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# Study of the Workability of Self-Compacting Concrete (SCC) Using Experimental Methods and Artificial Neural Networks (ANN)

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**Abstract**
The self-compacting concrete (SCC) flows under its weight and does not require external vibration for compaction. However, its formulation requires careful calculation of its constituents. Three methods are considered: the first is an empirical method represented by an approach based on mortar optimization, a solution proposed by Japanese researchers who originally introduced the concept of self-compacting concrete; the second is a graphical method by Dreux-Gorisse used for ordinary concrete, which optimizes the composition of the aggregate skeleton by selecting fractions without additives and superplasticizers; and the third is a statistical method that we developed using an approach based on Artificial Neural Networks (ANN) built from a database from previous research projects. The objective is to characterize workability through an ANN model and compare it with experimental methods. Therefore, we focused on the slump flow, L-box, and sieve stability segregation tests.
**Keywords:** Mixture design method; Fresh state properties; SCC; Workability; ANN.

## 1. Introduction

The formulation of self-compacting concrete (SCC) requires specialised expertise and know-how. This type of concrete is renowned for its characteristics in the fresh state, which are assessed by workability tests such as the L-Box and V-Funnel tests. SCC is characterised by its fluidity, allowing it to flow without mechanical vibration (Rao, M *et al.*, 2023). It differs from ordinary concrete in its properties in the fresh state (Raheman, A. Modani, P.O., 2013; Merabti, S., 2022). It is also relatively easy to produce (Merabti, S *et al.*, 2023). To obtain the desired fluidity and flow characteristics, admixtures and additives are incorporated into the mixtures (Rao, M *et al.*, 2023; Matos, A.M *et al.*, 2015; Turcry, P., 2003; Bensebti, S., 2015).

The SCC is typically manufactured following European standards (Nachbaur. L *et al.*, 2003). Numerous research studies have been conducted to enhance physicochemical properties by incorporating various materials, including fly ash (Kovler, K *et al.*, 2005), cork waste (Matos, A. M *et al.*, 2015), waste glass powder (Matos, A.M *et al.*, 2016), blast furnace slag (Klemczak, B *et al.*, 2023), and ceramic waste powder (Gautam, L *et al*., 2023; Mohit, M *et al*., 2023; Gautam, L *et al*., 2022). Other research has explored using an eco-friendly Ferrock material as a cement replacement and replacing 60% of the cement with fly ash (Jeffy Pravitha, J *et al*., 2023; Palou, M. T *et al*., 2016). Additional work has also involved the incorporation of powders such as limestone (LP), basalt (BP), and marble (MP) in SCC production (Uysal, M. Sumer, M., 2011).

The formulation design for SCC is a complex process often developed empirically. Several methods for designing SCC are based on mortar optimization (Okamura, H *et al*., 2000; Billberg, P., *et al*., 1999; Jacobs, F. Hunkeler, F, 1999). In contrast, others rely on paste volume optimization and experimental planning (Turcry, P., 2003), as well as the use of the Mortar Equivalent Concrete (MEC) (Nachbaur, L., *et al*., 2003). It is important to note that the composition influences the behavior of SCC. Khayat, K.H., *et al*., (2000) conducted a study considering the factors of each component. The impact of the formulation design method on shrinkage and cracking is addressed by Turcry and Loukili (2003). Questions related to durability are studied by Assié, S., (2004). On the other hand, the relationship between formulation design and rheological, physicochemical, and mechanical properties has been the subject of research by Yammine., (2007).

Artificial Neural Networks (ANNs) are commonly used to assess SCC parameters (Bhuva, P *et al*., 2023). Najm *et al*., (2023) employed statistics and artificial neural networks to evaluate and predict the compressive strength of SCC. Uysal and Tanyildizi., (2011) utilized ANN to predict the compressive strength of concrete cores. The same authors also employed ANN to estimate the compressive strength of self-compacting concrete containing mineral admixtures and steel fibers (Uysal, M *et al*., 2012). Bhuva et al. explored various ANNs for predicting the stability of self-compacting concrete. The results demonstrated the potential of ANN modeling for accurately predicting strength values and, consequently, the optimal dosage of SCC mix constituents (Bhuva, P *et al*., 2023). Other research has examined the rheological behavior of SCC using ANN (El Asri, Y *et al*., 2022; Ben Aicha, M *et al*., 2022). Ramkumar *et al.* (2020) also utilized artificial neural networks to analyze the performance of SCC using mineral admixtures and steel fibers

In this study, we employed a statistical method based on Artificial Neural Networks (ANNs). This method was fueled by a database derived from previous research projects (Raheman, A. Modani, P.O., 2013). This method aims to develop a model capable of predicting the quantitative proportions of each concrete component without relying on regulations based on numerical methods. The network connects strength and workability characteristics. four inputs, namely compressive strength, Abrams cone flow test, L-Box test, and sieve stability segregation test, are used to determine six outputs corresponding to the quantities of each concrete component. This research focuses on analyzing the impact of SCC formulation on its behavior in the fresh state, aiming to explore aspects related to their design and rheology control. Our contribution aims to develop a novel methodology for SCC mixture design and establish a procedure for characterizing their workability based on test results. This process involves examining the influence of composition parameters on various fresh-state properties of SCC.

## 2. Mixture design methods

In the literature, there are many mixture design approaches and methods; for our study, we have selected three large families, from the most empirical to the most sophisticated. In this study, we represent the detailed principle of the different approaches.

### *2.1 The Japanese method*

Following the Japanese approach, the mixture design of self-compacting concrete (SCC) is considered safe when it prioritizes the paste volume over aggregates. However, the resulting concrete mixtures have lower aggregate content and are far from an economic optimum. The fundamental principle of mixture design involves determining the proportions of each component in the concrete (Okamura, H *et al*., 2000). Japanese researchers have found that the risk of blockage is minimized when the volume of coarse aggregates in 1 $m^3$ of concrete is limited to half of its total volume. Compactness is crucial and depends on the compaction method: the aggregate volume ratio to full volume.

Additionally, the volume of sand is fixed at 40% of the concrete mortar volume, ensuring concrete fluidity through reduced granular friction. Water and superplasticizer dosages are determined through mortar tests, with the sand volume consistently set at 40%. Japanese researchers have also established a linear relationship between spread and flow when the water dosage varies with a constant amount of superplasticizer. It allows for determining an optimal admixture-to-water ratio to enhance mortar fluidity. The superplasticizer dosage found is 1% of the mass of fines. The formulas obtained are shown in Table 5.

### *2.2 Dreux-Gorisse method*

The procedure is based on exploiting the experience acquired in producing ordinary concrete by traditional methods. According to Dreux, (1981) and Dreux and Festa, J., (1998), the quality of concrete is defined by two key aspects: strength and workability. Starting the transformation of regular concrete made by the graphic process of Dreux, (1981), it aims to optimize the aggregate skeleton of new self-compacting concrete, with the use of a superplasticizer which ensures sufficient fluidity with limestone filler at an optimum dosage to produce a self-compacting paste. The principle of this method is first to define the Cement/Water *(C/W)* ratio to achieve the strength objective and then to adjust the parameters to obtain a strength adapted to the chosen processing conditions.
To determine the ratio (*C/W*), we choose the BOLOMEY relationship (Rajamane, N.P., 2012; Ambily, P.S., 2012).

$$R_c = G.R_{ce}.\left(\frac{C}{W} - 0.5\right) \qquad (1)$$

Where:
$R_c$: Compressive strength of concrete at 28 days (bars);
G: Granular coefficient given in Table 3.
$R_{ce}$: Compressive strength of cement at 28 days (bars);
C: Cement content ($kg/m^3$);
W: Water content in dry materials ($l/m^3$).

The cement content differs from the aggregate content. The Cement/Water ratio (*C/W*) is approximately evaluated using the overage strength and the required plasticity through the formula (1). Cement content is determined using an abacus (see Figure 1), which gives the ratio *C/W* as a function of workability (Abrams cone slump). Determining the appropriate cement content to achieve the desired water content.: *W=C/(C/W)*. However, this value remains approximate and will be refined later through plasticity and workability tests.

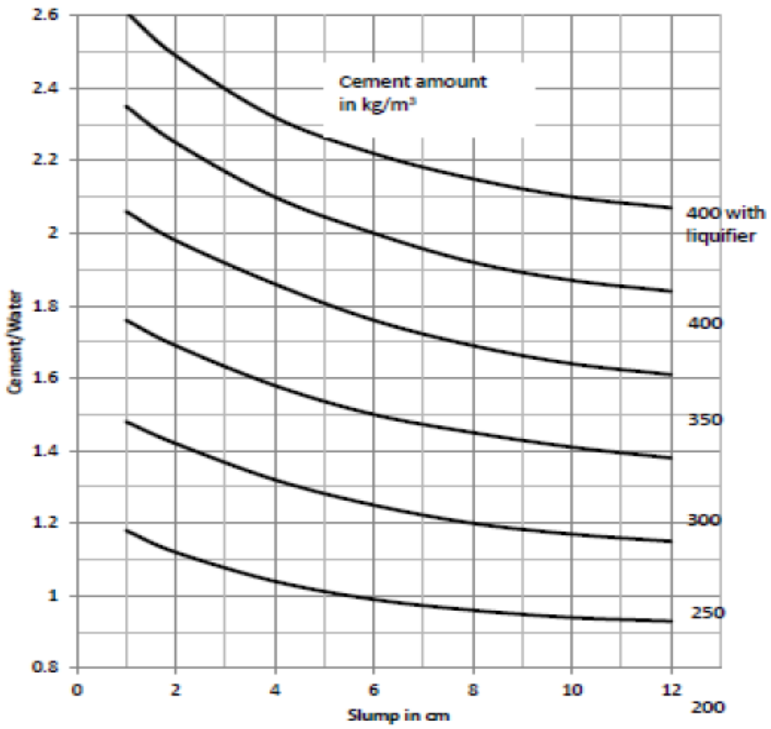


**Figure 1 -** Estimation of the cement content to be used based on the water-to-cement ratio and workability (Dreux, G., 1981).

Concerning aggregate dosing, a reference composition labeled AOB is depicted on a particle size analysis graph in Figure 2. Point B (at 100%) corresponds to the size D of the largest aggregate. The following abscissa coordinates define the stopping point A (based on sieve size D).

- If $D \leq 20$ mm, the abscissa is D/2
- If $D > 20$ mm, the abscissa is located in the middle of the "gravel segment" limited by modulus 38 (corresponding to 5 mm) and the related modulus to D at :

$$Y = 50 - \sqrt{D} + K \qquad (2)$$

With:
K: is a correction factor that depends on the cement content, the effectiveness of compaction, and the shape of the aggregates, whether they are rounded or crushed.

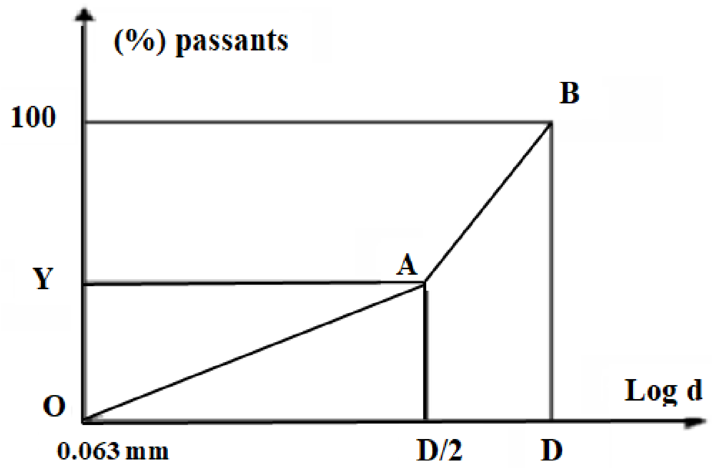


**Figure 2 -** Reference curve Dreux-Gorisse method (Dreux, G., 1981).

The dosage of the filler and superplasticizer is determined empirically to achieve sufficient fluidity to transform ordinary concrete into self-compacting concrete. Table 5 below provides the different quantities of constituents for each formulation method.

### *2.3 Artificial Neural Networks (ANN)*

#### *2.3.1 Database*

The development model employed relies on learning algorithms to construct a simplified version of the artificial neural network (ANN). The approach involves providing input and output data to the ANN, allowing it to learn and model the relationship between the two datasets (Gautam, L *et al*., 2022).

The database comprises 163 results; 130 are used to train the network, and 33 for validation. Normalizing the input variables in the interval [-1, 1] makes it possible to reduce disparities between variables and order very different variables. Tables 1, 2, and 3 respectively present the descriptive statistics of the input and output variables, as well as the correlation matrix.

**Table 1. Descriptive statistics for input variables.**

| Input | Database | Mean | Minimum | Maximum | Variance | S.D |
|---|---|---|---|---|---|---|
| Slump flow (cm) | 163 | 68,44 | 15 | 80 | 51,19 | 7,15 |
| L-Box ($H_2$ /$H_1$) | 163 | 0,82 | 0,25 | 1 | 0,02 | 0,14 |
| Sieve Segregation (%) | 163 | 9,33 | 0,39 | 29,58 | 31,50 | 5,61 |
| Rc28 (MPa) | 163 | 41,26 | 20,04 | 71 | 103,66 | 10,18 |

**Table 2. Descriptive statistics for output variables.**

| Output | Database | Mean | Minimum | Maximum | Variance | S.D |
|---|---|---|---|---|---|---|
| Gravel | 163 | 791,92 | 557,00 | 1121,10 | 7619,28 | 87,29 |
| Sand | 163 | 836,72 | 578,00 | 1062,00 | 9787,62 | 98,93 |
| Cement | 163 | 394,81 | 290,00 | 658,70 | 4138,49 | 64,33 |
| Filler | 163 | 117,62 | 0,00 | 330,00 | 4600,77 | 67,83 |
| S/plast | 163 | 8,33 | 0,50 | 74,00 | 98,85 | 9,94 |
| Water | 163 | 198,76 | 75,00 | 275,00 | 1088,06 | 32,99 |

**Table 3. Correlation matrix.**

| | Gravel | Sand | Cement | Filler | S/Plast | Water | S/ flow | L-Box | Sieve S | CS28 |
|---|---|---|---|---|---|---|---|---|---|---|
| Gravel | 1 | -0,213 | -0,229 | -0,048 | 0,006 | -0,178 | -0,147 | -0,180 | 0,018 | -0,021 |
| Sand | -0.213 | 1 | -0,207 | -0,077 | -0,169 | -0,167 | -0,295 | -0,105 | -0,207 | 0,114 |
| Cement | -0.229 | -0,207 | 1 | -0,428 | 0,106 | 0,227 | 0,177 | 0,199 | -0,071 | 0,194 |
| Filler | -0.048 | -0,077 | -0,428 | 1 | 0,384 | 0,006 | 0,016 | -0,123 | 0,203 | -0,295 |
| S/plast | 0.006 | -0,169 | 0,106 | 0,384 | 1 | -0,094 | 0,086 | -0,135 | -0,090 | -0,054 |
| Water | -0.178 | -0,167 | 0,227 | 0,006 | -0,094 | 1 | 0,132 | 0,079 | 0,274 | -0,374 |
| S/ flow | -0.147 | -0,295 | 0,177 | 0,016 | 0,086 | 0,132 | 1 | 0,363 | 0,077 | 0,179 |
| L-Box | -0.180 | -0,105 | 0,199 | -0,123 | -0,135 | 0,079 | 0,363 | 1 | 0,349 | 0,120 |
| Sieve S | 0.018 | -0,207 | -0,071 | 0,203 | -0,090 | 0,274 | 0,077 | 0,349 | 1 | -0,308 |
| Rc28 | -0.021 | 0,114 | 0,194 | -0,295 | -0,054 | -0,374 | 0,179 | 0,120 | -0,308 | 1 |

### *2.3.2 Application of ANN on the database*

The proposed model consists of an input layer of four neurons, one hidden layer of ten neurons, and an output layer of six neurons (4-10-6). The model architecture is described in Figure 3; it should be noted that the numerical simulations made it possible to determine the optimal architecture for the network. The activation function used for all neurons is of the sigmoid type.

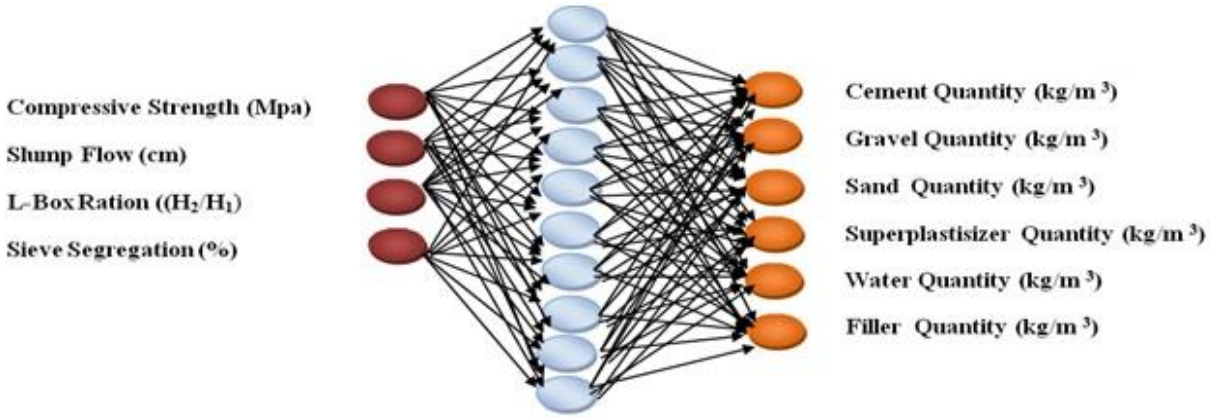


**Figure 3 -** The proposed neural network architecture.

The collection process was carried out in two phases. The objective of the first phase was to collect data in the literature, the second they have involved normalizing selected data according to the rules of the characteristics of self-compacting concrete. The results obtained are shown in Table 5.

## 3. Experimental Study

In this research, we will conduct an experimental study on the workability of self-compacting concrete parameters based on the influence of the mixture design method.

### *3.1. Materials used*

The physical characteristics and their sources used in the experimental part are shown below in Table 4. Considering that ordinary tap water is used in the production of self-compacting concrete.

**Table 4: Materials used in the experimental section.**

| Materials | Density ($kg/m^3$) | Fineness ($cm^2/g$) | Origin |
|---|---|---|---|
| CPJ-CEM II/A 42.5 | 3075 | 3601 | Sétif, Algeria |
| Gravel (3/15) | 2593 | - | Sétif, Algeria |
| Sand (0/3) | 2503 | | Sétif, Algeria |
| Fillers | 2735 | 2900 | Béjaïa, Algeria |
| Superplasticizer GLENIUM® 27 | 1048 | - | BASF, Algeria |

### *3.2 Granulometric analyses*

In order to create the overall structure of the concrete using the Dreux-Gorisse technique, granulometric analysis is performed on our aggregates (see Figure 4).

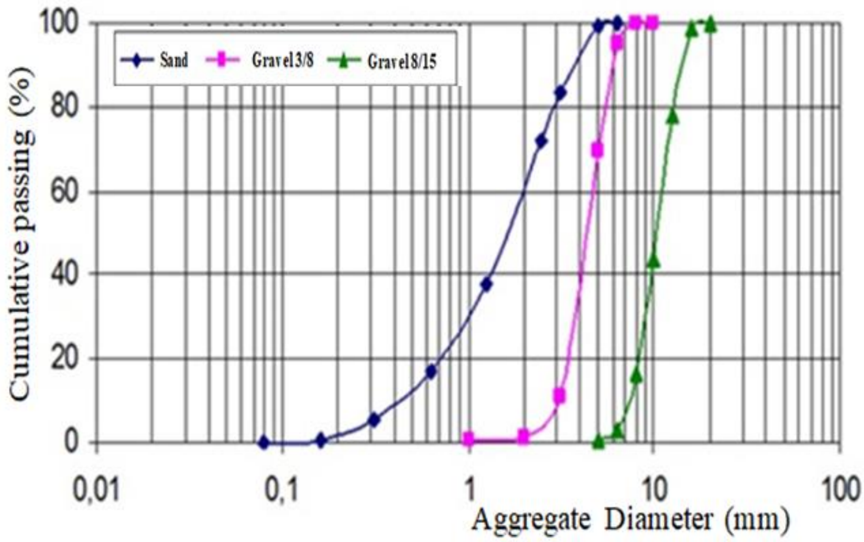


**Figure 4 -** Curves of granulometric analyses of aggregates.

### *3.3 Mixture Proportions*

The compositions of the chosen concrete were researched and optimized using each method, which varied based on the principles of each technique. The design of SCC mixtures is detailed in Table 5, adhering to the recommendations outlined in the NF EN 206-9., (2010) European standard.

**Table 5: Formulation proportions of different methods.**

| **Components ($Kg/m^3$)** | **Japanese method** | **Dreux-Gorisse method** | **ANN method** |
|---|---|---|---|
| Cement | 400 | 350 | 380 |
| Filler | 280 | 200 | 187 |
| Water | 185 | 175 | 190 |
| Sand | 715 | 792 | 852 |
| Gravel | 865 | 790 | 767 |
| Superplasticizer | 8 | 7 | 8,40 |
| Paste volume | 426 | 370 | 391 |
| G/S | 1,2 | 1 | 0,9 |
| W/Fine | 0,27 | 0,31 | 0,42 |
| F/C | 0,7 | 0,57 | 0,33 |
| W/C | 0,46 | 0,5 | 0,57 |

## 4. Results and Discussion

Workability study relies mainly on two criteria: limiting the quantity of water by using admixtures and optimizing the aggregate skeleton to reduce friction between aggregates to increase flow (Lozach, D., 2006).

Fluidity and homogeneity are the general characteristics of fresh self-compacting concrete. These characteristics have been studied from many angles and can be separated into three empirically measurable criteria: fillability, fluidity, and segregation resistance (De Schutter, G., 2005). After nine tests, the experimental results for characterizing the workability of self-compacting concrete are presented in Table 6.

**Table 6. Results of characterization tests.**

| Tests | Japanese method | Dreux-Gorisse method | (ANN) method | Target |
|---|---|---|---|---|
| Slump flow (cm) | 77 | 70 | 72 | ≥60 |
| L-Box ($H_2$ /$H_1$) | 0,88 | 0,75 | 0,80 | ≥0,80 |
| Sieve segregation (%) | 12,7 | 11 | 3,4 | ≤15 |

### *4.1 Slump flow test*

The slump width of all concrete compositions is between 70 and 77 cm and has high fluidity according to European standards (AFGC., 2008), classifying them as self-compacting. Tests reveal significant bleeding at the center of the sample for concretes produced using the artificial neural network method. This bleeding is attributed to the water/cement ratio, although the observed signs of bleeding have largely disappeared, and the spread diameter has remained nearly constant. The spread of all the concrete compositions is between 70-77 cm and has a high fluidity according to European standards (AFGC., 2008), which classifies them as SCC. The tests revealed significant bleeding in the center of the sample for concretes produced using the artificial neural network method. This bleeding was attributed to the W/C ratio, although the signs of bleeding observed largely disappeared and the spreading diameter remained virtually constant. The spreading diameter of the concretes produced by the Japanese method and the artificial neural networks exceeded that of the concretes produced by the Dreux-Gorisse method, this phenomenon being justified by the high G/S and F/C ratios. Despite the relatively low W/C ratio compared with other mixtures, a reduction in spreading diameter of 9.09% and 6.49% was observed for the mixtures produced by the Dreux-Gorisse method and ANN.

### *4.2 L-Box test*

A single box test concrete with a filling ratio ($H_2/H_1$) below 0.8 is typically associated with the Dreux-Gorisse method, even if its Abrams Cone Spread Test measures 70 cm (see Table 6). Such concrete may lead to blockages and a lack of continuous flow in the L-box. This improvement is particularly evident in the case of concrete produced using the Japanese method, which exhibits an $H_2/H_1$ ratio of 0.88.

The results establish a strong correlation between paste volume and the outcome of the L-Box test. We observe that adding filler can marginally enhance the viscosity of the cement mixture, leading to an increase in the $H_2/H_1$ ratio when its dosage exceeds a critical value, which, in our study, was determined to be 33%. The mortar reaches its maximum compactness when this required filler dosage is reached (Yahia, A *et al*., 2005).

The F/C ratio (Filler/Cement) is inadequate for the Dreux-Gorisse method, as the filling ratio ($H_2/H_1$) is less than 0.8. However, the two other methods meet the standards for self-compacting concrete, where the filling ratio is equal to or greater than 0.8.

### *4.3 Sieve stability segregation test*

The results of the sieve stability segregation test presented in Table 6 indicate that all concretes exhibit a segregation rate of less than 15%, signifying satisfactory stability and consistent static segregation. However, the SCC produced using the ANN method demonstrates a higher laitance value ($\pi$=3.4%), which poses a risk of blockage and reduced workability. Concretes with a laitance percentage below 15% generally exhibit reasonable stability. Table 6 demonstrates that including 33% fines results in a homogeneous SCC.

All the concretes fall within the self-compacting range, with their laitance percentages below 15%. Notably, the concrete produced using the Japanese method ($\pi$=12.7) exhibits the highest stability, primarily attributed to the increased paste volume compared to the other concretes.

### 4.4 Comparison between the Different Mixture Design Methods

The different approaches to mixture design are based on various criteria, making comparisons very difficult. This process is influenced by the properties of the materials used, the number of experiments carried out, and the rheological results.

In contrast to other methods, the Japanese method provides larger amounts but also has the lowest sand content due to fixing the sand volume at 40% of the mortar volume. Unlike the other two methods, the authors of this method do not specify the nature of the gravel (crushed or rounded), which can influence the risk of blockage. The simplicity of the method lies in optimizing water and superplasticizer dosages through mortar tests, as there is a strong correlation between the fresh state behavior of concrete and its mortar. Nevertheless, this method faces economic viability challenges as it requires a high dosage of cement (400 kg/m$^3$), resulting in a cost price of 15% to 20% higher than that of other methods. Despite the validation of all tests recommended by the French Civil Engineering Association (AFGC., 2008), this method does not reveal the viscosity of the obtained concretes.

The Dreux-Gorisse method optimizes paste volume by adding fillers and aggregating aggregates by selecting granular fractions and conducting granulometric analyses to identify missing classes (Dreux, G. Festa, J., 1998). This method offers relatively low quantities of cement, water, and superplasticizers, resulting in a smaller paste volume than other methods. Originally designed for ordinary concrete mixture design, it provides a more cost-effective and realistic industrial solution. The cement dosage is standard (350 kg/m$^3$), and the manufacturing process is straightforward: aggregates are introduced, mixing water is added in small proportional quantities, followed by the equivalent binder (cement + addition) after mixing, and any remaining water is presented along with an admixture. While some tests recommended by regulations are validated, such as the slump flow test (SF=70cm) and sieve stability ($\pi$=11%), the method falls short in the L-box test ($H_2/H_1$=0.75), which is close to the norm. Improving the paste volume to more than (370 kg/m$^3$) is essential to stabilize the concrete and prevent blockage. To apply this method correctly, experimental determination of the required coefficients is necessary. Interestingly, there is no correlation between dynamic segregation ($H_2/H_1$=0.75) and static segregation represented by the percentage of laitance collected during sieve stability tests ($\pi$=11%). The Japanese formulas are theoretically the most stable despite having the highest rates of milt.

The ANN method offers an alternative for mathematical modeling based on algorithmic calculation (Dreyfus, G et al., 2002., Dreyfus, G et al., 2008). The approach involves presenting data extracted and collected from literature research to build a comprehensive database. The ANN method has relatively high quantities of sand, water, and superplasticizers, influenced by the W/C and W/F ratios, while gravel and filler quantities are lower than other methods. The mixture generated by this method is random, as the database comprises information from 24 different sources, all representing experimental projects on SCC. The data underwent a filtering process to reduce anomalies and variations within the database.

Based on simulations, the model allowed for studying the relationships and dependencies among the various components of concrete and its rheological properties. It produced acceptable results in mixture design. This approach can lead to more precise and faster SCC mixtures based on the fundamental properties characterizing their fresh state, particularly 'workability.'

All tests recommended by regulations (AFGC., 2008) are validated and deemed acceptable, including the slump flow test (SF=72 cm), stability to the sieve test ($\pi$=3.4%), and the L-box test ($H_2/H_1$=0.80). The results of this model demonstrate that the ANN approach is a valuable and powerful tool for addressing a wide range of workability issues and predicting concrete properties compared to statistical and conventional methods. However, it is worth noting that the applicability of this approach may vary depending on the specific materials used in each concrete mixture (Sarıdemir, M et al., 2009).

## Conclusion

The study aimed to identify, understand, and assess the possible relationship between mixture design methods and rheological parameters of SCC, as well as determine the optimal approach to achieving these objectives. We developed three mixture design methods, each consisting of nine tests, to cover a wide range of rheological properties. The following conclusions were drawn from our analysis:

- All three mixture design methods produced SCC that met European Requirements. However, the L-Box test for the Dreux-Gorisse method ($H_2/H_1$=0.75) has not yet been validated. Characterization tests confirmed the reliability of the paste volume calculated by all three methods.
- A strong correlation was found between the spread and L-Box tests. Notably, the paste volume emerged as a key factor in achieving the L-Box test requirements, particularly when a mixture resulted in very fluid concrete (slump flow test greater than 65 cm). This indicates a significant correlation between paste volume and L-Box test results.
- The correlation between paste volume and spread was more significant than that between superplasticizer dosage and the L-Box test, suggesting that superplasticizer indirectly influences flow through its effect on concrete rheology rather than directly impacting flow.
- The relationships observed between the three tests underscore the importance of conducting all tests despite potential challenges, to minimize testing costs and ensure accurate characterization of concrete. However, each method requires a certain number of tests to characterize constituents or interactions effectively.
- Regardless of the chosen method, laboratory testing is essential for concrete mixture design, as SCC does not conform to a theoretical formula. Factors such as aggregate type, shape, granulometry, fineness, chemical composition of admixtures and binders, and workability outcomes of combinations are all critical considerations.

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