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Abderrezak Bouziane
Faculty of Technology, Laboratory of Construction Engineering and Architecture (LGCA), University of Bejaia, 06000 Bejaia, Algeria, abderrezak.bouziane@univ-bejaia.dz

Houssam Slimanou
Faculty of Technology, Laboratory of Construction Engineering and Architecture (LGCA), University of Bejaia, 06000 Bejaia, Algeria

Mohamed Amin Bouzidi
Faculty of Technology, Laboratory of Construction Engineering and Architecture (LGCA), University of Bejaia, 06000 Bejaia, Algeria

Nedjima Bouzidi
University of Bejaia, Laboratory of Materials Technology and Process Engineering (LTMGP), 06000 Bejaia, Algeria

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RESEARCH ARTICLE

Ceramic Waste as Sustainable Material in Self-Compacting Concrete: Experimental Study and ANN Predictive Modeling

Abderrezak Bouziane [a,*], **Houssam Slimanou** [a], **Mohamed Amin Bouzidi** [a], **Nedjima Bouzidi** [b]

[a] Faculty of Technology, Laboratory of Construction Engineering and Architecture (LGCA), University of Bejaia, 06000 Bejaia, Algeria
[b] University of Bejaia, Laboratory of Materials Technology and Process Engineering (LTMGP), 06000 Bejaia, Algeria

ABSTRACT

Recycling of ceramic waste in the construction sector is a promising option for reducing the environmental impacts of the concrete industry. The main objective of this study is the elaboration of a solid predictive model for ceramic waste based self-compacting (SCC) concrete properties, using artificial neural networks (ANN). This further, reduces its environmental impact without compromising satisfactory performance. An experimental approach was adopted with different substitution ratios: 0 to 30 wt% and particle sizes ranging from 3–8 mm and 8–15 mm. Tested properties of modified SCC as compressive strength at 7 and 28 days (f_{c7}, f_{c28}), spread (L), sieve stability segregation (ST), porosity (n), density (ρ) and absorption water (A) were investigated. Addition of ceramic waste affects the properties of the obtained material (SCC). The compressive strengths of all mixes composed were larger than that of the control sample. Despite the results workability property, which remain unsatisfactory; this shows that this parameter was within controlled limits. Moreover, predictive modeling of SCC properties was implemented through the artificial neural network (ANN). These models can predict the physico-mechanical properties according to the substitution percentages. As per the ANN, strong correlation between the experimental and predicted value proved the efficacy of the ANN for optimising the multi-response.This research highlights the potential of ceramic waste to produce durable and efficient SCC while leveraging advanced modeling tools to optimize formulations. It opens promising prospects for sustainable waste management in the construction industry.

Keywords: Ceramic waste recycling, Self-compacting concrete (SCC), Artificial neural network (ANN) modeling, Environmental impact

1. Introduction

The impact of human activities on the environment has prompted the scientific community and industries to seek sustainable solutions, particularly in the construction sector. Primarily for key materials as concrete, that is responsible for significant consumption of natural resources and a substantial contribution to CO_2 emissions [1–5]. Therefore, incorporating recycled materials or industrial waste into concrete formulations has become a promising approach to reducing the environmental footprint of this sector [6–14]. In addition, the use of bio-based materials, such as natural fibers and plant-derived aggregates, is gaining increasing attention as a viable alternative to conventional components, offering benefits in terms of renewability, biodegradability, and carbon sequestration [5, 15–18].

Ceramic waste, primarily generated by the construction and ceramic industries, represents a

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* Corresponding author.
E-mail address: abderrezak.bouziane@univ-bejaia.dz (A. Bouziane).

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considerable volume of solid waste [19–21]. However, its chemical composition and mechanical properties make it an attractive candidate for reuse in concrete, either as a partial substitute for cement or aggregates [20–23].

Recent studies have highlighted innovative approaches and sustainable practices in construction materials and systems. Araújo et al. [24] demonstrated the potential of reusing industrial silicon sludge from the semiconductor industry as an additive in ceramic products, offering both environmental and economic benefits. Venkatesh et al. [25] and Mujkanović et al. [26] investigated the effects of mineral admixtures and calcareous fly ash on the properties of self-compacting concrete (SCC), showing that optimized incorporation and curing can significantly enhance workability, strength, and durability. Chava Rao et al. [25] emphasized the role of wet curing in improving the microstructure and performance of SCC, while Mujkanović et al. [26] identified an optimal fly ash content range beyond which fresh and hardened properties may deteriorate. In the domain of decision-making, Seyhan et al. [27] applied the fuzzy Analytic Hierarchy Process (AHP) to rank refrigerant selection criteria, identifying energy efficiency as the most critical factor. Additionally, Otter et al. [28] reviewed the impact of deep learning advancements on natural language processing, highlighting their applicability in various engineering fields. Collectively, these works underline the importance of integrating sustainable materials and intelligent modeling techniques in modern construction practices.

Self-compacting concrete (SCC), an innovative material designed to flow and compact under its own weight without the need for mechanical vibration, has garnered increasing interest due to its technical, economic, and environmental benefits [29–32]. However, the use of alternative materials in SCC formulations requires special attention, as the properties of this concrete are highly dependent on its composition. Incorporating ceramic waste in the form of aggregates could offer an effective solution for recycling these wastes while meeting the durability and performance requirements of SCC.

In this study, a fraction of natural gravel was replaced with crushed ceramic waste of similar particle size. The primary objective is to evaluate the effects of this substitution on the physical and mechanical properties of SCC, such as density, compressive strength.

Artificial intelligence (AI), particularly machine learning techniques, has emerged as a powerful tool in the field of construction materials. AI applications, such as artificial neural networks (ANN), enable the prediction and optimization of material properties by modeling complex, nonlinear relationships between composition variables and performance metrics. Recent studies have successfully employed AI to forecast concrete durability, optimize mix designs, and assess the environmental impact of materials, thus accelerating innovation in sustainable construction practices [33–40].

In addition to the experimental study, predictive modeling of concrete characteristics was performed using artificial neural networks (ANN). These advanced modeling tools offer exceptional capabilities in capturing complex relationships between input and output parameters, thereby enhancing the understanding of interactions between different concrete components and accurately predicting its performance [30, 37, 41, 42].

The growing demand for sustainable and environmentally friendly construction materials has led researchers to explore alternative solutions that can reduce the consumption of natural resources and limit carbon emissions. In this context, the recycling of ceramic waste in self-compacting concrete (SCC) offers a promising path toward circular economy and waste valorization. However, the effects of such waste on the fresh and hardened properties of SCC remain insufficiently studied. Moreover, the development of reliable prediction models, especially using artificial intelligence such as artificial neural networks (ANN), can facilitate the design and optimization of SCC mixtures incorporating waste. This research thus aims to promote a sustainable solution for managing ceramic waste while contributing to the improvement of self-compacting concrete properties, by offering a solid predictive model using ANN. The results obtained pave the way for better integration of recycled materials into current construction practices, relying on a combination of experimental methods and innovative modeling techniques.

2. Materials and methods

2.1. Materials

The raw materials used in this study include two types of sand (S0/4 and S0/1), two gravel fractions (G3/8 and G8/15), CPJ CEM II/42.5N cement, a SIKA VISCOCRETE TEMPO 12 superplasticizer, limestone fillers, and ceramic waste that was crushed into two fractions, similar to those of the usedgravel (C3/8 and C8/15), to ensure representativeness and reliability of the samples during laboratory tests.

The prepared concrete mixes were cast into 15 cm cubic molds for the production of test specimens. Unlike traditional concrete, the self-compacting concrete (SCC) did not require vibration, as it flows and consolidates under its own weight. After casting, the molds were left undisturbed for 24 hours to allow initial setting. The specimens were then carefully demolded and placed in a water basin maintained at 20 ± 2°C for curing. This water curing process ensured optimal hydration conditions for the cement, enhancing the reliability of the test results. The curing period varied depending on the type of test, with compressive strength being measured at both 7 and 28 days.

2.2. Methods

The raw materials were thoroughly characterized in terms of their physical, chemical, and mineralogical properties.

2.2.1. Physical characterization

The physical characterization included particle size distribution and true density. The particle size distribution was determined in accordance with the NF EN 933-1 standard. The absolute density of cement was measured using a Micromeritics helium pycnometer. The absolute density of sand was determined according to the NF P 18–554 standard.

2.2.2. Chemical and mineralogical characterization

The chemical composition was analyzed using X-ray fluorescence spectrometry (XRF) with a Philips Magix Pro (PW-2440) spectrometer. The identification of mineral phases was performed by X-ray diffraction (XRD) on dried powder samples over a 2θ range from 5° to 80°. The analysis was conducted using a PANalyticalX'Pert MPD diffractometer with Cu Kα radiation, and the resulting spectra were processed using X'PertHighScore Plus software (version 2.1, PDF2 database).

2.2.3. Properties of self-compacting concrete (SCC)

The key parameters for SCC workability are fluidity, viscosity, and resistance to segregation. These properties were assessed using the following tests:

- L-box test (NF EN 12350-10)
- Slump flow test (NF EN 206-9)
- Sieve stability test (applicable standard)
- Fresh-state density

Physical Properties of SCC

Physical properties such as apparent porosity, bulk density, and water absorption were determined using the Archimedes principle, in accordance with the ASTM C20standard.

Mechanical Properties

Compressive strength was evaluated on three specimens per formulation, in accordance with the NF P18-406 standard.

2.3. Formulation method

In this study, the formulation method adopted closely follows the approach proposed by [43] for Self-Compacting Concrete (SCC). The primary aim of the mix design method is to optimize the proportions of key constituents -gravel, sand, cement, water, and superplasticizer- while ensuring the desired properties of flowability, segregation resistance, and self-compacting ability are achieved. The expressions provided for calculating the quantities of each component play a crucial role in determining the optimal mix design. By adhering to this method, the study seeks to establish a balanced composition that enhances the performance of SCC, aligning with the requirements set forth by previous research in the field.

Calculation of gravel and sand contents

The amounts of gravel and sand can be determined using Eqs. (1) and (2) respectively:

$$G = PF \times \rho_{gapp} \left(1 - \frac{S}{a}\right) \tag{1}$$

$$S = PF \times \rho_{sapp} \times \frac{S}{a} \tag{2}$$

where:
G: Gravel content in SCC (kg/m^3),
S: Sand content in SCC (kg/m^3),
ρ_{gapp}: Density of loosely piled, saturated surface-dry of gravel in air (kg/m^3),
ρ_{sapp}: Density of loosely piled, saturated surface-dry of sand in air (kg/m^3),
$\frac{S}{a}$: Volume ratio of sand to total aggregates (gravel + sand), typically ranging from 50% to 57%,
PF: Packing factor, representing the ratio of the mass of tightly packed aggregates in SCC to that of loosely packed aggregates in air. Investigations conducted as part of this study determined a PF value of 1,16.

Calculation of cement content

The cement content to be used is determined by Eq. (3)

$$C = 7,25 f_c' \tag{3}$$

where C: cement content (kg/m^3); f_c': designed compressivestrength (MPa). In this study, f_c' was set to 60 MPa.

Calculation of mixing water content required by cement

The relationship between the compressive strength and the water-to-cement ratio in SCC closely resembles that of conventional concrete. The water-to-cement ratio can be established by Eq. (4) following the guidelines of ACI 318 or other methodologies from previous research.

$$E_C = \left(\frac{E}{C}\right) C \tag{4}$$

Where

E_C: content of mixing water content required bycement (kg/m^3);

E/C: The water/cement ratio by weight, which can be determined by compressive strength. In this study, E/C was set to 0,4.

Calculation of limestone fillers content

The volume of limestone fillers can be calculated as follows by Eq. (5):

$$V_F = 1 - \frac{G}{1000 \times d_{Gabs}} - \frac{S}{1000 \times d_{Sabs}} - \frac{C}{1000 \times d_{Cabs}} - \frac{E_C}{1000} - V_a \tag{5}$$

Where: d_{Gabs}, d_{Sabs} and d_{Cabs} are the specific gravities of gravel, sand, cement respectively, V_a is the air content in the SCC (%). In this study $V_a = 1\%$ for all mixtures.

Then, the limestone fillers content (F) can be calculated using the following Eq. (6)

$$F = \frac{V_F \times 1000 \times d_{Fabs}}{1 + \frac{E}{F}} \tag{6}$$

Where: $\frac{E}{F}$ is the water/limestone-filler ratio by weight. According to the flow table tests (ASTM C230/C230M-20) with Ottawa sand, the E/F ratio is equal to 0,36.

Then mixing water content required by limestone filler paste can be calculated using Eq. (7)

$$E_F = \left(\frac{E}{F}\right) F \tag{7}$$

Calculation of superplasticizer dosage

The dosage of superplasticizer (SP) is expressed as $n\%$ of the total binder content, which includes both cement (C) and filler (F), with its solid content denoted as $m\%$. The dosage can be calculated using Eq. (8):

$$SP = n\%(C + F) \tag{8}$$

Then mixing water content (E_{SP}) required by superplasticizer can be calculated using Eq. (9)

$$E_{SP} = (1 - m\%)\, SP \tag{9}$$

In this study, laboratory pretests were conducted to determine the optimal SP dosage, which was set at $n = 1\%$. This dosage was established based on the combined content of cement and filler incorporated into the SCC.

Mixing water content needed in SCC

The mixing water content required by SCC corresponds to the total amount of water needed for the cement and limestone filler in the mix, minus the water contributed by the superplasticizer. It can be calculated by Eq. (10):

$$E = E_C + E_F - E_{SP} \tag{10}$$

Table 1 presents the composition of various self-compacting concrete (SCC) mixtures formulated in this study. Each mixture varies the proportions of gravel and ceramic waste (C3/8 and C8/15) while maintaining a constant binder content.

Table 1. Mixture proportions of self-compacting concrete with partial replacement of gravel by ceramic waste.

	Component (kg/m^3)									
Mixture	G3/8	G8/15	C3/8	C8/15	S0/1	S0/4	C	F	E	SP
M1	587	252	0	0	655	281	435	25	178	4.6
M2	527	252	58.7	0	655	281	435	25	178	4.6
M3	467	252	117.4	0	655	281	435	25	178	4.6
M4	407	252	176.1	0	655	281	435	25	178	4.6
M5	587	227	0	25.2	655	281	435	25	178	4.6
M6	587	202	0	50.4	655	281	435	25	178	4.6
M7	587	177	0	75.6	655	281	435	25	178	4.6
M8	557	239.5	29,35	12.6	655	281	435	25	178	4.6
M9	527	227	58.7	25.2	655	281	435	25	178	4.6
M10	497	214.5	88.08	37.8	655	281	435	25	178	4.6
M11	407	177	176.1	75.6	655	281	435	25	178	4.6

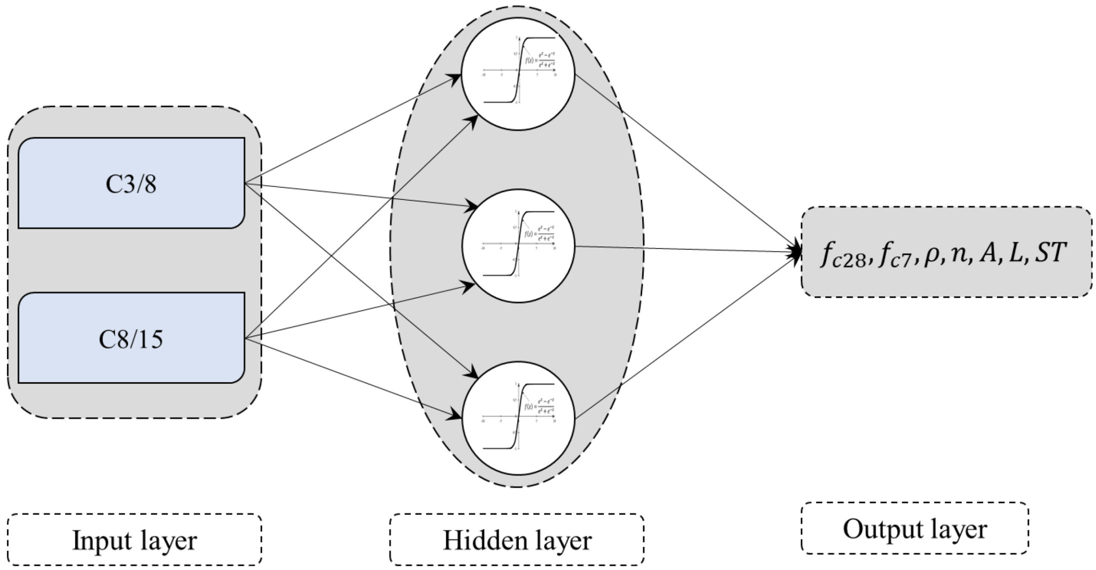

Fig. 1. Artificial neural network architecture used for predicting SCC properties.

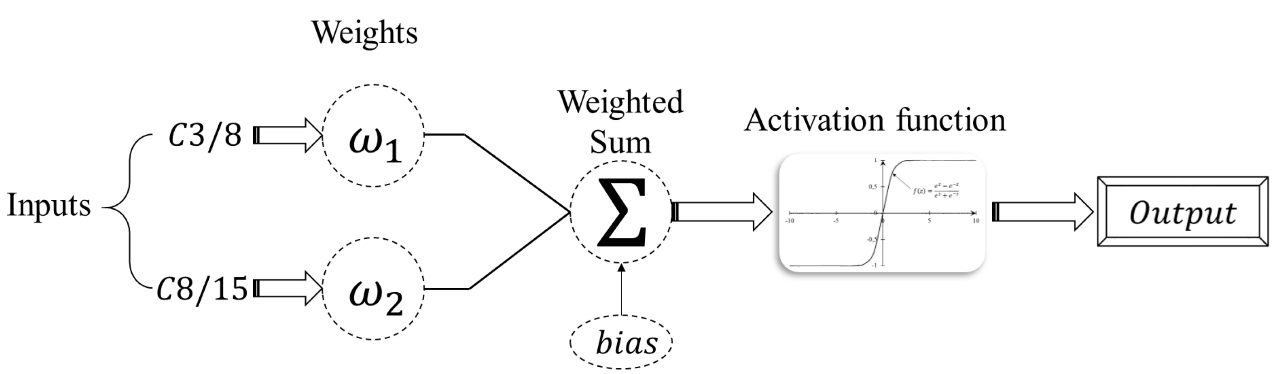

Fig. 2. Multilayer perceptron (MLP) structure with Tanh activation function.

In the mixtures presented, the gravel is divided into two fractions: G3/8 and G8/15. The 3/8 fraction represents 70 wt% of the total gravel content, while the 8/15 fraction constitutes the remaining 30 wt%. Similarly, for sand, the 0/1 mm fraction accounts for 70 wt% of the total sand content, and the 0/4 mm fraction represents the remaining 30 wt%. These proportions were determined based on preliminary laboratory tests, as they provide an optimal Packing Factor (PF) of 1.16, ensuring the best compactness and workability for the self-compacting concrete.

2.4. ANN modeling

To model the behavior of this modified SCC, an artificial neural network (ANN) approach was employed using JMP Pro software, which offers a user-friendly platform for implementing ANN models. The model architecture consists of three layers: an input layer with nodes corresponding to the input parameters, specifically the percentages of ceramic waste incorporated at various particle sizes; a hidden layer for non-linear transformations and feature extraction; and an output layer representing the SCC properties under investigation (Fig. 1). These properties include compressive strength, density, porosity, water absorption coefficient, slump flow test results, and sieve stability. A hyperbolic tangent activation function was applied to ensure efficient mapping of non-linear relationships between inputs and outputs.

Each neuron in the hidden layer processes the inputs by computing a weighted sum of the input variables, adding a bias term, and then applying the activation function (Fig. 2). This operation can be expressed mathematically as:

$$H = \tanh\left(\sum_{i=1}^{n} \omega_i x_i + b\right)$$

where H is the output of the neuron, x_i are the input variables representing the dosages of ceramic waste

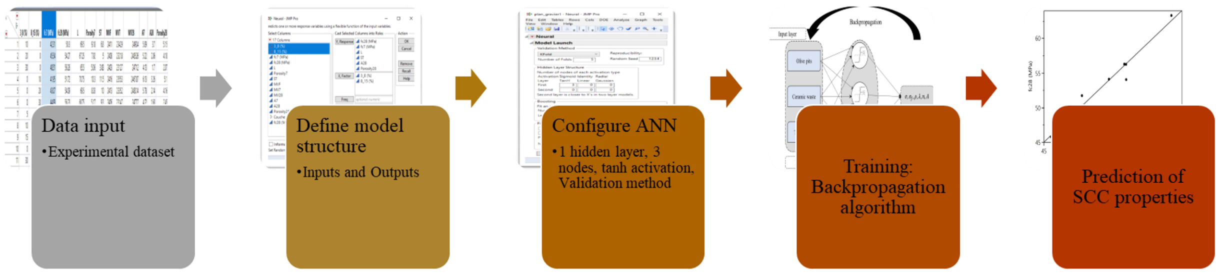

Fig. 3. Flowchart illustrating the ANN modeling process in JMP Pro software used for predicting SCC properties.

with different particle sizes (specifically C3/8 and C8/15), ω_i are their corresponding weights, b is the bias, and *tanh* is the hyperbolic tangent function. This formulation allows the network to capture complex, non-linear interactions between the input parameters and the predicted SCC properties.

The model was validated using the k-fold cross-validation method, ensuring robust and reliable predictions while minimizing the risk of overfitting. This approach offers a comprehensive framework for optimizing the composition and characteristics of SCC incorporating ceramic waste.

Fig. 3 presents the step-by-step process followed in the development of the artificial neural network (ANN) model using JMP Pro software. The modeling begins with the input of experimental data, including the ceramic waste substitution percentages and the measured properties of the SCC. The next step involves defining the network architecture, where the selected input parameters (C3/8 and C8/15) and target outputs (mechanical and physical properties of SCC) are specified.

The network is configured with a single hidden layer composed of three neurons, and the hyperbolic tangent (tanh) function is used as the activation function due to its ability to model nonlinear relationships. The training phase uses the backpropagation algorithm to iteratively adjust the connection weights and biases, minimizing the prediction error.

To ensure the robustness and generalization of the model, k-fold cross-validation (with $k = 5$) is applied. This technique divides the dataset into five subsets, rotating the training and validation phases across folds. Finally, the trained model is used to predict the SCC properties based on the input composition parameters.

3. Results and discussions

3.1. Raw materials

Fig. 4 represents the particle size distribution of the gravel and the ceramic waste used in this study. It shows that ceramic waste (C) grain size distribution was identical to those of gravel (G) for the G3/8 and G8/15 fractions.

According to the physical properties results (Table 2), it is observed that the absolute and apparent densities of the gravel derived from ceramic waste are lower than those of natural gravel. However, the water absorption coefficient is higher for the ceramic waste. Additionally, the methylene blue test confirms that the sand used is clean.

Table 3 reveals notable differences in the chemical composition of the used sands. Sand (S0/1) is predominantly composed of silica (94.36 wt%), whereas sand (S0/4) contains a significantly higher amount of CaO (62.77 wt%) and a substantial Loss on Ignition (L.O.I) of 34.95 wt%, attributed to the decomposition of calcite. Additionally, the chemical composition of limestone fines remains closer to that of sand (S0/4) and gravel. Additionnaly, the chemical composition of ceramic tile waste (C) is mainly composed by SiO_2, Al_2O_3, CaO, and Fe_2O_3, with minor amounts of MgO, K_2O, P_2O_5, and TiO_2. The Loss On Ignition was around 3.49 wt%, featuring probably the loss in mass of the carbonates and organic matter stucked inside the ceramic tile during the pressing process [44].

According to the XRD results of the used materials (Fig. 5), the ceramic waste was composed mainly by quartz beside anortite, orthose (feldspar phases) and mullite phases. On the other side, the 0/4 sand (which has the same composition as gravel) is composed mainly by calcite, while for pure 0/1 sand, the main peaks were attributed to the quartz phase.

The experimental evaluation of fresh and hardened self-compacting concrete (SCC) was conducted according to standardized procedures. In the fresh state, the rheological properties were assessed using slump flow, L-box, and sieve stability tests. The slump flow values for all mixtures ranged from 65.5 to 72.25 cm (Table 4), satisfying the requirements of EN 206-9 for SCC workability (550–850 mm). A slight decrease in flow diameter was observed with increasing ceramic waste content, attributed to the material's water absorption capacity.

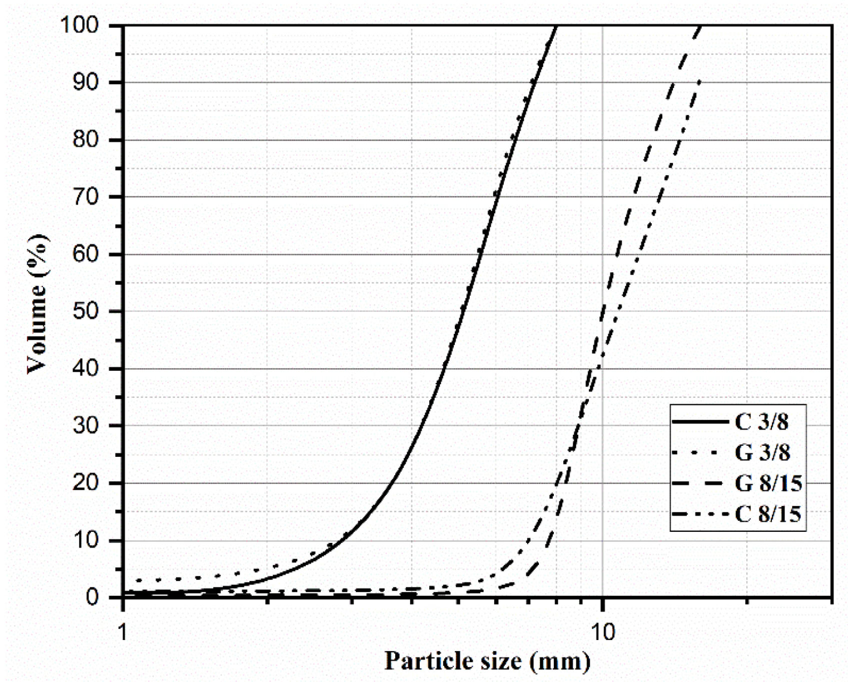

Fig. 4. Particle size distribution of used gravel: C3/8: 3/8 ceramic waste fraction, C8/15: 8/15 ceramic waste fraction, G3/8: 3/8 gravel fraction, G8/15: 8/15 gravel fraction.

Table 2. Physical and mechanical properties of materials used in self-compacting concrete.

Material	S0/1	S0/4	G3/8	G8/15	C3/8	C8/15	Cement	Limestone filler
Apparent density (g/cm^3)	1.62	1.56	1.50	1.44	0.79	0.77	1.1	1.23
Absolute density (g/cm^3)	2.59	2.677	2.715	2.717	1.96	2.09	3.12	2.7
Absorption A (%)	/	/	1.66	1.33	12.66	10	/	/
VB (g/kg)	1	0.25	/	/	/	/	/	/

Table 3. Chemical composition of materials used in self-compacting concrete.

Oxides	SiO_2	CaO	Fe_2O_3	Al_2O_3	MgO	SO_3	K_2O	Na_2O	P_2O_5	TiO_2	Cl	L.O.I
S0/1	94.36	0.95	1.27	0.99	0.17	0.04	0.31	0	0.02	0.09	0.012	1.35
S0/4 + Gravel	0.35	62.77	0.22	0.99	0.65	0.03	0.01	0.04	0.01	0.01	0.002	34.95
Ceramic waste	59.71	7.56	6.17	15.69	1.34	0.1	3.28	1.44	/	/	0.015	3.4
Cement	20.62	61.49	4.37	3.96	1.38	1.59	0.29	0.12	/	/	0.01	6.18
Limestone filler	0.06	56.04	0.02	0.09	0.01	0.01	/	/	/	/	/	43.8

Sieve stability results remained well below the permissible limits (<20%), indicating good resistance to segregation, particularly in mixtures incorporating the 3/8 mm ceramic fraction, which improved particle packing. L-box ratios were consistently around 1, confirming proper passing ability through congested reinforcement zones.

Fresh concrete density slightly decreased with the replacement of natural gravel by ceramic aggregates due to their lower specific gravity. However, after hardening, the density tended to increase slightly in mixtures with ceramic waste, suggesting improved compactness and particle rearrangement during hydration and curing.

In the hardened state, tests included compressive strength at 7 and 28 days, porosity, absolute density, and water absorption. Results showed that compressive strength increased with higher ceramic content, reaching up to 63 MPa at 28 days. Porosity and water absorption decreased significantly with ceramic additions, enhancing concrete compactness. These findings validate the feasibility of using ceramic waste as a partial gravel replacement in SCC, without compromising performance in fresh or hardened states.

To provide a clearer overview of the experimental data, Table 4 presents the descriptive statistics (mean, minimum, maximum, and standard deviation) for

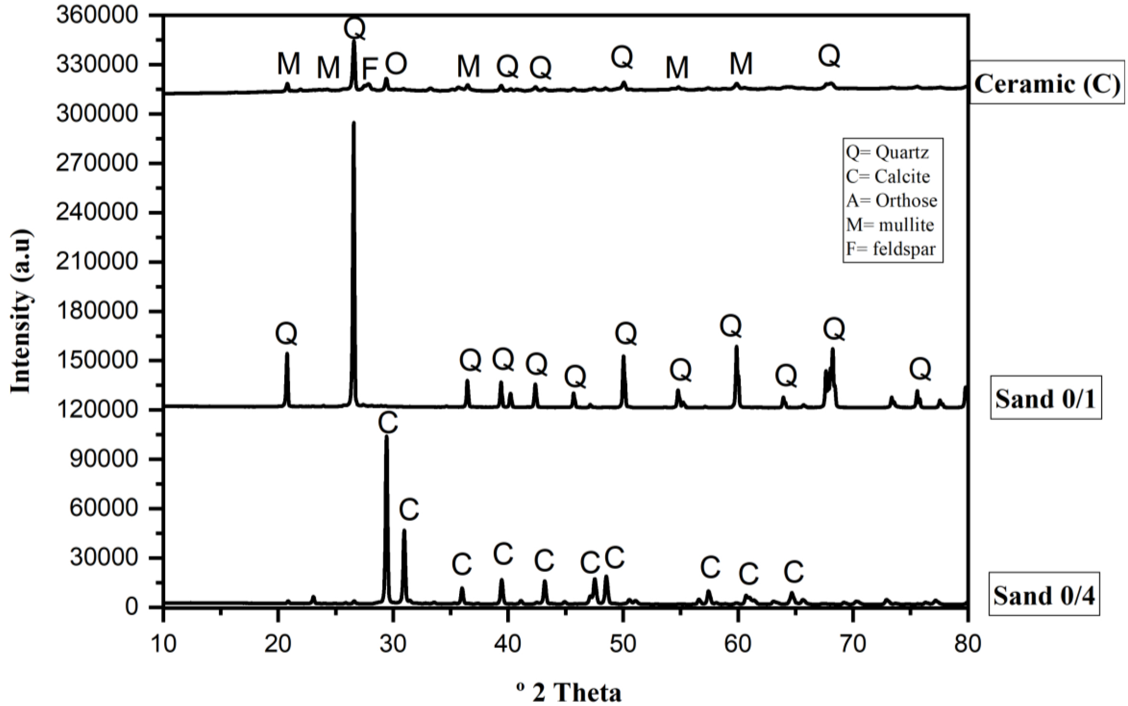

Fig. 5. XRD patterns of the raw materials.

Table 4. Descriptive statistics of the experimental properties of self-compacting concrete incorporating ceramic waste.

Property	Mean	Min	Max	Standard deviation
Compressive strength (28 days), f_{c28} (MPa)	53.57	45.78	63.28	4.43
Compressive strength (7 days), f_{c7} (MPa)	44.80	41.20	51.79	3.19
Slump flow, L (cm)	69.20	65.50	72.25	2.04
Sieve stability, ST (%)	7.64	2.55	12.33	3.34
Porosity, n (%)	3.84	1.29	5.21	1.39
Density, ρ (kg/m^3)	2476.28	2466.60	2490.40	7.65
Water absorption, A (%)	2.56	0.71	4.94	1.20

the key measured properties of the self-compacting concrete (SCC) mixtures. These properties include compressive strength at 7 and 28 days, slump flow, sieve stability, porosity, density, and water absorption. The values confirm the consistency of the tests and the variability observed due to the incorporation of ceramic waste in different proportions.

3.2. ANN results

The results of experimental and predicted data (by ANN – Artificial Neural Networks) for various material characteristics were presented on Table 6. All mixtures exhibit higher compressive strengths compared to the control sample (M1). The only property that was negatively influenced is workability property, but this effect remains within an acceptable range. The reduction in workability is likely due to the addition of ceramic waste, which may affect the flow and placement ease of the material due to its higher water absorption. However, the overall impact on the performance remains relatively minor. Therefore, while the strength properties are enhanced, the slight reduction in workability is a manageable trade-off.

The modeling of experimental results led to the development of the following prediction equations (Eq. (11) for 28-day compressive strength, Eq. (12) for 7-day compressive strength, Eq. (13) for spread test. Eq. (14) for density, Eq. (15) for sieve stability, Eq. (16) for porosity and Eq. (17) for absorption coefficient). These equations accurately describe the relationships between the proportions of granulometric fractions (3/8 and 8/15) of gravel substituted with ceramic waste and the properties of self-compacting concrete.

$$f_{c28} = 51.765 + 9.857H_1 + 2H_2 + 25.11H_3 \ \ (MPa) \tag{11}$$

Where:
$H_1 = \tanh(0.5(3.0831 - 0.0484X_1 - 0.1683X_2))$
$H_2 = \tanh(0.5(-9.7614 + 0.9866X_1 - 0.5955X_2))$
$H_3 = \tanh(0.5(-1.107 + 0.02578X_1 + 0.0785X_2))$

$$f_{c7} = 45.769 - 1.2037H_1 - 2.7924H_2 - 5.1802H_3 \ (MPa) \quad (12)$$

Where:
$H_1 = \tanh(0.5(-3.0436 + 0.5885X_1 - 0.2173X_2))$
$H_2 = \tanh(0.5(0.9188 - 0.1602X_1 + 0.0176X_2))$
$H_3 = \tanh(0.5(2.531 - 0.1009X_1 - 0.07846X_2))$

$$L = 61.8403 - 8.6335H_1 + 6.6003H_2 - 11.3874H_3 \ (cm) \quad (13)$$

Where:
$H_1 = \tanh(0.5(-0.5163 - 0.0937X_1 + 0.14733X_2))$
$H_2 = \tanh(0.5(2.4011 - 0.0009X_1 - 0.0295X_2))$
$H_3 = \tanh(0.5(-0.4694 + 0.1019X_1 - 0.1173X_2))$

$$\rho = 2485.11 - 50.029H_1 - 50.88H_2 - 14.51H_3 \ \left(kg/m^3\right) \quad (14)$$

Where:
$H_1 = \tanh(0.5(1.2422 - 0.2437X_1 + 0.09446X_2))$
$H_2 = \tanh(0.5(0.3 + 0.1305X_1 - 0.0728X_2))$
$H_3 = \tanh(0.5(-6.0274 + 0.31317X_1 + 0.8X_2))$

$$ST = 5.38 - 3.9607H_1 + 2.9566H_2 + 2.8126H_3 \ (\%) \quad (15)$$

Where:
$H_1 = \tanh(0.5(-2.2552 + 0.0936X_1 - 0.0662X_2))$
$H_2 = \tanh(0.5(1.5946 - 0.0138X_1 - 0.1634X_2))$
$H_3 = \tanh(0.5(1.3243 - 0.5916X_1 + 0.442X_2))$

$$n = 1.9849 - 2.3988H_1 - 1.5284H_2 + 3.7H_3 \ (\%) \quad (16)$$

Where:
$H_1 = \tanh(0.5(-0.7425 + 0.03839X_1 - 0.057978X_2))$
$H_2 = \tanh(0.5(1.4094 - 0.1582X_1 + 0.0017X_2))$
$H_3 = \tanh(0.5(2.8651 - 0.1111X_1 - 0.1052X_2))$

$$A = 1.7989 + 3.82987H_1 + 6.95816H_2 + 5.532H_3 \ (\%) \quad (17)$$

Where:

$H_1 = \tanh(0.5(1.4733 - 0.1209X_1 - 0.1163X_2))$
$H_2 = \tanh(0.5(1.7056 - 0.0325X_1 - 0.04677X_2))$
$H_3 = \tanh(0.5(-1.929 + 0.07093X_1 + 0.0877X_2))$

Where: X_1 represent the 3/8 fraction percentage and X_2 represent the 8/15 fraction percentage of ceramic waste.

Through these models, it is possible to predict variations in mechanical characteristics as well as physical and rheological properties. These equations serve as a valuable tool for optimizing formulations and enhancing the performance of self-compacting concrete containing ceramic waste.

The graphs shown in Fig. 6 illustrate the correlation between experimental and predicted values of the properties of self-compacting concrete modified with ceramic waste, obtained using the artificial neural network (ANN) model. A strong linear correlation is observed for all the studied parameters. These results confirm the reliability and accuracy of the ANN model in representing the mechanical and physical properties of self-compacting concrete, demonstrating its effectiveness in optimizing formulations.

These 3D graphs illustrate the effect of interactions between the percentages of gravel substitution with ceramic waste for two grain size fractions (3/8 and 8/15) on the properties of self-compacting concrete (SCC) (Fig. 7). The 28-day compressive strength (f_{c28}) increases with the addition of waste, with a similar effect for both diameter fractions, while the 7-day strength (f_{c7}) follows the same trend but with a more pronounced effect for the 3/8 fraction. Sieve stability (ST) also increases with the waste percentage, with a more significant effect for the 3/8 fraction and an almost negligible effect for the 8/15 fraction. Porosity (n) decreases similarly for both fractions, as does the water absorption coefficient (A), which shows a declining trend. The slump flow test (L) decreases with increasing waste, with a more notable effect for the 3/8 fraction. Finally, density (ρ) remains relatively constant, indicating negligible variation regardless of the substitution percentage. These results highlight the importance of grain size fractions and their interaction in optimizing SCC properties.

The analysis of the residuals, calculated as the differences between experimental and predicted values, confirms the high predictive accuracy of the ANN model (Fig. 8). Across all tested mixtures and parameters (compressive strength, flow, sieve stability, porosity, density, and water absorption), the residuals are minimal and randomly distributed around zero,

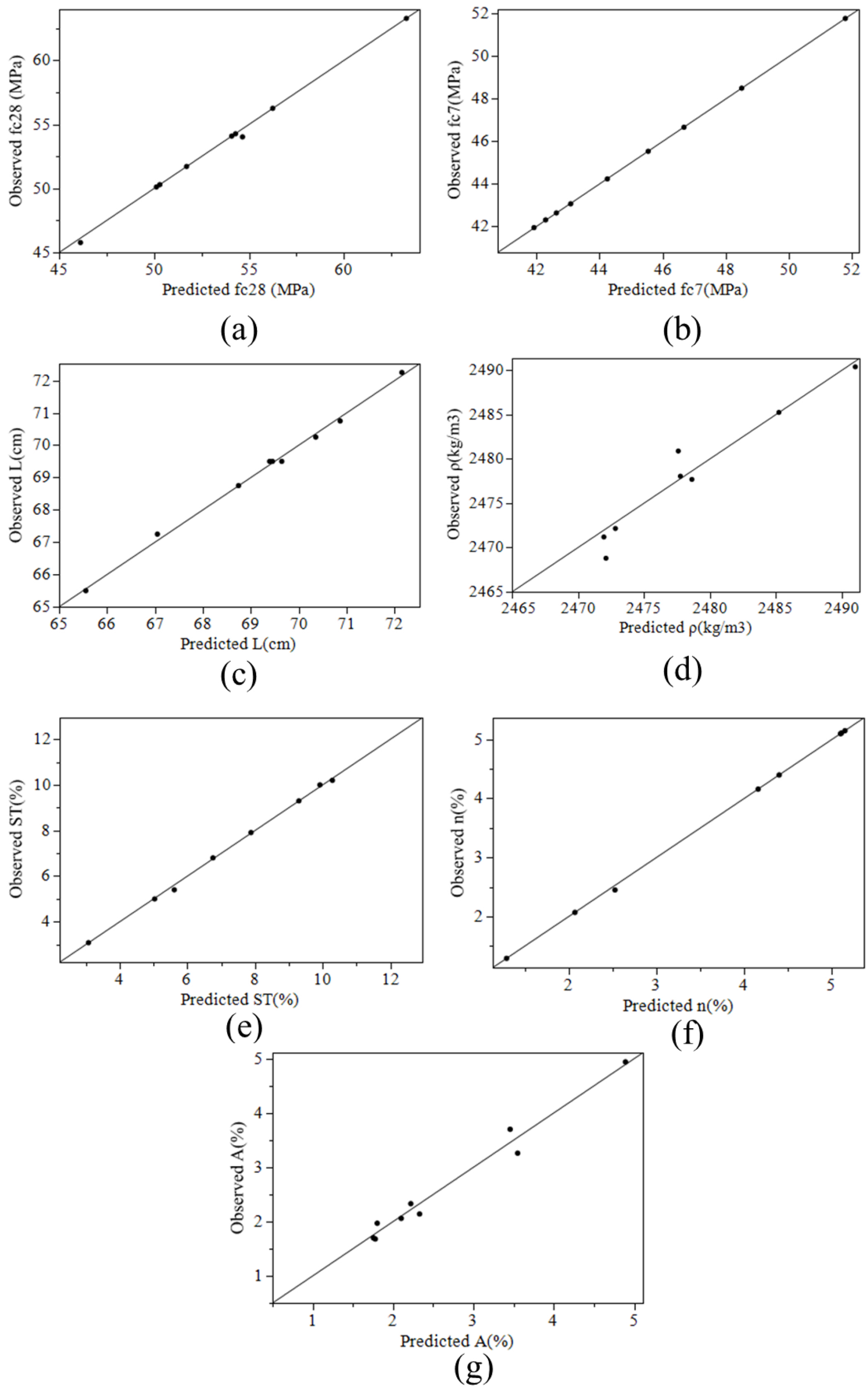

Fig. 6. Predicted vs Observed values of studied parameters: (a) 28-day compressive strength (f_{c28}) (b) 7-day compressive strength (c) Flowability (d) Density (e) Sieve stability (f) Porosity (g) Absorption coefficient.

indicating no systematic bias in the predictions. The small deviations observed in a few cases remain negligible and do not affect the overall performance of the model. These results demonstrate the model's robustness and its strong generalization capability, even for intermediate mixtures, confirming the reliability of the ANN approach for predicting the properties of self-compacting concrete incorporating ceramic waste.

4. Validation of ANN models

The validation of the models is supported by their excellent predictive performance, as indicated by the results represented in Table 5. The high coefficients of determination (R^2) values, 0.99 for compressive strength at 28 days (f_{c28}), slump flow (L), compressive strength at 7 days (f_{c7}), sieve stability (ST), and porosity (n); 0.98 for water absorption (A); and

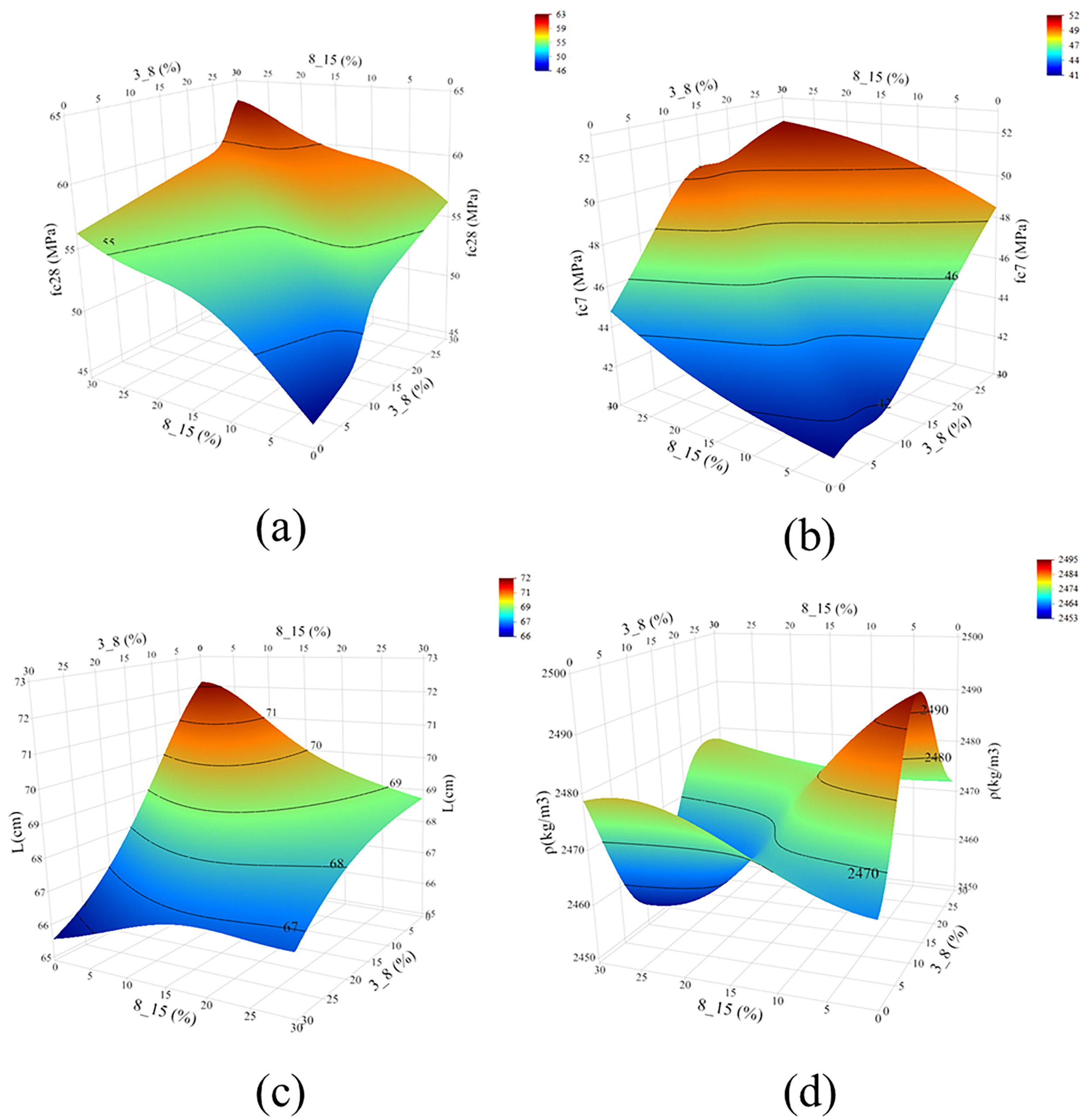

Fig. 7. The effect of the percentage of particle size fractions (3/8 and 8/15) on the properties of self-compacting concrete (SCC): (a) 28-day compressive strength (f_{c28}) (b) 7-day compressive strength (f_{c7}) (c) Flowability (d) Density (e) Sieve stability (f) Porosity (g) Absorption coefficient.

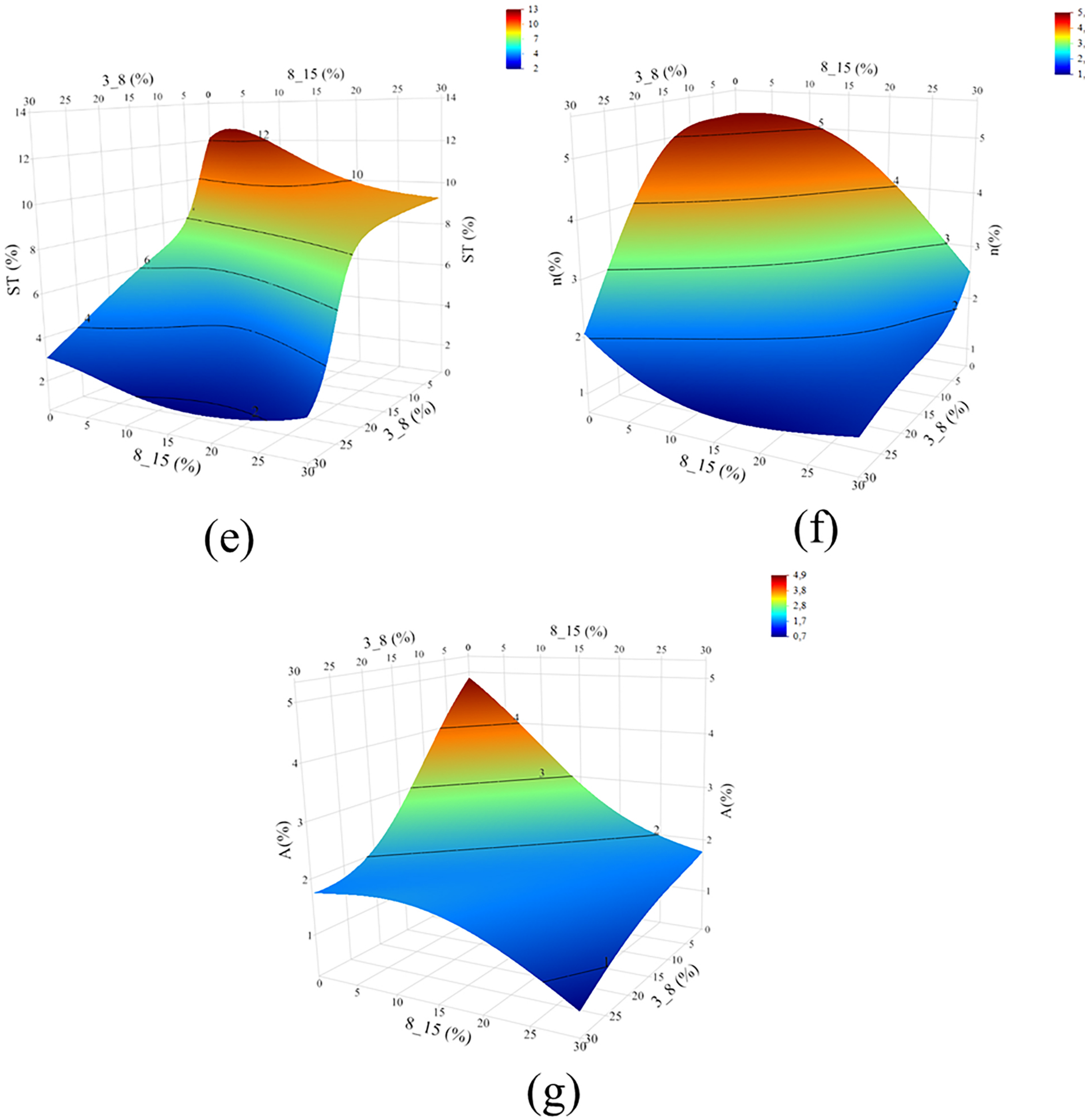

Fig. 7. Continued.

Table 5. Performance metrics of predictive models for self-compacting concrete properties.

Performance equation	f_{c28}	L	f_{c7}	ρ	$ST\,(\%)$	n	A
R^2	0,99	0,99	0,99	0,94	0,99	0,99	0,98
RMSE	0, 23	0,1115	0,0123	1,8	0,088	0,027	0,16

0.94 for density (ρ), demonstrate the strong correlation between experimental and predicted data. Moreover, the low root mean square error (RMSE) values, 0.23 for f_{c28}, 0.1115 for L, 0.0123 for f_{c7}, 1.8 for ρ, 0.088 for ST, 0.027 for n, and 0.16 for A, confirm the accuracy and reliability of the models in predicting the properties of self-compacting concrete. These results collectively validate the robustness of the developed models.

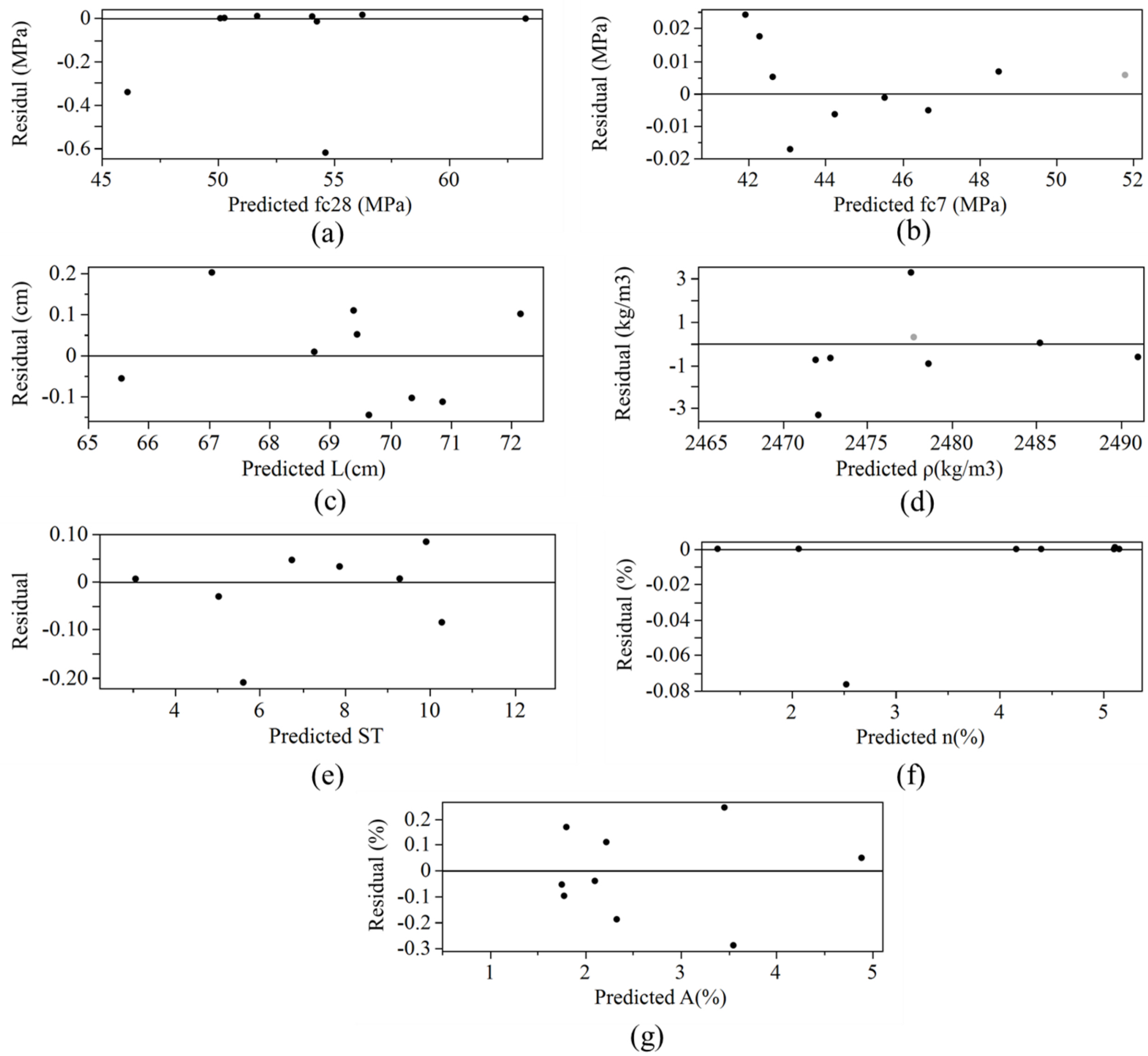

Fig. 8. Residuals between predicted and observed values for different studied parameters: (a) 28-day compressive strength (f_{c28}); (b) 7-day compressive strength; (c) Flowability (L); (d) Density; (e) Sieve stability; (f) Porosity; (g) Absorption coefficient.

Table 6. Comparison of experimental and ANN-predicted properties of self-compacting concrete mixtures.

	Independent variables		$f_{c28}(MPa)$		f_{c7} (MPa)		$L(cm)$		ST (%)		n (%)		ρ (kg/m^3)		A (%)	
Mixtures	3/8	8/15	EXP	ANN	EXP	ANN	EXP	ANN	EXP	ANN	EXP	ANN	EXP	ANN	EXP	ANN
M1	0	0	45.78	46.12	41.2	41.24	72.25	72.15	12.33	12.17	5.21	5.21	2466.6	2464.38	4.94	4.891
M2	10	0	50.3	50.3	42.31	42.29	69.5	69.64	6.8	6.75	5.15	5.15	2490.4	2491.02	3.7	3.456
M3	20	0	54.27	54.28	45.54	45.54	67.25	67.05	5	5.03	4.18	4.18	2485.26	2485.23	2.06	2.100
M4	30	0	56.26	56.24	48.51	48.50	65.5	65.55	3.08	3.07	2.07	2.069	2471.2	2471.96	1.7	1.754
M5	0	10	51.72	51.70	41.95	41.92	70.75	70.86	11.5	11.67	5.1	5.1	2467.87	2470.02	3.26	3.549
M6	0	20	54.09	54.08	43.07	43.08	69.5	69.45	10	9.91	4.16	4.16	2480.14	2477.96	2.14	2.328
M7	0	30	56.23	56.23	44.89	44.78	68.75	68.74	9.3	9.29	2.45	2.526	2477.7	2478.63	1.68	1.778
M8	5	5	50.12	50.12	42.64	42.63	71.25	71.28	10.2	10.28	5.11	5.108	2468.8	2472.12	3.66	3.502
M9	10	10	53.17	53.18	44.24	44.24	70.25	70.35	7.91	7.87	4.4	4.4	2480.9	2477.60	2.33	2.220
M10	15	15	54.03	54.65	46.67	46.67	69.5	69.39	5.4	5.61	3.1	3.1	2472.16	2472.83	1.97	1.802
M11	30	30	63.28	63.28	51.79	51.78	66.65	66.66	2.55	2.41	1.29	1.29	2478.06	2477.77	0.71	0.661

5. Conclusion

This study employed artificial neural networks (ANN) as a predictive tool to assess the impact of ceramic waste as a substitute for gravel in self-compacting concrete (SCC). The ANN models demonstrated high accuracy in predicting key properties such as compressive strength, density, porosity, and water absorption, with strong correlations between experimental and predicted values. This highlights the potential of ANN-based modeling as an efficient approach to optimize mix formulations while minimizing the need for extensive experimental testing. By providing reliable estimations, ANN enhances the design process and facilitates the development of sustainable and high-performance SCC.

The results revealed that the particle size distributions of ceramic waste are similar to those of gravel, ensuring compatibility without compromising the workability or consistency of SCC. Furthermore, the incorporation of ceramic waste significantly improved mechanical performance, particularly compressive strength at 7 and 28 days, while reducing porosity and water absorption. The analysis also indicated that using ceramic waste, especially in the 3/8 mm and 8/15 mm fractions, does not significantly affect concrete density.

In conclusion, the integration of ANN modeling in this study has proven to be a powerful tool for predicting and optimizing the properties of SCC incorporating ceramic waste. This approach not only enhances efficiency in material development but also supports the adoption of sustainable construction practices by promoting waste valorization and reducing the demand for natural aggregates.

Conflict of interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data availability statement

All graphs and data obtained or generated during the investigation appear in the published article.

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Author contributions

Abderrezak Bouziane: Conceptualization, Investigation, methodology, data analysis, writing-original draft.

Houssam Slimanou: Investigation, methodology, validation, and editing.

Mohamed Amin Bouzidi: Formal analysis, visualization, and editing.

Nedjima Bouzidi: Supervision, validation, review, and editing.

All authors have read and agreed to the published version of the manuscript.

Dataset

All data generated or analyzed during this study are included in the main manuscript.

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