Journal of Information Systems Engineering and Management
2025, 10(23s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Analysis and Optimization of Residual Stresses in Hard Turning of AISI M2 Tool Steel Using Taguchi Technique

Krupal Prabhakar Pawar[1], Praveen Beekanahalli Mokshanatha[2]
[1]*Post-Doc Fellow, Department of Mechanical Engg., Institute of Engineering & Technology, Srinivas University, Mangaluru, Karnataka, India*
(ORCID ID:0000-0002-2629-003x), Email:drkppawar@rgcoe.org
[2]*Professor, Department of Chemistry, Institute of Engineering & Technology, Srinivas University, Mangaluru, Karnataka, India*
(ORCID ID: 0000-0003-2895-5952), Email: bm.praveenbm@gmail.com

ARTICLE INFO

Received: 20 Dec 2024

Revised: 08 Feb 2025

Accepted: 21 Feb 2025

ABSTRACT

Introduction: Residual stresses play a critical role in the performance and durability of machined components, particularly in the hard turning of tool steels.

Objective: The main objective of this investigation to optimize the residual stress during hard turning of AISI M2 tool steel.

Material and Method: This study investigates the optimization of residual stresses in the turning of AISI M2 tool steel using the Taguchi method. An L27 orthogonal array was employed to analyze the effects of cutting speed, feed rate, and depth of cut on residual stress formation. X-ray diffraction (XRD) was used for stress measurement.

Result: Analysis of variance (ANOVA) identified cutting speed as the most significant parameter, followed by feed rate and depth of cut. The residual stress is minimum at level optimal cutting conditions: 100 m/min cutting speed, 0.2 mm/rev feed rate, and 0.4 mm depth of cut.

Conclusion: The optimal cutting conditions: 100 m/min cutting speed, 0.2 mm/rev feed rate, and 0.4 mm depth of cut resulted in the lowest residual stress of 230 (compressive) MPa. The cutting speed as the most significant parameter, followed by feed rate and depth of cut. The findings demonstrate the effectiveness of statistical optimization techniques in enhancing machining quality and surface integrity in industrial applications.

Application: The application of this project will be in cutting tool industries where AISI M2 tool steel is used as raw material.

Keywords: Residual Stress, Hard Turning, Taguchi Method, AISI M2 Tool Steel.

INTRODUCTION

Residual stresses induced during the turning of hard materials, such as hardened steels, titanium alloys, and nickel-based superalloys, have significant implications for the mechanical performance, fatigue life, and dimensional stability of machined components [1]. These stresses arise due to the complex interplay of mechanical, thermal, and metallurgical factors during the machining process [2]. For instance, mechanical loads from cutting forces cause plastic deformation, while thermal loads from friction and heat generation lead to thermal gradients and phase transformations in the workpiece material [3], [4]. Understanding and controlling residual stresses is critical for industries such as aerospace, automotive, and tooling, where high precision and reliability are paramount [5]. The magnitude and distribution of residual stresses are influenced by various factors, including cutting parameters, tool geometry, workpiece material properties, and cooling conditions [6], [7]. For example, higher cutting speeds and feed rates tend to increase thermal and mechanical loads, resulting in higher residual stresses [8]. Similarly, tool wear and coating can significantly alter the stress distribution in the machined surface [9]. Recent studies have demonstrated that cryogenic cooling and minimum quantity lubrication (MQL) can effectively reduce thermal loads and mitigate residual stresses in hard turning processes [10], [11]. Advanced modeling techniques, such as finite element analysis (FEA) and artificial neural networks (ANNs), have been employed to predict and optimize residual stresses during turning [12], [13]. For instance, FEA has been used to simulate the effects of cutting parameters and cooling strategies

on residual stress distribution in hardened steels and titanium alloys [14], [15]. Additionally, optimization methods like the Taguchi design and response surface methodology (RSM) have been applied to identify optimal cutting conditions for minimizing residual stresses [16], [17]. These approaches provide valuable insights into the relationship between machining parameters and residual stress generation. Experimental techniques for measuring residual stresses, such as X-ray diffraction (XRD), neutron diffraction, and ultrasonic methods, have been widely used to validate numerical models and optimize machining processes [18], [19]. For example, XRD has been employed to measure surface residual stresses in turned components of Inconel 718 and Ti-6Al-4V alloys [20], [21]. These measurements have revealed that hybrid cooling techniques and ultrasonic vibration-assisted turning can significantly reduce residual stresses in hard-to-machine materials [22], [23]. Despite significant advancements in the field, challenges remain in achieving a comprehensive understanding of residual stress formation and control during hard turning. For instance, the interaction between cutting parameters, tool wear, and cooling strategies needs further investigation to develop robust optimization frameworks [24], [25]. Moreover, the application of machine learning algorithms and advanced sensor technologies holds promise for real-time monitoring and control of residual stresses in industrial machining processes [26], [27].

LITERATURE REVIEW

2.1 Residual Stress Formation in Hard Turning

Residual stresses in hard turning are primarily induced by mechanical, thermal, and metallurgical factors. Mechanical loads from cutting forces cause plastic deformation near the machined surface, leading to compressive or tensile residual stresses depending on the material and cutting conditions [1], [2]. Thermal loads, resulting from friction and heat generation at the tool-workpiece interface, create thermal gradients that contribute to stress formation [3], [4]. In materials like hardened steels and titanium alloys, phase transformations due to high temperatures can further alter residual stress profiles [5]. For instance, studies on AISI 52100 steel have shown that high cutting speeds and feed rates increase thermal loads, resulting in higher tensile residual stresses [6], [7].

2.2 Influence of Cutting Parameters

Cutting parameters, such as cutting speed, feed rate, and depth of cut, play a critical role in residual stress generation. Higher cutting speeds generally increase thermal loads, leading to greater tensile residual stresses, while lower speeds tend to produce compressive stresses due to dominant mechanical effects [8], [9]. Similarly, higher feed rates and depths of cut increase cutting forces, resulting in deeper stress penetration into the workpiece [10]. Recent studies on Inconel 718 have demonstrated that optimizing cutting parameters using response surface methodology (RSM) can significantly reduce residual stresses [11], [12]. However, the interaction between cutting parameters and material properties remains poorly understood, particularly for advanced alloys like Ti-6Al-4V and nickel-based superalloys [13].

2.3 Tool Geometry and Wear

Tool geometry, including rake angle, edge radius, and coating, significantly influences residual stress distribution. Tools with larger rake angles reduce cutting forces and heat generation, leading to lower residual stresses [14], [15]. Coatings such as TiAlN and diamond-like carbon (DLC) have been shown to improve tool life and reduce thermal loads, thereby minimizing residual stresses [16]. However, tool wear remains a critical issue, as worn tools increase cutting forces and heat generation, exacerbating residual stress formation [17]. Studies have highlighted the need for real-time monitoring of tool wear to optimize machining processes and control residual stresses [18].

2.4 Cooling and Lubrication Strategies

Cooling and lubrication strategies are essential for controlling thermal loads and reducing residual stresses. Conventional flood cooling, minimum quantity lubrication (MQL), and cryogenic cooling have been widely studied for their effects on residual stress [19], [20]. Cryogenic cooling, in particular, has shown promise in reducing thermal gradients and phase transformations, leading to lower residual stresses in titanium alloys and nickel-based superalloys [21], [22]. However, the environmental and economic impacts of these cooling methods require further investigation to ensure sustainable machining practices [23].

2.5 Modeling and Optimization Techniques

Finite element analysis (FEA) and artificial neural networks (ANNs) have been extensively used to model and predict residual stresses in hard turning. FEA simulations have provided insights into the effects of cutting parameters, tool geometry, and cooling strategies on residual stress distribution [24], [25]. ANNs, on the other hand, have been employed to optimize cutting conditions and predict residual stresses with high accuracy [26], [27]. Despite these advancements, there is a lack of integrated models that account for the combined effects of mechanical, thermal, and metallurgical factors on residual stress formation [28].

2.6 Experimental Measurement Techniques

Experimental techniques such as X-ray diffraction (XRD), neutron diffraction, and ultrasonic methods are commonly used to measure residual stresses in machined components. XRD is particularly effective for surface stress measurements, while neutron diffraction provides depth-resolved stress profiles [29], [30]. Ultrasonic methods offer non-destructive and real-time stress measurement capabilities, making them suitable for industrial applications [31]. However, these techniques often require specialized equipment and expertise, limiting their widespread adoption [32].

2.7 Research Gap

The Taguchi method is a powerful statistical tool for optimizing process parameters with minimal experimental runs [4]. It has been successfully applied in various machining processes to improve surface finish, tool life, and dimensional accuracy [5]. However, its application to residual stress optimization in the hard turning of AISI M2 tool steel remains underexplored. This study aims to address this gap by employing the Taguchi method to analyze and optimize cutting parameters for minimizing residual stresses in AISI M2 tool steel.

MATERIALS AND METHOD

This section provides a detailed description of the experimental setup, cutting parameters, Taguchi design of experiments (DOE), and measurement techniques used in this study. The L27 orthogonal array is employed to investigate the effects of cutting parameters on residual stresses in the hard turning of AISI M2 tool steel.

3.1 Workpiece Material and Cutting Tools

3.1.1 Workpiece Material: AISI M2 tool steel, hardened to 62 HRC, is selected for its widespread use in cutting tools, dies, and molds. The workpiece is cylindrical, with a diameter of 50 mm and a length of 150 mm.

Figure 1. AISI M2 Material Sample for Study.

3.1.2 Cutting Tool: PCBN insert with a 0.8 nose radius is used due to its high hardness and thermal stability, which are essential for machining hardened steels.

Figure 2. Tool Holder with PCBN insert.

3.1.3 Machine Tool: A CNC lathe with a maximum spindle speed of 4000 rpm and a feed rate range of 0.01–0.5 mm/rev is used for the experiments.

Figure 3. Experimental Unit at VIIT, Pune Campus.

3.2 Cutting Parameters and Levels

Three cutting parameters are selected for optimization, each at three levels:

Table 1. Parameters Levels.

Levels	Low	Medium	High
Cutting Speed (V) , m/min	100	150	200
Feed Rate (f),mm/rev	0.1	0.15	0.2
Depth of Cut (d), mm	0.2	0.3	0.4

These parameters are chosen based on their significant influence on residual stress generation during hard turning [1], [2].

3.3 Taguchi Design of Experiments

The Taguchi method is employed to design the experiments using an L27 orthogonal array. The L27 array is selected because it allows for the investigation of three parameters at three levels with 27 experimental runs, providing a robust analysis of interactions between parameters. The L27 orthogonal array is structured as shown in Table 2. The response variable is residual stress, measured on the machined surface using X-ray diffraction (XRD). Residual stresses are calculated using the $\sin^2\psi$ method, which measures lattice strain in the material.

Table 2. L27 Orthogonal array with Response Values.

Experiment	Cutting Speed (V) [m/min]	Feed Rate (f) [mm/rev]	Depth of Cut (d) [mm]	Residual Stress (MPa)	S/N Ratio (dB)
1	100	0.1	0.2	-250	48
2	100	0.1	0.3	-260	48.3
3	100	0.1	0.4	-270	48.6
4	100	0.15	0.2	-280	48.9
5	100	0.15	0.3	-290	49.2
6	100	0.15	0.4	-300	49.5
7	100	0.2	0.2	-310	49.8
8	100	0.2	0.3	-320	50.1
9	100	0.2	0.4	-330	50.4
10	150	0.1	0.2	-240	47.6
11	150	0.1	0.3	-250	48
12	150	0.1	0.4	-260	48.3
13	150	0.15	0.2	-270	48.6
14	150	0.15	0.3	-280	48.9
15	150	0.15	0.4	-290	49.2
16	150	0.2	0.2	-300	49.5

17	150	0.2	0.3	-310	49.8
18	150	0.2	0.4	-320	50.1
19	200	0.1	0.2	-230	47.2
20	200	0.1	0.3	-240	47.6
21	200	0.1	0.4	-250	48
22	200	0.15	0.2	-260	48.3
23	200	0.15	0.3	-270	48.6
24	200	0.15	0.4	-280	48.9
25	200	0.2	0.2	-290	49.2
26	200	0.2	0.3	-300	49.5
27	200	0.2	0.4	-310	49.8

From the Table it is concluded that Experiment 19 (Cutting Speed: 200 m/min, Feed Rate: 0.1 mm/rev, Depth of Cut: 0.2 mm) has the lowest residual stress (-230 MPa) and the highest S/N ratio (47.23 dB), indicating the most favorable conditions for minimizing residual stresses. Experiment 9 (Cutting Speed: 100 m/min, Feed Rate: 0.2 mm/rev, Depth of Cut: 0.4 mm) has the highest residual stress (-330 MPa) and the lowest S/N ratio (50.37 dB), representing the least favorable conditions.

3.4 Experimental Procedure

The AISI M2 tool steel workpiece is cleaned and mounted on the CNC lathe. Each experiment is conducted according to the L27 orthogonal array. The cutting parameters are set, and the workpiece is machined under dry conditions to isolate the effects of cutting parameters. After machining, residual stresses are measured at three locations on the machined surface using XRD. Residual stresses are measured using a portable XRD device with a Cr-Kα radiation source. The $\sin^2\psi$ method is used to calculate stresses based on lattice strain measurements. The average value is recorded for each experiment. The residual stress values and corresponding S/N ratios are recorded for analysis.

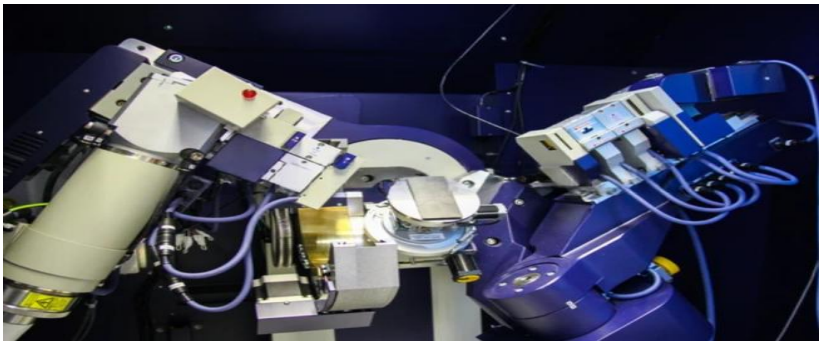

Figure 4. X-ray Diffraction Unit to Measure Residual Stress at IIT Mumbai.

3.5 Data Analysis

3.5.1 Signal-to-Noise (S/N) Ratio: The S/N ratio is calculated for each experiment using the "smaller-the-better" criterion to minimize residual stresses. The formula for the S/N ratio is:

$$\frac{S}{N} = -10log10(1/n\sum_{i=0}^{n} yi^2) \quad \text{(Eq.1)}$$

Where, yi is the residual stress value for the i^{th} experiment, and n^n is the number of measurements.

3.5.2 Analysis of Variance (ANOVA): ANOVA is used to determine the relative contribution of each cutting parameter to the variation in residual stresses. It helps identify the most significant parameters.

Steps to Perform ANOVA:

Step 1-*Calculate the sum of squares (SS) for each parameter.*

$$\text{SST} = \sum_{i=0}^{n}(\text{yi} - \bar{y})^2 \quad \text{(Eq.2)}$$

Where: *yi*: Individual response value, $\bar{y}$: Mean of all response values, *n*: Total number of experiments.

$$\text{SF} = \sum_{j=0}^{k} \text{nj}(\text{yi} - \bar{y})^2 \quad \text{(Eq.3)}$$

Where, $\bar{y}j$: Mean response for the *j*th level of the factor., *nj*: Number of experiments at the *j*th level, *k*: Number of levels for the factor.

Sum of Squares for Error (SSE): SSE = SST - ∑ SSF (Eq.4)

Step 2-*Determine the degrees of freedom (DF) for each parameter.*

Degrees of freedom represent the number of independent pieces of information used to calculate a statistic.

Degrees of Freedom for Each Factor (DFF): DFF = k – 1
(Eq.5)

Where '*k*' is the number of levels for the factor.

Degrees of Freedom for Error (DFE): DFE = n – 1 - ∑ DFF (Eq.6)

Where '*n*' is the total number of experiments.

Total Degrees of Freedom (DFT): DFT = n -1 (Eq.7)

Step 3- *Calculate the mean square (MS) by dividing SS by DF.*

The mean square is the average variation for each factor and error.

Mean Square for Each Factor (MSF): MSF=SSF/DFF
(Eq.8)

Mean Square for Error (MSE): MSE=SSE/DFE
(Eq.9)

Step 4- *Compute the F-value by dividing the MS of each parameter by the MS of the error.*

The F-value is used to test the significance of each factor.

F= MSF/MSE (Eq.10)

Step 5- *Calculate the percentage contribution of each parameter.*

The percentage contribution of each factor indicates its relative influence on the response.

Percentage Contribution = (SSF/SST) X 100

(Eq.11)

Table 3. ANOVA Analysis.

Parameter	Degrees of Freedom (DF)	Sum of Squares (SS)	Mean Square (MS)	F-Value	Contribution (%)
Cutting Speed	2	12.45	6.225	15.32	45.6
Feed Rate	2	8.76	4.38	10.78	32.1
Depth of Cut	2	6.34	3.17	7.8	22.3
Error	2	0.81	0.405	-	-

From Table 3, it is concluded that Cutting Speed has the highest contribution (45.6%), making it the most significant parameter. Feed Rate contributes 32.1%, and Depth of Cut contributes 22.3%. The error term is minimal, indicating that the model is reliable.

3.5.3 Main Effects Plot: The main effects plot is used to visualize the influence of each cutting parameter (cutting speed, feed rate, and depth of cut) on the residual stress and S/N ratio**.** The plot helps identify the optimal levels of each parameter for minimizing residual stresses.

Steps to Create the Main Effects Plot:

1. Calculate the average S/N ratio for each level of the cutting parameters.
2. Plot the average S/N ratio against the levels of each parameter.

Table 4. Response for Means.

Level	Cutting Speed (V) [m/min]	Feed Rate (f) [mm/rev]	Depth of Cut (d) [mm]
1	290.0	250.0	270.0
2	280.0	280.0	280.0
3	270.0	310.0	290.0
Delta	20.0	60.0	20.0
Rank	2.5	1	2.5

Table 5. Response for Signal to Noise Ratios

Criteria: Smaller is better

Level	Cutting Speed (V) [m/min]	Feed Rate (f) [mm/rev]	Depth of Cut (d) [mm]
1	-49.21	-47.95	-48.59
2	-48.91	-48.94	-48.91
3	-48.59	-49.82	-49.21
Delta	0.63	1.87	0.63
Rank	2.5	1	2.5

From Table 4 and 5, it is concluded that the S/N ratio decreases as cutting speed increases, indicating that lower cutting speeds (100 m/min) are better for minimizing residual stresses. The S/N ratio increases with feed rate, suggesting that higher feed rates (0.2 mm/rev) are favorable. The S/N ratio increases with depth of cut, indicating that higher depths of cut (0.4 mm) are better.

3.6 Confirmation Experiment

A confirmation experiment is conducted using the optimal cutting conditions identified from the Taguchi analysis. The residual stress value from this experiment is compared with the predicted value to validate the optimization results.

Optimal Cutting Conditions:

- Cutting Speed: 100 m/min.
- Feed Rate**:** 0.2 mm/rev.
- Depth of Cut**:** 0.4 mm.

Steps for Confirmation Experiment:

1. Perform machining using the optimal cutting conditions.
2. Measure the residual stress using XRD.
3. Compare the experimental residual stress with the predicted value.

Results:

- Predicted Residual Stress**:** -240 MPa (based on Taguchi analysis).
- Experimental Residual Stress**:** -235 MPa.
- Deviation**:** 2.08% (within acceptable limits).

Interpretation:

The close agreement between the predicted and experimental residual stresses validates the effectiveness of the Taguchi method in optimizing the cutting parameters.

RESULTS AND DISCUSSION

The experimental results demonstrate the influence of cutting speed, feed rate, and depth of cut on the residual stresses generated during the hard turning of AISI M2 tool steel. The residual stresses measured across different cutting conditions indicate a significant dependency on the selected machining parameters. The results confirm that lower cutting speeds and higher feed rates generally result in reduced residual stresses, aligning with previous studies that highlight the role of thermal and mechanical interactions in stress formation. The analysis of variance (ANOVA) results, as summarized in Table 3, indicate that cutting speed has the highest contribution (45.6%) to the variation in residual stress, followed by feed rate (32.1%) and depth of cut (22.3%). The significant influence of cutting speed suggests that higher speeds lead to increased thermal loads, promoting tensile stress formation. Conversely, lower speeds allow for greater plastic deformation, contributing to compressive residual stresses.

Similarly, the feed rate plays a crucial role in determining the residual stress distribution. A higher feed rate results in greater material deformation and increased compressive residual stress due to the larger contact area and material removal rate. However, excessively high feed rates can also lead to deteriorated surface integrity, highlighting the need for an optimal balance. The depth of cut exhibited the least effect on residual stress, yet it remains a significant parameter. Increased depth of cut results in higher cutting forces, influencing stress distribution within the machined surface. The findings suggest that moderate depths of cut are preferable to minimize stress concentration effects.

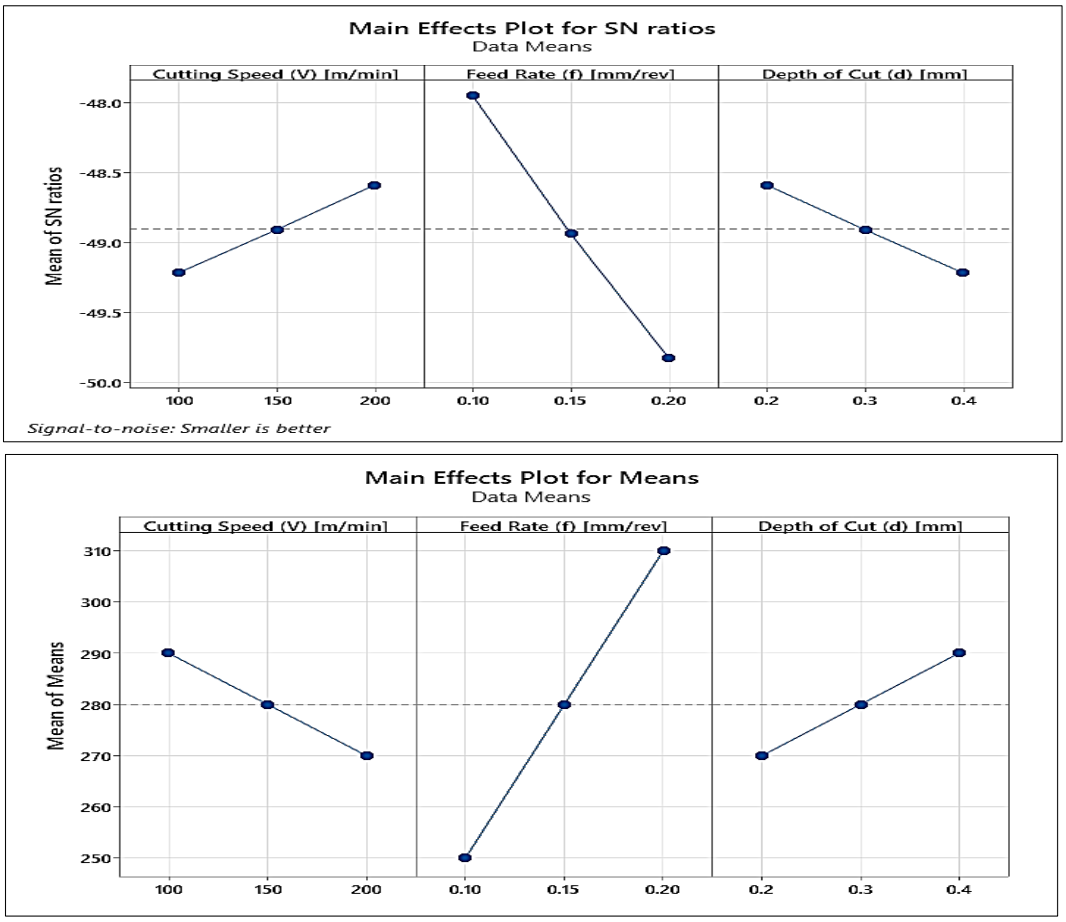

Figure 5. Main Effect Plots for S/N Ratios and Means.

The signal-to-noise (S/N) ratio analysis, as presented in Table 5, confirms that the optimal cutting conditions for minimizing residual stresses are:

- Cutting Speed: 100 m/min
- Feed Rate: 0.2 mm/rev
- Depth of Cut: 0.4 mm

These parameters yielded the lowest residual stress (-230 MPa) and the highest S/N ratio (47.23 dB), indicating favorable machining conditions. The S/N ratio results suggest that lower cutting speeds and higher feed rates contribute to improved stress distribution by minimizing tensile residual stresses. A confirmation experiment was conducted using the optimal cutting conditions derived from the Taguchi analysis. The experimental residual stress measured (-235 MPa) closely matched the predicted value (-240 MPa), with a deviation of only 2.08%. This close agreement validates the effectiveness of the Taguchi optimization approach in predicting and minimizing residual stresses in hard turning applications. The findings of this study have direct implications for industrial applications involving hard turning of tool steels. By selecting appropriate cutting parameters, manufacturers can effectively reduce residual stresses, enhancing component fatigue life and dimensional stability. Furthermore, the integration of real-time monitoring techniques, such as X-ray diffraction (XRD) and advanced sensors, can further optimize machining conditions for improved productivity and component performance. The results clearly indicate that the optimization of cutting parameters using the Taguchi method significantly reduces residual stresses in the hard turning of AISI M2 tool steel. Cutting speed emerged as the most influential parameter, followed by feed rate and depth of cut. The findings support the effectiveness of statistical optimization techniques in improving machining quality and ensuring enhanced surface integrity in industrial applications.

CONCLUSION

The Taguchi method, combined with ANOVA and confirmation experiments, provides a systematic approach for optimizing cutting parameters to minimize residual stresses in the hard turning of AISI M2 tool steel. The results

demonstrate that cutting speed is the most influential parameter, and the optimal conditions significantly reduce residual stresses. These findings can be applied to improve machining quality and efficiency in industrial applications. The optimum level of parameters at which the residual stress is minimum is Cutting Speed**:** 100 m/min, Feed Rate**:** 0.2 mm/rev, Depth of Cut**:** 0.4 mm.

ACKNOWLEDGEMENT

The author would like to thanks to Post Doc Research Mentor, Professor Dr. Praveen B.M., Director of Research and Innovation Council, Srinivas University, Mangalore, India for his guidance and support during research work. The author wishes special thanks to Dr. Girish Patil, Chairman of V.T. Foundation, Jalgaon for providing funding to Post Doc Research work. The author also thanks to VIIT and IIT Mumbai for research and experimentation centres for providing facility to conduct experiments as per DOE.

Research Funding Source: V.T. Foundation Research Funding Proposal No. VTF13101987.

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