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Using fractal dimensions for determination of porosity of robot laser-hardened specimens

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Abstract

The porous structure of a 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 porosity of robot laser-hardened specimens. In this paper, we describe how the parameters (speed and temperature) of the robot laser cell affect porous metal materials using a new method, fractal geometry. We describe a new technological process of hardening, which can decrease the porosity of hardened specimens. The new process uses robot laser hardening with an overlapping laser beam. First, we hardened specimens using different velocities and temperatures and then repeated the process. In addition, we present how the speed and temperature affect the porosity in two different processes of robot laser hardening. Furthermore, we present the improved results after hardening with the overlap process. To analyse the results, we used one method of intelligent system, neural networks and a relationship was obtained by using a four-layer neural network. We compare both processes.

Keywords: **Fractal dimension, robot, laser, porous, hardening,**

1. Introduction

Many objects observed in nature are typically complex, irregular in shape and thus, cannot be described completely by Euclidean geometry. Fractal geometry [1] is becoming increasingly popular in material science to describe complex irregular objects [2, 3]. The aim of the present study is to find those parameters of a robot laser cell, which improve porosity after a hardening process. Moreover, the aim of the contribution is to outline possibilities of applying artificial neural networks for the prediction porosity after robot laser heat treatment and to judge their perspective use in this field. The achieved models enable the prediction of final porosity on the basis of decisive parameters of laser beam influencing these properties. The modelling of the relationship was obtained by a four-layer neural network. Robot laser surface-hardening [4, 5] heat treatment is complementary to conventional flame or inductive hardening. 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 hardness values of up to 65 HRc. Laser hardening involves features, such as non-controlled energy intake, high performance constancy and accurate positioning processes. A hard martensitic microstructure provides improved surface properties such as wear resistance and high strength. The porosity [6-8] of robot laser-hardened specimens was observed using scanning electron microscopy (SEM). Porosity is defined as the volume of shared pores in a material and is measured as a percentage. Porosity is usually the worst mechanical property of a material; the question is how to improve it? In this article, we present a new process of hardening [9] to improve porosity by robot laser hardening.

2. Method and materials

2.1 Materials

Our study was limited to tool steel of DIN standard 1.7225 (Fig. 1). The chemical composition of the material contained 0.38% to 0.45% C, 0.4% maximum Si, 0.6% to 0.9% Mn, 0.025% maximum P, 0.035% maximum S and 0.15% to 0.3% Mo [10].

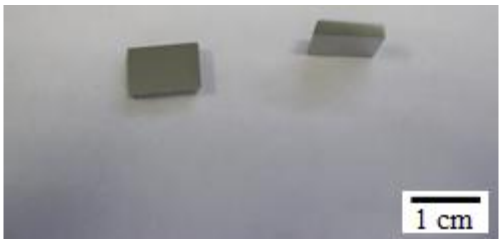


Fig. 1: Transverse and longitudinal cross-section of hardened specimen

The specimen test section had a cylindrical form of dimension 25×10 mm (diameter × height). Specimens with porosity of about 19% to 50%, were prepared by laser technique, followed by hardening at T ∈ [1000, 1400] °C and v ∈ [2, 5] mm/s. First, we changed two parameters of the robot laser cell: speed v ∈ [2, 5] mm/s with steps of 1 mm/s and temperature T ∈ [1000, 1400] °C in steps of 100 °C (Fig. 2). Secondly, we repeated the process (Fig. 3). In addition, we hardened the specimens again with equal parameters of the robot laser cell. The microstructure of the specimens was observed with a field emission scanning electron microscope (JSM-7600F, JEOL Ltd.). An irregular surface texture was observed with a few breaks, which are represented by black islands (Fig. 4). Fig. 5 presents the boundary between the hardened and non-hardened material.

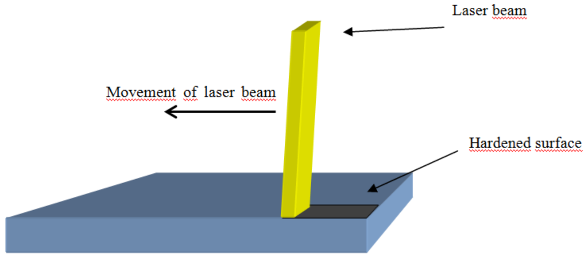


Fig. 2: Robot laser hardening with different temperature and speed

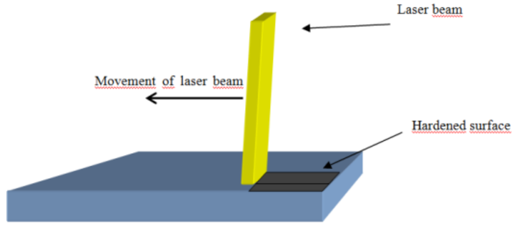


Fig. 3: Repeated process of robot laser hardening

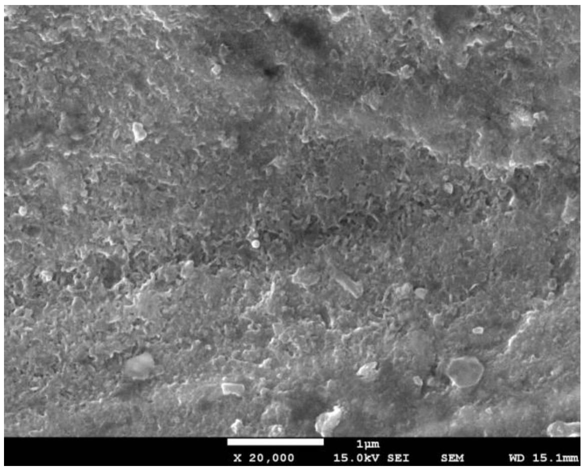


Fig. 4: SEM picture of robot laser re-hardened specimen

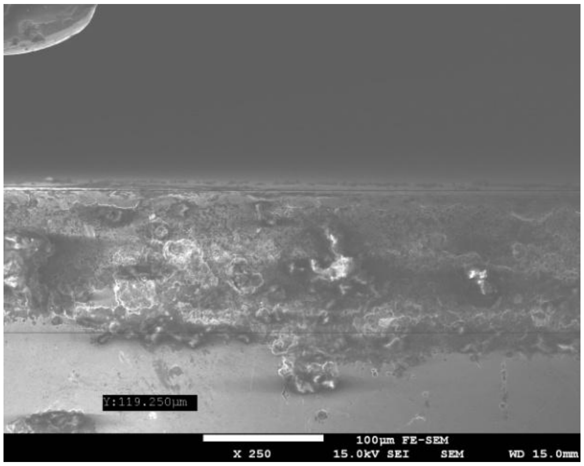


Fig. 5: The boundary between work-hardened and non-hardened material

2.1 Method

We used the method of determining the porosity from SEM images of the microstructure. It is known that in a homogenously porous material the area of pores is equal to the volume of pores in specimens. The SEM pictures were converted to binary images (Fig. 6), from which we calculated the area of pores of all pictures using the ImageJ program (ImageJ is a public domain, Java-based image processing program developed at the National Institutes of Health). The area of pores on each picture of the material was calculated and then the arithmetic mean and standard deviation of porosity were determined. To analyze he possibility of the application of 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 the fractal dimension D. The relationship between the 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 higher calculation speed and more accuracy by Dougan [17] and Shi [18].

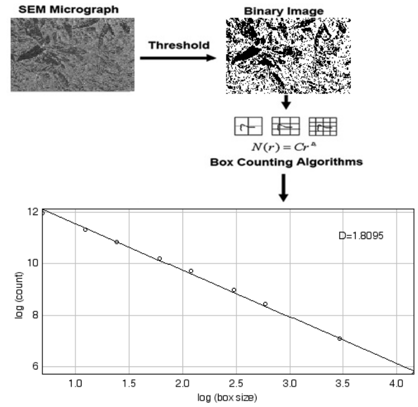


Fig. 6: Calculation of fractal dimensions with box-counting method

To analyse the results we used one method of intelligent system; the neural network [19]. Artificial neural networks (ANN) are simulations of collections of model biological neurons. A neuron operates by receiving signals from other neurons through connections called synapses. The 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 to a neuron firing. What we call thinking is believed to be the collective effect of the presence or absence of firings in the patterns of synaptic connections between neurons. In this context, neural networks are not simulations of real neurons, in that they do not model the biology, chemistry, or physics of a real neuron. However, they do model several aspects of the information combination and pattern recognition behaviour of real neurons, in a simple yet meaningful way. This neural modelling has shown incredible capability for emulation, analysis, prediction and association. Neural networks can be used in a variety of powerful ways: to learn and reproduce rules or operations from given examples; to analyse and generalise sample facts and to make predictions from these; or to memorise characteristics and features of given data and to match or make associations with new data. Neural networks can be used to make strict yes-no decisions or to produce more critical, finely valued judgments. Neural network technology is combined with genetic optimisation technology to facilitate the development of optimal neural networks to solve modelling problems. Genetic optimisation uses an evolution-like process to refine and enhance the structure of a neural network until it can model the problem in the most efficient way. Neural networks are models of biological neural structures. The starting point for most neural networks is a model neuron, as shown in Fig. 7. This neuron consists of multiple inputs and a single output. Each input is modified by a weight, which multiplies with the input value.

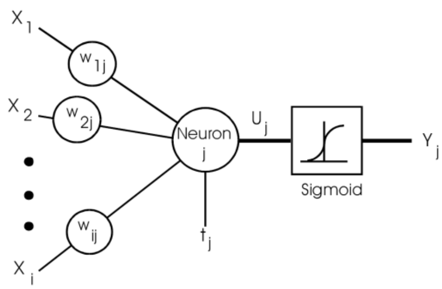


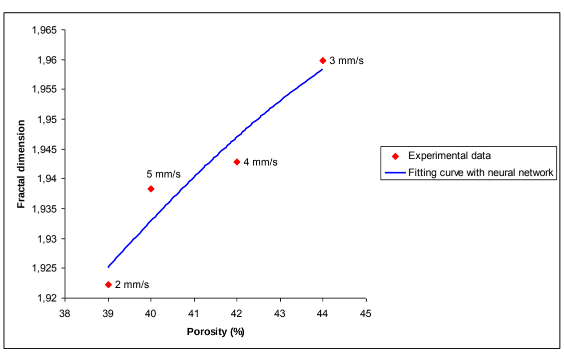
Fig. 7: A model neuron

We use program Neuralyst. Neuralyst is a general purpose neural network engine that has been integrated with Microsoft Excel on Windows or Macintosh systems. In a feed forward ANN system, the input data is processed from input to output. The neurons are classified in four layers called input layer, hidden layer and output layer. In supervised training, ANN applications require a training data set to learn the relationship between inputs and outputs. The training set should consist of sufficient number of samples that define a process. Otherwise, insufficient learning can limit the performance of the ANN approach.

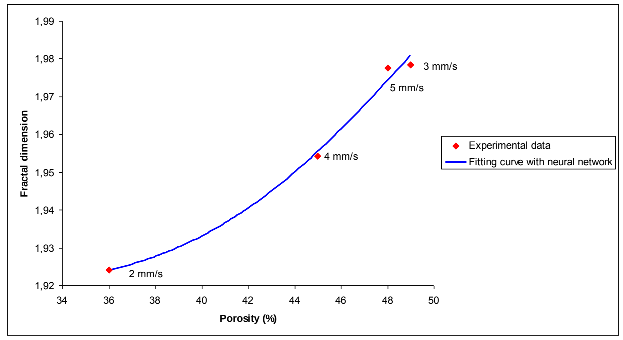
3. Result and discussion

3.1 Result

Graphs [1-2] present the relationship between fractal dimension and porosity of specimens hardened at 1000 °C and 1400 °C with different speeds.

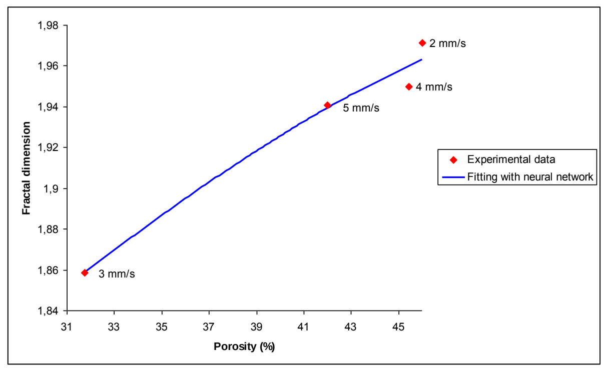


Graph 1: Relationship between fractal dimension and porosity of hardened specimens with different speeds at 1000 °C

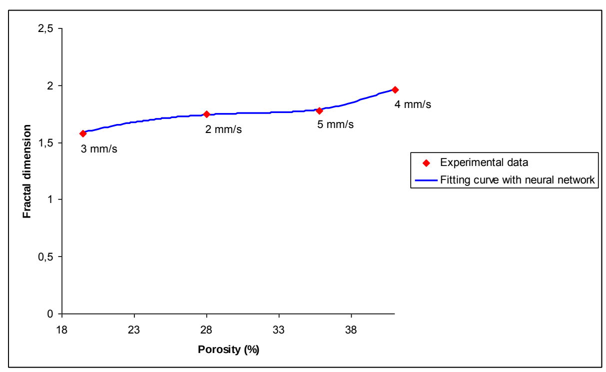


Graph 2: Relationship between fractal dimension and porosity of hardened specimens with different speeds at 1400 °C

Graphs [3-4] present the relationship between fractal dimension and porosity of specimens hardened at 1000 °C and 1400 °C with different speeds and with overlapping.

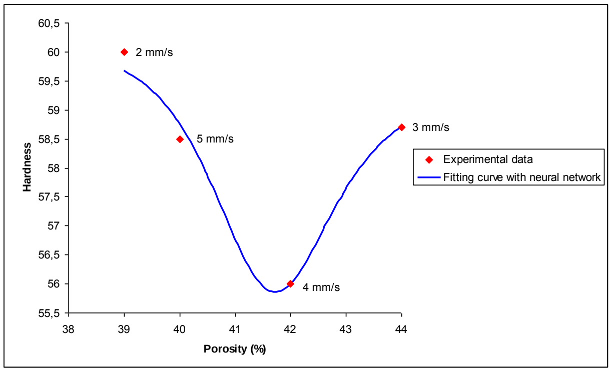


Graph 3: Relationship between fractal dimension and porosity of hardened specimens with overlap and different speeds at 1000 °C

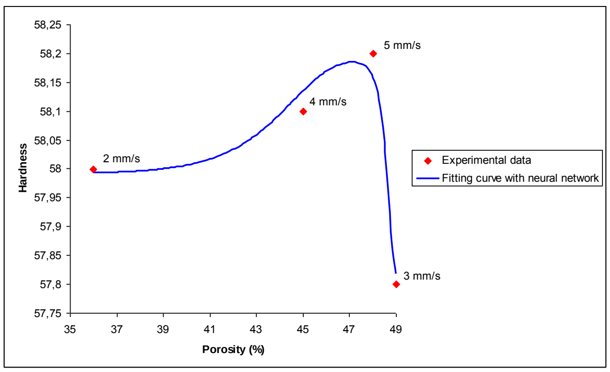


Graph 4: Relationship between fractal dimension and porosity of hardened specimens with overlap and different speeds at 1400 °C

Graphs [5-6] present the relationship between porosity and hardness of hardened specimens at 1000 °C and 1400 °C with different speeds.

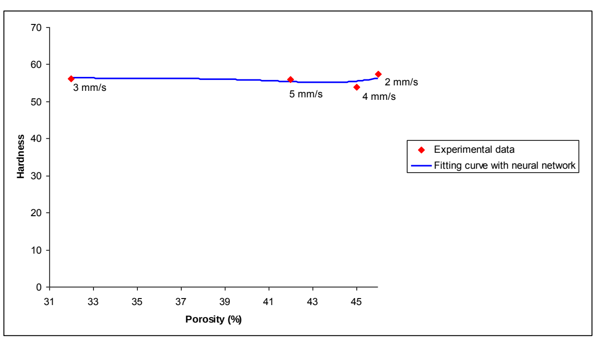


Graph 5: Relationship between porosity and hardness of hardened specimens with different speeds at 1000 °C

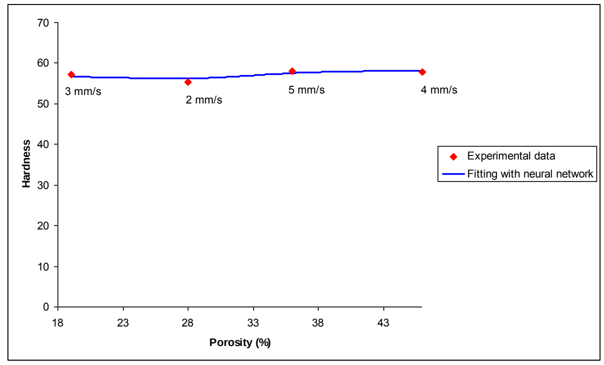


Graf 6: Relationship between porosity and hardness of hardened specimens with different speeds at 1400 °C

Graphs [7-8] present the relationship between hardness and porosity of specimens hardened at 1000 °C and 1400 °C with different speeds and with overlapping.



Graph 7: Relationship between hardness and porosity of specimens hardened at 1000 °C with different speeds and with overlapping



Graph 8: Relationship between hardness and porosity of specimens hardened at 1400 °C with different speeds with overlapping

3.2 Discussion

Porosity has a large impact on the mechanical properties of a material. With fractal dimensions, we describe the porosity of robot laser hardened specimens with overlap. We found the optimal parameters of the robot laser cell that gave minimal porosity. We used the new method of robot laser hardening with overlap to decrease the porosity of hardened specimens. If we increase the temperature from 1000 °C to 1400 °C in the case of hardening with overlap, then the fractal dimension decreases for speeds of 2, 3 and 4 mm/s. The improved results in hardening with overlap mean that the porosity is decreased for the laser-hardened specimens. Hardening with overlap at 1000 °C decreased the porosity in the specimen with a speed of 3 mm/s but for other speeds, the porosity is not decreased; moreover, the porosity is increased, which is not the result we seek. Hardening with overlap at 1400 °C decreased the porosity for specimens with a speed of 2, 3 and 5 mm/s but for a speed of 4 mm/s, the porosity increased. We repeated the process of robot laser hardening and measured the hardness. Graphs 5 and 6 presented the relationship between hardness and porosity of specimens hardened with different speeds at 1000 °C and 1400 °C, respectively. Graphs 7 and 8 present the relationship between hardness and porosity for specimens hardened at 1000 °C and 1400 °C, respectively with different speed with overlapping. Following the overlapping process, we cannot increase hardness. Similar results of hardness are obtained with parameters of temperature of 1400 °C and speeds of 3, 4 and 5 mm/s. However, we improved the results for hardness and porosity with the process of overlapping of robot laser hardening at 1400 °C with a speed of 3 and 4 mm/s; the optimal result was with a temperature of 1400 °C and speed of 3 mm/s, which gave us the smallest fractal

dimension. The fractal approach is more appropriate in the characterization
of complex and irregular surface microstructures observed in the surface of robot laser hardenend specimens and can be effectively utilized for predicting the properties of material from fractal dimensions of the microstructure.

With artificial neural networks we predict porosity after robot laser heat treatment with different parameters of temperature and speed and to judge their perspective use in this field.

4. Conclusions

The paper presents using fractal geometry to describe the porosity of robot laser-hardened specimens with overlap. We use the relatively new method of fractal geometry to describe the complexity of laser-hardened specimens. The main findings can be summarised as follows:

1. There exists a fractal structure in the robot laser-hardened specimens.
2. We describe the complexity of the robot laser-hardened specimens with fractal geometry.
3. We use the box-counting method to calculate the fractal dimension for robot laser-hardened specimens with different parameters.
4. The fractal dimension varies between 1 and 2. By increasing the temperature of the robot laser cell, the fractal dimension becomes larger and grain size becomes smaller. However, by increasing the temperature of the robot laser cell during hardening with overlap, the fractal dimension becomes smaller. Thus, we can use the fractal dimension as an important factor to define the grain shape.
5. We describe the relationship between hardness and the parameters of the robot laser cell using fractal dimensions. This finding is important if we know that certain mixed alloys perform poorly because they have different melting temperatures; however, such alloys have much higher hardness and better technical characteristics. By varying different parameters (temperature and speed), the robot laser cells produce different fractal patterns with different fractal dimensions.
6. With fractal dimensions, we describe the relationship between porosity and the parameters of the robot laser cell.
7. We find the optimal parameters of the robot laser cell to decrease the porosity of hardened specimens.
8. We find the process, overlapping that decreases the porosity of robot laser hardening.

The relationship between porosity and the parameters of robot laser cells may be better understood through exploration of the fractal dimensions of the microstructure.

Acknowledgments

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References

[1] Mandelbrot, B. B. The fractal geometry of nature. New York: W. H. Freeman, 1982:93.
[2] Babič, M., Muhič, T. 2010, Fractal structure of the robot laser hardened materials. In: 18th Conference on Materials and Technology, 15th–17th November 2010, Portoroz, Slovenia. Program and abstracts book. [Ljubljana: Institute of Metals and Technology,], p. 73. (In Slovene)
[3] Babič, M. 2010, Fractal dimension of the robot laser hardening tool steel. V: ROBNIK, Marko (ur.), KOROŠAK, Dean (ur.). 9th Symposium of Physicists at the University of Maribor, Hotel Pyramid, Maribor, 9, 10 and 11 December, 2010. Book of Abstracts. London: CAMTP, [2] F. (In Slovene)
[4] Babič, M., Milfelner, M., Stepišnik, S. 2010, Laser hardening metals. Y: PERME, Tomaž(ur.), ŠVETAK, Darko (ur.), BALIČ, Jože (ur.). IRT Industrial Forum, Portoroz, 7–8 June 2010. Source of knowledge and experience for the profession: Proceedings of the Forum. Skofljica: Profidtp.
[5] Babič, M. 2010, Optimal parameters of a robot cell for laser hardening of metals at different angles. 19. Proceedings of the International Electrotechnical and Computer Conference ERK 2010, Portoroz, Slovenia, 20–22 September 2010, (Zbornik. Electrical and Computer Conference ERK ...). Ljubljana: Slovenian section of the IEEE. (In Slovene).
[6] Yu, B. M., Cheng, P. A fractal permeability model for bi-dispersed porous media, International journal of Heat Mass Transfer 45 (2002) 2983–2993.
[7] Chen, Z. Q., Cheng, P., Hus, C. H. A theoretical and experimental study on stagnant thermal conductivity of bi-dispersed porous media, Int. Commun. Heat Mass Transfer 27(2000) 601–610.
[8] Pitchumani, R., Ramakrishnan, B. A fractal geometry model for evaluating permeabilities of porous preforms used in liquid composite molding, Int. J. Heat Mass Transfer 42 (1999) 2219–2232.
[9] Grumm J., Žerovnik, P., Šturm, R. 1996, Measurement and analysis of residual stresses after laser hardening and laser surface melt hardening on flat specimens; Proceedings of the Conference "Quenching '96", Ohio, Cleveland.
[10] http://www.splav.kharkov.com/steelgrade/mat_start_eu.php?name_id=335.
[11] Barton, C. C. 1995, Fractal analysis of scaling and spatial clustering of fractures. In: Barton, C.C. and La Pointe, P.R.

(eds.), Fractals in the earth sciences. Plenum Press. New York, p. 141–178.

[12] Eghball, B., Mielke, L. N., Calvo, G. A., Wilhelm, W. W. 1993, Fractal description of soil fragmentation for various tillage methods and crop sequences. Soil Sci. Soc. Am. J. 57:1337–1341.

[13] Hatano, R., Kawamura, N., Ikeda, J., Sakuma, T. 1992, Evaluation of the effect of morphological features of flow paths on solute transport by using fractal dimensions of methylene blue staining patterns. Geoderma 53:31–44.

[14] Crawford, J. W., Sleeman, B. D. 1998, From particles to architecture: Fractals, aggregation and scaling in environmental soil science. p. 41–45. *In* P. M Huang, N. Senesi, and J. Buffle (ed.) Structure and surface reactions of soil particles. IUPAC Environ. Anal. Phys. Chem. Ser. Vol. 4. John Wiley & Sons, New York.

[15] Crawford, J. W., Matsui, N. 1996, Heterogeneity of the pore and solid volume of soil: Distinguishing a fractal space from its nonfractal complement. Geoderma 73:183–195.

[16] Fan, L. W., Hu, Y. C., Tian, T., Yu, Z. T. The predication of effective thermal conductivities perpendicular to the fibres of wood using a fractal model and an improved transient measurement technique, International journal of Heat Mass Transfer 49 (2006) 4116–4123.

[17] L.T. Dougan, P.S. Addison, Estimating the cut-off in fractal scaling of fractured concrete, Cement and Concrete Research 31 (2001) 1043–1048.

[18] Y. Shi, X.P. Lou, S.H. Quan, Fractal dimension computation methods for gas diffusion layer of PEM fuel cells (in Chinese), Journal of Wuhan University of Technology 29 (2005) 79–82.

[19] El. Hafnawi M, Mysara M. Recurrent Neural Networks and Soft Computing. Rijeka: Intech; 2012.

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