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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 regession 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
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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 |
|-----------------------------|--------------|-------------|
| SiO₂ (%)                    | 21.54        | 93.09       |
| Al₂O₃ (%)                   | 5.99         | 1.42        |
| CaO (%)                     | 65.30        | 0.00        |
| MgO (%)                     | 0.77         | 0.93        |
| MnO (%)                     | 0.01         | 0.08        |
| Fe₂O₃ (%)                   | 0.31         | 0.23        |
| SO₃ (%)                     | 1.41         | 0.10        |
| TiO₂ (%)                    | 0.21         | 0.08        |
| Fe₂O₃ (%)                   | 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 (m² kg⁻¹) | 402.00      | .           |
| Specific surface area, Blaine (m² 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)            | 0.4-4.75       | 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 m³ 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:

\[
y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ij} x_i^2 + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ij} x_i x_j + \varepsilon
\]

where, \( y \) is the response (strength or slump); \( x_i \) are the independent variables; \( \beta_0 \) is the independent term; \( \beta_i \), \( \beta_{ij} \), and \( \beta_{ij} \) are the coefficients of independent variables and interactions, representing their contribution to the response; \( \varepsilon \) is the random residual error term representing the effects of
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:

\[ Y = 364 - 0.057X_1 - 0.19X_2 - 1.15X_3 - 0.22X_4 + 0.08X_5 - 0.65X_6 \]  

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:

\[ Y = 8766 + 2.18X_1 + 64.2X_2 - 10.1X_3 - 4.05X_4 - 16.3X_5 - 3.01X_6 - 0.00331X_1^2 - 0.517X_2^2 + 0.0212X_3^2 + 0.003X_4^2 + 0.0078X_5^2 + 0.071X_6^2 \]  

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.

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**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
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.

\[
Y = -95331 + 35.2 X_{1} + 44 X_{2} + 48.0 X_{3} + 68.3 X_{4} + 125 X_{s} - 0.56 X_{1}X_{2} + 0.094 X_{1}X_{3} - 0.01 X_{1}X_{4} - 0.009 X_{2}X_{s} - 0.030 X_{3}X_{s} - 0.68 X_{2}X_{4} - 0.33 X_{3}X_{4} - 0.47 X_{2}X_{s} - 0.05 X_{3}X_{s} - 0.10 X_{4}X_{s} - 0.24 X_{1}X_{2}X_{s} - 0.07 X_{1}X_{3}X_{s} - 0.03 X_{2}X_{4}X_{s} \]

(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:

\[
Y = -715145 + 1189 X_{1} + 295 X_{2} + 1312 X_{3} + 485 X_{4} + 1104 X_{s} - 3.41 X_{1}X_{2} - 0.73 X_{1}X_{3} - 0.799 X_{1}X_{4} - 0.085 X_{2}X_{3} - 1.62 X_{2}X_{4} - 7.58 X_{3}X_{4} - 3.25 X_{2}X_{s} - 1.91 X_{3}X_{s} - 8.68 X_{4}X_{s} - 1.03 X_{1}X_{2}X_{s} - 1.01 X_{1}X_{3}X_{s} - 1.18 X_{1}X_{4}X_{s} - 0.110 X_{2}X_{3}X_{s} - 0.80 X_{2}X_{4}X_{s} + 0.807 X_{3}X_{4}X_{s} - 0.286 X_{1}^2 - 9.67 X_{2}^2 + 0.44 X_{3}^2 - 0.373 X_{4}^2 - 0.263 X_{s}^2 + 0.477 X_{e}^2 \]

(5)
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 (R²) 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.

\[
Y = 205 - 0.44 X_1 - 3.32 X_2 - 2.07 X_3 - 0.96 X_4 - 0.44 X_5 - 3.14 X_6
\]  

(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:

\[
Y = -8332 + 0.81 X_1 + 47.3 X_2 - 12.2 X_3 + 0.79 X_4 + 15.8 X_5 - 2.65 X_6 - 0.0009 X_1^2
\]

\[
- 0.39 X_2^2 + 0.033 X_3^2 - 0.001X_4^2 - 0.0078 X_5^2 - 0.028 X_6^2
\]  

(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:

\[
Y = -15990 + 25.0 X_1 + 142 X_2 + 23 X_3 + 5.4 X_4 + 6.7 X_5 + 25 X_6 - 0.161 X_1 X_2 - 0.0026 X_1 X_3
\]

\[
- 0.0013 X_1 X_4 - 0.0137 X_1 X_5 - 0.032 X_1 X_6 + 0.34 X_2 X_3 - 0.21 X_2 X_4 - 0.007 X_2 X_5 - 1.25 X_2 X_6
\]

\[
- 0.0051 X_2 X_7 - 0.0432 X_3 X_4 + 0.068 X_3 X_5 + 0.0101 X_3 X_6 - 0.010 X_4 X_5 - 0.0145 X_4 X_6 - 0.010 X_5 X_6
\]  

(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-12        |
| Pure quadratic | 8.231| 83.5    | 76.7          | 12.24   | 2.60 e-06        |
| 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-14        |

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

$$Y = 185466-859 X_1-888 X_4+919 X_5-483 X_6+3.52 X_2 X_3+0.61 X_1 X_2+0.56 X_1 X_3-0.059 X_1 X_5$$
$$+1.11 X_2 X_6+9.6 X_3 X_4+3.50 X_4 X_5+2.61 X_2 X_7+10.2 X_2 X_8+0.60 X_2 X_9-1.31 X_2 X_1+0.03 X_2 X_0-0.152 X_3 X_3$$
$$+0.67 X_3 X_0-1.03 X_3 X_6+0.264 X_4 X_4+5.23 X_2^2-0.69 X_1^2+0.218 X_4^2-0.355 X_5^2+0.033 X_6^2$$
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        | 189.4      | 645.2       | 1043.2      | 8.4        | 210        | 77.72                  |
| 3       | 0.25  | 500        | 55.0        | 186.0      | 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

| Model used | Mix No. | Experiment | Prediction | Slump (mm) | Experiment | Prediction | Variation (%) |
|------------|---------|------------|------------|------------|------------|------------|---------------|
| Linear     | 1       | 44.6       | 46.1       | 180        | 194.5      | 213.3      | -3.3          |
|            | 2       | 77.7       | 76.2       | 210        | 213.5      | 213.3      | -1.6          |
|            | 3       | 83.3       | 84.7       | 210        | 219.0      | 219.0      | -4.3          |
| Pure quadratic | 1     | 44.6       | 44.4       | 180        | 190.8      | 190.8      | -6.0          |
|            | 2       | 77.7       | 79.8       | 210        | 212.9      | 212.9      | -1.4          |
|            | 3       | 83.3       | 79.6       | 210        | 207.7      | 207.7      | -1.1          |
| Interaction | 1      | 44.6       | 44.7       | 180        | 181.2      | 181.2      | -1.3          |
|            | 2       | 77.7       | 82.3       | 210        | 216.7      | 216.7      | -3.2          |
|            | 3       | 83.3       | 82.8       | 210        | 210.5      | 210.5      | -0.5          |
| Full quadratic | 1    | 44.6       | 44.6       | 180        | 181.5      | 181.5      | -2.0          |
|            | 2       | 77.7       | 76.9       | 210        | 216.8      | 216.8      | -4.1          |
|            | 3       | 83.3       | 83.3       | 210        | 212.0      | 212.0      | -2.1          |

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

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

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

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
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