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Surface Hardness Prediction Model of Turning Duplex Stainless Steel under Different Cutting Variables

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ABSTRACT

The quality of machine components surfaces plays an important impact on their functional performance. Product performance may be restricted by changes to surface integrity, which includes changes to roughness, hardness, and microstructure. In this research, the impact of cutting variables in CNC turning under the conventional cooling condition on surface hardness of Duplex Stainless Steel. Cutting variables under conventional cooling, including cutting speed, feed, and depth of cut, have been optimized utilizing Taguchi's L9 orthogonal array designed with three stages of turning variables. The optimal variable stages and the degree of significance of the cutting variables, respectively, were determined utilizing the analysis of means (ANOM) and analysis of variance (ANOVA). Effectiveness tests with optimum stages of variables were done to prove the viability of optimization by utilizing Taguchi. It has been found that the maximum surface hardness is most strongly affected by the feed 71.29%, followed by the depth of cut 12.1%, and finally the cutting speed 11.61%.

Keywords: CNC turning, orthogonal array, ANN, signal-to-noise ratio.

INTRODUCTION

Duplex stainless steels are a type of stainless steel which are planned to supply better quality and corrosion resistance than standard austenitic stainless steel. So they are utilized broadly in the risers, manifolds, petrochemical industry in the form of pressure vessels and pipelines, and offshore gas and oil industry for systems of pipework [1].

The problems such as poor surface hardness are familiar whereas machining duplex stainless steel. Hence, efforts have been made to increase the machinability of these materials by selecting proper machining variables to get the optimum surface hardness [2].

The idea of Taguchi variable design which is utilized in off-line quality control procedures was first developed in the early 1950s by Dr. Genichi Taguchi [3]. Off-line techniques for quality control are carried out throughout the process (or product) design and improvement. The idea of fractional factorial design serves as the concept of the Taguchi method which is an active technique for finding the best values of the cutting variables to produce a process or a product resistant to noise sources [4, 5, 6]. The Taguchi method is dependent on experimental matrices which are unique orthogonal arrays (OA's), allowing evaluation of the concurrent impacts of many process variables [5, 6]. The goal of the design of the experiment is to identify the best stage for each cutting variable as well as the comparative importance of each variable on the characteristic of performance [5, 6]. The traditional design of experiment techniques is overly complex, consuming time, and difficult to apply. Several tests must be carried out when more variables are involved. The Taguchi approach uses an orthogonal array (OA) special purpose design to explore the entire variable with a smaller number of experiments to tackle this issue. According to Taguchi, the primary goal function for the trails related to orthogonal matrix is the signal versus noise (S/N) ratio [5, 6]. The signal-to-noise ratio is a metric for measuring the characteristics of performance and illustrates the stage that may be anticipated in the presence of noise elements. Depending on the type of goal function, Taguchi divides the S/N ratio into three categories: "smaller the better," "larger the better," and "nominal the best". The optimal stages of the cutting variables in Taguchi's design of experiment are chosen utilizing the "Analysis of Means" (ANOM) based on the S/N ratio. The stage of results at which the highest signal versus noise ratio is present within experimental category is the ideal stage for a cutting variable. To determine the comparative importance of the cutting variables and their contributions to the S/N ratio, the "Analysis of Variance" (ANOVA) in the design nominated as Taguchi was employed [5, 6].

There are considerable numbers of studies in the existing literature regarding the prediction model for determining the surface hardness of turned materials. Omar José et al. [7] investigated the impacts of different turning cutting variables on the surface hardness of annealed AISI 1020 steel utilizing carbide insert tools. The measured results demonstrated that as all the investigated variables increase, hardness also rises. To investigate how each variable affected the response variable, an "analysis of variance (ANOVA)" was utilized. The results show that cutting speed (69.2%) has the greatest influence on surface hardness, followed by feed rate (24.4%), and depth of cut (6.4%). Komson et al. [8] studied the cutting variables, which were influencing the hardness of turning stainless steel. The design of the experiment was carried out as two variables (feed rate and cutting speed) and three stages. Additionally, the experiment involved both turning with cooling and non-cooling. They concluded that these variables were not significant impact on hardness. Grzegorz et al. [9] determined the hardness of the turned surface of duplex stainless steel under various cutting variables. Different cutting speeds and both cooling and non-cooling cutting variables were utilized to test the hardness of materials. Arumugam et al. [10] analyzed the difference in the hardness of the machined surface as a result of turning, taking into account the feed rate, cutting speed, and depth of cut. The hardness of EN353 forged steel was calculated utilizing a Rockwell hardness tester by adjusting these cutting variables according to Taguchi's design of the experiment.

Wojtowicz et al. [11] investigated the impacts of turning cutting variables on the integrity of a wrought Mg-Zn-Zr-RE alloy surface. First, rate of feed, speed of cutting, nose radius, and the depth of affected cut were utilized as input variables in a design of experiments to produce turned surfaces. Second, correlations between cutting variables and changes in surface integrity, like microhardness, roughness and residual stress were found. This study recommended the best cutting variables for specific surface integrity and fatigue life. Krolczyk et al. [12] evaluated the microhardness of surface integrity after cooling and non-cooling turning of duplex stainless steel by coated sintered carbide wedges. The study examined the microhardness related the integrity of tested surafce for different speeds of cutting. The results demonstrated the increase of microhardness and the depth of hardening versus rounded radius of the wedge cutting edge increases, whilst cooling cutting causes to reduce surface integrity hardening depth. Bombale et al. [13] investigated the impact of the conditions accompanied cut process on the resultant hardness of mild steel surface. The tested steel was of rank A. The cutting process accomplished by CNC turning machine under traditional cooling conditions. The Taguchi method has been utilized to optimize cutting conditions like the speed of cut process, the rate of feed, and the depth of cut. The experiments covered by turning with familiar cooling were organized utilizing Taguchi's L9 orthogonal array, that contains three layers of cutting variables using turning, and the best cutting variable values were found. To show the success of Taguchi optimization, effectiveness tests were carried out with ideal variable settings. The results of the optimization showed that the depth of cut is crucial for maximizing hardness. Sada [14] studied the use of an artificial neural network to simulate the surface integrity of mild steel after turning. He utilized the cutting conditions (feed rate, cutting speed, and depth of cut) to predict the surface integrity in his model. He employed the Levenberg-Marquart and Scaled Conjugate Gradient methods along with a 40 observations training dataset to construct the neural network.

Table 1. Duplex stainless steel's chemical composition [1]

Elements	C	Mn	Si	P	S	Cr	Mo	Ni	N
Wt. (%)	0.03 max	1.9 max	0.9 max	0.03 max	0.03 max	min: 20.0 max: 24.0	min: 2.6 max: 3.4	min: 4.4 max: 6.6	min: 0.07 max: 0.19

It was discovered that the Levenberg-Marquardt method produced a precise and successful estimation of the experimentally gathered data with an optimal number of 10 hidden neurons. Benedict et al. [15] examined the surface integrity of turned AISI 4140 QT utilizing surface microhardness and roughness measurements. Different cutting variables are considered, namely cutting speed, tool corner radius, tool wear, and feed rate. The resultant data is examined by several algorithms, to develop real-time process control, and analytical models. The models are rated based on their stage of complexity, quality, and physical plausibility.

It is clear from the previous research that although researchers have attempted to investigate the relationship between surface hardness and various cutting variables of turning machining operation, there is still a gap in understanding the precise impact of these cutting variables on work piece surface hardness after turning operation, so that we choose this aspect for this study work. Our major objective is to investigate the impacts of cutting variables on turned Duplex Stainless Steel workpiece surface hardness by employing an uncoated carbide inserts tool on a medium CNC turning machine under conventional cooling conditions, by utilizing "Analysis of Variance (ANOVA)" and design of experiments via Taguchi method.

METHODOLOGY

Experimental procedure

Turning is a common cutting process where a cutting tool gets outs the undesirable material from the outer layer of the spinning cylindrical workpiece. The modern machining industry's efforts to increase product quality and profitability by utilizing "Computer Numerical Controlled (CNC) machines" [16].

A duplex stainless steel rod was utilized as the investigation's workpiece material. A circular workpiece with dimensions of 300 mm in length and 50 mm in diameter was employed in the current work. Table 1 displays the stated chemical compositions from the manufacturers determined by the PMI-master pro, while Table 2 displays the mechanical and physical properties of duplex stainless steel. Turning experiments were conducted utilizing a medium CNC turning machine under a conventional cooling condition with an uncoated carbide insert.

Three stage controllable variables and one response variable are utilized in the experiments. Table 3 lists three stages of these variables: the cutting speed (v_c (m/min)), the feed (f (mm/rev)), and the depth of cut (a_p (mm)) [17]. According to full factorial designs, 3^3 designs require a total of 27 runs. Turning operations are done for 27 sets of cutting variables that are listed utilizing the L27 orthogonal array. After turning, Vickers microhardness (HV) is selected as a quality objective of the workpieces.

Larger microhardness values are typically preferred for surface integrity in turning operations. Nine trial runs according to the orthogonal array L9 are required to test the surface hardness of 27 turned components. The L9 O.A. (orthogonal array) table is utilized to determine the selection of the nine cutting trial runs. Wire cutting was done for only 9 turned portions amongst 27 referring to L9 O.A. This was achieved to cut down the time and expense of experimentation.

Table 2. Duplex stainless steel's mechanical and physical properties [1]

Property	Value
Yield strength (MPa)	448
Tensile strength (MPa)	621
Density(Kg/m³)	782
Poisson's ratio	0.3
Fracture strain	25%
Elastic modulus (GPa)	190

Table 3. Control variables and stages [17]

Control Variables	Unit	Stages		
		Stage 1	Stage 2	Stage 3
Cutting speed, v_c	m/min	56	36	24
Feed, f	mm/rev	0.3	0.13	0.07
Depth of cut, a_p	mm	0.6	0.4	0.2

Measuring device

In order to measure the surface hardness along the length and around the perimeter of the round bar, its nine-turned surface was cut using wire cut technology. Next, utilizing the hardness tester shown in Figure 1, apply a 300 g load from the specimen's surface to its depth. For each specimen, six measurements values were averaged. The hardness property was utilized to describe turning variables impact on surface modification.

Signal to noise ratio

The Taguchi robust design approach is an effective methods for creating systems with high-quality. He considered the system, variable, and tolerance design steps of the process and product development. In system design, the engineer chooses the basic configuration based on technical and scientific concepts. In the variable design process, the precise system variable values are chosen. The best tolerances for the variables are chosen via tolerance design. [18]

These differences in an index named "signal-to-noise ratio (S/N)" are utilized for optimization. It is mainly of three categories: "Nominal-is-the-best (S/N_T)", "Larger-is-the-better (maximize) (S/N_L)", and "Smaller-is-the-better (minimize) (S/N_S)". S/NL is utilized when the response is large enough to ensure optimized system, S/N_T is utilized when the target is to ensure reduction in the variability around a particular target, and S/N_S is utilized when the response is enough small to ensure optimized system. Since the goal of this work was to create maximum hardness during a turning process, a larger value refers better hardness. Therefore, as refered in equation 1, enhanced quality behavior was adopted and utilized in this research.

$$\frac{S}{N_L} = -10 \log(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}) \quad (1)$$

where: y – the observed data and n is the number of observations. Notice that this S/N ratio is given in decibels. [19]

Figure 1. Vickers hardness tester

RESULTS AND DISCUSSION

Analysis of means and analysis of variance

The goal of the present research is to increase the hardness after turning Duplex stainless steel. Hence, a larger-the-better quality characteristic

Table 4. Orthogonal array L9 of the experimental runs with measured responses and corresponding S/N ratios

No.	Cutting Speed (v_c) m/min	Feed (f) mm/rev	Depth of Cut (a_p) mm	Hardness HV	S/N ratio dB
1	56	0.3	0.6	210	46.444
2	56	0.13	0.4	256.7	48.188
3	56	0.07	0.2	270	48.627
4	36	0.3	0.4	252.8	48.055
5	36	0.13	0.2	246.4	47.832
6	36	0.07	0.6	288	49.187
7	24	0.3	0.2	228	47.158
8	24	0.13	0.6	229	47.196
9	24	0.07	0.4	277	48.849

Table 5. ANOM for microhardness depended on S/N ratio

Control Variables	Stages			Optimum Stage
	1	2	3	
Cutting speed, *vc*	47.74	48.36	47.75	2
Feed, *f*	48.98	47.74	47.22	1
Depth of cut, ap	47.87	48.36	47.61	2

Table 6. ANOVA for microhardness depended on S/N ratio

Control variables	DF	Adj SS	Adj MS	% Contribution
Cutting speed, v_c	2	598.6	299.3	11.61
Feed, *f*	2	3676.4	1838.2	71.29
Depth of cut, a_p	2	623.9	312.0	12.10
Error	2	257.8	128.9	5.00
Total	8			100.00

for hardness has been chosen. Equation 1 was utilized to calculate the S/N ratios for each orthogonal array trial, and the results are shown in Table 4.

The "Analysis of Means (ANOM)" depending on the "S/N ratio" was utilized to establish the best cutting variables stages [5]; Table 5 shows the ANOM results for surface hardness (HV). The best combination stage variable is that stage which has the highest value of "S/N ratio". For maximum hardness, it has been discovered that cutting speed of 36 m/min, feed of 0.3 mm/rev, and depth of cut of 0.4 mm are the optimum variable settings.

The "Analysis of Variance" (ANOVA) depending on the S/N ratio has been utilized to investigate the impacts of variables in turning process considerably [5, 6], Table 6 summarizes the results of ANOVA for surface hardness. The ANOVA table reveals that the feed (71.29%) plays a significant impact in maximizing the hardness while the cutting speed (11.61%) and the depth of cut (12.1%) have no discernible influence on hardness control.

Analysis of main impact plots

The analysis is carried out utilizing the software program MINITAB-16 [19]. Figure 2 shows the major impact of the plot. It clearly illustrates how hardness varies depending on three variables: speed of cut process, feed, and the depth of cut. The x-axis of the plot represents of each cutting variable value, while the y-axis represents the value of hardness. A horizontal line refers the response's mean. The major impact plots are utilized to obtain the best conditions in the design to find the ideal hardness. Main impact plots show that cutting speed at stage 2 (36 m/min), feed at stage 1 (0.3 mm/min), and depth of cut at stage 2 (0.4 mm) are the best stages for the most extreme hardness.

Tests implemented to verify results optimization

After choosing the best stage of cutting variables, the final stage is to estimate and validate the behavior of such performance. The expected best S/N ratio value (η_{opt}) is shown in equation 2 [4]:

$$\eta_{opt} = m + \sum_{j=1}^{p} \left[\left(m_{i,j} \right)_{max} - m \right] \quad (2)$$

where: p is the number of variables that have an impact on the characteristics of machinability;

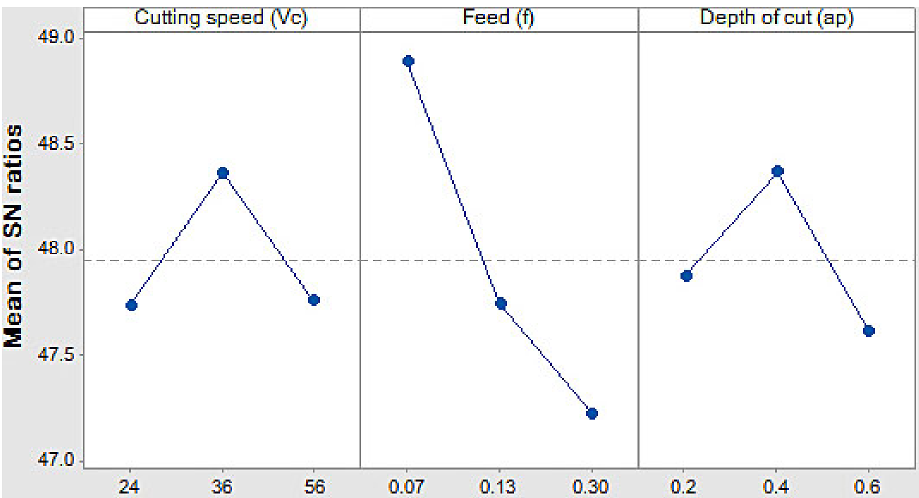

Figure 2. Impact of cutting variables on hardness

m is the average of the S/N ratio; $(m_{i,j})_{max}$ is the S/N ratio of best stage i of variable j.

The confidence interval (CI) of (η_{opt}) for the best cutting variable stage combination at the 95% stage is calculated to assess how closely the experimental value of the S/N ratio (η_{expt}) corresponds to that of the expected value (η_{opt}). The interval of such confidence is shown in equation 3 [4, 5]:

$$CI = \sqrt{F_{(1,ve)}\ V_e\ \left(\frac{1}{\eta_{eff}} + \frac{1}{\eta_{ver}}\right)} \quad (3)$$

where: $F_{(1,ve)}$ – the value related to F to ensure 95% confidence;
ν_e – the error freedom degrees;
V_e – error mean square;
$\eta_{eff} = N/1 + \nu$, N = total number of trails in the orthogonal array, and υ = freedom degrees of p variables; η_{ver} is the confirmatory test trial number.

The workpieces from identical lots were turned after the optimum possible combination values for the cutting variables were determined utilizing Taguchi optimization. The expected S/N ratio value (η_{opt}) and experimental S/N ratio value (η_{expt}) were analyzed. The results of the corroboratory tests are shown in Table 7, and it is clear from this table that the expected error, i.e., ($\eta_{opt} - \eta_{expt}$) encloses the confidence interval, demonstrating the sufficiency of the surface hardness preservative models. The optimal combinations of cutting variable for maximizing surface hardness with the accompanying ideal values are shown in Table 8. We would like to point out here that the obtained results are consistent with what was stated in the literatures about the effect of cutting variables on the hardness of steel alloys [7, 9, 13].

Table 7. Confirmatory test results

Performance measures	Hardness
Stages	2, 1, 2
Experimental value	252.8 Hv
S/N experimental (η_{expt}), dB	48.055
S/N predicted (η_{opt}), dB	48.04
Expected error, dB ($\eta_{expt} - \eta_{opt}$)	-0.015
Confidence interval value (CI), dB	±1.905

Table 8. Optimal variable setting

Response	Optimal cutting variable setting			
	Cutting speed (m/min)	Feed (mm/rev)	DOC (mm)	Optimal value
Hardness	36	0.3	0.4	252.8 Hv

CONCLUSIONS

The following conclusions were reached after conducting an experimental examination on duplex stainless steel utilizing an uncoated carbide insert tool under traditional cooling circumstances at three stages to identify the ideal stage of cutting variables. The feed has the largest impact on hardness with a percentage of 71.29% while speed of cut and depth of cut have negligible impact on the hardness. Maximum hardness is achieved at 36 m/min cutting speed, 0.3 mm/min feed, and 0.4 mm depth of cut, which is the optimum cutting variable combination. According to the verification tests, the obtained results are precise up to a 95% confidence stage. The Taguchi method is expected to be the optimum way of optimizing different cutting variables since it minimizes the number of experiments.

REFERENCES

1. Marina K., Michael P. Duplex Steels: Part I: Genesis, Formation, Structure. Metallography, Microstructure, and Analysis 2013; 2: 113–121.
2. Ihsan K., Mustafa K., Ibrahim C., Ulvi S. Determination of optimum cutting parameters during machining of AISI 304 austenitic stainless steel. Materials & Design. 2004; 25: 303–305.
3. Antony J., Kaye M. Experimental Quality—A Strategic Approach to Achieve and Improve Quality. Kluwer Academic Publishers, 1999.
4. Douglas C. Design and Analysis of Experiments. John Wiley & Sons, 1997.
5. Madhav S. Quality Engineering Using Robust Design. Prentice-Hall International, 1989.
6. Philip J. Taguchi Techniques for Quality Engineering. McGraw-Hill, 1996.
7. Omar J., Verónica C., María C. Surface hardness prediction based on cutting parameters in turning of annealed AISI 1020 steel. DYNA. 2017; 84(203): 31–36.
8. Komson J., Choobunyen K. Effect of Turning Parameters on Roundness and Hardness of Stainless Steel: SUS 303. AASRI Procedia. 2012; 3; 160–165.
9. Krolczyk G., Legutko K., Stoic A. Influence of cutting parameters and conditions onto surface hardness of duplex stainless steel after turning process. Tehnički vjesnik. 2013; 6: 1077–1080.

10. Arumugam A., Ragothsingh R. Optimization of Turning Process Parameters for Hardness in Forged Steel. International Journal of Engineering Research & Technology (IJERT). 2013; 2(12): 2401–2405.
11. Wojtowicz N., Danis I., Frederic M., Pascal L., Chieragati R. The influence of cutting conditions on surface integrity of a wrought magnesium alloy. Procedia Engineering. 2013; 6: 20–28.
12. Krolczyk G., Nieslony P., Legutko S. Microhardness and surface integrity in turning process of duplex stainless steel (DSS) for different cutting conditions. Journal of Materials Engineering and Performance. 2014; 3: 859–866.
13. Bombale R., Kadlag V., Mahajan D. Effect of Cutting Parameters on Surface Quality of Mild Steel (Grade A) in CNC Turning – A Case Study. International Advanced Research Journal in Science, Engineering and Technology. 2016; 3(1): 210–216.
14. Sada S. Improving the predictive accuracy of artificial neural network (ANN) approach in a mild steel turning operation. The International Journal of Advanced Manufacturing Technology. 2021; 112(9–10): 2389–2398.
15. Benedict S., Jeanine B., Daniel G., David B., Michael G., Gisela L., Bernd W., Volker S. Modeling of surface hardening and roughness induced by turning AISI 4140 QT under different machining conditions. Procedia CIRP. 2022; 108: 293–298.
16. Tian-Syung L. Taguchi optimization of Multi objective CNC machining using TOPSIS. Information Technology Journal. 2009; 8(6): 917–922.
17. Osamah F., Prediction of Surface Roughness after Turning of Duplex Stainless Steel (DSS). Al-Khwarizmi Engineering Journal. 2021; 17(2): 8–17.
18. Anthony X., Adithan M. Determining the influence of cutting fluids on tool wear and surface roughness during turning of AISI 304 austenitic stainless steel. Journal of Materials Processing Technology. 2009; 209: 900–909.
19. Minitab Inc., "Minitab User Manual", Version 16, 2011; State College, Pennsylvania, USA.