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# Automatic classification of the 13CrMo4-5 steel worked in creep conditions

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**Methodology of research**

## ABSTRACT

**Purpose:** In material engineering the images obtained by various methods are the source of different information about materials. The artificial intelligence tools can be employed for automatic method for analysis of scanning electron microscope metallographic images of elements after long time operating in creep services.

**Design/methodology/approach:** The methodology allows to work out a system of automatic classification of internal damages in 13CrMo4-5 steel working in creep conditions on the base of computational images analysis by the use of artificial neural networks. Input vectors of artificial neural networks were optimized by the use of genetic algorithms.

**Findings:** The methodology of digital image analysis allowing identification of geometrical coefficients characterizing damages in the materials after long-time operating in creep conditions and methodology of classification of these damages by the use of artificial neural network were evaluated.

**Practical implications:** The presented method can be use as a practical application for classification of creep-damages of elements power industry installations components operating in creep conditions.

**Originality/value:** Applying of images analysis and neural networks to identification and classification of internal damages of 13CrMo4-5 steel working in creep conditions could shorten the time of classification and eliminate of many subjective errors made by humans.

**Keywords:** Creep; Neural networks; Steels; Image analysis

## 1. Introduction

Steel 13CrMo4-5 is one of the base materials use for devices in refinery-petrochemical, chemical and power engineering industry operating under extreme conditions of temperature, pressure and aggressive environment. The development of power plant technology towards larger units and higher efficiencies is linked to the development of creep resistant ferritic steels.

Seamless tube and pipes for boilers are manufactures from materials, which are able to withstand high temperatures and high pressures. Greatest technical requirements of the production process and also the most stringent control regulations in order to guarantee their durability and reliability over a period. The boiler tubes must be able to operate at high pressures and temperatures for long periods. At high temperature a constant load produces a micro structural variation of the metallic material, this brings a progressive reduction of the properties of the material itself [2,4].

Exploitations in these conditions caused changes of the material's structure, decreasing of properties and the development of damage processes of materials. Element operating in such conditions should be manufacture from materials characterizing good ability to remain mechanical properties in elevated temperature under loading and the resistance on the acting of chemical factors in elevated temperature, mainly on the acting of oxidizing gases. High costs of installations increase of working parameters, efficiency and reliability cause intensification in the area of modernization, diagnostic and durability extension of devices and their elements [11,12].

Artificial neural networks have wider application possibilities in the area of materials science that allow to their use in solving new and classical problems and matters because they allows to solve non-linear problems which are the main issue in that field [6-8,10,15,16].

The paper shows the computer assisted method employing image analysis, shape coefficients, neural networks and genetic algorithms for the automatic classification of damages of materials use for power systems in creep service.

## 2. Experimental procedure

Creep resistant steels are mainly use to build turbines, whereas tubes, pipes, plates and fittings are the typical products for application in pressure vessels, boilers and piping systems. Material for investigation was acquired from these elements of power industry pressure installation long-time operating in creep conditions. Elements were made from the 13CrMo4-5 steel and their working conditions were as follows: calculation temperature 520-560°C, real stress 35-120MPa, working time 60000-230000h. The chemical composition of this steel is shown in Table 1.

Table 1.
Chemical composition of 13CrMo4-5 steel according to the Polish standard PN-EN 10028-2:2005 [9]

| Mass chemical composition [wt.%] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| C | Mn | Si | P | S | Cr | Mo | N | Cu |
| 0.08-0.18 | 0.4-1 | <0.35 | ≤0.025 | ≤0.01 | 0.7-1.15 | 0.4-0.6 | <0.012 | ≤0.3 |

During the creep process in the structure of materials are formed singular voids, chains of voids, coalescence of voids, and micro- macrocracks. These elements allow characterizing the degree of materials exhaust.

One of the method allowing to obtain essential information about materials' structure and properties is image analysis so this method is more commonly use in material science. Images from scanning electron microscope, transmission electron microscope or confocal microscope are saved or converted to digital format and allow for objective interpretation.

To solve the problem of internal damages classifications in steels working in creep conditions, the metallographic structure images from scanning electron microscope (Fig. 1) were used and the following methodology was applied:

- initial processing of images (unification of format, contrast and resolution),
- analysis of image,
- calculation of area (S) number of pixels inside the damage,
- calculation of circumferences of chosen element (L) number of pixels on the damage's circumstance, distance between neighbouring pixels is equal 1 (side) and $\sqrt{2}$ (diagonal),
- calculation of distances between objects,
- Feret's diameter describing extent of damages in vertical $D_f(0°)$ and in horizontal $D_f(90°)$,
- Feret's coefficient characterizing elongation of damage described by:

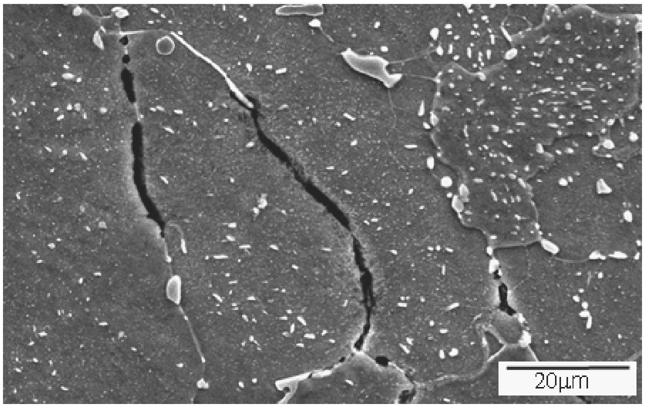


Fig. 1. Structure of internal damages of 13CrMo4-5 steel (SEM)

$$W_F = \frac{D_f(0^o)}{D_f(90^o)},$$

- evaluation of geometrical coefficients, which were defined below [13,14],
- coefficient to roundness

$$W_k = \frac{4 \cdot \pi \cdot S}{L},$$

- Malinowska's coefficient (Wm)

$$W_m = \frac{L}{2 \cdot \sqrt{\pi \cdot S}} - 1,$$

- coefficient of circularity1 (Wc1) and circularity 2 (Wc2) determining circularity of damage:

$$W_{C_1} = 2 \cdot \sqrt{\frac{S}{\pi}}$$

$$W_{C_2} = \frac{L}{\pi},$$

- nondimensional coefficient (Ws) for quantitative characterization of the damage's shape

$$W_S = \frac{L^2}{4\pi S},$$

- Blair-Bliss coefficient (Wbb)

$$W_{bb} = \frac{S}{\sqrt{2\pi \cdot \sum_i r_i^2}},$$

$r_i$ - distance of the object's pixel from the object's centre of gravity,
$i$ - number of object's pixel,

- Haralick's coefficient (Wh)

$$W_h = \sqrt{\frac{(\sum_i d_i)^2}{n \cdot \sum_i d_i^2 - 1}},$$

$d_i$ - distance of the outline's pixel from the object's centre of gravity,
$i$ – number of outline's pixel,
$n$ – number of objective's outline pixel,

- coefficient of contents (Wz)

$$W_Z = \frac{L^2}{S}$$

- application of neural networks to degree of internal damages classifications,
- optimization of input vector of artificial neural network by the genetic algorithms,
- evaluation of computer program for internal damages' degree classification.

Quantitative values describe the features of analysed image and allow for converting the image into the set of digit describing it than the direct draw of conclusions is possible. Interpreted features can be divided into local (averaging of image element) and global one (group of image elements). The features are determined in indirect way on the base of the measurements made for analyzed image. Attributes describing element are converted to determine their characteristic features. Shape analysis converts the features that correctly determine their shapes and for elements with similar shape equal values are assigned. For calculation of numerical values of geometrical shapes are used shape's coefficients.

The procedure should take into account the minimization of measurements errors (good sample lighting, magnification, grey threshold ) to obtain required boundaries separation.

The presence of internal damages, independent of the degree of structure changes, decides the possibilities of the element exploitations. The classification of damages versus the degree of material exhaust consists of four main classes A, B, C, and D with subclasses. The classification of internal damages was simplified to 5 main classes to meet the needs of neural network model, the additional 0 classes with no internal damages of the structure is introduced [1,3]:

- class 0 – structure close to the initial state,
- class A – nucleation of voids,
- class B – development of voids,
- class C – development of micro-cracks,
- class D – development of macro-cracks.

The choice of the number and kind of artificial neural network input data were made by the use of genetic algorithms. For optimisation the mask determining which of the geometrical coefficients should be applied as the input of neural network were used.

Genetic algorithms choose the best input vectors of the artificial neural network on the base of chains creating and selection. The choice is based on so called population of offspring. They take the main features of their parents and modify properties and specific problem is solved by them a little bit better or worse than their parents. Further multiplication is based on the selection of that individuals, that classify the damaged of materials and make the smallest errors.

The optimisation taking into account the quality of classification of variable independent vector with the use of ordinal crossing was applied. This method allows for creating new individuals by the combination of their parents features and mutation. Table 2 shows option of genetic algorithms for which the smallest value of error of geometrical coefficients were obtained.

Table 2.
Options of genetic algorithms

| | |
|---|---|
| Size of population | 140 |
| Number of generation | 110 |
| Coefficient of mutation | 0.2 |
| Coefficient of crossing | 1 |

Correct classification is able thanks to use of many geometrical coefficients. They allow to distinguish damages with the same values of geometrical coefficients (classification to the same class) and with the different ones (classification to different class).

In worked out initial model of artificial neural network on the entry there was 15 geometrical coefficients: area (S), circumferences (L), coefficient to roundness (Wk), Malinowska's coefficient (Wm), coefficient of circularity1 (Wc1) and circularity 2 (Wc2), maximum (MinOdl) and minimum distance (MaxOdl), horizontal and vertical Feret's diameters (SFpoz, SFpion), Blair-Bliss coefficient (Wbb), Feret's coefficient (Wf), Haralick's coefficient (Wh), nondimensional coefficient (Ws), coefficient of contents (Wz) [13,14]. Based on genetics algorithms artificial neural network with 10 input neurons with calculated geometrical coefficients was worked out (Table 3).

Table 3.
The parameters of the best neural network used for the classification of internal damages

| | |
|---|---|
| Input vectors | Po, Ob, Wm, Wc1, Wc2, MinOdl, SFpoz, SFpion, Ws, Wz |
| Network structure | Multilayer Perceptron 10-31-5 |
| Training method | Back Propagation/ Conjugate Gradient Descent |
| Number of training epochs | 416/50 |

The weight of synaptic junctions are chosen in the way to minimize the network errors that means to find the minimum of sum square between values calculated by the network and real values.

The choice of optimal network learning way was made on the base of the following methods:

- non-linear optimisation (Lavenberg-Marquardt's),
- radial base functions,
- errors back propagation,
- coupled gradients,
- non-linear optimisation (quasi-Newton's).

The best worked out artificial neural network MLP 10-31-5 (Fig. 2) was used in he computer program, which allows the classification of internal damages of low alloyed chromium-molybdenum steels on the based on images from scanning electron microscope [5].

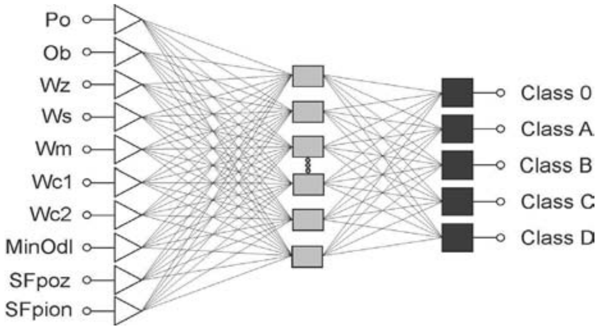


Fig. 2. Schema of neural network MLP 10-31-5

On the input of the computer program the user supplies the image of the structure while the program calculates the values of geometrical coefficients of internal damages and classifies the damage degree by the use of artificial neural networks (Fig. 3).

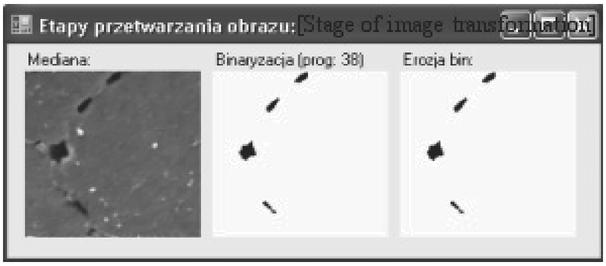


Fig. 3. Program window for the image analysis

## 3. Conclusions

Computer classification of the internal damages can be used with success as forecast support tools in engineering practice. The accuracy and the dependability of this method vastly depends on the place choosing to take the metallographic structure, the proper interpretation of observed metallographic structure and the need of engagement of expert with sufficient practical knowledge.

Applying of genetic algorithms allows to increase the correctness of internal damages classification in steels operating in creep conditions by the proper choice of essential geometrical coefficients describing damages.

The advantage of worked out methodology over the statistics methods is the possibility of correct classification even with close values of geometrical coefficients.

This methodology in connection with computer program allows to more objective and quicker identification and classification in comparison with classical metallographic method.

## References

[1] L.A. Dobrzański, M. Sroka, J. Dobrzański, Application of neural networks to classification of internal damages in steels working in creep service, Journal of Achievements in Materials and Manufacturing Engineering 20 (2006) 303-306.

[2] J. Dobrzański, Internal damage processes in low alloy chromium–molybdenum steels during high-temperature creep service, Journal of Materials Processing Technology 157-158 (2004) 197-303.

[3] J. Dobrzański, A. Zieliński, M. Sroka, Structure, properties and method of the state evaluation of low-alloyed steel T23 (HCM2S) worked in creep conditions, Proceedings of the 11th International Scientific Conference Contemporary "Achievents in Mechanics, Manufacturing and Materials Science" CAM3S'2005, Gliwice–Zakopane, 2005, (CD-ROM).

[4] J. Dobrzański, M. Sroka, A. Zieliński, Methodology of classification of internal damage the steels during creep service, Journal of Achievements in Materials and Manufacturing Engineering 18 (2006) 263-266.

[5] M. Sroka, Methodology of computer forecasting of residual life of elements in creep service, PhD Thesis, Gliwice (2006) (unpublished) (in Polish).

[6] L.A. Dobrzański, M. Krupinski, J.H. Sokolowski, Computer aided classification of flaws occurred during casting of aluminum, Journal of Materials Processing Technology 167 (2005) 456-462.

[7] L. Miaoquan, Ch. Dunjun, X. Aiming, Li. Long, An adaptive prediction model of grain size for the forging of Ti–6Al–4V alloy based on fuzzy neural networks, Journal of Materials Processing Technology 123 (2002) 377-381.

[8] L.A. Dobrzański, M. Kowalski, J. Madejski: Methodology of the mechanical properties prediction for the metallurgical products from the engineering steels using the artificial intelligence methods, Journal of Materials Processing Technology 164–165 (2005) 1500-1509.

[9] Polish standard, PN-EN 10028-2:2005 Flat products made of steels for pressure purposes - Part 2: Non-alloy and alloy steels with specified elevated temperature properties

[10] H. Zheng, L.X. Kong, S. Nahavand, Automatic inspection of metallic surface defects using genetic algorithms, Journal of Materials Processing Technology 125-126 (2002) 427-433.

[11] J. Dobrzański, M. Sroka, Computer aided classification of internal damages the chromium-molybdenum steels after creep service, Journal of Achievements in Materials and Manufacturing Engineering 24/2 (2007) 143-146.

[12] D. Renowicz, A. Hernas, M. Cieśla, K. Mutwil, Degradation of the cast steel parts working in power plant pipelines, Journal of Achievements in Materials and Manufacturing Engineering 18 (2006) 219-222.

[13] R. Tadeusiewicz, P. Korohoda, Computer assisted image analysis and processing, Development in telecommunication Press, Cracow 1997 (in Polish).

[14] L. Wojnar, K.J. Kurzydłowski, J. Szala, Practice of image analysis, PTS, Cracow, 2002 (in Polish).

[15] L.A. Dobrzański, S. Malara, J. Trzaska, Project of neural network for steel grade selection with the assumed CCT diagram, Journal of Achievements in Materials and Manufacturing Engineering 27 (2008) 155-158.

[16] L.A. Dobrzanski, M. Kremzer, J. Trzaska, A. Wlodarczyk-Fligier, Neural network application in simulations of composites Al-$Al_2O_3$ tribological properties, Archives of Materials Science and Engineering 30/1 (2008) 37-40.