Asian Journal of Scientific Research

ISSN 1992-1454

Asian Journal of Scientific Research 8 (3): 264-277, 2015
ISSN 1992-1454 / DOI: 10.3923/ajsr.2015.264.277

Prediction of Strength and Slump of Silica Fume Incorporated High-Performance Concrete

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ABSTRACT

This study describes the development of statistical models to predict strength and slump of silica fume incorporated High-Performance Concrete (HPC). Experimental data of silica fume incorporated HPC mixes were used to develop and validate models. The HPC having compressive strength range of 40-113 MPa and slump range of 180-250 mm were used. Statistical models were developed by regression analysis. The results of prediction by the models showed good agreement with those of experiments and other researchers. The developed models can be used to predict slump and 28 days compressive strength of silica fume incorporated HPC.

Key words: High-performance concrete, silica fume, strength, slump, statistical model, prediction, regression analysis

INTRODUCTION

High-Performance Concrete (HPC) is defined as concrete, which meets special combinations of performance and uniformity requirements that cannot always be achieved routinely using conventional constituents and normal mixing, placing and curing practices (Zia *et al*., 1991). The requirements may involve enhancement of characteristics such as placement and compaction without segregation, long-term mechanical properties, early-age strength, volume stability or service life in severe environments. The HPC is a relatively new product and its characteristics differ from that of normal concrete (Zain *et al*., 2002).

In HPC mix design and quality control, compressive strength and slump are regarded as important properties. Many other properties of HPC, such as elastic modulus, water tightness or impermeability, resistance to weathering agents, etc., are directly related to the strength. A majority of HPC elements are designed to take advantage of the higher compressive strength of the material. Most often, an ultimate target in the mixture design is the 28 days compressive strength. The 28 days compressive strength is usually determined based on a standard uniaxial compression test and are accepted universally as a general index of concrete strength (Patel, 2003; Kim *et al*., 2004, 2005). However, a typical compression test is performed about 28 days after placing the concrete. Should the test results fall short of the required strength, costly remediation efforts must be undertaken. Therefore, it is important to be able to estimate the compressive strength of concrete before placing it at construction sites (Kim *et al*., 2004, 2005). The more we know about the concrete composition versus strength relationship, the better we can understand the nature of concrete and how to optimize the concrete mixture (Popovics, 1990; Yeh, 1998). Statistical regression analysis techniques can be used to utilize experimental results and to estimate concrete strength from the mix components. Although several models were developed for prediction and/or optimization of concrete properties (Bouzoubaa and Fournier, 2003; Gupta *et al*., 2006; Hossain and Lachemi, 2006; Lee, 2003; Lim *et al*., 2004; Muthukumar *et al*., 2003; Nataraja *et al*., 2006; Simon, 2003; Sobolev, 2004; Tesfamariam and Najjaran, 2007), few of them includes the prediction of slump of fresh HPC (Patel, 2003; Baykasoglu *et al*., 2009; Marcia *et al*., 1997; Sonebi, 2001, 2004; Yeh, 1999), very few of them deal with silica fume incorporated HPC. Some of them consider only linear models and do not consider nonlinear models. Most of the statistical models were developed considering less than six concrete ingredients, though the making of HPC usually requires six or more ingredients. This study presents the application of statistical regression analysis for predicting the compressive strength and slump of HPC using both linear and nonlinear models. Models were developed using six common ingredients of HPC mix (i.e., cement, silica fume, water, fine aggregate, coarse aggregate and superplasticizer) as input. The HPC specimens were prepared and tested in the laboratory and the obtained data were used to develop the models. The strengths and slumps predicted by the models were compared with those of the experiments and other researcher (Marcia *et al*., 1997). Thus, using these models, sustainable development can be achieved by producing HPC incorporating silica fume as it reduces use of cement, consumes industrial waste, increases strength and durability of concrete. Finally, the use of these models will allow the concrete industry to avoid the risk of faulty or deficient concrete that often entails durability and safety problems.

MATERIAL PROPERTIES

Ordinary Portland cement (Type I) was used that meets the ASTM C150-92 specifications. The chemical and physical properties of the cement and silica fume are shown in Table 1. Natural river sand and crushed limestone were used as aggregates. The gradation of both fine and coarse aggregates met the ASTM C33-93 specification. The details of physical properties of both aggregates are shown in Table 2. Glenium 100 M superplasticizer complying with the requirements of ASTM C494-92 and ASTM C1017-92 was used (solid content = 25.25% and specific gravity = 1.28). Normal tap water (pH = 6.9) was used as mixing water and for curing.

Table 1: Chemical and physical properties of cement and silica fume

Chemical/physical properties	Cement	Silica fume
SiO_2 (%)	21.54	93.09
Al_2O_3 (%)	5.99	1.42
CaO (%)	65.30	0.00
MgO (%)	0.77	0.93
MnO (%)	0.01	0.08
P_2O_5 (%)	0.31	0.23
SO_3 (%)	1.41	0.10
TiO_2 (%)	0.21	0.08
Fe_2O_3 (%)	4.45	4.09
C (%)	0.71	2.19
Loss on ignition (LOI) (%)	1.06	1.49
Specific gravity	3.16	2.23
Specific surface area (m^2 kg^{-1})	402.00	-
Specific surface area, Blaine (m^2 g^{-1})	-	216.00
Fineness >45 mm (%)	-	3.50

Table 2: Physical properties of fine and coarse aggregates

Physical property	Fine aggregate	Coarse aggregate
Size (mm)	0-4.75	4.75-19
Bulk specific gravity	2.6	2.61
Absorption (%)	1.47	0.82
Fineness modulus	3.04	6.68

CONCRETE MIXES, SPECIMEN PREPARATION AND TESTING

Thirty nine series of silica fume incorporated HPC were prepared in the laboratory. Table 3 shows water-to-binder ratio (W/B), Cement (C), Silica Fume (SF), Water (W), Fine Aggregate (FA), Coarse Aggregate (CA) and Superplasticizer (SP) contents of these mixes.

A rotating pan-type mixer of 0.05 m^3 capacity was used to mix concrete. Each batch included sufficient concrete for three slump tests and four 100×200 mm cylinders for compressive strength test. The cylinders were fabricated in accordance with ASTM C192. To obtain adequate consolidation, the cylinders were rodded. The cylinders were covered with plastic and left in the molds for 24 h, after which they were stripped and placed in limewater-filled curing tanks for moist curing at 23±2°C. Slump test of fresh concrete was carried out as per ASTM C143. Compressive strength tests (ASTM C39) were conducted on the cylinders at the age of 28 days. In most cases, three cylinders were tested. A fourth test was performed in some cases if one result was significantly lower or higher than the others. Before testing, the cylinder ends were ground parallel to meet the ASTM C39 requirements using an end-grinding machine designed for this purpose. The average strength of three cylinders was reported as result of the test. Results of slump test (range: 180-250 mm) and compressive strength test (range: 40.32-113.15 MPa) are also shown in Table 3.

MODEL DEVELOPMENT

Six variables were selected to derive statistical models and ultimately to evaluate the properties of silica fume incorporated HPC. The limits of the variables were decided by conducting some preliminary tests performed in the laboratory and from past experience. The notations used and limits of the variables are as follows:

- x_1 is cement content (kg m^{-3}) (range: 367.1-508.8)
- x_2 is silica fume content (kg m^{-3}) (range: 58.1-67.3)
- x_3 is water content (kg m^{-3}) (range: 137.2-195.5)
- x_4 is fine aggregate content (kg m^{-3}) (range: 588.4-685.5)
- x_5 is coarse aggregate content (kg m^{-3}) (range: 960.8-1088.5)
- x_6 is superplasticizer content (l m^{-3}) (range: 3.8-24.8)

The MATLAB software was used to derive eight models by the least square approach. The general structure of the statistical model is as follows:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_1^2 + \sum_{i<j} \sum \beta_{ij} x_i x_j + \varepsilon \tag{1}$$

where, y is the response (strength or slump); x_i are the independent variables; β_0 is the independent term; β_i, β_{ii} and β_{ij} are the coefficients of independent variables and interactions, representing their contribution to the response; ε is the random residual error term representing the effects of

Table 3: Mix proportions and properties of silica fume incorporated HPC

Mix No.	W/B	C (kg m^{-3})	SF (kg m^{-3})	W (kg m^{-3})	FA (kg m^{-3})	CA (kg m^{-3})	SP (l m^{-3})	Slump (mm)	28 days strength (N mm^{-2})
1	0.40	430.0	65.0	195.5	641.3	960.8	5.8	200	40.32
2	0.42	367.1	67.2	180.5	670.3	1024.9	4.4	190	45.84
3	0.39	385.8	63.7	173.6	675.4	1018.5	6.9	195	49.51
4	0.39	384.7	64.0	174.0	684.9	1024.1	8.4	185	59.95
5	0.40	380.0	64.3	178.0	682.1	1020.4	3.8	180	45.03
6	0.40	379.8	64.3	177.9	682.6	1020.7	4.1	195	60.58
7	0.40	376.2	64.6	177.8	685.5	1020.8	4.0	190	59.01
8	0.37	391.9	67.3	170.9	658.1	1038.2	5.8	195	52.68
9	0.35	408.4	62.9	165.6	664.7	1027.1	9.0	195	62.07
10	0.35	407.7	64.1	165.7	670.8	1040.6	10.4	185	72.21
11	0.36	402.1	64.2	168.3	664.2	1032.9	5.7	195	64.27
12	0.36	402.0	64.2	168.2	665.5	1034.9	4.9	220	70.45
13	0.36	400.5	64.3	167.5	666.3	1034.4	5.9	210	68.64
14	0.33	455.0	60.0	167.4	660.0	989.0	10.2	205	62.96
15	0.33	418.3	67.1	161.8	644.1	1049.8	7.8	200	59.90
16	0.32	430.6	62.0	158.5	653.3	1033.5	11.5	220	71.91
17	0.32	430.4	64.0	158.3	657.0	1055.1	12.6	200	67.54
18	0.33	423.8	63.9	159.7	653.2	1042.3	8.3	205	85.61
19	0.33	423.8	63.9	159.7	654.7	1044.6	7.2	220	81.07
20	0.30	470.0	60.0	156.4	665.0	997.0	11.6	225	64.70
21	0.30	446.5	66.7	153.1	627.2	1057.7	10.5	210	78.02
22	0.30	452.6	60.9	152.0	642.8	1040.5	14.2	220	69.07
23	0.29	453.1	63.7	151.6	643.4	1067.7	12.6	205	78.60
24	0.30	445.7	63.4	151.9	641.6	1049.2	11.2	225	97.75
25	0.30	445.8	63.4	151.9	643.2	1052.0	9.8	230	93.67
26	0.30	443.4	63.2	152.0	642.2	1047.2	12.7	220	88.28
27	0.27	480.0	60.0	145.8	669.0	1002.0	15.6	210	71.32
28	0.27	476.7	66.0	144.9	608.6	1063.5	14.5	215	91.89
29	0.27	474.7	59.6	146.1	630.3	1043.5	17.7	223	81.79
30	0.27	476.0	63.3	145.4	629.7	1078.8	15.6	205	96.50
31	0.27	467.8	62.7	144.7	627.2	1050.5	16.7	230	100.67
32	0.27	468.1	62.8	144.8	631.6	1058.2	12.3	235	102.71
33	0.28	465.0	62.4	145.3	629.2	1050.2	16.9	230	102.20
34	0.24	508.8	64.9	137.2	588.4	1066.9	19.5	245	99.95
35	0.25	497.1	58.1	140.6	616.9	1044.7	22.4	215	70.64
36	0.25	499.3	62.8	139.6	615.8	1088.5	19.2	200	103.10
37	0.25	490.5	61.9	138.0	614.1	1053.0	20.7	225	103.56
38	0.25	491.0	62.0	138.1	615.1	1055.2	19.6	250	113.15
39	0.25	487.1	61.4	139.0	612.5	1045.7	24.8	230	108.90

W/B: Water-to-binder ratio, C: Cement, SF: Silica fume, W: Water, FA: Fine aggregate, CA: Coarse aggregate, SP: Superplasticizer

variables or higher order terms not considered in the model (Kutner *et al*., 2004). Using the data of 39 mixes of HPC presented in Table 3, four different statistical models were developed for 28 days compressive strength prediction and four different statistical models were also developed for slump prediction. The models are linear, interaction, pure quadratic and full quadratic models. The mathematical expressions of the models and brief discussion about each model are given in the following sections. Statistical summary e.g., RMSE (Root Mean Square Error), R^2 (coefficient of determination), R^2(adj) (adjusted coefficient of determination), F-value and significance (p) of each model are also given in tabular form.

Statistical models for 28 days compressive strength: In design and quality control of concrete, 28 days compressive strength is normally specified. The 28 days compressive strength is a universally accepted index to know the strength of concrete which is usually determined by a standard axial compression test. The linear, pure quadratic, interaction and full quadratic models for prediction of the 28 days compressive strength are described in the following sections.

Linear strength model: The linear strength model contains only linear and constant terms. Equation 2 shows the linear strength model:

$$Y = 364-0.057X_1-0.19X_2-1.15X_3-0.22X_4+0.08X_5-0.65X_6 \tag{2}$$

Equation 2 shows that all the six variables such as cement (X_1), silica fume (X_2), water (X_3), fine aggregate (X_4), coarse aggregate (X_5) and superplasticizer (X_6) have direct influence on the response (28 days compressive strength, Y). Figure 1 shows plot of the residuals of linear strength model versus the data order of concrete mix. The plot indicates that the errors are independent. The residuals appear to be randomly scattered about zero. Table 4 shows the statistical summary of the model. It appears that the probability greater than "F statistic" (Fisher statistic) is less than 0.0005 (Table 4). The model is highly statistically significant with confidence level more than 99.95%. It indicates a good model for the data. Coefficient of determination (R^2) of the model is 80.7%, which indicates a good fit. Figure 2 shows scatter plot of experimental and predicted compressive strengths versus the data order of the experiments. It shows that the predicted values are close to those of the experiments.

Pure quadratic strength model: The pure quadratic model contains pure quadratic (squared), linear and constant terms. Equation 3 shows the pure quadratic strength model:

$$\begin{aligned} Y = 8766&+2.18\ X_1+64.2\ X_2-10.1\ X_3-4.05\ X_4-16.3\ X_5-3.01\ X_6-0.00331\ X_1^2- \\ &0.517\ X_2^2+0.0212\ X_3^2+0.003\ X_4^2+0.0078\ X_5^2+0.071\ X_6^2 \end{aligned} \tag{3}$$

Table 4 shows the statistical summary of the pure quadratic strength model. It can be seen that significance (p) value of the model is close to zero, which indicates a good model for the data.

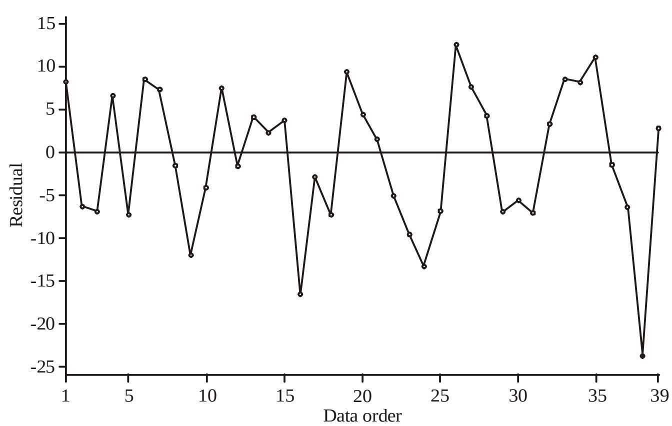

Fig. 1: Residuals vs. data order for linear strength model

Table 4: Statistical summary of strength models

Model	RMSE	R^2 (%)	R^2 (adj) (%)	F-value	Significance (p)
Linear	9.302	80.7	77.4	24.40	3.80 e^{-11}
Pure quadratic	6.998	91.0	87.2	24.29	6.43 e^{-12}
Interaction	5.850	95.6	91.1	20.89	2.23 e^{-09}
Full quadratic	5.533	97.3	92.0	18.47	5.25 e^{-07}

RMSE: Root mean square error; R^2: Coefficient of determination, R^2 (adj): Adjusted coefficient of determination

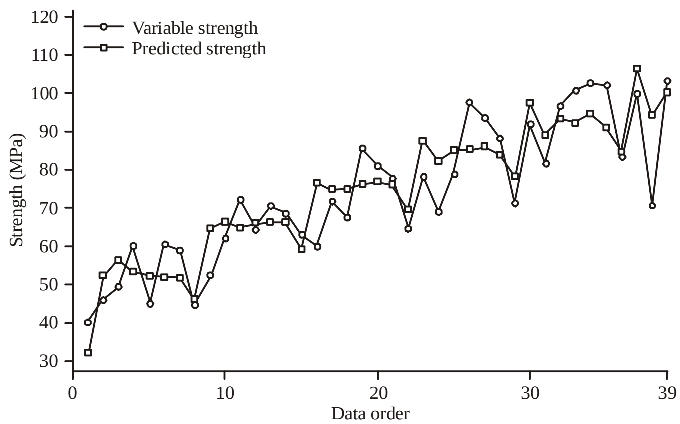

Fig. 2: Experimental and predicted compressive strengths vs. data order for linear strength model

Coefficient of determination (R^2) of the model is 91.0%, which is higher than that of the linear strength model. Root Mean Square Error (RMSE) of the pure quadratic model is 6.998, which is less than that of the linear strength model (9.302). These are indications of better fit of the pure quadratic model than linear strength model. This model fits the data in a better way than that of the linear model because the adjusted determination coefficient is higher and the root mean square error is lower for pure quadratic strength model.

Interaction strength model: The interaction model contains interaction (product), linear and constant terms. Equation 4 shows the interaction strength model.

$$\begin{aligned} Y = &-95331+35.2 X_1+1036 X_2+44 X_3+48.0 X_4+68.3 X_5+125 X_6-0.56 X_1X_2+0.094 X_1X_3 \\ &-0.01X_1X_4-0.009 X_1X_5+0.030 X_1X_6-0.68 X_2X_3-0.33 X_2X_4-0.47 X_2X_5+1.94 X_2X_6+0.05 X_3X_4 \\ &-0.07 X_3X_5- 0.52 X_3X_6-0.03 X_4X_5+0.10 X_4X_6-0.24X_5X_6 \end{aligned} \quad (4)$$

Table 4 shows the statistical summary of the interaction strength model. It can be seen that significance (p) value of the model is close to zero, which indicates a good model for the data. Coefficient of determination (R^2) of the model is 95.6%, which is higher than that of the pure quadratic strength model (91.0%). Root Mean Square Error (RMSE) of the interaction strength model is 5.85, which is less than that of the pure quadratic strength model (6.998). These are indications of better fit of the interaction strength model than pure quadratic strength model. This model fits the data in a better way than the pure quadratic model because the adjusted determination coefficient is higher and the root mean square error is lower for the interaction strength model.

Full quadratic strength model: The full quadratic model contains pure quadratic (squared), interaction (product), linear and constant terms. Equation 5 shows the full quadratic strength model:

$$\begin{aligned} Y = &-715145+1189 X_1+8090 X_2+295 X_3+1312 X_4-485 X_5+1104 X_6-3.41 X_1X_2-0.73 X_1X_3-0.779 X_1X_4 \\ &-0.085 X_1X_5-1.62 X_1X_6-7.58 X_2X_3-3.25 X_2X_4-1.91 X_2X_5-8.68 X_2X_6-1.03 X_3X_4+1.01X_3X_5-1.18 X_3X_6 \\ &-0.110 X_4X_5-0.80 X_4X_6+0.807 X_5X_6-0.286 X_1^2-9.67 X_2^2+0.44 X_3^2- 0.373 X_4^2+0.263 X_5^2+0.477 X_6^2 \end{aligned} \quad (5)$$

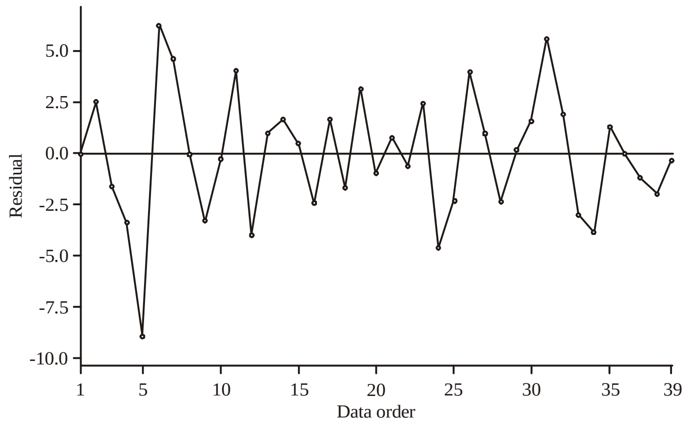

Fig. 3: Residuals vs. data order for full quadratic strength model

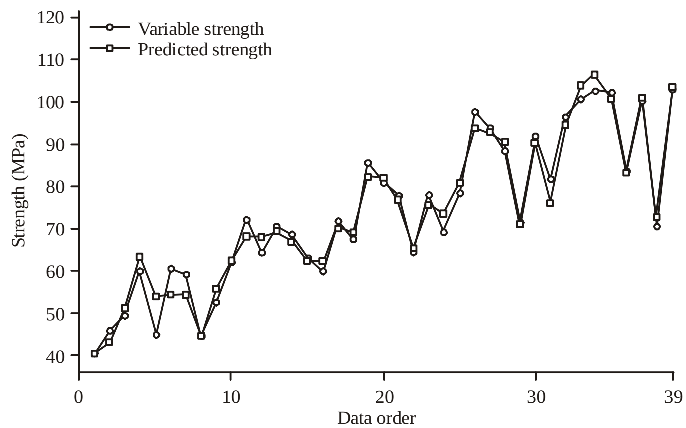

Fig. 4: Experimental and predicted compressive strengths vs. data order for full quadratic strength model

Figure 3 shows that the residuals of the full quadratic strength model are randomly scattered about zero. No evidence seems to exist that the error terms are correlated with one another. Table 4 shows the statistical summary of the model. It can be seen that significance (p) value of the model is close to zero, which indicates a good model for the data. Coefficient of determination (R^2) of the model is 97.3%, which is the highest among the determination coefficients of all the strength models. Root Mean Square Error (RMSE) of the full quadratic strength model is 5.533, which is the lowest of all the RMSE values of all the strength models. Thus the full quadratic strength model best fits the experimental data. Figure 4 shows scatter plot of experimental and predicted compressive strengths versus the data order of the experiments. It shows that the predicted values are very close to those of the experiments. This model fits the data in the best way of all the strength models discussed above.

Statistical models for slump: The slump is one of the most important properties of HPC. Based on the experimental tests done in laboratory and it is also observed that if the slump of fresh concrete is between 180 and 220 mm without any segregation, the concrete can be qualified for

HPC (Patel, 2003). Of course, other fresh concrete tests are also important to evaluate thoroughly the fresh HPC properties. However, one can take decision from slum test, if other test set-ups are not available. The linear, pure quadratic, interaction and full quadratic models for prediction of slump of silica fume incorporated HPC are described in the following sections.

Linear slump model: Equation 6 shows the linear slump model.

$$Y = 2051-0.44\ X_1-3.32\ X_2-2.07\ X_3-0.96\ X_4-0.44\ X_5-3.14X_6 \tag{6}$$

The statistical details of this model are presented in Table 5. It appears that the probability greater than “F statistic” (Fisher statistic) is less than 0.0005. The model is highly statistically significant with a confidence level more than 99.95%. It can be seen that significance (p) value of the model is close to zero, which indicates a good model for the data. Coefficient of determination (R^2) of the model is 76.4%, which indicates a reasonably good fit.

Pure quadratic slump model: The following Eq. 7 shows the pure quadratic slump model:

$$\begin{aligned} Y = &-8332+0.81\ X_1+47.3\ X_2-12.2\ X_3+0.79\ X_4+15.8\ X_5-2.65\ X_6-0.0009\ X_1^2 \\ &-0.39\ X_2^2+0.033\ X_3^2-0.001X_4^2-0.0078\ X_5^2-0.028\ X_6^2 \end{aligned} \tag{7}$$

Table 5 shows the statistical summary of the pure quadratic slump model. It can be seen that significance (p) value of the model is close to zero, which indicates a good model for the data. Coefficient of determination (R^2) of the model is 83.5%, which is more than that of the linear strength model. Root Mean Square Error (RMSE) of the pure quadratic model is 8.231, which is less than that of the linear strength model (8.972). These are indications of better fit of the pure quadratic model than linear slump model. This model fits the data in a better way than the linear model because the adjusted determination coefficient is higher and the root mean square error is lower for pure quadratic slump model.

Interaction slump model: The following Eq. 8 shows the interaction slump model:

$$\begin{aligned} Y = &-15990+25.0\ X_1+142\ X_2+23\ X_3+5.4\ X_4+6.7\ X_5+25\ X_6-0.161\ X_1X_2-0.0026\ X_1X_3 \\ &-0.0013X_1X_4-0.0137\ X_1X_5-0.032\ X_1X_6+0.34\ X_2X_3-0.21\ X_2X_4-0.007\ X_2X_5+1.25\ X_2X_6 \\ &-0.0051X_3X_4-0.0432\ X_3X_5+0.068\ X_3X_6+0.0101\ X_4X_5-0.145\ X_4X_6-0.010\ X_5X_6 \end{aligned} \tag{8}$$

Figure 5 shows that the residuals of the interaction slump model are randomly scattered about zero. No evidence seems to exist that the error terms are correlated with one another. Table 5 shows the statistical summary of the interaction strength model. It can be seen that significance

Table 5: Statistical summary of slump models

Model	RMSE	R^2 (%)	R^2 (adj) (%)	F-value	Significance (p)
Linear	8.972	76.4	72.3	24.40	3.77 e^{-11}
Pure quadratic	8.231	83.5	76.7	12.24	2.60 e^{-08}
Interaction	7.511	90.5	80.6	9.11	3.25 e^{-06}
Full quadratic	8.288	91.9	76.4	5.91	5.64 e^{-04}

RMSE: Root mean square error; R^2: Coefficient of determination, R^2 (adj): Adjusted coefficient of determination

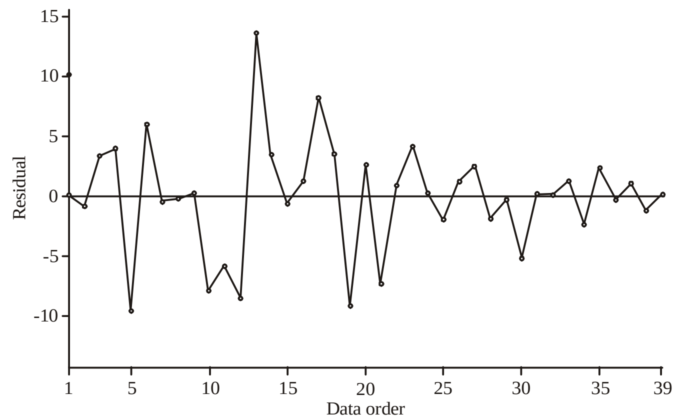

Fig. 5: Residuals vs. data order for interaction slump model

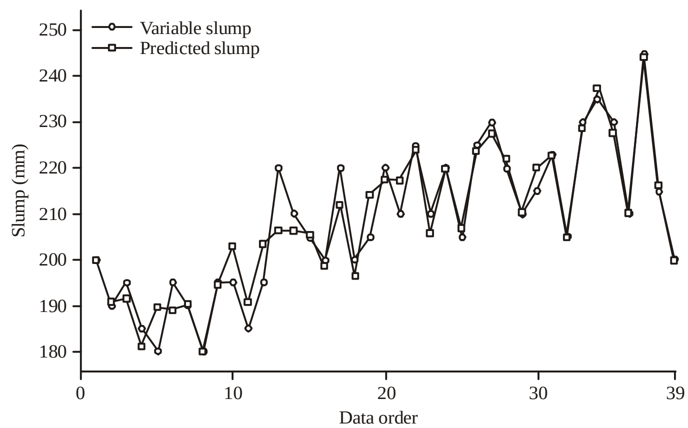

Fig. 6: Experimental and predicted slumps vs. data order for interaction slump model

(p) value of the model is close to zero, which indicates a good model for the data. Coefficient of determination (R^2) of the model is 90.5%, which is more than that of the pure quadratic strength model (83.5%). Root Mean Square Error (RMSE) of the interaction strength model is 7.511, which is less than that of the pure quadratic strength model (8.231). These are indications of better fit of the interaction strength model than pure quadratic strength model. This model fits the data in a better way than that of the pure quadratic model because the adjusted determination coefficient is higher and the root mean square error is lower for interaction slump model. Figure 6 shows scatter plot of experimental and predicted slumps versus the data order of the experiments. It shows that the predicted values are very close to those of the experiments.

Full quadratic slump model: The following Eq. 9 shows the full quadratic slump model:

$$\begin{aligned} Y = {} & 185466-859\,X_1-8807\,X_2+324\,X_3-688\,X_4+919\,X_5-483\,X_6+3.52\,X_1X_2+0.61\,X_1X_3+0.56\,X_1X_4-0.059\,X_1X_5 \\ & +1.11\,X_1X_6+9.6\,X_2X_3+3.50\,X_2X_4+2.61\,X_2X_5+10.2\,X_2X_6+0.60\,X_3X_4-1.31\,X_3X_5+0.03\,X_3X_6-0.152\,X_4X_5 \\ & +0.67\,X_4X_6-1.03\,X_5X_6+0.264\,X_1^2+5.23\,X_2^2-0.69\,X_3^2+0.218\,X_4^2-0.355\,X_5^2+0.033\,X_6^2 \end{aligned} \tag{9}$$

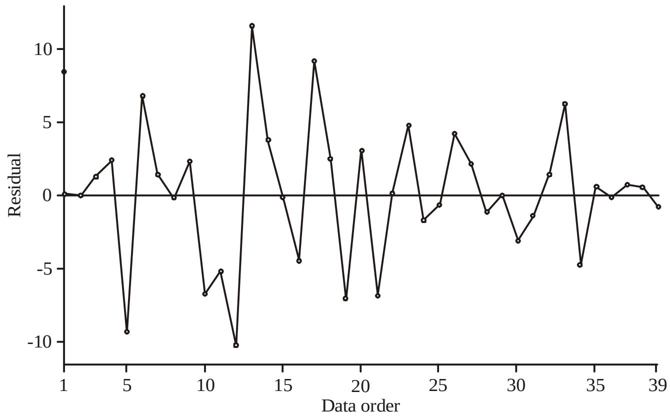

Fig. 7: Residuals vs. data order for full quadratic slump model

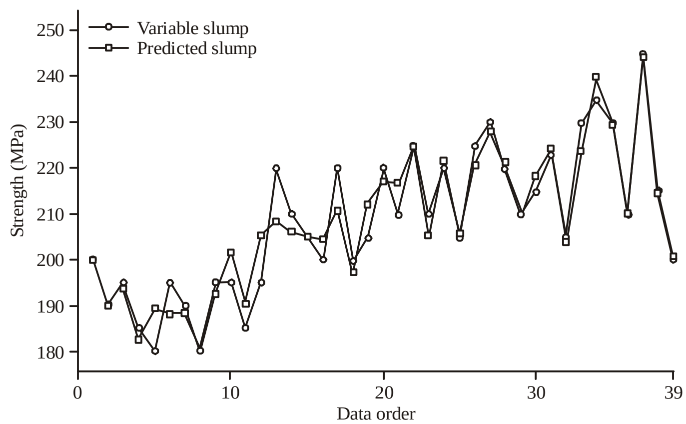

Fig. 8: Experimental and predicted slumps vs. data order for full quadratic slump model

Figure 7 shows that the residuals of the full quadratic slump model are randomly scattered about zero. No evidence seems to exist that the error terms are correlated with one another. Table 5 shows the statistical summary of the model. It can be seen that significance (p) value of the model is close to zero, which indicates a good model for the data. The adjusted determination coefficient (76.4%) is lower than that of the interaction model (80.6%), which indicates that interaction model fits the data better than the full quadratic model. Root mean square error of the model (8.288) is higher than that of the interaction model (7.511), which means interaction model fits data in a better way. Thus the interaction slump model fits the experimental data in a better way than the full quadratic model. Figure 8 shows scatter plot of experimental and predicted slumps versus the data order of the experiments. It shows that the predicted values are very close to those of the experiments. This indicates a reasonably good fit of the model.

MODEL VALIDATION

Model validation using concrete of same ingredients: Three HPC mixtures were prepared and tested with the same ingredients to verify the ability of the proposed models to predict the responses. Table 6 shows the quantities of the ingredients, 28 days strength and slump of these

Table 6: Data for validation of the models using concrete of the same ingredients

Mix No.	W/B	C (kg m^{-3})	SF (kg m^{-3})	W (kg m^{-3})	FA (kg m^{-3})	CA (kg m^{-3})	SP (l m^{-3})	Slump (mm)	28 day Strength (MPa)
1	0.36	440	65.0	181.1	650.0	974.0	7.5	180	44.64
2	0.33	422	63.8	159.4	655.2	1043.2	8.4	210	77.72
3	0.25	500	55.0	136.0	667.0	999.0	22.9	210	83.36

W/B: Water-to-binder ratio, C: Cement, SF: Silica fume, W: Water, FA: Fine aggregate, CA: Coarse aggregate, SP: Superplasticizer

Table 7: Model validation using the data of Table 6

		Strength (MPa)		Slump (mm)		Variation (%)	
Model used	Mix No.	Experiment	Prediction	Experiment	Prediction	Slump	Strength
Linear	1	44.6	46.1	180	194.5	-8.1	-3.3
	2	77.7	76.2	210	213.3	-1.6	1.9
	3	83.3	84.7	210	219.0	-4.3	-1.7
Pure quadratic	1	44.6	44.4	180	190.8	-6.0	0.5
	2	77.7	79.8	210	212.9	-1.4	-2.7
	3	83.3	79.6	210	207.7	1.1	4.4
Interaction	1	44.6	44.7	180	181.2	-1.3	5.8
	2	77.7	82.3	210	216.7	-3.2	-5.9
	3	83.3	82.8	210	210.5	-0.5	1.0
Full quadratic	1	44.6	44.6	180	181.5	-2.0	-3.6
	2	77.7	76.9	210	216.8	-4.1	1.1
	3	83.3	83.3	210	212.0	-2.1	-0.5

Table 8: Data for validation of the models using concrete of different ingredients (Marcia *et al*., 1997)

Mix No.	W/B	C (kg m^{-3})	SF (kg m^{-3})	W (kg m^{-3})	FA (kg m^{-3})	CA (kg m^{-3})	SP (l m^{-3})	Slump (mm)	28 day Strength (MPa)
1	0.43	312.9	21.9	141.1	506.3	845.3	3.52	102	48.5
2	0.37	312.9	21.9	122.3	592.2	810.1	3.52	57	53.2
3	0.35	312.9	45.4	122.3	532.2	836.0	5.66	76	59.8
4	0.37	312.9	21.9	122.3	549.2	853.0	3.52	67	51.0
5	0.37	323.3	27.8	126.6	513.6	857.5	5.12	95	60.8
6	0.38	335.8	21.9	131.5	526.1	829.9	4.59	99	50.2
7	0.38	335.8	21.9	131.5	526.1	829.9	4.59	92	54.1
8	0.38	335.8	21.9	131.5	526.1	829.9	4.59	102	54.6
9	0.34	337.0	33.6	122.3	530.6	834.4	4.59	99	61.0
10	0.38	354.8	21.9	141.4	506.3	810.1	3.52	67	48.2
11	0.32	361.1	45.4	126.6	506.3	810.1	5.66	51	58.1
12	0.33	361.1	21.9	122.3	548.8	810.1	4.59	51	54.5
13	0.33	361.1	21.9	122.3	526.1	829.9	5.66	57	55.2
14	0.33	361.1	21.9	122.3	526.1	829.9	5.66	108	65.3
15	0.33	361.1	21.9	122.3	506.3	852.6	4.59	64	54.6
16	0.35	361.1	21.9	130.8	529.0	810.1	3.52	51	53.2

W/B: Water-to-binder ratio, C: Cement, SF: Silica fume, W: Water, FA: Fine aggregate, CA: Coarse aggregate, SP: Superplasticizer

three concrete mixes. The slump and the 28 days compressive strength were also predicted by the respective models and compared with those of the experiments. The experimental and model predicted values of slump and 28 days compressive strength are shown in Table 7. The tests were carried out with the same materials and under the same testing conditions. Table 7 shows that the variations among model predicted and experimental values for slump and strength were not significant. The percentage errors of full quadratic model were the least for predicting the 28 days strength, which is an indication that the full quadratic model for predicting strength is the best model. Table 7 also shows that percentage variations in slump in case of interaction slump model were the least, which is an indication that the interaction model for predicting slump is the best model. Thus, the models predict 28 days strength and slump with reasonable accuracy.

Model validation using concrete of different ingredients: The developed models were used to predict strength and slump of HPC incorporating ingredients having slightly different physical properties. The data (Table 8) was obtained from Marcia *et al*. (1997). The validation results are

Table 9: Model validation using the data of Table 8

		Strength (MPa)		Slump (mm)		Variation (%)	
Model used	Mix No.	Experiment	Prediction	Experiment	Prediction	Slump	Strength
Full quadratic	1	48.5	44.0	102	110.0	7.8	-9.2
	2	53.2	50.0	57	61.5	7.9	-6.0
	3	59.8	56.0	76	80.0	5.2	-6.3
	4	51.0	47.0	67	62.5	-6.7	-7.8
	5	60.8	63.0	95	93.0	-2.1	3.6
	6	50.2	46.5	99	92.5	-6.5	-7.3
	7	54.1	50.5	92	96.0	4.3	-6.6
	8	54.6	51.5	102	107.5	5.4	-5.6
	9	61.0	66.0	99	104.0	5.1	8.2
	10	48.2	53.0	67	71.0	5.9	9.9
	11	58.1	62.0	51	53.0	3.9	6.7
	12	54.5	49.0	51	55.5	8.8	-10.1
	13	55.2	51.0	57	60.5	6.1	-7.6
	14	65.3	70.0	108	101.0	-6.4	7.1
	15	54.6	60.0	64	68.0	6.2	9.8
	16	53.2	48.5	51	48.5	-4.9	-8.8

shown in Table 9. Table 9 shows that the variations among predicted and experimental values for slump were from 2.1-8.8% and those for strength were from 3.6-10.1%. These variations may be due to the variations in the properties of the ingredients and experimental conditions. However, the variations were not significant. Thus, the models can be used for prediction of strength and slump of HPC having different ingredients but within the range of properties considered for the development of the models.

LIMITATIONS OF THE MODELS

The proposed statistical models were derived from thirty nine HPC mixes with ingredients described earlier (Table 1-3). It is very important to note that derived models are material specific. The absolute responses from the models can differ if the properties of materials vary considerably from the materials used to derive the models. The method is not applicable to extrapolation beyond the domain of the data used in the development of the models. However, the models may be useful for prediction of strength and slump of silica fume incorporated HPC having different ingredients in future.

CONCLUSION

The following conclusions can be drawn from the present study:

- Using statistical analysis and experimental data, eight models for predicting strength and slump of silica fume incorporated HPC were developed. The best models for strength and slump were indicated within the ranges of the properties of materials used (Table 7, 9)
- Developed models were evaluated. The results of prediction were reasonably accurate and reliable. The derived statistical models are useful tools in understanding the effect of various variables (ingredients) and their interaction on the HPC properties
- Like other data-fitting techniques, the regression analysis only processes predictive capability within the range of data employed for model fitting. The range of applicability of the present work is limited to the range of the various parameters of experimental data used for the development of the models. The models can substantially reduce time, effort and cost associated with selection of trial batches

ACKNOWLEDGMENTS

The research study reported in this paper was funded by the Ministry of Science, Technology and Innovation, Malaysia and University Kebangsaan Malaysia (UKM). Materials were supplied by Ready Mixed Concrete (M) Sdn Bhd, Malaysia. The authors would like to express sincere gratitude for all the supports provided. The second author (M.R. Karim) and third author (M.N. Islam) express their sincere gratitude to Dhaka University of Engineering and Technology (DUET), Gazipur, Bangladesh for granting him leave for the research.

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