

METHOD FOR MECHANICAL PROPERTIES EVALUATION OF STEEL STRUCTURES WITH CONSIDERATION OF ITS MICROSTRUCTURE

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Metallic structures of long-term operation life in oil and gas industry are exposed to such factors as the cyclic loads, temperature changes, pressure pulsations, aggressive medias, etc. For example, the operation of pipelines under the influence of residual internal pressure steel pipeline withstands tensions that are close to the normative strength characteristics of metal pipes. Such situation relates with a complicated scheme of pipeline interaction with the soil, presence of deviations from regulatory requirements during construction of the pipeline, presence of flaws in metal, weldments and failuring modes of technological operations. Moreover, 'aging' of pipelines has been reported from many operators based on their performance experience. In oil and gas pipeline steels most common failures are caused by strain ageing. This is mostly due to not only cyclic nature of the loading, but also due to some specific alloying elements. Availability of the atomic hydrogen in the soil electrolytes, hydrogen sulfide oils, its generation during cathodic reactions leads to a significant growth of embrittlement of tube steels in case of prolonged cyclic loading. Combination of these processes cause change of the microstructure and physical-mechanical properties of steel, i.e. ageing [1]. Thus aging of the pipeline steels during operation can be associated with changes at the level of crystalline structure of metal and with redistribution of impurity atoms and dislocations. Some investigators report about significant changes of such mechanical properties as yield/tensile strength (changes up to 20%), impact toughness (up to 30%) etc. Accurate determination of the actual technical state of biggest number of long-term metallic structures in the basic industries is linked with determination of actual mechanical properties and the estimation of stress-strain state using non-destructive methods [2]. Factors involved in ageing process negatively affect the remaining life of the structure and can cause fatigue defects and structure damage [3]. Therefore, determination of actual mechanical properties and evaluation of the stress-strain state of steel structures, especially of long-term operation is an important scientific and technical problem, which solution will eventually lead to more accurate evaluation of their technical state. We consider the results of experimental investigations aimed on improvement of methods for determination of actual mechanical properties. Previously new method for evaluation of mechanical properties of steel has been proposed [4], which lays in measurement of hardness and the heat conductive parameter and use of artificial neural networks for calculation of yield strength. Special experimental device FMH-1 has been develop for implementation of the proposed method [5]. However, in these works due attentioan was not paid to the investigation of dependence between mechanical properties and electric resistivity as only in work [3] only structural sensitivity of this parameter was mentioned without any experimental verification.

The aim of this work was to study structural sensitivity of the electrical resistivity and improve method of mechanical properties evaluation. For the evaluation of microstructure of steel measurement of structural-sensitive parameters such as thermal conductivity and electrical resistivity shall be done. Given the structural sensitivity of thermal conductivity and electrical resistivity, it is reasonable to investigate how the parameters are combined depending on the type of steel structures. The fact of the relationship of electrical resistivity and thermal conductivity of pure metals has been known and lay the foundation of Widemann-Franz law [6]. Firstly, based on reference data for different structural types of steel verification of the law has been done. Widemann and Franz based on experimental data found that for all metals ratio of thermal conductivity λ to electrical conductivity σ is constant at the same temperature:

$$\frac{\lambda}{\sigma} = const, \quad (1)$$

where λ - thermal conductivity coefficient, $\frac{W \cdot m}{K}$, σ - electric conductivity $\frac{Sm}{m}$.

Also Lorentz showed that the ratio $\frac{\lambda}{\sigma}$ is directly proportional to absolute temperature T :

$$\frac{\lambda}{\sigma} = L \cdot T, \quad (2)$$

where L – constant same for all metals, called the Lorentz number [6].

Correlation of electric conductivity and thermal conductivity is explained by the fact that both these properties of metals caused, basically, by movement of electrons. Widemann-Franz law is valid only for pure metals. Given the fact that steel is a complex compound or mechanical mixture of iron, carbon and alloying elements assumption that ratio (1) is not constant for different steel grades depending on its microstructure can be made. In the course implementation of the State Scientific-Technical Programme “Resurs” in Ivano-Frankivsk National Technical University of Oil and Gas a specialized problem-oriented database that contains information about the physical and mechanical properties of steels that are used in oil and gas industry has been created [5]. In order to check the above mentions theoretical idea, we used data from the developed database for selected properties of 142 foreign steel grades, which were selected according to the different types of microstructure:

- 1) austenitic steels (88 grades);
- 2) ferritic steels (12 grades);
- 3) duplex steels (26 grades);
- 4) martensitic steels (16 grades).

Here are the ranges of the target properties of the selected steel grades:

- Tensile strength: 400-2200 MPa;
- Yield strength: 145-1800 MPa;
- Hardness: 140-332 HB;
- Thermal conductivity: 9.1-32.3 W/m·K;
- Electrical resistivity - 500-1450 nOhm·m.

Electrical resistivity and electrical conductivity are linked by inversely proportional dependence:

$$\sigma = \frac{1}{\rho} \quad (3)$$

Substituting expression (3) into (1) and given the assumption that the ratio (1) is not constant for steel within different microstructural groups index K_i was calculated for every steel grade:

$$K_i = \rho_i \cdot \lambda_i, \quad (4)$$

as well as the mean value K_c for each microstructure:

$$K_c = \frac{\sum_{i=1}^n K_i}{n}, \quad (5)$$

where: ρ_i - electrical resistivity of i-index steel grade, $Ohm \cdot m$; λ_i - thermal conductivity of i-

index steel grade, $\frac{W}{m \cdot K}$; n – number of grade in microstructural group. Results of K_c calculation are given in Table 1.

Table 1 - Results of the calculation of the K_c coefficient

No	Microstructure	Value of $K_c \cdot 10^{-6}$	Range of values $K \cdot 10^{-6}$
1	Austenitic	12.05	9.9-13.6
2	Duplex	12.55	11.8-13.6
3	Martensitic	15.45	13.7-18.0
4	Ferritic	15.72	14.0-17.7

As can be seen from Table 1, coefficient K_c is different for different types of steel microstructure. But clear identification of the of the steel grade belonging to any of the microstructure is possible only for two groups of steels. The first group includes austenitic and duplex steels, second one includes ferritic and martensitic steels. Obviously that after some additional investigation with possible use of nonlinear classification methods this approach can lead to determination of the steel grade.

Considering complicated nature of the relationship between input parameters and mechanical properties [3] neural networks were used for non-linear approximation of the mechanical properties as function of hardness, electrical resistivity and thermal conductive parameter [7]. As neural networks routine require training and testing procedures the structural sets of steels were formed into training and testing sets:

- 1st set includes austenitic and duplex steel grades (90 grades were used for training and 5 grades – for testing);
- 2nd set includes ferritic and martensitic steel grades (37 grades were used for testing and 3 for testing):
- 3rd set includes all steel grades (127 steel grades were used for testing and 8 grades for testing).

Electrical resistivity and thermal conductive parameter were used as input parameters for the neural network while yield strength was used as output. It shall be noted that according to the established practice [7], testing the neural networks need to be performed on data which were not used for training (unknown for the neural network) in order to ensure the ability of the network to approximate the desired function and meet the NDT requirements.

Levenberg-Marquardt algorithm has been used as training algorithm for all data sets as this algorithm is recommended for small networks training. Neural network architecture selection, data preparation, selection of testing sets and training algorithms usually are based on the investigators experience [7] and depends on the nature and complexity of the task to be solved. After comparative studies of the various neural network architectures scheme which can be described as fully connected neural network with 2 hidden layers (20 and 10 neurons respectively) and single output neuron.

Testing results of the trained networks for 3 structural data sets are given in the Table 2.

Based on the results given in the Table 2 the following conclusion can be made:

1) Evaluation of the mechanical properties of steels within the groups of same or similar microstructure allow to increase for 2-3 times the accuracy of the given procedure. This conclusion is consistent with the prior idea of the relationship between thermal conductivity and electrical resistivity of steel grades with its microstructure.

Table 4 – Neural network testing results

Testing steel grade		1	2	3	4	5	6	7	8	Testing error	
										MPa	%
Dataset	Real values of yield strength	275	310	485	280	450	275	350	560		
1 st	Neural network outputs	271	313	492	283	430	-	-	-	7.4	3.52
2 nd	Neural network outputs	-	-	-	-	-	273	384	562	12.6	4.42
3 rd	Neural network outputs	276	316	483	273	379	328	345	478	28.3	9.92

2) Use of artificial neural networks allow establishment of the relationships between informative parameters and target mechanical properties (i.e. yield strength).

3) Achieved results confirm choice of the NDT informative parameters (thermal conductivity and electrical resistivity).

Additionally the achieved results were partly confirmed in the frame of the Indo-Ukrainian projected “Microstructural evaluation of steel used in petrochemical industry by NDE technique”, which is being performed by Ivano-Frankivsk National Technical University of Oil and Gas (Ukraine) and National Metallurgical Laboratory (Jamshedput, India). Series of samples which were put into operation in Ukrainian gas transport system were examined using non-destructive means (including thermal conductive parameter measurement) and microscopic methods.

Figures 1 and 2 represent microstructural patterns of the two different steel samples. At Figure 1 there is ferrite-pearlite structure which is evenly distributed through out the sample. At Figure 2 grain sizes are very irregular, large patches of very fine pearlitic colony is unevenly distributed.

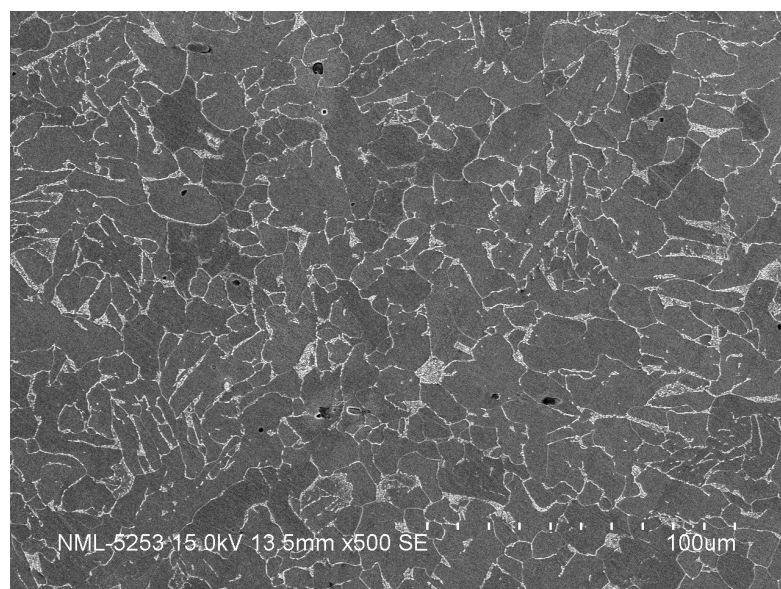


Figure 1 – Ferrite-pearlite structure of the steel used in gas pipelines

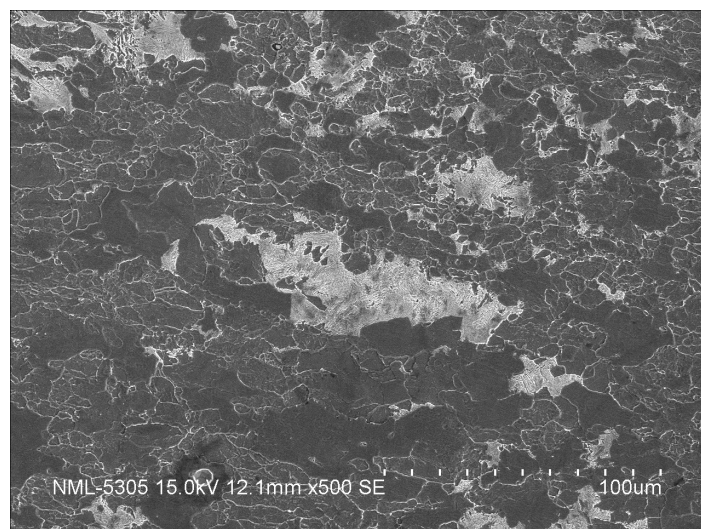


Figure 2 –

used in gas pipeline

Another steel sample

Structural difference of the samples, shown at Figures 1 and 2 was confirmed by the measurements of the thermal conductive parameter as their values differ for more than 20%.

Obviously, the obtained theoretical results have to be confirmed by electrical resistivity measurements and tensile tests.

Thus, as a result of research a new approach to the evaluation of the mechanical properties of metallic structures was developed, which lays in:

- calculation of the product of thermal conductivity and electrical resistivity (according to the Widemann-Franz law) for determination of the microstructure group of the steel;
- use of neural network within the defined microstructural group for prediction of the mechanical properties with thermal conductive parameter and electrical resistivity as input parameters.

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