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USE NEW PROCESS IN ROBOT LASER HARDENING TO DECREASE WEAR OF SPECIMENS

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Abstract: The mechanism of wear is very complex and the theoretical treatment without the use of rather sweeping simplifications is not possible. The material intrinsic surface properties such as hardness, strength, ductility, work hardening etc. are very important factors for wear resistance, but other factors like surface finish, lubrication, load, speed, corrosion, temperature and properties of the opposing surface etc. are equally important. Robot laser surface-hardening 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. We describe a new technological process of hardening, which can decrease the wear 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 wear 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: Wear, robot, laser, hardening, process of overlapping,

1. INTRODUCTION

In materials science, wear is erosion or sideways displacement of material from its "derivative" and original position on a solid surface performed by the action of another surface. Wear is related to interactions between surfaces and more specifically the removal and deformation of material on a surface as a result of mechanical action of the opposite surface. The need for relative motion between two surfaces and initial mechanical contact between asperities is an important distinction between mechanical wear compared to other processes with similar outcomes.

The definition of wear may include loss of dimension from plastic deformation if it is

originated at the interface between two sliding surfaces.

However, plastic deformation such as yield stress is excluded from the wear definition if it doesn't incorporates a relative sliding motion and contact against another surface despite the possibility for material removal, because it then lacks the relative sliding action of another surface.

2. MATERIALS AND METHOD

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].



Figure 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 $T \in [1000, 1400]$ °C and $v \in [2, 5]$ mm/s. First, we changed two parameters of the robot laser cell: speed $v \in [2, 5]$ mm/s with steps of 1 mm/s and temperature $T \in [1000, 1400]$ °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.



Figure 2. Robot laser hardening with different temperature and speed



Figure 3. Repeated process of robot laser hardening



Figure 4. SEM picture of robot laser re-hardened specimen



Figure 5. The boundary between work-hardened and non-hardened material

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 to the heattreated 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:

$$V \sim L^{D}$$
 (1)

Fractal dimensions were determined using the box-counting method which has been proven to have higher calculation speed and more accuracy by Dougan and Shi.



Figure 6. Calculation of fractal dimensions with boxcounting method

To analyse the results we used one method of intelligent system; the neural network. 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.



Figure 7. A neuron model

3. RESULT

Graph [1-2] present relationship between roughness R_a and hardness in specimens hardened at different speeds at 1000 °C with both process.



Graph 1. Relationship between roughness R_a and hardness in specimens hardened at different speeds at 1000 °C



Graph 2. Relationship between roughness R_a and hardness in specimens hardened at different speeds at 1000 °C with process of overlapping

4. CONCLUSION

The paper presents using fractal geometry to describe the wear of robot laser-hardened specimens with overlap. We use the relatively new method of fractal geometry to describe the complexity of laser-hardened specimens.

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