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REVIEW ARTICLE

Optimization of cementitious mixes through response surface method: a systematic review

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Abstract

The pursuit of cement-based materials with enhanced mechanical performance in the construction industry involves formulating numerous mixtures with varied contents of raw materials. However, the scarcity or contamination of these materials demands optimization methods to minimize the number of trials required. Response Surface Methodology (RSM) is a statistical experimental optimization method with which relations between sets of factors and responses can be established. This systematic review aims to analyze the existing literature on RSM models developed to achieve optimum levels in cementitious mixes. Over 100 papers were analyzed in accordance with the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) format. A comprehensive review of the RSM analyses in those studies and their effectiveness is conducted, through the evaluation of their optimized factors and responses, the selection of their design models, their use of ANalysis Of VAriance (ANOVA), and the determination of their coefficients of determination (R^2). Factors such as water/cement ratio and binder content prevailed in most models, the predominant responses of which were, respectively, compressive strength and workability. Although the use of ANOVA is commonly used to demonstrate the validity of the models, the studies replicating the mix with optimal levels of all factors are necessary to validate the results. On the basis of this review and depending on the responses that need to be maximized or minimized, the application of RSM can clearly be very crucial when quantifying the effects of new raw materials, whether recovered waste or natural resources, on mix behaviour.

Keywords Optimization · Response surface method · Factors · Responses · Supplementary cementitious materials

Abbreviations

RSM	Response surface method
SCM	Supplementary cementitious materials
CCD	Central composite design
FFD	Full factorial design
BBD	Box–Behnken design
FCCD	Face-centred central composite design
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
SCC	Self-consolidating concrete
GGBFS	Ground granulated blast-furnace slag
ANOVA	ANalysis Of VAriance
OPC	Ordinary Portland cement

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1 Introduction

High consumption levels of cementitious materials are among the major contributors to CO_2 atmospheric emissions [1]. Such high levels were reflected in the figures of the International Energy Agency that estimated global cement production at 4.2 Gt in 2020 [2]. Fossil-fuel calcination and heating processes required to supply sufficient energy for cement manufacturing release roughly 600 kg of carbon dioxide for every ton of cement that is produced [2]. Moreover, approximately 14 billion metric tons of Portland cement-based concrete, the most widely used material in the construction industry, are produced each year [3]. The cement industry has, therefore, set itself the urgent task of decarbonizing the building sector by 2050 [3].

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On the one hand, the use of natural aggregates is a key issue to be solved in concrete production, given that natural aggregates comprise between 75 and 80% of the total mix [4]. Their extraction and processing result in environmental damage, scarred landscapes, the destruction of natural habitats, and the contamination of natural watercourses, among others [5]. On the other hand, assuming that infrastructural development will develop at the same rate as the rapid growth of the global population, then the relative scarcity of natural aggregates will soon be turned into a harsh reality [6].

Appropriate substitution of raw materials by recovered waste offering equivalent performance levels has been investigated for the development of sustainable mixtures, such as supplementary cementitious materials (SCM) in the case of total or partial cement replacement [7], and the use of various alternative sustainable aggregates to replace natural aggregates [8]. Other recycled materials are proposed as partial substitutes for those constituents, leading to a dual solution: recycling the waste itself, and conserving the natural resources required for concrete mixture production [9].

The desire to achieve optimal concrete mixes through the addition of recovered waste, in terms of economic and performance-related requirements, has led many researchers to use optimization methods for different wastes such as plastics [10], waste-tire steel fibres [11], PET [12], and crumb rubber [13], among others. The experimental optimization is typically based on trial-and-error or single factor experimental design method. Among the different methods that can be used, Response Surface Method (RSM) optimizations of mix proportions have been investigated in many studies [14]. RSM is based on mathematical models (linear, square polynomial functions, and others) [15], and statistical analyses for experimental design where each response is connected to a number of variables for exploring impacts [16], interaction of parameters, and optimization processes [17]. RSM analysis considers the experimental design along with its responses, also known as the experimental results [18]. The numerical response surface model then validates the accuracy and optimizes the variables to achieve the desired responses [19].

In recent decades, the number of publications focusing on RSM as a central aspect of research has undergone exponential growth. Figure 1 illustrates the number of publications on RSM available in the search database "SCOPUS" between the years 2000 and 2024. It is evident that at the beginning of the Millennium the volume of publications concerning RSM is scarce, failing to reach 1800 by 2000. Contrasting those earlier numbers with the 15,000 publications or so for 2023, the interest in the subject has very clearly increased at a steady rate. It reflects the significant use of this method not only within fields such as engineering, but also across disciplines where the efficacy of scientific research is pursued, *e.g.*, biotechnology and environmental science.

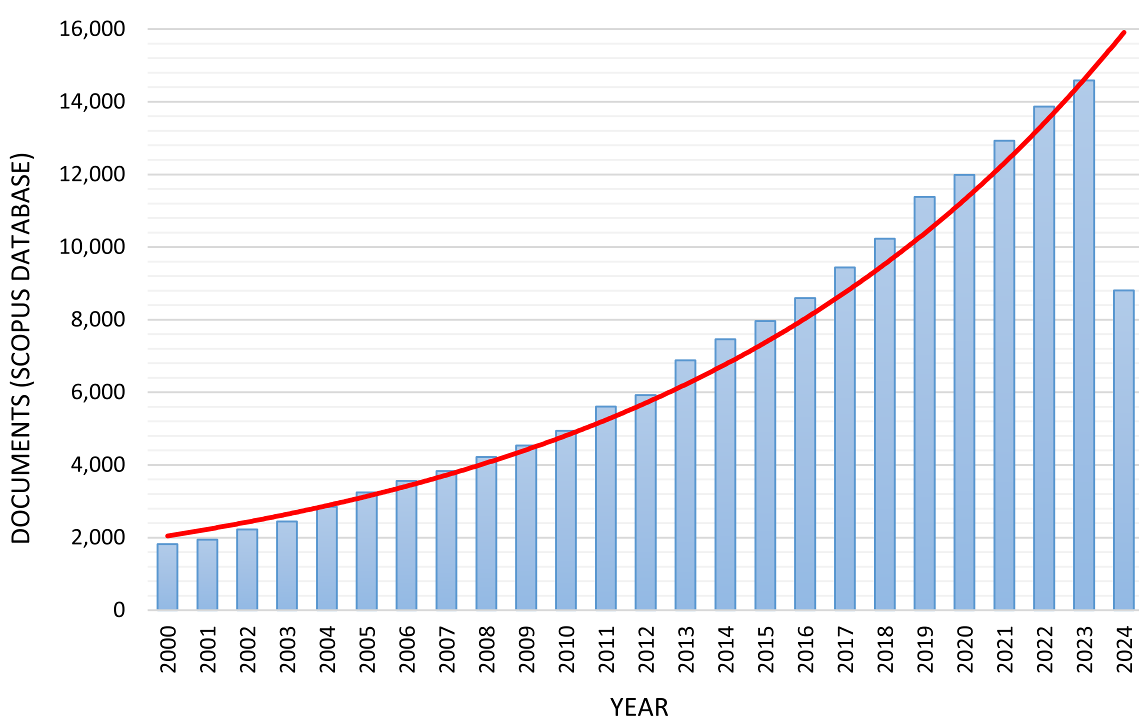

Fig. 1 Number of publications on Response Surface Methodology (RSM) by year since 2000

There are multiple studies on RSM optimization of cementitious mixes, where a large number of variables influence the responses [20]. The studies on the effectiveness of RSM as a method for concrete mix optimizations abound, although the addition of waste materials to create more sustainable mixes is an area that requires further investigation, as so many sorts of sustainable materials may be analyzed [14].

Despite the usefulness of RSM experimental optimization to estimate the optimum content of sustainable raw materials in concrete mixes, the method has certain drawbacks. The chief among those drawbacks is the considerable number of samples and tests required to obtain the optimum mixture [21], resulting in higher material consumption and laboratory work [22]. Moreover, the results obtained from individual studies on experimental optimization are of limited applicability and validity, due to specific characteristics and origin of constituents and environmental variables such as temperature and humidity that condition the mix design and concrete performance [23]. Nevertheless, although RSM results can in each particular case be used to find the approximate optimal mix dosage [14], a degree of methodical generalization might be useful for the widespread use of various sustainable raw materials. Some researchers have focused on designing and verifying computational design optimization tools for concrete mix proportioning [23].

The main objective of this review is to summarize the basics of RSM and its application to the optimization of cementitious materials, by performing a novel classification of the reviewed scientific articles into four groups based on the aim of the RSM optimization. A further aim is to evaluate the efficacy of RSM at defining the optimum amounts of sustainable materials through a combined analysis of various studies on content optimization through RSM, an approach that is also novel in literature. The review is organized as follows. A brief explanation of the research methodology, based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), is provided in Sect. 2. Fundamentals of RSM and strategies for experimental design are then briefly reviewed in Sect. 3. In Sect. 4, literature on optimization design for cement-based material applications is presented to uphold the feasibility of the optimization strategies that are selected for each material. Finally, the main conclusions of the review are summarized in Sect. 5.

2 Research methodology

2.1 Systematic review

A systematic approach based on PRISMA format was closely observed to conduct this comprehensive literature review [24]. Involving the selection of the most relevant papers in a given discipline, and their analysis and evaluation, PRISMA is a highly efficient and widely used technique for the systematic review of past research papers. It also implies the synthesis of results to complete lines of knowledge that have not previously been investigated, providing a solid basis for the conclusions reached. Furthermore, if it is conducted by several people simultaneously, a high degree of objectivity in the article identification process can be achieved.

2.2 Data extraction

Two databases were used in this literature review: SCOPUS and Web of Science. Initially, 371 and 165 results, respectively, were returned in a search for articles with keywords related to “Optimization” and “Concrete” between 2000 and 2024. Duplicate articles were removed and papers that were unrelated to engineering, and materials were discarded, narrowing the search to English language documents. After the initial screening, a total of 171 articles were selected. Further refinement of the query, using “Cement” as a keyword and focusing on response surface method resulted in a total of 132 articles, some of which were discarded as being beyond the scope of this review. In all, 100 relevant papers were finally included for in-depth examination, as shown below in the following flow-chart (Fig. 2).

A word cloud visualization was generated to present the most common keywords found in the selected articles, as shown in Fig. 3a., highlighting such terms as “Concrete”, “Design”, and “Response Surface Method”. Those words signify the topics that will be further covered in the course of this systematic review and validate the PRISMA methodology conducted to select the reviewed papers. This word cloud was created with an online Word Cloud Generator. Among the 100 articles selected for review, 72 were Q1 quality according to the JCR database criteria. A ranked order of their sources is shown in Fig. 3b.

3 Response surface method

The enhancement of concrete mix mechanical properties is dependent on the optimal content of each component: first and foremost, the cement, and then the materials that not only improve mix behaviour, but also mitigate the environmental impact caused by its production. To optimize the selected variables, a large number of parameters involved in the mixing process requires significant amount of trials to be manufactured [10], which can be time-consuming and resource-intensive. RSM has, therefore, been proposed as an efficient concrete mix optimization method. Its underlying principle is that correlations may be established between

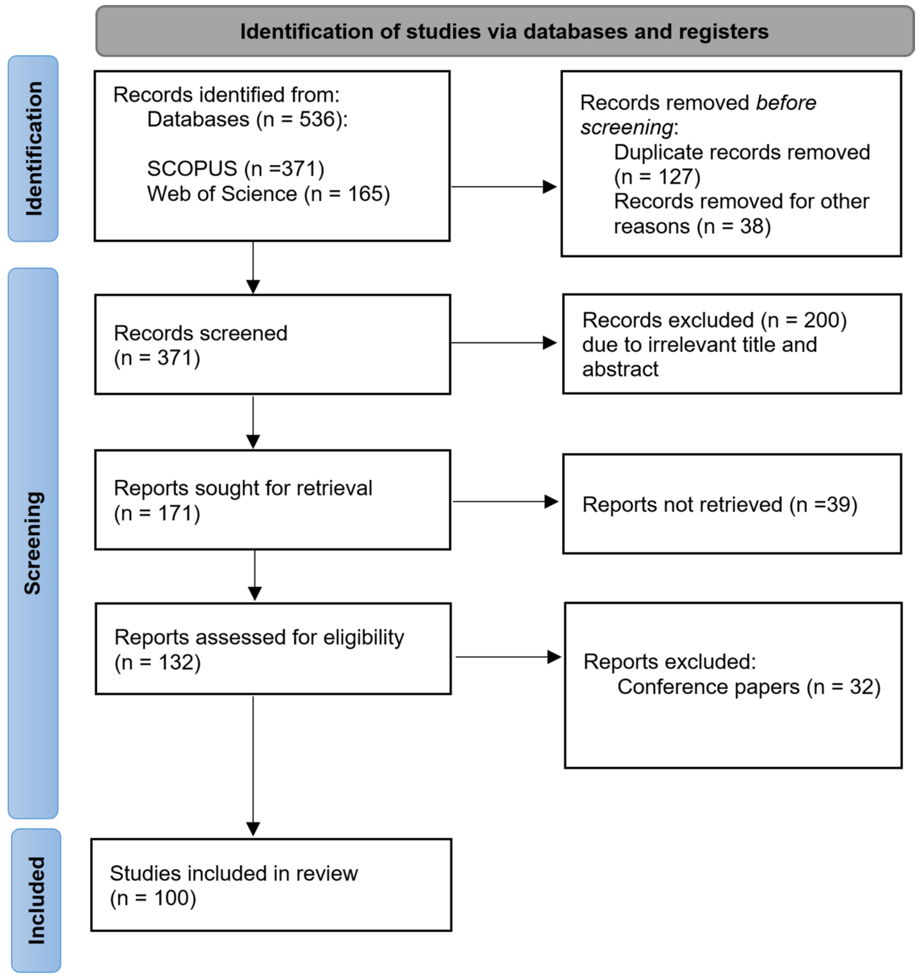

Fig. 2 PRISMA statement flow diagram [25]

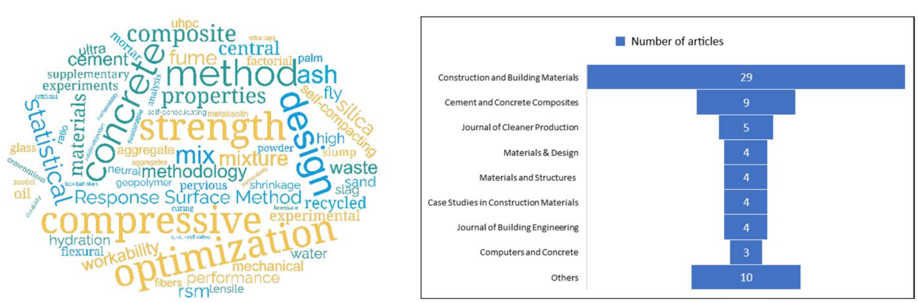

Fig. 3 **a** Keywords Word cloud visualization; **b** List of Journals that published Q1 articles between 2000 and 2024 on RSM-based optimizations of concrete mixes

different factors and their responses through various mathematical procedures and statistical analyses.

3.1 Selection of factors and responses

To comprehensively grasp the utilization of this method, it is advantageous to define the two principal terms governing its application: factors, also known as “independent variables”, and responses, referred to as “dependent variables”. A factor is an experimental variable that is adjusted for testing, regardless of the other variables that constitute the mixture design. The response is the value of the property that is measured after conducting the corresponding trials [26] and after having set the value of the factor. It is standard practice to consider cement or binder content, water/cement ratio, volume of aggregates and admixtures as factors in concrete mix designs. Compressive strength, flexural strength and slump are responses used in most of those optimizations. Existing literature [20] highlights the use of RSM to optimize the addition of new materials, often waste recovered from industrial processes that can be added to concrete mixes to improve their mechanical behaviour. The number of factors that can be optimized for each design will vary in relation to both the number of mix variables [27] and the interval in which the variables lie. This decision will result in a certain number of combinations that constitute what is referred to as "Experimental design".

3.2 Selection of experimental design strategy

A correct experimental design strategy will result in a polynomial function, either linear or quadratic, that accounts for response variations based on independent variables [28]. In cases where the model is quadratic, the result of defining Eq. (1) is a curvature or surface that can be defined as:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i=1}^{k} \sum_{j>1}^{k} \beta_{ij} X_i X_i + \varepsilon_0, \quad (1)$$

where Y represents the response; β represents the regression coefficients; X_i represents the factor or independent variables; k represents the number of optimized variables; and ε_0 refers to the measured error. The quadratic model performs well in cases where the surface is narrow, *i.e.*, the range of values between which the variables to be optimized fluctuate is considered to be small [14]. Rather than linear models, second-order models provide a more comprehensive description of the relationships between different factors and their interactions.

In addition, higher-order models are used to define non-linear or more complex relationships. Some of the most widely used designs for the optimization of concrete mixtures are full factorial design, central composite design, and Box–Behnken design [29].

3.2.1 Full factorial design

Full factorial design (FFD) is an experimental design in which all factors are replicated at two or three levels. In a two-level FFD, each factor has a low value (− 1) and a high value (+ 1), whereas in a three-level FFD, an additional value is considered as the centre value. The total number of designs is defined as either 2^k or 3^k, respectively, where k denotes the number of design factors. Figure 4a. shows a schematic representation of the combination obtained with a three-level FFD. Many experimental runs are required for a three-level FFD; its application is, therefore, only convenient for less than five factors [30], otherwise it will produce undesirable higher-order interactions.

3.2.2 Central composite design

Central composite design (CCD) stands out as the most popular RSM method for defining a quadratic model to establish the statistical relations between factors and their responses. Its major advantage is the capability to predict linear and quadratic effects for the responses while minimizing experimental trials. CCD requires the three-level FFD with complementary centre and axial points, providing greater scope and representativeness. It has contributed to the widespread adoption of CCD in the concrete design industry and engineering.

The number of design points required for CCD design is determined by Eq. (2):

$$\text{Number of design points} = 2\text{k} + 2^{\text{k}} + \text{c}, \quad (2)$$

where k is the number of independent variables, $2k$ refers to the axial runs, 2^k refers to the factorial runs, and c refers to the centre-point runs. Factorial points include

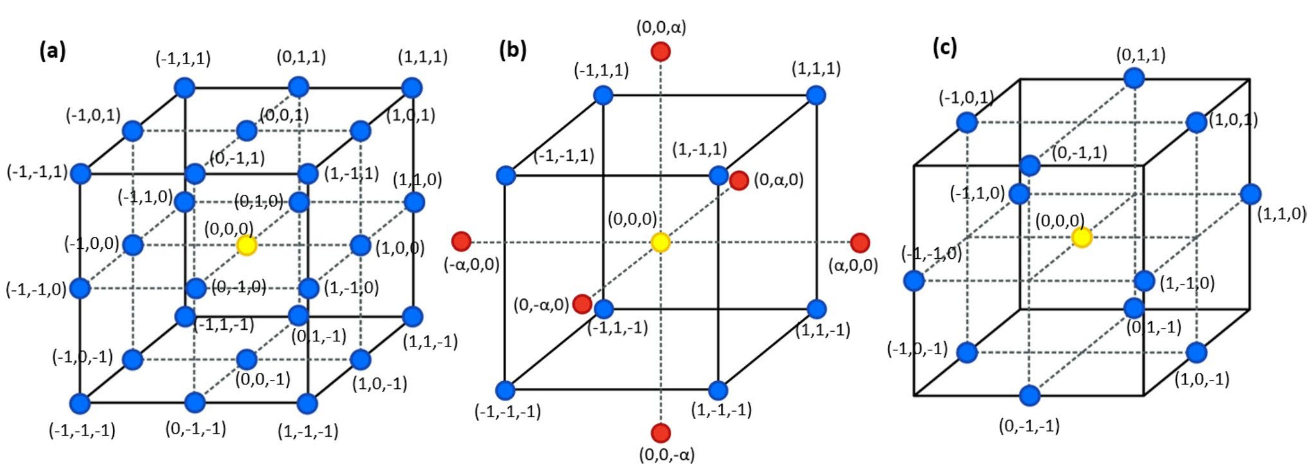

Fig. 4 (a) Three-level full factorial design approach (k = 3); (b) Axial, factorial, and centre points in a central composite design for k = 3; (c) Spherical design for a Box–Behnken Design for k = 3

all combinations of coded values placed at the corners of the cube, while axial points are located at a fixed distance from the origin, defined by an alpha value ($\pm\alpha$). A three-dimensional CCD design with k = 3 independent variables is shown in Fig. 4b.

3.2.3 Box–Behnken design

Box–Behnken design (BBD), an alternative to FFD, is commonly applied for quadratic models. Its distinguishing aspect is that no factorial points are used, so it therefore has neither impractical low nor high extreme points where factors reach their maximum and minimum values. The spherical nature and quasi-rotational capability of BBD means that it is suitable for accurate estimation of the behaviour of defined factors. The number of design points in BBD is determined by Eq. (3).

$$\text{Number of design points} = 2k(k-1) + c, \tag{3}$$

where k is the number of independent variables and c refers to the centre-point runs. Notwithstanding the numerous advantages of the BBD over the FFC and the CCD methods, there are specific limitations to its applicability. The method is unsuitable for experiments requiring the inclusion of extreme points for optimization. Its applicability is, therefore, dependent on the presence of three or more factors. It is particularly relevant in situations where the optimal value falls within an intermediate range of factors. The arrangement of points for a Box–Behnken Design is shown in Fig. 4c.

Beyond the three predominant designs employed for RSM, it is crucial to recognize the existence of additional strategies, which are utilized in some models examined in the literature. These designs include Bucher–Bourgund design, fractional factorial design, simplex centroid design, simplex lattice design, factorial design and face-centred central composite design.

3.3 Statistical analysis and model validation

Optimization through RSM relies on the robust statistical tool known as ANalysis Of VAriance (ANOVA), which facilitates a comprehensive examination of factors that significantly influence responses. The coefficients of determination (R^2) and *P*-value analyses are used to assess the predictive quality of the ANOVA results. The R2, a measure of the disparity between predicted and experimental values, is indicative of model quality, while *P*-values below 0.05 signify model adequacy. This criterion serves to validate optimized models. The examination of *p*-values across models featuring different optimized factors for the same concrete mix allows for inferences regarding the optimal combination of several factors within a given model. This stage in the optimization process is acknowledged as model validation.

The flow diagram shown in Fig. 5 serves to enhance the comprehension of the main steps of a standard RSM model optimization process, particularly focusing on concrete and cementitious mixes.

4 Literature on RSM optimization of concrete mix design

The papers selected for this review were classified into four separate groups for their effective analysis. The primary criterion to distinguish between groups was based on the raw materials of the mixtures which served as factors for the optimization process.

The first group, labelled "Studies on the use of the Response Surface Method (RSM) for mix design optimization", was a compilation of publications where the key optimization factors included water/cement ratio, cement content, or the content by volume of different aggregate-sized particles. It is, therefore, a compilation of all the models for which the enhancement of mix properties is related to optimum levels and interactions between the design parameters, unrelated to the replacement of traditional materials for alternative or sustainable ones. The references in this group are presented in Table 1.

The second group included papers on varied types of SCM that were incorporated into concrete mixtures, either as complete or partial replacement of conventional cement, their content being optimized through RSM. Table 2, "Studies on the use of the Response Surface Method (RSM) for Supplementary Cementitious Material (SCM) content optimization in concrete mixes" presents optimizations that involve different binders other than Ordinary Portland Cement (OPC), such as silica fume, fly ash, ground granulated blast furnace slag (GGBFS), etc. This group had the highest number of optimized models on cementitious materials that served to provide insight into optimal binder contents when optimizing responses such as compressive strength and workability.

Furthermore, many recovered waste materials are incorporated as new raw materials to provide alternatives in partial replacement of the natural aggregate content, leading to what is known as "sustainable concrete". Literature on the optimization of sustainable concrete mixes using RSM is still limited. Table 3, "Studies on the use of the Response Surface Method (RSM) for waste content optimization in concrete mixes" provides an analysis of optimized mixture models that include the content of a specific waste as one of the factors.

Finally, the optimized mixes could further reduce the environmental impact of their production compared to

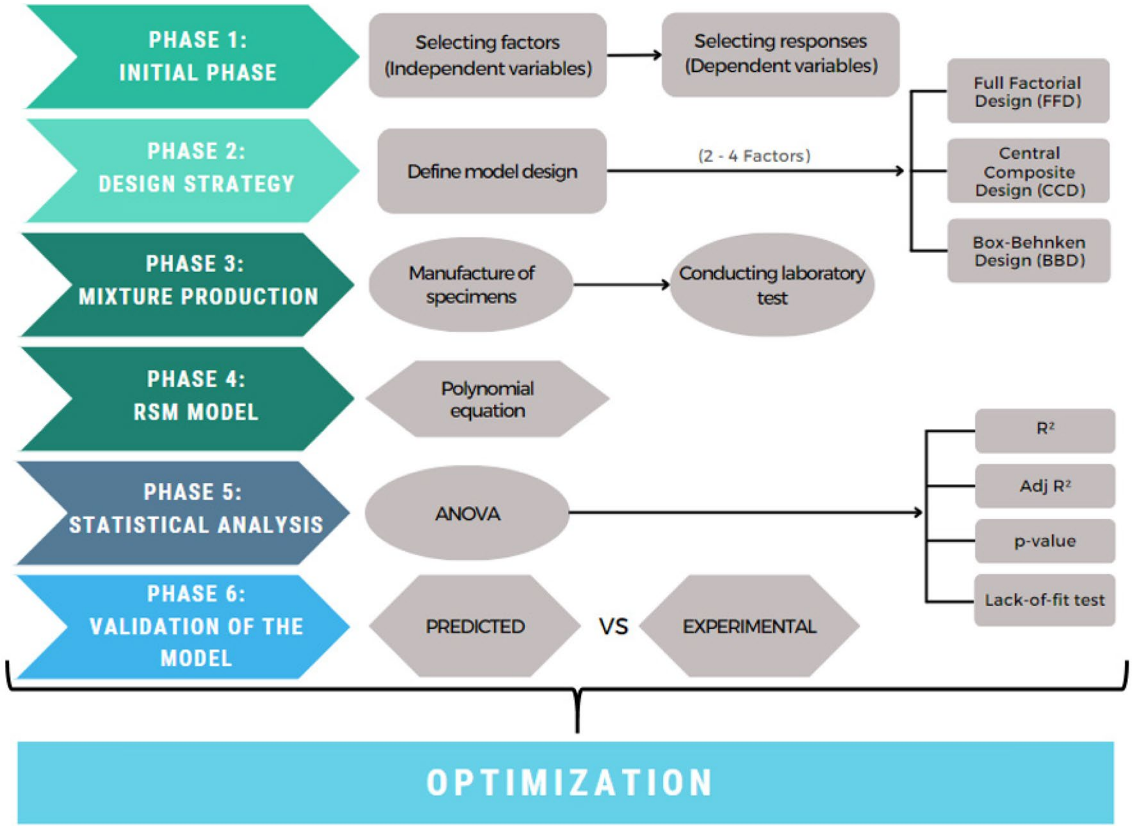

Fig. 5 Flow diagram of the RSM optimization process for concrete mixes

conventional concrete when their waste materials are combined as aggregates with different types of SCM. These are the cases reviewed in the fourth group of the classification, reflected in Table 4, "Studies on the use of the Response Surface Method (RSM) for Supplementary Cementitious Material (SCM) and waste content optimization in concrete mixes presented".

When an article could be classified within two different groups according to the factors considered in the RSM optimization, a meeting was held between the authors of this review article to discuss the most appropriate group to include it in. For this purpose, the relevance given in the RSM optimization to each aspect covered in each classification group suitable for the article was examined and discussed. The fact that this work was carried out jointly by all the authors enabled the subjectivity component to be reduced, which would have been greater if this task had been performed by a single person.

In the tables, fundamental information on each publication is provided on the optimization models, including RSM design, software, factors and responses, and finally the optimum levels of the optimized variables in each case.

4.1 Optimization of mix design

Among the different types of design models selected for this PRISMA review, the initial applications of statistical optimization processes can be said to highlight the use of factorial models to optimize the design parameters of the cementitious mixtures [31]. When addressing the analysis of the most commonly used designs strategies, CCD and BBD stand out as the most frequently applied [14]. CCD is the most common one, appearing in 39% of the models, as shown in Table 1. The inclusion of both factor orthogonality and single-factor boundaries means that its experimental points are significantly more comprehensive and representative [29], thus positioning it as the most widely adopted method in mix design. The reduced number of trials needed in CCD is also a significant factor contributing to its increased adoption. For instance, Sun et al. [32], using only three central points and combinations of two factors, achieved their model design after 11 trial tests. Similarly, in CCD designs involving three factors, the increment in the number of tests was not substantially higher. Şimşek et al. [33] devised a model comprising eight factor points,

Table 1 Studies on the use of the Response Surface Method (RSM) for mix design optimization by year of publication

Reference	RSM design/software	Factors	Responses	Optimum	Year
[37]	CCD / -	W/B ratio, binder, SP, volume coarse aggregate	Workability, rheology, compressive strength	-	2000
[42]	CCD / -	Cement, limestone, filler, SP, W/B ratio	Workability, compressive strength	W/B = [0.38—0.72], cement = [250 -400 kg/m^3], limestone filler > 120 kg/m^3, HRWR = [0.12—0.75% mass of binder]	2002
[34]	BBD / Design Expert	Types of silica sand	Void content	Void content = [21.96%—31.4%]	2003
[40]	FFD / Design Expert	Aspect ratio, volume of steel fibre	Fracture energy, characteristic length	Volume of steel fibre = 0.558%, aspect ratio = 75.87	2004
[45]	Bucher–Bourgund design / -	W/B ratio, entrained air pore, number of cycles	Residual strain	-	2007
[46]	CCD / -	Cement, degree of compaction	Moisture content, dry density	-	2012
[41]	FFD / Design Expert	W/B ratio, cement, volume coarse aggregate	Fresh density, compressive strength, hardened density, void ratio	W/C = [0.28 – 0.40], cement = [350 – 415 kg/m^3], coarse aggregate = [1200–1400 kg/m$^{3]}$	2013
[47]	Fractional factorial design / Design Expert 7.1	W/B, cement, fineness modulus of aggregate, SP	Compressive strength	-	2013
[19]	CCD / Design Expert	Steel fibre, powder/aggregate ratio	Flexural strength, workability	1 vol. (%) VF_1 (steel fibre 10/0.15) 1.1 vol. (%) VF_2 (steel fibre 13/0.2)	2014
[44]	FFD / MiTab 13	Binder, W/B, volume fine aggregate/volume coarse aggregate	Compressive strength	Cementitious materials = 350 kg/m^3, w/c ratio = 0.38, fine/total aggregate ratio = 0.45	2014
[33]	CCD / MiTab	W/B, volume coarse aggregate, SP	Workability, compressive strength, splitting tensile strength, cost	-	2014
[35]	BBD / -	Alkali, W/B ratio, ground clay	Expansion, compressive strength, flexural strength, modulus of elasticity	-	2014
[36]	BBD / -	SP, Viscosity modifiers, set retarders	Paste thickness slump, film drying paste	-	2015
[38]	Simplex centroid design/ -	Gravel, sand	Bulk density	-	2018
[39]	Simplex centroid design/ -	Cement, mineral admixture, hydrated lime	Workability, compressive strength, hydration heat, porosity, non-evaporable water	-	2018
[48]	Simplex centroid design/ -	SP, stone powder, gravel, sand, cement	Slump flow, compressive strength	-	2018
[28]	BBD / MiniTab	Cement, foam, water	Compressive strength, dry density, cost	-	2018
[32]	CCD/-	Porous aggregate, concentration of shrinkage reducing admixture	Autogenous shrinkage	25% PA + 70% SRA	2019
[49]	CCD/-	Cement, slump, recycled coarse aggregate	Compressive strength	-	2019
[50]	BBD/Design Expert 8	Aggregate size	Bulk density, apparent density, void	Target porosity = 35%, target paste content = 15%, aggregate content = 50%	2020
[51]	CCF / Minitab	Manufactured sand, metakaolin, wastepaper sludge ash	Compressive strength, permeability coefficient, sorptivity	-	2020
[29]	CCD / Design Expert	W/C ratio, dune sand/fly ash ratio, sand/aggregate ratio, basalt fibre dosage	Slump, compressive strength, flexural strength	-	2023

Table 1 (continued)

Reference	RSM design/software	Factors	Responses	Optimum	Year
[43]	CCD / Design Expert	Maximum aggregate particle size, W/C ratio, porosity	Compressive strength, permeability coefficient	(Max. size 10 mm, w/c = 0.2, target porosity = 15%). (Max. size 20 mm, w/c = 0.3, target porosity = 20%)	2023

Central Composite Design (CCD); Water/Binder (W/B); SuperPlasticizer (SP); Box-Behnken Design (BBD); Full Factorial Design (FFD); High-Range Water-Reducing admixtures (HRWR); Water/Cement (W/C); Volume Fraction 1 (VF1); Volume Fraction 2 (VF2); Porous Aggregates (PA); Shrinkage Reducing Admixture (SRA); Not available data (-)

six axial points, and six centre points, resulting in a total of 20 combinations. In another investigation, the CCD model was selected for multi-objective optimization of a concrete mixture aiming for maximum flexural strength with minimal metallic hybrid fibre content [19], in which the production of the same mix under optimum conditions confirmed the rigor of the model.

Moving from the discussion of CCD to BBD models, it is noteworthy that the BBD strategy has also been employed to model concrete mixes, with almost 18% of the models using this approach. However, its usage is comparatively lower than CCD, due to the absence of factorial points, implying that neither the upper nor lower limits for each variable are considered as constraints for response optimization during its application. Evaluations of the effect of three independent variables have been simultaneously performed in BBD models [34]. The BBD strategy can be successfully used to elucidate, for instance, how factors such as alkali content, w/c ratio, and ground clay affect the mechanical behaviour of alkali–silica reaction concrete [35], how the interaction of three different admixtures affects the permeability of the concrete mix [36], and how different proportions of silica aggregates affect the void content of the mix [28]. However, this strategy has proved inadequate when attempting an accurate determination of the optimum levels to be used. Asadzadeh et al. [28] conducted both individual and multi-objective optimization of variables related to cost, compressive strength, and dry density of foam concrete exploring possible applications by fixing desired values; rather than obtaining a specific proportion of each factor, BBD was used to establish nine combinations of the three factors (cement, water, and foam).

Despite it being a traditionally popular method, the simplex-centroid design is not currently applied in most investigations, and it was not even detailed in Sect. 3.2. Its basic premise is an interdependence between different factor levels, which are all represented within a tri-linear coordinate system using the three sides of the same triangle. Nevertheless, some authors have applied this methodology to optimize the design parameters of their concrete mixes [37]. Its application to determine minimum cement content through compact aggregate packing [38] yielded an effective design with highly linear design spaces. The above was also applicable to the investigation of Wu et al. [39] where a type of low-carbon cement combining cement, hydrated lime, and mineral admixtures was obtained with simplex-centroid design that demonstrated rapid convergence to the optimum.

The success of RSM applications is based on careful selection of the factors that influence a mix. Since cementitious mixes are compositionally variable, a slight variation in the values of the components may improve the desired property but result in a deterioration of another property.

Table 2 Studies on the use of the Response Surface Method (RSM) for Supplementary Cementitious Material (SCM) content optimization in concrete mixes by year of publication

Reference	RSM Design / Software	Factors	Responses	Optimum	Year
[60]	Factorial design / -	Silica fume, fly ash, GGBFS	SP, setting time, drying shrinkage, compressive strength, cost	-	2002
[68]	CCD / Design Expert 5.0	Pulverized fuel ash, SP, cement, W/B ratio	Workability, rheology, segregation ratio, compressive strength	-	2004
[61]	Simplex centroid design / -	Cement, fly ash, GGBFS, SP, volume coarse aggregate, volume fine aggregate	Workability, compressive strength	-	2008
[73]	CCD / MiniTab	Cement, W/B ratio, fly ash, SP	Compressive strength, modulus of Elasticity	-	2009
[74]	BBD / Design Expert	Temperature, binder content, binder type	Specific gravity, water absorption, crushing strength	-	2011
[75]	Fractional factorial design / -	-	Workability, compressive strength, shrinkage, creep	-	2012
[62]	CCD / -	GGBFS, fly ash, W/B ratio, SP	Workability, compressive strength, durability	-	2012
[55]	CCD / MiniTab	Cement, W/B ratio, fly ash, SP	Workability, compressive strength, modulus of elasticity	Cement = 426 kg/m^3, w/p ratio = 0.34, fly ash = 130 kg/m^3, SP = 9.0 kg/m^3	2012
[76]	CCD / Design Expert 8.0.3	SP, supplementary cementitious materials, temperature	Yield stress, plastic viscosity	-	2012
[79]	CCD / Design Expert 6.0.7	Ordinary Portland Cement, silica fume	Compressive strength, workability	OPC = 720.49 kg/m^3, SF = 214.25 kg/m^3	2013
[78]	CCD / Design Expert 6.0.7	[OPC-UPOFA]%, [DSF-UPOFA]%	Slump, compressive strength	[OPC-UPOFA] = 50%, [DSF-UPOFA] = 0.0%	2013
[79]	CCD / Design Expert	[OPC-UPOFA]%, [DSF-UPOFA]%	Ultimate flexural strength, uniaxial tensile strength	UPOFA = 50%, UPOFA = 0.0%	2013
[80]	Simplex lattice design / JMP7	Cement, grinded dune sand, limestone filler	Workability, compressive strength, Flexural strength	-	2014
[54]	Factorial design / -	Fly ash, metakaolin, testing age	Compressive strength, chloride permeability, sorptivity, water absorption	Fly ash = 13.3%, metakaolin = 10.0%	2014
[57]	BBD / Design Expert	Sol ratio, slag, age on fracture toughness	Initiation fracture toughness, unstable fracture toughness, crack mouth opening displacement, critical effective crack	-	2015
[65]	Simplex lattice design / Design Expert	Cement, sand, silica fume, quartz flour, water, SP, steel fibre	Workability, flexural strength	-	2015
[81]	CCD / Design Expert 8.0.3	HRWRA, W/B ratio, SP	Workability, compressive strength, filling capacity, sieve segregation	-	2015
[82]	CCD / -	Binder, W/B ratio, SCM's	Workability, compressive strength, segregation factor	Total binder = 490 kg/m^3, W/B ratio = 0.39, metakaolin = 19.9%	2015
[83]	CCF / -	W/B ratio, fly ash/B ratio, nano-iron oxide /B	Workability, compressive strength	W/B = 36%, FA/B = 29.5%, NI/B = 0.78%	2015
[59]	Simplex lattice design / -	Portland cement, fly ash, slag	Alkali-silica reaction	-	2016

Table 2 (continued)

Reference	RSM Design / Software	Factors	Responses	Optimum	Year
[84]	CCD / Design Expert 9.0.3	Cement, steel fibre, silica fume, SP, W/C ratio	Flexural toughness	-	2016
[85]	Simplex lattice design / MiniTab 13	Cement, silica fume, nano-silica	Workability, compressive strength, flexural strength, density, absorption, capillary water	-	2016
[86]	CCD / MiniTab	W/B ratio, cement, volume fine aggregate, fly ash, SP	Workability, compressive strength, cost	Cement = 439.4 kg/m^3, W/B ratio = 35.5%, fly ash = 49.85 kg/m^3, SP = 7.76 kg/m^3	2016
[64]	CCD / Design Expert	Silica fume, sand, ultra-fine fly ash	Workability, compressive strength	-	2017
[87]	Simplex centroid design / -	GGBFS, fly ash	Binder, curing time, curing temperature, compressive strength	Curing temperature = 60 °C	2017
[88]	Simplex lattice design / -	Cement, silica fume, quartz powder, quartz sand	Workability, compressive strength, air void	-	2017
[89]	CCF / -	Clinker, fly ash, debit grinding agent	Compressive strength (7, 28, 90 days)	Fly ash / binder = 0%, clinker/ binder = 66.4%, debit grinding agent / binder = 306 kg/t	2017
[90]	CCD / Design Expert	NaOH molarity, curing temperature, Na_2SiO_3/NaOH ratio	Compressive strength, elastic modulus, flexural strength, flexural toughness, ductility index, ultimate tensile strength, tensile strain capacity	-	2018
[91]	CCD / -	Modulus of sodium silicate, Liquid/Fly ash, mineral admixture	Compressive strength	-	2018
[53]	Simplex centroid design / -	Volume coarse aggregate, volume fine aggregate, paste, cement, fly ash, slag	Rheology, compressive strength	Fly ash = [15–20%], slag = [15–25%]	2018
[92]	BBD / Origin	Cement, fly ash, microsilica, metakaolin	Workability, compressive strength, flexural strength, shrinkage	-	2018
[27]	CCD / MiniTab	Silica fume, slag, SP, W/B ratio	Workability, compressive strength, segregation	-	2018
[58]	CCF / Design Expert	Sodium metasilicate anhydrous, GGBS	Compressive strength, flexural strength, water absorption	GGBS = 100% + sodium metasilicate = 11.19%	2019
[93]	FFD / -	Cement, fly ash, W/B, SP	Workability, compressive strength	-	2019
[12]	CCD / MiniTab 17	Limestone powder, fly ash, SP	Workability, compressive strength	LP = 20.1%, PET = 2.4%, SP = 1.16	2019
[94]	CCD / MiniTab 17	W/B ratio, SCM, distribution modulus	Workability, rheology, compressive strength, fracture toughness	-	2020
[69]	- / Design Expert 8	Forta ferro fibre volume, calcium aluminate cement	Compressive strength, tensile strength, volume fraction, desirability	FF fibre = 0.11% for OPC / FF fibre = 0.04% for CAC for the non-acidic state FF fibre = 0.32% for OPC / FF fibre = 0.18% for CAC for the acidic state	2020
[72]	BBD / -	Cement, silica fume, fly ash, quartz powder	Flow diameter, hydration heat, compressive strength (3/28 days)	FA = 27.62%, QP = 14.30%, SF = 0%	2020

Table 2 (continued)

Reference	RSM Design / Software	Factors	Responses	Optimum	Year
[95]	CCD / -	Cement, curing time	Compressive strength	-	2020
[96]	CCD / -	Molarity, binder, sodium silicate/sodium hydroxide ratio	Compressive strength, drying shrinkage	NaOH molarity = 9.892 M, binder amount = 600 kg/m^3, SS/SH ratio = 0.5	2020
[70]	CCD / DX8 Trial	W/C, sodium silicate content, PEG content, PS content	Workability, gel time, bleeding, compressive strength	W/C = 0.9, sodium silicate = 8.7%, PEG = 4%, PS = 1%	2020
[52]	CCD / MiniTab 18	Recycled aggregate, GGBFS, silica fume	Durability, compressive strength	SF = 7.78%, GGBFS = 18.58%, RA = 0%	2021
[97]	CCD / Design Expert 13	W/CM, fly ash/CM, volume percentage	Flowability, bleeding, segregation index, compressive strength	-	2022
[71]	- / MiniTab 19	Binder content (MK or LSP), Alkaline ratio (NNR or NKR)	Compressive strength	(70% MK + sodium silicate/KOH ratio = 2.5) (70% LSP + sodium silicate/KOH ratio = 4.0)	2022
[98]	BBD / -	Calcium formate ratio, W/B ratio, defoaming agent ratio	Compressive strength	Calcium formate content = 0.64%, W/B ratio = 0.21, defoamer content = 0.26%	2022
[67]	CCD / Design Expert 13	UPOFA, silica fume	Compressive strength (28 and 90 days)	37.5% UPOFA + 20% SF	2024
[63]	BBD / Design Expert	GGBS, W/S ratio, activator dosage	Flowability, compressive strength, initial setting time, final setting time	GGBS substitution = 51.39%, W/S = 0.32, activator content = 12.35%	2024
[66]	CCD / Design Expert 13	UPOFA, silica fume	Compressive strength, rapid chloride penetration	30% UPOFA, 20% SF	2024

SuperPlasticizer (SP); Central Composite Design (CCD); Water/Binder (W/B); Box-Behnken Design (BBD); Ordinary Portland Cement (OPC); Silica Fume (SF); Ordinary Portland Cement by ultra-fine Palm Oil Fuel Ash (OPC-UPOFA); by ultra-fine Palm Oil Fuel Ash (DSF-UPOFA); ultra-fine Palm Oil Fuel Ash (UPOFA); High-Range Water-Reducing admixtures (HRWRA); Supplementary cementitious materials (SCM); Fly ash/Binder (FA/B); Nano-Iron oxide to Binder NI/B); Water/Cement (W/C); Face-Centred Central Composite Design (CCF); Full Factorial Design (FFD); Limestone Powder (LP); Polyethylene Terephthalate (PET); Forta-Ferro (FF); Ordinary Portland Cement to Forta-Ferro (OPC/FF); Calcium Aluminate Cement (CAC); Fly Ash (FA); Quartz Powder (QP); Sodium Silicate to Sodium Hydroxide (SS/SH); Polyethylene Glycol (PEG); Polycarboxylate Superplasticizer (PS); Recycled Aggregate (RA); MetaKaolin (MK); LimeStone Powder (LSP); Na_2SiO_3/NaOH ratio (NNR); Na_2SiO_3/KOH ratio (NKR); Not available data (-)

Table 3 Studies on the use of the Response Surface Method (RSM) for waste content optimization in concrete mixes by year of publication

Reference	RSM Design / Software	Factors	Responses	Optimum	Year
[99]	Simplex centroid design / Statistica 6.0	Red clay, granite waste, kaolin waste	Water absorption, shrinkage, modulus of rupture	-	2008
[20]	CCD / Design Expert 10	W/C, crumb rubber replacement	Compressive strength, flexural strength, modulus of elasticity	-	2018
[10]	CCD / Design Expert 6.0.7	Two types of plastic, segregation waste aggregate	Workability, compressive strength	[FA-PWAR] = 0.0% + [FA-PWAI] = 24%	2018
[103]	CCD / Design Expert 11.1.2	Plastic wastewater bottle caps, W/C ratio	Compressive, split tensile, flexural strength	-	2023
[101]	FCCD / Design Expert	Recycled concrete aggregate, cement content	Unconfined compressive strength, flexural strength, elastic modulus, indirect tensile strength	-	2023
[102]	CCD / Design Expert 13	Banana fibre, waste glass powder	Compressive strength (7, 28 and 56 d)	7 days (1% banana fibre, 17.4% cement replacement); 28 days (1.1% banana fibre, 20.8% cement replacement); 56 days (1% banana fibre, 21% cement replacement)	2023
[100]	CCD / -	W/C ratio, residual mortar coefficient	Workability, compressive strength, flexural strength, elastic modulus	w/c ratio = 0.40 + residual mortar coefficient = 1.78	2023

Water/Cement (W/C); Fine Aggregates by plastic waste aggregates regular (FA-PWAR); Fine Aggregates by plastic waste aggregates irregular (FA-PWAI); Not available data (-)

One conclusion following an analysis of some studies was that more than one variable was optimized in the most effective methods, adjusting a high number of factors—more than three [29]. In addition to the careful selection of the variables, defining the levels of each variable was almost equally important, to obtain a valid optimization process; something which may be seen in the investigation of Bayramov et al. [40]. Having previously set the design points of the FFD model that was employed, those authors were able to define an optimum fibre content. Their design points were neither too close nor too distant, both of which may have otherwise prompted less effective model applications.

With regard to the selection of factors for Table 1, mix design optimization mainly included cement content and w/c ratio [41]. It is noteworthy that even minor alterations of those factors can considerably alter the properties of the cementitious blends. Likewise, when a variable selected for variation represents a significant portion of the total constituents within the mixture, as exemplified by aggregate volume, it assumes critical importance in numerous models [41]. A clear example is shown for self-consolidating concrete (SCC) mixes [37], where achieving the required balance between deformation and stability to produce SCC occasionally required a higher cement content and hence the adjustment of the w/c ratio. Therefore, Ghezal et al. [42] introduced a CCD model in which SCC mixes were optimized by limiting the cement and admixture content, resulting in valid models for cement contents ranging from 250 to 400 kg/m^3.

Several cases of CCD model applications were found in which the optimized responses were primarily compressive strength and workability [36], as a balance between both is key for proper use of the resulting mixture. In addition to optimization of the two aforementioned properties, the importance of the mechanical properties of concrete is such that many models are focused on optimizing flexural strength [19] and the permeability coefficient [29].

Li et al. [43] applied RSM to develop an optimization model for recycled aggregate concrete. Their model incorporated compressive strength and the permeability coefficient as responses, with factors including maximum aggregate particle size, w/c ratio, and target porosity, but not the waste content, hence the classification in this group. They sought to optimize the mix performance by adjusting the mix design for certain waste contents, without defining the amounts that might result in the best performance. Figure 6 illustrates, through response surfaces and contour plots, the interaction between factors affecting the compressive strength of RAC. Each model depicts the two optimized factors on the x-axis and y-axis respectively, with the response always represented on the z-axis. Thus, for each pair of interacting factors, a surface is provided displaying the resulting values on the response. In the cases of Fig. 6b, c, the maximum compressive strength value could be identified on both surfaces,

Table 4 Studies on the use of the Response Surface Method (RSM) for SCM and waste content optimization in concrete mixes by year of publication

Reference	RSM Design / Software	Factors	Responses	Optimum	Year
[56]	CCD / -	Filler/cement ratio, fly ash, foam volume	Compressive strength, dry density	49% fly ash as fine aggr. replacement (28 d) 71% fly ash as fine aggr. replacement (90 days)	2006
[107]	- / MiniTab	W/C ratio, residual content (Serie 1) Waste content, fly ash/CM (Serie 2)	Slump, compressive strength (28 and 90 days)	-	2012
[108]	Simplex centroid design / MiniTab 14.20	Portland cement, fly ash, mine flotation	Compressive strength	PC = 5 wt%, FA = 15 wt%, SS = 80 wt%	2013
[13]	CCD / MiniTab	Crumb rubber, metakaolin	Compressive strength, water absorption, unit weight	3.3% replacement of sand with CR + 19.5% replacement of cement with MK	2016
[109]	CCF / Design Expert	Micro-coral sand/cement ratio, coral sand/cement ratio	Compressive strength	Micro coral = 15% + coral sand = 30%	2017
[110]	CCD / Design Expert	W/B, marble powder/cement ratio	Workability, compressive strength	W/C ratio = [0.52—0.55] + M/C ratio = 0.6	2017
[111]	CCD / Design Expert	Alkali content, waste glass powder ratio	Flexural strength, compressive strength	Glass powder = 14.57% + Na_2O = 8.31%	2018
[17]	CCD / Design Expert 10.0.6	Fine aggregates, waste foundry sand, fly ash	Compressive strength	Replacing fine aggregates with WFS = 38% + fly ash = 30%	2019
[105]	CCD / Maple 17	Sisal fibre, activator, curing time	Modulus of elasticity, tenacity	Sisal fibres = 5.15%	2019
[104]	CCD / Design Expert 10	Nano-silica, waste glass powder	Workability, compressive strength, drying shrinkage	Nano-silica fume = [0–5%] + waste glass powder = [0–20%]	2019
[11]	CCRD / -	Aspect ratio, cement5, W/B ratio	Workability, compressive strength, Flexural strength, split tensile strength, water absorption	-	2019
[112]	CCD / Design Expert 12	NPOFA %, POC %	UPV, flexural strength, tensile strength	5.331% NPOFA = 5.331%, POC = 2.408%	2022
[113]	CCD / Design Expert 12	Temperature, heating rate, residence time	Yield, carbon, potassium, silica, oxygen	Conditions (pyrolysis experiments) = 409 °C, 15 °C/min, 120 min	2023
[106]	CCD / Design Expert 13	Laterite aggregates, fly ash, sisal fibres, SP	Compressive strength, split tensile strength, flexural strength	25% Laterite aggregate, 10.52% replacement of fly ash, 1% addition of sisal fibres, 1.48% addition of SP	2024

Water/Cement (W/C); fly ash to cementitious material (fly ash/CM); Portland Cement (PC); Fly Ash (FA); Silica Sand (SS); Crumb Rubber (CR); MetaKaolin (MK); Marble powder to cement (M/C ratio); Water to Binder (W/B); Waste Foundry Sand (WFS); Nano-Palm Oil Fuel Ash (NPOFA); Palm Oil Clinker (POC); Ultrasonic Pulse Velocity (UPV); SuperPlasticizer (SP); Not available data (-)

which occurred when the maximum aggregate particle size was incorporated together with the lowest w/c ratio, and the lowest target porosity in the mixture.

There were few investigations within the group of references reviewed in this section, which were focused on mix-design optimization and that validated their models in subsequent laboratory campaigns with the optimized mix design. Şimşek et al. [33] demonstrated the effectiveness of the method by assessing the response of the model and subsequently its reproduction at an experimental scale, achieving very low standard deviation values (< 0.347). In all cases, the effectiveness of RSM was demonstrated through the ANOVA results, as explained earlier in this review; not only was a relevant R^2 value obtained, which in most cases exceeded 0.90, but it was also essential when verifying that the model formulation corresponded to the experimental reality. In the study of Ghezal et al. [42], validation was particularly crucial when considering compressive strength as the main response where the models for both cement and admixture content adjustment proved valid with correlation coefficient values above 0.96, guaranteeing adequate mechanical behaviour of the mixtures. Once the optimized

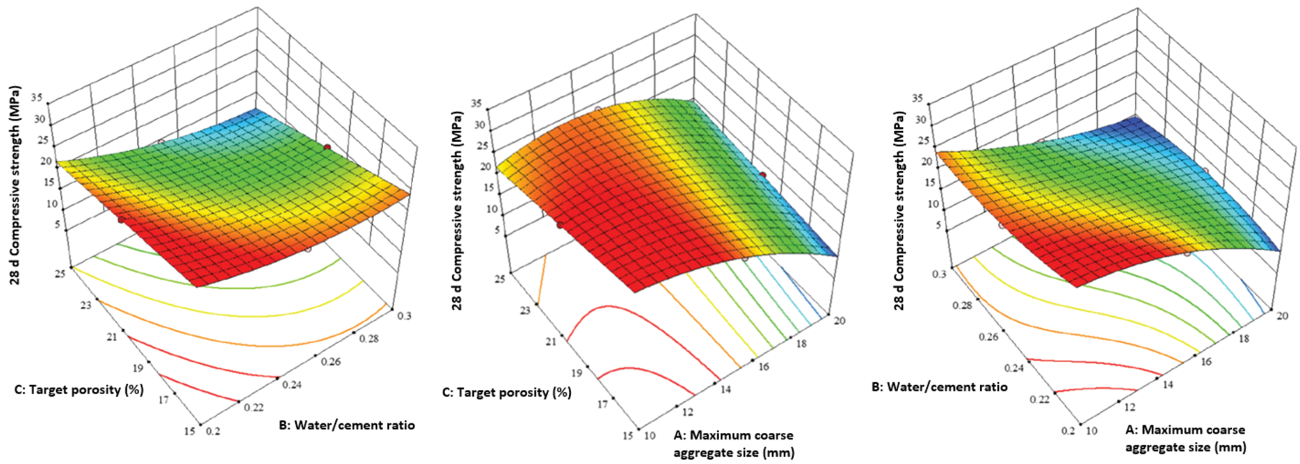

Fig. 6 Response surface for optimization of compressive strength: (**a**) maximum coarse aggregate diameter—w/c ratio interaction; (**b**) maximum coarse aggregate diameter – target porosity interaction; (**c**) w/c ratio—target porosity interaction. Image from Ref. [43]

mix design is achieved, it must be reproduced, for more accurate comparisons between the experimental results and the model. Ahmad et al. [44] meticulously replicated the optimized mixture by finely adjusting the w/c ratio and fine/total aggregate ratio within fixed upper and lower limits, achieving optimal mix designs tailored to various strength targets. That sort of validation practice was only described in a few papers among the group of references analyzed in this section, whose conclusions were usually limited to model effectiveness rather than the optimized mixture itself.

4.2 Optimum SCM content

In recent years, it has become increasingly common in the construction industry to replace a percentage of cement with recycled industrial manufacturing by-products as binders [52]. The use of these materials, known as supplementary cementitious materials (SCMs), not only reduces production costs, but also mitigates CO_2 emissions associated with the clinkering process required for cement production [53]. Whether fly ash, GGBFS, or silica fume, many of the optimization models are focused on optimizing those contents.

Table 2 provides a detailed categorization of the design parameters from a perspective that is focused on the type of SCM used for each mixture. Among the references that were analyzed, the following were the most commonly used binders:

- Fly ash was the most optimized factor among all the SCM that were studied, with 42% of the cases using a CCD model. In the particular investigation conducted by Fauzi et al. [95], the application of the CCD model with the objective of developing a sustainable controlled low-strength material demonstrated that an increase in fly ash/cementitious materials ratio enhanced the plastic properties of the mix. Not only was the CCD model found valid for optimizing fly ash quantities; percentages of that binder ranging between 15–20% of the total cement replacement were determined using the simplex-centroid design method [53]. Furthermore, factorial design established that a quantity of 13.3% was optimal to maximize compressive strength for concrete production with binary blends [54]. Regarding the selected responses, compressive strength was chosen for all those models, either as the sole response or, in cases of multi-objective analysis, it was evaluated usually along with workability [12]. In some other cases, compressive strength was used together with the modulus of elasticity [55] or density in the case of a foamed concrete [56]. ANOVA applied to those models not only demonstrated the suitability of their optimization, but also determined the substitution percentages based on the response to be either maximized or minimized.
- GGBFS, as an optimization factor, was not found in any uniform design strategy. In the literature, models such as CCD [52], BBD [57], face-centred central composite design (FCCD) [58], simplex-centroid design [59], and factorial design [60] were utilized to optimize this SCM. As with fly ash, the amount of binder in the total concrete mix has a major impact on the compressive strength results, which is the fundamental reason why the optimized response of the models is invariably compressive strength [61]. The optimization of more complex models involving independent variables such as the water/binder ratio or superplasticizer entailed the development of more intricate models [62]. Those models consistently proved to be successful at providing valuable insight into the optimization of GGBFS mixes, with R^2 values

exceeding 0.94 [62]. It is important to note that the optimized response significantly influences the efficacy of each model. Specifically, the R2 value for slump optimization surpassed that obtained for compressive strength in this instance. In the absence of experimental validation of the optimal results obtained in each mixture, Mohammed et al. demonstrated the validity of the optimization through replication of the model-derived outcome, endorsing the combination of 100% GGBFS with 11.9% solid sodium metasilicate that provided the highest strength values [58]. In the study from Srinivasa et al. [63], a three-level BBD model was applied with GGBFS as one of the independent variables, represented on the X_1-axis. A depiction of the test points corresponding to the BBD model is illustrated in Fig. 7., with Fig. 7a. showing the coded values and Fig. 7b. showing the corresponding uncoded values for each variable: GGBFS, w/s, and activator (%).

- Silica fume as the primary independent variable was optimized in models that used CCD (58% utilization of the model) [64], and simplex-centroid design [65] strategies, the main responses of which were compressive strength and workability. Aziminezhad et al. [27] determined through a CCD model that silica fume significantly affected the workability of self-consolidating mortar while simultaneously enhancing compressive strength values. Since the study conducted was multi-objective, it was established that, compared to superplasticizer or water added to the mortars, as indicated by contour plots, silica fume was more efficient in improving hardened properties, as indicated in the contour plots. The high influence of the water/binder ratio in all these models, as demonstrated by the corresponding ANOVAs, usually exceeded the water/cement ratio, and was a dominant factor for compressive strength. As with the previous GGBFS optimization models, only the most recent designs were found to achieve the optimal silica fume content for a specific concrete mixture. An example of a mixture categorized as "green" or "sustainable", owing to the partial substitution of cement by other SCM such as recycled aggregate concretes, indicated that incorporating 7.78% silica fume [52] yielded the highest compressive strength values. Conversely, employing two CCD models, Azmi et al. [66] and Alani et al. [67] found that a 20% silica fume content significantly enhanced that property at both 28 and 90 days for green ultra-high strength concrete mixes.

In addition to the three main binder types, there were models with other independent variables such as pulverized fuel ash [68], calcium aluminate silicate [69], sodium silicate content [70], and metakaolin [71]. The response surfaces obtained to optimize the compressive strength of mixes with metakaolin in Ahmad et al. [96] are shown below in Fig. 8. The meta-kaolin content is represented on the *x*-axis, while the *y*-axis is used to depict the values of the Na_2SiO_3/NaOH ratio and Na_2SiO_3/KOH ratio, respectively. Notably, both graphs revealed a significant decline in compressive strength values with increasing meta-kaolin content. Furthermore, the concave curvature suggests that the optimal values of NNR and NKR, in both scenarios, were likely to be situated at the center of the interval.

Clearly, the above models confirm that binders are commonly used in combination with each other when using SCM

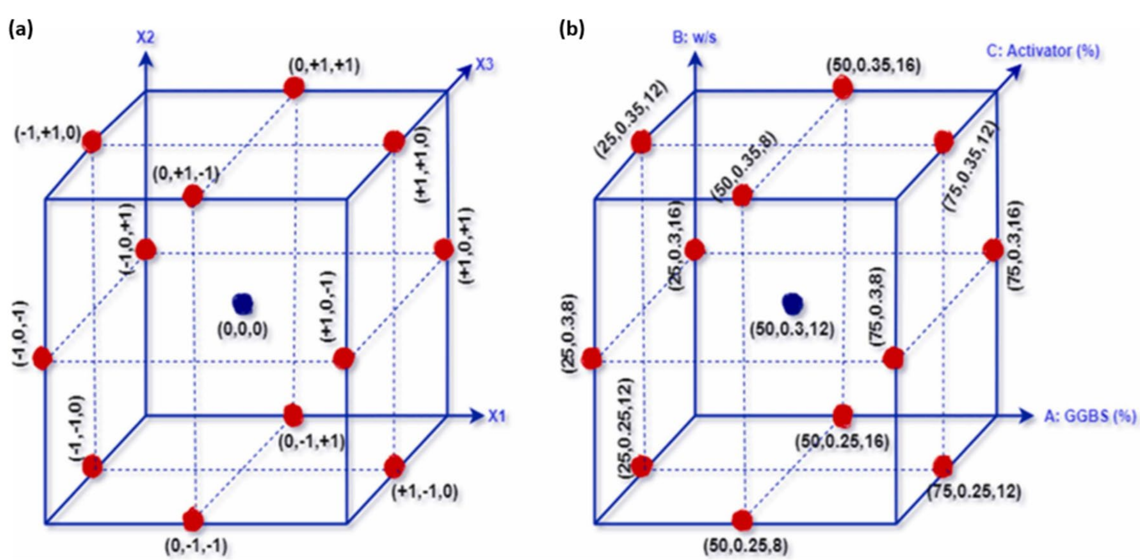

Fig. 7 Three-level Box–Behnken design for one-part geopolymer binder with GGBFS, W/S and activator as independent variables: (**a**) coded values arrangement, (**b**) uncoded values arrangement. Image from Ref. [63]

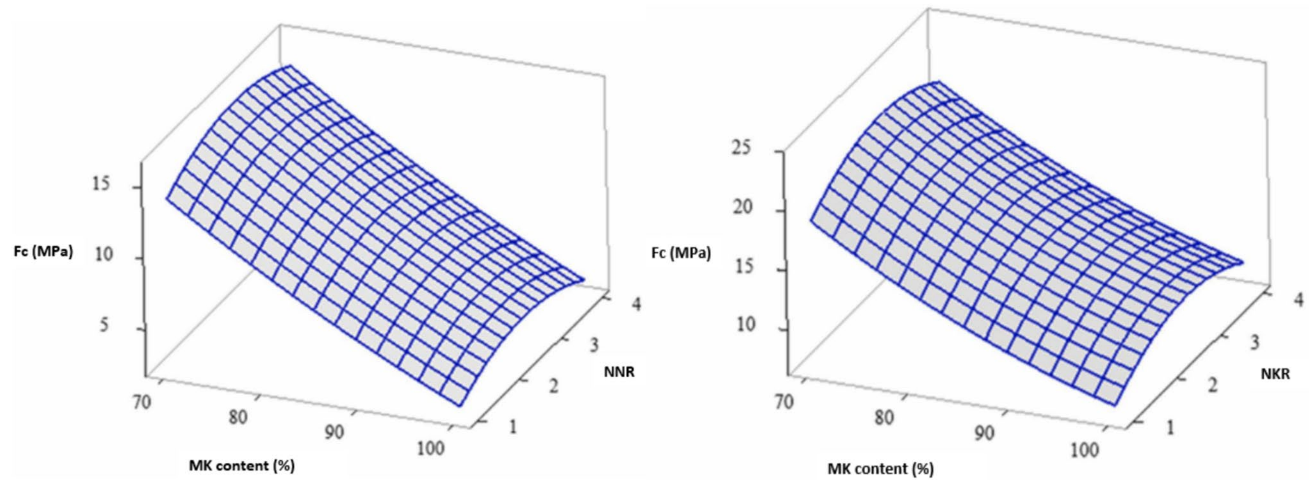

Fig. 8 Response surface for compressive strength (Fc) of meta-kaolin (MK) based mixtures. Image from Ref. [71]

for concrete mixes. There is no evidence that model efficacy is more pronounced with certain types of binders compared to others. It is evident that RSM is an excellent tool for multi-objective analysis when combining various types of SCM, as they all have effects on the mechanical properties of concrete. Despite the fact that the use of ANOVA usually reveals a high degree of correlation between independent variables and responses such as compressive strength, specific models such as the ones developed by Li et al. [72] for optimizing hydration heat, yield stress, and plastic viscosity showed that the adjustment was not statistically significant, as indicated by the p-values > 0.05. A result that emphasizes the intricate variability in model significance across various variables.

4.3 Optimum waste content

Economic advances coupled with demographic growth have resulted in high rates of industrial activity, causing significant environmental issues. First, there is the depletion of natural resources that are essential to the construction industry, and second, there are high levels of waste streams. All those issues form the basis of the papers found in Table 3. After analyzing the models within that group, it was asserted that comprehensive knowledge of the waste to be optimized as part of the mixes is crucial. It posed no problem when conducting the RSM described in Sects. 4.1 and 4.2, as the boundaries within which each of the independent variables was defined could be understood thanks to the extensive previous literature. It highlights that the selection of variables, and their levels is crucial when incorporating waste materials.

Despite the limited availability of studies within this group, a distinct pattern has emerged with regard to the model, which differs little from both groups analyzed in previous sections: CCD remains the most utilized model. Seventy-one percent of the literature analyzed for this section applies this design, with rare exceptions opting for the simplex-centroid design model [99].

Granite waste, crumb rubber, plastic wastewater caps, and banana fibre were among the various types of waste selected as the primary factors, showcasing the diversity inherent in these models. While those factors served as primary variables, the models were always multi-objective, so they were always optimized in conjunction with other factors such as the w/c ratio [100] or cement content [101]. For instance, Mohammed et al. [20] attempted to optimize, "rubbercrete" mixes by simultaneously evaluating the content of crumb rubber along with the w/c ratio; they demonstrated through response surfaces that a high rubber content in that case resulted in a mix that was susceptible to strength loss.

In the pattern of the responses that were evaluated, compressive strength remained the most frequent alongside flexural strength. In most models, the choice of those responses was not based on their effectiveness within the context of a specific set of variables, but instead on an exploration of the properties of the resulting material. In the study of Menezes et al. [99], for example, whose authors proposed the optimization of ceramic-tile waste content, and evaluated its effect on water absorption and shrinkage, the usual RSM responses were not selected for the cementitious mixtures. Thus, setting the extreme values of the batches, based on prior knowledge of the waste, meant that the statistical analyses returned successful models for the investigation.

Defining optimal waste contents, especially when studying novel materials, is a complex task that is reflected in some of the models found in the literature [102]. Aldahdooh et al. successfully optimized cementitious mixtures with a waste that exists in large quantities such as plastic [10]. Given their inherent resistance to degradation, some researchers have also investigated the possibility of introducing plastic bottle caps as a replacement for up to 12% of coarse aggregate [103]. In a novel approach to determine the effectiveness of RSM, they performed the same model using the artificial neural network-Levenberg–Marquardt tool. After developing the models and conducting the corresponding ANOVA, the good performance and the precision of the RSM results were demonstrated through comparisons. Olukayode et al. [102] demonstrated another example of waste recovery in a proposal for an optimal combination of waste glass with banana fibre. With coefficients of determination of 0.97, 0.94, and 0.95 for responses such as compressive strength, the test results were sufficient to establish optimal conditions for the models using RSM.

The following case [100] offered an example of concrete-mix aggregate optimization using gravel and waste rock aggregates. The *w/c* ratio and the residual mortar coefficient (α) were defined as independent variables and the optimization process included, among others, workability, compressive strength, flexural strength, and the modulus of elasticity. The response surfaces for each of the aforementioned responses are depicted in Fig. 9. The RSM model proved to be suitable for predicting both the fresh and the hardened properties of the concrete with a reduced number of tests. Regarding the hardened properties, the response surfaces showed concave curves, contrasting with the curve observed for the single fresh property that was analyzed: slump flow. The difference arose due to the optimization objective of maximizing compressive strength, flexural strength, and the modulus of elasticity. In the case of slump flow, a higher value will not necessarily correlate with improved workability. Therefore, the convex shape of the curve indicated that the optimal point was likely to be found towards the lower end of the curve.

4.4 Optimum combination of SCM and waste content

The distinctive feature underlying the classification of studies listed in Table 4 lies in the overarching goal pursued by the RSM. As reiterated throughout this review, the RSM is used in those studies to minimize the requisite number

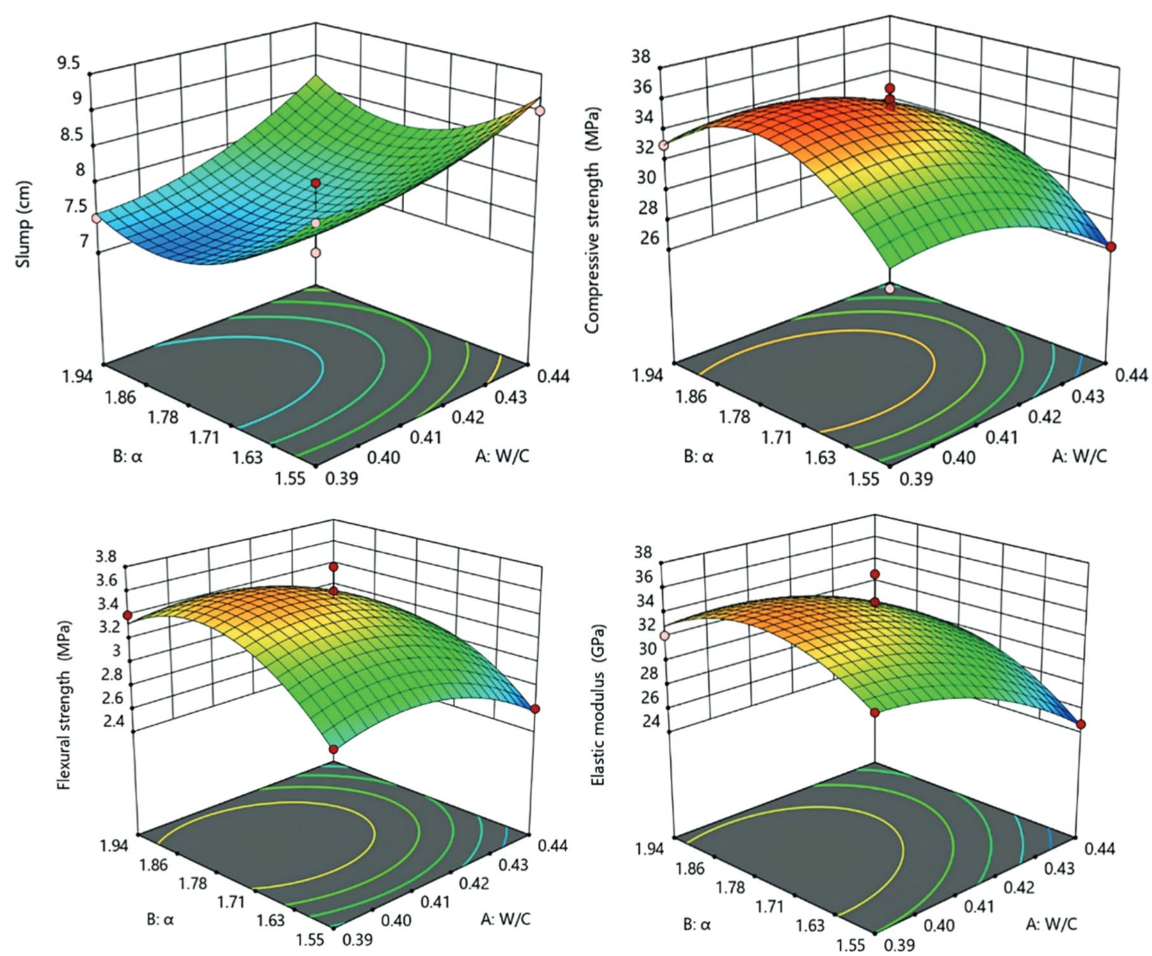

Fig. 9 3D surface graphs for: (**a**) slump, (**b**) compressive strength, (**c**) flexural strength, (**d**) elastic modulus. Image from Ref. [100]

of tests for understanding and enhancing the behaviour of cementitious mixes based on the interplay between their components and properties. Following a comprehensive analysis of around 100 appropriately categorized papers, it became evident that the binders and the waste materials had the most substantial influence on the experimental results. The review was therefore to categorize the models that were focused on optimizing both factors as the main objective.

As for the design strategy, there was no particularity within this group, as the most effective approach remained the CCD (71% utilization), focusing on compressive strength as the primary response. Given that the models classified in this group were after 2012, all of them were capable of defining the optimal contents of both binders and wastes after model validation thanks to more efficient models and software.

Achieving the optimal balance between binder content and its substitute waste content can be complex, necessitating the use of response surface plots for the optimization process. The research by Mosaberpanah et al. [104], for instance, showed a comparison between content A (nano-silica) and content B (waste glass powder) through response surface plots, (Fig. 10.) on two of the most optimized responses of the models (flowability, compressive strength). On the one hand, a higher amount of nano-silica combined with an increased content of waste glass powder in the mixture resulted in an increase in strength at 28 days, leading to a concave surface as shown in Fig. 10a. However, the same trend was not observed for flowability, as a descending trend is evident in Fig. 10b. with the increase in factor A [104]. In another study, Rezaifar et al. [13] developed an additional experimental test for concrete mixes made with crumb rubber and metakaolin, demonstrating a close alignment between the statistical analysis and the optimization results, with a mean error of 3.3%.

Optimization efforts have also been extended to novel waste materials. The paper from da Silva Alves et al. [105], for example, was focused on sisal fibres alongside metakaolin, with a specific focus on evaluating their influence on the modulus of elasticity and the toughness of the concrete mixes. It is noteworthy that the CCD model was initially employed to determine the optimal combination of sodium silicate and sodium hydroxide molarities and, subsequently, another CCD model was utilized to establish the optimum percentage of sisal fibres at 5.15% to maximize the modulus of elasticity. The RSM optimization approach proved to be a superior strategy when selecting four factors to optimize [106], including one binder and one waste product. Design time was reduced with that method, enhancing the functionality of the existing process, reinforcing reliability, and ensuring robustness.

5 Conclusions

The objective of this systematic review has been to analyze studies within the existing literature on the use of RSM for developing cementitious mixtures with optimal quantities of each component, whether they involve traditional raw materials or new blends that incorporate waste materials in their models. Furthermore, all the parameters for the development of the model have been evaluated in order to determine the effectiveness of the methodology. The conclusions drawn from this analysis are presented below:

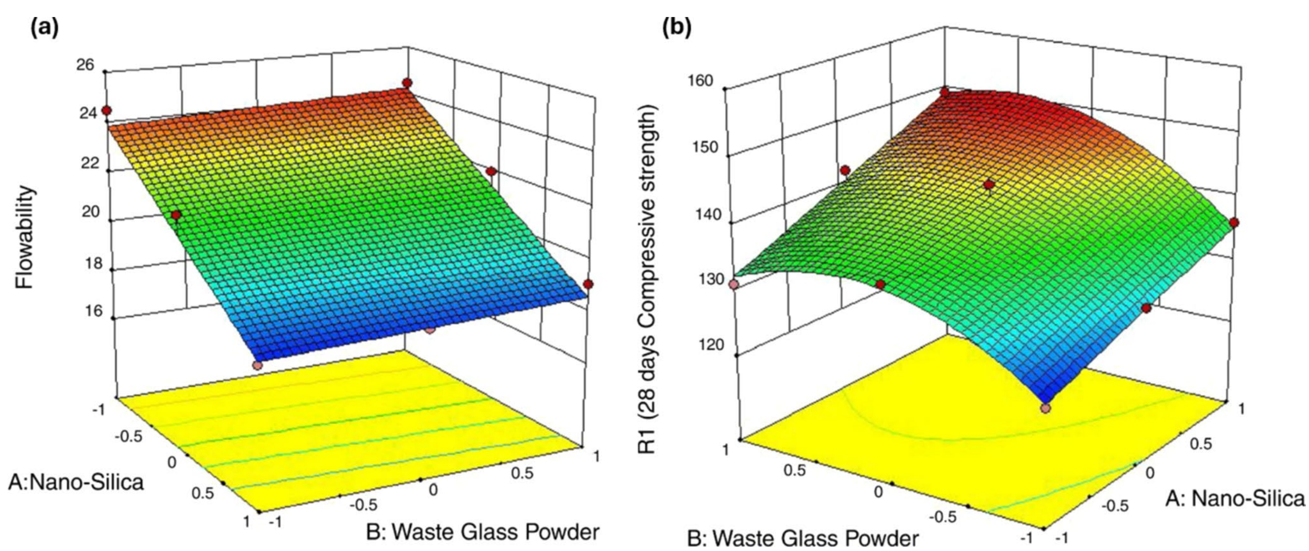

Fig. 10 Response surface for UHPC: **a** flowability, **b** compressive strength. Image from Ref. [104]

(1) The two most commonly used strategies are CCD and BBD, offering different approaches to explore interactions between variables and responses in cementitious mix design. Simplex-centroid design emerges as a particularly effective strategy for the optimization of ternary blends involving three different components, promoting a more sustainable and resource-efficient approach to concrete formulation.
(2) Factors such as cement content and w/c ratio stand out as the most widely utilized variables, playing a key role in determining the mechanical properties of concrete. Compressive strength and workability are among the most frequently employed responses.
(3) During the enhancement of concrete mix design, it is essential to categorize the independent variables based on the desired levels of the response variables and their corresponding levels. Additionally, the choice of those levels, commencing with testing frequencies, should be made appropriately to reduce losses and to align with the concurrency level.
(4) Model validation is crucial for ensuring precision and dependability when depicting the connections between independent variables (factors) and responses. It is crucial to conduct replications using the optimal parameters determined by the models to cultivate credible and dependable models, which serve as the cornerstone of the optimization process.
(5) It is imperative to develop models in which the focal points of optimization are wastes, aiming to transition the concrete industry towards greater sustainability. Further research is required to advance the development of multi-objective models, concurrently aiming to optimize multiple variables.

Through the comprehensive review of more than 100 references, it has been established that RSM offered valuable behavioural models when applied as an optimization technique for cementitious mixtures, with which the relations between variables and responses could be elucidated. That approach has facilitated concrete mix design and has reduced testing requirements. Its simplified trial processes and minimization of raw material consumption are aligned with the commitment of the construction industry to sustainability.

It is imperative to integrate waste materials from industries into these models, to further advance sustainability goals in the construction sector. Therefore, in-depth study of the optimization of cementitious mixtures through RSM is needed as it will likely become even more critical as the industry faces increasing pressures to reduce environmental impact and improve efficiency. It is necessary both to define optimum contents of new residues that can be used in cementitious mixtures, so as to evaluate their validity in this type of mixtures, and to establish optimum contents of wastes that are widely accepted as valid in cementitious mixtures when there are small variations in the mix design of the cementitious mixes or in the characteristics of the residue. In this way, the certainty for the successful use of these residue contents in cementitious mixtures will be increased. As the construction sector continues to prioritize sustainability, RSM will play a key role in achieving these objectives, driving innovation, and setting new standards for eco-friendly practices.

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Data availability The authors declare that the data supporting the findings of this study are available within the paper. The authors are available for further clarifications.

Declarations

Conflict of 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.

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