Advances and Applications in Mathematical Sciences
Volume 21, Issue 9, July 2022, Pages 5085-5100

REVIEW ON OPTIMIZATION OF HARD TURNING

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Abstract

Work piece is grown in popularity as a cost-effective and thing replacement to cutting. Obviously, due to the technical difficulties involved, accurate estimation of the layer thickness formed during severe turning is challenging. As a result, it is currently the subject of a huge amount of study. The objective of this work is to examine the current state of optimization strategies for predicting layer thickness in a difficult turn. It is divided into three sections: a layer thickness prediction model, cutting parameters, work piece characteristics, and cutting tool characteristics. The properties of hard turning and layer thickness are first discussed, followed by a framework of optimization strategies. The three important areas are then thoroughly examined. Finally, the conclusions are reached.

2020 Mathematics Subject Classification: 49.
Keywords: layer thickness prediction, optimization techniques, hard turning, review.
Received February 13, 2022; Accepted May 23, 2022.

Introduction

Manufacturers face increasingly difficult expectations as demand for product individuality grows, along with improving amount and variety, reducing production cycle, and, very importantly, reducing retail prices [1]. During latest days, significant advances have been made in the processing characteristics of tough metals. Grinding large components versus tougher substances has a number of advantages, including major cost reductions. Greater production levels, enhanced surface condition, and avoidance for defects due to differential cut temperatures [2]. Work piece is a manufacturing technique that uses 45-65 HRC strength components (Rockwell scale). It's a manufacturing technique that provides substances with a 45-65 HRC roughness. Because of the various Rockwell ratings, substance's roughness can be defined as HRC, HRB, and etc.) Separate pieces of exceptional strength and hardness are used to turn them. Polycrystalline cubic boron nitride (CBN) and ceramic work piece are commonly used [3]. Several metal cutting methods employ that production of gears, motors, steels, overhead cams, equipment, and machine edges ease of fabrication and wear resistance requirements [4]. Work piece can cut production costs by up to 30 times in the manufacturing of difficult products [5]. Conventional machining varies to standard cutting operation for smooth surfaces in a number of approaches, along with the thickness of the item, the layer thickness, a work piece required, as well as the processor mechanics. Because hardened steels are considered complicated components in hard turning, caution must be exercised while selecting appropriate reaction conditions that often have a narrow set of possible values. If the wrong process parameters are chosen, the work piece's surface quality will suffer, as will equipment usage, measurement precision, separating strength.

Figure 1. Hard turning.

Rough turning, heat treatment, and grinding are the most popular methods for machining hardened steels. Faster cycle times, enhanced system adjustability, improved work piece rates, acceptable layer thickness, and reduced external risk are all potential benefits. Hard machining was developed as a possible replacement to conventional grinding (Figure 1).

Optimization Techniques

Because of their major impact here to total price of the goods, conventional machining optimization approaches have piqued the interest of numerous academics. In addition, as the number of processing factors grows, the number of tests necessary grows as well. Hard turning, like most machining processes, requires a high level of specificity; this means that a different model is needed for Depending on the purpose, the feed stock, as well as the operating environment.

A. Layer Thickness (Surface Roughness) Prediction Model

Roughness of the surface plays a crucial influence in the manufactured element's structural features. Understanding how work piece layer thickness is generated can help improve the quality of the work piece's surface [8]. Departures from the standard material's centreline are commonly referred to as "layer thickness." The course of development of variations from multiple patterns results in the thin films of a work item.

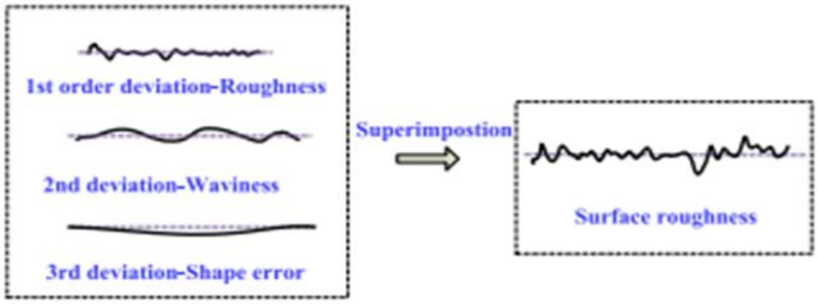

Figure 2. Surface form deviations.

The advancement form and particle output are primarily linked to Variance Type 1 (grossness), as shown in Figure 2. Hard turning is the primary cause of Deviation Type 2 (waviness). Figure 2. Deviations in surface shape. Circularity and waviness of work piece surface morphology is mostly induced by homogeneities in work piece material. Variance Type 3 (contour distortion), which is usually linked to smoothness, is caused by incorrect configurations and cutting parameters displacement. The hard turning cutting mechanism is mostly based on numerical simulation [19], it is based on the mathematical surface and organization study discussed before. Simulation results of conventional machining, on the other hand, are primarily used to investigate definite important factors that contribute to handling efficiency, like the effect of metal cutting material, tool diameter, work piece substance, and work piece on machined surface, grey surface, depth of cut, outer layer stress, and wear resistance [10]. Layer thickness formation mechanisms are rarely explored [11], hence they will not be discussed in this work.

Finite element modelling ignores a lot of useful limitations, including slicing vibrations, instrument damage, and particle binding, despite the fact that it may quickly get many characteristics and is difficult to notice when spinning quickly. As a result, observations may not always match projections [12]. Although there is considerable evidence that production variables including work piece or metal cutting characteristics have a significant impact in layer thickness creation [13], their involvement in layer thickness mechanisms is unknown. It’s challenging to create mathematical frameworks for conventional machining operations that are straightforward since there are so many variables with intricate interconnections.

As a result, optimization methods, also known as passive metrics in this article, are frequently used in research and development to gather more information on layer thickness states and efficiently evaluate it for online layer thickness prediction. Such approaches can anticipate layer thickness avoid dealing with the operation of conventional machining, resulting in increased speed and the ability to make real-time modifications [14]. To accomplish so, grinding quality can be evaluated using data like as disturbances, slicing pressures, visuals, direct charge, reducing temperature, noise pollution, noise, or work material [15]. Using edge detection from such data, a modelling approach may be established and developed. After that, the approach will be used to forecast the thickness of layers.

When hard turning AISI H11 at varied degrees of workpiece hardness with a CBN tool, Response surface methodology (RSM) was utilized by Aouici et al. [41] to improve the reducing variable's impact (v, f, d) on Layer thickness and shear force components. The layer thickness and the density of the material are have the greatest influence on the cutting force components. Nevertheless, for either feed rate or material toughness, layer thickness was statistically significant. When dealing with AISI H11 metal, Dureja et al. [42] employed RSM to study how cutting factors effect flank wear and layer thickness. Speeds and material roughness were found to be the most major elements affecting Layer thickness, whereas speeds, surface roughness, and material roughness were found to be the most important factors causing edge erosion.

B. Cutting Parameters

Spindle parameters, rotational speed, and slice thickness are all important characteristics in conventional machining. These are essential for achieving excellent surface quality [16] and will result in the desired work piece surface roughness (i.e., satisfy the operational specifications). Algorithms that anticipate, are overly reliant on the most critical elements influencing mechanical characteristics and unable to arrive at the correct variables to use it, several studies have used ANOVA to compare all important implications for each system that makes [17]. Throughout the rest of this study, cutting parameters refer to depth of cut (vc), input speed (f), and cut thickness (d) (ap).

Cutting parameters were used as controlling factors by Pontes et al. [18] to forecast the layer thickness of turned AISI 52100 hardened steel. For layer thickness prediction, the variation of experimental-based strategy for generating radial basis function, artificial neural networks was already developed. The toolmaker's functional constraints are represented by the various cutting situations. They were able to collect development/certification information for an Artifical neural network with 720 instances by developing an experiment with 60 runs. According to their findings, the recommended radial basis function can achieve a relative standard accuracy of 0.388 percent after with 36 learning samples. Khamel et al. [7] examined the impact of reducing variables on work piece, layer thickness, and reducing pressures when completing difficult spinning using a CBN machine, 60 HRC AISI 52100 core metal was machined. The merged impact of the depth of cut on technical specifications was investigated using ANOVA. The findings show that cutting parameters and material removal rate get a significant impact both layer thickness and cutting force. However, the layer thickness has a significant impact on depth of cut.

Lalwani et al. [19] examined the impact of independent variables on friction coefficient and layer thickness in completing difficult machining of MDN250 metal. The findings reveal that the cutting parameter has a substantial impact on layer thickness. To optimize cutting parameters inside this conventional machining of AISI 4140 (51 HRC) utilizing tool steel wire cutters, Asiltürk and Akkuş [2] applied the Taguchi technique (Ra and Rz). Using statistical methodologies such as signal-to-noise ratio and analysis of variance, they discovered also that rotational speed will have the most major impact on layer thickness (Ra and Rz) at a 95 percent reliability level. The effects of cutting parameters on tool wear and layer thickness were examined by Saini et al. [24]. The level of significance of experimental data acquired during conventional machining of tempered AISI H-11 steel was evaluated by analysis of variance.

Panda et al. [6] In EN31 steel conventional machining, the impact of slice thickness on material performance criteria (Ra, Rz, and Rt) was investigated. To number out which cutting factors had an impact on surface quality, ANOVA was used. To forecast layer thickness, Pontes et al. [25] as input for Radial basis function networks, a collection comprising depth of cut acquired via Department of environment was used. Agrawal et al. [26] ran 39 experiments to see how cutting parameters affected layer thickness in drought conditions, during rough machining an AISI 4340 metal component (hardened to 69 HRC). Bouacha et al. [27] employed cutting parameters as model parameters for response surface methodology calculations on layer thickness or depth of cut elements when rough machining strengthened AISI 52100 bearing metal with a CBN tool (Fa, Fc, and Fp). To use the Taguchi method [28], reducing variables were employed as feed to an artificial neural network for layer thickness estimation in the conventional machining of AISI H13 steel with little material removal usage. Cutting parameters were used in a multiple regression model by Fnides et al. [29]. Analysis of variance was used to improve machining parameters such as cutting speed, velocity, and cut thickness. Das et al. [20] devoted slicing variables as feed to polynomial estimations of layer thickness in conventional machining. The cutting forces was improved using analysis of variance, also with important impact that cutting parameters, followed by cutting speed, is the most indicator to determine layer thickness.

Layer thickness tests and a repeated measures experiment are used to establish the cutting parameters and layer thickness, respectively. Then, using Minitab 15 software, the experimental data of layer thickness (Ra) and cutting parameters are evaluated using ANOVA to discover the important factors. At a significance threshold of 0.05, the layer thickness ANOVA is calculated (95 percent confidence). The result represents the significance level of the relevant event (Cont. percent) in the ANOVA. For example, the primary contributions are for the interaction f 2 (40.70 percent), 21.96 percent for CS, and 15.74 percent for *f*. The tool wear is vc, the process parameters is *f*, the slice thickness is ap, and the obtained output component is CS.

Bouacha et al. [43] employed slicing variables as model parameters for response surface methodology calculations of layer thickness or depth of cut components when rough machining reinforced AISI 52100 bearing metal with a CBN machine (Fa, Fc, and Fp). The Taguchi method was used to tough bend AISI H13 iron with little cutting fluid application, and the thickness of the slice are being used as feed to an artificial neural network for process parameter prediction. Aouici et al. [44] While difficult machining AISI H11 iron with 40, 45, and 50 HRC using CBN, an algorithm was created to estimate layer thickness and depth of cut components. After an ANOVA investigation of four factors, the terms with significant impacts on the layer thickness and depth of cut elements have been used in the resulting nonlinear designs. During severe turning, Bouacha et al. [45] used the response surface method to assess and anticipate mechanical characteristics and tool wear. The combined effect of slicing settings on layer thickness or cutting forces was investigated using ANOVA.

C. Work piece and Cutting Tool Characteristics

Many criteria other than cutting parameters can be used to anticipate layer thickness more accurately and effectively along with obtaining more detailed condition information throughout difficult cutting operation. The work piece's substance and tool geometry qualities. Aouici et al. [5] studied work piece material has a consequence and work piece availability of layer thickness and depth of cut elements in tool wear of AISI H11 metal tempered to 40, 45, and 50 HRC using CBN 7020. Analysis of variance are devoted with multiple (laser power, rotational speed, tool geometry, and roughness) with multiple simultaneous conceptual frameworks. Machining preforming is affected by cutting speed and work piece roughness, whereas layer thickness is principally influenced by process parameters or tool geometry toughness.

Chinchanikar and Choudhury [30] investigated the impact of tool geometry concrete strength and depth of cut upon that efficiency of tool steel tools, particularly conventional machining, layer thickness, and cutting force. The most significant parameters were determined using ANOVA, it indicated that layer thickness is consequence by input the thickness of the slice. Mia et al. [19] used tool wear, rotational speed, and steel beams as independent factors, while layer thickness (Ra) and average flash memory surface temperature have been used as variables. The effects of control factors were determined using ANOVA. They also used an ANN to predict bond strength in hardened EN 24T iron machining utilizing changing slicing rates, input levels, chipboard, or wet / high intensity greasing for data [31].

Azizi et al. [32] examine the impact of tool geometry and material roughness the layer thickness or tool geometry while rough machining AISI 52100 metal. The findings demonstrate the layer thickness is influenced by rotational speed, component toughness, and tool geometry, while slicing displacements are determined by cutting speed, work piece toughness, and rotational speed. The influence of work piece sharpness and tool rotational on layer thickness (Ra) in Analysis of variance was used to analyze tough bending, with the conclusions revealing the component toughness has a significant impact in layer thickness [33]. Many research have looked at the influence of cutting tool properties on workpiece layer thickness in addition to workpiece material characteristics [34].

Zel et al. [35] and Tang et al. [36] examine the impacts of developing advanced design, material hardening, rotational speed, and tool geometry on layer thickness or pressures with in completion rough AISI 52100 H13 metal using CBN. Multiple (toughness, surface design, rotational speed, and tool geometry) and multiple studies was examined using analysis of variance. In an estimation of Ra in the surface roughness of X40CrMoV5-1 steel using a CBN tool, Yurtkuran et al. [37] used slicing factors and finishing parameters. To discover their correlations, an efficiency research concerned with the study of signal-to-noise ratios was done. In predicting layer thickness and tool wear, Manivel and Gandhinathan [38] employed the instrument diameter and tool geometry as separate parameters. Analysis of variance and signal-to-noise ratios were used to optimize the independent variables.

Ferreira et al. [41] examine the impact of tool geometry, rotational speed, including the use of standard and cross excellent mechanical properties on layer thickness while conventional machining AISI H13 metal. According to ANOVA, the inter clay instrument and input speed had the biggest influence on layer thickness. Singh and Rao [34] employed response surface methods to forecast layer thickness using tool wear, rotational speed, curvatures, and tip diameter as variables. The most critical component impacting layer thickness is the rotational speed, which is followed by edge radius, tool geometry, and blade angle. The most critical component impacting layer thickness is the rotational speed, which is accompanied by rake angle, tool rotational speed, and slope degree.

Azizi et al. [46] studied the impacts of tool geometry and material toughness upon layer thickness and tool material in the tough AISI 52100 steel. The findings reveal that layer thickness is influenced by rotational speed, component roughness, and tool geometry, while slicing displacements are influenced by tool geometry, component durability, and injection pressure. The effects of material firmness and rotational speeds upon machining parameters (Ra) during dry machining were explored using ANOVA, also with findings revealing that workpiece hardness has a significant impact on layer thickness.

Azizi et al. [47] investigated the effect of process parameters on work material hardness in hard turning (cutting depth, flow rate, and cutting force) of AISI 52100 steel using Al2O3+TiC blended clay clipping using Taguchi's orthogonal array, ANOVA, and regression analysis. Taguchi's orthogonal array protects these instruments. Cutting force, flow velocity, and the hardness of the working piece all have an impact.

Table 1. Arguments of Models in Hard Turning.

Factors	Models	Response	Authors
Work material hardness, cutting parameters	Response Surface Methods	Cutting force, layer thickness	T. Mabrouk et al. (2016)
Cutting parameters	Response Surface Methods	Cutting force, layer thickness	T. Mabrouk et al. (2018)
Cutting parameters	Random forest	Cutting force, layer thickness, tool wear	M. Price et al. (2017)
Cutting parameters	ANN	layer thickness	P. P. Balestrassi et al. (2018)
Cutting parameters	Multiple Regression Model	layer thickness	J.-F. Rigal et al. (2019)

Cutting parameters, tool geometry	ANN	Cutting force, layer thickness	R. J. Thangaiah et al. (2019)
Cutting parameters, tool geometry	Response Surface Methods	Cutting force, layer thickness	A. Khellaf et al. (2020)
Cutting parameters, tool geometry and cutting vibration	Response Surface Methods	layer thickness	M. A. Yallese et al. (2018)
Cutting parameters, cutting vibration	Response Surface Methods	layer thickness	G. F. Batalha et al. (2020)
Cutting parameters, cutting vibration	HMM-SVM	layer thickness	N. K. Sahu et al. (2021)
Cutting parameters, force, sound, vibration	Multiple Regression Model	Cutting force, layer thickness, tool wear	H. Yurtkuran, et al. (2018)
Cutting parameters, tool geometry	ANN	layer thickness, Productivity	M. E. Korkmaz et al. (2019)

Conclusion

An overview of optimization strategies for forecasting layer thickness in hard turning processes is presented in this paper. A lot of study has been done in the last several years, and there have been a lot of interesting outcomes. The following is a summary of the essential information about optimization strategies for layer thickness prediction in hard turning: The majority of the data used to forecast layer thickness in tool wear is dynamic, including machining variables, processing parameter, and workpiece toughness. As the references show, the hyper parameter for layer thickness prediction in hard turning are mostly determined by optimization methods. The methods analyses whether major elements influence this reaction, enabling polynomial models to be developed that include the components in question and their statistical significance. According to the studies cited, the majority of predictive models for layer thickness in models that are harder to convert are stable that only consider a few static characteristics. However, for a more accurate picture of layer thickness generation, must be incorporated. In addition, inter prediction has been more common for metal cutting layer thickness prediction. In addition to the layer thickness of the workpiece, it considers slicing strength, specific cutting, workpiece material as well as other aspects.

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