EVALUATION OF MECHANICAL PROPERTIES OF STEELS USING NEURAL NETWORK APPROACH

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Abstract

Previous theoretical and experimental investigations of the new developed method for mechanical properties non-destructive evaluation which consist in simultaneous accounting of thermal conductivity, hardness and resistivity using neural networks showed that the following challenges will be faced in the future.

Challenge 1. Expansion of the informative parameters and target properties.
Challenge 2. Technical support.

The solution of the above stated challenges will help to create scientifically based methodology for physical and mechanical properties evaluation of the new and long-term used metallic structures.

Key words: mechanical properties, non-destructive evaluation

The problem of actual mechanical properties evaluation is a very important for wide range of structures and its solution will lead to its real technical state assessment in order to prolong exploitation period. This problem is considered to be provisional component of technological safety of Ukraine [1] at the state level.

The common base of metalwork used in basic branches of Ukrainian economy is near 35 million tons. The rated resource of more than 50% of the structures is already expired; the other part is very close to similar condition. During the exploitation period a number of factors influence on the structures (high pressures and temperatures, local overloads, aggressive environments) what results in microstructure degradation, mechanical properties alteration and afterwards in defect initiation and growth [2].

From economic and resource saving points of view the most effective way to control changes of mechanical properties is its non-destructive evaluation (NDE).

There are several main methods of NDE: ultrasonic [3,4], magnetic [5,6], eddy-current and electrical. Analysis of these methods showed that none of them has strict theoretical background which could provide establishment of analytic dependences between mechanical properties and informative parameters that can be measured. Obviously the informative parameters should be structure sensitive and measurable.

Thus the objective of the paper is the development of new method for mechanical properties evaluation using new informative parameters.

First of all the analysis of normative documents for steels was done. The main idea of investigation was to select new informative parameter among physical properties of steel set by relevant regulations. Second, several parameters were chosen to be considered to solve the stated problem. From technological point of view yield strength was selected as target mechanical property in our work. The stated problem
can be referred as non-linear multiparameter approximation problem. Neural networks are very suitable tool for solving such a problems in material characterization [7].

Reference data for steel grades 440, 630, 431, UR52N+, 420, 2205, 416, 409, 3CR12, 304, 310, 321/347, 430, 430F, S30815 which mechanical and physical properties were defined according to ASTM standards were used in theoretical investigations to determine optimal complex of parameters for yield strength evaluation. Physical properties which were investigated are as follows: hardness, density, heat capacity, thermal conductivity, heat expansion coefficient and resistivity. Graph-analytic, correlation and neural network based analysis showed that such parameters as hardness, thermal conductivity and resistivity enable yield strength evaluation to be done with mean error less than 3%.

No information about interrelation between thermal conductivity and yield strength was found and thus requires experimental proof.

For the implementation of the above mentioned method, a special device called FMH-1 has been developed [4].

See Figure 1 for general view of portable FMH-1 experimental model.

![Figure 1 - FHM-1 Assembly](image)

1 – information processing block, 2 – hardness meter TDM-1, 3 – block of temperature detectors, 4 – heater block, 5 – unit under test (sample of tubing)

The paper is aimed at the improvement of informative parameter calculation algorithm and measuring data processing.

On the theoretical level, the first stage of the formulated task is limited to the change of informative parameter calculation algorithm that would let enhance repeatability of thermal conductivity measurement results and larger value of correlation coefficient with real yield stress values of material of unit under test.

At the same time physical content of the parameter is likely to be as follows: quantity of heat which went through the cross-section of unit under test per unit of time. Due to the fact that in the course of real objects testing it’s impossible to determine cross-section through which heat transport process has been carried out, reduction of this informative parameter to cross-sectional area will be fulfilled in the course of the correction of its value, calculated with the consideration of specific samples thickness.

On the assumption of theoretical thermal transport process basis [5] it has been suggested to use the following dependence (1) for heat flow that went through the cross-section of the object:

\[ q = |\text{grad} T| \cdot \lambda \]  

(1)

where \( q \) – heat flow; \( \text{grad} T \) – temperature gradient of thermal field in the unit under test; \( \lambda \) – thermal conductivity coefficient.
From formula (1) it’s easy to calculate thermal conductivity:

\[ \lambda = \frac{q}{|\text{grad}T|} \]  

The graphs of temperature increase while heating at six points lined up with 1-cm pitch with the help of FMH-1 [7] are presented in Fig 1. According to formula (2) we calculate thermal conductivity from the graph (Fig. 2), which represents the character of heat dissemination over the surface of the unit under test.

**Figure 2 – Explanation of informative parameter which characterizes thermal conductivity**

Heat flow \( q \) is a quantity of heat which went through the unit under test per time unit – area of \( ABCD \) tracing in Fig. 2. Temperature gradient \( \text{grad}T \) can be defined as a temperature difference on extreme measurement points \( x_0 \) and \( x_5 \) (distance between them is 5 cm) – that’s the length of \( FE \) section in Fig. 2.

Thus, informative parameter which characterizes thermal conductivity \( M \) can be defined as a ratio of \( ABCD \) tracing area to the length of \( FE \) section.

Following these considerations, algorithm of FMH-1 device functioning has been changed and a series of experimental tests, proving the introduced hypotheses, have been conducted.

The first stage of experimental tests was performed on three samples made from 17GS grade steel (according to GOST 19282-73) each of which had different thickness (11.8 mm, 18.6 mm and 23.5 mm) [3] – Fig. 3. These tests were aimed at determination of repeatability of measurement results of informative parameter, characterizing thermal conductivity as well as its existence and character of its dependence on the thickness of units under test.

Multiple measurements with the help of FMH-1 device have been carried out. Fig. 3 has been plotted on the basis of the results of experimental tests aimed at approximation of the dependence of informative parameters value on samples thickness.
Judging by Figure 3 we can say that there is some dependence between values of informative parameter $M$ and thickness (correlation coefficient is 0.95) and it may be approximated by means of linear function. In order to reduce the measurement results to unified thickness one should use the following ratio: 1 mm $\equiv$ 2.58 standard units.

Next stage of investigations dealt with the determination of existence and character of informative parameter dependence on mechanical properties (yield stress) values. Such tests were conducted on samples made from steel grades which are used in gas-transport industry (17G5, 10G2SB, 9G2S, St3vp).

In the course of experiment, 9-times measurements of informative parameter $M$ (with the help of FMH-1 device) and hardness (dynamic hardness meter TDM-1) have been conducted on each sample. Yield stress was determined with the help of breakdown tests/breaking tests on tensile-testing machine in accordance with [6].

Correlation analysis of the results of experimental tests has shown/demonstrated that yield stress correlation coefficient $\sigma_T$ with hardness $H_B$ is 0.86, and with the informative parameter $M$ it is (-0.65). Minus sign for parameter $M$ indicates inverse character of the dependence.

Next stage in the work with tests results was use of integrated approach to the determination of yield stress [3] with the help of artificial neural networks algorithms for approximation of the dependence of mechanical property as a nonlinear function of two parameters (hardness and informative parameter which characterises thermal conductivity).

A neural network which has 3 inputs, one hidden layer and one output was developed. Hidden layer had 24 neurons, like the previous one. It means that at the point of network input we had hardness, thermal conductivity parameter and thickness of samples and the value of informative parameter was taken without consideration of thickness.

Totally in the course of investigation 7 networks have been trained and after testing (on the basis of selected data that weren’t used during training) the best network has been selected. The result of testing of the selected network is given in Table 1.

Average absolute error of yield stress determination in this case was $\pm 9.5 \text{ MPa}$, error, reduced to the yield stress range of values is 2.3%.

In order to solve another important task – evaluation of the deflected mode of metallic constructions – experimental tests on the example of pumping unit rod were carried out. They were aimed at determination of dependence between stresses that occur in metallic constructions material.
and structurally sensitive material characteristics.

Table 1 – Results of neural network testing

<table>
<thead>
<tr>
<th>Sample</th>
<th>10G2SB</th>
<th>17GS</th>
<th>9G2S</th>
<th>St3_1</th>
<th>St3_2</th>
<th>St3_3</th>
<th>St3_4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real values</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>of yield</td>
<td>490</td>
<td>540</td>
<td>470</td>
<td>300</td>
<td>300</td>
<td>200</td>
<td>240</td>
</tr>
<tr>
<td>stress</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outputs of</td>
<td>505.3</td>
<td>536.1</td>
<td>473.8</td>
<td>310.5</td>
<td>295.0</td>
<td>190.0</td>
<td>259.7</td>
</tr>
<tr>
<td>neural network</td>
<td></td>
<td></td>
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</tbody>
</table>

Thus the analysis of the results of experiments described above creates the basis for the following conclusions.

**Conclusions**

The suggested new informative parameter calculation algorithm, characterizing thermal conductivity, changed according to the physical basis of the heat transport process, has allowed to decrease the scattering of the measurement results and to increase the accuracy of the yield strength determination.

The suggested changes in the processing of the results of measuring hardness and thermal conductivity, concerning the input of neural network of values of real thickness of units under test, have allowed further increasing the accuracy of the yield strength determination on the samples of main lines. This innovation will allow simplifying the work with the device on new samples, as well as simplifying the metrological analysis of the suggested method and means of determining physical and mechanical properties of the metallic constructions material by eliminating the error resulting from the approximation of dependence of the informative parameter on thickness.

**References**

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