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PREDICTION OF THE HARDNESS OF HARDENED SPECIMENS WITH A NEURAL NETWORK

NAPOVED TRDOTE KALJENIH VZORCEV Z NEVRONSKIMI MREŽAMI

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In this article we describe the methods of intelligent systems to predict the hardness of hardened specimens. We use the mathematical method of fractal geometry in laser techniques. To optimize the structure and properties of tool steel, it is necessary to take into account the effect of the self-organization of a dissipative structure with fractal properties at a load. Fractal material science researches the relation between the parameters of fractal structures and the dissipative properties of tool steel. This paper describes an application of the fractal dimension in the robot laser hardening of specimens. By using fractal dimensions, the changes in the structure can be determined because the fractal dimension is an indicator of the complexity of the sample forms. The tool steel was hardened with different speeds and at different temperatures. The effect of the parameters of robot cells on the material was better understood by researching the fractal dimensions of the microstructures of hardened specimens. With an intelligent system the productivity of the process of laser hardening was increased because the time of the process was decreased and the topographical property of the material was increased.

Keywords: fractal dimension, laser, hardening, neural network

V tem članku je uporabljena metoda inteligentnih sistemov za napovedovanje trdote kaljenih vzorcev. Uporabljena je matematična metoda fraktalne geometrije v laserski tehniki. Za optimiranje strukture in lastnosti orodnega jekla je treba upoštevati vpliv samoorganizacije strukture z lastnostmi fraktalov. Fraktalna znanost o materialu raziskuje odnos med parametri fraktalne strukture in disipativnimi lastnostmi orodnega jekla. Članek opisuje uporabo fraktalne dimenzije pri robotskem laserskem kaljenju vzorcev. Z uporabo fraktalne dimenzije se lahko določi sprememba v sestavi, ker je fraktalna dimenzija pokazatelj kompleksnosti oblike vzorcev. Orodno jeklo je bilo kaljeno z različnimi hitrostmi z različnih temperatur. Učinek parametrov robotske laserske celice na orodno jeklo se da boljše razumeti z raziskovanjem fraktalne dimenzije mikrostrukture kaljenih vzorcev. Z inteligentnimi sistemi je bila povečana produktivnost procesa laserskega kaljenja, ker se zmanjša trajanje procesa in se povečajo topografske lastnosti materialov.

Ključne besede: fraktalna dimenzija, laser, kaljenje, nevronske mreže

1 INTRODUCTION

Of all the microscopic methods, electron-microscopy images give the best resolution, the most accurate information of the distribution of crystals in a building, the best morphology of various structural types and the best structural surface topography. Fractal geometry provides a new approach in describing the structures of various irregular facilities. Fractal theory is also used in the field of materials science. Models of fractal lines and surfaces are created to describe the properties of the microstructures of materials. The subject of fractals can be used to assist in an analysis of the surfaces encountered in robot laser hardening. It should be noted that the morphology of a surface will change if the material is hardened with robot laser cells. An analysis of fractal dimensions is a method used to study the surface properties of materials. A fractal dimension[1,2] is a property of fractals that is maintained with all the magnifications and is, therefore, well-defined but, in addition, it also reveals the complexity of the fractal. In general, we cannot calculate the fractal dimension for the above-mentioned procedure, as this is possible only for purely mathematical constructs and not in reality. In practical terms, to determine the dimensions the most used method is that 'of counting the boxes' (the box-counting dimension) that studies a fractal cover using a square grid, which is then reduced and the change in the number of the squares needed to cover the entire crowd is observed. The result is, of course, an approximation, which is calculated using the desired number of places. In this research, a fractal analysis is used to determine how the parameters of robot laser hardening affect the hardness of a hardened material. Robot laser surface-hardening heat treatment[3–6] is complementary to the conventional flame or inductive hardening. The energy source for laser hardening is a laser beam that heats up very quickly achieving the metal surface area of points up to 1.5 mm and a hardness of 65 HRc. Laser hardening is a process of projecting the features such as non-controlled energy intake, high performance constancy and accurate positioning process. A hard martensitic microstructure provides improved surface properties such as wear resistance and high strength.[7,8] A fractal analysis[9,10] is useful when classical geometry cannot be sufficiently useful to precisely describe the results of irregular facilities. A profound feature of fractals is the fractal dimension D[11–13] providing an important view of the physical properties of various materials. This article describes the fractal structure[14,15] of robot laser-hardened tool steel. Fractal patterns were found in different mechanical properties of hardened materials (Mandelbrot 1982, Feder 1988). Fractal features were also observed in a mechanical computer simulation, which can be explained with Gauss-Marc fractal random fields. In this work, we have used a scanning electron microscope (SEM)[16,17] to search and analyse the fractal structure of the robotic-laser-hardened material. The aim of the research is to ascertain how the robotic-laser-cell parameters for an optimum tempering affect the fractal dimension of the hardened material.

2 MATERIAL PREPARATION AND EXPERIMENTAL METHOD

2.1 Material preparation

The study was undertaken using the tool steel of DIN standard 1.7225. The chemical composition of the material included 0.38 % to 0.45 % C, 0.4 % maximum Si, 0.6–0.9 % Mn, 0.025 % maximum P, 0.035 % maximum S and 0.15–0.3 % Mo. The specimen test section was in a cylindrical form with the dimensions of 25 mm × 10 mm. After hardening the test specimen was cut into smaller parts. The tool steel was forged with laser at different speeds and different powers. So, we changed two parameters, speed $v \in 2{,}5$ mm/s with the steps of 1 mm/s and temperature $T \in (1000, 1400)$ °C in 50 °C steps. In all these tests we recorded the microstructure.

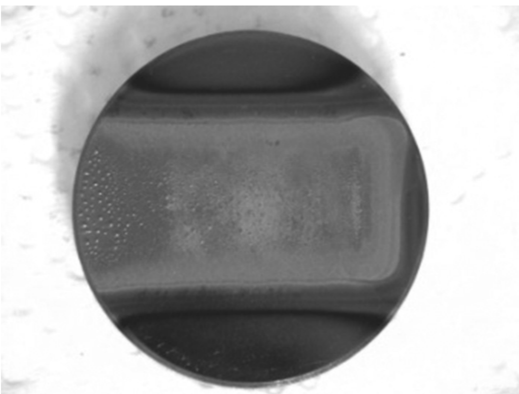

Figure 1: Hardened specimen
Slika 1: Kaljen vzorec

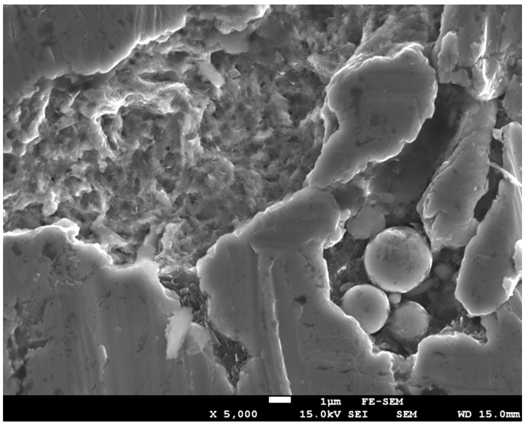

Figure 2: SEM image of a hardened specimen
Slika 2: SEM-posnetek kaljenega vzorca

We recorded the hardened surface area as well as the deep hardened zone of the clips. Of interest to us was whether the robotic laser-hardening parameters for different fractal structures resulted in microparticles. Also, we wanted to understand or ascertain the fractal structure of the optimum hardening parameters. **Figure 1** shows the longitudinal and transverse cross-section of the hardened tool steel. **Figure 2** shows the microstructure of the hardened tool steel. Prior to testing, the specimens were first subjected to mechanical and then to electrolytic polishing[18] in $H_3PO_4 + CrO_3$. After polishing the microstructure was examined with a light microscope and with field-emission scanning electron microscope, JEOL JSM-7600F. Irregular surface textures with a few breaks, presented as black islands, are seen in **Figure 2**.

2.2 Experimental method

The porosity was determined from the SEM images of the microstructure. It is known that in a homogenously porous material the area of the pores is equal to the volume of the pores in specimens. The SEM pictures were converted to binary images (**Figure 3**), from which we calculated the areas of the pores for all the pictures using the ImageJ program (ImageJ is a public domain, a Java-based image processing program developed at the National Institutes of Health). The area of the pores on each picture of the material was calculated and then the arithmetic mean and the standard deviation of the porosity were determined. To analyze the possibility of an application of the fractal analysis[11–16] to the heat-treated surface, we examined the relation between the surface porosity and fractal dimensions depending on various parameters of the robot laser cell. In fractal geometry, the key parameter is fractal dimension D. The relationship between fractal dimension D, volume V and length L can be indicated as follows:

$$V \sim L^D \tag{1}$$

Fractal dimensions were determined using the box-counting method which has been proven to have a higher

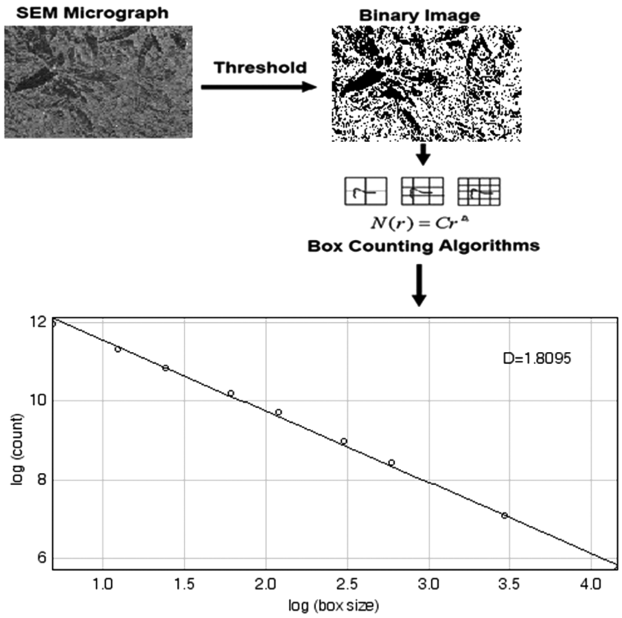

Figure 3: Calculation of fractal dimensions with the box-counting method
Slika 3: Računanje fraktalne dimenzije z metodo rezanja škatel

calculation speed and better accuracy by Dougan[19] and Shi[20].

To analyse the results we used one method of the intelligent system: the neural network.[21] Artificial neural networks (ANNs) are simulations of collections of model biological neurons. A neuron operates by receiving signals from the other neurons through the connections called synapses. A combination of these signals, in excess of a certain threshold or activation level, will result in the neuron firing, i.e., sending a signal to another neuron, to which it is connected. Some signals act as excitations and others as inhibitions of neuron firing. What we call thinking is believed to be a collective effect of the presence or absence of firings in the patterns of the synaptic connections between neurons. In this context, neural networks are not simulations of real neurons, as they do not model the biology, chemistry or physics of a real neuron. The basic building element of the neural

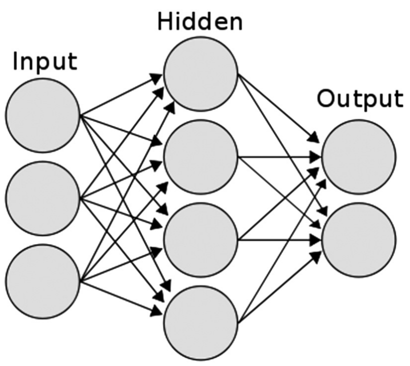

Figure 4: General multi-layer neural-network system
Slika 4: Splošni sistem večplastne nevronske mreže

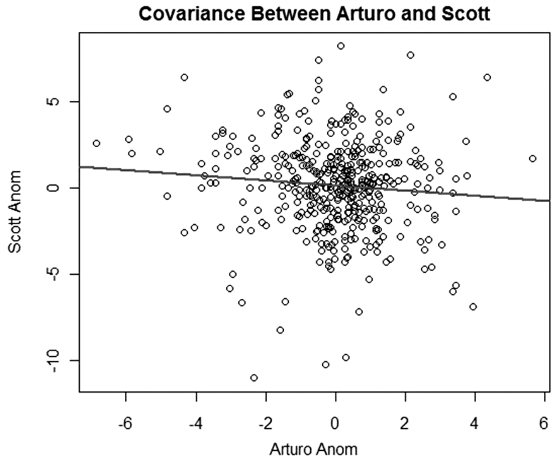

Figure 5: Analysis of covariance
Slika 5: Analiza kovariance

network used is an artificial-neural-network cell (ANN) (**Figure 4**).

The analysis of covariance (generally known as ANCOVA) is a technique that brings together the analysis of variance and regression analysis. Covariance is a measure of how much two variables change together and how strong the relationship is between them. ANOVA can be extended to include one or more continuous variables that predict the outcome or dependent variable. **Figure 5** presents the analysis of covariance.

3 RESULTS AND DISCUSSION

3.1 Results

Table 1 presents the parameters of the hardened specimens that have an impact on the hardness. We marked the specimens with the codes from P1 to P19. Code *X*1 stands for the parameter of the temperature (°C), *X*2 is the speed of hardening (mm/s), *X*3 is the fractal dimension and *X*4 is the base hardness (the hardness before hardening). The last parameter, *Y*, is the measured hardness of the robot laser-hardened specimens. **Table 2** lists the experimental and prediction hardnesses of the robot laser-hardened specimens. With the fractal dimension we described the complexity of the hardened specimens. In **Table 1**, we can see that specimen P11 has the largest fractal dimension, 1.978 4. Thus, specimen P11 is the most complex. Specimen P1 has the highest hardness after hardening, that is 60 HRc. Specimen P17 has the lowest hardness after hardening, that is 52 HRc. **Figure 6** shows a graph presenting the measured and predicted hardnesses of the robot laser-hardened specimens. This figure also presents a model of regression. **Table 2** lists the experimental and prediction data. The first column gives the codes of the hardened specimens. The column for Hardness (experimental data) gives the experimental data for the hardness after hardening. The predictions with a neural network are presented in the column for Hardness (prediction with NN 36 %); in our case we

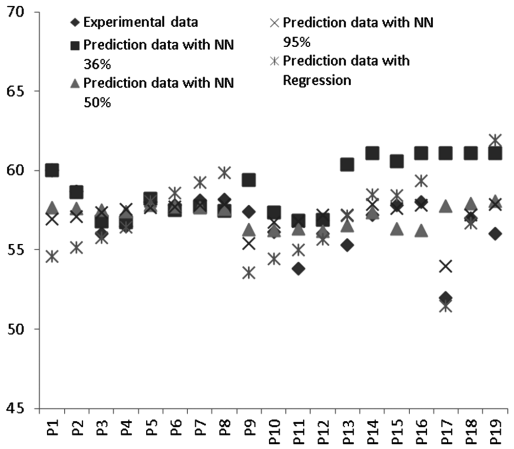

Figure 6: Measured and predicted hardnesses of the hardened specimens
Slika 6: Izmerjene in napovedane trdote kaljenih vzorcev

used 12 datasets for the learn test set and 7 datasets for the test set. In the column for Hardness (prediction with NN 52 %) we used 10 datasets for the learn test set and 9 datasets for the test set; and in the column for Hardness (prediction with NN 95 %) we used 18 datasets for the learn test set and 1 dataset for the test set; we used the leave-one-out method. We used program Neuralyst. Neuralyst is a general-purpose neural-network engine that was integrated with Microsoft® ExcelTM in the WindowsTM or MacintoshTM systems. Neuralyst provides a user-friendly interface and a powerful, flexible neural network that is self-programming. A researcher acts as a coach to Neuralyst providing it with data and letting it know the goals it should learn. Neuralyst will then train itself on the data and goals the researcher has set. During its training, it will report on how well it is

Table 1: Parameters of the hardened specimens
Tabela 1: Parametri kaljenih vzorcev

Specimen	*X*1	*X*2	*X*3	*X*4	*Y*
P1	1000	2	1.9135	34	60
P2	1000	3	1.9595	34	58.7
P3	1000	4	1.9474	34	56
P4	1000	5	1.9384	34	56.5
P5	1400	2	1.9225	34	58
P6	1400	3	1.9781	34	57.8
P7	1400	4	1.954	34	58.1
P8	1400	5	1.9776	34	58.2
P9	1000	2	1.972	60	57.4
P10	1000	3	1.858	58.7	56.1
P11	1000	4	1.9784	56	53.8
P12	1000	5	1.941	56.5	56
P13	1400	2	1.9782	58	55.3
P14	1400	3	1.581	57.8	57.2
P15	1400	4	1.965	58.1	57.8
P16	1400	5	1.8113	58.2	58
P17	800	0	1.9669	34	52
P18	1400	0	1.9753	34	57
P19	2000	0	1.9706	34	56

Table 2: Experimental and prediction data
Tabela 2: Eksperimentalni in napovedani podatki

Specimen	Hardness (experimental data)	Hardness (prediction with NN 36 %)	Hardness (prediction with NN 52 %)	Hardness (prediction with NN 95 %)	Hardness (prediction with regression)
P1	60	60.04404	57.66478	56.95868	54.56465
P2	58.7	58.65453	57.60106	57.12015	55.12693
P3	56	56.79983	57.5164	57.37326	55.7891
P4	56.5	56.75793	57.42825	57.5548	56.44594
P5	58	58.21552	57.79482	57.63685	58.04714
P6	57.8	57.48934	57.73722	57.68834	58.5924
P7	58.1	57.72849	57.65605	57.80268	59.27572
P8	58.2	57.478	57.58361	57.85767	59.87651
P9	57.4	59.39293	56.29186	55.42167	53.57422
P10	56.1	57.33137	56.21767	56.71604	54.4561
P11	53.8	56.83125	56.31979	56.76928	54.98285
P12	56	56.89147	56.19585	57.17863	55.67142
P13	55.3	60.36785	56.5345	57.19434	57.12963
P14	57.2	61.11235	57.35906	57.85592	58.46115
P15	57.8	60.55724	56.33986	57.59233	58.43199
P16	58	61.11235	56.2168	57.84021	59.33421
P17	52	61.11235	57.76515	53.96322	51.44111
P18	57	61.11235	57.93535	57.20306	56.67362
P19	56	61.11235	58.0907	57.87076	61.92865

doing. We used a 4-layer network, learning at the rate of 0.6, with the moment of learning being 0.5, the tolerance of the test set being 0.01 and the tolerance of the learning set being 0.3. The neural-network modelling with the 36 % training data shows a 7.7 % deviation from the measured data, the modelling with the 52 % training data shows a 5.2 % deviation from the measured data and the modelling with the 95 % training data shows a 2.3 % deviation from the measured data. The regression model shows a 4.7 % deviation from the measured data.

3.1.1 Model regression

$$Y = 48.99076743 + 0.008744915 \cdot X1 + 0.641369094 \cdot X2 - 1.71942784 \cdot X3 - 0.034224818 \cdot X4$$

We checked the reliability model with pattern P20 heat treated at 1200 °C at a speed of 6 mm/s. We calculated the fractal dimension of the sample, which had a value of 1.9692. Sample P20 had a hardness of 57 HRc. The data were inserted into the model and we determined the deviations of the experimental values from the model values. **Table 3** shows the deviation of the predicted value for sample P20 from the experimental measurements after heat treatment.

Table 3: Deviation of the predicted values for specimen P20 from the experimental measurements after heat treatment
Tabela 3: Odmik napovedanih vrednosti vzorca P20 od eksperimentalnih meritev po toplotni obdelavi

Specimen	Hardness (prediction with NN 36 %)	Hardness (prediction with NN 50 %	Hardness (prediction with NN 95 %)	Hardness (prediction with regression)
Deviation	4.32 %	2.91 %	1.23 %	3.12 %

3.2 Discussion

The hardness structure of the material is an important mechanical property that affects the hardness of materials. We cannot apply Euclidian geometry to describe the porosity of hardened specimens because porosity is very complex. Here we use fractal geometry to describe the hardness of the robot laser-hardened specimens. In this paper we describe how the parameters (speed and temperature) of a robot laser cell affect the hardness of metal materials using a new method, fractal geometry. Hardness has a large impact on the mechanical properties of a material. The fractal approach is more appropriate for characterizing complex and irregular surface microstructures observed in the surfaces of robot laser-hardened specimens and can be effectively utilized for predicting the properties of the material from the fractal dimensions of the microstructures. The fractal analysis of a series of digitized surface microstructures of the robot laser-surface-modified specimens indicated that useful correlations can be derived between the fractal dimensions and the surface microstructural features such as hardness. Specimen P17 has the minimum hardness after hardening, which is 52 HRc. We used two methods of intelligent systems to make a prediction of the hardness of the robot laser-hardened specimens. The neural-network model gave us a better prediction than the regression.

4 CONCLUSION

The paper presents the use of the method of an intelligent system to predict the hardness of hardened specimens. We used fractal geometry to describe the mechanical property, the hardness of robot laser-hardened specimens. Fractal structures were also found in the robot laser-hardened samples when viewed under sufficient magnification. The hardening of various metal alloys has shown that when the melting occurs, fractal geometry can be used to calculate the fractal dimension. Using the box-counting method, we analysed the samples of equal-tempered metal, after subjecting them to the robot laser hardening using various parameters. The main findings can be summarized as follows:

- A fractal structure is found after the robot laser hardening.
- The box-counting method allows us to calculate the fractal dimensions for different parameters of laser hardening robotic cells.
- The optimum fractal dimensions of different-parameter robot-laser-hardened tool steel have been identified.
- As in the robot-laser-hardening heat treatment of the material, a deformation occurs, which is a self-similar fractal dimension and can be used to describe the level irregularity.
- The fractal dimension varies between 1 and 2. By increasing the temperature of the robot laser cell, the fractal dimension becomes larger and the grain size becomes smaller. Consequently, we can use the fractal dimension as an important factor to define the grain shape.
- The dependence of the fractal dimension on the hardness was ascertained. This finding is important if we know that certain alloys mix poorly because they have different melting temperatures, but such alloys have much higher hardnesses and better technical characteristics. By varying different parameters (temperature and speed) robot laser cells produce different fractal patterns with different fractal dimensions.
- Materials with higher fractal dimensions are less porous than those with lower fractal dimensions.
- Specimens with lower fractal dimensions are the hardest.
- With the correlation coefficients we show a connection between the hardness and the fractal dimensions of the robot laser-hardened specimens.
- For the prediction of the porosity of hardened specimens we used a neural network, a genetic algorithm and multiple regressions.

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