Fuzzy Modeling of the Functional Service Life of Architectural Heritage Buildings

A. J. Prieto[1]; J. M. Macías-Bernal[2]; María-José Chávez[3]; and F. J. Alejandre[4]

Abstract: This paper addresses maintenance planning in heritage buildings. Currently, social, economic, and environmental factors raise concerns about the durability and service life of buildings. This study on the service life of historical buildings in terms of functionality presents a complex analysis that has yet to be developed in great depth. In this sense, a new expert system based on fuzzy logic for the prognosis of the functional service life of buildings is established. The system developed intends to manage vulnerabilities and risk variables that affect a building's performance. These parameters are involved in the building management and maintenance process and indicate durability in terms of serviceability as an output model parameter. The aim of this paper is to describe a new application of a fuzzy inference system based on expert knowledge. This approach discusses the serviceability of architectural heritage buildings using a Mamdani fuzzy model. In this methodology, the vulnerability and risk condition of nine theoretical case studies and five real buildings located in southern Spain are analyzed. In this case study, the application model is shown in a set of a five heritage buildings situated in southern Europe (Andalusia, Spain), which were only analyzed through in situ visual inspections. This system is able to give priorities relating to preventive conservation activities in homogeneous groups of heritage buildings. The approach gives useful information based on a functional criterion regarding the current state of the buildings. The fuzzy model aims to be an indicator for the future evolution of a building's functionality. **DOI: 10.1061/(ASCE)CF.1943-5509.0001021.**

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Introduction

In ISO 15686-4 (ISO 2014), the service life of a building is defined as the "period of time from its construction until the building, or any of its parts, ceases to be adequate for the use it was intended for." Periodic inspections of buildings are carried out to assess and identify the performance deficiencies in architectural constructions, thus avoiding possible damage and future costly interventions. If maintenance actions are not carried out or are incorrectly planned, this will generate a loss of performance of the constructions over time (Hallberg 2009). Notwithstanding this, the definition of these requirements is quite subjective and depends on technical, economic, and social issues (Marteinsson 2005).

In an empirical study, Aikivuori (1999) stated that maintenance actions are influenced by a subjective perception of the decision makers, and that they rarely depend on technical or economic factors. In this sense, it was shown that decision makers define maintenance actions based on a building's deterioration in only 17% of cases. Therefore, the degradation of buildings in terms of their functional maintenance can be understood as a subjective question solved through different parameters that contain a certain degree of uncertainty (Sadegui et al. 2015). Consequently, the preservation of architectural assets requires the development of methods, strategies, and planning for building preservation (Vicente et al. 2015).

One way of optimizing the planning of a building's maintenance actions is to understand the way its elements degrade and the stage beyond which intervention is necessary (Talon et al. 2005). Maintenance activities must be seen as an investment opportunity that needs to be optimized and not as a cost that must be minimized. Academics have recognized this and many maintenance optimization models have been published over the years (Okasha and Frangopol 2009; Ilgin and Tunalu 2007; Liu and Frangopol 2005). Most of these models focus on one optimization criterion or objective, making multiobjective optimization models an underexplored area in maintenance optimization. Moreover, currently there is a lack of academic models and applications in practice to optimize maintenance strategies (Van Horenbeek et al. 2010).

Maintenance must be regarded as a series of measures to prevent both material and functional degradation. According to the definition given earlier, functional service life can be used to establish a building's obsolescence (Thomsen and Van der Flier 2011). Usually, the minimization of a building's degradation is related to an increase in its serviceability. These processes have inherent characteristics that are difficult to predict. A methodology to evaluate the serviceability of architectural heritage using fuzzy systems is proposed to manage these uncertainties.

The aim of this paper is to develop a fuzzy inference system (FIS) to estimate functional service life for architectural heritage. A theoretical and practical application of the model is performed, for which the serviceability index is determined through in situ visual inspections. The system provides a ranking of critical interventions in buildings with homogeneous construction features. This

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tool can help public and private administration, as well as other kinds of companies, in the development of preventive maintenance for heritage buildings.

Background

There is growing evidence that heritage building conservation confers benefits in many urban environments. Responsible decision makers, institutions, and authorities involved in urban development programs have recognized the urgent need to preserve cultural resources and assets, and moreover, to relate cultural values to development. In the construction area, it has been estimated that 50% of all building refurbishments in European cities relate in some way to heritage preservation (European Commission 2000).

Long et al. (2001) justified service-life studies due to the fact that buildings currently account for a high proportion of the national wealth of developed countries. The costs of maintenance, estimated to be between 15 and 40% of construction costs, along with the trend towards automation, have forced managers to pay more attention to maintenance. The management of preservation costs has become a very important instrument in the strategic planning of buildings since these costs can be reasonably controlled. The purpose of maintenance management is to reduce the adverse effects of damage, maximizing construction availability at minimum cost (Löfsten 2000). The criteria to look after heritage buildings are defined as a set of maintenance actions and policies and the general support-structure decisions in which they are planned and supported (Pintelon and Van Puyvelde 2006).

Preventive maintenance (PM) is defined as all actions performed at defined intervals to retain an item in a serviceable condition by systematic inspection, detection, replacement of items that have worn out, adjustment, calibration, and cleaning (Gonzales-Vega et al. 2016). In this way, optimization models can help to determine effective and efficient maintenance schedules and plans in complexes of architectural heritage buildings.

The degradation of constructions and the loss of serviceability performance are complex problems that depend on many factors and strongly affect the constructed assets (Ortiz et al. 2014). Moreover, degradation agents and their possible effects on building materials depend on numerous agents and their combinations; there are also possible synergistic effects on the deterioration processes. Several studies have been developed using external claddings as an essential role in the performance of buildings (Shohet and Paciuk 2006; Silva et al. 2015). These elements work as the building's skin, providing comfort and controlling the influence of the external degradation agents on the quality of life of users and owners. In these situations, it is sometimes hard to define what must be carefully analyzed since this depends mostly on the acceptance criteria of the building's owners (Chai et al. 2015).

The modeling of the deterioration process for components and systems is a very important input for maintenance optimization models. Fuzzy models can be successfully applied in this area. Therefore, this study intends to develop a new fuzzy model that can be easily applied by stakeholders. These methodologies are able to deal with the uncertainty associated with the performance loss of buildings.

Macías-Bernal et al. (2014) proposed the evaluation of the functional service life based on a fuzzy expert system. Several studies that address the application of the fuzzy theory presented by Zadeh (1965) to solve problems related with civil and construction engineering have been developed (Vieira et al. 2015; Jamshidi et al. 2013; Alcalá et al. 2005)

The main advantage of fuzzy modeling is its ability to deal with uncertain and vague data. The model proposed in this study, designated as fuzzy building service life (FBSL), was initially designed to preserve and manage architectural heritage property in the Archdiocese of Seville in southern Spain. This model has been recently improved through the study of a main reference standard in the risk management area, namely international standard ISO 31000 (ISO 2009; Prieto et al. 2015). The fuzzy model has been established in compliance with the specifications provided for in the standard. Prieto et al. (2016) established a correlation between the FBSL model and quantitative criteria associated with physical service life and degradation of building elements (S_w). The deterioration of 203 natural stone claddings located in Portugal was analyzed to carry out this analysis. A strong relationship between the two indices taken into account was obtained (with a determination coefficient of 0.756), revealing an inverse correlation between the two indices.

This model is able to manage the risks and vulnerabilities affecting architectural heritage complexes under the specifications of the aforementioned standard. This fuzzy model can be used to prioritize the management of a building's functionality in homogeneous construction sets, contributing to preventive maintenance in the scientific and professional areas.

Fuzzy Model for Predicting Functional Service Life

In many engineering and architectural problems, stakeholders are faced with a lack of or too little information or incomplete data to model real-world phenomena, such that vagueness and uncertainty are inseparable aspects of knowledge. Fuzzy logic, introduced by Zadeh (1965), is a powerful tool to be able to approach these kinds of uncertain situations.

One of the most important advantages of fuzzy modeling is that it combines numerical accuracy with transparency in the form of linguistic rules (Babuška 1998). Hence, fuzzy models take an intermediate place between numerical and symbolic models. This technique uses linguistic terms to generate an inference system, modeling complex and sophisticated structures (Zeng et al. 2007). These models present the following main gains: (1) ability to tolerate accurate and inaccurate data, (2) ability to model naturally systems that other models find vague and difficult to describe, (3) ability to be developed using the expertise of professionals, and (4) ability for input information to be based on human observations (Silva et al. 2016).

Fuzzy systems assume that while Boolean logic sees reality in terms of zero or one, not taking into account any other possibilities in the range, fuzzy logic theory is able to deal with subjective concepts and the uncertainty associated with reality. Fuzzy modeling using real measures of system variables is a tool that tolerates a control of nonlinear systems when there is no prior knowledge of the structure and dynamics system or when this is only partially known (Vieira et al. 2005).

A fuzzy set is a generalization of a conventional set where the degree of membership of its elements has values in the closed interval [0, 1], where 1 refers to the maximum membership value and 0 refers to the minimum membership value (no membership); while crisp sets only allow the values 0 or 1. In this way, the resulting fuzzy model obtained usually has better performance and accuracy than classical linear models.

The fuzzy sets theory was used to describe a FIS to estimate a serviceability index for the buildings analyzed. Performance of the model proposed is implemented in open-access software *Xfuzzy*. This software is an open environment using the common specification language XFL3. The last version of this software is called

Xfuzzy 3.0, and has been programmed in Java, so it can be run on any platform using Java-Runtime-Environment (JRE). The tool has also been renovated to include new algorithms to generate graphical outputs to monitor inference processes in two and three dimensions (2D and 3D). The tool includes a wide set of supervised learning algorithms and is able to adjust to hierarchical fuzzy systems. Moreover, fuzzy functions can be freely and easily defined by users, like membership or connective functions, defuzzification methods, and of course linguistic rules.

The following documents were reviewed to establish these parameters in the model: Spanish Technical Building Code (CTE 2007), National Cathedral Plan, Heritage Conservation Network (Palacio et al. 2002), Law on Construction Planning (2007), UNE 41805 IN (UNE 2009), ISO 15686-1 (ISO 2011). A total of 15 experts in heritage building management were consulted during the model's design stage. A Delphi methodology, using the *Opina* software owned by the University of Seville was used to obtain all of the experts' survey. For this purpose, the experts consulted had the following profiles (Macías-Bernal et al. 2014; Prieto et al. 2016): a businessman in a construction company; a director of an accredited laboratory for building materials; a restoration artist; an architect; a technical architect and an archaeologist, all with recognized professional experience of more than 20 years; an expert in quality management of buildings, with numerous publications on this subject, the director of an insurance company at international level; the person in charge of the preservation of a Port Authority; the director of a World Heritage preservation building; two professors of rehabilitation and pathology; two firefighter company officers, from Madrid and Seville, respectively; and the head of building maintenance in a provincial capital town with 700,000 inhabitants.

The model will enable building users, owners, and public administrations, as well as companies to use this open-access software to manage a building's condition. The system is able to emulate human reasoning to study relations between vulnerability factors and risk factors of buildings through a fuzzy sets theory. Moreover, this system can increase with the users' inputs and could be upgraded in a continuous improvement cycle.

Fuzzification

The fuzzification process comprises of the transformation of the crisp values into grades of membership for linguistic terms of fuzzy sets. Input vector may be translated into linguistic terms, such as Very Good, Good, Regular, Bad, or Very Bad. The membership function (MF), which has different types of linear and nonlinear shapes, is used to associate a grade to each linguistic term. The type of the MF depends on the modeled problem and experts' knowledge and backgrounds (Silva et al. 2016).

These applications assign a degree of membership to each element in the discourse universe U on which the fuzzy set in question is defined. The membership function $\mu_A(u)$ of Fuzzy Set A can take any value in the range [0, 1] [Eq. (1)]

$$\mu_A(u){:}\mathrm{U} \rightarrow I[0,1] \tag{1}$$

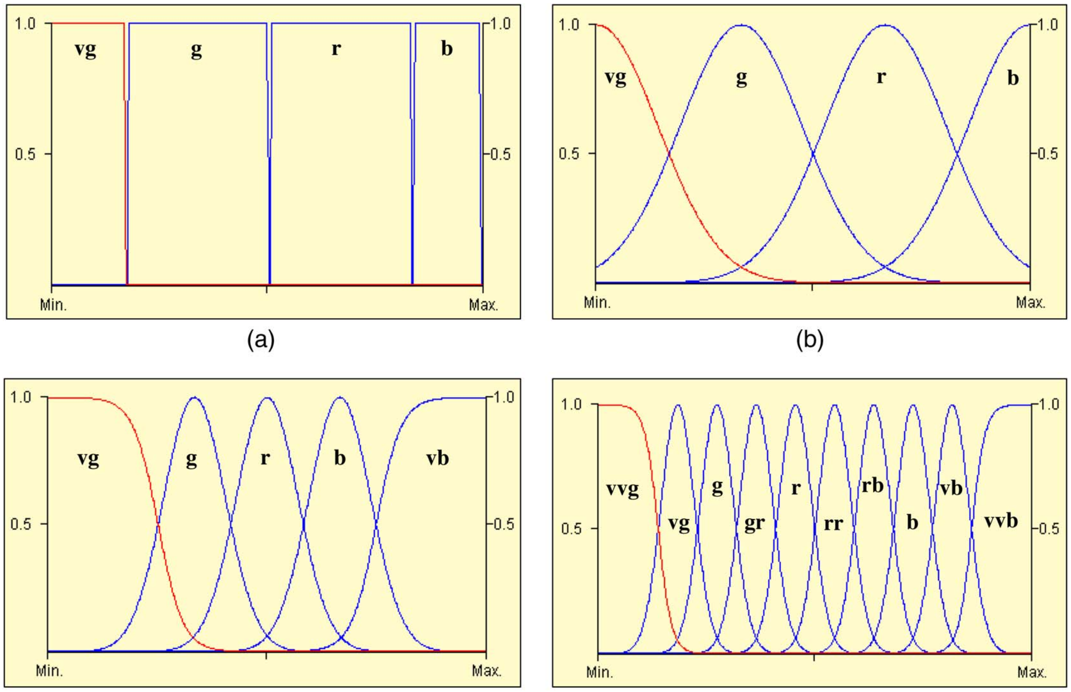
The FBSL model is supported by 17 inputs (5 vulnerabilities and 12 risks) (Table 1) and the output variable of the fuzzy model (building's serviceability) is established and defined.

The variables of the model are fuzzified through the Gaussian and trapezoidal membership functions shown in Fig. 1. Gaussian-type membership functions are generally used, as they are considered the most appropriate for modeling the degradation conditions of the buildings and also because a non-zero value can be reached at all points (Ross 2010). This happens in all membership functions of the fuzzy inference model, except in the membership function of the input variable v_1 (geological location), this membership function is trapezoidal (it establishes four types of terrain).

Each one of the membership functions for the input, intermediate and output variables of the model (Fig. 1) have a linguistic label associated to them, from the minimum values—Very, Very Good (VVG), or Very Good (VG), which indicate very low vulnerability or risk, to Bad (B), Very Bad (VB), or Very, Very Bad (VVB), which indicates a very high vulnerability or risk.

Table 1. Definition of the Input Variables of the Fuzzy Model

Vulnerability and risks	IDs	Input factors	General descriptions factors
Vulnerability	v_1	Geological location	The Geological Institute of Spain (IGME) establishes evaluation criteria based on terrain that exists in each area.
	v_2	Roof design	Water evacuation capacity of the building's roof is considered.
	v_3	Built context	Buildings without constructions next to them have lower vulnerability than other buildings with many constructions added to them.
	v_4	Constructive system	Functional and structural requirements of the building are studied.
	v_5	Preservation	Foundation, structure, roof, exterior walls, and facilities: the current state of conservation of various building elements is considered.
Static-structural risks	r_6	Load state modification	Partial or substantial initial load state changes.
	r_7	Overloads	Overload situations of the building (people and furniture), which is produced using different areas.
	r_8	Ventilation	Good ventilation from the point of view of the real possibilities of the building, regardless of the use made of the property.
	r_9	Facilities	In general, the facilities work under the current standards.
	r_{10}	Fire	Possibility that a fire occur considering the speed and intensity of its spread.
	r_{11}	Inner environment	Health, cleanliness, and hygiene of the spaces that affect the speed of deterioration of the building.
Atmospheric risks	r_{12}	Rainfall	Risk factor that causes changes in maintenance state of the building and generates deterioration.
	r_{13}	Temperature	Comparison of the maximum and minimum half temperatures on the year.
Anthropic risks	r_{14}	Population growth	Increase or decrease in population affects the potential number of people that have relationship with the property.
	r_{15}	Heritage value	Degree of legal protection, social, cultural, and liturgical appreciation is valued.
	r_{16}	Furniture value	Degree of legal protection, social, cultural, and liturgical appreciation of furniture is valuated.
	r_{17}	Occupancy	Activities conducted inside the property are assessed.



(a) (b) (c) (d)

Fig. 1. Kind of membership functions in the fuzzy model: (a) inference functions input variable (v_1); (b) other input variables (v_2-v_5 and r_6-r_{17}); (c) intermediate variables; (d) output variable (serviceability/FBSL)

Knowledge Base and Inference Rules

It is well known that the core of a fuzzy system is the knowledge base comprised of two components: the database and rule base.

This step is the principal part of a fuzzy expert system that combines the facts derived from the fuzzification process with the rule base generated previously and carried out in the modeling process. The FIS uses the fuzzy if-then rules to assign a map from fuzzy inputs to fuzzy outputs based on fuzzy composition rules. Thus, fuzzy models can be considered grey boxes and transparent (Babuška 1998) models, since they describe relationships by means of if-then rules.

Several FIS have been applied in different kinds of engineering applications. The Mamdani fuzzy model, one of the most accepted algorithms, is used in this methodology (Mamdani and Assilian 1975), and consists of fuzzy rules where each rule describes a local input-output relationship.

The rule base is a collection of fuzzy control rules, comprising of linguistic labels, representing the expert knowledge of the controlled system. The fuzzy logic inference model, known as a generalized modus ponens, is established in the FBSL model, Eq. (2), together with its hierarchical structure. The min-max or Mamdani inference mechanism is used in the composition of fuzzy propositions. Unlike in a conventional expert system, in a fuzzy system, various rules can be activated simultaneously.

This type of method works with the minimum operator as the implication function and the maximum as the aggregation operator (Ross 2010)

$$\text{Rule}(j)\text{:IF}v_1 \text{ is } A_{1^j} \quad \text{AND} \quad v_2 \text{ is } A_{2^j}, \ldots, v_n \text{ is } A_{n^j} \text{ THEN } y \text{ is } B^1 \tag{2}$$

where $v_i(x)$ = input (output) linguistic variables; A_i^j (B) = linguistic labels used in the input (output) variables; n = inputs numbers; and j = rules numbers.

All the fuzzy rules are extracted from engineering and architect knowledge, an experts' judgments and experience (Prieto et al. 2016). Inference rules applied to the input variables generate three levels of new intermediate variables. The full hierarchical structure of the fuzzy model is shown in Fig. 1, where it is possible to clearly see the interrelation of the variables developed in the different levels of the fuzzy model.

As can be seen in Fig. 2, the first level of intermediate fuzzy variables on the hierarchical structure is the next one. For Vulnerability-A (Va), Vulnerability-B (Vb), Static-Structural Risk-A (Ssa), Static-Structural Risk-B (Ssb), and Anthropic Risk (Ant), these variables are generated by inference rules based on the entry variables. For example Vulnerability-A (Va) is generated through 16 diffuse rules involving the variables Roof Design (v_2) and Preservation (v_5). (Table 2). As mentioned previously, for the composition of fuzzy proposals, the min-max composition or Mamdani inference mechanism was used.

The association between membership functions of the aforementioned variables are shown in Fig. 3. After the second level is arranged, the input variables are grouped in each new level as shown, and they are able to generate the next output level. In this sense Vulnerability-A (Va), Vulnerability-B (Vb), and Anthropic risk (Ant) all arrange Strength (Str) in the second rule level. Moreover Vulnerability-A (Va), Static-Structural Risk-A (Ssa), and Static-Structural Risk-B (Ssb) generate the Static-Structural Risk (Ss) output.

Finally, the third level, made up by Strength (Str), Static-Structural Risk (Ss), and Atmospheric Risk (Atm), generates the next Durability (Dur) output, and through this intermediate output and through the 66 inference rules of this level, the level of functionality is obtained as the final output (FBSL) (Macías-Bernal et al. 2014; Prieto et al. 2015).

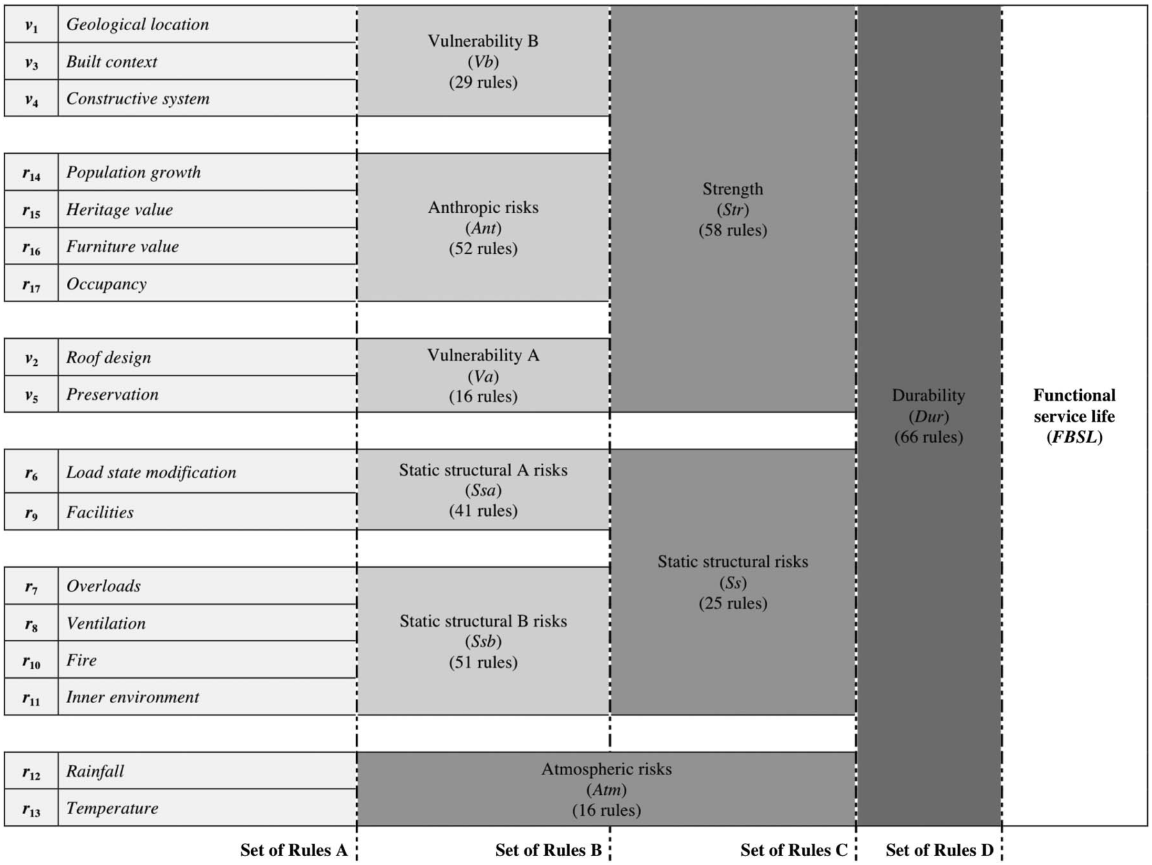


Fig. 2. Hierarchical structure of the fuzzy inference system

Table 2. If-Then Fuzzy Rules Generated by a Group of Professional Experts

Rule number	If	And	Then
Rule 1	If (v_2 is *VG*)	And (v_5 is *VG*)	Then (*Va* is *VG*)
Rule 2	If (v_2 is *VG*)	And (v_5 is *G*)	Then (*Va* is *G*)
Rule 3	If (v_2 is *VG*)	And (v_5 is *R*)	Then (*Va* is *R*)
Rule 4	If (v_2 is *VG*)	And (v_5 is *B*)	Then (*Va* is *B*)
Rule 5	If (v_2 is *G*)	And (v_5 is *VG*)	Then (*Va* is *VG*)
Rule 6	If (v_2 is *G*)	And (v_5 is *G*)	Then (*Va* is *G*)
Rule 7	If (v_2 is *G*)	And (v_5 is *R*)	Then (*Va* is *R*)
Rule 8	If (v_2 is *G*)	And (v_5 is *G*)	Then (*Va* is *B*)
Rule 9	If (v_2 is *R*)	And (v_5 is *VG*)	Then (*Va* is *G*)
Rule 10	If (v_2 is *R*)	And (v_5 is *G*)	Then (*Va* is *R*)
Rule 11	If (v_2 is *R*)	And (v_5 is *R*)	Then (*Va* is *B*)
Rule 12	If (v_2 is *R*)	And (v_5 is *B*)	Then (*Va* is *VB*)
Rule 13	If (v_2 is *B*)	And (v_5 is *VG*)	Then (*Va* is *R*)
Rule 14	If (v_2 is *B*)	And (v_5 is *G*)	Then (*Va* is *B*)
Rule 15	If (v_2 is *B*)	And (v_5 is *R*)	Then (*Va* is *VB*)
Rule 16	If (v_2 is *B*)	And (v_5 is *B*)	Then (*Va* is *VB*)

Defuzzification

Finally, the defuzzification stage is used to obtain a (crisp) value representing the fuzzy information produced by the inference. The FBSL system uses the center of the area (COA), also known as the center of gravity or centroid; it uses the center of the area of Fuzzy Set B as a proxy value, FBSL (Jager et al. 1993; Moreno-Velo et al. 2007), which is one of the most common and successful methods for defuzzification processes. The most notable property of this method are that it is continuous, which means that a small change in the inputs does not imply an abrupt change in the outputs. Its discrete version can be interpreted as a Riemann sum [Eq. (3)]. The output of the fuzzy model due to convenience is often interpreted by the same acronym that defines the fuzzy model (FBSL)

$$\mathrm{FBSL} = \frac{\sum_i y_i \cdot \mu_B(y_i)}{\sum_i \mu_B(y_i)} \tag{3}$$

The influence of certain inputs in the functionality index–FBSL output system can be appreciated by observing the control surfaces (3D mapping) that appear in Fig. 4.

Fig. 4 shows 3D mapping related with the input and output surfaces and where it can be clearly seen that the variations in the input parameters are transformed into variations in building functionality.

For this purpose, the range from minimum to maximum, of certain entrance model factors has been gone over; keeping the rest of factors constant and the behavior of the functionality index (FBSL) obtained has been analyzed. Among the vulnerability factors of the model, the Preservation (v_5) variable is considered by the experts as one of the most influential in the functional life of the buildings, which is why it has been maintained in all the charts, in order to observe the other influence of the variables, both for vulnerability as well as for risks, in the overall functionality level of the building (FBSL).

In this simplified sensitivity study, Preservation (v_5) has been studied next to

- Vulnerability factors of Geological Location (v_1) and Roof Design (v_2) [Figs. 4(a and b)]. In general, it is seen that the worse the geological location, the lower the functionality rate; however, a small anomaly is observed in extreme values of the

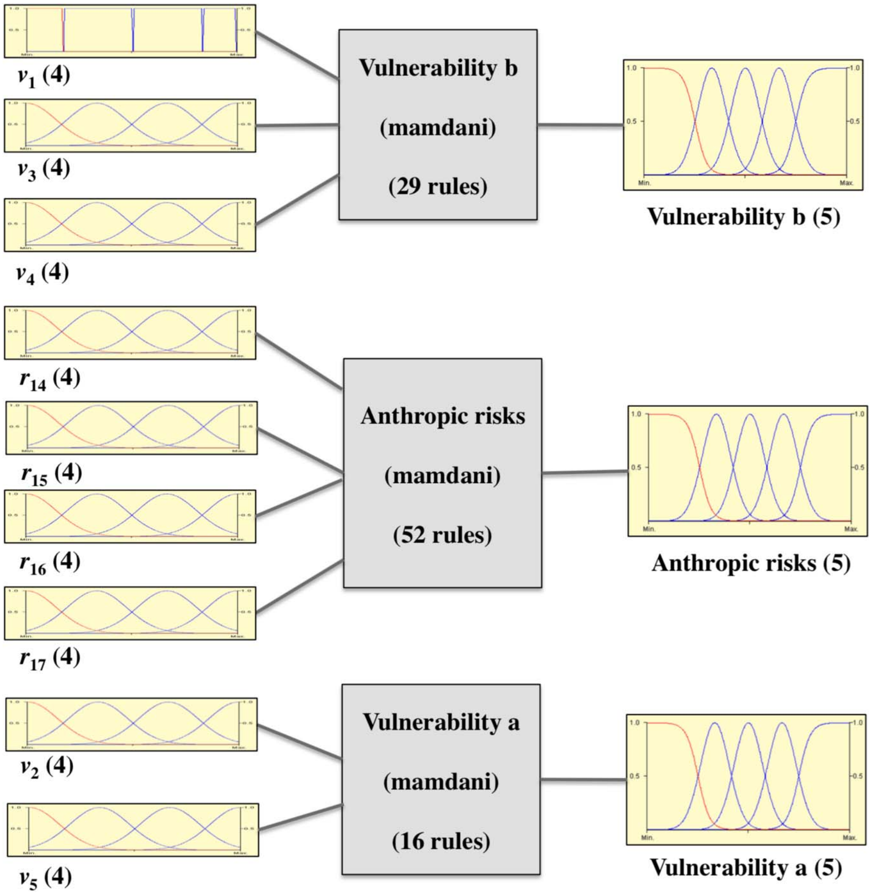


Fig. 3. First inference level of the hierarchical structure, set of Rules A

variable v_1 and FBSL. Fig. 4(b) shows effectively that v_5 and v_2 generate a minimum in the output values of the model;

- Static-structural risk factors of Load State Modification (r_6) and Facilities (r_9) [Figs. 4(c and d)]. The influence of both on the output of the model is very similar: the greater the risk, the lower the functionality rate. A slight increase of FBSL is seen when the variable r_6 takes values (6.0, 7.0), returning to decrease rapidly in the values close to 8.0 points (maximum risk);
- Atmospheric risk factors of Rainfall (r_{12}) and Temperature(r_{13}) [Figs. 4(e and f)]. It is clear that the greater the risk the lower the useful life but with a minor influence; and
- Anthropic risk factors of Population Growth (r_{14}) and occupancy (r_{17}) [Figs. 4(g and h)]. The variables of anthropic risks have similar behavior to that of the atmospheric factors.

To summarize, the vulnerabilities v_5 (Preservation) and v_2 (Roof Design) have a strong influence on the model's output. On the contrary, the influence of anthropogenic factors (r_{14}–r_{17}) has a lower weight when compared with that of atmospheric risks (r_{12}–r_{13}) or static-structural risks (r_6–r_{11}). These approaches are used to clearly show the theoretical application of the FIS in the next section.

Results and Discussion

The first part of this section mainly organizes the results and discussion into a hypothetical application of the model and where a classification is established based on the different functionality levels of buildings. A second part shows a practical application of the methodology with real case studies.

Theoretical Application of the Fuzzy Model

A theoretical study was performed, dividing the vulnerability case studies (v_1, v_2, v_3, v_4, and v_5) into three possible hypothetical buildings (Table 3). The first case study considered a Building B1 with vulnerability characteristics or variables in optimal conditions. In the second one, a Building B2 was considered with vulnerability in average conditions. And finally, the third case study considered a Building B3 with poor vulnerability, considering the worst-case scenario possible; (B3) > (B2) > (B1):

Building B1: $v_1 = 1.0$; $v_i = 1.0$ to $i = 2, \ldots, 5$ [vulnerability: best case (optimal)];

Building B2: $v_1 = 2.5$; $v_i = 4.5$ to $i = 2, \ldots, 5$ [vulnerability: average case (average)]; and

Building B3: $v_1 = 4.0$; $v_i = 8.0$ to $i = 2, \ldots, 5$ [vulnerability: worst case (worst)].

These three types of buildings with figurative vulnerability characteristics (B1, B2, and B3) were positioned in three theoretical external risk locations (TR1, TR2, and TR3). A total of nine possibilities were considered: three situations of vulnerability in three situations of degradation caused by static-structural risks (r_6, r_7, r_8, r_9, r_{10}, and r_{11}), atmospheric risks (r_{12} and r_{13}), and anthropic risks (r_{14}, r_{15}, r_{16}, and r_{17}); (TR3) > (TR2) > (TR1):

Total risks (TR1): $r_j = 1.0$ to $j = 6, \ldots, 17$ (low external impact risks);

Total risks (TR2): $r_j = 4.5$ to $j = 6, \ldots, 17$ (average external impact risks); and

Total risks (TR3): $r_j = 8.0$ to $j = 6, \ldots, 17$ (high external impact risks).

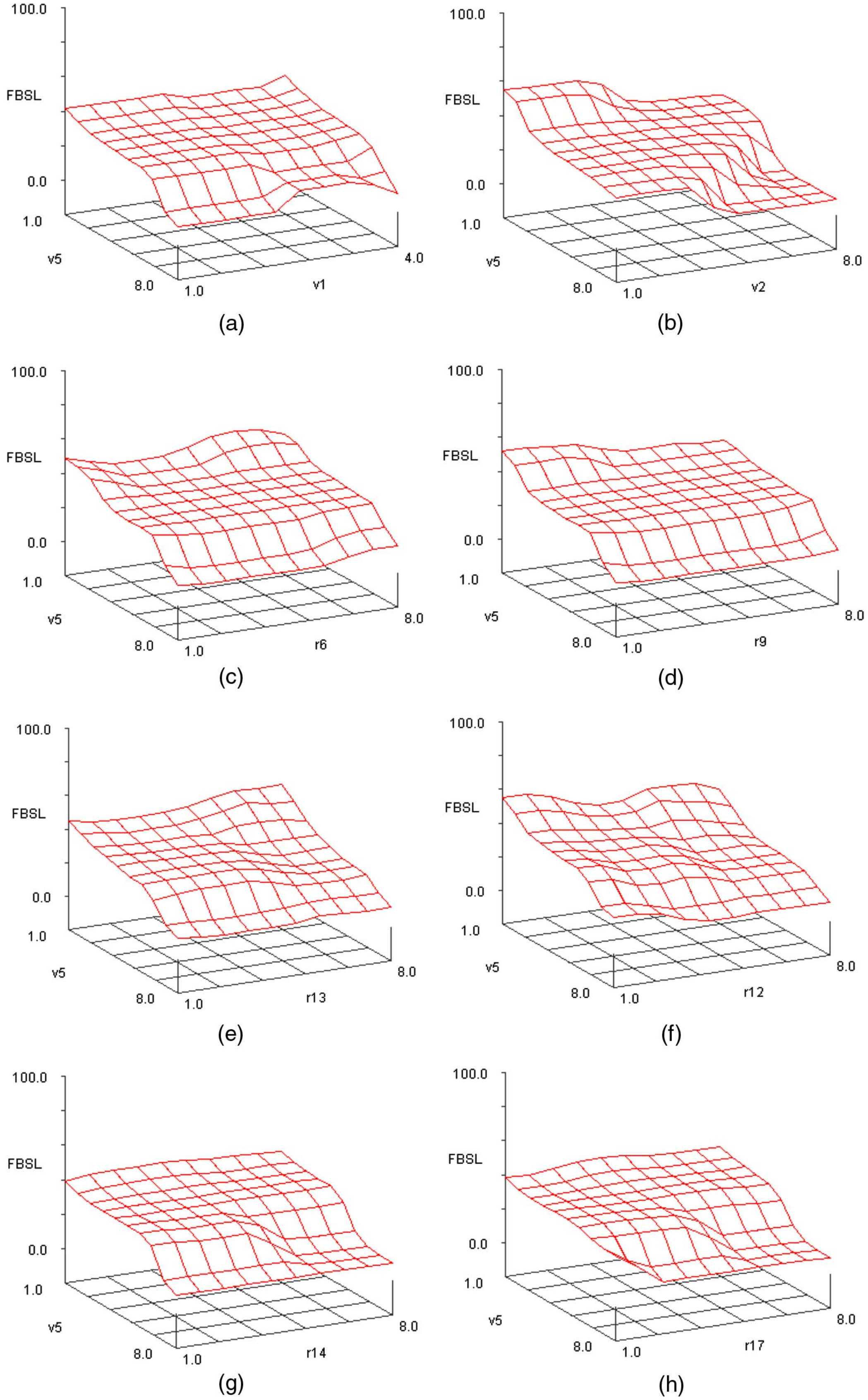


Fig. 4. Three-dimensional mapping between inputs and the output: (a) v_5, v_1, FBSL; (b) v_5, v_2, FBSL; (c) v_5, r_6, and FBSL; (d) v_5, r_9, and FBSL; (e) v_5, r_{12}, and FBSL; (f) v_5, r_{13}, and FBSL; (g) v_5, r_{14}, and FBSL; (h) v_5, r_{17}, and FBSL

Table 3. Theoretical Vulnerability Case Studies (B1, B2, and B3) in Three Virtual Risk Locations (RT1, RT2, and RT3)

Case study	Variables involved in the functional service life																	
	Vulnerability					Risks												Output
	v_1	v_2	v_3	v_4	v_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}	r_{13}	r_{14}	r_{15}	r_{16}	r_{17}	FBSL
B1 (RT1)	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	93.0
B2 (RT1)	2.5	4.5	4.5	4.5	4.5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	58.0
B3 (RT1)	4.0	8.0	8.0	8.0	8.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	27.0
B1 (RT2)	1.0	1.0	1.0	1.0	1.0	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	55.0
B2 (RT2)	2.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	33.0
B3 (RT2)	4.0	8.0	8.0	8.0	8.0	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	19.0
B1 (RT3)	1.0	1.0	1.0	1.0	1.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	40.0
B2 (RT3)	2.5	4.5	4.5	4.5	4.5	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	15.0
B3 (RT3)	4.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	9.0

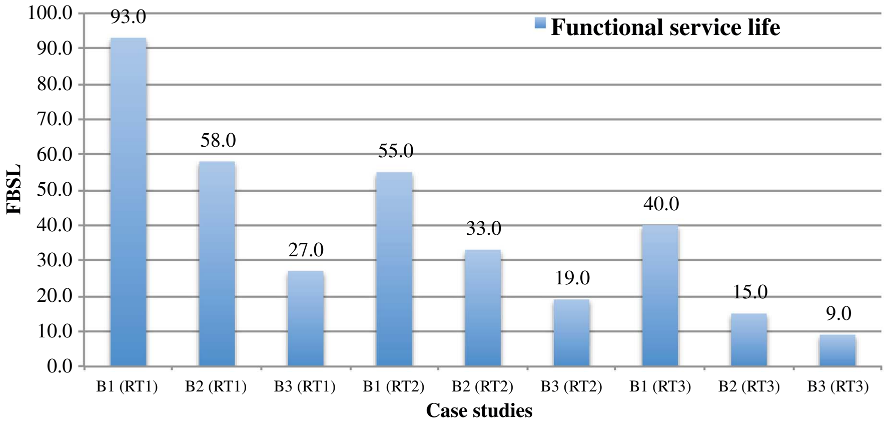


Fig. 5. Functional service life evolution related with the nine theoretical case studies

Table 3 shows the functional criterion of the buildings (B1, B2, and B3) according to three virtual risk sites (RT1, RT2, and RT3). Modeling the service life of buildings cannot be seen as an exact science; there is always some uncertainty associated with estimates, since there are several mechanisms and degradation agents that influence a building's degradation phenomena (Silvestre et al. 2015). The results presented in Table 3 and illustrated in Fig. 5 both show that the proposed model detects the decrease or increase in the inherent vulnerability of the three hypothetical buildings (B1, B2, and B3) in specific situations of external hazard degradation (RT1, RT2, and RT3). It shows the influence of a building's degradation condition in the preservation states provided and gives some useful information on the reliability of the expert system proposed. It shows that the fuzzy modeling developed in this study took into account the relative importance between the different variables of vulnerability and risk that affected the building, because the FBSL model analyzes the building as a whole.

This analysis was performed with theoretical case studies, analyzing the worst and best possible scenarios (to analyze the extreme conditions of a building's vulnerability and risks), also encompassing situations in the middle. In practice, one of the most-effective ways of optimizing maintenance actions in buildings is through the knowledge of how the building and its components deteriorate over time, estimating the instant after which it is necessary to intervene (Talon et al. 2005). The Burra Charter (ICOMOS 1987, Article 1.5) suggests where "cultural importance" is identified, maintenance should be the first priority.

In this sense, the functionality prediction model (FBSL) intends to make a new contribution in the preventive maintenance area of historic buildings by establishing a classification of priorities for action in some buildings compared with others. Fig. 5 clearly shows the functionality evolution of nine theoretical buildings based on various vulnerability and risk situations, showing which contexts influence the output of the model to a greater or lesser extent (FBSL). Contexts with a lower functionality level are those that should be prioritized in terms of maintenance actions and preventive preservation. In this sense, maintenance priorities should take into account the cultural importance of each of the buildings and their components, in addition to their vulnerability, as a starting point and without forgetting the functional issues of historical buildings (Dann and Wood 2004).

For example, Building B1 (vulnerability: the best) in risk situation RT3 (the worst) generates a FBSL of 40.0 points. However Building B3 (vulnerability: the worst) in a risk situation (RT1, the best), the FBSL score is around 27.0 points. These two cases clearly show how the proposed definition and situation of the building, taking into account its state of preservation and characteristics of its construction materials, have greater importance in the development of the building's functionality over time, compared to risk situations to which buildings may be externally subjected. This will clearly have an impact on the maintenance and preservation times of buildings. Buildings with high levels of risk but with more than acceptable vulnerability conditions will need less action over time than a building located in an environment with hardly any external risks but with terrible vulnerability conditions.

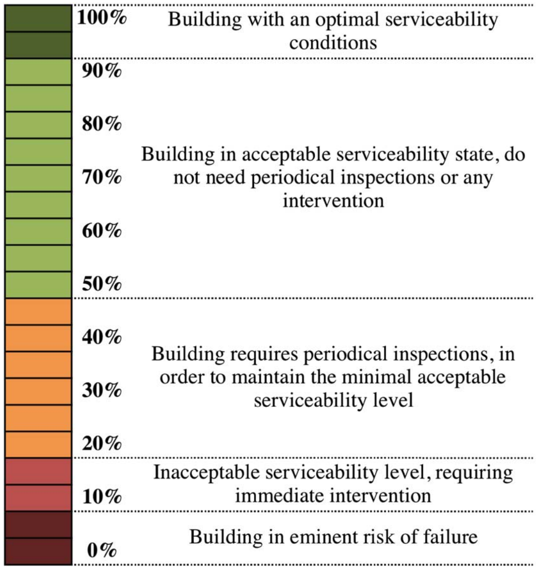


Fig. 6. Serviceability range conditions on the fuzzy model

Dann and Wood (2004) considered the maintenance of buildings like the process of keeping the building in operation over time, with there being a balance between the performance of the building (functionality) and the resources required for this to occur. This implies that the management and maintenance of historic buildings consists of identifying a series of relative priorities in terms of preventive maintenance.

This study continues by taking a further step in using the theoretical cases analyzed earlier in order to establish a ranking for the functionality conditions of buildings that will help define functional degradation conditions. This ranking is based on the functional performance of the buildings based on vulnerability and risk conditions (static-structural, atmospheric, and anthropic) in order to establish five possible functionality situations of buildings that may later help in the definition of preventive maintenance programs.

There are five possible functional conditions. A range of recommendations in terms of performance, where the buildings analyzed could be arranged depending on serviceability, achieves a range between 0 and 100% in terms of functional degradation phenomena. It is necessary to explain the two extreme situations, since the extreme values usually do not occur in reality. Buildings with optimal serviceability (100–93%) (Fig. 6) are ideal situations, because this is very complicated to achieve even when a building is recently finished, since there are several factors that may affect the service life of building materials or components even before their service life begins or before they become a part of the building (Happio and Viitaniemi 2008). The other serviceability extreme condition is the worst possible serviceability (9–0%) (Fig. 6). It is a situation where the buildings have unsustainable functional characteristics.

Intermediate functionality levels are (1) between 92–50%, where buildings in acceptable functionality conditions therefore do not require periodic inspections over time, (2) between 49 and 20%, where buildings that require periodic inspections in order to maintain minimum functionality levels, and (3) between 19 and 10%, where buildings with unacceptable functionality conditions require immediate intervention (Fig. 6). This classification of the functionality index into five functional degradation conditions can assist in defining priorities for action within maintenance programs in a complex of heritage buildings with similar construction features. Taking into account the range of functionality conditions defined in Fig. 6, buildings positioned closest to 90–100% would not need conservation or preventive maintenance programs. However, when buildings are positioned at lower functionality levels close to 20, 10, or 0%, they need immediate attention from competent authorities with regard to interventions that seek to anticipate major damage in the building.

Visible degradation of buildings and their living, safety, and health conditions indicates that buildings have reached such a level where taking action must be somewhat urgent but prudent (Vicente et al. 2015). They would need to have the highest level in priority intervention terms. These kinds of circumstances could occur, for example, after an earthquake, a fire, or even other large-scale natural disasters when the building does not have a possible functional service. In general, these kinds of situations are difficult to predict using a clear pattern.

In the FBSL model, the variables related to discrete situations of external risks like a seismic risk (earthquakes) or flood risks, are not included in the current version of the model, as the historical buildings analyzed are not in an area of high seismic risk or in areas at high risk of flooding. These external risk situations will be incorporated in future versions of the model.

A practical application could be applied to these theoretical results, using the performance of real buildings as case studies for the ranking. Enough information can be provided to manage decision-making of stakeholders and to prioritize maintenance actions in groups of buildings with homogeneous characteristics. It seems that decision-makers do not perform in a technically economical rational manner. As the rationality behind the majority of refurbishment building program decisions is very subjective in nature (Aikivuori 1999), the approach developed in this study can help in the automation of maintenance activities decreasing subjectivity and future costs in the construction area and of course contributing to reducing consumption of natural resources (Chai et al. 2015).

Practical Application of the Fuzzy Model

This subsection discusses the practical implementation and correlation of the output of the FBSL methodology with the opinions of experts in the field. During the phase for design, development, and testing of the system, the model was tested on a total of 14 heritage buildings of the Archdiocese of Seville, different to the initial sample of 50 buildings. Two different experts were chosen from those who took part during the design phase of the model; these were responsible for carrying out the test and correlation phase with the results that the FBSL methodology provided. The experts' valuations made by direct estimate was compared with the output of the model after valuation using the 17 input parameters (vulnerabilities and risks). In order to carry out the valuation using a direct estimate, the experts estimated the functionality index of the buildings addressing first and foremost a security criteria that would affect the integrity of their constructive elements, which would ensure their use or habitability by their occupants or users as well as by third parties (outdoor spaces and party walls) bearing in mind that no intervention would be made related to preservation or maintenance actions, and considering in each case the influence or impact that the building would have on its construction typology and environment. Finally, the results of the experts were compared with indices obtained through the model, and it was seen that the arithmetic mean of the direct estimation of the functional life carried out by the expert professionals and the fuzzy model FBSL exhibited an r correlation of 0.90 (Macías-Bernal et al. 2014).

A case study is discussed next in relation to the analysis and practical application carried out on a total of five real heritage buildings located in the province of Seville, Spain. This region has a total area of $14,036.09\ \mathrm{km}^2$. The buildings in the sample were built

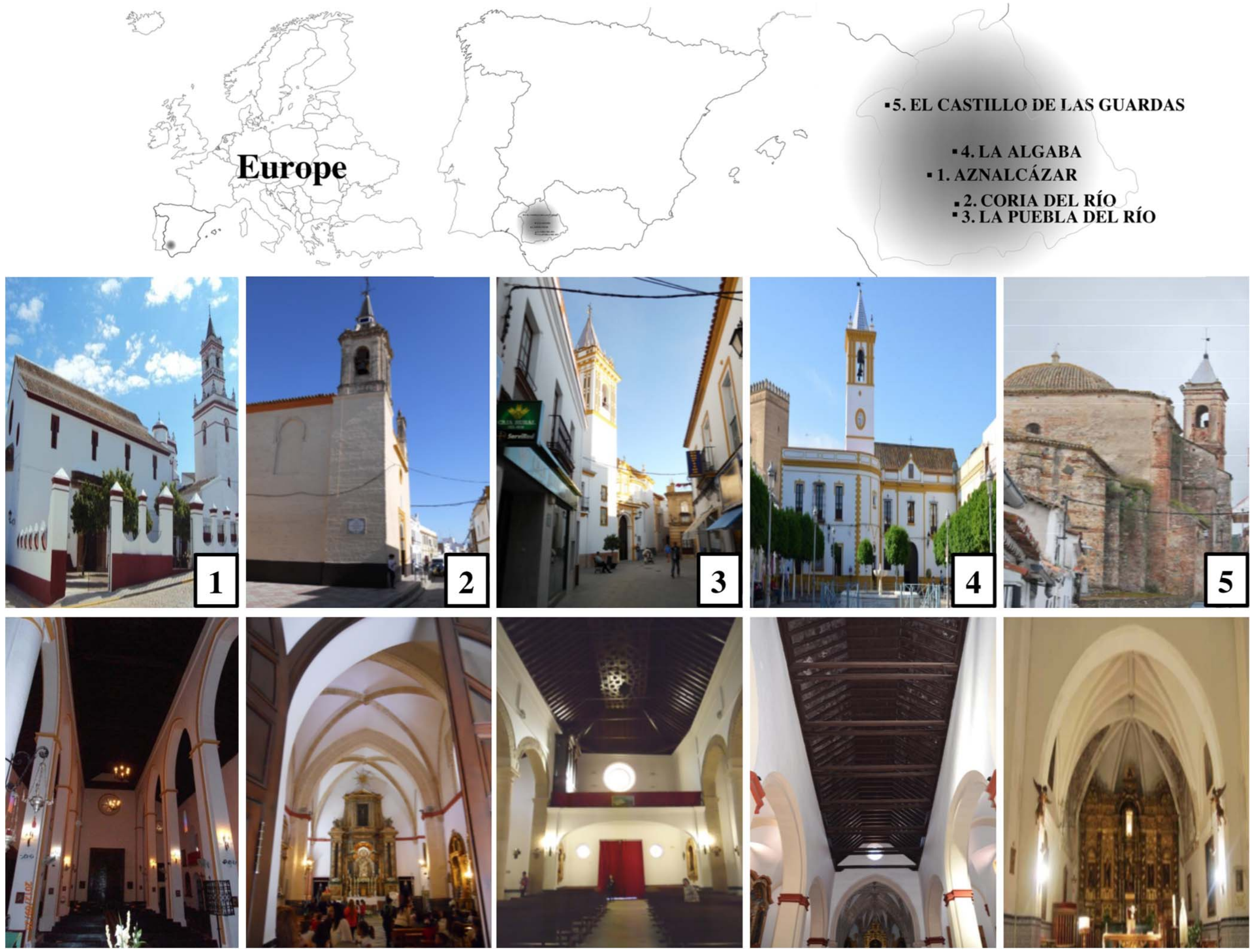


Fig. 7. Heritage buildings randomly selected in the practical application (images by A. J. Prieto)

between the fifteenth and sixteenth centuries (Fig. 7). Consequently, the parish churches have homogeneous construction, cultural, political, and regulatory features. However, the chronology and stylistic characteristics of Moorish buildings in the province of Seville display features that are unique to this kind of building.

The predominant materials used in the monuments analyzed in the province of Seville were bricks, limestones, mortar, and marble. In Gothic-Mudejar churches, they are either stonework or brickwork (in some cases, covered with rendered mortar) as a support structure, a horizontal timber covered with jointed rafters, and a finish of ceramic tiles on top. The foundations are made of continuous footings of bricks or stones. On the columns, the foundations are made from brick or stone footings (Ortiz and Ortiz 2016). The churches analyzed show that the materials used in the construction system and in the structure are very similar.

The preservation of the traditional values in the context of preservation and revitalization of architectural heritage is in a sense safeguarding culture. The main goal of conservation is to reinvigorate cultural properties by evaluating their architectural, historical, environmental, visual, and aesthetic characteristics (Ipekoglu 2006). Selecting this region (southern Spain) as the case study makes it effective to explore the potential benefits related to preventive maintenance in policies promoting architectural heritage previously applied to building stock. In general, preventive conservation is generally considered to imply measures to minimize the deterioration and damage of heritage, thus avoiding major restoration interventions (Cebron Lipovec and Van Balen 2008). However, real situations are different and these buildings have suffered many structural alterations that were required due to the functional adaption of these building to new functions. In spite of this, these changes can solve functional problems and can provide significant improvements. These kinds of functional adaptation works are able to incorporate alterations, conversions, or extensions to the serviceability of heritage buildings.

Fig. 7 shows the inside and outside of the buildings evaluated. This information is useful to understand how the functional life is obtained through the fuzzy model. With this visual information, it is possible to analyze the correlation between the functionality index values with the visual and physical condition of buildings. Table 4 provides the system of the variables and values defined earlier. A functional service-life ranking is obtained with these values, considering 100 as the highest serviceability level and 0 as the lowest value.

Throughout the theoretical serviceability range (Fig. 6), it is possible to achieve the characteristic classifications of the real heritage buildings selected. In the random case selected, it is easy to appreciate the building's position on the functional conditions range. The buildings used in this practical application are positioned between the 93 and 50% functional levels, which indicates "buildings in an acceptable serviceability state,

Table 4. Practical Application in Five Real Building Locations

Case study	Variables involved in the functional service life																	
	Vulnerability					Risks												Output
	v_1	v_2	v_3	v_4	v_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}	r_{13}	r_{14}	r_{15}	r_{16}	r_{17}	Serviceability
1	1.00	1.25	1.25	1.50	1.25	1.50	1.25	1.50	1.75	1.50	1.75	2.50	3.00	2.00	2.00	2.00	2.00	91.5
2	1.00	1.25	1.50	1.25	1.50	2.00	2.25	2.25	2.50	2.50	2.25	2.50	3.00	2.75	2.00	2.00	2.75	82.0
3	1.00	2.25	2.25	2.25	2.00	2.50	2.25	2.25	2.50	3.50	3.00	2.50	3.00	2.75	2.50	2.50	2.50	71.0
4	1.00	1.75	2.00	2.00	1.50	2.50	2.75	2.75	2.50	4.00	2.75	2.50	3.00	3.25	3.75	3.75	3.25	66.5
5	1.00	2.75	2.50	2.25	2.75	2.50	2.50	2.50	2.25	3.75	3.00	3.50	4.50	3.00	3.25	3.25	3.50	57.0


(a) (b)

Fig. 8. Illustrative case studies in the serviceability range conditions: (a) Santa Marina church in 2016 (Seville) (image by A. J. Prieto); (b) Ominum Sanctorum church (Seville) (image courtesy of the University of Seville)

do not need periodical inspections or any intervention" (Table 4). In the case study analyzed, despite buildings presenting a wide range of functionality of between 91.5 and 57.0% for Case Studies 1 (S. Paul of Aznalcázar) and 5 (S. Juan Bautista of El Castillo de las Guardas), Fig. 7 clearly shows that Building 5 apparently presents greater functional degradation than the rest.

Analyzing the images of the case studies positioned at the ends, it is clearly seen that although they do not need critical maintenance and preservation actions, Case Study 5 shows degradation conditions higher than in Case Study 1 (Fig. 7). In Case Study 5, the valuation of the variables v_2 and v_5 is 1.50 points worse than in Case Study 1. Therefore, and as has been previously considered in the hypothetical application of the model and the 3D mapping, by way of graphically analyzing sensitivity of input and output variables of the model, vulnerability variables v_5 associated with Preservation and variable v_2 relating to Roof Design present greater weight in the model. In addition, Atmospheric Risk (r_{12} and r_{13}) variables are also considered to have a greater effect in the building in Case 5 than in Case 1, which also significantly impacts on the output of the model, because these external risks have a higher effect in the situation of Case Study 5 compared to the situation of Case Study 1 (Prieto et al. 2015).

Two more illustrative and visual degradation conditions are shown; they are situated in the 50–20% and 19–10% ranges. Fig. 8(a) shows the Santa Marina church situated in the city of Seville. In this building, a functional index of around 40 points was obtained, indicating that "building requires periodical inspections, in order to maintain the minimal acceptable serviceability level." In Fig. 8(a), it is possible to appreciate the main façade of the church, where different deficiencies such as humidity by capillarity, erosion, and some vegetation growing on the top of the roof can be seen. Fig. 8(b) shows the Omnium Sanctorum church, also situated in the city of Seville. The picture illustrates the functional condition of the building just after the Spanish Civil War (around 1939) where a functional index of around 20% was estimated, indicating "unacceptable serviceability level, requiring immediate intervention." This valuation was interpreted using historical documents, files, and other kind of materials saved in different archives from that period.

This study's focus on the functional degradation levels of architectural constructions is intended to minimize the interventions on heritage buildings, slowing down their decay, through preservation and preventive maintenance actions. For these actions to be effective, they must be prolonged over time and of low importance, as well as low cost for the administrations responsible for their maintenance. This approach leads to a further step in the development of efficient and effective techniques to help in the conservation of heritage buildings, through the classification of buildings based on their overall functionality level. This will help in the development of preventive maintenance programs by detailing the minimum necessary economic investment as generally, major interventions in architectural heritage are often very costly and have a great impact (Watt 1999).

Conclusions

The renovation of historic buildings, as a strategic activity, requires an integrated and leveled mechanism of appraisal and diagnosis as a first step, because the maintenance and renovation of historic buildings are critical issues for a sustainable construction, especially in Europe. The functional service-life model based on visual appraisal of the functional anomalies is presented together with the quantification and transposition of the results into the proposed fuzzy inference system. The model is able to classify sets of buildings with homogeneous construction features, providing different rankings of constructions with priorities of interventions. In this study, the functional life of buildings is determined based on 17 variables, 5 related to vulnerabilities and 12 with risk assessment.

In the individual analysis of the degradation factors, it was found that the most influential factor were exposure to v_5 (Preservation) and v_2 (Roof Design), since both variables gained high relevance during the experts' survey. In these sense, maintenance actions will only be effective and efficient if they specifically address the most-relevant deterioration factors and failure mechanisms. The estimated maintenance operation hierarchy obtained through fuzzy modeling can help to better understand the buildings' serviceability as a whole.

Theoretical and practical applications of the FBSL functionality model help in understanding how the model operates. On the other hand, the practical application of the FBSL system demonstrates its utility in real case studies, showing different functional degradation conditions in a total of seven heritage buildings (churches) located in the south of Spain.

The Mamdani fuzzy model proposed in this study can help in the systematization of maintenance interventions in terms of decision making by stakeholders. The automation of maintenance actions can reduce the consumption of natural resources, allowing more-rational management of future maintenance operations. This information is paramount, since it can be applied by different stakeholders within the construction sector and of course can promote an effective and efficient maintenance approach to heritage buildings.

In future works, the model may be adjusted to other scenarios and environments by adapting it to circumstances prevailing in other regions and identifying new variables that could be significant in the description of the functional buildings criteria. This reflects the fact that buildings' functional degradation is a complex phenomenon that depends on various variables and that seriously affects building stocks.

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