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Research Article

DEFORM 3D Simulations and Taguchi Analysis in Dry Turning of 35CND16 Steel

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Steel (35CND16) has excellent strength with good hardenability and dimensional stability, and it could be widely used in engineering, mining, and tooling. The present study focused on minimizing cutting forces, flank wear, and temperature generation in the machining zone. The machining process factors include cutting speed, feed rate, and depth of cut. DEFORM 3D simulation outputs closely agreed with the experimental results. The predictive model developed by DEFORM 3D can predict the cutting force and temperature before the actual experiment; therefore, the machining cost can be avoided, which would incur due to improper selection of machining factors. Further, the machining factors were optimized based on ANOVA and regression analysis. Flank wear was increased at high level factors of speed and feed; however, flank wear tends to reduce at the middle level of depth of cut. The average percentage error for cutting force and temperature generation between experimental values and simulated values for force and temperature at machining zone was found to be 2.21% and 1.22%, respectively.

1. Introduction

35NCD16 steel contains low alloy, and it has excellent strength, good hardenability, and stability in dimension. It finds application in aircraft structures and is widely applied to make a mold and bolster. 35NCD16 has high tensile strength and toughness. It finds applications in manufacturing complex parts. This material is widely used in aeroengine parts and automobile components such as axles, levers, connecting rods, and rocker's arms.

Trevisiol et al. [1] conducted a wear test and hardness test on the samples of 35NCD16 steel; the samples were prepared, quenched, and tempered at various temperatures. Finite element analysis is very useful for studying and analyzing the deformation process and minimizing the manufacturing cost. Many researchers are using FEA simulation to evaluate the influence of machining factors on machining attributes. The JC model connects the stress, strain, and temperature [2]. Liu et al. [3] used finite element simulation to study the state of tool wear and surface morphology based on contact stress and temperature generated at the machining zone. The perfectness of the FEA model's results was compared and validated with experimental values.

For the method to reduce the number of experiments, an orthogonal array is chosen, and the orthogonal array is selected depending upon the degrees of freedom. Taguchi techniques allow a standard sequence and it states the primary function, response variables, and the selection of objective function called a signal-to-noise ratio [4]. Wu et al.

[5] conducted a turning process on AISI 5140 steel to study the temperature at the insert tip and flank wear. The outputs are evaluated based on acoustic emission during the turning process. Orthogonal array L27 is used to carry out experiments. The impact of the factors on responses is studied with the help of ANOVA and a predictive model is developed using FUZZY. Dutta and Suresh Kumar et al. [6] described the statistical analysis of flank wear, MRR, the temperature at the tooltip, and surface roughness in turning EN24 steel. The Taguchi analysis is used to analyze the outputs, and L27 orthogonal is used to conduct the experiments. The depth of cut is identified as a highly influential factor other than cutting speed feed rate on roughness and flank wear; whereas, the cutting speed influence is much on the insert tip temperature. Kuntoglu and Saglam [7] performed the turning process on SS304 steel, and they have used a gray-based Taguchi approach. They used the L9 array for the experiment, and speed, feed, and DOC were considered as input variables. With the help of ANOVA, the significance of the factor on life of the insert and production time is determined. Further, the factors were optimized using gray relational analysis.

Das et al. [8] examined the effect of coating with the TiAlSiN insert in turning AISI 420 martensitic stainless steel. The experimental trials were done based on the Taguchi method, and the responses were modeled and optimized based on MCDM tools. Rathod et al. [9] optimized the turning process factors using the gray technique. The turning was carried out on EN-24steel in MQL conditions using SiC as a base nanofluid. Moganapriya et al. [10] investigated the influence of the factors in the hard turning of martensitic stainless steel (AISI 420) with the help of the Taguchi design and ANOVA. The response surface method and ANN tools developed a predictive model. The predicted results were compared with experimental values. Surface roughness was significantly influenced by feed rate, and the depth of cut has much influence on cutting force. Thakur et al. [11] have conducted a turning operation on AISI630 steel with the help of FEA and experimental methods. The insert temperature and cutting force were evaluated. Zerti et al. [12] have proposed a finite element method to investigate the breakage of the chip in machining AISI 1045 steel. The simulation was done using DEFORM 3D to predict cutting force and chip breakage. This numerical analysis used the material constitutive model (JC) and Cockcroft-Latham (C-L) ductile fracture criterion.

Japheth et al. [13] have used the Taguchi design and ANOVA to identify the significant impact on cutting force, power, and temperature and optimize the outputs. Mathivanan et al. [14] investigated the machining performance of AISI 304 steel in terms of force, the temperature at the tool edge, and stress. Predictive models were also developed using DEFORM 3D and Taguchi analysis. The manufacturing sector is to make products in a large scale with less lead time; therefore, optimization and prediction of the responses are vital to forecast the machining characteristics before actual machining. The Taguchi design and response surface design are widely used to develop the predictive model and optimize the responses [15, 16]. It is necessary to investigate the impact of machining factors on machining responses to identify the most effective machining/control factors and their levels [17, 18]. The DEFORM 3D model for predicting cutting forces based on cutting speed, feed, and the depth of cut has been developed, and it will be valid for turning AISI H13 with a ceramic tool [19]. DEFORM 3D is an appropriate tool that allows for an infinite number of variables and conditions to be processed and a graphical analysis of the results. DEFORM 3D software simulated the turning operation on titanium grade 2 with a CVD-coated tungsten carbide insert [20]. The survey found no adequate investigation of machining characteristics in turning 35CND16 steel. Therefore, an attempt is made to find out the machinability of this steel using the Taguchi design. Further, the machining outputs such as cutting force and temperature in the machining zone are simulated using DEFORM 3D. The simulated results were compared with experimental values.

2. Materials and Methods

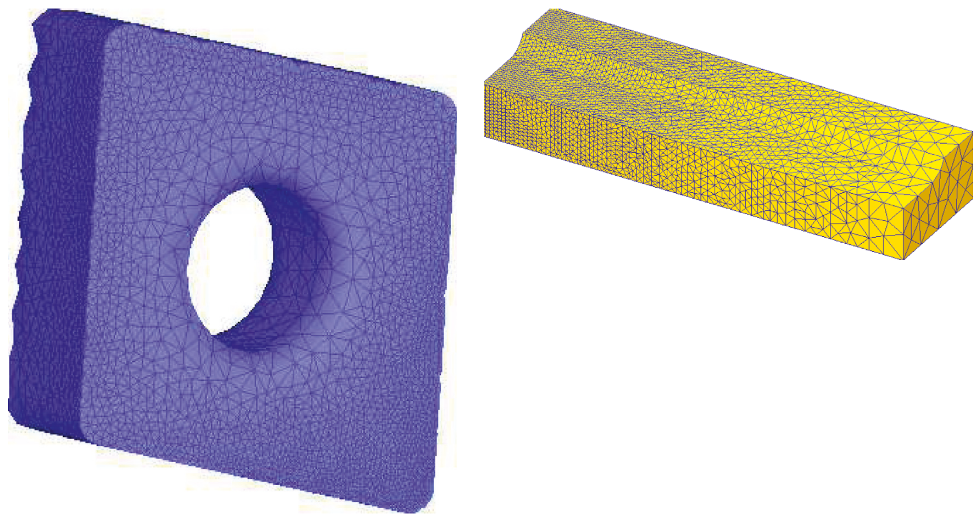
35CND16 is a low alloyed steel. A specimen size 50 mm diameter and 150 mm length was used for turning operation in a dry environment. The Taguchi technique was used to design the experiment. L_9 OA was used. The machining factors such as speed, feed rate, and depth of cut were considered in this experiment. The responses such as cutting force, temperature generation, and flank wear were all considered. The PVD-coated carbide insert was used for the turning operation. The central lathe was used to turn the workpiece. A piezoelectric dynamometer and thermocouple setup measured the force and temperature generation. The levels of machining factors are shown in Table 1.

2.1. DEFORM 3D Simulation. Further, the finite element method has been adopted to simulate the machining factors to predict the outputs. DEFORM-MACH3 v11.0 software simulated the machining factors in turning the 35CND16 steel. The meshed insert and workpiece are seen in Figures 1(a) and 1(b). The DEFORM software library chose the insert CNMA432 and holder DCKNL used in this simulation work. The geometrical details of the insert holder and insert are default as they are defined in the software. The identified material 35CND16 steel was chosen from the DEFORM library. The parameters used for simulation are shown in Table 2. The simulation is done based on L9 OA. The shape of the workpiece was considered a simplified model with a diameter of 50 mm and a length of 150 mm. The workpiece was considered a plastic object, and the mesh size was considered 35000 mesh elements. The mesh size was used to mesh the workpiece with a size ratio of 7.

The tetrahedron elements were generated during the meshing of the workpiece. The insert was considered rigid, and the best mesh elements were identified as 40000. The incremental Lagrangian formulation was used in this simulation. Tungsten carbide was considered as the insert material. The shear friction between the insert and workpiece was considered constant, and 0.5 was used as a friction

Table 1: Factors for experiments and simulation.

S.No	Variables/factors	Level 1	Level 2	Level 3
1	Cutting speed (m/min): V	60	120	150
2	Feed rate (mm/rev): S	0.15	0.25	0.50
3	Depth of cut (mm): a_p	0.75	1.00	1.25



(a) (b)

Figure 1: (a, b) Meshed WC tool and 35NCD16 work piece.

Table 2: Simulation details.

S. No	Parameters set	Unit	Values
1	Temperature: workpiece	°C	25
2	Temperature: insert	°C	25
3	Temperature: environment	°C	25
4	Factor: friction		0.5
5	Coefficient: convection	N/s mm °C	0.02
6	Coefficient: heat transfer	N/s mm °C	45

factor. The simulation conditions used in this work and simulated results are listed in Table 2. The simulated images of cutting force and temperature in the machining zone are shown in Figures 2 and 3, respectively. DEFORM 3D simulated results for cutting force and temperature are shown in Table 3.

2.2. Taguchi Technique. The Taguchi technique is a statistical model, and it is meant to design the experiment and analyze the impact of the variables on the responses. This method is the easiest one and can realize the connectivity among the variables in any processes in all kinds of industries. The method is widely used to improve the quality of the product and processes. OA was used to do the experiments, and it was chosen based on the number of variables and levels. This work optimized the cutting force and temperature generation for the chosen number of factors and their levels. Three factors and three levels were chosen, as seen in Table 1. L_9 orthogonal array was chosen to conduct the experiments and simulate. Statistical software MINITAB 19 was utilized to conduct the Taguchi analysis for experiment results. The experimental results of the output are given in Table 4.

3. Results and Discussion

The machining cost reduction is essential when machining superalloys like 35CND16 steel. However, due to its properties, the more experimental cost and tough associated with machining 35CND16 steel have involved a lot of tooling costs and machinability issues. The finite element method with the Taguchi technique would be beneficial for analyzing the machining issues during the machining of this alloy and would pave the way to reduce the machining cost. The minimum manufacturing cost can be achieved with the help of optimum factors. Usually, the machinability can be studied in the surface roughness, flank wear, integrity, and metal removal rate. These machinability factors are

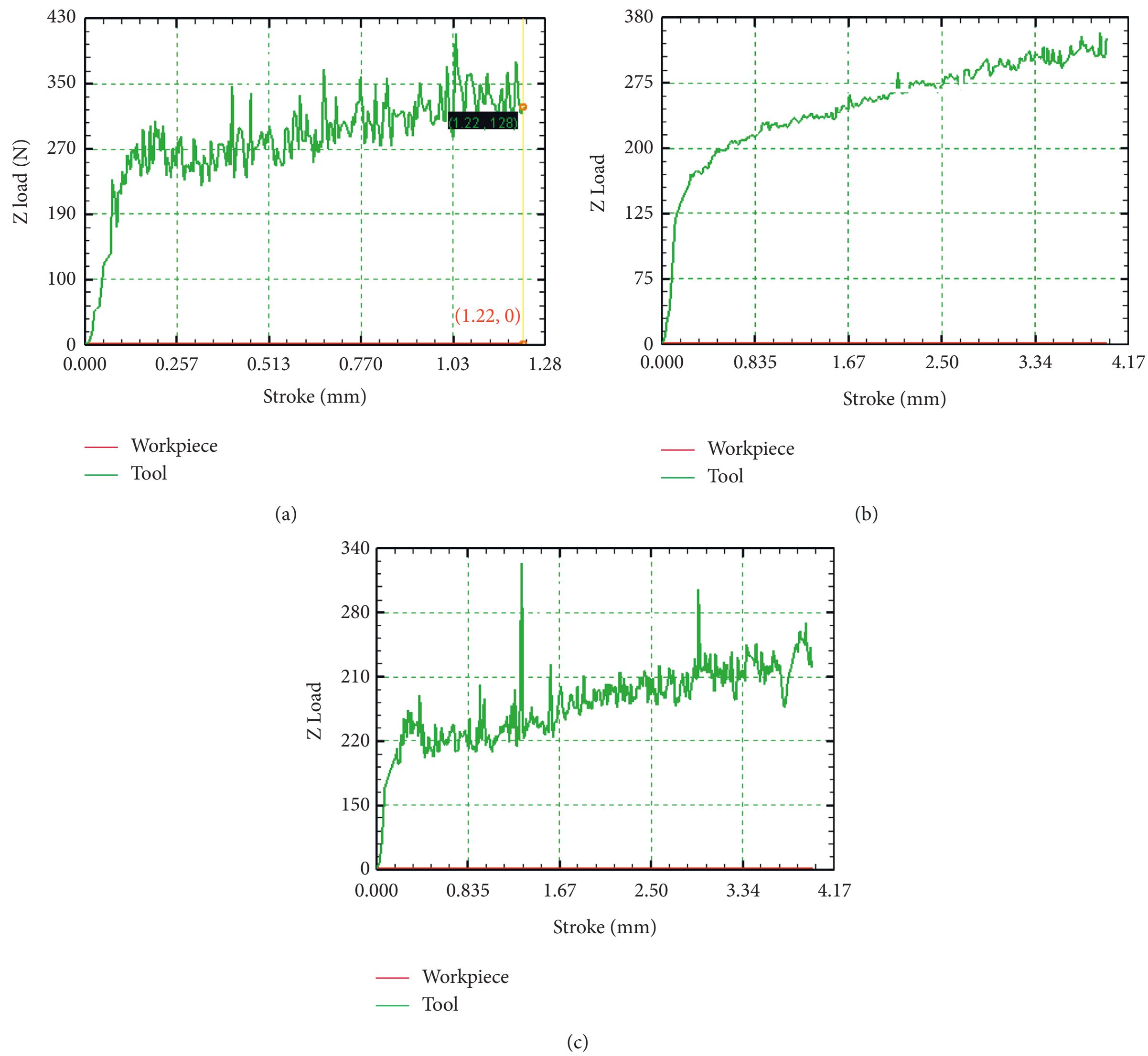


Figure 2: Simulated images of cutting force in the machining zone. (a) Cutting force: simulated at (V) 60 m/min, (S) 0.15 mm/rev, ap: 0.75 mm. (b) Cutting force: simulated at (V) 120 m/min, (S) 0.25 mm/rev ap: 1.25 mm. (c) Cutting force: simulated at (V) 150 m/min, (S) 0.55 mm/rev a_p: 1.0 mm.

influenced by forces, the temperature at the machining zone, flank wear, and integrity. This paper discussed the cutting forces, temperature, and flank wear induced while turning this alloy. Further, this paper focused on identifying the optimum factors to reduce the cutting force, temperature, and flank wear in turning the 35CND16 steel. The predictive model was also developed using DEFORM 3D and Taguchi analysis.

Taguchi, ANOVA, and regression analyses were used to identify the optimum factors to minimize the responses, identify the influence of the factors on the responses, and develop an empirical model equation. The most influential factor was identified based on the Taguchi and ANOVA analyses. The speed contributes to cutting force, temperature, and flank wear, followed by feed rate. The results evaluated from the simulations are to be validated and compared with the experimental results. The simulated cutting force and temperature generation are compared with experimental results, and the percentage error is found to be with a permissible error. The experimental results were used to complete Taguchi, ANOVA, and regression analyses to evaluate the optimum machining factors. The optimum factors were used to simulate using DEFORM 3D for confirmation.

3.1. Experimental Design: Taguchi. The machining variables such as cutting speed feed rate, depth of cut, tool material, tool geometry, coolant type, etc., are factors which affect the performance of the machining. In this paper, speed, feed rate, and depth of cut are considered as input machining variables and cutting force and temperature at the machining zone are experimentally measured. As the machining factors and their interrelationships affect the machining performances, the machining factor's impact and optimum factors are needed to be identified. The quality

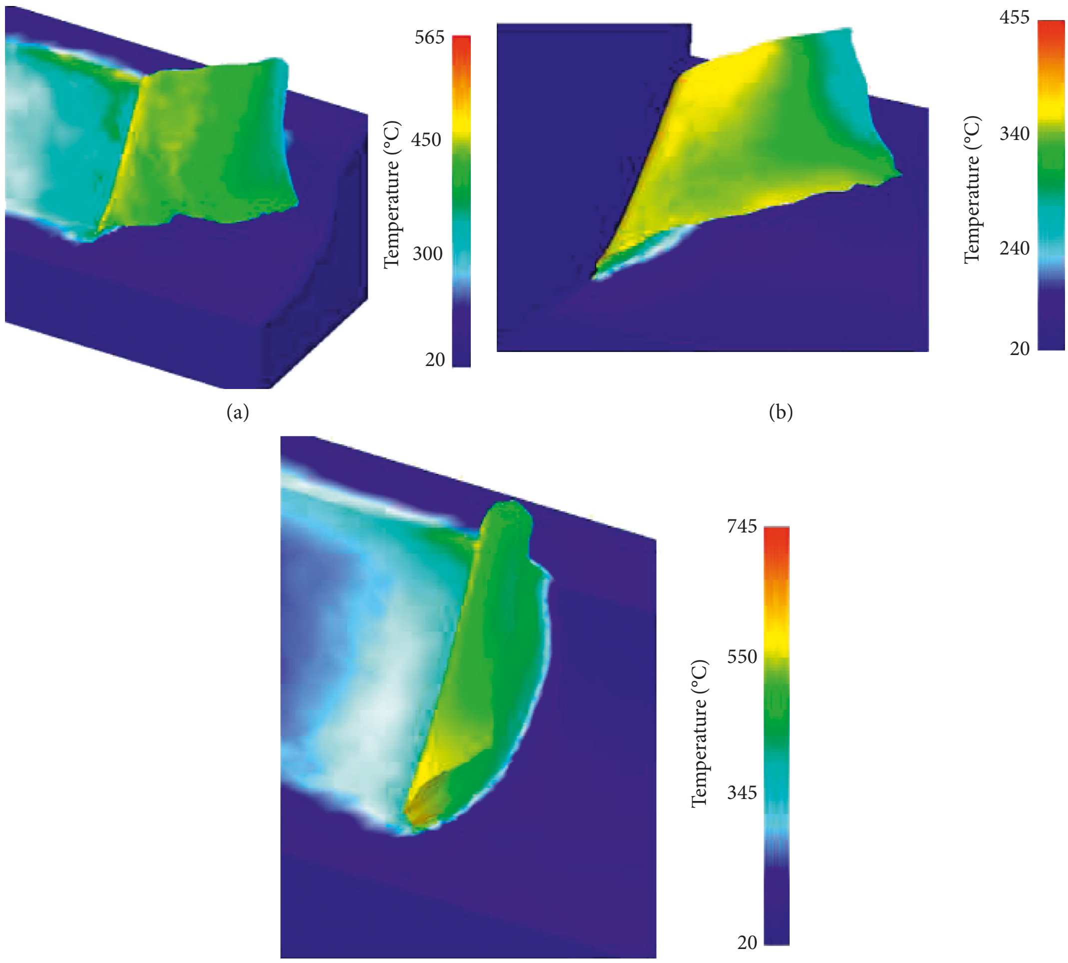


Figure 3: Temperature generation in the machining zone. (a) Temperature: simulated at (V) 60 m/min, (S) 0 .15 mm/rev, ap: 0.75 mm (b) Temperature: simulated at (V) 120 m/min, (S) 0.25 mm/rev ap: 1.25 mm, and (c) Temperature: simulated at (V) 150 m/min, (S) 0.55 mm/rev a_p: 1.00 mm.

Table 3: DEFORM 3D simulated results.

	V (m/min)	S (mm/rev)	a_p (mm)	Fz (N)	Θ°C
1	60	0.15	0.75	430	455
2	60	0.25	1.00	455	460
3	60	0.50	1.25	475	510
4	120	0.15	1.00	395	640
5	120	0.25	1.25	380	565
6	120	0.50	0.75	425	685
7	150	0.15	1.25	280	585
8	150	0.25	0.75	300	625
9	150	0.50	1.00	340	745

characteristics S/N ratio for all the machining characteristics is given in Table 4 and the smaller value is chosen for all the responses.

3.2. Cutting Force. The simulated images of cutting force are shown in Figures 2(a)–2(c). DEFORM 3D simulated results for cutting force are shown in Table 3. The results evaluated from the simulations are to be validated and compared with the experimental results. The simulated cutting force is compared with experimental results. The percentage error is found to be with a permissible error. The experimental results were used to complete Taguchi, ANOVA, and regression analyses to evaluate the optimum machining factors. The optimum factors were used to simulate using DEFORM 3D for confirmation.

The S/N for cutting force is given in Table 4, and the signal-to-noise ratio for 3 machining factors is shown in

Table 4: Taguchi response table and S/N ratios.

	V (m/min)	S (mm/rev)	a_p (mm)	Fz (N)	Θ °C	VB (mm)	S/N: Rof "F_z"	S/N: R of Θ	S/N: R of VB
1	60	0.15	0.75	420	445	0.23	−52.25	−52.96	12.76
2	60	0.25	1.00	445	450	0.29	−52.46	−52.96	10.75
3	60	0.50	1.25	485	500	0.27	−53.53	−53.97	11.37
4	120	0.15	1.00	385	645	0.31	−51.48	−56.19	10.17
5	120	0.25	1.25	390	560	0.32	−51.93	−54.96	9.89
6	120	0.50	0.75	420	690	0.34	−52.56	−56.77	9.37
7	150	0.15	1.25	285	580	0.33	−48.94	−55.26	9.62
8	150	0.25	0.75	310	620	0.31	−49.82	−55.84	10.17
9	150	0.50	1.00	345	750	0.37	−50.50	−57.50	8.63

Figure 4. The large signal-to-noise ratio is considered for minimizing the output, and level 3, level 1, and level 3 with respect to speed (150 m/min), feed rate (S: 0.15 mm/rev), and DOC (1.25 mm) were chosen as optimum factor levels to minimize the cutting force. It is also observed that feed rate has much influence on cutting force followed by cutting speed and DOC with reference to the delta value as shown in Table 5. The main effects' plot for the signal-to-noise ratio of 3 machining factors is shown in Figure 4. The increase in the cutting force was observed at a higher level of feed and middle level of depth of cut; however, the force reduced at a higher level of speed. It would owe thermal softening of the work piece at high level of cutting speed [21].

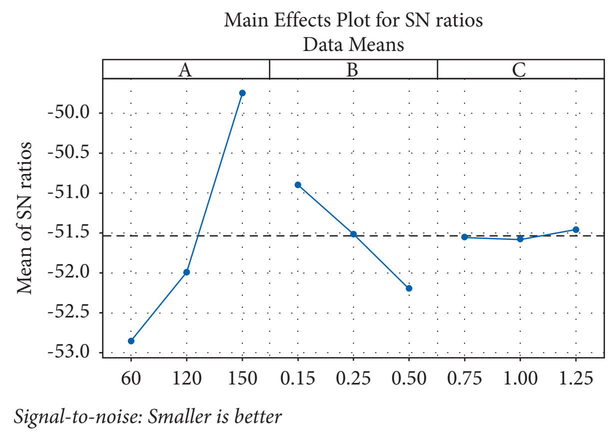


Figure 4: S/N ratio's main effects for cutting force.

Table 5: Signal to noise ratio for "F_z": response table.

Level	V (m/min)	S (mm/rev)	a_p (mm)
1	−52.85	−50.89	51.55
2	−51.99	−51.51	51.58
3	−49.76	−52.20	51.47
Delta	3.10	1.31	0.11
Rank	1	2	3

Table 6: Signal-to-noise ratio for Θ°C: response table.

Level	V (m/min)	S (mm/rev)	a_p (mm)
1	−54.38	−54.40	−55.20
2	−55.72	−55.08	−55.48
3	−56.21	−56.82	−55.63
Delta	1.83	2.42	0.43
Rank	2	1	3

3.3. Temperature Generation at the Machining Zone. The simulated temperature images in the machining zone are shown in Figures 3(a)–3(c). DEFORM 3D simulated results for temperature are shown in Table 3. The results evaluated from the simulations are to be validated and compared with the experimental results. The simulated temperature generation is compared with experimental results, and the percentage error is found to be with a permissible error. The experimental results were used to complete Taguchi and ANOVA analyses to evaluate the impact of machining factors on temperature generation in the machining zone.

The response table signal-to-noise ratio for temperature generation is shown in Table 6, and the impact of the machining factors on temperature generation is shown in Figure 5. From Figure 5, the optimum level was noticed as level 1 for all machining factors. The optimum machining factor's condition to get minimum of temperature at the machining zone is found to be 60 m/min, 0.15 mm/rev, and 0.75 mm. The feed rate is found to be more influential on temperature followed by speed and DOC.

The main effect plot for the signal to noise ratio of 3 machining factors is shown in Figure 5. The increase in the temperature generation was observed at a higher level of machining factors; however, the temperature generation reduced at a lower level of machining factors. It would owe inducing minimum of friction among cutting edge and work piece surface at the machining zone [22]. It was also reported by many researchers [9, 10] and had a good agreement with experimental values. The temperature increases at the machining zone as the level of cutting speed increases. At high cutting speed, friction at machining zone increases. Due to increase in friction, temperature increases and the cutting edge would obviously get affected. As there is no adequate time to dissipate the heat during machining, the temperature increases.

3.4. Flank Wear. The S/N for flank wear is shown in Table 7, and the impact of the machining factors on flank wear is shown in Figure 6. From Figure 6, the optimum level was noticed as level 1 for all machining factors. The optimum machining factor's condition to get a minimum of flank wear is 60 m/min, 0.15 mm/rev, and 0.75 mm. The speed is more influential on temperature, followed by feed rate and DOC.

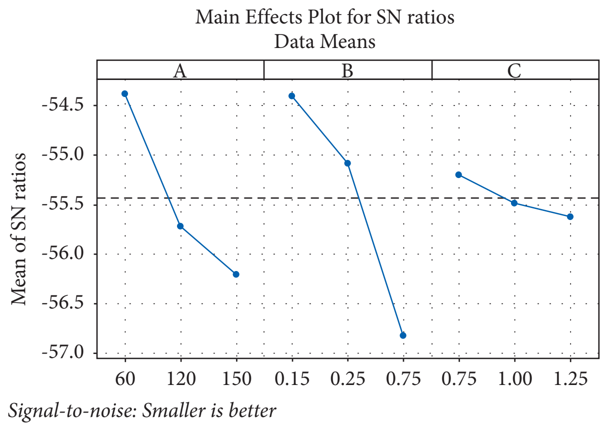


FIGURE 5: S/N ratio's main effects for temperature.

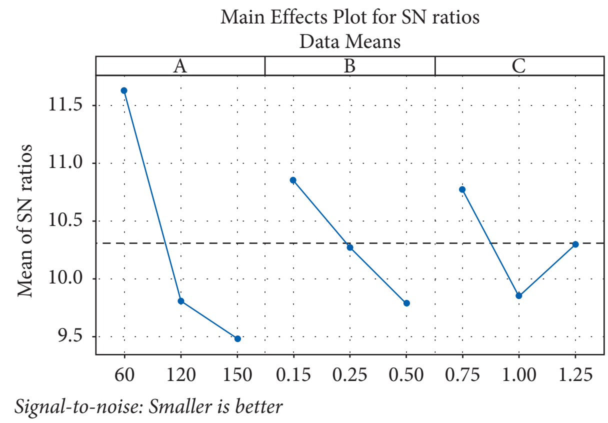


FIGURE 6: S/N ratio's main effects for flank wear.

TABLE 7: Signal-to-noise ratio for "VB": response table.

Level	V (m/min)	S (mm/rev)	a_p (mm)
1	11.630	10.856	10.770
2	9.813	10.274	9.854
3	9.479	9.793	10.300
Delta	2.151	1.063	0.916
Rank	1	2	3

The main effects' plot for the signal to noise ratio of 3 machining factors is shown in Figure 6. The increase in the flank wear was observed at a higher level of machining factors; however, the flank wear reduced at the middle level of the depth of cut. The increase in flank wear at high speed and feed level would cause high-temperature generation in the cutting zone. The increase in the temperature would damage the cutting edge and the flank wear increases [23].

3.5. ANOVA and Regression Analysis. The ANOVA was used to further analyze the effect of the machining factors in turning 36CND16 steel and the results are shown in Table 8. In ANOVA, the p value is utilized to find out the significant impact of the machining variables on the output. In addition, the F value is used to check whether the test is statistically significant.

The feed rate has *P* values lesser than 0.05 and indicates a significance impact on cutting force followed by cutting speed and depth of cut. The feed rate has high significance and it is found that the percentage of contribution is about 91.84% for the cutting force, whereas the cutting speed and depth of cut have the percentage contribution in influencing the cutting force are 7.84% and 0.102%, respectively. Further, the *F* values indicate rejection of null hypothesis; therefore, all the input factors influence the cutting force. The predictive model to predict the cutting force is perfect and ensured with a *R*-sq value: 99.80%.

Similarly, ANOVA analysis was conducted for temperature and flank wear. ANOVA Table 8 shows that speed was identified as the most significant factor on temperature generation with percentage contribution equal to 70.53%; whereas, the feed and DOC have the percentage contribution of 21.48% and 7.45%, respectively. The P values for temperature with respect to cutting speed, feed rate, and depth of cut are 0.007, 0.24, and 0.065, respectively, for temperature generation. The values of F for the factors with respect to temperature are higher than unity; therefore, the null hypothesis is rejected and all the factors influence on temperature generation. The predictive model to predict the temperature generation is significant and ensured with a *R*-sq value: 99.48%.

Further, the influence of the factors on flank wear is analyzed based on ANOVA. The most significant factor on flank wear is found to be cutting speed (percent contribution: 68.55%), followed by feed (percent contribution: 15.13%) and depth of cut (percent contribution: 10.15%). The F values of factors are found to be 11.14, 2.46, and 1.65 with respect to cutting speed, feed rate, and depth of cut for flank wear. The predictive model to predict the flank wear is significant and ensured with a R-sq value: 93.84%.

Further, the regression analysis was carried out to know the correlation among factors and responses and this analysis was carried out for cutting force, temperature, and flank wear. The developed regression model based on regression analysis for the responses is given in equations (1)–(3) with respect to cutting force, temperature generation, and flank wear. The percentage error among experimental and predicted values was found to be within the permissible limit.

$$Fz = 481.2 - 1.353 * \text{cutting speed} + 155.1 * \text{feed rate} + 3.3 * \text{depth of cut}, \quad (1)$$

$$T = 3538 + 2.179 \text{ cutting speed} + 169 \text{ feed rate} - 76.7 \text{ depth of cut}, \quad (2)$$

$$VB = 0.1586 + 0.000841 \text{ cutting speed} + 0.1000 \text{ feed rate} + 0.0267 \text{ depth of cut}. \quad (3)$$

3.6. Confirmation Simulation. The optimal machining factors were evaluated using the Taguchi design, and cutting speed, feed rate, and depth of cut were all considered as machining factors in turning 35CND16 steel considering

Table 8: ANOVA: results for Fz, Θ, and VB.

Factors	DoF	Adj SS	Adj MS	*F* value	P value	Contribution (%)
Fz						
V (m/min)	2	27172.2	13586.1	305.69	0.003	84.63
S (mm/rev)	2	4838.9	2419.4	54.44	0.018	15.07
a_p (mm)	2	5.6	2.8	0.06	0.941	0.017
Error	2	88.9	44.4			0.13
Total	8	32105.6				100
R-Sq: 99.72%						
Θ						
V (m/min)	2	63516.7	31758.3	136.11	0.007	70.53
S (mm/rev)	2	19350.0	9675.0	41.46	0.024	21.48
a_p (mm)	2	6716.7	3358.3	14.39	0.065	7.45
Error	2	466.7	233.3			0.51
Total	8	90050				100
R-Sq: 99.48%						
VB						
V (m/min)	2	0.009156	0.004578	11.14	0.082	68.55
S (mm/rev)	2	0.002022	0.001011	2.46	0.289	15.13
a_p (mm)	2	0.001356	0.000678	1.65	0.378	10.15
Error	2	0.000822	0.000411			
Total	8	0.013356				
R-Sq: 93.84%						

Table 9: Optimum factors and machining characteristics: confirmation by simulation.

Optimal conditions	Cutting force (N)		Temperature generation (°C)	
	Experimental values	Simulated values	Experimental values	Simulated values
V:150 m/min, S: 0.15 mm/rev, a_p: 1.25 mm (for cutting force)	285	280	—	—
V: 60 m/min, S: 0.15 mm/reva_p: 0.75 mm (for temperature generation)	—	—	445	455

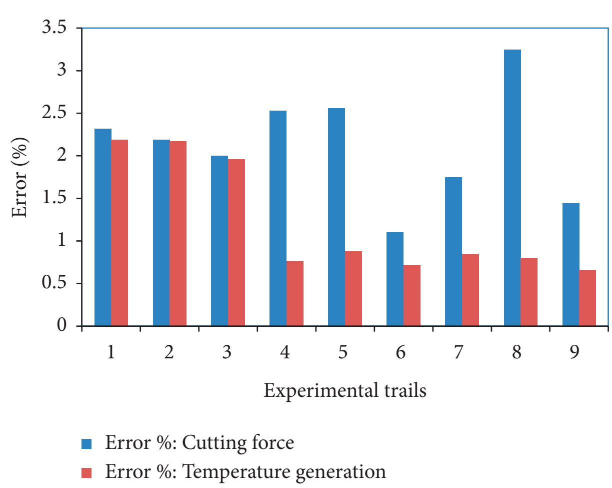


Figure 7: Percentage error: experimental trails and simulated results: cutting force and temperature.

cutting force, temperature, and flank wear. The experimental and predicted values are compared and shown in Figure 7. The percentage error for experimental and predicted values was found to be within the permissible limit. The optimum factors are given in Table 9.

The optimum factors were fed into DEFORM 3D and simulated the turning process, and the corresponding simulated results of cutting force and temperature generation were observed. The simulated results indicate that the optimization of machining factors for cutting force resulted as 280 N and temperature: 455°C. The experimental results show that the optimization of turning parameters considering cutting force as the response resulted in the lowest cutting force (285 N) and temperature (445°C). The percentage error among the experimental values and simulated value is shown in Figure 7 for force and temperature. The average percentage error with respect to cutting force and temperature generation was identified as 2.21% and 1.22%, respectively.

4. Conclusion

In this research paper, simulation using DEFORM 3D, Taguchi analysis, and ANOVA were all utilized in turning 35CND16 steel to study the influence of the factors on cutting force, temperature, and flank wear. The following results are observed:

(i) The developed DEFORM 3D simulation model could be paved in manufacturing industries to assess the machining characteristics of 35CND16 steel and predict the cutting force, temperature generation in the cutting zone, and flank wear.

(ii) Optimum factors for cutting force, temperature, and flank wear were identified using the Taguchi analysis, and the impacts of the factors on the responses were studied with the help of ANOVA.

(iii) The cutting speed was significant in the responses, followed by the feed rate. Depth cut is not influenced much by the responses compared to speed and feed rate.

(iv) A higher amount of flank wear was noticed in turning 35CND16 steel at a higher level of speed and feed; however, the flank wear was reduced at the middle level of depth of cut.

(v) The percentage contribution of cutting speed equals to 84%, 70%, and 68% concerning cutting force, temperature generation, and flank wear was reported.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication.

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