Optimization of Machining Parameters for Improved Surface Integrity of AISI H13 Tool Steel

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Abstract: The surface integrity plays a very important rule in this functional performance, being dependent of a large number of machining parameters. The major concern of the industry is to know which combination of machining parameters provides a better surface integrity of the machined components.
AISI H13 tool steel has been applied widely to produce many different types of hot working dies due to its excellent mechanical properties, such as: good resistance to thermal softening, high hardenability, high strength and high toughness. Traditionally, the surface roughness is considered to be the principal parameter to assess the surface integrity of the machined component. However, residual stress becomes an important parameter because it may increase the mould/die lifetime and their ability to withstand more severe thermal and mechanical cyclic loadings (fatigue) during its service. Therefore, significant improvements in the quality of the mould/die can be achieved with the control of the residual stresses induced during its manufacturing.
This paper examines the residual stresses induced by dry turning of AISI H13 tool steel. Residual stress was evaluated experimentally in function of the tool geometry, cutting speed, feed and depth of cut. The DOE method developed by G. Taguchi was used to reduce the number of experiments. An modelling and optimization procedure based in Artificial Neural Network (ANN) and a Genetic Algorithm (GA) was developed and applied to modelling the residual stresses and to identify the optimum combination of cutting parameters, which induces low tensile or compressive residual stresses, which contributes to a better surface integrity of machined components.

Keywords: Surface integrity, Residual Stresses, Surface Roughness, Modelling, Optimization.

1. Introduction

Growing concerns in the aeronautic, energy and biomedical sectors of the industry are to build in absolute reliability with maximum safety of the functional performance of machined components. The surface integrity plays a very important rule in this functional performance, being dependent of a large number of machining parameters. The major concern of the industry is to know which combination of machining parameters provides a better surface integrity of the machined components.

AISI H13 tool steel is characterized by good resistance to thermal softening, high hardenability, high strength and high toughness. Therefore, this steel has been applied widely to produce many different types of hot working dies, such as forging dies, extrusion dies, die-casting dies, etc. The process of making dies/moulds is one of the most demanding tasks in manufacturing engineering. Complex workpiece geometries, high material hardness, as well as short lead times, are among the main obstacles. At the same time, quality and reliability requirements become more and more important, due to the intensified competition and quality awareness. This quality and reliability is directly related to the surface integrity [1]. Traditionally, the surface roughness is the principal parameter to assess the surface integrity of the machined hot working dies made in AISI 13H tool steel. However, residual stresses become an important parameter since its control during manufacturing will increase the mould/die lifetime and their ability to withstand severe thermal and mechanical loading cycles (fatigue) in service. Therefore, significant improvements in the quality of the mould/die can be achieved with the control of the residual stresses induced during its manufacturing.

Earlier surface integrity studies in machining AISI H13 tool steel have focused mainly on the experimental assessment of the effects of cutting process parameters, tool geometry and tool-wear on workpiece surface roughness, residual stress and subsurface alteration such white layer formation [2-4]. The residual stresses induced by machining AISI H13 tool steel have mostly investigated for orthogonal cutting and milling operation, using PCBN and coated/uncoated cemented carbide cutting tools. Axinte and Dewes [2] studied the influence of cutting speed, feed and workpiece angle on residual stress induced by high speed milling of AISI H13 (47-49 HRc) tool steel, using solid carbide ball nose end mills coated with TiAlN, cooled by compressed air at 8 bar. They found compressive surface residual stresses in the direction of feed motion, reaching -760 MPa. Using a full factorial experimental design with two levels of each factor they concluded that all the three cutting parameters affects significantly the residual stresses. In this case, increasing all the three cutting parameters the compressive surface residual stress decreases. Marques et al. [4] analyzed the residual stresses induced by dry face milling of AISI H13 (50 HRc) tool steel with improved machinability (ESR) using both coated cemented carbide (with edge hone) and CBN (with chamfer) cutting tools. They found predominantly compressive residual stresses at the machined surface and subsurface, being these stresses more compressive when using the coated cemented carbide tools. This difference in the residual stresses between the two kind of cutting tools is attributed to the different cutting speeds (50 m/min using the coated tool and 600 m/min using the CBN) and tool geometry/material. Outeiro et al. [3] analyzed the influence of tool geometry (tool cutting edge preparation), cutting speed, uncut chip thickness and tool wear on residual stress distribution in the machined surface and subsurface of AISI H13 (51 HRc) using CBN cutting tools under dry orthogonal cutting conditions. Although the residual stresses are predominantly compressive, their magnitude decreases, becoming in some cases tensile, as the cutting speed, uncut chip thickness and tool wear increase. Moreover, the chamfered tools produce lower compressive or tensile residual stresses when compared with the edge honed tools.

The investigation of the residual stresses induced by machining AISI H13 tool steel isn't restricted to experimental studies. Modeling and simulation of the residual stress has been also performed, mainly using the FEM. Chen et al. [5] also used FE modelling and experimental procedures to investigated the effects of edge preparation and feed on tool life and residual stresses induced by dry orthogonal cutting of AISI H13 (52 HRc) tool steel, using chamfered and honed PCBN cutting tools. They show that, although the chamfered tools produce slight higher tensile residual stresses at the machined surface, when compared with the honed tools, the combination of high feed and chamfered tools produce higher and depth compressive residual stresses in sub-surface. Outeiro et al. [6] developed a two-dimensional FE model of the orthogonal cutting process of AISI H13 (52 HRc) tool steel using PCBN cutting tools. They applied this model to investigate the influence of tool geometry, cutting regime parameters and tool wear on residual stress distribution in the machined surface and subsurface. They concluded that in order to reduce the magnitude of the surface residual stresses the cutting speed should be increased, the uncut chip thickness (or feed) should be reduced and machining with honed tools having large cutting edge radius produce better results than chamfered tools. Moreover, the tool wear should be controlled in order to reduce the magnitude of the surface residual stresses.
Concerning to the application of Artificial Neural Networks (ANN) to predict the residual stresses induced by machining, Ambrosio et al proposed a predictive hybrid model based on ANN and FEM that was applied to determine the in-depth residual stresses profile for a given cutting conditions (cutting tool, work material and cutting regime parameters). This hybrid approach was also used to determine the cutting conditions based in a given residual stress profile.

This paper examines the residual stresses induced by dry turning of AISI H13 tool steel using coated cemented carbide cutting tools. Residual stress was evaluated experimentally in function of the tool geometry, cutting speed, feed and depth of cut. An modelling and optimization procedure based in ANN and a Genetic Algorithm (GA) was developed and applied to predict the residual stresses and to identify the optimum combination of cutting parameters, which induces low tensile or compressive residual stresses.

2. Experimental and Modelling Procedures

2.1 Experimental set-up, work materials and cutting conditions

Turning tests were performed in a CNC lathe KOVOSVIT MAS model SP 180 SY, equipped with a specially designed experimental set-up for cutting forces and infrared temperature measurement. Longitudinal turning tests were performed on round bars of AISI H13 tool steel (hardness equal to 51 HRc) using coated cemented carbide cutting tools (TiCN/Al_2O_3/TiN, CVD coating). A Taguchi orthogonal array was used to reduce the number of experiments. The cutting parameters and tool geometry are summarized in Table 1. All the tests were conducted under dry cutting conditions.

Table 1 Tool geometry and cutting parameters.

Tool cutting edge radius - r_n (μm)	40; 50; 67
Tool nose radius - r_ε (mm)	0.4; 0.8; 1.2
Normal rake angle - γ_n (º)	-6
Normal flank angle - α_n (º)	6
Inclination angle cutting edge - λ_s (º)	-6
Tool cutting edge angle - κ_r (º)	75; 95
Tool minor cutting edge angle - κ'_r (º)	5
Cutting speed - v_c (m/min)	80; 100; 130
Feed - f (mm/rev)	0.1; 0.15; 0.2
Depth of cut - a_p (mm)	0.2; 1; 1.5

The residual stress state in the machined surface and subsurface layers of the work-piece has been analyzed by the X-ray diffraction technique (XRD) using the sin2ψ method [7]. The experiments were carried out in a SET-X equipment, using the parameters listed in Table 2. The residual stresses were determined at the machined surface in the direction of primary motion (circumferential direction) and in the direction of the workpiece axis (axial direction). Due to circularity of the workpieces, a rectangular mask was applied to limit the region under analysis.

Table 2 Parameters used in the XRD analysis of AISI H13 tool steel.

Young Modulus (GPa)	210
Poisson ratio	0.29
Radiation	*Cr-Kα*
Bragg angle 2θ (º)	156,33 *(hkl)* = (211)
Number of ψ angles	13
ψ tilt (º)	5

2.2 Modelling and Optimization Procedure and Parameters

The objective of the modelling and optimization procedure is to find the optimal cutting conditions, which induces low tensile or compressive residual stresses in the machined components. As shows Figure 1, this procedure uses as input data the residual stress values obtained experimentally. Then, it uses the generalization capability of the ANN to find the residual stress for a wide range of cutting conditions, thus the residual stress function. This function is the objective function, which is used in the GA. The optimization procedure was implemented in a computer program, developed under MATLAB environment.

Artificial Neural Network (ANN)

The ANN is composed by three layers (Figure 2): input, hidden and output. The input layer corresponds to the cutting conditions (v_c, f, a_p and tool geometry parameters (κ_r, r_ε and r_n), having 6 neurons, the same number of cutting conditions. An optimization procedure was applied to determine the best number of neurons in the hidden layer, being this number equal to 50. The output layer is composed by a single neuron corresponding to the residual stress parameter. Each neuron of the input layer is connected to each neuron of hidden layer through weights and the biases. The same happens between the each neuron of hidden and each neuron of output layer.
The backpropagation algorithm together with Bayesian regularization was used in training neural networks. In this way a good generalization capability is obtained with a limited amount of data. Moreover, this approach decreases the possibility of overfitting.
The non-linear sigmoid activation function is used in the input-hidden layers and a linear activation function in the hidden-output layers. The input data are normalized in the range of [-1, 1]. The weights and the biases of the network are initialized to small random values to avoid immediate saturation in the activation functions. Throughout this study, the data set is divided into two sets, one for training and another for validation. These two sets consisted into 6 input parameters (v_c, f, a_p, κ_r, r_ε and r_n) and the maximum principal residual stress. The data for the training and validation sets were selected to cover the entire domain of the input data.

Genetic Algorithm (GA)

The objective of the GA is to find the optimum set of cutting conditions (v_c, f, a_p and tool geometry parameters (κ_r, r_ε and r_n), which induces low tensile level or compressive residual stress in machined component (minimization). This search is performed for the range of cutting conditions (including tool geometry) presented in Table 1 and under specific machining constraints.

The developed GA model is characterized by the following general specification:

- A fitness function or objective function, which is created using the ANN.
- The number of variables of the objective function was 6, corresponding to the number of cutting conditions.
- Constraints: the cutting or machining conditions must be in the range of input data (avoidance of extrapolation), which depends on the specific work material/cutting tool material pair.
- The population at each generation is composed by 100 individuals (population size).
- For this population size, the elite children are set to 10, and the crossover fraction is 0.8. Thus, the numbers of each type of children in the next generation are:
    - 10 elite children.
    - From remain 90 individuals, 80% will be the number of crossover children and 20% will be number of mutation children.
- The algorithm stops as soon as any one of the following conditions is met (stopping criteria):

– The maximum number of generations is equal to 40.
– The tolerance of the objective function becomes less than 1E-20.

Figure 1 Modelling and optimization procedure.

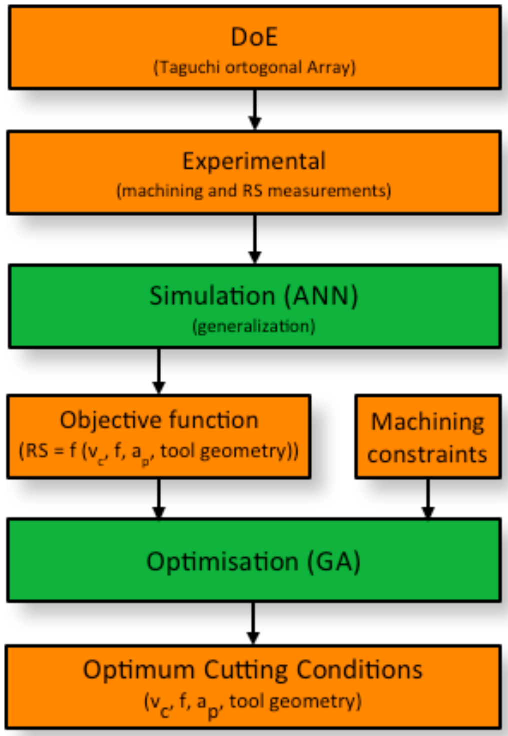
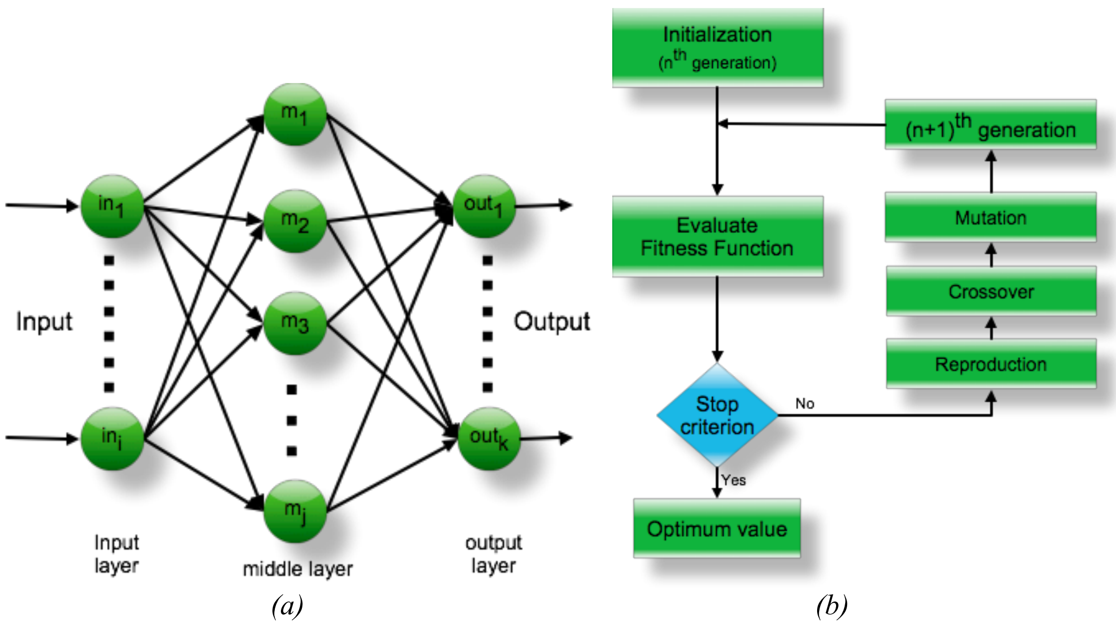


Figure 2 ANN (a) and GA (b) architectures.



3. Results and Discussion

3.1 Experimental results

Table 3 summarizes the maximum and minimum principal residual stresses at the machined surface, for the range of cutting conditions presented in Table 1. As shown in Table 3, the maximum principal residual stress is tensile while the minimum principal residual stress is compressive. Therefore, the former stress is critical for component performance and for this reasons only this stress was used in the modelling and optimization procedure.

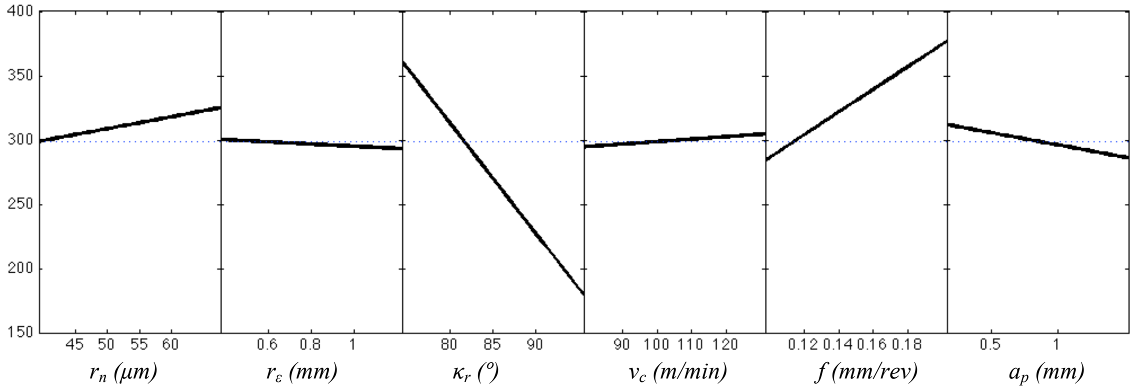
Using a Response Surface Methodology (RSM) it was possible to analyse the influence of the cutting conditions in the maximum principal residual stress, as shown Figure 3. It seems that the most influencing parameters in the residual stress are the tool cutting edge angle and the feed. In this case, high tool cutting edge angles combined with low feeds will produce the lowest values of tensile maximum principal residual stresses. The same conclusion was obtained when turning AISI 316L stainless steel [8]

Table 3 Maximum and minimum principal residual stresses.

Test Number	r_n (µm)	r_ε (mm)	K_r (º)	v_c (m/min)	f (mm/rev)	a_p (mm)	S_{max} (MPa)	S_{min} (MPa)	θ (º)
1	50	0.4	75	100	0.1	1.5	204	-297	32.81
2	50	0.4	75	100	0.1	1	347	-224	30.4
3	50	0.4	75	80	0.1	1	447	-125	34.78
4	50	0.4	75	130	0.1	1	510	-152	25.71
5	50	0.4	75	100	0.15	1	487	-156	21.43
6	50	0.4	75	100	0.2	1	353	-297	34.8
7	50	0.4	75	100	0.1	0.2	170	-415	38.37
8	50	0.4	75	80	0.1	0.2	369	-214	39.3
9	50	0.4	75	130	0.1	0.2	290	-313	32.42
10	50	0.4	75	100	0.15	0.2	389	-47	33.53
11	50	0.4	75	100	0.2	0.2	508	69	31.95
12	50	0.4	75	100	0.1	0.2	534	-115	33.3
13	40	0.8	75	100	0.1	1.5	171	-181	28.06
14	50	0.4	95	100	0.1	1.5	117	-521	34.67
15	40	0.8	95	100	0.1	1.5	168	-267	36.68
16	67	1.2	95	100	0.1	1.5	323	-29	22.25
17	40	0.8	75	100	0.1	1	461	-62	30.76

18	50	0.4	95	100	0.1	1	242	-314	31.26
19	40	0.8	95	100	0.1	1	193	-243	30.12
20	67	1.2	95	100	0.1	1	44	-494	25.14
21	50	0.4	95	100	0.1	0.2	148	-424	33.09

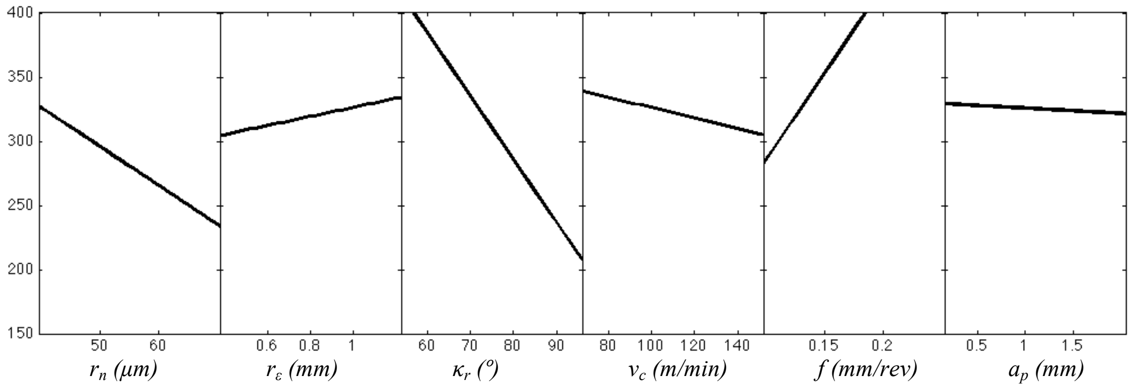
Figure 3 Influence of the cutting conditions in the maximum principal residual stress (experimental results).



3.2 Predicted results

After training and verification, the ANN was applied to simulate the influence of cutting parameters on residual stresses. Figure 4 shows the predicted maximum principal stress in function of the cutting parameters obtained by RSM. Comparing these results with those presented in Figure 3, both the tool cutting edge angle and the feed are still the most influencing parameters in the residual stress. Concerning to the other cutting parameters, the effects of the cutting edge radius, nose radius and cutting speed are opposite to those verified experimentally, being this remarkable for the edge radius. Increasing the amount of experimental data can reduce these differences between predicted and measured results.

Figure 4 Influence of the cutting conditions in the maximum principal residual stress (predicted results).



3.3 Optimal cutting conditions

After the simulation, the GA was applied to find the optimum set of cutting conditions (v_c, f, a_p, κ_r, r_ε and r_n), which induces low tensile level or compressive residual stress in machined component. Table 4 shows these optimum cutting conditions that induced the lowest maximum principal residual stress at the machined surface.

Table 4 Optimal cutting parameters for the lowest maximum principal residual stress.

Work Material	Cutting Tool			v_c (m/min)	f (mm/rev)	a_p (mm)
	r_n (μm)	r_ε (μm)	κ_r (°)			
AISI H13 (51 HRC)	40	1.2	95	87	0.1	0.2

4. Conclusions

This work analyse the residual stresses induced by longitudinal turning of AISI H13 (51 HRc) tool steel using coated cemented carbide cutting tools. The full residual stress tensor was determined, where the maximum principal residual stress is predominantly tensile (reaching about 550 MPa) and the minimum principal residual stress is compressive (reaching about -320 MPa). The feed and tool cutting edge angle are the most influencing parameters on the maximum principal stress. In order to decrease the magnitude of the tensile residual stresses the feed should be reduced while the tool cutting edge angle should be increased.

An modelling and optimization procedure based in ANN and a GA was developed and applied to predict the residual stresses and to identify the optimum combination of cutting parameters, which induces low tensile, which contributes to a better surface integrity of machined components.

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