	0.1313	15.15
Model B	A, C, D	58	0.7159	11.50	B	20	0.4655	10.11
Model C	A, B, D	58	0.8429	9.00	C	20	0.3044	22.29
Model D	A, B, C	60	0.7174	11.15	D	18	0.4461	10.81
Integral testing set					A, B, C, D	78	0.3230	15.57

5. Modeling slump flow using second-order regressions

In the conventional material modeling process, regression analysis is an important tool for building a model. The types of second-order regression formulas adopted were as follows:

$$y = \sum_{i=1}^{q} \beta_i x_i + \sum_{i<j}^{q} \sum \beta_{ij} x_i x_j \tag{1}$$

where x_i = the ith component content; β_i,β_{ij} = the regression coefficients.

In this study, seven component contents of HPC were employed to build the regression formulas. Table 3 shows the coefficients of determination (R^2) and the root mean squared error (RMSE). The coefficient of determination R^2 is 0.32 for the integral testing set, which included the testing set of Model A, B, C, and D. The coefficients indicate a low correlation.

The predicted values of these four models compared with the values actually observed in lab for the training examples and testing examples are shown in Figs. 2 and 3. They also verify that when the testing sets are used instead of the training sets as the basis for evaluating the slump flow models derived with second-order regressions, the predictions become much more inaccurate for all the models used in this study.

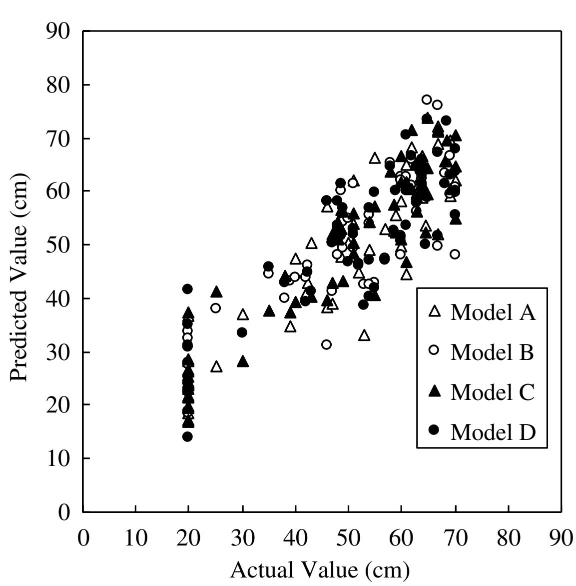

Fig. 2. Predicted slump flow values using second-order regression vs. laboratory test values (training set).

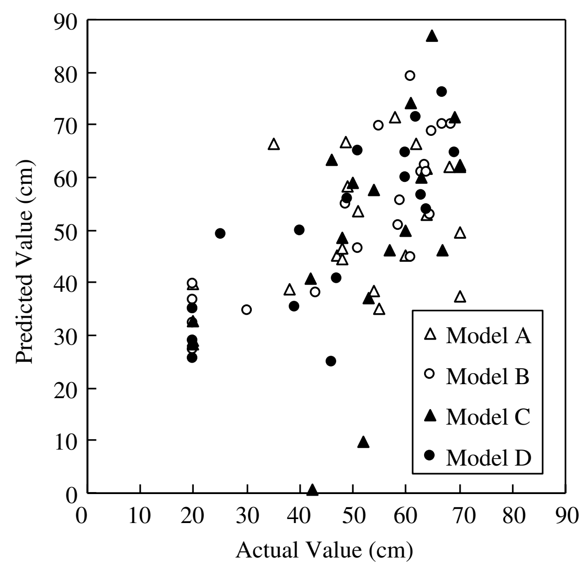

Fig. 3. Predicted slump flow values using second-order regression vs. laboratory test values (testing set).

6. Modeling slump flow using artificial neural networks

The neural network developed in the investigation has seven units in the input layer and one unit in the output layer. The values of network parameters considered in this approach are as follows: number of hidden layers = 0, 1, and 2; number of hidden units = 5, 7, 10, and 14; learning rate = 0.1, 0.3, 1.0, and 3.0; momentum factor = 0.0, 0.25, 0.5, and 0.75; and learning cycles = 500, 1000, 2000, and 5000 (each cycle covers the entire database available for training). Based on the error of integral testing set, the best network parameters are as follows: number of hidden layers = 1; number of hidden units = 7; learning rate = 1.0; momentum factor = 0.5; and learning cycles = 2000.

Table 4 shows the coefficients of determination (R^2) and the roots of mean squared error (RMSE). The coefficient of determination R^2 is 0.72 for the integral testing set, which included the testing set of Model A, B, C, and D. The coefficients indicate a significant high correlation.

The predicted values of these four models compared with the values actually observed in lab for the training

Table 4
The results of slump flow model of artificial neural networks

Model	Training set				Testing set			
	Data group	Number of data	R^2	RMSE	Data group	Number of data	R^2	RMSE (cm)
Model A	B, C, D	58	0.8976	5.47	A	20	0.6960	9.93
Model B	A, C, D	58	0.8266	6.53	B	20	0.8127	9.10
Model C	A, B, D	58	0.8606	6.16	C	20	0.7751	7.51
Model D	A, B, C	60	0.8055	6.82	D	18	0.8032	8.14
Integral testing set					A, B, C, D	78	0.7240	8.51

examples and testing examples are shown in Figs. 4 and 5. They also verify that when the testing sets are used instead of the training sets as the basis for evaluating the slump flow models derived with ANN, the predictions remain accurate for all the models used in this study.

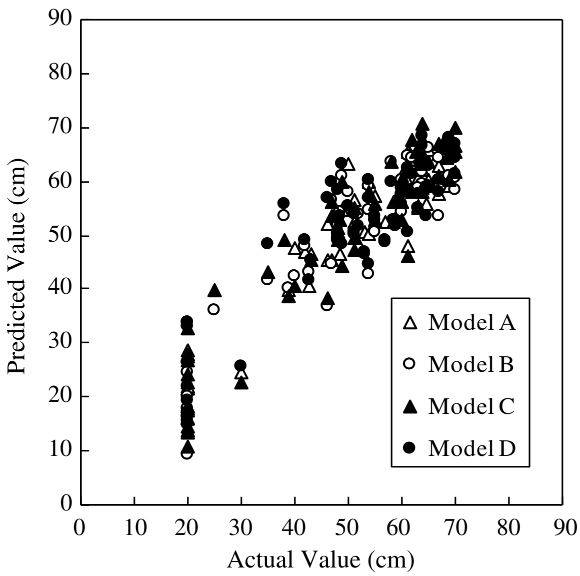

Fig. 4. Predicted slump flow values using artificial neural networks vs. laboratory test values (training set).

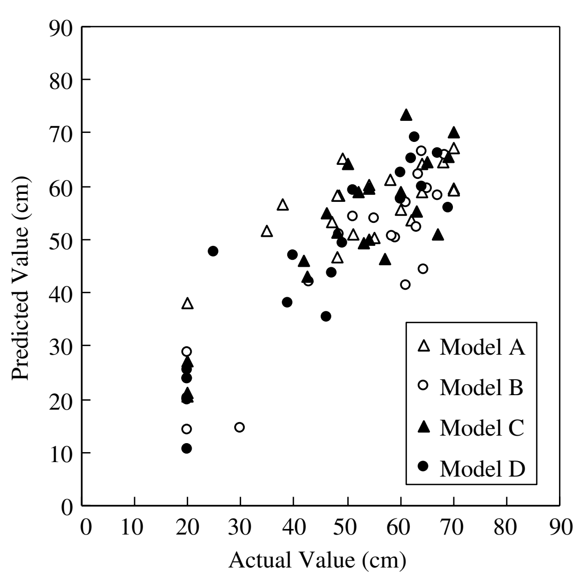

Fig. 5. Predicted slump flow values using artificial neural networks vs. laboratory test values (testing set).

7. Comparison between regressions and artificial neural networks

The comparison between Tables 3 and 4 shows that the neural network models ($R^2 = 0.72$) are supported better by the experimental data than the regression analysis ($R^2 = 0.32$). It is shown that although the use of the models is not as simple as that of the regression formulas, they provide a much more accurate tool for the prediction of concrete slump flow.

8. Exploration of slump flow models

After the neural network model mentioned above has been built based on the experimental dataset, the predictions of the response of other concrete mixtures were therefore possible. The response trace is a plot of the estimated response values as we move away from a "reference mixture" and along the component axes depicting the content of components. Consider the ith component and suppose we move away from the reference mixture by changing the proportion of this component by an amount Δ_i (note that we could make Δ_i either positive or negative). Along the ith axis as the value of x_i either increases or decrease, the values of other component proportions x_j, $j \neq i$, either decrease or increase, but the relative proportions for these other components remain the same [16].

To evaluate the effects of each components to concrete slump flow, seven response trace plots are gotten based on the reference mixture listed in Table 5. The maximum and minimum contents in Table 5 are the same as those indicated in Table 1. The reference mixture is the overall center of the data set. Because according to these plots only the contents of fly ash, water, and superplasticizer have strong effects on slump flow, only the plots derived from these three components are shown in Figs. 6–8.

The response trace plots derived with second-order regressions are confined to simple second-order curves, but those derived with artificial neural networks are more delicate. Because the coefficient of determination of artificial neural networks (0.72) are much higher than second-order

Table 5
Reference mixture of the response trace plot of slump flow

	Cement (kg/m^3)	Fly ash (kg/m^3)	Slag (kg/m^3)	Water (kg/m^3)	SP (kg/m^3)	CA (kg/m^3)	Sand (kg/m^3)	Volume (m^3)
Maximum	374	193	260	240	18.8	1049	902	
Minimum	137	0	0	160	4.6	708	650	
Middle	256	97	130	200	11.7	879	776	1.030
Adjusted	248	94	126	194	11.4	853	753	1.000

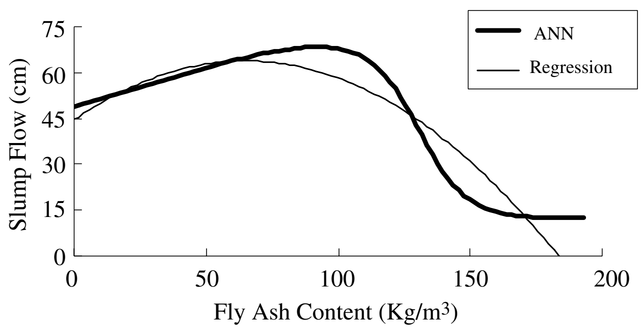

Fig. 6. Response trace plot of slump flow along the component axis of fly ash.

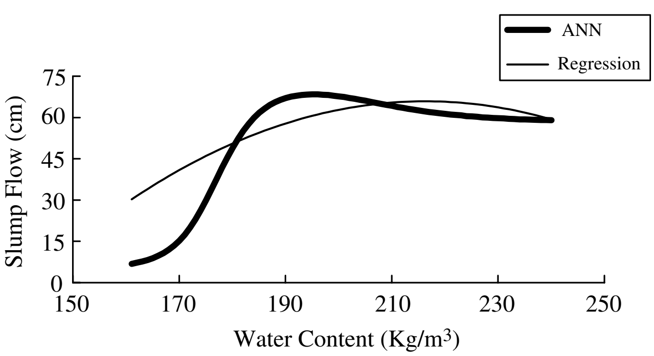

Fig. 7. Response trace plot of slump flow along the component axis of water.

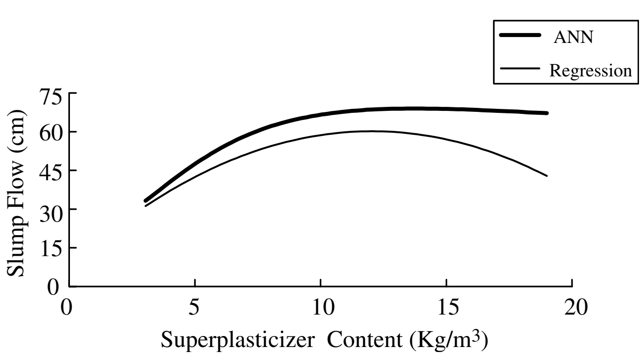

Fig. 8. Response trace plot of slump flow along the component axis of SP.

regressions (0.32), that the response trace plots derived with ANN should be much more accurate than those derived with regressions.

The following conclusions can be drawn from the response trace plots derived with artificial neural networks:

1. The slump flow increases and then decreases very sharply as the fly ash content increases at the level of 95 kg/m^3 and above (refer to Fig. 6). The plot showed that concretes containing a very high proportion of fly ash might show excellent consistency, but tend to be sticky. Therefore, the slump flow decreases very sharply as the fly ash content increases at the high level.
2. The slump flow increases very sharply and then decreases very slightly as the water content increases at the level of 195 kg/m^3 and above (refer to Fig. 7). The plot showed that the slump flow or consistency of concrete is proportional to the water content within the limit under the level of 195 kg/m^3. The reason why the slump flow decreases very slightly as the water content exceeds one level could be that the plastic concrete mixture loses a little water-holding capacity (the opposite of bleeding), when it contains too much water.
3. The plot of superplasticizer is similar to that of water. The slump flow increases very sharply and then decreases very slightly as the superplasticizer content increases at the level of 10 kg/m^3 and above (refer to Fig. 8). The plot showed that when the water content of a concrete mixture is held constant, the addition of a superplasticizer will increase the consistency until it reaches the limit (about 10 kg/m^3).

9. Conclusions

Because of the broad variation in chemical compositions and physical characteristics of concrete materials, it is usually difficult to provide an accurate model that is suitable to predict the workability of the HPC. This paper is aimed at demonstrating the possibilities of adapting second-order regressions and artificial neural networks to model the slump flow of the concrete. The method presented facilitates the development of more accurate models of the behavior of fresh concrete. The proposed methodology provides a guideline to model complex material behaviors using only a limited amount of experimental data.

This study led to the following conclusions:

1. The coefficient of determination R^2 (0.72) of slump flow model of ANN is much greater than that (0.32) of second-order regression. Therefore, the slump flow model based on ANN is much more accurate than the model based on the regression analysis.
2. The slump flow can be calculated using the models built with this methodology. It becomes convenient and easy

to use these models for numerical experiments to review the effects of each variable on the mix proportions.

3. Using response trace plots, it is found that the slump flow increases and then decreases sharply as the fly ash content increases; increases sharply and then decreases slightly as the water content increases; and increases sharply and then decreases slightly as the superplasticizer content increases, at one level and above.
4. The response trace plots of slump flow derived with second-order regressions are confined to simple second-order curves, while those derived with artificial neural networks are more delicate; therefore, the latter are potentially more accurate.

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