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Statistical analysis of the effective factors on the 28 days compressive strength and setting time of the concrete

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ABSTRACT

In this study, the effects of various factors (weight fraction of the SiO_2, Al_2O_3, Fe_2O_3, Na_2O, K_2O, CaO, MgO, Cl, SO_3, and the Blaine of the cement particles) on the concrete compressive strength and also initial setting time have been investigated. Compressive strength and setting time tests have been carried out based on DIN standards in this study. Interactions of these factors have been obtained by the use of analysis of variance and regression equations of these factors have been obtained to predict the concrete compressive strength and initial setting time. Also, simple and applicable formulas with less than 6% absolute mean error have been developed using the genetic algorithm to predict these parameters. Finally, the effect of each factor has been investigated when other factors are in their low or high level.

Introduction

Cement is a mixture of complex compounds. The reaction of cement with water leads to setting and hardening. Concrete is an important structural material being used in most of the construction industry and the setting time and strength are two of the most important properties for its quality. The mixture of the initial mineral materials should have a certain composition to lead a suitable setting time and compressive strength after passing high temperatures in the furnace and then mixing with water. This certain composition of mineral materials is being estimated by different modulus such as SiO_2, Al_2O_3 or hydraulic modulus. These moduluses determine the quantity of the initial materials composition to reach a suitable strength and setting time. Some recent articles have described effect of various parameters on the strength of the concrete using the fuzzy logic [1–9]. However statistical analysis has been used rarely to study effect of raw materials composition on the strength and setting time of concrete. In the previous study, a fuzzy logic model was designed and

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optimized to estimate the compressive strength of 28 days age concretes [8]. Input variables of the fuzzy logic model were the water to cement weight ratio and coarse aggregate to fine aggregate weight ratio, whereas the output variable was 28 days concrete compressive strength (*CCS*). Another study investigated effects of these input variables on the compressive strength of various ages of the concrete [9].

The effect of the initial materials on the CCS and IST was investigated in some of the previous studies through four clinker phases, weight percent of CaO, SiO_2, Al_2O_3, and Fe_2O_3 components [10–12]. Other initial materials such as Na_2O, K_2O, MgO, Cl and SO_3, which usually have a low weight percent in the cement, can have important effects on the CCS and also IST, which should be determined [13–18]. Cement physical properties such as Blaine value also have a special effect on the CCS and IST [17–22]. The Blaine values of the initial materials indicate the specific surface area and also the volume of the cement particles. The role of this physical parameter on the CCS and IST should be investigated to have a suitable predictive model for these two objective parameters.

In the present study, effect of the initial materials composition and Blaine of the cement particles on the compressive strength and initial setting time (*IST*) of concrete has been analyzed by statistical methods through 663 experiments on the raw materials and concrete. The aim of this investigation is presenting empirical equations to calculate confidentially values of these two important parameters verses composition and Blaine of the initial materials. The range of the raw materials composition of Portland cement (type II) during the experiments was as follows: SiO_2 (20.23–22.24)%, Al_2O_3 (4.25–5.1)%, Fe_2O_3 (3.65–4.38)%, CaO (61.43–65.31)%, MgO (1.03–1.79)%, SO_3 (2.1–3)%, Na_2O (0.45–0.76)%, K_2O (0.58–0.77)%, Cl (0.002–0.044)%, and about 2% of the other materials. The raw material Blaine was in the range of 2820–3280 cm^2/gr. Finally, impacts of each effective factor are investigated when the other factors are fixed in a high or low level.

Experimental

The method of determining compressive strength and also initial setting time of cement are described in this section. The laboratory where preparation of specimens took place was maintained at a temperature of 20 °C and a relative humidity of more than 50%.

The specimens were cast from a batch of mortar containing one part cement, three parts Germany Standard sand and one half part of water. The Standard sand is natural, siliceous materials consisting of rounded particles with at least 98% silica. The cement was exposed to ambient air for the minimum time possible. It was stored in a completely filled and airtight container which is not able to react with cement. The mortar was prepared by mechanical mixing as shown in Fig. 1 and was compacted in a steel mold using a jolting apparatus. The jolting apparatus consisted of a rectangular table rigidly connected by two light arms to a pivot at 800 mm from the center of the table.

The mold was consisted of three compartments so that three specimens 40 mm × 40 mm in cross section and 160 mm in length can be prepared simultaneously. The specimens were stored in the mold in a moist atmosphere (20 °C and a relative humidity of more than 90%) for 24 h. After demolding, the specimens were put in water until strength testing.

Fig. 1 Mechanical mixer used for preparation of specimens.

The initial setting time of the prepared samples was measured by the vicat apparatus. TONI TECHNIK Company was brand of this apparatus. After 28 days, the specimens were taken from moist room, broken by a testing machine) brand of the machine is also TONI TECHNIK, with ± 1% accuracy) in order to determine compressive strength. Rate of load was 2600 N/s. The testing machine has been equipped with platens made of tungsten carbide. These platens had 10 mm thick, 40 mm wide and 40 mm long. A jig was placed between the platens of the machine to transmit the load from machine to the surfaces of the mortar specimen. A lower plate is used in this jig and it can be incorporated in the lower platen. The upper platen receives the load from the upper platen of the machine through an intermediate spherical seating.

Methods

Procedure of the statistical analysis

As previously mentioned, the weight percentage of the cement ingredients and Blaine of the initial materials are the most effective factors on the *CCS* and *IST*. Interaction of these 10 factors also may have significant effect on the targets. Therefore countless combination of factors may effect on the goal parameters. The analysis of variance is a proper way to find out the degree of significance of these factors. For better analysis there is a need to repeat experiments in this analysis to find out experimental errors.

Since the composition and Blaine of the cement raw materials are changed in each experiment, these factors have to be classified in certain levels and the influence of each factor should be investigated in these levels. Therefore each factor is coded as follows and classified into 20 levels:

$$x_i = \frac{w_i - \frac{1}{2}(\max(w_i) + \min(w_i))}{\frac{1}{2}(\max(w_i) - \min(w_i))} \tag{1}$$

x_i is the code of each factor and w_i is the weight percentage of each component or value of materials Blaine. Each factor gets a level between -1 and $+1$ by this coding. This coding procedure causes that some of the experiments have a same level of factors and random errors can be calculated. Each factor's degree of freedom can be determined from a number of experiments which have different levels for the factor. P value also is determined based on the obtained degree of freedom and is a criterion which specifies whether effect of a special factor is located in a normal distribution zone or not. Therefore regarding value of random experimental errors, effect of each factor or combination of factors with a special degree of confidence can be determined.

Tables 1 and 2 show the result of analysis of variance. These tables show only effective factors on the *CCS* and *IST* with a more than 97.5% (P value less than 0.025) confidence after rejection of about 4000 item. The rejected cases had a P value more than 0.025. As presented in these Tables, the calculated F value of the effective factors is greater than critical value of this function ($F_{0.025,1,663}$ or $F_{0.025,1,644}$) which is 5.01. It means that the effects of the presented factors are not located in the normal distribution of the random errors area i.e. these factors or combination of the factors are the effective parameters on the objective functions.

Equations derived through regression

When the effective combination of factors was obtained, the regression equations may be able to predict the results. For this aim, a set of coefficients is required to be multiplied by the effective factors and summation of these terms predicts the *CCS* or *IST*. These equations have a general form as follows [23]:

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i \quad i = 1, 2, \ldots, n \tag{2}$$

where x is the independent variables (combination of factors), y is the dependent variables (*CCS* or *IST*), k is the number of experiments with a same level of the ith combination of factors, and n is the total number of the effective factors. The intercept (β_0) of these equations is the arithmetic average of the total CCS or IST values and the coefficient of each term is concerned to the effect of that combination of factors when other factors are in the high or low level. The method of least squares obtains the intercepts and coefficients by minimizing the sum of squares of errors as the following equations [23]:

$$\sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ij} \right) = 0 \tag{3}$$

$$\sum_{i=1}^{n} \left[x_{ij} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ij} \right) \right] = 0 \quad j = 1, 2, \ldots, k \tag{4}$$

There are $k + 1$ equations, one equation for each unknown regression coefficient, and the solution of these equations obtains all of the intercepts and the coefficients. Using the mentioned method, the calculated regression equations for prediction of *CCS* and *IST* are obtained as follows:

Table 1 The analysis of variance of the factors which are effective on the *CCS* with more than 97.5% confidence.

Source	Degree of Freedom	Sum of Squares	Mean of Squares	F
x_{SiO_2}	1	2259	2259	16.7
x_{K_2O}	1	6224	6224	46.01
$x_{SiO_2} \cdot x_{MgO}$	1	5207	5207	38.49
$x\mathrm{SiO_2} \cdot x_{K_2O}$	1	2255	2255	16.67
$x_{Fe_2O_3} \cdot x_{MgO}$	1	1527	1527	11.29
$x_{CaO} \cdot x_{SO_3}$	1	1607	1607	11.88
x_{MgO^2}	1	1106	1106	8.18
$x_{MgO} \cdot x_{Na_2O}$	1	6961	6961	51.46
$x_{SiO_2} \cdot x_{Fe_2O_3} \cdot x_{MgO}$	1	4551	4551	33.64
$x_{SiO_2} \cdot x_{Fe_2O_3} \cdot x_{K_2O}$	1	3285	3285	24.29
$x_{SiO_2} \cdot x_{CaO} \cdot x_{Na_2O}$	1	1629	1629	12.05
$x_{SiO_2} \cdot x_{K_2O} \cdot x_{Cl}$	1	2818	2818	20.83
$x_{SiO_2} \cdot x^2_{Blaine}$	1	1588	1588	11.74
$x^2_{Fe_2O_3} \cdot x_{MgO}$	1	1536	1536	11.35
$x_{Fe_2O_3} \cdot x^2_{CaO}$	1	2767	2767	20.46
$x_{Fe_2O_3} \cdot x_{K_2O} \cdot x_{Blaine}$	1	5937	5937	43.89
x^3_{MgO}	1	1015	1015	7.51
$x_{SiO_2} \cdot x_{CaO} \cdot x_{MgO} \cdot x_{SO_3}$	1	9311	9311	68.83
$x_{SiO_2} \cdot x_{CaO} \cdot x^2_{K_2O}$	1	4028	4028	29.78
$x_{SiO_2} \cdot x_{CaO} \cdot x_{K_2O} \cdot x_{Cl}$	1	2292	2292	16.94
$x_{SiO_2} \cdot x_{MgO} \cdot x_{SO_3} \cdot x_{Blaine}$	1	3362	3362	24.86
$x_{SiO_2} \cdot x_{SO_3} \cdot x_{K_2O} \cdot x_{Blaine}$	1	2713	2713	20.06
$x_{Al_2O_3} \cdot x^2_{Fe_2O_3} \cdot x_{Cl}$	1	4052	4052	29.95
Error	639	86,437	135.27	
Total	662			

Table 2 The analysis of variance of the factors which are effective on the *IST* with more than 97.5% confidence.

Source	Degree of freedom	Sum of squares	Mean of squares	*F*
x_{Na_2O}	1	1474.1	1474.1	26.42
$x_{SiO_2} \cdot x_{MgO}$	1	2119.2	2119.2	37.99
$x_{Fe_2O_3} \cdot x_{Na_2O}$	1	2440.0	2440.0	43.74
$x^2_{SiO_2} \cdot x_{K_2O}$	1	1003.2	1003.2	17.98
$x_{SiO_2} \cdot x_{Al_2O_3} \cdot x_{K_2O}$	1	350.6	350.6	6.28
$x_{Al_2O_3} \cdot x_{Fe_2O_3} \cdot x_{SO_3}$	1	669.4	669.4	12
$x_{Al_2O_3} \cdot x_{Fe_2O_3} \cdot x_{K_2O}$	1	1532.2	1532.2	27.47
$x_{Al_2O_3} \cdot x_{MgO} \cdot x_{Na_2O}$	1	767.2	767.2	13.75
$x_{Al_2O_3} \cdot x_{Na_2O} \cdot x_{K_2O}$	1	1038.4	1038.4	18.61
$x_{Fe_2O_3} \cdot x_{CaO} \cdot x_{MgO}$	1	413.4	413.4	7.41
$x_{Fe_2O_3} \cdot x_{MgO} \cdot x_{Cl}$	1	810.9	810.9	14.54
$x_{Fe_2O_3} \cdot x^2_{Blaine}$	1	1345.8	1345.8	24.12
$x_{CaO} \cdot x^2_{MgO}$	1	946.6	946.6	16.97
$x_{CaO} \cdot x_{MgO} \cdot x_{K_2O}$	1	672.2	672.2	12.05
$x_{CaO} \cdot x_{MgO} \cdot x_{Blaine}$	1	439.8	439.8	7.88
$x_{SiO_2} \cdot x_{MgO} \cdot x_{Na_2O} \cdot x_{K_2O}$	1	1328.5	1328.5	23.81
$x_{SiO_2} \cdot x_{Na_2O} \cdot x^2_{K_2O}$	1	1050.2	1050.2	18.83
$x_{Al_2O_3} \cdot x^3_{SO_3}$	1	335.2	335.2	6.01
Error	644	35925.4	55.78	
Total	662			

$$\begin{aligned} y_{CCS} = {} & 468.86 - 15.1x_{SiO_2} + 15.95x_{K_2O} - 92.23x_{SiO_2}x_{MgO} \\ & + 48.91x_{SiO_2}x_{K_2O} - 28.14x_{Fe_2O_3}x_{MgO} \\ & + 18.9x_{CaO}x_{SO_3} - 15.94x^2_{MgO} + 28.02x_{MgO}x_{Na_2O} \\ & - 151.12x_{SiO_2}x_{Fe_2O_3}x_{MgO} + 85.66x_{SiO_2}x_{Fe_2O_3}x_{K_2O} \\ & - 43.5x_{SiO_2}x_{CaO}x_{Na_2O} + 39.44x_{SiO_2}x_{K_2O}x_{Cl} \\ & - 24.87x_{SiO_2}x^2_{Blaine} - 26.52x^2_{Fe_2O_3}x_{MgO} \\ & - 32.46x_{Fe_2O_3}x^2_{CaO} + 28.13x_{Fe_2O_3}x_{K_2O}x_{Blaine} \\ & - 16.11x^3_{MgO} + 132.67x_{SiO_2}x_{CaO}x_{MgO}x_{SO_3} \\ & - 66.46x_{SiO_2}x_{CaO}x^2_{K_2O} + 71.96x_{SiO_2}x_{CaO}x_{K_2O}x_{Cl} \\ & + 245.35x_{SiO_2}x_{MgO}x_{SO_3}x_{Blaine} \\ & - 158.14x_{SiO_2}x_{SO_3}x_{K_2O}x_{Blaine} \\ & + 77.45x_{Al_2O_3}x^2_{Fe_2O_3}x_{Cl} \end{aligned} \quad (5)$$

$$\begin{aligned} y_{IST} = {} & 124.1 - 10.21x_{Na_2O} - 23.24x_{SiO_2}x_{MgO} \\ & - 19.05x_{Fe_2O_3}x_{Na_2O} - 15.4x^2_{SiO_2}x_{K_2O} \\ & + 11.4x_{SiO_2}x_{Al_2O_3}x_{K_2O} - 25.63x_{Al_2O_3}x_{Fe_2O_3}x_{SO_3} \\ & - 21.7x_{Al_2O_3}x_{Fe_2O_3}x_{K_2O} + 39.75x_{Al_2O_3}x_{MgO}x_{Na_2O} \\ & - 34.85x_{Al_2O_3}x_{Na_2O}x_{K_2O} - 13.85x_{Fe_2O_3}x_{CaO}x_{MgO} \\ & - 17.42x_{Fe_2O_3}x_{MgO}x_{Cl} - 15.4x_{Fe_2O_3}x^2_{Blaine} \\ & + 32.78x_{CaO}x^2_{MgO} - 21.6x_{CaO}x_{MgO}x_{K_2O} \\ & + 13.32x_{CaO}x_{MgO}x_{Blaine} + 69.92x_{SiO_2}x_{MgO}x_{Na_2O}x_{K_2O} \\ & - 40.7x_{SiO_2}x_{Na_2O}x^2_{K_2O} - 15.92x_{Al_2O_3}x^3_{SO_3} \end{aligned} \quad (6)$$

Regarding complexity of the problem (as seen in the regression equations), obtaining the effect of each factor lonely is impossible and these effects have to be considered beside other factors. Figs. 2 and 3 show that the experimental errors have a normal distribution around zero. Therefore, the experimental errors are uniformly dispersed on the all of experiments. The obtained regression Eqs. (5) and (6), predict 28 and 31 unusual cases for the *CCS* and *IST*, respectively from 662 experiments (less than 5% of experiments) which removed from regression calculations. The criterion for unusual case is standardized absolute residuals more than 2 $\left(\left|\frac{y_{Experimental} - y_{Predicted}}{\sqrt{\text{Mean of Square of Error}}}\right| > 2\right)$ [23].

Equations derived by genetic algorithm

The Bogue equations are widely used by cement manufacturers, when the ratio of Al_2O_3 to Fe_2O_3 is more than 0.64 [24] (that is more than 0.97 in our case). Furthermore it could be justified theoretically and also is simple to use. Therefore, the predictions of Bogue equations are suitable for our samples which have a low impurities and high ratio of Al_2O_3 to Fe_2O_3. These equations were also used in the other studies to calculate the high purity cement type II phases without worry

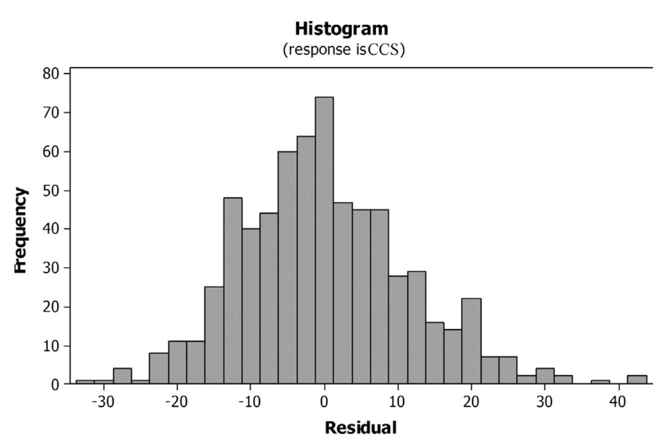

Fig. 2 The histogram of experimental errors for the *CCS tests*.

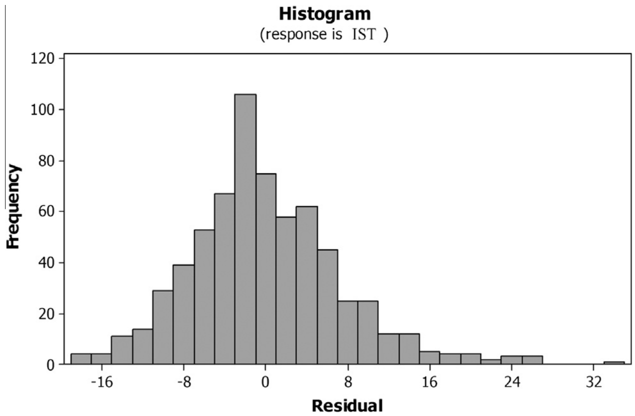

Fig. 3 The histogram of experimental errors for the *IST* tests.

about accuracy [10,11]. The experimental results of the subsequent investigations using electron microprobe data on actual materials had a good agreement with Bogue predictions in the similar cases as our samples [12,25].

The four clinker phases (C_3S: $3CaO{\cdot}SiO_2$, C_2S: $2CaO{\cdot}SiO_2$, C_3A: $3CaO{\cdot}Al_2O_3$, C_4AF: $4CaO{\cdot}Al_2O_3{\cdot}Fe_3O_4$) are defined by just four parameters, weight percent of CaO, SiO_2, Al_2O_3, and Fe_2O_3 components. The lime saturation factor controls the C_3S to C_2S ratio in cement. C_3S controls the early age compressive strength development while C_2S controls the later age strength. Bogue represented the below equations for calculating values of these phases [26]:

$$C_3S = 4.07w_{CaO} - 7.6w_{SiO_2} - 6.72w_{Al_2O_3} - 1.43w_{Fe_2O_3} - 2.85w_{SO_3} \tag{7}$$

$$C_2S = 2.87w_{SiO_2} - 0.75C_3S \tag{8}$$

$$C_3A = 2.65w_{Al_2O_3} - 1.69w_{Fe_2O_3} \tag{9}$$

$$C_4AF = 3.04w_{Fe_2O_3} \tag{10}$$

Genetic algorithm is a member of the larger class of evolutionary algorithms, which generate solutions to optimization problems using techniques inspired by natural evolution. In a genetic algorithm, a population of candidate solutions (a member of a set of possible solutions to a given problem) to an optimization problem is developed for better solutions [27]. This algorithm was utilized to search various simple candidates formulas (including: C_3S, C_2S, C_3A, C_4AF and Blaine (cm^2/gr)) and then optimized the coefficients of the most suitable formula with the minimum *Error* ($\frac{y_{Predicted}-y_{Experimental}}{y_{Experimental}} \times 100$). The best fitted formulas by genetic algorithm to predict the *CCS* and *IST* was obtained as the following forms:

$$y_{CCS}^{Fitted} = \frac{6.769C_3S - 44.216C_2S + 282.606C_3A + 34.565C_4AF}{C_3S + C_2S + C_3A + C_4AF} + 0.146\text{Blaine} \tag{11}$$

$$y_{IST}^{Fitted} = \frac{23.864C_3S + 70.709C_2S - 119.593C_3A - 15.003C_4AF}{C_3S + C_2S + C_3A + C_4AF} + 0.035\text{Blaine} \tag{12}$$

Results and discussion

In the present paper effect of ten different factors, weight percent of the nine components and Blaine of the particles on the CCS and IST were investigated. Tables 1 and 2 show the effective combinations of factors on the *CCS* and *IST* with a more than 97.5% confidence. Figs. 4 and 5 show the mean of the calculated absolute *Error* for predicted values of *CCS* and *IST* is 1.92% and 4.3%, respectively for regression equations and 2.43% and 5.52% for equations obtained by genetic algorithm. This level of accuracy indicates that statistical analysis and genetic algorithm are the reliable tools for predicting CCS and IST.

In this section we try to find out behavior of the CCS and IST against variation in the mentioned factors. In Figs. 6–15, all of the factors are fixed in a high level (+0.5) or a low level (−0.5) and only one of the 10 factors is changed from the low level (−1) to the high level (+1). Designated legends in these Figs. x_i, indicate level of the other factors which has been fixed in the experiments.

Fig. 6 shows increasing of SiO_2 decreases the *CCS* as a linear function, when other factors are in their low or high level. Increasing of SiO_2 decreases *IST* with a slow slope at first and it will increase as a nonlinear function finally, when other factors are fixed in their low level, while increasing of SiO_2 make a nearly symmetric curve when other factors are fixed in their high level.

Figs. 7–9 show effect of the variation in the Al_2O_3, Na_2O and Cl on the *CCS* and *IST* of the prepared concrete. Increasing these components in the raw materials decreases *CCS* when other factors are in their low level and increases the *CCS* when other factors are in their high level. Increasing these components decreases the *IST* in any case.

Fig. 10 shows that increasing MgO decreases *CCS* nonlinearly when other factors are in their low or high level while increasing MgO has a different effect on the *IST* at high and low level fixation of the other factors. As can be observed from this Figure Fixation of the other factors at high or low level has made a parabolic curve with a minimum or maximum at 0.1 of MgO respectively.

As shown in Fig. 11, increasing of K_2O causes a nonlinear increase in the *CCS* and nonlinear decrease in the *IST*. This behavior is the same when other factors are in their low or high level.

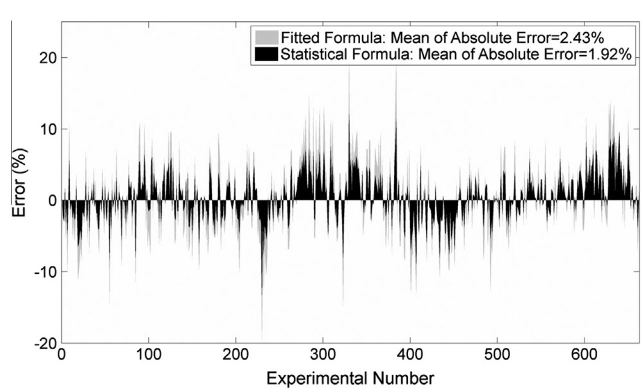

Fig. 4 The calculated *Error* of the predicted *CCS* by the predictive equations for each experiment.

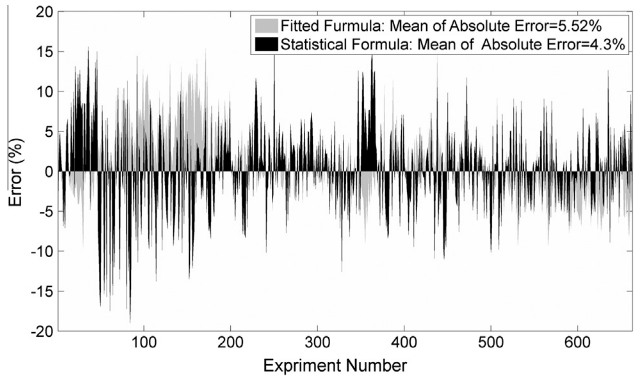

Fig. 5 The calculated *Error* of the predicted *IST* by the predictive equations for each experiment.

Variation in Fe_2O_3 causes to vary *CCS* as a curve with a minimum at zero level when other factors are stabilized at low level and have a descending nonlinear curve when other factors are stabilized at high level. Increasing of Fe_2O_3 decreases *IST* linearly in both cases, i.e. other factors are stabilized in their high or low level. This variation has been shown in Fig. 12.

Increasing of CaO causes a nonlinear decrease in the *CCS* when other factors are in their low level. The *CCS* varies as a curve with a maximum at level 0.6 of the CaO, when other factors are in their high level. Increasing of CaO causes a negligible linear increase in the *IST* in both cases when other factors are in their high or low level. This behavior of the concrete has been shown in Fig. 13.

Fig. 14 shows that increasing of SO_3 causes an increase or decrease in the *CCS* linearly when other factors are in their high or low level, respectively. This increment has a more complex effect on the *IST*. Increasing of this factor causes a nonlinear decrease in the *IST* when other factors are in their high level. This Figure shows that variation in the SO_3 value has no important effect on the *IST* when other factors are in their low level.

As can be observed from Fig. 15 variation in Blaine has no significant effect on the CCS and IST when the concrete composition is stabilized at their low level. When composition of

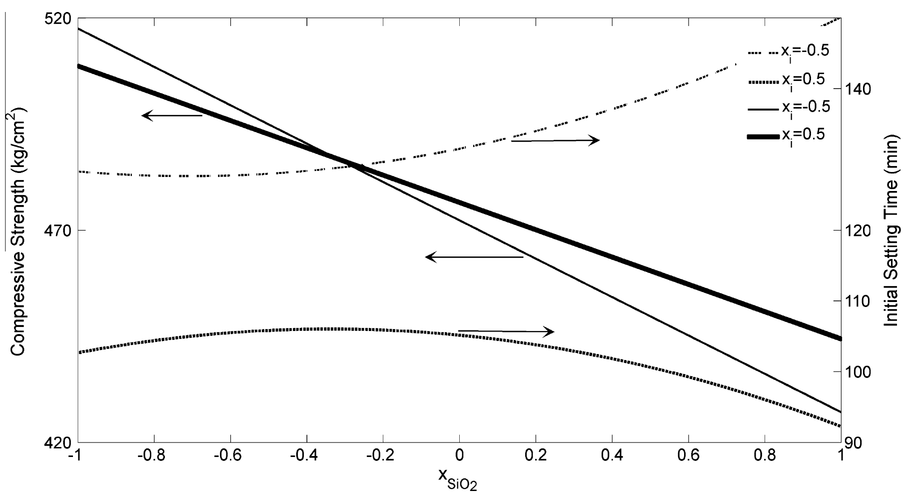

Fig. 6 The effects of SiO_2 on the *CCS* and *IST* when other factors are in their low or high level.

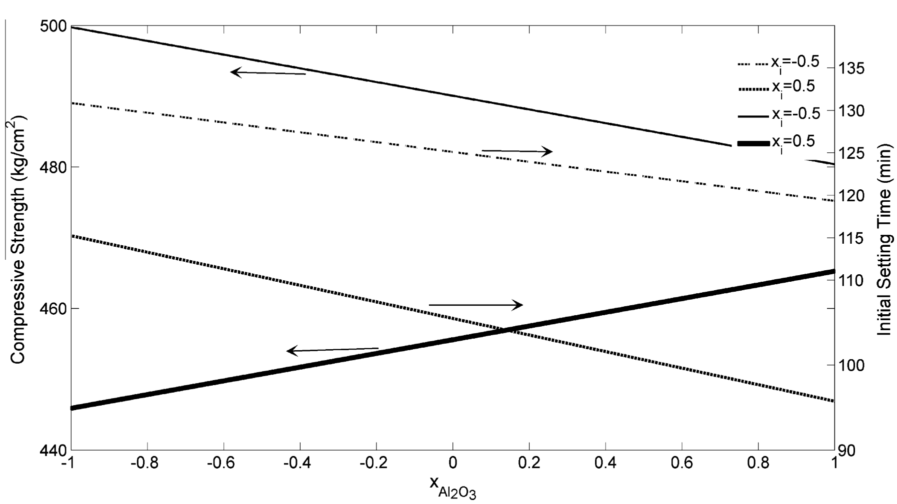

Fig. 7 The effects of Al_2O_3 on the *CCS* and *IST* when other factors are in their low or high level.

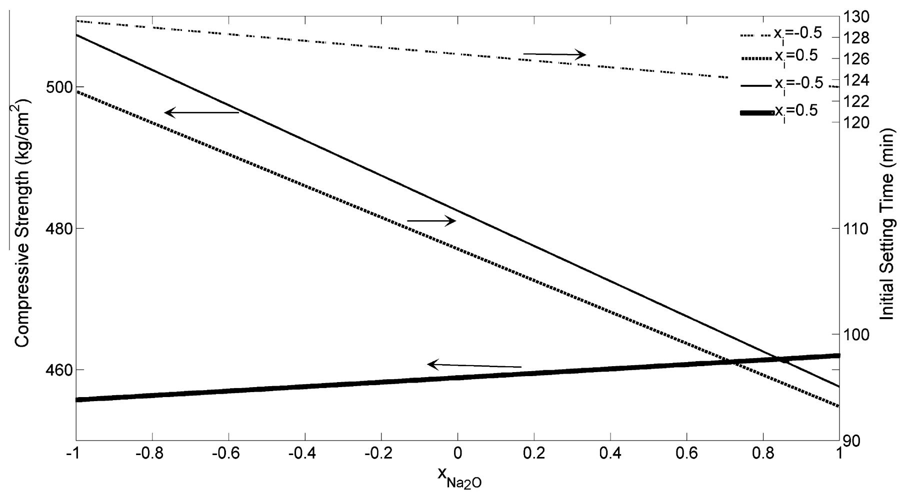

Fig. 8 The effects of Na_2O on the *CCS* and *IST* when other factors are in their low or high level.

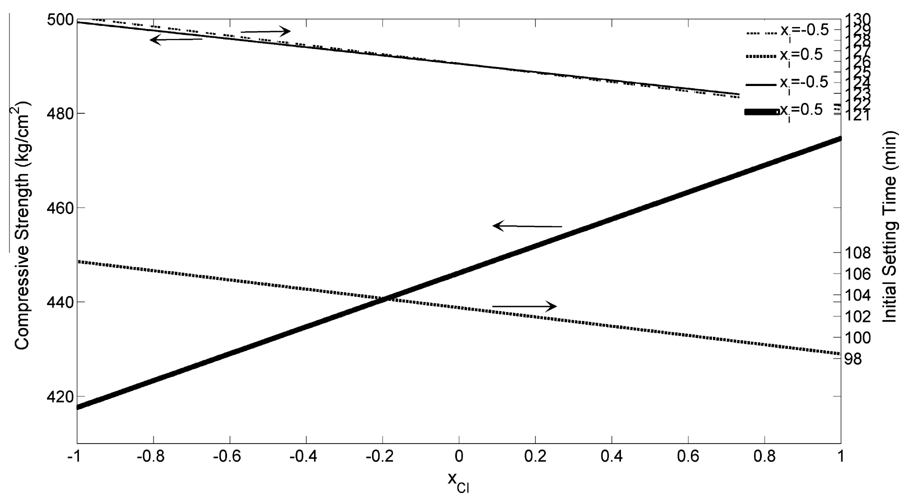

Fig. 9 The effects of Cl on the *CCS* and *IST* when other factors are in their low or high level.

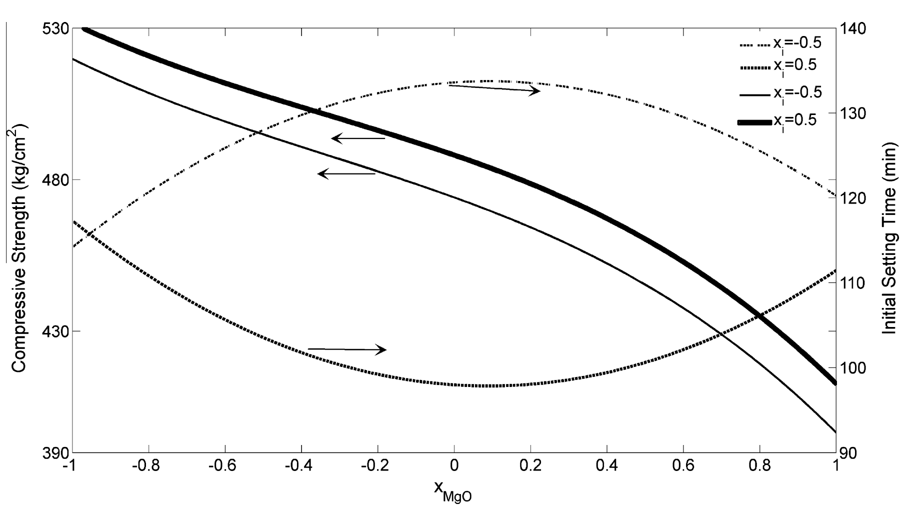

Fig. 10 The effects of MgO on the *CCS* and *IST* when other factors are in their low or high level.

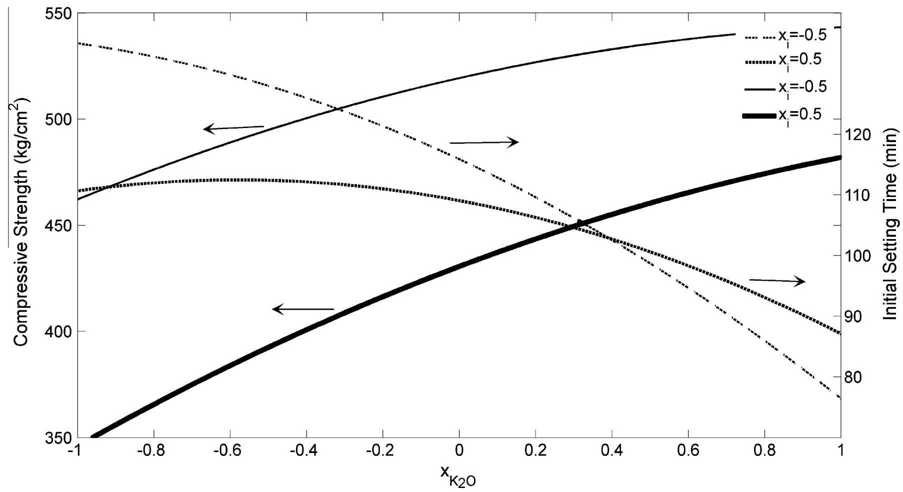

Fig. 11 The effects of K_2O on the *CCS* and *IST* when other factors are in their low or high level.

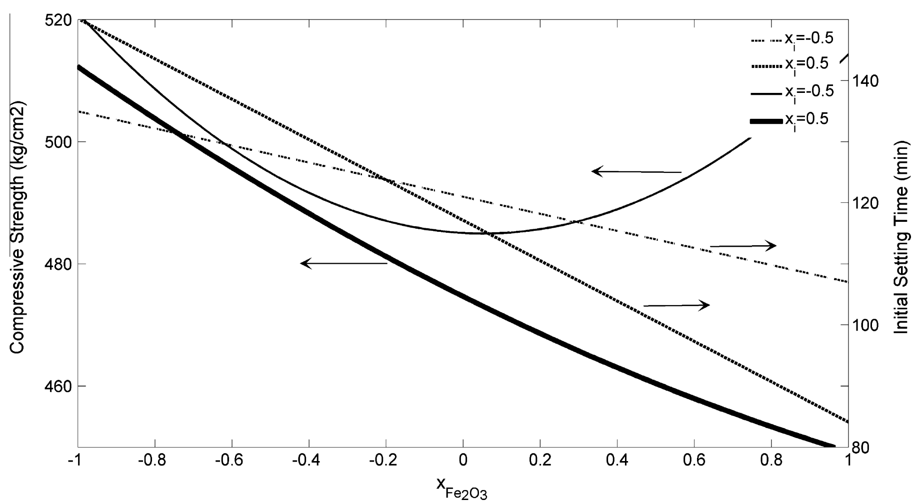

Fig. 12 The effects of Fe_2O_3 on the *CCS* and *IST* when other factors are in their low or high level.

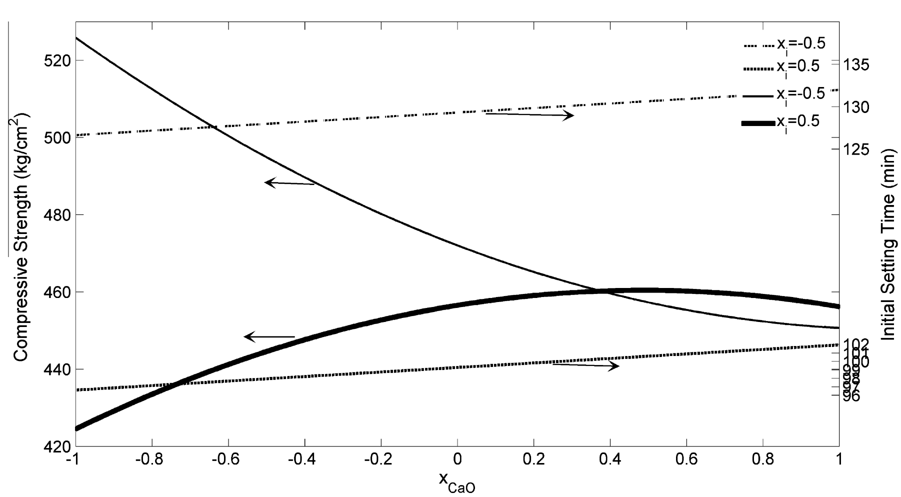

Fig. 13 The effect of CaO on the *CCS* and *IST* when other factors are in their low or high level.

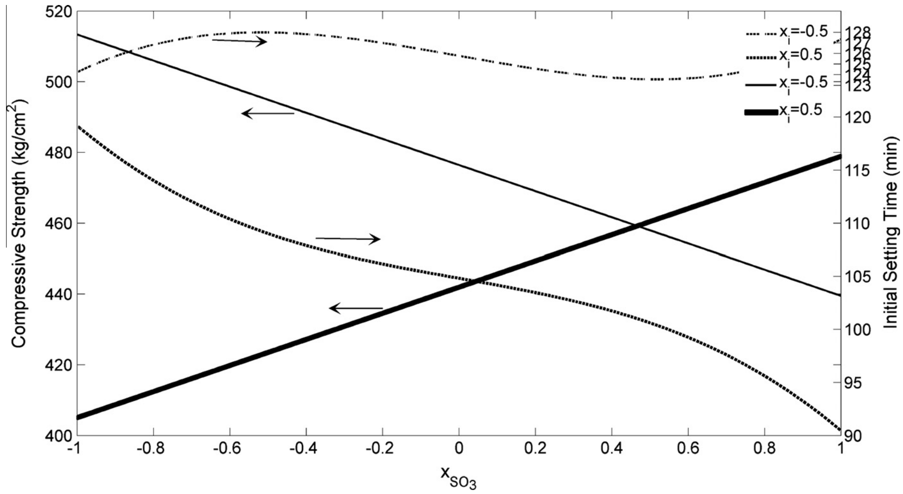

Fig. 14 The effects of SO_3 on the *CCS* and *IST* when other factors are in their low or high level.

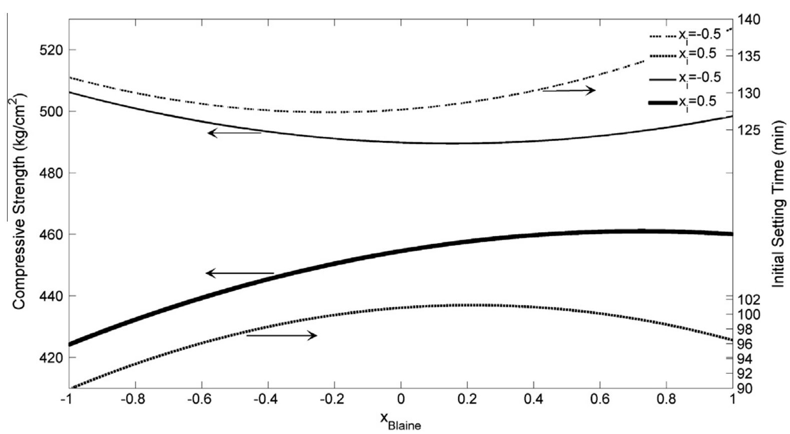

Fig. 15 The effects of Blaine on the *CCS* and *IST* when other factors are in their low or high level.

Table 3 The effect of factors on the *CCS* and *IST*.

Considered factor	Level of other fixed factors										Effect on the CCS	Effect on the IST
	x_{SiO_2}	$x_{Al_2O_3}$	$x_{Fe_2O_3}$	x_{CaO}	x_{MgO}	x_{Na_2O}	x_{K_2O}	x_{SO_3}	x_{Cl}	x_{Blaine}		
x_{SiO_2}		+	+	+	+	+	+	+	+	+	Decrease	Complex
		–	–	–	–	–	–	–	–	–	Decrease	Complex
$x_{Al_2O_3}$	+		+	+	+	+	+	+	+	+	Increase	Decrease
	–		–	–	–	–	–	–	–	–	Decrease	Decrease
$x_{Fe_2O_3}$	+	+		+	+	+	+	+	+	+	Decrease	Decrease
	–	–		–	–	–	–	–	–	–	Complex	Decrease
x_{CaO}	+	+	+		+	+	+	+	+	+	Complex	Increase
	–	–	–		–	–	–	–	–	–	Decrease	Increase
x_{MgO}	+	+	+	+		+	+	+	+	+	Decrease	Complex
	–	–	–	–		–	–	–	–	–	Decrease	Complex
x_{Na_2O}	+	+	+	+	+		+	+	+	+	Increase	Decrease
	–	–	–	–	–		–	–	–	–	Decrease	Decrease
x_{K_2O}	+	+	+	+	+	+		+	+	+	Increase	Decrease
	–	–	–	–	–	–		–	–	–	Increase	Decrease
x_{SO_3}	+	+	+	+	+	+	+		+	+	Increase	Decrease
	–	–	–	–	–	–	–		–	–	Decrease	Complex
x_{Cl}	+	+	+	+	+	+	+	+		+	Increase	Decrease
	–	–	–	–	–	–	–	–		–	Decrease	Decrease
x_{Blaine}	+	+	+	+	+	+	+	+	+		Increase	Complex
	–	–	–	–	–	–	–	–	–		Complex	Complex

the concrete is stabilized at high level, increasing of Blaine will increase *CCS* by an ascending curve and changes *IST* through a curve with a maximum at about level 0.2.

The setting and hardening of cement are the result of chemical reactions between cement and water (i.e. hydration). The hydration reactions starts directly after adding water to cement and in the first 30 min a part of C_3A and sulfate carrier is dissolved and results more strength in concrete. This very fast process produces heat during the initial period of hydration. C_3A phase sets quickly with evolution of heat and enhances strength of the silicates. Coarse cements with low specific surface area usually take longer times to set due to the sluggish hydration kinetics. On the other hand, high content of C_3A speeds up the reactions resulting in relatively short setting times. Increasing the amount of C_3A causes a significant increase in the CCS and also decreases the IST as Eqs. (11) and (12).

Conclusions

In this study, the effects of various factors on the concrete compressive strength and also initial setting time have been investigated. The effective factors are weight percent of the SiO_2, Al_2O_3, Fe_2O_3, Na_2O, K_2O, CaO, MgO, Cl, SO_3 of the raw materials and the Blaine of cement particles. Interactions of these factors with probability of a 97.5% confidence have been obtained using analysis of variance. Then the equations have been obtained through regression to predict the concrete compressive strength and initial setting time as function of the mentioned factors. The mean of the calculated absolute *Error* for predicted values of *CCS* and *IST* was 1.92% and 4.3%, respectively for regression equations. Attention to the coefficients of these regression equations shows that the quadruplet combinations of $x_{SiO_2} \cdot x_{MgO} \cdot x_{SO_3} \cdot x_{Blaine}$ and $x_{SiO_2} \cdot x_{SO_3} \cdot x_{K_2O} \cdot x_{Blaine}$ have the most positive and negative effect on the *CCS*, respectively. Also the quadruplet combinations of $x_{SiO_2} \cdot x_{MgO} \cdot x_{Na_2O} \cdot x_{K_2O}$ and $x_{SiO_2} \cdot x_{Na_2O} \cdot x^2_{K_2O}$ have the most positive (increasing) and negative (reducing) effect on the *IST* of concrete, respectively. Also, simple and applicable formulas have been developed using the genetic algorithm to predict these parameters. The accuracy of these predictive equations is completely acceptable. They have a less than 6% absolute mean error. Finally the effect of each factor has been investigated when other factors are in their low or high level and summary of the results has been presented in Table 3.

Conflict of interest

The authors have declared no conflict of interest.

Compliance with Ethics Requirements

This article does not contain any studies with human or animal subjects.

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