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Research Article

Fundamental Fresh State Properties of Self-Consolidating Concrete: A Meta-Analysis of Mix Designs

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The study reported in this paper is the first meta-analysis aimed at obtaining statistical models for the fresh state behavior of self-consolidating concrete (SCC) mixes which effectively reproduce the complex relationships between mix design and fresh state performance. A database compiled with data from more than 120 different sources was analyzed. This study proves that SCC fresh state performance is determined by three fundamental, uncorrelated properties: flow time, flow spread, and resistance to segregation, which constitute a robust mathematical framework for the optimization of SCC mixes. The models obtained for these fundamental properties have proved consistent and reproduce very well the general trends and interactions implicit in SCC mix design recommendations, which in effect constitute the mathematical validation of recommendations well sanctioned by practice. It has been proved that, if no supplementary cementitious materials (SCMs) are used, there is a remarkably narrow margin in which the three fundamental properties of fresh SCC mixes can be simultaneously optimized. The most stable mixes were found to be associated with sand-to-coarse aggregate ratios of at least 1.1. The flowability of SCC mixes in terms of both flow times and flow spread can be optimized when the following conditions concur: w/c ratio of 0.45, SCMs content below 100 kg/m^3, and sand content not lower than 750 kg/m^3. Furthermore, it was also proved that, in general, it is best to keep the dosages of superplasticizers (HRWRs) and viscosity-modifying agents (VMAs) below 1.7% and 0.7%, respectively, subject of course to variation across the different types of products available.

1. Introduction

Self-compacting or self-consolidating concrete (SCC) does not need any compaction and instead flows under its own weight, entirely fills the required formwork, and provides a homogeneous material upon placing [1–4]. Chemical admixtures are incorporated to provide higher workability and increased performance [5], namely, superplasticizers or high range water reducers (HRWR) and viscosity modifying agents (VMA). Superplasticizers increase the workability of the mix [6, 7], whilst VMAs are often added to control the risk of segregation or, more generally, the stability of fresh SCC mixes [8]. The most salient differences between SCC and normal vibrated concrete in terms of mix design are lower coarse aggregate contents, increased paste content, lower water/powders ratio, an increased superplasticizer dosage, and the addition of VMAs when necessary [9]. A study summarizing eleven years of case studies where SCC was used [10] also concluded that the maximum aggregate size was between 16 and 20 mm in around 70% of the cases, and that, in most of them, Portland cement was blended with one or more additions or supplementary cementitious materials (SCMs), such as ground-granulated blast slag, silica fume, pulverized fuel ash, or limestone powder.

Three main characteristics are said to define SCC, most usually referred to as filling ability, passing ability, and stability or resistance to segregation [9], and are controlled by the rheology of the fresh mix, with yield stress and plastic viscosity as the governing rheological parameters [2,11–13]. The terms “stability” and “resistance to segregation” are sometimes used indistinctly, although stability is a broader concept than resistance to segregation. Segregation is concerned with concrete remaining homogeneous [9, 14], whilst the term “stability” also includes the resistance to bleeding, surface settlement after casting, and separation of the mix constituents during placement or "dynamic stability" [15].

A variety of different tests have been proposed for characterizing the fresh state performance of SCC mixes. The most widely used tests are slump flow, V-funnel, J-ring, and the L-box [9]. In the slump-flow test, the maximum spread (SF, in mm) is measured along with the time it takes for the mix to reach a spread diameter of 500 mm (T_{500}, in seconds) to evaluate the flowability of the mix. Resistance to segregation can be assessed during the slump-flow test by means of the visual stability index (VSI) [16]. It is based on a visual examination of the mix once it has stopped flowing, and a value between 0 and 3 is assigned (0 for very stable mixes showing no segregation and 3 for cases of severe segregation). In the V-funnel test, the time it takes for the mix to pass through the funnel is measured (T_v, in seconds) as an indirect measure of the mix viscosity: higher T_v times are indicative of higher viscosity values [17]. The passing ability can be assessed by means of the J-ring test, in which the mix passes through a set of bars and the difference in height at both sides is measured. In the L-box test, the blocking ratio (H_2/H_1, nondimensional) is informative of both passing and filling ability [18].

Different mix design methods have been proposed for SCC, which can be grouped in five different categories based on their methodological approach [19]: empirical, based on the compressive strength of concrete, based on the aggregates packing, and based on paste rheology, and statistical methods. Empirical methods were the first to be formulated, and the first was proposed in 1995 by Okamura and Ozawa [3], which keeps the fine and coarse aggregate content constant, so that self-compactibility can be achieved by adjusting only the water/powder ratio and the superplasticizer dosage. Methods based on aggregates packing models follow a more theoretical principle, as they aim at minimizing the voids in the combined aggregates mix, which are to be filled with paste [20, 21]. Compressive strength methods are more recent and determine the proportions of SCC constituents based on compressive strength requirements, although they require adjustments to all parameters in order to finalize the mix design [19]. Paste rheology models, such as the one developed by Saak et al. [22], was built on the assumption that the rheology of the paste affects the flowability and the resistance to segregation of the mix. They postulate that there are minimum yield stress and viscosity requirements in order to avoid segregation. These models can help to reduce the amount of trial mixes required to adjust the mix proportioning and provide a way to increase the quality control of the SCC [19]. Statistical methods are based on the application of multilinear regression and other statistical techniques to the results obtained from testing different SCC mixes, in order to derive equations that relate the parameters obtained from fresh and hardened state tests to the mix proportions and the type of constituents used [23, 24].

Significant efforts have been made to try and rationalize the SCC proportioning process based on the application of statistical tools, mostly by fitting descriptive equations to a set of experimental results obtained from different fresh state tests [23–26]. In most of these studies, the equations reported fitted very well the experimental results they were based upon, yielding extremely high R^2 values. However, descriptive equations with very high R^2 values must be approached with caution, for a number of reasons. Firstly, models built on data obtained from 20 to 30 mix designs are based on sample sizes that, in the context of multivariate statistics, are generally regarded as small [27, 28]. Secondly, there is the issue of overdetermination or overfitting: when statistical models are formulated in an effort to obtain an almost perfect fit with observations, they tend to have limited general validity [29]. Statistical models which have a high level of accuracy in terms of goodness of fit are usually the least robust when it comes to prediction and optimization, which is commonly known as the "accuracy paradox" in data mining and machine learning [30, 31]. In contrast, models derived from the analysis of a broader range of data collected from different sources are less precise from a purely predictive point of view (i.e. lower R^2 values) but are often substantially more robust in representing general trends and complex interactions, thus providing a more stable framework for optimization. To date, no research concerning SCC has been undertaken from this perspective. The study reported in this paper is the first of its kind concerning SCC, and it aimed at obtaining statistical models for the fresh state behavior of SCC which do not necessarily produce highly accurate predictions but rather are effective in reproducing the relationships between any SCC mix design and its fresh state performance and therefore have general validity for use in the automated optimization of SCC mixes.

2. Methodology

A meta-analysis is a type of analysis that involves collecting experimental results from multiple different studies and aggregating them to form a larger set of results [32]. This way, the variability that exists amongst SCC mixes produced by different people, using different materials and equipment, following different mixing regimes, and under different conditions, is embedded in the database used for the analysis. After adequately treating and cleaning the database, data mining techniques, namely, principal component analysis (PCA) and multiple linear regression [33–35], were applied to extract meaningful information from this variability. An overview of the different stages of this study is shown in Figure 1.

2.1. Data Collection. For this research, data were collected from previous studies concerned with SCC. The main challenges to address when compiling the database were selecting what studies could be used so that the compiled database was sufficiently representative and treating the information that is sometimes incomplete [36]. The size of the database (sample size or number of cases) was also carefully considered. In multivariate statistics, sample sizes of less than 30 cases are generally considered insufficient, but excessively large samples can also cause problems as sample sizes over 1000 tend to make tests of statistical significance too sensitive, which causes most relationships to be

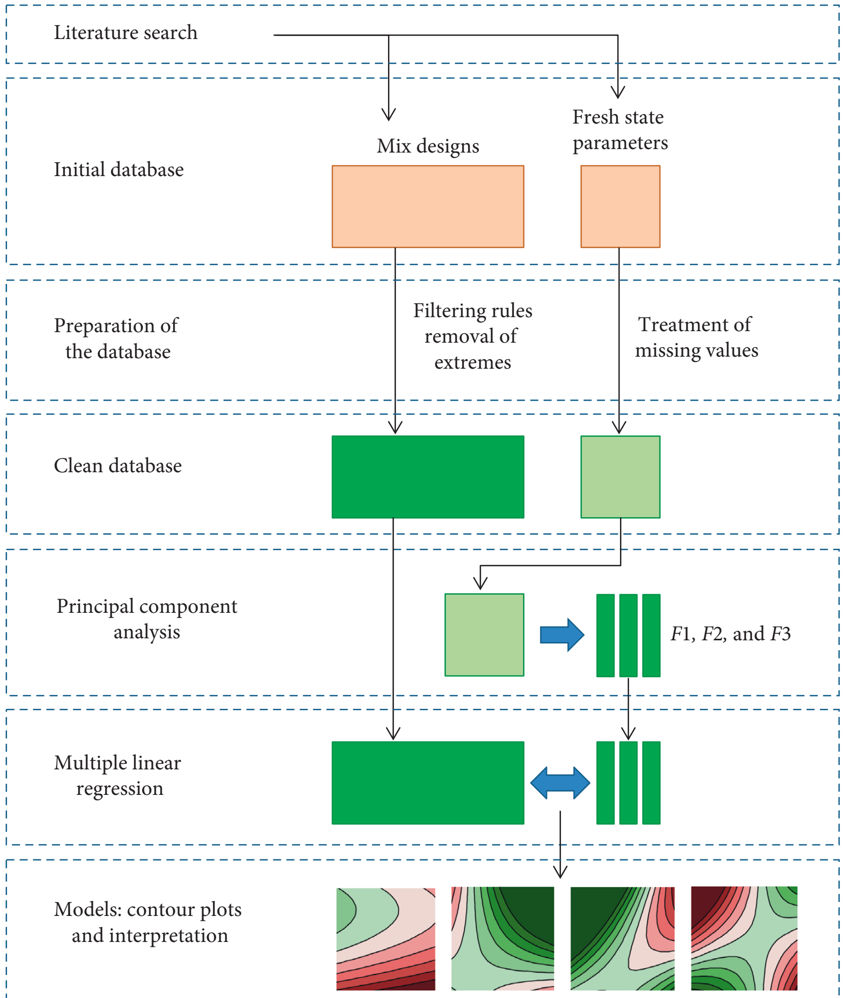

Figure 1: Overview of the methodology followed in this study.

statistically significant when in reality they are not necessarily so [28]. Therefore, it was established that the size of the database had to be in the range of 30 to 1000 cases.

2.2. Principal Component Analysis (PCA). Each individual datum or case in the database consisted of information regarding the mix constituents and their relative proportions (mix design parameters) and the results from different fresh state tests (fresh state parameters). Fresh state parameters are not independent variables. For example, the T_v time obtained from the V-funnel test and the T_{500} time obtained from the slump-flow test are markedly correlated with one another. When two or more variables that describe the same phenomena are highly correlated, they effectively constitute indirect measures of the same fundamental property or latent variable [37]. It is possible to group such variables in a reduced set of uncorrelated variables or factors, which compress the original information and eliminate the difficulties associated with multicollinearity [28, 38]. In this study, principal component analysis (PCA) was applied to the fresh state parameters to extract three factors, after centering and scaling all parameters to unit variance, and a Varimax rotation was applied [37, 39].

2.3. Multiple Linear Regression. Multiple linear regression was used for modelling the relationships between the mix design parameters (predictors) and each of the three factors derived from the PCA representing the fresh state performance of SCC mixes (responses). Initial models that included all pairwise interactions between the mix design parameters were considered, and stepwise regression algorithms [33] were applied to these initial models in order to detect and discard any terms and interactions that were not statistically significant. The resulting models were then described and discussed based on their visualization by means of contour plots, in order to verify that they were consistent with SCC mix design recommendations [9], which in effect constitutes the mathematical validation of recommendations well sanctioned by practice.

3. Construction and Preparation of the Database

The database prepared for this study consisted of information extracted from 124 different papers published between 2001 and 2016 and in total comprised 652 SCC mixes.

The main source of the data was http://www.sciencedirect.com with the search terms being "self-compacting concrete" and "self-consolidating concrete." The complete list of sources from which the database was compiled is given in the Supplementary Material File that accompanies this paper.

3.1. Variables in the Database. The mix design parameters included in the database were the relative amounts, in kg/m^3, of water, cement, limestone powder, fly ash, silica fume, slag, sand, coarse aggregate, superplasticizer or high-range water reducer (HRWR), and viscosity-modifying admixture (VMA) and the maximum aggregate size, in mm. Some of these parameters, namely, limestone powder, fly ash, silica fume, and slag, were zero in a high percentage of cases. Having so many variables that follow highly skewed distributions would have compromised the robustness of the regression models, and therefore, a transformation of these variables was necessary before proceeding with the analysis. It was decided to group them all in one single parameter, supplementary cementitious materials (SCMs), which corresponded to the total amount of powders other than cement, instead of maintaining them as separate variables. This simplification was a necessary compromise, but the grouping of variables has proven a simple and effective approach to handle the problems associated with highly skewed datasets [40].

The fresh state parameters initially included in the database were from the slump-flow test, the maximum spread (SF, in mm), the T_{500} time (in seconds), and the visual stability index (VSI, ranging between 0 and 3); from the V-funnel test, the T_v time (in seconds); from the L-Box test, the ratio H_2/H_1 (nondimensional); and from the J-ring test, the maximum spread (SF$_J$, in mm) and the passing ability index (PJ, nondimensional). The information contained in the database is summarized in Table 1 (mix design parameters) and Table 2 (fresh state parameters). In both tables, the minimum, maximum, and average values are shown for all parameters, after the database was cleaned and treated as described in the following section.

3.2. Cleaning of the Database and Treatment of Missing Data. After a preliminary examination of the original database, it was concluded that some extreme cases had to be removed to ensure that the database remained sufficiently representative of the wide range of SCC mixes most commonly used in practice. The database was cleaned in a systematic way to avoid the introduction of unconscious bias: for all parameters, the average (m) and standard deviation (s) were calculated, and the values outside the range between $m - 2s$ and $m + 2s$ were considered outliers [41]. This resulted in the following "filtering" rules, and those cases that did not satisfy all of them were discarded:

(i) Water/binder ratio between 0.25 and 0.65

(ii) Total binder content between 300 and 650 kg/m^3

(iii) Cement content between 150 and 550 kg/m^3

(iv) Coarse aggregate between 400 kg/m^3 and 1100 kg/m^3

(v) Total aggregates content between 1250 kg/m^3 and 2050 kg/m^3

Table 1: Mix design parameters after cleaning the database.

Variables	Minimum	Maximum	Average
Cement (kg/m^3)	180	500	367
SCMs (kg/m^3)	58	378	120
Water (kg/m^3)	126	265	190
Fine aggregate (kg/m^3)	392	1135	904
Coarse aggregate (kg/m^3)	420	1187	705
Maximum aggregate size (mm)	8	20	16
HRWR (kg/m^3)	0.8	13	5
VMA (kg/m^3)	0	6	0.2

Table 2: Fresh state parameters after randomized removal of incomplete cases.

Variables	Minimum	Maximum	Average	Missing (%)
SF (mm)	565	830	686	0
T_{500} (s)	0.5	7	2.6	25
T_V (s)	1.2	23	7.8	28
H_2/H_1	0.3	1	0.85	26
VSI	0	2	0.5	25

Table 3: Factors extracted by PCA of the fresh state parameters.

Fresh state parameters	$F1$	$F2$	$F3$
SF (mm)	0.075	0.862	−0.153
T_{500} (s)	0.821	−0.103	−0.006
T_V (s)	0.854	0.008	−0.038
$(H_2/H_1)^{-1}$	0.197	−0.784	−0.214
VSI	0.022	−0.022	−0.981
Explained variance	32.2%	24.8%	20.1%

It was also necessary to treat those cases where the information was incomplete, since not all sources reported values for all fresh state parameters. The removal of all cases with partially missing data was not a viable option as it would have negatively affected the statistical power of the analysis, but the fresh state parameters from the J-ring test could not be kept in the analysis because their percentages of missingness were very high (86%). Data mining techniques for the treatment of missing data, such as multiple imputation, could be applied to variables with a missingness percentage of up to 30% [28, 42]. Since the percentage of missing values was higher than that for all fresh state parameters initially considered, it was necessary to remove some of the incomplete cases in the database to reduce the percentage of missingness prior to the multiple imputation process. It was decided to remove half of the cases with missing data following an automated, fully randomized process. Table 2 shows the final percentage of missingness, together with the minimum, maximum, and average values for each of the fresh state parameters. Multiple imputation was then applied to complete the missing data, performing a regression imputation based on the predictive mean matching algorithm, where missing values were estimated based on the relationships amongst the different variables in

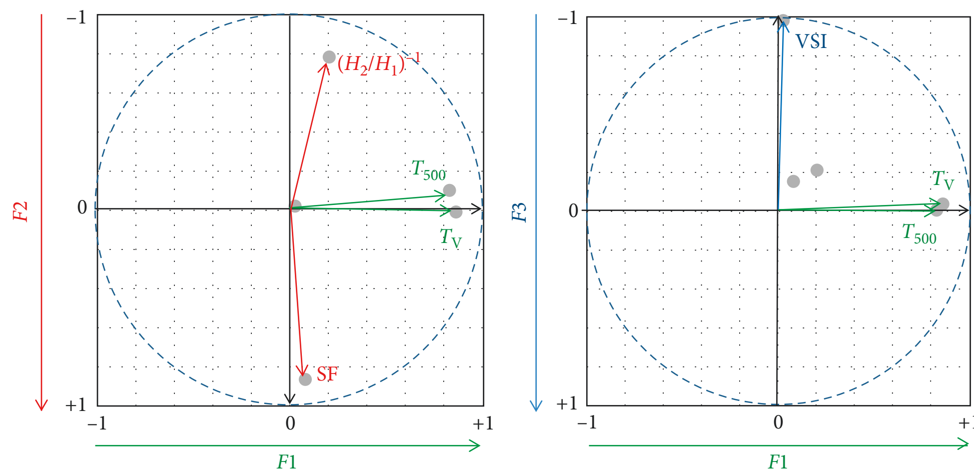

Figure 2: Biplots resulting from the principal component analysis (PCA).

the dataset [43]. This method was chosen because it successfully handles variables inside predefined boundaries, such as the L-box H_2/H_1 ratio (between 0 and 1) and the VSI (between 0 and 3).

4. Factor Analysis and Modelling

4.1. Principal Component Analysis of Fresh SCC Properties. As a result of the PCA on the fresh state parameters, three factors referred to as $F1$, $F2$, and $F3$ were obtained. Each of these factors was a linear combination of the original variables, centered and scaled to unit variance, where the coefficients that multiply each fresh state parameter are known as loadings and have absolute values between 0 and 1.

The loadings obtained are shown in Table 3 and give a clear indication of the physical interpretation of $F1$, $F2$, and $F3$. The variables with the highest loadings on $F1$ were T_{500} from the slump-flow test and T_v from the V-funnel test, and therefore, $F1$ directly represents the flow times. On the contrary, $F2$ was mostly determined by the spread as measured in the slump-flow test and the L-box ratio, and therefore, it can be said to represent the spread of the flow. $F3$ was clearly determined by the VSI, and therefore, it represents the resistance to segregation. Bearing in mind that these three factors are, by the very nature of PCA, completely uncorrelated, it follows that these loadings mathematically proved that there are three fundamental properties describing the performance of fresh SCC mixes: the flow time, the flow spread, and the resistance to segregation, and that they are uncorrelated to one another.

This separation of the original fresh state parameters into three different factors derived by PCA is shown graphically in Figure 2, where the loadings are projected unto two biplots: one where the axes correspond to $F1$ and $F2$, and one where the axes correspond to $F2$ and $F3$.

Table 3 shows the percentage of variance explained by each of these three factors, referred to the total variance in the dataset formed by all the values of fresh state parameters. Added together, the total explained variance was 77%, which was high enough to conclude that $F1$, $F2$, and $F3$ adequately reproduce the information in the database [44].

Table 4: Summary of the models developed: statistical tests.

Model	R-squared (goodness-of-fit)	Overall significance F-test: p value	Lack-of-fit test: p value
$F1$	0.61	<0.0001	0.35
$F2$	0.48	<0.0001	0.73
$F3$	0.65	<0.0001	0.31

4.2. Multiple Linear Regression Models. The final regression models obtained for the relationships between $F1$, $F2$, and $F3$ (responses) and the mix design parameters (predictors) are summarized in Tables 4 and 5. The terms that were found to be statistically significant, as well as the fitted coefficients multiplying each of these terms in the regression models, are shown in Table 5.

The three models were checked to ensure that the assumptions of normally distributed residuals, homoscedasticity, and no multicollinearity were satisfied [28]. Table 4 shows the outcomes of the statistical tests corresponding to the aforementioned diagnostics. The F-test of overall significance yielded p values lower than 0.05 for the three models, confirming that the relationships between responses and predictors were statistically significant. Furthermore, the corresponding lack-of-fit tests [45] yielded p values significantly higher than 0.05, thus confirming that no alternative models could better reproduce the information in the database.

5. Interpretation and Discussion of the Models

The models obtained for $F1$, $F2$, and $F3$ were visually examined by means of contour plots, where average values were plotted against the mix design parameters. Given the multivariate nature of the models developed, it was impossible to visualize at the same time the trend followed by any of these factors with respect to all mix design parameters. In consequence, the contour plots in Figures 3–8 are

Table 5: Summary of the models developed: statistically significant terms and fitted coefficients.

F1		F2		F3	
Term	($\times 10^{-3}$)	Term	($\times 10^{-3}$)	Term	($\times 10^{-3}$)
(Constant)	−11660.00	(Constant)	7000.00	(Constant)	−4600.00
HRWR	863.00	HRWR	1060.00	MAS	455.00
VMA^2	−44.20	SCM	40.40	MAS^2	−13.56
Cement	34.27	Sand	−18.92	Coarse VMA	3.51
Coarse	10.62	HRWR^2	−18.25	Sand VMA	−2.44
Water HRWR	1.38	Cement VMA	11.91	Water HRWR	2.32
HRWR SCM	−0.65	Coarse VMA	−6.34	Sand HRWR	−0.48
Cement HRWR	−0.62	MAS^2	4.92	Water^2	−0.29
Cement MAS	0.60	Water HRWR	−2.71	Water cement	0.25
SCM MAS	0.60	HRWR SCM	1.02	Water SCM	0.24
Sand HRWR	−0.57	Coarse HRWR	−0.43	Cement SCM	0.10
Coarse HRWR	−0.43	Water cement	−0.24	Sand SCM	−0.07
Coarse MAS	−0.21	Water SCM	−0.18	SCM^2	0.05
Sand MAS	−0.12	Coarse MAS	−0.18	Coarse SCM	−0.05
Cement^2	−0.04	Water^2	0.13	Cement coarse	−0.04
SCM^2	0.03	Water sand	0.06	Sand cement	−0.03
Water coarse	−0.02	Cement sand	0.04	Coarse^2	0.01
Cement coarse	−0.01	Coarse SCM	−0.02	Sand^2	0.01
Coarse SCM	−0.01	Cement coarse	0.01	Sand coarse	0.01
Sand coarse	0.01	Sand^2	−0.01		

All variables are in kg/m^3, except MAS, which is the maximum aggregate size, in mm.

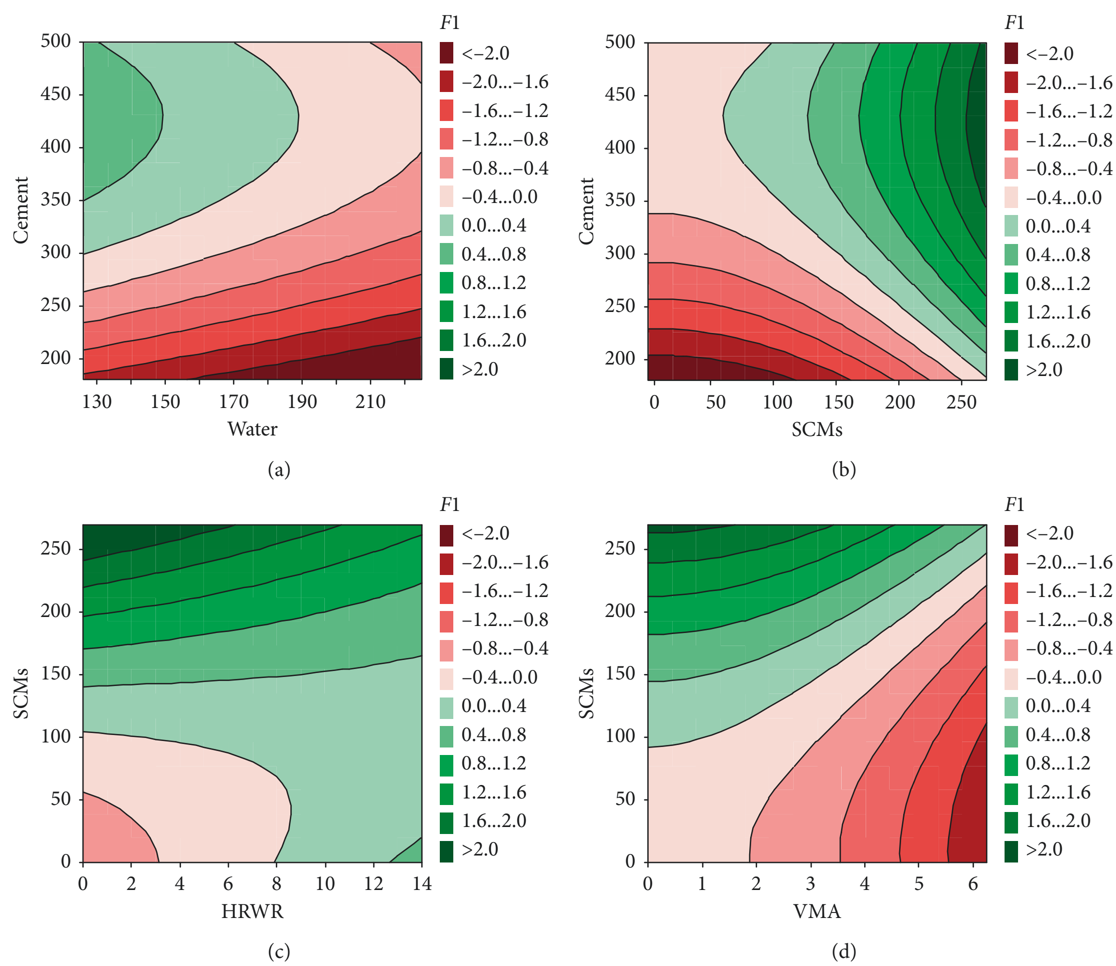

Figure 3: Effect of the paste composition on the quickness of the flow ($F1$).

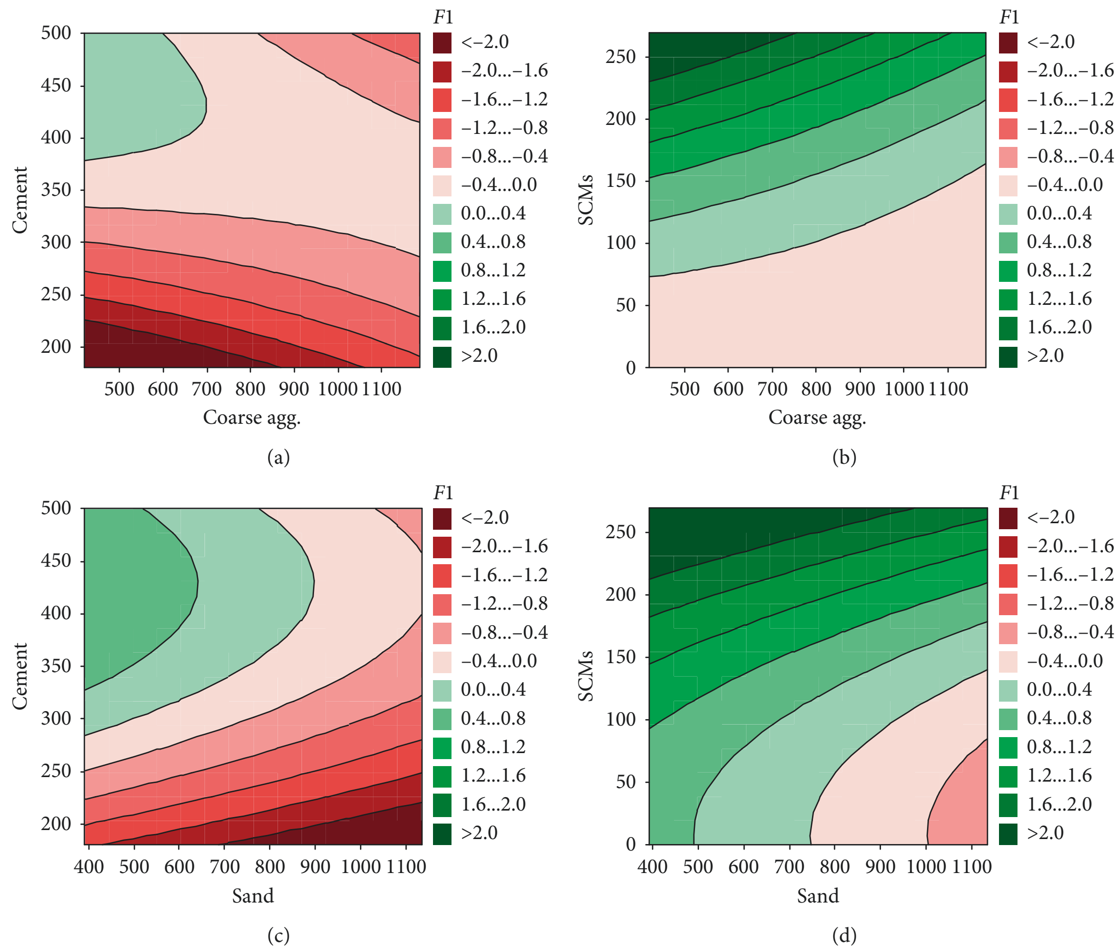

Figure 4: Effect of the amount of aggregates and powders on the quickness of the flow ($F1$).

partial representations of the models developed and cannot be regarded in isolation. Their detailed discussion confirmed that the models obtained were consistent and, in fact, reproduced very well the general trends and interactions implicit in SCC mix design recommendations and in previous literature.

5.1. Factor F1, or Flow Time. Figure 3 shows the flow time, as represented by factor $F1$, with respect to different variables related to the composition of the paste. The line that corresponds to $F1 = 0$ is representative of the average flowability of the mixes in the database and separates better-than-average (in red) and worse-than-average (in green) mixes in terms of their flowability.

Figure 3(a) shows that increasing the water content reduces $F1$, that is, the flow times, and is therefore consistent with the fact that higher water contents are generally associated with higher flowability. More interestingly, it is observed that a water content of 190 kg/m^3 proves sufficient to keep the flow times low, irrespective of the cement content, and in consequence, higher water contents would not be justified on the sole grounds of improving flowability. For that particular water content, an average flowability is obtained with a cement content of 425 kg/m^3, corresponding to a w/c ratio of 0.447. For water contents below 190 kg/m^3, the maximum cement contents and the corresponding w/c ratios to ensure an average flowability ($F1 = 0$) can be obtained. In general, to achieve better-than-average flowability, there is a lower limit to the w/c ratio, which is between 0.44 and 0.48 depending on the cement content.

Figure 3(b) shows that the addition of SCMs tends to increase the flow times, as they tend to adsorb additional water due to their small particle size and high specific surface, although there is of course significant variation amongst different SCMs. However, Figure 3(b) shows that relatively low dosages of SCMs are compatible with good levels of flowability. When the cement content is 425 kg/m^3, the incorporation of SCMs in dosages not higher than 60 kg/m^3 does not have a noticeable effect on flowability. For cement contents lower than 425 kg/m^3, higher dosages of SCMs can be introduced without being detrimental to flowability. Considering both Figures 3(a) and 3(b), it can be concluded that the addition of SCMs in dosages of up to 100 kg/m^3, when the cement content is between 350 and 500 kg/m^3, is generally compatible with better-than-average flowability.

The dosage of SCMs also influences the effectiveness of chemical admixtures, as shown in Figures 3(c) and 3(d), although there is important variation across different

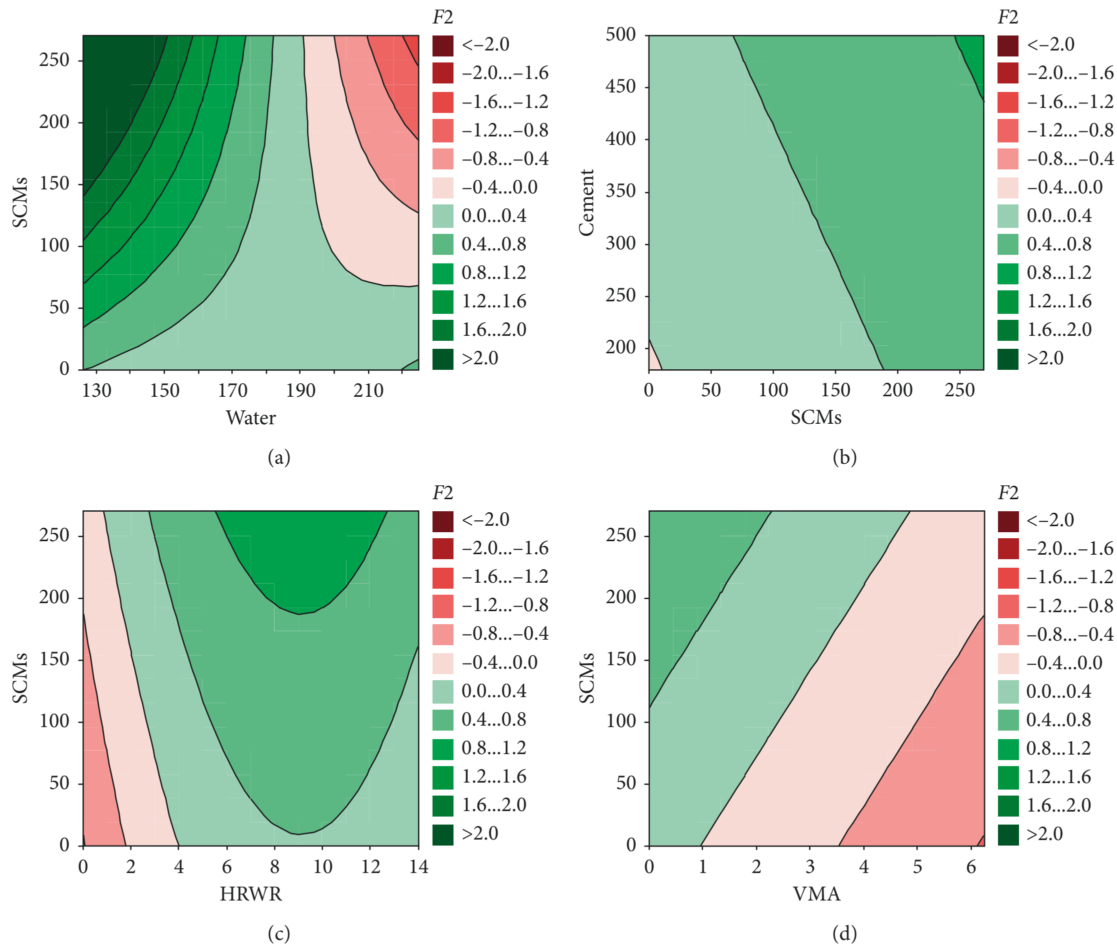

Figure 5: Effect of the paste composition on the flow spread (*F*2).

HRWRs and VMAs depending on their formulation. Figure 3(c) shows that, when the SCMs content is below 100 kg/m^3, good flowability can be achieved using no more than 8 kg/m^3 of HRWR, which means that in general there is no need to dose HRWR beyond 1.6% over weight of cement. Figure 3(d) shows that, as long as the SCMs content is limited to 100 kg/m^3, VMA is not necessary to achieve better-than-average flowability. For SCMs contents higher than 100 kg/m^3, the required VMA content to maintain flowability increases linearly.

In summary, the contour plots in Figure 3 prove that, to attain good flowability, the following recommendations are valid in general: (i) there is no need to increase water content beyond 190 kg/m^3; (ii) for cement contents between 350 kg/m^3 and 500 kg/m^3, the dosage of SCMs should not be higher than 100 kg/m^3; (iii) HRWR dosages below 1.6% over weight of cement should suffice; and (iv) when SCMs are added above 100 kg/m^3, the use of VMA is necessary.

The contour plots in Figure 4 complement those in Figure 3 by incorporating the effect that the relative amounts of sand and coarse aggregate have on flowability. Figure 4(a) shows that, for cement contents between 400 kg/m^3 and 500 kg/m^3, good flowability is associated with coarse aggregate contents above 600 kg/m^3 or 700 kg/m^3, depending on the cement content. When the cement content is 425 kg/m^3, at least 700 kg/m^3 of coarse aggregates are necessary to keep the flow times low. On the contrary, when the cement content is not higher than 375 kg/m^3, variations in the coarse aggregate content are not decisive to controlling flowability. When powders other than cement are present in the mix, Figure 4(a) must be interpreted together with Figure 4(b), which shows that the impact of coarse aggregate content on flow times gains significance when the SCMs content is increased. When SCMs are added at 100 kg/m^3, better-than-average flowability requires coarse aggregate contents higher than 800 kg/m^3. However, a wider range of coarse aggregate contents is compatible with good flowability when the SCMs content is less than 60 kg/m^3. In summary, Figures 4(a) and 4(b) together show that the coarse aggregate content is not key to controlling flowability when the relative amounts of cement and SCMs are below 375 kg/m^3 and 60 kg/m^3, respectively.

Concerning the amount of sand, Figure 4(c) shows that better-than-average flowability generally requires sand contents above a certain minimum, which is 750 kg/m^3 when the cement content is in the region of 350 kg/m^3 but increases to 900 kg/m^3 for higher cement contents. However, when powders other than cement are added to the mix, Figure 4(d) shows that the minimum sand content required to maintain good flowability increases beyond 750 kg/m^3. In

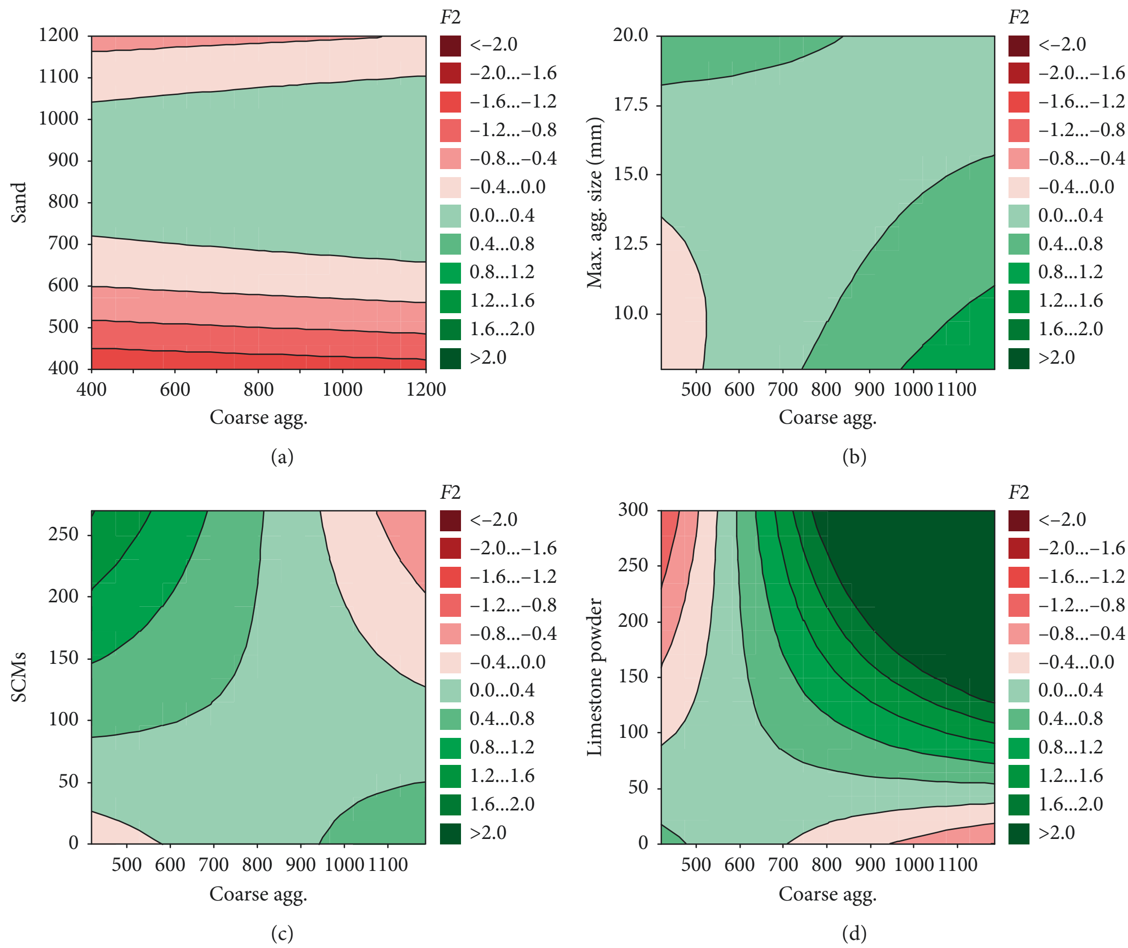

Figure 6: Effect of the aggregates and powders on the flow spread ($F2$).

particular, if SCMs are incorporated at 100 kg/m^3, the minimum sand content required to keep the flow times low is 900 kg/m^3.

In summary, the contour plots in Figure 4 prove that, to optimize flowability, the following recommendations are generally valid: (i) sand should not be proportioned below 750 kg/m^3; (ii) for cement contents in the region of 425 kg/m^3, the minimum sand and coarse aggregate contents are 900 kg/m^3 and 700 kg/m^3, respectively, which corresponds to a total of 1600 kg/m^3; and (iii) when up to 100 kg/m^3 of SCMs are added, the minimum sand and coarse aggregate contents required are 900 kg/m^3 and 800 kg/m^3, respectively, which corresponds to a total aggregates content of 1700 kg/m^3. This last combination is the best as a general recommendation, since it is the most likely to yield better-than-average flowability for cement contents between 350 and 550 kg/m^3 and SCMs contents up to 100 kg/m^3.

5.2. Factor F2, or Spread of the Flow. The contour plots for the flow spread, as represented by factor $F2$, in relation to the composition of the paste, are given in Figure 5, where the line $F2 = 0$ separates the regions corresponding to high spread mixes (in green) and low spread mixes (in red). Figure 5(a) shows that better-than-average flow spread levels are associated with water contents below 190 kg/m^3 as long as SCMs are not added in excess of 100 kg/m^3. Increasing the SCMs content can improve the spread of the flow, but only when the water content is low. In fact, the addition of SCMs at 100 kg/m^3 only has a noticeable effect on flow spread when the water content is not higher than 150 kg/m^3.

Figure 5(b) shows that, in general, variations in the cement content do not have an important effect on the flow spread. However, increasing the cement content above 425 kg/m^3 can slightly improve the flow spread when SCMs are added at relatively high dosages, in the region of 100 kg/m^3. The effect of HRWR dosage, on the contrary, is of more significance. Figure 5(c) shows that, for SCMs contents below 100 kg/m^3, there is no need to increase the HRWR dosage beyond 6–8 kg/m^3 to obtain better-than-average flow spread levels, which is consistent with Figure 3(c). That corresponds to an average HRWR dosage of 1.7% over the weight of cement. This is consistent with the definition of the optimal dose or saturation point of superplasticizers, which is usually between 1.5% and 2% [46], and therefore, the models obtained for $F1$ and $F2$ prove that, in order to optimize both flow times and the flow spread of SCC mixes, the use of HRWRs beyond their saturation points is very rarely justified. Concerning VMA, Figure 5(d) shows that

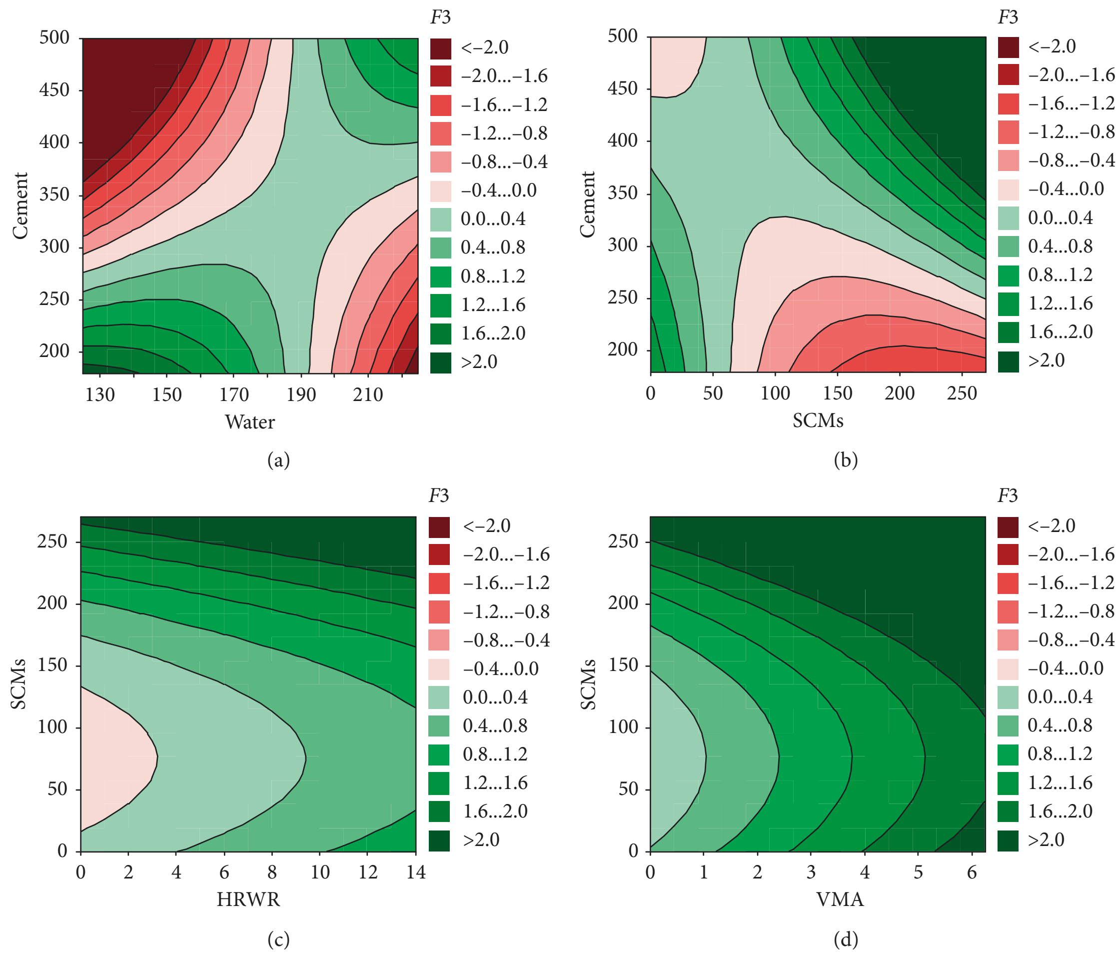

Figure 7: Stability of the fresh mix with respect to changes in paste composition (*F*3).

the flow spread can be negatively affected if the VMA dosage is higher than 1 kg/m^3 in the absence of SCMs, or higher than 2.5 kg/m^3 when the SCMs content is 100 kg/m^3 (0.3% and 0.7% by weight of cement, respectively). In summary, this meta-analysis proves that, generally, the maximum dosage for HRWRs and VMAs is 1.7% and 0.7% by weight of cement, respectively, subject of course to variation across the different types of products available.

Figure 6 shows the effect of the aggregates mix on the flow spread. In general, changes in the coarse aggregate content do not make a significant difference in terms of flow spread as long as the sand content is kept between 700 and 1000 kg/m^3, as can be observed in Figure 6(a). A reduction in maximum aggregate size can slightly improve the flow spread, as shown in Figure 6(b), but only when the coarse aggregate content is 900 kg/m^3 or higher.

As already discussed in relation to Figure 5, increasing the SCMs content has generally a positive effect on the spread of the flow, particularly for low water contents. Figure 6(c) shows that the effect of the addition of up to 100 kg/m^3 of SCMs on flow spread is not sensitive to changes in the coarse aggregate content. However, the effect of limestone powder is of particular relevance, as observed in Figure 6(d), which shows that optimal levels of flow spread were generally associated with limestone powder contents of at least 50 kg/m^3.

5.3. Factor F3, or Segregation Resistance. The contour plots for the stability against segregation, as represented by factor *F*3, in relation to the composition of the paste, are presented in Figure 7.

Figure 7(a) shows that, for cement contents above 350 kg/m^3, adequate stability is associated with water contents not lower than 180 kg/m^3, and that the segregation resistance of the mix can be improved by increasing both. However, it has been established in previous sections that water contents of 190–200 kg/m^3 are generally inadequate from the point of view of optimizing the flow spread. Therefore, by adjusting the water and cement contents only, there is only a narrow margin where the three factors *F*1, *F*2, and *F*3 can be all optimized. This is in agreement with the fact that SCC mixes are highly sensitive to variations in water content [47]. Figure 7(b) shows that incorporating SCMs to the mix can be a more effective strategy, as an increase in SCMs and/or cement contents generally yields more stable mixes. This positive effect of SCMs on stability is noticeable when they are added in dosages above 50 kg/m^3 and is most

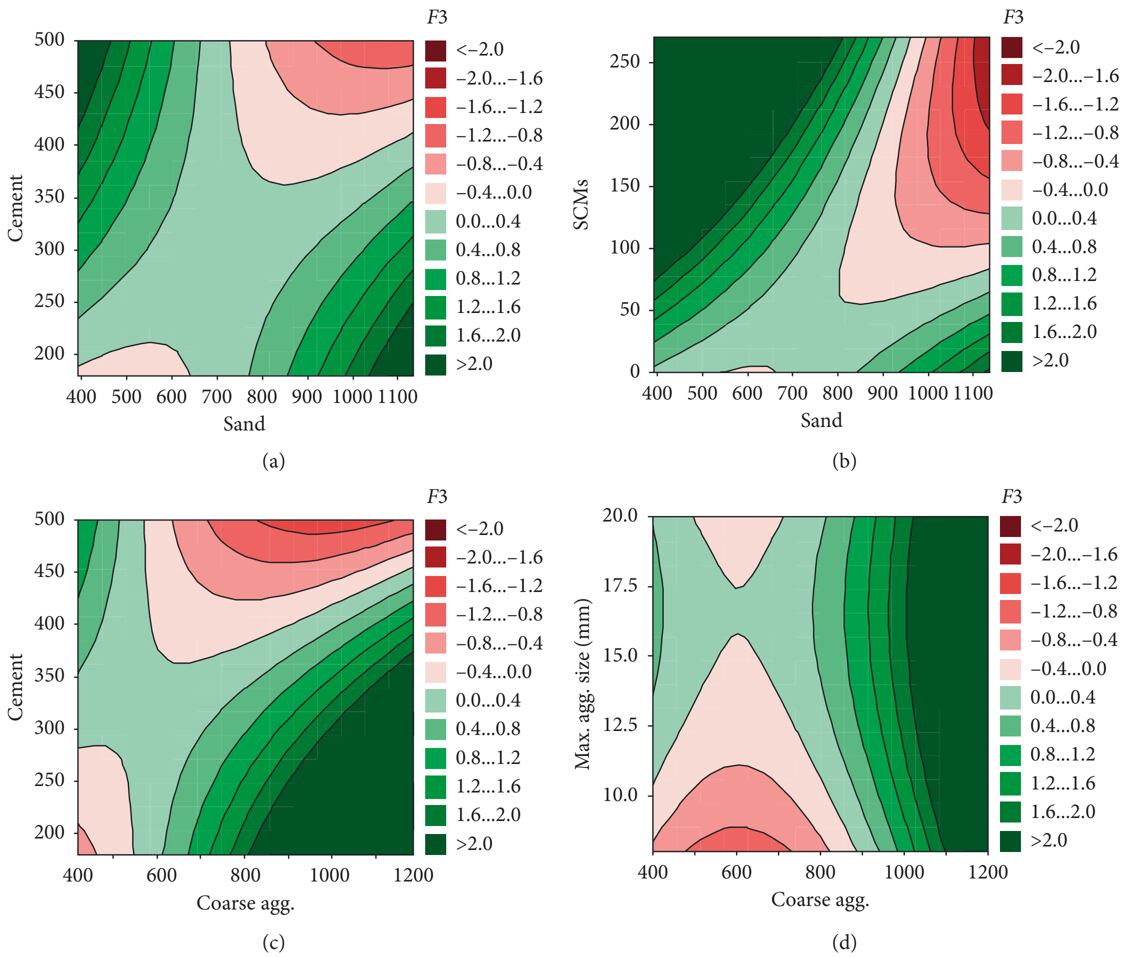

Figure 8: Effect of the dosage of aggregates and powders on the mix stability ($F3$).

significant when added between 100 kg/m^3 and 200 kg/m^3. When added at those levels, SCMs also moderate the sensitivity of the mix to variations in the HRWR dosage, as can be observed in Figure 7(c). However, as discussed in the previous sections, only SCMs contents below 100 kg/m^3 are compatible with optimal flowability, and their effect on stability is only noticeable when the cement content is 425 kg/m^3 or above. The incorporation of VMA improves the mix stability, and Figure 7(d) shows that the addition of SCMs above 50 kg/m^3 reduces the VMA dosage required to improve stability, thus improving its effectiveness.

Figure 8 completes the discussion by examining the effect of the aggregates on the resistance to segregation, for different contents of cement and SCMs.

Figure 8(a) shows that, in general, high cement contents combined with high sand contents tend to compromise stability. When cement is dosed in the region of 350–400 kg/m^3, changes in sand content alone do not have a significant impact on the mix stability. However, for higher cement contents, sand needs to be proportioned at no more than 750 kg/m^3 in order to maximize the resistance to segregation. Figure 8(b) shows that the addition of SCMs tends to improve the mix stability, and in that respect, it is consistent with what has been discussed in relation to Figure 7. In particular, it can be observed that the addition of 100 kg/m^3 of SCMs can yield very stable mixes when the sand content is relatively low.

Figure 8(c) is consistent with Figure 8(a) in showing that high cement contents combined with high coarse aggregate contents yield the most unstable mixes and limits the coarse aggregate content to 600 kg/m^3 in the absence of SCMs in order to optimize stability. Considered together, Figures 8(a) and 8(c) prove that, in very stable mixes, sand and coarse aggregate contents are not too dissimilar, especially if the cement content is relatively high. In other words, the model developed for $F3$ implicitly reproduces the effect that the sand-to-coarse aggregate ratio has on cohesion and therefore stability. From these figures, it is obtained that, for better-than-average stability, the sand-to-coarse aggregate ratio is at least 1.15. Also, Figures 8(a) and 8(b) together indicate that the advantageous effect of SCMs on stability is maximized when the total aggregates content is relatively low, which is equivalent to the more general recommendation to increase the relative volume of paste. Figure 8(d) shows that variations in the maximum aggregate size between 12 mm and 20 mm are not key to segregation resistance, although the range between 15 mm and 18 mm is the most compatible with high levels of stability.

6. Conclusions

This paper presents the results of a meta-analysis of SCC mix designs and their fresh state performance by means of multivariate statistics methods. The models obtained for *F*1, *F*2, and *F*3 reproduce the relationships between the fundamental characteristics of fresh state performance of SCC mixes and their composition and are applicable to the SCC mixes most common in practice. The most relevant conclusions of this study are as follows:

(i) The PCA on the fresh state parameters proved that there are three fundamental properties which describe the fresh state performance of SCC: flow time (*F*1), flow spread (*F*2), and resistance to segregation (*F*3). These three dimensions constitute a robust mathematical framework for the optimization of SCC mixes.

(ii) Three models relating *F*1, *F*2, and *F*3 to the mix design parameters were developed by means of multiple linear regression analysis. Contour plots were used to discuss how changes in the mix design affect the fundamental properties of fresh SCC mixes. These models were found to reproduce very well the general trends and interactions implicit in SCC mix design recommendations and in previous literature, which in effect constitutes the mathematical validation of recommendations well sanctioned by practice.

(iii) The flowability of SCC mixes in terms of both flow times and flow spread can be optimized when the following conditions concur: w/c ratio of 0.45, SCMs content below $100\,kg/m^3$, and sand content not lower than $750\,kg/m^3$. Furthermore, it was concluded that, in general, it is best to keep the dosages of HRWRs and VMAs below 1.7% and 0.7%, respectively.

(iv) It was proved that, if no SCMs are used, there is a remarkably narrow margin where the three fundamental properties of fresh SCC mixes can be simultaneously optimized. The highest levels of segregation resistance were generally associated with sand-to-coarse aggregate ratios of at least 1.15, and increasing the cement and/or SCMs contents was found to yield more stable mixes at the same time it moderates their sensitivity to variations in the dosage of chemical admixtures.

Data Availability

The list of all sources from which information was extracted and incorporated to the database used in this study is presented in the Supplementary Material File that accompanies this paper. The complete database, in mineable, text format, or as a spreadsheet, is available upon request to the author.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

Supplementary Materials

The Supplementary Material File that accompanies this paper contains the complete bibliographical information of all the papers and other publications from which the database used in this study was compiled. (*Supplementary Materials*)

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