Development of a numerical tool for the seismic vulnerability assessment of vernacular architecture

Abstract

Aiming at protecting the vernacular heritage located in earthquake prone areas, the paper presents the development and validation of the numerical tool that constitutes the core of a novel seismic vulnerability assessment method: Seismic Assessment of the Vulnerability of Vernacular Architecture Structures (SAVVAS). An extensive numerical modeling campaign was carried out to evaluate and quantify the influence of several parameters on the seismic response of vernacular buildings. The results were compiled into a database on which regression analysis could be performed to extract correlations between seismic capacity and qualitative and simple quantitative data that can be obtained from visual inspection.

1. Introduction

Seismic vulnerability assessment methods for the built environment play an important role on risk mitigation because they are the main components of models capable of predicting damage to buildings and estimating losses in future earthquakes. That is why they have become a valuable tool for the preservation of the built heritage, since they allow identifying the most vulnerable elements at risk. As a result, structural retrofitting strategies at an urban or regional level can be defined and optimized by highlighting those buildings where the biggest efforts should be concentrated. This has a particular importance when dealing with the preservation of the built vernacular heritage, which is rarely represented by single structures, but usually involves a group of buildings and settlements within a rural region or within an historical city center.

Several definitions and interpretations have been given to vernacular architecture [Rapoport 1972; Rudofsky 1990; Oliver 1997; ICOMOS 1999]. A common understanding of this wide concept is that vernacular buildings are usually owner or community built. Thus, they are not designed by specialists but, on the contrary, are part of a process that involves many people over many generations, being based on empirical knowledge and reflecting the tradition and life style of a community, as well as the inhabitant's bonding with the natural environment. That is why vernacular architecture is also often defined as the opposite of high or monumental architecture.

Precisely because of its empirical and traditional nature, vernacular architecture is nowadays considered in many places as an obsolete way of building and only valued as part of the region's identity [Correia 2017]. Typically, people tend to see vernacular construction technologies as unsafe and eventually abandon and substitute them with modern ones. This leads to a homogenization of the way of building throughout the world, providing a type of architecture that can be observed in any geography, jeopardizing the local building culture. Besides the loss of authenticity, the current global urbanization tendency that results in the adoption of new modern alien technologies enables structures to be erected quickly and cheaply, but not necessarily safely [Degg and Homan 2005]. The risk of vernacular heritage to disappear due to this economic, cultural and architectural homogenization was already highlighted by ICOMOS [1999]. Traditional building knowledge, technologies and materials face subsequently problems of obsolescence in a parallel way [May 2010]. As a result of this progressive abandonment, there is also an increasing vulnerability of vernacular architecture facing natural disasters, including earthquakes.

The main objective of the present research is to contribute to the awareness and protection of the vernacular heritage located in earthquake prone areas. For that matter, the present paper proposes the development of a novel seismic vulnerability assessment method particularly adapted for vernacular architecture. There exist a wide variety of methods in the literature suitable for different types of analysis with different goals. The different issues previously discussed introduce some constraints to the development of a seismic vulnerability assessment method adequate to the characteristics of vernacular architecture. First of all, given the typical lack of resources assigned to the study and preservation of the vernacular heritage, the targeted method should be easy-to-use and mostly make use of qualitative data that can be rapidly obtained from simple visual inspections. More detailed and sophisticated approaches that demand a deep investigation of the structures including, for example, historical research, non-destructive evaluation or advanced structural analysis are typically restricted for individual monumental buildings. Secondly, given the great heterogeneity of vernacular architecture in terms of geometry, materials or construction techniques, the new method should also allow the individual assessment of the buildings.

The method proposed is referred as Seismic Assessment of the Vulnerability of Vernacular Architecture Structures (SAVVAS). This new method aims at the estimation of the maximum seismic capacity of a building based on the identification and characterization of a set of geometrical, structural, constructive and material characteristics that are more influential in the seismic response of the building. The use of key qualitative and quantitative parameters to evaluate the seismic vulnerability of masonry buildings was firstly proposed by Benedetti and Petrini [Benedetti and Petrini 1984]. They defined a vulnerability index formulation on the basis of a vast set of post-earthquake damage observations and expert judgment. They selected a total of eleven parameters related to four classes of increasing vulnerability and weighted them according to their relative importance in determining the seismic behavior of the building. Each parameter is qualified individually, and the overall vulnerability of the building is calculated as the weighted sum of the parameters, expressed through a vulnerability index (I_V), which can be understood as a measure of the building safety under seismic loads [Barbat et al. 1996]. The vulnerability index method has been extensively applied in Italy [GNDT 1999] and variations of the method, such as the one proposed by Vicente [Vicente 2008], have been recently implemented in several historic city centers in Portugal [Vicente et al. 2011; Neves et al. 2012; Ferreira et al. 2013].

The vulnerability index method and its variations have provided useful and reliable results as a first level approach for large-scale assessments. However, they are based solely on empiric observation and the resulting vulnerability index (I_V) is an empirical factor with no physical meaning. It is usually correlated with an estimated damage for a given earthquake. The present research thus acknowledges the need of strengthening the reliability and robustness of existing methods by gaining a better insight of the seismic behavior of vernacular structures. For this purpose, the SAVVAS method has been developed using advanced numerical analysis. In this work, after the selection of the key parameters, detailed finite element (FE) modeling and nonlinear static (pushover) analysis were used to perform an extensive parametric study. The influence of the selected parameters could thus be evaluated and quantified numerically. The strategy consists of modifying a reference model according to the different parameters considered. The variations on the seismic performance of the structure are analyzed and compared in order to define each parameter influence. The use of pushover analysis allows defining the seismic performance of the building quantitatively, in terms of base shear coefficient. From the extensive numerical analysis, classes of increasing seismic vulnerability could be also established for each parameter.

The results of the extensive numerical parametric campaign could be assembled into a database. A statistical approach was thus followed for the development of the SAVVAS method, based on quantitative data analysis and Knowledge Discovery in Databases (KDD), using Data Mining (DM) techniques. These techniques allowed obtaining regression models that intend to predict the seismic capacity of vernacular structure using as inputs simple variables based on the selected key vulnerability parameters. These regression models are the main component of the SAVVAS method.

The use of an analytical process instead of an empirical one to develop an expedited method for the seismic vulnerability assessment of vernacular structures is considered a step forward in the contribution to scientific knowledge. The first part of the present paper shows in detail the process followed to obtain the regression models of the SAVVAS method. Secondly, the paper presents the validation of these regression models using numerical and experimental works gathered from the literature that deal with the seismic analysis of traditional masonry constructions. The regression models are applied to a total of six cases collected and the predictions are compared with the results provided by the literature. After the validation of the prediction capability of the regression models, the SAVVAS formulation is presented at the end of the paper as the main outcome, together with a summary of the steps that need to be followed to apply it.

2. Numerical parametric study for the definition of seismic vulnerability classes

The idea behind the SAVVAS method consists of developing a novel seismic vulnerability assessment method that is able to estimate the seismic capacity of vernacular buildings in quantitative terms. The quantification of the seismic capacity required an extensive numerical parametric study, designed according to the parameters considered to be more influential in determining the seismic behavior of vernacular buildings. This study helps understanding the seismic behavior and resisting mechanisms of vernacular constructions that present different characteristics in terms of construction, geometry and materials.

The numerical analysis is based on FE modeling and pushover analysis. FE modeling following a common macro-model approach has already been extensively and successfully applied with the aim of analyzing the seismic behavior of complex masonry and rammed earth structures [Mallardo et al. 2008; Lourenço et al. 2011; Saloustros et al. 2014; Karanikoloudis and Lourenço 2018]. Pushover analyses with distribution of forces proportional to the mass is also a generally accepted and recommended tool used for the seismic assessment of existing masonry buildings without box-behavior [Lourenço et al. 2011]. This approach allows determining the ability of the building to resist the characteristic horizontal loading caused by the seismic actions taking into account the material nonlinear behavior. Despite the limitations of simulating the earthquake loading as a set of equivalent static forces, pushover analysis is a powerful tool since it can be performed with relatively low computational efforts in comparison with other more sophisticated nonlinear analysis, such as nonlinear dynamic time-history analysis.

The development of the new method firstly required to identify and define a number of parameters that represent appropriately distinctive characteristics of vernacular buildings and influence their seismic behavior. The definition of these seismic vulnerability assessment parameters was based on the work developed by other authors that have proposed different vulnerability index formulations [Benedetti and Petrini 1984; Sepe et al. 2008; Boukri and Bensaibi 2008; Vicente 2008; Ferreira et al. 2014; Shakya 2014] and on the earthquake performance of vernacular constructions reported in past earthquakes [Blondet et al. 2011; Bothara et al. 2012; Neves et al. 2012; Sorrentino et al. 2013; Gautam et al. 2016]. It should be noted that the SAVVAS method has been developed with a main focus on vernacular architecture typologies whose structural system typically consists on load bearing masonry or earthen walls as the main vertical resisting elements, coupled with horizontal timber diaphragms. Parameters are selected according to the singular behavior of these structural types, acknowledging that many vernacular constructions around the world share a similar concept at the structural level. The ten parameters finally selected are shown schematically in Figure 1.

The definition of classes of increasing seismic vulnerability for each parameter is also based on the approach proposed by existing vulnerability index methods [Benedetti and Petrini 1984]. The methodology adopted for the definition of the seismic vulnerability classes consists of seven clearly defined steps that are presented in Figure 2, using one of the parameters as an example. The readers are referred to Ortega [Ortega 2018] for a full detailed explanation of the parametric study performed and the resulting seismic vulnerability assessment classification obtained for each parameter.

The first step involves the preparation of reference FE models based on typical vernacular stone masonry and rammed earth constructions targeted by the SAVVAS method (Figure 3). These reference models are prepared in a generic way so that they can easily accommodate the variations required to assess the influence of the different parameters. Several reference models are constructed for the evaluation of each parameter, aiming at providing a more comprehensive understanding of each parameter influence on buildings showing different characteristics. As an example, Figure 2 shows the two reference models prepared for the parametric analysis aimed at defining the seismic vulnerability classes of P2 (maximum wall span): (1) one-floor rammed earth building with flexible diaphragm; and (2) two-floor rammed earth building with rigid diaphragm. The use of these two different building typologies as reference models allows understanding the influence of the maximum wall span when the building is prone to show an out-of-plane failure mode and when the building is prone to present in-plane collapse mechanisms. After the definition of the different reference models, the second step consists of preparing sets of models by modifying each reference model according to a range of variation established for each parameter, taking into account typical values observed within vernacular architecture.

Once all the models from each set are constructed, they are subjected to a pushover analysis in the direction in which the parameter under evaluation is supposed to have a greater influence. Continuing with the example above, parameter P2 evaluates the variations in the response of the building when the maximum length of a wall prone to out-of-plane movements varies. Thus, the direction selected for the pushover analysis had to be perpendicular to the walls whose span is being modified. All models from each set of models are then tested in the same direction. DIANA software [TNO 2011] was used for the construction of the models and to perform the pushover analyses. There are some modeling specifications that are shared by all the models constructed for the parametric analysis. Walls are simulated with ten-node isoparametric 3D solid tetrahedron elements (CTE30), using at least two elements within the thickness. When modeled, floors are assumed to be composed by: (a) timber beams simulated using three-node beam elements (CL18B); and (b) cross-board sheathing, modeled using six-node triangular shell elements (CT30S). The roof is modelled as distributed vertical load along the load bearing walls and, when expected to exert thrust to the walls, a distributed horizontal load is also applied at the top of the walls. The displacements of the walls elements at the base are fully restrained.

Different materials are considered for the walls (“parameter P3”), from earthen materials (namely adobe masonry or rammed earth) to brick and stone masonry of different quality. Timber is used for the lintels and floor construction elements. Only the materials used for the walls are considered to present nonlinear behavior and the material model adopted is a standard isotropic Total Strain Rotating Crack Model (TSRCM). This model describes the tensile and compressive behavior of the material with one stress-strain relationship and assumes that the crack direction rotates with the principal strain axes. The tension softening function selected is exponential and the compressive function selected to model the crushing behavior is parabolic. It was selected because of its robustness and simplicity, showing successful results in previous analysis of complex stone masonry and earthen structures [Miccoli et al. 2014; Lourenço et al. 2015; Karanikoloudis and Lourenço 2018]. Timber elements were always considered to present elastic behavior. The material properties adopted varied for the different models constructed for the parametric analysis and are based on data collected from different authors and codes [NTC 2008; Lourenço 2009; Gomes et al. 2011; Angulo-Ibáñez 2012; Gallego and Arto 2014]. Other model details vary among the different models, such as the geometry and the level of connection between the structural elements, see [Ortega 2018] for full details.

The fourth and fifth steps are intended to analyze the results of the pushover analyses carried out on each model from each set to obtain a better understanding of the seismic behavior of vernacular buildings. Step four aims at understanding how the seismic response of the building changes in terms of damage patterns and failure mechanisms according to the variations in the parameter under evaluation. Step five analyzes the variations in the seismic behavior of the building in terms of the pushover curve. Pushover analyses allow describing the global seismic response of the structure and the formation of global collapse mechanisms in terms of the capacity or pushover curve. This curve is given as a relation between the base shear coefficient or load factor (i.e. the ratio between the horizontal forces at the base and the self-weight of the structure, expressed as an acceleration in terms of g) and the displacement at the control node (usually taken as the node where the highest displacements take place). It is noted that this node may vary according to the collapse mechanism obtained, which can differ between buildings. Thus, the curves are representative of the global structural behavior of the different buildings subjected to horizontal loading, not individual structural elements composing the buildings.

Furthermore, in order to have a common basis of comparison of the seismic capacity of the buildings in quantitative terms, four structural limit states (LS) associated to specific damage levels exhibited by the structure were defined following recommendations available in the literature [Rota et al. 2010; Mouyiannou et al. 2014]. The LS are determined according to the pushover curve obtained for each building (Figure 4). LS1 is associated to the Immediate Occupancy Limit State before which the structural behavior of the building is essentially elastic, and it can be considered as fully operational. LS1 thus corresponds to the onset of cracking, which is assumed to start after a reduction of the initial stiffness of the global response of the building up to 2%. It is noted that the value is relatively low but is related to the low tensile strength of the materials considered in this study and is defined after observing that the first cracks in the numerical models are visible after this reduction of the initial stiffness. LS2 is associated to a Damage Limitation Limit State. It depicts the transition between a state where the structure is still functional, showing minor structural damage and cracks, and a state of significant damage. The definition of LS2 from the pushover curve is made by satisfying two energy criteria: (1) the first energy criterion assumes that the area below the three-linear curve formed by LS1, LS2 and LS3 coincides with the area below the pushover curve from LS1 to LS3; and (2) the second criterion assumes that the LS2 point is on the slope associated to the secant stiffness corresponding to 70% of the maximum strength. LS3 is defined by the load factor corresponding to the attainment of the building maximum strength. It is referred as Life Safety Limit State. Finally, LS4 refers to the Near Collapse Limit State and corresponds to the point where the building resistance deteriorates below an acceptable limit, which is set at the 80% of the maximum strength, following recommendations by Eurocode 8 [EN 1998-3 2005].

Step five thus consists of transforming the pushover curves of the buildings into four-linear capacity curves according to the points associated to each LS. Through these capacity curves, the seismic behavior of each building is described by four equivalent static horizontal loads (load factors) that the buildings can withstand before reaching each LS. However, they also provide information about the deformation capacity of the building, allowing an easier and quantitative comparison between the structural response of the models from each set in terms of capacity, stiffness and ductility.

The sixth step consists of comparing the values of load factor corresponding to LS1 and LS3 for the different models within each set. LS2 and LS4 are not included because they are mathematically determined through LS1 and LS3. The load factor variations for LS1 and LS3 can be expressed in terms of a percentage normalized using the maximum value of load factor obtained among the buildings analyzed within the set. This procedure results in the construction of curves that show in a clear manner the variation of the seismic capacity of the building as a function of the variations defined for each parameter (Figure 2).

Finally, the seventh and last step consists of the definition of the seismic vulnerability classes according to the variation of the load factor corresponding to the attainment of the maximum capacity of the building (LS3). The criterion followed for the definition of the typical four vulnerability classes of increasing vulnerability consists of dividing equally the total range of variation within each set into four parts. Each interval is associated with a vulnerability class and buildings are classified according to the interval they lie within, see Figure 2. It is noted that the ranges of variation obtained for each set can differ, resulting in differences in the definition of the seismic vulnerability classes. The final classification is made by adopting the most unfavorable class.

3. Methodology adopted to obtain the regression models of the SAVVAS method

In total, the parametric study carried out involved the construction of 277 numerical models with varying geometrical, construction, material and structural characteristics. Since most models were analyzed in the two orthogonal directions, results from more than 400 pushover analyses were obtained. This allowed determining the global seismic response of each building in different seismic loading directions. The results of each pushover analysis performed on each numerical model could compose a wide, reasonably robust, database containing two main pieces of information: (1) the differing characteristic of the numerical models according to the ten key parameters selected; and (2) the seismic load capacity of the different buildings, defined in terms of load factors leading to the attainment of four damage limit states (LS1, LS2, LS3 and LS4).

The application of DM algorithms to extract models or patterns that explain relationships between variables from databases is one of the main steps of KDD [Fayyad et al. 1996]. The employment of these tools allows analyzing the complex database obtained from the numerical analyses performed, which presents a large number of variables and complex and unclear relationships among them. The SAVVAS method arises precisely from the intention of delving more deeply into the research question of whether the simple key parameters variables selected can be used to predict the seismic load capacity of vernacular buildings. The final objective of the method is to derive regression models able to quantitatively estimate a value of a load factor that causes the structure to reach the different LS, which can later be correlated with different degrees of structural damage suffered by the building. Moreover, since the load factors that define each LS are expressed in terms of g, they can be compared in a straightforward way with an expected seismic event. The seismic input used for comparison is expressed in terms of Peak Ground Acceleration (PGA) or, when a more refined assessment is required, the site response spectra and the building fundamental period can be used to take into account specific accelerations adapted to each building and site.

There are several DM algorithms that can be applied for the desired deeper analysis and the extraction of patterns explaining relationships between variables, such as multiple linear regression, artificial neural networks (ANN), support vector machines (SVM) and decision trees. There is an increasing amount of research in different fields that make use of the abovementioned techniques. This includes research in structural engineering where, for example, DM techniques have been widely applied to formulate models able to predict the mechanical properties of different materials based on experimental data [Baykasoglu et al. 2008; Miranda et al. 2011; Garzón-Roca et al. 2013a Martins et al. 2014; Martins et al. 2018] or the structural behavior of different structural elements [Marques and Lourenço 2013; Garzón-Roca et al. 2013b; Plevris and Asteris 2014; Aguilar et al. 2016]. This exemplifies that there is an increasing research focus on developing regression models for the prediction of the mechanical properties of different materials and the structural behavior of different structural elements. However, with the exception of [Garzón-Roca et al. 2013b], who used as the database for developing the ANN models the results of a parametric study with finite elements comprising 3700 models [Sandoval and Roca 2012], all abovementioned studies have developed the models based on large databases of experimental data. This research work makes use of a database composed solely of numerical data obtained from the results of the nonlinear parametric study carried out.

3.1. Methodology

Figure 5 presents an overview of the steps of the methodology adopted to obtain the regression models necessary for the development of the SAVVAS method. The first step concerns the organization of the database. The target data include the load factor corresponding to the attainment of LS1, LS2 and LS3. The load factor defining LS4 is not taken into consideration because it is by definition proportional to the load factor defining LS3. These three load factors associated to the different LS are considered to define the seismic response of the buildings because they depict the seismic load (in terms of g) that would cause the building to reach different damage levels. The regression models are thus intended to predict these three LS using as the input simple variables based on the previously selected parameters.

Since the SAVVAS method relies directly upon the regression models, an effort was placed on increasing their prediction accuracy. Thus, while some of the parameters can be defined by the seismic vulnerability classes previously defined, others could be more precisely described using more specific quantitative attributes. For example, P2 (maximum wall span) can be directly defined by the span (in m), instead of by the vulnerability class. The same occurs for P1, defined by the wall slenderness ratio (λ), P8, defined by the number of floors (N) of the building and P10, defined by the in-plane index (γ_i). It should be noted that the in-plane index is defined as the ratio between the in-plane area of earthquake resistant walls in each main direction (A_{wi}) and the total in-plane area of the earthquake resistant walls (A_w), see Figure 1. In the particular case of P7, which concerns the amount and area of walls openings, the parameter was also further divided into two parameters, aiming at distinguishing between the area of wall openings at the walls perpendicular to the loading direction (P7a) from the area of wall openings at the walls parallel to the loading direction (P7b). The remaining parameters, including the type of material (P3), the quality of the wall-to-wall connections (P4), the horizontal diaphragms (P5), the roof thrust (P6) and the previous structural damage (P9), are defined as a function of their class, in qualitative terms. Thus, they are described in a discrete form, assuming four countable numbers from 1 to 4, associated to the classes A to D, respectively.

As a result, the data was structured in a database composed of 14 attributes: (a) eleven variables associated to the parameters; and (b) three variables with the values of load factor associated to LS1, LS2 and LS3 obtained for each model. The parameters variables are either: (1) expressed in a discrete form from 1 to 4 when the parameters are described by classes; or (2) expressed as continuous variables using different units depending on the parameter. The load factors are all continuous variables expressed in g, typically ranging from 0 to 1.

In terms of applied DM algorithms, the SAVVAS method explores the use of two different techniques to develop the regression models: (a) multiple linear regression (MR); and (b) artificial neural networks (ANN). Nevertheless, it is noted that the ANN models are mainly developed for reference and comparison purposes, intended to show a research path open to further research. The focus is here placed on multiple regression models, whose physical meaning is easier to interpret [Miranda et al. 2011]. The resulting regression models obtained are able to predict the seismic behavior of vernacular buildings based on the simple eleven parameters variables defined. They constitute the core of the SAVVAS method.

3.2. SAVVAS database

A preliminary data analysis performed in a first stage concluded that the extension of the database was not deemed enough to define robust regression models. Therefore, additional numerical models were built in order to enlarge the database, intending to have a more balanced distribution of buildings belonging to the different classes for each parameter. The database needed to be diverse and representative enough of all classes of each parameter. Considering the pattern of variability within each parameter variable (i.e. the distribution of buildings belonging to each class), a lack of balance (or asymmetry) was detected. Due to the use of reference models showing similar initial conditions for the definition of the classes, some seismic vulnerability classes in certain parameters are more frequent than others. The first step of the database extension process consisted of identifying those classes in each of the ten parameters that were less represented in the original database. The main criterion applied for the enlargement of the database was to ensure that there are a minimum of 25 models representing each parameter class, in order to contain a meaningful statistical amount for all of them. Additionally, some new models were constructed aimed at assessing the efficiency of traditional earthquake resistant techniques for vernacular architecture [Ortega et al. 2018]. The results of these analyses were also added to the initially constructed database. In total, the extension process led to a final database composed of 567 results obtained from pushover analyses performed on FE models. The precise information on the process of extension of the database is detailed in [Ortega 2018].

Several operations can be also applied on the attributes selected for the database in order to eventually help improving the prediction capabilities of the regression models. For instance, the dependence of the output variable on a specific predictor may be not linear, which can lead to errors in the prediction. Different transformations of the input and output data, such as logarithms and powers, were considered to help to linearize this relationship and to better describe the effect of each parameter in the seismic behavior of the building. Indeed, all the output variables had to be transformed in order to assure that the predicted values from the multiple linear regression models are always positive. The output variables are the load factors that measure the seismic action that causes the building to reach specific LS and they are expressed in terms of g. Therefore, as a measure of the seismic load, they cannot be negative. However, in some specific cases, the load factor defining LS1 can be 0, if the building is assumed to present an initial level of structural damage (e.g. because of the state of conservation or the roof thrust), but can never show values below 0. This led to the adoption of a logarithmic transformation of the three output variables (LS1, LS2 and LS3), since the predicted values from a log-transformed regression will never be negative, respecting the physical meaning of the variable. The logarithmic transformation involves the adoption of a natural logarithm of the output variables. It should be noted that, since there are zero values among the data of the variable LS1 and there is no logarithm of the value zero, a constant ($c = 0.01$) was added to all LS1 values before applying the log transformation. A small positive constant between 0 and the smallest non-zero observation that preserves the order of magnitudes of the data is usually recommended [McCune and Grace 2002; Field et al. 2012].

As a summary, the list of the input and output transformed and untransformed variables considered, together with general statistical measurements, is presented in Table 1. It should be noted that the transformations of the variables result from a trial and error process and only those that revealed to have a notable influence in improving the prediction capabilities of the regression models are presented.

4. Regression models

The statistical analysis and the definition of the regression models are carried out by using R open source software [R Development Core Team 2008]. Different regression models were prepared and compared in order to conclude with the final formulation of the SAVVAS method. The discussion of the results presented herein also allowed a deeper understanding of the relationships among the parameters and their influence on the seismic behavior of vernacular buildings. The selection of the final expressions is based on a compromise between the accuracy in the prediction and the choice of patterns whose physical meaning is more understandable.

4.1. Multiple linear regression models

The first DM technique applied is multiple linear regression (MR). Regression analysis is a popular statistical method used to study the relationship among variables [Kottegodo and Rosso 2008]. In the present case, MR is intended to investigate the dependence of LS1, LS2 and LS3 (output variables) on the eleven key parameter variables (the input variables), as well as to define and quantify the relationship among them through a mathematical model. A multiple regression model is required because there is more than one input variable [Montgomery et al. 2012]. The relationship between variables is often very complex and the simplest approach consists of fitting a multilinear equation to the data:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \tag{1}$$

where Y is the output variable and k is the number of input explanatory variables (x_k). The parameters β_k are called the regression coefficients and ε is the error. The line defined by the regression equation (1) describes how the response changes according to the explanatory variables. Different regression models were prepared using always multiple regression analysis, but varying the input variables taken into consideration. This section is thus meant to provide a comparison of the performance of the different models concerning their capability in predicting the load factors associated to the different limit states (LS). In total, six regression models are presented and discussed next.

The first regression model (*MR0*) is a simple model that uses as input only the seismic vulnerability classes for all ten parameters (i.e. discrete values between 1 and 4) and is mainly meant to serve as reference. Then, aiming at further improving the precision of the regression models, five more regression models were constructed assuming different combinations of: (a) input variables; (b) transformations of the attributes; and (c) interactions among the attributes. It is noted that, in a first step, the regression models are constructed using LS3 as the output variable. Different combinations were thus created using the continuous variables and transformations defined and presented in Table 1 and the interactions among them. This latter condition was considered as a very critical aspect because the results of the numerical parametric study confirmed that the influence of some parameters is sensitive to the variations of other parameters. Thus, several interactions between the parameters were tested in different regression models. For example, when the building presented a rigid diaphragm able to distribute the load among all structural elements ($P5$), the influence of the area of wall openings in the in-plane walls ($P7b$) is decisive. On the contrary, if the buildings present a flexible diaphragm, the failure of the building is typically controlled by the out-of-plane failure of the walls and, thus, the area of wall openings in the in-plane walls has a negligible effect on the response of the building. That is why the interaction between parameters that influence themselves mutually was introduced in the multiple regression models. Considering the previous example, a new interaction term composed by the product $P5 \times P7b$ can be included in the regression models, keeping also the independent terms $P5$ and $P7b$. With the new predictor term, the influence of $P7b$ on the variation of $LS3$ is different for different values of $P5$, reflecting better what was observed in the numerical parametric study.

The six different regression models with different sets of input variables and considering the different interactions among them are shown in Table 2. Regarding the notation adopted, it is noted that label I (ex. *MR_I1*) is added to the models that include interaction among parameters. The table shows measurements of the predictive performance of the models in terms of error and coefficient of determination (R^2). It should be noted that the k-fold cross-validation method, with $k = 10$, was applied for developing the models and assessing the predictive capacity of the models, since it is considered as one of the most robust methods [Cortez 2010]. The method consists of randomly partitioning the data into k sets of roughly the same size. A model is then trained using all the sets except the first subset, which is used for testing, calculating the prediction error and accuracy of the model. The same operation is repeated ten times (for each partition) and the performance of the model is evaluated by averaging the errors (MAE and RMSE) of the different test sets. Finally, once the most appropriate set of input variables and intersections is selected, the final models are developed using all the data.

The models show different levels of complexity in order to find the abovementioned compromise between accuracy in the prediction and a clear and simple physical meaning. The adoption of more accurate attributes to define the parameter variables in *MR1*, together with the logarithmic transformation of the output variable, already results in a significant improvement in its prediction performance in comparison with the *MR0* model. However, the models that consider interaction among parameter showed an overall improvement with respect to two models *MR0* and *MR1*, reaching values of R^2 close to 0.9. The introduction of the interactions leads to an improvement in the prediction capability, reducing the errors, but the level of complexity of the formulation increases as well. This is the case of models *MR_I1, MR_I2* and *MR_I3*. The use of a robust cross-validation method reduces the risk of overfitting, i.e. the risk of creating excessively complex models that fit very well the data because of describing random error instead of the actual patterns of variability. However, the limitations of the database, such as the narrow range of variability within some parameters, may result in models that are very adequate for this dataset but are not so representative of scenarios outside of it. That is why, in the end, a more general expression was preferred. *MR_I4* tried to simplify the model to the maximum extent possible in terms of number of predictors, using only those showing the highest relative importance in the prediction. It shows a good performance, but it neglects some parameters that proved to be also influential in the parametric analyses and thus can be critical as well when evaluating other sets of data. Figure 6 shows the predicted versus observed values obtained for the six models with different sets of input variables and interactions.

After evaluating the performance of the different models, as well as the compromise between simplicity and prediction capability, model *MR_I1* was adopted as MR_LS3 due to its relatively simple formulation. It uses all the untransformed input variables for the prediction, but adds the interaction between P5 and P7b that had an obvious influence and proves to have an important prediction weight. By adding this interaction term, the regression model reaches a R^2 of 0.877, explaining 88% of the variation of the output data, which is considered satisfactory. It should be highlighted that it provides a quite accurate value of LS3 based only on the ten parameter variables and on one single simple interaction. The errors are also reduced with respect to models *MR0* and *MR1*, showing a maximum error of 0.318g. The predicted versus observed values obtained for this model are further shown in Figure 7a. Figure 7b presents the predicted value with the residuals. The graph shows clearly that the highest deviations occur for higher values of LS3, approximately over 0.6g. Those buildings with LS3 > 0.6g can be already considered to have low vulnerability so that the accuracy of the model is less critical. The main part of the dataset includes models with values of LS3 ranging from 0.15g to 0.6g and is well matched. Besides, all values bounce over the 0 line, but the great majority of them lies between -0.1g and 0.1g. Only 16% of the models are outside this range, i.e. showed an absolute error higher than 0.1g. Thus, results were deemed acceptable to adopt *MR_I1* as the regression model for LS3. By comparing the models shown in Figure 6, it is clear that, with the exception of the simple *MR0* regression model, the performance of the different models is similar in terms of accuracy of the prediction, which justifies the selection of *MR_I1* as the final regression model, given its simpler formulation. The regression equation obtained from *MR_LS3* is:

$$\ln(LS3) = 2.523 - 0.044 \times \lambda - 0.063 \times s - 0.238 \times P3 - 0.186 \times P4 - 0.279 \times P5 - 0.091 \times P6 + 0.273 \times P7a - 2.833 \times P7b - 0.396 \times N - 0.156 \times P9 + 0.684 \times \gamma_i + 0.438 \times P5 \times P7b \quad (2)$$

The regression models intended to predict the load factors corresponding to LS1 and LS2 were constructed following the same procedure previously explained for LS3. Only the final models adopted are presented and discussed. Figure 8 presents the predicted versus observed values of both models. Table 3 shows the variables used for the final models constructed and the measurements of the performance, in terms of errors (MAE and RMSE) and coefficient of determination (R^2).

In the case of the regression model prepared for the prediction of the load factor associated to LS1 (*MR_LS1*), different sets of input variables and different interactions were trained and tested until reaching the final formulation. As an example, particular attention was put in the use of the variables representing the seismic vulnerability parameters P6 (roof thrust) and P9 (previous structural damage), which can lead LS1 to take zero values for some classes. The logarithmic transformation of both variables allowed capturing properly this characteristic. The same parameters interaction used for the selected *MR_I1* model for LS3 was also adopted for this model ($P5 \times P7b$). The overall behavior of the model is considered quite acceptable for the relatively simple formulation obtained (Figure 8a), presenting low errors and a high R^2 of 0.811. The final regression equation from MR_LS1 model reads:

$$\ln(LS1 + c) = 2.201 - 0.061 \times \lambda - 0.099 \times s - 0.712 \times \ln(P3) - 0.156 \times P4 - 0.289 \times P5 - 0.521 \times \ln(P6) - 3.668 \times P7b - 0.847 \times \ln(N) - 2.31 \times \ln(P9) + 0.679 \times P5 \times P7b \quad (3)$$

In the case of the regression model constructed for the prediction of the load factor associated to LS2, instead of using the parameter variables, the variables previously used as output (LS1 and LS3, expressed in *g*) are now used as the only input for the model. These new inputs are selected because the definition of this damage limit state is mathematically dependent on LS1 and LS3 [Ortega 2018]. Therefore, it can be calculated using solely those two input variables. This simplified its calculation while leading to very accurate predictions and an almost perfect correlation with much reduced errors (Figure 8b). The final regression equation from MR_LS2 model is:

$$LS2 = 0.152 \times LS1 + 0.781 \times LS3 \quad (4)$$

4.2. Artificial neural networks

An artificial neural network is a computational scheme whose basic unit are neurons organized in layers. Each neuron receives a series of inputs, multiplies them by previously defined weights and combines them adding a predetermined constant called bias to send an output. Most common neural networks are composed by different parallel layers of neurons. The first layer contains the input variables, the intermediate layer or layers are known as hidden layers, and the last layer contains the output. Typically, besides the predefined input and output variables that are intended to be predicted, an ANN is also described by the number of hidden layers and the number of neurons in each hidden layer. This work uses a feedforward network, which means that the connections always go from inputs to outputs (there is no connection between the neurons within the same layer) and there are no cycles in the network. It uses the sigmoid function as the activation function, which is a particular case of logistic function that is commonly used within ANN architecture [Montgomery et al. 2012; Günther and Fritsch 2010]. Finally, the learning process algorithm applied is back propagation, which consists of setting initial random values for the weights and biases, leading to a specific output. The error is measured and propagated backwards in order to adjust the weights and biases. This process is repeated so that gradually the actual output from the model gets closer to the desired output after rounds of testing, until reaching a minimum error specified.

The *neuralnet* package [Fritsch et al. 2016] for the R software was used for the preparation and training of the ANN models. ANN models are able to detect the interactions among the parameters and, since they are not based on a linear combination of the input variables, the transformations proposed for the input variables are no longer necessary either. However, the logarithmic transformations were still applied to the output variables in order to prevent them to reach negative values. Two models were prepared, each of them with one output variable: LS1 and LS3. The ANN model for LS2 was deemed unnecessary because the linear regression model already obtained, shown in Equation (4), was considered accurate enough. The variables used as input are those that proved to be significant predictors of LS1 and LS3 when preparing the multiple linear regression models. This way, the models could also be directly compared. The ANN models have a unique hidden layer with four neurons. This number was determined by a trial and error process. The *10*-fold method was used for training and validating the models.

The results obtained showed that the ANN models slightly outperformed the multiple linear regression models. Figure 9 shows the predicted versus observed values in both models, showing the improvement in the behavior when compared to the predicted versus observed values obtained for the multiple regression models for LS1 (Figure 8a) and LS3 (Figure 7a). The results lie notably closer to the 45º line, even for the highest values of LS1 and LS3, which were less accurately estimated by the multiple regression models. Table 4 shows the variables adopted for each regression model and the measurements of performance of both models in terms of errors (MAE and RMSE) and coefficient of determination (R^2). The errors (MAE and RMSE) of the ANN models were reduced around 20% in both models, while the coefficient of determination also increased around 7% for the model predicting the load factor associated with LS1 and 5% for the model predicting the load factor associated with LS3.

Besides the aforementioned improvement obtained with the ANN models, they have the disadvantage of not being as straightforward as the MR models. The resulting formulation is not a simple expression such as the ones presented in Equations (2), (3) and (4), but a structure composed of hidden layers, multiple weights and inner functions, as previously explained. Thus, for practical matters, the complexity of the ANN architecture makes the MR models desirable for practical use. They are easy to implement and calculate, while keeping a robust prediction. It is noted that the SAVVAS method is conceived to provide a first seismic assessment that can be carried out in an expedited way, even for large numbers of buildings. Thus, it is preferable that it is based on simple visual inspection and relatively simple formulations.

Another main advantage of the multiple regression models is that they are easier to interpret. This is important because the method is also intended to allow performing an initial evaluation of the effect of different retrofitting strategies in reducing the seismic vulnerability of vernacular buildings. Each parameter can be assessed independently directly from Equations (2), (3) and (4), in order to better understand their influence. For instance, the term of Equations (2) involving P4 is is $(0.186 \times P4)$, where *P4* refers to the seismic vulnerability class of the building corresponding to the parameter P4 (wall-to-wall connections). Thus, the use of a strengthening solution that can improve the wall-to-wall connections and supposes an increase in the seismic vulnerability class from 4 to 1, leads to a quantifiable increase in the maximum capacity of the building (LS3) that can be easily calculated. This increase goes from $e^{(a-0.744)}$ up to $e^{(a-0.186)}$, where a represents the sum of the rest of the terms concerning the other variables and is kept constant, since the strengthening is only applied at the level of the wall-to-wall connections. Since $e^{(a+b)} = e^a \times e^b$, $e^{(-0.744)} = 0.475$ and $e^{(-0.186)} = 0.83$, upgrading the class of P4 from 4 to 1, will suppose a significant increase of LS3, by the order of 1.75 times $(0.83/0.475)$. This can be evaluated for every parameter. It also shows that the log transformation of the data adopted seemed to be enough for the multiple regression models to capture adequately the nonlinear relationships and interactions among the variables.

5. Validation of the regression models

The regression models proposed are based on numerical simulations and, sometimes, the accuracy of the regression models might be biased with the intrinsic limitations of the database used for their development, which certainly cannot cover all possible cases. That is why some numerical and experimental studies were gathered from the literature and their results are compared with the model predictions. They consist of six examples of the seismic assessment of different structures that could be associated to the vernacular heritage because of their geometric, construction techniques and material characteristics. The following studies were selected because they provide sufficient information about the buildings to perform the parameter survey and inform about the maximum capacity of the buildings. In this way, the results from the studies can be compared in a straightforward way with the results obtained when applying the regression expressions.

As an example of the process of validation followed, the first study consists of a detailed numerical study of the seismic safety analysis of a representative stone masonry structure typology from Lisbon, in Portugal [Mendes and Lourenço 2015]. The buildings belonging to this typology are commonly known as gaioleiro buildings. It represents an appropriate study because the building was studied by means of numerical modeling and pushover analysis, which were the analytical tools also applied for the development of the SAVVAS method. Additionally, the results of the maximum capacity of the building are given in terms of base shear coefficient or load factor, which is the same information that can be obtained after applying the regression equations. Thus, results can be directly compared. Table 5 presents the results obtained in terms of: (1) values adopted for each parameter, according to the attributes necessary to apply the regression models; (2) numerical or experimental seismic coefficient provided by the paper; and (3) the estimated load factor associated to LS3 obtained using two different regression models.

It should be highlighted that the regression models also allow to distinguish the seismic behavior of the building in the four principal directions (+/-X and +/-Y), which is not possible using other simplified formulations. Since the value of most parameters depends on the evaluated direction, assessing each resisting direction leads to different values of the maximum capacity. This is in agreement with the reviewed study, which revealed that the capacity of the building is very different in each principal direction (X and Y). This feature is well-captured by the SAVVAS regression models which shows a good correlation between the numerical seismic coefficient from the paper and the predicted load factor obtained from the method. The reviewed paper also included a parametric analysis that consists of varying the material properties of the masonry walls. The results of this parametric study were also correlated with the results obtained from the regression models modifying parameter P3, assuming varying material quality of the masonry walls. The change in the material properties is indicated in Table 5 with (+) when they were increased and with (-) when they were reduced. A very good correlation between the results from the paper and the predicted load factor can be highlighted. The method is thus able to simulate accurately the variations in the parametric analysis simply by increasing or decreasing one vulnerability class in P3. Both models (MR and ANN) provide a good accuracy with a maximum difference of 0.08g.

Another example consists of the validation of the regression models with the results of another experimental test conducted at the EUCENTRE research center in Pavia, Italy [Magenes et al. 2014]. The test campaign consisted on shaking table tests on two full-scale two-story unreinforced masonry buildings with timber floors. The first prototype was an unstrengthened reference prototype (URM) without seismic resistant detailing, while the second specimen introduced some reinforcement measures (RM). In this case, only the results of the experimental campaign are available, so the results of the method were compared with the maximum resisted base shear coefficient.

Even though detailed information about the construction of the two specimens is given in the paper, some of the qualitative parameters have to be assumed by the photos or by the descriptive qualitative information provided.

For example, for the URM building, the type of horizontal diaphragm is considered as class D. According to the plans shown in the paper, the beams are only connected to the walls by a partial embedment within the wall but there is no strengthened connection between the floor sheathing and the walls. This class was upgraded to class B for the RM buildings, since the strengthening interventions were destined to improve the wall-to-floor and wall-to-roof connections and to moderately improve the in-plane stiffness of the floor, aimed at preventing the occurrence of premature out-of-plane failure mechanisms. The undressed double-leaf stone masonry of the walls is considered as class B because of the assumed good workmanship at the laboratory. Also, the authors report that some damage took place on the RM building during the transportation phase, with observed cracks below 1 mm. Thus, a class B on the previous structural damage (P9) was adopted.

The regression models predict very accurately the maximum capacity of the building and capture very well the improvement in the seismic behavior when applying the strengthening intervention in the floors. Table 6 shows that the errors in the prediction of the multiple linear regression models are below 0.03g. Even though the uniaxial shaking table only imposed the base motion in +/- X direction, the performance of the building was evaluated in all directions, including +/-Y, because the regression models can estimate the weakest direction of the building. Thus, it is interesting to see how the method predicts that the unreinforced building, which is prone to out-of-plane collapse, is more vulnerable in Y direction while, after the intervention in the diaphragms, the building is more likely to fail in X direction. The method is thus able to show that reinforcing the diaphragms will have an effect in the failure mode of the building, leading to the development of in-plane resisting mechanisms. This change in the failure mode was also reported in the reviewed paper.

A third example consisted of the application of the regression models to a study conducted at EUCENTRE research center in Pavia, Italy, consisting of a unidirectional shaking table test of a full-scale unreinforced clay brick masonry building [Kallioras et al. 2018]. The study provides the results of the experimental campaign in terms of maximum accelerations measured in *g*, which were compared with the results obtained after the application of the regression models. The paper provided information about the base-shear coefficients (*BSC*) that led the building to reach different damage states, including: (a) the *BSC* corresponding to the onset of the first significant cracks, which can be correlated with the load factor related to the reaching of LS1; and (b) the maximum attained overall *BSC* for the building, which can be correlated with the load factor related to the reaching of LS3. Thus, the two regression models aimed at the estimation of the load factors associated with LS1 and LS3 could be used and the results compared with the ones observed experimentally, see Table 7. Results for all limit states show a good agreement between the predicted values with the multiple regression models and the experimentally obtained values, with minimum errors, validating the results obtained with the two regression expressions. Errors are slightly higher for the ANN models.

The remaining three case studies consists of: (1) an experimental campaign carried out on a two-story unreinforced stone masonry building that was tested on a shaking table test at the CNR-ENEA research center of Casaccia, in Rome, Italy [Betti et al. 2014]. The results of the experimental analysis were replicated with finite element modelling and pushover analysis. These numerical results were compared with the results obtained after the application of the regression equations from the SAVVAS method; (2) an experimental campaign carried out at the LEE/NTUA research center in Athens, Greece [Mouzakis et al. 2012], where two reduced scaled (1:2) two-story stone masonry buildings were tested on a bi-directional shaking table: one unstrengthened reference prototype (URM) and a second specimen with some reinforcement measures (RM). This study also just provides the results of the experimental campaign and thus the results obtained after the application of the regression models were compared with the values of maximum accelerations measured in *g* given by the paper; and (3) an experimental campaign of two-story unreinforced stone and brick masonry buildings tested on a shaking table by ISMES, in Bergamo, Italy and LEE/NTUA, in Athens, Greece [Benedetti et al. 1998]. The results obtained from the test on a stone masonry specimen (STM) and a brick specimen (BM) are provided in terms of maximum lateral force coefficients so they can be compared with the results provided after the application of the SAVVAS regression models.

As a summary, Table 8 provides the most relevant results obtained for the validation of the regression models. All the results correspond to the load factor associated with LS3 because it could be calculated in the six cases. The prediction capability of the models was considered validated, given the low errors obtained, particularly for the multiple regression models. The regression models are also able to detect the most vulnerable direction of the buildings and simulate well the effect of the reinforcing techniques.

6. SAVVAS formulation

The prediction capability of the regression models was considered validated with the examples available in the literature, given the low errors obtained, particularly for the multiple regression models. This confirmed also the potential of the method and, consequently, a final formulation for the SAVVAS method is proposed using the expressions for the three limit states shown in Equations (2), (3) and (4). Table 9 summarizes the process and provides the final formulation of the SAVVAS method. As observed during the validation process, the application of the method simply consists of three steps: (1) collection of the data related to the ten key seismic vulnerability assessment parameters, defined either by specifying different quantitative attributes or by assigning a seismic vulnerability class from 1 to 4; (2) application of the regression models expressions to determine the three different values of load factor defining each limit state (LS1, LS2 and LS3). With the obtainment of these values, it is possible to have an estimation of the seismic actions that can cause the building to reach the different structural limit states for each direction, expressed as an acceleration (in terms of g); and (3) estimation of the minimum load that will cause the building to reach the different limit states. Since this method allows calculating a different load factor in each main direction of the building, the load factor representing the global vulnerability of the building is defined as the minimum value obtained among the four resisting directions. Moreover, since the load factors related with the different structural damage limit states are expressed as accelerations, they can be used in a straightforward way to eventually correlate the seismic action in terms of peak ground acceleration (PGA) with the expected damage. Alternatively, as previously stated, when a more refined assessment is required, the site response spectra and the building fundamental period can be used to take into account specific accelerations adapted to each building and site.

7. Final considerations

The main objective of the present paper has been the presentation and validation of the numerical tool that constitute the core of a new method for the seismic vulnerability assessment of vernacular architecture, referred as Seismic Assessment of the Vulnerability of Vernacular Architecture Structures (SAVVAS). The method is intended to be an expedited simplified approach that provides the possibility of performing a primary seismic safety assessment of a vernacular building or group of buildings based on simple surveys that can be carried out even solely by means of visual inspection. These methods are particularly appropriate when addressing large number of buildings or when the necessary amount of resources required in order to perform more sophisticated analyses cannot be assigned to the assessment of the targeted buildings, which is generally the case when dealing with the study of vernacular constructions.

The SAVVAS method is considered innovative method because it provides a new formulation that allows defining the seismic capacity of the building through seismic load factors associated with different damage limit states using simple parameters and classes typically used in classical simplified seismic vulnerability index methods. Since these load factors expressed as accelerations (in terms of g) are related with structural damage limit states, the SAVVAS method is intended to directly correlate accelerations induced by the seismic event with the expected damage. For that matter, we can use as seismic input the peak ground acceleration (PGA) for a simplified assessment or we can use the site response spectra and the building natural frequency for a more detailed assessment that uses specific accelerations adapted to each building and site. This is one main advantage of the SAVVAS method over more classical seismic vulnerability index approaches. Vulnerability index formulations calculate a vulnerability index (I_v), which is just an intermediate step to estimate the damage suffered by a building under an earthquake of a specific intensity, because empirically developed expressions have to be later implemented to correlate I_v with damage. The vulnerability functions resulting from the SAVVAS method are able to directly relate the seismic accelerations with structural limit states and, subsequently, with expected damage. This correlation is necessary in order to perform damage and loss assessments.

Even though the parameters selection was done through a combination of empirical observation and expert judgment, this method is considered analytical in its development because it relies on a solid numerical parametric study. The influence of the different parameters was validated through detailed finite element modeling and pushover analysis. Results helped to obtain a comprehensive understanding of the seismic behavior of vernacular architecture and to provide a quantitative definition of seismic vulnerability classes. The use of an analytical procedure for the definition of the seismic vulnerability assessment classes helps to strengthen the reliability of the existing simplified methods that typically rely solely on empirical knowledge obtained from post-earthquake damage observation.

In a second step, data mining (DM) techniques were applied on the database resulting from the numerical campaign. The primary goal was to obtain regression models able to predict the load factors corresponding to different structural limit states using as predictors variables associated to the seismic vulnerability assessment parameters previously defined. Several multiple regression and ANN models were developed and proved to be reliable in their predictive capabilities. The development of the models also allowed a better understanding of the role of the seismic vulnerability parameters on defining the seismic response of vernacular buildings and helped to discover complex relationships among them. The regression models were validated with their application on numerical and experimental examples found in the literature, revealing a very good correlation between the predicted and observed seismic load factor. During this validation process, they were also confirmed to be useful in assessing the effect of some reinforcement techniques on the final seismic capacity of the building. Moreover, they also provide information about the capacity of the building in each main direction, which is another advantage of this method because it allows identifying the weakest direction and possible failure mechanisms. Thus, it can be of great help in identifying deficiencies of the structure before making decisions on strengthening interventions.

The robustness of the regression models is conditioned by the limitations and assumptions existing in nonlinear static analysis of masonry and earthen vernacular buildings. The results obtained when applying the regression expressions would simulate the results obtained as if we were performing a pushover analysis on a structure with such characteristics. The method is also conditioned by the size of the database which, even though is considered exhaustive, cannot comprehend the vast amount of possibilities observed in vernacular buildings. It should be here noted that, in any case, the database used can always be further enlarged with more results in order to make it more comprehensive. The SAVVAS formulation and procedure have been defined but the database remains open for future extension. Nonetheless, the results obtained with the current form are deemed satisfactory, since the models are able to provide a reliable first estimate of the seismic capacity of a building based solely on limited information related to the ten key seismic vulnerability parameters.

References

Aguilar V, Sandoval C, Adam JM, Garzón-Roca J, Valdebenito G (2016) Prediction of the shear strength of reinforced masonry walls using a large experimental database and artificial neural networks, Structure and Infrastructure Engineering 12 (12): 1661-1674

Angulo-Ibáñez Q, Mas-Tomás Á, Galvañ-Llopis V, Sántolaria-Montesinos JL (2012) Traditional braces of earth constructions. Constructions and Building Materials 30: 389-399

Barbat A, EERI M, Yépez Moya F, Canas JA (1996) Damage Scenarios Simulation for Seismic Risk Assessment in Urban Zones, Earthquake Spectra 12 (3): 371-394

Baykasoglu A, Güllü H, Çanakçi H, Özbakir L (2008) Prediction of compressive and tensile strength of limestone via genetic programming, Expert Systems with Applications 35: 111-123

Benedetti D, Petrini V (1984) Sulla Vulnerabilità Di Edifici in Muratura: Proposta Di Un Metodo Di Valutazione, L'industria delle Costruzioni 149 (1): 66-74

Benedetti D, Carydis P, Pezzoli P (1998) Shaking table tests on 24 simple masonry buildings, Earthquake Engineering and Structural Dynamics 27: 67-90

Betti M, Galano L, Vignoli A (2014) Comparative analysis on the seismic behaviour of unreinforced masonry buildings with flexible diaphragms, Engineering Structures 61: 195-208

Blondet M, Villa García GM, Brzev S, Rubiños A (2011) Earthquake-resistant construction of adobe buildings: a tutorial, Earthquake Engineering Research Institute (EERI), Oakland, California, USA

Bothara J, Brzev S (2012) A tutorial: improving the seismic performance of stone masonry buildings, Earthquake Engineering Research Institute (EERI), Oakland, California, USA

Boukri M, Bensaibi M (2008) Vulnerability Index of Algiers Masonry Buildings, in: Proc. of 14th World Conference on Earthquake Engineering, Beijing, China

Correia M (2002) A habitação vernácula rural no Alentejo, Portugal, in: Memorias del IV Seminario Iberoamericano sobre vivienda rural y calidad de vida en los asentamientos rurales, Santiago del Chile, Chile

Correia M (2007) Taipa no Alentejo, Argumentum, Lisboa, Portugal

Correia M (2017) Experiences from past for today’s challenges, in: The road to sustainable development. Chapter 6 – Traditional and generational change, La fábrica, Fundación Contemporánea, Madrid, Spain

Cortez P (2010) Data Mining with Neural Networks and Support Vector Machines Using the R/rminer Tool, in: Proc. of 10th Industrial Conference, ICDM 2010, Berlin, Germany

Degg MR, Homan J (2005) Earthquake vulnerability in the Middle East, Geography 90 (1): 54-66

EN 1998-3 (2005) Eurocode 8: Design of structures for earthquake resistance – Part 3: Assessment and retrofitting of buildings. CEN, Brussels, Belgium

Fayyad U, Piatetsky-Shapiro G, Smyth P (1996) From Data Mining to Knowledge Discovery in Databases, Al Magazine 17 (3): 37-54

Ferreira TM, Vicente R, Mendes da Silva JAR, Varum H, Costa A (2013) Seismic vulnerability assessment of historical urban centres: case study of the old city centre in Seixal, Portugal, Bulletin of Earthquake Engineering 11 (5): 1753-1773

Ferreira TM, Vicente R, Varum H (2014) Seismic vulnerability assessment of masonry facade walls: development, application and validation of a new scoring method, Structural Engineering and Mechanics 50 (4): 541-561

Field A, Miles J, Field Z (2012) Discovering Statistics Using R, SAGE Publising

Fritsch S, Günther F, Suling M, Müller S (2016) Package ‘neuralnet’, R manual

Gallego R, Arto I (2014) Evaluation of seismic behaviour of rammed earth structures, in: Mileto, Vegas, Soriano & Cristini (eds), Earthen architecture: past, present and future, Taylor & Francis Group, London, UK

Garzón-Roca J, Marco C, Adam JM (2013a) Compressive strength of masonry made of clay bricks and cement mortar: Estimation based on neural networks and fuzzy logic, Engineering Structures 48: 21-27

Garzón-Roca J, Adam JM, Sandoval C, Roca P (2013b) Estimation of the axial behavior of masonry walls based on artificial neural networks, Computers and Structures 125: 145-152

Gautam D, Prajapati J, Paterno KV, Bhetwal KK, Neupane P (2016) Disaster resilient vernacular housing technology in Nepal, Geoenvironmental Disasters 3 (1)

GNDT (1994) Scheda di esposizione e vulnerabilita ` e di rilevamento danni di primo livello e secondo livello (muratura e cemento armato), Gruppo Nazionale per la Difesa dai Terremoti (GNDT), Rome, Italy

Gomes MI, Lopes M, de Brito J (2011) Seismic resistance of earth construction in Portugal, Engineering Structures 33 (3): 932-941

Günther F, Fritsch S (2010) neuralnet: Training of Neural Networks, The R Journal 2 (1): 30-38

ICOMOS (1999) Charter on the built vernacular heritage, International Council of Monuments and Sites (ICOMOS), ICOMOS 12th General Assembly, Mexico

Kallioras S, Guerrini G, Tomassetti U, Marchesi B, Penna A, Graziotti F (2018) Experimental seismic performance of a full-scale unreinforced clay-masonry building with flexible timber diaphragms, Engineering Structures 161: 231-249

Karanikoloudis G, Lourenço PB (2018) Structural assessment and seismic vulnerability of earthen historic structures. Application of sophisticated numerical and simple analytical models, Engineering Structures 160: 488-509

Kottegodo N, Rosso R (2008) Applied Statistics for Civil and Environmental Engineers, Blackwell Publishing, New Jersey, USA

Lourenço PB (2009) Recent advances in masonry structures: micromodelling and homogenization, in: Galvanetto & Ferri Aliabadi (eds), Multiscale modeling in solid mechanics: computational approaches, pp. 280-300, Imperial College Press, London, UK

Lourenço PB, Mendes N, Ramos LF, Oliveira DV (2011) Analysis of masonry structures without box-behavior, International Journal of Architectural Heritage. Conservation, Analysis and Restoration 5 (4-5): 369-382

Lourenço PB, Karanikoloudis G, Mendes N, Corallo C (2015) Assessment of the South aisle in Canterbury, in: Proc. of the 2nd International conference on preservation, maintenance and rehabilition of historical buildings and structures, Porto, Portugal

Magenes G, Penna A, Senaldi IE, Rota M, Galasco A (2014) Shaking Table Test of a Strengthened Full-Scale Stone Masonry Building with Flexible Diaphragms, International Journal of Architectural Heritage. Conservation, Analysis and Restoration 8: 349-375

Mallardo V, Malvezzi R, Milani E, Milani G (2008) Seismic vulnerability of historical masonry buildings: a case study in Ferrara, Engineering Structures 30: 2223-2241

Marques R, Lourenço PB (2013) A model for pushover analysis of confined masonry structures: implementation and validation, Bulletin of Earthquake Engineering 11: 2133-2150

Martins F, Vasconcelos G, Miranda T (2014) The performance of ultrasonic pulse velocity on the prediction of tensile granite behaviour: a study based on artificial neural networks, in: Proc. of 9th International Masonry Conference, Guimarães, Portugal

Martins F, Vasconcelos G, Miranda T (2018) Prediction of the mechanical properties of granite under tension using DM techniques, Geomechanics and Engineering 15(1): 631-643

May J (2010) Handmade houses & other buildings: the world of vernacular architecture, Thames & Hudson, London, UK

Mendes N, Loureno PB (2010) Seismic assessment of masonry ‘Gaioleiro’ buildings in Lisbon, Portugal, Journal of Earthquake Engineering 14: 80-101

Mendes N, Lourenço PB (2015) Seismic vulnerability of existing masonry buildings: nonlinear parametric analysis, in: Psycharis, Pantazopoulou & Papadrakakis (eds), Seismic assessment, behavior and retrofit of heritage buildings and monuments. Computational methods in applied sciences, Vol. 37, Springer

McCune B, Graces J (2002) Analysis of Ecological Communities, MjM Software Design, Gleneden, USA

Miccoli L, Oliveira DV, Silva R, Müller U, Schueremans L (2014) Static behaviour of rammed earth: experimental testing and finite element modelling, Materials and Structures 48 (10): 3443-3456

Miranda T, Correia AG, Santos M, Ribeira e Sousa L, Cortez P (2011) New Models for Strength and Deformability Parameter Calculation in Rock Masses Using Data-Mining Techniques, International Journal of Geomechanics 11 (1): 44-58

Montgomery DC, Peck EA, Vining GG (2012) Introduction to linear regression analysis, John Wiley & Sons, Inc., New Jersey, USA

Mouyiannou A, Rota M, Penna A, Magenes G (2014) Identification of suitable limit states from nonlinear dynamic analyses of masonry structures, Journal of Earthquake Engineering 18 (2): 231-263

Mouzakis C, Vintzileou E, Adam CE, Karapitta L (2012) Dynamic tests on three leaf stone masonry building model before and after interventions, in: Proc. of Structural Analysis of Historical Constructions, SAHC 2012, Wroclaw, Poland

Neves F, Costa A, Vicente R, Oliveira CS, Varum H (2012) Seismic vulnerability assessment and characterization of the buildings on Faial Island, Azores, Bulletin of Earthquake Engineering 10 (1): 27-44

NTC (2008) Norme Tecniche per le Costruzioni. D.M. 14 gennaio 2008, S.O. No. 30, G.U. No. 29/2008, Rome, Italy

Oliver P (1997) Encyclopedia of vernacular architecture of the world, Cambridge University Press, Cambridge, UK

Ortega J, Vasconcelos G, Rodrigues H, Correia M (2018) Assessment of the efficiency of traditional earthquake resistant techniques for vernacular architecture, Engineering Structures 173

Ortega J (2018) Reduction of the seismic vulnerability of vernacular architecture with traditional strengthening solutions, Ph.D. thesis, University of Minho, Guimarães, Portugal

Plevris V, Asteris PG (2014) Modeling of masonry failure surface under biaxial compressive stress using neural networks, Construction and Building Materials 55: 447-461

R Development Core Team (2008) R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria

Rapoport A (1969) House, form and culture, Prentice-Hall, Englewoods Cliffs, USA

Rota M, Penna A, Magenes G (2010) A methodology for deriving analytical fragility curves for masonry buildings based on stochastic nonlinear analyses, Engineering Structures 32: 1312-1323

Rudofsky B (1964) Architecture without architects – a short introduction to non-pedigreed architecture, Museum of Modern Art, New York, USA

Saloustros S, Pelà L, Roca P, Portal J (2014) Numerical analysis of structural damage in the church of the Poblet Monastery, Engineering Failure Analysis 48: 41-61

Sandoval C, Roca P (2012) Study of the influence of different parameters on the buckling behaviour of masonry walls, Construction and Building Materials 35: 888-899

Shakya M (2014) Seismic vulnerability assessment of slender masonry structures, Ph.D. thesis, Universidade de Aveiro, Aveiro, Portugal

Sorrentino L, Liberatore L, Liberatore D, Masiani R (2013) The behaviour of vernacular buildings in the 2012 Emilia earthquakes, Bulletin of Earthquake Engineering 12(5): 2367-2382

Sepe V, Speranza E, Viskovic A (2008) A method for large-scale vulnerability assessment of historic towers, Journal of Structural Control and Health Monitoring 15: 389-415

TNO (2011) DIsplacement method ANAlyser. User's manual, release 9.4.4., Netherlands

Vicente R (2008) Estratégias e metodologias para intervenções de reabilitação urbana. Avaliação da vulnerabilidade e do risco sísmico do edificado da Baixa de Coimbra, Ph.D. thesis, Universidade do Aveiro, Aveiro, Portugal

Vicente R, Parodi S, Lagomarsino S, Varum H, Mendes da Silva JAR (2011) Seismic vulnerability and risk assessment: a case study of the historic city centre of Coimbra, Portugal, Bulletin of Earthquake Engineering 9 (4): 1067-1096

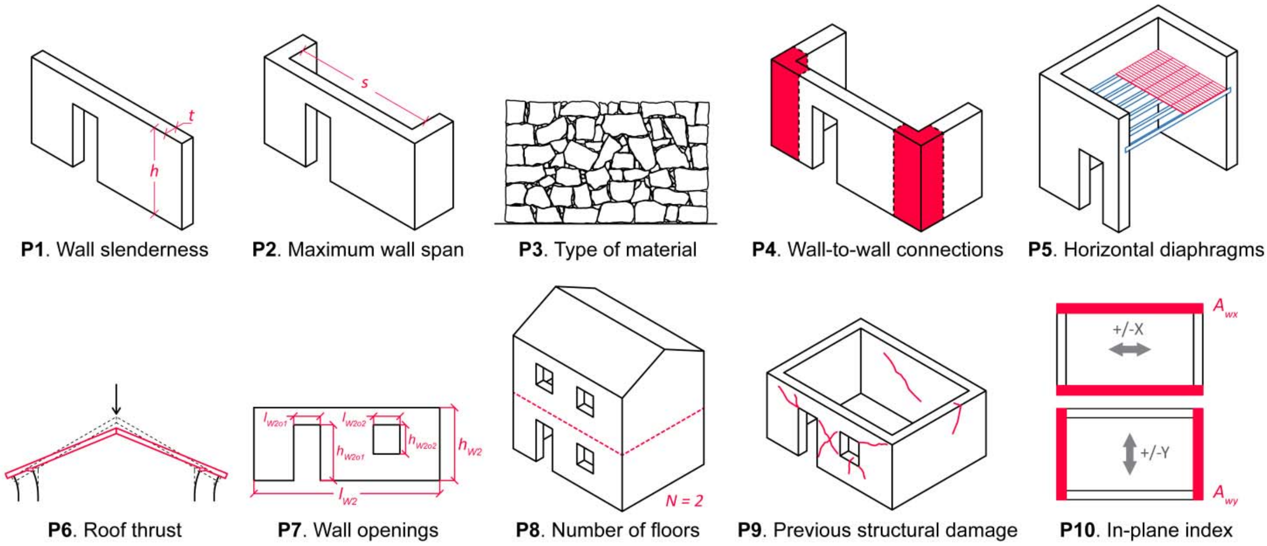

Figure 1. Seismic vulnerability assessment parameters considered for the SAVVAS method

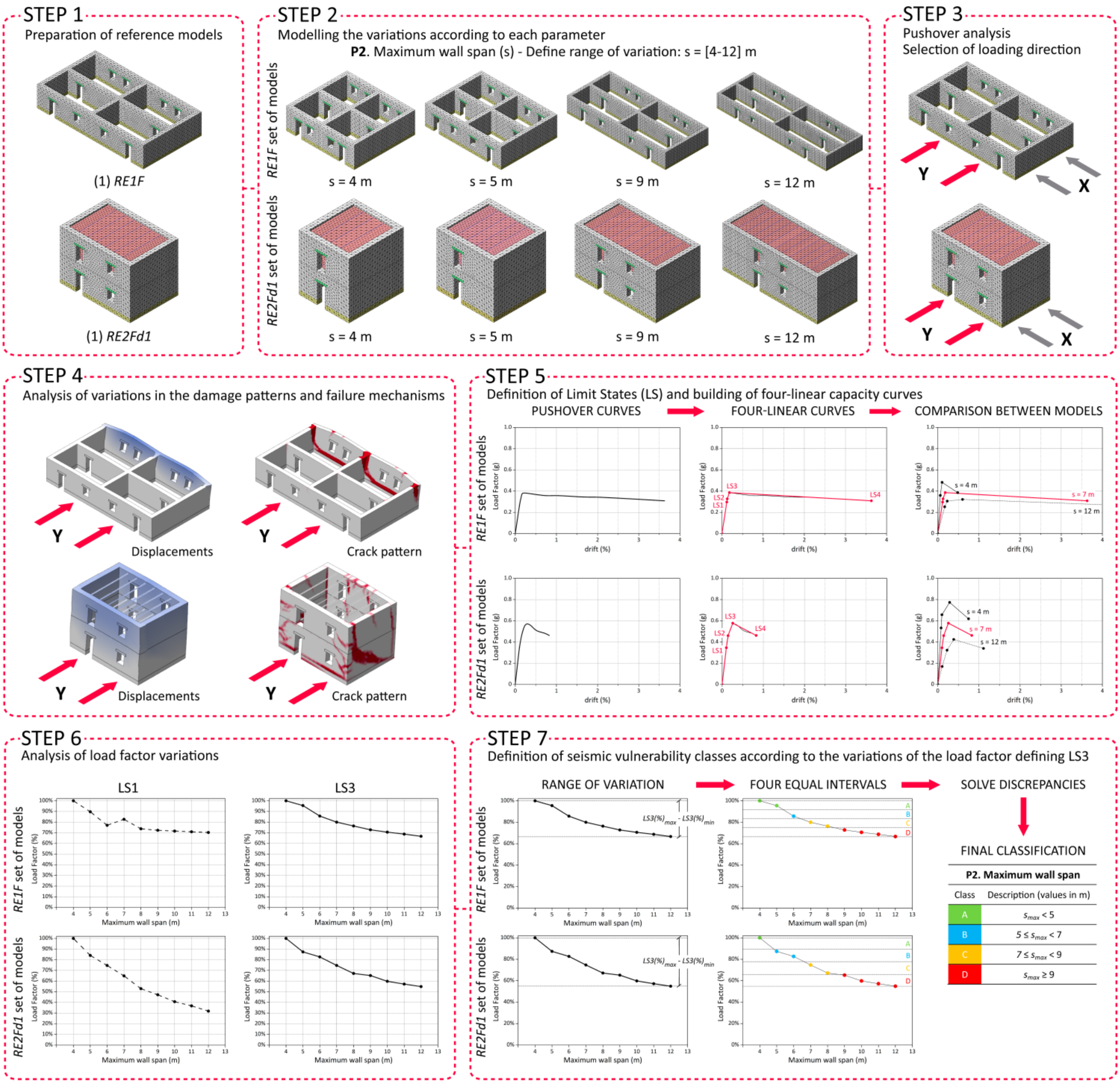

Figure 2. Seven steps followed for the definition of the seismic vulnerability classes using parameter P2 (maximum wall span) as an example

Figure 3. Examples of vernacular buildings targeted by the SAVVAS method in Portugal: (a) stone masonry buildings in Vila Real de Santo António historic city center; (b) adobe masonry rural construction in Alentejo [Correia 2002]; (c) rammed earth urban building in Serpa [Correia 2002]; (d) stone masonry buildings in Lagos historic city center; and (e) rammed earth rural construction in Alcácer do Sal [Correia 2007]

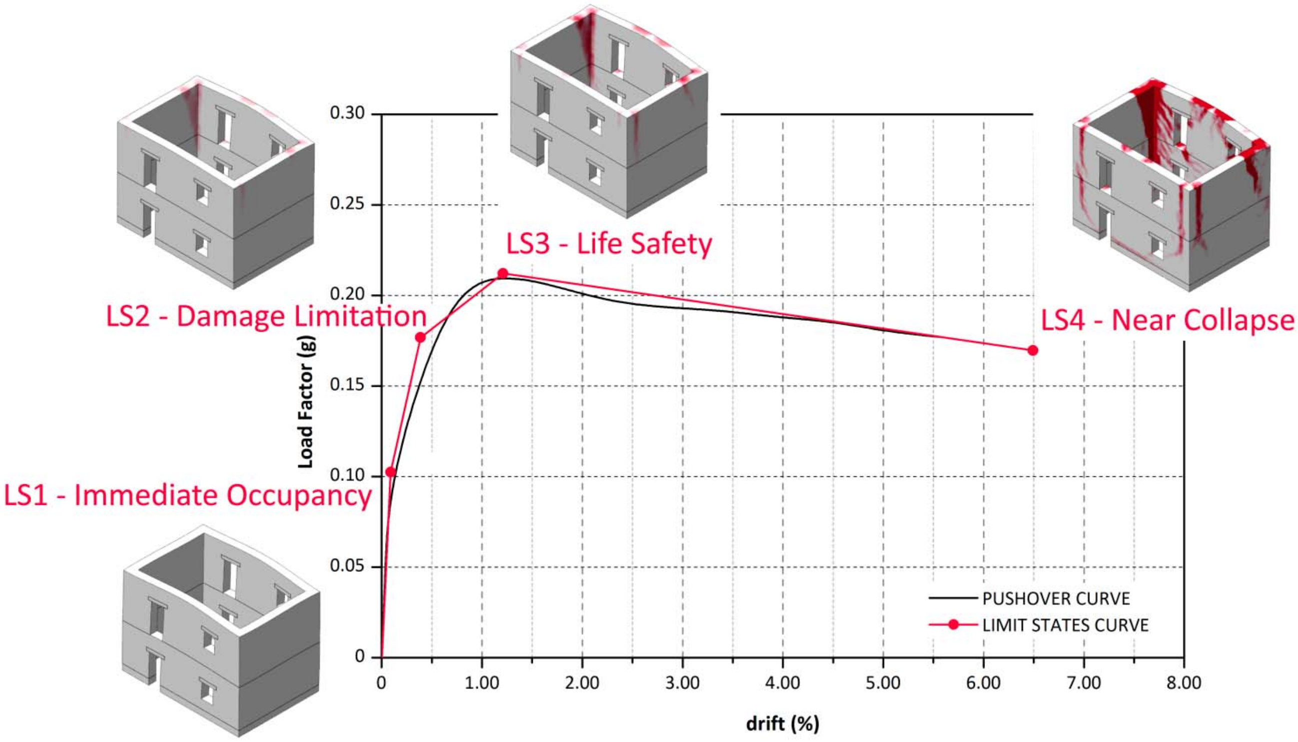

Figure 4. Definition of the four limit states according to the pushover curve

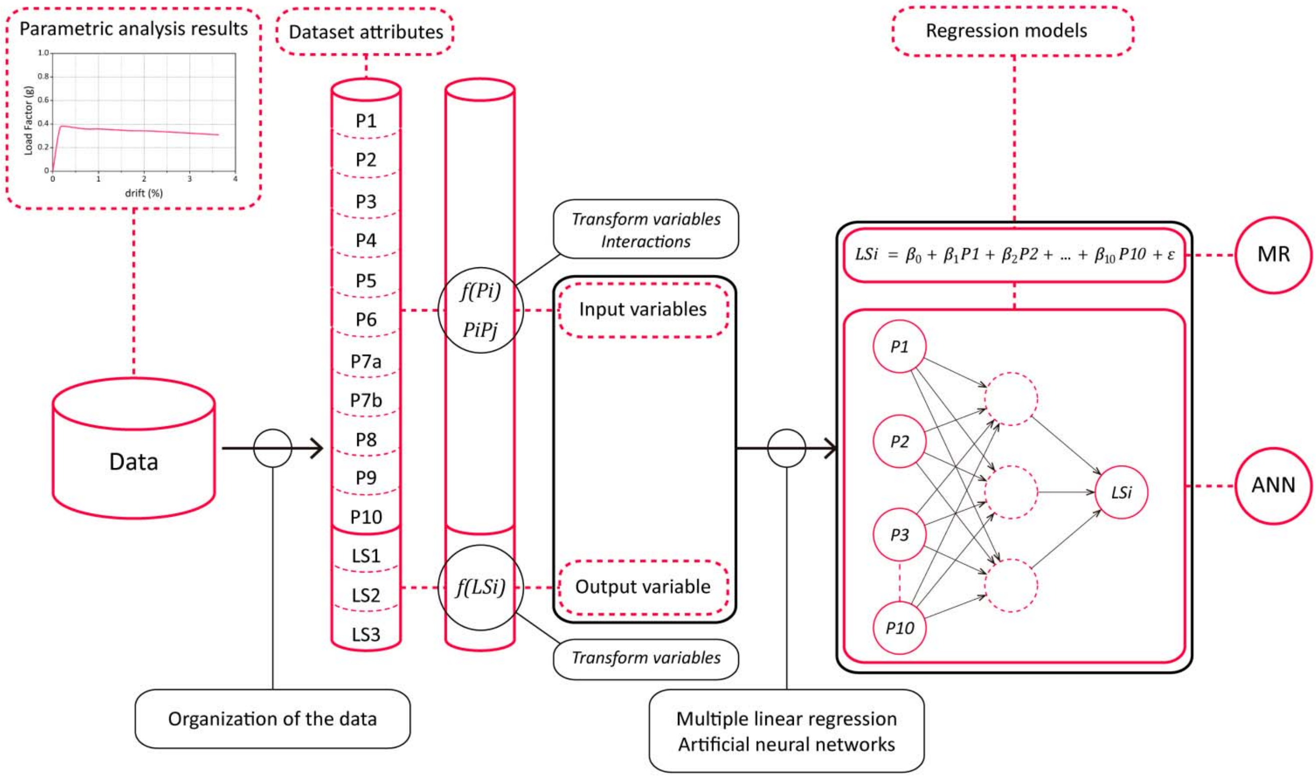

Figure 5. Methodology adopted **to obtain the regression models of** the SAVVAS method

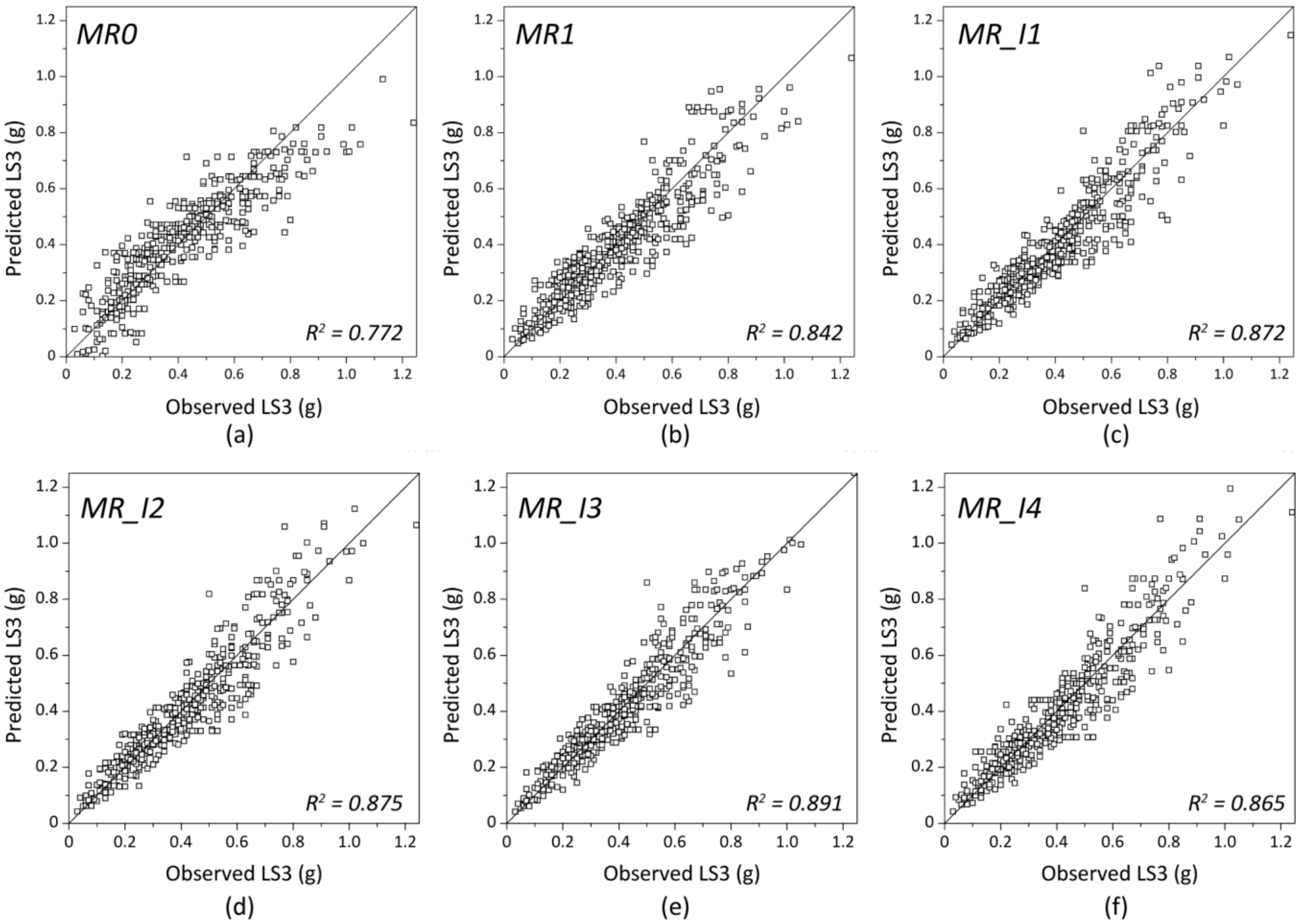

Figure 6. Comparison of predicted versus observed values for the six regression models constructed

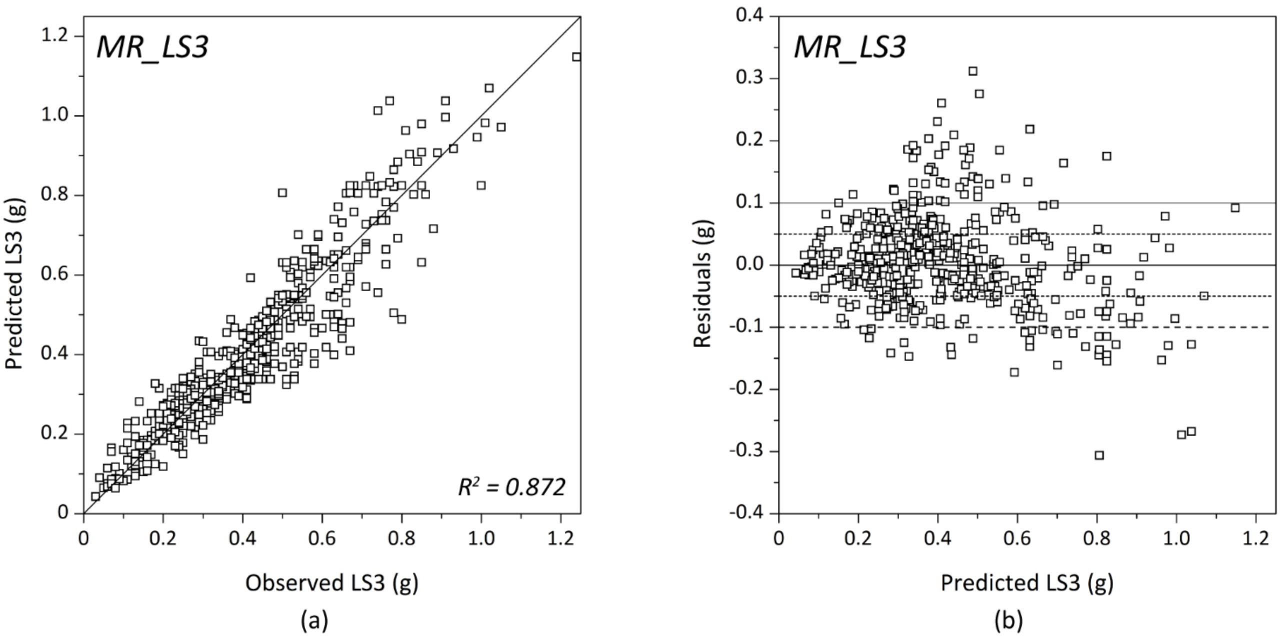

Figure 7. (a) Predicted versus observed values for the *MR_LS3* model; and (b) residual versus fitted values

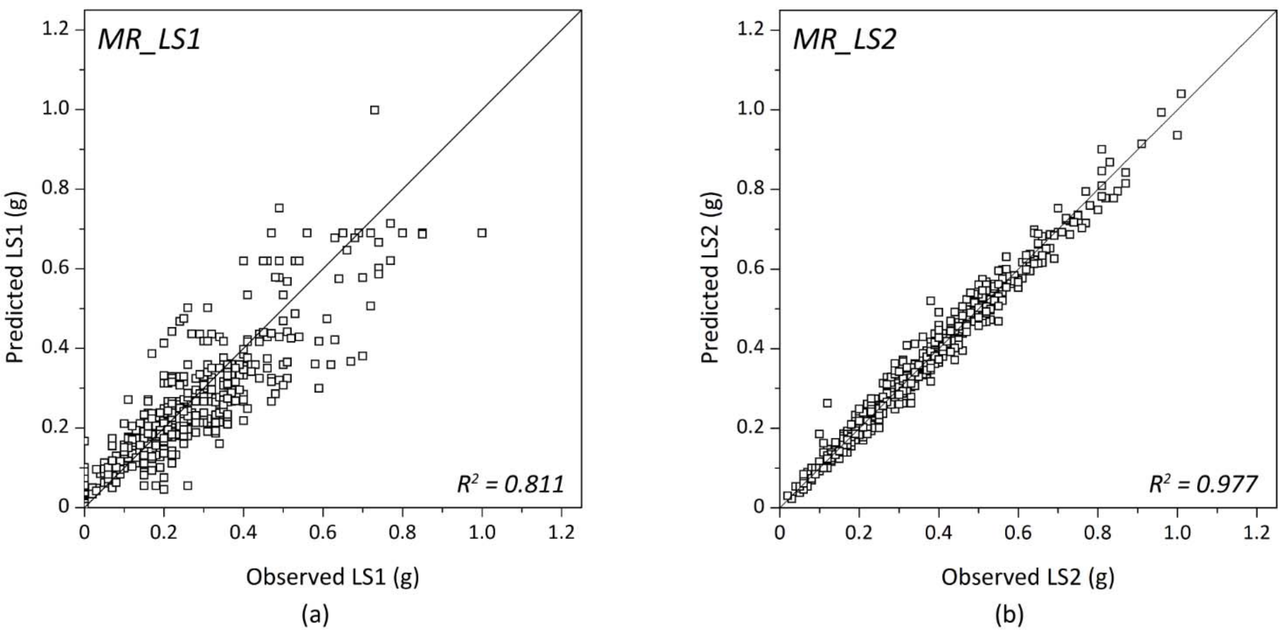

Figure 8. Predicted versus observed values for: (a) *MR_LS1* model; and (b) *MR_LS2* model

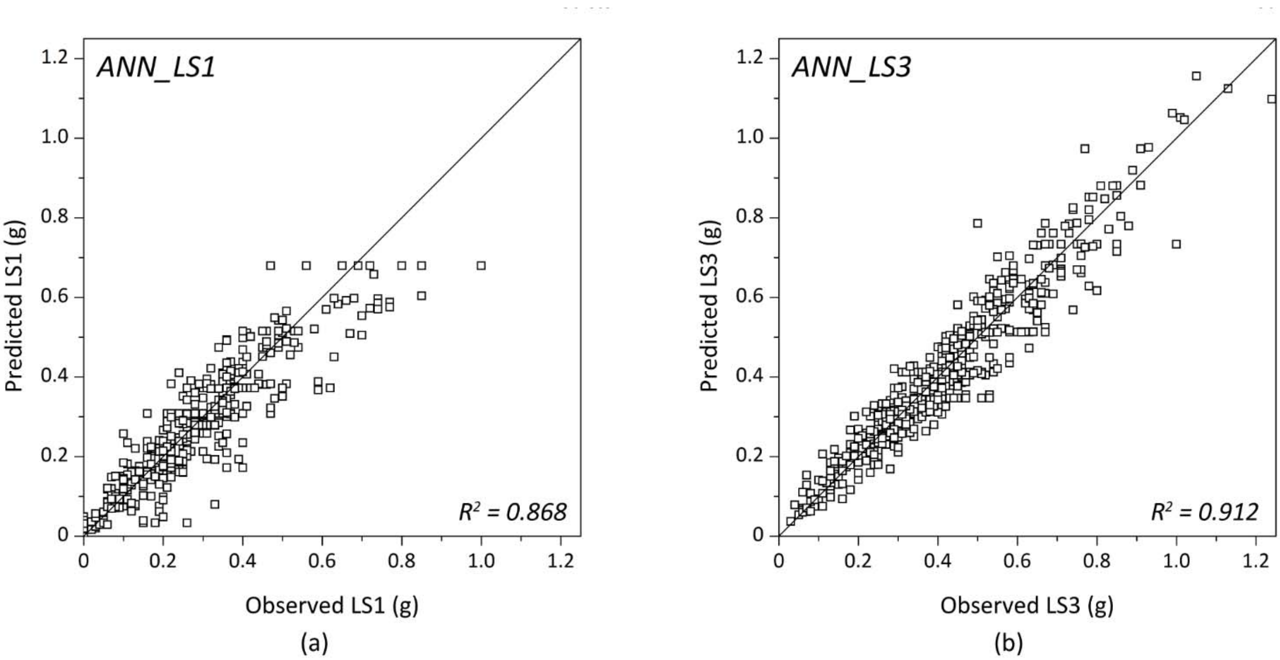

Figure 9. Predicted versus observed values for: (a) *ANN_LS1* model; and (b) *ANN_LS3* model

Table 1. List of variables and general statistical measures

	Variables		Description	Minimum	Maximum	Mean	Median	Mode	STD
Input	**P1**	λ	Ratio between the effective wall inter-story height (*h*) and its thickness	4	22.5	7.34	6	5.6	3.43
		$\lambda^{-1/2}$	Power transformation of the variable	0.21	0.50	0.39	0.41	0.42	0.06
	P2	*s*	Maximum wall span without intermediate supports, measured in meters (*m*)	2.5	12	5.90	5.25	7	1.87
		ln(s)	Log transformation of the variable	0.92	2.48	1.73	1.66	1.95	0.30
	P3	*P3*	Seismic vulnerability class of the building according to P3	1	4	3.36	4	4	1.04
		ln(P3)	Log transformation of the variable	0	1.39	1.14	1.39	1.39	0.44
	P4	*P4*	Seismic vulnerability class of the building according to P4	1	4	1.44	1	1	0.94
	P5	*P5*	Seismic vulnerability class of the building according to P5	1	4	2.71	3	4	1.38
		ln(P5)	Log transformation of the variable	0	1.39	0.82	1.10	1.39	0.64
	P6	*P6*	Seismic vulnerability class of the building according to P6	1	4	1.24	1	1	0.70
	P7	*P7a*	Ratio between the maximum area of wall openings in a wall perpendicular to the loading direction and the total area of the considered wall	0	0.7	0.09	0.06	0	0.16
		P7b	Ratio between the area of wall openings in all in-plane resisting walls and the total area of all in-plane resisting walls	0	0.69	0.12	0	0	0.18
	P8	*N*	Number of floors	1	4	1.87	2	1	0.89
		ln(N)	Log transformation of the variable	0	1.39	0.51	0.69	0	0.47
	P9	*P9*	Seismic vulnerability class of the building according to P9	1	4	1.29	1	1	0.77
		ln(P9)	Log transformation of the variable	0	1.39	0.15	0	0	0.39
	P10	γ_i	Ratio between the in-plan area of earthquake resistant walls in the loading direction and the total in-plan area of earthquake resistant walls	0.26	0.79	0.53	0.50	0.50	0.11
Output	**LS1 (*g*)**	*LS1(g)*	Load factor associated to LS1	0	1	0.24	0.23	0	0.18
		ln(LS1+c)	Log transformation of the variable	-4.61	0.01	-1.86	-1.43	-4.61	1.28
	LS2 (*g*)	*LS2(g)*	Load factor associated to LS2	0.02	1.01	0.36	0.35	0.38	0.19
		ln(LS2)	Log transformation of the variable	-3.91	0.01	-1.17	-1.05	-0.97	0.62
	LS3 (*g*)	*LS3(g)*	Load factor associated to LS3	0.03	1.24	0.42	0.41	0.41	0.21
		ln(LS3)	Log transformation of the variable	-3.51	0.22	-1.02	-0.89	-0.89	0.59

Table 2. Different regression models constructed with measurements of their performance

	Variables						
Model	**Output**	**Input**	**Interactions**	R^2	ε_{max}	**MAE**	**RMSE**
MR0	*LS3*	*P1; P2; P3; P4; P5; P6; P7; P8; P9; P10*	-	0.772	0.405g	0.075g	0.095g
MR1	*ln(LS3)*	λ; *s; P3; P4; P5; P6; P7a; P7b; N; P9;* γ_i	-	0.842	0.296g	0.064g	0.084g
MR_I1	*ln(LS3)*	λ; *s; P3; P4; P5; P6; P7a; P7b; N; P9;* γ_i	*P5:P7b*	0.872	0.318g	0.057g	0.078g
MR_I2	*ln(LS3)*	$\lambda^{-1/2}$; *ln(s); ln(P3); P4; P5; P6; P7a; P7b; ln(N); ln(P9);* γ_i	*P5:P7b* *P7b:ln(N)*	0.875	0.320g	0.056g	0.076g
MR_I3	*ln(LS3)*	$\lambda^{-1/2}$; *ln(s); ln(P3); P4; P5; ln(P5); P6; P7a; P7b; ln(N); ln(P9);* γ_i	*P5:P7b* *P7b:ln(N)* *ln(N):P10* *P5:P10* *P7b:P10*	0.891	0.345g	0.051g	0.069g
MR_14	*ln(LS3)*	$\lambda^{-1/2}$; *ln(P3); P4; P5; P7b; ln(N); ln(P9);* γ_i	*P5:P7b*	0.865	0.338g	0.057g	0.077g

Table 3. Characteristics of the regression models constructed for the definition of LS1 and LS2

Model	Variables		Interactions	R^2	ε_{max}	MAE	RMSE
	Output	Input					
MR_LS1	*ln(LS1+c)*	*λ; s; ln(P3); P4; P5; ln(P6); P7b; ln(N); ln(P9)*	*P5:P7b*	0.811	0.319g	0.057g	0.079g
MR_LS2	*ln(LS2)*	*LS1; LS3*	-	0.977	0.143g	0.022g	0.028g

Table 4. Characteristics of the ANN regression models constructed for the definition of LS1 and LS3

	Variables						
Model	**Output**	**Input**	**Interactions**	R^2	ε_{max}	**MAE**	**RMSE**
ANN_LS1	*ln(LS1+c)*	*λ; s; ln(P3); P4; P5; ln(P6); P7b; ln(N); ln(P9)*	-	0.868	0.321g	0.044g	0.066g
ANN_LS3	*ln(LS3)*	*λ; s; P3; P4; P5; P6; P7a; P7b; N; P9;* γ_i	-	0.912	0.286g	0.048g	0.062g

Table 5. Application of regression models to [Mendes and Lourenço 2015] and comparison of the results

												LS3(g)	
Model	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7a**	**P7b**	**P8**	**P9**	**P10**	**Literature**	**MR_LS3**	**ANN_LS3**
Y	7.06	12.45	**3**	2	1	1	0	0.33	4	1	0.46	0.10	0.12	0.14
X	7.06	9.45	**3**	2	1	1	0.33	0	4	1	0.59	0.46	0.38	0.42
Y (+)	7.06	12.45	**2**	2	1	1	0	0.33	4	1	0.46	0.15	0.16	0.17
X (+)	7.06	9.45	**2**	2	1	1	0.33	0	4	1	0.59	0.51	0.48	0.56
Y (-)	7.06	12.45	**4**	2	1	1	0	0.33	4	1	0.46	0.07	0.10	0.12
X (-)	7.06	9.45	**4**	2	1	1	0.33	0	4	1	0.59	0.29	0.30	0.31

Table 6. Application of regression models to [Magenes et al. 2014] and comparison of the results

												LS3(g)	
Model	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7a**	**P7b**	**P8**	**P9**	**P10**	**Literature**	**MR_LS3**	**ANN_LS3**
+Y (URM)	8.35	5.2	2	2	4	2	0.1	0.07	2	1	0.46	-	0.38	0.32
-Y (URM)	8.35	5.2	2	2	4	2	0.32	0.07	2	1	0.46	-	0.40	0.35
+X (URM)	8.35	3.75	2	2	4	1	0	0.22	2	1	0.61	0.43	0.41	0.36
-X (URM)	8.35	3.75	2	2	4	1	0.14	0.22	2	1	0.61	0.43	0.43	0.38
+Y (RM)	8.35	5.2	2	2	2	1	0.1	0.07	2	2	0.46	-	0.58	0.60
-Y (RM)	8.35	5.2	2	2	2	1	0.32	0.07	2	2	0.46	-	0.62	0.66
+X (RM)	8.35	3.75	2	2	2	1	0	0.22	2	2	0.61	0.54	0.51	0.58
-X (RM)	8.35	3.75	2	2	2	1	0.14	0.22	2	2	0.61	0.54	0.53	0.62

Table 7. Application of regression models to [Kallioras et al. 2018] and comparison of the results

												LS3(g)			LS1(g)	
Model	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7a**	**P7b**	**P8**	**P9**	**P10**	**Lit.**	**MR_LS3**	**ANN_LS3**	**Lit.**	**MR_LS1**	**ANN_LS1**
+Y	13	4.04	1	2	3	1	0.20	0.18	2	1	0.54	**0.54**	0.54	0.41	**0.39**	0.35	0.34
-Y	13	4.91	1	2	3	1	0.18	0.18	2	1	0.54	**0.54**	0.52	0.39	**0.39**	0.32	0.31

Table 8. Summary of the results obtained for the application of the regression models to all the cases studied

	LS3(g)												
	[Mendes and Lourenço 2015]		**[Magenes et al. 2014]**		**[Kallioras et al. 2018]**	**[Betti et al. 2014]**				**[Mouzakis et al. 2012]**		**[Benedetti et al. 1998]**	
	Y	**X**	**URM**	**RM**	**Y**	**+X**	**-X**	**+Y**	**-Y**	**URM**	**RM**	**STM**	**BM**
Literature	**0.10**	**0.46**	**0.43**	**0.54**	**0.54**	**0.27**	**0.29**	**0.29**	**0.29**	**0.48**	**0.88**	**0.19**	**0.3**
MR_LS3	0.12	0.38	0.43	0.53	0.54	0.23	0.23	0.27	0.28	0.52	1.01	0.20	0.29
ANN_LS3	0.14	0.42	0.38	0.62	0.41	0.26	0.25	0.30	0.31	0.42	0.83	0.20	0.29

Table 9. SAVVAS formulation and procedure

Step 1	**Definition of the seismic vulnerability assessment parameters**										
	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**		**P8**	**P9**	**P10**
	λ (h/t)	*s (m)*	*P3 [1-4]*	*P4 [1-4]*	*P5 [1-4]*	*P6 [1-4]*	*P7a*	*P7b*	*N*	*P9 [1-4]*	γ_i
Step 2	**Calculation of the load factors associated to the limit states in each main direction *i***										
	$\boldsymbol{LS1_i(g) = e^{(1.97-0.06\lambda-0.1s-0.68\ln(P3)-0.14P4-0.28P5-0.39\ln(P6)-3.43P7b-0.82\ln(N)-2.27\ln(P9)+0.63P5P7b)} - c}$										
	$\boldsymbol{LS2_i(g) = 0.16 \times LS1(g) + 0.78 \times LS3(g)}$										
	$\boldsymbol{LS3_i(g) = e^{(2.16-0.04\lambda-0.05s-0.24P3-0.16P4-0.28P5-0.08P6+0.3P7a-2.79P7b-0.37N-0.15P9+0.74\gamma_i+0.44P5P7b)}}$										
Step 3	**Calculation of the global load factors defining the limit states of the building**										
	$\boldsymbol{LS1(g) = \min(LS1_i(g))}$										
	$\boldsymbol{LS2(g) = \min(LS2_i(g))}$										
	$\boldsymbol{LS3(g) = \min(LS3_i(g))}$										