Computers and Concrete, Vol. 5, No. 1 (2008) 1-20
DOI: http://dx.doi.org/10.12989/cac.2008.5.1.001

Prediction of workability of concrete using design of experiments for mixtures

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(Rceived March 20, 2007, Accepted November 30, 2007)

Abstract. In this study, the effects and the interactions of water content, SP-binder ratio, and water-binder ratio on the workability performance of concrete were investigated. The experiments were designed based on flatted simplex-centroid experiment design modified from standard simplex-centroid one. The data gotten from the design was used to build the concrete slump model using neural networks. Research reported in this paper shows that a small number of slump experiments can be performed and meaningful data obtained with the experiment design. Such data would be suitable for building slump model using neural networks. The trained network can be satisfactorily used for exploring the effects of the components and their interactions on the workability of concrete. It has found that a high water content and a high SP/b ratio is essential for high workability, but achieving this by increasing these parameters will not in itself guarantee high workability. The w/b played a very important role in producing workability and had rather profound effects; however, the medium value about 0.4 is the best w/b to reach high slump without too much effort on trying to find the appropriate water content and SP/b.

Keywords: fly ash; superplasticizer; water-binder ratio; slump; workability; artificial neural networks; design of experiments.

1. Introduction

The workability prediction of concrete is an important piece of information in the design process of concrete mixture. Especially, with the development of concrete technology, high-performance concrete has been increasingly used in practice. There is, therefore, an urgent need to take a consistent and reliable approach to estimate the workability of concrete made with modern materials.

For the first time in the history of concrete technology workable concrete can be made with a water content in the mixture no greater than the amount of water theoretically required to hydrate all the cement present. This is possible because of the outstanding dispersing properties of modern superplasticizers (Aitcin and Neville 1993). For production of high-performance concrete that is characterized by low water-cement ratio and a high dosage of superplasticizer, workability properties may be more complex than that of normal concrete. The effect of superplasticizer on workability has been the subject of many investigations (Faroug, *et al*. 1999, Punkki, *et al*. 1996, Kwan 2000).

When fly ash is incorporated as an additional component, the situation is rendered even more complicated. There are few literatures that unambiguously define the effect of fly ash quantity on the behavior of the fresh concrete mix. Lacking such information, optimization of a concrete mix proportion incorporating fly ash is rarely attained (Olek and Diamond 1989).

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One traditional method of studying the effects of various components is to vary one component at a time and keep all others constant. Response readings are then taken for different levels of this component. This process is repeated by varying other components one by one until all the components have been treated. This approach may not be satisfactory because of interactions between components. Therefore, the method does not seem appropriate to build the model of concrete workability since the interactions between factors of workability are usually very large (Yen 1999). To overcome this difficulty, recourse is made to mixture experiment design.

A mixture experiment design is a special type of response surface experiment design in which the factors are the components of a mixture, and the response is a function of the proportions of each component. These proportionate amounts of each component are typically measured by weight, by volume, by mole ratio, and so forth (Myers and Montgomery 1995).

Although response in experiment design may be able to be modeled by statistical polynomial regression methods, this often involves a complicated approach, particularly for nonlinear relationships and complex interactions for concrete slump. Also, to formulate the statistical regression model, a specific mathematical relationship between the input and output variables must be known, which is usually impossible for concrete slump.

The growing interest in neural networks among researchers is due to its excellent performance in modeling nonlinear multivariate interrelationships, in place of conventional mathematical modeling techniques.

Neural network-based material models differ in some fundamental ways from the traditional mathematical models (Ghaboussi 1991). By comparison, the modeling process in neural networks is more direct, since there is no necessity to specify a mathematical relationship between the input and output variables. Irrelevant input variables are assigned low connection weights. These variables can then be omitted. Other attractions of neural networks are its ability to (1) Construct nonlinear mapping between input and output data. (2) Train correctly even when the data are noisy or imprecise (3) Generalize correct responses even for patterns not included in the training set (Goh 1995, Lippmann 1987). Some recent applications of neural networks in concrete material include those references (Ghaboussi, *et al.* 1991, Oh, *et al.* 1999, Basma, *et al.* 1999, Yeh 1998a, Yeh, 1998b, Yeh 1999, Yeh, *et al.* 2002, Haj-Ali, *et al.* 2001, Nehdi, *et al.* 2001a, Nehdi, *et al.* 2001b, Peng, *et al.* 2002, Kim, *et al.* 2004, Stegemann and Buenfeld 2004, Ji and Lin 2006). However, little research has been done on modeling workability of concrete containing large amount of fly ash and superplasticizer using neural networks associated with experiment design.

In this study, the effects and the interactions of SP-binder ratio, water-binder ratio, and water content on the workability performance of concrete were investigated. The experiments were designed based on a flatted simplex-centroid experiment design modified from standard simplex-centroid one. The data gotten from the design was used to build the concrete slump model using neural networks. Then, the model, trained network, can be used for exploring the effects and interactions on the workability of concrete.

2. Introduction of design of experiments for mixtures

Design of experiments (DOE) is a collection of statistical and mathematical techniques useful for developing and optimizing products and/or processes. The main applications of DOE are in the industrial world, particular in situations where several input variables and their interactions

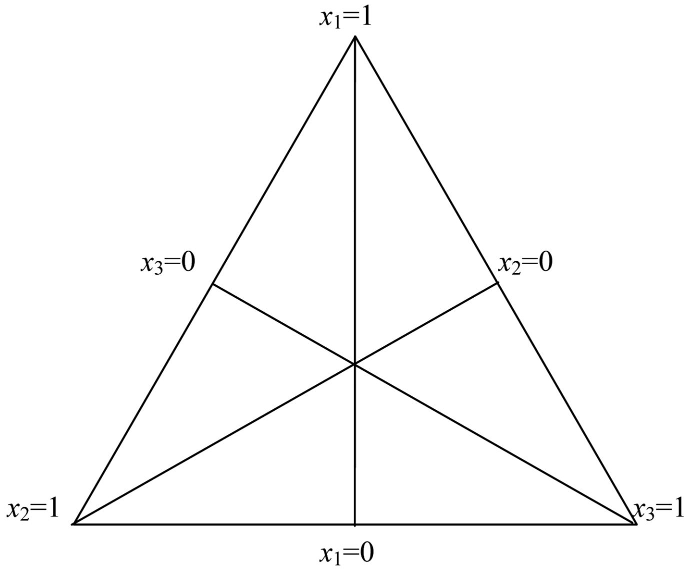

Fig. 1 Simplex coordinate system with three components

potentially influence some performance quality characteristic of the product or process (Myers and Montgomery 1995).

The coordinate system for mixture proportions is a simplex coordinate system. For example, with q=3 components, the experimental region is shown in Fig. 1. Interior points in the triangle represent mixtures in which all three ingredients are present at nonzero proportionate amounts. The centroid of the triangle corresponds to the mixture with equal proportions $x_1 = 1/3, x_2 = 1/3, x_3 = 1/3$ all ingredients. Each of the three vertices in the equilateral triangle corresponds to a pure blend, and each of the three sides of the triangle represents a mixture that has none of one of the three components (Myers and Montgomery 1995).

A q-component simplex-centroid design consists of 2^q–1 distinct design points. These design points are the q permutations of (1, 0, 0, ..., 0) or single-component blends, the $\binom{q}{2}$ permutations of (1/2, 1/2, 0, ..., 0) or all binary mixtures, the $\binom{q}{3}$ permutations of (1/3, 1/3, 1/3, 0, ..., 0), and so forth, and the overall centroid (1/q, 1/q, …, 1/q). For example, a 7-component simplex-centroid design consists of 2^q–1=127 distinct design points, including

seven 1-component blends: (1,0,0,0,0,0,0), (0,1,0,0,0,0,0,0), …, (0,0,0,0,0,0,0,1);
twenty-one 2-component blends: (1/2,1/2,0,0,0,0,0), …, etc;
thirty-five 3-component blends: (1/3,1/3,1/3,0,0,0,0), …, etc;
thirty-five 4-component blends: (1/4,1/4,1/4,1/4,0,0,0), …, etc;
twenty-one 5-component blends: (1/5,1/5,1/5,1/5,1/5,0,0), …, etc;
seven 6-component blends: (1/6,1/6,1/6,1/6,1/6,1/6,0), …, etc;
one 7-component blends: (1/7,1/7,1/7,1/7,1/7,1/7,1/7).

A 3-component simplex-centroid design is illustrated in Fig. 2. Note that the design points are located at the centroid of the (q-1)-dimensional simplex and at the centroids of all the lower-dimensional simplices contained within the (q-1)-dimensional simplex (Myers and Montgomery 1995).

The design points in the simplex-centroid design will support the polynomial

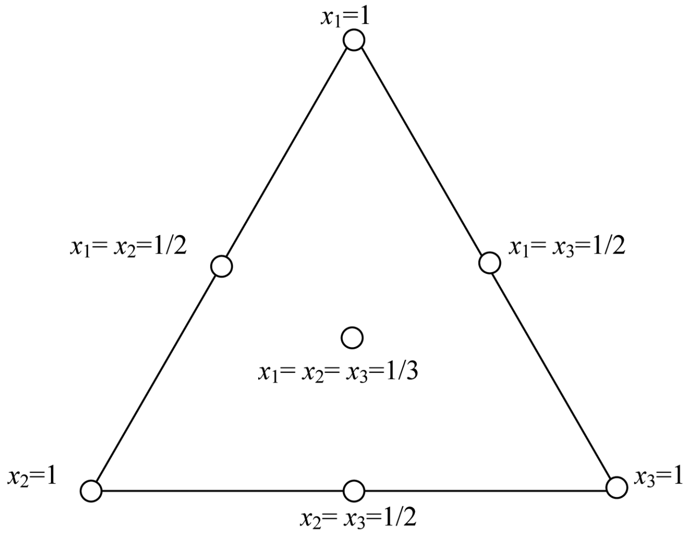

Fig. 2 Simplex-centroid design with three components

$$E(y) = \sum_{i=1}^{q} \beta_i x_i + \sum_{i<}\sum_{j}^{q} \beta_{ij} x_i x_j + \sum_{i<}\sum_{j<}\sum_{k}^{q} \beta_{ijk} x_i x_j x_k + \ldots + \beta_{12\ldots q} x_1 x_2 \ldots x_q \tag{1}$$

which is a qth-order mixture polynomial. For q = 3 components, this model is

$$E(y) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 + \beta_{123} x_1 x_2 x_3 \tag{2}$$

which is the special cubic polynomial from Eq. (1) (Myers and Montgomery 1995).

3. Introduction of artificial neural networks

Neural network simulations represent attempts to mirror biological methods of information processing. The fundamental concept is that of a neuron, a biological cell that receives electrical or chemical inputs from one or many sources and processes those inputs to generate a unique output. The output may, in turn, be passed on to other neurons (Brown 1991). This description of a neuron is excessively simple, but it captures those features that are relevant to neural models of computation. In particular, each computational unit is a simple shareholding device that receives signals from other units and passes a signal on to other units when its threshold is exceeded. Instead of using explicit symbols and operations, the knowledge of the system emerges out of the entire network of neural connections and threshold values. A thorough treatment of the neural network methodology is beyond the scope of this paper. The basic architecture of neural networks has been covered widely (Lippmann 1987).

During training the network performance is monitored by Root-Mean-Square (RMS) to achieve a better understanding of the network performance. Once trained, the values for the input parameters for the project are presented to the network. Then the network calculates the node outputs using the existing weight values and thresholds developed in the training process. The neural network will produce almost instantaneous results of the output for the practical inputs provided. The predictions should be reliable, provided the input values are within the range used in the training set (Goh 1995).

4. Design of experiments for mixtures for concrete slump

There are three steps in the DOE process in this study: initial design, adjusted design, and filtrated design.

4.1. Step 1. Initial design

Because there is a constant volume constraint for concrete mixture design, the experimental design must satisfy

$$V_C + V_F + V_S + V_W + V_{SP} + V_{CA} + V_{FA} = 1000\text{(liter)} \tag{3}$$

where V_C, V_F, V_S, V_W, V_{SP}, V_{CA}, V_{FA} is volume of cement, fly ash, slag, water, SP, coarse aggregate (CA), and fine aggregate (FA).

However, in laboratory, it is easier to perform the mixture test in weight. Therefore, the design variables will be transfer into weight by the following formula:

$$W_i = G_i \cdot V_i \tag{4}$$

where V_i, W_i, G_i is the volume, weight, and specific gravity, respectively.

The lower bound of weight and volume for each component is listed in Table 1. There are 127design points obtained in the step. Some of the mixtures (design points) are listed in Table 2. The concept of initial design is illustrated in Fig. 3. Notice that only 3-component can be illustrated in a 2-dimension figure.

The values in Table 2 are pseudo-component, and can be transfer into volume-component by the following formula:

$$V_i = V_i^{\min} + (V - \sum V_i^{\min}) \times X_i \tag{5}$$

where V_i: volume of each component (liter); $V_i^{\min}$: lower limit of volume of each component (liter);

Table 1 The lower bound of each component

Component	Weight (kg)	Specific Gravity	Volume (liter)
Cement	150	3.15	47.62
Fly ash	0	2.22	0
Slag	0	2.85	0
Water	125	1	125
SP	3.5	1.2	2.92
Coarse Aggre.	850	2.645	321.36
Fine Aggre.	675	2.66	253.76

Table 2 Some of the designed mixtures represented by pseudo-components

No.	Cement	Fly ash	Slag	Water	Super-plasticizer	Coarse Aggre.	Fine Aggre.
1	1	0	0	0	0	0	0
2	0	1	0	0	0	0	0
3	0	0	1	0	0	0	0
4	0	0	0	1	0	0	0
5	0	0	0	0	1	0	0
6	0	0	0	0	0	1	0
7	0	0	0	0	0	0	1
:	:	:	:	:	:	:	:
120	0	1/6	1/6	1/6	1/6	1/6	1/6
121	1/6	0	1/6	1/6	1/6	1/6	1/6
122	1/6	1/6	0	1/6	1/6	1/6	1/6
123	1/6	1/6	1/6	0	1/6	1/6	1/6
124	1/6	1/6	1/6	1/6	0	1/6	1/6
125	1/6	1/6	1/6	1/6	1/6	0	1/6
126	1/6	1/6	1/6	1/6	1/6	1/6	0
127	1/7	1/7	1/7	1/7	1/7	1/7	1/7

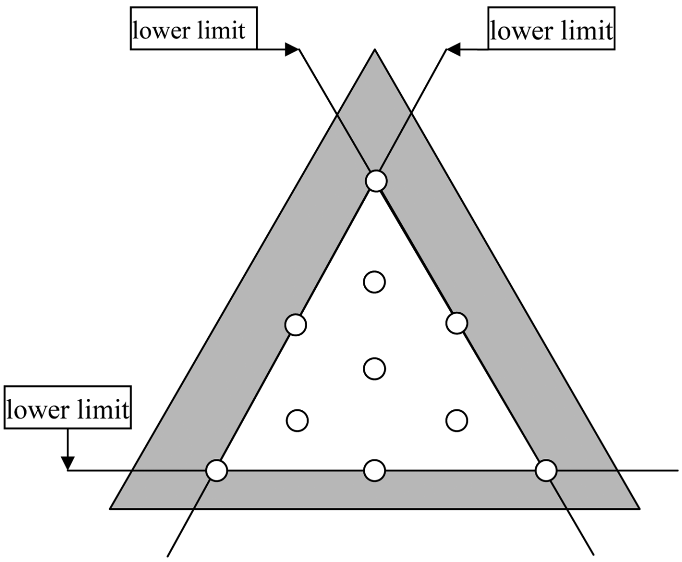

Fig. 3 Illustration of initial design constrained by lower limits

V: total volume of mixture design (1000 liter); X_i: pseudo-component of each component, $1 \geq X_i \geq 0$, and $\sum X_i = 1.000$.

According to the formula, when the pseudo-component of one component equals to 0, its volume reaches its lower limit. Some of the volume-component mixtures are listed in Table 3. However, in laboratory, it is easier to perform the mixture test in weight. Therefore, the volume-component design was be transfer into weight and listed in Table 4.

Table 3 Some of the designed mixtures represented by volume-components

No.	Volume of each component (liter)							Total Volume
	Cement	Fly ash	Slag	Water	Super-plasticizer	Coarse Aggre.	Fine Aggre.	
1	297.0	0.00	0.00	125.0	2.9	321.4	253.8	1000
2	47.6	249.3	0.00	125.0	2.9	321.4	253.8	1000
3	47.6	0.00	249.3	125.0	2.9	321.4	253.8	1000
4	47.6	0.00	0.00	374.3	2.9	321.4	253.8	1000
5	47.6	0.0	0.0	125.0	252.3	321.4	253.8	1000
6	47.6	0.0	0.0	125.0	2.9	570.8	253.8	1000
7	47.6	0.0	0.0	125.0	2.9	321.4	503.2	1000
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120	47.6	41.6	41.6	166.6	44.5	362.9	295.3	1000
121	89.2	0.0	41.6	166.6	44.5	362.9	295.3	1000
122	89.2	41.6	0.0	166.6	44.5	362.9	295.3	1000
123	89.2	41.6	41.6	125.0	44.5	362.9	295.3	1000
124	89.2	41.6	41.6	166.6	2.9	362.9	295.3	1000
125	89.2	41.6	41.6	166.6	44.5	321.4	295.3	1000
126	89.2	41.6	41.6	166.6	44.5	362.9	253.8	1000
127	83.3	35.6	35.6	160.6	38.6	357.0	289.4	1000

Table 4 Some of the initial design mixtures represented by weight-components

No.	Weight of each component (kg)						
	Cement	Fly ash	Slag	Water	Super-plasticizer	Coarse Aggre.	Fine Aggre.
1	935.6	0.0	0.0	125.0	3.5	850.1	675.1
2	149.9	553.4	0.0	125.0	3.5	850.1	675.1
3	149.9	0.0	710.5	125.0	3.5	850.1	675.1
4	149.9	0.0	0.0	374.3	3.5	850.1	675.1
5	149.9	0.0	0.0	125.0	302.8	850.1	675.1
6	149.9	0.0	0.0	125.0	3.5	1509.8	675.1
7	149.9	0.0	0.0	125.0	3.5	850.1	1338.5
:	:	:	:	:	:	:	:
120	149.9	92.4	118.6	166.6	53.4	959.9	785.5
121	281.0	0.0	118.6	166.6	53.4	959.9	785.5
122	281.0	92.4	0.0	166.6	53.4	959.9	785.5
123	281.0	92.4	118.6	125.0	53.4	959.9	785.5
124	281.0	92.4	118.6	166.6	3.5	959.9	785.5
125	281.0	92.4	118.6	166.6	53.4	850.1	785.5
126	281.0	92.4	118.6	166.6	53.4	959.9	675.1
127	262.4	79.0	101.5	160.6	46.3	944.3	769.8

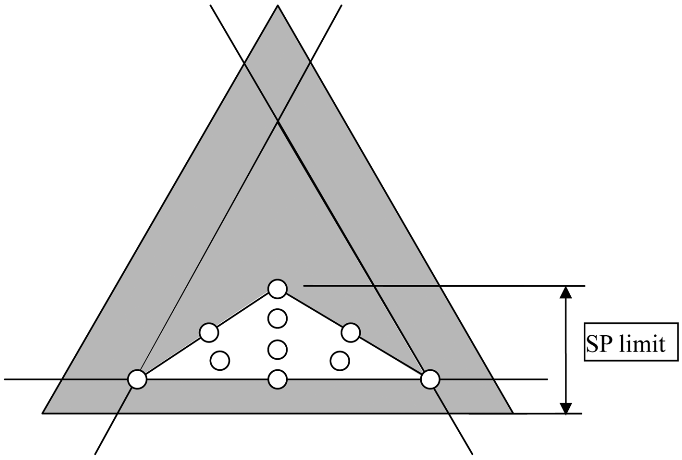


Fig. 4 Illustration of design adjusted by SP upper limit

4.2. Step 2. Adjusted design

In the initial design, there are eight values, 3.5, 46.3, 53.4, 63.4, 78.3, 103.3, 153.2, and 302.8 kg/m^3 for superplasticizer (SP). They are greater than the reasonable limit except for the 3.5 kg/m^3; therefore, adjustment is necessary. The adjustment is based on transferring the maximum to the reasonable upper limit, transferring the minimum to the reasonable lower limit, and linear interpolating the others to the range between the upper and lower limit. In this study, the lower and upper limit is set as 3.5 kg/m^3 and 15.5 kg/m^3, respectively. However, this adjustment will reduce the total volume of mixture. To deal with the problem, the volume of the other components will be increased to keep the total volume to be 1000 liter (1 m^3). The concept of adjusted design is illustrated in Fig. 4. The process is as follows

1. Calculate the volume reduced by adjusting the SP

$$\Delta V = (W_{sp} - W'_{SP}) \div G_{SP} \tag{6}$$

where ΔV: volume reduced by adjusting the SP (liter); W_{SP}: weight of SP in the initial design (kg); : W'_{SP} weight of SP in the adjusted design (kg); G_{SP}: specific gravity of SP.

2. Calculate the adjustment factor for the other components

$$\alpha = 1 + \frac{\Delta V}{V - V_{SP}} \tag{7}$$

where α: adjustment factor; V: total volume of mixture design (1000 liter); V_{SP}: volume of SP in the initial design (liter).

3. Adjust the other components

$$W'_i = W_i \times \alpha \tag{8}$$

where W'_i = weight of component in the adjusted design (kg); W_i = weight of component in the initial design (kg).

The weight-component adjusted design is listed in Table 5.

Table 5 Some of the adjusted design mixtures represented by weight-components

No.	ΔV	α	Weight of each component (kg)						
			Cement	Fly ash	Slag	Water	Super-plasticizer	Coarse Aggre.	Fine Aggre.
1	0.0	1.00	935.6	0.0	0.0	125.0	3.5	850.1	675.1
2	0.0	1.00	149.9	553.4	0.0	125.0	3.5	850.1	675.1
3	0.0	1.00	149.9	0.0	710.5	125.0	3.5	850.1	675.1
4	0.0	1.00	149.9	0.0	0.0	374.3	3.5	850.1	675.1
5	239.3	1.32	197.9	0.0	0.0	165.0	15.5	1122.1	891.1
6	0.0	1.00	149.9	0.0	0.0	125.0	3.5	1509.8	675.1
7	0.0	1.00	149.9	0.0	0.0	125.0	3.5	850.1	1338.5
:	:	:	:	:	:	:	:	:	:
120	39.9	1.04	156.2	96.3	123.6	173.6	5.50	1000.0	818.3
121	39.9	1.04	292.7	0.0	123.6	173.6	5.50	1000.0	818.3
122	39.9	1.04	292.7	96.3	0.0	173.6	5.50	1000.0	818.3
123	39.9	1.04	292.7	96.3	123.6	130.2	5.50	1000.0	818.3
124	0.0	1.00	281.0	92.4	118.6	166.6	3.5	959.9	785.5
125	39.9	1.04	292.7	96.3	123.6	173.6	5.50	885.6	818.3
126	39.9	1.04	292.7	96.3	123.6	173.6	5.50	1000.0	703.3
127	34.2	1.03	270.3	81.4	104.5	165.4	5.21	972.6	792.9

4.3 Step 3. Filtrated design

Although the adjusted design has improved the availability of the initial design; however there are still several unreasonable design points in the design. For example, in Table 5, the cement content of mixture No.1 equals to 935 kg/m^3, and the w/b ratio equals to 0.137. To delete these unreasonable designs, upper limit for each component content and upper and lower limit of ratios between component contents were employed on these design. Any mixtures violated any constraints would be deleted. The upper limit of each component is listed in Table 6.

The ratio constraints were imposed on w/c, w/b, etc. Their definitions are listed as follows

$$\text{Water-cement ratio} = (W_W + W_{SP}) / W_C \tag{9}$$

$$\text{Water-binder ratio} = (W_W + W_{SP}) / (W_C + W_F + W_S) \tag{10}$$

Table 6 The upper bound of each component

Component	Upper limit (kg)
Cement	350
Fly ash	200
Slag	260
Water	240
SP	12
Coarse Aggre.	1160
Fine Aggre.	980

Table 7 The lower and upper bound of each ratio

Ratio	Lower limit	Upper limit
Water-cement ratio	0.37	1.46
Water-binder ratio	0.25	0.70
Water-solid ratio	0.07	0.12
SP-binder ratio	0.01	0.03
Fly ash-binder ratio	0	0.55
Slag-binder ratio	0	0.61
Fly ash plus slag-binder ratio	0	0.68
Coarse aggregate-binder ratio	2.72	6.86
Fine aggregate-total aggregate ratio	0.39	0.51

$$\text{Water-solid ratio} = (W_W + W_{SP}) / (W_C + W_F + W_S + W_{CA} + W_{FA}) \quad (11)$$
$$\text{SP-binder ratio} = W_{SP} / (W_C + W_F + W_S) \quad (12)$$
$$\text{Fly ash-binder ratio} = W_F / (W_C + W_F + W_S) \quad (13)$$
$$\text{Slag-binder ratio} = W_S / (W_C + W_F + W_S) \quad (14)$$
$$\text{Fly ash plus slag-binder ratio} = (W_F + W_S) / (W_C + W_F + W_S) \quad (15)$$
$$\text{Aggregate-binder ratio} = (W_{CA} + W_{FA}) / (W_C + W_F + W_S) \quad (16)$$
$$\text{Fine aggregate-total aggregate ratio} = W_{FA} / (W_{CA} + W_{FA}) \quad (17)$$

In this study the upper and lower limit of each ratio is listed in Table 7. The concept of filtrated design is illustrated in Fig. 5 and Fig. 6.

The experiment process was summarized as follows:

(1) Total of 127 initial design points are produced using the simplex-centroid design with component lower limit.

(2) The initial design points are adjusted to make the SP content reasonable.

(3) Total of 57 design points are obtained after filtrating the adjusted design points with

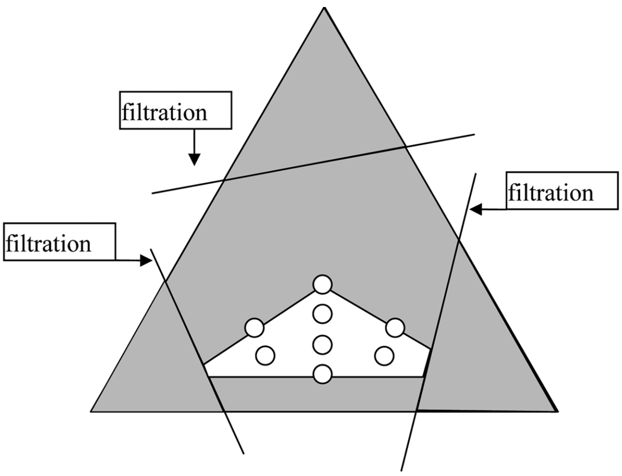


Fig. 5 Illustration of design filtrated by component upper limits and ratio limits

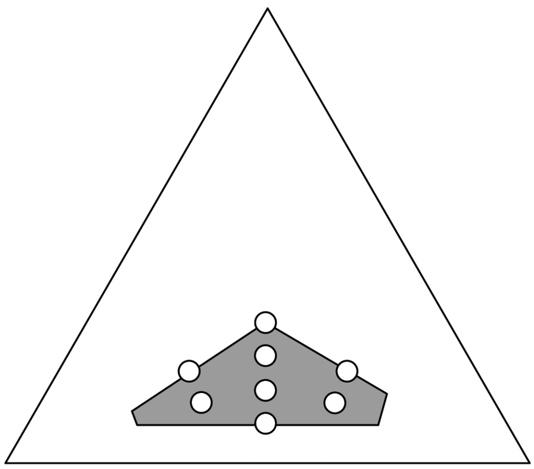


Fig. 6 Illustration of the design space

component upper limits and ratio limits.

(4) In mixing, some mixtures had serious bleeding problem; on the other hand, some mixtures can not mix to produce reasonable consistence. When these problems happened, we either gave up them or modified them by adding more water or SP. These modifications were recorded, and would be used to re-calculate the proportion of each component in 1 m^3. Finally, total 78 available mixtures were obtained.

The fresh concrete was assessed by the slump test. This convenient and simple test was adequate to quantify the fresh properties of the concrete for the purposes of this program. The slump test, however, provides only a single parameter to describe the concrete, and is insufficient to fully describe its workability.

To reduce the effects of error of measurement, each quoted slump value is the average of slump from three tests. Moreover, the sequence in which the experimental points were investigated was randomized to avoid any statistical significance of a blocking effect.

The sequence in which the mixture design points were investigated was randomized to avoid any statistical significance of a blocking effect. To reduce the error of measurement,.

Besides, to evaluate the accuracy of model built with the mixture design, 25 concrete mixtures and their test results collected from literature (Yeh, *et al*. 2002) will be used. Although there are only 25 mixtures in the literature, they covered five different levels of strength about 25, 32.5, 40, 47.5, and 55 MPa, and five different levels of workability about 5, 10, 15, 20, 25 cm in slump. Therefore, there are 5×5=25 mixtures. It may be sure that these will form a fairly representative group covering all the ranges of practical use for concrete mixtures and present rather complete and independent information required for such an evaluation.

The results of the concrete slump tests were subjected to polynomial regression using a computer program. Various polynomials were tried to represent the measured slump data for seven component contents. The best fit for the slump was obtained with RMS error of 4.35 cm (R^2=0.715) and RMS error of 8.29 cm (R^2=0.392) for training data and testing data, respectively. Predictions of the slump for concrete using regressions for training data and testing data are shown in Fig. 7. It is shown that

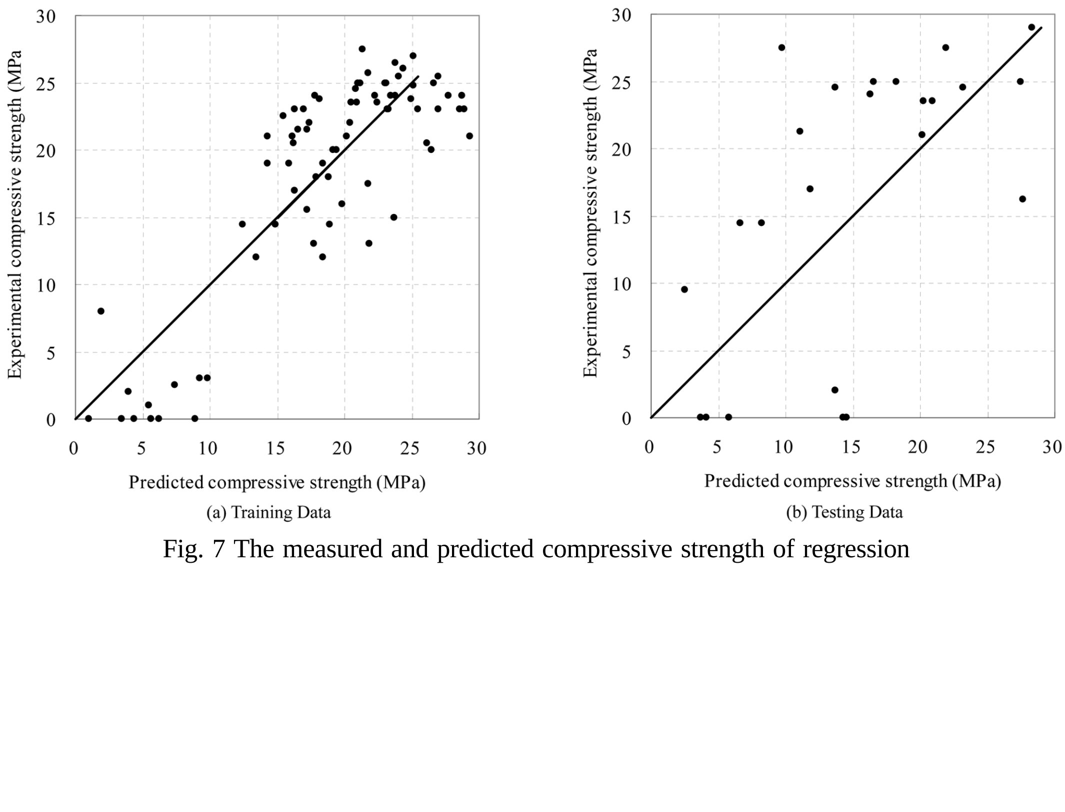


Fig. 7 The measured and predicted compressive strength of regression

although the RMS error for training data is rather low, the RMS error for testing data is so high as to provide inaccurate predictions. In other words, the model lacks for generalization.

5. Artificial neural networks for concrete slump

To efficiently generate response surfaces of concrete slump, instead of commercially available neural network software, the program adopted in this study was written in C language and essentially followed the formulations of Lippmann (1987).

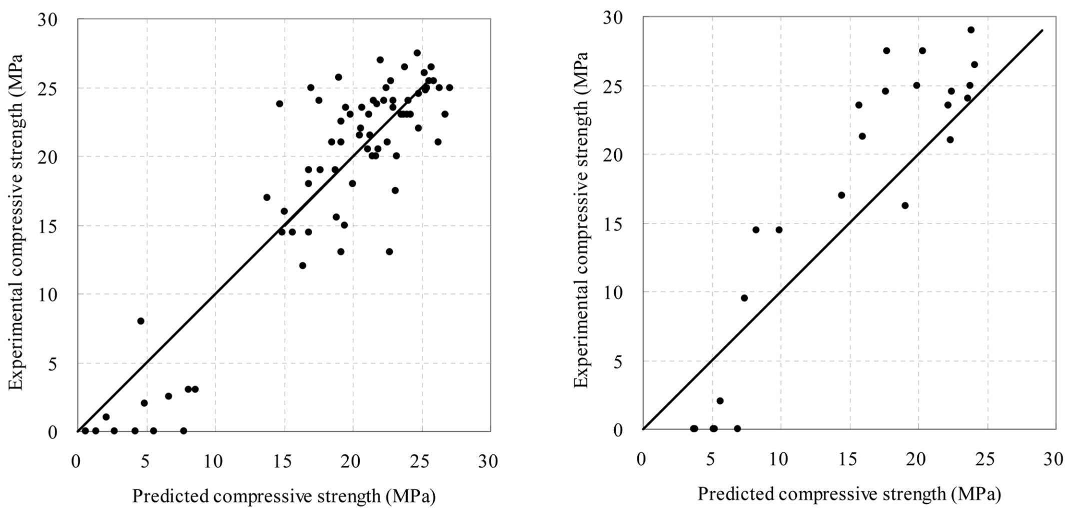
For this slump modeling problem the obvious inputs are seven component contents (cement, fly ash, slag, water, SP, coarse aggregate, and fine aggregate), and the output is concrete slump. After a number of trials, the best network architecture and parameters which minimize the RMS error of testing data were selected as follows:

- number of hidden layer=1
- number of hidden unit=3
- learning rate=1.0
- learning epoch=20000

The RMS error is 3.45 cm (R^2=0.82) and 4.80 cm (R^2=0.85) for training data and testing data, respectively. Predictions of the slump for concrete using the network for training data and testing data are shown in Fig. 8. Compared Fig. 8 with Fig. 7, it may be seen that the model obtained by neural networks much better predicts the experimental results for the testing data in this study.

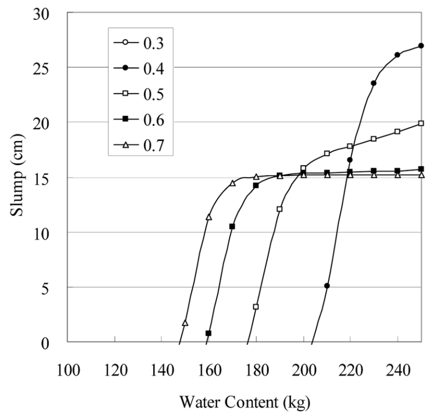
6. Response surfaces for concrete slump

When the neural network model for concrete slump had been built, the predicted slump can be regarded as a function of all the input variables. The simulation of the slump of other mixture

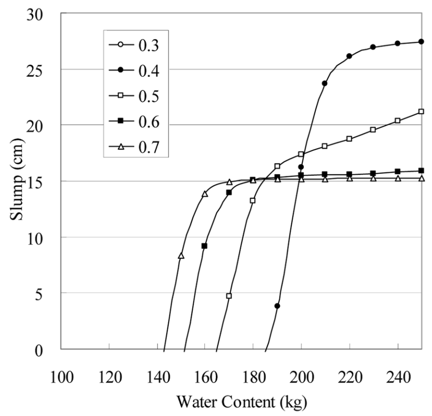


(a) Training Data (b) Testing Data

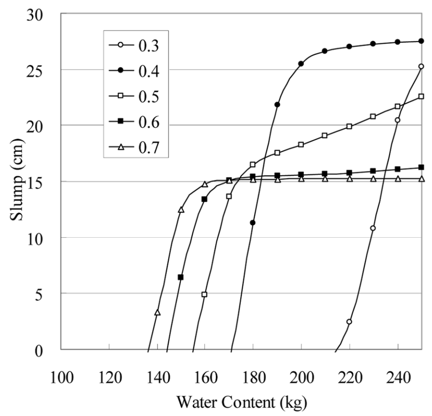
Fig. 8 The measured and predicted compressive strength of ANN points in the experimental domain was therefore possible. The simulations were designed based on a neural network model which allowed the response surfaces for the slump to be obtained over the



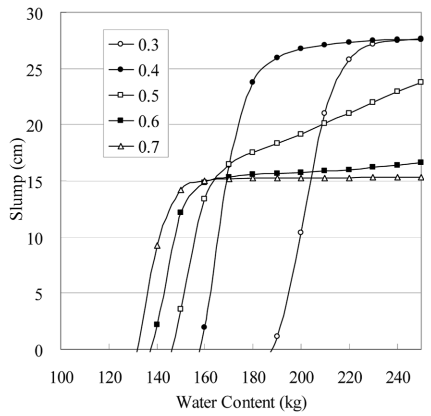
(a) SP/b=0%



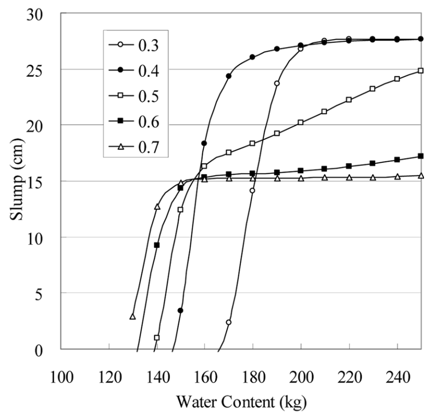
(b) SP/b=1%



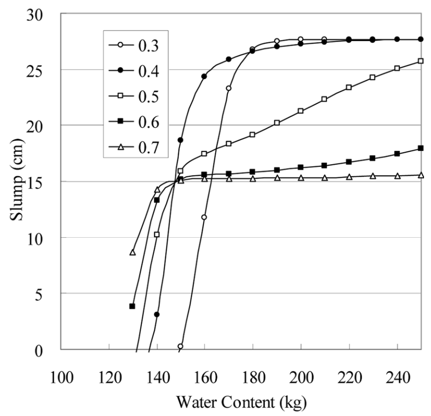
(c) SP/b=2%



(d) SP/b=3%



(e) SP/b=4%

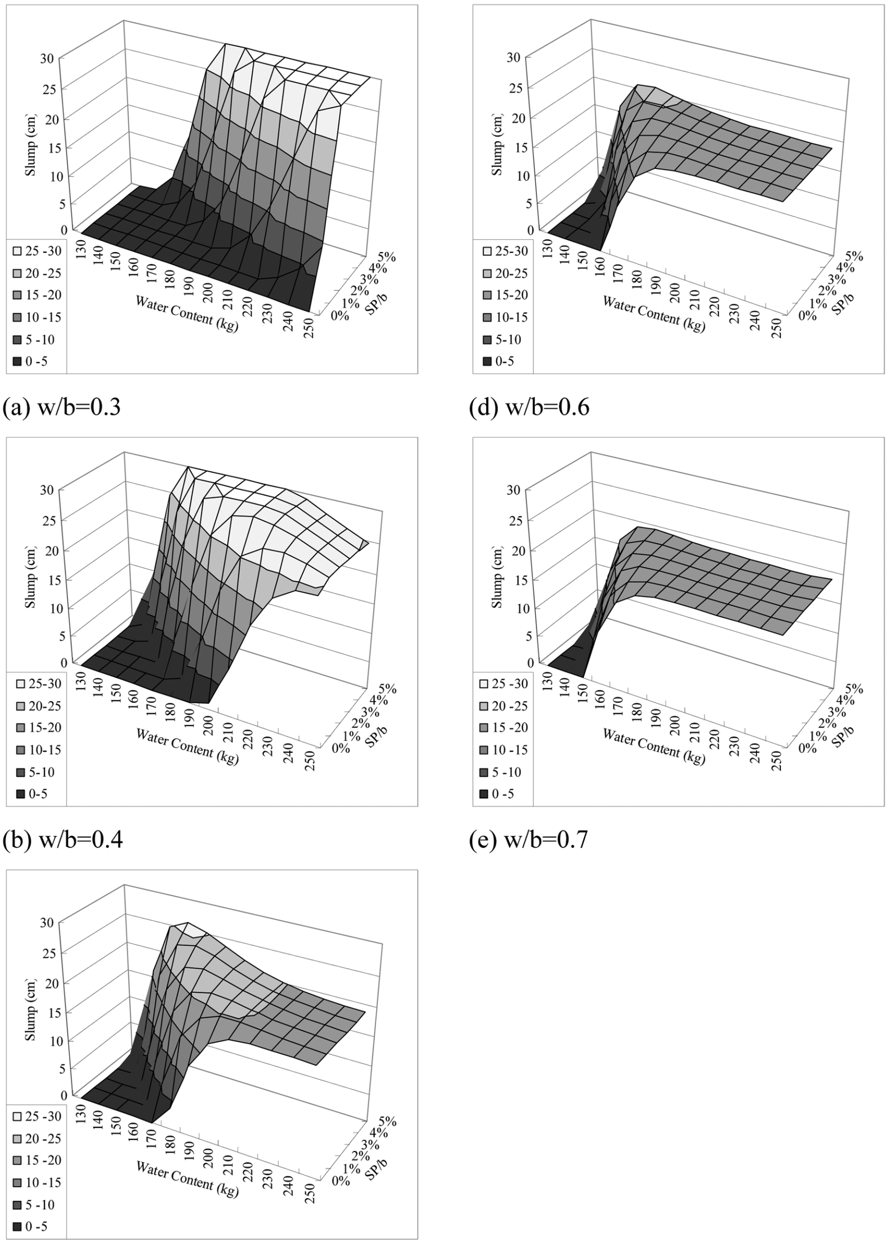


(f) SP/b=5%

Fig. 9 The water content-slump curves

experimental domain.

Although there are seven input variables in the model, it is more meaningful to investigate the response surface and relations between the slump and water content two ratios of components, water-binder ratio and SP-binder ratio. The binder means cementitious material, that is, cement plus fly ash and slag. The range of each variable is listed as follows:



(a) w/b=0.3

(d) w/b=0.6

(b) w/b=0.4

(e) w/b=0.7

(c) w/b=0.5

Fig. 10 The response surfaces of slump at various w/b

1. The water-binder ratio (w/b) was varied with 0.3, 0.4, 0.5, 0.6, and 0.7.
2. The SP-binder ratio (SP/b), the amount of superplasticizer by weight of binder, was varied with 0, 1, 2, 3, 4, and 5%.
3. The amount of water was varied from 130 to 250 kg/m^3.

Besides, the fly ash-binder ratio and slag-binder ratio was kept constant 25% and 25%, respectively, by weight of binder; the CA/FA was kept constant 1.0; the total volume of concrete was 1.000 m^3.

From the water-slump curves generated using the trained neural network developed in this study with the above combinations, five sets of curves have been shown in Fig. 9 to explore the effects of water and w/b at SP/b=0, 1, 2, 3, 4, and 5%. The vertical axis is the predicted slump, and the horizontal axis is the incremental change Δ_i, made in water content for each w/b ratio (0.3, 0.4, 0.5, 0.6, and 0.7). Besides, three sets of response surfaces have been shown in Fig. 10, 11, and 12 to explore the interactions between the three variables. Considering the fact that validity of a slump test is generally recommended for concrete with a slump value ranging from 2.5 to 25 cm; therefore, these parts of curves that outside the range may be unreliable and should be ignored. It was found that

- **The effects of water content (refer to Fig. 9)**

(1) At low water content, the lower the water content, the lower the slump.
(2) At high water content, when water content reach a saturate level, only a small increase in slump can be gotten as the water content increases. The saturate level for water content depends on SP/b and w/b.

- **The effects of SP/b (refer to Fig. 9)**

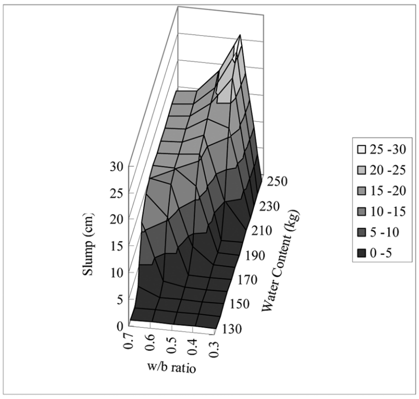
(1) Low SP/b concretes need higher water content to start to produce workability, and only w/b=0.4 can reach very high workability.
(2) High SP/b concretes need lower water content to start to produce workability, especially for low w/b concretes, and concretes at w/b=0.3 to 0.5 can reach very high workability.

- **The effects of w/b (refer to Fig. 9)**

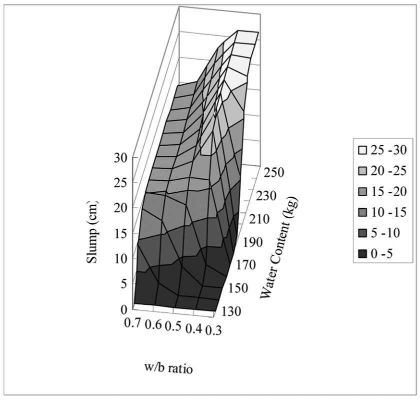
(1) Low w/b concretes must require higher water content to start to produce workability, but they can reach very high workability.
(2) High w/b concretes can easily start to produce workability, but there is an upper limit about 15 cm.

- **The interactions of water content and SP/b (refer to Fig. 10)**

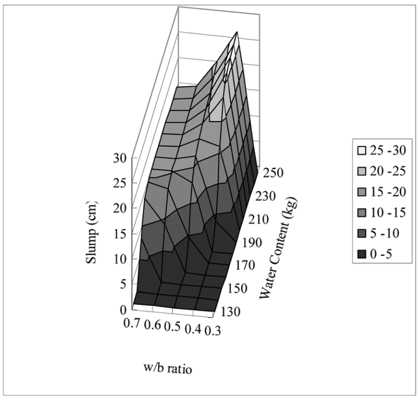
(1) At low w/b (0.3), the higher the water content and SP/b, the higher the slump. The water content required to reach 25 cm in slump is 240, 210, 190, and 170 kg/m^3 for SP/b=2, 3, 4, and 5%, respectively. However, at SP=1%, even adding high water content can not reach 10 cm in slump.
(2) At medium w/b (0.5), it became easier to produce workability. Even without SP, it is possible to start to produce workability only using 180 kg/m^3. However, there was the optimum water content that maximized the slump, especially for mixes with high SP/b. At high SP/b, mixes with the optimum water content were shown to have a slightly higher workability than those with the too high water content. The optimum water content depended on SP/b.
(3) At high w/b (0.7), the tendency is similar to medium w/b; however, there is an upper limit about 15 cm in slump that can be gotten by adding water content to a saturate level. The upper limit of slump did not depend on SP/b; however the saturate level of water content did; the higher the SP/b, the lower the saturate level of water content.



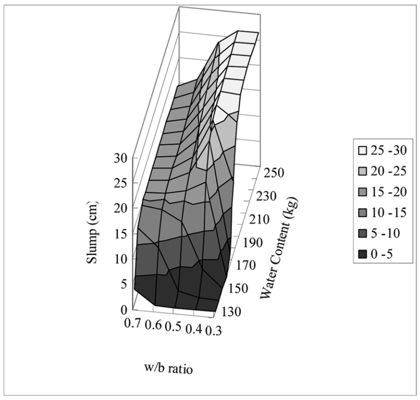
(a) SP/b=0%



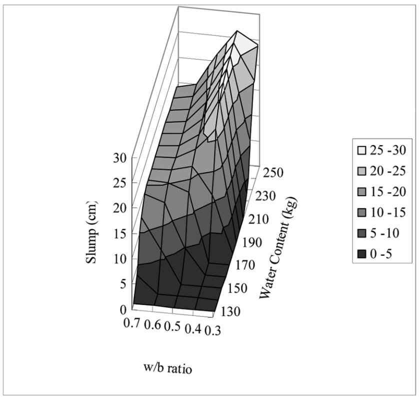
(d) SP/b=3%



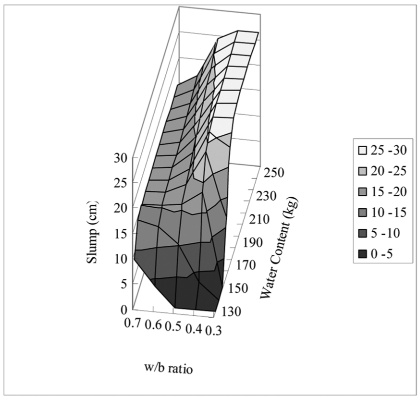
(b) SP/b=1%



(e) SP/b=4%



(c) SP/b=2%

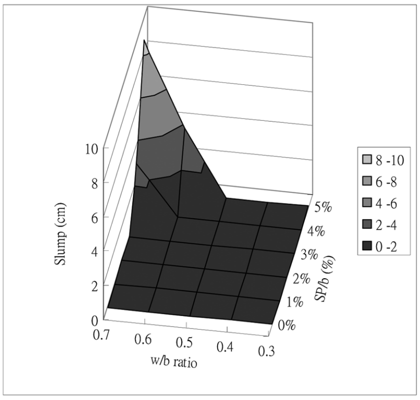


(f) SP/b=5%

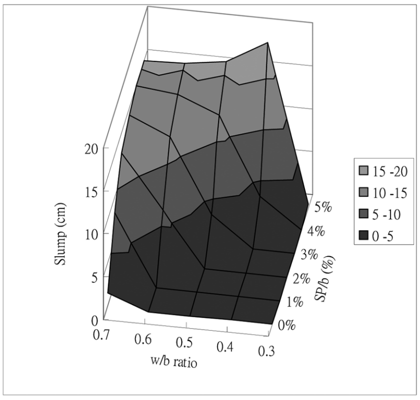
Fig. 11 The response surfaces of slump at various SP/b

(4) Compared with concrete without SP, to remain the 15 cm in slump, at w/b=0.4, 1 to 4% of SP/b can effectively replace from 65 to 20 kg/m^3 of water; at w/b=0.5, 1 to 4% of SP/b can

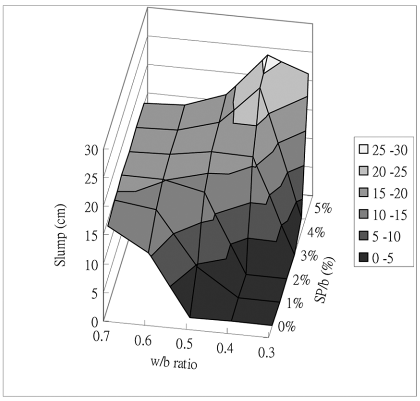
effectively replace from 50 to 15 kg/m^3 of water; however, at w/b=0.6, 1 to 4% of SP/b can only effectively replace from 30 to 10 kg/m^3 of water. It can be seen that the smaller the w/b,



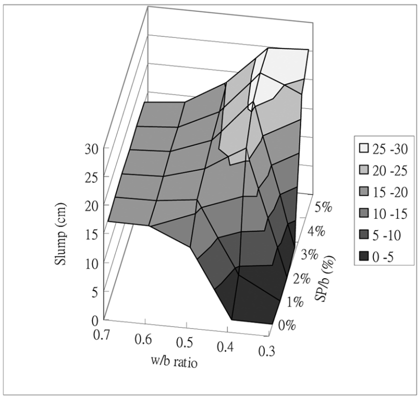
(a) water content=130 kg/m^3



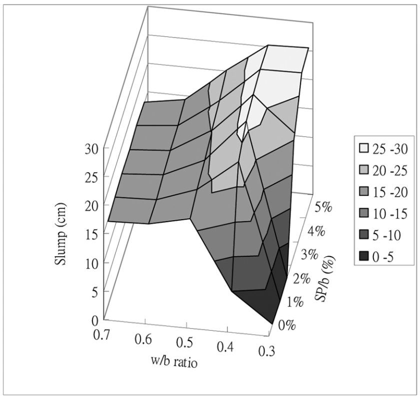
(b) water content=150 kg/m^3



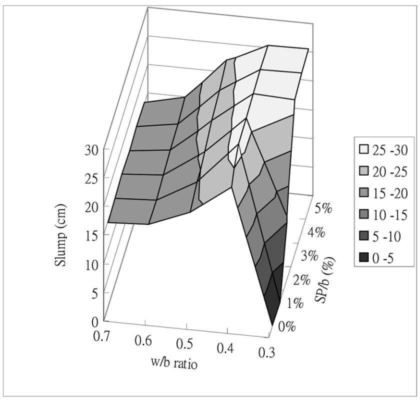
(c) water content=170 kg/m^3



(d) water content=190 kg/m^3



(e) water content=210 kg/m^3



(f) water content=230 kg/m^3

Fig. 12 The response surfaces of slump at various water content the more effectively the SP replace water.

• **The interactions of water content and w/b (refer to Fig. 11)**

(1) At low SP/b (0%), at high w/b, the slump increases sharply and reaches a medium slump about 15 cm and then remain the constant as we move along the water content axis from the low toward the high water content. At medium w/b (0.4), when the water reaches a start level, the slump increases sharply and reaches a high slump more than 25 cm. However, regardless of water content, at low w/b (0.3), concretes have no slump at all.

(2) At medium SP/b (2%), the tendency is similar to low SP/b; however, it is easier to start to produce workability with increasing water content even at low w/b (0.3).

(3) At high SP/b (4%), concretes with high w/b and water content more than 150 kg/m^3, regardless of water content, the slumps are about the same (15 cm). However, concretes with low w/b and low water content have no slump, but those with low w/b and high water content have high slump (25 cm).

• **The interactions of SP/b and w/b (refer to Fig. 12)**

(1) At low water content, only at high w/b and high SP/b can produce small workability.

(2) At medium water content, there are high interactions between w/b and SP/b. At high w/b, the SP/b has no effects on slump, the same slump about 15 cm can be reached. However, at low w/b, the SP/b has strong effects on workability, the slump increases sharply as the SP/b increases.

(3) At high water content, the tendency is similarly to medium water content; however, the SP/b required to reach high slump at low w/b is much lower.

7. Conclusions

The mechanism for workability of concrete is rather complex, and a number of factors are involved. Although the present experimental and simulating investigation was based on a limited number of variables, the following conclusions can be drawn (results should not be extrapolated outside the experimental domain or to other combinations of materials):

1. Research reported in this paper shows that a small number of slump experiments can be performed and meaningful data obtained with a flatted simplex-centroid mixture experiment design. Such data would be suitable for building slump model using neural networks. A q-component simplex-centroid design consists of 2^q-1 distinct design points. Therefore, because there are seven components in this study, there are $2^7-1=127$ mixtures. Considering that if there are five levels for each component, the complete combinations are therefore $5^7=78125$ mixtures. The difference is very huge.

2. The neural network's performance was found to be more accurate and more effective than regression analysis for modeling the strength of concrete. The use of neural network for the modeling of workability of concrete looks very promising.

3. The trained network can be satisfactorily used for exploring the effects of the components and their interactions on the workability of concrete. The three exploring variables are the water-binder ratio, SP-binder ratio, and water content. All other controllable parameters were kept constant. In this study, concrete slump is very sensitive to changes in all three variables, and there are strong nonlinear effects of all the three variables and complex interactions between them.

4. A high water content and a high SP/b ratio is essential for high workability, but achieving this

by increasing these parameters will not in itself guarantee high workability. The w/b played a very important role in producing workability.

5. The effects of w/b are rather profound. At high w/b, it is easy to produce medium slump. However, at low w/b, the situation is totally different. Concretes with low w/b have high slump at high water content and high SP/b; otherwise, they would have low slump. In summary, the slump of concretes with low w/b became very sensitive to water content and SP/b ratio. The medium value about 0.4 is the best w/b to reach high slump without too much effort on trying to find the appropriate water content and SP/b.

Acknowledgments

This work was supported by the National Science Council, ROC, under Grant NSC-92- 2211-E-216-015.

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