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MODELING AND OPTIMIZATION TECHNIQUES IN MACHINING OF HARDENED STEELS: A BRIEF REVIEW

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Abstract. A unique behavior is on display in hard turning. The process demonstrates high flexibility and an ability to fabricate the geometry of a complex workpiece in a set. It makes a variety of precision components with substantial potential benefits. Many studies have shown aspects and problems that have to be understood and dealt with if the process is to improve. The main factors affecting the reliability of hard turning are surface integrity and tool wear. The prediction of surface roughness, cutting force, and tool life in machining is a challenging task but necessary for proper optimization of the process. This article presents a brief review of the techniques of modeling and optimization that have significant influence in hard turning.

1. INTRODUCTION

In their investigation of the process performance of turning hardened steel, researchers have looked at the effects of coatings, tool materials, and different shapes of inserts. Researchers have also investigated, experimentally, the effect of process parameters (namely residual stresses and white layer formation) on cutting forces and surface integrity. White layers are micro-structural changes observed in the surface layers of machine-hardened steels. Because the hard-turning process boasts several advantages over the grinding process, researchers have paid considerable attention to the machining of hardened steels, working with materials of hardness ranging from 45 to 65 HRC [1]. Some of the advantages include the cutting of production costs, reducing each operation's processing time, and removing cutting fluid [2]. These advantages, however, can only be achieved with suitable values for the process parameters—such things as the cutting speed (*Vc*), feed rate (*f*) and the depth of cut (*ap*). To better understand hard turning, researchers have studied the effect of these cutting parameters (*Vc*, *f*, *ap*) on tool wear, surface roughness, and surface residual stress distribution in a workpiece [3]. Fig. 1 lays out the main factors to be studied for a better understanding of hard turning.

Smith et al. [4] addressed the relationship between surface integrity and fatigue life of hard-turned AISI 52100 steel with a hardness of (60–62 HRC). The results suggest that the effect of white layer outweighs that of surface residual stress on fatigue life. Delijaicov et al. [5] studied the influence of cutting vibrations on the hard turning of AISI 1045 steel with a hardness of 53 HRC. The results provided important implications concerning the surface roughness of hardened steel. Grzesik [6] explored the mechanisms of wear occurring with the mixed ceramic inserts during the hard machining of AISI 5140 having a hardness of 60 HRC. Grzesik [6] considered both microscopic and microstructural aspects, such as abrasion, fracture, plastic flow, adhesive tacking, and material transfer. Warren and

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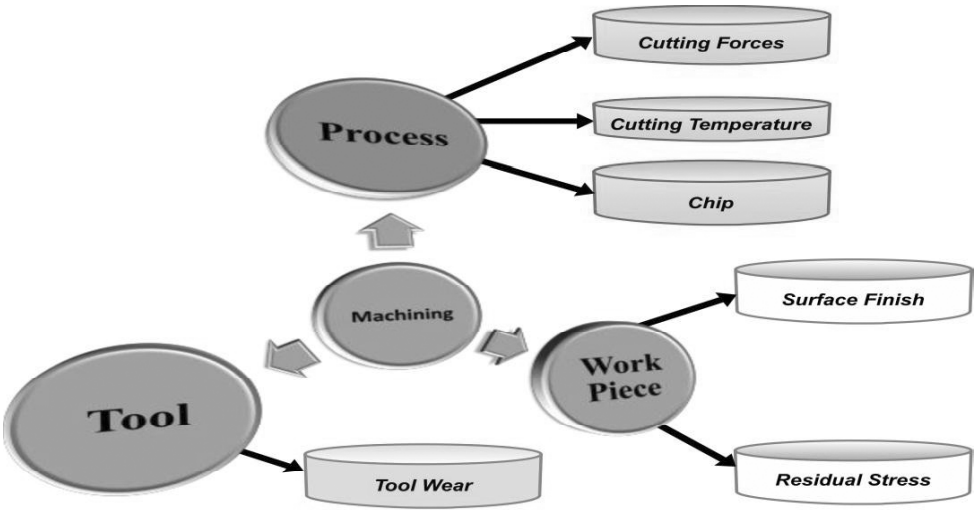

Fig. 1. Main factors to consider when working with hard turning.

Guo [7] determined the difference in surface residual stress profiles generated in gentle and abusive hard turning and grinding of AISI 52100 steel with a hardness of 62 HRC. They found distinct differences in the surface residual stress profiles for the various machining conditions used in their analysis. Umbrello and Felice [8] presented a study that predicted the white layer formation during the machining of hardened AISI 52100 steel with a hardness of 56, 62, and 66 HRC. This study produced excellent results in terms of cutting force, temperature, chip morphology, and white layer. Umbrelo et al. [9] developed a study on the influence of cutting parameters and initial hardness on white and dark layer formation during the hard machining of AISI 52100 steel with a hardness of 53 HRC. Experimental and numerical results indicated that the white layer increased with both cutting speed and feed rate. The dark layer, however, decreased as cutting speed increased. According to Attanasio et al. [10], white and dark layers are normally associated with tensile stress and hence the ability to reduce the fatigue life of machined components. Logically, each layer has its own structural characteristics. A hard-turned surface with a white layer usually consists of three layers, as seen in Fig. 2: the white layer (WL; untempered martensite), the dark layer (DL; over tempered martensite), and the bulk material.

2. LITERATURE REVIEW

During the hard-turning process, complex and mutual interactions are created, at the contact surface, between tool and workpiece. Consequently, significant forces and high temperatures cause wear and sometimes breakage of the tool. Usually, such conditions lead to both contact surfaces being damaged. Moreover, the geometrical shapes' exactness can be reduced or the mechanical characteristics modified. Davim and Figueira [11] investigated the machinability of cold work tool D2 steel heat-treated to a hardness of 60 HRC. They concluded that with an appropriate choice of cutting parameters it is possible to obtain a surface roughness R_a smaller that 0.8 μm. Aouici at al. [12] experimentally studied the effects, in hard turning, of cutting speed, feed rate, workpiece hardness, and depth of cut on surface roughness and cutting force components. AISI H11 steel had a hardness of 40, 45, and 50 HRC), machined using a CBN tool. Results showed that the cutting force components were influenced principally by the depth of cut and workpiece hardness. Sahoo et al. [13] carried out some machinability studies on flank wear, surface roughness, chip morphology, and cutting forces in finish hard turning of AISI 4340 steel with a hardness of 47 HRC. The results indicated that a surface finish close to that of cylindrical grinding was produced by the best tool, type of chip, the components of the forces, and mixed alumina inserts. Yallese et al. [14] investigated experimentally the behavior of a CBN tool during hard turning of 100Cr6 tempered steel. The results showed that a CBN tool offers good wear resistance despite the aggressiveness of the 100Cr6 with hardness of 60 HRC. Kamely et al. [15] studied the tool life, wear mechanism, and surface roughness in turning steel AISI D2 with a hardness of 60 HRC using mixed ceramic (Al_2O_3 + TiCN) coated with TiN. Regarding roughness measurements, hard turning may be presented as a real alternative to substitute grinding operations. Table 1 summarizes

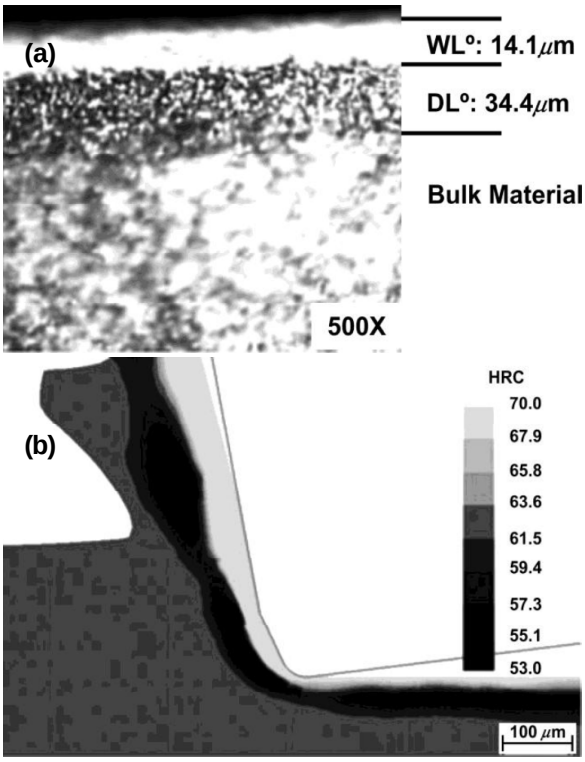

Fig. 2. Observed (a) and simulated (b) white and dark layers' formation and initial hardness 53 HRC, reprinted with permission from [9].

the workpiece material, tool materials, and cutting conditions used for hard turning by several studies.

Chavoshi et al. [16] studied, using a CBN tool, the influence of hardness and spindle speed on surface roughness in hard turning of AISI 4140 steel with a hardness of 55 HRC. The results indicated hardness has a significant effect on the surface roughness; the surface roughness dropped as the hardness increased up to 55 HRC. Bouchelaghem et al. [17] described wear tests on CBN tool behavior during hard turning of AISI D3 steel with a hardness of 60 HRC. Results showed that the CBN tool is wear resistant. Cakir et al. [18] investigated how surface roughness was affected by cutting parameters (cutting speed, feed rate, and depth of cut) and two coating layers. Results indicated that feed rate had the greatest influence on surface roughness followed by cutting speed. Fnides et al. [19] evaluated cutting pressures, resulting force, and maximum temperature in hard turning of hot work steel AISI H11 steel with a hardness of 50 HRC. The results made it possible to study the influence of cutting variables (feed rate, cutting speed, and depth of cut) on cutting pressures, resulting force, and temperature in the cutting zone. Ramesh and Melkote [20] presented a study on white layer formation in orthogonal machining of hardened AISI

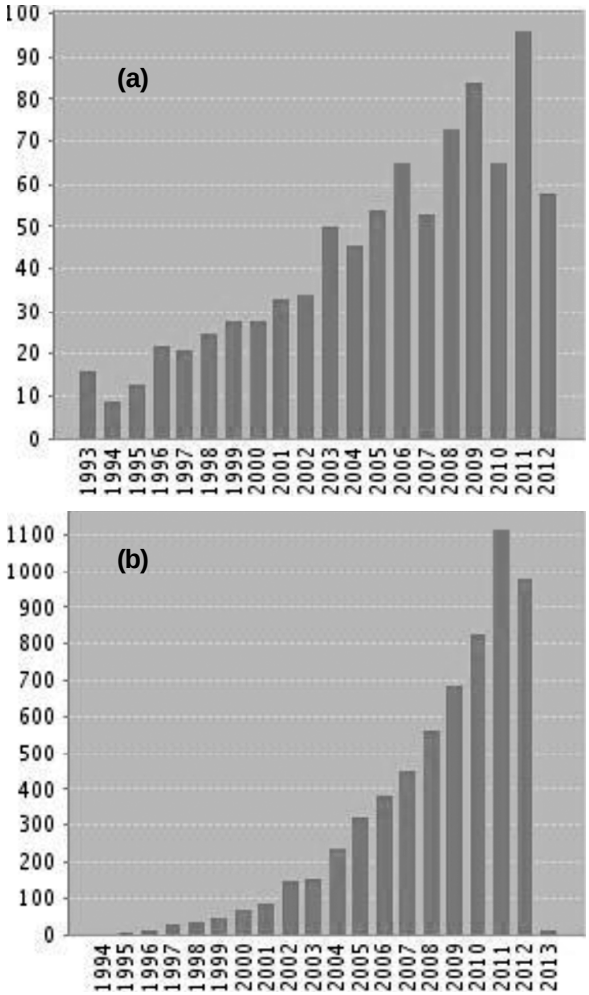

Fig. 3. Papers on hard turning: (a) published items each year; (b) citations each year.

52100 steel with a hardness of 62 HRC. The results show that white layer formation does have a significant impact on the magnitude of surface residual stress and on the location of the peak compressive surface residual stress. Fig. 3 shows the results of a search, using scientific resource bases, for papers containing "hard turning machining." This figure reflects articles to source items indexed within all databases: ISI Web of Knowledge (Thomson Reuters**c**), (17/12/2012). The figure indicates the growing interest in this subject.

3. MODELING AND OPTIMIZATION TECHNIQUES

In research on hard turning techniques of modeling and optimization has attracted the attention of a number of researchers in view of its significant contribution to the overall cost of the product. Additionally, as the number of machining parameters increase, a greater number of experiments have to

Table 1. Workpiece material, tool materials, and cutting conditions used by various studies.

Workpiece material	Tool materials	Cutting conditions
AISI (52100, 4340, 1045, 5140, H11, MDN250, H13, P20, D2, D13), hardened to 45-65 HRC.	CBN (low and high content), coated CBN. Ceramics, Coated ceramics Al_2O_3 + TiCN, /TiN, TiAlN, /ZrCn.	Cutting speed = 100–250 m/min Feed = 0.05–0.2 mm/rev Depth of cut = 0.2-0.3 mm

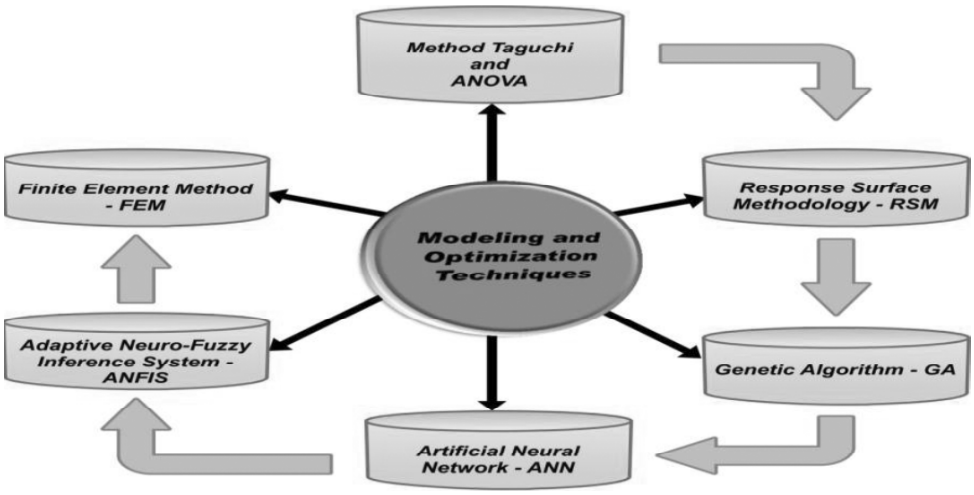

Fig. 4. Modeling and optimization techniques used by various researches.

be carried out. As with most parts of machining processes, hard turning calls for a high degree of specificity, which means for every application, piece of raw material, and cutting condition, a unique model is required. Fig. 4 shows modeling and optimization techniques in hard turning.

3.1. Taguchi method and analysis of variance (ANOVA)

The Taguchi method is an experimental design technique useful at reducing the number of experiments by using orthogonal arrays. It also tries to minimize the effects of the factors out of control [21]. Suhail et al. [22] tried to optimize the cutting parameters using two performance measures workpiece surface temperature and surface roughness. Optimal cutting parameters for each performance measure were obtained employing Taguchi techniques. The experimental results showed that the workpiece surface temperature could be sensed and used effectively as an indicator for controlling the cutting performance and thereby improved the optimization process. Using the Taguchi method, Xueping et al. [23] investigated the residual stress distribution in a hardened steel-bearing component 63 HRC. The study was able to obtain a desirable compressive residual stress distribution. Also using the Taguchi method, Pontes et al. [24] presented a study on the applicability of radial base function (RBF) neural networks to predict the roughness average (R_a) in the turning process of AISI 52100 steel with a hardness of 55 HRC. The results showed that RBF networks and Taguchi method performed well at predicting roughness average. Sahin [25] used the Taguchi method to compare the tool lives of ceramic and CBN cutting tools when machining hardened AISI 52100 steel with a hardness of 52 HRC. ANOVA was employed to determine the effective cutting parameters on the tool life. Sahin [25] found the parameter having the greatest effect on tool wear was cutting speed, followed by hardness of cutting tool, and lastly feed rate. Asilturk et al. [1] conducted a study, based on the Taguchi method, on optimizing parameters to minimize surface roughness (R_a and R_z) during the machining of AISI 4140 steel with a hardness of 51 HRC. Results of this study indicated that roughness was most affected by feed rate.

3.2. Response surface methodology (RSM)

One approach to determine the relationship between various factors and responses is response surface methodology (RSM). RSM also ascertains the significance of these parameters on the responses.

RSM is useful in developing, improving, and optimizing the processes, providing an overall perspective of the system response within the design space [26]. Utilizing the RSM, Gaitonde et al. [27] studied the effects of cutting speed, feed rate, and machining time on hard turning of AISI D2 steel with a hardness of 59 - 61 HRC. The results showed that the ranges of the parameters met all variations. Bouacha et al. [28] carried out an experimental study with RSM on hard turning, using CBN tool, of bearing steel with a hardness of 64 HRC. The results showed how much surface roughness is mainly influenced by feed rate and cutting speed. Lalwani et al. [29] investigated the effect of cutting parameters and surface roughness on finish hard turning of MDN250 steel with a hardness of 52 HRC. The machining experiments were conducted based on RSM. The results showed that cutting forces and surface roughness vary little with cutting speed.

3.3. Genetic algorithm (GA)

Genetic Algorithm is an optimization method based on the genetic evolution of natural species. It differs from most optimization techniques because of its global searching criterion [30]. According Jin [31], the method bears a likeness to natural selection as it searches for better characteristics within a changing population. Kishawy et al. [32] studied and evaluated carbide tool performance during machining of hardened steel AISI 4340 steel with a hardness of 56 HRC. The research developed a GA to identify the constants in the proposed model. Results showed that the developed model is capable of predicting the rate of tool flank wear progression. Gomes et al. [33], utilizing GA, developed a multiple response optimization procedure for the AISI 52100 steel with a hardness of 55 HRC. This method was successfully applied and a result was optimized with good levels of quality, productivity, and economy. In hard turning operations Nandi and Davim [34] utilized GA to optimize the critical machining parameters to obtain a desired surface roughness on AISI D2 steel with a hardness of 60 HRC. Both the model's results and the experimental results showed that surface roughness improved with cutting speed for constant values of feed rate and depth of cut.

3.4. Artificial neural network (ANN)

An artificial neural network (ANN), according to Haykin [35], is a distributed parallel system composed of simple processing units called nodes or neurons; the nodes performs specific mathematic functions (generally non-linear), thus corresponding to a non-algorithmic form of computation. Sharma et al. [36] held that to maximize their gains from utilizing the finish process, they needed ANN-constructed predictive models for to gauge surface roughness and tool wear. Relying on ANN, Singh and Rao [37] conducted an experimental investigation to determine the effects of cutting conditions and tool geometry on surface roughness in AISI 52100 steel with a hardness of 58 HRC. Results showed that the dominant factor in determining surface finish was the feed rate, followed by nose radius and cutting speed. Also using ANN, Quiza et al. [38] presented an investigation into predicting tool wear in the hard machining of AISI D2 steel with a hardness of 60 HRC. The results showed that neural network model was more capable of accurately predicting tool wear.

3.5. Adaptive neuro-fuzzy inference system (ANFIS)

Adaptive neuro-fuzzy inference systems (ANFISs) have been widely used in modeling, identifying, and monitoring complex systems. Since its origin in the early nineties, ANFIS has undergone various changes, giving rise to various trends in research. Its principle is based on extracting fuzzy rules in each level of a neural network. Once the rules have been obtained, they provide the necessary information on the global behavior of the system. [39]. Akkus and Asilturk [40] used ANFIS to model the surface roughness average values obtained when turning AISI 4140 steel with a hardness of 51 HRC. The high accuracy of the results demonstrated ANFIS's ability to accurately model surface roughness.

3.6. Finite element method (FEM)

The finite element method (FEM), also known as finite element analysis (FEA), is a numerical technique for finding approximate solutions to partial differential equations and their systems as well as to integral equations (though less often). Hua et al. [41] investigated the residual stress profile in the machined surface of steel AISI 52100 steel with a hardness of 60 HRC. The researchers applied FEM at various levels of cutting conditions, workpiece hardness, and tool geometry. Numerical results showed that the best residual stress profile was obtained through an optimal combination between chamfer tool and feed rate. Umbrello and Jawahir [42] presented a FEM that predicted white layer formation during machining of hardened AISI 52100 steel with a hardness of 56, 62, and 66 HRC. Re-

sults indicated that the proposed FEM model was suitable for studying the influence of cutting parameters and initial hardness on white layer formation. Caruso et al. [43] used FEM to study residual stresses induced by orthogonal cutting as well as the influence of flank tool wear on hardened steel AISI H13 steel with a hardness of 51 HRC. Results showed the developed FE model was able to reproduce experimentally observed surface residual stresses in orthogonal machining of AISI H13 tool steel. Using FEM, Duan et al. [44] investigated serrated chip morphology and cutting force during the machining of AISI 1045 steel with a hardness of 45 HRC. The investigation indicated that the simulation results were consistent with the experiments and that this FEM method could be used to predict chip morphology and cutting force. Using FEM, Manková et al. [45] investigated the influence of experimental cutting parameters on cutting force, material hardness, chip deformation, temperature, and heat flow. For this process, the researchers used hardened steel AISI 1045 steel with a hardness of 55 HRC. Results indicated that the proposed model fits quite well with and is suitable for practical applications, mainly industrial.

4. CONCLUSIONS

This paper has presented a brief review of the application of modeling and optimization techniques in machining of hardened steels. The major observations gleaned from the literature are the following:

- In hard turning, the Taguchi method and ANOVA have proved to be efficient tools for controlling the effect on tool wear and surface roughness.
- Response surface methodology (RSM) presented the desired criteria optimization for determining the relationship between the various factors (cutting speed, feed rate, and depth of cut) and the responses (cutting forces and surface roughness).
- Genetic algorithm (GA) was used to identify the constants of the proposed model; the result is optimizing the predicting of tool wear rate and improving surface roughness.
- In general, artificial neural networks (ANNs) were well suited for accurate surface roughness prediction, cutting-tool flank wear prediction, and cutting tool state diagnosis.
- Adaptive neuro-fuzzy inference systems (ANFISs) were able to accurately model the surface roughness prediction, cutting-tool flank wear prediction, and cutting parameter selection for optimal surface roughness.
- The finite element method (FEM) model performed quite well at finding approximate solutions for white layer formation, residual stresses, chip morphology, and cutting forces.

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