STOCHASTIC, DETERMINISTIC, STATISTICAL AND ARTIFICIAL INTELLIGENCE BASED MODELS TO PREDICT THE SERVICE LIFE OF RENDERED FACADES

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ABSTRACT

Service life prediction has a primary role in today's context, allowing a more rational use of construction elements, reducing the costs associated with rehabilitation procedures. In the literature, the most common methods used to estimate the service life of buildings and its components can be classified as deterministic, probabilistic and engineering (a symbiosis of the previous two). In this study, the application of deterministic (graphical method), stochastic (logistic regression and Markov chains), statistic (multiple linear and non-linear regression techniques) and artificial intelligence based models (artificial neural networks) is proposed to predict the service life of rendered facades. Rendered facades are one of the most common types of claddings applied in Portugal. However, the predominance of this type of coating is related with the low investment applied in this solution, which often implies an unacceptable degradation of the building heritage. A comparative study is performed to analyse the applicability of each method proposed. This analysis relates the ease of application with the effectiveness of the proposed models. The results obtained through the different methods applied in this study are coherent from an empirical point of view. Furthermore, the results obtained are consistent with other studies performed in this field of knowledge.

**Keywords:** Service life prediction; deterministic; stochastic; statistic; artificial intelligence based models; rendered facades.

1 INTRODUCTION

The durability of constructions is essential to the quality of urban spaces. Presently, the degradation of buildings and their components has become a complex problem from the economic, cultural and environmental points of view. The increasing scarcity of funding for the maintenance and rehabilitation of infrastructures requires a more rational approach to decision-making, in terms of inspection, maintenance and rehabilitation (Paulo et al., 2013). For this, an efficient evaluation of the service life must be considered, taking into account the properties of materials, the environmental conditions of exposure, the workmanship, the service conditions and the maintenance planning (ISO 15686-1:2000).

Service life [SL] is generally estimated based on knowledge on the material and its deterioration state, using as indicators given measurable properties. According to various authors (Hovde, 2004), (Lacasse & Sjöström, 2004) there are three basic methods of service life prediction: the deterministic methods, the probabilistic methods and the engineering methods. The first are based on the study of the degradation factors that affect the elements under analysis, on
the understanding of the mechanisms involved, and on their quantification translated into degradation functions. Probabilistic methods, usually based on matrices or probabilistic calculus, define the likelihood of a change of the state of an element occurring with the objective of overcoming the uncertainty related to the degradation evolution and the unpredictability of the in-service conditions. Finally, engineering methods are often based on dose/response functions that model the performance of building materials for a given set of degradation agents.

2 METHODOLOGY

In order to compare the results obtained for the estimated service life of rendered facades through each of the three basic methods, a sample of 100 rendered facades was chosen. The sample analyzed is composed of 100 cases studies located in Lisbon, whose degradation state had been previously determined through in situ visual inspections. The results were obtained through the application of a numerical index that expresses the global degradation of the coatings analyzed. This index is obtained as the ratio between the extent of the façade degradation - weighted according to the degradation level and the severity of defects - and a reference area, equivalent to the maximum theoretical extent of the degradation for the facade in question (Gaspar and de Brito, 2011):

$$S_w = \frac{\sum(d_n \times k_n \times k_{a,n})}{A \times k}$$

where $S_w$ is the weighted severity of degradation of the facade (%); $A_n$ is the area of coating affected by a defect $n$; $k_n$ is the multiplying factor for defect $n$, as a function of its condition (between 0 and 4); $k_{a,n}$ is the weighting coefficient corresponding to the relative importance of each defect ($k_{a,n} \in \mathbb{R}^+$) (based on the cost of repair of defects); $k$ is the weighting factor equal to the highest degradation level in the façade (4, in the case of renderings); $A$ is the total area of the cladding. The degradation condition of rendered facades was thus characterized and classified according to a range of discrete levels from A (no visible degradation) to E (widespread deterioration, requiring an immediate corrective action), Table 1. These data - along with the building, environmental, use and maintenance characteristics - was then fed into each of the three methodologies and the results obtained were compared.

3 DETERMINISTIC MODELS

Deterministic models are usually straightforward mathematical operations or matrices, obtained through empirical evidence (ageing tests, real life assessment, laboratorial testing), easy to apply and to be understood by all actors in the building cluster. Not surprisingly, these methods are those which have produced the most practical results serving as the basis for the international standard for the durability of construction (ISO 15686:2000). However, most deterministic methods tend to regard SL as an absolute value, independent of the degradation processes (or the transitions from a degradation condition to the next one), therefore neglecting all the variability associated with them. In the present study, overall degradation of the facade was quantified using a graphical procedure in which a function was adjusted to the scatter of point samples of the sample (average degradation curve), whose abscissa measure the variable “age” and whose ordinates measure the variable “severity”. In theory, by establishing the degradation curves of a given construction element it is possible to predict the end of its service life, having
defined a maximum acceptable degradation level. In this study the average degradation curve for the 100 case studies was obtained through simple regression by adjusting a 2nd order polynomial line to the cloud of points obtained from the field work (Figure 1). This degradation path corresponds to the occurrence of physical and chemical phenomena whose action is felt slowly at first but whose degradation potential grows with time, i.e. the greater the degradation level the higher the probability it will increase, and at a faster pace (Shohet et al., 1999).

Table 1. Proposed classification of degradation condition of renderings

<table>
<thead>
<tr>
<th>Condition level</th>
<th>Example</th>
<th>Physical and visual assessment</th>
<th>Severity of degradation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level A</td>
<td><img src="image1.png" alt="Image" /></td>
<td>Complete mortar surface with no deterioration. Surface even and uniform. No visible cracking or cracking ≤ 0.1 mm. Uniform colour and no dirt. No detachment of elements.</td>
<td>&lt; 1%</td>
</tr>
<tr>
<td>Level B</td>
<td><img src="image2.png" alt="Image" /></td>
<td>Non-uniform mortar surface with likelihood of hollow localized areas determined by percussion, but no signs of detachment. Small cracking (0.25 mm to 1.0 mm) in localized areas. Changed in the general colour of the surface. Eventual presence of microorganisms.</td>
<td>1 to 5%</td>
</tr>
<tr>
<td>Level C</td>
<td><img src="image3.png" alt="Image" /></td>
<td>Localized detachments or perforations of the mortar. Hollow sound when tapped. Detachments only in the socle. Easily visible cracking (1.0 mm to 2.0 mm). Dark patches of damp and dirt, often with microorganisms and algae.</td>
<td>5 to 15%</td>
</tr>
<tr>
<td>Level D</td>
<td><img src="image4.png" alt="Image" /></td>
<td>Incomplete mortar surface due to detachments and falling of mortar patches. Wide or extensive cracking (≥ 2 mm). Very dark patches with probable presence of algae.</td>
<td>15 to 30%</td>
</tr>
<tr>
<td>Level E</td>
<td><img src="image5.png" alt="Image" /></td>
<td>Incomplete mortar surface due to detachments and falling of mortar patches. Wide or extensive cracking (≥ 2 mm). Very dark patches with probable presence of algae.</td>
<td>&gt; 30%</td>
</tr>
</tbody>
</table>

Figure 1: Development of rendered facades degradation over time (average degradation curve).

The analysis of the square of the Pearson product correlation coefficient ($R^2$) reveals that the regression curve has a relatively high value ($R^2 = 0.876$). In this case 87.6% of the variability of the degradation (dependent variable) is explained by the model, i.e. 89% of the variability of $y$ (degradation) is explained by $x$ (age of the painting) and 12.4% is due to other factors. Assuming that level D corresponds to the end of service life of rendered facades, it is possible to determine graphically their reference service life, through the intersection of the degradation curve with the horizontal line that represents the minimum performance level. The value obtained is 18 years.

4 STOCHASTIC MODELS

Due to the high dependence on time and the uncertainty associated with the performance of buildings, it is often necessary to use stochastic models to predict the SL of building components. Within these methods, Markov chains can be used to emulate the evolution of the degradation state of constructions, defining the probability of a future state based only on the present condition, independently of previous deterioration history (Neves et
al., 2006), modelling the probability of transitions between given states (Morcous and Lounis, 2005). For the sample studied, Figure 2 shows the mean longevity in each degradation state, Ti. The results show that transitions between condition states of facades occur faster in less deteriorated facades (changes from level A to level B occur in only 2.5 years). Renders remain for a longer period of time in higher degradation levels (condition C and D). The transition between levels associated with higher degradation states imply the presence of a larger number of defects and/or more hazardous defects, including simultaneous occurrence of defects and synergies between them.

Figure 2: Mean longevity in each degradation state (Markov chains).

Figure 3 illustrate the probabilistic distribution of the degradation condition over time. As expected, the probability of renders being in level A decreases rapidly in time, becoming lower than 2% at year 10. The probability of renders being in level B initially increases and reaches a peak at around year 3 (probability of 43.5%) and then steadily decreases as the probability of higher levels of degradation increases. Probability for levels C and D displays skewed distribution curves, with rapid increases and peaks at year 10 (P = 51.4%) and year 19 (P = 38.5%) for levels C and D respectively. Finally, the probability of level E steadily increases with age as expected, i.e. it is practically nil before year 9, and above 75% after year 38.

Figure 3: Probabilistic distribution of the degradation of renders according to the age (using Markov chains).

The mean relative error obtained for the estimated number of cases belonging to each degradation condition is relatively low: the mean relative error for all states is 7.55% and all results are lower than 16%. Taking into account all the variability associated with the degradation phenomena it is considered that the model is suitable and able to correctly classify the cases analysed. The overall sample reaches the maximum probability (38.5%) of belonging to level D (which marks the end of service life) at year 19. The probability of the renderings being in Level D or E (i.e. unacceptable) reaches 50% at year 14.

Logistic regression is another stochastic method that allows establishing an empirical relation between variables, thus producing a probabilistic analysis of the degradation condition of rendered façades, as a function of age. As expected, the probability of a render to belong to level A decreases over time and is practically nil at year 5. The younger coatings have a greater probability of belonging to the lower degradation condition classes. The probability of level B increases initially reaching a peak at around 5 years (probability of 43%) and then decreasing. As for level C the maximum probability (74.2%) is reached at year
10. For level D the peak is reached at around year 19 (probability of 78.3%). Finally, the probability of level E increases with age and after year 30 it is higher than 70%. After year 20 the probability of levels A, B and C of degradation is practically nil. The time intervals when the probability of belonging to a given level is similar to that of the next level are also the moments where the probability of transition from one level of degradation to the next is greatest. As time goes by, the probability of the rendered façades reaching the end of their SL increases. After year 17 the probability is higher than 50% and after year 21 it is higher than 90%. Therefore and unless there is some intervention, there is then an increasing probability that rendered façades are significantly degraded after reaching a certain stage of degradation.

5 STATISTIC MODELS

Regression analysis is one of the statistical techniques used most often to study the influence of a dependent variable, in comparison with other independent variables, which are responsible for the performance of the dependent variable. The main objective of this type of analysis is to explain a given reality and try to anticipate the role of a dependent variable as a function of the independent variables. Using this method, it was concluded that the severity of degradation depends on the age of the facades, the orientation of facades, on render type, the exposure to damp, the facade protection level and the level of protection in the balconies. In expression (2) is presented the mathematical equation which expresses the severity of degradation in function of the six explanatory variables. These six variables are able to explain 90.5% of the variability of the degradation and the remaining 9.5% can be explained by factors extrinsic to the analysis. The average estimated SL thus obtained is 15.7 years, with a standard deviation of 3.02 years.

\[
S_w = 0.013 \cdot A - 0.166 \cdot O - 0.088 \cdot B - 0.2 \cdot R - 0.109 \cdot D - 0.152 \cdot P + 0.757
\]  

where \(S_w\) is the weighted severity of degradation of the facade (%); A the age of the rendered facades; O the facades orientation; B the level of protection in the balconies; R the render type; D the exposure to damp; P the facade protection level.

Simple and multiple linear regressions are the most known and most commonly functions used in SL prediction. However, in most cases, the degradation phenomena, whether they are physical, chemical or biological, can be better represented by other functions. In this study various non-linear models to estimate the degradation of rendered facades were analysed. Table 2 shows the results obtained by the various functions used.

<table>
<thead>
<tr>
<th>Estimated service life</th>
<th>Polynomial model</th>
<th>Gompertz curve</th>
<th>von Bertalanffy curve</th>
<th>Richards curve</th>
<th>Weibull curve</th>
<th>Brody curve</th>
<th>Exponential model</th>
<th>Potential model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(R^2)</td>
<td>0.904</td>
<td>0.872</td>
<td>0.872</td>
<td>0.872</td>
<td>0.902</td>
<td>0.905</td>
<td>0.875</td>
<td>0.900</td>
</tr>
</tbody>
</table>

6 ARTIFICIAL INTELLIGENCE BASED MODELS

Artificial neural networks (ANNs) have been successfully used to solve complex problems in various application fields (Silva et al., 2013). The commonest type of ANN is the
multilayer perceptron (MLP). An MLP is a network with three or more layers of neurons: an input layer, one or more intermediate (hidden) layers and an output layer. In this study, MLPs were used to develop a model to estimate the degradation severity of rendered facades. In the model obtained, the degradation severity was a function of the render type, the exposure to damp, the facade protection level and the render age, as seen in expressions (3) and (4). Coefficients $h_0$ to $h_4$ and $c_{i0}$ and $c_{i1}$ are presented in Table 3.

\[
S_i = h_0 + \sum_{j=1}^{4} h_j \cdot H_i
\]

\[
H_i = \tanh \left( c_{i0} + \sum_{n=1}^{11} c_{in} \cdot V_n \right)
\]

Where $V_1$ represents the age of the render, $V_2$ marble agglomerate, $V_3$ monomass, $V_4$ cement and lime mortar, $V_5$ cementitious mortar, $V_6$ a favourable exposure, $V_7$ an unfavourable exposure, $V_8$ a normal exposure, $V_9$ a poor facade protection and $V_{10}$ a good facade protection and $V_{11}$ an average facade protection.

### Table 3. Coefficients for the ANN-based model

<table>
<thead>
<tr>
<th>$i$</th>
<th>$h_i$</th>
<th>$c_{i0}$</th>
<th>$c_{i1}$</th>
<th>$c_{i2}$</th>
<th>$c_{i3}$</th>
<th>$c_{i4}$</th>
<th>$c_{i5}$</th>
<th>$c_{i6}$</th>
<th>$c_{i7}$</th>
<th>$c_{i8}$</th>
<th>$c_{i9}$</th>
<th>$c_{i10}$</th>
<th>$c_{i11}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5.522E-1</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
</tr>
<tr>
<td>2</td>
<td>2.456E-1</td>
<td>-6.857</td>
<td>6.033E-2</td>
<td>2.119</td>
<td>1.695</td>
<td>2.129</td>
<td>-1.065</td>
<td>-1.183</td>
<td>1.730</td>
<td>1.219</td>
<td>6.100E-1</td>
<td>-4.122E-2</td>
<td>1.188</td>
</tr>
</tbody>
</table>

The average estimated SL obtained using ANN based methods is 17.5 years, with a standard deviation of 2.74 years.

### 7 RESULTS AND DISCUSSION

The deterministic model (graphical method) is a simple and expedient method. This method is easy to apply and gives information on the performance loss over time. However, it only provides an absolute value of the estimated service life of rendered facades.

Stochastic models consider the rate of transition between degradation states to predict the behaviour of the rendered facades and estimate the time after which they will be unable to meet the performance requirements for which they were designed. With this methods it is possible to: i) predict the probability of occurrence of each of various degradation conditions in each case study and define an equivalent probabilistic model; ii) evaluate the probability of transition from each condition level (i.e. degradation state) to the next one; and iii) translate the data collected in the field work into statistical distributions allowing probabilistic analyses of the degradation phenomena.

Statistic methods (multiple linear and non-linear regressions), albeit more complex, allow evaluating the influence of the different variables considered as factors for degradation severity, thus leading to a ‘wider scope’ analysis.

Through artificial neural networks based methods empirical knowledge can be acquired from a learning data set relative to a given problem. These methods are thus capable of learning and generalizing based on experience and examples, adapting to new situations, an
ability that is extremely important since it means that complex problems can be solved, which are difficult to solve either analytically or numerically. However, these methods are usually highly complex. In fact one does not intuitively grasp how a network functions; additionally, they use thousands of synaptic weights that are not subject to a logical/intuitive interpretation.

Besides the prediction ability of each method, the ease with which each one can be used was also assessed. Neural networks are the most complex, but lead to the lowest errors. Statistic methods are relatively simple and lead to good results. Deterministic models are the most simple but the less accurate. Stochastic models give a probabilistic analysis of the degradation phenomena and are relatively simple to apply.

The size of the sample is paramount when establishing SL prediction models. In fact the more complex the behaviour in terms of the reality one intends to model, the more data are needed. The main disadvantage of all the methods studied is that they react to data modification, so that their ability to generalize increases, in principle, with the size of available data. All the methods can be easily complemented with more data over time.

Finally, it is found that the results for the models proposed are logical from a physical point of view, and match reality found in the field work. Furthermore these results agree with those of studies performed by another authors. Shohet and Paciuk (2004) took two distinct levels of requisites: for the most stringent one the service life of rendered facades was estimated as 15 years (with a range between 12 and 19 years); for a lower level of requirement the service life rose to 23 years (with a range of 19-27 years). Figure 5 shows the results obtained using the various methods proposed. The mean estimated service life obtained is 18.5 years (with a range of 15.7-22 years); this value is indicated with a line in Figure 4. These values are coherent with the values in the literature. The graphic method, the simplest, gives an estimated service life of 18 years, relatively close to the mean value from the various methods. Therefore, it seems reasonable to accept that this method may be applied in current applications, as the planning of maintenance actions, leaving the more complex methods as a reference for more detailed investigations about the service life of rendered facades.

![Figure 4: Results obtained using the different methods proposed.](image)

8 CONCLUSIONS

This study intended to provide a comparison of distinct SL prediction models. The models proposed to estimate the service life of rendered facades are useful tools and are relatively simple that balance cost and speed, enabling its practical application to buildings. The study of service life prediction contributes to a more rational management of the maintenance of buildings. The models proposed can be employed in various scopes of service life prediction and maintenance of constructions and are therefore capable of providing indications relative to a
complex phenomenon such as cladding degradation, giving some information on the synergy between the degradation agents and the way they influence the degradation levels. Furthermore, the stochastic models make it possible to evaluate the probability of transition from one condition level (i.e. degradation state) to the next. The methodology tested in this study on rendered facades may be applied to other facade coatings or other construction elements.

All the models proposed were found to be valid and to adjust to the reality they are intended to model. However, their main disadvantage is that they react to data changes. In fact the quality of the models is directly related to the amount of data available. Future studies may lead to improvements of the accuracy of the models proposed, with the acquisition of new and more abundant data. Furthermore, as new data are added new variables may be included in the models if they are found to be better at explaining the degradation of this type of coating. A greater complexity of the service life prediction models does not always lead to better results. In most cases, highly complex models produce a decrease in the errors obtained between the predicted and the observed service lives of rendered facades. However, errors obtained by the most complex model (ANN) are relatively close to the errors obtained with more simple models (multiple regression analysis). Often it seems more reasonable to sacrifice the accuracy of the model in exchange for greater applicability and simplicity.

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REFERENCES