Computational models applied to the service life prediction of ETICS

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Extended abstract

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Abstract: The degradation of the constructions, associated to high maintenance and repair costs, increases the relevance of the studies about the durability of the construction elements. The ETICS systems are a recent cladding solution with a growing popularity in the construction industry, due to their advantages, especially the energetic related ones. This study proposes a methodology to predict the service life of ETICS, through two computational methods: artificial neural networks and fuzzy logic systems. The results obtained in this study aid the adoption of more durable and sustainable solutions at design and maintenance stages, improving the quality of the adopted construction solutions, reducing the costs of these elements during their life cycle.

1. Introduction

Nowadays, the construction sector is among the ones with higher impact in terms of energy and materials consumption. This sector is responsible for a high consumption of resources and carbon emissions into the atmosphere, at all stages of the buildings' life cycle. The raising awareness on sustainability (at economic and environmental levels) makes this sector very attractive for the implementation of preventive and corrective measures, in accordance with the trend sustainability principles [1].

Façades are the buildings' components most conditioning to their energy needs. They act as a frontier between the inside and the outside and they contribute to the maintenance of a proper environment in the interior spaces [2]. Therefore, the technology and materials used as cladding solution have a high influence on this aspect, so the selection of the best alternative is a complex process.

ETICS systems are a very interesting technology in this context. The acronym means External Thermal Insulation Composite System and, as the name suggests, it is a way of thermally insulating the buildings' envelope, in which the insulation material is placed on the exterior side of the wall. This solution has gained an increasing popularity in the construction sector due to its many advantages, which are suitable for new constructions and rehabilitation works. The recognition of its advantages by the competent certifying entities has promoted an increase of confidence in these systems, which contributes to the proliferation of their application [3].

Buildings and their elements inevitability suffer a gradual degradation process over time, due to the exposure to a combined action of several degradation agents and mechanisms. This phenomenon decreases the level of performance of the constructions until they cease to be able to fully meet their expected requirements. In this context, service life prediction acquires a high importance, since allows a more rational use of the constructive elements, as well as the planning of appropriate maintenance actions. Thus, an adequate performance is ensured for a longer time and eventual costs of urgent repairs are reduced [4].

Service life prediction is not an easy task. The degradation process of the constructive elements is complex and there is no full understanding of it, since it is influenced by several factors that act in a synergistic [5]. In recent times, many methodologies for service life prediction have emerged, which can have a great importance for the decision-making process. The use of the information provided by this mean allows a design that extends the expected service life of the constructions with a minimization of the costs. Therefore, buildings become more durable and sustainable.

2. Service life definition

Like any organic or inorganic element, buildings also have a limited lifetime. The service life is understood as the period of time during which a building or its components meet or exceed the established performance requirements [5,6]. These correspond to the minimum acceptable performance of a given property, which is conditioned by the individual performance of all buildings' components. In fact, as mentioned by Brand [7], the constructions do not degrade homogeneously; on the contrary, the various components have different rates of degradation.

During constructions' service life, safety, functionality and aesthetic appearance are the main performance requirements. According to Moser [8], when the minimum threshold of the performance requirements of one of these properties is exceeded, the end of the service life has been reached. The safety aspects are those that should be set to the lowest acceptable levels of degradation, from all properties. The service life prediction intends to assess the ability of a construction to guarantee a good performance over a reasonable period, before any replacement or repair. ISO 15686-2 [6] is the most relevant document in this context, which specifies the principles and procedures that facilitate the service life prediction of the buildings' components.

3. ETICS systems

In the construction industry, the application of exterior insulation on buildings' walls is a solution that provides an improvement of their energy efficiency. Thermal insulation solutions are classified according to the position of the insulation material applied. The main alternatives are: i) interior insulation; ii) insulation in the air box, between masonry layers; iii) external insulation. The advantages associated with external thermal insulation systems have promoted their use in different contexts. ETICS systems belong to this category and their efficiency and versatility contribute to their prominence in relation to the remaining solutions. In energy terms, the use of these systems promotes an increase in the efficiency of buildings by the reduction of the energy consumption. In addition, this solution also provides more protection to the buildings' structure.

3.1. Systems characterization

In simple terms, the ETICS system usually applied is composed by a thermal insulation material, in the form of boards, which is fixed to the substrate. Subsequently, the system receives a thin, continuous and reinforced outer layer, with the possible application of an additional coating.

The substrate is the base where the system is applied. There are various types of substrate suitable for the application of these systems. However, some require a better surface preparation than others. The system's adhesion to the substrate is achieved through bonding products, mechanical fasteners or both. The insulation material is responsible for the desired thermal properties of the buildings. Expanded polystyrene (EPS) is the most widely used material, although there are other alternatives, such as extruded polystyrene (XPS), mineral wool (MW) or black cork agglomerate (ICB). The base layer consists of a mortar and it is applied directly onto the boards of insulating material. Its thickness should be enough to allow completely covering the reinforcement, which is inserted in this layer to improve the mechanical behaviour and to increase the durability of the systems. Then, a regularization primer can be applied over the base layer. The final coating is the outermost layer of the systems, and it has decorative, protective and watertight functions.

The ease of application is a factor with a major contribution for the use of ETICS. However, errors made during this phase severally influence the quality of the cladding. Thus, the analysis of technical documentation and the respect of good construction practices, during the application phase, are essential to ensure a system with good properties.

3.2. Anomalies and probable causes

The integrity of the systems is essential to achieving the desired building efficiency, expected from the application of this solution. The occurrence of anomalies compromises the ETICS' performance. Hence, there is a need to identify and correct any existent pathological manifestation, in order to obtain the expected level of performance. The multiplicity of defects that can occur in these systems justifies the creation of classification systems. Their purpose is the division of the anomalies, by types or groups, according to the same type of effects caused in the façades. In this study, the following division of the most common defects of ETICS is adopted [4,9,10]:

- Staining/colour or texture changes: dirt deposition; surface moisture; chromatic alterations; efflorescence/criptoflorescence and carbonation; biodeterioration/biological colonization; parasitic vegetation;
- Joint defects: warping, swelling, deformations and other flatness defects;
- Loss of continuity/integrity defects: cracking (oriented or mapped); defects in the corners;
- Loss of adhesion defects: bulging and blisters; detachment; loss of adherence; material gap.

The difficulties in understanding the degradation processes of these systems are due to the assessment of the causes of the defects. As a rule, the development of anomalies is influenced by the combination of several factors. Simultaneously or not, the degradation factors lead to a gradual worsening of the degradation condition, which implies a consequent loss of performance. Marques [4] proposes the distinction of the principal factors in the following groups:

- Factors related to environmental actions: water; temperature; solar radiation; wind; biological;
- Factors related to the characteristics of buildings: type of surrounding environment; orientation;
- Factors related to the characteristics of the materials;
- Design, execution, use and maintenance errors;
- Factors associated with other causes.

4. Field work

The main objectives of the field work were to collect data for the study of the degradation process of the ETICS systems and to perform a survey of the most relevant variables that influence this process. The data gathered during this phase was collected through visual inspections on a set of buildings with this type of coating. Simple and non-intrusive procedures were used in order to enable the inspection activities. With all the collected data, different methodologies were applied to predict the service life of these systems.

4.1. Methodology of investigation

Despite the high importance of the inspection activities, some previous and subsequent procedures were also necessary. The field work was divided in two main phases: i) field work planning, which included the aspects related to the identification and selection of the claddings to be analysed; ii) collection of information, which included obtaining prior information, mainly of qualitative nature (characteristics of each cladding), as well as concrete information about the identified anomalies. All data was registered in an inspection and diagnosis file. A photographic survey of all claddings and of all anomalies detected in them was also carried out.

4.2. Sample analysed

The total sample comprises 378 façades and the following data were collected: i) age of the claddings; ii) characteristics of the surrounding area: orientation; distance from the sea; exposure to moisture; wind-rain action; exposure to pollutants); (iii) characteristics of the claddings (type of coating, type of finishing, colour, peripheral protection). In general, the above-mentioned aspects showed a balanced distribution, in terms of the number of cases in reach of their classes.

Regarding the anomalies detected, the analysis of the total sample revealed that stains or aesthetic changes are the most common anomalies, which were identified in practically all claddings. In contrast, anomalies associated with loss of adhesion were only identified in 10,5% of the sample.

5. Degradation models

One of the objectives of this study was to apply the graphical method to obtain degradation curves of ETICS systems. These curves are the graphical representation of the deterioration processes and they evaluate the loss of performance of ETICS over time. These curves are an interesting procedure since allow estimating the service life of these claddings in a simple way. For that, the overall degradation condition of the claddings should be determined. In this sense, the methodology of Gaspar and Brito [11] was used, which consists of the estimation of a numerical value called severity degradation index (S_w). This index is the ratio between the weighted extent of degradation of the cladding and the maximum possible level of degradation - Equation (1).

$$S_w = \frac{E_w}{k} = \frac{\sum(A_n \times k_n)}{A \times k} \quad \textbf{(1)}$$

Where: S_w represents the degradation severity (expressed in percentage); E_w the weighted degradation extension (expressed in percentage); k the multiplying factor corresponding to the highest degradation condition level of the cladded area A (in this case, k=4); A_n the cladding area affected by any defect n (in m^2); k_n the multiplication factor for n anomalies, in terms of their degradation level; A the total façade area with ETICS (in m^2). The k_n coefficient intends to classify the degradation level of the defects identified through the visual inspections. It only has integer values, ranging from 0 to 4 (Table 1).

Table 1 - Illustrative examples of the degradation levels of ETICS

Level 1 Barely perceptible changes	**Level 2** Slight degradation	**Level 3** Moderate degradation	**Level 4** Generalized degradation
			

5.1. Degradation curves

The degradation curves allow correlating the age of the ETICS (which is the independent variable) and their degradation condition (which is the dependent variable). The degradation curves of the total sample (Figure 1) were generated by simple regression analysis, in which a third-degree polynomial function was adjusted to the points composed by the severity of degradation indices of each cladding and the respective ages.

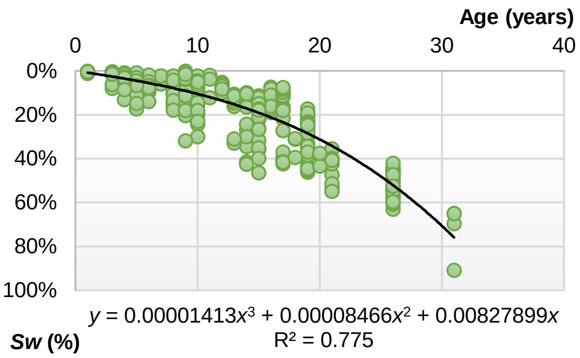

Figure 1 - Degradation curve obtained for the sample analysed

The high determination coefficient of the curve ($R^2 = 0.78$) shows a good correlation between the model and the observed reality. The convex curve pattern suggests that the deterioration follows a slow pattern at early life stages. However, at later stages, the evolution becomes more accelerated, leading to a higher degradation.

The service life is predicted from the intersection of the curve with the maximum acceptable degradation level for the systems. In this study, this limit corresponds to a severity of degradation index of 30%, which indicates that a given cladding that reaches this level has reached the end of its service life. Under this condition, the cladding is no longer capable to fulfil the expected demands, thus requiring an intervention to restore its initial characteristics. From the degradation curve in Figure 1, a service life around 20 years was obtained. This value is similar to the service life value obtained by Marques et al. [4], also 20 years, based on the same assumptions. These values are in line with those found in the literature. For example, ETAG 004 [12] suggests a service life of 25 years, with adequate conditions of use and regular maintenance actions. A similar value is suggested by Tůmová et al. [13], from 25 to 30 years, assuming the same conditions. In this study, the admission of the lack of maintenance actions, under normal service conditions, led to a service life value lower than those mentioned before.

Subsequently, different degradation curves were obtained, each one associated with the variables that influence the durability of the ETICS systems. Based on these curves, the following results were achieved:

(i) the service life of façades facing N/NE and O/NO (19 years) is shorter than that of façades facing S/SO and E/SE (20 years); (ii) the service life of façades closer to the sea (19 years) is shorter than that of façades farther from the sea (20 years); (iii) the service life of façades with a strong humidity exposure (19 years) is lower than that of façades with a weaker humidity exposure (20 years); (iv) the service life of façades exposed to a strong action of the rain-wind (19 years) is lower than that of facades exposed to a weak action (21 years); (v)the service life of façades exposed to a strong action of pollutants (18 years) is lower than that of facades exposed to a weak action (20 years); (vi) the data do not allow drawing unequivocal conclusions about the influence of the type of coating because of the poor representativeness of cases in one of its classes; however, the results indicate a longer service life for reinforced coatings when compared to traditional ones; (vii) regarding the finishing type, the conclusions are similar to those mentioned about the previous factor (low representativity of cases in one of the classes); (viii) colour coating results indicate lower service life values for white and light colours, although the number of dark-coloured cases is not significant enough to corroborate this evidence; (ix) regarding the peripheral inferior protection, the results obtained do not allow drawing conclusions, since the degradation patterns observed differ slightly from the physical expectation.

6. Computational models

Modelling of real phenomena is particularly interesting in situations where its direct observation does not allow an adequate understanding. Among the existent modelling techniques, computational ones have been used successfully in several areas. These models combine knowledge based on human reasoning and mathematical inference, which is very useful for modelling problems with a complex mathematical representation, frequently associated with nonlinear and variable processes in time [14].

The main objective of this study was the application of computational methods, based on artificial neural networks and fuzzy logic, to the service life prediction of ETICS. The general considerations and the most relevant theoretical foundations of these models will be briefly described in next sections. Prior to the application of the methods, a sensitivity analysis was performed, through an analysis of regression, in order to determine the most significant variables for the explanation of the observed degradation of ETICS. The inclusion of these variables in the models improves their performance and the quality of the obtained results.

6.1. Identification of the explanatory variables - Multiple linear regression (MLR) models

Regression analysis is a statistical technique widely used in modelling real phenomena. A simple regression evaluates the behaviour of the dependent variable based on a single independent variable. In a multiple regression, the same occurs based on more than one independent variable. The inclusion of more variables in the regression models usually leads to more effective models, i.e. with more explanatory power [15].

In this study, a multiple linear regression (MLR) was performed with the software SPSS®. For this, 10 independent variables were chosen based on the factors that condition the deterioration of ETICS. First, given their categorical nature, most variables were converted into numerical values. For this, the service life values obtained with the degradation curves were used, and the variables are quantified by the ratio between these values and the global average service life value, obtained by the global degradation curve.

A regression analysis, through the stepwise method, identified five variables with high statistical significance in the explanation of the observed degradation: age; sea pollutants; type of finishing; and orientation (by decreasing order of relevance). However, the type of finishing presented a lack of representativeness in one of its classes. Thus, to avoid a potential negative influence of this variable in the model, a new regression analysis was performed without this factor. The new analysis led to the identification of only three variables with high statistical relevance: age; sea; pollutants. With these results, it was considered relevant to explore the use of both sets of variables to create two different models.

This regression analysis also allows obtaining two models for the service life prediction of ETICS. In the construction of these regression models, the hypotheses related to the regression analysis were ensured. At the same time, the statistical significance of both models was also ensured through statistical indicators, provided by SPSS®. In particular, the *F* statistic, associated with each model, and the *t* statistics, associated with the explanatory variables and the independent term, in each model, always revealed higher values than the critical ones. This evidence allowed the rejection of the null hypotheses admitted in both situations. Equations 2 and 3 present the quantification of the severity of degradation of ETICS, adopting three and five variables, respectively. In these equations, *A* represents the age of the cladding, *S* the distance from the sea, *P* the exposure to pollutants, *F* the type of finishing and *O* the façades orientation. The use of these equations requires the variables quantification presented in Table 2.

$$S_{w_{RML}} = 0.020 \cdot A - 1.219 \cdot S - 0.445 \cdot P + 1.524 \quad \textbf{(2)}$$

$$S_{w_{RML}} = 0.020 \cdot A - 1.189 \cdot S - 0.470 \cdot P - 0.055 \cdot F - 0.290 \cdot O + 1.862 \quad \textbf{(3)}$$

Table 2 - Explanatory variables quantification

Explanatory variable		Quantification
Façades orientation	N/NE	0,959
	S/SO	1,021
	E/SE	1,041
	O/NO	0,969
Type of finishing	Smooth	1,000
	Rough	0,990
	Ceramic	2,754
Distance from the sea	< 5 km	0,959
	> 5 km	1,010
Exposure to pollutants	High	0,903
	Low	1,031

Both equations lead to logical results, from a physical point of view, with respect to the influence of each variable on the severity of degradation of the ETICS. The positive coefficient of age indicates that its influence is felt by the increasing of the severity of degradation. The remaining variables have negative coefficients, since the favourable classes present a higher quantification. Therefore, favourable conditions contribute to the reduction of the degradation of the coatings, while unfavourable conditions contribute to their increase.

The predictive capacity of the models was analysed by the comparison of the values provided by the models, when applied to the claddings, and the values observed during the field work. Ensuring an adequate predictive capacity is an essential requirement for the validation of the models, in order to obtain reliable predictions. For this evaluation, some statistical indicators were used (Equations 4 to 6), namely: i) mean percentage error normalized to the maximum; (ii) standardized percentage error; iii) normalized mean square error (NMSE); iv) Pearson correlation coefficient (*r*); v) percentages of patterns with errors greater than 5%; 10%, 20% and 30%.

$$\bar{\varepsilon} = \frac{1}{P}\sum_{p=1}^{P}(\varepsilon_p)\,, \quad with \quad \varepsilon_p = \left|\frac{z_p - t_p}{t_{máx}}\right| .100\ \% \quad \textbf{(4)}$$

$$NMSE = \frac{MSE}{\bar{t}}\,, \quad with$$
$$MSE = \sqrt{\frac{1}{P}\sum_{p=1}^{P}(z_p - t_p)^2} \quad e \quad \bar{t} = \frac{1}{P}\sum_{p=1}^{P} t_p \quad \textbf{(5)}$$

$$r = \frac{\sum_p (z_p - \bar{z})\,(t_p - \bar{t})}{\sqrt{\sum_p (z_p - \bar{z})^2\ \sum_p \left(t_p - \bar{t}\right)^2}}\,,$$
$$with \quad \bar{z} = \frac{1}{P}\sum_{p=1}^{P} z_p \quad \textbf{(6)}$$

The statistical parameters associated with each proposed regression model are shown in Table 3. From this table it can be concluded that, in both models, the error indicators have relatively low values. The Pearson coefficient, with a value greater than 0.8, shows a good correlation between the observed values and the values predicted by the regression models.

Table 3 - Error estimators of the proposed MLR models

Model	$\bar{\varepsilon}$	ϵ_{max}	$NMSE$	$PP_{\epsilon>5\%}$	$PP_{\epsilon>10\%}$	$PP_{\epsilon>20\%}$	$PP_{\epsilon>30\%}$	r
3 variables	7.87%	31.17%	48%	62%	35%	4%	0%	0.847
5 variables	7.70%	36.20%	47%	60%	33%	4%	0%	0.851

6.1.1. Application to service life prediction

The determination of the service life, based on the proposed regression models, consists of the determination of the age at which each cladding reaches the maximum limit of degradation allowed (S_w = 30%). In each model, the application of this methodology led to the following average values: i) three-variable model: estimated service life of 20.9 years, with a standard deviation of 1.8 years; ii) five-variable model: estimated service life of 20.8 years, with a standard deviation of 2.0 years.

For the first model, the possible combinations of variables led to the results shown in Figure 2. These results were in agreement with the expected physical reality: i) the worst combination of variables (closer to the sea and high exposure to pollutants) leads to the lowest service life value; ii) the most favourable combination of variables (far from the sea and low exposure to pollutants) leads to the highest value of service life; iii) the remaining two combinations lead to intermediate values.

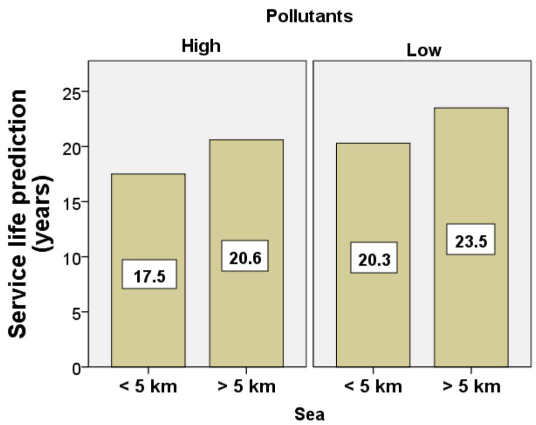

Figure 2 - Service life values provided by the MLR model with three variables

For the five-variable model, the analysis of the results allows concluding that: i) a lower distance from the sea always leads to lower values of service life; ii) the same applies to the situation of high exposure to pollutants, whose effect on the value of the service life is equal; iii) the N/NE orientation leads to lower service values in the majority of the combinations, with very similar values to the O/NO orientation; iv) the E/SE orientation always leads to a higher service life, with very similar values to the S/SO orientation; v) the types of finishing smooth and rough originate service life value always lower than those originated by the other finishing class. According to this model, the overall service life of ETICS range between 16.8 years and 28.9 years, which is also in accordance with the expected physical reality.

6.2. Artificial neural networks

Artificial neural networks (ANNs) belong to the field of Artificial Intelligence, which proposes an approach to the modelling of cognitive processes according to the processing mechanisms that are believed to occur in the biological brain [16]. ANNs are composed by several interconnected processing units, called neurons, which give the network the ability to acquire and maintain knowledge. The similarity with the biological brain lies in the fact that knowledge is acquired from the outside, through learning processes, and it is stored in the connections between the neurons [5]. The applicability of this tool to this is due to its predictive capacity, which enables the estimation of future values of a given problem by considering the knowledge acquired with the observation of previous examples of the same problem.

The neurons of ANNs are modelled as versions of the existent neurons in the biological neuronal systems. The architecture of the network refers to the definition of neurons' organization, namely the positioning of each neuron in relation to the rest. This aspect conditions the connections that can later be established. The most common type of ANNs is the multilayer perception (MLP), which has been widely used due to its adaptation ability to a wide range of problems. MLP has a unidirectional operation, which implies the connection of each neuron to everyone in the next layer and to no other in the network. The learning procedure of ANNs requires two phases: training; and testing. The training strategy is based on the presentation of examples to the network, which constitute the training set. When this happens, the network produces output patterns, which can be compared with the desired target patterns, enabling the measure of the model accuracy. The training phase consists of the successive presentation of the training set to the network, in order to change its characteristics until the errors obtained reach satisfactory minimum values. The test phase allows evaluating the network's performance in the presence of new data and requires unrecognized examples (test set) [17].

6.2.1. Models construction

The definition of the variables for the models was based on the results provided by the MLR analysis. Thus, the same two sets of variables mentioned in the previous subchapter were used. However, given the categorical nature of most variables, it was necessary, once again, to convert them into numerical values. In this case, all qualitative variables were converted into dummy variables. This type of variable is characterized by the values of 0 or 1, showing the absence or the presence of a given characteristic.

The networks were produced using the software Neuro-Solutions®. In both cases MLPs of the type *N-H-1* were used, where *N* is the number of neurons in the input layer, *H* the number of neurons in the intermediate layer and the number "1" refers to the single neuron in the output layer. During the training phase, several architectures were tested for each case and only the one that led to the best overall result was selected. In the case of the three-variable model, the final architecture adopted had a 3-5-1 organization (Figure 3), where the entries were age, distance to sea (< 5 km or > 5 km) and exposure to pollutants (high or low). In the case of the five-variable model, the final architecture adopted had a 10-4-1 organization, where the inputs were age, distance from the sea, exposure to pollutants, type of finishing (smooth, rough or other) and façades' orientation (N/NE, S/SO, E/SE or O/NO).

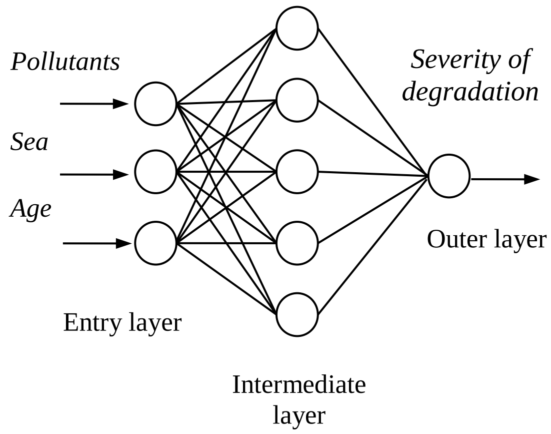

Figure 3 - MLP adopted on the ANN-based model with three variables

The construction of the models enabled the formulation of the mathematical equations to obtain the severity of degradation. The analysis of the models' predictive capacity was based on the statistical parameters mentioned in subchapter 6.1. Table 4 presents the values obtained for the proposed ANN-based models. The absence of abnormally high error values is a proof of the adequate predictive capacity evidenced by the proposed models. The high Pearson coefficient, in both cases, suggests the existence of a good adjustment of the models to the observed reality.

Table 4 - Error estimators of the proposed ANN-based models

Model	$\bar{\varepsilon}$	ϵ_{max}	$NMSE$	$PP_{\epsilon>5\%}$	$PP_{\epsilon>10\%}$	$PP_{\epsilon>20\%}$	$PP_{\epsilon>30\%}$	r
3 variables	8.69%	28.37%	43%	57%	38%	5%	0%	0.903
5 variables	11.69%	47.62%	52%	80%	46%	15%	9%	0.846

6.2.2. Application to service life prediction

The determination of the service life consists, once again, of obtaining the age after which each cladding reaches the maximum allowed degradation value (S_w = 30%). In each model, the application of this methodology led to the following average values: i) a three-variable model lead to an estimated service life of 21 years, with a standard deviation of 1.5 years; ii) a five-variable model led to an estimated service life of 22 years, with a standard deviation of 3.2 years.

For the first model, the possible combinations of variables led to the results shown in Figure 4, which are in accordance with the expected physical reality and are coincident with the conclusions obtained with the three-variable MLR model.

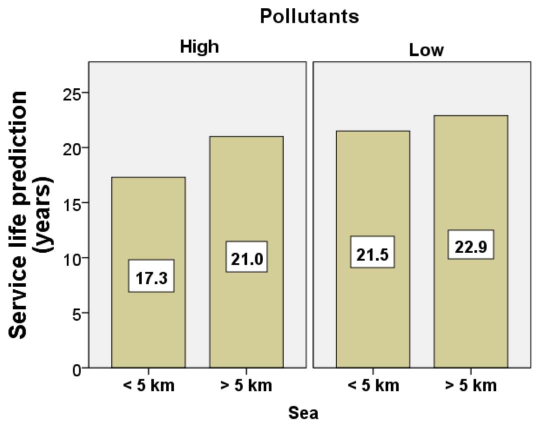

Figure 4 - Service life values provided by the ANN-based model with three variables

For the five-variable model, the analysis of these results reveals that: i) a greater proximity to the sea leads to lower values of service life; (ii) the same applies to the situation of high exposure to pollutants, whose effect on the value of the service life is equal; iii) the N/NE orientation leads to lower service life values in the majority of the combinations; iv) the E/SE and S/SO orientations lead to a longer service life in equal number of combinations. The type of finishing doesn't lead to credible results since the class related to the ceramic finishing doesn't have a statistically relevant sample. The estimated service life of ETICS, according to the ANNs' models, ranges between 6.1 years and to 26.9 years, which is also in agreement with the expected physical reality.

6.3. Fuzzy logic systems

Fuzzy logic belongs to the non-classical part of logic. This method arises from a line of thought that breaks with the principle of ambivalence, proposing that a proposition can be partially false and partially true [18]. In many situations, the explanation of reality according to this principle is more appropriate than according to the classical logic. Fuzzy logic has been applied successfully in the resolution of problems in various areas. In computational terms, fuzzy models are mathematical structures of several inputs and a single output and are known for their properties of universal approximators.

This study applies rule-based fuzzy systems, characterised by representing the relations between the variables through *if-then* relations. Of the various types of inference mechanisms associated with fuzzy models, the Takagi-Sugeno (TS) is one of the most popular. The main singularity of TS models lies in the relationship between the variables: the antecedent part is fuzzy, but the consequent part is crisp. This is the characteristic that allows its interpretation as a combination between linguistic modelling and a mathematical regression analysis [5]. A TS model is characterized by a number C of rules with the following structure:

Rule R_i: If x_1 is A_{i1} and … x_n is A_{in},
Then $y_i(x) = f_i(x)$, $i = 1, 2, \dots, C$.

The inputs of the model (explanatory variables) are defined by the vectors x_n, whose elements are associated with the fuzzy sets A_{in} through membership functions. The consequent functions $f_i(x)$ allow obtaining the outputs defined by the elements $y_i(x)$. Thus, a TS model is composed by a set of fuzzy rules that describe the local relations of input-output data. Another particularity of these models is related with the polynomial nature of the consequent function. In a first order TS model this function is linear and it is defined by Equation 7 [19].

$$f_i(x) = a_i x + b_i, i = 1, 2, \dots, C \tag{7}$$

In the TS model, the output is obtained through the consideration of the degree of activation of the model's rules, β_i. For each rule, this value is obtained based on the membership functions of the fuzzy sets, through Equation 8 [5]. The final output is achieved by considering the influence of the different rules, as shown in Equation 9.

$$\beta_i = \prod_{j=1}^{n} \mu_{A_{ij}}(x) \tag{8}$$

$$y(x) = \frac{\sum_{i=1}^{C} \beta_i \cdot y_i(x)}{\sum_{i=1}^{C} \beta_i}, i = 1, 2, \dots, C \tag{9}$$

6.3.1. Model construction

The variables included in the models were chosen from the results of the MLR analysis. As in the previous modelling techniques, two different fuzzy models were created. However, although the first model was based on the set of three variables, the second one was only based on four of the five variables identified by the regression analysis. In a first attempt, the use of five variables originated an unstable model, without physical meaning. The variable type of finishing presents three mutually exclusive classes, in which one of them does not present statistical relevance, which led to biased results. In this sense, this variable was removed, which increase the accuracy of the fuzzy logic model proposed.

After the definition of the rules in each fuzzy model, through the training sample, the proposed models were used to determine the severity of degradation of each case belonging to the test sample. The values of the severity of degradation were obtained from Equation 10. The degrees of activation β_i were determined through a toolbox for Matlab®.

$$S_w = \frac{\sum_{i=1}^{C} \beta_i \cdot y_i(x)}{\sum_{i=1}^{C} \beta_i},\, i = 1, 2, \ldots, C. \quad \textbf{(10)}$$

The models' predictive capacity was analysed through the statistical parameters of Equations 4, 5 and 6. Table 5 presents the values obtained for the proposed models. The absence of abnormally high error values is a proof of the adequate predictive capacity of the models. The high Pearson coefficient, in both cases, suggests the existence of a good correlation between the models and the observed reality.

Table 5 - Error estimators of the proposed fuzzy logic models

Model	$\bar{\varepsilon}$	ϵ_{max}	$NMSE$	$PP_{\epsilon>5\%}$	$PP_{\epsilon>10\%}$	$PP_{\epsilon>20\%}$	$PP_{\epsilon>30\%}$	r
3 variables	8.72%	32.37%	43%	68%	34%	6%	2%	0.902
4 variables	8.27%	57.14%	42%	57%	34%	8%	1%	0.894

6.3.2. Application to service life prediction

As in the previous methods, the service life is estimated based on the severity of degradation limit (S_w = 30%). In each model, the following values were obtained: i) for the three-variable model, an estimated service life of 21 years was obtained, with a standard deviation of 1.4 years; ii) for the four-variable model, an estimated service life of 22 years was obtained, with a standard deviation of 0.8 years.

For the first model, the possible combinations of variables led to the results shown in Figure 5. Through its analysis, an agreement with the expected physical reality is found, which coincides with the conclusions of the previous models of three variables. For the four-variable model, the analysis of a similar model allows concluding that: i) the different classes of distance from the sea lead to service life values with a few difference between them, nevertheless, ETICS closer to the sea reach first the end of their service life; (ii) the high exposure to pollutants leads to lower service life values; iii) the orientations N/NE and E/SE are the ones that led to the lowest and highest values of service life, respectively, although all the orientations have very similar values. According to the fuzzy logic models, the estimated service life of ETICS ranges between 20.3 years and 22.5 years, which is coherent with the other models and other studies related with the durability of this type of cladding.

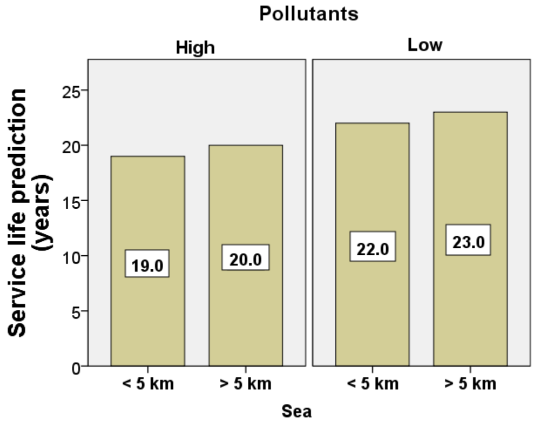

Figure 5 - Service life values provided by the fuzzy logic model with three variables

6.4. Comparative analysis of models

Through this chapter, three distinct approaches have been employed to model the degradation of the ETICS systems. All the techniques allowed the formulation of a mathematical equation that allows estimating the severity of degradation of ETICS, according to the characteristics of the claddings and its conditions of exposure.

The use of different techniques led to different models, with common characteristics. Although the modelling process allowed the same assumptions, in most situations, the samples used in the construction of the models were different. For this reason, the comparison between the proposed models should be done carefully.

The comparison of the service life values of the ETICS systems, provided by all models, is shown in Figure 6, which reveals a similarity among the values obtained. The results obtained allow drawing the following conclusions: i) in all the models based on the set of three explanatory variables, the average estimated service life was 21 years; ii) in computational models, based on sets of four or five variables, the average estimated service life was 22 years; iii) in the RML model with five variables, the average estimated service life was 21 years. These results show similarity to the service life of 20 years, estimated from the graphical method (degradation curve). Although, the existent bibliography about the ETICS systems suggest slightly higher values for its service life [12,13, 20]. This is due to the consideration of a regular maintenance on the claddings, which should promote the increasing of the claddings' expected service life. Kunzel et al. [21] refer a value of 20 years as a reference for the need for rehabilitation actions on façades with ETICS systems.

The estimation errors of the models of three or five variables, which were based in the same samples, allows indicating that the increase of complexity of the models with the inclusion of more explanatory variables does not translate into better results. Although the errors decrease, the difference is residual. Thus, the evidence suggests that the use of simpler models is more advantageous.

In terms of the influence of the explanatory variables on the degradation process, the distance from the sea and exposure to pollutants were identified as the most significant variables for the variation of the service life values obtained with the models. In fact, the distance from the sea conditions the degree of exposure of buildings to the sea breeze, which contains high moisture and dissolved salts. The condensation of water vapor and the crystallization of the salts (inside or outside the systems) promotes the presence of anomalies, which increases the degradation of the façades [9]. Regarding the exposure to pollutants, the presence of these substances in the atmosphere may induce their deposition on the surface of the claddings, depending on the concentration degree or on the roughness and porosity of the coatings. The pollutants may react chemically with the coating materials, causing their dissolution or the creation of new substances, which increases the ETICS' degradation condition [22].

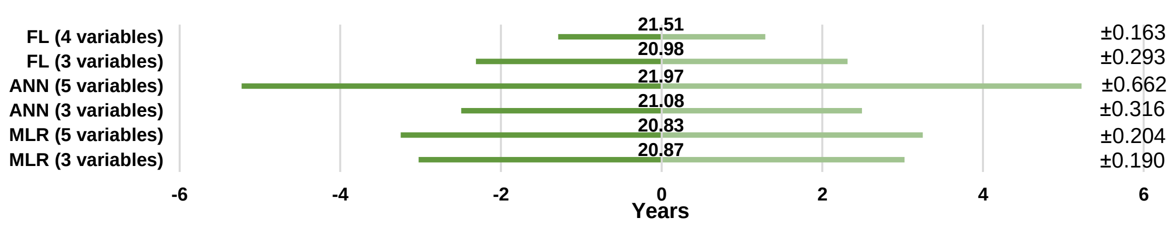

Figure 6 - Service life values predicted by each model and its 95% of confidence intervals, with the representation of the interval with a probability greater than 95% and 5% of being exceeded (with the data normally distributed)

7. Conclusions

Growing concerns with the impacts of the construction sector have led to the adoption of measures to promote sustainability, mainly at the environmental and economic levels. The evidences suggest that, in the near future, this trend will continue, and we will face an even more holistic and inclusive implementation of measures in this sector.

In this sense, the prediction of the service life of buildings and their elements assumes a high importance, which has been increasingly recognized by the stakeholders in the design and construction management processes. Service life prediction aids: i) the recognition of the factors that influence the degradation of materials; ii) the minimization of the consequences associated with these phenomena, by optimizing the maintenance actions to be performed; iii) the reduction of possible repair costs and environmental impacts. The practical application of service life prediction methods guarantees the design of buildings in a more sustainable way.

Despite the existence of studies with applicability in the prediction of the service life of buildings' elements, in most cases, the available information is based on empirical experience or on the behaviour of the materials when subjected to laboratory tests, under the action of controlled conditions [5]. The complexity of the degradation phenomenon (due to the specificity of each construction, in terms of its own characteristics and the interaction of the various factors of degradation that act on it, requires the development of new approaches, which can provide adequate responses even in the face of an environment of high variability and uncertainty.

However, more than merely provide a service life value for ETICS systems, this study intends to present the usefulness of different approaches in the service life prediction activities. Notwithstanding their conceptual complexity and the requirement of specific software and more processing time, the modelling techniques used in this study present advantages over other simpler approaches. Computational techniques are based on algorithms that are capable of learning directly from observations of a real phenomenon (even if subjected to any type of imprecision). Hence, they use the knowledge acquired for the formulation of complex nonlinear equations, that enable the effective modelling of the phenomenon. The degradation of the elements is an inevitable physical manifestation, which is associated with many uncertainties of several origins: i) lack of knowledge of all factors that cause degradation over time; ii) lack of full knowledge of the properties of the materials when affected by the previous degradation factors; iii) subjectivity associated with the maximum acceptable degradation limit that establishes the end of service life of the element under analysis [5]. Since the degradation is characterized by all these sources of uncertainty, the use of computational methods is very appropriated since allow transforming information with vague nature in numerical data.

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