New method for modeling the topographical property of metals and its application in robot laser hardening with overlapping

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Abstract. Robot laser surface hardening is the part necessary for hardening instantly absorbs light energy, turning it into thermodynamic, due to which the temperature rises and austenite forms, then, after instant cooling, the martensite microsubstance is obtained. Due to the technology of heat treatment, it is possible to obtain other high-strength layers. The combination of laser hardening technology with the advantages of high cooling rate, uniform temperature distribution, minimum thermal stress, high strength, wide processing capabilities of various parts, etc. made this machine advanced in the processing of molding tools. In the laser a flat semiconductor is used as a heat source. The laser, in turn, has a high photoelectric conversion efficiency, has a short wavelength, low energy consumption and other advantages. In this article, we present the technology of robot laser hardening with overlapping and new method for predicting the topographical property of overlapping hardening process.

1. Introduction
Surface hardening through additional surface treatment processes represents an extremely competitive strategy to efficiently offer properties materials that they would not otherwise have [1,2]. This general concept is true for many materials, even belonging to families for which the idea of surface hardening is not obvious, as for example in the case of composites [3,4] or cermets [5].

Otherwise, it is precisely in metals and their alloys, and, in particular, in steel alloys that surface processes for hardening maybe reach the highest levels in terms of the variability and choice of treatments, technological advances, performance achieved by the materials, and so on [6-9].

The laser hardening technology [10], the core of one of these metal treatments, involves the study of principles of light energy in physics. Laser is an acronym for Light Amplification by Stimulated Emission of Radiation. The laser hardening [11-13] can be used as a metal surface treatment process, complementary to conventional flame and induction hardening or other processes [14]. A high-power laser beam is applied 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. It is used exclusively on ferrous materials suitable for hardening including, steels and cast iron with a carbon content of more than 0.2 %. Laser beam hardening is employed to locally improve the surface properties of components.
Use of this treatment can increase wear and fatigue resistance in parts of steel and cast iron [15,16], respect their traditional alloys [17]. Through a locally restricted heat treatment arises a minimum heat input, thereby minimized distortion. The associated high heating and cooling rates result in fine microstructures with good mechanical properties. During the laser skin hardening, the material (carbonaceous material) is heated up for a short time above austenitizing temperature and is transubstantiated by fast cooling down into the martensite structure. Different tool steels are widely introduced in industrial applications [18] due to good performance, a wide range of mechanical properties, machinability and wear cheapness.

With the laser hardening surface of the material, we can significantly improve their wear properties (Fig. 1 and 2). Heat is generated by absorbing the laser radiation on the surface and the material is quenched by heat transportation inside. The surface may not melt up.

In brief, robot laser hardening have many advantages:

- 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,
- superior wear resistance of hardened surface,
- selective hardening of complex geometrical shapes.

On the other side, surface treatments, including laser hardening, can be surely benefit from the adoption of intelligent systems and their modern tools for an optimal processing.

The term intelligent systems [19-21] is subject to the state of development of modern computer systems and their application inside the manufacturing processes. However, there are some characteristic features of intelligent systems that are independent of technological development. Intelligent systems process data electronically and can interpret information and their meaning from data and data records and link them to each other on a topic-specific basis. They are capable of learning, have artificial intelligence, and have cognitive abilities. Other characteristic features are their adaptability to various tasks and environmental conditions, their fault tolerance and safety. Intelligent systems are networked and can access other systems: knowledge-based systems, knowledge bases, expert systems and other software solutions.

In this work, in line with a methodological approach dealing with the intelligent systems, we will use the artificial intelligent techniques to investigate and optimise the robot laser hardening as done with success in the past on different materials and process technologies [22-24].
2. Materials preparation and experimental method
We made patterns of a standard label on the materials according to DIN standard GGG 70 and GGG 70 L. We hardened an ordinary tool steel with the laser at different temperature $T \in [1000, 1400] ^\circ C$ with steps 100 $^\circ C$ and different speed $v \in [2, 5]$ mm/s. We repeated this process in the way to produce specimens hardened with overlapping (Fig. 3).

![Figure 3. Process of robot laser hardening with overlapping.](image)

In all these attempts we made pictures of the microstructure. We made recordings of hardened surface area. Each pattern was etching and polished before recording images by microscope. First, we made recordings using an optical microscope and then with an electron microscope. Images were made by field emission scanning electron microscope JSM-7600F JEOL company. To model the results, we used intelligent system methods, i.e. the neural network and support vector machine methods. In general, it can be said that the neural networks NN [25] 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. Support vector machines [26] (SVM) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Hybrid evolutionary computation [27] is a generic, flexible, robust, and versatile method for solving complex global optimization problems and can also be used in practical applications. We present a new intelligent hybrid systems model in Fig. 4.

![Figure 4. Hybrid system method of machine learning.](image)

3. Results and discussion
In Table 1, the parameters of hardened specimens that impact on hardness are presented. We mark specimens from S1 to S20. Parameter X1 presents the parameter of temperature in degree of Celsius [C], X2 presents the speed of hardening [mm/s] and X3 presents base hardness of hardened specimens. The last parameter Y presents hardness of hardened specimens. Table 2 presents experimental and prediction hardness of laser hardened robot specimens. In Table 2 present symbol S name of specimens, E experimental data, NN prediction with neural network, SVM prediction with support vector machine and H prediction with new hybrid system of machine learning.
Table 1. Parameters of robot laser hardened specimens.

|   S   | X1 | X2 | X3   | Y   |
|------|----|----|------|-----|
|   S1  | 1000| 2  | 34.0 | 60.0|
|   S2  | 1000| 3  | 34.0 | 58.7|
|   S3  | 1000| 4  | 34.0 | 56.0|
|   S4  | 1000| 5  | 34.0 | 56.5|
|   S5  | 1400| 2  | 34.0 | 58.0|
|   S6  | 1400| 3  | 34.0 | 57.8|
|   S7  | 1400| 4  | 34.0 | 58.1|
|   S8  | 1400| 5  | 34.0 | 58.2|
|   S9  | 1000| 2  | 60.0 | 57.4|
|   S10 | 1000| 3  | 58.7 | 56.1|
|   S11 | 1000| 4  | 56.0 | 53.8|
|   S12 | 1000| 5  | 56.5 | 56.0|
|   S13 | 1400| 2  | 58.0 | 55.3|
|   S14 | 1400| 3  | 57.8 | 57.2|
|   S15 | 1400| 4  | 58.1 | 57.8|
|   S16 | 1400| 5  | 58.2 | 58.0|
|   S17 | 800 | 0   | 34.0 | 52.0|
|   S18 | 1400| 0  | 34.0 | 57.0|
|   S19 | 2000| 0  | 34.0 | 56.0|
|   S20 | 950 | 0   | 34.0 | 58.0|

Table 2. Experimental and predicted data.

|   E   |   NN   |   SVM   | H     |
|------|--------|--------|-------|
| 60.0 | 60.16710 | 59.87995 | 59.42609 |
| 58.7 | 58.16926 | 58.14569 | 58.48085 |
| 56.0 | 56.56679 | 56.48387 | 55.92964 |
| 56.5 | 56.30757 | 56.38787 | 56.42103 |
| 58.0 | 58.12300 | 58.48259 | 57.90567 |
| 57.8 | 57.88996 | 57.98160 | 57.97986 |
| 58.1 | 57.65343 | 57.53997 | 58.53496 |
| 58.2 | 58.44157 | 58.36040 | 58.18148 |
| 57.4 | 58.65890 | 57.56091 | 57.36191 |
| 56.1 | 57.86290 | 55.93925 | 55.98725 |
| 53.8 | 58.94343 | 53.82327 | 53.70487 |
| 56.0 | 56.52490 | 52.81287 | 39.39352 |
| 55.3 | 58.61613 | 58.55416 | 55.34749 |
| 57.2 | 57.74158 | 56.35732 | 57.11229 |
| 57.8 | 57.97462 | 52.35552 | 57.73809 |
| 58.0 | 56.31630 | 52.13819 | 57.95978 |
| 52.0 | 60.90898 | 61.26072 | 51.93134 |
| 57.0 | 60.61049 | 60.23867 | 57.50505 |
| 56.0 | 59.79442 | 58.61351 | 55.85109 |
| 58.0 | 60.91160 | 61.19265 | 57.53997 |

The measured and predicted surface hardness of the RLH specimens are shown in Fig. 5. The neural network model presents a 2.26% deviation from the measured data. The support vector machine model presents a 2.57% deviation from the measured data. The hybrid method of machine learning presents a 1.77% deviation from the measured data.

Figure 5. Experimental and predicted hardness.
4. Conclusion

The paper presents application of intelligent system methods in process of robot laser hardening with overlapping. We present hybrid method of intelligent system to predict topographical property of robot laser hardened specimens. The main findings can be summarized as follows:

1. For prediction of the hardness of hardened specimens we use neural network and support vector machine methods.
2. Predictions are in an acceptable accordance with experiments. The neural network and support vector machine models are almost equivalent in terms of accuracy. The hybrid method for machine learning leads to better results in predictions.
3. With the hybrid method of intelligent systems, we increase production of the process of laser hardening, because we decrease the time of the process and increase topographical properties of materials.
4. We describe the relationship between hardness and the parameters of the robot laser cell. This finding is important regarding 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), robot laser cells produce different patterns.
5. The present research can be easily extended with the scope of involving different material properties with valuable results in the case of cast irons (as done in [28]).

References

[1] Davis J R 2002 Surface hardening of steels: understanding the basics, ASM international
[2] Lampman S 1991 Introduction to surface hardening of steels, ASM Handbook 4 259-267.
[3] Fotouhi M, Saghafi H et al. 2017 Effect of PVDF nanofibers on the fracture behavior of composite laminates for high-speed woodworking machines, P I Mech Eng C-J Mech 231(1) 31-43, doi: 10.1177/0954406216650711
[4] Zivkovic I, Pavlovic A and Fragassa C 2016 Improvements in wood thermoplastic composite materials properties by physical and chemical treatments, International Journal of Quality Research 10(1) 205-218
[5] Guaglianoni W C, Cunha M A et al. 2018 Synthesis, Characterization and Application by HVOF of a WCCoCr/NiCr Nanocomposite as Protective Coating Against Erosive Wear, Tribology in Industry 40(3) 477-487, doi: 10.24874/ti2018.40.03.13
[6] Béjar M A and Henríquez R 2009 Surface hardening of steel by plasma-electrolysis boronizing, Mat & Des 30(5) 1726-1728.
[7] Chou, Y K 2002 Surface hardening of AISI 4340 steel by machining: a preliminary investigation, J Mat Proc Techn 124(1-2) 171-177.
[8] Zou J X, Zhang K M et al. 2010 Mechanisms of hardening, wear and corrosion improvement of 316 L stainless steel by low energy high current pulsed electron beam surface treatment, Thin Solid Films 519(4) 1404-1415.
[9] Sirin S Y, Sirin K and Kaluc E 2008 Effect of the ion nitriding surface hardening process on fatigue behavior of AISI 4340 steel, Materials Characterization 59(4) 351-358.
[10] Totten G E 2006 Steel heat treatment, 2nd edition.
[11] Xu Z, Leong K H and Reed C B 2008 Nondestructive evaluation and real-time monitoring of laser surface hardening, Journal of Materials Processing Technology 206 (1-3) 120-125
[12] Dutta Majumdar J and Manna I 2011 Laser material processing, International materials reviews 56(5-6), 341-388.
[13] Ion J. C. 2005 Laser processing of Engineering Material - Principles, procedures and industrial applications, Elsevier
[14] Santacruz G, Takimi A S, de Camargo F V, Bergmann C P and Fragassa C 2019 Comparative Study of Jet Slurry Erosion of Martensitic Stainless Steel with Tungsten Carbide HVOF Coating, Metals 9(5) 600; doi:10.3390/met9050600
[15] Kennedy E, Byrne G, Collins D N 2004 A review of the use of high power diode lasers in surface hardening, Journal of Materials Processing Technology 155, 1855-1860.
[16] Chen C H, Altstetter C J and Rigsbee, J M 1984 Laser processing of cast iron for enhanced erosion resistance, Metallurgical Transactions A 15(4), 719-728.
[17] Fragassa C, Minak G and Pavlovic A 2016 Tribological aspects of cast iron investigated via
fracture toughness, *Tribology in Industry* 38(1) 1-10

[18] Fragassa C, Lucisano G, Marinkovic D and Campana G 2019 A Practical Guideline for the Design and Use of Tools in Woodworking, *FME Transactions* 47(2) 487-495, doi: 10.5937/fmet1903487F

[19] Serenko A and Dohan M 2011 Comparing the expert survey and citation impact journal ranking methods: Example from the field of Artificial Intelligence, *Journal of Informetrics* 5(4) 629–649, doi:10.1016/j.joi.2011.06.002

[20] Lukic L, Djapic M, et al. 2018 Optimization Model for Machining Processes Design in Flexible Manufacturing Systems, *Journal of Advanced Manufacturing Systems* 17(2) 137-153, doi: 10.1142/S0219686718500099

[21] Djapic M, Lukic L, et al. 2017 Multi-agent team for engineering: a machining plan in intelligent manufacturing systems, *International Journal of Machining and Machinability of Materials* 19(6) 505-521, Doi: 10.1504/IJMMM.2017.10006404

[22] Babic M, Cali M, et al. 2018 Surface Roughness Evaluation in Hardened Materials by Pattern Recognition Using Network Theory, *International Journal on Interactive Design and Manufacturing* 13(1) 211-219. Doi: 10.1007/s12008-018-0507-3

[23] Fragassa C, Babic M and Minak G 2019 Predicting the tensile behaviour of cast alloys by a pattern recognition analysis on experimental data, *Metals* 9, 557; doi:10.3390/met9050557

[24] Christopher C M L, Sasikumar T, et al. 2018 Neural network prediction of aluminum–silicon carbide tensile strength from acoustic emission rise angle data, *FME Transactions* 46(2) 253-258. doi:10.5937/fmet1802253M.

[25] Ciresan D, Giusti A, Gambardella L and Schmidhuber J 2012 Deep Neural Networks Segment Neuronal Membranes in Electron Microscopy Images, *Advances in Neural Information Processing Systems* (NIPS 2012), Lake Tahoe

[26] Campbell C and Ying Y 2011 *Learning with Support Vector Machines*, Morgan & Claypool, ISBN 978-1-60845-616-1

[27] Senanayke S M N, Malik O A, Iskandar P and Zaheer D 2013 Anterior cruciate ligament recovery monitoring system using hybrid computational intelligent techniques, *International Journal of Hybrid Intelligent Systems* 10(4) 2015-235

[27] Fragassa C, Babic M and Minak G 2019 Predicting the tensile behaviour of cast alloys by a pattern recognition analysis on experimental data, *Metals* 9(557), doi:10.3390/met9050557