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Cost effective optimal mix proportioning of high strength self compacting concrete using response surface methodology

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Abstract. Optimization of the concrete mixture design is a process of search for a mixture for which the sum of the cost of the ingredients is the lowest, yet satisfying the required performance of concrete. In this study, a statistical model was carried out to model a cost effective optimal mix proportioning of high strength self-compacting concrete (HSSCC) using the Response Surface Methodology (RSM). The effect of five key mixture parameters such as water-binder ratio, cement content, fine aggregate percentage, fly ash content and superplasticizer content on the properties and performance of HSSCC like compressive strength, passing ability, segregation resistance and manufacturing cost were investigated. To demonstrate the responses of model in quadratic manner Central Composite Design (CCD) was chosen. The statistical model showed the adjusted correlation coefficient R2adj values were 92.55%, 93.49%, 92.33%, and 100% for each performance which establish the adequacy of the model. The optimum combination was determined to be 439.4 kg/m3 cement content, 35.5% W/B ratio, 50.0% fine aggregate, 49.85 kg/m3 fly ash, and 7.76 kg/m3 superplasticizer within the interest region using desirability function. Finally, it is concluded that multiobjective optimization method based on desirability function of the proposed response model offers an efficient approach regarding the HSSCC mixture optimization.

Keywords: central composite design; high strength self-compacting concrete; response surface method; optimization; desirability function.

1. Introduction

Concrete is a widely used essential element in construction industry and has become pervasive. The conventional concrete is generally not cost effective with high water to cement ratio and low workability is difficult to place. In addition, it has some extra problems such as honeycomb, bleeding etc. To get rid of this, high strength self-compacting concrete with high workability and high durability has recently been developed.

Self-Compacting Concrete (SCC) is categorized as a high performance concrete for its

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capability to spread into place under its own weight without the need for vibration, and its capability to avoid segregation and blocking. The advantages of SCC are high durability, low onsite labor requirement and high quality. Many researchers have investigated the use of SCC in composite materials, as a self-flowing concrete in building constructions by using different theoretical, empirical, and computer simulation approaches (Alqadi *et al*. 2012b).

The process by which one reaches at the suitable combination of binder (cement), fine aggregate, coarse aggregate, admixtures and water for creating concrete according to the granted specifications is a generic mix proportion of concrete. The intention of mix proportioning is to get a product which will fulfill a definite predetermined requirements (Murali and Kandasamy 2009). Aïtcin (1998) points out that the selection of the cementitious materials and the optimization of the composition of a high performance concrete are more of an art than a science and it is always a heavy task to develop an optimized composition using trial batches.

Researchers have used different approaches for mix proportioning. Recently, most studies are based on artificial intelligent techniques such as Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS). It has been investigated seen that the ANN can model nonlinear relationships and gives the result with less error. However, the training of ANN comprises an essential step in its performance which requires a sufficiently large data generation i.e. experimental work. Moreover, they do not provide a mathematical model of the problem, and the knowledge contained in an ANN model is maintained in the form of a weight matrix that is hard to interpret (Ahmadi-Nedushan 2009, Shanker and Sachan 2014).

A response surface design is a tool for advanced Design of Experiments (DOE) techniques for better understanding and response optimization. Response Surface Design Methodology (RSDM) is often used to refine models after determining important factors. Especially when curvature is presence suspected in the response surface. There are two main types of response surface designs i.e. Central Composite designs and Box-Behnken designs. A central composite design is the most commonly used response surface designed experiment. Central composite designs are a factorial or fractional factorial design with center points, augmented with a group of axial points (also called star points) that estimate curvature.

Alqadi *et al.* (2009) made statistical model to find the effect of the concrete constituents (cement, water-powder ratio, fly-ash and superplasticizer) on hardened properties of self-compacting concrete. The model was valid for defined range of mixing proportion. A central composite design could be a useful tool to evaluate parameters effects of mixture and the interaction between the parameters on SCC that can reduce the number of trials to achieve balance among mix variables. The result of the study showed that full quadratic models is the best fit model for all the responses.

Murali and Kandasamy (2009) suggested a Statistical design of experiment that can be used to systematically investigate the selected range of combination of ingredients for the desired characteristics. It was concluded that the proposed models can identify optimum binder composition concrete mixtures for the designed strength. Li *et al.* (2012) deduced that the Box-Wilson Central Composite Design (CCD) method can be a reasonable way to optimize mixtures of medium strength High Flowing Concrete (HFC) by using fresh properties, strength, and durability models to cut down the cost, improve workability with maintaining the compressive strength and the durability.

Ahmad and Alghamdi (2014) proposed a step-by-step statistical approach to obtain optimum proportioning of concrete mixtures. The researchers concluded that the optimum values of water/cement ratio and fine/total aggregate ratios have resulted in a higher compressive strength at

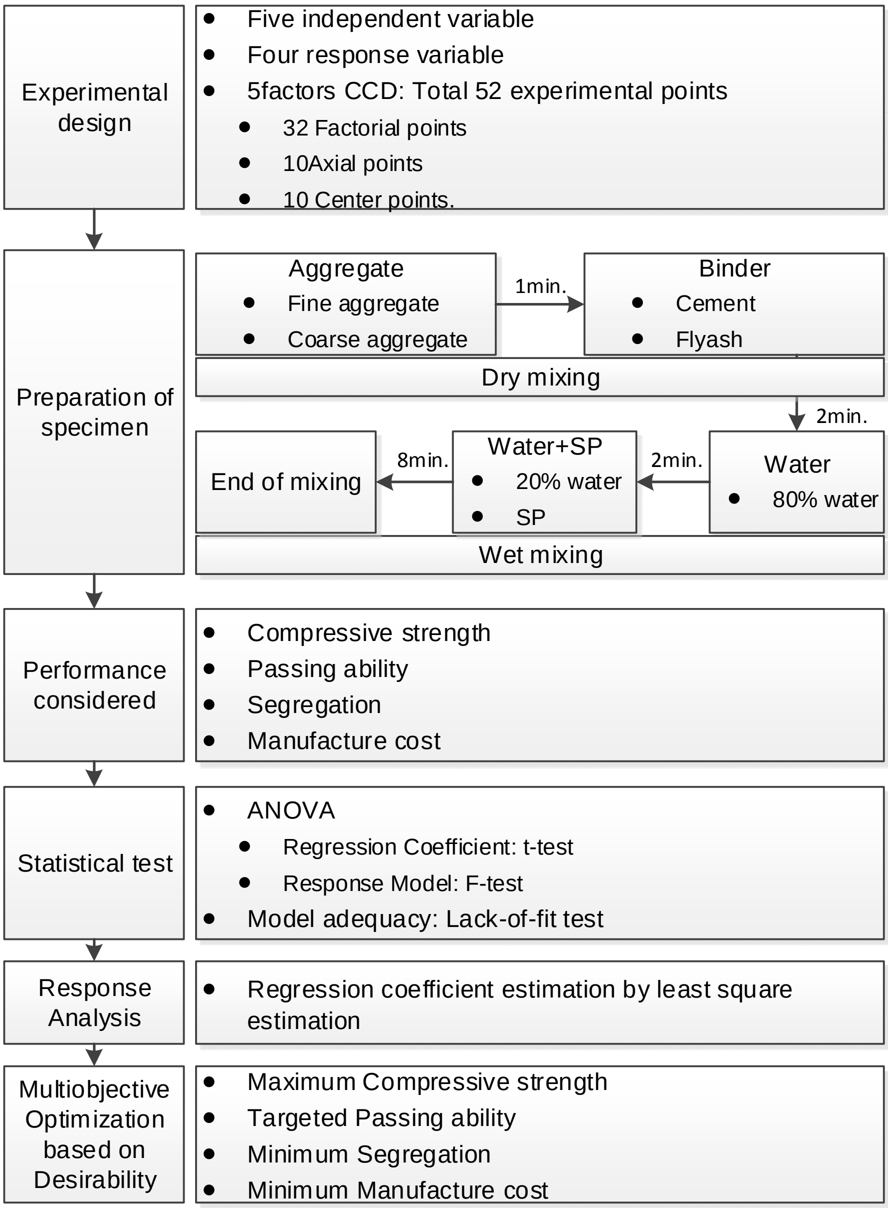


Fig. 1 Flow diagram of research process

a lower cement content resulting a significant cost saving in concrete production. Simon (2003) concluded that Statistical methods also require a certain amount of experimental works but they have an additional advantage in a sense that the expected properties (responses) can be characterized by an uncertainty (variability). This has important implications for specifications and for production of the cost-effective concrete mixture.

This research emphasizes the concrete constituent proportions and their response optimization by considering cost. However, there is a deficiency in HSSCC mixture standardization. Therefore, it is necessary to search some alternative methods such as central composite design based on response surface methodology and multiobjective optimization desirability function to maximize compressive strength and to reduce cost and experiment trials of HSSCC. The objective of this study is to demonstrate the application of a statistical approach for cost effective optimal mix proportioning of high strength self-compacting concrete using the data of DOE considering water-binder ratio, cement content, fine aggregate percentage, fly ash content, and superplasticizer content as a key design factor. Design of experiment, response surface methodology, overlaid contour and finally desirability function were used for response optimization of HSSCC.

2. Multiple optimization procedure of HSSCC

2.1 Experimental design

To evaluate the mix-proportioning effect, many researchers have used Design of Experiment (DOE) techniques. DOE techniques yield a method to ascertain the influence of the different parameters in a sound manner with limited number of experimental runs compared to factorial design. The central composite design method has been chosen to be employed it by using Minitab software tools. Central composite plan offers modelling of the mixture proportions involving linear, interaction, full and pure quadratic manner. These models were used for optimization of the high strength self-compacting concrete mixes. The CCD method composed of three parts: the fraction factorial portion, the center portion, and the axial portion. The fraction factorial portion represent the interaction between two variables and the axial portion permit the estimation of curvature. To estimate experiment error, it is useful to repeat the experiments for the central portion. In this study, as represented in Fig. 1, a five factors at two level experiment, the central composite design is composed of five components, the factorial portion (2^5) =32, the axial (star) portion (2×5) = 10. A statistical experimental design (five factors at two levels) response surface consisting of 5 factors and 52 points (32 factorial points, 10 axial points, and 10 central points) were used to assess the effect of two different levels for each key mixture parameter on the relevant HSSCC properties.

2.2 Materials used

The binding materials of SCC used in the present study were type 1 Ordinary Portland Cement (OPC) and Class F fly ash (FA) in order to explore the response surfaces that represent the relation of experimental variables with response variables and to decide the optimal levels of experimental variables based on these. The specific gravity and specific surface area of the OPC were 3.15 and 3,408cm^2/g, respectively. Those of the FA were 2.19 and 3,552cm^2/g successively, and the calcium content of the FA was 1.2%. The coarse aggregate used was crushed granite with a specific gravity of 2.63 and a fineness modulus of 6.32 and maximum particle size was 19mm. The fine aggregate was quartz sand with a specific gravity of 2.62 and a fineness modulus of 2.31. Polycarboxylic type superplasticizer (liquid, brown, specific gravity 1.12) was used to achieve the desired self compactability. All mixtures prepared at the design points listed in Table 2 and Table 3, were mixed using rotating pan compulsory mixer for total 13 minutes.

2.3 Specimen preparation and test method

Table 1 Key factors and experimental region

Experiment region (Uncoded)						
factor	Unit	Interest region				
		Low axial point	Low	Center	High	High axial point
water-binder ratio (W/B)	%	28.12	35	40	45	51.9
Cement content (cement)	Kg/m^3	337.3	420	480	540	622.7
Fine aggregate percentage (S/a)	Vol %	33.12	40	45	50	56.9
Fly ash content (Fly Ash)	Kg/m^3	3.65	45	75	105	146.4
Superplasticizer (SP)	Kg/m^3	1.24	4	6	8	10.8

Compressive strength, passing ability and segregation resistance were chosen among the several requirements reported in The European Guidelines for Self Compacting Concrete by SCC European Project Group. Specimens for compressive test were prepared without compacting after pouring into 100 by 200mm cylinders. After the curing period of 28 days, compressive strength of cylindrical specimens were measured in conformance to ASTM C 39. Passing ability was quantified by the flow value of J-ring test that was conducted according to the test procedure specified by EFNARC (2002). Segregation test was conducted according to GTM screen stability test method by EFNARC (2002). Production cost of 1m^3 of SCC was calculated for each mixture only by considering unit material costs of each material in Korea.

2.4 Statistical model development

In this study, the response surface models were developed by using Minitab software. Central composite design (CCD) method was selected to design mixture variables. Five key factors at two levels were used to find the effect of variable parameter on HSSCC. Such a two-level factorial design requires a minimum number of tests for each variable (Montgomery 2012). The fact that the expected responses do not vary in a linear manner with the selected variable and to enable the quantification of the prediction of the responses, a central composite plan was selected, where the response could be modelled in a linear, interaction, full and pure quadratic manner. Since the error in predicting the responses increases with the distance from the center of the modelled region, it is advisable to limit the use of the models to an area bound by values corresponding to $-\alpha$ to $+\alpha$ limits. The parameters were meticulously chosen to accomplish central composite design, where the influence of each factor was assessed in codified values of $-\alpha$, $+\alpha$. The value of α was chosen so that the variance of the response predicted by the model would depend only on the distance from the center of the modelled region. ± 2.37841 was taken as α value. For the statistical analysis of the results suitable Minitab software was used.

Five key parameters that have a significant influence on the mix characteristics of SCC were selected to derive the mathematical models for evaluating relevant HSSCC properties. The experimental levels of the variables (maximum and minimum), water-binder ratio, cement content, fine aggregate percentage, fly ash content and superplasticizer content were defined. The modeled experimental region consisted of mixes transformed into the coded variables of -2.37841 to +2.37841 as given in Table 1. The derived statistical models are valid at the ranges, 35 to 45% for water binder ratio, 420 to 540 kg/m^3 for cement content of, 40 to 50% (by volume) for fine aggregate percentage, 45 to 105 kg/m^3 for fly ash content, 4 to 8 kg/m^3 for superplasticizer.

Table 2 Experimental Design Run (Factorial point)

Run	W/B	Cement	FA	Fly Ash	SP
3	-1	-1	-1	1	1
6	1	-1	-1	-1	-1
7	-1	-1	-1	-1	-1
8	-1	1	1	-1	-1
10	-1	-1	1	-1	1
11	1	1	-1	1	-1
12	1	1	1	-1	1
13	1	-1	1	-1	1
14	-1	1	-1	1	-1
15	1	-1	-1	1	1
16	-1	1	-1	1	1
20	1	1	1	1	1
21	-1	1	1	1	-1
23	-1	1	-1	-1	-1
25	1	1	-1	-1	1
27	-1	-1	1	-1	-1
29	1	1	-1	1	1
30	1	1	1	-1	-1
32	1	1	1	1	-1
33	-1	-1	-1	-1	1
34	-1	-1	1	1	-1
35	-1	1	1	-1	1
36	1	-1	-1	-1	1
37	1	-1	1	1	-1
38	-1	-1	1	1	1
39	-1	1	1	1	1
40	-1	-1	-1	1	-1
41	1	1	-1	-1	-1
47	1	-1	-1	1	-1
48	-1	1	-1	-1	1
51	1	-1	1	-1	-1
52	1	-1	1	1	1

2.5 Desirability function for multiobjective optimization

The desirability function approach is one of the most widely used methods for the optimization of multiple response processes. It is a useful approach for optimization of multiple responses is to utilize the simultaneous optimization technique popularized (Montgomery, 2012). It is based on the idea that the "quality" of a product or process that has multiple quality characteristics, with one of them outside of some "desired" limits, is completely unacceptable.

Their procedure makes use of desirability functions. The common approach is to first transform each response y into an individual desirability function d_i that varies over the range $0 \leq d_i \leq 1$. The value of d_i increases as the "desirability" of the corresponding response increases. Then the design variables are chosen to maximize the overall desirability where there are m responses.

$$D = (d_1 \cdot d_2 \cdot d_3 \cdots d_m)^{1/m} \tag{1}$$

If the target *T* for the response y is a maximum value (larger the better),

$$d = \begin{cases} 0 & y < L \\ \left(\dfrac{y-L}{T-L}\right)^r & L \leq y \leq T \\ 1 & y > L \end{cases} \tag{2}$$

Where, *r* represent the weight which will have the influence the individual desirability function. If the target for the response is a minimum (smaller the better),

$$d = \begin{cases} 1 & y < T \\ \left(\dfrac{U-y}{U-T}\right)^r & T \leq y \leq U \\ 0 & y > T \end{cases} \tag{3}$$

Manufacture cost and segregation is targeted as minimum in this study. If the target for the response is to locate between the lower specification limit (L) and upper specification limit (U), and to be as close as possible to the target (nominal-is-best), the individual desirability function is defined as

$$d = \begin{cases} 0 & y < L \\ \left(\dfrac{y-L}{T-L}\right)^{r1} & L \leq y \leq T \\ \left(\dfrac{U-y}{U-T}\right)^{r2} & T \leq y \leq U \\ 0 & y > U \end{cases} \tag{4}$$

In this study, compressive strength is targeted to be maximum, manufacture cost and segregation is targeted as minimum and passing ability is targeted as 605 mm (J-Ring test). The upper and lower parameter limits for different responses are tabulated in Table 2.

3. Results and discussion

The effect of the water-binder ratio, cement content, fine aggregate percentage, fly ash content and superplasticizer content on the properties and performance of HSSCC like compressive strength, passing ability, segregation resistance, and manufacturing cost were investigated by central composite design based on RSM.

The key parameters and interest region have shown in Table 1 and the experimental design point of HSSCC is tabulated as Table 2 and Table 3.

Table 3 Experimental Design Run (center and axial point)

Factor point	Run	W/B	Cement	FA	Fly Ash	SP
Center point	1	0	0	0	0	0
	22	0	0	0	0	0
	24	0	0	0	0	0
	28	0	0	0	0	0
	42	0	0	0	0	0
	43	0	0	0	0	0
	44	0	0	0	0	0
	46	0	0	0	0	0
	49	0	0	0	0	0
	50	0	0	0	0	0
Axial point	2	0	0	0	-2.37841	0
	4	-2.37841	0	0	0	0
	5	0	2.37841	0	0	0
	9	0	-2.37841	0	0	0
	17	0	0	0	0	2.37841
	18	0	0	0	0	-2.37841
	19	0	0	2.37841	0	0
	26	0	0	0	2.37841	0
	31	2.37841	0	0	0	0
	45	0	0	-2.37841	0	0

3.1 Model adequacy

Correlation coefficient (R^2) is a statistical measure of how close the data are to the fitted regression line. R-squared is always between 0 and 100%. 0% indicates that the model explains none of the variability of the response data around its mean. 100% indicates that the model explains all the variability of the response data around its mean.

An analysis of variance (ANOVA) were carried out to check the model adequacy. The result of the statistical model represents the correlation of coefficients and the relative significance. Table 5 shows the regression equation, R^2 and R^2_{adj} for full quadratic model of HSSCC response variables. The R^2 values of the response surface models for compressive strength, passing ability, segregation resistance and manufacturing cost were 95.47%, 96.04%, 95.34% and 100% for the full quadratic equation. The R^2_{adj} values of the response surface models for Compressive strength, passing ability, segregation resistance and manufacturing cost were 92.55%, 93.49%, 92.33% and 100% for the full quadratic equation. It is seen that R^2 and R^2_{adj} shows a high correlation coefficient for the responses i.e. model shows a good correlation of the measured values. Therefore, it is evident that established model is adequate and thus can be applied for the predicted models.

Moreover, Analysis of variance (ANOVA) were performed to confirm the applicability of the model. For 95% confidence level, if the p-value that is used for testing a statistical hypothesis is

Table 4 ANOVA result of full quadratic model

Response	Unit	Sources	Sum of squares	DOF	Mean Square	F-value	P-value	R
Compressive Strength, y1	MPa	Model	488.920	20	24.446	32.67	0.000	Sign.
		Residual error	23.196	31	0.748			
		Lack of fit	17.385	22	0.790	1.22	0.393	Not sign.
		Pure error	5.811	9	0.646			
		Sum	512.116	51				
Passing ability, y2	mm	Model	130210	20	6510.5	37.62	0.000	Sign.
		Residual error	5364	31	173.0			
		Lack of fit	4696	22	213.5	2.88	0.052	Not sign.
		Pure error	668	9	74.2			
		Sum	135575	51				
Segregation,y3	%	Model	617.227	20	30.861	31.71	0.000	Sign
		Residual error	30.168	31	0.973			
		Lack of fit	19.592	22	0.891	0.76	0.717	Not sign.
		Pure error	10.576	9	1.175			
		Sum	647.394	51				
Production Cost, y4	10^3 Won	Model	931.849	20	46.592	2.49647E +08	0.000	Sign.
		Residual error	0.000	31	0.000			
		Lack of fit	0.000	22	0.000	*	*	
		Pure error	0.000	9	0.000			
		Sum	931.849	51				

Table 5 Regression equation for full quadratic model of HSSCC response variables

Response	R^2 (%)	R^2_{adj} (%)	Regression Equation (Uncoded)
Compressive Strength, y1	95.47	92.55	Fck = -105.5 + 2.600 W/B + 0.1282 Cement + 2.671 S/a + 0.3639 FlyAsh + 2.31 SP- 0.03832 W/B*W/B - 0.000188 Cement*Cement - 0.02640 S/a*S/a - 0.000595 FlyAsh*FlyAsh- 0.1204 SP*SP +0.001085W/B*Cement- 0.00142 W/B*S/a 0.00275 W/B*FlyAsh- 0.0278 W/B*SP + 0.000569 Cement*S/a - 0.000099 Cement*FlyAsh + 0.00165 Cement*SP- 0.00183 S/a*FlyAsh - 0.0043 S/a*SP - 0.00261 FlyAsh*SP
Passing ability, y2	96.04	93.49	Jring = -1736 + 28.93 W/B + 2.191 Cement + 37.14 S/a + 1.18 FlyAsh + 24.9 SP- 0.3469 W/B*W/B- 0.002241 Cement*Cement- 0.3796 S/a*S/a - 0.00737 FlyAsh*FlyAsh - 1.738 SP*SP+ 0.00141 W/B*Cement + 0.1068 W/B*S/a + 0.0009 W/B*FlyAsh - 0.402 W/B*SP - 0.00127 Cement*S/a + 0.00047 Cement*FlyAsh + 0.0355 Cement*SP + 0.0002 S/a*FlyAsh+ 0.005 S/a*SP + 0.0551 FlyAsh*SP

Table 5 Continued

Response	R^2 (%)	R^2_{adj} (%)	Regression Equation (Uncoded)
Segregation,y3	95.34	92.33	Segregation = 28. - 1.376 W/B + 0.1084 Cement- 0.338 S/a+ 0.0662 FlyAsh - 4.74 SP + 0.02004 W/B*W/B - 0.000008 Cement*Cement - 0.00117 S/a*S/a - 0.000553 FlyAsh*FlyAsh + 0.0612 SP*SP - 0.002229 W/B*Cement + 0.00575 W/B*S/a+ 0.00454W/B*FlyAsh + 0.1319 W/B*SP + 0.000125 Cement*S/a - 0.000271 Cement*FlyAsh - 0.00312 Cement*SP - 0.00067 S/a*FlyAsh + 0.0038 S/a*SP + 0.00417 FlyAsh*SP
Production Cost, y4	100	100	Cost = 18.8416 - 0.001151 W/B + 0.070904 Cement - 0.007155 S/a + 0.091010 FlyAsh + 0.134023 SP - 0.000006 W/B*W/B - 0.000000 Cement*Cement - 0.000006 S/a*S/a - 0.000000 FlyAsh*FlyAsh - 0.000017 SP*SP - 0.000174 W/B*Cement + 0.000036 W/B*S/a- 0.000174 W/B*FlyAsh - 0.000003 W/B*SP + 0.000004 Cement*S/a - 0.000000 Cement*FlyAsh+ 0.000000 Cement*SP + 0.000005 S/a*FlyAsh + 0.000009 S/a*SP + 0.000008 FlyAsh*SP

Table 6 Statistical tests in coded coefficient of full quadratic model of y1 and y2

Term	Compressive strength, y1				Passing ability, y2			
	Effect	Coef	T-Value	P-Value	Effect	Coef	T-Value	P-Value
Constant	-	64.01	235.44	0.000	-	681.73	164.89	0.000
W/B	-3.821	-1.91	-14.54	0.000	43.14	21.57	10.79	0.000
Cement	2.316	1.158	8.81	0.000	34.48	17.24	8.63	0.000
S/a	3.487	1.744	13.27	0.000	66.72	33.36	16.69	0.000
FlyAsh	1.152	0.576	4.38	0.000	40.81	20.4	10.21	0.000
SP	0.648	0.324	2.46	0.019	37.28	18.64	9.33	0.000
W/B*W/B	-1.916	-0.958	-8.47	0.000	-17.35	-8.67	-5.04	0.000
Cement*Cement	-1.353	-0.677	-5.98	0.000	-16.13	-8.07	-4.69	0.000
S/a*S/a	-1.32	-0.66	-5.84	0.000	-18.98	-9.49	-5.52	0.000
FlyAsh*FlyAsh	-1.07	-0.535	-4.73	0.000	-13.27	-6.64	-3.86	0.001
SP*SP	-0.963	-0.482	-4.26	0.000	-13.9	-6.95	-4.04	0.000
W/B*Cement	0.651	0.325	2.13	0.041	0.84	0.42	0.18	0.857
W/B*S/a	-0.071	-0.035	-0.23	0.818	5.34	2.67	1.15	0.259
W/B*FlyAsh	-0.826	-0.413	-2.7	0.011	0.28	0.14	0.06	0.952
W/B*SP	-0.556	-0.278	-1.82	0.079	-8.04	-4.02	-1.73	0.094
Cement*S/a	0.342	0.171	1.12	0.273	-0.76	-0.38	-0.16	0.871
Cement*FlyAsh	-0.355	-0.177	-1.16	0.255	1.7	0.85	0.37	0.717
Cement*SP	0.396	0.198	1.3	0.204	8.52	4.26	1.83	0.077
S/a*FlyAsh	-0.549	-0.275	-1.8	0.082	0.05	0.02	0.01	0.992
S/a*SP	-0.085	-0.043	-0.28	0.782	0.09	0.05	0.02	0.984
FlyAsh*SP	-0.314	-0.157	-1.03	0.313	6.61	3.31	1.42	0.165

less than 0.05, the term is considered as significant. The result of ANOVA is presented in Table 4.

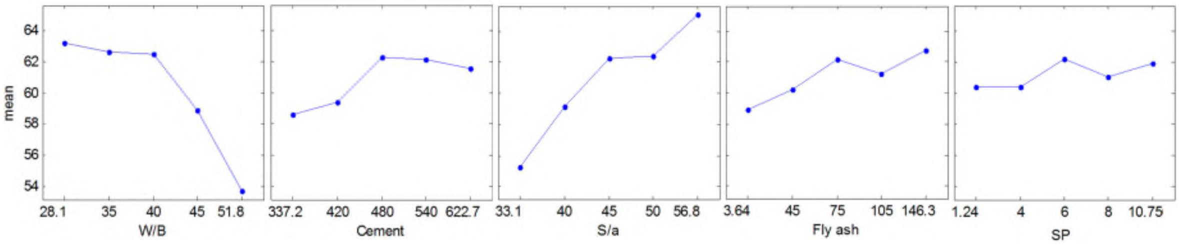
Table 7 Statistical tests in coded coefficient of full quadratic model of y3 and y4

Term	Segregation resistance, y3				Production cost, y4			
	Effect	Coef	T-Value	P-Value	Effect	Coef	T-Value	P-Value
Constant		10.775	34.75	0.000		56.4349	415636.55	0.000
W/B	5.482	2.741	18.29	0.000	-0.965305	-0.482652	-7352.79	0.000
Cement	-2.634	-1.317	-8.79	0.000	7.69611	3.84805	58621.78	0.000
S/a	-1.81	-0.905	-6.04	0.000	-0.036659	-0.01833	-279.24	0.000
FlyAsh	1.795	0.897	5.99	0.000	5.05882	2.52941	38533.36	0.000
SP	0.988	0.494	3.3	0.002	0.539327	0.269664	4108.09	0.000
W/B*W/B	1.002	0.501	3.89	0.001	-0.00031	-0.000155	-2.74	0.01
Cement*Cement	-0.058	-0.029	-0.23	0.822	-0.000133	-0.000066	-1.18	0.248
S/a*S/a	-0.058	-0.029	-0.23	0.822	-0.00031	-0.000155	-2.74	0.01
FlyAsh*FlyAsh	-0.995	-0.498	-3.86	0.001	-0.000133	-0.000066	-1.18	0.248
SP*SP	0.49	0.245	1.9	0.067	-0.000133	-0.000066	-1.18	0.248
W/B*Cement	-1.337	-0.669	-3.83	0.001	-0.104312	-0.052156	-682.95	0.000
W/B*S/a	0.288	0.144	0.82	0.416	0.001813	0.000906	11.87	0.000
W/B*FlyAsh	1.363	0.681	3.91	0.000	-0.052187	-0.026094	-341.68	0.000
W/B*SP	2.637	1.319	7.56	0.000	-0.000062	-0.000031	-0.41	0.685
Cement*S/a	0.075	0.037	0.22	0.831	0.002688	0.001344	17.6	0.000
Cement*FlyAsh	-0.975	-0.487	-2.8	0.009	-0.000062	-0.000031	-0.41	0.685
Cement*SP	-0.75	-0.375	-2.15	0.039	0.000062	0.000031	0.41	0.685
S/a*FlyAsh	-0.2	-0.1	-0.57	0.57	0.001563	0.000781	10.23	0.000
S/a*SP	0.075	0.038	0.22	0.831	0.000188	0.000094	1.23	0.229
FlyAsh*SP	0.5	0.25	1.43	0.162	0.000937	0.000469	6.14	0.000

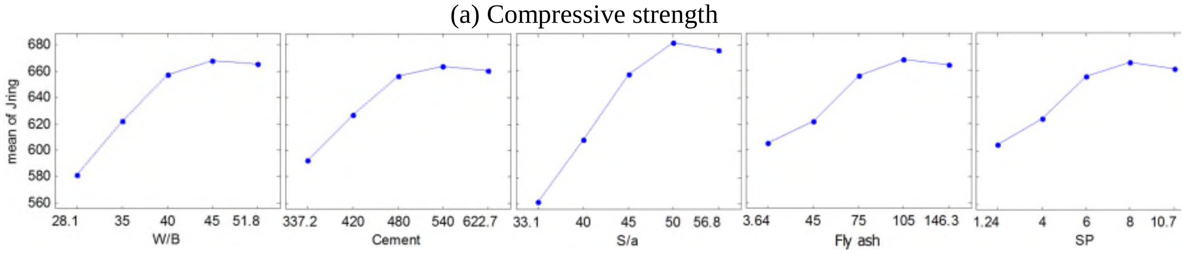
It is seen that p-value for Compressive strength, passing ability, segregation resistance and manufacturing cost are 0. Therefore, the model is adequate for full quadratic manner.

Lack-of–fit test: A regression model exhibits lack-of-fit when it fails to adequately describe the functional relationship between the experimental factors and the response variable. Lack-of-fit can occur if important terms from the model such as interactions or quadratic terms are not included. If the p-value is less than or equal to α, it can be concluded that the model does not accurately fit the data. To get a better model, it is require to add terms or transform your data. If the p-value is larger than α, it cannot be concluded that the model does not fit the data well. Table 4 shows the p-values for lack-of-fit for the responses. The P-value (lack-of –fit) of the response surface models for Compressive strength, passing ability and segregation resistance were 0.393, 052, .717 for the full quadratic equation where all p-values are greater than 0.05. Hence, model has no significant lack-of-fit at 95% confidence level. Therefore, it shows that, model fit the data well.

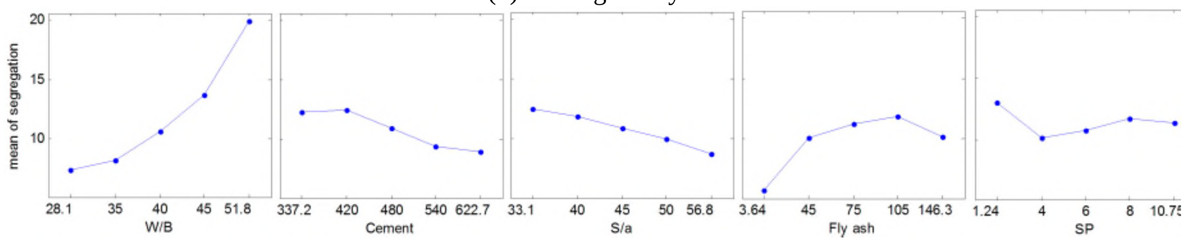
Statistical test was carried out to identify the individual and interactive effects of variable factors (independent variable) on responses (dependent variable). The results of test is presented in Table 6 and Table 7. A factor was considered as significant if p-value is found to be less than 0.05 (95% confidence level).



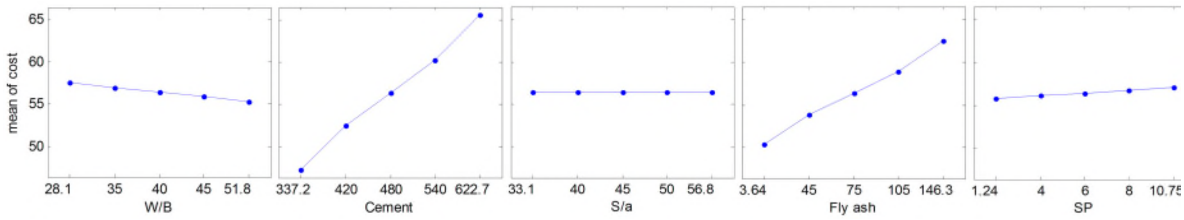
(a) Compressive strength



(b) Passing ability



(c) Segregation

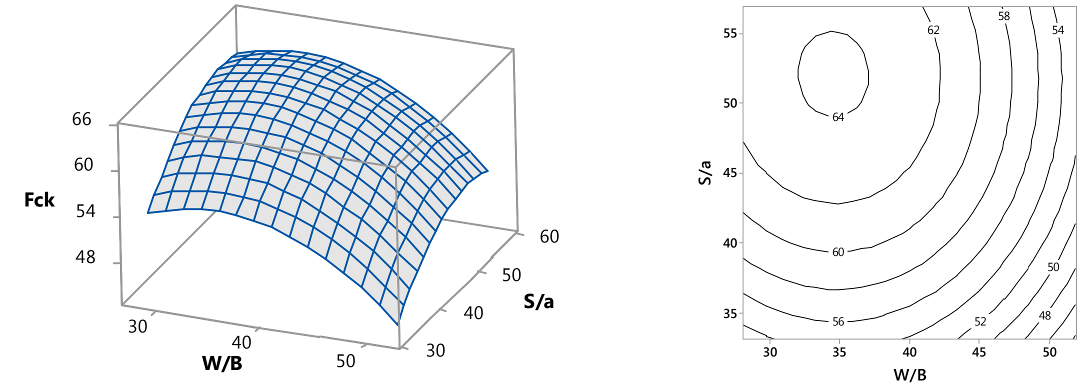


(d) Cost

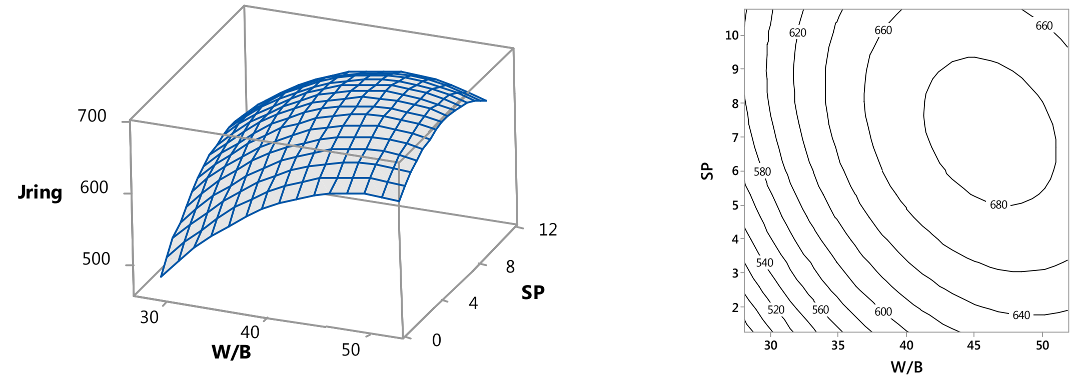
Fig. 2 Main effect plot for Fck, J-Ring, segregation and Production cost (fitted means)

3.2 Main effect of each independent variable on response

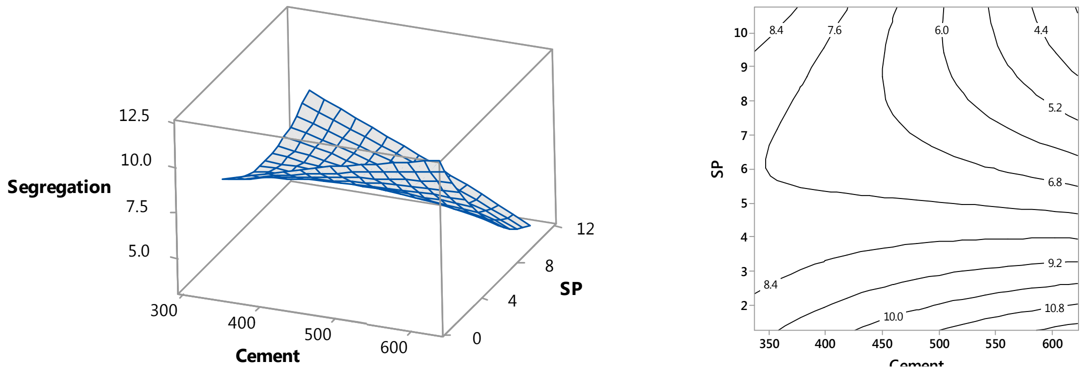
Main effect plot helps to rank list of factors from most important to least important. The steepest line indicates the most important factor, next steepest line indicates the second important factor and so on. Fig. 2 depicts the main effects for (a) compressive strength, (b) passing ability (J-Ring), (c) segregation and (d) Production cost depending on water-binder ratio, cement content, fine aggregate percentage, fly ash content and superplasticizer content. Fig. 2(a) shows that all factors have significant effect on compressive strength where W/B and cement content have larger



(a) F_{ck} depending on W/B and S/a



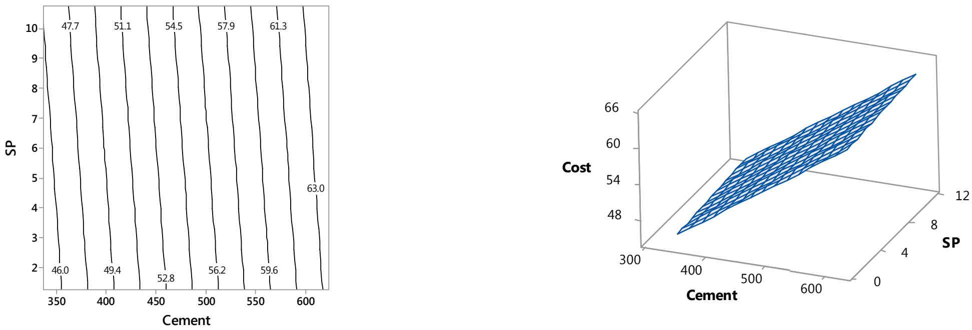
(b) Passing ability depending on W/B and SP



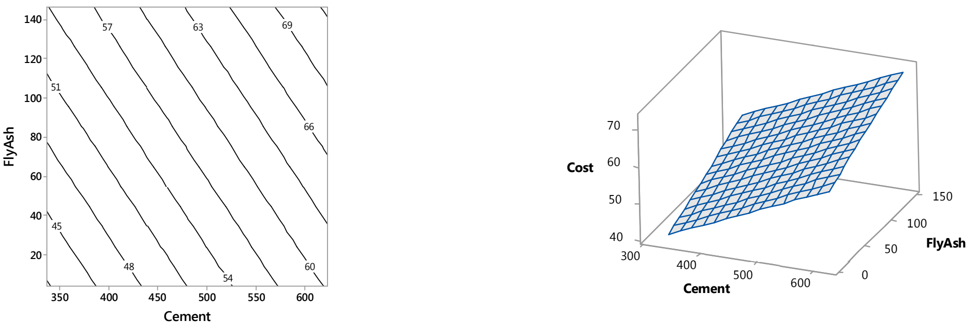
(c) Segregation depending on Cement and SP

Fig. 3 The response surface and contour plot of (a) Fck as function of S/a and W/B, (b) J-Ring as function of SP and W/B, (c) segregation as function of cement and SP, (d) Cost as function of Fly ash and cement

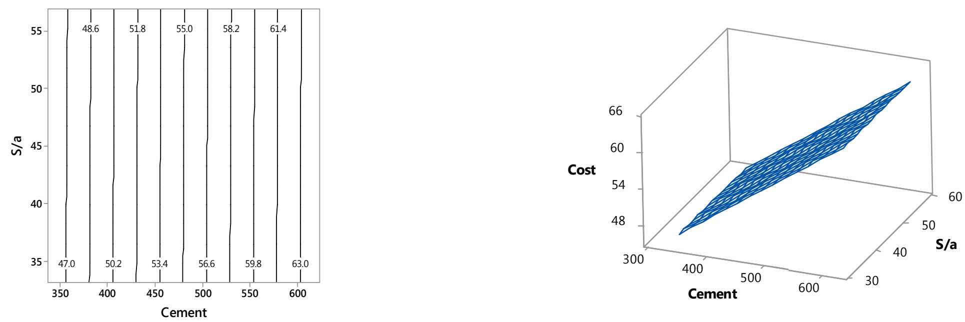
effect. Compressive strength decreases with the increase of W/B and increase with the increase of cement content, fine aggregate percentage by volume of total aggregate in concrete(S/a), fly ash and Sp. Fig. 2(b) depicts that Segregation rise up significantly with the increase of W/B but decrease with the increase of cement content and S/a. Fly ash and SP have minor effect on segregation. Fig. 2(c) indicates that all the factors appears as significant on passing ability which increases with the increase of factors. Fig. 2(d) will be explained in cost analysis section (3.5).



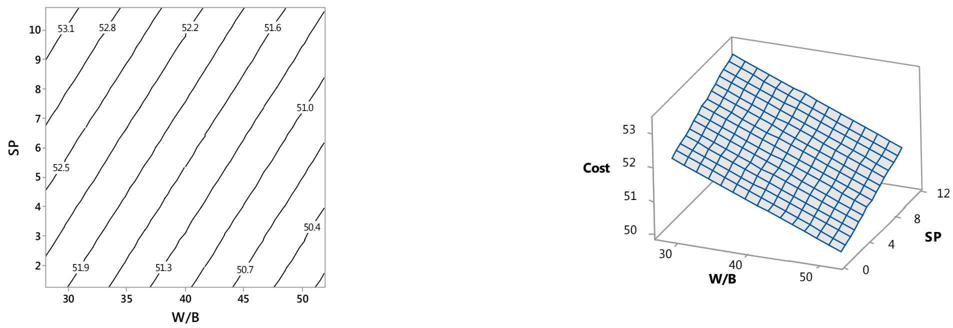
(a) Cost depending on Cement and SP



(b) Cost depending on Cement and FlyAsh

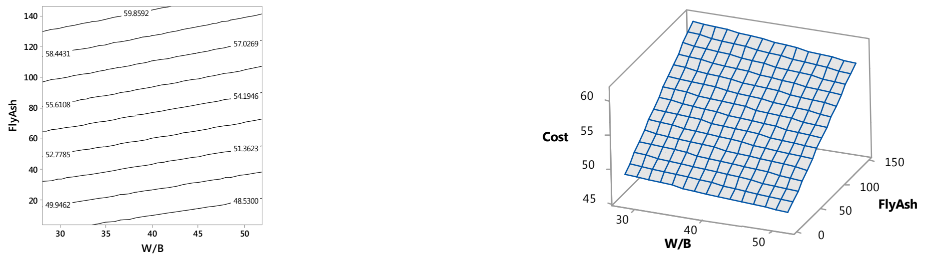


(c) Cost depending on Cement and S/a

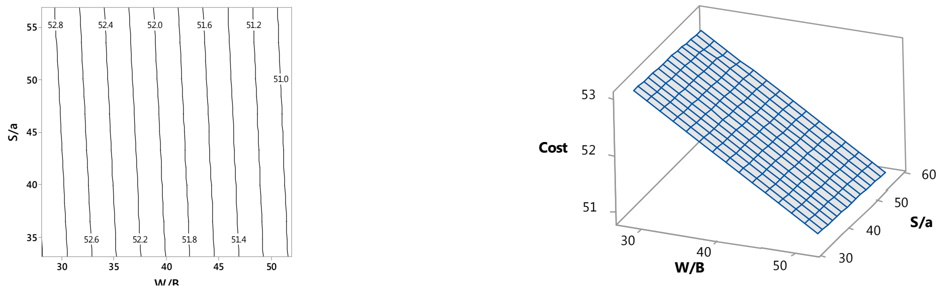


(d) Cost depending on W/B and SP

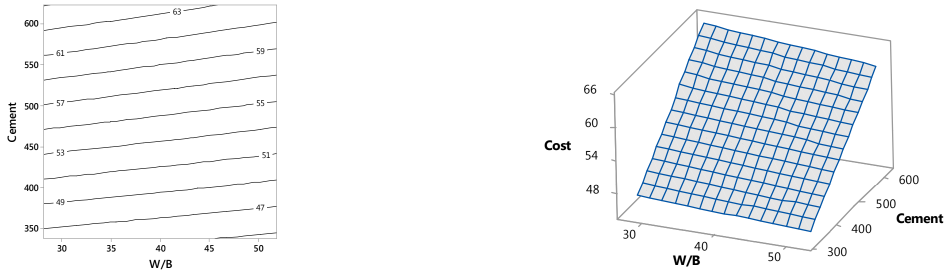
Fig. 4 Response surface plot for manufacturing cost as function of (a) cement and SP, (b) cement and fly ash, (c) cement and S/a, and (d) W/B and SP, (e) W/B and fly ash, (f) W/B and S/a, (g) W/B and cement content, (h) fly ash and SP, (i) S/a and SP, (j) S/a and fly ash.



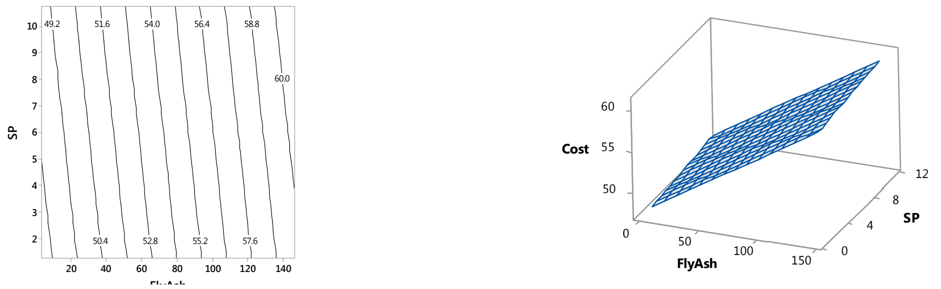
(e) Cost depending on W/B and FlyAsh



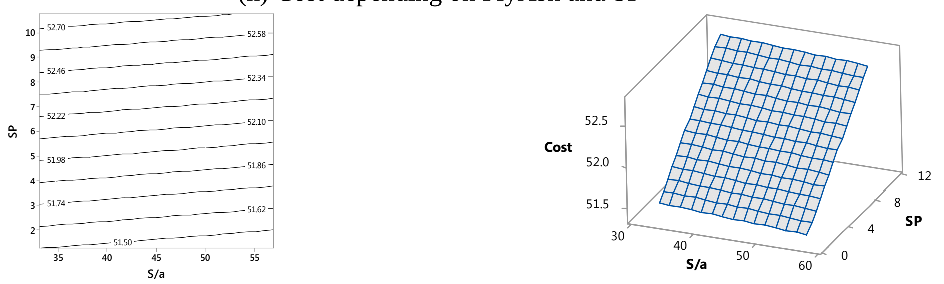
(f) Cost depending on W/B and S/a



(g) Cost depending on W/B and Cement

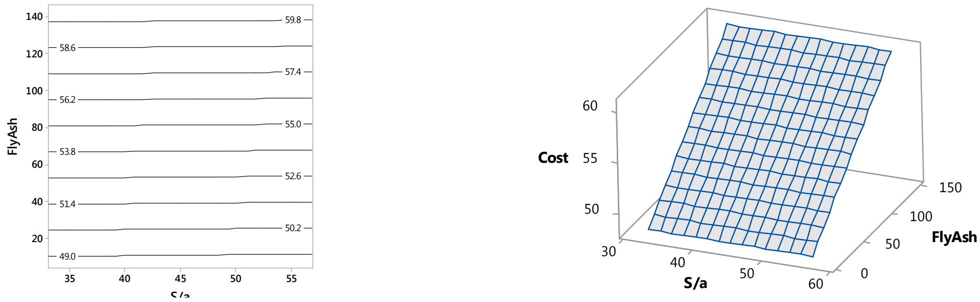


(h) Cost depending on FlyAsh and SP



(i) Cost depending on S/a and SP

Fig. 4 Continued



(j) Cost depending on S/a and FlyAsh

Fig. 4 Continued

3.4 Response properties

Contour and surface plots are useful for establishing desirable response values and operating conditions. In a contour plot, the response surface is viewed as a two-dimensional plane where all points that have the same response are connected to produce contour lines of constant responses. A surface plot displays a three-dimensional view that provides a clearer picture of the response surface. Fig. 3 shows the response surface and contour plot of (a) compressive strength(F_{ck}) as function of S/a and W/B, (b) J-Ring as function of SP and W/B, (c) segregation as function of cement and SP, (d) Cost as function of Fly ash and cement.

Fig. 3(a) shows that the surface plot has quadratic effect for W/B and S/a on compressive strength. For any changes in any variable response surface shows curvature when other variable are constant. The plot also demonstrates that as W/B ratio increases F_{ck} decreases, while by S/a increases F_{ck} increases slightly. Fig. 3(b) illustrates a response surface of a rising ridge showing the quadratic effect which deduce that, with the increase of W/B and SP passing ability increases, Fig. 3(c) depict the variation of segregation with cement and SP. It shows that segregation increases gradually with an increase in cement content whereas Segregation decreases with the increase of SP.

3.5 Cost analysis

Present study emphasizes to find an efficient method for cost effective concrete mixture satisfying certain criteria. Main effect identify the effect of independent variable on responses ignoring the interaction of all other independent variable. Fig. 2(d) depict the main effects of production cost depending on five independent variables like water-binder ratio, cement content, fine aggregate percentage, fly ash content and superplasticizer content. It demonstrates that cement content and fly ash appears as more significant than other factors on manufacture cost. Higher cement content and fly ash are associated with the higher cost. On the other hand, W/B, S/a and SP have hardly effect on manufacture cost.

The contour and response surface plot helps to envisage the effect of different factors on properties of concrete mixture. Fig. 4 shows the contour and surface plot for manufacturing cost as function of (a) cement and SP, (b) cement and fly ash, (c) cement and S/a, and (d) W/B and SP, (e) W/B and fly ash, (f) W/B and S/a, (g) W/B and cement content, (h) fly ash and SP, (i) S/a and SP, (j) S/a and fly ash assuming others as constant. It has been found that all the plots show a linear

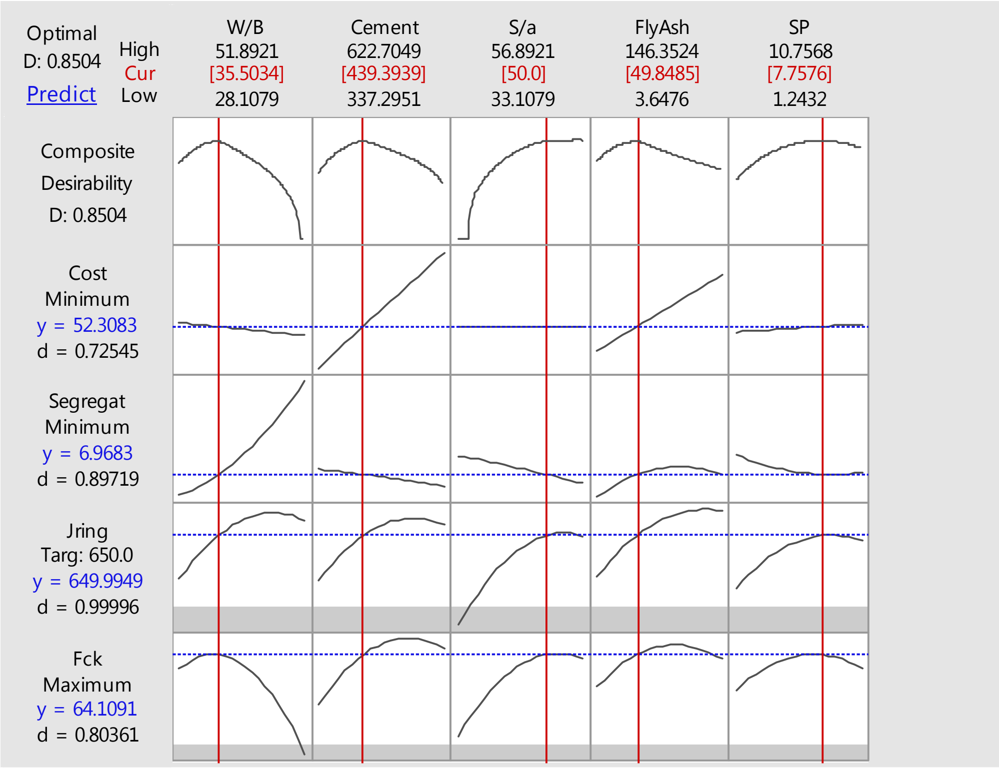


Fig. 5 Optimization plot of the responses

relationship with the factor variables. Fig. 4(a) shows the relation between cement and SP and it demonstrates that SP has a very little effect on cost. Fig. 4(b) gives the contour and surface plot of cement and fly ash. It depict that manufacture cost increase significantly with the increase of cement content and fly ash. Fig. 4(c) shows the variation of cost with cement and S/a. It illustrates that as cement content and S/a increases manufacture cost increases. Fig. 4(d) represents that cost slumps gradually with the increase of W/B ratio and SP content. Fig. 4(e) demonstrates that manufacture cost rise up significantly with the increase of fly ash whereas cost decline slightly with the increase of W/B ratio. Fig. 4(f) shows a relation between W/B and S/a and indicates that cost reduces with the increase of W/B ratio. However, there is no significant effect of S/a in manufacture cost. Fig. 4(g) shows that manufacture cost decreases gradually with the increase of W/B ratio whereas cost increases sharply with the increase of cement content. Fig. 4(h) illustrates that cost rises up sharply as fly ash content rises and cost increase gradually as SP increases. Fig. 4(i) represents the relation between S/a and SP. It indicates that cost climb up with the SP content but cost remain almost constant with the increase of S/a. Fig. 4(j) shows that S/a has barely has any effect on cost whereas cost rise up as fly ash content increases. This contour and response surface plot helps to visualize how the response reacts with the changes in the independent variables. However, as variable is more than two (five), it is difficult to maximize the yield. Therefore, to find the cost effective concrete mixture, desirability function is used where cost will be relatively low yet satisfying the other requirements (compressive strength, passing ability (J-Ring), and segregation) and described hereunder.

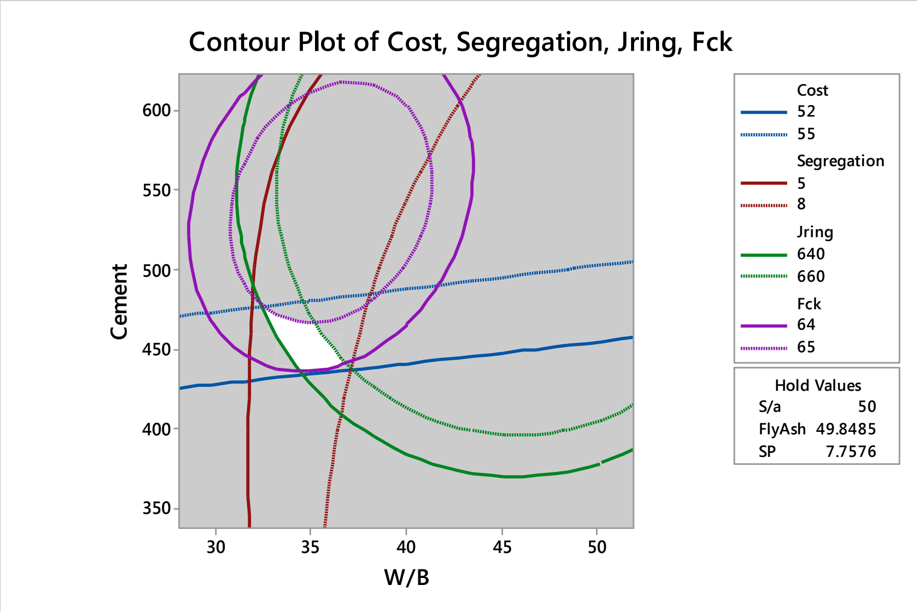


Fig. 6 Overlaid contour plots of responses dependent on W/B and cement content

3.6 Multiobjective optimization using Minitab

Individual and composite desirability evaluate how effectively a group of variables fulfill the targets which have predefined for the responses. Desirability ranges from zero to one. One indicates the absolute perfection and zero represents that one or more responses are beyond their satisfactory region (Montgomery 2012). Fig. 5 shows the individual and composite desirability of production cost, segregation, J-Ring value and compressive strength with the different settings of water-binder ratio, cement content, fine aggregate percentage, fly ash content and superplasticizer content. During the optimization, key parameters were kept constrain with the ranges of water binder ratio of 35 to 45%, cement content of 420 to 540 kg/m^3, fine aggregate percentage of 40 to 50% (by volume), fly-ash content 45 to 105 kg/m^3, superplasticizer 4 to 8 kg/m^3.

In this research, four responses are competing each other on the basis of five key mixture parameters to determine the best setting. The maximum predicted values of the responses are manufacturing cost of 52.3×10^3 Won, segregation resistance of 6.9%, passing ability of 649.9 mm (J-ring) and Compressive strength of 64.1 MPa along with the individual desirability of 0.725, 0.897, 1.0 and 0.804 respectively (Fig. 5). This individual desirability signify that the settings are effective in minimizing cost, segregation, targeted J-Ring of 650 mm and maximizing compressive strength. Each response has its own setting for the individual desirability which evaluates how it optimize a single response. To optimize all responses at the same time composite desirability is required which ascertain how it optimize a set responses together. In this study, the composite desirability is found 0.8504 which is close to 1 (one), point out that settings are favorable for all responses as whole. Therefore, it can said that, for the optimum responses of Compressive strength, J-ring, segregation resistance and manufacturing cost, the parameter settings are 439.4 kg/m^3 cement content, 35.5% W/B ratio, 50.0% fine aggregate, 49.8 kg/m^3 fly ash, and 7.8 kg/m^3 superplasticizer.

To encapsulate it can be said that this study emphasizes the cost minimization. For the minimum manufacturing cost of 52.3×10^3 Won, the individual desirability is found 0.725 and for the aforementioned factor settings composite desirability is found 0.850 which is close to the target. Therefore, it indicates that this method is effective for cost minimization.

3.7 Justification of overall desirability by overlaid contour

To get the complete picture of feasible region, overlaid contours are plotted. It takes into account of different responses at the same time which is practiced here to visually identify the feasible variables for multiple responses for a response surface design experiment. Fig. 6. demonstrates the overlaid contour plots of responses (compressive strength, passing ability, segregation resistance, and manufacturing cost) depending on W/B and cement content while holding the other parameter are constant. The plot point out the specific space (White part in Fig. 6.) where all responses are within their limits which is recognized as the feasible region.

4. Conclusions

The effect of the mixture constituent such as water-binder ratio, cement content, fine aggregate percentage, fly ash content and superplasticizer content on the properties and performance of high strength self-compacting concrete (HSSCC) were investigated. Based on the result of this research the following conclusions can be drawn:

The statistical models developed in this research can be used to prognosticate the proportions of concrete constituents. These statistical models (full quadratic) show adequacy in possessing with a less significant lack of fit than the other models (linear, interaction, and pure quadratic) with correlation coefficient R^2 of 95.47%, for compressive strength, 96.04%for passing ability, 95.34% for segregation resistance and 100% for manufacturing cost.

The established numerical model based on RSM shown in Table 5 can be efficient in design of HSSCC and selecting important constituent materials. Response surface method (RSM) can be used to find the optimum concrete mixture ingredient combination for intended characteristics.

To find the cost effective mix proportion, composite desirability function was used to estimate the factor settings to optimize all responses. Using the desirability function, it is found that individual desirability for manufacture cost is 0.725 and the composite desirability of 0.850 which is close to 1 (one), point out optimal mixture parameter combination for all responses as a whole. The parameter combination are 439.4 kg/m^3 cement content, 35.5% W/B ratio, 50.0% fine aggregate, 49.85 kg/m^3 fly ash, and 7.76 kg/m^3 superplasticizer for overall optimum response. Therefore, it emphasizes that the central composite design based on response surface methodology and multiobjective optimization desirability function has been successfully used for cost effective optimal mix proportioning.

Acknowledgements

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References

Ahmad, S. and Alghamdi, S.A. (2014), “A statistical approach to optimizing concrete mixture design”, *The Scientific World J.*

Aïtcin, P.C. (1998), *High-Performance Concrete*, E&FN SPON, New York, NY10001, USA.

Alqadi, A.N., Mustapha, K.N., Al-Mattarneh, H. and Al-Kadi, Q.N. (2009), “Statistical models for hardened properties of self-compacting concrete”, *Am. J. Eng. App. Sci.*, **2**(4), 764-770.

Alqadi, A.N., Mustapha, K.N., Naganathan, S. and Al-Kadi, Q.N. (2012), “Uses of central composite design and surface response to evaluate the influence of constituent materials on fresh and hardened properties of self-compacting concrete”, *KSCE J. Civil Eng.*, **16**(3), 407-416

Ahmadi-Nedushan, B. (2009), “Estimation of concrete compressive strength using advanced multivariate statistical techniques”, *Proceedings of the 8th International Congress on Civil Engineering*, Shiraz, Iran, May.

EFNARC (2002), *Specification and Guidelines for Self Compacting Concrete*, Association House, 99 West Street, UK.

Li, M.C., Chen, Y.S., Chan, Y.W. and Hoang, V.L. (2012), “A study of statistical models application for mixture of high-flowing concrete”, *J. Mar. Sci. and Tec.*, **20**(3), 325-335.

Montgomery, D.C. (2012), *Design and Analysis of Experiments*, (8th Edition), Wiley, New York, USA.

Murali, T.M. and Kandasamy, S. (2009), “Mix proportioning of high performance self-compacting concrete using response surface methodology”, *The Open Civil Eng. J.*, **3**, 93-97.

Shanker, R. and Sachan, A.K. (2014), “Concrete mix design using neural network”, *Int. J. Civil Arch. Struct. Cons. Eng.*, **8**(8), 883-886.

Simon, M.J. (2003), *Concrete Mixture Optimization Using Statistical Methods*, Final Report FHWA-RD-03-060, Infrastructure Research and Development, Federal Highway Administration, Georgetown Pike McLean, Va, USA.

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