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ORIGINAL ARTICLE

Probabilistic analysis of degradation of façade claddings using Markov chain models

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Abstract In this study, the time-dependent stochastic degradation of three types of claddings is analysed. For this purpose, 203 façades with stone claddings (directly adhered to the substrate), 195 with adhered ceramic claddings and 220 with painted surfaces were analysed. All the façades are located in Lisbon, Portugal. Their degradation condition was assessed through an extensive field work. Based on the data gathered, Markov chains are used to predict the degradation of claddings and to understand, in some detail, how the characteristics of the claddings contribute to the overall degradation. The results show that the distance from the sea and exposure to damp are significant to the degradation of all types of cladding. The type and size of stone plates also influence the degradation of stone claddings. The exposure to wind-rain action has a high impact on the degradation of ceramic claddings. The models proposed provide useful information on the probability of failure of the claddings; these results are fundamental in the context of insurance policies and in the definition of building maintenance plans.

Keywords Degradation · Claddings · Markov chains · Stochastic analysis

1 Introduction

In the last decades, there has been a growing need for information on the durability and service life of building materials and components, an essential for life cycle assessment or costing analysis methodologies [1, 2]. This interest arises from two main factors [3]: (i) the increasing awareness of the concept of sustainability and concern about the environmental impact of the construction sector; (ii) the scarcity of resources that demands a commitment towards a more rational and balanced use of materials and energy. Since the management and maintenance of the built heritage is a significant part of the economy of societies, and since construction has such high environmental impact, the knowledge of the lifetime of materials needs to be carefully analysed.

There are various methodologies available for service life prediction and the best approach to the problem must be chosen, considering the advantages and limitations of each methodology. Shohet and Paciuk [4] list different approaches from the point of

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view of data gathering, which could be grouped in four categories: (i) experimental models; (ii) empirical models; (iii) analytical models; and (iv) statistical models. Experimental and empirical models are based on the observation and study of the deterioration of materials and components—either in laboratory conditions or through fieldwork assessment—a process that can be translated into degradation functions that express the loss of performance of buildings and their components over time until the end of service life is reached. Several authors [4, 7–9] have applied these methods to the service life of façade's coatings, as they are easy to apply and understand and can be rapidly implemented. However, they have also been criticized since they often deal with service life as an absolute value and provide little information on the degradation process, or about the change from a degradation state to the next one, neglecting the variability associated with the degradation process [5]. Analytical models are based on mathematical equations to predict and estimate the deterioration of building components that may be deduced from experimental observation [6, 7]. Statistical methods are based on the analysis of large datasets and can therefore provide some detailed information, including identifying the characteristics of the claddings more influential on the degradation process. A number of more or less complex statistical tools have been used in order to model the service life prediction of claddings, including multiple linear regression analysis [8] or artificial neural networks [9]. However, statistical models tend to be more complex than empirical and analytical methods and their application can be time consuming and not always achievable for stakeholders who are not familiarized with such methods or with the software needed to implement them.

With different combinations, the models described before can be grouped into three main families, referred to in the literature as deterministic, probabilistic and engineering methods [10]. Essentially, all service life prediction models try to forecast the future behaviour of construction elements and materials, providing an indication of the moment when interventions may be required. Deterministic models provide service life data by means of relatively simple, cause-effect sets of conditions or functions that can be straightforwardly applied in the early stages of design of constructions. In probabilistic methods, deterioration of buildings is regarded as a stochastic process, ruled by random variables [11]. According to Leira et al. [12], these models provide a better understanding of degradation process and should be used to complement the experience and knowledge of the behaviour of materials. Probabilistic methods are usually rather complex and require an extensive collection of data in order to ensure representative samples, which is not always possible due to time and cost constraints [13]. Engineering "design" methods blend the two previous methods; are as easily understood and implemented as deterministic methods, but describe the degradation processes using stochastic models [14].

According to Basso et al. [15], the degradation phenomena of materials and components can be described as the transition between condition states, characterized by different degradation levels. In reality, the actual and future degradation condition of buildings is associated with various degrees of uncertainty, due to the many durability factors that may affect a given material or element. To overcome this difficulty, a stochastic approach to service life prediction can be used [16]. Coles [16] refers that the basic ingredients of a statistical model are: the random variable (in this case, the degradation condition of wall claddings), whose outcome is uncertain; and the probability distribution, which allows associating probabilities to the events related to the random variable analysed. Markov chains are one of the most common methods applied to assess stochastically the future condition of the building components [17]. According to various authors [18] [19], when a process can be described by a set of distinct observations in which each observation has several possible outcomes (or states), it is necessary to decide whether the probabilities of the various outcomes depend on the immediately preceding outcomes, in which case a Markov chain is the appropriate model. Markov chains are able to simulate the evolution of the degradation state of buildings, defining the probability of the future performance of a building element based only on its current performance - i.e. condition state - ignoring its age, history of deterioration and maintenance, among other factors [20]. Unlike deterministic models, Markov chains model the degradation of construction elements as a probabilistic process, providing a period of time when the probability of failure is acceptably low and indicating the most probable instant for the loss of performance of the element under analysis.

In this study, Markov chains are applied to the prediction of degradation of three types of claddings: stone claddings (directly adhered to substrate); adhesive ceramic claddings; and painted surfaces. The method proposed in this study allows predicting the probabilistic condition of degradation over time and the understanding, in some detail, how the characteristics of the claddings and environmental factors contribute to the overall degradation of the façades. The methodology proposed provides reliable information concerning the risk of failure of the building's components, through probability distributions of estimated conditions over time for each cladding, which can be used in maintenance management methodologies.

2 Background

Markov models have often been applied as approximations of time-dependent processes. Markov chains are practically ubiquitous in stochastic modelling, for two main reasons [21]: i) many models are naturally Markovian, as the future states can be accurately estimated based only on present performance; ii) the simple structure of the Markov processes allows developing powerful mathematical techniques and computer algorithms that would be intractable by other methods.

Markov chains present various advantages [22]: (i) they are relatively simple to apply—and thus become a practical model to predict the future performance of building elements; (ii) they may use information on the degradation state of building components under real in-service conditions, encompassing the interaction of different degradation agents, the uncertainty and variability associated with the degradation mechanisms. Markov chains also have some limitations though [23, 24]: (i) the model assumes that the degradation condition of the building element can both stay the same or decay, not contemplating the rehabilitation actions that can be performed; (ii) the interaction between the degradation mechanisms and the deterioration of buildings components remains inaccurately treated; (iii) the history of deterioration is neglected, as prediction are performed based only on the last observed state.

Markov chains are based on a set of discrete states that characterize the performance of buildings and their elements. They can therefore be used to emulate the evolution of the degradation state of constructions, defining the probability of a future state. In recent decades, Markov chains have been successfully applied to various fields of civil engineering, including the deterioration of bridges [25]; Bocchini et al. [17], for example, use Markov chain models for life cycle analysis of bridges, including the effect of degradation and maintenance actions. Markov chains have also been used in the optimization of maintenance policies: Augenbroe and Park [26] argue that Markov chains are able to describe the randomness inherent of buildings performance and can be used in the decision process related with the systematic replacement of building components; Lacasse et al. [27] apply a maintenance system previously used in bridges to the maintenance of buildings façades. Markov chains have also been applied to service life prediction: Silva et al. [28] analysed the service life prediction of rendered façades based on their characteristics, using a methodology similar to the method proposed in this study.

Concerning the time of transition between states of deterioration, Markov chains can be divided in two common types: discrete and continuous. Discrete chains are useful when transitions can only occur at specific moments, whilst continuous chains are more appropriate when transitions can occur at any time, as is, in general, the case of deteriorating performance. The uncertainty in the rate of transitions between the states is defined by a transition probability matrix (denoted $\boldsymbol{P}$) for discrete-time processes and by an intensity matrix (denoted $\boldsymbol{Q}$) for continuous-time processes [29]. In this study, only the continuous-time models are analysed.

For deterioration processes, it is in general assumed that, for an infinitesimal time period, transitions can only occur between one state—or condition—and the next. It is also assumed that improvements cannot occur, and every observed improvement corresponds to an inspection error or undocumented maintenance action. Under these assumptions, a generic intensity matrix $\boldsymbol{Q}$ is shown [30] in Eq. (1).

$$Q = \begin{bmatrix} -q_{0,1} & q_{0,1} & 0 & \cdots & \cdots & 0 \\ 0 & -q_{1,2} & q_{1,2} & \cdots & \ddots & 0 \\ 0 & 0 & -q_{2,3} & q_{2,3} & \ddots & 0 \\ 0 & 0 & \cdots & \cdots & \ddots & 0 \\ 0 & 0 & \cdots & \cdots & -q_{n-1,n} & q_{n-1,n} \\ 0 & 0 & \cdots & \cdots & 0 & 0 \end{bmatrix} \tag{1}$$

The transition between states of degradation depends solely on the last recorded state and the transition rate between the current state and the future state (given by the matrix $\boldsymbol{Q}$). In this study, in order to define the intensity matrix $\boldsymbol{Q}$ the following data is needed: (i) the initial condition of claddings (assuming that in instant zero, the façade is in perfect condition); (ii) the current condition state (observed through field work and evaluated based on the criteria established in the next section); and (iii) the time required to transit from one condition to another. Based on the transition rates, the probability of transition between states of condition and the probability of duration in these states can be computed using the Chapman-Kolmogorov differential equation:

$$\frac{\mathrm{d}}{\mathrm{d}t}P(\Delta t) = \mathbf{Q} \cdot P(\Delta t) \tag{2}$$

The solution of this system of differential equations is given by [31]:

$$P(\Delta t) = \exp(\mathbf{Q} \cdot \Delta t) \tag{3}$$

Where the matrix exponential is defined by $\exp(\mathbf{Q} \cdot \Delta t) = \sum_{n=0}^{\infty} \frac{\Delta t^n \cdot \mathbf{Q}^n}{n!}$.

Thus, it is possible to relate the infinitesimal generator matrix $\boldsymbol{Q}$ with the Markovian transition matrix $\boldsymbol{P}$ [32].

The calibration of the deterioration model to the results of inspections can be carried out using approaches of different complexity. If regular inspection intervals are used, the transition matrix can be computed directly as:

$$P_{ij} = \frac{n_{ij}}{\sum_{k=1}^{m} n_{ik}}, \tag{4}$$

where n_{ij} is the number of observed transitions between condition i and j, m is the total number of condition states considered, and P_{ij} in the probability of transition between conditions condition i and j is the time interval between inspections.

If irregular inspection times are considered, the calibration must be carried out for the intensity matrix $\boldsymbol{Q}$. A consistent and accurate method to estimate this matrix is based on the minimization of the likelihood function.

Firstly, the observed results are organized in transitions, where a transition represents the time interval between two consecutive inspections (*initial* and *final*) and the resulting condition indices ($C_{initial}$ and C_{final}). An initial estimate of the $\boldsymbol{Q}$ matrix can be computed as [33]:

$$\theta_i = Q_{ij} = \frac{n_{ij}}{\sum \Delta t_i} \tag{5}$$

where n_{ij} is the number of transitions with $C_{initial} = i$ and $C_{final} = j$, and $\sum \Delta t_i$ is the sum of the time intervals associated with transitions associated with $C_{initial} = i$.

The optimization of the matrix $\boldsymbol{Q}$ is based on the concept of maximum likelihood given by Kalbfleisch and Lawless [33]:

$$L(\mathbf{Q}) = \prod_{k=1}^{n} \prod_{j=1}^{m} P_{ij}^{\Delta t} \tag{6}$$

where n is the number of inspected facades, m is the number of observed transitions for facade k (i.e. the number of inspections minus 1), and $P_{ij}^{\Delta t}$ is the predicted probability of transition between the observed initial condition C_i and the observed final condition C_j in the time interval between inspections computed using Eq. (3).

To increase the stability of the optimization algorithm, in this case the logarithm of the likelihood was maximized as [34]:

$$\boldsymbol{Find\theta} \overset{\text{maximize}}{\rightarrow} \log(L(\boldsymbol{Q})) = \sum_{k=1}^{n} \sum_{l=1}^{m} \log(P_{ij}^{\Delta t}) \tag{7}$$

A wide range of optimizations algorithms can be used to find the optimum values of θ. In the present case, the constrained optimization problem was solved with the active-set numerical algorithm [35, 36].

3 Degradation condition of façade claddings

The purpose of this study is to model the deterioration process of various façade claddings under service conditions. In this case, the estimation and optimization of the intensity matrix ($\boldsymbol{Q}$) is based only on the initial condition (assuming that at time zero, the elements are in perfect conditions) and current condition (based on fieldwork assessment of the façades), corresponding to the date of inspection.

There are various methods of assessing the degradation state of buildings and their components; usually these methods take into account the importance rating of the construction elements, the severity rating of the defects, and the definition of the condition parameters associated with the defects detected. Several authors have established classification systems for defects and degradation ratings in order to express the physical and functional degradation of the elements under analysis [37, 38]. In this study, the levels proposed vary from 0 (no visible degradation) to 4 (generalized degradation) and are associated with a qualitative scale (based on the evaluation of the physical and visual condition of the sample analysed) and a quantitative index that defines the global performance of the façades. This quantitative index, proposed by Gaspar and de Brito [39, 40], referred to as severity of degradation, is obtained as the ratio between the extent of the façade degradation, weighted as a function of the degradation level and the severity of the defects, and a reference area, equivalent to the maximum theoretical extent of the degradation for the façade in question (expression 8).

$$S_w = \frac{\Sigma\left(A_n \times k_n \times k_{a,n}\right)}{A \times k}, \tag{8}$$

where S_w is the weighted severity of degradation of the facade (%); A_n is the area of coating affected by an defect, in m^2; k_n is the defect's nth multiplying factor, 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 based on the cost of repair ($k_{a,n}$ Є R^+); k is the weighting factor equal to the highest degradation level in the facade; A is the total area of the cladding, in m^2. Since distinct defects detected in claddings have different levels of severity. The coefficient $k_{a,n}$ takes into account the relative importance of each defect, concerning their repair cost. The cost of repair is calculated as the ratio between the sum of the costs of each operation within the required intervention and the cost of replacing the cladding. If no further data are provided, it is assumed that $k_{a,n} = 1$.

In this study, three types of claddings are analysed based only on visual inspections: stone claddings (directly adhered to substrate)—203 samples; adhesive ceramic claddings (195 samples); and painted surfaces (220 samples):

- The defects in stone cladding have been divided into four groups [9, 41] —Table 1: (i) visual or surface degradation (defects that generally affect the appearance of the cladding); (ii) joint defects; (iii) loss of bond to the substrate; and (iv) loss of integrity. In this study, no claddings belong to the most unfavourable condition of degradation (condition E).
- For adhesive ceramic claddings, four defect groups are considered [42, 43] —Table 2: (i) visual defects; (ii) cracking; (iii) defects in joints; and (iv) detachment.
- In painted surfaces, the degradation scales are mainly qualitative and are defined based on Portuguese standards [44–48]. Four main families of defects affecting paint coatings are considered [49] —Table 3: (i) staining and colour change; (ii) chalking; (iii) cracking; and (iv) loss of adherence.

Having defined the scale of degradation of façades (Tables 1, 2, 3), it is possible to establish a degradation model using Markov chains. Equations (9)–(11) show the intensity matrix obtained for the model applied to stone claddings, ceramic tiling systems and painted surfaces, respectively.

$$Q_{(\text{stone claddings})} = \begin{bmatrix} q_{\mathrm{A,B}} \\ q_{\mathrm{B,C}} \\ q_{\mathrm{C,D}} \end{bmatrix} = \begin{bmatrix} 0.2210 \\ 0.0190 \\ 0.0115 \end{bmatrix} \tag{9}$$

$$Q_{(\text{ceramic claddings})} = \begin{bmatrix} q_{A,B} \\ q_{\mathrm{B,C}} \\ q_{\mathrm{C,D}} \\ q_{\mathrm{D,E}} \end{bmatrix} = \begin{bmatrix} 0.1519 \\ 0.0403 \\ 0.0252 \\ 0.0100 \end{bmatrix} \tag{10}$$

$$Q_{(\text{painted surfaces})} = \begin{bmatrix} q_{A,B} \\ q_{B,C} \\ q_{C,D} \\ q_{D,\mathrm{E}} \end{bmatrix} = \begin{bmatrix} 0.4868 \\ 0.1962 \\ 0.1524 \\ 0.1062 \end{bmatrix} \tag{11}$$

The procedure employed does not take into account the statistical uncertainty resulting from the limited sample size. This limitation can be overcome by defining confidence intervals for the maximum likelihood estimates, q, using the delta method of the profile likelihood method [16]. An alternative approach, specifically for Markov chain models, was developed by Fuh [19] using the bootstrap method.

After the estimation of the intensity matrix ($\boldsymbol{Q}$), the mean time of duration in each degradation state can be determined [Eq. (12)].

$$T_i = \frac{1}{q_{ij}} \tag{12}$$

Table 1 Proposed degradation conditions for natural stone claddings

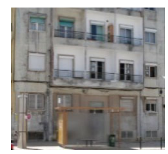
Degradation condition	Defects		% of cladding area affected	Illustration of the degradation conditions
Condition A: ($S_w \leq 1$ %)	No visible degradation		–	
Condition B: Good ($1\ \% < S_w \leq 8$ %)	Visual or surface degradation defects	Surface dirt	>10	
		Moisture stains	≤15	
		Localized stains		
		Colour change		
		Flatness deficiencies	≤10	
	Loss-of-integrity defects	Material degradation[a] ≤ 1 % plate thickness	–	
		Material degradation[a] ≤ 10 % plate thickness	≤20	
		Cracking width ≤ 1 mm		
Condition C: Slight degradation ($8\ \% < S_w \leq 20$ %)	Visual or surface degradation defects	Moisture stains	>15	
		Localized stains		
		Colour change		
		Moss, lichen, algae growth	≤30	
		Parasitic vegetation		
		Efflorescence		
		Flatness deficiencies	>10 and ≤50	
	Joint defects	Joint material degradation	≤30	
		Material loss—open joint	≤10	
	Bond-to-substrate defects	Scaling of stone near the edges	≤20	
		Partial loss of stone material		
	Loss-of-integrity defects	Material degradation[a] ≤10 % plate thickness	>20	
		Material degradation[a] >10 % and ≤30 % plate thickness	≤20	
		Cracking width ≤1 mm	>20	
		Cracking width >1 mm and ≤5 mm	≤20	
		Fracture	≤5	
Condition D: Moderate degradation ($20\ \% < S_w \leq 45$ %)	Visual or surface degradation defects	Moss, lichen algae growth	>30	
		Parasitic vegetation		
		Efflorescence		
		Flatness deficiencies	>50	
	Joint defects	Joint material degradation	>30	
		Material loss—open joint	>10	
	Bond-to-substrate defects	Scaling of stone near the edges	>20	
		Partial loss of stone material		
		Loss of adherence	≤10	
	Loss-of-integrity defects	Material degradation[a] >10 % e ≤30 % plate thickness	>20	

Table 1 continued

Degradation condition	Defects		% of cladding area affected	Illustration of the degradation conditions
		Material degradation[a] >30 % plate thickness	≤20	
		Cracking width >1 mm and ≤5 mm	>20	
		Cracking width ≥5 mm	≤20	
		Fracture	>5 and ≤10	
Condition E: Generalized degradation ($S_w \geq 45$ %)	Bond-to-substrate defects	Loss of adherence	> 10	–
	Loss-of-integrity defects	Material degradation[a] >30 % plate thickness	>20	
		Cracking width >5 mm		
		Fracture	>10	

[a] Material degradation is meant to be every anomaly that involves loss of volume of the stone material

In order to evaluate the accuracy of Markov chains in predicting the deterioration process of façades, the number of expected and observed façades in each condition state is shown in Table 4. The similarity between the values predicted by the model and those observed in the visual inspections shows that an acceptable fit was achieved. The results corresponding to the observed condition states represent a concatenation of the results presented in the "Appendix" section. The expected number of claddings is each state was computed as:

$$E(C_j) = \sum_{k=1}^{n} P_{ij}^{k}, \tag{13}$$

where n is the number of transitions observed, P_{ij}^{k} is the probability of transition between the initial condition i and the final state j for the time interval between inspection for transition k, and i is the initial condition in transition k.

4 Probabilistic analysis of degradation condition of façade claddings

Table 5 shows the average time in each degradation state for the claddings analysed. The results show that the evolution is faster in the less advanced conditions, as only slight alterations to the surface of the claddings will cause a change from condition A to B. As age increases, claddings tend to remain longer in their respective conditions.

Tables 6, 7 and 8 show the probabilistic distribution of the degradation condition of each cladding over time.

The probability of stone claddings belonging to condition A decreases over time, to less than 2 % after year 8 (Table 6). The probability of belonging to condition B increases initially to a peak (79.2 %) at year 12 and then slowly declines. As for condition C, the maximum probability (46.1 %) is reached between years 71 and 73. Finally, the probability of stone claddings belonging to condition D increases over time and reaches 60 % after year 145. At years 3 to 4 there is nearly the same probability for stone claddings belong to either condition A or B. Around years 49 to 50 the probability of being in condition B is similar to that of being in condition C. Between years 103 and 104 the probability of belonging to condition C is similar to that of condition D.

The same trend is observed for ceramic claddings (Table 7). In fact, there is practically the same probability of belonging to either condition A or B at years 4 to 5; of belonging to either condition B or C, at years 28 to 29; and to either condition C or D, after years 58 to 59. Finally, at year 134 the probability of condition D is practically the same as that of condition

Table 2 Proposed degradation conditions for adhesive ceramic claddings

Condition condition	Defects		% of cladding area affected	Illustration of the degradation conditions
Condition A: ($S_w \leq 1$ %)	No visible degradation		–	
Condition B: Good (1 % < $S_w \leq 6$ %)	Visual or surface degradation defects	Surface dirt	–	
		Small surface craters	≤10	
		Wear or scratches		
		Crushing or scaling of the borders		
		Change of shine and/or colour		
		Damp stains		
	Cracking	Cracked glazing[a]	–	
		Markedly orientated cracking (<0.2 mm)[1] without leakage[a]		
	Joint deterioration	Staining or change in colour	–	
Condition C: Slight deterioration (6 % < $S_w \leq 20$ %)	Visual or surface degradation defects	Small superficial craters	>10 and ≤50	
		Wear or scratches		
		Crushing or scaling of the borders		
		Change of shine and/or colour		
		Damp stains		
		Biological growth	≤30	
		Graffiti		
		Efflorescence		
	Cracking	Cracking with no predominant direction[a]	≤30	
		Markedly orientated cracking (> 0.2 mm)[2] without leakage[a]		
	Joint deterioration	Without loss of filling material[a]	≤30	
		With loss of filling material[a]	≤10	
	Detachment	Loss of adherence	≤20	
		Swelling		
Condition D: Moderate degradation (20 % < $S_w \leq 50$ %)	Visual or surface degradation defects	Small superficial craters	>50	
		Wear or scratches		
		Crushing or scaling of the borders		
		Change of shine and/or colour		
		Damp stains		
		Biological growth	>30	

Table 2 continued

Condition condition	Defects		% of cladding area affected	Illustration of the degradation conditions
		Graffiti		
		Efflorescence		
	Cracking	Cracking with no predominant direction[a]	>30 and ≤ 50	
		Markedly orientated cracking (> 1 mm)[3] without leakage[a]		
	Joint deterioration	Without loss of filling material[a]	>30 and ≤ 50	
		With loss of filling material[a]	>10 and ≤ 30	
	Detachment	Loss of adherence	>20	
		Swelling		
		Localized detachment	≤ 10	
Condition E: Generalized degradation ($S_w \geq 50$ %)	Cracking	Cracking with no predominant direction[a]	>50	
		Markedly orientated cracking (>5 mm)[4]		
	Joint deterioration	Without loss of filling material	>50	
		With loss of filling material	>30	
	Detachment	Generalized detachment	>10	

E (around 45 %). These milestones mark the threshold of transitions between states. For painted surfaces (Table 8) transitions from condition A to condition E occur at years 1 to 2; at years 6 to 7; at years 12 to 13 and at years 16 to 17.

4.1 Probabilistic analysis of the degradation of claddings according to their characteristics

Claddings display significant differences in terms of deterioration due to the great variety of their characteristics. In this study, the most relevant characteristics that explain the degradation of claddings are identified and Markov chain models are used to analyse the probability of belonging to each degradation condition over time according to the claddings' characteristics.

Table 9 presents the probability of belonging to a condition level as a function of the variables considered for stone claddings. The results obtained led to the following conclusions (valid for the sample analysed):

(i) Granite claddings have a very high probability ($P = 94.4$ %) of belonging to the more favourable conditions of degradation (A and B), and very low probability of belonging to condition D; marble claddings are those with lower probability of belonging to the most favourable conditions and greater probability of being in the most unfavourable degradation condition (E); these results confirm the study by Schouenborg et al. [50], who tested the mechanical resistance of the samples from 200 case studies and concluded that granite claddings are the most durable, followed by limestone claddings and marble claddings (the least durable);

(ii) Stone claddings with large plates have a maximum probability of transition between conditions B and C after years 39 to 40 and a maximum probability of transition between conditions C and D after years 73 to 74. For claddings with medium-sized plates the maximum probability of transition between conditions occurs later: after years 64 to 65 (for transition between B and C) after years 121 to 122 (for transition between C and D). Thus claddings with medium-size plates have higher probability of belonging to more favourable conditions and a low probability of belonging to condition E; this suggests that

Table 3 Proposed degradation conditions for painted surfaces

Condition condition	Defects		Description	Illustration of the degradation conditions
Condition A: ($S_w \leq 1$ %)	No visible degradation		–	
Condition B: Good ($1 \% < S_w \leq 10 \%$)	Visual or surface degradation defects	Slight or little perceptible changes		
		Uniform surface dirt; Change in colour or brightness	Slight or little perceptible changes	
	Chalking	Clearly perceptible		
	Cracking	Small number of cracks		
Condition C: Slight deterioration ($10 \% < S_w \leq 20 \%$)	Visual or surface degradation defects	Moderate or quite perceptible changes	Quite perceptible uniform surface dirt and change in colour	
		Uniform surface dirt; Change in colour or brightness		
		Localized surface dirt; Humidity stains; Efflorescence	Light humidity stains	
	Cracking	Moderate width or number of cracks		
	Peeling and blistering	Blistering	Small amount and size up to 3 cm	
Condition D: Moderate degradation ($20 \% < S_w \leq 40 \%$)	Visual or surface degradation defects	Moderate or quite perceptible changes	Quite perceptible humidity stains	
		Humidity stains; Efflorescence; Biological growth; Localized surface dirt	Quite perceptible biological growth	
			Quite perceptible localized surface dirt	
			Quite perceptible efflorescence	
		High or very perceptible changes	Very perceptible uniform surface dirt and change in colour	
		Uniform surface dirt; Change in colour or brightness	Very perceptible localized surface dirt	
			Very perceptible change in colour (discolouration)	
	Chalking	Quite perceptible		
	Cracking	Considerable number of cracks		
	Peeling and blistering	Blistering	Small amount and size between 3 and 5 cm	
			Moderate amount and smaller than 3 cm	
		Peeling	Small amount (area affected up to 1 %) e size up to 3 cm	

Table 3 continued

Condition condition	Defects		Description	Illustration of the degradation conditions
Condition E: Generalized degradation ($S_w \geq 40$ %)	Visual or surface degradation defects	High or very perceptible changes	Very perceptible biological growth	
		Biological growth		
	Chalking	Very perceptible		
	Cracking	High number or density of cracks		
	Peeling and blistering	Blistering	Larger than 5 cm, regardless of the amount	
			Dense pattern regardless of the size	
			Moderate amount e and dimension between 3 and 5 cm	
		Peeling	Dense and moderate pattern (affected area more than 1 %) regardless of the size	
			Small amount, but larger than 5 cm	

larger plates reach the end of their service life sooner, especially when compared with medium-size plates; which can be explained by the lower relative area of the joints in the larger plates and consequent higher concentration of stresses [8].

(iii) Claddings highly exposed to damp remain less time without degradation (condition A) and are more likely to belong to the highest degradation condition (P = 14.3 %) when compared to coatings less exposed to damp ($P = 9.2$ %). Likewise maximum probability of belonging to conditions B and C are of $P = 83.3$ % (at year 8) and of $P = 38.7$ % (year 51), for claddings highly exposed to damp, and of $P = 72.7$ % (year 17) and of $P = 48.4$ % (after year 80) for less exposed cases, respectively.

(iv) Claddings located more than 5 km away from the sea are more prone to belonging to degradation conditions A and B ($P = 68.6$ % as opposed to 51.9 % for coatings located less than 5 km away); claddings in coastal areas have a higher probability of belonging to the more unfavourable condition of degradation ($P = 26$ %, substantially higher than those away from the coast, with 2.5 %).

Table 10 shows the probability of belonging to a degradation condition as a function of the variables considered for ceramic claddings. For the sample analysed the following conclusions can be drawn:

(i) Claddings less exposed to damp are more prone to remain in lower degradation conditions (A and B), with $P = 54.9$ %; none of the façades less exposed to damp belong to the most unfavourable condition (condition E); on the contrary, claddings highly exposed to damp are more prone to belong to the most unfavourable conditions, and have a relatively small probability of belonging to conditions A and B ($P = 28.5$ %);

(ii) Claddings located in coastal areas have higher probability ($P = 67,7$ %) of reaching higher degradation levels (conditions C, D and E); on the contrary, claddings located more than 5 km away from the sea have a probability of 71.4 % of belonging to conditions A and B;

Table 4 Classification capability of the model obtained for façade coatings

Condition	Natural stone claddings		Ceramic claddings		Painted surfaces	
	Observed	Estimated	Observed	Estimated	Observed	Estimated
A	9	12	15	16	37	33
B	114	105	70	65	73	75
C	57	64	64	67	48	59
D	23	22	43	39	29	35
E	–	–	3	8	20	18

Table 5 Mean time of duration in each degradation condition

Cladding system	Condition A (years)	Condition B (years)	Condition C (years)	Condition D (years)
Natural stone claddings	4.5	52.6	87.0	–
Ceramic claddings	6.6	24.8	39.7	100.0
Painted surfaces	2.1	5.1	6.6	9.4

Table 6 Probability of belonging to a condition as a function of the age for stone claddings

Range in years	Probability of belonging to a condition level			
	Condition A (%)	Condition B (%)	Condition C (%)	Condition D (%)
[0:10]	41.81	53.94	4.11	0.14
[10:20]	3.95	77.34	17.32	1.40
[20:30]	0.43	67.08	28.42	4.07
[30:40]	0.05	55.84	36.29	7.83
[40:50]	0.00	46.23	41.42	12.34
[50:60]	0.00	38.25	44.44	17.31
[60:70]	0.00	31.65	45.82	22.53
[70:80]	0.00	26.18	45.98	27.84
[80:90]	0.00	21.66	45.23	33.11
[90:100]	0.00	17.92	43.83	38.25
[100:110]	0.00	14.82	41.97	43.21
[110:120]	0.00	12.27	39.81	47.93
[120:130]	0.00	10.15	37.47	52.39
[130:140]	0.00	8.39	35.04	56.57
[140:150]	0.00	6.94	32.58	60.47

(iii) Claddings with severe exposure to the combined action of wind and rain are the most prone to undergo higher degradation ($P = 37.8$ % of belonging to conditions D and E) and the lowest probability of belonging to the most favourable conditions.

Similar conclusions can be drawn for painted surfaces (valid for the sample analysed). When considering their distance from the sea, the results show that painted surfaces in coastal areas (less than 5 km away) transit between conditions C and D after years 10 to 11, earlier than claddings farther from the coast, whose transition occurs after years 14 to 15. Regarding their exposure to damp, claddings less exposed change between conditions C and D after years 13 to 14; claddings highly exposed transit earlier, after years 11 to 12. Claddings with current exposure to pollutants are more prone to belong to the most favourable degradation conditions ($P = 56.9$ %); conversely, claddings unfavourably

Table 7 Probability of belonging to a condition as a function of the age for ceramic claddings

Range in years	Probability of belonging to a condition level				
	Condition A (%)	Condition B (%)	Condition C (%)	Condition D (%)	Condition E (%)
[0:10]	52.38	40.89	6.27	0.45	0.01
[10:20]	10.42	59.19	25.76	4.41	0.22
[20:30]	2.28	45.94	38.82	11.94	1.02
[30:40]	0.50	32.10	43.87	20.88	2.65
[40:50]	0.11	21.76	43.49	29.47	5.18
[50:60]	0.02	14.61	40.13	36.73	8.50
[60:70]	0.01	9.78	35.43	42.32	12.47
[70:80]	0.00	6.54	30.3	46.18	16.91
[80:90]	0.00	4.37	25.5	48.48	21.65
[90:100]	0.00	2.92	21.08	49.44	26.56
[100:110]	0.00	1.95	17.23	49.31	31.51
[110:120]	0.00	1.30	13.9	48.35	36.39
[120:130]	0.00	0.87	11.22	46.75	41.15
[130:140]	0.00	0.58	8.97	44.72	45.73
[140:150]	0.00	0.39	7.14	42.38	50.09

Table 8 Probability of belonging to a condition as a function of the age for painted surfaces

Range in years	Probability of belonging to a condition level				
	Condition A (%)	Condition B (%)	Condition C (%)	Condition D (%)	Condition E (%)
[0:5]	40.91	39.90	15.26	3.47	0.47
[5:10]	2.55	31.95	37.43	21.05	7.02
[10:15]	0.22	13.21	31.42	33.22	21.93
[15:20]	0.0	5.06	20.17	34.45	40.30
[20:25]	0.00	1.91	11.50	29.21	57.37
[25:30]	0.00	0.72	6.16	22.12	71.01
[30:35]	0.00	0.27	3.17	15.59	80.97
[35:40]	0.00	0.10	1.59	10.48	87.83
[40:45]	0.00	0.04	0.79	6.82	92.36
[45:50]	0.00	0.01	0.38	4.33	95.28

exposed to pollutants only display a relatively low probability of belonging to conditions A and B ($P = 10.4$ %). These results reveal that coatings subject to unfavourable environmental conditions tend to reach higher degradation conditions faster.

5 Results and discussion

The three types of cladding analysed present different degrees of sensitivity to the characteristics analysed. Besides the age, which is the most influential parameter in the explanation of claddings' degradation, the most influential parameter in the degradation of all the claddings analysed is the distance from the sea. This fact confirms the results from several studies that show that salt-induced deterioration of building materials is drastically accelerated in coastal areas, thus reducing the durability and service life of façades [51]. The second most influential parameter is the exposure to damp; this parameter is highly relevant in the claddings' degradation due to the occurrence of

Table 9 Probability of belonging to a condition as a function of the variables considered relevant for natural stone claddings

Variables	Probability of belonging to a condition level			
	Condition A (%)	Condition B (%)	Condition C (%)	Condition D (%)
Type of stone				
Limestone	4.2	45.8	38.9	11.1
Granite	5.6	88.9	5.6	0
Marble	3.9	42.9	33.8	19.5
Size of stone plates				
Large	1.4	40.5	33.8	24.3
Medium	6.2	65.1	24.8	3.9
Exposure to damp				
High	6.0	60.7	19.0	14.3
Low	3.4	52.9	34.5	9.2
Distance from the sea				
Less than 5	7.8	44.2	22.1	26.0
>5 km	2.5	66.1	28.9	2.5

Table 10 Probability of belonging to a condition as a function of the variables considered relevant for ceramic claddings

Variables	Probability of belonging to a condition level				
	Condition A (%)	Condition B (%)	Condition C (%)	Condition D (%)	Condition E (%)
Exposure to damp					
High	7.1	21.4	38.1	29.8	3.6
Low	8.1	46.8	28.8	16.2	0.0
Distance from the sea					
Less than 5 km	5.8	26.6	36.0	29.5	2.2
>5 km	12.5	58.9	25.0	3.6	0.0
Wind-rain action					
Low	2.2	42.2	35.6	20.0	0.0
Moderate	10.3	42.3	29.9	17.5	0.0
Severe	7.5	18.9	35.8	32.1	5.7

wetting and drying cycles and the weathering induced by crystallization of soluble salts. In stone claddings, the third most important parameter is the dimension of the stone plates, followed by the type of stone. These results are coherent with the suggestions present in other studies addressing other service life prediction techniques. Different studies performed by Silva et al. [8, 52, 53], using multiple linear regression, logistic regression and artificial neural networks, respectively, reveal that age, distance from the sea and the size of stone plates are extremely relevant variables to describe the degradation condition of stone claddings. Chai et al. [54] and Dias et al. [55] applied multiple regression analysis and artificial neural networks to the service life prediction of painted surfaces, revealing that the distance from the sea is one of the most influential parameters in the degradation of painted surfaces.

The probabilistic distribution of degradation conditions over time can be seen as an assessment of risk of loss of performance due to degradation. Thus, by establishing a threshold of acceptable risk, a stakeholder may estimate the need for repair based on the probabilistic analysis of a set of data. To illustrate this concept, one can consider that “high”, “average” and “low” probabilities of a given condition correspond to “high”, “average” and “low” risks associated to the consequences of the defects and the cost of repair and thus produce an indication of the urgency to maintenance and repair actions [28]. Low risk (no actions required apart from monitoring) may correspond to $P > 75$ % of belonging to either condition levels “A” or “B”. High risk (need to extensive repair) may correspond to $P > 25$ % of belonging to condition levels “D” (for stone or ceramic claddings, more durable) and “E” (for painted surfaces, with lower service lives) and average risk may correspond to the intermediate states. The interpretation of the results, which depends on the assumptions made previously, leads to the following recommendations:

(i) For stone claddings: (i) monitor until year 20; (ii) perform light maintenance actions before year 70; (iii) consider their replacement after year 70, subject to on-site confirmation of their condition state.
(ii) For ceramic claddings: (i) monitor until year 13; (ii) light maintenance actions should be performed before year 40; (iii) full replacement should be considered after 40 years subject to on-site confirmation.
(iii) For painted surfaces: (i) monitor every 3 years; (ii) light maintenance actions should be performed before year 13; (iii) repainting should be considered after year 13 subject to on-site confirmation.

In spite of the fact that these recommendations can vary according to the social and economic context of the buildings analysed, the probabilistic results obtained using Markov chains can be used to define adequate maintenance policies, avoiding the unnecessary costs associated with unrequired maintenance or excessive costs due to urgent unforeseen maintenance actions. Probabilistic models associated to service life prediction of wall claddings are extremely useful to the cost optimization of maintenance actions during buildings life cycle [56–58]. An accurate optimization of maintenance actions requires a balanced consideration of both the claddings performance and the total cost accrued over the entire life-cycle [59, 60].

These recommendations are directly related to the estimated service life of the wall claddings analysed. The full replacement of the cladding should be considered when the end of their service life is reached. According to the studies performed by Silva et al. [8, 9, 52, 53], the estimated service life of stone claddings (directly adhered to the substrate) varies between 68 (simple regression analysis) [9] and 80 years (artificial neural networks) [53]. The study performed by Shohet and Paciuk [4], using an empirical method based on a simple regression analysis, results on an average estimated service life of 64 years (with a range between 59 and 70 years) for stone claddings subjected to normal conditions. For ceramic claddings, the study performed by Bordalo et al. [42] and Galbusera et al. [43] results on an average estimated service life of 50 years. Chai et al. [49, 54] and Dias et al. [55] obtained an estimated service life for painted surfaces of 9.75 years, 8.5 years and 9.5 years for simple regression analysis, multiple regression analysis and artificial neural networks, respectively. The values obtained in this study, using a Markov chain model are thus within the results obtained previously using different service life prediction techniques.

6 Conclusion

In this study, the future performance of three façade claddings (stone claddings, ceramic claddings and painted surfaces) is analysed using Markov chain based models. Markov chains are a stochastic model widely used to model the durability of construction and their elements, requiring limited information for calibration. The models proposed in this study are able to provide indications concerning a complex matter such as the degradation of the façades, giving information on the synergy between degradation agents (as is the case of environmental exposure conditions) and degradation conditions. Furthermore, this study provides indications on the probabilistic distribution of the degradation conditions over time (and according to the most relevant characteristics of each of the claddings), as well as expert-based knowledge of the mean time of duration in each condition of degradation until the transition to the following condition, revealing the effects of degradation on the durability of claddings.

Markov chains also allow estimating the probability of each case study to reach the end of its service life according to the features analysed. As for stone claddings, granites are the most durable and marbles are the less durable material. Stone claddings with large plates are more prone to degradation, reaching the end of their service life after 53–54 years. On the other hand, stone claddings with medium-size plates are more susceptible of belonging to most favourable conditions (A and B), reaching the end of their service life at years 86 to 88 (latter than claddings with large plates).

Concerning the environmental actions, the exposure to damp is a relevant parameter for all the claddings analysed. Claddings with high exposure to damp are the ones with the highest probability of belonging to the most unfavourable degradation conditions, reaching the end of their service life sooner. The distance from the sea is one of the most influential parameter in the degradation of claddings. Claddings in coastal areas are more prone to belong to higher degradation levels; on the other hand, claddings located more than 5 km from the sea reach the end of their service lives later than claddings in coastal areas. Considering the other characteristics analysed, it is possible to conclude that: (i) ceramic claddings reach the end of their service life after year 45 for less exposed façades to wind-rain action and at year 32 for claddings severely exposed; (ii) concerning painted surfaces, the end of their service lives is reached at year 8 for façades with current exposure to pollutants and at same age for painted surfaces with unfavourable exposure to pollutants.

The information from this study is useful to enable the definition (in a rational and technically-informed way) of a set of maintenance strategies throughout the life cycle of the building. Moreover, when such information is available for various building components, it is possible to define joint maintenance strategies for different parts of the building. Stochastic models, such as Markov chains, provide crucial information within the context of insurance policies, since they allow assessing the risk of failure of the coatings in order to evaluate the most probable delay time to failure of building elements according to their specific characteristics.

In future studies, the model proposed can be applied to other cladding systems, in other contexts and countries, with the necessary adjustments. Furthermore, other environmental agents can be analysed (e.g. freeze–thaw cycles in cold countries) and a more comprehensive sample can be acquired in future developments.

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Appendix

Age (years)	Sw (%)	Degradation condition	Type of stone	Dimension of stone plates	Exposure to damp	Distance from the sea (km)
39	2.42	B	Granite	Large	High	<5
39	2.83	B	Granite	Large	Low	<5
60	7.64	B	limestone	Medium	Low	<5
16	0.86	A	Granite	Medium	Low	<5
16	0.85	A	Granite	Medium	Low	<5
60	8.98	C	Limestone	Large	Low	<5
50	2.66	B	Marble	Medium	High	<5
50	4.59	B	Limestone	Medium	High	<5
64	13.06	C	Limestone	Medium	Low	<5
62	17.82	C	Limestone	Medium	Low	<5
64	15.13	C	Limestone	Medium	Low	<5
63	20.63	D	Limestone	Large	Low	<5
64	14.99	C	Limestone	Medium	High	<5
42	3.42	B	Marble	Medium	Low	>5
42	6.73	B	Marble	Medium	Low	>5
63	37.42	D	Limestone	Large	High	<5

Age (years)	Sw (%)	Degradation condition	Type of stone	Dimension of stone plates	Exposure to damp	Distance from the sea (km)
63	30.27	D	Limestone	Large	High	<5
42	6.11	B	Marble	Large	Low	>5
62	11.12	C	Limestone	Medium	Low	<5
44	8.60	C	Marble	Medium	High	>5
56	5.17	B	Limestone	Medium	Low	>5
46	10.22	C	Limestone	Medium	High	>5
70	30.18	D	Marble	Large	High	<5
23	1.23	B	Granite	Large	Low	<5
65	30.39	D	Marble	Large	Low	<5
37	10.71	C	Marble	Medium	Low	<5
37	9.98	C	Marble	Medium	High	<5
69	14.06	C	Limestone	Large	Low	>5
21	2.46	B	Granite	Medium	Low	>5
69	19.14	C	Limestone	Large	Low	>5
22	3.23	B	Granite	Medium	High	>5
69	17.22	C	Limestone	Large	Low	>5
21	3.70	B	Granite	Large	Low	>5
69	18.26	C	Limestone	Large	Low	>5
45	5.39	B	Limestone	Medium	High	>5
45	4.87	B	Limestone	Large	High	>5
22	1.94	B	Granite	Medium	Low	>5
69	15.00	C	Limestone	Large	Low	>5
22	3.01	B	Granite	Medium	Low	>5
13	3.55	B	Marble	Large	High	>5
13	4.55	B	Marble	Large	High	>5
26	8.33	C	Limestone	Medium	High	>5
26	2.08	B	Marble	Medium	Low	>5
21	2.79	B	Granite	Medium	Low	>5
14	3.83	B	Granite	Medium	Low	>5
48	7.77	B	Limestone	Medium	High	>5
48	9.99	C	Limestone	Large	Low	>5
19	2.17	B	Limestone	Medium	High	>5
14	1.67	B	Granite	Medium	Low	>5
49	11.97	C	Limestone	Medium	Low	>5
49	10.15	C	Limestone	Medium	High	>5
19	3.28	B	Limestone	Medium	High	>5
14	4.55	B	Granite	Medium	Low	>5
14	1.41	B	Granite	Medium	Low	>5
45	13.12	C	Marble	Medium	High	>5
45	7.51	B	Limestone	Medium	High	>5
64	14.10	C	Limestone	Medium	High	<5
17	4.10	B	Limestone	Medium	High	>5
17	1.69	B	Limestone	Medium	High	>5
47	9.32	C	Limestone	Large	High	>5
47	8.70	C	Limestone	Large	High	>5

Age (years)	Sw (%)	Degradation condition	Type of stone	Dimension of stone plates	Exposure to damp	Distance from the sea (km)
64	16.60	C	Limestone	Large	High	<5
69	10.73	C	Limestone	Medium	Low	>5
37	2.86	B	Limestone	Medium	High	>5
65	14.22	C	Limestone	Large	High	<5
65	11.48	C	Limestone	Medium	Low	<5
69	17.83	C	Limestone	Large	Low	>5
69	16.70	C	Limestone	Large	Low	>5
60	12.11	C	Limestone	Medium	Low	<5
27	2.08	B	Marble	Medium	Low	>5
61	11.92	C	Marble	Large	Low	<5
59	22.18	D	Marble	Large	High	<5
81	27.63	D	Marble	Large	Low	<5
81	26.62	D	Limestone	Large	Low	<5
89	42.91	D	Marble	Large	Low	<5
58	15.88	C	Marble	Large	Low	<5
75	26.18	D	Marble	Medium	Low	<5
79	25.29	D	Limestone	Medium	Low	<5
63	21.30	D	Marble	Large	High	<5
61	24.60	D	Limestone	Large	High	<5
61	23.14	D	Limestone	Large	High	<5
23	1.88	B	Marble	Medium	High	>5
23	3.46	B	Marble	Medium	High	>5
23	1.82	B	Marble	Medium	High	>5
22	3.18	B	Marble	Medium	High	>5
22	4.71	B	Marble	Medium	High	>5
26	3.93	B	Marble	Medium	Low	>5
26	5.32	B	Marble	Medium	Low	>5
25	3.82	B	Marble	Medium	Low	>5
27	8.43	C	Marble	Medium	Low	>5
24	3.35	B	Marble	Medium	High	>5
24	3.57	B	Marble	Medium	High	>5
15	6.76	B	Granite	Large	Low	>5
15	4.52	B	Granite	Large	Low	>5
12	1.93	B	Granite	Large	Low	>5
12	0.39	A	Granite	Large	Low	>5
15	4.50	B	Granite	Medium	Low	>5
40	3.00	B	Granite	Large	Low	<5
73	27.79	D	Marble	Medium	Low	<5
73	19.09	C	Marble	Medium	Low	<5
40	7.15	B	Granite	Medium	Low	<5
21	4.09	B	Granite	Medium	Low	>5
21	1.57	B	Granite	Large	Low	>5
23	3.43	B	Granite	Large	Low	>5
23	1.46	B	Granite	Large	Low	>5
15	1.30	B	Granite	Medium	Low	>5

Age (years)	Sw (%)	Degradation condition	Type of stone	Dimension of stone plates	Exposure to damp	Distance from the sea (km)
15	2.81	B	Granite	Medium	Low	>5
38	7.98	B	Granite	Large	Low	>5
38	3.18	B	Granite	Large	Low	>5
38	1.45	B	Granite	Large	Low	>5
12	2.32	B	Granite	Medium	Low	>5
14	3.13	B	Granite	Large	Low	>5
61	21.97	D	Marble	Medium	Low	<5
61	18.23	C	Marble	Medium	Low	<5
68	23.88	D	Marble	Large	High	<5
68	20.58	D	Marble	Large	High	<5
70	24.36	D	Marble	Large	High	<5
59	22.23	D	Marble	Large	High	<5
82	40.18	D	Marble	Large	Low	>5
5	0.14	A	Marble	Medium	High	<5
5	0.40	A	Marble	Medium	High	<5
5	0.07	A	Marble	Medium	High	<5
15	5.61	B	Granite	Large	Low	>5
40	3.18	B	Granite	Medium	Low	>5
9	1.29	B	Limestone	Medium	High	<5
9	2.71	B	Limestone	Medium	High	<5
7	2.05	B	Limestone	Large	High	<5
48	5.27	B	Granite	Medium	Low	>5
7	2.84	B	Limestone	Large	High	<5
51	2.21	B	Granite	Large	Low	>5
51	10.42	C	Granite	Large	Low	>5
43	5.29	B	Marble	Medium	Low	>5
39	2.29	B	Granite	Large	Low	>5
42	9.77	C	Marble	Large	Low	>5
4	2.14	B	Limestone	Medium	High	<5
50	4.30	B	Marble	Medium	Low	>5
50	2.09	B	Marble	Medium	Low	>5
48	10.08	C	Marble	Medium	Low	>5
31	1.54	B	Granite	Medium	Low	>5
35	8.12	C	Marble	Medium	Low	>5
5	2.04	B	Marble	Medium	High	<5
5	1.84	B	Marble	Medium	High	<5
5	1.50	B	Marble	Medium	High	<5
48	5.16	B	Marble	Medium	Low	>5
47	8.93	C	Limestone	Large	Low	>5
5	0.96	A	Limestone	Medium	High	<5
48	12.93	C	Marble	Large	Low	>5
46	12.16	C	Marble	Medium	Low	>5
46	5.43	B	Limestone	Medium	Low	>5
7	1.23	B	Granite	Medium	High	<5
7	1.36	B	Granite	Medium	High	<5

Age (years)	Sw (%)	Degradation condition	Type of stone	Dimension of stone plates	Exposure to damp	Distance from the sea (km)
48	6.46	B	Limestone	Medium	Low	>5
1	0.05	A	Limestone	Medium	Low	>5
2	1.77	B	Limestone	Medium	High	>5
2	1.29	B	Limestone	Medium	High	>5
54	7.29	B	Marble	Medium	Low	>5
53	12.25	C	Marble	Medium	Low	>5
53	10.39	C	Marble	Medium	Low	>5
53	6.16	B	Marble	Medium	Low	>5
2	1.61	B	Limestone	Medium	High	>5
2	0.86	A	Limestone	Medium	High	>5
54	8.14	C	Marble	Medium	Low	>5
53	11.25	C	Marble	Medium	Low	>5
53	6.50	B	Marble	Medium	Low	>5
56	14.98	C	Marble	Medium	High	>5
42	5.27	B	Marble	Large	Low	>5
42	2.82	B	Marble	Large	Low	>5
53	7.48	B	Limestone	Large	Low	>5
56	21.41	D	Marble	Large	High	>5
53	4.02	B	Limestone	Medium	Low	>5
56	15.36	C	Marble	Large	High	>5
56	14.22	C	Marble	Large	High	>5
53	8.80	C	Marble	Medium	Low	>5
53	11.73	C	Marble	Large	High	>5
5	1.39	B	Granite	Medium	High	<5
5	1.79	B	Granite	Medium	High	< 5
53	4.87	B	Limestone	Medium	Low	>5
53	4.71	B	Marble	Large	Low	>5
6	1.74	B	Limestone	Medium	High	<5
6	1.93	B	Limestone	Medium	High	<5
6	1.93	B	Limestone	Medium	High	<5
53	10.82	C	Marble	Large	Low	>5
37	3.79	B	Granite	Medium	Low	>5
7	2.97	B	Limestone	Medium	High	<5
53	15.96	C	Marble	Large	Low	>5
44	5.87	B	Granite	Large	Low	>5
7	2.20	B	Limestone	Medium	High	<5
7	2.14	B	Limestone	Medium	High	<5
7	1.25	B	Limestone	Medium	High	<5
53	14.84	C	Marble	Large	Low	>5
54	17.32	C	Limestone	Medium	Low	>5
6	3.26	B	Marble	Medium	High	<5
6	1.73	B	Marble	Medium	High	< 5
38	10.07	C	Granite	Medium	low	>5
9	1.66	B	Granite	Medium	High	<5
38	11.68	C	Granite	Medium	Low	>5

Age (years)	Sw (%)	Degradation condition	Type of stone	Dimension of stone plates	Exposure to damp	Distance from the sea (km)
4	1.71	B	Limestone	Medium	High	<5
31	5.28	B	Granite	Medium	Low	>5
69	20.41	D	Limestone	Medium	Low	>5
45	1.07	B	GRANITE	Large	Low	>5
9	1.50	B	Granite	Medium	High	<5
9	2.25	B	Granite	Medium	High	<5
9	2.68	B	Granite	Medium	High	<5

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