

Article

Numerical Methods for Topological Optimization of Wooden Structural Elements

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Abstract: Timber represents a building material that aligns with the environmental demands on the impact of the construction sector on climate change. The most common engineering solution for modern timber buildings with large spans is glued laminate timber (glulam). This project proposes a tool for a topological optimized geometry generator of structural elements made of glulam that can be used for building a database of topologically optimized glulam beams. In turn, this can be further used to train machine learning models that can embed the topologically optimized geometry and structural behavior information. Topological optimization tasks usually require a large number of iterations in order to reach the design goals. Therefore, embedding this information into machine learning models for structural elements belonging to the same topological groups will result in a faster design process since certain aspects regarding structural behavior such as strength and stiffness can be quickly estimated using Artificial Intelligence techniques. Topologically optimized geometry propositions could be obtained by employing generative machine learning model techniques which can propose geometries that are closer to the topologically optimized results using FEM and as such present a starting point for the design analysis in a reduced amount of time.

Keywords: glulam; topological optimization; finite element method; machine learning; artificial neural network

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1. Introduction

The construction industry contributes to approximately 40–50% of greenhouse gas emissions. This figure includes both the energy consumed during building operations on site and the energy used in the manufacturing of construction materials and products. Two main strategies have been thoroughly investigated to mitigate the environmental impact of building elements: structural optimization by minimizing the elements' section and the use of low-carbon materials [1–4]. This is the reason why wood and wood products such as glued laminated timber are valued and have gained success as a construction material nowadays.

Glued laminated timber, known as “glulam” or GLT, is a composite material made of overlapping layers of wood bonded with synthetic resins and pressed into the desired shape. This type of product is one of the most popular options in civil engineering—while the ability to absorb carbon from the environment makes it a sustainable material. Additionally, the good mechanical properties of the material along with its low self-weight make it a great seismic performance solution [5,6].

The production of GLT elements represents a major advantage in terms of reducing workmanship on site, through the quality of the machined elements and the obtaining of

complex geometries with various sizes that can be customized to meet individual specifications and requirements. The design and execution of civil structures is, however, still dependent on inertia in terms of the geometric dimensioning of structures, which favors constant rectangular sections, easy to size.

Another significant advantage of wood is its strength-to-weight ratio when compared to materials like concrete and steel, making it an excellent choice [1]. Reducing the weight of the element diminishes the dead loads along with the size of elements in the structure.

Recent studies have shown that topological optimization can lead to better dimensions of the element able to support the forces applied. According to existing studies in the field, the characteristics of the model resulting from different types of analysis in the Finite Element Method [5,7], simple regression on metamodels [8], tests on models [4] or by Monte-Carlo simulation [9] may produce material reductions of over 10% [10].

The topological optimization is used in a multitude of fields such as aerospace field (for application in the manufacturing process) [11,12]; robotics (in order to reduce the weight of the product, while maintaining the mechanical properties) [13,14]; medical devices (for the shape of the element), the energy and battery life [15–17], cases where different scenarios were considered with the variation of geometric dimensions and structural properties [18], architecture [19,20]; and civil engineering which was the focus in this current research with the findings presented below.

Optimization model examples are presented in [21,22] where structural analysis and dimensioning constraints defined by Eurocode standards are used in order to create a model of profiles that can reduce the cost of a building with elements made of glued laminated timber and steel.

Moreover, the study of [23] demonstrates that optimization techniques reduce the mass of elements up to 30% creating high-performance with low-weight design and reduction of deflection by 15–20% [8]. The variation in geometric dimensions of elements, materials, curved elements with large span, height and volume of buildings creates new designs where the elements can be used in a rational manner, reducing the manufacturing process and the cross sections while maintaining the resistance [24–28].

At the same time, during the current research campaigns, topological optimization can be carried out using AI that gives new perspectives and a multitude of possible scenarios [29]. The methods mentioned above improve cost efficiency and optimize the mechanical performance of structural elements in GLT. However, they derive from analyses that require financial resources, whether in laboratory experiments or through time-consuming programs. This happens considering that the operation research processing on models using the Finite Element Method (FEM) involves systems solving inequations having as input data the results of the FEM and the geometry variation until the objective function is reached.

This is the current scientific context, where the premises exist for the use of machine learning techniques in order to embed geometry and structural behavior data obtained by topological optimization and to reduce the computation requirements for the deployment of such a solution [30]. Techniques such as deep neural networks [31] or generative adversarial networks [32] have already proven useful for this kind of application. The part this paper addresses is the training data for such an algorithm. The success of any development in this direction depends on the quality of the training data; for example, the present project proposes some domain limits for the exploration of topologically optimized solutions and presents an algorithm for computing this kind of optimization task, using the Dassault ABAQUS 2023 software package.

For the experimental campaign, GLT elements were used in the experiments and tested as well as their combination to ascertain the contact properties.

In terms of the wood species used, spruce was the best solution considering that it is a common species used for the realization of glued laminated timber elements according to [8].

The GLT elements are formed by joining together layers of wood material in the form of lamellas with the thickness $n_l = 2$ cm with a structural epoxy resin-based adhesive. The adhesive used for processing the glued laminated timber elements, Melamine-urea-formaldehyde (MUF), is one of the most commonly used adhesives in the wood industry. A representation of a glued laminated timber element can be seen in Figure 1 where the lamellas can be identified. However, the adhesive is not visible in the glued laminated timber section being a part of the element. The element is good quality which means that poor glue bonding between the layers is not encountered so the section is evenly created.

Given the natural composition of wooden material in the form of annual growth rings, the position of the fibers is essential when using the material in a structure. The mechanical properties are different along the axis of the element and for maximum utilization of it they have to be parallel to the longitudinal axis [33–35].

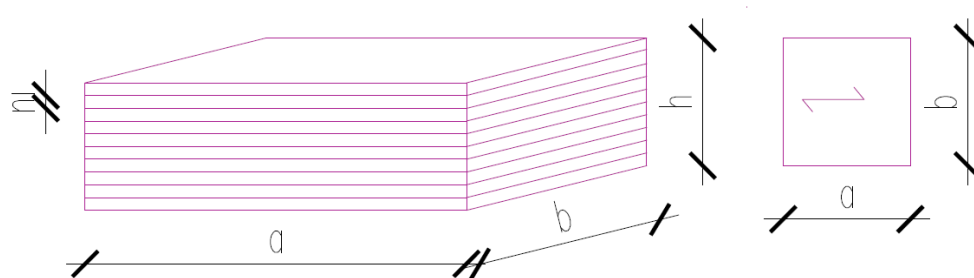


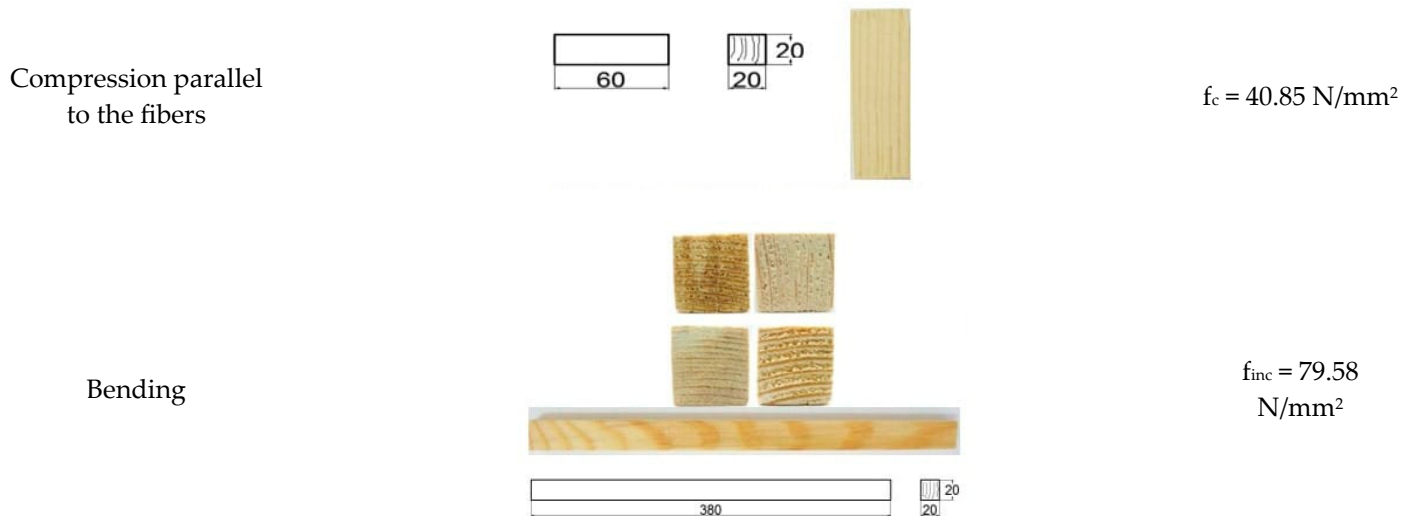
Figure 1. Representation of a physical model of a glued laminated timber element with a section representing the position of the fibers in the element; a = depth; b = width; h = height.

The laboratory determinations were carried out in two stages: in the first one, the strength parameters of glued laminated timber were directly determined, and in the second one, the shear strength parameters on the glulam material were determined. The tests revealed values much higher than the shear strength of wood material, which makes it so that the FEM modeling of the glulam-type element can be achieved either in the form of homogeneous material or using “tie”-type contact elements. The experimental campaign was conducted in the laboratories of the Technical University of Civil Engineering Bucharest.

First of all, the fundamental characteristics of wood in the form of glued laminated timber can be seen in Table 1 with some dimensions of elements, the types of forces applied on the elements (traction and compression parallel with the fibers and bending) and the average value of the strength results. Ten samples for each test were performed.

Table 1. Results of laboratory tests on wooden samples according to [36].

Test Number	Test Specimen Sample Size ($w \times h - L$)	Average Strength Value
Traction parallel to the fibers		$f_t = 93.61 \text{ N/mm}^2$



Secondly, 20 samples of glued laminated timber elements with dimensions $60 \times 60 \text{ mm} \times 20 \text{ mm}$ were inserted into a shear box where force was applied on them until breaking point. In Figure 2a, the shearing box can be observed, with specific dimensions in which the wood sample can be inserted perfectly with the force being applied on the center of the piece following [1]. After the breaking point, the sample is retrieved and in Figure 2b,c the breaking pattern is visible. The wooden piece has been broken completely.

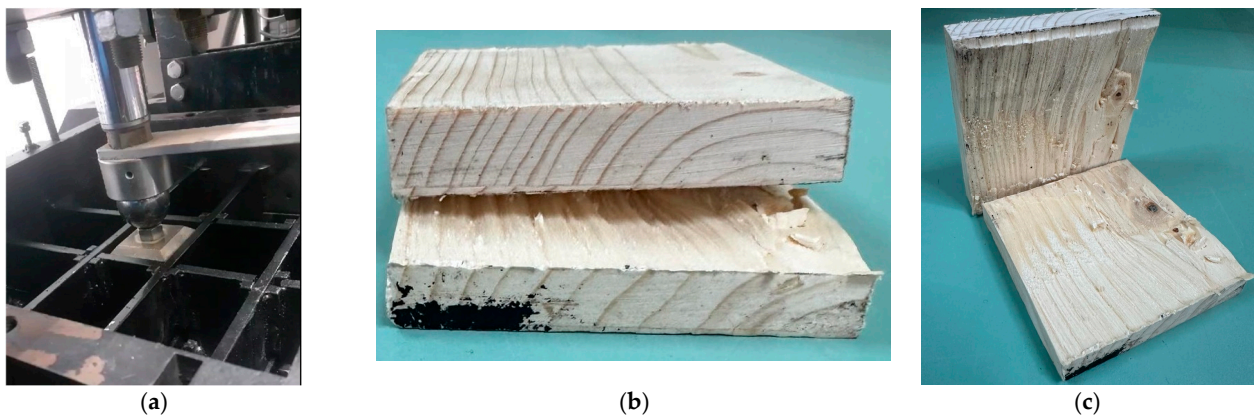


Figure 2. Shear tests in the laboratory: (a) The force applied on the wooden sample in the shear box. (b) The wooden sample after the application of the force. (c) The broken sample.

2. Test Equipment

The experimental campaign was carried out following some test steps that were needed in order to verify the correctness of the results considering the correlation between the Mohr–Coulomb parameters and the unitary forces.

In order to verify the mechanical parameters obtained, elasto-plastic modeling was performed in explicit dynamics formulations in order to be able to follow the evolution of the deformations over time. The geometry of the element takes into consideration the restrictions of the model in the experimental campaign due to the dimensions of the shear box [8].

The model created consisted of replicating the sample used in the direct shearing machine with the parallelepiped sample dimensions mentioned above. The shear plan was determined midway through the test, based on the boundary conditions (Figure 3).

The load was applied by a certain imposed deformation, with constant speed. The color map represents the sensitivity of parts of the wooden elements when force is applied.

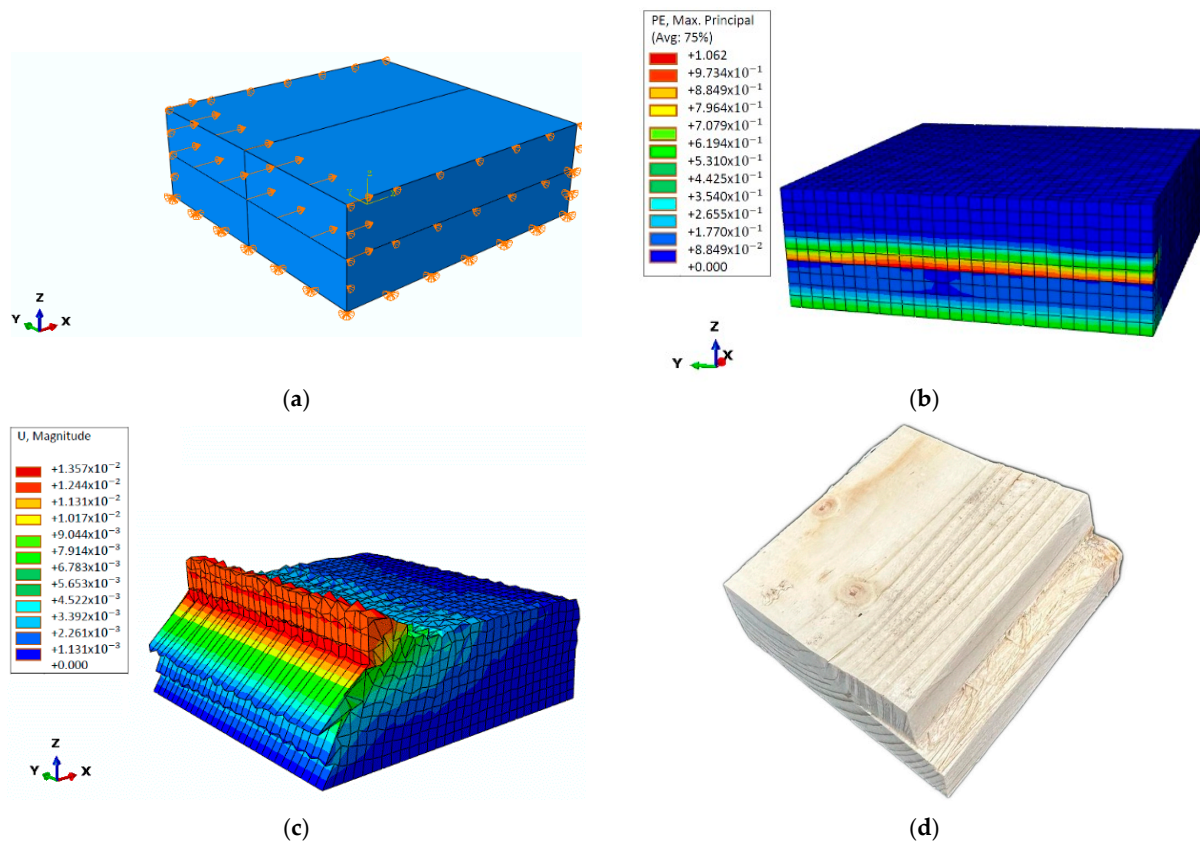


Figure 3. Deformation model using FEM: (a) The model created. (b) Formation of the plastic zones of tangents in the sample. (c) Deformation of the model [6]. (d) The real model sample of GLT.

The deformation model using the parameters defined beforehand can be identified in Figure 3a. After the identification of the plastic zones in the sample, the deformation of the proposed glued laminated timber sample can be seen Figure 3b,c.

The model with the same parameters and characterizations as the wooden sample subjected to deformations by the Finite Element Method can be compared directly with the samples subjected to loadings in the shearing box. It can be seen in the two images in Figure 3c (deformation of the model) and Figure 3d (the real wooden sample) that the pattern follows the same distribution of the deflection.

Strain compatibility was monitored by recording the strain history at a point belonging to the failure surface (Figure 4). Comparing these results with those obtained from the laboratory determination, it can be seen that the mobilization of deformations occurs in a similar way.

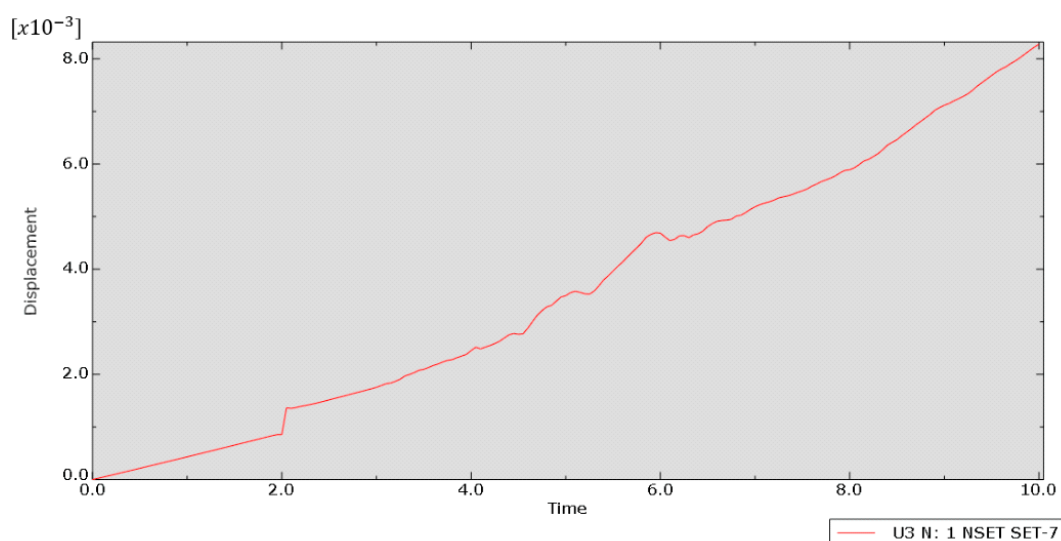


Figure 4. Shear mobilization curves at different vertical stresses for the industrially made samples [36].

3. Numerical Modeling and Methods

Following the steps described above, a database was created with optimized models obtained by generating, following Monte-Carlo simulation principle multiple models that are created by using scripts for the automation of FEM runs. The general characterization of the samples considered for the FEM model can be seen in Figure 5a. The dimensions of the elements are 10,000 mm $\times$ 160 mm $\times$ 40 mm with two fixed supports of 600 mm $\times$ 160 mm $\times$ 40 mm. The number of wooden samples used is 23. The discretization of the model can be analyzed in Figure 5b.

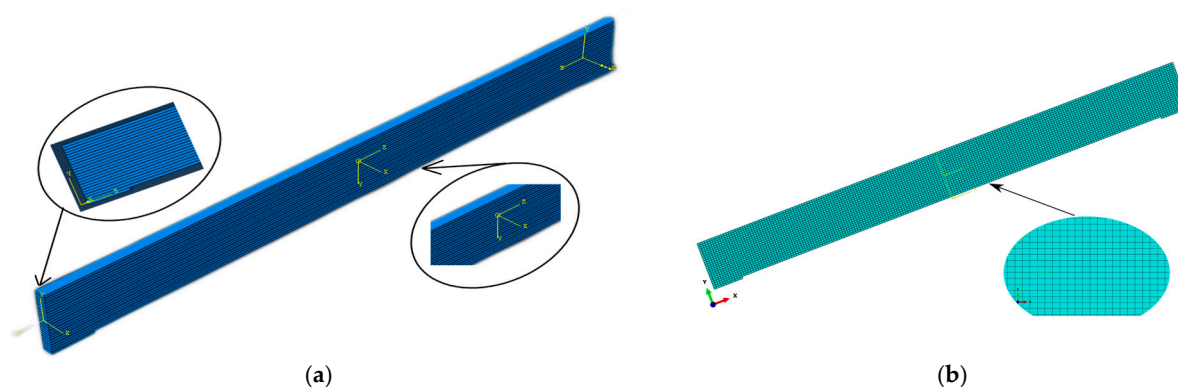


Figure 5. (a) Three-dimensional compute assembly. (b) Discretization of the model.

For the optimization, the topological optimization method was chosen, blocking the areas of application of the conditions on the contour and the area of application of the uniform pressure. In the optimization process, the finite element density was allowed to vary between 1 and 0.001 with a maximum variation per analysis cycle of 0.25. Three design response functions have been defined, namely “Energy Stiffness Measure”, “Volume” and “Signed Von Mises Stress”. The objective of the optimization was to minimize the design response values for “Volume”. The optimization task initially applied to the model was to limit the volume variation below 45%. Unfortunately, the software applied the 45% material reduction directly to the model and then reshaped it in order to withstand the increased interior stresses, so it was not a correct approach. Due to this shortcoming, in the final models, the optimization task was to have displacements under the

allowable limits specified in the current norms (beam span/200). This instructed the software to gradually remove material until the allowable displacement is reached, and then remodel it to create a more uniform distribution of stresses.

The software allows the application of several types of geometric constraints to the model in order to control how the material is removed (see Figure 6). All of them were tested in the early models, but, since some of them did not show a significant optimization or were not pertinent to the tested model, only three were chosen for the final analysis: “Planar symmetry”, “Rotational symmetry”, “Point symmetry”. The “Planar symmetry” constraint forces the optimized model to be symmetric about a specified plane, the “Rotational symmetry” constraint forces the optimized model to be symmetric about a specified axis and the “Point symmetry” constraint forces the optimized model to be symmetric about a specified point.

Based on the laboratory tests carried out within the current project, a Monte Carlo analysis was carried out using a proprietary script in which the material parameters were varied using the mean and the standard deviation resulting from the laboratory tests. For each model to which different geometric constraints were applied, the script was applied to run 30 models with different mechanical parameters. The results were collected in a database compared and contrasted.

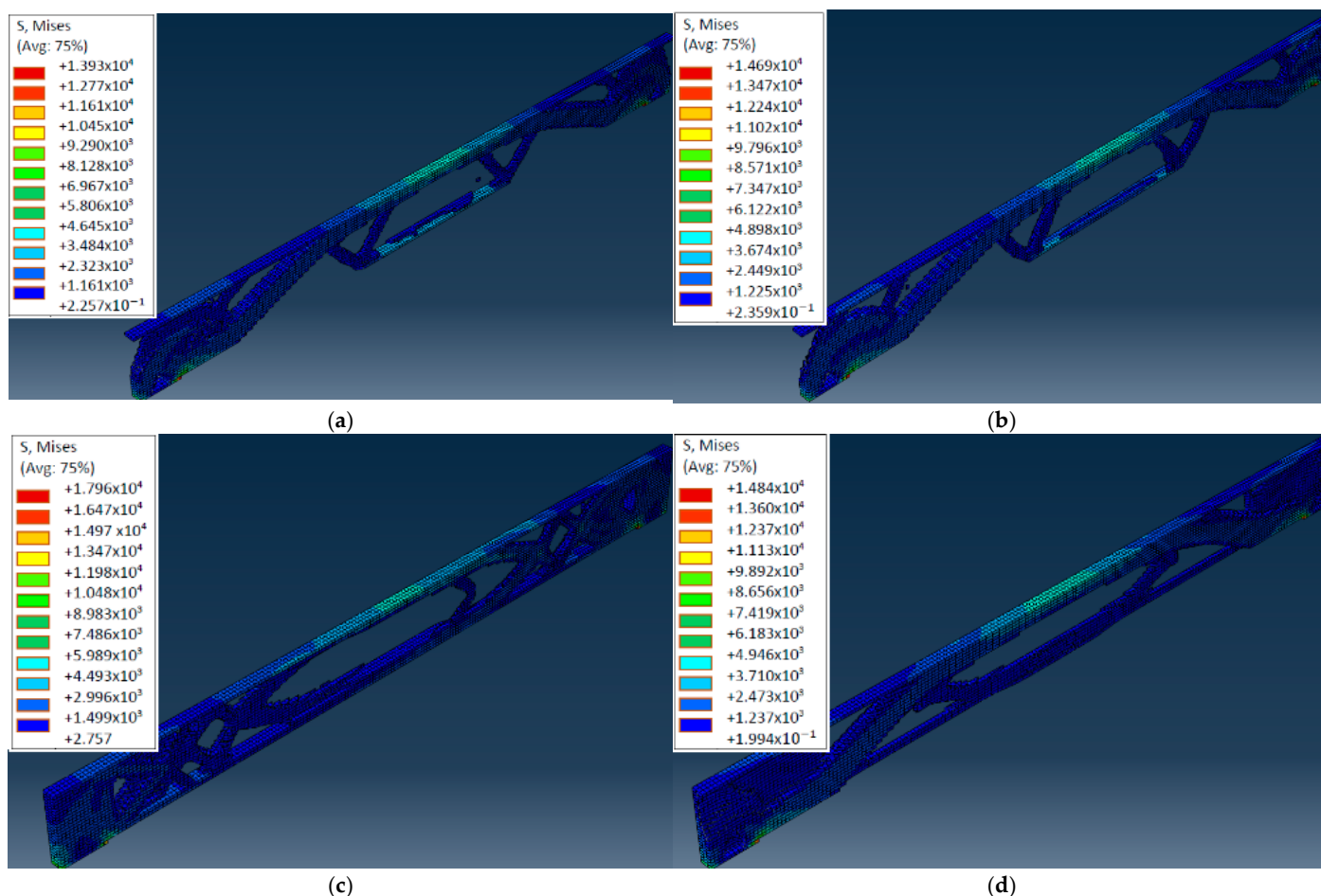


Figure 6. Geometric restriction results for the topology optimization tasks: (a) Condition Demold. (b) Milling condition. (c) Planar symmetry condition. (d) Condition Symm Point [36].

In order to incorporate as close as possible the geometric results obtained by Monte-Carlo simulation, it was initially proposed to use a generative machine learning model (diffuser) which, starting from the synthetic data of each beam (opening, spans, loads),

can generate topologically optimized glued laminated timber elements in elevation. The first attempts resulted in a lack of alignment of the machine learning model.

Noting the lack of alignment of the generative model, another machine learning method took the place of the current one, namely an artificial neural network (ANN) that would embed the results of topological optimizations and be able to indicate, based on the data of the problem, a measure of the stiffness of a topologically optimized beam in order to be able to identify whether or not such optimization would produce satisfactory results from the design point of view.

4. Results

For the characterization of the model, it was preferred to generate all possible dimensional combinations of beams (Table 2), respectively, to vary the dimensions as presented below:

Table 2. Dimensional combination of beams.

Type of Element	Dimensions	Pitch
Beam length (L)	from 4 to 8 m	10 cm
Beam width (W)	From 65 cm to 1.65 m	5 cm
Beam span	from 3 to 5 m	50 cm
Thickness of a plank	4 cm	-
Length of the support area	20 cm, 30 cm and 40 cm	-

The height of the section was established through pre-dimensioning rules.

Following the combinations in the model resulted in 6526 geometrically distinct patterns. Running these models required over 24,000 h/core, which was executed by outsourcing the service.

Each of these patterns were statically analyzed in the Abaqus 2023 program with the following optimization strategies:

- Planar symmetry with respect to the vertical plane perpendicular to the longitudinal axis of the beam in the center of gravity;
- Planar symmetry with respect to the horizontal median plane;
- Polar symmetry with respect to the center of gravity of the beam.

Each optimizer was run with 100 iterations and the final iteration was processed.

Due to the large space occupied by the results of a turnover, only the useful synthetic information presented in the Annexes was saved.

In order to test the feasibility of embedding the topological optimization information into a machine learning model, the first step is to create a regressive model and to test how it responds to the input parameters and objectives. The approach chosen was to develop a deep neural network in order to see if it is possible to predict useful information such as a deflection for a beam in the case of the topologically optimized elements, without having to run the topological optimization. This represents a tried and tested technique for civil engineering applications as shown by [31]. The architecture of the deep neural network is described in Figure 7.

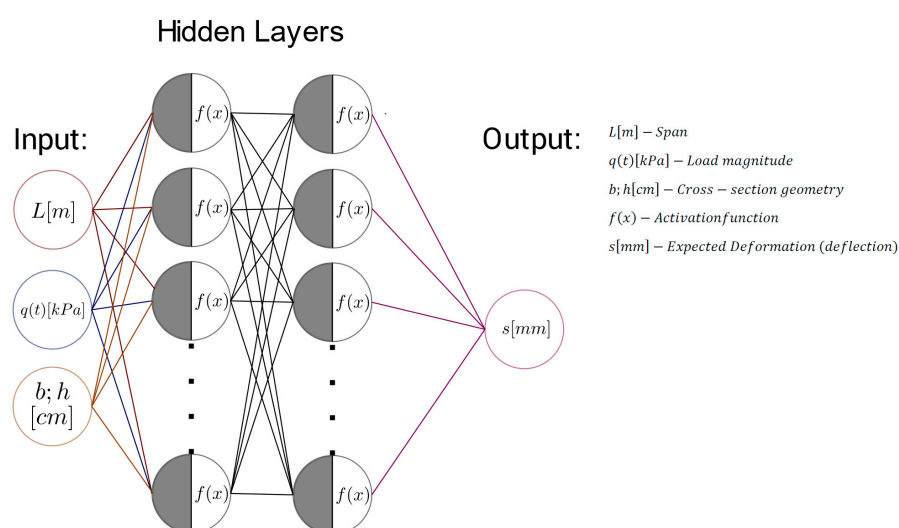


Figure 7. Neural network architecture.

A total of 6526 topologically optimized models/datasets (pairs of synthetic parameters—displacements) was divided into two parts: 6388 models for ANN training and 138 models for validating the result. The ANN optimization algorithm was the SGD (Stochastic Gradient Descent) algorithm with the hyper parameters $\text{lr} = 0.001$ and Momentum = 0.9.

In order to preprocess the input and output data (key–value pairs), the normalization constants presented in Table 3 were used.

Table 3. Normalization parameters for the proposed ANN.

Parameter	Minimum Value	Δ
Beam length (L)	4.0	2.2
Beam span	3.0	2.0
Beam width (W)	0.065	0.1
Optimization constraint	0	2
Deflection	0.019020382	0.029697631

The ANN model thus obtained shows a good alignment both from the point of view of predictions for training data and from the point of view of predictions for the set dedicated to validation as shown in Figure 8 where the prediction of the ANN model is represented on the horizontal axis, and the actual value is displayed on the vertical axis. Figure 8 also showcases some edge-cases where the model tends to underpredict the actual deflection; this is why there are more points above the 100% alignment line, which can be improved by further developing the ANN architecture. After finalizing the training, a benchmark was run over the training dataset (6388 models) in order to benchmark how much faster the neural network is in predicting the deflection than running the FEM optimization task using the `timeit` Python (3.13.0) library. The results obtained indicate that this information can be obtained in 1.4 milliseconds using the ANN (best result out of 10,000 runs).

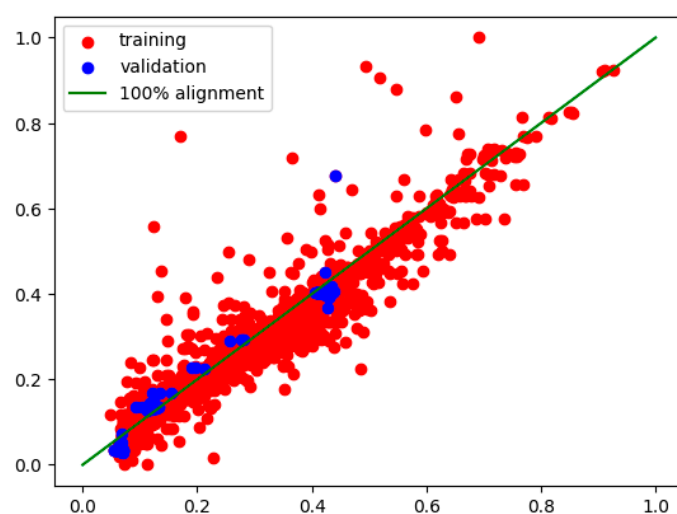


Figure 8. Alignment of trained ANN to input data, and validation data.

Figure 9 shows the evolution of the objective function value over the training epochs. In this case, the objective function value was considered to be the sum of the Mean Squared Loss value for each data point, over one training epoch.

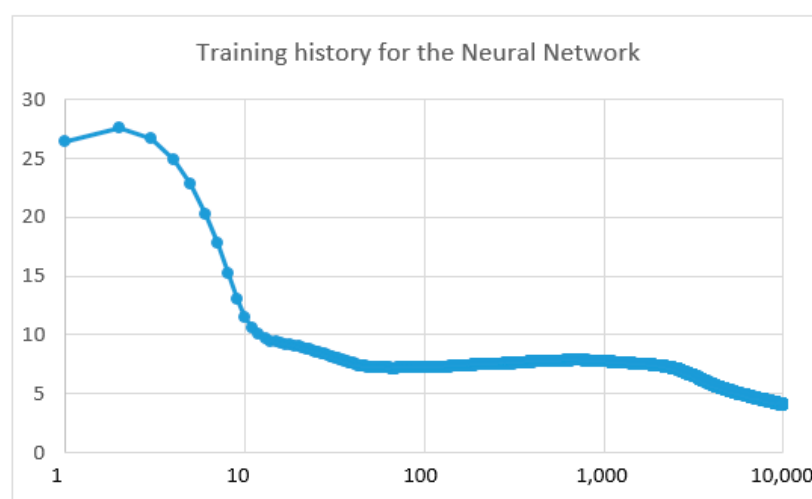


Figure 9. Training history for the neural network.

5. Conclusions

The current project aims to start the development of an expert software tool, based on Artificial Intelligence, which will provide optimized geometric solutions for glulam elements.

The formation of the database for training the Artificial Intelligence model is carried out based on numerical modeling using FEM analysis of a number of glued laminated wood samples and laboratory testing to confirm the correctness of the material model. The training of the AI model involves the use of bent glulam beams characterized by a series of variable parameters, obtaining a large number of topologically optimized models/datasets (pairs of synthetic parameters—displacements). These models were used for ANN training and for the validation of the result.

A deep neural network model is proposed herein with the goal of testing whether or not a useful alignment can be obtained from machine learning techniques for this kind of problem and this kind of optimization task.

The ANN network obtained can indicate based on the problem data a measure of the stiffness of a topologically optimized beam in order to be able to identify whether such optimization will produce satisfactory results from a design point of view. The resulting neural network can be used as it is for the task mentioned in the present work, being properly sized as to avoid overfitting issues. Further iteration on this neural network will be developed in order to improve the architecture in terms of size and activation function for the task previously mentioned. The models proposed for this paper follow certain parameters chosen beforehand which means that further improvements can be added for future models and experimental campaigns. These parameters are related to the properties of the wood material (type of wood, density, modulus of elasticity), dimensions and then the discretization of the model. The results obtained herein indicate that in the case of beam models, larger cross-section sizes and spans will benefit even more from the topological optimization. Also, the topological optimization task can be improved to take into account the lamellar structure of glulam and optimize the element such that the final geometry could rather be obtained by placing the correctly cut lamella inside the element without having to do a CNC machining step for the element.

Future developments will need to account for larger structural element sizes (cross-sections and span) and also take into account different loading conditions such as unevenly distributed loads or point loads. Also, it is clear that a great step in developing machine learning applications for this kind of task is to deploy a generative adversarial network architecture that can eventually propose geometries that can then be optimized in fewer steps.

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