An International Journal of Optimization and Control: Theories & Applications
ISSN: 2146-0957eISSN: 2146-5703
Vol.7, No.1, pp.90-97 (2017)
https://doi.org/10.11121/ijocta.01.2017.00345

RESEARCH ARTICLE

Assessment and optimization of thermal and fluidity properties of high strength concrete via genetic algorithm

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ARTICLE INFO

Article history:
Received: 15 May 2016
Accepted: 26 November 2016
Available Online: 22 December 2016

Keywords:
Genetic algorithm
High strength concrete
Optimization
Thermal properties

AMS Classification 2010:
80M50, 78M32, 62K20

ABSTRACT

This paper proposes a Response Surface Methodology (RSM) based Genetic Algorithm (GA) using MATLAB® to assess and optimize the thermal and fluidity of high strength concrete (HSC). The overall heat transfer coefficient, slump-spread flow and T_{50} time was defined as thermal and fluidity properties of high strength concrete. In addition to above mentioned properties, a 28-day compressive strength of HSC was also determined. Water to binder ratio, fine aggregate to total aggregate ratio and the percentage of super-plasticizer content was determined as effective factors on thermal and fluidity properties of HSC. GA based multi-objective optimization method was carried out by obtaining quadratic models using RSM. Having excessive or low ratio of water to binder provides lower overall heat transfer coefficient. Moreover, T_{50} time of high strength concrete decreased with the increasing of water to binder ratio and the percentage of superplasticizer content. Results show that RSM based GA is effective in determining optimal mixture ratios of HSC.

1. Introduction

Optimizing the mixture parameters of high performance concrete is important to save raw materials used [1-3]. Although many studies on finding the optimal mixture proportions for various concrete types [3] such as steel fiber reinforced concrete composition [4], recycled aggregate concretes [5], paper mill residuals mixed concrete [6], geopolymer concrete [7], and high strength self-compacting concrete [8], there is still a need for hybrid optimization techniques. In optimization phase; experimental design such as response surface methodology (RSM) is not widely practiced with Genetic algorithm (GA). However, there are some studies to optimize wire electric discharge machining process [9], cutting parameters [10], biodiesel production process [11], and optimal cultivation [12]. In recent years, genetic algorithm was generally preferred to optimize parameters due to the success in solving complex optimization problems.

RSM comprise of a group of mathematical and statistical techniques that can be used to identify the relationships between the response and the factors[13], [14]. RSM describes the effect of the factors, alone or in combination, in the processes [15]. Moreover in analyzing the effects of the factors, this experimental method also creates a mathematical model [16-18]. GAs show a classic strong optimization method in solving involution optimal problems that could be nonlinear or linear [15, 19]. GA consults the information from the achieved probable solution in the former stages to form the new set of points where improved results are anticipated [15, 20]. In the initial generation, GA is an evolutionary algorithm which can be used for the solution of more complicated optimization problems [15, 20]. GA can be described through three stages briefly: initial generation; operations such as reproduction, mutation, crossover etc.; determination of fitness value [15, 20].

This paper proposes a systematic methodology including experimental design based GA to assess and optimize thermal and fluidity properties of high strength concrete (HSC). Certainly, the overall heat transfer coefficient should be evaluated with the other essential properties such as T_{50} time, slump-flow spread and comprehensive strength for the HSC. For this purpose, the RSM must be applied with multi-objective optimization methods such as genetic

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algorithm. The main contribution of this article, the overall heat transfer coefficient of HSC was modeled empirically as a function of mixture parameters. The overall heat transfer coefficient was also optimized with other parameters using RSM-based GA. Furthermore, the overall heat transfer coefficient and T_{50} time were also analyzed in accordance with the mixed ingredients.

2. Materials and method

2.1. Materials

CEM I 42.5R type cement with 425 kg/m^3 dosage was used in this study. The cement has a specific gravity of 3.11 and Blaine fineness of 3696 cm^2/g.120 kg/m^3 of fly ash with a specific gravity of 2.38 is used. A polycarboxylic ether based superplasticizer was used in all concrete mixtures. Super-plasticizer content is identified as the ratio of SP amount of 100 kg cement. Crushed sands (with a size of smaller than 4 mm as fine aggregate and with a size between 4 mm to 11mm as the coarse aggregate are used in concrete mixtures. The fine and coarse aggregates has specific gravities of 2.61 and 2.72 and mean water absorptions of 1.4% and 1.1 %, respectively.

2.2. Proposed methodology

Low heat loss provides benefits in energy savings. The overall heat transfer coefficient was evaluated with other important criteria for HSC such as slump-spread diameter, T_{50} time and 28th day compressive strength to meet HSC qualifications. The flow chart which consists of 10 steps and which is aimed at optimizing the HSC performance was given in Figure 1.In this research, GA was used for the optimization of useful models obtained with RSM for the overall heat transfer coefficient, slump-spread diameter, T_{50} time and 28th day compressive strength.

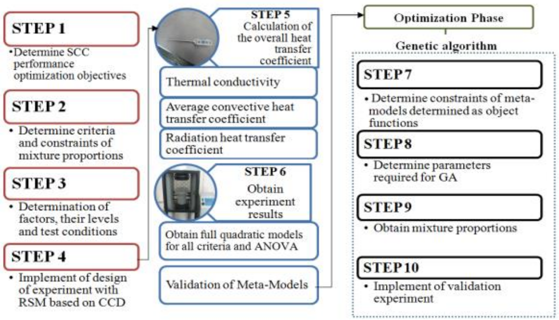

Figure 1. Proposed performance optimization and modeling framework

2.3. Thermal and fluidity properties of high strength concrete

In Turkey, 80% of the energy consumption in households is used for heating aims [21]. New methods have to be designed in order to contribute building professionals in their effort to optimize designs and to improve energy performance [22]. In our study, radiation heat-transfer coefficient was calculated to predict and model the overall heat transfer coefficient taking into account relationship radiation heat-transfer coefficient between convective heat transfer coefficients. Lakatos and Kalmar examines the change of the overall heat transfer coefficient of building structures in function of water content [23]. The first criterion is identified as the overall heat transfer coefficient that should be low. Quality characteristics for modeling phase are presented in Table 1.

Table 1. Quality criteria and their target values for optimization phase

Quality feature	Sign	Definition	Kind of concrete test	Objective
1	U	The overall heat transfer coefficient (W/m^{2}K)	Freshly mixed concrete	Minimize
2	S	Slump-spread diameter (mm)	Freshly mixed concrete	Maximize
3	T_{50}	T_{50} time (s)	Freshly mixed concrete	Minimize
4	f_{cs28}	Compressive strength (N/mm^2) 28 days	Hardened concrete test	Maximize

2.4. Determination of factors and their levels

The ranges of factors and their levels were determined taking into account the findings obtained by TOPSIS-based Taguchi Optimization [8]. Three factors (variables) are characterized as A, B, C and their five levels are given in Table 2. The factors in our experiment are percentage of water to binder materials (A), fine aggregate (I) amount to total aggregate amount ratio (B) and the percentage of PCE (C).

Table 2. Factor levels for response surface methodology

Factors	Description	Levels				
		-2	-1	0	1	2
		First level	Second level	Third level	Fourth level	Fifth level
A	Water to binder materials ratio	0.36	0.365	0.37	0.375	0.38
B	Fine aggregate (I) amount to total aggregate amount ratio	0.58	0.59	0.60	0.61	0.62
C	The percentage of PCE (%)	1.15	1.20	1.25	1.30	1.35

3. The calculation of heat transfer coefficients

Δx is the specimen length (150 mm), λ_c is thermal conductivity of concrete, h_c is convective heat transfer coefficient [8, 24] and h_f is radiation heat transfer coefficient; The heat transfer process may be represented by the resistance network and the overall heat transfer can be calculated as the ratio of the

Table 3. The overall heat transfer coefficient

Exp.No.	T_c, ^{0}C	T_∞, ^{0}C	T_f, K	Re	Nu	λc(W/mK)*	hc(W/ m²K)‡	hf(W/ m²K)#	U(W/ m²K)
1	21.8	14.2	291.15	20169.02	84.11580	1.639177	14.40864	3.527020	2.250035
2	21.4	14.2	290.95	20191.28	84.16466	1.639919	14.40781	3.519696	2.247241
3	20.8	14.2	290.65	20224.76	84.23810	1.641032	14.40657	3.508735	2.243049
4	20.6	14.2	290.55	20235.95	84.26262	1.641404	14.40616	3.505088	2.241652
5	20.9	14.2	290.70	20219.18	84.22585	1.640847	14.40678	3.510560	2.243748
6	21.0	14.2	290.75	20213.59	84.21360	1.640661	14.40698	3.512385	2.244446
7	21.4	13.8	290.75	20213.59	84.21360	1.639919	14.40698	3.512505	2.244287
8	21.3	13.8	290.70	20219.18	84.22585	1.640104	14.40678	3.510678	2.243588
9	20.7	13.8	290.40	20252.75	84.29944	1.641218	14.40554	3.499732	2.239393
10	20.1	13.8	290.10	20286.44	84.37321	1.642332	14.40431	3.488815	2.235199
11	20.6	13.8	290.35	20258.36	84.31172	1.641404	14.40533	3.497910	2.238694
12	20.5	13.8	290.30	20263.97	84.32401	1.641589	14.40513	3.496089	2.237995
13	20.8	13.8	290.45	20247.15	84.28716	1.641032	14.40574	3.501554	2.240093
14	21.0	13.8	290.55	20235.95	84.26262	1.640661	14.40616	3.505201	2.241491
15	21.1	14.3	290.85	20202.43	84.18912	1.640476	14.40740	3.516010	2.245884
16	20.8	14.3	290.70	20219.18	84.22585	1.641032	14.40678	3.510532	2.243789
17	21.9	14.3	291.25	20157.90	84.09140	1.638991	14.40906	3.530655	2.251471
18	20.2	14.3	290.40	20252.75	84.29944	1.642146	14.40554	3.499599	2.239598
19	20.6	14.3	290.60	20230.36	84.25036	1.641404	14.40636	3.506884	2.242392
20	20.7	14.3	290.65	20224.76	84.23810	1.641218	14.40657	3.508708	2.243090

* The average of the lower thermal conductivity and upper thermal conductivity of the concrete
‡ The average of the coefficients of the convection heat transfer of three 150 mm specimens [8]
# The average of the coefficients of the radiation heat transfer of three 150 mm specimens

overall temperature difference to the sum of the thermal resistance (U) [25]:

$$U = \frac{1}{\left(\frac{1}{h_c} + \frac{\Delta x}{\lambda_c} + \frac{1}{h_f}\right)} \quad (1)$$

The thermal conductivity of concrete λ_c (in W/m*K), 20^0C < T_w< 1200^0C, can be calculated between the lower(LL) and upper limit (UL)values as follows [25]:

$$\lambda_c = \begin{cases} 2 - 0.245(T_w/100) + 0.011(T_w/100)^2, \mathrm{UL} \\ 1.36 - 0.136(T_w/100) + 0.006(T_w/100)^2, \mathrm{LL} \end{cases} \quad (2)$$

In this study, the average thermal conductivity ($\bar{\lambda}_c$), which is the average of the lower thermal conductivity and upper thermal conductivity of the concrete, was calculated by using Eq. (2) for all experiments given in Table 3.

The details of calculation of the convective heat transfer coefficient can be found in [8]. T_w, T_∞ and T_f are the temperature of the concrete surface, the temperature of the air and film temperature, respectively.

The coefficient of the average convection heat transfer (h_c) which is the average of the coefficients of the convection heat transfer of three 150 mm cubes given in Table 3 [8].

The radiation heat transfer coefficient ($\bar{h}_f$) which is the average of the coefficients of the radiation heat transfer of three 150 mm cubes given in Table 3, are calculated by using Eq. (3) for all experiments[8].

$$h_f = \frac{\sigma^* \varepsilon^* F_{1,2}}{T_w - T_\infty}[T_w^4 - T_\infty^4] \quad (3)$$

ε is emissivity 0.63 for concrete; σ is Stephan-Boltzmann constant 5,67*10^{-8} W/m^{2}K^4 and $F_{1,2}$ = 1 radiation shape factor [8, 26].

4. Modeling and optimization

4.1. Modeling

Experimental matrix of RSM based Central Composite Design (CCD) were given in third, fourth and fifth columns of Table 4. In our study, rotatable experimental design is carried out as central composite design (CCD) which consists of 20 experiments. As shown in Table 4, three independent variables was symbolized as A (water to binder materials ratio), B (fine aggregate (II) amount to total aggregate amount ratio) and C (super plasticizer amount ratio to one hundred kilogram binder materials) [16].

The regression equations given in Table 5 were achieved from the analysis of variances (ANOVA). From the “p” values ($p < 0.05$) presented in also Table 5, regression equations were found significant for all thermal and fluidity properties [16]. The results demonstrate that the experimental results approximate to the estimated results (see R^2 values in Table 5). The estimated and theoretical values for the all thermal and fluidity properties were given in Table 5.

Table 4. Experimental results

Exp. No.	CCD						Responses			
	Factors have been fixed, 1 m3			Factors used in experimental design, 1 m3 (%)			U (W/m^2K)	S mm	T_{50} s	f_{cs28} N/m^3
	Cement, kg	Fly ash, kg	Total aggregate, kg	A	B	C				
MD1	425	120	1668	36.5	59	1.15	2.250035	680	5.1	71.0
MD2	425	120	1668	37.5	61	1.15	2.247241	710	4.7	68.1
MD 3	425	120	1668	37.5	59	1.30	2.243049	780	3.8	68.6
MD 4	425	120	1668	36.5	61	1.30	2.241652	750	4.1	69.0
MD 5	425	120	1668	37.0	60	1.25	2.243748	750	4.5	68.7
MD 6	425	120	1668	37.0	60	1.25	2.244446	750	4.6	68.1
MD 7	425	120	1668	37.5	59	1.20	2.244287	760	4.2	67.3
MD 8	425	120	1668	36.5	61	1.20	2.243588	720	5.0	68.4
MD 9	425	120	1668	36.5	59	1.30	2.239393	750	4.8	71.3
MD 10	425	120	1668	37.5	61	1.30	2.235199	790	4.2	66.9
MD 11	425	120	1668	37.0	60	1.25	2.238694	740	4.4	68.3
MD 12	425	120	1668	37.0	60	1.25	2.237995	750	4.5	67.8
MD 13	425	120	1668	36.0	60	1.25	2.240093	670	5.2	71.5
MD 14	425	120	1668	38.0	60	1.25	2.241491	750	4.3	67.3
MD 15	425	120	1668	37.0	58	1.25	2.245884	740	4.4	68.5
MD 16	425	120	1668	37.0	62	1.25	2.243789	740	4.5	68.2
MD 17	425	120	1668	37.0	60	1.15	2.251471	700	5.1	69.9
MD 18	425	120	1668	37.0	60	1.35	2.239598	770	3.8	70.4
MD 19	425	120	1668	37.0	60	1.25	2.242392	750	4.5	68.7
MD 20	425	120	1668	37.0	60	1.25	2.243090	750	4.5	69.0

Table 5. Regression equations and analysis of variances of all responses

Regression equations (obtained by uncoded variables)	R^2, %	P value
$U = -2.36 + 23.91X1+1.98X2-0.74X3-13.30X1^2+5.88\ X2^2+0.30\ X3^2-23.94X1X2+0.21X1X3-0.208X2X3$	77.29‡	0.024*
$S = -65018 + 296687X1+33056X2+45X3-327126X1^2-6782X2^2-720X3^2-81954X1X2-1316X1X3+4342X2X3$	91.75‡	0.000*
$T_{50} = 971.54 – 3970.44X1-873.44X2+66.41X3+1929.89X1^2-267.53X2^2-21.56X3^2+3743.68X1X2+197.37X1X3-151.32X2X3$	93.88‡	0.000*
$f_{cs28} = 2271.0 – 9524.57X1-991.79X2-148.74X3+7661.11X1^2-709.72X2^2+139.11X3^2+6011.11X1X2+23.68X1X3-338.16X2X3$	87.03‡	0.002*

*significant at 5% (p-value)
‡regression coefficient values plotted predicted values against observed values for validation meta-models

Table 6. The results of genetic algorithm

No.	Variables			Responses							
				U, W/m^2K		S, mm		T_{50}, sec		f_{cs28}, N/mm^2	
	A	B	C	GA*	PV‡	GA	PV	GA	PV	GA	PV
1	0.3800	0.5800	1.1500	2.2537	2.2537	734.9912	734.9912	3.1423	3.1423	66.5157	66.5157
2	0.3800	0.5800	1.2038	2.2492	2.2492	754.8319	754.8189	3.2983	3.2982	66.0818	66.0618
3	0.3800	0.6130	1.3139	2.2334	2.2334	766.9671	766.8106	4.2555	4.2569	67.6885	67.6903
4	0.3600	0.5805	1.3327	2.2362	2.2362	680.0251	679.5703	5.2985	5.3040	74.9295	74.9462
5	0.3607	0.5825	1.3210	2.2365	2.2365	688.6627	688.2686	5.2184	5.2226	74.0219	74.0352
6	0.3601	0.5809	1.1512	2.2449	2.2449	625.4983	625.9799	6.0024	5.9954	73.2638	73.2440
7	0.3672	0.5815	1.2033	2.2445	2.2445	714.7011	714.9063	4.8445	4.8408	69.7007	69.6999
8	0.3648	0.5960	1.2466	2.2396	2.2396	718.0428	718.3367	4.9185	4.9155	70.0038	69.9997
9	0.3616	0.5836	1.1845	2.2426	2.2427	658.3094	658.6406	5.6925	5.6874	72.0325	72.0178
10	0.3617	0.5820	1.2611	2.2383	2.2383	683.9930	684.3451	5.4638	5.4590	72.3077	72.2926
R^2, %				100.0		100.0		100.0		100.0	

*Predicted results for response using GA; ‡Predicted values for response using meta-models obtained RSM

The regression meta-models obtained from RSM experiments were determined as the objective functions for genetic algorithm were given in Table 5. Bounds were defined as $0.36 \leq A \leq 0.38$, $0.58 \leq B \leq 0.62$ ve $1.15 \leq C \leq 1.35$ used in RSM. The trial and error method was used to determine the parameters in GAs using MATLAB® optimization toolbox [15]. In all combinations of parameters used the trial and error method was achieved over 99% fitness value. Genetic algorithm parameters which have the highest fitness value and selected by trial and error method; the number of initial population, crossover rate, and number of generations are 40, 0.8 and 150 respectively. Ten runs have been executed with these parameters to determine genetic algorithm method efficiency (Table 6).

In order to confirm the optimum mix-design proportion achieved using genetic algorithm, one empirical study was implemented to check whether the genetic algorithm could really predict of quality criteria by the proposed optimum mixture proportions. Optimal mixture parameters were determined as A = 0.38, B = 0.58 and C = 1.15 for genetic algorithm. The results prove that the experimental results are very close to the estimated results (Table 7).

5. Discussion

Having excessive or low ratio of water to cement materials provides less heat transfer due to low overall heat transfer coefficient as shown in contour plot (Figure 2 and 3) [17]. Fine aggregate to total aggregate ratio should be fixed at 0.60-0.61 also decreases heat transfer. The percentage of super plasticizer content, factor C, causing the highest variation in the overall heat transfer coefficient is the most important factor. The relationship between the overall heat transfer coefficient (U) and factors (A, B, C) can be analyzed using this contour plots. As shown in Figure 2, the stationary point of the response surface shows the saddle point for that property (the third factor was kept constant at 1.25). Moreover, T_{50} time of high strength concrete decreased with the increasing of water to binder ratio and the percentage of super plasticizer content. Also, T_{50} time did not change the fluctuation of fine aggregate ratio (Figure 3). T_{50} time of fresh concrete has been negatively affected by the interaction between water to binder materials and fine aggregate ratio (Figure 3).

Table 7. The results of genetic algorithm

Number	Responses	Estimated values	Confirmation experiment	Difference (d)	Mean, $\bar{d}$	Standard deviation	Test Statistics‡	$t_{3;0.025}$ ($t_{n-1,\alpha/2}$)
1	U	2.1537	2.1539	-0.0002	1.26	2.49	*1.012	3.18
2	S	734.9912	730	4.9912				
3	T_{50}	3.1423	3.1	0.0423				
4	f_{cs28}	66.5157	66.5	0.0157				
Total	n=4							

*Null hypothesis H_0= The X_i's are interdependent and identically distributed random variables with distribution function F. Since 1.012<3.18, null hypothesis would not reject. ‡$t = \bar{d}\sqrt{n/s_d}$[17]

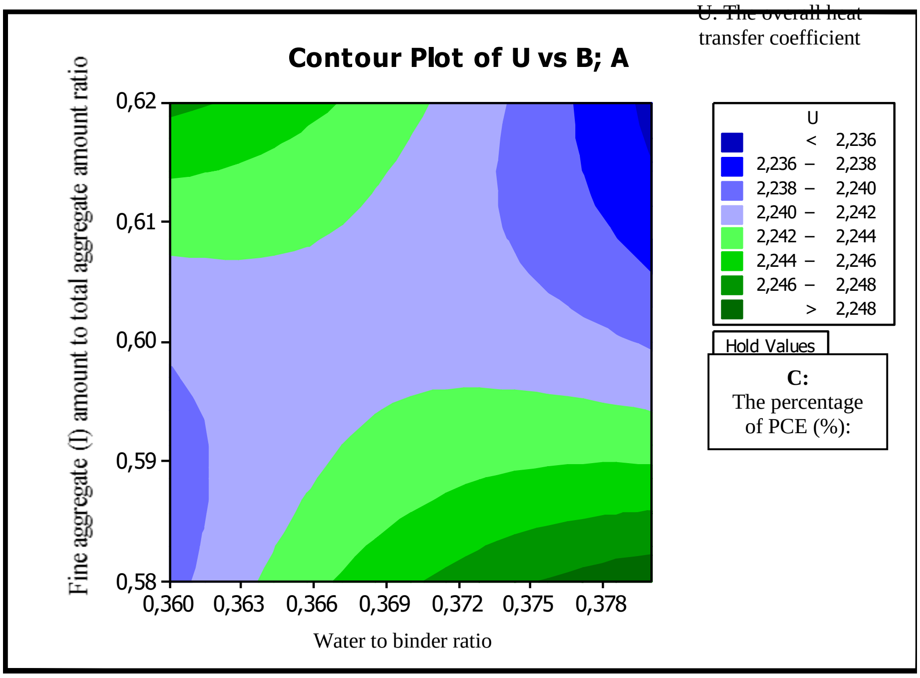

Figure 2. Contour plots of the overall heat transfer coefficient in uncoded values

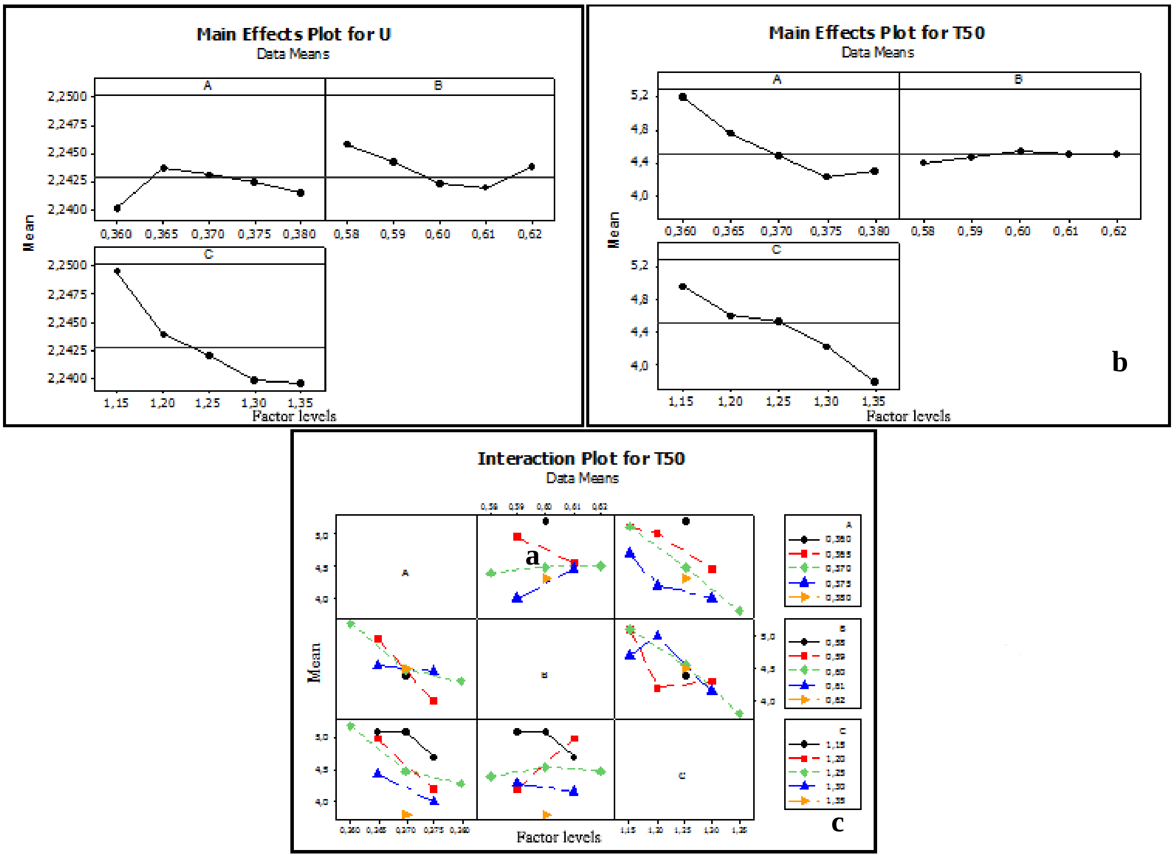

Figure 3. a) Main effect plot for overall heat transfer coefficient b) Main effect plot for T_{50} time c) Interaction effects plot for T_{50} time

6. Conclusion

In this study, the modeling of mixture proportions including overall heat transfer coefficient of high strength concrete was performed by using a RSM. The quadratic models based on RSM were useful and significant at % 5 statistically for prediction of overall heat transfer coefficient (with a p-value of 0.024), slump-spread diameter (with a p-value of 0.000), T_{50} time (with a p-value of 0.000) and 28th day compressive strength (with a p-value of 0.002).

Response surface methodology is such a design of experiment technique; it can be used to optimize only one response. If there is more than one response, response surface methodology should be used with other optimization techniques such as the desirability function approach, the nonlinear programming methodologies, and the metaheuristic algorithms. Non-linear programming or desirability function approach contains complex mathematical operations and requires algorithm knowledge. However, genetic algorithm application is easy to perform compared to non-linear programming or desirability function approach. Moreover, genetic algorithm has been preferred to solve the multi-response optimization more quickly.

According to these findings; RSM can be used the modeling of the thermal and fluidity properties of high strength concrete. Following the RSM stage; genetic algorithm using MATLAB® optimization toolbox based experiments was applied to determine optimal mixture parameters of HSC. The results show that response surface methodology based on genetic algorithm is quite an effective tool in solving the mixture proportions optimization problem.

The RSM-based GA can be used effectively in the other possible application areas such as product design and improvement in material engineering, parameter design in control engineering, mix design in chemical engineering.

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