Propagation of Visual Inspection on Timber Members through Bayesian Methods

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ABSTRACT: In this work, the variation of bending stiffness parameters of existing timber elements is assessed by analysis of an existing database of empirical results and by using Bayesian inference methods. The framework of this study initially considers the analysis of existing results from visual inspection and bending tests made to chestnut timber elements including a statistical analysis of the significance of different visual grades within the same size scale. After, Bayesian Probabilistic Networks are used to analyze the distribution of defects and to infer on the visual grading of neighboring segments for predicting the mechanical properties of the element. Finally, the results of the inference process are implemented in a finite element model of random generated elements where the information given by visual inspection on a local level is propagated to the global scale. The comparison between the experimental results and the results obtained through this methodology provided low percentage errors (lower than 3%) given that a significant benchmark sample size was available.

1. INTRODUCTION

Timber constructions have an important significance in the cultural, architectural and historical heritage in all civilizations around the globe. The preservation of these constructions often goes through an initial visual inspection. However, due to the uncertainty of this method (Sousa *et al*. 2017) and sometimes due to information limited to only parts of the structure or elements, a reliable safety level assessment may be not possible. Nowadays, timber elements are usually modelled considering a strict separation between sections with defects and clear wood segments (Riberholt and Madsen, 1979; Fink and Köhler, 2011; Machado and Palma, 2011). However, the location of a weak section and its influence on the surrounding segments still needs to be further analyzed and discussed.

Aiming at the characterization of timber elements, hierarchical modelling is commonly used, where one of the main objectives is to understand how properties, composition and structure at lower scale levels may influence and be used to predict the material properties on a macroscopic and structural engineering scale. For that purpose, Bayesian Probabilistic Networks can be used, as they provide a simple and graphical mapping representation of the system properties and features, as they explicitly define the dependency among variables (Sousa *et al*., 2018).

In this work a combination of Bayesian Probabilistic Networks, with numerical modelling is proposed in order to propagate information of visual grading from a specific segment to the global scale of the element.

2. METHODOLOGY

2.1. Experimental campaign

Aiming at evaluating existing timber elements through tests on small specimens, twenty chestnut beams were taken from a construction site and tested in different size scales. The experimental methodology consisted in testing a full scale element, then continually cutting it into smaller specimens and retesting it. The final objective was to gather relevant correlations to predict the global mechanical properties of an element with information about small clear specimens and the distribution of defects along the element. Special interest was given in the determination of the modulus of elasticity (MOE) of the elements regarding 4-point bending tests, accordingly to EN 408 (2010), and to the visual inspection of the elements using UNI 11119 (2004).

The tested elements correspond to twenty old chestnut (*Castanea sativa* Mill.) beams retrieved from a construction site located in North Portugal. They served as structural floor beams and were supported, in both endings, by granite masonry walls. The building was constructed on the early XX century and the beams were removed and replaced due to remodelling works. The length of the elements varied between 4 m to 6 m. The floor consisted in a traditional structural solution with wooden boards connected to the top surface of the beams by iron nails.

The experimental campaign was composed by three main phases, regarding the size scale of the elements. The order of testing and sample origin is shown in Figure 1. The first phase considered the old beams in the same state of conservation as they were in the construction site, thus only visual inspection was made. Afterwards, in the second phase the beams were cut to $7\times15\times300$ cm^3 samples. The beams were marked on 7 segments of 40 cm and the defects found in each segment were accounted. Then 4-point bending tests, within the elastic range, were made to each beam, obtaining the global modulus of elasticity in bending ($E_{m,g}$). After the bending tests, in phase 3 the beams were sawn into 3 boards with $7\times4\times300$ cm^3. Each board was then visually inspected on each 40 cm segment. To each segment of each board a 4-point bending test was made in order to assess the variation of MOE along the element's length.

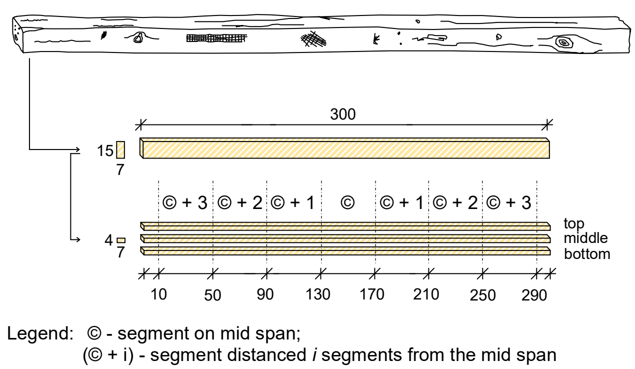


Figure 1: Experimental campaign phases, adapted from Sousa et al. (2016). Measurements in cm.

This work will analyze the results obtained in phases 2 and 3 of the experimental, and especial attention will be given to the mid span segment (identified as ©) from where the prior information will be considered from. Further detail on the full experimental campaign results may be found in Sousa *et al.* (2016), where it was found that for bending MOE, strong correlations within the same size scale (coefficient of determination r^2 from 0.82 to 0.89) and moderate to high correlations for different phases (r^2 from 0.68 to 0.71) could be obtained.

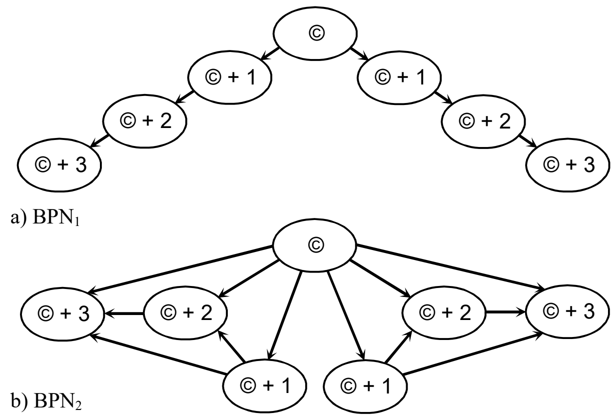
In Sousa *et al*. (2014), the use of visual grading combined with bending MOE results in smaller size scale specimens (sawn boards' segments) was considered as prior information for prediction models of $E_{m,g}$ of structural size members (sawn beams). These models, by use of random sampling selection, predicted the behaviour of full size scale elements accurately, with strong correlations to the experimental results (r^2 from 0.70 to 0.79).

2.2. Bayesian Probabilistic Networks

Bayesian Probabilistic Networks (BPN) are used to represent knowledge based on Bayesian regression analysis describing the causal interrelationships and the logical arrangement of the network variables. BPNs are represented by directed acyclic graphs (DAG), composed by a set of nodes, representing each system variable, connected by a set of directed edges, linking the variables according to their dependency or cause-effect relationship. Each variable node represents a random variable, either defined as a continuous random variable or as a finite set of mutually exclusive discrete intervals.

The main objective of a BPN is to calculate the distribution probabilities regarding a certain target variable, by considering the factorization of the variables' joint distribution based on the conditional relations within the developed generic algorithm. In this light, the DAG is the qualitative part of a BN, whereas the conditional probability functions serve as the quantitative part.

In this work, BPNs were developed in order to propagate information from the visual grading of a segment to the neighboring segments, as to obtain a global result from local assessment of a critical segment. To that aim, visual grading is propagated from segment to segment and each of those segments are attributed a corresponding MOE. The database to define the conditional probabilities is based on the results on the sawn board scale (Phase 3) and the consequent results will be compared to the numerical modelling of elements with scale equal to the sawn beams (Phase 2). The proposed networks are presented in Figure 2.



Legend: © - segment on mid span;
(© + i) - segment distanced *i* segments from the mid span

Figure 2: Directed acyclic graphs of the proposed Bayesian Probabilistic Networks: a) BPN_1; b) BPN_2

For both the proposed BPNs, it was intended to define the prior information only to the mid span segment which commonly corresponds to the critical segment on a single supported beam). The states of each node correspond to the visual grades given in UNI 11119 (2004), thus class I, II, III and non-classifiable (NC).

The first BPN (BPN_1) represents how information from consecutive segments can be propagated individually. This means that an imposed evidence will only influence the conditional probabilities for the segment located just aside to the segment with known information. On the other hand, the second proposed BPN (BPN_2) allows to propagate information for all the segments of the full scale element, independently of the distance to the segment with a given evidence. In this case, the probability of each state corresponds to the joint conditional probability of all segments in between the mid spam segment and the segment in analysis.

2.3. Numerical model

The information obtained in the BPNs regarding the probability of having a certain visual grade for a segment and its correspondent value of MOE was implemented in a numerical model. The model consists on the reconstruction of a full size scale beam (geometry according to Phase 2) by joining the different segments obtained in the sawn board scale (Phase 3).

A finite element model was created using volume elements to define each of the segments of the beam. The model was constructed using simple general purpose hexahedral elements with reduced integration to avoid locking problems. A refined mesh was considered in order to minimize the effect of the low number of integration points by element.

According to the results of the BPNs the value of MOE was given to each of the segments of the beam. To that purpose, Monte Carlo simulation was used to create random values of MOE assuming the probability of each state. For each segment 1000 simulations were made, thus 7000 simulations were considered for the attribution of the MOE along the 7 segments of each beam. The Monte Carlo simulation was made assuming that the variables (MOE for each visual class) were modelled by a lognormal distribution with mean and variance based on the experimental results database of Phase 3 (results from the segments of the sawn boards).

3. RESULTS

3.1. Experimental campaign

According to the visual grading rules, an element is classified as the lowest grade found in the critical segments of that element. The sample of results for the bending tests were divided into visual classes, as to verify the difference that may be found between segments of those different visual classes. The results are given in Table 1.

However, it must be noted that an element may be graded with a low grade (III or NC) due to a localized defect, even if the remaining element is clear of defects (graded I). In order to take into account these situations, Figure 3 presents the percentage distribution of visual grades by each element. Moreover, Table 2 provides the values of MOE for beams divided by the visual grading of the mid span segment.

In order to discern if the measurements made to obtain the MOE in bending vary significantly when considering different scales (from phase 2 to 3) or when considering segments with different visual classes (in phase 3), an ANOVA was made. This analysis is made since it is important to verify if the mechanical properties of each segment can be significantly divided according to their visual grade.

Table 1: Values of MOE for different scales and for each visual class.

Scale	*Visual grade*	*Mean (N/mm^2)*	*CoV (%)*	*Sample size*
Global Beam	*all*	*10940*	*22.0*	*20*
	I	*--*	*--*	*0*
	II	*12630*	*21.3*	*5*
	III	*11380*	*35.4*	*2*
	NC	*10220*	*18.7*	*13*
Board segment	*all*	*11600*	*22.8*	*336*
	I	*12580*	*17.6*	*211*
	II	*11250*	*18.8*	*56*
	III	*10030*	*24.7*	*35*
	NC	*8210*	*30.1*	*34*

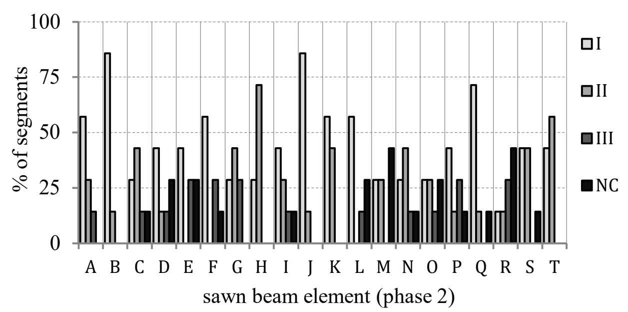


Figure 3: Percentage distribution of segments for each visual grade, adapted from Sousa et al. (2012) .

Table 2: Values of MOE for beams divided by the visual grading of the mid span segment.

Scale	*Visual grade*	*Mean (N/mm^2)*	*CoV (%)*	*Sample size*
Beam mid span	*all*	*10940*	*22.0*	*20*
	I	*11440*	*22.7*	*10*
	II	*10930*	*13.1*	*6*
	III	*14230*	*--*	*1*
	NC	*8210*	*16.5*	*3*

An analysis of variance, usually known as ANOVA, tests the effect of interest on a response variable of interest by analyzing how much of the total variation in the response can be explained by the effect (Doncaster, 2007). ANOVA is based in a hypothesis test where the null hypothesis is taken when the mean (average value of the dependent variable) is the same for all groups. The alternative hypothesis is that the means are not the same for all groups and therefore a significant variance is found. The ANOVA method produces an F-statistic, which is used to calculate the *p-value*. The obtained value of F is the ratio of how different the means are relative to the variability within each sample, the larger its value the greater the likelihood that the differences between groups are not relative to random error. The F ratio is then compared to a limit value F_{crit} that when exceeded indicates a significant variation. The *p-value* is the probability that the variation between conditions may have occurred by chance, so samples with smaller *p-value* are varying more significantly. Often a confidence level of 95% is used, which leads to a limit for *p-value* of 0.05, thus if *p-value* < 0.05 the null hypothesis is rejected indicating that the mean of the dependent variable is not the same for all groups.

A single-factor ANOVA with confidence level of 95% was made to $E_{\text{m,g}}$ considering the scale (sawn beam or board) as independent variable and the results corresponded to a non-significant variance in stiffness between the different scales, which indicates that the value of $E_{\text{m,g}}$ may be taken from either phase's mean value.

On the other hand, to assess the effect of visual classification in stiffness, a sample of each visual strength class is picked randomly from within the population of interest (test results of the chestnut elements). These samples serve as the replicate sampling units in each of the four levels (classes I, II, III and NC) of the visual grading, thus these levels are defined as independent variables within this analysis. The ANOVA on these samples of independent and random replicates will indicate a significant effect of visual grading if the average difference in stiffness between levels is large compared to the variation within each sample. In this case, for $E_{\text{m,g}}$, a single-factor ANOVA and a confidence level of 95% revealed a significant variance in stiffness means between the different considered visual strength classes, as $F > F_{\text{crit}}$ (40.53 > 2.63) and *p-value* < 0.05 ($2.47 \times 10^{-22} < 0.05$). The existence of a significant variance evidences that the means of the MOE of segments classified in different visual classes in fact differ between then, thus the sub-samples may be considered to have different origins. A significant variance, in this case, may also be indicative that the visual inspection allowed to differentiate between segments with different MOE. However, ANOVA only indicates a significant variance within the four levels of visual inspection, without indicating if a particular level presents a mean significantly different from another. In order to assess the statistical difference between MOE means in different visual classes, the classes were analyzed individually to each other (Table 3).

Table 3: Single-factor ANOVA results for MOE given the analysis of different visual classes.

Classes	*F*	F_{crit}	*p-value*
I - II	*16.332*	*3.877*	6.97×10^{-5}
II - III	*6.207*	*3.948*	*0.015*
III - NC	*6.771*	*3.986*	*0.011*
I - III	*38.352*	*3.880*	2.49×10^{-9}
II - NC	*30.429*	*3.951*	3.51×10^{-7}
I - NC	*95.438*	*3.880*	3.23×10^{-19}

The number of analysis is given by a combination without repetition, obtaining six possible combinations. Three correspond to combinations where two consecutive visual classes are considered (I-II, II-III and III-NC), and the remaining correspond to combinations of alternate visual classes (I-III, II-NC and I-NC). A significant variance is found between all combinations, thus revealing that the separation between visual classes reveals different groups of MOE results. A more significant variance in the means is found when considering the higher classes (combination I-II), whereas the difference for the lower classes, namely classes III and NC is less defined. In both cases it is visible that the alternate combinations lead to higher variation within the means, as it could be expected. The F value for combinations distanced by one intermediate class (I-III and II-NC) was similar, while for the combination where the two extreme classes are considered (I-NC) reveals the most significant variance.

3.2. Bayesian Probabilistic Networks

The results of the BPNs are presented in Figure 4 regarding BPN_1 and in Figure 5 regarding BPN_2. In both cases the results are given if no information is provided or if information, about the visual grade, is known for the mid span segment. This information is given by imposing an evidence on a state of that node, thus the probability of that node becomes 100%.

As expected, having a prior information on the mid span element in the case of BPN_1 only produced significant changes for the segments immediately located after (or before) that segment (segments © + 1), whereas no significant change regards the more distant segments. On the other hand, BPN_2 evidences significant changes even for the more distant segments (segments © + 2 and © + 3). This happens because all nodes of that BPN are connected to node © and to each of the previous segments, therefore the joint probability of each node comes conditioned by the information obtained on each of the previous nodes. It is worth noting that the results presented for BPN_2 are only considering prior information on node ©, but if new information would become available (e.g. evidence in nodes © + 1, © + 2, and/or © + 3), it would be possible to update that information into the network and propagate that information among all other nodes.

From analysis of Figure 5 it is noticeable that when the mid spam element decreases in visual grading (from I to NC) the probability of finding also lower grades increases even for segments not directly in contact with the mid spam segment, such as © + 2 and © + 3. Also is noted that the probability of finding a given grade is higher when the neighboring segments have that same grade, evidencing that, even if defects (e.g. knots) are a local irregularity, there is a correlation between segments' grading.

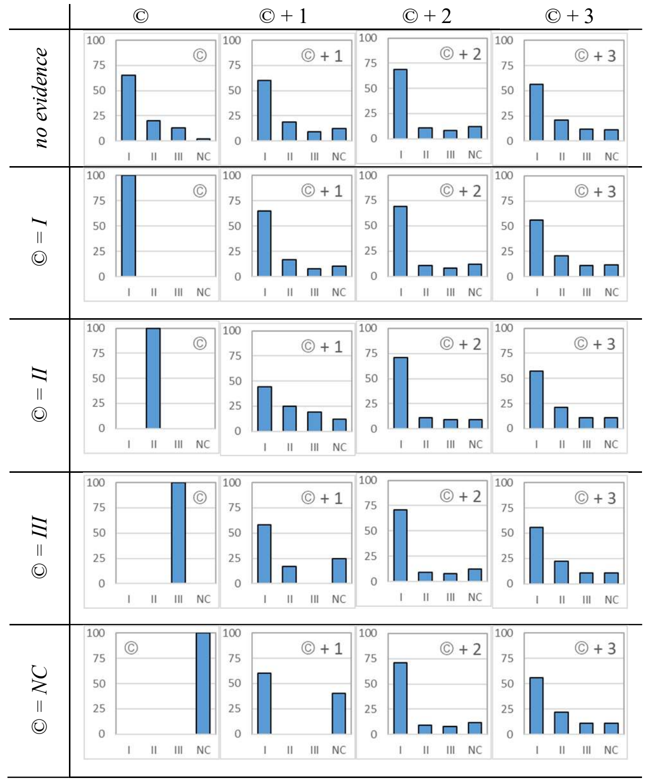


Figure 4: Results of BPN_1 with different evidences in node © (mid span segment).

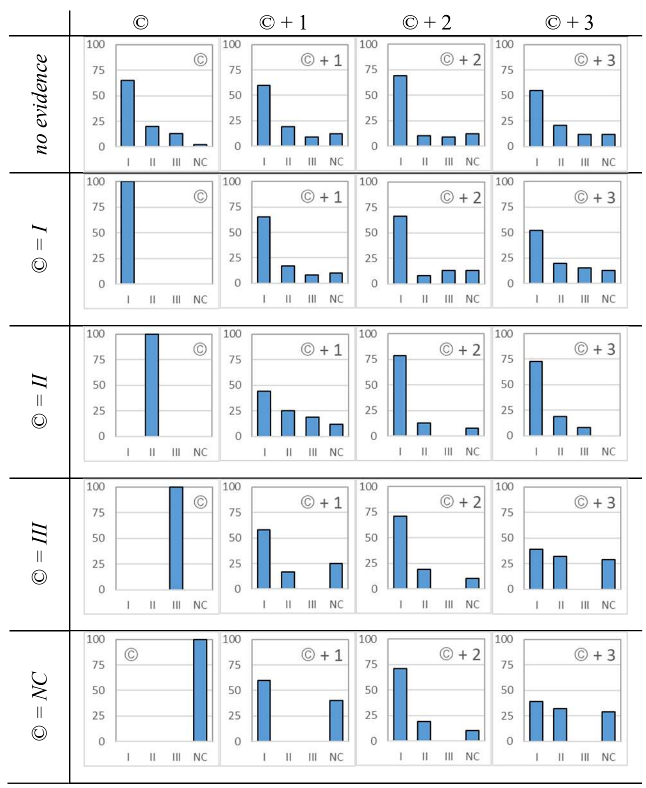


Figure 5: Results of BPN_2 with different evidences in node © (mid span segment).

3.3. Numerical model

The finite element model was made in order to simulate the tests made to obtain the MOE of each beam. Therefore, the geometry of the sample, load and support locations were equivalent to the test layout proposed in EN 408 (2010), with a 4-point bending configuration. Two load points were located at one third of the span distanced from each one of the supports. The random attribution of $E_{m,g}$ for each localized segment was made automatically by Monte Carlo simulation accounting the location of the segment (distance to the segment ©) and the distribution of conditional probabilities for each node (corresponding to a segment) of the proposed BPNs. For each segment, and a given evidence scenario, 1000 simulations were made to obtain a value of MOE.

Following in Figure 6 and Table 4, the results regarding the validation of BPN_2 are presented, for five evidence scenarios corresponding to: *i)* no evidence; *ii)* © = I; *iii)* © = II; *iv)* © = III; and *v)* © = NC. From the results it is found that the combination of BPN_2 and the numerical modelling allowed to obtain small prediction errors (below 3%) in almost all cases. The exceptions are for the cases where the sample size related to the number of tests is low (less than 5 specimens) being especially noted for the case where the comparison was made with only 1 specimen (mid span grade = III).

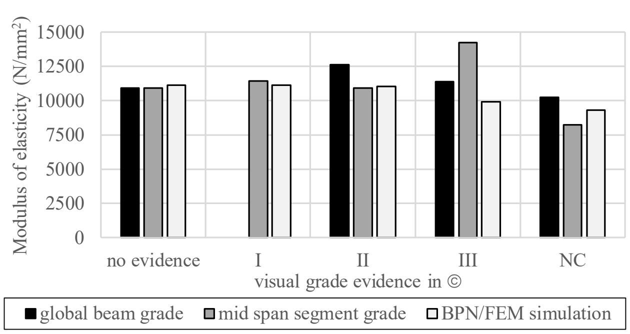


Figure 6: Numerical model MOE results with different evidence scenarios and comparison to the MOE by global visual grading of beams or by visual grade of the mid span segment..

Table 4: Percentage error between the numerical model MOE results and different grading scenarios (global element or mid span segment grading).

Evidence	*Mean (N/mm^2)*	*CoV (%)*	*[% error]*	
			global beam	*beam mid span*
No evidence	*11120*	*13.1*	*1.7*	*1.7*
© = I	*11110*	*12.0*	*--*	*2.9*
© = II	*11050*	*14.4*	*12.0*	*1.1*
© = III	*9940*	*16.0*	*2.9*	*30.2*
© = NC	*9310*	*19.6*	*2.8*	*13.4*

4. DISCUSSION OF RESULTS

The results of the experimental campaign and the ANOVA indicate that visual inspection proved to be efficient in qualitatively define the different classes of stiffness for the chestnut members in study. Moreover, a more significant variance in the means is found when considering the higher visual classes (combination I-II), whereas the difference for the lower classes, namely classes III and NC, is less defined evidencing that when a larger concentration of defects is found the difference between grades decreases.

Regarding the proposed BPNs it was verified that the conditional probabilities between visual grades of different segments allowed to propagate the information from a local segment to the global element.

Verification of the BPN results was made through numerical modelling of the full scale beams and low percentage errors were found when a significant benchmark sample size was available for comparison. This evidences the possibility of use of this method for the case of onsite visual inspections where information is made available only to critical sections.

Although, this work focused on the example of providing only information for a segment, the BPNs can be further used and updated if new information is available. However, since the percentage errors were low, it was found that providing further information was not needed for a normal assessment analysis.

5. CONCLUSIONS

This work presented the implementation of Bayesian Probabilistic Networks combined with numerical modelling in order to propagate the information of visual inspection from a specific segment of a timber element to the full size scale.

The comparison between the experimental results and the results obtained through this methodology provided low percentage errors given that a significant benchmark sample size was available.

This methodology may be applied for the case of onsite visual inspections where information is made available only to critical sections. However, it must be noted that further verification and calibration is needed when a different sample is addressed (e.g. other wood species and or different levels of wood conservation/decay) and further work should deal with a larger sample of beams in order to obtain representative benchmark values.

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