NEW HYBRID METHOD OF INTELLIGENT SYSTEMS USING TO PREDICT POROSITY OF HEAT TREATMENT MATERIALS WITH NETWORK AND FRACTAL GEOMETRY

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ABSTRACT: In this article we present new method of hybrid intelligent systems using in to predict topographical property of robot laser hardened specimens. In robot laser hardening we have many open problem. Many CNC operators must test many materials with different parameters of robot laser cell before find the best topological properties of materials. Thus, in this article we present solution of these problems. Methods of intelligent systems and models are very useful to make prediction in mechanical engineering. Sometimes we have problem with this models, because we cannot find some parameter of models. Also, we cannot calculate or measurement this parameter. Thus we develop new hybrid system of intelligent system. We develop hybrid of genetic programming, neural network and multiple regression to make prediction of porosity of robot laser hardened specimens. With hybrid method of intelligent system we increase production of robot laser hardening process, because we decrease time of process and decrease topographical property porosity of materials

KEY WORDS: Hybrid machine learning, visibility graphs, fractal dimension, heat treatment;

1 INTRODUCTION

To investigate the possibility of application of fractal analysis and graph theory to heat-treated surface, we have examined the relation between surface porosity and fractal dimensions and density of visibility graph in 3D space depending on various parameters of robot laser cell. In fractal geometry is the key parameter fractal dimension, 2D and 3D which should be determined complexity microstructure of robot laser hardened specimens.Different tool steels are widely used in industrial applications based on good performance, a wide range of mechanical properties, machinability, wear resistance, and cheapness. By laser remelting the surface of the materials, we can significantly improve their wear properties. Robot laser surface remelting is one of the most promising techniques for surface modification of the microstructure of a material to improve wear and corrosion resistance. Laser hardening [1] is a metal surface treatment process complementary to conventional flame and induction hardening processes. A high-power laser beam is used to rapidly and selectively heat a metal surface to produce hardened case depths of up to 1.5 mm with a hardness value of up to 65 HRc. Greater hardening depth requires a larger volume of surrounding material to ensure that the heat dissipates quickly and the hardening zone cools fast enough. Relatively low power densities are needed for hardening. At the same time, the hardening process involves treating extensive areas of the workpiece surface. Therefore the laser beam is shaped so that it irradiates an area that is as large as possible. The irradiated area is usually rectangular.

Scanning optics are also used in hardening. They are used to move a laser beam with a round focus back and forth very rapidly, creating a line on the workpiece with a power density that is virtually uniform. The high hardness of the martensitic microstructure provides improved properties such as wear resistance and strength. Advantages of laser hardening: laser is source of energy with outstanding characteristics (contactless methods, controlled input of energy, high capacity, constant process, precise positioning), lower costs for additional machining, no use of cooling agents or chemicals, high flexibility, the process can be automated and integrated in the production process and superior wear resistance of hardened surface. The modern world is full of artificial, abstract environments that challenge our natural intelligence. The goal of our research is to develop Artificial Intelligence that gives people the capability to master these challenges, ranging from formal methods for automated reasoning to interaction techniques that stimulate truthful elicitation of preferences and opinions. Another aspect is characterizing human intelligence and cognitive science, with applications in human-computer interaction and computer animation.

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Machine Learning aims to automate the statistical analysis of large complex datasets by adaptive computing. A core strategy to meet growing demands of science and applications, it provides a data-driven basis for automated decision making and probabilistic reasoning. Machine learning applications at EPFL range from natural language and image processing to scientific imaging as well as computational neuroscience. In this article we use three method of intelligent system multiple regression, neural network and genetic programming to images analyze with calculate fractal dimension in 2D space, 3D space and calculate density of visibility graphs in 3D space. At the end we use new method of hybrid intelligent systems to predict porosity of hardened specimens.

2 EXPERIMENTAL METHOD AND MATERIALS PREPARATION

In our study we limited of material EN100083 – 1 (Fig. 1). Specimens was hardened with robot laser cell with different speed v [2-5] mm/s and temperature [850-2000] °C. After hardening, we polished and etched all specimens. We use JEOL JSM-7600F field emission scanning electron microscope (SEM) to make picture of microstructure of robot laser hardened specimens. To analyse these pictures we use the program ImageJ (available from the National Institute of Health, USA). We use three method to analyse robot laser hardened specimens. These method are fractal geometry (calculate fractal dimension with box counting [2] and with new method presented in [3]) and graph theory (calculate density of visibility graphs in 3D space presented in [4]).

The porous structure [5] is a term which is used to describe an important physical property of most materials. The porosity of a material is determined by measuring the amount of void space inside, and determining what percentage of the total volume of the material is made up of void space. Porosity measurements can vary considerably, depending on the material, and high or low porosity will impact the way in which the material performs. The property of porosity is actually slightly more complex than the simple percentage of void space inside a material. Another important consideration is the shape and size of the void spaces in the material.

For modelling of the results of predicting porosity of robot laser hardened specimens, we used an intelligent system methods, namely multiple regression, a neural network, genetic programming method.

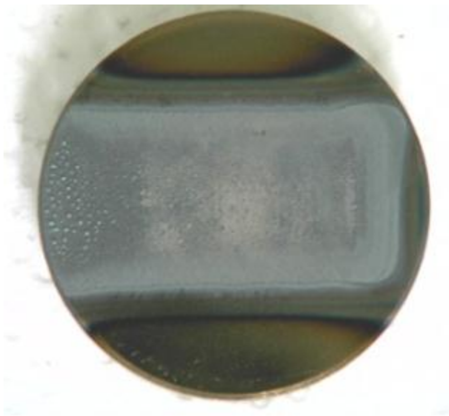

Figure 1. Robot laser hardened material EN100083.

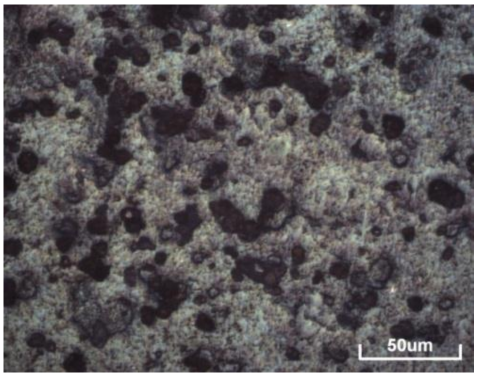

Figure 2. Microstructure of robot laser hardened specimen.

Multiple regression [6] is the oldest and most widely used predictive model in the field of machine learning. The goal is to minimize the sum of the squared errors to fit a straight line to a set of data points. The linear regression model fits a linear function to a set of data points. The form of the function is (1):

$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \ldots + \beta_n * X_n \qquad (1)$$

Where Y is the target variable, and X1, X2, ... Xn are the predictor variables and β1, β2, … βn are the coefficients that multiply the predictor variables. β0 is constant.

Learn about artificial neural networks [7] and how they're being used for machine learning, as applied to speech and object recognition, image segmentation, modeling language and human motion, etc. Neural networks use learning algorithms that are inspired by our understanding of how the brain learns, but they are evaluated by how well they work for practical applications such as speech recognition, object recognition, image retrieval and the ability to recommend products that a user will like. As computers become more powerful, Neural Networks are gradually taking over from simpler Machine Learning methods. They are already at the heart of a new generation of speech recognition devices and they are beginning to outperform earlier systems for recognizing objects in images. The course will explain the new learning procedures that are responsible for these advances, including effective new procedures for learning multiple layers of non-linear features, and give you the skills and understanding required to apply these procedures in many other domains.

Genetic algorithms [8,9] are probably the least practical of the ML algorithms I cover, but they're fascinating and they do a good job of introducing the "cost function" or "error function", and the idea of local and global optima — concepts both important and common to most other ML algorithms. Genetic algorithms are inspired by nature and evolution, which is seriously cool to me. It's no surprise, either, that artificial neural networks ("NN") are also modelled from biology: evolution is the best general-purpose learning algorithm we've experienced, and the brain is the best general-purpose problem solver we know. These are two very important pieces of our biological existence, and also two rapidly growing fields of artificial intelligence and machine learning study.

Hybrid system of intelligent system is [10]is a generic, flexible, robust, and versatile method for solving complex global optimisation problems and can also be used in practical applications. In fig. 3 is presented Intelligent systems model and hybrid intelligent system.

Intelligent systems engineering [11] is a blanket term used to refer to a variety of Artificial Intelligence (AI) approaches, including neural networks, evolutionary algorithms, model-based prediction and control, case-based diagnostic systems, conventional control theory, and symbolic AI. The term intelligent systems engineering is most frequently used in the context of AI applied to specific industrial challenges such as optimizing a process sequence in a sugar factory. Intelligent systems engineering tends to refer to the creation of short-term, narrow-task, marketable AI, rather than long-term, flexible, generally intelligent AI. 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. Intelligent systems are meant to be adaptive, to solve problems as creatively as possible with minimal human input. The field has received substantial investment from both private sectors and the military. Intelligent systems generally follow a sequence of events in diagnosing and addressing a potential problem. First, the system identifies and defines the problem. Then it identifies evaluation criteria to apply to the situation, which it uses to generate a set of alternatives to the problem.

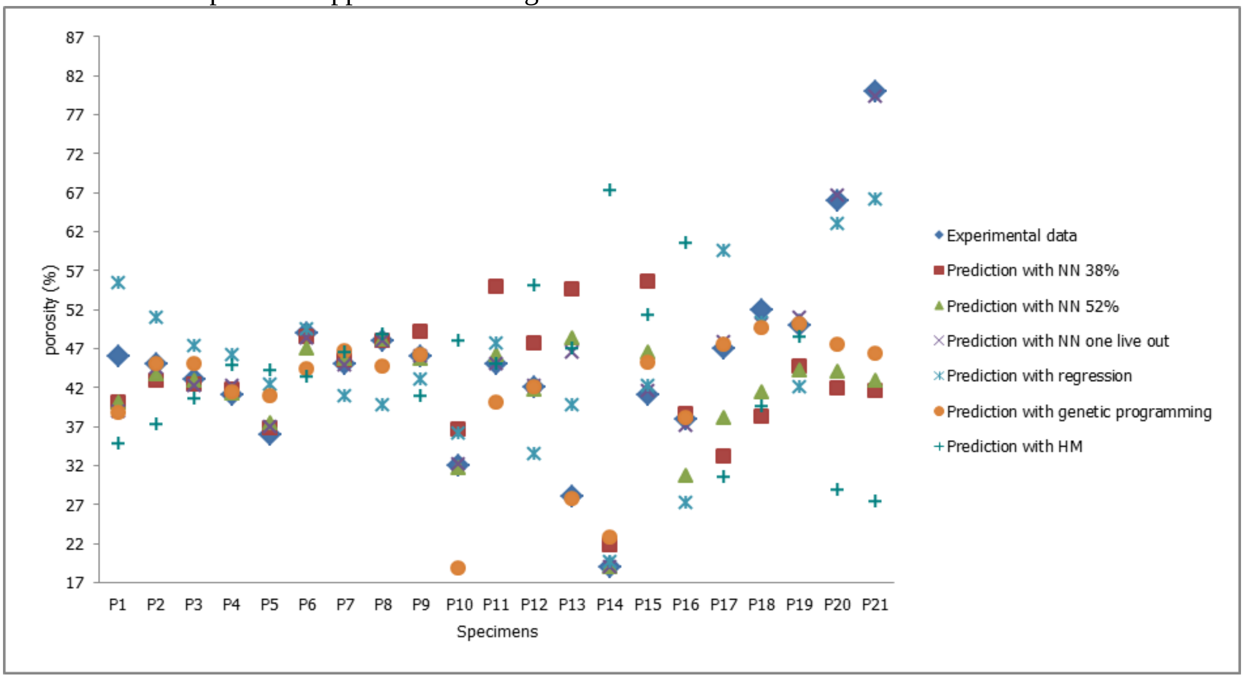

Figure 3. The measured and predicted surface roughness of robot laser hardened specimens .

3 RESULTS AND DISCUSSION

In Table 1, the parameters of hardened specimens that impact on porosity are presented. We mark specimens from P1 to P21. Parameter X1 presents the parameter of temperature in degree of Celsius [C], X2 presents the speed of hardening [mm/s], X3 presents fractal dimension in 2D space, X4 presents fractal dimension in 3D space, X5 presents density of visibility graphs in 3D space and parameter X6 present basic porosity of specimens. The last parameter Y is the measured surface porosity of laser-hardened robot specimens. Table 2 presents experimental and prediction data regarding the surface porosity of laser hardened robot specimens. In Table 2 present symbol S name of specimens, E experimental data, NM1 prediction with neural network with 30% learn set, NM2 prediction with neural network with 50% learn set, NM3 prediction with neural network with method one live out, R prediction with regression, GP prediction with genetic programming and HM present prediction with hybrid method of intelligent systems. In Table 1, we can see that specimen P17 has the largest density of visibility graphs (network) in 3D; 0.2832, thus specimen P17 have most complex graph. Specimen P14 has minimal porosity after hardening, that is 19%. The measured and predicted surface porosity of robot laser hardened specimens is shown in the graph in Fig. 3. The genetic programming model is presented on (2). Model of regression is presented on (3). The genetic programming model presents a 10,22% deviation from the measured data, which is less than the regression model, which presents a 18,11% deviation. The best neural network present 5,04% deviation from the measured data.

$$Y = -0.123654\times\left(-X_2^2 - X_6 + \frac{X_2^2+X_6+X_2}{-X_2+X_2\times(X_2^2-X_2)} + \frac{X_6}{X2\times\left(-X_3+\frac{X_6}{X_2^2-X_3}\right)}\right) + \frac{1}{X_4}\times$$
$$\left(\frac{X_6^2}{X_2-X_1+X_2^2\times(X_2+X_3\times X_2)+X_6-\frac{X_6}{X_2^2-X_3}+\frac{(X_2\times(X_3+X_2)+X_6)\times(X_3+2\times X_3\times(X_3+X_2)+X_6)}{X_2+X_1-X_2^2}-\frac{X_2\times X_6\times\left(X_6+\frac{X_6}{X_3}\right)}{X_2-X_1}}\right)+$$
$$\frac{1}{X_4}\times\left(\frac{X_6}{7.71283+2\times X_2-X_6-\frac{X_6}{X_2^2-X_3}+\frac{(X_3\times X_2+X_6)\times\left(X_6+\frac{X_6}{X_3}\right)}{X_2+X_1}}\right)+\frac{(X_3\times X_2+X_6)}{X_4} \quad (2)$$

Model of regression present equation (3):

$$Y = -99{,}0509 - 0{,}0178\times X_1 - 3{,}25717\times X_2 + 46{,}65489\times X_3 + 38{,}06208\times X_4 - 63{,}3748\times X_5 + 0{,}165097\times X_6 \quad (3)$$

$$Y^2 + Y\times(A+B) + A\times B - C = 0$$
$$A = 0.123654\times\left(-X_2^2 - X_6 + \frac{X_2+X_6+X_2^2}{(-X_2+X_2^2)\times X_2 - X_2} + \frac{X_6}{\left(-X_3+\frac{X_6}{X_2^2-X_3}\right)\times X_2}\right)$$
$$B = 99.0509 + 0.0178\times X_1 + 3.25717\times X_2 - 46.65489\times X_3 + 63.3748\times X_5 - 0.165098\times X_6$$
$$C = X_3\times X_2 + X_6 + \left(\frac{X_6^2}{X_2-X_1+X_2^2\times(X_2+X_3\times X_2)+-\frac{X_6}{X_2^2-X_3}+\frac{(X_2\times(X_3+X_2)+X_6)\times(X_3+2\times X_3\times(X_3+X_2)+X_6)}{X_2+X_1-X_2^2}-\frac{X_2\times X_6\times\left(X_6+\frac{X_6}{X_3}\right)}{X_2-X_1}}\right)$$
$$+\frac{X_6}{\frac{(X_2\times X_3+X_6)\times\left(X_6+\frac{X_6}{X_3}\right)}{X_2-X_1}+\frac{X_6}{X_2^2-X_3}+7.71283+2\times X_2} \quad (4)$$

Table 1. The measured and predicted surface roughness of robot laser hardened specimens.

S	X_1	X_2	X_3	X_4	X_5	X_6	Y
P1	1000,0	2,0	1,9135	2,304	0,1936	85	46
P2	1000,0	3,0	1,9595	2,264	0,2208	85	45
P3	1000,0	4,0	1,9474	2,258	0,2144	85	43
P4	1000,0	5,0	1,9384	2,341	0,2256	85	41
P5	1400,0	2,0	1,9225	2,222	0,2445	85	36
P6	1400,0	3,0	1,9784	2,388	0,2221	85	49
P7	1400,0	4,0	1,9540	2,250	0,2036	85	45
P8	1400,0	5,0	1,9776	2,286	0,2096	85	48
P9	1000,0	2,0	1,9720	2,178	0,2352	39	46
P10	1000,0	3,0	1,8580	2,183	0,2288	45	32
P11	1000,0	4,0	1,9784	2,408	0,2144	43	45
P12	1000,0	5,0	1,941	2,210	0,2352	41	42
P13	1400,0	2,0	1,9784	2,257	0,2208	36	28
P14	1400,0	3,0	1,5810	2,265	0,2320	49	19
P15	1400,0	4,0	1,9650	2,433	0,1984	45	41
P16	1400,0	5,0	1,8113	2,289	0,1904	48	38
P17	800,0	0,0	1,9669	2,232	0,2832	85	47
P18	1400,0	0,0	1,9753	2,235	0,2688	85	52
P19	2000,0	0,0	1,9706	2,261	0,2416	85	50
P20	950,00	0,0	1,9631	2,282	0,2128	85	66
P21	850,00	0,0	1,9537	2,319	0,2080	85	80

Mathematical model hybrid system of intelligent system is presented in (4). We express variable X4 of multiple regression and insert into model of genetic programming. Mathematical problem of hybrid system present second-order equation, which mean, that we have two solutions. Because the mechanical property is positive we must take positive number y of equation.

We use method of intelligent systems; genetic programming, neural network and multiple regression to predict topographical property porosity of robot laser hardened specimens. The best parameters of robot laser cell which give us minimal porosity after hardening are velocity 3 mm/s and temperature 1400 °C. A statistically significant relationship was found between porosity, the parameters of the robot laser cell and topological property density of visibility graphs (network) in 3D and fractal dimension of 2D and 3D space. We show that the neural network gives us the best predicted results. The genetic programming model is better than the regression model. Hybrid system method of intelligent systems present a 37,07% deviation from the measured data, which is less than regression model, genetic programming model and neural network.

Table 2. Experimental and prediction data

S	E	NM1	NM2	NM3	R	GP	HM
P1	46	40,09349	40,06469	38,97906	55,36781	38,7	34,77166
P2	45	42,88955	43,72925	44,52686	51,01049	45,0	37,31646
P3	43	42,36224	42,8674	42,24925	47,36602	45,0	40,6062
P4	41	41,79284	41,21014	42,26919	46,13831	41,4	44,7802
P5	36	36,81666	37,47247	36,98061	42,32083	40,8	44,17657
P6	49	48,45951	46,9219	48,31771	49,40957	44,3	43,31873
P7	45	45,48399	45,60142	44,86363	40,93389	46,7	46,44582
P8	48	48,06292	48,10059	48,05849	39,76776	44,6	48,86256
P9	46	49,14634	45,63908	45,97363	43,07044	46,2	40,84608
P10	32	36,64606	31,62556	32,07754	36,08111	18,8	47,98058
P11	45	54,87139	46,25058	44,98105	47,58756	40,0	44,99144
P12	42	47,7328	41,77955	42,26033	33,40081	42,0	55,07892
P13	28	54,62324	48,33544	46,47878	39,67325	27,7	47,04963
P14	19	21,8305	19,02115	18,98792	19,61638	22,8	67,34997
P15	41	55,53828	46,46328	41,54248	42,13812	45,2	51,32295
P16	38	38,57361	30,68173	37,07588	27,23145	38,0	60,4967
P17	47	33,12772	38,09061	47,86352	59,51467	47,4	30,50053
P18	52	38,30552	41,39847	50,11233	50,25335	49,7	39,57598
P19	50	44,67752	44,26321	51,00742	42,06748	50,1	48,54167
P20	66	41,9435	44,03279	66,65382	63,03207	47,5	28,93206
P21	80	41,54691	42,81422	79,25159	66,08601	46,4	27,35292

4 CONCLUSION

The paper presents application of mathematical method of graph theory, fractal geometry in robot laser hardening proces. We present hybrid method of intelligent system to predict porosity of robot laser hardened specimens. The main findings can be summarised as follows:

1. We use method graph theory and fractal geometry to analyze robot laser hardened specimens.

2. We describe the porosity of the hardened specimens by using the topological properties of the visibility graphs in 3D space and fractal dimension in 2D and 3D space.
3. For prediction of porosity of hardened specimens we use method of intelligent systems namely; neural network, genetic algorithm and multiple regression.
5. With hybrid method of intelligent system we increase production of robot laser hardening process, because we decrease time of process and increase topographical property porosity of materials.

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