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Multivariate Analysis of the Fresh State Parameters of Self-Consolidating Concrete

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Abstract Different tests can be performed to measure the fresh state performance of SCC mixes and to ensure that the specified requirements in terms of filling ability, passing ability and segregation resistance are satisfied. The parameters obtained from the slump flow test, V-funnel, L-box and J-ring, dependent on the characteristics of the materials used and their amounts, are also strongly interdependent. This paper studies the structure of correlations among these fresh state parameters and exploits it to develop a general model that relates fresh state performance to mix design characteristics. Experimental results from different papers and reports were collected in a database that was analyzed using data mining and multivariate analysis techniques. The most important aspects of the model developed are described and discussed as a first step towards its further development into a comprehensive tool for a systematic assessment of the fresh state performance of SCC mixes.

Keywords: database, fresh state, multivariate analysis, testing.

Introduction

In addition to chemical admixtures, SCC mixes typically include mineral powders, lower coarse aggregate volumes and higher fine aggregate dosages than in conventional concrete [1–3]. The relatively high volume of paste facilitates the enhancement of the material's fresh state performance to reach appropriate levels of self-compactability. The key characteristics of SCC are filling ability, passing ability, and stability or resistance to segregation. The different approaches and mix design strategies that have been proposed [4–9] have two aspects in common:

- Fresh state performance is in most cases measured by means of some of the following tests: slump flow, V-funnel, L-box, or J-ring [10].
- Filling and passing ability are to be maximized while avoiding segregation.

As these three key characteristics are functions of the mix design parameters, the search for a trade-off is a multi-objective optimization problem where two functions are to be maximized (filling ability, passing ability) and a third one is to be minimized (risk of segregation). However, the problem is extraordinarily complex as these three aspects are not independent from each other, the parameters obtained from the different tests are highly correlated, and there are important non-linear effects and interactions between the mix design parameters that are not easily accounted for.

Scope and Objectives

A review of the literature published on SCC and self-compacting fiber reinforced concrete (SCFRC) offers plenty of data concerning many different mix designs and their fresh state properties. All this information can be put together and analyzed using data mining techniques to take advantage of the high number of cases reported and their correlations. This paper reports a first attempt to achieve these objectives:

- Construction of a database with SCC and SCFRC mix designs and fresh state results previously published.
- Study of the correlations between the parameters that are most commonly used to describe the fresh state performance of SCC and SCFRC mixes.
- Reduction of this information to a minimal set of independent variables.
- Analysis of the relationships between these variables and mix design parameters.

Description of the Database

Summary of the Information Compiled

At the time of writing, the following information about 193 SCC and SCFRC mixes reported in papers published between 2010 and 2014 [11–22] had been collected:

- Slump-flow test: maximum spread (SF, in mm) and T_{500} time (in seconds).
- Visual segregation index (VSI), ranging between 0 (no segregation) and 3 (severe segregation).
- L-box test: ratio between heights H2/H1 (adimensional).
- V-funnel test: flow time T_v (in seconds).
- J-Ring test: maximum spread (SFj, in mm) and passing index (Pj, in mm).

Table I summarizes the composition of the mixes in the database. The percentage of non-zeros informs of the relative presence of each mix component in the database. Minimum, maximum and average contents are given as representative values.

Table I. Summary of the SCC mixes included in the database.

Component	Percentage of non-zeros	Representative values (kg/m^3)		
		Minimum	Maximum	Average
Water	100.0%	120	266	172
Binder	100.0%	225	708	475
Cement	100.0%	200	536	406
Fly ash (FA)	39.9%	39	354	109
Silica fume (SF)	32.6%	12	61	33
Ground granulated blast-furnace slag (GGBS)	5.7%	200	300	232
Sand	100.0%	525	1134	803
Coarse aggregate	100.0%	570	1695	877
Limestone powder (LSP)	21.7%	64	296	144
Superplasticizer	100.0%	1	18	6.2
Viscosity modifying admixtures (VMA)	28.5%	0.1	2	0.6
Air entrainer	19.2%	0.025	0.1	0.05
Fibers	22.2%	2	115	39

Treatment of Missing Values

The choice of fresh state parameters to be measured was not consistent throughout the different papers considered, and as a result the number of missing data in some of the variables was not negligible. Table II summarizes the relative impact of unreported data in the database under study. The slump-flow test was always carried out, although in some cases the T_{500} time was not measured. On the other hand, the J-Ring was the least common test, with a prevalence of only 29%.

Table II. Missing values corresponding to unreported fresh state results.

Parameter	Percentage of missing values
Slump-flow test: maximum spread	0.0%
Slump-flow test: T_{500}	12.4%
Visual Segregation Index (VSI)	39.9%
L-box test: height ratio	49.2%
T_v, V-funnel test: T_v	52.3%
J-Ring: maximum spread	71.0%
J-Ring: passing index	71.0%

Situations like this are not unusual in the context of multivariate statistics, data mining or machine learning techniques [23] and different approaches can be followed. The complete removal of incomplete cases is the most straightforward but the least convenient, as it implies a significant loss of information.

It was decided to completely discard the parameters from the J-Ring test, while a multiple imputation by fully conditional specification was performed to reconstruct the missing values of other parameters [24].

Multivariate Analysis of Fresh State Parameters

Bivariate Correlations

Table III shows the correlation coefficients (r) between any two fresh state parameters in the database under study. A strong direct correlation (r = 0.787) was observed between $1/T_{500}$ and $1/T_v$. The parameter with the highest degree of correlation with others was the L-box ratio H2/H1, directly correlated with SF (r = 0.842) and $1/T_v$ (r = 0.519) and inversely correlated with the VSI (r = -0.640). This structure of correlations between the fresh state parameters justified the need for the analysis presented in the following sections.

Table III. Correlation matrix.

	SF	$1/T_{500}$	VSI	H2/H1	$1/T_v$
SF	(1.00)	0.305	0.180	0.842	0.370
$1/T_{500}$		(1.00)	-0.474	0.355	0.787
VSI			(1.00)	-0.640	-0.166
H2/H1				(1.00)	0.519
$1/T_v$					(1.00)

Principal Component Analysis (PCA)

The fresh state performance of any SCC mix in the database under study was described by 5 parameters. From an algebraic point of view, this means that any mix was a point in the 5-dimensional space, where the coordinate axes were the fresh state parameters measured. However, as they were strongly correlated, they did not constitute an orthogonal coordinate system, making the analysis, visualization and interpretation of the dataset very problematic.

Principal Component Analysis (PCA) was used to condense this information into a reduced set of variables, facilitating a simplified, global representation of the dataset under study [25]. It is based on a matrix decomposition procedure, which is geometrically illustrated in Figure 1. Prior to the application of PCA, all fresh state parameters were centered and scaled to unit variance. Principal components were extracted by singular value descomposition of the correlation matrix, applying a Varimax rotation with Kaiser normalization [26]. The first three principal components (PC1, PC2, and PC3) were retained as sufficiently informative, as they explained 94.66% of the total variance in the original variables.

Each principal component is a linear combination of the original variables. The coefficients given in Table IV define the directions of the new, rotated axes PC1, PC2 and PC3 in the original coordinate system.

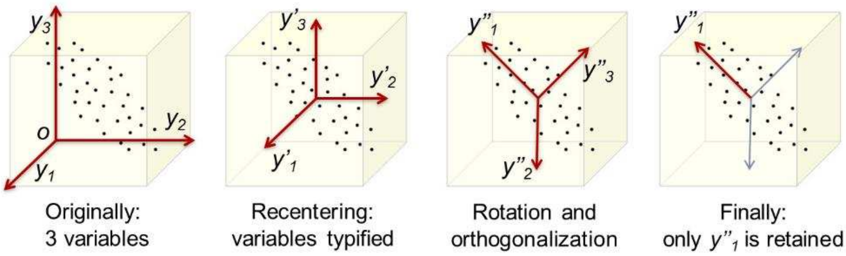

Figure 1. Illustrative example of PCA for an initial set of three variables.

Table IV. Principal components as function of the original variables.

	PC1	PC2	PC3
SF	0.962	0.169	0.093
$1/T_{500}$	0.234	0.896	-0.219
VSI	0.140	-0.187	0.971
H2/H1	0.897	0.361	0.109
$1/T_v$	0.258	0.921	-0.081

If the coefficients in Table IV are plotted in the new coordinate system defined by the three principal components extracted, Figure 2 is obtained. Three clusters are clearly identified, meaning that the variables that are close in these plots are clearly associated. PC1 (mostly SF and H2/H1) represented flowability in terms of spread and filling capacity, while PC2 (mostly $1/T_{500}$ and $1/T_v$) represented the quickness of the flow. The last principal component PC3 (mostly VSI) was representative of the mix stability.

Obtention of the Latent Variables

The values of the original fresh state parameters in the database were rewritten in this new coordinate system by linear combination using the loadings in Table IV. As a result, the values of the three new variables, LV1, LV2 and LV3 were obtained for each of the SCC mixes in the database.

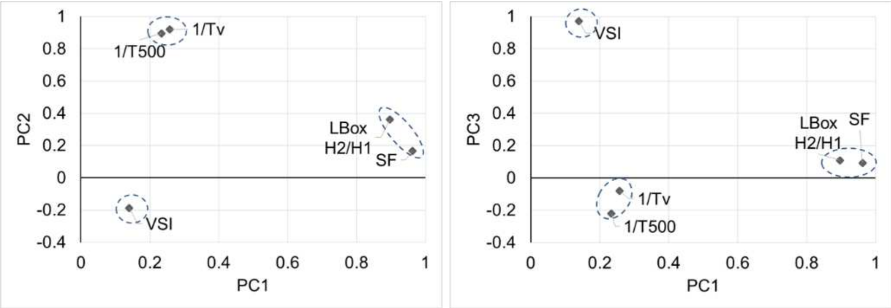

Figure 2. Component plots after PCA.

Effect of Mix Design on Fresh State Performance

Regression on the Latent Variables

Multiple linear regression and logistic binary regression were used for the development of models that relate LV1, LV2 and LV3, representing particular aspects of SCC fresh state performance, to the mix design parameters and their interactions. These models made it possible to identify statistically significant effects and synergies on SCC fresh state performance, and to interpret the trends identified.

A sequential modelling approach was followed. Initial models that included all variables and interactions were iteratively simplified by discarding terms that were identified as non significant. The final models for LV1, LV2 and LV3 showed the best fit to the database and considered only statistically significant terms. Table V summarizes these models. Statistically significant terms are marked with an asterisk, and the R-squared value is given for each of the three models.

Response Surfaces for LV1

Figure 3 shows the response surfaces for LV1 (flowability in terms of spread) with respect to the aggregates. The impact of the total weight of aggregates on LV1 was strongly related to the maximum aggregate size to the point that it can reverse the trends (Figure 3 left). However, the most influential parameter on LV1 was the ratio between coarse aggregate and sand contents (Figure 3 right).

The effect of chemical admixtures on LV1 was significantly affected by the addition of LSP, as shown in Figure 4. Increasing the LSP content was shown to enhance the efficiency of the superplasticizer especially when used at lower dosages. At higher dosages, adding VMA tends to reduce LV1 due to its viscosity controlling function.

Table V. Summary of MLR analysis results.

	Statistically significant terms		
	LV1	LV2	LV3
water/binder ratio	*	*	
Cement	*	*	*
LSP	*		*
SCM = SF+FA+GGBS	*	*	*
x LSP		*	
Water content		*	*
x Cement			*
x SCM			*
x LSP			*
Sand weight	*		*
Coarse aggregate weight	*		*
Maximum aggregate size	*		
x Sand weight	*		*
x Coarse aggr. weight	*		*
Fibers content (V_f)	*	*	
x Aspect ratio	*		*
x Material	*		
Superplasticizer	*	*	*
x Water		*	
x LSP	*		
x VMA	*		
R-squared	0.58	0.60	0.73

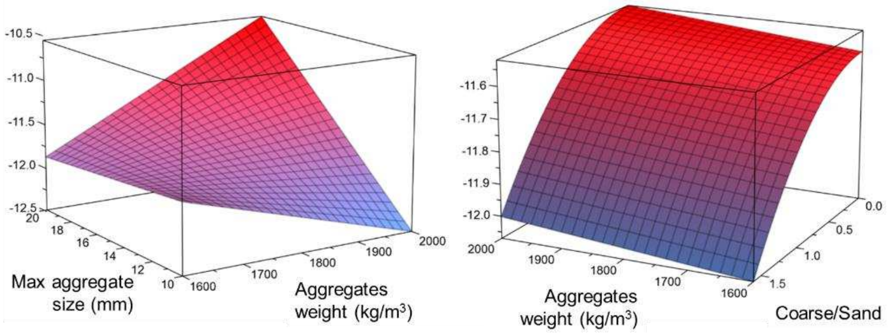

Figure 3. Effect of the aggregates on LV1.

Figure 5 shows the effect of fibers on LV1 as per the model developed. When steel fibers are used, increasing their content and their aspect ratio had a negative impact on LV1. However, the interference of fibers was significantly reduced when polypropylene fibers were considered.

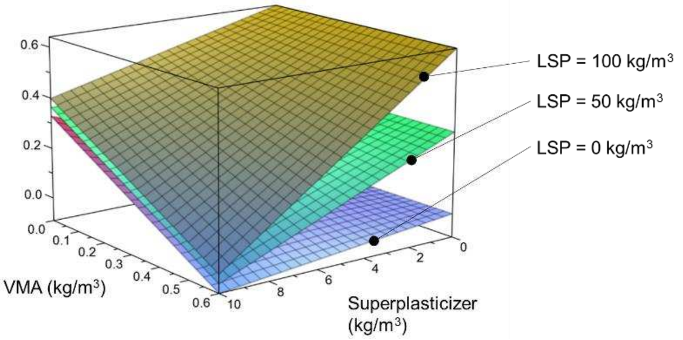

Figure 4. Interaction between chemical admixtures and LSP on LV1.

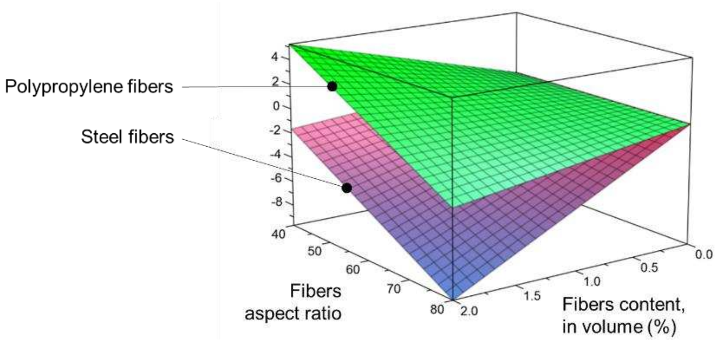

Figure 5. Effect of fibers on LV1.

Response Surfaces for LV2

Figure 6 shows the response surface for LV2 (flowability in terms of quickness) with respect to the contents of supplementary cementitious materials and LSP. The effect of reducing the cement intensity of the binder was shown to follow a different trend depending on LSP content. Better flowability was observed for higher amounts of supplementary cementitious materials, but this effect was reversed in the absence of LSP or when added in small amounts; the threshold appears to be 85 kg/m^3.

Response Surfaces for LV3

LV3 was representative of the mix stability as it accounted for VSI almost exclusively. As the VSI is a discrete parameter, the model developed for LV3 was more complex than the ones developed for LV1 and LV2. This model correctly reproduces quite complex synergies and therefore it constitutes a promising development as it will allow numeric predictions to account for the risk of segregation. Figure 7 shows two plots that illustrate the response surfaces for LV3 derived from this model, where the vertical axis is the risk of segregation: 0 stands for high stability, while 1 corresponds to severe segregation. A detailed discussion of this model is not presented here due to space limitations but will be made available in upcoming publications.

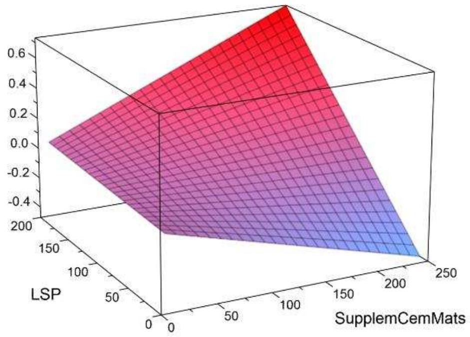

Figure 6. Effect of supplementary cementitious materials and LSP on LV2.

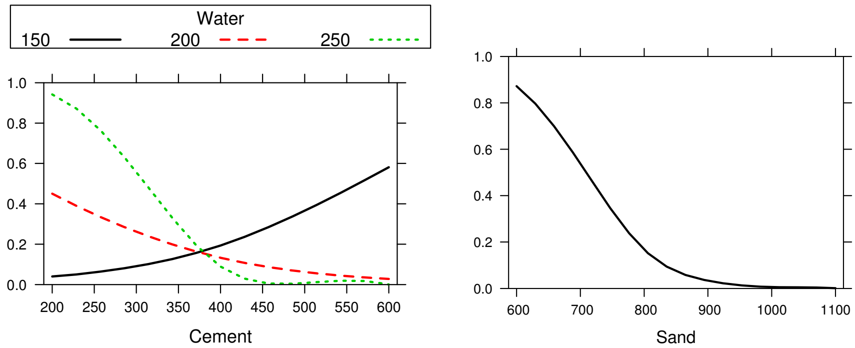

Figure 7. Partial plots for LV3.

Conclusions

- A database of SCC and SCFRC mixes has been put together with information about the mix components and their amounts as well as the experimental values obtained from fresh state tests as reported in previous papers.
- The parameters obtained from the most usual tests to characterize the fresh state performance of SCC and SCFRC mixes are significantly interdependent.

- Principal Component Analysis has proven that the associations between fresh state parameters clearly define three latent variables corresponding to the following distinct aspects: flowability (T_{500}, T_v), filling capacity (H2/H1, SF), and stability (VSI).
- The impact of the mix design on the fresh state performance of SCC and SCFRC mixes has been related to the aforementioned latent variables by means of generalised linear regression models.
- The methodology applied has identified those synergies between mix design characteristics that have a statistically significant effect on fresh state performance.

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