

Advancing Timber for the Future Built Environment

# A MULTI-FIDELITY APPROACH BASED THERMO-MECHANICAL CAPACITY ASSESSMENT OF GLULAM TIMBER CONNECTIONS SUBJECTED TO FIRE HAZARD

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ABSTRACT: This research develops a innovative multi-fidelity approach based assessment method to conduct comprehensive thermo-mechanical analysis of glulam timber connections exposed to standard fire conditions. The framework is specifically designed to integrate low-fidelity features derived from finite element models with high-fidelity experimental data. This integration allows for the efficient utilization of both data types to achieve a rapid and accurate prediction across the entire domain, significantly improving the prediction accuracy and reducing computational costs. The heat transfer within the wood is analyzed based on the results of finite element models (low-fidelity model database) and experimental data (high-fidelity model database), and temperature-dependent properties such as thermal conductivity, specific heat capacity and density are determined. Variou factors such as bolt count, diameter, beam thickness, wood density and edge distance are taken into account to predict temperature distribution within connections. Additionally, using Johansen's yield theory, load-bearing capacity was analyzed to determine fire resistance of connections, establishing a comprehensive understanding of their structural resilience in fire scenarios. This approach provides analysts with accurate connection data while significantly reducing the time and computational resources required, enhancing the efficiency of structural fire safety evaluations.

KEYWORDS: glulam timber connection, multi-fidelity approach, thermo-mechanical analysis

## 1-INTRODUCTION

Fire resistance in timber structures is currently a focal point in structural design and research. However, existing standards offer limited guidance on calculating the fire load-bearing capacity of glulam timber connections, highlighting a need for further investigation. The fire resistance of connection is typically analyzed using finite element simulations [1], encompassing both temperature field and thermo-mechanical coupling models. The temperature field model calculates internal temperature variations within the connection over time based on the thermodynamic properties of materials at varying

temperatures. The thermo-mechanical coupling model uses finite element methods to mechanically simulate the connections, incorporating temperature data to reflect changes in material properties due to heat exposure. Additionally, fire resistance models for connections can also be computed using mechanical analysis, which requires preliminary temperature field results. For example, researchers like Palma [2], Erchinger [3], and Racher [4] have derived fire resistance models for connections using the Johansen yield model adapted to temperature variations. These models provide a reference for developing fire load-bearing capacity models for this study's connections. However, these models, requiring

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extensive finite element temperature data, can be computationally intensive and economically inefficient for complex or large-scale models. This study proposes building a probabilistic model based on parameters such as bolt number, diameter, beam thickness, wood density (species), and heating duration. A finite element database for the temperature field of the connections is established, along with the development of a deep learning algorithm for low-fidelity data analysis and high fidelity data analysis of the glulam timber connection[5]. This approach aims to rapidly and accurately obtain temperature data of the connections, enabling the establishment of a more efficient and accurate fire load-bearing capacity calculation model for the connections.

## 2- METHODOLOGY

The framework of this method can be divided into two steps: the heat transfer model and the theoretical load-carrying model. The heat transfer model requires a multifidelity framework. This entire framework is consisted of two sub-networks. A low-fidelity network is trained to conduct analysis of the temperature field in glulam timber connections using large finite element datasets. The residual subnetwork is trained based on experimental results to to ensure rapid and accurate acquisition of the complete temperature data field for the connections, enhancing both the precision and speed of engineering evaluations. In theoretical load-carrying model, Johansen's model is used to calculate the load-carry capacity at an angle of  $\theta_1$  based on the integral of

embedment strength along the bolt line. The temperature field is obtained from the heat transfer model in the first step. The ultimate moment strength is defined when the farthest bolt reaches its ultimate state.

#### 2.1 A multi-fidelity framework

The proposed framework consists of a low-fidelity subnet and a residual subnet, as illustrated in Figure 1. The input parameter vector is defined as  $p = (d, n, \rho, b, e)$ , representing the bolt diameter (mm), number of bolts, wood density (kg/m³), beam thickness (mm), and edge distance (mm), respectively. The output is the three-dimensional temperature field T(m), where m denotes (x, y, z, t). Here, (x, y, z) are the sectional coordinates of the node, and  $t \in [0, 3600]$  s represents the fire exposure duration.

The low-fidelity subnet is constructed using a standard DeepONet architecture, consisting of a Branch Network and a Trunk Network. In the Branch Network, a 5-layer fully connected neural network with 256 neurons per layer and Swish activation functions is employed to encode the input parameters p into a 128-dimensional feature vector b(p). Meanwhile, the Trunk Network is designed as a 3-layer fully connected network, where normalized spatiotemporal coordinates are transformed into a corresponding 128-dimensional feature vector. The final temperature field prediction is obtained through the inner product of these feature vectors.

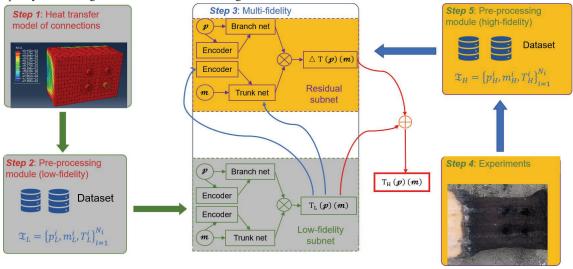


Figure 1. A multi-fidelity framework

The Residual Subnet is designed with a lightweight U-Net architecture, taking the low-fidelity prediction TLF as input and producing the residual field  $\Delta T = THF - TLF$  based on the differences between high-fidelity results (test) and low-fidelity predictions (simulation).

The input augmentation approach proposed in by Lu et al. [6] is used, and the low-fidelity prediction  $T_L(p)(m)$  is appended to the trunk net inputs to make the residual operator  $\Delta$  T easier to learn, ensuring the effective preservation of fine-grained information throughout the

network. It consists of four down-sampling and upsampling stages, with the number of channels progressively increasing from 64 to 128, 256, and finally 512.

# 2.2 A load-bearing capacity model based on the temperature field

Figure 2 shows the internal forces of bolted timber connections under coupled shear force (V<sub>k</sub>) and bending moment  $(M_k)$ .

The vertical load  $V_k$  acting on the connections is assumed to be evenly distributed among the bolts at the beam end. The shear force resisted by a single bolt, denoted as  $F_{v}$ , can be expressed as:

$$F_{v} = \frac{Vk}{n}$$
 (2)

The bolt located farthest from the rotation center experiences the highest load and is selected for individual analysis. This bolt resists the bending moment in the connections region, generating a reaction force  $F_{M,1}$ , while also resisting the shear force with a reaction  $F_v$ . The resultant force  $F_{r1}$  forms an angle with the wood grain direction, which can be expressed as:

$$\theta_1 = \arctan(\frac{F_{M,1} \sin \alpha_1 + F_v}{F_{M,1} \cos \alpha_1})$$
 (3)

The embedment strength of the wood under the inclined grain, denoted as  $f_{e\theta 1}$ , can be determined using the following equation:

$$f_{e0} = 0.082 \times (1-0.01d) \times \rho$$
 (4)

$$f_{e90} = f_{e0} / k_{90} \tag{5}$$

$$\begin{array}{ll} f_{e0} = 0.002 \times (1 \text{ o.td}) \times \beta & \text{ (1)} \\ f_{e90} = f_{e0} / (k_{90} & \text{ (5)} \\ f_{e01} = f_{e0} / (k_{90} \sin^2 \theta_1 + \cos^2 \theta_1) & \text{ (6)} \\ k_{90} = 1.35 + 0.015 d & \text{ (7)} \end{array}$$

$$k_{00} = 1.35 + 0.015d$$
 (7)

Where fe0 represents the embendment strength of the glulam parallel to the grain, d denotes the bolt diameter of the wooden beam,  $\rho$  is the density of the glulam, and fe90 refers to the embendment strength perpendicular to the grain.

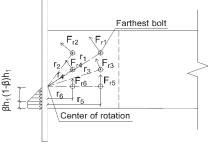


Figure 2. Internal forces of bolted timber connections

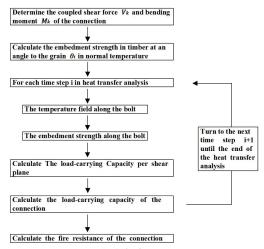


Figure 3. Calculation process

The calculation process consists of three main steps. First, a finite element heat transfer model is used to determine the temperature field distribution along the bolts in the connection region. Next, using the selected bilinear model for the embedment strength of the wood dowel slots, the embedment strength at each time step is obtained by applying the temperature field distribution and the corresponding strength reduction factors from the bilinear model. Finally, the shear capacity of a single bolt in a single shear plane is calculated by integrating the bearing strength along the bolt distribution and applying the Johansen yield model. The detailed process is illustrated in Figure 3.

# 3-RESULTS

The low-fidelity dataset is generated using the ABAQUS finite element software, employing parametric modeling and batch processing techniques to ensure efficient data production. A parameterized template model is developed using Python scripts, with the bolt diameter (d), number of bolts (n), wood density ( $\rho$ ), beam thickness (b), and edge distance (e) defined as variable parameters. The ABAQUS CAE interface is used to dynamically adjust the geometric dimensions and material properties.

A total of 3300 parameter combinations are generated to produce temperature field data, stored in ODB files. Postprocessing scripts are then applied to extract the timeseries temperature data at the connection region.

Figure 4 illustrates a typical finite element model of the joint, utilizing C3D8T elements (8-node linear heat transfer hexahedral elements). Heat conduction and radiation are simulated on the surfaces of both the wood and steel components, with a refined mesh applied around the bolt contact areas to improve accuracy.

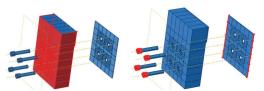


Figure 4. Heat conduction and thermal radiation region

The high-fidelity dataset is obtained from furnace fire tests, as shown in Figure 5. The experimental parameters are carefully aligned with those used in the simulations to ensure consistency. Thermocouples are used to capture the temperature field data during the tests.





Figure 5. Fire tests

The predictions of the Low-Fidelity Subnet on 300 independent test datasets demonstrate a coefficient of determination ( $R^2$ ) of 0.97, indicating that it can function as a surrogate model for numerical simulation.

After training the multi-fidelity model with five sets of experimental data, the R<sup>2</sup> score of the multi-fidelity DeepONet prediction results reaches 0.85, and the prediction accuracy is significantly improved compared to the 0.79 R<sup>2</sup> score obtained by directly using the surrogate model.

## 4 - CONCLUSION

The fire resistance of these connections is crucial for the overall fire load-bearing capacity of timber frame structures. Typically, the fire load-bearing capacity of these connections is calculated using finite element methods, a process that can be time-consuming and computationally demanding due to the detailed modeling

and extensive calculations required. This project aims to streamline this process by employing deep learning techniques to rapidly acquire temperature field data for timber connections. Based on this temperature data, a fire load-bearing capacity model for the connections is developed. This approach enhances predictive accuracy and structural safety assessments.

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