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Fuzzy model for predicting the strength of mortars made with Pozzalani cement and volcanic sand from electrical resistivity

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ABSTRACT

Coating mortars act as a physical barrier to protect the load-bearing structure against corrosion. However, not all mortars have the same protective capacity. Hydration in the early ages of manufactured mortars is a very influential parameter in their electrical resistivity values and in the evolution of their mechanical performance. In this work, the electrical resistivity data and its relationship with the evolution of the mechanical strength in different mortar dosages are analysed. From the data obtained, a predictive system with fuzzy logic is designed with the aim of predicting the value of the compressive strength of the mortar at the age of 28 days based on the electrical resistivity measurement obtained within the first seven days after its manufacture. The designed system has been validated with data from other mortar dosages not included in the design, proving to be a useful tool for establishing quality criteria for coating mortars.

1. Introduction

Currently, more than half of the world's population lives within 60 km of the coast [1]. This means that many buildings are located in an aggressive marine environment where chloride ions are the main depassivating agent for reinforcement [2]. The durability of the reinforced concrete structure depends on the thickness and quality of the reinforcement coating [3]. For this reason, the addition of a coating mortar provides a physical barrier against corrosion and contributes to improving the useful life of these structures. An indicator of the quality of this coating is the compressive strength of the mortar [4].

From more than two decades ago to the present day, the importance of evaluating the quality of mortars as a coating material to improve the durability of concrete has been highlighted in numerous investigations. Thus, for example [5], reported the results of a study carried out to evaluate the durability of concrete covered with surface coatings of different polymeric natures [6]. determined the effects of commercial coating mortars with polymeric additions in relation to their resistance to chloride penetration and the service life of concrete coatings [7]. studied the properties of mortars with different additions to determine their physical properties, such as compressive strength and chloride diffusion coefficient. Recently [8], addressed the study of the efficiency of seven polymer-based cement repair mortars when applied on concrete supports. However, no bibliographic references have been found on the contribution of mortars made with nonreactive volcanic aggregates of basaltic nature as a coating for reinforced concrete. This paper analyses this type of mortar. The behavior of these mortars is unique because they are nonlightweight aggregates with high absorption [9].

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This work addresses a methodology based on fuzzy logic to evaluate the quality of these particular mortars. The application of this methodology allows predicting the 28-day compressive strength of the mortar from the measured value of electrical resistivity in the first hardening ages. Fuzzy set theory is used to model the relationship between these variables. Fuzzy logic is an alternative to classical logic for representing human reasoning and situations with uncertainty, since it allows phenomena and observations to have more than two logical states. The basis of this theory is the "fuzzy sets" and the so-called "membership functions", which qualify the membership of an element to different fuzzy sets simultaneously.

The research literature collects some studies for other types of mortars within this subject [10,11]. These works suggest methods to predict the standard compressive strength from the measurement of electrical resistivity. Other researchers [12,13], on the contrary, raise the danger of using indirect correlations such as compressive strength and indirect durability indices whose relationship may lead to incorrect deductions. In both works, the conclusions result from the application of relationship models between variables that do not apply adaptive fuzzy logic models.

Artificial Intelligence techniques other than Fuzzy Logic have been used to predict the compressive strength of different types of concrete, such as Artificial Neural Networks [14,15], Decision Trees and Random Forest algorithms [16,17]. In contrast, the works of [18–23] apply Fuzzy Logic to evaluate the compressive strength of mortars. It is important to highlight that all these works propose methods for evaluating mortars made with components different from those used in our work, and analysing other types of variables.

The present work provides a fuzzy system that allows estimating the 28-day compressive strength of a basaltic mortar by introducing into the system only the amount of cement used in the manufacture of the mortar, the electrical resistivity measurement and the number of days elapsed between the manufacture of the mortar and the instant at which the measurement was made. Therefore, this work provides a novel tool that contributes to the control of mortars made in situ without the need to carry out destructive tests that require a curing time of 28 days. In this sense, the application of a fuzzy model has already reported favorable results for the prediction of other variables related to the dosage of cementitious mortars [24]. The results of this current work also show that the application of this model is very useful in this new problem.

The following section (section 2) presents a brief description of the theoretical foundations of Fuzzy Logic and Fuzzy Rule-Based Systems (FRBSs), which are the basis of the predictive system designed in this work. Our research work comprises two distinct phases. First, an experimental phase was developed in the laboratory, where basaltic mortars with three different dosages and different curing periods were manufactured in a controlled manner. In these experiments interest is focused on measuring the electrical resistivity of each sample. Subsequently, 28 days after its manufacture, the mechanical compressive strength is measured. All the data collected in these experiments are analysed in depth to study the relationship between the electric resistivity and the compressive strength. In the second phase, a fuzzy system is designed and adjusted to model this relationship, and is evaluated with different validation tests. The methodology followed is detailed in section 3 (Material and Methods). Section 4 (Results and Discussion) first shows the results obtained in the laboratory, as well as the complete analysis performed on these data to estimate the relationship between electrical resistivity and compressive strength. This analysis will be the basis of the designed fuzzy system, as will be explained in the second part of this section. Finally, at the end of section 4, the results of the different validation studies performed will be presented and discussed. The article ends with the conclusions and future research lines (section 5).

2. Fuzzy logic and Fuzzy Rule-Based Systems

The Theory of Fuzzy Sets, introduced by Zadeh [25], is an extension of classical logic. In a classical set, the value 1 or 0 is assigned to each element to indicate whether it belongs to that set, but in the context of Fuzzy Logic, an element can belong to several sets at once, with varying degrees of membership. Mathematically, this is achieved by assigning a membership function to each fuzzy set that returns a value between 0 and 1, indicating the element's degree of membership in a given fuzzy set. By considering an element's membership in several sets simultaneously, we can model the imprecision that exists in human reasoning. As a result, Fuzzy Set Theory is more suitable than classical logic to represent human knowledge, since it allows phenomena and observations to have more than two logical states.

The first step in modelling a system with fuzzy logic is to define the system's input and output variables as *linguistic variables*. Linguistic variables (for example, *Resistance*) are variables whose possible values can be represented by *linguistic terms* (for example, *High, Somewhat High, Medium, Somewhat Low, and Low*), and each linguistic term has a fuzzy set associated with it. This step is very important since it allows converting the semantic concept used in human reasoning (the linguistic label) to a mathematical function that is used to represent the fuzzy set. This process is shown graphically in Fig. 1.

The second step consists of relating the system's input and output variables to each other with fuzzy rules of the "if-then" type: If x is A, then y is B, where A and B are linguistic labels for the respective linguistic variables. The term "x is A" is called the antecedent, while the term "y is B" is called the consequent [26]. Fig. 2 shows a graphical example with an if-then rule. The rule relates the linguistic labels of two input variables (A and B) to a linguistic label for one output variable (C). The membership functions are shown graphically in red for the input variables and in blue for the output variable. Using fuzzy rules, we can model the knowledge of an expert in the field: the degree to which an output variable is modified depending on the input variables that affect it.

The third step involves fuzzy inference, which yields the conclusions from a set of fuzzy if-then rules, and known real facts. This relies on fuzzy reasoning, also known as approximate reasoning. In this work, fuzzy inference is carried out as explained graphically in Fig. 3. For each rule of the fuzzy system, each antecedent is analysed, and the intersection between the fuzzy sets of the antecedent of the rule (in red) and the fact (in green) is calculated. The minimum value is chosen, and this value is used to activate the proportional part of the fuzzy set that represents the consequent. Once the activated parts of each rule's consequents are obtained, the output of the

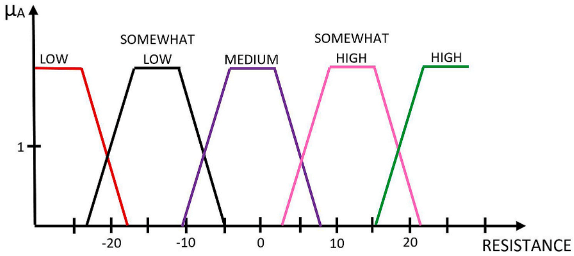

Fig. 1. Definition of the "resistance" linguistic variable and its linguistic labels (low, somewhat low, medium, somewhat high and high) expressed as fuzzy sets with a trapezoidal shape.

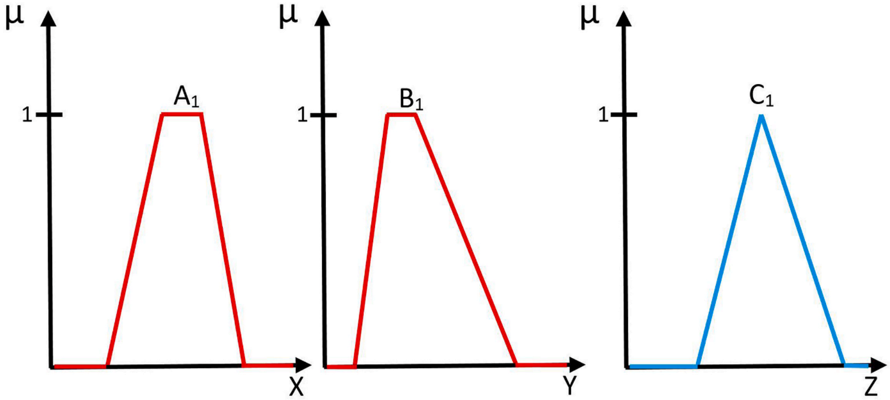

Fig. 2. Example of a fuzzy rule with two input variables and one output variable: if input X is A_1 and input Y is B_1, then output Z is C_1.

system is calculated as the union of all these activated parts (final fuzzy set C′ in Fig. 3). This type of inference, proposed by Mamdani [27], is widely used in the literature.

The resulting set C′ is a fuzzy set. In the last step of the process, the numerical value that best represents the resulting fuzzy set (defuzzification process), which will be the system's output, has to be extracted. In this paper, we use the centroid of the area of the output fuzzy set.

In this work, a Fuzzy Rule-Based Systems (FRBS) capable of predicting the 28-day compressive strength of a mortar from the measured value of electrical resistivity at the first hardening age (7 days) was designed. Based on the knowledge extracted from the experiments carried out with mortars in the laboratory, the input and output variables involved in the decision-making process (linguistic variables with their corresponding linguistic labels) have been identified, the fuzzy sets and the mathematical functions that represent them have been properly defined, and the rules that model the relationship between the variables have been extracted.

3. Materials and methods

3.1. Materials

The materials used in this research correspond to cement mortars manufactured in situ for the execution of coatings. The cement used was type IV, pozzolanic cement with the addition of natural pozzolan (P), with a strength of 32.5 N. Its designation, according to UNE 80303–2 [28], is CEM IV/A (P) 32.5 N. The sand used comes from a local quarry and the petrographic analysis carried out according to UNE-EN 12407 [29] classifies it as basalt and trachybasalt sand [30].

3.2. Determination of compressive strength and electric resistivity

Cylindrical test tubes 300 × 150 mm in height and diameter, and prismatic test tubes 40 × 40 × 160 mm in width, height and length respectively, were made with three types of mortars of different recipes. The mortar recipes used according to the *cement:sand:water* ratio are as follows: dosage 1 (1:5:1.25), dosage 2 (1:4:1.25) and dosage 3 (1:3:1.25).

These test-tubes were subjected to different days of curing (0, 1, 3 and 7 days), and to the test for the determination of electrical resistivity [31] at different times (1, 2–3, 7 days). Finally, the test-tubes were broken at 28 days of age, in accordance with the standardised test for cylindrical test-tubes [32] and prismatic test-tubes [33].

The results of the experiments carried out on the cylindrical test-tubes have been used for the analysis of the behavioural factors of the mortar, and for the subsequent design of the fuzzy prediction system proposed in this work. The results of the prismatic test-tubes have been used to validate the designed intelligent system, as independent tests.

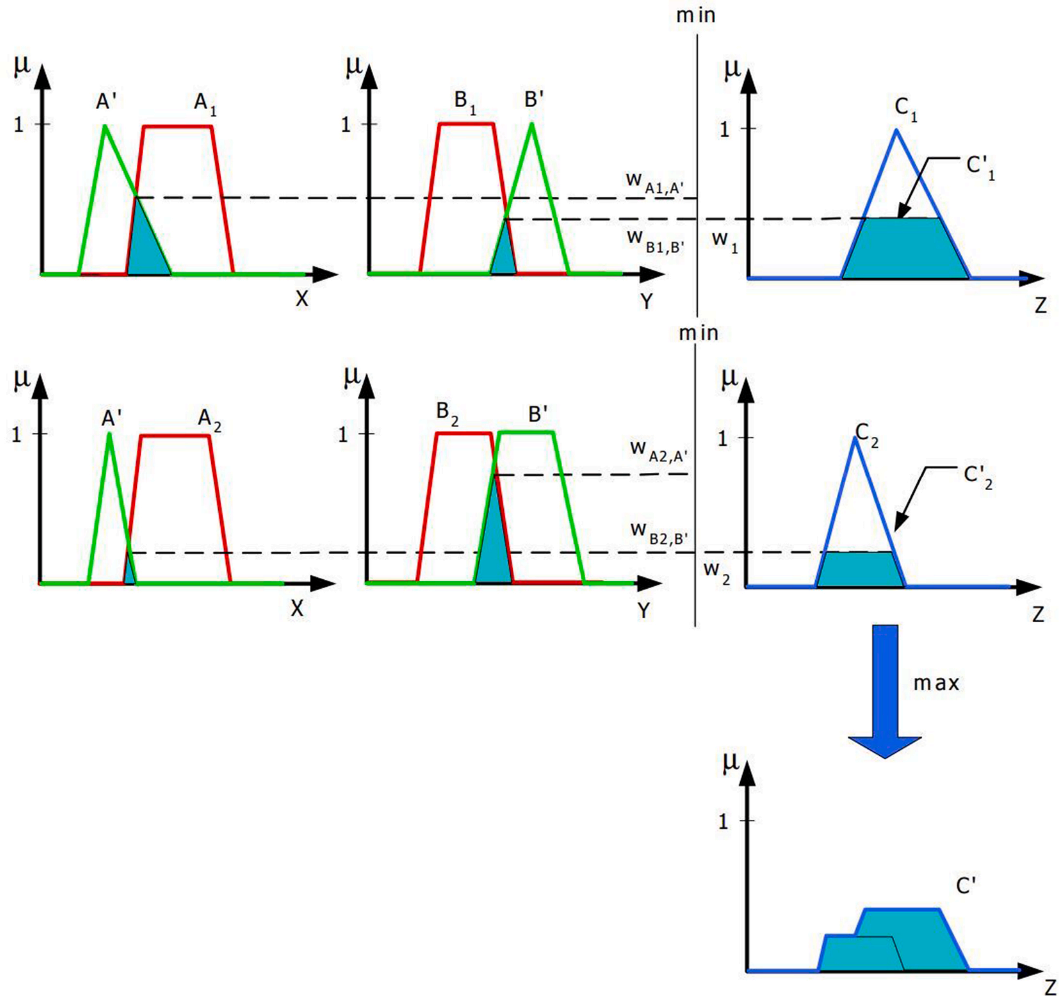

Fig. 3. Fuzzy system with two rules, each with two antecedents and one consequent. It shows the use of Mamdani's fuzzy implicator (minimum) and the max-min compositional operator to carry out the inference.

3.3. Fuzzy Rule-Based Systems (FRBS) design methodology

The proposed system, based on fuzzy rules, is appropriate for modelling the problem mainly due to two aspects: 1) the fuzzy nature of the system allows us to handle the diversification of the input variables that influence the behaviour of the mortars, and 2) the construction of these mortars and their quality depend to a large extent on human interpretations. The fuzzy system allows working with "approximate" definitions and evaluations, close to those used in human reasoning.

In order to design this system, a study was carried out with mortars manufactured with different dosages and degrees of hydration. Based on the electrical resistivity and mechanical strength data at different ages, the design of a predictive system with fuzzy logic is proposed with the aim of predicting the value of the compressive strength of the mortar at the age of 28 days based on the electrical resistivity measurement obtained within the first seven days of its manufacture.

The designed system is validated with data obtained from the laboratory and with data from other mixtures. This tool could be used by professionals in the sector to predict the evolution of mortars during their manufacture, quickly and nondestructively.

Two phases can be distinguished in the methodology followed in this work. The first phase, carried out in the laboratory, consisted of the design and development of a series of experiments and tests with different mixtures of cement and sand mortars manufactured in the Canary Islands. The objective of these experiments was to verify the existence of a direct relationship between the amount of cement in the dosages, the age of curing, and the measurements of electrical resistivity in the first seven days and the mechanical compressive strengths at 28 days.

After this objective was achieved, the information collected in the laboratory was used during the second phase. The experimental data from the laboratory, that show the relationship between the mortar manufacturing variables and its mechanical properties, have been used to constitute the knowledge base of the Fuzzy Rule-Based System (FRBS) and to build the rule base. Fig. 4 shows a summary of the methodology followed.

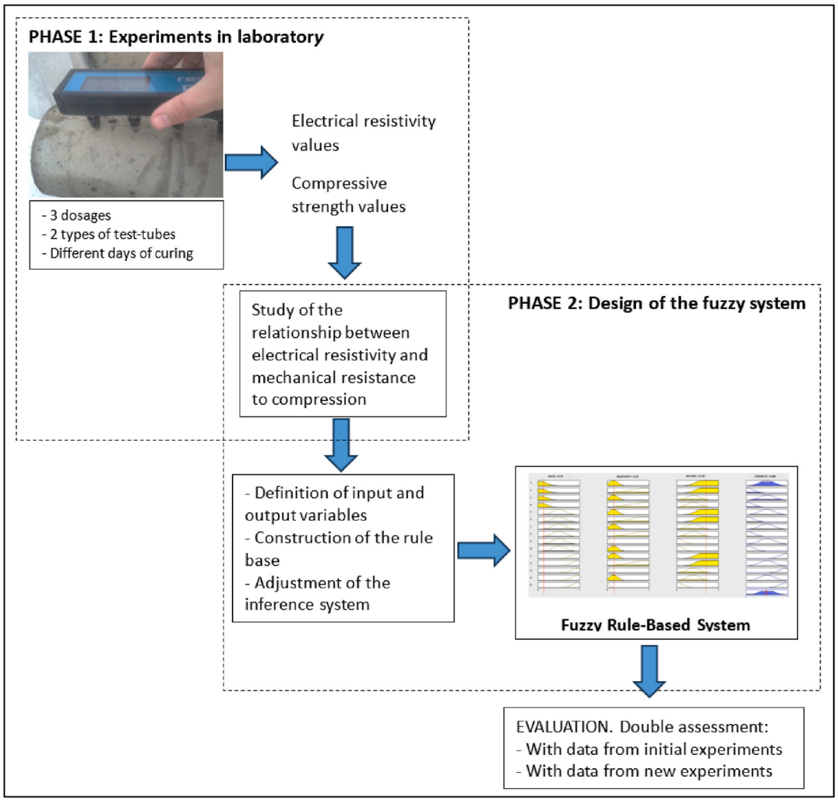

Fig. 4. Schematic view of the methodology followed in this work.

4. Results and discussion

4.1. Compressive strength and electric resistivity experimental results

Table 1 shows the experimental results obtained (according to the dosages, the type of test-tube and the days of curing) for the values of electrical resistivity measured at different instants and the value of mechanical strength to compression measured at the age of 28 days.

One of the objectives of this work is to analyse in depth the behaviour of the mortar, in order to determine the variables and parameters that influence its mechanical compressive strength at 28 days. To this end, we focused especially on the study of the experimental results obtained with the cylindrical test tubes (shown in the lower rows of each dosage in Table 1), which are those that have been considered for the subsequent design of the proposed fuzzy system.

In the cylindrical test tubes the compressive strengths at 28 days of age reach values between approximately 10.90 N/mm^2 and 24.65 N/mm^2. The amount of cement present in the dosage of each mortar is directly related to the increase in the mechanical strength of the mortar, together with the degree of curing applied. It can be observed that mortars cured at seven days improve their strengths compared to uncured mortars by up to 43%. The increase in the strength value of the longer cured mortars is due to the presence of water throughout this time. The hydration of the mortar components is more complete in these cases, as the water necessary for hydration does not evaporate due to the heat generated by the exothermic reactions that occur during the setting and hardening of the mortar.

In this work, electrical resistivity measurements were carried out at 1, 2–3 and 7 days after their manufacture (which we will call "INITIAL", "MIDDLE" and "FINAL" measurement instants, respectively) on each of the dosages manufactured in the laboratory (dosages 1, 2 and 3, which we will call "POOR", "NORMAL" and "IMPROVED" dosages, respectively).

The measurements made at the INITIAL instant (1 day) reflect low resistivity values, in the range of 1.00–1.50 kΩcm for all dosages. These electrical resistivity values vary for the following measurement instants (MIDDLE and FINAL), independently for each dosage, but increase in value in all cases. This is because in the INITIAL instant the mortars retain a large part of the mixing water. At that moment, the exothermic reactions of the components of the dosage (cement-sand-water) have not been completed, and therefore, water is conserved in the solid mass of each test-tube. After 48–72 h, the hydration phase and at least 80% of the hardening have been completed, so the water present in the solid mass depends on the curing carried out on it. Proof of this is that in the MIDDLE measurement instant (2–3 days) a slight increase in the measured values of electrical resistivity is observed, but it is in the FINAL measurement instant (7 days) when the value obtained is maximum.

Analysing the results according to the curing time, the highest electrical resistivity measurements correspond to the test-tubes subjected to fewer days of curing. Conversely, the lowest electrical resistivity results are obtained in the test-tubes that have undergone

Table 1
Experimental results: Electrical Resistivity and Mechanical Compressive Strength.

Dosage	Test-tube	Curing (Days)	Electrical Resistivity (KΩcm) Measurement instant (Days)			Mechanical Compressive Strength at 28 days (N/mm²)
			1	3	7	
1	Prismatic	0	1.40	2.80	8.10	11.37
		1	1.10	2.00	6.10	12.18
		3	1.10	1.60	4.10	12.45
	Cylindrical	0	1.40	2.90	8.70	10.90
		1	1.10	2.10	6.60	11.65
		3	1.10	1.70	4.70	13.58
		7	1.10	1.60	2.50	15.67
Dosage	**Test-tube**	**Curing (Days)**	**Electrical Resistivity (KΩcm) Measurement instant (Days)**			**Mechanical Compressive Strength at 28 days (N/mm²)**
			1	**3**	**7**	
2	Prismatic	0	1.50	4.20	4.80	11.92
		1	1.30	2.90	3.30	12.53
		3	1.30	3.00	3.40	14.27
		7	1.30	2.10	2.30	15.47
	Cylindrical	0	1.50	4.10	4.60	13.97
		1	1.30	3.00	3.50	14.52
		3	1.30	3.10	3.40	14.76
		7	1.30	2.20	2.30	15.15
Dosage	**Test-tube**	**Curing (Days)**	**Electrical Resistivity (KΩcm) Measurement instant (Days)**			**Mechanical Compressive Strength at 28 days (N/mm²)**
			1	**2**	**7**	
3	Prismatic	0	1.20	2.00	7.50	18.55
		1	1.10	1.40	6.10	23.13
		3	1.20	1.40	5.80	24.33
		7	1.20	1.40	2.90	26.70
	Cylindrical	0	1.00	1.90	7.30	19.66
		1	1.00	1.30	5.70	22.56
		3	1.10	1.30	5.50	21.59
		7	1.00	1.30	2.70	24.65

more days of curing. For example, in dosage 1 (POOR), with 7 days of curing, it is observed that the measured values are 1.10 kΩcm at the INITIAL measurement instant, 1.60 kΩcm at the MIDDLE instant and 2.50 kΩcm at the FINAL instant. All these values are lower than those measured with less days of curing.

On the other hand, it can be observed that the mechanical strength values of each dosage increase with the days of curing, with the highest values obtained in the mixes subjected to the maximum curing time (7 days). Therefore, an inverse correspondence relationship can be established between the electrical resistivity values and mechanical strength values. Fig. 5 shows that the electrical resis-

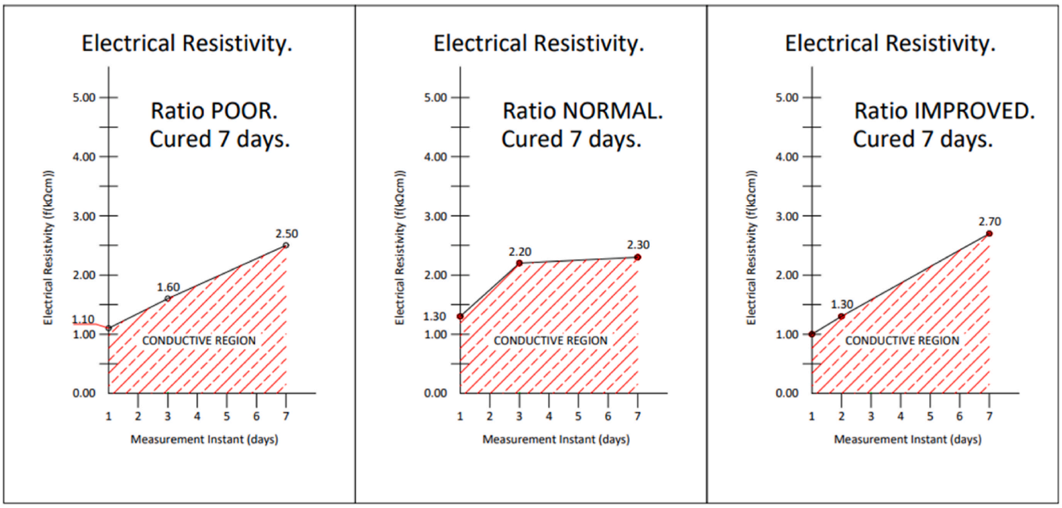

Fig. 5. Electrical resistivity of each dosage with 7 days of curing and delimitation of the CONDUCTIVE REGION (red zone).

tivity values of the three dosages cured for 7 days represent a region of minimum electrical resistivity, which we call the "CONDUCTIVE REGION".

It can be observed that the values of mechanical compressive strengths measured in mortars with 1 and 3 days of curing represent a range of intermediate values. These values are higher than those obtained in mixtures subjected to 0 days of curing, and lower than those obtained in mixes subjected to 7 days of curing. For example, for the NORMAL dosage (dosage 2), the values are lower than 1.30 kΩcm at the INITIAL measurement instant, 3.10 kΩcm at the MIDDLE instant and 3.50 kΩcm at the FINAL instant. According to the data, a relationship can be established between the electrical resistivity values and the mechanical strength values, so intermediate electrical resistivity values correspond to the intermediate values of mechanical strength to compression. With these data corresponding to 1 and 3 days of curing, we can identify an "INTERMEDIATE REGION", as shown in Fig. 6.

The electrical resistivity values of the test-tubes that have not been subjected to any curing (0 days of curing) are the maximum values obtained. For example, for dosage 3 (IMPROVED) these values are 1.00 kΩcm at the INITIAL measurement instant, 1.90 kΩcm at the MIDDLE instant and 7.30 kΩcm at the FINAL instant. As previously done, we establish a relationship between the values of electrical resistivity and mechanical strength according to the data obtained. In this case, it is observed that for these maximum electrical resistivity values, the measured values of mechanical strengths are minimal, which delimits a new region, called "ADVERSE REGION", as shown in Fig. 7.

The measured values of the compressive mechanical strengths are inversely related to the measured values of electrical resistivity at all dosages (POOR, NORMAL and IMPROVED). According to the observed distribution, the highest mechanical strength values ("HIGH MECHANICAL STRENGTH") are presented by those mortars whose electrical resistivity values are in the region identified as CONDUCTIVE REGION. Mortars with electrical resistivity values within the region identified as INTERMEDIATE REGION show intermediate values of mechanical strength ("MODERATE MECHANICAL STRENGTH"). Finally, mortar mixtures with electrical resistivity values in the region identified as ADVERSE REGION reach the lowest values of mechanical strength ("LOW MECHANICAL STRENGTH").

4.2. Design of the Fuzzy Rule-Based Systems (FRBS)

The general design of an FRBS involves the following tasks.

1. Identify the variables of the system to be modelled. Define these variables as linguistic variables and assign them the necessary linguistic labels. As these labels are represented by fuzzy sets, it is necessary to define the form and situation of these fuzzy sets in the universe of discourse.
2. Construct the rule base: relate input and output variables by means of if-then rules.
3. Build the fuzzy inference system.

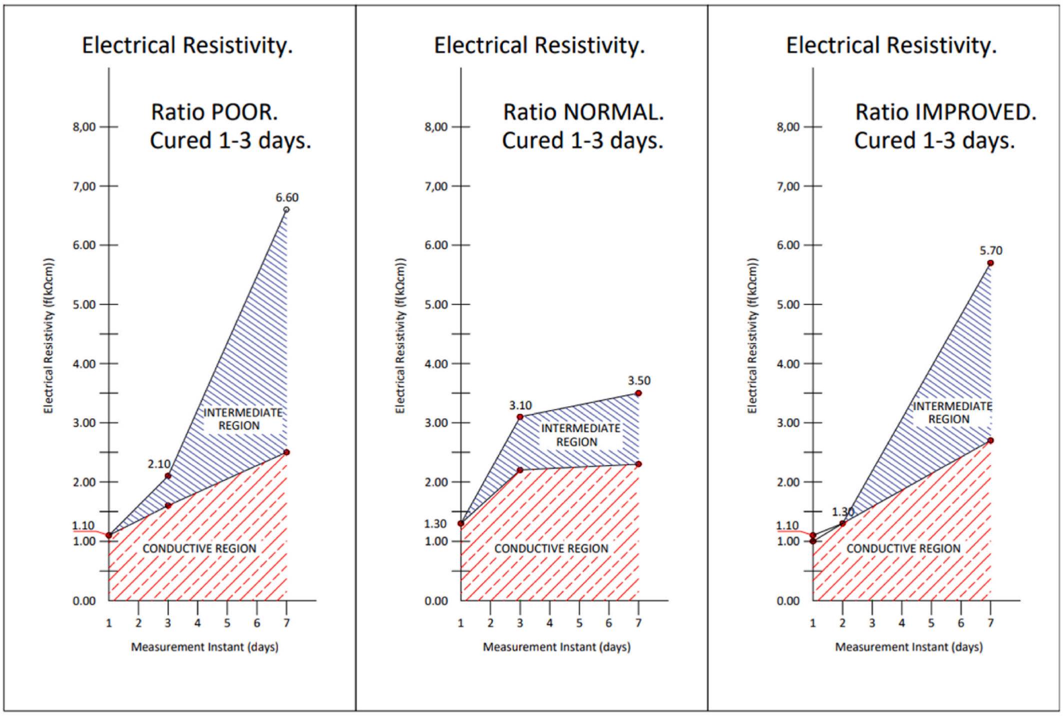

Fig. 6. Electrical resistivity of each dosage with 1–3 days of curing and delimitation of the INTERMEDIATE REGION (blue zone).

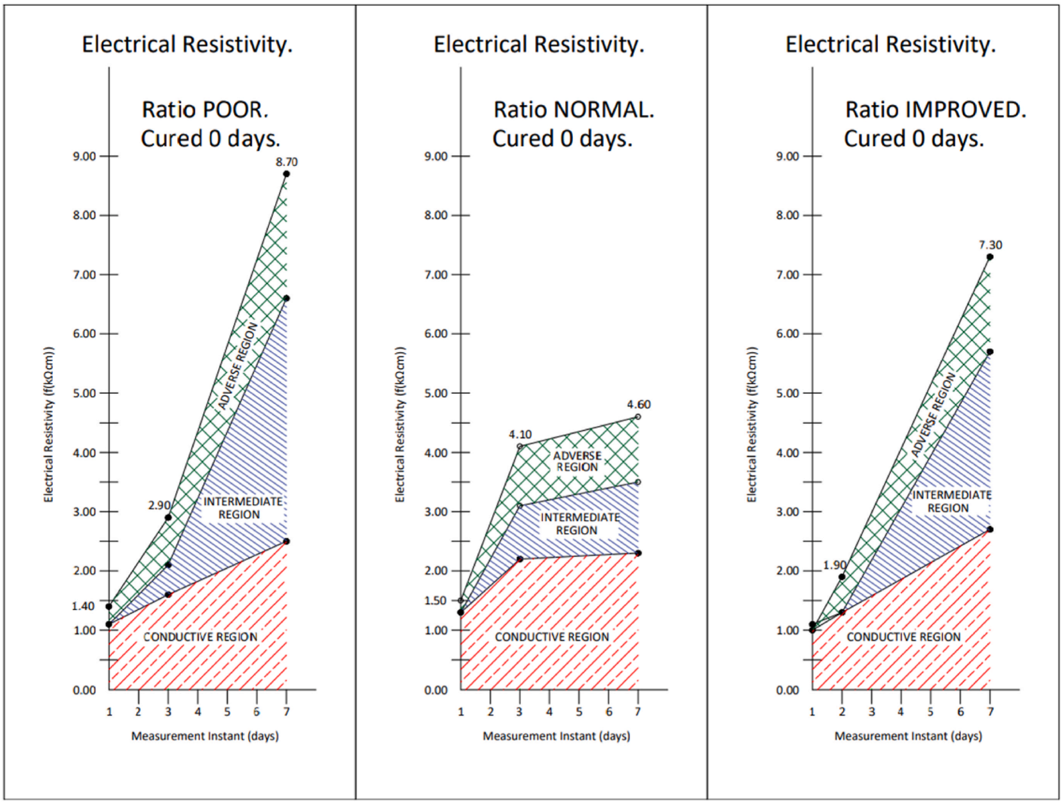

Fig. 7. Electrical resistivity of each dosage with 0 days of curing and delimitation of the ADVERSE REGION (green zone).

In many cases, these tasks are performed in collaboration with a domain expert, in order to properly translate the expert knowledge into variables and rules. Defining the variables, the labels, what the fuzzy sets should look like, their shape, etc., is not a trivial task. In this work, the knowledge necessary to correctly choose the variables and labels and to adjust the rule base is extracted from the data obtained in the mortar tests carried out in the laboratory.

First, the relevant variables that determine the behaviour of the mortar are selected, defined as linguistic variables and assigned linguistic labels that represent the problem to be modelled. In our case, the input linguistic variables are "Dosage", "Electrical resistivity" and "Measuring instant", and the output variable is "Mechanical strength". The labels assigned to each variable are shown in Table 2. For example, for the variable "Dosage", the labels considered are "Poor", "Normal" and "Improved" corresponding to cement-sand ratios of the mortars of 1:5, 1:4 and 1:3, respectively.

Once the variables and their labels have been identified, it is necessary to assign fuzzy sets to them. Gaussian membership functions have been chosen for all the fuzzy sets because the smooth form of this function allows to better represent the gradual transition between labels. The ranges where the membership functions of each label should be placed are taken from the experimental results obtained in the laboratory.

Table 2
Input and output linguistic variables and linguistic labels. Ranges assigned.

Linguistic variables		Linguistic labels	Distribution	Normalised range [0–1]
INPUTS	Dosage	Poor	1:5	0.00–0.33
		Normal	1:4	0.33–0.66
		Improved	1:3	0.66–1.00
	Electrical resistivity	Conductive	1.00–1.39	0.00–0.05
		Intermediate	1.40–2.89	0.05–0.25
		Adverse	2.90–8.70	0.25–1.00
	Measurement instant	Initial	From 0 to 1 day	0.00–0.14
		Middle	From 2 to 3 days	0.14–0.43
		Final	From 4 to 7 days	0.43–1.00
OUTPUT	Mechanical strength	Low	10.90–14.00	0.00–0.23
		Moderate	14.10–19.66	0.23–0.64
		High	19.67–24.65	0.64–1.00

The universe of discourse of each input variable has been normalised to the range [0,1]. For example, for the variable "Mechanical strength", the universe of discourse is the range of values of the mechanical compressive strengths obtained, from 10.90 N/mm^2 to 24.65 N/mm^2. Following the distribution column in Table 2, we will assign the first section of mechanical strengths labelled "Low" to the values between 10.90 and 14.00 N/mm^2. The range of this first label corresponds to approximately 23% of the total universe of discourse, so that within the universe of discourse [0.1], the result is [0.00–0.23]. For the second label of this variable, label "Moderate", the operation is the same and the range corresponds to approximately 41% of the total universe of discourse, resulting in a range of [0.23–0.64]. Finally, for the label "High", the range corresponds to 36% of the total universe, resulting in a remaining range of [0.64–1.00].

The FRBS rule base has been constructed by analysing the experimental data obtained in the laboratory reflecting the behaviour of the manufactured mortars. In this work, 15 rules have been designed, as shown in Table 3. The first rule is interpreted as follows: IF "Dosage" is "Poor", "Electrical resistivity" is "Intermediate" and "Measuring instant" is "Final" THEN "Mechanical strength" is "Moderate". The other rules are interpreted similarly.

4.3. Evaluation of the Fuzzy Rule-Based Systems (FRBS)

Two independent evaluations of the fuzzy system have been performed. The first evaluation checks that the output of the fuzzy system corresponds to the behaviour observed in the experiments with the cylindrical test-tubes, which are the experiments whose results have been used to adjust it. In this first validation, the aim is to confirm the correct design of the system. Although all possible combinations of inputs have been tested, only the four most relevant tests are presented here. In a second validation, the data from the prismatic test-tubes are introduced into the fuzzy system, and its output is analysed. The aim is to study its performance when processing data other than those used in its design. This section will show four of these tests.

4.3.1. First validation

Table 4 presents four validation tests using data corresponding to the experiments performed on the cylindrical test-tubes. The measurements of the input variables ("Experimental data") are introduced into the system previously normalised ("Normalised input"), according to the ranges of the corresponding linguistic labels ("Input and output labels"). It is verified that the numerical output provided by the FRBS corresponds to the range of the expected output label in all cases (mechanical strength value measured in the laboratory experiments), so it can be concluded that the FRBS is well designed.

For example, in validation test 1, a mortar type 1:5:1.25, with 7 days of curing, has an electrical resistivity value of 2.5 kΩcm. Its mechanical compressive strength at 28 days yielded 15.67 N/mm^2. The FRBS input values are as follows: for the variable "Dosage" the label "Poor", for the variable "Electrical Resistivity", the label "Intermediate"; and for the variable "Measuring instant", the label "Final". The expected output would be a "Moderate" "Mechanical Resistivity", according to the behaviour collected in the rule base. The input values are normalised according to the ranges defined in the linguistic labels, and an output of 0.485 is obtained, a numerical value corresponding to the range of the "Moderate" label, coinciding with the real output of the experiment. As seen in the graphical representation of the behaviour of the designed FRBS (Fig. 8), the output value is within the range proposed for the "Moderate" label, and the most activated rule is number 1.

4.3.2. Second validation

Table 5 presents four validation tests using data corresponding to tests performed on prismatic tet-tubes (data not used in the system design). The measurements of the input variables ("Experimental data") are introduced into the system previously normalised ("Normalised input"), according to the ranges of the corresponding linguistic labels ("Input and output labels"). It is verified that the

Table 3
Set of fuzzy rules of the designed system.

Rule	INPUTS			OUTPUT
ID	Dosage	Electrical resistivity	Measurement instant	Mechanical strength
1	Poor	Intermediate	Final	Moderate
2	Poor	Adverse	Final	Low
3	Poor	Intermediate	Middle	Moderate
4	Poor	Adverse	Middle	Low
5	Normal	Intermediate	Final	Moderate
6	Normal	Adverse	Final	Low
7	Normal	Intermediate	Middle	Moderate
8	Normal	Adverse	Middle	Low
9	Normal	Conductive	Initial	Moderate
10	Normal	Intermediate	Initial	Low
11	Improved	Intermediate	Final	High
12	Improved	Adverse	Final	Moderate
13	Improved	Conductive	Middle	High
14	Improved	Intermediate	Middle	Moderate
15	Improved	Conductive	Initial	High

Finally, a fuzzy inference system is selected. In this work we have used the Mamdani inference system explained in section 2 [27]. The tool used for the design and construction of the system was the MATLAB Fuzzy Logic library [34].

Table 4
Examples of tests performed in the first validation of the FRBS.

Validation test 1	Dosage ratio	Electrical resistivity (KΩcm)	Measurement instant (day)	Mechanical strength at 28 days (N/mm^2)
Experimental data	1:5:1.25	2.5	7	15.67
Input and output labels	Poor	Intermediate	Final	Moderate
	0.00–0.33	0.05–0.25	0.43–1.00	0.23–0.64
Normalised input	0.14	0.16	0.705	
FRBS output				Moderate
				0,486
Correspondence between expected output and obtained FRBS output:				**YES**
Validation test 2	**Dosage ratio**	**Electrical resistivity (KΩcm)**	**Measurement instant (day)**	**Mechanical strength at 28 days (N/mm^2)**
Experimental data	1:5:1.25	6.6	7	11.65
Input and output labels	Poor	Adverse	Final	Low
	0.00–0.33	0.25–1.00	0.43–1.00	0.00–0.23
Normalised input	0.077	0.465	0.604	
FRBS output				Low
				0.178
Correspondence between expected output and obtained FRBS output:				**YES**
Validation test 3	**Dosage ratio**	**Electrical resistivity (KΩcm)**	**Measurement instant (day)**	**Mechanical strength at 28 days (N/mm^2)**
Experimental data	1:4:1.25	1.5	1	13.97
Input and output labels	Normal	Intermediate	Initial	Low
	0.33–0,66	0.05–0.25	0.00–0,14	0.00–0.23
Normalised input	0.455	0.199	0.045	
FRBS output				Low
				0.207
Correspondence between expected output and obtained FRBS output:				**YES**
Validation test 4	**Dosage ratio**	**Electrical resistivity (KΩcm)**	**Measurement instant (day)**	**Mechanical strength at 28 days (N/mm^2)**
Experimental data	1:3:1.25	2.7	7	24.65
Input and output labels	Improved	Intermediate	Final	High
	0.66–1.00	0.05–0.25	0.43–1.00	0.64–1.00
Normalised input	0.832	0.162	0.731	
FRBS output				High
				0.695
Correspondence between expected output and obtained FRBS output:				**YES**

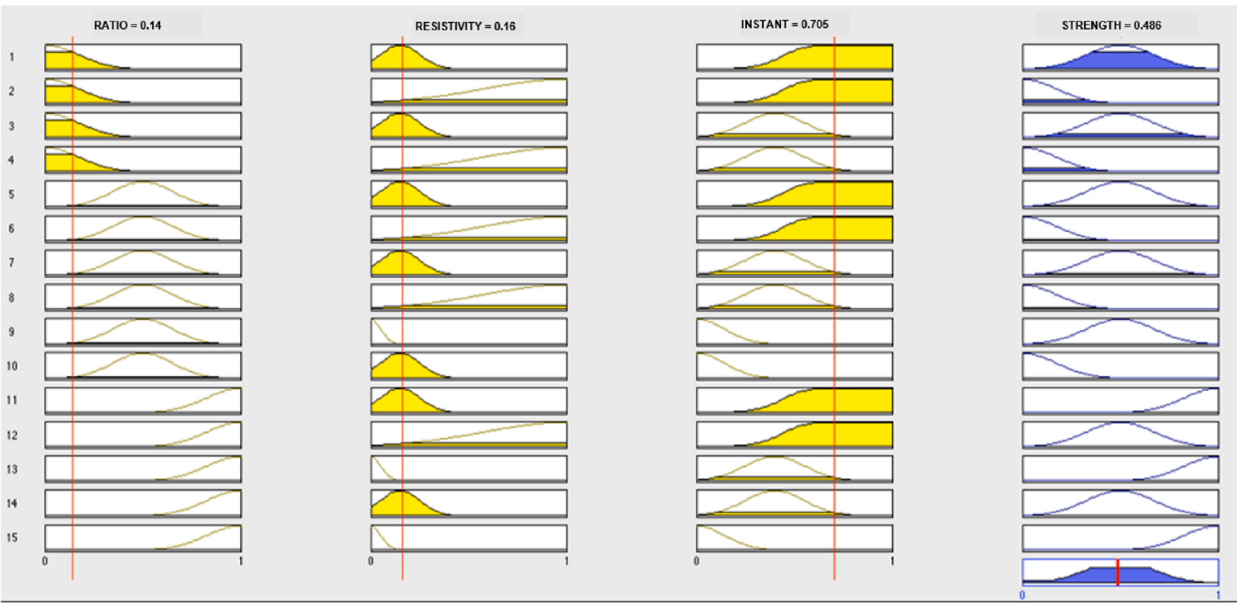

Fig. 8. Behaviour of the proposed FRBS in validation test 1 of the first evaluation.

numerical output offered by the FRBS corresponds to the range of the expected output label in all cases (mechanical strength value measured in the laboratory experiments), so it can be concluded that the FRBS works correctly with data different from those used in its design, and that, therefore, it is able to generalise. Fig. 9 shows the graphical representation of the behaviour of the designed FRBS for validation test 1 of this second evaluation. It can be seen that the output value is within the range proposed for the "Moderate" label, and that the most activated rule is number 15.

Table 5
Examples of tests performed in the second validation of the FRBS.

Validation test 1	Dosage ratio	Electrical resistivity (KΩcm)	Measurement instant (day)	Mechanical strength at 28 days (N/mm²)
Experimental data	1:3:1.25	1.10	1	23.13
Input and output labels	Improved	Conductive	Initial	High
	0.66–1.00	0.00–0.05	0.00–014	0.64–100
Normalised input	0.832	0.0399	0.13	
FRBS output				High
				0.663
Correspondence between expected output and obtained FRBS output:				**YES**
Validation test 2	**Dosage ratio**	**Electrical resistivity (KΩcm)**	**Measurement instant (day)**	**Mechanical strength at 28 days (N/mm²)**
Experimental data	1:4:1.25	3.00	3	14.27
Input and output labels	Normal	Adverse	Initial	Moderate
	0.33–0.66	0.25–1.00	0.14–0.43	0.23–0.64
Normalised input	0.407	0.396	0.386	
FRBS output				Moderate
				0,264
Correspondence between expected output and obtained FRBS output:				**YES**
Validation test 3	**Dosage ratio**	**Electrical resistivity (KΩcm)**	**Measurement instant (day)**	**Mechanical strength at 28 days (N/mm²)**
Experimental data	1:4:1.25	3.30	7	12.53
Input and output labels	Normal	Adverse	Final	Low
	0.33–0.66	0.25–1.00	0.43–1.00	0.00–0.23
Normalised input	0.529	0.428	0.513	
FRBS output				Low
				0.213
Correspondence between expected output and obtained FRBS output:				**YES**
Validation test 4	**Dosage ratio**	**Electrical resistivity (KΩcm)**	**Measurement instant (day)**	**Mechanical strength at 28 days (N/mm²)**
Experimental data	1:5:1.25	4.10	7	12.45
Input and output labels	Poor	Adverse	Final	Low
	0.00–0.33	0.25–1.00	0.43–1.00	0.00–0.23
Normalised input	0.21	0.566	0.673	
FRBS output				Low
				0.162
Correspondence between expected output and obtained FRBS output:				**YES**

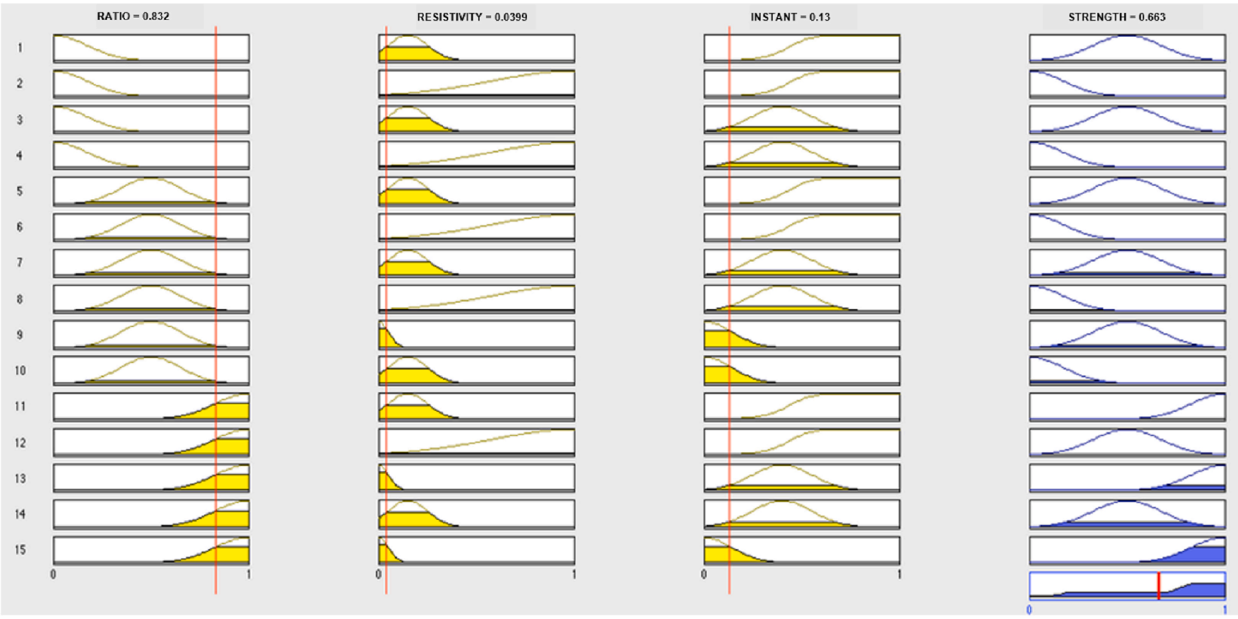

Fig. 9. Behaviour of the proposed FRBS in validation test 1 of the second evaluation.

5. Conclusions

In this work, several laboratory experiments were carried out to measure the electrical resistivity of mortars manufactured with different degrees of hydration. The objective of this empirical study is to adequately evaluate the relationship between the electrical resistivity and the mechanical strength offered by the mortar at 28 days after its manufacture. With this information, an intelligent system based on fuzzy rules is subsequently designed, capable of predicting the mechanical strength at 28 days of a mortar by using the measured values of electrical resistivity in the first days of hardening.

The factors that have been studied in each experiment are the amount of cement in the dosage, the days of curing, the value of the electrical resistivity at different measurement instants, and the mechanical strength obtained after 28 days. The data from these experiments show that the amount of cement present in the dosages is directly proportional to the mechanical compressive strength measured at 28 days. It has also been observed that the longer the curing process of the mortars, the greater the final mechanical strength obtained, due to better hydration in the initial phase, and consequently, a complete reaction between the components of the mortar.

The proposed fuzzy logic system models the complex relationship between the input variables, which are "dosage ratio", "electrical resistivity", and "measurement instant", and the output variable, which is "mechanical strength at 28 days". With this fuzzy system, the user could estimate the compressive strength at 28 days of a mortar without having to wait that time to measure it. The user could estimate the compressive strength simply by entering into the system the amount of cement used in the manufacture of the mortar, the electrical resistivity value that has been measured, and the number of days that have elapsed between the manufacture of the mortar and the moment in which this measurement has been carried out. We believe that this work provides, therefore, an interesting tool for professionals in the sector, which can help in the control of mortars made in situ, by estimating their mechanical strength value without the need to carry out preliminary disposable tests.

The proposed system, based on fuzzy rules, is appropriate to model the problem mainly due to three aspects.

1. The parameters of the approached problem can be represented by fuzzy sets. The fuzzy nature of the system allows us to handle the diversification of the input variables that influence the behavior of the mortars.
2. The quantities used in the preparation of the mortars and the quality of the resulting mortars depend to a great extent on human interpretations. The FRBS allows working with "approximate" definitions and evaluations, close to those used in human reasoning.
3. The available information, obtained through laboratory experiments, allows us to adjust the rules in an efficient way.

The FRBS has been validated by comparing the calculated outputs of the system with real data from new laboratory tests. The system has shown that it is capable of outputting the mechanical strength of the mortar even in situations not considered during the design process.

In future research work, new laboratory tests will be developed with different mortar dosages and other types of cement and sand to determine other behavior factors that allow improving the proposed fuzzy system. Likewise, it is planned to implement a comfortable interface for the management of the fuzzy system, such as an application in handheld devices, which facilitates the use of the system for professionals in the sector.

Author statement

Francisco-Javier Gutiérrez-García, Silvia Alayón, Eduardo González: Conceptualization, Methodology, Formal analysis, software, validation, writing.

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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