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New Hybrid System Using in Modelling Process of Hardening with Intelligent System

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Abstract: Machine learning, concerns the construction and study of systems that can learn from data. Learning is the fundamental and most important element of biological intelligent systems. We use methods of intelligent system in industrial process. Moreover, with fractal geometry, we analysed the complexity of robot laser-hardened patterns. We analysed patterns hardened with different robot laser cell parameters; namely, the two parameters of speed and temperature. Fractal dimensions were calculated with a method for estimating the Hurst exponent H for 3D object. Also, fractal dimensions were used for pattern recognition and for describing the roughness of the hardened patterns. However, owing to the complexity of real-world problems, the development of intelligent learning systems still remains a challenging topic. For the analysis of results, we use an intelligent system method, namely, a neural network, genetic programing and regression. The general goal of Artificial Intelligence and Machine Learning research is to: develop new intelligent methods to make rational decisions based on observations; learn from experience; and automatically extract knowledge and patterns from data. Thus, this paper explores the use a hybrid method to improve existing hybrids. We present a new method for a hybrid system, based on the spiral method.

Keywords: intelligent systems, fractal dimension, Hybrid system, hardening.

1. Introduction

In nature there are many geometrical patterns which are irregular and cannot be described by classical Euclidian geometry. Thus we need a new method for describing the complexity and irregularity of patterns. A relatively new method is fractal geometry [1]. Recently, a concept of fractal geometry, which was developed originally for the analysis of irregular features in nature, has been finding increased applications in the fields of materials science [2, 3], for the characterization of microstructures. The key to fractal geometry is the fractal dimension [4 -16], which describes the complexity of a fractal and geometrically irregular microstructure. Measuring fractal dimensions has become a common practice for describing the structural properties of roughness and hardness of heat-treated materials. We use fractal geometry in mechanical engineering and in laser techniques. Laser hardening [17] is a metal surface treatment process that is complementary to the conventional aim and induction hardening processes. A high-power laser beam is used to heat a metal surface rapidly and selectively, so as to produce hardened case depths of up to 1.5mm, with the hardness of a martensitic microstructure, providing improved properties, such as wear resistance and increased strength. Fractal patterns are observed in the computational mechanics of elastic-plastic transitions. The origin of the term 'fractal' is the fact that some objects show a self-similarity over a wide

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length scale and possess some fractal dimension. But most of the fractal objects encountered in nature show a self-similarity that is generally random, and they are not created by deterministic rules like those for the Koch curve. Numerous objects found in nature demonstrate not exactly self-similarity, but statistical self-affinity. Statistical self-affinity implies that these objects exhibit self-similarity in some average sense, and over a certain local range of length scales. In this work, we have used a scanning electronic microscope (SEM) to discover and analyse the fractal structure of robot laser-hardened specimens. The present study is intended to use the new method of fractal geometry to describe completely the mechanical properties of robot laser-hardened specimens. Finally, the concept of fractal geometry is applied to characterize the microstructure, and derive useful relationships between the fractal dimension and microstructural features. The aim of the contribution is to outline possibilities of applying an intelligent system, artificial neural networks, genetic programming and regression for the modelling of mechanical steel properties after robot laser heat treatment, and to judge their perspective use in this field. The achieved models enable the prediction of final mechanical material properties, on the basis of decisive parameters of a laser beam influencing these properties. The modelling of the relationship was obtained by neural network, genetic programming and regression. We use new method of a Hybrid system to predict the roughness of hardened patterns.

2. Materials preparation

Firstly, we use tool steel standard label DIN standard 1.7225. We hardened the tool steel with a robot laser cell, polished and etched all patterns, after hardening, and used a field emission scanning electron microscope, JEOL JSM-7600F, to take microstructure pictures of hardened patterns. On these patterns we made measurements of roughness after hardening. In Fig. 1 some microstructure of a hardened pattern are presented.

In this article we present how parameter temperature and speed of the robot laser cell impact on the topography of the hardened pattern. The characterization of surface topography in important to the function of many materials. We

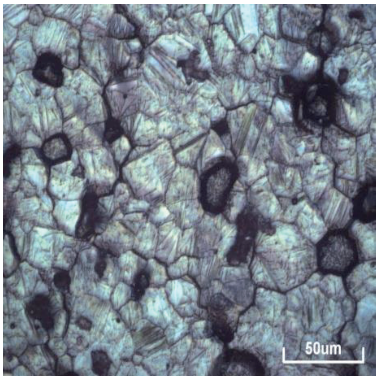

Fig. 1: *Microstructure of robot laser-hardened pattern.*

analyse the roughness surface of robot laser-hardened patterns. Roughness is often a good predictor of the performance of a mechanical component. For the measurement of the surface roughness parameter R_a (arithmetic mean deviation of the roughness profile) a profilometer of the robot laser-hardened patterns was used. A profilometer can measure small surface variations in vertical stylus displacement as a function of position. Fig. 2 present a roughness of robot laser-hardened pattern.

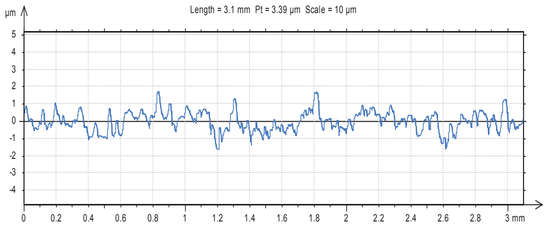

Fig. 2: *Roughness of robot laser-hardened pattern.*

3. Experimental method

The Hurst parameter [18] is understood as the correlation between random steps X_1 and X_2, which are followed by time-to-time difference Δt. The relationship between the fractal dimension D and H Hurst parameter is given by the equation $D=2-H$ for $2D$ objects, and $D=3-H$ for $3D$ objects. There is also a form called statistical self-similarity. With a method for estimating the Hurst exponent H for $3D$ objects [19], we analyse robot laser-hardened patterns. With fractal dimension $D=3-H$, we were able to determine the complexity of hardened patterns.

We used an intelligent system method; namely, a neural network, genetic programming and regression for modelling results. In information technology, a neural network (NN) is a system of programs and data structures that approximates the operation of the human brain. Researchers from many scientific disciplines are designing artificial neural networks, to solve a variety of problems in pattern recognition, prediction, optimization, associative memory, and control. An artificial neural network is composed of many artificial neurons that are linked together according to a specific network architecture. The objective of the neural network is to transform the inputs into meaningful outputs. An artificial neural network (ANN) is a machine-learning approach that models the human brain and consists of a number of artificial neurons. Neurons in ANNs tend to have fewer connections than biological neurons. Each neuron in an ANN receives a number of inputs. An activation function is applied to these inputs, which results in activation level of neuron (output value of the neuron). Conventional approaches have been proposed for solving these problems.

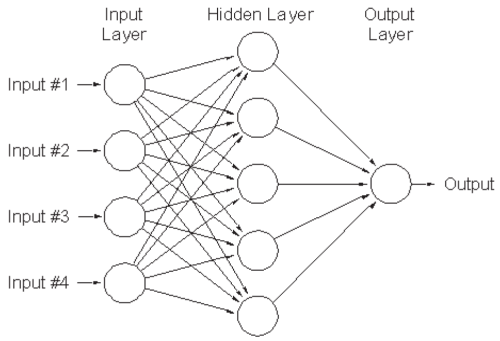

Fig. 3: *Symbolic representation of the artificial neural network cell.*

Genetic Programming [20] is inspired by biological evolution. It is a machine-learning technique used to optimize a solution based on a fitness score. Genetic programming may be more powerful than neural networks and other machine-learning techniques that are able to solve problems in a wider range of disciplines. The general idea behind genetic programming is: to start with a collection of functions and combine them randomly into programs; then run the programs and see which gives the best results; keep the best ones (natural selection), mutate some of the others, and test the new generation; repeat this process until a clear best program emerges. Since the dawn of the computer age, computer scientists have been trying to find a way to train computers so that they can automatically find solutions to problems; i.e. to make computers which can do something without telling them explicitly how to do it. Genetic programming (GP) is a rapidly maturing technology that is making significant strides towards applications which demonstrate that it is a sustainable science.

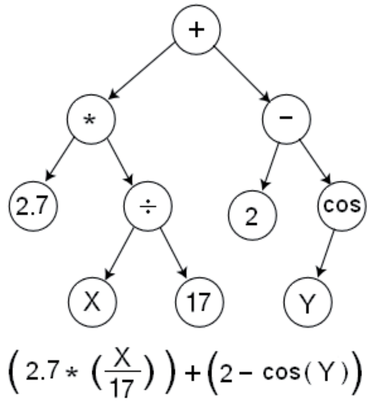

Fig. 4: *Genetic programming model.*

Multiple regression is a statistical tool used to derive the value of a criterion from several other independent, or predictor, variables. It is the simultaneous combination of multiple factors to assess how and to what extent they affect a certain outcome. Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable, by fitting a linear equation to observed data. Every value of the independent variable x is associated with a value of the dependent variable y.

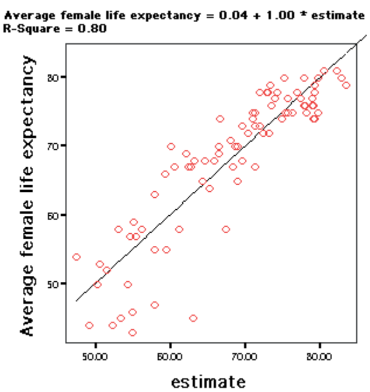

Fig. 5: *Regression model.*

Hybrid evolutionary computation [21] is a robust method for solving complex global optimization problems. It can be used in practical applications in industry, especially in laser technology of hardening. As well-known method of Hybrid systems is sequences, parallel, outdoor and built-in Hybrid. In this article we present a new method of a hybrid system; spiral Hybrid (see Fig. 6). Spiral hybrid methods are connected in series in the spiral of the entrance to the method n. All methods work independently of the other methods. The results of input method 1 are transferred to input method n; the results of input method n are transferred to input method 1; the results of input method 1 are transferred to input method n-1; and so on. The results of input method i are transferred to the input of the spiral Hybrid. Method 1 presents Neural Network 36% (in our case we use 8 data for a learn test set and 14 data for a test set); method 2 presents method of Neural Network 50% (in our case we use 11 data for a learn test set and 11 data for a test set); method 3 presents method of Neural Network one live out (in our case we use 21 data for a learn test set and 1 data for a test set); method 4 presents method of multiple regression; and method 5 presents method of genetic programming.

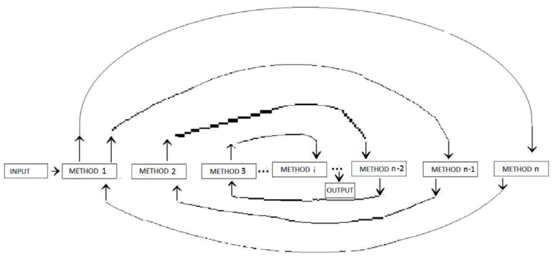

Fig. 6: *Spiral Hybrid.*

4. Result and discussion

Fig. 1 presents the microstructure before robot laser-hardening. Fig. 2 present the microstructure after robot laser-hardening with different velocity and temperature parameters. Irregular surface textures with a few breaks, represented by black islands, were revealed. Here we can see the impact of the parameters of the robot laser cell on the morphological properties of the surface. The roughness before robot laser-hardening of the material is between 24 and 1,320 nm. In all these pictures we can see the impact of the parameters of the robot laser cell on the hardness and roughness. Roughness increased after hardening by between 76 nm and 1.32 μm.

In Table 1, the parameters of hardened specimens that impact on roughness are presented. We mark specimens from P1 to P22. Parameter X1 presents the parameter of temperature [°C], X2 presents the speed of hardening [mm/s], X3 presents the fractal dimension in 3D space, and X4 presents the base roughness (roughness before hardening). The last parameter is the measured surface roughness of laser-hardened robot specimens. With the fractal dimension we describe the complexity of hardened specimens. Pattern P13 has the most roughness, at 2,350 nm. Table 2 presents experimental and prediction data regarding the surface roughness of laser-hardened robot patterns. Column 1 present patterns, column 2 presents experimental data, column 3 presents prediction with NN 36% (in our case we use 8 data for a learn test set and 14 data for a test set), column 4 presents prediction with NN 50% (in our case we use 11 data for a learn test set and 11 data for a test set), and column 5 presents prediction with NN one live out (in our case we use 21 data for a learn test set and 1 data for a test set). Prediction with regression is presented in column 6. Column 7 presents prediction with new method of genetic programming. Column 8 presents prediction with a new method of hybrid system. The measured and predicted surface roughness of laser-hardened robot specimens is shown in the graph in Fig. 7. The neural network model presents a 27.96% deviation from the measured data, which is less than the regression model, which presents a 133.97% deviation. The genetic programming model presents a 40.49% deviation from the measured data. The new Hybrid method presents a 55.32% deviation from the measured data.

Model Regression:

$$Y = 517{,}2268591 + 1{,}067646392 \times X1 - 124{,}954681 \times X2 - 411{,}0529109 \times X3 + 0{,}991431029 \times X4$$

Model of regression

$$Y = 71{,}82942368 + 0{,}006682914 \times X1 - 0{,}172405205 \times X2 - 102{,}024491 \times X3$$

Methods of intelligent systems are very usefull. In this research we present different methods of intelligent systems to predict topographical

$$
\begin{aligned}
Y = X_4 &+ \frac{X_1 \cdot \left(\frac{-3,77509+X_1}{X_3}+X_4\right)}{(X_2+X_3)\cdot\left(X_1+\frac{(X_2^2+X_3)\cdot\left(X_1-\frac{3,77509}{X_1+\frac{-3,77509+X_1}{X_4}}\right)}{X_4}\right)} \\
&+ \frac{3,43166\cdot X_1\cdot\left(\frac{-3,77509+X_1}{X_2}+\frac{X_1+\frac{-3,77509+X_1}{X_2+X_3+X_4}}{X_4}\right)}{\left(X_4+\frac{-3,77509+X_1+X_3}{2\cdot X_1^2}\right)\cdot\left(X_1-\frac{3,77509}{X_1}+\frac{\left(X_2-\frac{0,132447\cdot(X_1-3,77509\cdot X_2)}{X_4}\right)\cdot\left(X_1+\frac{(X_2^2+X_2\cdot X_3)\cdot\left(X_1-\frac{3,77509}{X_4}\right)}{X_4}\right)}{X_4-\frac{0,264894\cdot(X_1-3,77509)}{X_4}}\right)} \\
&+ \frac{X_1+\frac{\left(X_2-\frac{0,132447\cdot(-3,77509+X_1)}{X_4}\right)\cdot\left(X_1+\frac{2\cdot X_1\cdot(X_2^2+X_3\cdot(X_2+X_4))}{X_4}\right)}{X_4-\frac{0,264894\cdot(-3,77509+X_1)}{X_4}}}{\left(-3,77509-\frac{3,77509}{X_2\cdot X_4}\right)\cdot X_4} \\
&+ \frac{X_1+\frac{\left(X_2-\frac{0,132447\cdot(-3,77509+X_1)}{X_4}\right)\cdot\left(X_1+\frac{\left(x_1-\frac{3,77509}{x_4}\right)\cdot(X_2^2+X_3\cdot(X_2+X_4))}{X_4}\right)}{X_4-\frac{0,264894\cdot(-3,77509+X_1)}{X_4}}}{\left(-3,77509-\frac{x_2^2}{X_1\cdot X_4\cdot(x_2^2+x_2\cdot x_3)}\right)\cdot X_4}
\end{aligned}
$$

Fig. 7: *Model of genetic programming*

Table 1: *Parameters of hardened specimens*

S	X1	X2	X3	X4	Y
P1	1000	2	2,304	24	201
P2	1000	3	2,264	24	171
P3	1000	4	2,258	24	109
P4	1000	5	2,341	24	76,3
P5	1400	2	2,222	24	1320
P6	1400	3	2,388	24	992
P7	1400	4	2,25	24	553
P8	1400	5	2,286	24	652
P9	1000	2	2,178	201	337
P10	1000	3	2,183	171	307
P11	1000	4	2,408	109	444
P12	1000	5	2,21	76	270
P13	1400	2	2,257	1320	2350
P14	1400	3	2,265	992	1900
P15	1400	4	2,433	553	661
P16	1400	5	2,289	652	759
P17	800	0	2,408	24	183
P18	1400	0	2,21	24	1330
P19	2000	0	2,257	24	1740
P20	950	0	2,265	24	502
P21	850	0	2,433	24	166
P22	0	0	2,289	24	24

property of robot laser-hardened specimens roughness. In machine learning s Hybrid system is a very interesting method. We present s new method of Hybrid system: spiral Hybrid. Spiral hybrid presents a 55.32% deviation from the measured data.

5. Conclusions

The paper presents the use of fractal geometry to describe the mechanical properties of robot laser-hardened patterns. We use a relatively new method, fractal geometry, to describe the complexity of laser-hardened specimens. The main findings can be summarized as follows:

- *The results demonstrate the viable potential in using artificial neural networks, genetic programming and the regression approach in predicting roughness of robot laser hardened specimens, even with limited data sets.*
- *We use fractal dimensions for pattern recognition.*
- *With a method for estimating the Hurst exponent H for $3D$ objects, we analyse the complexity of hardened patterns.*
- *We found which parameters of the robot laser cell*

Table 2: *Experimental and prediction data*

S	E	NM1	NM2	NM3	R	GP	HM
P1	201	170,21	174,66	207,30	411,69	236,76	130,17
P2	171	171,14	210,11	103,06	303,17	162,58	239,30
P3	109	104,70	269,68	171,64	180,69	113,01	168,77
P4	76	112,43	75,030	78,816	21,61	73,86	152,52
P5	1320	1333,63	1325,90	1331,7	872,45	1242,35	735,97
P6	992	948,77	991,560	967,74	679,26	984,04	645,40
P7	553	625,74	539,619	550,23	611,03	565,16	496,99
P8	652	603,49	485,11	576,24	471,28	307,72	500,93
P9	337	308,80	334,34	177,39	638,96	359,70	621,85
P10	307	209,56	485,97	484,57	482,21	288,01	290,34
P11	444	104,70	269,68	271,64	203,30	181,17	273,87
P12	270	163,41	65,504	344,28	127,31	130,63	235,18
P13	2350	1033,02	1303,49	177,00	2142,96	1774,50	2010,51
P14	1900	1085,64	504,01	1323,41	1689,53	1294,92	1374,78
P15	661	574,83	799,94	232,75	1060,28	723,30	1081,82
P16	759	414,53	150,69	802,22	1092,67	818,47	924,21
P17	183	557,65	503,23	250,85	477,66	196,09	432,41
P18	1330	1698,59	1038,09	1332,70	1117,02	533,02	1048,65
P19	1740	2058,86	331,29	1177,16	1746,92	1803,73	1479,58
P20	502	301,54	138,82	578,22	617,26	233,06	275,57
P21	166	195,58	137,96	158,90	495,28	198,64	163,12
P22	24	-53,72	9,5973	34,118	-395,35	23,97	-68,65

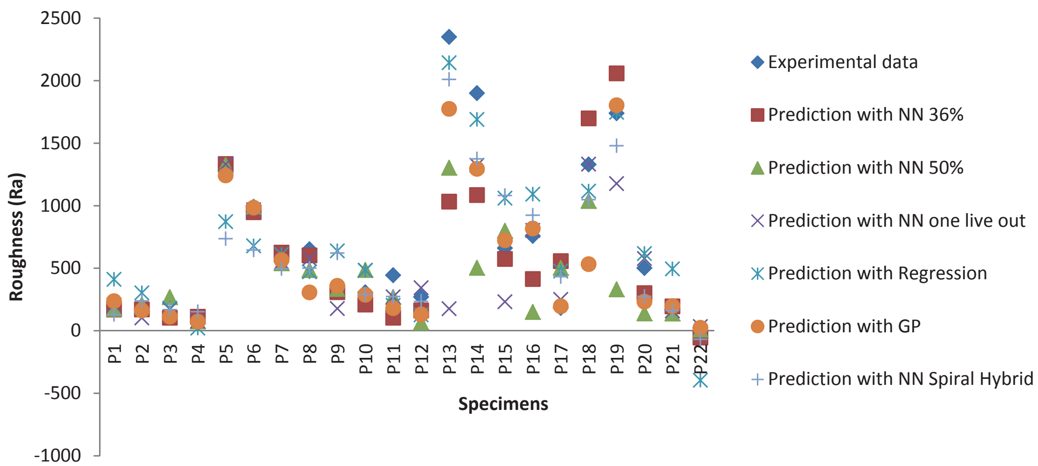

Fig. 8: *The measured and predicted surface roughness of robot laser hardened specimens*

give us optimal hardness of surface.

- *We present a new method of Hybrid system; the spiral Hybrid.*

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