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Neural network utilization for evaluation of the steel material properties

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Abstract: The aim of this work is to develop and test a new method for identification of material properties of the steel. This work deals with application of the small punch test for evaluation of material degradation of power station in the ČEZ company (main Czech energetic company) within the project TE01020068 “Centre of research and experimental development of reliable energy production, work package 8: Research and development of new testing methods for evaluation of material properties”. The main effort is here an improvement of empirical correlation of selected steel materials used in power industry for manufacturing of the critical components (rotors, steam-pipes, etc.). The effort here is on the utilization of the finite element method (FEM) and the neural network (NN) for evaluation of mechanical properties (Young modulus of elasticity, yield stress, tensile strength) of the selected material, based on SPT results only.

Keywords: Small Punch Test, Neural Network, Power Plant Steel, Mechanical properties

1. Introduction

Currently, there is an effort to maximize the service life of nearly worn out operating components while maintaining the conditions for reliable and safety operation. Consequently, the new test methods for evaluation of residual service life or for determination of the actual strength values and brittle fracture properties of the exploited components are being developed. One of the methods used to evaluate the current state of mechanical properties is the small punch test (SPT) [1-4]. Such experimental method is used for both assessing the current condition of the material as well as evaluating the so-called zero states of newly manufactured power plants components.

The main aim of this paper is to create a numerical tool, which could estimate material parameters of the particular steel, on basis of already performed experiments for penetration test (SPT) and tensile test. There will not be a requirement to perform the tensile test with the currently tested material and to identify from this test these parameters. Only SPT and database of previously performed (SPT and tensile test) tests is used together with the Neural network tool. This approach can significantly reduce time and cost of the material parameters assessment.

The standard process of identifying yield stress, tensile strength is to perform tensile test and based on this test, the material properties can be evaluated [5, 6]. Moreover, fracture toughness [7] needs to be also evaluated from the individual test. However, tensile test as well as fracture toughness assessment requires large specimen of the material and it could be financially and time demanding task. The small punch test has advantage of small specimen required for the test and relatively cheap cost, but it does not allow us to directly evaluate the material properties. To ensure the safe operation of the component, it is necessary to find out the actual values of the material parameters. With the advantage of this work, one would avoid the necessity to perform an expensive tensile test. It would be sufficient to perform just a penetration test and using a suitable mathematical apparatus identified such mechanical parameters. This newly developed approach could facilitate identification of the actual material parameters of steel in a timely and economical manner.

2. Methods

A neural network (NN) was chosen as a suitable mathematical apparatus. The neural network is a computational system originally inspired by nature and the human brain. Dr. Robert Hecht-Nielsen defined the neural network as follows:

“...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.

In "Neural Network Primer: Part I" by Maureen Caudill, AI Expert, Feb. 1989 [8].

The original idea of the neural network was to solve the problems in a way that human brain would do. However, over time many other applications were discovered for this method. The main idea is that the network can be trained/taught using input and output data to give reasonable outputs for new inputs. The structure of the neural

network is seen in Figure 1, where the first layer is the input; the last layer is the output and between them is (optional) number of the hidden layers. Each layer contains mutually connected nodes, and these are further connected to other nodes in the next layer. In this way, we get to the last layer, i.e. to the output data. However, it is necessary to properly train the network in order to create suitable connections between the layers and the nodes. There should be several hundred to several thousand input/output pairs required to properly train the network [9, 10].

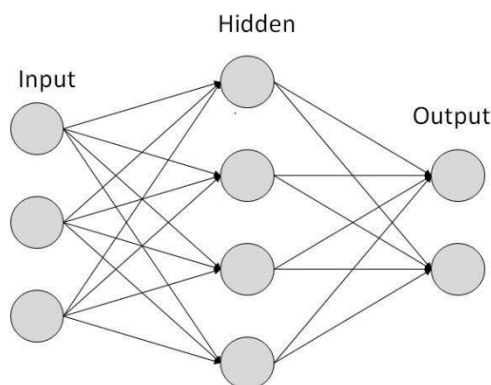


Figure 1. Structure of the neural networks.

In this case, the network would have the data from the penetration test (curve of Force versus Strain) as input and one of the following material parameters as an output: Young's modulus of elasticity E , yield stress R_{p02} and tensile strength R_m , see Figure 2. For each material value, one single network was created.



Figure 2. Diagram of the neural network based program.

The neural network has to be trained with a known data pair set (input-output). Here, experimental testing of SPT and tensile test of the given material were considered. From the standard tensile test, the material parameters were identified using standard identification method in company MATERIÁLOVÝ A METALURGICKÝ VÝZKUM, s.r.o. and directly used for the neural network as a training output. The input here was the force curve measured during SPT experiment. Consequently, the training dataset for the neural networks consist of the material parameters (E , R_{p02} and R_m) as an output and SPT curve as an input. The reference values of these material parameters come from experimental tensile test. The neural network must not only be trained, it is always necessary to test it with the use of some known pair of the input-output, which was not used in the training process. Here only one dataset of 100 specimens was available for the material 10GN2MFA. Number of 99 pairs was used for network training and one remaining pair for testing. This was done gradually with all 100 values (each of this will become ones a testing value). The final error of the neural network prediction was then evaluated. However, this process of training with the relatively small data set (100 pcs.) of only one material would predict reasonable results only for this particular material or similar one. To build a robust algorithm for prediction of any kind of material properties, one would need to build very large database of the reference specimens. Such database should contain various materials in a various state of residual life. Thus, to build the database, one must perform the SPTs as well as tensile tests, from which the reference material properties are determined. Since the database is filled up, you will only perform a SPT with the new/monitored material and the experimental curve will be used in the neural network to predict Young's modulus of elasticity, yield stress or tensile strength.

2.1 Experimental methods

In order to obtain experimental data, structural steels 10GN2MFA were used. This particular material is exploited in nuclear power engineering on a long term basis and particularly in the nuclear power engineering for power station of type VVER 1000 and MIR 1200. It was subjected to real heat treatment procedures in order to achieve real level of mechanical properties and to provide thus enough experimental data for the neural networks.

For investigated state the tensile tests was performed with subsequent determination of the curve of actual stress-strain (current state of the material), SPT or fracture toughness tests that resulted in the R curves. Since the characteristic feature of the fracture behaviour at the laboratory temperature for all of the above materials and their states after heat treatment was a stable growth of a ductile crack.

Due to the fact that both tensile and fracture toughness tests are standardized and adequately described in the literature [9,10], the next paragraph will deal only with the method of the SPT penetration tests.

The SPT method belongs to advanced testing methods developed on the long term basis in the company MATERIÁLOVÝ A METALURGICKÝ VÝZKUM, s.r.o. This method makes possible to obtain a number of mechanical properties with the use of the relatively small size of the test specimen. This method is used mainly for evaluation of the current state of mechanical properties of the components exploited in standard power engineering. In the recent past, this method was newly used also for determination of the impact of the sigma phase on the brittle fracture properties of steels used for the USC parameters [11-13].

The main advantage of the SPT method lies in the low volume of the experimental material and also in the fact that it is possible to obtain from the conducted SPT tests a number of properties. The SPT principle is illustrated in Figure 3. The test corpuscle is a disc with a diameter $d_1 = 8$ mm and a thickness $h = 0.5$ mm, which is penetrated by a hemispherical punch with a radius $r = 1$ mm till the failure. The diameter d_2 of the hole in the lower die is 4 mm. Record of the SPT test is shown in Figure 4. Such curve can be further used for the neural network to obtain the required values of mechanical properties [4]. In this experimental SPT, the deflection was controlled value, and thus remains very similar across the measurements and thus it was not used for the analysis.

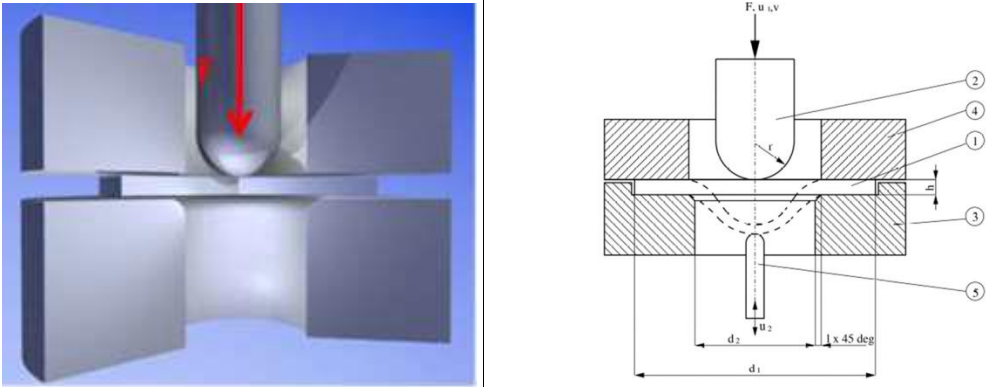


Figure 3. Principle of small punch test.

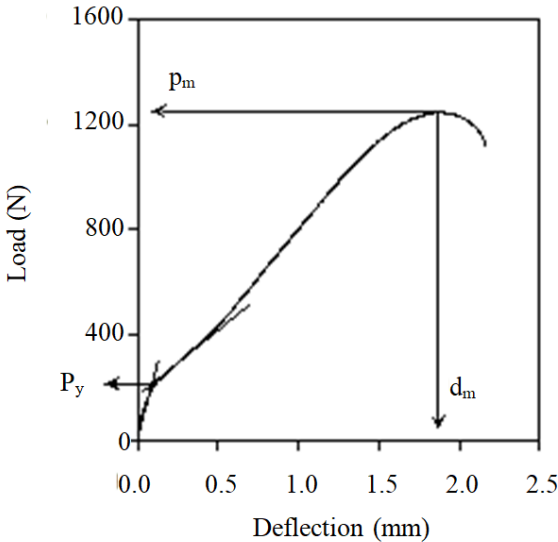


Figure 4. Record of the Small Punch Test.

3. Results

One investigated material 10GN2MFA was tested within the algorithm for evaluation of the steel material properties based on the Small Punch Test and neural network. The given 100 experimental pairs were gradually used for the training and testing of the neural network. There were always 99 pairs for the training of the network and one for the testing. The pair changes in the way, that each pair was ones a testing and 99 times a training one. The neural network provides a prediction of the material values (output) for the testing input (force vs displacement). Since these values are known (from the experiment), but not used for the training, the quality of such prediction can be assessed just with the comparison of the predicted and real values (output – E , R_{p02} and R_m). The error was calculated in absolute (MPa) and relative (%) values and the mean error was evaluated.

Table 1. Results of the Neural Network simulation of the mechanical properties.

| | | Mean Absolu | Max Absolu | Mean Relati | Max. Relati |
|--------------|-------|-------------|------------|-------------|-------------|
| | | [MPa] | | [%] | |
| 10GN2MF A | E | 516 | 45190 | 0.0663 | 20.5 |
| | R_p | -0.09 | 61.6 | -0.07 | 11.18 |
| | R_m | 0.291 | 51.2 | -0.016 | 7.87 |

The obtained results summarised in Table 1 show good quality of the predicted values for the Young modulus of elasticity E . Maximal error of the estimation is about 20% while the mean error is less than 0.1%. Moreover, the 20% error of the prediction is still significant value. The maximal error of the predicted values for the yield stress and tensile strength is about 10%. Such estimation is considered as a good estimation, since we have only 99 training examples. For each three cases, the mean relative error is less than 0.1% and this indicates the reasonability of this approach. The complete results of the neural network (reference values, predicted values and the error is the Appendix A). Where, the name *SIM* (E_{sim}) refers to a simulated (predicted) value, while the *ORIG* (E_{orig}) refers to reference one.

4. Discussion

It follows from the obtained results summarized in Table 1, that the simulations here have good agreement with the experimental results. In our previous work started 3 year ago only limited number of data set do not exceeding 18 results was available. Such number of data set was found to be not acceptable as the scatter was too high. After improving NN methodology and increasing number of experimental data, the good agreement was found. Further work will be focused on the continuing of the experimental tests and building the material database using material like P91, P92 and A508 to get more relevant data.

5. Conclusions

The work describes the essence and the results obtained within the framework of the TAČR project TE01020068, work package 8. The project is focused on the use of the Small Punch Tests for evaluation of material degradation of critical components of conventional power plants. The aim of this work consists, in the creation of a connection between the SPT tests performed within the frame of evaluation of the actual material properties of the exploited and newly manufactured components and numerical calculation using neural networks. The first results indicate the possible application of the neural network method, especially for determining the values of mechanical properties. This work exploited the results obtained in [1], where authors tested such method on the three materials, with the maximal number of 18 values. Here, only one material, but with the larger number of specimens (100) were used. The results given here indicate/prove that the higher number of the training pairs can build better neural network with the better estimation. However there is still quite high maximal error. Moreover, the material 10GN2MFA is homogeneous material and the dispersion and quality of tested specimen was good. When the particular material would have non-linear behaviour and the scatter of the experimental data would increase, the prediction based on 100 examples only would vary significantly.

Achievement of consistent results when estimating material characteristics using neural networks would surely require a much bigger number of training samples. This is consistent with the literature, which states the need for at least several hundred or thousands pairs, for the proper functioning of the neural network. Consequently, this method

would require a wide database of the experiments for each material used in the real power plants. One could not assume that building one wide database for any kind of material will bring much more reasonable results.

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