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Using intelligent-system metods in mechanical engineering to predict the topographical property of materials with the topological property of visibility graphs in a 3D space

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Abstract. Intelligent systems are a new wave of the embedded and real-time systems that are highly connected, with a massive processing power and performing complex applications. Their pervasiveness is reshaping the real world and teh way, we interact with our digital life. These intelligent systems are creating new opportunities for industry and business, and new experiences for users and consumers. They can be found in all domains: automotive, rail, aerospace, defence, energy, healthcare, telecoms and consumer electronics. In this paper we use an intelligent system method to predict the roughness of hardened specimens. We use an algorithm for the construction visibility graphs in a 3D space to analyse topographical properties of hardened specimens. Drawing graphs as nodes connected by links in 3D space is visually compelling but computationally difficult. Thus, the construction of the 3D visibility graphs is highly complex and requires in their professional computers or supercomputers. The microstructure of the robot-laser-hardened specimens is very complex; however, we can present it using 3D visibility graphs. For predicting the surface roughness of the hardened specimens we use the neural network, genetic algorithm and multiple regression. Using the intelligent systems we increase production of the laser-hardening process by decreasing the time process and increasing the topographical property of materials.

Keywords: intelligent system, visibility graph, engineering, topography,

Uporaba metod inteligentnih sistemov v inženirstvu za napoved topografske lastnosti materialov

Inteligentni sistemi so nov val vgrajenih sistemov v realnem času, ki so zelo povezani, z veliko procesorske moči in izvajajo zahtevne aplikacije. Njihova vseprisotnost je vplivala tudi na realni svet in na interakcijo na naše digitalno življenje. Ti inteligentni sistemi ustvarjajo nove priložnosti za industrijo in podjetja in nove izkušnje za uporabnike in porabnike. Te je mogoče najti na vseh področjih: avtomobilske, železniške in vesoljske industrije, obrambe, energije, zdravstva, telekomunikacij in zabavne elektronike. V tem članku smo uporabili metode inteligentnih sistemov za napovedovanje hrapavosti kaljenih vzorcev z metodami inteligentnih sistemov. Uporabili smo algoritem za graditev grafov vidljivosti v 3D prostoru za analiziranje topografske lastnosti kaljenih vzorcev. Risanje grafov vidljivosti v 3D prostoru je vizualno privlačno, vendar računsko težko. Tako je graditev grafov vidljivosti v 3D prostoru zelo zapletena in zahteva zmogljive računalnike ali superračunalnike. Mikrostruktura robotskih lasersko kaljenih vzorcev je zelo kompleksna; vendar jo lahko opišemo s pomočjo grafov vidljivosti v 3D prostoru. Za napovedovanje hrapavosti kaljenih vzorcev bomo uporabili nevronske mreže, genetske algoritme in multiplo regresijo. Z inteligentnim sistemom smo povečali proizvodnjo procesa laserskega kaljenja, saj smo pridobili čas procesa in povečali topografske lastnosti materiala.

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1 INTRODUCTION

Philosophers have been trying for over two thousand years to understand and resolve two big questions of the universe: how does a human mind work, and do non-humans have minds? However, these questions are still unanswered. Some philosophers have picked up the computational approach originated by computer scientists and accepted the idea that machines can do everything that humans can do. Requirements for an intelligent system [1] include security, connectivity, ability to adapt according to the current data and capacity for remote monitoring and management. Essentially, an intelligent system is anything that contains a functional, although not usually general-purpose, computer with Internet connectivity. An embedded system may be powerful and capable of complex processing and data analysis, but it is usually specialized for tasks relevant to the host machine. Intelligent systems exist all around us in point-of-sale (POS) terminals, digital televisions, traffic lights, smart meters, automobiles, digital signale and airplane controls, and among a great number of other possibilities. As this ongoing trend continues, many foresee a scenario known as the Internet of Things (IoT), in which objects, animals and people can all be provided with unique identifiers and the ability to automatically transfer data over a network without requiring human-to-human or human-to-computer interaction. In this paper we use an intelligent system to predict topography of specimens after heat treatment. 3D visibility graphs can be used in many 3D geometric problems. In this work, the visibility network in a 3D space, which contains more information than the visibility graph, is used to analyse the microstructure of the robot laser-hardened specimens. This algorithm is also useful in many other cases, such as: illumination and rendering, motion planning, pattern recognition, computer graphics, computational geometry and sensor networks. The robot laser surface-hardening [2] heat treatment is complementary to the conventional flame or inductive hardening. Laser hardening is a process of projecting features, such as a non-controlled energy intake, high-performance constancy and an accurate positioning process. A hard martensitic microstructure provides improved surface properties, such as wear resistance and high strength [3]. The aim of the paper is to outline the possibilities of applying the neural network, genetic programming and multyple regression for the prediction of the roughness after robot-laser heat treatment with the topological property density visibility graphs in a 3D space of a microstructure and to assess their perspective use in this field. An application of the algorithm for construction of a 3D visibility graph to analyse the microstructure of the laser technique in hardening a specimen is illustrated in Section 3.

2 MATERIALS PREPARATION

The study was undertaken using the tool-steel standard label DIN standard 1.7225. The tool steel was forged with the laser at different speeds and at different powers. So we changed two parameters the speed v ∈ [2, 5] mm/s with steps of 1 mm/s and the temperature T ∈ [1000, 1400] °C. Prior to testing, the specimens were subjected first to the mechanical and then to electrolytic polishing in $H_3Po4+CrO_3$ at the Institute of Metals and Technology of Ljubljana, Slovenia. After polishing we made images with a scanning electron microscope, JEOL JSM-7600F. Fig. 1 presents the microstructure of the robot-laser-hardened specimens. On these specimens we measured the roughness and hardness before and after the robot-laser-hardening. A profilometer (available from the Jozef Stefan Institute of Ljubljana) was used to measure the surface roughness parameter R_a (arithmetic mean deviation of the roughness profile) and hardness of the robot-laser-hardened specimens.

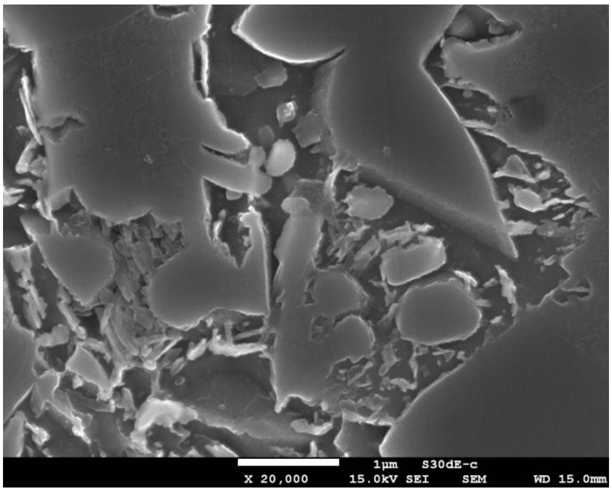

Figure 1. Microstructure of the robot-laser-hardened specimen

3 METHOD

We used a new mathematical method to describe the geometry microstructure the of robot-laser-hardened specimens. In this paper we use the mathematical method graph theory to describe the complexity geometry of the robot-laser-hardened specimens and visibility graphs in a 3D space. Teh algorithms for the *2D* visibility graphs already exist [4]. Two arbitrary data values (x_a, y_a) and (x_b, y_b) will have visibility, and consequently will become two connected nodes of the associated graph, if any other data (x_c, y_c) placed between them fulfills (1).

$$y_c < y_b + (y_a - y_b)*(x_b - x_c)/(x_b - x_a) \; . \tag{1}$$

Firstly, we have a point (vertex) in a *3D* space and know how to connect it in a *3D* space.

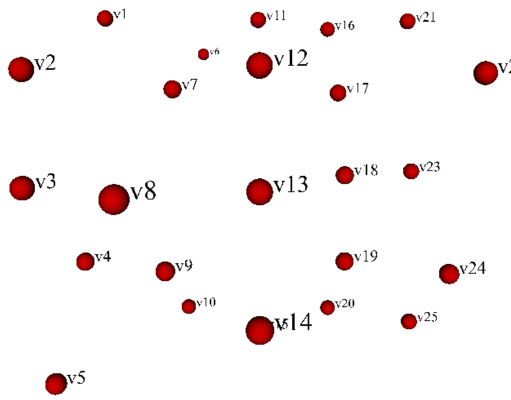

Figure 2. Point in a *3D* space microstructure of Fig. 1

The problem of constructing the visibility graph in a *3D* space was solved in [5]. Fig. 3 presents a solution of the visibility graph in a *3D* space microstructure of Fig. 1. Density *ρ* for each visibility graph was calculated with equation (2)

$$\rho = 2m/n\times(n-1), \tag{2}$$

wher m is the number of the edges and n is the number of verteces in the visibility graphs.

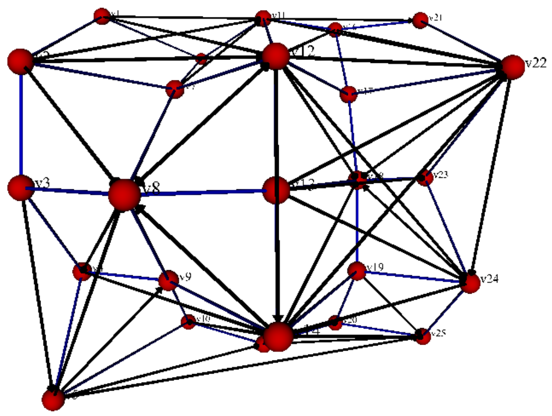

Figure 3. Visibility graph in a 3D space microstructure of Fig. 1

To model the results, we used the intelligent system methods, i.e. the neural network, genetic programming method and multiple regression.

The neural networks [8] have a large appeal to many researchers due to their great closeness to the structure of the brain, a characteristic not shared by more traditional systems. In an analogy to the brain, an entity made up of interconnected neurons, the neural networks are made up of interconnected processing elements called units, which respond in parallel to a set of the input signals given to each. The unit is an equivalent of its brain counterpart, the neuron. Learning is essential to most of these neural network architectures and hence the choice of a learning algorithm [9] is a central issue in the network development. Learning implies that a processing unit is capable of changing its input/output behavior as a result of changes in the environment. Since the activation rule is usually fixed when the network is constructed and since the input/output vector cannot be changed, to change the input/output behavior, the weights corresponding to that input vector need to be adjusted. A method is thus needed with which, at least during the training stage, the weights can be modified in response to the input/output process. Their is a number of such learning rules available for the neural network models. In a neural network, learning can be supervised, in which the network is provided with a correct answer for the output during training, or unsupervised, in which no external teacher is present.

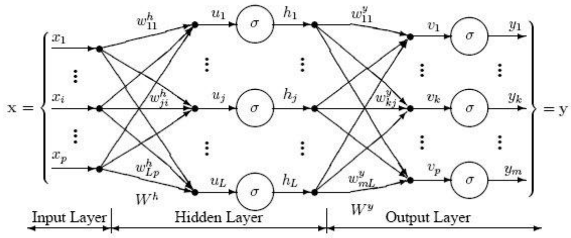

Figure. 4. General multi-layer neural network system

Genetic programming (GP) [9] is an automated method for creating a working computer program from a high-level problem statement of a problem. GP starts from a high-level statement of “what needs to be done” and automatically creates a computer program to solve the problem. GP starts with a primordial ooze of thousands of randomly created computer programs. This population of programs is progressively evolved over a series of generations. 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 the tournament size 7 was used.

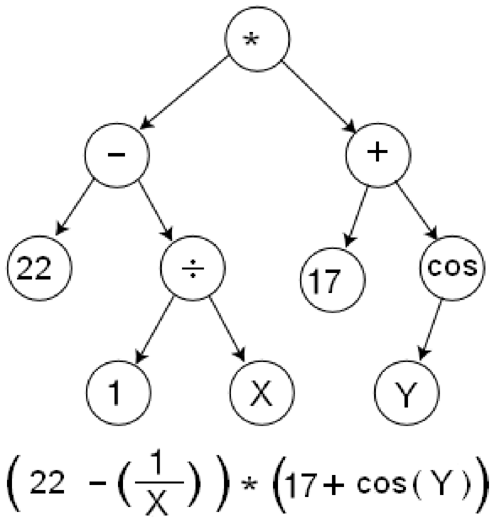

Figure. 5. Randomly generated mathematical model for the surface roughness of the hardened specimens prediction, represented in the program-tree form

The multiple regression [6] is a straightforward extension of the simple regression from one to several quantitative explanatory variables. In the multiple regression, we still make the xed-x assumption which indicates that each of the quantitative explanatory variables is measured with a little or no imprecision. All the error model assumptions also apply. They assume teh outcome that for each subject having the same level of the explanatory variables is normally distributed around the true mean (or that the errors are normally distributed with the mean zero), and that the variance, σ^2, of the outcome around the true mean (or of the errors) is the same for every other set of the values of the explanatory variables [7]. It is assumed that the errors are independent from each other. The standard ANCOVA model incorporates covariates into an ANOVA model in a straightforward way. If there is one grouping variable, for example, the model for the multiple linear regression, given m observations, is (3)

$$Y = b + b_1X1 + b_2X2 + ... + b_mXm + \varepsilon, \quad (3)$$

where α_i is the corrected effect on y given that you are in group i (corrected in the sense that the covariates $x_1, . . . , x_m$ are taken into account).

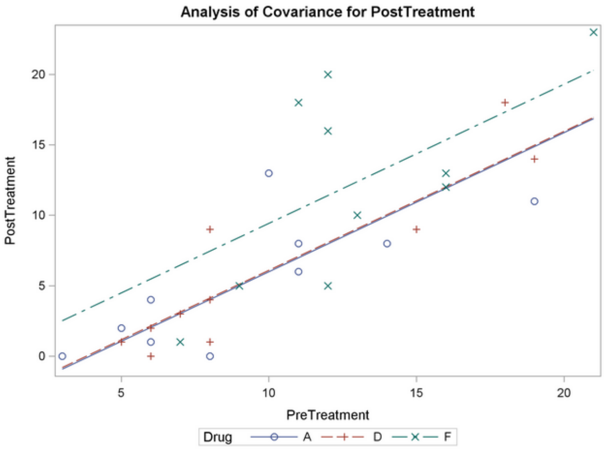

Figure 6. Analysis of covariance

4 RESULTS

In Table 1, the parameters of the hardened specimens impacting the roughness are presented. The specimens from P1 to P22 are marked. Parameter X1 presents the temperature in degrees of Celsius [C], X2 presents the speed of hardening [mm/s], X3 presents the density of the visibility graphs in a 3D space and X4 presents the basic roughness of specimens. The last parameter Y is the measured surface roughness of the laser-hardened robot specimens. Table 2 presents experimental and prediction data regarding the surface roughness of the laser hardened robot specimens. In Table 2, symbol S presents the name of the specimens, E experimental data, R prediction with regression, NM1 prediction with the neural network with a 50% learn set, NM2 prediction with the neural network with the method one live out, and GP prediction with genetic programming. In Table 1, we can see that specimen P20 has the largest density of the visibility graphs in 3D; 0.2960, thus specimen P20 is most complex. Specimen P13 has most roughness after hardening, that is 2350nm. The measured and predicted surface roughness of the laser-hardened robot specimens is shown in the graph in Fig. 8. The genetic programming model is presented in Fig. 7. The genetic programming model presents a 19. 67% deviation from the measured data, which is less than the regression model, which presents a 133. 97% deviation. The best neural network presents a 39. 10% deviation from the measured data.

Y=40,2767-

$$\frac{-8,6395+2\times X2-\frac{9,70913}{X2+X3}}{40,2767-\frac{X2+\frac{9,70913}{X2+X3}}{X3}-\frac{X3+\frac{9,70913}{2\times X2\times X3+\frac{9,70913}{X2}}-\frac{X3-X2+\frac{9,70913}{X3}-\frac{9,70913}{X2+X3}}{-8,63695+X2}}{-1,32381+X2}}-$$

$$\frac{X3+\frac{9,70913}{2\times X3-X2+\frac{9,70913}{X2+X3}}}{-1,32381+X2}-$$

$$\frac{\frac{\frac{9,70913}{X2+X3}-\frac{9,70913-X2+(-5,0744-X2-5,50744\times X3)\times X3}{X2+X3}}{-8,63695+X2+X3-\frac{\frac{4,85457}{X2}+\frac{9,70913+X2}{X2+X3}}{-8,63695+\frac{9,70913+X2}{2\times X2}}}}{-1,32381+X2}-$$

$$\frac{\frac{\frac{\left(5,0744\times(-X2+X3+\frac{9,70913+X2}{X2+X3}\right)}{-17,2739+\frac{9,70913}{X3}}}{-8,63695+X2+X3-\frac{\frac{4,85457}{X2}+\frac{9,70913+X2}{X2+X3}}{-8,63695+\frac{9,70913+X2}{2\times X2}}}}{-1,32381+X2}$$

Figure 7. Model of genetic programming

Table 1. Parameters of the hardened specimens

S	X1	X2	X3	X4	Y
P1	1000	2	0,1936	24	201
P2	1000	3	0,2208	24	171
P3	1000	4	0,2144	24	109
P4	1000	5	0,2256	24	76,3
P5	1400	2	0,2445	24	1320
P6	1400	3	0,2221	24	992
P7	1400	4	0,2036	24	553
P8	1400	5	0,2096	24	652
P9	1000	2	0,2352	201	337
P10	1000	3	0,2288	171	307
P11	1000	4	0,2144	109	444
P12	1000	5	0,2352	76,3	270
P13	1400	2	0,2208	1320	2350
P14	1400	3	0,232	992	1900
P15	1400	4	0,1984	553	661
P16	1400	5	0,1904	652	759
P17	800	0	0,2832	24	183
P18	1400	0	0,2688	24	1330
P19	2000	0	0,2416	24	1740
P20	950	0	0,2128	24	502
P21	850	0	0,208	24	166
P22	0	0	0,296	24	24

Table 2. Experimental and prediction data

S	ED	R	NM1	NM2	GP
P1	201	305,65	199,6	317,1	214,1
P2	171	407,70	151,2	150,2	205,1
P3	109	305,54	105,3	67,9	137,3
P4	76,3	310,35	101,0	129,8	83,9
P5	1320	1187,6	1314,0	1240,0	1779,3
P6	992	988,25	993,0	987,8	936,6
P7	553	812,56	569,6	706,8	567,1
P8	652	785,76	641,0	562,0	431,3
P9	337	558,47	354,6	419,5	331,7
P10	307	456,31	291,2	215,3	218,0
P11	444	305,54	440,1	404,7	137,3
P12	270	368,69	138,0	19,2	83,4
P13	2350	1043,6	1372,8	2302,5	1367,2
P14	1900	1048,4	953,5	1928,5	1032,7
P15	661	780,95	1465,8	684,4	540,0
P16	759	669,08	673,7	749,4	372,0
P17	183	690,38	465,8	170,9	193,3
P18	1330	1461,8	1990,3	1350,3	731,1
P19	1740	2155,5	2367,7	1759,8	1742,5
P20	502	477,27	621,2	365,0	201,3
P21	166	304,94	266,5	272,9	151,7
P22	24	-377,1	115,2	-64,6	24,3

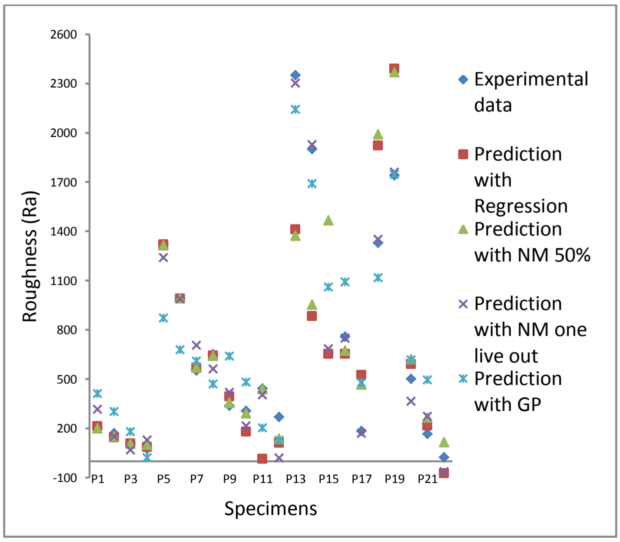

Figure 8. Measured and predicted surface roughness of the laser-hardened robot specimens

Model Regression

$$Y=-2176{,}047851+1{,}431627245\times X1-63{,}25871916\times X2+6077{,}409979\times X3$$

5 DISCUSSION

We use the topological property of the visibility graphs to describe the topographical properties of the hardened specimens. Using an algorithm for constructiong the visibility graphs in a 3D space, we describe the complexity of the hardened specimens. A statistically significant relationship was found between the roughness, parameters of the robot-laser cell and topological property density of the visibility graphs in 3D. In addition, image analysis of the SEM images of the robot-laser-hardened specimens is an interesting approach. We use three methods of the intelligent system to predict porosity of the robot-laser-hardened specimens. We show that the genetic programming model gives the best prediction results. The neural network model is better than the regression model and as good as the genetic programming model.

6 CONCLUSSION

In the paper we present the use of an intelligent system method, genetic programming and multyple regression to predict the hardness of hardened specimens. We describe a method of the visibility graph in a 3D space to analise complexity of the robot-laser-hardened specimens. The main findings can be summarised as follows:

1. We describe the topographical properties of the hardened specimens by using the topological properties of the visibility graphs in a 3D space.
2. We describe the relationship between roughness and the parameters of the robot-laser cell by using the topological properties of the 3D visibility graphs. This finding is important with regard to certain alloys that are hard to mix because they have different melting temperatures; however, such alloys have better technical characteristics. By varying different parameters (e.g., temperature), the robot-laser cells produce different patterns with different topological properties of the 3D visibility graphs.
3. To predict the roughness of the hardened specimens, we use a neural network, genetic algorithm and multiple regression.
4. Using the presented intelligent system we increase production of the laser-hardening process by decreasing time of the process and increase the topographical property of materials.

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