Using of genetic programming to predict hardness of hardened materials

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***Abstract*—In this article we use methods of intelligent system to predict hardness of hardened specimens. Intelligent systems are usually meant to be coupled with robotics in industrial process settings, though they may be diagnostic systems connected only to passive sensors. We use method of intelligent systems in technology of robot laser hardening. Laser hardening is a metal surface treatment process complementary to conventional aim and induction hardening processes. A high-power laser beam is used to heat the metal surface rapidly and selectively to produce hardened case depths of up to 1.5 mm, with the hardness of the martensitic microstructure providing improved properties such as wear resistance and increased strength. We use mathematical method fractal geometry to describe complexity of robot laser hardened specimens. With method of intelligent system, genetic programming and multiple regression we increase production of process of laser hardening, because we decrease time of process and increase topographical property of materials. Laser hardening is a metal surface treatment process complementary to conventional aim and induction hardening processes. A high-power laser beam is used to heat the metal surface rapidly and selectively to produce hardened case depths of up to 1.5 mm, with the hardness of the martensitic microstructure providing improved properties such as wear resistance and increased strength. The genetic programming modelling results show good agreement with measured hardness of hardened specimens.**

Keywords—Genetic programming, Intelligent systems, hardeness, fractal geometry

I. INTRODUCTION

Robot laser hardening [1-4] is a metal surface treatment process complementary to the conventional flame and induction hardening processes. A high-power laser beam is used to heat a metal surface rapidly and selectively to produce hardened case depths of up to 1,5 mm with the hardness values of up to 65 HRc. Hard martensitic microstructure providing improved properties such as wear resistance and increased strength. To harden the work piece, the laser beam usually warms the outer layer to just under the melting temperature. Many objects observed in nature are typically complex, irregular in shape and thus, cannot be described completely by Euclidean geometry. Fractal geometry [5] is becoming increasingly popular in material science to describe complex irregular objects. The subject of fractals can be used to assist in the analysis of surfaces encountered in robot laser hardening. It should be noted that the morphology of the surface will change if material is hardened with robot laser cells. Analysis of fractal dimensions [6] is a method used to study the surface properties of materials. Today, technologists who operate various CNC machines only have knowledge based on practical experience. Each technologist must consider numerous CNC machine parameters to get the best results. Because this is a very time-consuming process, we used the method of intelligent systems [7], which allows us to obtain results more quickly. Also, the aim of the contribution is to outline possibilities of applying method of intelligent systems for the prediction of mechanical steel properties after robot laser heat treatment and to judge their perspective use in this field.

II. MATERIAL PREPARATION AND METHODS

We made samples of a standard label on the materials according to DIN standard EN 100083 − 1. Tool steel was forged with the laser at different speeds and at different powers. So we changed two parameters speed $v \in [2, 5]$ mm/s and temperature $T \in [1000, 1400]$ °C. The surface of a metallographic specimen is prepared by various methods of polishing, and etching. Images were made by field emission scanning electron microscope *JMS-7600F JEOL* company. We use box-counting method to calculated fractal dimension of Images. Fractal structure of robot laser hardened specimens is presented on Fig. 2.

Fig. 1: Hardened specimens

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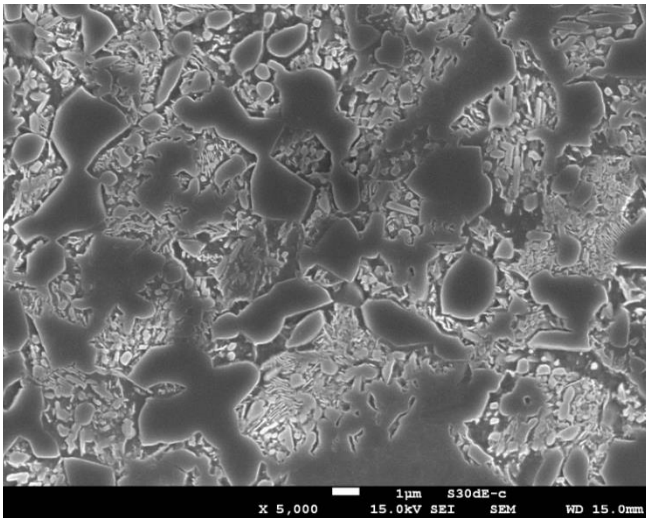

Fig. 2: Fractal structure of robot laser hardened specimens

For analysis of the results, we used an intelligent system methods, namely a genetic programming method and multiple regression.

Genetic programming (GP) [8], may be more powerful than neural networks and other machine learning techniques, able to solve problems in a wider range of disciplines. In this ground-breaking book, John Koza shows how this remarkable paradigm works and provides substantial empirical evidence that solutions to a great variety of problems from many different fields can be found by genetic ally breeding populations of computer programs. Genetic Programming contains a great many worked examples and includes a sample computer code that will allow readers to run their own programs. In getting computers to solve problems without being explicitly programmed, Koza stresses two points: that seemingly different problems from a variety of fields can be reformulated as problems of program induction, and that the recently developed genetic programming paradigm provides a way to search the space of possible computer programs for a highly fit individual computer program to solve the problems of program induction. Good programs are found by evolving them in a computer against a fitness measure instead of by sitting down and writing them. A type of programming that imitates genetic algorithms, which uses mutation and replication to produce algorithms that represent the "survival of the fittest." While genetic algorithms yield numbers, genetic programs yield ever-improving computer programs. Written in languages such as LISP and Scheme, genetic programming requires the determination of a fitness function, which is a desired output (result). The degree of error in the fitness function determines the quality of the program. Fig. 3 present model of GP.

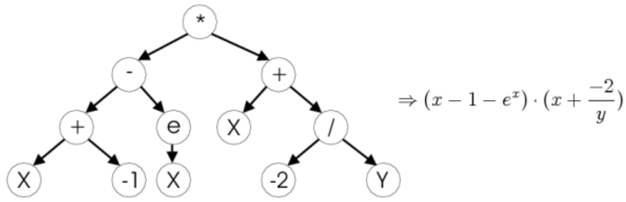

Fig. 3: Model of genetic programming

The following evolutionary parameters were selected for the process of simulated evolutions: 500 for the size of the population of organisms, 100 for the maximum number of generations, 0.4 for the reproduction probability, 0.6 for the crossover probability, 6 for the maximum permissible depth in the creation of the population, 10 for the maximum permissible depth after the operation of crossover of two organisms, and 2 for the smallest permissible depth of organisms in generating new organisms. Genetic operations of reproduction and crossover were used. For selection of organisms the tournament method with tournament size 7 was used.

The multiple linear regression model [9-11] is an extension of a simple linear regression model to incorporate two or more explanatory variable in a prediction equation for a response variable. Multiple regression modeling is now a mainstay of statistical analysis in most fields because of it's power and flexibility. As you will quickly learn it requires very little effort (and sometimes even less thought) to estimate very complicated models with large numbers of variables. Practical experience has shown however, that such models may be very hard to interpret and give very misleading impressions. As a first example, we will consider a reasonably uncomplicated analysis with two predictor variables, beginning with an initial analysis based on simple linear regressions. Formally, the model for multiple linear regression, given *n* observations, is

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + . \beta_p x_{ip} + \beta_i \text{ for } i = 1,2, . n.$$

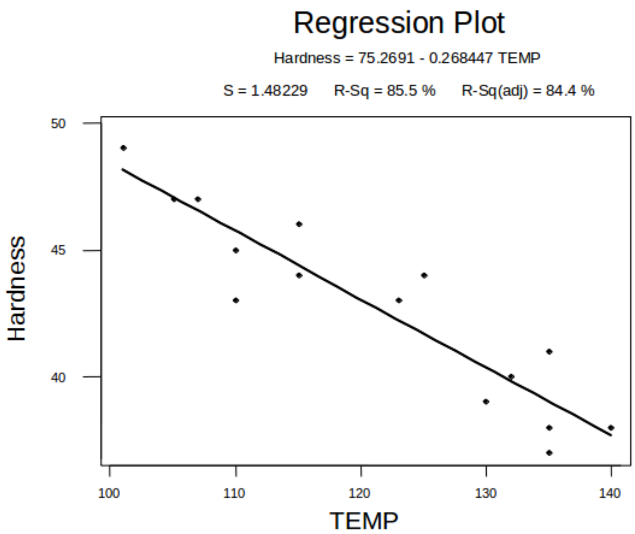

Fig. 4: Multiple regression

III. RESULTS AND DISCUSSION

In Table 1, the parameters of hardened specimens that impact on hardness are presented. We mark specimens from P1 to P19. Parameter X1 presents the parameter of temperature [°C], X2 presents the speed of hardening [mm/s], X3 presents the fractal dimension and X4 presents the base hardness (hardness before hardening). The last parameter is the measured hardness of laser-hardened robot specimens. With the fractal dimension we describe the complexity of hardened specimens. In Table 1, we can see that specimen P1**3** has the largest fractal dimension, 1,9784. Thus specimen P13 is the most complex. Specimen P1 has the most hardness after hardening, that is 60 HRc. In table 2, the experimental and prediction data are presented. Column 1 present name of specimens, column 2 present experimental data. Prediction with genetic programming is presented in columns 3. Prediction with multiple Regression are presented in columns 4. The measured and predicted surface hardness of laser-hardened robot specimens is shown in the graph in Fig. 6. The regression model is presented under Table 2. Genetic programming model is presented in Fig. 5. The genetic programming model presents a 2,09% deviation from the measured data, which is less than the regression model, which presents a 2,92% deviation.

S	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	1,9782	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	1,9783	56	53,8
P12	1000	5	1,941	56,5	56
P13	1400	2	1,9784	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 1: Parameters of hardened specimens

Model of GP

$$Y = 48,9908+0,00874*X_1+0,64137*X_2-0,03422*(-6,87772-1,71943*X_2-1,71943*X_3+0,64173*X_3^2+0,64173*X_3^3+X_3^3*(-1,71943-1,71382*X_2+0,00874*X_1*X_3+0,00874*X_2*X_3-1,71943*X_3^2)*(-2,79749+0,64137*(0,00874*X_1+1,00561*X_2)-1,71382*X_3^2)+X_4)$$

Fig. 5: Model of genetic programming

Specimen	Hardness (Experimental data)	Hardness (Prediction with GP)	Hardness (Prediction with Regression)
P1	60	56,1662	54,56465
P2	58,7	56,1339	55,12693
P3	56	56,1675	55,7891
P4	56,5	56,5323	56,44594
P5	58	58,1793	58,04714
P6	57,8	58,29	58,5924
P7	58,1	58,1006	59,27572
P8	58,2	58,3858	59,87651
P9	57,4	55,5624	53,57422
P10	56,1	55,0932	54,4561
P11	53,8	55,4208	54,98285
P12	56	55,7571	55,67142
P13	55,3	57,8599	57,12963
P14	57,2	56,8077	58,46115
P15	57,8	57,3149	58,43199
P16	58	57,593	59,33421
P17	52	55,1506	51,44111
P18	57	60,2902	56,67362
P19	56	55,9978	61,92865

Table 2: Experimental and prediction data

Model Regression

$Y = 48,99076743 + 0,008744915 \times X_1 + 0,641369094 \times X_2 - 1,71942784 \times X_3 - 0,034224818 \times X_4$

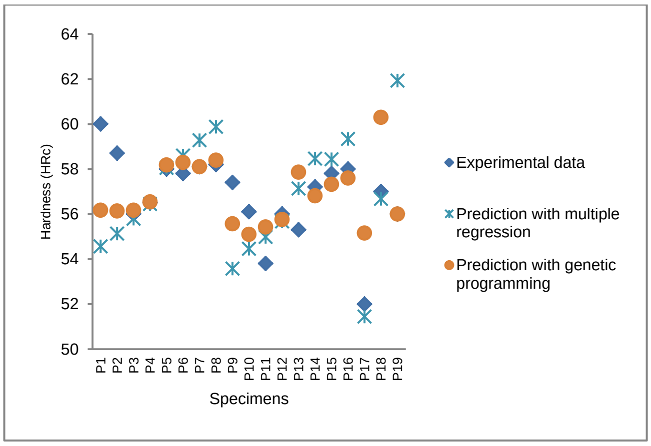

Fig. 5: Measured and predicted hardness of hardened specimens

The hardness structure of a material is an important mechanical property that affects the hardness of materials. We cannot apply Euclidian geometry to describe the hardness of hardened specimens because hardness is very complex. Here we use fractal geometry to describe the hardness of robot laser-hardened specimens. The fractal approach is more appropriate in the characterization of complex and irregular surface microstructures observed in the surface of robot laser hardened specimens and can be effectively utilized for predicting the properties of material from fractal dimensions of the microstructure. The fractal analysis of a series of digitized surface microstructures from 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. In this paper, we describe how the parameters (speed and temperature) of the robot laser cell affect hardness metal materials using a new method, fractal geometry. A statistically significant relationship was found between hardness and the parameters of the robot laser cell. We use methods of intelligent system namely; genetic programming and multiple regression to make prediction of porosity of robot laser hardened specimens. The genetic programming model presents a 2,09% deviation from the measured data, which is less than the regression model, which presents a 2,92% deviation.

IV. Conclussion

The paper presents the use of method of intelligent system to predict hardness of hardened specimens. We use fractal geometry to describe the mechanical property, hardness of robot laser hardened specimens. Using the box-counting method, we analysed specimens of equal tempered metal after subjecting them to robot laser hardening using various parameters. The main originality findings can be summarized as follows:

1. There exist a fractal structure in the robot laser hardened specimens.

2. With fractal dimension we describe complexity of hardened specimens.

3. We have identified the optimal fractal dimension of different parameters robot laser hardened tool steel.

4. For prediction of hardness of hardened specimens we use genetic algorithm and multiple regression.

5. The genetic programming modeling results show good agreement with measured porosity of hardened specimens.

In the future plan we suggest use method of intelligent system to predict more mechanical properties of robot laser hardened specimens.

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