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Non-destructive density-corrected estimation of the elastic modulus of slag-cement self-compacting concrete containing recycled aggregate

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ABSTRACT

Non-destructive tests that cause no damage to concrete components can be used in rehabilitation works to determine concrete mechanical properties, such as the modulus of elasticity. In this paper, models are presented to predict the modulus of elasticity of Self-Compacting Concrete (SCC) with Recycled Aggregate (RA) and slag cement through the hammer rebound index and ultrasonic pulse velocity. Simple- and multiple-regression models were developed to estimate the modulus of elasticity according to the monotonic relation between variables shown by Spearman correlations. In these models, the modulus of elasticity was always inversely proportional to the square root of the non-destructive property under consideration, and the hardened density raised to the power of 2.5 as correction factor always increased estimation accuracy and robustness. The multiple-regression model with density correction yielded the most precise estimations of the elastic modulus with deviations below ±10% and ±20% in 82% and 94% of cases, respectively.

1. Introduction

Two key points within the construction and civil-engineering sector make it quite evident that current trends are moving towards a production system based on the circular economy (Charef et al., 2022). On the one hand, the development of construction materials made from sustainable raw materials, where concrete is the most representative example (Balletto et al., 2021; Dominguez-Santos, 2021). No longer limited to laboratory testing, sustainable concrete is spreading on an industrial scale (Deresa et al., 2020; Krour et al., 2022). Real sustainable-concrete structures with robust and durable properties, such as building foundations and harbor dikes can now be found (Santamaría et al., 2020). On the other hand, repair and rehabilitation works on concrete elements are increasingly common (Hofer et al., 2018). Thus, instead of demolishing the structure, whenever proper performance can no longer be guaranteed, the health of the structure can be evaluated and any necessary actions, such as strengthening, can be undertaken to extend its service life (Toska et al., 2021). If an existing concrete structure can still be useful and adapted to a new use, then there is no need to build a new one.

There are various procedures to determine the health of concrete structures. The most obvious option is direct sampling, for which purpose cores are extracted from the structure and subsequently tested. However, the drilling of test cores clearly damages the structure and can even aggravate its deterioration (Qasrawi, 2019). A range of techniques has therefore been developed for non-destructive testing of concrete structures since the mid-20th century (Jones, 1949). Certain mechanical properties of a concrete structure, principally compressive strength, can be determined with these non-destructive test results and statistical models, based on field work, observations and *in situ* tests (Zima and Kędra, 2020). These very varied non-destructive tests include electrical resistivity, penetration resistance, hammer rebound index, and Ultrasonic Pulse Velocity (UPV), the last two being the most traditional (Hoła, 2020).

The hammer rebound index is used to assess the surface hardness of concrete. A higher value implies a more resistant cementitious matrix and, therefore, better mechanical behavior (Saha and Amanat, 2021). The device used for its determination is called the Schmidt hammer, which impacts a calibrated mass against a concrete surface that is projected by a spring with a force that is also calibrated. The hammer rebound index is a numeric reading of the rebound height of the mass, expressed on a dimensionless calibrated scale (Nguyen et al., 2013).

Abbreviations: RA, Recycled Aggregate; SCC, Self-Compacting Concrete; UPV, Ultrasonic Pulse Velocity.

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Unlike the hammer rebound index, the UPV is not limited to the evaluation of the surface quality of concrete, as it is a non-destructive test that passes an ultrasonic pulse through the structure to evaluate the quality of the concrete as a whole (Jones, 1963). The higher the density, the shorter the travel time of the ultrasonic pulse and the higher the UPV, which implies fewer pores and internal fissures within the concrete, and better overall mechanical strength and behavior (Zima and Kędra, 2020).

In the 21st century, different types of improved-performance concretes have been developed. One is high-performance concrete, with strength and durability superior to conventional vibrated concrete (He et al., 2022). Another is Self-Compacting Concrete (SCC), characterized by improved fresh behavior. The particular composition of SCC, based on a high fine-aggregate content, a reduced amount of coarse aggregate, and the use of plasticizing admixtures, means that this concrete type requires no vibration (Okamura, 1997), but it modifies the traditional patterns of the relations between non-destructive tests and the mechanical behavior of the concrete (Nepomuceno and Bernardo, 2019). The values of density, porosity, and surface hardness of SCC are different from those of a conventional vibrated concrete of similar mechanical behavior, which modifies both the UPV and the hammer-rebound-index values (Revilla-Cuesta et al., 2021c). Thus, the models available for conventional vibrated concrete are not valid for SCC, so different studies have been conducted to evaluate this relation and to develop suitable models (Nepomuceno and Bernardo, 2019; Singh and Singh, 2018).

The addition of sustainable raw materials to concrete has led to a similar phenomenon. Thus, the use of alternative binders or aggregates not only modifies the mechanical behavior (Teixeira et al., 2021), but also the properties upon which the non-destructive tests depend (Nedeljković et al., 2021). Therefore, the relations between non-destructive tests and the mechanical behavior of concrete made with conventional raw materials, and the models derived from them, are no longer valid for these sustainable materials (Revilla-Cuesta et al., 2021c; Singh and Singh, 2018). For example, Recycled Aggregate (RA), traditionally used to replace natural aggregate, reduces concrete density and surface hardness while increasing porosity (Etxeberria, 2021). This behavior is caused by hardened-mortar fragments adhering to the larger particles and non-hydrated mortar and cement particles within the finer fractions (Bravo et al., 2021). The use of ground granulated blast-furnace slag, often in the form of standardized slag cement, EN 197–1 (EN-Euronorm), delays strength development while density and porosity values are not significantly affected (Niş et al., 2021). However, these properties, as well as surface hardness, will largely depend on the mix design (Meko et al., 2021).

All of the above points can simultaneously concur when SCC contains RA and slag cement. Although highly sustainable and easily poured, tools to assess its potential pathologies are essential to encourage its widespread use in any concrete component, so that its sound performance can be assessed and adequate repair and rehabilitation options can be discussed (Hofer et al., 2018). So, a complete circular economy with this concrete type could be achieved, both through the use of sustainable raw materials and by guaranteeing a possible second life for the concrete element (Charef et al., 2022).

The authors of this study are currently engaged in research to analyze the behavior of this type of concrete and to show that its use is absolutely valid in building and civil-engineering applications. In these sorts of concrete mixes, their temporal fresh behavior (Revilla-Cuesta et al., 2021b), mechanical properties (Revilla-Cuesta et al., 2022a), and resistance to deformation (Revilla-Cuesta et al., 2022b) have previously been analyzed. The feasibility of their use has even been demonstrated through a multi-criteria analysis that considered these properties, their carbon footprint, and their cost (Revilla-Cuesta et al., 2021a). The purpose of this paper is to provide reliable and safe models for the non-destructive estimation of the modulus of elasticity of components composed of this concrete type, not only for safe initial use, but also for potential repair and rehabilitation (Cecilia et al., 2020). This paper complements previously published research providing models for estimating compressive strength (Revilla-Cuesta et al., 2021c), thereby offering alongside the other paper a complete view of the non-destructive tests that can be used to estimate the mechanical properties *par excellence* of concrete: the compressive strength, which characterizes its strength behavior, and the modulus of elasticity, which defines its elastic deformational behavior.

2. Materials and data considerations

In this section, the fundamental aspects of the SCC mixes considered for the development of the models are outlined.

2.1. Composition of the SCC mixes

A total of 24 SCC mixes were tested for the development of the models, which widely covered the different design proportions of slag-cement SCC with RA. The properties of the raw materials and the mix design of the SCC mixes can be found elsewhere (Revilla-Cuesta et al., 2021c). The key features of the composition of these mixes were:

- The full complement of coarse RA of size between 4 and 12.5 mm (4/12.5 mm) was added to all the mixes. SCC sustainability was maximized by using 100% coarse RA without compromising proper mechanical behavior.
- Three replacement ratios were considered for fine RA of size between 0 and 4 mm (0/4 mm): 0%, 50%, and 100%.
- Half of the mixes incorporated CEM I, and the other half CEM III/A, containing 45% ground granulated blast-furnace slag, as *per* EN 197–1 (EN-Euronorm).
- Each cement type and percentage of fine RA was combined with each of the four aggregate powders under consideration: a mix of limestone filler <0.063 mm and coarse limestone 0/1 mm, limestone filler <0.063 mm, fine limestone 0/0.5 mm, and powdery RA 0/0.5 mm.

2.2. Starting data for model development

The data used for the development of the models are shown in Table 1, the detailed analysis of which can be found elsewhere (Revilla-Cuesta et al., 2021a, 2021c). The modulus of elasticity was measured on 10 × 20-cm cylindrical specimens according to EN 12390–13 (EN-Euronorm). On the other hand, the hardened density, hammer rebound index and UPV were measured on 10 × 10 × 10-cm cubic specimens according to EN 12390–7, EN 12504–2 and EN 12504–4 (EN-Euronorm), respectively. Furthermore, the mixes fulfilled all the fresh requirements to be considered as self-compacting, which exhibited a slump-flow class SF3 (slump flow of 800 ± 50 mm) (Revilla-Cuesta et al., 2021b).

The key aspect of these data for developing the model was that the modulus of elasticity, the hammer rebound index, and the UPV followed the same behavioral trends with the modification of the raw materials, revealing the direct interrelation between the measures of those properties. Thus, the higher cement content in the mixes with CEM III/A led to improved properties, in so far as it compensated for the lower strength and higher deformability of ground granulated blast-furnace slag with respect to ordinary Portland cement (Chandru et al., 2021). The additions of fine RA worsened the SCC behavior, as it increased porosity and weakened the interfacial transition zones (Evangelista and De Brito, 2014). Finally, limestone filler provided the highest elastic stiffness, although the highest values of the non-destructive tests were obtained with the use of fine limestone. Powdery RA concentrated all the negative effects of fine RA and led to the worst SCC behavior.

Table 1
Model starting data.

Mix [a]	28-day hardened density (Mg/m^3)	Modulus of elasticity at 7–28 days (GPa)	Hammer rebound index at 7–28 days	UPV at 7–28 days (km/s)
I-0/F	2.26	34.8–41.6	34–39	4.03–4.12
I-50/F	2.19	28.4–29.5	30–34	3.96–4.05
I-100/F	2.05	21.1–23.2	26–28	3.53–3.71
III-0/F	2.30	40.2–49.3	39–42	4.17–4.30
III-50/F	2.23	31.1–34.3	31–33	3.98–4.07
III-100/F	2.12	20.9–25.8	25–30	3.47–3.90
I-0/L	2.24	31.4–36.4	33–41	4.02–4.22
I-50/L	2.09	24.9–26.7	31–40	4.00–4.09
I-100/L	1.93	21.5–22.1	26–29	3.59–3.82
III-0/L	2.24	36.9–45.3	40–46	4.21–4.63
III-50/L	2.16	27.0–31.4	38–45	4.11–4.53
III-100/L	2.02	19.7–22.5	27–32	3.89–3.99
I-0/M	2.24	31.2–35.8	35–39	4.05–4.17
I-50/M	2.17	25.8–27.9	31–34	3.95–4.10
I-100/M	1.97	20.3–21.7	26–29	3.46–3.82
III-0/M	2.27	37.5–44.3	36–42	4.10–4.48
III-50/M	2.21	26.8–32.4	31–40	3.98–4.21
III-100/M	2.07	18.8–22.9	31–33	3.81–4.05
I-0/R	2.15	24.0–25.9	28–29	3.90–3.95
I-50/R	1.95	19.3–22.8	22–26	3.35–3.87
I-100/R	1.76	14.8–15.2	12–18	2.77–2.98
III-0/R	2.15	26.6–29.3	28–31	3.83–4.03
III-50/R	2.08	24.5–27.1	26–28	3.75–3.94
III-100/R	1.81	13.9–16.1	20–26	3.21–3.68

[a] Code *A-B/C: A,* cement type (*I*, CEM I; *III*, CEM III/A); *B,* percentage of fine RA (*0%*, *50%* or *100%*); *C,* aggregate powder (*F*, limestone filler; *L*, fine limestone; *M*, mix of limestone filler and coarse limestone; *R*, powdery RA).

2.3. Statistical calculations

Statistical models were developed from the above data, to estimate the modulus of elasticity of slag-cement SCC containing RA in a non-destructive way. For this purpose, simple- and multiple-regression procedures were considered, also ensuring the significance of the models and their components. Both the mean expected values and the minimum expected values were calculated to guarantee valid and safe estimations of the modulus of elasticity.

3. Results and discussion: estimation of the modulus of elasticity

In this section, the models are presented to predict the modulus of elasticity of the mixes from the hardened density, hammer rebound index, and UPV test results, whose values have all been presented in the

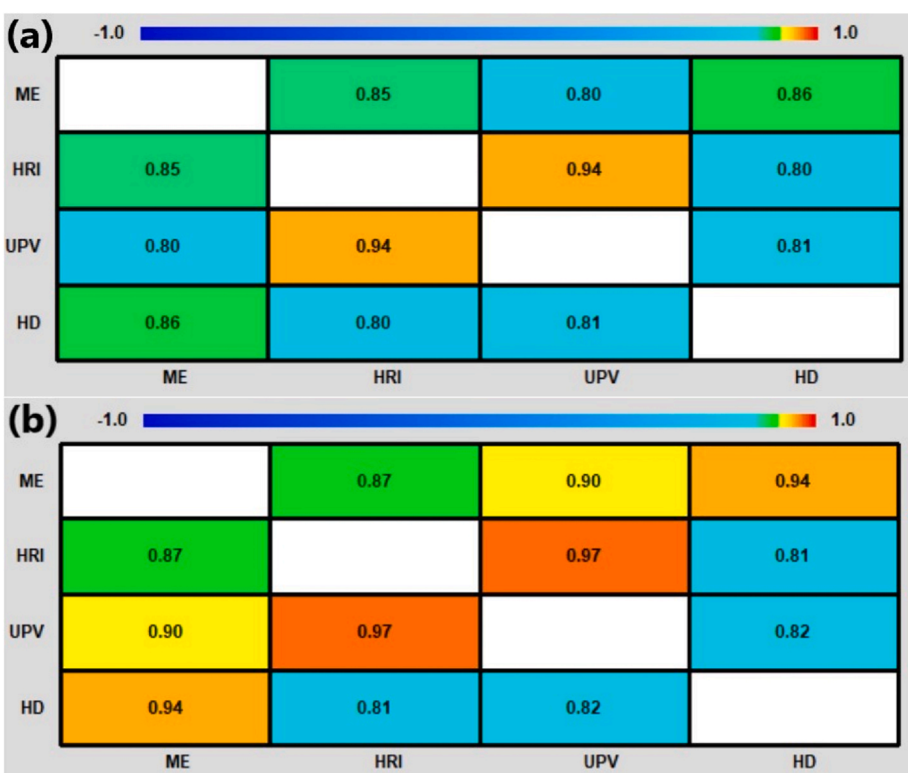

Fig. 1. Correlations between variables: (a) Pearson; (b) Spearman.

previous section. These models can be used for the estimation of the modulus of elasticity of previously constructed concrete components.

3.1. Dependence between variables: correlations analysis

The first step in determining whether a variable can be estimated by other variables is to establish whether there is a relation of statistical dependence between them (Zhang et al., 2022). Both the Pearson and the Spearman correlations between the modulus of elasticity (*ME*), the hammer rebound index (*HRI*), the UPV (*UPV*) and the hardened density (*HD*) were therefore evaluated. The variables were considered without age separation for developing broadly applicable models (Revilla-Cuesta et al., 2021c). The correlation matrices for both correlation types are shown in Fig. 1.

The Pearson correlation coefficient tests for linear dependence between two data sets: the closer the absolute value of the correlation is to 1, the greater the dependence. The correlation with a positive sign indicates that when the value of one variable increases, the other also increases, while a negative sign indicates that when the value of one variable increases, the other decreases. The Pearson correlations were always positive for the variables analyzed in this study (Fig. 1a), showing that there was a correct linear correlation (between 0.80 and 0.90) of the modulus of elasticity with the other variables.

The Spearman correlation has the same interpretation as the Pearson correlation with regard to absolute values and signs, but it explores whether both variables have a monotonic relationship, *i.e.*, whether when one variable varies the other also varies, and whether the variations of both variables are in some way proportional, *i.e.*, linearly, quadratically, *etc*. In other words, it examines whether two variables vary *"at the same rate"*. The Spearman correlations (Fig. 1b) for the variables in this study showed that the modulus of elasticity presented a clear positive monotonic relation with the other variables. In addition, the absolute values of the Spearman correlations were higher than those of the Pearson correlations, in excess of 0.90. A result that shows the greater intensity of the monotonic rather than the linear relationship between the variables.

According to the correlation analysis, it can be stated that statistical models can be developed with which the modulus of elasticity may be estimated from the hammer rebound index, the UPV and the hardened-density test results. However, it will be necessary to resort to potential models where the independent variables are raised to a coefficient to improve model accuracy, as the variables show a monotonic rather than a linear correlation.

3.2. Estimation by using a single non-destructive test

In this section, models are presented for estimating the modulus of elasticity from a single non-destructive test, either the hammer rebound index or the UPV. Two SCC ages, 7 and 28 days, were simultaneously considered in the development of the models, for a wider range of application (Revilla-Cuesta et al., 2021c).

3.2.1. Simple regression

The models were developed from the mathematical relations of the correlations analysis between the dependent variable of the model, the modulus of elasticity, and the independent variables, the hammer rebound index and the UPV. The validity of each formulation was analyzed and both the precision and the likelihood of the estimation were improved by maximizing the correlation coefficient R^2. The model formulation that offered the most precise estimation for both non-destructive tests was the one shown in Equation (1), in which *ME* is the modulus of elasticity in GPa; *NDM* is the non-destructive test (either the hammer rebound index, a dimensionless value, or UPV, in km/s); and *A*, *B*, *C,* and *D* are adjustment coefficients. This formulation yielded an inversely proportional relationship between the modulus of elasticity and the power of the non-destructive test results.

$$ME = \frac{A}{B + C \times NDM^D} \tag{1}$$

The least-squares fitting of the coefficients *A*, *B*, *C,* and *D* balanced the precision of the estimation and the simplicity of the model, *i.e.*, looking for the simplest coefficients that would provide the greatest precision in the estimation. It led to the models shown in Table 2, which provides the formulas for calculating the mean expected value and the minimum expected value at a confidence level of 95%. Both non-destructive tests had the same exponent, 0.5. The parameters listed in Table 3 confirmed the statistical significance of the models at a confidence level of 95% (α=*0.05*): a coefficient R^2 greater than 75%; a correlation coefficient greater than 0.85 in absolute value; *p*-values of the significance of the intercept and the slope lower than 0.05; and the absence of autocorrelation between the residuals, confirmed by the *p*-values of the Durbin-Watson statistic that were higher than 0.05.

The modulus of elasticity of the SCC mixes could be accurately estimated with these models, as shown in Fig. 2. The deviation of the predicted values of the modulus of elasticity from the experimental values for the hammer rebound index was less than 10% in 55% of the cases and less than 20% in 85% of the cases. Regarding the UPV test, these percentages were, respectively, 63% and 80%. For both non-destructive tests, the deviation levels were adequate, considering other models available in the literature for estimating the mechanical properties of concrete containing RA (Silva et al., 2016; Yu et al., 2021). If standard safety coefficients are used, then the validity of the modulus of elasticity values estimated with these simple-regression models is guaranteed (Luo et al., 2021).

The minimum expected values of the modulus of elasticity were lower than the experimental values in 45 out of 48 cases for the hammer rebound index and in 47 out of 48 cases for the UPV, providing adequate values from the safety-theory viewpoint (EC-2, 2010). However, the authors recommend that the minimum expected values only be considered for mean expected values of the modulus of elasticity below 25 GPa, in order to maximize the precision of the estimation. It can be

Table 3
Significance parameters of simple-regression models (α = 0.05).

Non-destructive test	Hammer rebound index	UPV
Coefficient R^2 (%)	75.7644	75.9381
Correlation coefficient	−0.8704	−0.8714
Intercept *p*-value	0.0000	0.0000
Slope *p*-value	0.0000	0.0000
Durbin-Watson statistic	1.8228	1.6279
Durbin-Watson-statistic *p*-value	0.2543	0.0910

Table 2
Simple-regression models.

Non-destructive test	Hammer rebound index	UPV
Mean expected value	$ME = \frac{1}{0.130 - 0.016 \times HRI^{0.5}}$	$ME = \frac{1}{0.262 - 0.113 \times UPV^{0.5}}$
95%-confidence-level minimum expected value	$ME = \frac{1}{0.142 - 0.016 \times HRI^{0.5}}$	$ME = \frac{1}{0.278 - 0.113 \times UPV^{0.5}}$

ME, modulus of elasticity in GPa; *HRI*, hammer rebound index, dimensionless; *UPV*, ultrasonic pulse velocity in km/s.

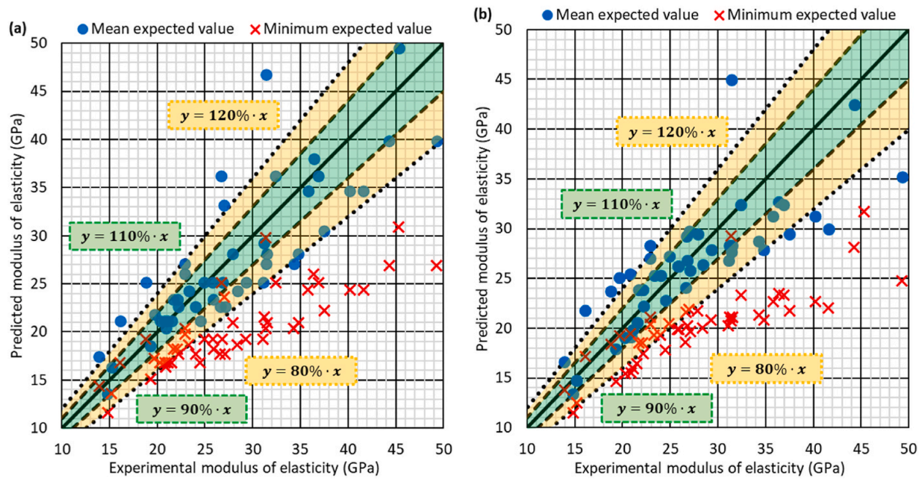

Fig. 2. Comparison of experimental moduli of elasticity and moduli of elasticity estimated with the simple-regression models: (a) hammer rebound index; (b) UPV.

Table 4
Simple-regression models with density correction.

Non-destructive test	Hammer rebound index	UPV
Mean expected value	$ME = \frac{1.953 \times HD^{2.5}}{1.123 - 0.115 \times HRI^{0.5}}$	$ME = \frac{0.526 \times HD^{2.5}}{0.593 - 0.234 \times UPV^{0.5}}$
95%-confidence-level minimum expected value	$ME = \frac{1.765 \times HD^{2.5}}{1.561 - 0.178 \times HRI^{0.5}}$	$ME = \frac{0.211 \times HD^{2.5}}{0.389 - 0.162 \times UPV^{0.5}}$

ME, modulus of elasticity in GPa; *HD*, hardened density in Mg/m^3; *HRI*, hammer rebound index, dimensionless; *UPV*, ultrasonic pulse velocity in km/s.

noted in Fig. 2 that this is the area where the simple-regression models resulted in the largest overestimations (higher than +20%) of the experimental modulus of elasticity, so wherever there was a high overestimation, then it was safer to use the minimum expected values. Using mechanical property values that are overestimated implies concrete strength and stiffness values that are higher than the real values, which could lead to inadequate concrete designs (Farzad et al., 2019; Yu et al., 2022).

3.2.2. Simple regression with density correction

Although the estimation accuracy obtained through the simple-regression models was correct, it was decided to develop models of higher accuracy to guarantee their successful use in all cases (Yu et al., 2021). To do so, a complementary property to the non-destructive tests was sought that could serve as a correction factor for the models. After evaluating different possibilities, the hardened density of concrete was chosen for three main reasons:

- Firstly, non-destructive concrete tests, especially the UPV, have a close relationship with hardened density, in so far as they share similar variation trends (Jones, 1963).
- Secondly, the determination of hardened density is simple and fast on surface samples of the concrete structural element for which the modulus of elasticity is to be estimated in repair or rehabilitation work. In this way, the damage caused to the concrete element is almost nil (Qasrawi, 2019).

Table 5
Significance parameters of simple-regression models with density correction ($\alpha = 0.05$).

Non-destructive test	Hammer rebound index	UPV
Coefficient R^2 (%)	92.1375	90.5676
Durbin-Watson statistic	1.6375	1.6718
Limit of Durbin-Watson statistic [a]	1.5776	1.5776

[a] A Durbin-Watson statistic over the limit indicates no autocorrelation of the residuals.

- Finally, density is already applied as a correction factor in some models for estimating the modulus of elasticity of concrete. The clearest example is the formula contained in Eurocode 2 (EC-2, 2010) for estimating the modulus of elasticity of concrete from the compressive strength, detailed in Equation (2) (*ME*, modulus of elasticity in GPa; *CS*, compressive strength in MPa; *HD*, hardened density in Mg/m^3).

$$ME = 21500 \times \left(\frac{CS}{10}\right)^{0.3} \times \left(\frac{HD}{2.2}\right)^{2} \tag{2}$$

Thus, in view of the model formulation that achieved the best simple-regression accuracy (Equation (1)), the formulation of the Eurocode-2 density correction factor (third term in Equation (2)), and the higher monotonic than linear correlation between the variables (Fig. 1), a simple-regression model with density correction for each non-destructive test was proposed for the estimation of the modulus of elasticity of the SCC. These models were formulated along the lines of Equation (3), in which *ME* is the modulus of elasticity in GPa; *NDM* the non-destructive test (either the hammer rebound index, a dimensionless value, or the UPV, in km/s); *HD* the hardened density in Mg/m^3; and *A*, *B*, *C*, *D*, and *E* adjustment coefficients. It can be seen that this formulation is identical to the one in Equation (1), but a power of the hardened density (HD^B) is introduced as a correction factor.

$$ME = \frac{A \times HD^B}{C + D \times NDM^E} \tag{3}$$

The calculation of coefficients *A*, *B*, *C*, *D*, and *E* with least squares, while seeking the simplest exponents (easiest use of the models) that would provide the highest estimative precision, led to the models shown in Table 4. The formulas are provided for calculating the mean expected value and the 95%-confidence-level minimum expected value of the modulus of elasticity. It can also be noted that the exponent of the non-destructive tests was the same as for the simple-regression model without density correction, 0.5. The very high coefficient R^2, above 90%, and the Durbin-Watson statistic that was higher than the required upper bounds, which pointed to the absence of autocorrelation between

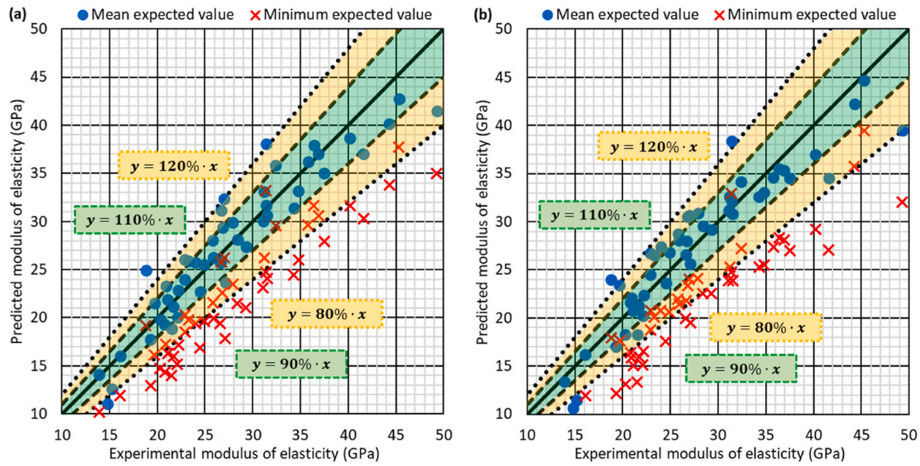

Fig. 3. Comparison of experimental moduli of elasticity and moduli of elasticity estimated with simple-regression models with density correction: (a) hammer rebound index; (b) UPV.

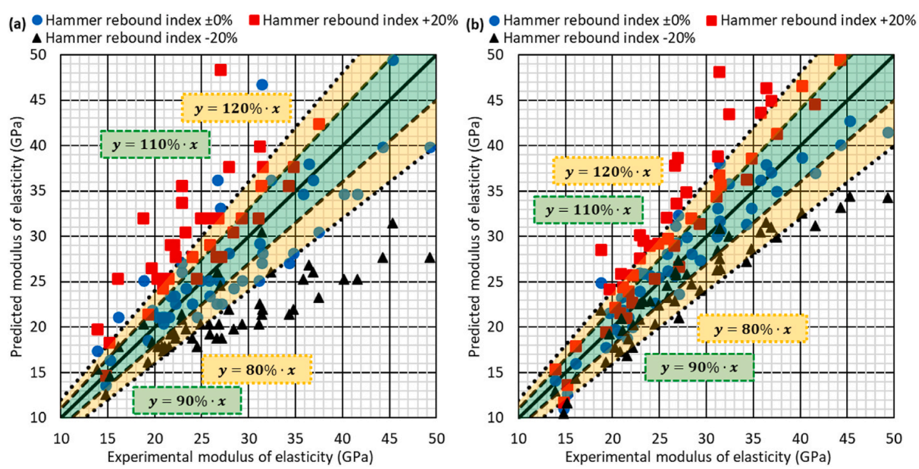

Fig. 4. Robustness of simple-regression models dependent on the hammer rebound index: (a) without correction; (b) with density correction.

the residuals, guaranteed the validity of these models, as can be noted in Table 5.

The simple-regression models with density correction showed a higher estimation precision than the simple-regression models without correction, as shown in Fig. 3. Thus, the hammer-rebound-index model showed an estimation deviation of less than 10% in 83% of the cases and less than 20% in 94% of the cases. These percentages for the UPV model were 70% and 92%, respectively. The estimation accuracy when introducing density correction was higher for the hammer rebound index, although both non-destructive tests provided good reliability for the estimation of the modulus of elasticity of the SCC containing RA (Golafshani and Behnood, 2021; Silva et al., 2016). The minimum

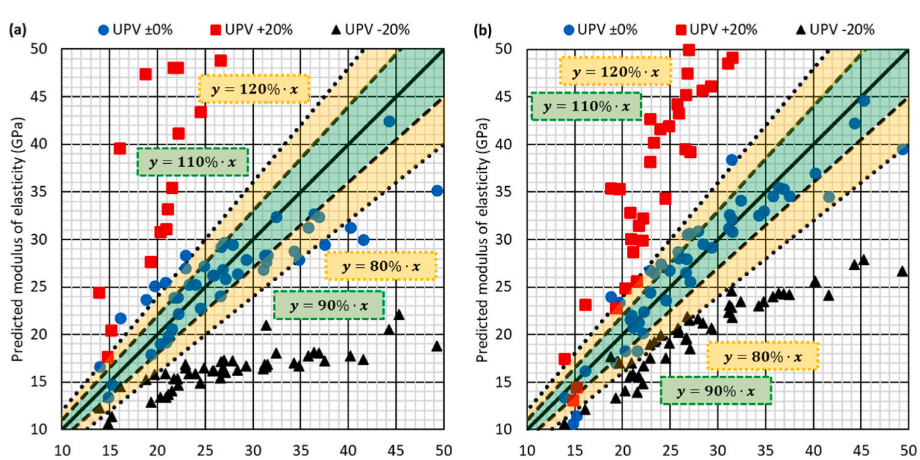

Fig. 5. Robustness of simple-regression models dependent on the UPV: (a) without correction; (b) with density correction.

Table 6
Multiple-regression model.

Mean expected value	$ME = \frac{0.710}{(0.862 - 0.098 \times HRI^{0.5}) \times (0.166 - 0.040 \times UPV^{0.5})}$
95%-confidence-level minimum expected value	$ME = \frac{0.465}{(0.965 - 0.119 \times HRI^{0.5}) \times (0.246 - 0.078 \times UPV^{0.5})}$

ME, modulus of elasticity in GPa; *HRI*, hammer rebound index, dimensionless; *UPV*, ultrasonic pulse velocity in km/s.

expected values showed a similar trend to the one shown in the simple-regression models without correction; in practically all cases lower than the experimental value, so their use will always be on the safe side. However, the authors recommend that the expected mean value is used in these models, as no large overestimates (higher than +20%) of the modulus of elasticity were observed that cannot be corrected by using the safety coefficients listed in the concrete-design regulations (EC-2, 2010; Luo et al., 2021).

Non-destructive concrete measures show high variability. The hammer rebound index and the UPV are therefore usually measured three times on the same structural component at the same point to obtain three different values which are then averaged out. A practice that can sometimes make the estimation of the modulus of elasticity unreliable (Jones, 1963). One solution is to calculate the modulus of elasticity for each value of the non-destructive tests (Nguyen et al., 2013). Another option is to complement the non-destructive tests with another test method that presents less variability, to add to the robustness of the model (Sajid et al., 2019). As shown in Fig. 4 for the hammer rebound index and in Fig. 5 for the UPV, the use of a density correction factor reduced the estimation error in comparison with the simple-regression models without correction when variations of ±20% in the value of the non-destructive tests were considered. This behavior was especially notable in the case of the hammer rebound index (Fig. 4), as the predicted value of the modulus of elasticity in many cases showed a deviation with regard to the experimental value of less than ±20% when this non-destructive test varied by ±20%. However, increased robustness when using UPV was not as high (Fig. 5). Thus, multiple-regression models were developed to provide greater robustness to the estimation, in which the estimation of the modulus of elasticity was conducted through the simultaneous use of both non-destructive tests.

3.3. Estimation by simultaneously using two non-destructive tests

In this section, the models are specified for estimating the modulus of elasticity from the simultaneous use of both non-destructive tests: the hammer rebound index and UPV. In this case, there was no differentiation on the basis of age, so as to increase the range of application of the model (Revilla-Cuesta et al., 2021c).

3.3.1. Multiple regression

The formulation that provided the highest accuracy in the simple-regression models, shown in Equation (1), was used as a starting point for the development of the multiple-regression model, as no increase in the estimation accuracy of the modulus of elasticity was observed in the other formulations. Therefore, both non-destructive tests, hammer rebound index and UPV, were combined maintaining that formulation. Furthermore, fit tests previously performed showed that the product of both non-destructive tests provided the highest estimation accuracy. In conclusion, the multiple-regression model that was developed conformed to the model formulation shown in Equation (4), in which *ME* is the modulus of elasticity in GPa; *HRI* the hammer rebound index, a dimensionless value; *UPV* the ultrasonic pulse velocity in km/s; and *A*, *B*, *C*, *D*, *E*, *F*, and *G* adjustment coefficients.

$$ME = \frac{A}{(B + C \times HRI^{D}) \times (E + F \times UPV^{G})} \tag{4}$$

The fitting of this model formulation to the experimental data, through a least squares procedure, looking for the simplest possible exponents, so that the model could be easily applied, led to the multiple-regression model shown in Table 6. In this table, both the mean expected value and the minimum expected value for a confidence level of 95% are detailed for the model. It can be observed that in this model the exponent of both non-destructive tests was 0.5, the same as in the simple-regression models (Tables 2 and 4). The model was shown to be valid according to the coefficient R^2, higher than that of the simple-regression models without correction (Table 3), and the value of the Durbin-Watson statistic, aspects shown in Table 7.

The model showed an adequate estimation accuracy, as shown in Fig. 6. Thus, 56% of the estimated values of the modulus of elasticity presented a deviation of less than ±10% with respect to the experimental values, while this percentage was 85%, if a deviation of ±20% is considered. The deviation levels were appropriate if the safety coefficients that need to be considered in concrete design according to the regulations (EC-2, 2010) and the precision level of other models available in the literature are taken into account (Silva et al., 2016; Zhang and Afzal, 2021). In addition, higher levels of accuracy than in the simple-regression models without correction (Fig. 2), but lower levels

Table 7
Significance parameters of the multiple-regression model (α = 0.05).

Coefficient R^2(%)	77.9076
Durbin-Watson statistic	1.6788
Limit of Durbin-Watson statistic [a]	1.5776

[a] A Durbin-Watson statistic over the limit indicates no autocorrelation of the residuals.

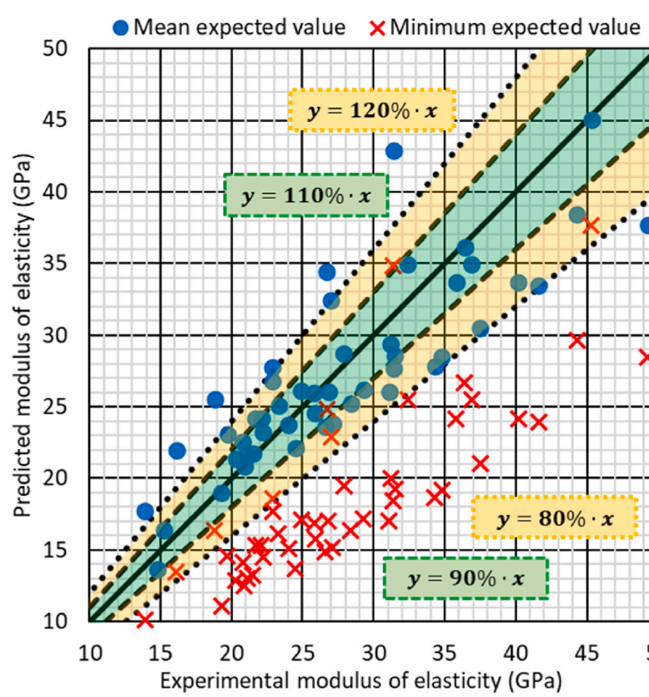

Fig. 6. Comparison of experimental moduli of elasticity and moduli of elasticity estimated by the multiple-regression model.

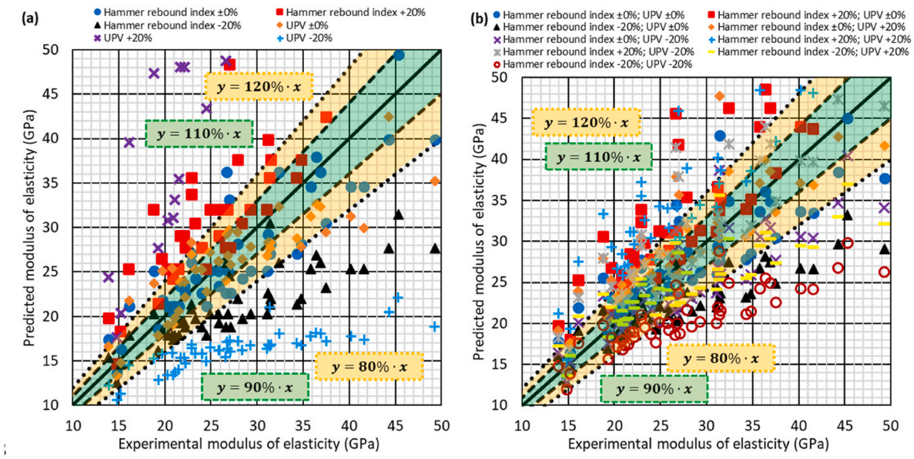

Fig. 7. Robustness of models without correction: (a) simple-regression models; (b) multiple-regression model.

Table 8
Multiple-regression model with density correction.

Mean expected value	$ME = \dfrac{0.808 \times HD^{2.5}}{(1.363 - 0.140 \times HRI^{0.5}) \times (0.333 + 0.005 \times UPV^{0.5})}$
95%-confidence-level minimum expected value	$ME = \dfrac{0.513 \times HD^{2.5}}{(1.278 - 0.140 \times HRI^{0.5}) \times (0.573 - 0.120 \times UPV^{0.5})}$

ME, modulus of elasticity in GPa; *HD*, hardened density in Mg/m^3; *HRI*, hammer rebound index, dimensionless; *UPV*, ultrasonic pulse velocity in km/s.

than in the simple-regression models with density correction (Fig. 3) were noted. Once again, the minimum expected values were in most cases lower (47 out of 48, 98%) than the experimental ones, thus guaranteeing safe estimations. However, in view of the estimative precision, their use is only recommended when adding 100% fine RA, as the highest overestimations were found when using that content of fine RA.

In relation to the robustness of the estimation, the multiple-regression model improved the robustness levels in the face of oscillations of the values of the non-destructive tests provided by the simple-regression models, as depicted in Fig. 7. Thus, with the multiple-regression model, the estimated value of the modulus of elasticity presented a deviation of less than ±20% with respect to the experimental value in around 75% of all cases. In addition, the multiple-regression model showed greater robustness than the UPV simple-regression model with density correction (Fig. 5b), but it was less robust than the hammer-rebound-index simple-regression model with density correction (Fig. 4b).

From all the above, it can be affirmed that the multiple-regression model was adequate. Nevertheless, the model had lower estimation precision when compared with the simple-regression models with density correction and lower levels of robustness when compared with the hammer-rebound-index simple-regression model with density correction. It was therefore decided to examine whether a density correction factor could be introduced in the multiple-regression model.

3.3.2. Multiple regression with density correction

The multiple-regression model with density correction was developed from the model formulation of Equation (4) (multiple-regression model without correction), bearing in mind the model formulation used in the simple-regression model shown in Equation (3) for the density correction factor. Thus, a density correction factor that consisted of a power of the hardened density (HD^B) of the SCC was introduced. The formulation finally considered is shown in Equation (5), in which *ME* is the modulus of elasticity in GPa; *HD* is the hardened density in Mg/m^3; *HRI* is the hammer rebound index, a dimensionless value; *UPV* is the ultrasonic pulse velocity in km/s; and *A*, *B*, *C*, *D*, *E*, *F*, *G*, and *H* are adjustment coefficients.

$$ME = \frac{A \times HD^B}{\left(C + D \times HRI^E\right) \times \left(F + G \times UPV^H\right)} \tag{5}$$

As with the other models, the adjustment coefficients were fitted by least squares looking for the simplest exponents, thus obtaining the mean expected value and the 95%-confidence-level minimum expected value shown in Table 8. Three aspects may be noted from Tables 8 and 9, which shows that the model was significant:

- In this model, as in all the others (Table 2, Tables 4 and 6), the exponent of the non-destructive tests was 0.5. The modulus of elasticity presented a consistent inverse relation with the square root of the non-destructive tests, regardless of the type of model and non-destructive test considered.
- In both simple regression (Table 4) and multiple regression, the density correction factor was the hardened density of the SCC raised to 2.5. The density correction factor was independent of the non-destructive test and the type of model that was considered.
- The multiple-regression model with density correction presented the highest coefficient R^2 (Table 3, Tables 5 and 7), so from a reliability approach it was the most accurate model for the estimation of the modulus of elasticity of the slag-cement SCC with RA.

Undoubtedly, the multiple-regression model with density correction was the one that showed the highest accuracy (Fig. 8), even better than that of the simple-regression models with density correction (Figs. 4 and 5). Thus, the estimated modulus of elasticity presented a deviation of less than ±10% with respect to the experimental value in 82% of the

Table 9
Significance parameters of the multiple-regression model with density correction (α = 0.05).

Coefficient R^2(%)	94.1372
Durbin-Watson statistic	1.6409
Limit of Durbin-Watson statistic [a]	1.5776

[a] A Durbin-Watson statistic over the limit indicates no autocorrelation of the residuals.

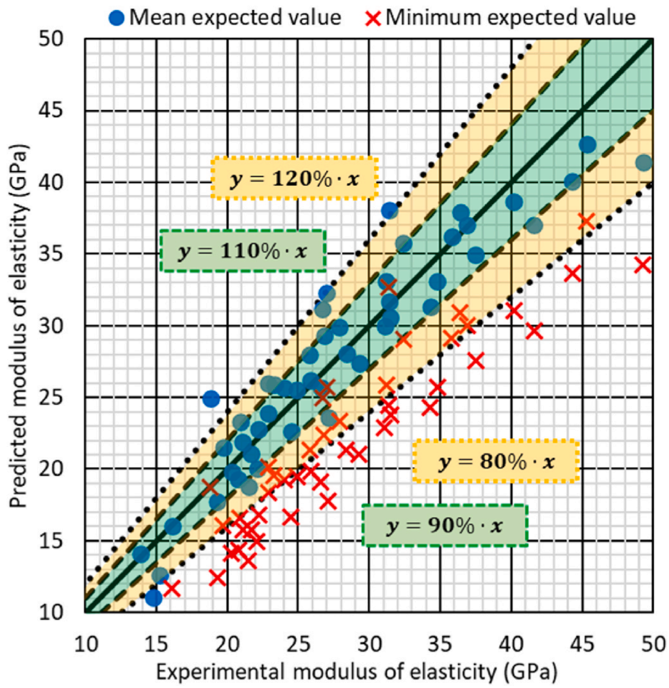

Fig. 8. Comparison of experimental moduli of elasticity and moduli of elasticity estimated using the multiple-regression model with density correction.

points used in the adjustment and this percentage rose to 94% when a deviation of ±20% was considered. Both considering the existing standards (EC-2, 2010) and other elastic-modulus prediction models available in the literature (Silva et al., 2016; Yu et al., 2021; Zhang and Afzal, 2021), it can be stated that the use of the mean expected value obtained by this model is adequate for the design of concrete elements and for measurements prior to rehabilitation and repair works. The minimum expected value of the modulus of elasticity provided by this model was lower than the experimental value in 47 of the 48 cases, assuming its use to be a safe estimate. However, in view of the levels of accuracy, the use of the mean expected value is recommended, considering the usual safety coefficients (EC-2, 2010).

In terms of predictive robustness, it can be appreciated in Fig. 9 that the multiple-regression model with density correction was also the one that presented the greatest stability, in view of the varied non-destructive test values. With variations of ±20% in the non-destructive test values, the estimated value of the modulus of elasticity presented a deviation of less than ±20% in many cases with respect to the experimental value. This robustness was achieved by decreasing the model dependence of the UPV, the most likely non-destructive test to record disparate value (Jones, 1963). Thus, this non-destructive test became a refinement measure to specify the value of the modulus of elasticity, but in no case was it treated as the main property for its estimation.

3.4. Model validation

The multiple-regression model with density correction that showed the highest accuracy and robustness is the model that the authors of this study recommend. It was therefore the model that was used for the validation. A literature review found no studies that allowed that validation to be conducted, *i.e.*, no study was found on slag-cement SCC with RA in which the modulus of elasticity, hardened density, hammer rebound index and UPV had been determined for the concrete mixes.

In view of the above, 5 SCC mixes were prepared with CEM III/A; 100% coarse RA; 0%, 25%, 50%, 75%, and 100% fine RA; and limestone filler <0.063 mm, in order to validate the model. All raw materials were of the same origin as those used in the mixes through which the models were developed (Revilla-Cuesta et al., 2021c). 300 kg/m^3 of CEM III/A and 165 kg/m^3 of limestone filler <0.063 mm were used to manufacture these SCC validation mixes. Limestone filler was considered, because it is widely used in the production of concrete for use in civil engineering (Fiol et al., 2021). Regarding the other components, their proportions were defined following the same procedure as the mixes used for the

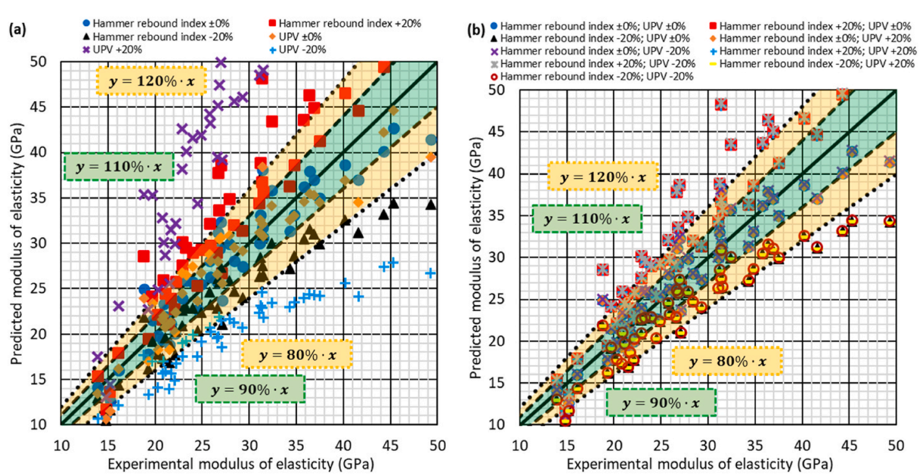

Fig. 9. Robustness of models with density correction: (a) simple-regression models; (b) multiple-regression model.

Table 10
Average values of the validation-mix properties.

Mix [a]	28-day hardened density (Mg/m^3)	Modulus of elasticity at 7–28 – 90 days (GPa)	Hammer rebound index at 7–28 – 90 days	UPV at 7–28 – 90 days (km/s)
V0	2.31	36.9–42.6 – 44.8	36–38 – 38	4.28–4.33 – 4.34
V25	2.28	32.8–40.1 – 41.7	33–35 – 36	3.99–4.21 – 4.29
V50	2.26	28.5–31.4 – 33.3	27–27 – 29	4.04–4.08 – 4.08
V75	2.15	18.8–20.7 – 21.9	21–25 – 26	3.62–3.79 – 3.79
V100	2.09	18.7–19.8 – 21.1	21–24 – 26	3.67–3.71 – 3.72

[a] Code *VX*: *V* is for *"validation mix"; X* is the percentage of fine RA in the mix.

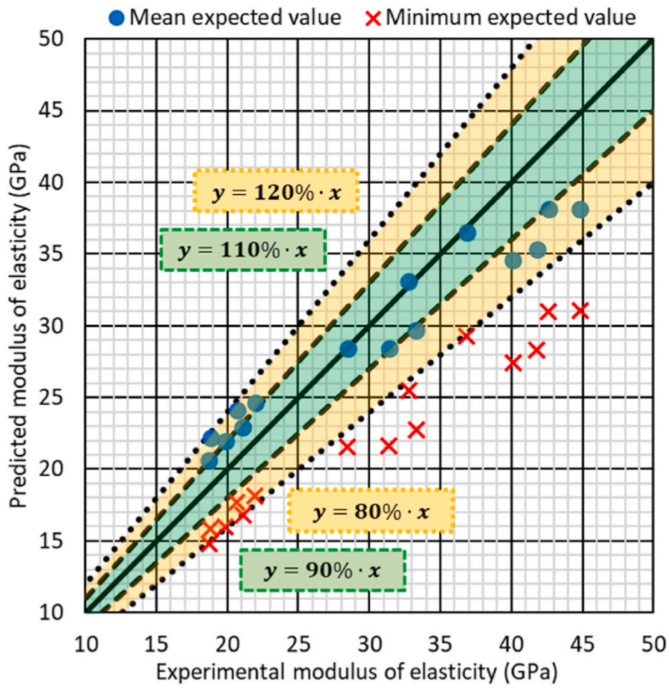

Fig. 10. Validation of the model.

development of the models (Revilla-Cuesta et al., 2021c). However, the validation mixes were modified in an attempt to achieve a slump-flow class SF2 (slump flow of 700 ± 50 mm) following a 2% reduction in the water content, to assess the validity of the model against changes in the fresh behavior of the SCC, as the model was developed with mixes of slump-flow class SF3 (slump flow of 800 ± 50 mm). In these mixes, the 28-day hardened density, and the modulus of elasticity, hammer rebound index and UPV at 7, 28, and 90 days were measured on the same type of specimens as those used in the model-development mixes as *per* European standards EN 12390–7, EN 12390–13, EN 12504–2, and EN 12505–4, respectively (EN-Euronorm). The results of these properties are shown in Table 10.

The comparison between the experimental values of the modulus of elasticity of the validation mixes and the values estimated through the multiple-regression model with density correction was correct, as the estimated value in all cases has a dispersion index of less than ±20% with respect to the experimental value (Fig. 10). The minimum value was lower than the experimental one in all cases, guaranteeing a safe estimate. However, it should be noted that this validation should only be considered as a first approach, as the model needs to be validated with mixes made with raw materials of different origin and following different SCC dosage procedures.

4. Conclusions

In this paper, the possibility of estimating the modulus of elasticity of Self-Compacting Concrete (SCC) made with Recycled Aggregate (RA) and slag cement with 45% ground granulated blast-furnace slag, through the use of non-destructive tests has been analyzed. 24 SCC mixes have been considered, incorporating 100% coarse RA and 0%, 50% or 100% fine RA. Half of them were produced with ordinary Portland cement, while the other half were manufactured with slag cement. In addition, four aggregate powders were considered to generalize the study: limestone filler <0.063 mm, coarse limestone 0/1 mm, fine limestone 0/0.5 mm, and powdery RA 0/0.5 mm.

Statistical analyses have been conducted with data from the hardened density at 28 days, the modulus of elasticity and two non-destructive tests, the hammer rebound index and the Ultrasonic Pulse Velocity (UPV), at 7 and 28 days on the SCC mixes. The aim has been to obtain simple-regression models without correction (Table 2) and with density correction (Table 4) and multiple-regression models without correction (Table 6) and with density correction (Table 8), so as to estimate the modulus of elasticity from the non-destructive tests. The following conclusions can be drawn from these models:

- The modulus of elasticity, hardened density, the hammer rebound index, and UPV showed behavioral variations of the same sign, either increasing or decreasing, when modifying the raw materials used in SCC production. This led to an intense positive correlation of around 0.85–0.95 of the modulus of elasticity with the rest of properties. This correlation was fundamentally monotonic, which is a sign of the potential relation between the variables.
- When seeking the highest estimation accuracy, the value of the modulus of elasticity was always inversely proportional to the square root of the non-destructive test result to which it was related. This relationship was always the same regardless of whether a single non-destructive test result (single regression) or both non-destructive test results (multiple regression) were used in the elastic-modulus estimation.
- The introduction in both the simple-regression and multiple-regression models of a density correction factor increased the estimative precision of the modulus of elasticity and the robustness of the estimation, in view of the fluctuating values of the non-destructive test results. The maximization of accuracy led in all models to the same correction factor: the hardened density of the SCC raised to 2.5. The utility of this correction factor was linked to the fact that density is a property that can be determined with a surface sample of the concrete, without any damage.

The multiple-regression model with density correction was the most accurate, with a predicted value of the modulus of elasticity that deviated from the experimental value by less than ±10% and ±20% in 82% and 94% of the cases, respectively. It was also the model that exhibited the highest robustness to variations in the non-destructive tests, as the UPV results were introduced as a refinement variable, not as a key property for the estimation. Finally, its validation was successful when considering mixes of different slump-flow classes. These three aspects make it the model (Table 8) that the authors of this study would recommend for estimating the modulus of elasticity of slag-cement SCC containing RA in rehabilitation and repair works. However, it is advisable to perform the validation of the model developed in this research with SCC mixes prepared with raw materials of different origin and designed through different dosing procedures. Furthermore, in this paper, the validation of the model was performed on mixes prepared in the laboratory and field tests might also represent a significant step forward in the development of this line of research.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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