Journal Pre-proof

Optimization of mixture proportions by statistical experimental design using response surface method - A review

Zhiping Li, Dagang Lu, Xiaojian Gao

PII: S2352-7102(20)33733-5

DOI: https://doi.org/10.1016/j.jobe.2020.102101

Reference: JOBE 102101

To appear in: *Journal of Building Engineering*

Received Date: 24 September 2020

Revised Date: 17 November 2020

Accepted Date: 14 December 2020

Please cite this article as: Z. Li, D. Lu, X. Gao, Optimization of mixture proportions by statistical experimental design using response surface method - A review, *Journal of Building Engineering*, https://doi.org/10.1016/j.jobe.2020.102101.

[1]

Optimization of mixture proportions by statistical experimental design using response surface method - A review

Zhiping Li[1], Dagang Lu[1,2,3,]*, Xiaojian Gao[1,2,]*

1. *School of Civil Engineering, Harbin Institute of Technology, Harbin 150090, China*
2. *Key Lab of Structures Dynamic Behavior and Control of the Ministry of Education, Harbin Institute of Technology, Harbin 150090, China*
3. *Key Lab of Smart Prevention and Mitigation of Civil Engineering Disasters of the Ministry of Industry and Information Technology, Harbin Institute of Technology, Harbin 150090, China*

Abstract: A comprehensive review of the statistical experimental optimization problem concerning the mixture design of various cement-based materials is presented herein. This review summarizes and discusses over 80 applications of optimum design regarding the basic test information under response surface method (RSM), including influence factor and corresponding response, statistical method, and coefficient of determination. The statistical experimental design reported in previous studies has shown that RSM is a sequential procedure to provide a suitable approximation for the mixture optimization. Then, linear, quadratic and interactive relationships of the statistical model can be evaluated available. Especially, the multi-objective optimization issues with multiple or competing performance requirements for various cement-based materials have also been reported, by considering fluidity, strength development, environmental impact, cost and durability. Overall, the results from existing publications have demonstrated that statistical inference and analysis of variance (ANOVA) are suitable for mix proportion design

* Corresponding author.
E-mail address: ludagang@hit.edu.cn (D. Lu); gaoxj@hit.edu.cn (X. Gao)

and process optimization of cement-based materials. The W/B ratio and mixture components are the prevalent factors in experimental design optimization, and then the fluidity and strength as the most popularly used response. Thus, theoretical optimum mixture proportioning can be used to predict valuable fresh and hardened properties. Finally, a critical discussion of the selection of design strategy, independent factors and their responses, and the experimental region involved in statistical experimental design, is provided. Based on this review, we conclude that the multi-objective optimization approaches need a further systematic study, and further studies of sustainable concrete optimization are needed by comparing the different chemical composition and particle characteristics.

Keywords: *experimental design optimization; supplementary cementitious materials (SCMs); response surface methodology (RSM); sustainable concrete; ultra-high performance concrete (UHPC)*

1. Introduction

The cement-based materials are prepared by using various types and quantities of individual constituents. These mixture proportions play an important role in fresh- and hardened-state performance, such as fluidity, rheological properties, strength development and durability. Therefore, many research studies have been dedicated to experimental optimization of cement and concrete mixtures.

Experimental design optimization is an adjustment process of selecting the available proportion of raw materials to prepare a cement-based mixture that satisfies specifiable requirements for a particular application. Generally, conventional optimization for mixture design can be classified as prescriptive and performance-based approaches [1]. Prescriptive-based methods are often stepwise selection to provide a mixture for a particular application, thereby satisfying the current mix proportion design standards and specifications, such as JGJ 55 [2] for concrete, JGJ/T 98 [3] for mortar, and JGJ/T 233 [4] for cement. The main advantage of these methods is that the mixture proportion is provided by the national or industry standard solely, not entirely depending on personal experience and subjective decision. Performance-based techniques emphasize no strict requirements on the type and quantities of components, but are designed with many laboratory trial experiments (defined as trial-and-error method). Trial-and-error or single variable method suffers from an exponential growth in experimental times when many test factors are considered as independent variables in the optimization process. Furthermore, detailed optimization designs of concrete mixtures are often time- and resource-intensive [1]. Response surface method (RSM) is a combination of mathematical and statistical techniques that are widely used in the area of concrete preparation optimization, where some nonlinear factors of concrete are added to obtain an optimum domain [5]. This method is especially suitable for multiple performance requirements of concrete, such as ultra-high performance concrete (UHPC) [6-9]. Over the past decade, the statistical experimental design of cement-based materials has gained increasing attention with the sustainable development of the concrete industry. Among these, lots of researchers have investigated the optimization of mixture proportions by using RSM.

Recently, the multiple response problem of cement-based materials has been widely reported in previous experimental studies. The simultaneous optimization process of several responses can be classified into two steps, as follows: (1) a fitting response surface model is established for every response, and (2) operating constraints optimized by all responses are identified or maintained in the desired region. Some related optimization methods, such as D-optimal design [10], overlay of the contour plots and constrained optimization, have been used in previous studies. Overlaying contour plots work effectively for a small number of design variables. If more than three independent factors exist, then this method is ineffective because the two-dimensional contour plot cannot obtain the best view of the response surface. The two other approaches can be used for cases with more variables.

This paper summarizes and discusses the main achievements including the applications of different RSMs and optimization methodologies in the experimental design of cement-based materials. This review is organized as follows. The basic procedure and certain theoretical models and its evaluation and validation are reviewed briefly in Section 2. Then, in Section 3, the typical applications of central composite design (CCD) and other optimization designs are summarized and investigated to measure the feasibility and validity of the selected RSM, especially for the sustainable concrete application. Finally, in Section 4, several related problems for further promising applications of RSMs in cement-based materials are discussed.

2. Theoretical basis of RSM for cement-based materials

2.1 General procedure using RSM in experimental design optimization

RSM has been used for various issues in the experimental optimization of cement-based materials [11]. This method aims to optimize mixture design to consider several attributes, involving workability, strength development, cost, durability and environmental impact. These features are achieved with sequential experimentation including factors such as water–binder ratio (W/B), mixture constituent, the proportion of supplementary cementitious materials (SCMs), preparation conditions and curing environment. In general, if the response is well expressed by a linear model of the independent factors, then the first-order regression model can be expressed as follows:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon, \quad (1)$$

where Y represents the response variable conforming to the regression coefficients (β); X_i represent the independent variables; k is the number of optimized variables; ε denotes the random error of the estimated response. If a curvature is found in the local experiments, then a second-order regression model can be given as follows:

$$Y=\beta_0+\sum_{i=1}^{k}\beta_i X_i+\sum_{i=1}^{k}\beta_{ii} X_i^2+\sum_{i=1}^{k}\sum_{j>1}^{k}\beta_{ij} X_i X_j+\varepsilon, \quad (2)$$

where the regression coefficients are expressed as β_0 for the intercept term, β_i for the first-order terms, β_{ii} for the quadratic terms and β_{ij} for the binary-interaction terms. A polynomial function cannot be a suitable approximation for all independent variable spaces. However, they usually work comparatively well for a relatively small area [12].

The main purpose of experimental optimization is to move quickly to the actual optimum by using a simple and economically experimental process [13]. The general flow chart of RSM for experimental design optimization can be summarized in Fig. 1. The design procedure by using RSM consists of the following sequential steps: (1) defining independent factors and desired responses, (2) selecting appropriate design strategy to fit the response surfaces, (3) confirming the fitted model by using analysis of variance (ANOVA) and statistical inference, and (4) determining the optimum set of operating conditions.

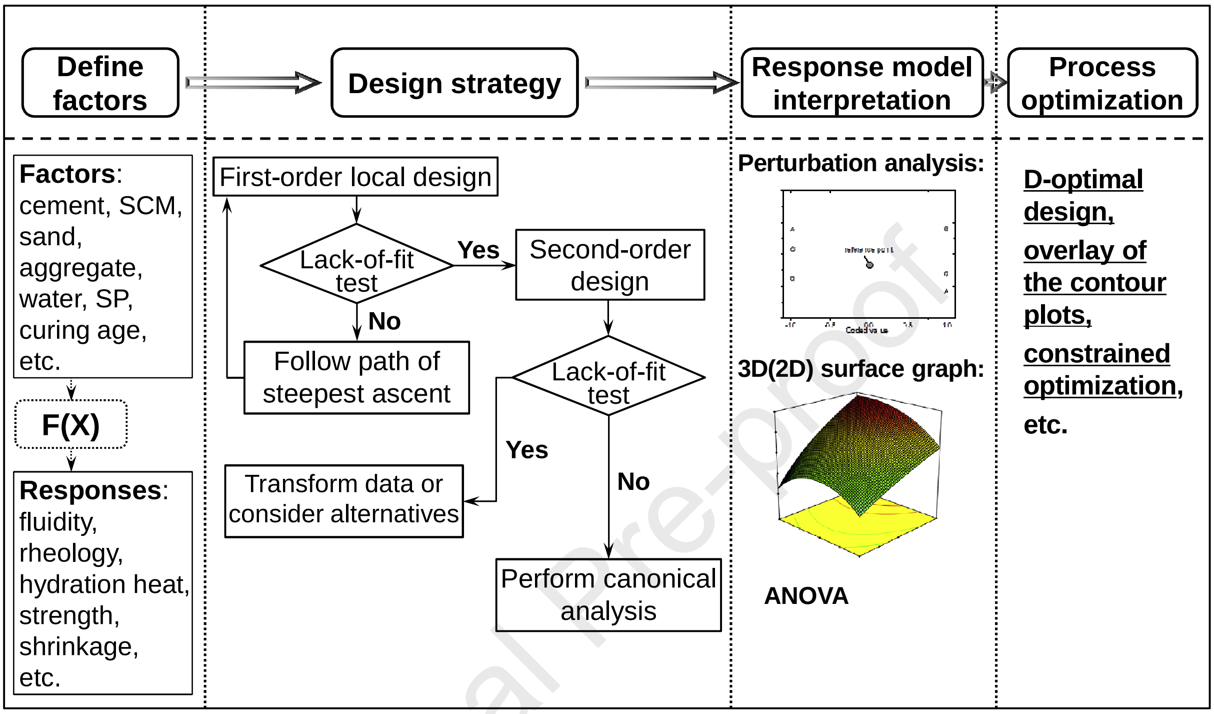

__Fig. 1__ General flow chart of RSM in experimental design optimization.

2.2 Designs of the first-order model

Designs for fitting the first-order model are called first-order designs. The most widely used first-order designs are 2^k factorial design, Plackett–Burman design and simplex design [14]. Among these designs, simplex lattice design has obtained considerable attention in the experimental design optimization of cement-based materials, which are described briefly in the following section.

Simplex lattice design is used to investigate the effects of the components or ingredients of a mixture on the response variable; it is also referred to as the mixture experiment. In general, the key feature of the given mixtures is that the volume or mass fractions of these components must sum to one. Furthermore, the response of the given mixture depends only on the relative fraction but not on the total amount of the mixture constituents [15]. For instance, if $x_1, x_2, ..., x_k$ represent the proportions of k ingredients of the given mixture, then

$$0 \leqslant x_i \leqslant 1 \quad (i = 1,2,...,k), \tag{3}$$

and

$$\sum_{i=1}^{k} x_i = 1. \tag{4}$$

Moreover, some addition boundary constraints are found on the components, thereby limiting the available region of the ingredients between the lower limit (L_i) and the upper limit (T_i). The general form of the mixture optimization could be expressed as follows:

$$0 \leqslant L_i \leqslant x_i \leqslant T_i \leqslant 1 \quad (i = 1,2,...,k). \tag{5}$$

The main types of simplex lattice designs in previous articles are shown in Fig. 2. The points presented in Fig. 2 denote experimental runs, and the three vertices, midpoints of the sides and the overall centroid of the triangle represent the pure blends, binary blends and ternary blends, respectively. The controversy of the simplex lattice design is that most test runs emerge in the boundary of the optimized area. Simplex lattice and simplex centroid design should be added with points in the internal region, as shown in [16].

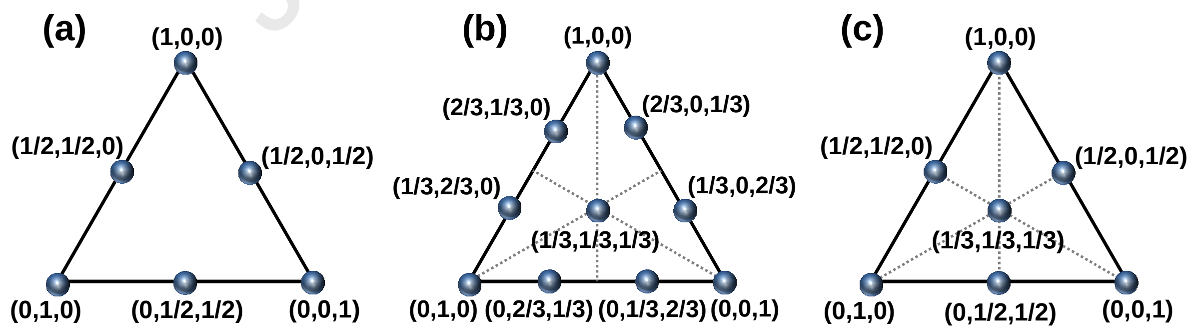

***Fig. 2** Simplex lattice designs for three-component mixture plans: (a) [3,2] lattice, (b) [3,3] lattice, and (c) simplex centroid.*

2.3 Designs of the second-order model

Designs for fitting the second-order model are called second-order designs. Applications of CCD and Box–Behnken design (BBD) to cement and concrete have become more increasingly popular over the past few decades.

CCD include 2^k factorial runs, $2k$ star runs and k_0 runs (centre-point replications, usually $3 \leqslant k_0 \leqslant 5$); it is a good alternative to the 3^k full factorial design because it provides comparable experimental results with a small number of tests [17]. Fig. 3 shows a CCD for the case of $k = 2$ and $k = 3$. In general, CCD is developed in a manner of the sequential experiment to investigate a first-order design, followed by adding axial runs to fit the second-order model. The first-degree model is used to obtain initial information on the experimental programs and to assess the importance of the component of the given mixture. Then, the quadratic terms are chosen to obtain additional information to determine the desired properties of the given constraints. The value of α and k_0 depend on the number of runs in the factorial region of the given experiment to ensure that CCD can achieve either the orthogonality behaviour or uniform precision behaviour.

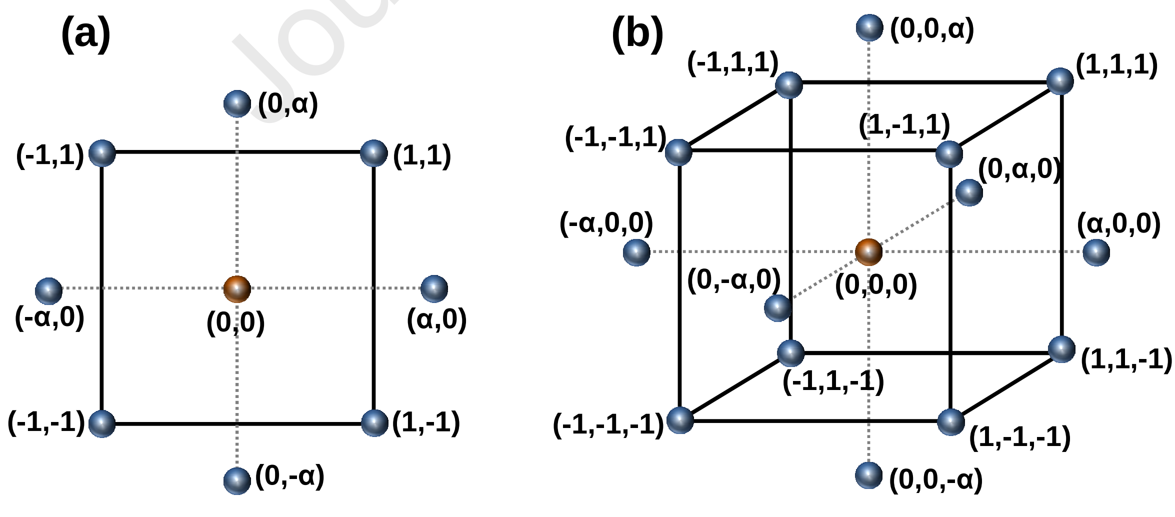

Fig. 3 *Central composite designs for (a) $k = 2$ variables and (b) $k = 3$ variables of experimental optimization (The red dot is the centre-point replication, generally, $3 \leqslant k_0 \leqslant 5$).*

BBD consists of 2^k factorial three-level designs with incomplete block to afford as either rotatable or nearly rotatable properties and to avoid the vertices of the cubic region, as shown geometrically in Fig. 4a. All points of BBD located at a spherical region of radius $\sqrt{2}$, to avoid the upper and lower limits of the given constraints. In addition, this would be available for BBD when the extreme vertices are prohibitively expensive or impossible to complete owing to the constraints of the experimental conditions. Face-centred design (CCF) is a useful variation of CCD, where $\alpha = 1$. Fig. 4b shows the star points of CCF located at the centre of the surface of the cube region, instead of the spherical area as in CCD. Using CCF often leads to a reasonable assessment of experimental errors because of more centre runs.

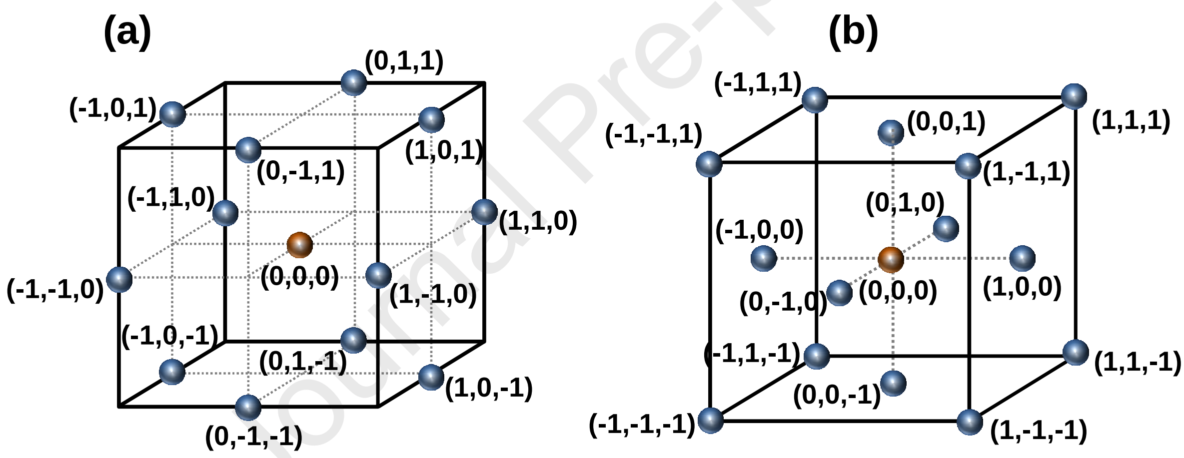

Fig. 4 *Spherical designs for three variables: (a) Box-Behnken design, and (b) face-centred central composite design (The red dot is the centre-point replication, generally,* $3 \leqslant k_0 \leqslant 5$*).*

2.4 Evaluation and validation of the fitting model

ANOVA is most often used to validate the predictive ability of the fitted model before prediction, to ensure that the mathematical model provides an adequate approximation of the actual response behaviour. The ANOVA expressions for regression model assessment and validation are summarised in Table 1. In general, the overall accuracy of the predicted model is often described by the coefficient of determination R^2, which is calculated as follows:

$$R^2 = \frac{SS_{\mathrm{mod}}}{SS_{\mathrm{tot}}} = 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}}. \quad (6)$$

The value of R^2 varies between 0 and 1. For the predicted model with good accuracy, the value of R^2 is close to 1. After considering the number of model terms, a related statistic parameter of adjusted R^2 can be obtained, as follows:

$$R^2_{\mathrm{adj}} = 1 - \frac{MS_{\mathrm{res}}}{MS_{\mathrm{tot}}} = 1 - \frac{SS_{\mathrm{res}}/(k\text{-}p)}{SS_{\mathrm{tot}}/(k\text{-}1)}. \quad (7)$$

The value of R^2_{adj} decreases as statistically insignificant variables in the model increase. The differences between the predicted and the actual values are defined as residual errors, which play a critical role in evaluating the model accuracy. Another statistic used to measure the predictive ability of the model, is expressed as follows:

$$R^2_{\mathrm{pre}} = 1 - \frac{SS_{\mathrm{pre}}}{SS_{\mathrm{tot}}}. \quad (8)$$

The value of R^2_{pre} and R^2_{adj} should be within 0.2.

Table 1 *Basic structure of the ANOVA test in the RSM-based experimental design.*

Source of variation	Degrees of freedom	Sum of squares	Mean square	F-value
Total corrected	k-1	$SS_{\mathrm{tot}} = \sum_{i=1}^{k}(y_i - \bar{y})^2$		
Model	p-1	$SS_{\mathrm{mod}} = SS_{\mathrm{tot}} - SS_{\mathrm{res}}$	$MS_{\mathrm{mod}} = SS_{\mathrm{mod}}/(p-1)$	$MS_{\mathrm{mod}}/MS_{\mathrm{res}}$
Residual	k-p	$SS_{\mathrm{res}} = \sum_{i=1}^{k}(y_i - \hat{y}_i)^2$	$MS_{\mathrm{res}} = SS_{\mathrm{res}}/(k-p)$	
Lack of fit	$m-p$	$SS_{\mathrm{lof}} = SS_{\mathrm{res}} - SS_{\mathrm{pe}}$	$MS_{\mathrm{lof}} = SS_{\mathrm{lof}}/(m-p)$	$MS_{\mathrm{lof}}/MS_{\mathrm{pe}}$
Pure error	$k-m$	$SS_{\mathrm{pe}} = \sum_{i=1}^{m}\sum_{j=1}^{k_i}(y_{ij} - \bar{y}_i)^2$	$MS_{\mathrm{pe}} = SS_{\mathrm{pe}}/(k-m)$	

Note: k= total number of experiments in the set; p= total number of parameters in the model; m= number of distinct level of factor combinations; k_i *= number of replications of the ith level; Adapted from* [18]

Desirability function is another useful method to optimize multiple responses simultaneously. Thus, this approach tends to satisfy each desirable response as soon as possible without excessively compromising any performance specifications. In general, every response Y_i is transformed into an individual desirability function as:

$$0 \leqslant d_i(Y_i) \leqslant 1, \tag{9}$$

where the value of $d_i(Y_i)$ ranges between 0 and 1. For the combination of the single responses near to the target values, the value of $d_i(Y_i)$ should be close to 1. The composite desirability function D can be expressed as follows:

$$D = (d_1(Y_1), d_2(Y_2)....d_k(Y_k))^{\frac{1}{k}} = \prod_{i=1}^{k} d_i(Y_i)^{\frac{1}{k}}, \tag{10}$$

where k represents the total responses involved in the optimization process.

3. Literature survey of RSM in mixture design optimization

In a review article published in 1999 [11], RSM is the first time systematically discussed and compared in mixture design optimization of high-performance concrete, and the multi-objective optimization by using material science-based statistical models is also presented to predict the concrete properties. Then, a comprehensive review of linear combination, statistical models, artificial intelligence method, and physics-based models was provided to optimize the design and proportioning of the concrete mixture [1]. Based on the previously surveyed, this paper attempted to evaluate the advances in cement and concrete mixture optimization by using RSM over the past two decades. Symbols used in this review are listed in Appendix A. Applications of RSM of mixture optimization of cement-based materials are shown in Appendix B.

Since the experimental results of Appendix B were obtained by various characteristics of raw materials and under various preparing conditions, this paper only collected the basic test information (influence factor and corresponding response, statistical method and coefficient of determination) for further discussion. For more corresponding details of the tests, one can refer to the references.

3.1. Optimization designs in cement-based materials applications

Over the past two decades, many studies on cement-based materials have focused on using RSM as a secondary analysis in multi-objective optimization that can be achieved with a series of separate experiments. This tool has been used successfully by previous researchers to optimize fresh and hardened properties for cement and concrete fields. However, mixture designs of some advanced cement-based materials are always difficult to standardize and reproduce owing to lack of available guidelines [19]. Herein, the focus is on summarizing the RSM applications; and the existing methods, including CCD, BBD and CCF are discussed in the following sub-sections.

3.1.1 Central composite design (CCD)

CCD is the most commonly used method of experimental optimization in the cement-based material field, which is used for fitting the second-order model. CCD is often used as a screening design to determine the critical factors and their interactions. As an example, Mohammend et al. [20] used CCD in modelling the fresh and hardened performance of rubbercrete mixture to develop available mix proportion. Two factors (W/B and crumb rubber) with five levels were selected and 45 runs were performed in this research. The response surface with three slump levels for compressive strength is presented in Fig. 5.

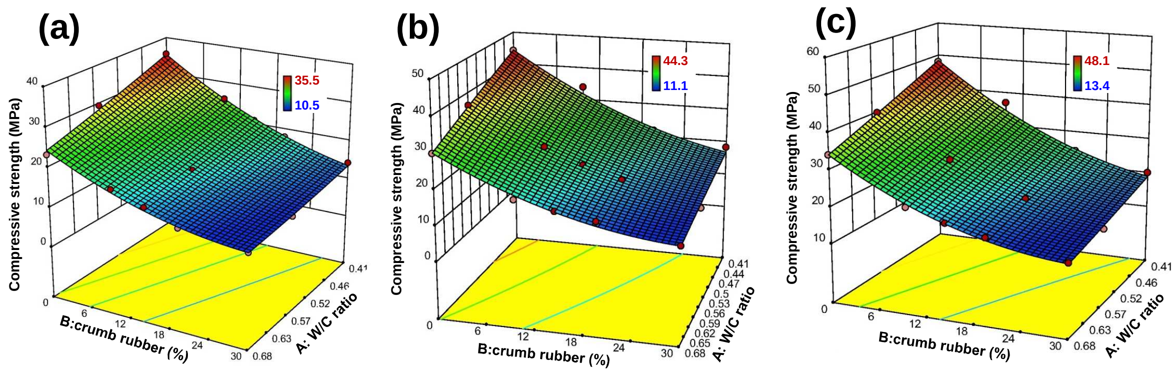

***Fig. 5** Response surface with three slump levels for compressive strength: (a) low slump, (b) medium slump and (c) high slump. Adapted from [20].*

Based on the previous CCD applications shown in Appendix B. the existing studies can be classified into three groups of research characteristics, as follows: (1) optimizing the raw materials and preparation condition to achieve the optimal performance or the most economical mix design results, (2) adding new components to investigate the performance range, and (3) combining with other modelling techniques and then evaluating the feasibility. Especially, geopolymer/alkali-activated materials have acquired wide attention as promising construction and maintenance materials due to their superior performance [21]. Venkatesan et al. [22] applied CCD to determine the optimal conditions of geopolymer concrete by using partial replacement of fine aggregate with waste foundry sand and fly ash (FA). Then, D-optimal design was used to conduct the proportion of mixture components to acquire the desired responses. Mohammed et al. [23] optimized the experimental parameters of ingredients, such as anhydrous sodium metasilicate, ground granulated blast-furnace slag (GGBS) and FA to produce cast in situ alkali-activated binders. The optimal condition was provided using CCF to evaluate the three responses (split tensile strength, compressive strength and water absorption). Da Silva Alves et al. [24] investigated the effect of sisal fibre, activator–metakaolin mass ratio, and curing time on toughness and modulus of elasticity. In addition, the optimization of the experimental parameters was conducted by CCD combined with canonical analysis to maximize the toughness and modulus of elasticity of the fibre metakaolin-based geopolymer. Zahid et al. [25] applied CCD technique to establish the effect of independent factors (NaOH molarity, NaOH–Na_2SiO_3 ratio and curing temperature) to evaluate several responses (such as setting time, modulus of elasticity, compressive strength, flexural strength, flexural toughness and ductility index) of FA-based engineered geopolymer composite. CCD was used to confirm the optimal mixture parameter of alkali-activated slag mortar with the maximum flexural strength and compressive strength, by considering the influence of usage of waste glass powder [26]. Revathi et al. [27] used CCD to establish the regression model of three factors (modulus of sodium silicate, liquid–FA ratio and mineral admixture) and these interactions with mechanical strength with 15 experimental trials.

UHPC is characterized by dense microstructures that possess ultra-high mechanical, ductility and durability performance. The optimization approach often starts with a combination of particle packing and statistical design method to obtain a mixture proportion of UHPC. The effects of three factors (distribution modulus, SCM and W/B ratio) on the rheological and mechanical properties of strain-hardening UHPC were optimized by combining CCD and modified Andreasen and Andersen particle packing model [28]. Sun et al. [29] used CCD to evaluate the effect of porous aggregate and shrinkage-reducing admixture on autogenous shrinkage of UHPC by using the modified dense particle-packing model. Wang et al. [30] used the modified Andreasen and Andersen particle packing models to achieve a compacting binder matrix of eco-friendly UHPC. Then, CCF was applied by maximum use of combined micro-coral sand and coral sand. The developed eco-friendly UHPC was evaluated by using the environmental impact indicator with the radar map (Fig. 6). On the other hand, the optimum design of UHPC usually diminishes the energy consumption and emissions of CO_2 with the reduction of cement content. Ferdosian and Camoes [31] used CCD to investigate the effect of SF, ultra-fine FA and sand of UHPC on fluidity and compressive strength. Then, a multi-objective optimization was conducted, and the cost and environmental influences were optimized by the overall desirability (Fig. 7). Furthermore, CCD shows an excellent fitting effect on other experiments [32-36].

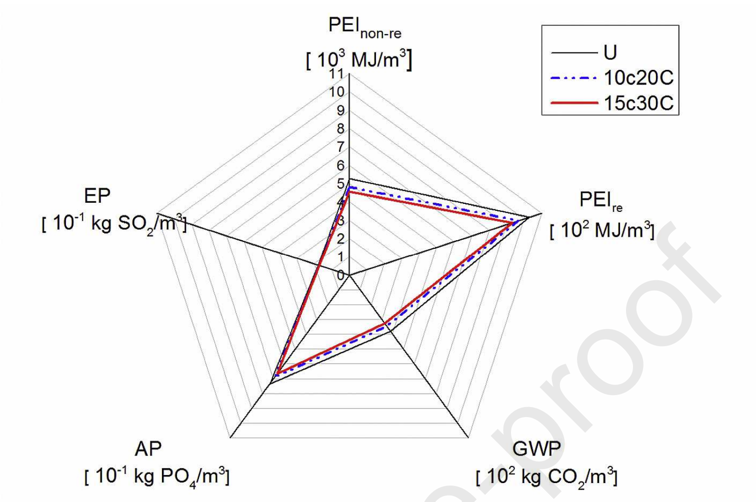

Fig. 6 *Ecological evaluation of eco-friendly ultra-high performance concrete with environmental impact indicator. Adapted from [30]*

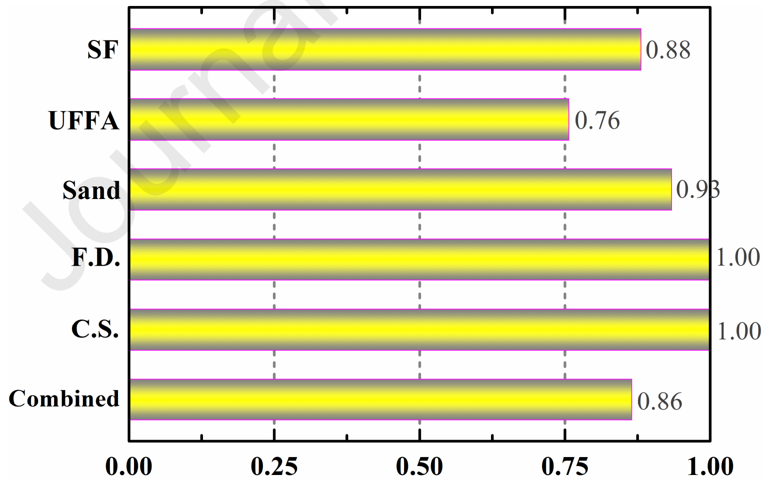

Fig. 7 *Desirability of ultra-high performance concrete for its main variable constituents. Adapted from [31]*

3.1.2 Other optimization designs

Factorial design is another method to optimize the mixture proportion of cement-based materials. It is often classified into two categories: full factorial design and fractional factorial design. Long et al. [37] applied fractional factorial design to build statistical models to investigate the influence of mixture proportion and raw material properties on workability, strength development, and visco-elastic performance of self-compacting concrete. Then eleven additional SCC mixtures were used to validate the statistical models for fresh properties. Including eight runs within the range of the factorial design to develop the wide range, three central points were used to evaluate the error in the 90% confidence limit (Fig. 8). Jiao et al. [38] applied simplex centroid design to optimize the paste consisting of cement, FA and slag for a given strength grade, then optimized the paste, fine aggregate and coarse aggregate based on rheological properties of SCC, and at last, overlapped the contour plots to acquire the multiple performance requirements (Fig. 9).

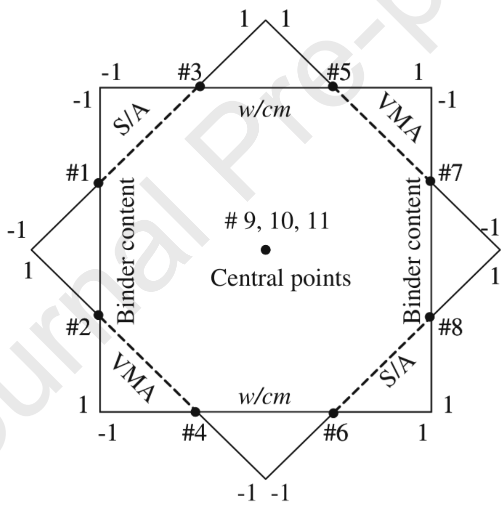

Fig. 8 *Additional SCC mixtures used to validate the derived statistical models. Adapted from [37]*

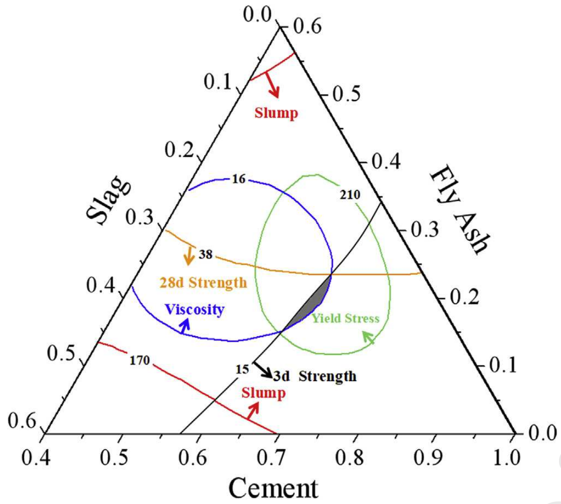

Fig. 9 *Optimization of cementitious materials composition by overlapping the contour plots. Adapted from [38]*

As for mix optimization of geopolymer/alkali-activated materials, Li et al. [39] proposed a mixture proportioning methodology according to the performance requirements of alkali-activated concrete and used the simplex centroid design for optimizing three types of aggregates to obtain the optimized bulk density. Mermerdas et al. [40] applied simplex lattice design to optimize three independent variables (curing age, curing temperature, and volume of binder) of geopolymer mortars and to maximize the compressive strength of FA and GGBS. Shi et al. [16] used simplex lattice design to correlate the ingredients of ternary cement blends (cement, slag and FA) on ASR expansion with only seven experimental trials. Then, the ternary contour diagram was used to analyse the composition effect on ternary composite blends (Fig. 10). Li et al. [41] used BBD to investigate the effect of the degree of sol ratio, the content of slag and age on fracture toughness and their interaction on fracture properties before and after freeze-thaw resistance of alkali–slag concrete. Bektas et al. [42] used BBD to investigate the influence of three critical mix factors (alkali content, W/B ratio and ground clay brick content) in three-levels to measure four responses (alkali–slag reaction expansion, Fc, Ft and modulus of elasticity) in two replicates of 15 runs. Cai et al. [43] applied BBD to analyse the influence of activator solution–slag ratio, sand ratio and slag content and their interaction on the freeze-thaw cycles of the alkali–slag concrete. Then, the predicted model was built to evaluate the effect of air bubble characteristic on freeze-thaw cycles in cold regions.

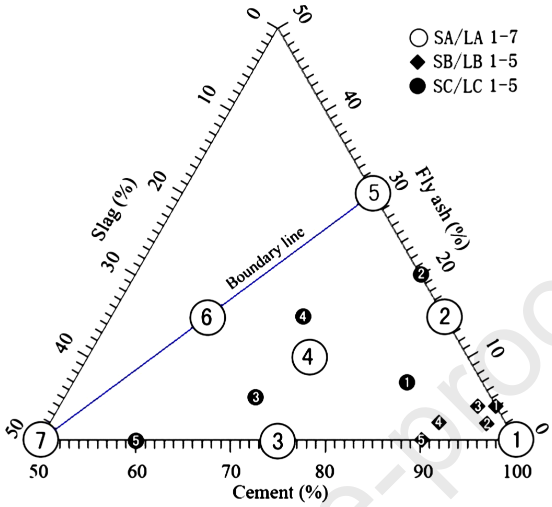

Fig. 10 *Ternary contour diagram of composition design for composite cement. Adapted from [16]*

As for mix optimization of UHPC, Ghafari et al. [15] present an accurate analytical approach based on simplex lattice design to optimize the component of UHPC. The main strategy of this method can be described in seven steps, as follows: (1) constructing the main optimum objective to obtain the highest compressive strength, acceptable scope of workability and economical cost of raw materials; (2) selecting the mixture design method, where D-optimal techniques are recommended; (3) defining the constraint bounds of mixture components, parameters and these variation ranges in the defined experiments; (4) developing the design matrix based on the D-optimal mixture trials; (5) collecting the experimental data; (6) building the analytical model to predict the properties of UHPC; (7) optimizing the mixture proportion of UHPC to satisfy the desirable value of the response variable. Soliman and Tagnit-Hamou [44] proposed a modified approach combining a full-factorial design approach and particle-packing model to optimize UHPC as follows: (1) particle packing of aggregates, and (2) building the optimized model by investigating the combined effect of W/B ratio and high range water-reducing admixture.

3.2. Optimization designs for sustainable concrete applications

Some industrial wastes are blended with cement clinker to prepare Portland cement or used as concrete constituents for sustainable application, which are widely investigated by academics and engineers. Existing experimental design of industrial wastes applications has attempted to explore the alternative of SCM and their performances in the concrete industry [22,26,30,31,33,40,45,65,85,94,98,101,102], which are summarized in Appendix B. However, further study of the sustainable concrete application is needed by comparing the different chemical composition and particle characteristics. De Brito et al. [46] presented a ternary phase diagram to provide the chemical composition of various binder types from 81 publications. As shown in Fig. 11, the chemical composition of industrial wastes are diversities and significantly determined on the source of the raw materials, and it cannot directly be replaced with the equivalent mass of cement because of the amorphous particles is different from the cement. Furthermore, certain experimental studies of sustainable optimization were focused on cost and environmental impact [53,76,84,88,91].

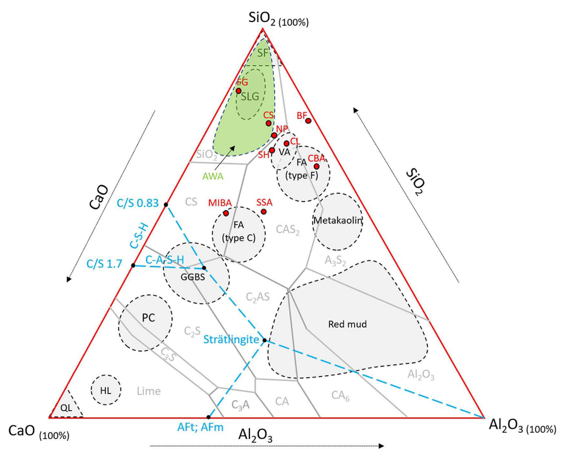

Fig. 11 *CaO-SiO$_2$-Al$_2$O$_3$ ternary phase diagram for the cement blends of sustainable concrete. Adapted from [46]*

4. Summary and discussion

Based on the 80 applications of RSMs in the existing literature and its analysis, some critical information of statistical models to optimize the mixture proportioning of cement-based materials, including RSM method, test specimen, factors (independent variables) and its responses (dependent variables), were collected. The summary is listed in Appendix B.

4.1 Selection of design strategy

As it is shown in Appendix B, CCD is the most popular method for mixture proportioning optimization in cement-based materials. CCD comprises a two-level factorial design, centre point and a star design in which test points with a distance α from the centre point. CCD provides a considerable high efficiency with up to six factors if all optimizations are carried in parallel instead of sequentially experiments. It is often used to be regarded as a better alternative of the full factorial design because it can offer similar results with a smaller number of experiments [17]. In addition, both linear and quadratic regression models are permitted to be determined by these design strategies, and the interactive effects of various independent factors and critical points (minimum, maximum and saddle points) can be evaluated.

Another popular method is simplex design, including the simplex-lattice design and simplex-centroid design. The factors of these strategies are the component of a mixture, and the factor levels are not independent. If there are three ingredients of the mixture, the constrained experimental region is constructed to a trilinear coordinate system as shown in [16,38]. Each of the three sides of the triangle represents a mixture that has only two components, and the missing component labelled on the opposite corner.

However, BBD has not been employed as extensive as the above-mentioned strategies in cement-based materials. While in BBD strategy, all points located at a spherical region of radius $\sqrt{2}$. And also, BBD does not contain any corner points of the cubic region to avoid the upper and lower limits of the given constraints. This would be available for BBD when the extreme vertices are prohibitively expensive or impossible to complete owing to the constraints of the experimental conditions.

Anyway, the prevalence of CCD usage in cement-based materials is partly attributed to that it is easy to follow the other researcher's steps. As for geopolymer/alkali-activated materials and UHPC with various ingredients and several performance requirements, D-optimal design or Doehlert design [47] or BBD might be a better beneficial strategy.

4.2 Selection of factors and responses

The W/B ratio and mixture components are the prevalent factors in experimental design optimization, then fluidity and strength as the most popularly used response. Each response of mixture optimization is often expressed with a polynomial function of factors such as W/B ratio, cement content, admixture dosage and SCM replacement. Changing of W/B ratio leads to a remarkable variation of concrete properties. In general, selection of the factors and its level should be according to the preliminary tests or practical experience and not depending on the researcher's convenience. Furthermore, performing heavy single-variable studies with the purpose to optimize with three or more factors should be avoided [14].

Recently，the multiple response problem of cement-based materials has become a concern. Jiao et al. [38] overlapped several critical contour lines of each response to acquire the multiple performance requirements. Ferdosian and Camoes [31] employed D-optimal design to develop a combined desirability with different important weights for their corresponding solutions. These multi-objective optimization approaches need a further systematic study.

Obviously, the choice of the variable levels in the optimization process is more important than the design itself. Every level of RSM must be appropriate and provide valuable information. When the design points are too close together, it will not result in the obvious influence of the corresponding response. On the contrary, if design points are at the extreme point of a reasonable region, the responses are often hard to adopt.

4.3 Selection of experimental domain

Although RSM has many outstanding characteristics and has been widely used for mixture design and process optimization of various experiments, the fitting models can be only suitable for the experimental domain and are not accurate for extrapolation. In addition, discrete variables cannot be selected for experimental optimization. For example, a specific type of SCM or any other mixture components cannot be considered in the mixture optimization problems.

In order to overcome the defects of RSM strategy, some researchers attempt to integrate of RSM with other machine learning algorithms, such as artificial neural networks [48-50], fuzzy classification [51]. These combined approaches have been demonstrated experimentally by providing well precision in data learning and prediction. Although these solutions have been used in several other fields, little research has been reported of these applications in mixture proportion optimization.

4.4 Current challenges for the applications of sustainable concrete

In general, reducing the environmental impact and resources consumption of sustainable concrete is related to replace cement clinker with solid wastes, which contains many ingredients and are always subject to multi-performance requirements. Statistical experimental design has been developed to optimize the mixture proportion of sustainable concrete. However, target performance during the optimization process may be mutually exclusive, which leads to numerous redundant works. The combined desirability of various weighted values and their corresponding solutions has been developed a multi-objective optimization [5,31,40,84]. The simultaneous nonlinear optimization with desirability function should be further studied in the future.

So far, many multi-variable problems for sustainable concrete optimization have become increasingly common. It is difficult to coordinate the raw materials properties and their dosage are often lacks a theoretical basis. Furthermore, little attention has been focused on the independent factors and their interactions of sustainable concrete applications.

5. Conclusions and Prospective

Based on the review and discussions in this paper, the conclusions can be drawn as below:

(1) The RSM is a sequential procedure to provide a suitable approximation for the fitting functional models between various independent factors and their responses. Then, linear, quadratic and interactive relationships of these models can be evaluated. And also, the minimum, the maximum and the saddle points of optimization region can be evaluated available. So, many applications in modelling a variety of cement-based materials field have been attempted, as shown in Appendix B.

(2) CCD is the most commonly used method in cement and concrete mixture design. Most studies considered four or less independent variables. The W/B ratio and mixture components are the prevalent factors in experimental design optimization, and then the fluidity and strength as the most popularly used response. However, D-optimal design or BBD or Doehlert design might be better for geopolymer/alkali-activated materials and UHPC with various ingredients and several performance requirements.

(3) The choice of factors and their levels is very important for experimental optimization by using RSM. Each level should be appropriate and provide valuable information, and it is necessary to assure the responses within the acceptable region of the optimum value.

(4) The multiple or competing performance requirement of mixture design has become a concern. The in-depth investigations are needed to combine and compare with other modelling techniques. Previous studies investigated the combination of D-optimal method and particle packing models. However, artificial neural network and fuzzy logic for modelling mixture optimization issues may be a promising research direction.

(5) Further study of sustainable concrete optimization is needed by comparing the different chemical composition and particle characteristics. However, target performance during the optimization process may be mutually exclusive, which leads to numerous redundant works. So, the simultaneous nonlinear optimization with desirability function should be further studied in the future.

(6) Although plenty of studies have been reported in the previous literature with the laboratory experiment in the cement-based materials field, little attention has focused on the applications in engineering practice. Thus, more attempts relating to the practical project by using RSM are needed.

Acknowledgements

The authors would like to thank for the financial support from the National Science Foundation of China (Grant Nos. 51678209, 41861134010).

478 ***Appendix A.*** *List of symbols.*

Symbol	Description
RSM	response surface method
CCD	central composite design
BBD	Box- Behnken design
CCF	face-centred central composite design
ANOVA	analysis of variance
UHPC	ultra-high performance concrete
HPC	high performance concrete
SCC	self-compacting concrete
ASR	alkali-silica reaction
W/B	Water-binder ratio
SCM	supplementary cementitious material
SF	silica fume
FA	fly ash
QP	quartz powder
GBFS	Granulated blast furnace slag
Vca	volume of coarse aggregate
Vfa	volume of fine aggregate
SP	superplasticizer
Fc	28-day compressive strength
Ft	flexure strength

479

Appendix B. *Applications of RSM for mixture optimization of cement-based materials.*

RSM method	Specimen	Factors	Reponse(s)	R^2	Number of experiments	Year	Ref.
CCD	SCC	W/B ratio, Binder, SP, Vca	fluidity, rheology, Fc	slump=0.95, Fc=0.83	15	2000	[52]
Factorial design	mortar	SF, FA, GBFS	SP, setting time, drying shrinkage,fc,cost		13/26*	2002	[53]
CCD	SCC	cement, limestone filler, SP, W/B ratio	fluidity, Fc	slump=0.98, Fc=0.97	21	2002	[54]
BBD	mineral aggregate	six types of silica sand	void content	0.96	54	2003	[55]
Full factorial design	steel fibre reinforced concrete	aspect ratio, volume of steel fibre	fracture energy, characteristic length		10	2004	[56]
CCD	SCC	pulverised fuel ash, SP, cement, W/B ratio	fluidity, rheology, segregation ratio, Fc	slump=0.99, rheology=0.98, segregation ratio=0.99, Fc=0.99	21	2004	[57]
CCD	foam concrete	filler-cement ratio, FA, foam volume	Fc, dry density	Fc=0.958, dry density=0.987	20	2006	[58]
BBD	bridge deck overlay concrete	SF, FA, slag	Fc, Ft, chloride permeability, abrasion resistance		15	2006	[59]
Bucher–Bourgund design	frost-resistant concrete	W/B ratio, entrained air pore, number of cycles	residual strain		7	2007	[60]
simplex centroid design	blends of industrial wastes	red clay, granite waste, kaolin waste	water absorption, shrinkage, modulus of rupture		10/40	2008	[61]
simplex centroid design	HPC	cement, FA, GBFS, SP, Vca, Vfa	fluidity, Fc		78	2009	[49]
CCD	SCC	cement, W/B ratio, FA, SP	Fc, modulus of elasticity	Fc=0.823	31	2009	[62]
simplex centroid design	drilling fluid	Bentonite, low molar carboxymethyl cellulose, high molar carboxymethyl cellulose	apparent viscosity, plastic viscosity		10/30	2010	[63]
BBD	high-strength lightweight concrete	temperature, binder content, binder type	specific gravity, water absorption, crushing strength		18	2011	[64]
fractional factorial design	SCC	binder, W/B, binder type, SP, sand-aggregate ratio	fluidity, Fc, shrinkage, creep		19	2012	[37]

(continued on next page)

RSM method	Specimen	Factors	Reponse(s)	R^2	Number of experiments	Year	Ref.
CCD	recycled masonry and concrete	cement, degree of compaction	moisture content, dry density		13	2012	[65]
CCD	High flowing concrete	GBFS, FA, W/B ratio, SP	fluidity, Fc, Durability	slump=0.9841, Fc=0.9315, carbonaion=0.9717	21	2012	[66]
CCD	SCC	cement, W/B ratio, FA, SP	fluidity, Fc, modulus of elasticity	fluidity=0.905, Fc=0.920, modulus of elasticity=0.818	31	2012	[67]
CCD	oil well cement slurry	SP, SCM, temperature	yield stress, plastic viscosity		40	2012	[68]
BBD	alkali–slag concrete	solution-slag ratio, slag, sand	Air bubble spacing coefficient, Air bubble specific surface area, Grades of freeze-thaw resistance		17	2013	[43]
Factorial design	pervious concrete	W/B ratio, cement, Vca	fresh density, hardened density, void ratio, Fc	fresh density=0.79, hardened density=0.97, void ratio=0.98, Fc=0.87	13	2013	[69]
fractional factorial design	concrete	W/B, cement, fineness modulus of aggregate, SP	Fc		46/92	2013	[70]
CCD	warm mix asphalt	binder, resident, compaction temperature	air void, bulk specific gravity, voids filled with asphalt binder, stability, fluidity	air void=0.94, bulk specific gravity=0.96, stability=0.77, fluidity=0.89	20	2013	[71]
CCD	UHPC	cement, SF	fluidity, Fc	slump=0.9949, Fc=0.9913	13	2013	[36]
simplex lattice design	HPC	cement, grinded dune sand, limestone filler	fluidity, Fc	slump=0.78, Fc=0.91	21	2014	[72]
						2014	
Factorial design	concrete	FA, metakaolin, testing age	Fc, chloride permeability, sorptivity, water absorption		9	2014	[73]
Full factorial design	concrete	binder, W/B, Vfa/Vca	Fc	0.8	27	2014	[74]
BBD	silicate cement	water-soluble polymer, chemical additive, SP	Fc		27	2014	[75]

(continued on next page)

RSM method	Specimen	Factors	Reponse(s)	R^2	Number of experiments	Year	Ref.
BBD	alkali–slag concrete	alkali, W/B ratio, ground clay	expansion, Fc, Ft, modulus of elasticity	expansion=0.886, Fc=0.889, Ft=0.900, modulus of elasticity=0.847	30	2014	[42]
CCD	normal weight concrete	W/B ratio, Vca, SP	fluidity, Fc, splitting tensile strength, cost	slump=0.992, Fc=0.837, splitting tensile strength=0.825, cost=1.000	20	2014	[76]
CCD	self-compacting UHPC	steel fibre, powder-aggregate ratio	Ft, fluidity	Ft=0.91, fluidity=0.92	20	2014	[35]
CCD	modified asphalt mixture	asphalt, polyethene terephthalate modifier	fluidity, void, stability, bulk specific gravity	slump=0.9880, void=0.9980, stability=0.9853, bulk specific gravity=0.9883	13	2015	[77]
CCD	SCC	binder, W/B ratio, SP	fluidity, Fc, filling capacity, sieve segregation	slump=0.96, Fc=0.86, filling capacity=0.95, sieve segregation=0.94	20	2015	[78]
CCD	SCC	binder, W/B ratio, SCM	fluidity, Fc, segregation factor		27	2015	[79]
CCF	cement paste	W/B ratio, FA/B ratio, nano-iron oxide-to-binder	fluidity, Fc	slump=0.855, Fc=0.852	20	2015	[80]
simplex lattice design	UHPC	cement, sand, SF, QP, SP, steel fibre	fluidity, Ft	slump=0.74, Ft=0.90	53	2015	[15]
BBD	pervious concrete	three admixture	paste thickness, slump, film drying time	paste thickness=0.92, slump=0.89, film drying time=0.69	18	2015	[81]
BBD	alkali–slag concrete	sol ratio, slag, age on fracture toughness	initiation fracture toughness, unstable fracture toughness, crack mouth opening displacement, critical effective crack		17	2015	[41]
simplex lattice design	mortar	cement, SF, nano-silica	fluidity, Fc, Ft, splitting strength, density, absorption, capillary water		13	2016	[82]
simplex lattice design	alkali-activated cement	cement, FA, slag	ASR expansion		17	2016	[16]

(continued on next page)

RSM method	Specimen	Factors	Reponse(s)	R^2	Number of experiments	Year	Ref.
CCD	concrete	crumb rubber, metakaolin	Fc, water absorption, unit weight	Fc=0.9703, water absorption=0.8751, unit weight=0.8321	9	2016	[83]
CCD	SCC	W/B ratio, cement, Vfa, FA, SP	fluidity, Fc, cost	fluidity=0.9604, Fc=0.9547, cost=1	52	2016	[84]
CCD	UHPC	SF, SP, fibre, cement, W/B	flexural toughness	flexural toughness=0.85	45	2016	[34]
simplex lattice design	geopolymer mortar	FA, GBFS	binder, curing time, curing temperature, Fc		7/14	2017	[40]
simplex lattice design	UHPC	cement, SF, QP, quartz sand	fluidity, Fc, air void	slump=0.99, Fc=0.99, air void=0.80	10	2017	[44]
CCF	eco-friendly UHPC	micro-coral sand, coral sand	Fc	0.97	10	2017	[30]
CCD	SCC	W/B, marble powder-cement ratio	fluidity, Fc		33	2017	[85]
CCF	mortar	clinker, FA, debit grinding agent	Fc	0.98	15	2017	[86]
CCD	warm mix asphalt	compaction temperature, test temperature	adhesion failure, direct tensile strength, fracture energy, broken aggregate		11/22	2017	[87]
CCD	high-strength SCC	W/B, cement, FA, SP, Vfa	Fc, fluidity, cost	Fc=0.955, fluidity=0.960, cost=1	52	2017	[88]
CCF	UHPC	QP, quartz sand, water curing	Fc, Ft	Fc=0.984, Ft=0.830	16	2017	[32]
CCD	UHPC	SF, sand, ultra-fine fly ash	fluidity, Fc	slump=0.9596, fc=0.9568	28	2017	[31]
simplex centroid design	low carbon cementitious material	cement, mineral admixture, hydrated lime	fluidity, Fc, hydration heat, porosity, non-evaporable water		7	2018	[89]
simplex centroid design	alkali-activated concrete	gravel, sand	bulk density		7	2018	[39]
simplex centroid design	concrete	Vca, Vfa, paste, cement, FA, slag	rheology, Fc		16	2018	[38]
BBD	grout material	cement, FA, microsilica, metakaolin	fluidity, Fc, Ft, shrinkage	slump=0.9647, Fc=0.9810, Ft=0.7966, shrinkage=0.8053	16	2018	[90]
BBD	foamed concrete	cement, foam	Fc, dry density, cost		15	2018	[91]

(continued on next page)

RSM method	Specimen	Factors	Reponse(s)	R^2	Number of experiments	Year	Ref.
simplex centroid design	SCC	SP, stone powder, gravel, sand, cement	fluidity, Fc		42	2018	[92]
CCD	geopolymeric binder	modulus of sodium silicate, liquid, mineral admixture	Fc	0.9736	15	2018	[27]
CCD	alkali-activated slag mortar	Na_2O, glass powder	Fc, Ft	Fc=0.9678, Ft=0.9754	13	2018	[26]
CCD	geopolymer composite	NaOH molarity, Na_2SiO_3, curing temperature	Fc, elastic modulus, Ft, flexural toughness, ductility index, tensile first crack strength, ultimate tensile strength, tensile strain capacity	Fc=0.9951, elastic modulus=0.9977, Ft=0.9924, flexural toughness=0.9837, ductility index=0.9731, tensile first crack strength=0.9876, ultimate tensile strength=0.9791, tensile strain capacity=0.9850	20	2018	[25]
CCD	rubbercrete mixture	W/B ratio, crumb rubber	fluidity, unit weight, void, Fc		45	2018	[20]
CCD	self-consolidating mortar	SF, slag, SP, W/B ratio	fluidity, Fc, segregation	slump=0.9589, Fc=0.8561, segregation=0.8141	30	2018	[93]
CCD	normal concrete	two types of plastic waste aggregate	fluidity, Fc	slump=0.8198, Fc=0.9750	13	2018	[94]
CCF	polymer nanocomposite-modified asphalt	nanosilica additive, temperature	complex modulus, phase angle, viscosity	complex modulus=0.9995, phase angle=0.9989, viscosity=0.9995	13	2019	[95]
Full factorial design	SCC	cement, FA, W/B, SP	fluidity, Fc	slump=0.9319, Fc=0.9343	18	2019	[51]
CCD	recycled concrete aggregate	cement, slump, recycled coarse aggregate	Fc	0.9881	17	2019	[96]
CCD	geopolymer	sisal fibre, activator, curing time	Fc, toughness, modulus of elasticity		18	2019	[24]

(continued on next page)

RSM method	Specimen	Factors	Reponse(s)	R^2	Number of experiments	Year	Ref.
CCRD	fibre reinforced concrete	aspect ratio, cement, W/B ratio	fluidity, Fc, Ft, split tensile strength, water absorption	slump=0.98, Fc=0.95, Ft=0.98, split tensile strength=0.93, water absorption=0.8640	20	2019	[97]
CCF	alkali-activated paste	slag, anhydrous sodium metasilicate activator	Fc, Ft, water absorption	Fc=0.9856, Ft=0.9913, water absorption=0.8994	15	2019	[23]
CCD	geopolymer concrete	Vfa, FA, waste foundry sand	Fc	0.99	14	2019	[22]
CCD	UHPC	porous aggregate, shrinkage reducing admixture	autogenous shrinkage	0.9296	11	2019	[29]
CCF	UHPC	nano-silica, waste glass powder	fluidity, Fc, drying shrinkage	slump=0.93, Fc=0.98, drying shrinkage=0.96	10	2019	[33]
CCD	eco-efficient SCC	limestone powder, FA, SP	fluidity, Fc	slump=0.9679, Fc=0.9695	20	2019	[98]
BBD	pervious concrete	aggregate size	bulk density, apparent density, void		24	2020	[99]
BBD	blended paste	cement, SF, FA, QP	fluidity, rheology, hydration heat, Fc, drying shrinkage	slump=0.9613, rheology=0.9818, hydration heat=0.9975, Fc=0.9955, drying shrinkage=0.9459	16	2020	[5]
CCF	concrete	manufactured sand, metakaolin, waste paper sludge ash	Fc, permeability coefficient, sorptivity	permeability coefficient=0.9745,	17	2020	[100]
CCD	cementitious composites	cement, curing time	Fc	0.97	14	2020	[101]
CCD	strain-hardening UHPC	W/B ratio, SCM, distribution modulus	fluidity, rheology, Fc, fracture toughness		20/60	2020	[28]
CCD	geopolymer mortar	molarity, binder, sodium silicate to sodium hydroxide ratio	Fc, drying shrinkage	Fc=0.9063, drying shrinkage=0.9296	27	2020	[102]

481 *Note: * two groups, 11 mixtures for each one.*

References:

[1] M.A. DeRousseau, J.R. Kasprzyk, W.V. Srubar: Computational design optimization of concrete mixtures: A review. Cement and Concrete Research, 109 (**2018**) 42-53. *https://doi.org/10.1016/j.cemconres.2018.04.007*

[2] Chinese National Institute of Standardization, Specification for mix proportion design of ordinary concrete, JGJ 55-2011, Beijing, 2011.

[3] Chinese National Institute of Standardization, Specification for mix proportion design of masonry mortar, JGJ/T 98-2010, Beijing, 2010.

[4] Chinese National Institute of Standardization, Specification for mix proportion design of cement soil, JGJ/T 233-2011, Beijing, 2011.

[5] Z. Li, D. Lu, X. Gao: Multi-objective optimization of gap-graded cement paste blended with supplementary cementitious materials using response surface methodology. Construction and Building Materials, 248 (**2020**) 118552. *https://doi.org/10.1016/j.conbuildmat.2020.118552*

[6] Q. Chen, H. Wang, H. Li, Z. Jiang, H. Zhu, J.W. Ju, Z. Yan: Multiscale modelling for the ultra-high performance concrete: From hydration kinetics to macroscopic elastic moduli. Construction and Building Materials, 247 (**2020**). *https://doi.org/10.1016/j.conbuildmat.2020.118541*

[7] C. Shi, Z. Wu, J. Xiao, D. Wang, Z. Huang, Z. Fang: A review on ultra high performance concrete: Part I. Raw materials and mixture design. Construction and Building Materials, 101 (**2015**) 741-751. *https://doi.org/10.1016/j.conbuildmat.2015.10.088*

[8] H. Wei, A. Zhou, T. Liu, D. Zou, H. Jian: Dynamic and environmental performance of eco-friendly ultra-high performance concrete containing waste cathode ray tube glass as a substitution of river sand. Resources, Conservation and Recycling, 162 (**2020**) 105021. *https://doi.org/10.1016/j.resconrec.2020.105021*

[9] Z. Mo, X. Gao, A. Su: Mechanical performances and microstructures of metakaolin contained UHPC matrix under steam curing conditions. Construction and Building Materials, (**2020**) 121112. *https://doi.org/10.1016/j.conbuildmat.2020.121112*

[10] J.H. Son, J.W. Baek, A.E. Sy Choi, H.S. Park: Thiomer solidification of an ASR bottom ash: Optimization based on compressive strength and the characterization of heavy metal leaching. Journal of Cleaner Production, 166 (**2017**) 12-20. *https://doi.org/10.1016/j.jclepro.2017.07.113*

[11] M. Simon, K. Snyder, F. G, Advances in concrete mixture optimization, Concrete Durability and Repair Technology Conference, Scotland, 1999, pp.21-32.

[12] D. C. Montgomery. Design and Analysis of Experiments (6nd Ed), Journal of the American Statistical Association, 2000, 16(2).

[13] S. Karimifard, M.R. Alavi Moghaddam: Application of response surface methodology in physicochemical removal of dyes from wastewater: A critical review. Science of the Total Environment, 640-641 (**2018**) 772-797. *https://doi.org/10.1016/j.scitotenv.2018.05.355*

[14] A. Khuri, S. Mukhopadhyay: Response surface methodology. Wiley interdisciplinary reviews: computational statistics, 2 (**2010**) 128-149. *https://doi.org/10.1002/wics.73*

[15] E. Ghafari, H. Costa, E. Júlio: Statistical mixture design approach for eco-efficient UHPC. Cement and Concrete Composites, 55 (**2015**) 17-25. *https://doi.org/10.1016/j.cemconcomp.2014.07.016*

[16] Z. Shi, C. Shi, R. Zhao, D. Wang, F. He: Factorial design method for designing ternary composite cements to mitigate ASR expansion. Journal of Materials in Civil Engineering, 28 (**2016**) 4016064. *https://doi.org/10.1061/(ASCE)MT.1943-5533.0001568*

[17] K.M. Sharif, M.M. Rahman, J. Azmir, A. Mohamed, M.H.A. Jahurul, F. Sahena, I.S.M. Zaidul: Experimental design of supercritical fluid extraction - a review. Journal of Food Engineering, 124 (**2014**) 105-116. *https://doi.org/10.1016/j.jfoodeng.2013.10.003*

[18] S. Bouzalakos, A.W.L. Dudeney, B.K.C. Chan: Formulating and optimising the compressive strength of controlled low-strength materials containing mine tailings by mixture design and response surface methods. Minerals Engineering, 53 (**2013**) 48-56. *https://doi.org/10.1016/j.mineng.2013.07.007*

[19] J.S.J. van Deventer, J.L. Provis, P. Duxson: Technical and commercial progress in the adoption of geopolymer cement. Minerals Engineering, 29 (**2012**) 89-104. *https://doi.org/10.1016/j.mineng.2011.09.009*

[20] B.S. Mohammed, V.C. Khed, M.F. Nuruddin: Rubbercrete mixture optimization using response surface methodology. Journal of Cleaner Production, 171 (**2018**) 1605-1621. *https://doi.org/10.1016/j.jclepro.2017.10.102*

[21] P. Zhang, K. Wang, Q. Li, J. Wang, Y. Ling: Fabrication and engineering properties of concretes based on geopolymers/alkali-activated binders - a review. Journal of Cleaner Production, 258 (**2020**) 120896. *https://doi.org/10.1016/j.jclepro.2020.120896*

[22] M. Venkatesan, Q. Zaib, I.H. Shah, H.S. Park: Optimum utilization of waste foundry sand and fly ash for geopolymer concrete synthesis using D-optimal mixture design of experiments. Resources, Conservation and Recycling, 148 (**2019**) 114-123. *https://doi.org/10.1016/j.resconrec.2019.05.008*

[23] B.S. Mohammed, S. Haruna, M. Mubarak Bn Abdul Wahab, M.S. Liew: Optimization and characterization of cast in-situ alkali-activated pastes by response surface methodology. Construction and Building Materials, 225 (**2019**) 776-787. *https://doi.org/10.1016/j.conbuildmat.2019.07.267*

[24] L.C. Da Silva Alves, R.A. Dos Reis Ferreira, L. Bellini Machado, L.A. de Castro Motta: Optimization of metakaolin-based geopolymer reinforced with sisal fibers using response surface methology. Industrial Crops and Products, 139 (**2019**) 111551.

https://doi.org/10.1016/j.indcrop.2019.111551

[25] M. Zahid, N. Shafiq, M.H. Isa, L. Gil: Statistical modeling and mix design optimization of fly ash based engineered geopolymer composite using response surface methodology. Journal of Cleaner Production, 194 (**2018**) 483-498. *https://doi.org/10.1016/j.jclepro.2018.05.158*

[26] L. Zhang, Y. Yue: Influence of waste glass powder usage on the properties of alkali-activated slag mortars based on response surface methodology. Construction and Building Materials, 181 (**2018**) 527-534. *https://doi.org/10.1016/j.conbuildmat.2018.06.040*

[27] T. Revathi, R. Jeyalakshmi, N.P. Rajamane: Geopolymeric binder: The effect of silica fume addition on Fly activation by using response surface methodology. Materials Today: Proceedings, 5 (**2018**) 8727-8734. *https://doi.org/10.1016/j.matpr.2017.12.299*

[28] K. Ragalwar, W.F. Heard, B.A. Williams, R. Ranade: Significance of the particle size distribution modulus for strain-hardening-ultra-high performance concrete (SH-UHPC) matrix design. Construction and Building Materials, 234 (**2020**) 117423. *https://doi.org/10.1016/j.conbuildmat.2019.117423*

[29] Y. Sun, R. Yu, Z. Shui, X. Wang, D. Qian, B. Rao, J. Huang, Y. He: Understanding the porous aggregates carrier effect on reducing autogenous shrinkage of Ultra-High Performance Concrete (UHPC) based on response surface method. Construction and Building Materials, 222 (**2019**) 130-141. *https://doi.org/10.1016/j.conbuildmat.2019.06.151*

[30] X. Wang, R. Yu, Z. Shui, Q. Song, Z. Zhang: Mix design and characteristics evaluation of an eco-friendly Ultra-High Performance Concrete incorporating recycled coral based materials. Journal of Cleaner Production, 165 (**2017**) 70-80. *https://doi.org/10.1016/j.jclepro.2017.07.096*

[31] I. Ferdosian, A. Camoes: Eco-efficient ultra-high performance concrete development by means of response surface methodology. Cement & Concrete Composites, 84 (**2017**) 146-156. *https://doi.org/10.1016/j.cemconcomp.2017.08.019*

[32] M.A. Mosaberpanah, O. Eren: Effect of quartz powder, quartz sand and water curing regimes on mechanical properties of UHPC using response surface modelling. Advances in Concrete Construction, 5 (**2017**) 481-492. *https://doi.org/10.12989/acc.2017.5.5.481*

[33] M.A. Mosaberpanah, O. Eren, A.R. Tarassoly: The effect of nano-silica and waste glass powder on mechanical, rheological, and shrinkage properties of UHPC using response surface methodology. Journal of Materials Research and Technology, 8 (**2019**) 804-811. *https://doi.org/10.1016/j.jmrt.2018.06.011*

[34] M.A. Mosabepranah, O. Eren: Statistical flexural toughness modeling of ultra high performance concrete using response surface method. Computers and Concrete, 17 (**2016**) 477-488. *https://doi.org/10.12989/cac.2016.17.4.477*

[35] E. Ghafari, H. Costa, E. Júlio: RSM-based model to predict the performance of self-compacting UHPC reinforced with hybrid steel micro-fibers. Construction and Building Materials, 66 (**2014**) 375-383. *https://doi.org/10.1016/j.conbuildmat.2014.05.064*

[36] M.A.A. Aldahdooh, N.M. Bunnori, M.A.M. Johari: Evaluation of ultra-high-performance-fiber reinforced concrete binder content using the response surface method. Materials & Design, 52 (**2013**) 957-965. *https://doi.org/10.1016/j.matdes.2013.06.034*

[37] W. Long, G. Lemieux, S. Hwang, K.H. Khayat: Statistical models to predict fresh and hardened properties of self-consolidating concrete. Materials and Structures, 45 (**2012**) 1035-1052. *https://doi.org/10.1617/s11527-011-9815-9*

[38] D. Jiao, C. Shi, Q. Yuan, X. An, Y. Liu: Mixture design of concrete using simplex centroid design method. Cement and Concrete Composites, 89 (**2018**) 76-88. *https://doi.org/10.1016/j.cemconcomp.2018.03.001*

[39] N. Li, C. Shi, Z. Zhang, D. Zhu, H. Hwang, Y. Zhu, T. Sun: A mixture proportioning method for the development of performance-based alkali-activated slag-based concrete. Cement & Concrete Composites, 93 (**2018**) 163-174. *https://doi.org/10.1016/j.cemconcomp.2018.07.009*

[40] K. Mermerdas, Z. Algin, S.M. Oleiwi, D.E. Nassani: Optimization of lightweight GGBFS and FA geopolymer mortars by response surface method. Construction and Building Materials, 139 (**2017**) 159-171. *https://doi.org/10.1016/j.conbuildmat.2017.02.050*

[41] Q. Li, L. Cai, Y. Fu, H. Wang, Y. Zou: Fracture properties and response surface methodology model of alkali-slag concrete under freeze－thaw cycles. Construction and Building Materials, 93 (**2015**) 620-626. *https://doi.org/10.1016/j.conbuildmat.2015.06.037*

[42] F. Bektas, B.A. Bektas: Analyzing mix parameters in ASR concrete using response surface methodology. Construction and Building Materials, 66 (**2014**) 299-305. *https://doi.org/10.1016/j.conbuildmat.2014.05.055*

[43] L. Cai, H. Wang, Y. Fu: Freeze－thaw resistance of alkali－slag concrete based on response surface methodology. Construction and Building Materials, 49 (**2013**) 70-76. *https://doi.org/10.1016/j.conbuildmat.2013.07.045*

[44] N.A. Soliman, A. Tagnit-Hamou: Using particle packing and statistical approach to optimize Eco-Efficient Ultra-High-Performance concrete. Aci Materials Journal, 114 (**2017**) 847-858. *https://doi.org/10.14359/51701001*

[45] L. Qin, X. Gao, A. Su, Q. Li: Effect of carbonation curing on sulfate resistance of cement-coal gangue paste. Journal of Cleaner Production, 278 (**2021**) 123897. *https://doi.org/10.1016/j.jclepro.2020.123897*

[46] J. de Brito, R. Kurda: The past and future of sustainable concrete: A critical review and new

strategies on cement-based materials. Journal of Cleaner Production, (**2020**) 123558. *https://doi.org/10.1016/j.jclepro.2020.123558*

[47] D.B. Hibbert: Experimental design in chromatography: A tutorial review. Journal of Chromatography B-Analytical Technologies in the Biomedical and Life Sciences, 910 (**2012**) 2-13. *https://doi.org/10.1016/j.jchromb.2012.01.020*

[48] W.E. Elemam, A.H. Abdelraheem, M.G. Mahdy, A.M. Tahwia: Optimizing fresh properties and compressive strength of self-consolidating concrete. Construction and Building Materials, 249 (**2020**). *https://doi.org/10.1016/j.conbuildmat.2020.118781*

[49] I. Yeh: Optimization of concrete mix proportioning using a flattened simplex–centroid mixture design and neural networks. Engineering with Computers, 25 (**2009**) 179-190. *https://doi.org/10.1007/s00366-008-0113-2*

[50] Z.M. Sbartai, S. Laurens, S.M. Elachachi, C. Payan: Concrete properties evaluation by statistical fusion of NDT techniques. Construction and Building Materials, 37 (**2012**) 943-950. *https://doi.org/10.1016/j.conbuildmat.2012.09.064*

[51] S. Selvaraj, S. Selvaraj, S. Sivaraman, S. Sivaraman: Prediction model for optimized self-compacting concrete with fly ash using response surface method based on fuzzy classification. Neural Computing and Applications, 31 (**2019**) 1365-1373. *https://doi.org/10.1007/s00521-018-3575-1*

[52] K.H. Khayat, A. Ghezal, M.S. Hadriche: Utility of statistical models in proportioning self-consolidating concrete. Materials and Structures, 33 (**2000**) 338-344. *https://doi.org/10.1007/BF02479705*

[53] M.L. Nehdi, J. Summer: Optimization of ternary cementitious mortar blends using factorial experimental plans. Materials and Structures, 35 (**2002**) 495-503. *https://doi.org/10.1007/BF02483137*

[54] A. Ghezal, K.H. Khayat: Optimizing self-consolidating concrete with limestone filler by using statistical factorial design methods. Aci Materials Journal, 99 (**2002**) 264-272.

[55] M. Muthukumar, D. Mohan, M. Rajendran: Optimization of mix proportions of mineral aggregates using Box Behnken design of experiments. Cement & Concrete Composites, 25 (**2003**) 751-758. *https://doi.org/10.1016/S0958-9465(02)00116-6*

[56] F. Bayramov, C. Taşdemir, M.A. Taşdemir: Optimisation of steel fibre reinforced concretes by means of statistical response surface method. Cement and Concrete Composites, 26 (**2004**) 665-675. *https://doi.org/10.1016/S0958-9465(03)00161-6*

[57] M. Sonebi: Medium strength self-compacting concrete containing fly ash: Modelling using factorial experimental plans. Cement and Concrete Research, 34 (**2004**) 1199-1208. *https://doi.org/10.1016/j.cemconres.2003.12.022*

[58] E.K.K. Nambiar, K. Ramamurthy: Models relating mixture composition to the density and strength of foam concrete using response surface methodology. Cement and Concrete Composites, 28 (**2006**) 752-760. *https://doi.org/10.1016/j.cemconcomp.2006.06.001*

[59] J.P. Won, J.M. Seo, C.G. Park, J.H. Kim: Statistical optimisation and durability characteristics of bridge deck overlay concrete. Magazine of Concrete Research, 58 (**2006**) 601-608. *https://doi.org/10.1680/macr.2006.58.9.601*

[60] T. Cho: Prediction of cyclic freeze – thaw damage in concrete structures based on response surface method. Construction and Building Materials, 21 (**2007**) 2031-2040. *https://doi.org/10.1016/j.conbuildmat.2007.04.018*

[61] R.R. Menezes, H.G.M. Neto, L.N.L. Santana, H.L. Lira, H.S. Ferreira, G.A. Neves: Optimization of wastes content in ceramic tiles using statistical design of mixture experiments. Journal of the European Ceramic Society, 28 (**2008**) 3027-3039. *https://doi.org/10.1016/j.jeurceramsoc.2008.05.007*

[62] A.N.S. Al Qadi, K. Nasharuddi, H. Al-Mattarn, Q.N.S. AL-Kadi: Statistical models for hardened properties of Self-Compacting concrete. American Journal of Engineering and Applied Sciences, 2 (**2009**) 764-770. *https://doi.org/10.3844/ajeassp.2009.764.770*

[63] R.R. Menezes, L.N. Marques, L.A. Campos, H.S. Ferreira, L.N.L. Santana, G.A. Neves: Use of statistical design to study the influence of CMC on the rheological properties of bentonite dispersions for water-based drilling fluids. Applied Clay Science, 49 (**2010**) 13-20. *https://doi.org/10.1016/j.clay.2010.03.013*

[64] N.U. Kockal, T. Ozturan: Optimization of properties of fly ash aggregates for high-strength lightweight concrete production. Materials & Design, 32 (**2011**) 3586-3593. *https://doi.org/10.1016/j.matdes.2011.02.028*

[65] D.X. Xuan, L.J.M. Houben, A.A.A. Molenaar, Z.H. Shui: Mixture optimization of cement treated demolition waste with recycled masonry and concrete. Materials and Structures, 45 (**2012**) 143-151. *https://doi.org/10.1617/s11527-011-9756-3*

[66] M. Li, Y. Chen, Y. Chan, L.H. Vihn: A study of statistical models application for mixture of high-flowing concrete. Journal of Marine Science and Technology-Taiwan, 20 (**2012**) 325-335.

[67] A.N.S. Alqadi, K.N.B. Mustapha, S. Naganathan, Q.N.S. Al-Kadi: 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 Journal of Civil Engineering, 16 (**2012**) 407-416. *https://doi.org/10.1007/s12205-012-1308-z*

[68] A. Shahriar, M.L. Nehdi: Optimization of rheological properties of oil well cement slurries using experimental design. Materials and Structures, 45 (**2012**) 1403-1423.

https://doi.org/10.1617/s11527-012-9841-2

[69] M. Sonebi, M.T. Bassuoni: Investigating the effect of mixture design parameters on pervious concrete by statistical modelling. Construction and Building Materials, 38 (**2013**) 147-154. *https://doi.org/10.1016/j.conbuildmat.2012.07.044*

[70] M.T. Cihan, A. Güner, N. Yüzer: Response surfaces for compressive strength of concrete. Construction and Building Materials, 40 (**2013**) 763-774. *https://doi.org/10.1016/j.conbuildmat.2012.11.048*

[71] M.O. Hamzah, B. Golchin, C.T. Tye: Determination of the optimum binder content of warm mix asphalt incorporating Rediset using response surface method. Construction and Building Materials, 47 (**2013**) 1328-1336. *https://doi.org/10.1016/j.conbuildmat.2013.06.023*

[72] R. Zaitri, M. Bederina, T. Bouziani, Z. Makhloufi, M. Hadjoudja: Development of high performances concrete based on the addition of grinded dune sand and limestone rock using the.mixture design modelling approach. Construction and Building Materials, 60 (**2014**) 8-16. *https://doi.org/10.1016/j.conbuildmat.2014.02.062*

[73] E. Güneyisi, M. Gesoğlu, Z. Algın, K. Mermerdaş: Optimization of concrete mixture with hybrid blends of metakaolin and fly ash using response surface method. Composites Part B, 60 (**2014**) 707-715. *https://doi.org/10.1016/j.compositesb.2014.01.017*

[74] S. Ahmad, S.A. Alghamdi: A statistical approach to optimizing concrete mixture design. TheScientificWorld, 2014 (**2014**) 561537-561539. *https://doi.org/10.1155/2014/561539*

[75] J. Zheng, G. Shao, X. Shen: Synergistic interactions of chemical additives on the strength development of silicate cement by a box - behnken model optimization. Journal of Applied Polymer Science, 131 (**2014**) n/a-n/a. *https://doi.org/10.1002/app.41071*

[76] B. Simsek, Y.T. Ic, E.H. Simsek, A.B. Guvenc: Development of a graphical user interface for determining the optimal mixture parameters of normal weight concretes: A response surface methodology based quadratic programming approach. Chemometrics and Intelligent Laboratory Systems, 136 (**2014**) 1-9. *https://doi.org/10.1016/j.chemolab.2014.05.001*

[77] T. Baghaee Moghaddam, M. Soltani, M.R. Karim, H. Baaj: Optimization of asphalt and modifier contents for polyethylene terephthalate modified asphalt mixtures using response surface methodology. Measurement, 74 (**2015**) 159-169. *https://doi.org/10.1016/j.measurement.2015.07.012*

[78] A. Lotfy, K.M.A. Hossain, M. Lachemi: Statistical models for the development of optimized furnace slag lightweight aggregate self-consolidating concrete. Cement and Concrete Composites, 55 (**2015**) 169-185. *https://doi.org/10.1016/j.cemconcomp.2014.09.009*

[79] A.A. Abouhussien, A.A.A. Hassan: Optimizing the durability and service life of self-consolidating concrete containing metakaolin using statistical analysis. Construction and Building Materials, 76

(**2015**) 297-306. *https://doi.org/10.1016/j.conbuildmat.2014.12.010*

[80] L. Soto-Perez, V. Lopez, S.S. Hwang: Response Surface Methodology to optimize the cement paste mix design: Time-dependent contribution of fly ash and nano-iron oxide as admixtures. Materials & Design, 86 (**2015**) 22-29. *https://doi.org/10.1016/j.matdes.2015.07.049*

[81] B.E. Jimma, P.R. Rangaraju: Chemical admixtures dose optimization in pervious concrete paste selection – a statistical approach. Construction and Building Materials, 101 (**2015**) 1047-1058. *https://doi.org/10.1016/j.conbuildmat.2015.10.003*

[82] M.F.A. El Hameed, M.F. Ghazy, M.A.A.A. Elaty: Cement mortar with nanosilica: Experiments with mixture design method. Aci Materials Journal, 113 (**2016**) 43-53. *https://doi.org/10.14359/51688632*

[83] O. Rezaifar, M. Hasanzadeh, M. Gholhaki: Concrete made with hybrid blends of crumb rubber and metakaolin: Optimization using Response Surface Method. Construction and Building Materials, 123 (**2016**) 59-68. *https://doi.org/10.1016/j.conbuildmat.2016.06.047*

[84] A. Khan, J. Do, D. Kim: Cost effective optimal mix proportioning of high strength self compacting concrete using response surface methodology. Computers and Concrete, 17 (**2016**) 629-648. *https://doi.org/10.12989/cac.2016.17.5.629*

[85] K.E. Alyamac, E. Ghafari, R. Ince: Development of eco-efficient self-compacting concrete with waste marble powder using the response surface method. Journal of Cleaner Production, 144 (**2017**) 192-202. *https://doi.org/10.1016/j.jclepro.2016.12.156*

[86] N.H. Mtarfi, Z. Rais, M. Taleb, K.M. Kada: Effect of fly ash and grading agent on the properties of mortar using response surface methodology. Journal of Building Engineering, 9 (**2017**) 109-116. *https://doi.org/10.1016/j.jobe.2016.12.004*

[87] M.O. Hamzah, S.Y. Teh, B. Golchin, J. Voskuilen: Use of imaging technique and direct tensile test to evaluate moisture damage properties of warm mix asphalt using response surface method. Construction and Building Materials, 132 (**2017**) 323-334. *https://doi.org/10.1016/j.conbuildmat.2016.11.092*

[88] A. Khan, J. Do, D. Kim: Experimental optimization of High-Strength Self-Compacting concrete based on D-Optimal design. Journal of Construction Engineering and Management, 143 (**2017**). *https://doi.org/10.1061/(ASCE)CO.1943-7862.0001230*

[89] M. Wu, Y. Zhang, G. Liu, Z. Wu, Y. Yang, W. Sun: Experimental study on the performance of lime-based low carbon cementitious materials. Construction & building materials, 168 (**2018**) 780-793. *https://doi.org/10.1016/j.conbuildmat.2018.02.156*

[90] M. Shamsuddoha, G. Hüsken, W. Schmidt, H. Kühne, M. Baeßler: Ternary mix design of grout material for structural repair using statistical tools. Construction and Building Materials, 189 (**2018**) 170-180. *https://doi.org/10.1016/j.conbuildmat.2018.08.156*

[91] S. Asadzadeh, S. Khoshbayan: Multi-objective optimization of influential factors on production process of foamed concrete using Box-Behnken approach. Construction and Building Materials, 170 (**2018**) 101-110. *https://doi.org/10.1016/j.conbuildmat.2018.02.189*

[92] A. Habibi, J. Ghomashi: Development of an optimum mix design method for self-compacting concrete based on experimental results. Construction and Building Materials, 168 (**2018**) 113-123. *https://doi.org/10.1016/j.conbuildmat.2018.02.113*

[93] M. Aziminezhad, M. Mandikhani, M.M. Memarpour: RSM-based modeling and optimization of self-consolidating mortar to predict acceptable ranges of rheological properties. Construction and Building Materials, 189 (**2018**) 1200-1213. *https://doi.org/10.1016/j.conbuildmat.2018.09.019*

[94] M.A.A. Aldahdooh, A. Jamrah, A. Alnuaimi, M.I. Martini, M.S.R. Ahmed, A.S.R. Ahmed: Influence of various plastics-waste aggregates on properties of normal concrete. Journal of Building Engineering, 17 (**2018**) 13-22. *https://doi.org/10.1016/j.jobe.2018.01.014*

[95] N. Bala, I. Kamaruddin, M. Napiah, M.H. Sutanto: Polymer Nanocomposite-Modified asphalt: Characterisation and optimisation using response surface methodology. Arabian Journal for Science and Engineering, 44 (**2019**) 4233-4243. *https://doi.org/10.1007/s13369-018-3377-x*

[96] A. Hammoudi, K. Moussaceb, C. Belebchouche, F. Dahmoune: Comparison of artificial neural network (ANN) and response surface methodology (RSM) prediction in compressive strength of recycled concrete aggregates. Construction and Building Materials, 209 (**2019**) 425-436. *https://doi.org/10.1016/j.conbuildmat.2019.03.119*

[97] T.F. Awolusi, O.L. Oke, O.O. Akinkurolere, A.O. Sojobi: Application of response surface methodology: Predicting and optimizing the properties of concrete containing steel fibre extracted from waste tires with limestone powder as filler. Case Studies in Construction Materials, 10 (**2019**) e212. *https://doi.org/10.1016/j.cscm.2018.e00212*

[98] M.K. Mohammed, A.I. Al-Hadithi, M.H. Mohammed: Production and optimization of eco-efficient self compacting concrete SCC with limestone and PET. Construction and Building Materials, 197 (**2019**) 734-746. *https://doi.org/10.1016/j.conbuildmat.2018.11.189*

[99] Q. Zhang, X. Feng, X. Chen, K. Lu: Mix design for recycled aggregate pervious concrete based on response surface methodology. Construction and Building Materials, 259 (**2020**) 119776. *https://doi.org/10.1016/j.conbuildmat.2020.119776*

[100] S. Vasudevan, V. Poornima, M. Balachandran: Influence of admixtures on properties of concrete and optimization using response surface methodology. Materials Today: Proceedings, 24 (**2020**) 650-661. *https://doi.org/10.1016/j.matpr.2020.04.319*

[101] C. Yan, H. Zhao, J. Zhang, S. Liu, Z. Yang: The cementitious composites using calcium silicate slag as partial cement. Journal of Cleaner Production, 256 (**2020**). *https://doi.org/10.1016/j.jclepro.2020.120514*

[102] K. Mermerdaş, Z. Algın, Ş. Ekmen: Experimental assessment and optimization of mix parameters of fly ash-based lightweight geopolymer mortar with respect to shrinkage and strength. Journal of Building Engineering, 31 (**2020**) 101351. *https://doi.org/10.1016/j.jobe.2020.101351*

Highlights

- Applications of statistical experimental optimization of cement-based materials are reviewed
- The characteristics of the applications of mixture optimization are summarized in table
- A critical discussion of mixture optimization and sustainable concrete application is presented

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.