Neural network modeling of conditions of destruction of wood plank based on measurements

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Abstract. The paper deals with the possibility of predicting the ultimate load breaking timber sample based on the loading force dependence on the deflection before destruction. Prediction of mechanical properties of wood is handicapped by complex anisotropic structures. The anisotropic nature of the material and, in a great measure, the random nature of wood grain local features defining moment of destruction lead to a significant dependence of the required load on the individual characteristics of a particular bar. The ultimate load is sought as a function of the coefficients of the neural network approximation of the loading force dependence on the deflection. For this purpose, a number of experiments on timber sample loading until the destruction is conducted. Modeling of the conditions of material destruction may provide the required safety control in building industry.

1. Introduction
Analysis of accidents in the industrial sector of human activity makes it possible to classify the three main types of causes of industrial injuries.

- Organizational;
- Technical – bad order of scaffolding, jigs and tools, as well as structural defects of machines, lifting tools, building structures and equipment;
- Psychophysiological and other.

Prevention of occupational injuries has always been, and remains a complex problem that requires special attention of specialists in different fields. The accidents related to human fall on height works, have especially severe consequences. So the security development for such works is especially important.

Falling of workers from a height may happen under different conditions: finding working near open doorways, at the edge of the roof and the absence at the same time (or bad order) the necessary barriers; the use of occasional guard rails and materials for closing of hatches and openings; exploitation of untested or defective scaffolding and cradles; movement of workers from one work site to another along girders, beams and other structures; elements of frail construction and others.

Traditionally, wood is used as the material of the structural elements of guard rails, scaffolding, beams, steps. In addition, the use of wooden structures in the coverage of
modern buildings of public and industrial purposes (sports, exhibition and entertainment halls, markets, warehouses) and apartment buildings (mansard floor), based on technologies combining maximal use of structural prefabricated elements with the convenience their transportation and installation in situ [5].

2. Problem statement
The study of the strength properties of building wood materials [1-4] is handicapped by their complex anisotropic structures. Tensile strength of a wooden beam depends strongly on the type of wood, its manufacturing technology, the specific features of planks (such as knots), etc. At the same time, it is necessary to predict the destruction of such constructions in view of their wide use in the building industry and in the case of historic construction timber assessment [5]. In this regard, interest is a prediction of an ultimate force by its behavior of a sample under load nondestructive.

In the work [6], an effort was made to model the deformation process and the destruction of the wooden sample using the commercial FE software ABAQUS. For this purpose, authors used a general approach combining fracture mechanics approaches within a continuum framework, classical flow theory of plasticity in combination with the Hill criterion, multi-surface plasticity models, and others [6], to construct one single 3D material model taking into account the anisotropy of wood. The results of calculations are compared with experimental data. Finally, the predicted value of critical displacement corresponding to the moment of destruction and experimental value differ in several times. This result suggests that it is necessary to use a much more complicated model for more realistic simulation.

In the paper [7], bending properties of beech wood are predicted using the stress-wave method. The authors developed the linear regression models based on coefficients calculated using load deformation curves, but they did not approve this choice.

The approaches described above have a number of restrictions on the experimental conditions, especially the moisture, and equipment used. We offer the neural network approach for modeling the destruction of conditions of the destruction of wood plank taking into account the different experimentation conditions in situ in the form of additional neural network parameters.

3. Measures
We have performed experiments (three-point bending) for loading the wood planks to the initial stage of destruction inclusive. The softwood beams were selected as the samples. The techniques used in the work can be applied to other species of wood. The sample is placed on a lower fixed support. The load is transmitted via the movable loading rod. The beam deflection is defined as the movement of the load transmitting rod. Figure 1 shows the scheme of loading.

![Figure 1. The wood plank loading scheme.](image)

The test was carried out on the double column testing system Instron-5965, Position Measurement Accuracy: ±0.01 mm or 0.05 percent of displacement (whichever is greater),
Load Measurement Accuracy: ±0.5 percent of reading down. Experiments were conducted with samples of sections of $20 \times 40$, $15 \times 20$ and $15 \times 30$ mm and loading rates of 10, 50 and 100 mm/min.

4. Neural network approach

4.1. network 1

Neural networks applying showed a good effectiveness in data hidden dependencies determinations [6,8]. Deflection-force dependence is looking as a neural network approximation with one neuron in the form

$$F(x, c, a, xc) = c \text{th}(a(x - xc)).$$

(1)

The network weights $a$, $c$ and $xc$ are determined during the minimization of the error functional

$$J = \sum_{i=1}^{m} (F(x_i) - F_i)^2,$$

(2)

where $x_i$ is a measured deflection and $F_i$ – corresponding loading force. The error functional optimization is conducted by RProp algorithm or by combination of Particle Swarm and RProp algorithms [9].

Figure 3 shows an example of a plot of neural network approximation and the measurements. We can build a much more precise approximation using a network with two neurons, but it does not allow posterior predicting the load accurately, which leads to the destruction of the wood plank.

4.2. network 2

The neural network approximation coefficients $c$, $a$ and $xc$ were calculated for the results of all $n = 27$ experiments. So, we have the data array $(F_{i}^{\text{max}}, D_{i}^{\text{max}}, c_i, a_i, xc_i)$, $i = 1, \ldots, 27$, etc.
Figure 3. The dependencies of the deflection (mm) against force (N), sample section $15 \times 20$ mm, loading rate 50 mm/min. Experimental data – dots, neural network approximation – solid line.

where $F_{i}^{max}$ is the ultimate force limit power and $D_{i}^{max}$ is the corresponding deflection in the experiment number $i$.

Neural network approximations of $F^{max}$ and $D^{max}$-dependencies were constructed using the neural network of type (1). The explicit connection appears only in the case of force. Figure 3 illustrates the ultimate force limit power dependence on the parameter $c$.

Note that while the sample standard deviation of the ultimate force is 643.3, the deviation of force measurements from neural network model corresponded to the parameter $c$ is equal to 197.1, to the parameter $a = 518.4$, to the parameter $xc = 412.9$.

In addition, we have obtained the common neural network model of the dependence of the ultimate force limit power from the three parameters together in the form

$$F(c, a, xc) = 2638.9^{th}[0.000617c - 0.36] + 5504.7^{th}[0.39a - 0.08] - 57.2^{th}[12.9xc + 23.6], \quad (3)$$

where $c \in (500; 3500)$, $a \in (0; 0.3)$, $xc \in (-2.5; 0)$.

The sample deviation of ultimate force from common neural network model is 167.1, so it can be possible to use neural network model instead of mean values of strength and modulus of elasticity from the tests of small tensile samples [5].

5. Prediction
The disadvantage of previous dependencies is that they are based on the whole sample until destruction. In the context of application it is desirable to predict the rupture before it occurred. One approach is to build a dynamic neural network approximation. The corresponding
algorithm assumes the dynamic addition of terms in the error functional. Another approach is the approximation of the moving sample.

Let us carry out a new experiment. The neural network model of the load force dependence on deflection is constructed by the first measurements before the destruction of the sample. Thus, we have the parameters $c_0$, $a_0$, and $x_c_0$ for a given wood plank.

Then we can determine the critical value of the load force for the sample using the dependence of the ultimate force at which the wood planks destruct on the parameters (the previous section). Figure 5 shows an example of such dependence for the parameter $c_0$.

![Figure 5.](image.png)

Such dependencies allow the dynamic prediction of timber sample destruction, relearning the specific sample neural network used the newly entered data in the process of loading.

6. Conclusions

Results of this study can find application in the building industry in justifying the choice of bricklayers scaffold constructions, used in conducting different kinds of building and repair work at height or height discontinuity. Work at heights is a dangerous type of work, which is associated with a large number of accidents caused by man fall in spite of the regulated safety measures. Therefore, it is important to ensure the structural solidity of timber floors; the material used in construction must hold certain loads both dynamic and static nature throughout the allotted time or be in time replaced. Modeling of the conditions of material destruction will provide the required safety control. To model behavior of such constructions under dynamic loads can be applied the methods and results of this work, together with the methods described in [8, 9].

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