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Computer-aided design for optimum concrete mixtures

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Abstract

Using neural networks and optimization technologies, it is possible to apply analytical methods to search for the optimum mixture of concrete composition, a mixture with the lowest cost and required performance, such as strength and slump. The concrete mixture design problem is first transformed into an optimization formulation, including objective function and constraint functions, appropriate for application of optimization technologies. Then the functions in the formulation, including strength and slump, can be modeled using a modeling module based on neural networks. Finally the optimization formulation can be solved using an optimization module based on nonlinear programming and genetic algorithms. These modules are integrated in a Computer-Aided Design (CAD) system. To evaluate the system, it was used to obtain a set of optimum concrete mixtures with wide ranges of workability (5–25 cm in slump) and strength (25–55 MPa in compression). It was found that (1) the modeling module can generate rather accurate models for compressive strength and slump for concrete, (2) the optimization module can generate the lowest cost mixtures for wide range of required strength and slump and their combinations, and (3) the dependence of required strength and slump on the design parameters (component contents) meets expectations.

Keywords: Mixture; Concrete; Compressive strength; Workability; Optimization; Neural networks

1. Introduction

Concrete mix design is the process of selecting the proportions of a concrete mix. It involves satisfying a balance between economics and the mix design specifications. The required characteristics, such as workability and strength, are governed by the expected use of concrete and by conditions expected to be encountered at the time of placement. These are often, but not always, reflected in concrete mix design specifications [1]. When mixtures are optimized on a quantitative basis, depending on the objective of the optimization, construction productivity could be improved, durability increased, and both material and construction costs reduced.

Several authors have presented results from laboratory programs for optimizing and confirming high-strength and high-workability mixes [2–6]. Many of these have involved an extensive series of tests, sometimes carried out on a trial-and-error basis, and the results have often only been applicable to a narrow range of locally available materials [5]. Nowadays, concrete can be made with about 4–10 different components. The number of properties to be adjusted has also increased, so that empirical methods are no longer sufficient in concrete mix design.

There has recently been a greater emphasis toward rationalizing the initial mix proportioning into a more logical and systematic process, the aim of being to reduce the number of trial mixes required [5,7–12]. Analytical methods search for concrete mix design based on predicting material behavior without implementing expensive and time-consuming experiments; therefore, they enable practical searches for the optimum design. "Optimum" means here the most economical solution, i.e., such a mix that the sum of the costs of the components is minimized, yet guaranteeing concrete of adequate strength and workability.

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The main scientific problem for automatic concrete mixture design lies in establishing analytical relationships between the mix composition and the engineering properties of concrete. Because of the complexity of material behavior of concrete, in this study neural networks are used to predict strength and workability. The use of neural networks to model the strength of concrete has been studied extensively [7,13–22], but little attention has been devoted to using neural networks for modeling the workability of concrete.

There have been a few systems developed for concrete mix design [1,23]; however, most of these systems have no function to perform the cost optimization of a mix design [1]. Using neural networks and optimization technologies, it is possible to apply analytical methods to search for the optimum mixture of concrete composition, a mixture with the lowest cost and required performance.

The purpose of this paper is to present a novel Computer-Aided Design (CAD) tool for undertaking the design of concrete mixes incorporating Super Plasticizer (SP), fly ash, and slag to attempt to insure that the resulting concrete product will not only be economical and strong enough for the intended purpose, but will have some assurance of adequate workability characteristics as well. Although workability is a more general concept with many different aspects than slump, in this study workability is measured by slump. In the CAD tool, the optimum mixture is proportioned using the concrete mixture optimization formulation reported in this paper. If the required performance (the input of the CAD system) corresponds to a feasible optimization problem, the optimum mixture with lowest cost and required specific performances and their predicted performance (the output of the CAD system) are immediately obtained. This tool can also be used to obtain a set of optimum concrete mixtures with wide ranges of workability (5–25 cm in slump) and strength (25–55 MPa in compressive strength).

2. Formulation for concrete mixture optimization

The problem of concrete mixture optimization can be formulated as a material cost objective and five sets of constraints related to strength requirements, workability requirements, component contents, component ratios, and absolute volume. The formulation is listed as follows:

$$\text{Min Cost} = C_c \cdot W_c + C_{fl} \cdot W_{fl} + C_{sl} \cdot W_{sl} + C_w \cdot W_w + C_{SP} \cdot W_{SP} + C_{CA} \cdot W_{CA} + C_{FA} \cdot W_{FA} \tag{1}$$

where C_c, C_{fl}, C_{sl}, C_w, C_{SP}, C_{CA}, C_{FA} are the unit costs of the cement, fly ash, slag, water, SP, coarse aggregate and fine aggregate; W_c, W_{fl}, W_{sl}, W_w, W_{SP}, W_{CA}, W_{FA} are weights (kg) of the cement, fly ash, slag, water, SP, coarse aggregate and fine aggregate in 1 m^3.

Eq. (1) is subject to

- Required strength constraints

$$S_t \geqslant f'_{cr,t} \quad (t = 3, 7, 14, 28, 56 \text{ days}) \tag{2}$$

where S_t is the predicted compressive strength at time t; $f'_{cr,t}$ is the required compressive strength at time t.

Characteristic strength of concrete, used to identify the strength of concrete in the job site, has to be exceeded by 95% of the compression tests carried out during the quality control process [3]. Therefore, the required average compressive strength is determined by the following formulas:

$$f'_{cr} = f'_c + 1.34 \cdot \sigma \tag{3}$$
$$f'_{cr} = f'_c + 2.33 \cdot \sigma - 3.5 \text{ (MPa)} \tag{4}$$

where f'_c is the characteristic compressive strength; σ is the standard deviation of the available test data of compressive strength.

- Required workability constraints

$$\text{Slump} \geqslant \text{Slump}^r \tag{5}$$

where Slump, Slump^r = predicted slump and required slump.

- Available range constraints

$$W_x^l \leqslant W_x \leqslant W_x^u \quad (x = \text{c, fl, sl, w, SP, CA, FA}) \tag{6}$$

where W_x^l and W_x^u are the lower and upper bounds for the weight (kg) of component x in 1 m^3, where x represents cement, fly ash, slag, water, SP, coarse aggregate and fine aggregate.

- Component ratio constraints

$$R_r^l \leqslant R_r \leqslant R_r^u \quad (r = \text{w/c, w/b, w/s, SP/b, fl/b, sl/b, po/b, a/b, fa/a}) \tag{7}$$

where R_x^l and R_x^u are the lower and upper bounds for component ratio r, where r represents water/cement ratio, water/binder ratio, water/solid ratio, SP/binder ratio, fly ash/binder ratio, slag/binder ratio, pozzolans/binder ratio, total aggregate/binder ratio, and fine aggregate/total aggregate ratio.

- Absolute volume constraints

The absolute volume equation represents a condition that the total volume of the components of concrete should correspond to the volume of one cubic meter (=1000 litre):

$$\frac{W_c}{G_c} + \frac{W_{fl}}{G_{fl}} + \frac{W_{sl}}{G_{sl}} + \frac{W_w}{G_w} + \frac{W_{SP}}{G_{SP}} + \frac{W_{CA}}{G_{CA}} + \frac{W_{FA}}{G_{FA}} = 1000 \tag{8}$$

where G_c, G_{fl}, G_{sl}, G_w, G_{SP}, G_{CA}, G_{FA} are the unit weights of the cement, fly ash, slag, water, SP, coarse aggregate, and fine aggregate.

3. Architecture of CAD tool for concrete mixture optimization

The paper presents a CAD tool for optimization using neural networks and optimization technologies. The central idea for performing optimum concrete mix design is the incorporation of the prediction models. Incorporating mathematical models of the neural networks described below in software allows the simulation of trial batches. It becomes easy to see what properties are attainable with certain components, and what the interrelations between properties are.

According to the proposed system, the mix design process consists of the following steps:

1. Collect data of concrete mixtures and their test results of material behavior, such as strength and slump, from the literature and/or laboratory experiments.
2. Develop analytical models relating the mix composition based on the data; these models can be used to predict the material behavior without implementing laboratory experiments.
3. Incorporate these models in a model base allowing an evaluation of the specified properties for a given mix.
4. Set requirements of strength and slump, and unit weight and unit cost of all components.
5. Optimize the mix with the help of the optimization routines, by lowering the cost while keeping the concrete properties predicted by these models in the required range.
6. Perform tests with a view to checking whether the designed mixture has the desired properties; if the results are too far from the predictions, put the data of concrete mixture and its test results of material behavior into the data set, and return to step 2 to re-develop the material behavior models.

A first version of such software, called CAFE (Computer-Aided Formulation Environment), permitting using optimization routines to optimize an objective function of up to 20 design variables (components) and not more than 50 constraint functions, has been developed.

The applicability of the system is limited to the following cases:

1. It is assumed that the users will have the concrete mix design specifications, including required strength and slump, upper and lower bound of component content and ratio, and information about material, such as unit weight and unit cost.
2. Physical and chemical properties of cement, fly ash, and slag are satisfactory according to the specifications.
3. Coarse and fine aggregates are graded within limits of generally accepted specifications.
4. The quality and properties of admixtures are satisfactory based on the given specifications.
5. The concrete proportions will be optimized by considering cost.

The architecture of the system is shown in Fig. 1. There are six modules in the system: (1) *User interface module*: communicates between the user and the other five modules. (2) *Design of experiment (DOE) module*: plans the experiments for collecting the data of mixtures and their material

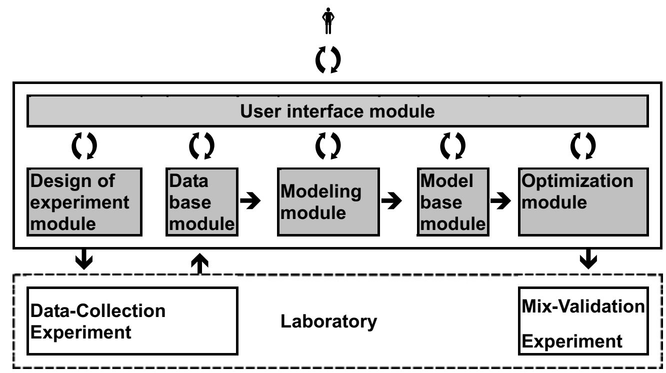

Fig. 1. Architecture of CAD tool for concrete mixture optimization.

behavior. (3) *Data base module*: stores the data of mixtures and their material behavior. (4) *Modeling module*: generates the models of mixtures-material behavior. (5) *Model base module*: stores the models of mixtures-material behavior. (6) *Optimization module*: generates the optimum mixture by lowering the cost while keeping the material behavior predicted by the models in the required ranges.

The paper focuses on the following two modules:

- *Modeling module:* Because of the complexity of material behavior of concrete, neural networks, which are good at modeling complex nonlinear systems, are adopted in the module. Neural networks are computer models whose architecture essentially mimics that of some components of the human brain. 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 [24].
- *Optimization module:* There are two types of optimization technology adopted in the module, nonlinear programming and genetic algorithms. A thorough treatment of these technologies is beyond the scope of this paper. The basic algorithms of nonlinear programming and genetic algorithms have been covered widely [25,26].

The inputs of the system include (1) required material performance, such as strength and slump; (2) upper bound and lower bound of component contents; (3) upper bound and lower bound of ratios between components; (4) unit weight of all components; (5) unit cost of all components.

The outputs of the system include (1) predicted material behavior, such as strength and slump; (2) optimized component contents; (3) calculated component ratio; (4) optimized cost.

To illustrate the applications of the optimization module, an example is provided as follows:

- *Input data:* The input interface of the tool is shown in Fig. 2, where is can be seen that the required average compressive strength is 40 MPa and required slump is 15 cm.
- *Process:* There are several optimization routines available in the optimization module, and the convergence histories using two of them, penalty function method

Component	Unit Cost	Lower Bound	Upper Bound	Specific Gravity	Lower Bound	Ratio	Upper Bound
Cement	2.25	140	350	3.15	0.6	w/c	1.6
Fly Ash	0.6	0	200	2.22	0.3	w/b	0.7
Slag	1.2	0	240	2.85	0.08	w/s	0.12
Water	0.01	150	250	1	0.013	SP/b	0.04
SP	25.1	3	15	1.2	0	fl/b	0.55
Coarse A.	0.236	780	1050	2.54	0	sl/b	0.6
Fine A.	0.28	640	900	2.66	0.25	(fl+sl)/b	0.7
Performance	Requirement				2.7	TA/b	6.4
Slump	15	cm			40	FA/TA	0.52
Slump Flow	40	cm					
fcr' (3-day)	18	MPa					
fcr' (7-day)	Undefined	MPa					
fcr' (14-day)	Undefined	MPa					
fcr' (28-day)	40	MPa					
fcr' (56-day)	Undefined	MPa					

Fig. 2. Input of the illustrative example.

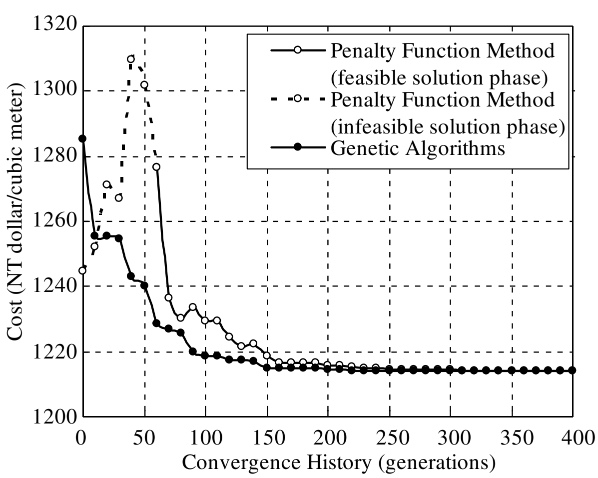

Fig. 3. Convergence history of costs for the illustrative example.

and genetic algorithm, are shown in Fig. 3. The figure shows that they have the same cost, which could imply that the optimum mixture was obtained.

- *Output data:* The concrete mix design determined by the tool is presented on the output interface of the tool as shown in Fig. 4.

Component	Content	Ratio	Value
Cement	140.6	w/c	1.312
Fly Ash	72.9	w/b	0.423
Slag	222.5	w/s	0.086
Water	178.8	SP/b	0.013
SP	5.67	fl/b	0.167
Coarse A.	830.0	sl/b	0.510
Fine A.	889.0	(fl+sl)/b	0.678
Performance	Predicted	TA/b	3.943
Slump	15.0	FA/TA	0.517
Slump Flow	41.2		
fcr' (3-day)	14.3		
fcr' (7-day)	19.8		
fcr' (14-day)	28.1		
fcr' (28-day)	40.0		
fcr' (56-day)	49.1		

Fig. 4. Output of the illustrative example.

4. Evaluation of CAD tool for concrete mixture optimization

To evaluate the performance of the modeling module, a set of 78 mixtures collected from the DOE module was modeled by the module. The slump and compressive strength at 3, 7, 14, 28, and 56-day of each mixture were measured. Materials in the experimental program are as follows: (1) cement is Portland cement (ASTM Type I);

(2) fly ash is obtained from a power generation plant; (3) water quenched blast-furnace slag powder is supplied by a steel production plant; (4) water is ordinary tap water; (5) chemical admixture is the superplasticizer that meets ASTM C494 type G with main ingredients of NF (Naphthalene–formaldehyde) condensate and fatty acid copolymer; (6) coarse aggregate is crushed natural rock with 10 mm maximum size; (7) fine aggregate is washed natural river sand with fineness modulus of 3.0.

Mixing was carried out in a laboratory pan mixer. The superplasticizer was premixed with water to ensure consistency of action throughout the test program. The fresh concrete was assessed by the slump test. All compressive strengths were measured on 15 cm cylinders. These were moist-cured 24 h, demolded, and then cured in water at 25 °C until testing. Each quoted strength value is the average of strengths from five cylinders.

Besides, to independently evaluate the accuracy of model built with the module, 25 concrete mixtures and their test results collected from literature [9] will be used. Although there are only 25 mixtures in the literature, they covered wide range of strength between 4000 psi (27.5 MPa) and 8000 psi (55 MPa), and wide range of workability between 5 and 25 cm in slump. These may 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. Table 1 shows the basic statistical data of these mixtures.

The root mean square error (RMS) was adopted to provide a measure of accuracy of the modeling module. Table 2 shows the values of RMS error for training set and testing set. It was found that there was small RMS error between the predicted values and measured values for the 78 mixtures in the training set and the 25 mixtures in the testing set.

To evaluate the performance of the optimization module, a set of concretes covered five different levels of characteristic compressive strength at 20, 27.5, 35, 42.5, and 50 MPa, and five different levels of workability at 5, 10, 15, 20, 25 cm in slump was designed by the module. Therefore, there are $5 \times 5 = 25$ concretes. Assuming that the standard deviation of the available test data of compressive strength is 3.65 MPa, according to Eqs. (3) and (4), the required average compressive strength is 25, 32.5, 40, 47.5, and 55 MPa, respectively. These may form a fairly representative group covering all the ranges of practical use for concretes and present rather complete information required for such an evaluation. The input data for the set of concretes consist of the unit cost, the available range, and the unit weight of each component, and are listed in Table 3. The rational ratios between components are listed in Table 4. The optimum proportion mixture obtained for each concrete is listed in Table 5.

To evaluate whether the strength and workability of mixtures obtained with the optimization module satisfy the required specifications, these mixtures were tested at laboratory. Measurements from laboratory and predictions from modeling module of the performance of these mixtures are shown in Figs. 5 and 6. Although some of them

Table 2
Validation of model for training data and testing data

Performance	Root mean square error (RMS)	
	Training data	Testing data
Slump (cm)	3.17	5.02
Slump-flow (cm)	6.89	9.95
Strength at 3-day (MPa)	2.67	3.72
Strength at 7-day (MPa)	2.92	3.84
Strength at 14-day (MPa)	2.98	4.01
Strength at 28-day (MPa)	3.32	4.22
Strength at 56-day (MPa)	3.45	4.38

Table 1
Basic statistical data of training data and testing data

Content and ratio of components	Training data			Testing data		
	Minimum	Average	Maximum	Minimum	Average	Maximum
Cement (kg)	137	241	374	140	194	349
Fly ash (kg)	0	82	193	0	66	162
Slag (kg)	0	122	260	198	234	240
Water (kg)	160	199	240	166	191	236
Superplasticizer (kg)	5	9.1	19	4.4	6.9	9.6
Coarse aggre. (kg)	708	867	1049	780	936	1050
Fine aggre. (kg)	650	754	902	641	696	841
Binder (kg)	315	445	611	340	494	589
Water/cement	0.50	0.97	1.74	0.63	1.10	1.52
Water/binder	0.33	0.48	0.68	0.30	0.41	0.61
Water/solid	0.075	0.101	0.125	0.080	0.093	0.120
SP/binder	0.010	0.021	0.038	0.013	0.014	0.023
Fly ash/binder	0.00	0.19	0.55	0.00	0.12	0.28
Slag/binder	0.00	0.27	0.61	0.39	0.49	0.60
Pozzolans/binder	0.00	0.46	0.74	0.39	0.61	0.70
Aggregate/binder	2.4	3.7	5.6	2.7	3.4	5.4
Fine aggre./aggre.	0.40	0.47	0.54	0.40	0.43	0.52

Table 3
Specifications of components

Component	Unit cost (NT dollar[a]/kg)	Lower bound (kg)	Upper bound (kg)	Specific gravity
Cement	2.25	140	350	3.15
Fly ash	0.6	0	200	2.22
Blast furnace slag	1.2	0	240	2.85
Water	0.01	150	250	1.00
Superplasticizer	25.1	3	15	1.20
Coarse aggregate	0.236	780	1050	2.54
Fine aggregate	0.28	640	900	2.66

[a] 1NT dollar = 0.029 US dollar.

Table 4
Component ratio constraints

Ratio	Lower bound	Upper bound
Water/cement	0.6	1.6
Water/binder	0.3	0.7
Water/solid	0.08	0.12
SP/binder	0.013	0.040
Fly ash/binder	0.0	0.55
Slag/binder	0.0	0.60
Pozzolans/binder	0.25	0.70
Aggregate/binder	2.7	6.4
Fine aggre./aggre.	040	0.52

did not satisfy the required strength and slump, most of them have the performance close to the required performance. The phenomenon can be explained by that because the system always tries to find the lowest cost mixture, and because the lower the cost of the mixture, in general, the lower the strength and slump of the concrete, the performance of the mixture may near their requirement margin; consequently, the chance that the performance of the mixture violates the required performance is about 50%. However, the required average compressive strength is based on the characteristic compressive strength plus a safety margin, and because the values of measured strength of the mixtures are greater than their characteristic strength, these mixtures are satisfactory in strength. With respect to slump, because the optimization module always tries to find the lowest cost mixture, and the lower the cost of the mixture, under the same required strength, the lower the slump of the concrete, to overcome the same problem, the user can specify the required slump as the specific slump plus a safety margin like the methodology used in strength.

5. Discussion on mixtures obtained with CAD tool

Although there are only 25 mixtures designed in the above section, they covered five different levels of strength and five different levels of workability. Therefore, these

Table 5
Mixtures designed with the optimization module for various requirements

f'_{cr} (MPa)	Slump (cm)	Component content (kg/m^3)							Water/binder ratio	Cost (NT dollar/m^3)
		Cement	Fly ash	Slag	Water	SP	Coarse aggre.	Fine aggre.		
25	5	140.1	11.1	135.1	196.3	3.7	1049.3	773.2	0.698	1047.7
	10	140.3	11.2	135.4	196.6	3.7	1040.7	780.7	0.698	1048.7
	15	144.4	68.7	137.5	226.4	4.6	893.1	779.9	0.659	1080.3
	20	150.0	109.6	121.2	234.1	5.0	821.0	795.4	0.628	1094.9
	25	148.2	152.6	126.3	231.6	5.6	780.4	788.6	0.555	1125.9
32.5	5	140.6	113.0	120.6	168.5	4.9	892.6	899.5	0.464	1119.3
	10	140.5	82.3	150.4	169.6	4.9	901.1	896.9	0.468	1136.4
	15	140.0	98.6	163.7	180.8	5.2	839.6	899.2	0.462	1156.7
	20	140.0	97.2	185.3	189.1	5.5	821.0	877.4	0.461	1177.7
	25	140.2	87.1	225.6	217.6	5.9	798.0	799.1	0.493	1203.2
40	5	140.0	102.1	172.5	169.0	5.4	858.7	897.8	0.421	1177.2
	10	140.3	72.4	199.9	170.0	5.4	865.9	897.5	0.425	1194.0
	15	140.6	72.9	222.5	178.8	5.7	830.0	889.0	0.423	1218.7
	20	146.4	89.0	239.3	191.4	6.2	791.5	854.9	0.416	1255.6
	25	191.0	76.6	239.2	204.6	6.6	782.6	805.1	0.417	1343.1
47.5	5	140.2	83.6	231.9	168.5	5.9	829.7	894.7	0.383	1243.7
	10	156.3	67.2	239.8	173.0	6.0	821.6	889.8	0.387	1278.6
	15	189.0	60.6	239.6	181.5	6.4	803.2	866.2	0.384	1345.8
	20	230.1	49.6	239.1	190.6	6.8	793.1	830.8	0.380	1428.2
	25	294.0	34.4	238.7	206.2	7.4	790.4	755.0	0.377	1557.2
55	5	216.1	60.7	239.8	169.0	6.8	806.5	872.0	0.340	1419.1
	10	242.1	36.5	239.8	173.7	6.8	804.9	868.0	0.348	1461.4
	15	287.6	22.9	239.9	182.5	7.2	804.9	821.6	0.345	1553.2
	20	331.6	13.3	239.8	188.3	10.6	784.2	794.8	0.340	1719.3
	25	390.0	0.0	230.0	200.0	11.0	780.4	742.3	0.340	1825.7

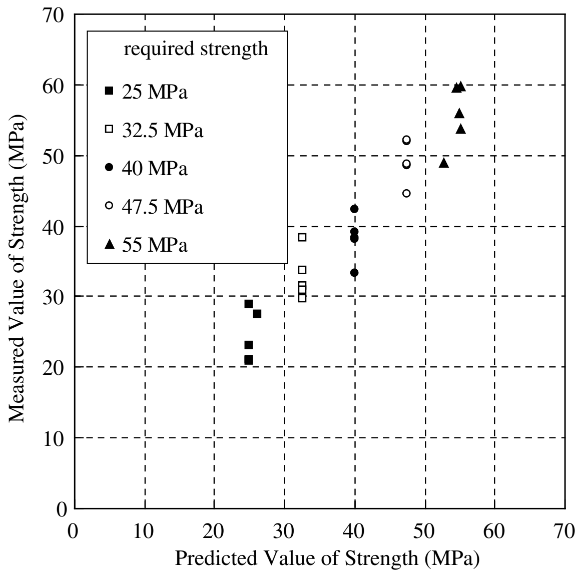

Fig. 5. Measured and predicted strength of neural network for designed mixtures.

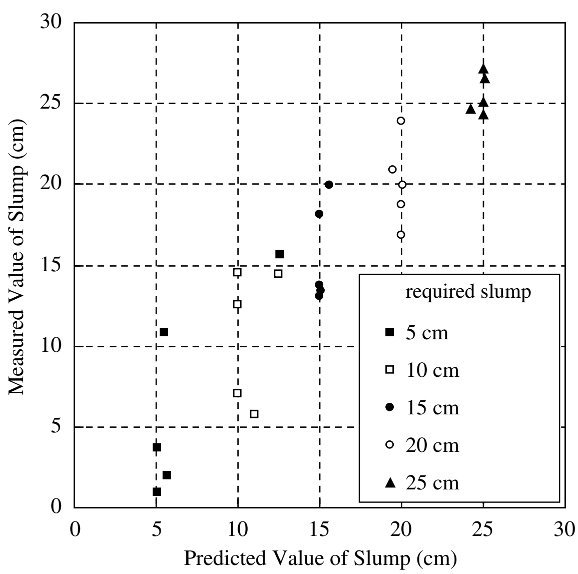

Fig. 6. Measured and predicted slump for designed mixtures.

may form a fairly representative group covering all the ranges of practical use for concrete mixtures. Consequently, the results of these mixtures may be meaningful to form a general concept on optimum concrete mixture design. These results are shown in Figs. 7–15. The results led to the following conclusions:

- Cement content (Fig. 7)
  It appears that the curves of the cement content fall into two different groups: a group with linear slope for the higher required strength or higher required slump, and a group with horizontal slope for the lower required strength and lower required slump. That is because the

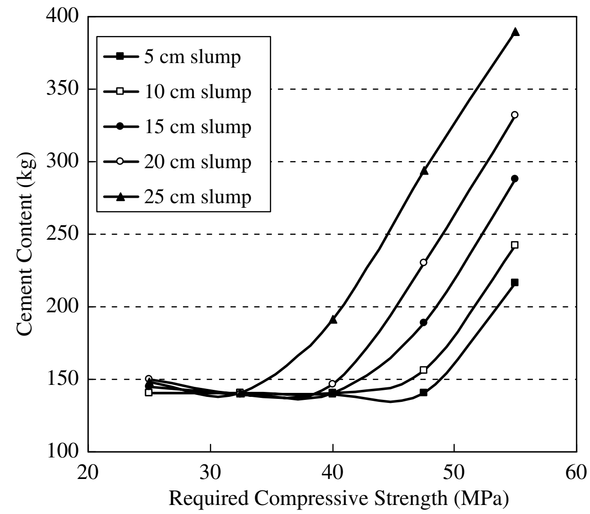

Fig. 7. Cement content for various requirements of concrete performance.

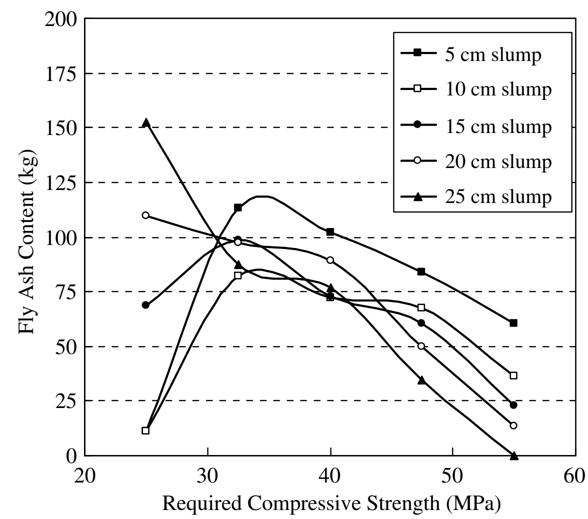

Fig. 8. Fly ash content for various requirements of concrete performance.

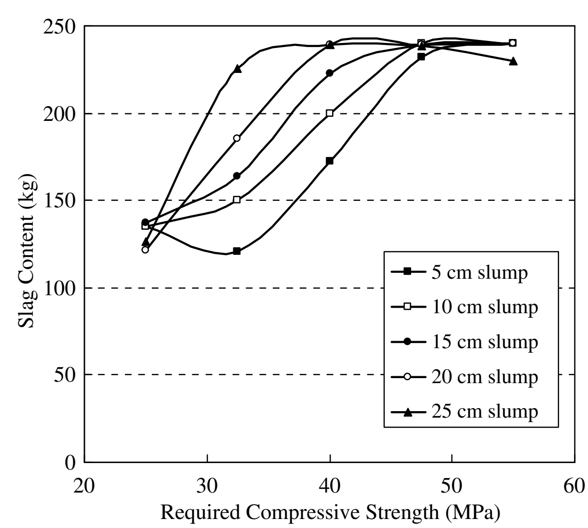

Fig. 9. Slag content for various requirements of concrete performance.

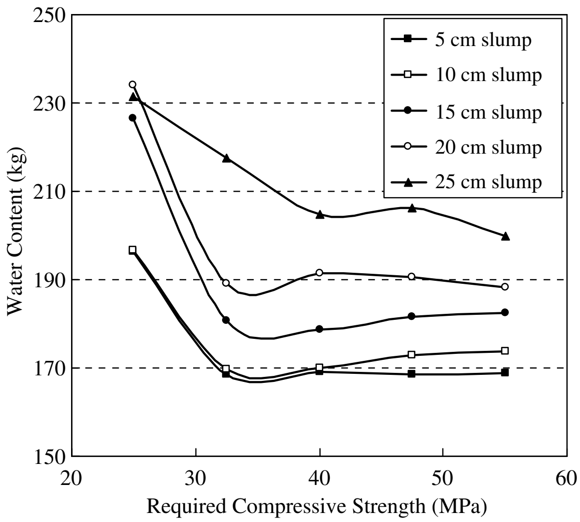

Fig. 10. Water content for various requirements of concrete performance.

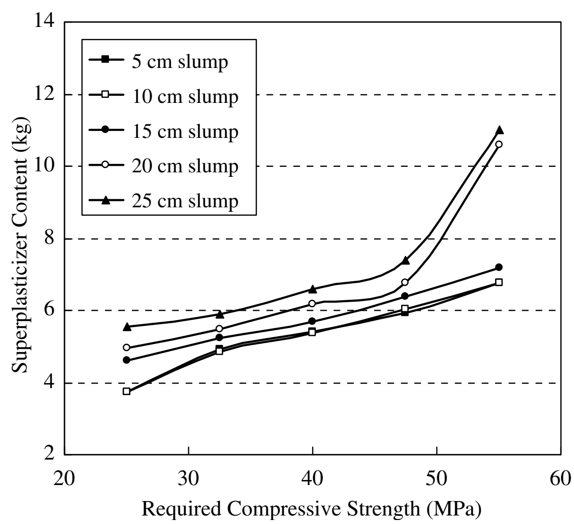

Fig. 11. SP content for various requirements of concrete performance.

lower bound of cement content limits the cement content in lower-strength lower-slump concrete.

- Fly ash content (Fig. 8)
  The plot concerning fly ash content is much more complicated in that several of the lines cross each other. However, except for low required strength cases, the increasing required strength decreases the fly ash content, and, in general, the increasing required slump also decreases the fly ash content. On the other hand, at low required strength cases, the larger the slump required, the higher the amount of fly ash required.
- Slag content (Fig. 9)
  It appears that some of the curves related to slag content exhibit an S-shape as the required strength increases. Besides, the larger the required slump, the larger the slag content.
- Water content (Fig. 10)
  The water content mainly varied with required slump and was independent on higher required strength

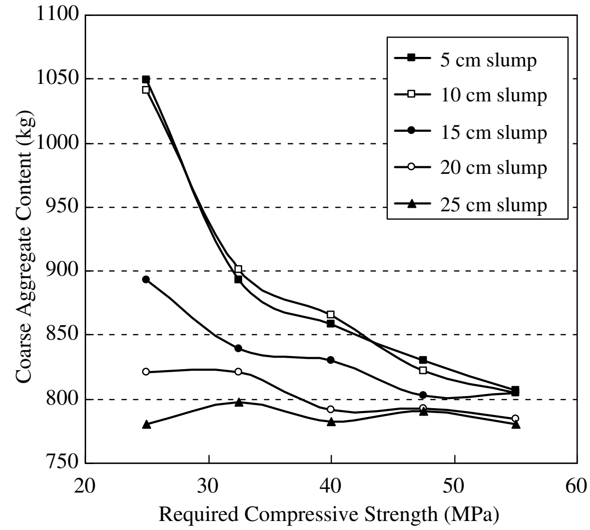

Fig. 12. Coarse aggregate content for various requirements of concrete performance.

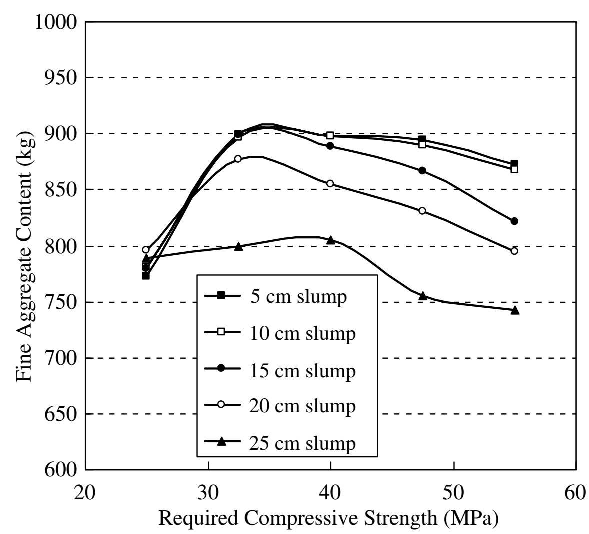

Fig. 13. Fine aggregate content for various requirements of concrete performance.

($\geqslant$40 MPa). Of particular interest is the effect of low strength requirement, rather high water content was obtained. The results may be explained by that there is a lower bound for cement in these cases, and at low required strength, cement content reaches the lower bound and cannot be reduced any more, as can be seen from Fig. 7; therefore, to keep the higher w/b for lower required strength, the required water content is higher.

- Super Plasticizer (SP) content (Fig. 11)
  The plot related to SP content is particularly simple to interpret, since the lines do not cross each other. An increasing SP was observed for increasing required strength and/or slump. However, at high required strength and high required slump, the SP content was especially high.

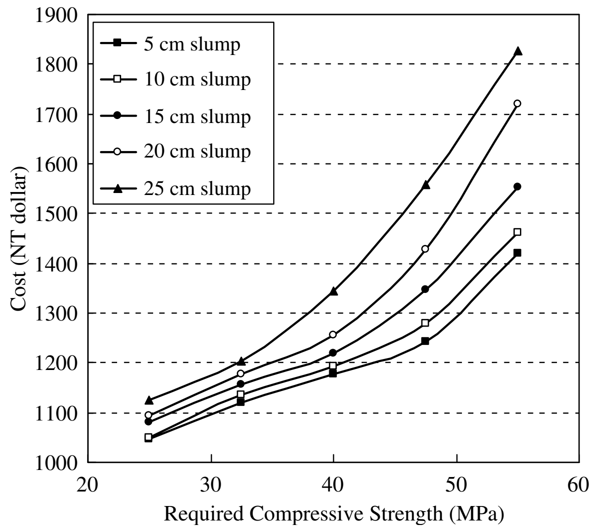

Fig. 14. Cost for various requirements of concrete performance.

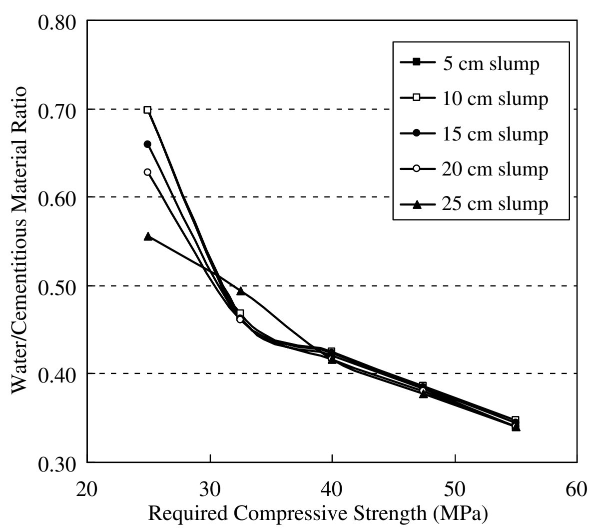

Fig. 15. w/b ratio for various requirements of concrete performance.

- Coarse aggregate (CA) content (Fig. 12)
  In general, increasing the required strength decreases the coarse aggregate content, and increasing the required slump also decreases the coarse aggregate content.
- Fine aggregate (FA) content (Fig. 13)
  In general, it appears that the larger the required slump, the smaller the required fine aggregate content.
- Cost (Fig. 14)
  The cost plot is particularly simple to interpret, since the lines do not cross each other. An increasing cost was observed for increasing required strength and/or slump. It can be explained by that (1) the higher the required strength, the lower the w/b ratio; then to make the w/b lower, the binder content must increase and the cost increase; (2) the higher the required slump, the higher the water content; then to keep the w/b constant, the binder content must increase and the cost increase.
- w/b ratio (Fig. 15)
  It can be seen that the w/b ratio decreased as the required concrete strength increased. Except for low required strength concrete, the w/b ratio was independent on the required slump. At low required strength, the w/b ratio decreased as the required slump increased.

6. Conclusions

The best approach to perform a concrete mix design is to use proportions previously established for similar concrete using the same materials. Where such prior information is limited or unavailable, the analytical method can be used to assist the user in selecting concrete proportions. The analytical method used in this paper is that of six equations, better known as the equations of material cost objective, strength requirement constraint, workability requirement constraint, component content constraint, component ratio constraint, and absolute volume constraint.

Attempts made towards achieving a rational mix proportioning method that will yield target workability and strength have led finally to developing CAD tool for them. The objective of the CAD tool is to find mix composition for a concrete with minimum cost of the components and satisfying the given strength and workability. The scope of the CAD tool is to help the user in mixture design for low- to high-strength concrete (25–55 MPa), and low- to high-workability concrete (5–25 cm in slump). The input data of the system are the intended values of strength and workability and unit weight and unit cost of each component.

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

1. The modeling module can generate rather accurate models for compressive strength and slump for concrete.
2. The optimization module can generate the lowest cost mixtures for wide range of strength and workability and their combinations. These mixtures were tested in the laboratory and validated.
3. Although the 25 mixtures considered are only for demonstrating the effectiveness of the CAD tool based on neural networks and optimization technologies to concrete mix design, they covered wide range of strength and workability and their combinations; therefore, the results of these mixtures may be useful in forming general concepts about optimal concrete mixture design. It was found that the dependence of required strength and workability on the design parameters (component contents) meets expectations.

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