

OPTIMIZATION OF MACHINING CHARACTERISTICS DURING HELICAL MILLING OF AISI D2 STEEL CONSIDERING CHIP GEOMETRY

*Uma Sai Vara Prasad Vookoti
Deemed to be university (VFSTR), India
E-mail: saiuma414@gmail.com*

*Venkata Rao K.
Vignan's Foundation for Science Technology and Research Deemed to be University, India
E-mail: kvenkatrama@gmail.com*

*Satish Kumar P.
Vignan's Foundation for Science Technology and Research Deemed to be University, India
E-mail: satishniyogi1972@gmail.com*

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ABSTRACT

Helical milling is one of the high-performance and high-quality hole manufacturing activities with strong prospects for the automotive and aerospace industries. Literature suggests chip geometry plays a significant role in optimizing machining operations. In the present study, a mechanistic approach is used to estimate the chip geometry, cutting force and power/energy consumption concerning the tool rotation angle. Experiments are conducted at different levels of spindle rotational speed, cutter orbital speed and axial depth of cuts using 8 and 10 mm diameter mill cutters. Experimental results for cutting speed in X, Y and Z directions are measured. A hybrid approach, which combines the Taguchi method and Graph theory and matrix approach (GTMA) technique is used and optimized process parameters. The highest aggregate utility process parameters are met by 2000 rpm spindle speed, 50 rpm orbital speed and 0.2 mm axial cutting depth during helical milling of AISI D2 steel. FEM simulation is used for predicting the chip thickness, cutting forces and power consumption and also validated the optimization.

Keywords: Helical milling; Cutting forces; Energy consumption; GTMA; Chip geometry

1. INTRODUCTION

Helical milling (HM) is a hole enlarging process in which the cutter rotates and moves in the helical path around the axis of the cutter. The hole on the flat workpiece is difficult to enlarge, which cannot be fixed on traditional drilling, bore and turning devices, but with the

help of milling equipment, it is easy to handle. HM is more beneficial as the finishing process of a sample is performed with the same tool, which leads to the reduction of production time (Haiyan & Xuda, 2016), (Wang et al., 2016). As not only time reduction HM is also providing benefits like reduced energy utilization, inferior cutting force and better chip transportation. Research investigators concluded that HM is a better machining operation than normal drilling and boring, with the help of many results comparisons of two operations when machining difficult-to-cut materials (Zitoune et al., 2016).

Helical Milling distinctiveness motivated the researchers' interest in modelling cutting forces, vibration, the surface quality of workpiece and chip development. In operations like helical milling, the cutter and its helical movement in the rotation vary the thickness of the chip across the cutting edge, which can lead to complexity in the estimation of the machining forces (Rey et al., 2016). (Shang et al., 2018) proposed a cutting force model with cutter motion and chip geometry, and a calibration approach was developed to predict the cutting force coefficients. Experiments were performed at certain levels of process factors and results were compared with estimated cutting forces.

The established cutting force models were concluded to be helpful for analysis and optimization of operation factors for good results. A cutting force model was developed by (Rey et al., 2016) using process factors and cutter geometry to improve productivity in Ti-6Al-4V helical milling. Initially, chip geometry was modelled using cutter geometry, machining factors such as axial depth of cut, rotational speed, the orbital rotational speed of cutter and path of cutting.

Then in the second phase, based on the instantaneous chip thickness cutting forces were modelled. They validated the estimated outcome values by conducting experiments at different levels of process factors and measured cutting forces in helical milling and also concluded that optimization of machining factors with the developed approaches to improve machining efficiency. These studies lead to innovative theoretical modelling of cutting forces and power consumption considering the chip geometry with respect to cutter rotation.

Making holes in carbon fiber composites utilized helical milling and assessed cutting forces. As a part of the study, experiments were performed at various process parameter levels and mathematical models were generated using a linear regression analysis method. They compared the findings with the traditional method of machining and determined that HM created less cutting force and a good hole surface. In terms of cutting force coefficients and

process parameters, mathematical facsimiles for cutting forces have been established to precisely envisage the cutting forces for Inconel 718 end milling.

Estimated cutting forces were compared with experimental outcomes to validate the exactness of mathematical models (Okafor & Sultan, 2016; Sultan & Okafor, 2016). The effect of process parameters on surface roughness, cutting forces and residual stresses of S50C medium carbon steel end milling have been studied by (Masmiati et al., 2016). They concluded that cutting forces, surface roughness and residual stresses are minimized by ideal machining conditions.

A relationship was there between the cutting forces and cutter vibration in end milling and the cutter vibration produce fluxes in the cutting forces. In combination with the dynamic undeformed chip thickness, the dynamic, cutting force model was developed. The model used to measure dynamic undeformed chip thickness to acquire cutting force coefficients. The models were used in various working conditions to predict the effect of cutter vibration on cutting forces (Yao, et al., 2018; Yao, et al., 2018).

A signal analysis tool for milling forces and acceleration to detect chatter along with its frequency during the Ti-6Al-4V helical milling was developed by (Huang et al.,2012). Due to chatter in milling, cutting forces and surface roughness were significantly increased by 62-67% and 34.2-40.5 %, respectively. The use of various sensor techniques is required for data acquisition. Vibration sensors with different degrees of precision have been used in the development of the application of real-time or continuous data acquisition methods, which include touch and noncontact sensors

This technique has several researchers who have examined the measurements of vibration for measuring tools and have been tested using various sensor tools and concepts. Different factors such as tool geometry, gear selection, feeding speed, and cutting depth are all contributing to the overall amount of vibrations described in this section. Also examined is the effect of vibration on surface roughness, tool wear, tool use, and power consumption (Murthy, Rao and Rao, 2018).

To optimize process parameters, various forms of optimization procedures are used, such as the ANOVA-a variance analysis approach (Ragavendran et al.,2018) Grey relationship analysis (Diyaley et al., 2017), response surface methodology (Kalita, Shvakoti & Ghadai,

2017), genetic algorithm (Ghadai et al., 2019), particle swarm optimization (Ghadai et al., 2018) and artificial neural networks (Behera et al., 2016).

Sivasakthivel, Sudhakaran and Rajeswari (2013) used the Taguchi approach centered grey relation analysis for optimization of process parameters for minimization of the amplitude of cutter and workpiece vibration in milling Al 6063. In some studies the burr deviation (disturbance) on a CNC vertical milling core, Al 61, of variables like cutting speed, feed rate, drill diameter, and point angle, and the effect of these on roughness (how difficult it is to mill) and burr deviation, A65.

Using Taguchi's experiment methodologies, the team has implemented a set of tests to get the results. An orthogonal array, signal to noise (S/N) ratio and analysis of variance (ANOVA) are employed to investigate machining characteristics of Al 6061 using HSS twist drill bits of variable tool geometry and maintain a constant helix angle of 45 degrees. These process parameters were then checked using subsequent experiments, which concluded that the currently used method resulted in 0.26 mm, 0.21mm, 3.451 mm, and 0.0 mm for burr height, burr thickness, and circularity.

Finally, an artificial neural network was employed to find excellent consistency between the expected outcomes and experimental values (Sreenivasulu, 2015). In micro electro-discharge machining, (Zhang et al., 2010) employed a support vector machine approach along with a genetic algorithm to optimize process parameters.

This research plans to use Taguchi methods to obtain the Al 2" tag information to finish and drill diameter control the 2% of bare areas in dry drilling of Al 2024 alloy. The hole dimensions are tested under three separate cutting speeds (30, 45, and 60 m/min), feed rates (0.15 mm/rev), and depths of drilling (all 25 mm), and a 118° drill angle.

This research used HSS drills. Taguchi's experimental design was used to define the drilling parameters. The orthogonal collection of the signal-to-noise, the measurement of variance, and the regression tests are used to find optimum levels and achieve better hole diameter reproducibility (Kurt, Bagci & Kaynak, 2009).

Concerning the findings, the Taguchi process is more effective in determining the optimum milling parameters. Four control variables (e.g., feed rate, flow, depth, and maximum) were studied by Naidu, Vishnu and Raju (2014), cutting speed, cut depth, and the flow of coolant, as well as other parameters at three different scales. EN-31 steel alloy is the expanded

material used in the project. The Taguchi method is good for managing workpiece surface roughness, or noise, for industrial-machining process parameters like the speed, feed rate, process pressure, or rpm.

Karabulut (2015) performed ANOVA and neural networks to investigate the significance of cutting force and surface quality for process conditions while milling AA7039/Al₂O₃ metal matrix composites. To forecast and recognize major outcome variables, ANOVA was used. It was revealed that the feed rate effect on the responses was more dominant. To determine optimum process parameters, neural networks (ANN) and regression analysis were used.

The tests were performed on a CNC vertical milling machine to produce slots for 6351T6 machining on the Aluminium workpiece using K10 carbide, which was used for machining of 6 flutes. Additionally, the feed rate and cutting depth are regulated in this experiment. Surface tests were done three times and the series Surf-211 and Digital Micrometer were used to determine surface roughness. Orthogonal specification concerns the absolute independence of process parameters.

The total degree of freedom of the three variables is equal to 6 (3X2). The array independence should be greater than or equal to the process specifications. By extension, an orthogonal sequence of degree eight has been analysed (Reddy, 2015). Rao et al. (2016) also employed the ANN for the prediction of optimal process parameters on multi responses during AISI 1040 steel boring. In the case of multi-response optimization employing the above-mentioned approaches, all responses are assigned an equal or random weight.

A few researchers have attempted to measure the weight of the responses with a Consumer Preference Rating to address the uncertainty and difficulty. Depending on the consumer preference ranking, all responses may be given different weights for each. For instance, surface roughness must be highly preferred, moderate weight must be given to the tool wear and less preference must be given to the removal rate of the metal.

An approach, Graph theory and matrix approach (GTMA) and utility concept (UC) are presented to determine the weights of outcomes while optimizing. The utility is the easiest weighted summation procedure employed in the multi-response optimization approach. In the utility model, to obtain utility values the outcomes are normalized and weights are assigned (Cheema, Dvivedi & Sharma, 2013).

Customer preference rating is deliberated in the utility concept to compute the weight of each outcome for multi-response optimization. This approach modifies the missing knowledge for the estimation of weights into statistical data (Nahm, Ishikawa and Inoue, 2013). The graph-theory and matrix-approach (GTMA) technique is a popular tool for different types of selection issues and is used by a variety of researchers for any kind of selection problem that uses any amount of selection criteria. However, to date, none of the researchers have attempted to employ GTMA for parameter selection, nor have they done so at some point in the past.

Gadakh and Shinde (2011) carried out the technique with the intent of being able to find the best cutting parameters to side milling. Another method of parameter collection is to expand the search space in order to include performance criteria (expand the search criteria) in order to define performance variables (which are not critical) and then choose the most relevant ones. Graph theory is a well-established and mathematical approach.

It is favourable in exploring the graph/digraph models expeditiously to apply the matrix method in order to find the function and index to the framework. It is modern and straightforward, and simple to implement, which means that it is less complex than the GTPL, but carries less weight in decision-making. According to the current trends, it appears that the present approach significantly reduces the optimization effort. Also, the confirmed findings show that, are that the most optimum criteria for cutting and metal removal, work life and metal removal, result in increased performance.

In the field of machining, Finite Element Method (FEM) -based techniques are used to analyse machining characteristics such as cutting forces, instrument vibration, pressures, metal deformation and temperature distribution, and are often used to model them under certain working conditions. To choose optimal process parameters, FEM based methods are employed. To examine the significance of thermal softening on the cutting process, Laakso and Niemi (2016) used FEM simulation, and also studied the effect of process parameters on cutting forces. Optimization of process parameters for profitable machining of titanium alloy was held by (Kuttolamadom et al., 2017) using a performance approach focused on tool wear. The optimization has been tested with FEM based simulation using Third Wave Systems AdvantEdge tools. To determine cutting forces, they also used FEM models.

Based on the literature, it is summarized that limited work was carried out on estimation and optimization of cutting forces, power/ energy consumption considering the chip geometry in helical milling. In the present study, a series of experiments are conducted on AISI D2 steel

at different levels of spindle rotational speed, tool orbital speed and axial depth of cut using 10 mm and 8 mm diameter mill cutters.

Helical milling process parameters are optimized for multi responses of cutting forces, power consumption and geometry of chip. Graph theory and matrix approach principle is employed to estimate response weights and multi-response optimization. FEM simulation is developed for the prediction of the cutting forces, energy/power consumption and chip geometry to validate the GTMA optimized process parameters.

2. APPROACH OF THE STUDY

In the present study, the following method was followed for multi-response optimization of experimental factors as shown in the flowchart below Figure.1.

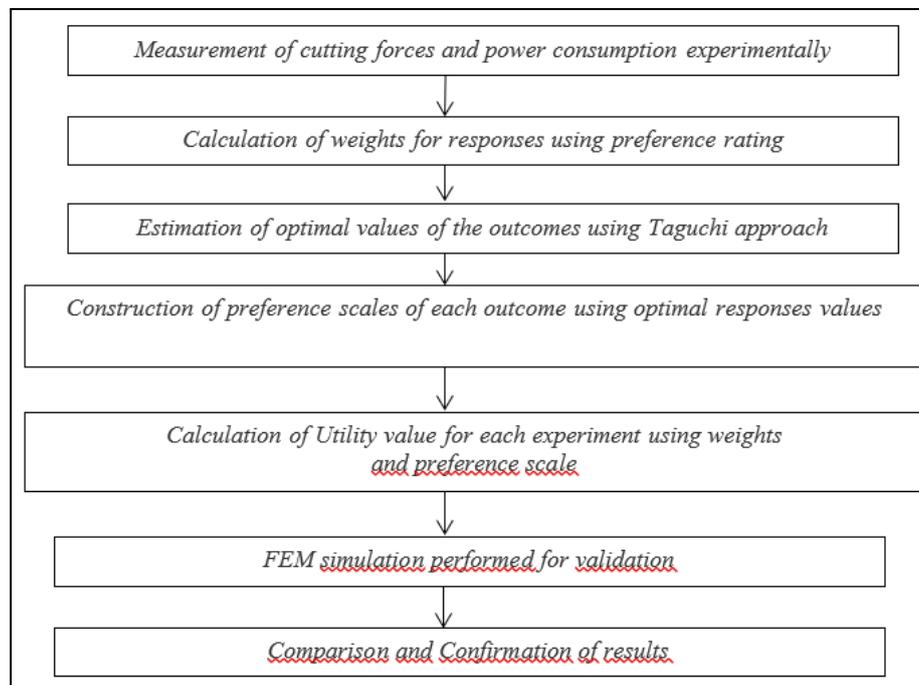


Figure 1: Flowchart of the study

2.1. Utility concept

Machining outcomes such as cutting forces, power consumption and chip geometry are considered for assessment of machining and cutter condition monitoring in helical milling. Utility values of outcomes are elucidated using their respective weights and overall or average utility value is elucidated. Taguchi method and ANOVA are used to analyse the average utility value for multi-response optimization (Kuttolamadom et al., 2017). The overall utility value of an outcome is numerically estimated using the following equation (1)

$$U(X_1, X_2, \dots, X_n) = \sum_{i=1}^n w_i U_i(X_i) \quad (1)$$

Where w_i is the weight assigned for an outcome, U is the overall process utility value, U_i is the utility value of each outcome.

2.2. Calculation of weights

The weights of each machining feature are computed considering the manufactures preference rating as presented in Figure. 2. A no. of three different manufactures has different preferences. As a 1st preference, preference is specified as P, b and F from high to low. In the 2nd preference, P and b are specified equally high preference and the next preference is specified to F. In the 3rd preference, b is specified high preference and next preference is F and last preference is specified to P. In this method, there is a foremost benefit that the machining features can be specified any number of preferences by individual consumers to compute their weightage (Rao et al., 2016).

Preference graphs represent a schematic presentation of diverse preferences of various users. Adjacent matrices of diverse preferences are attained.

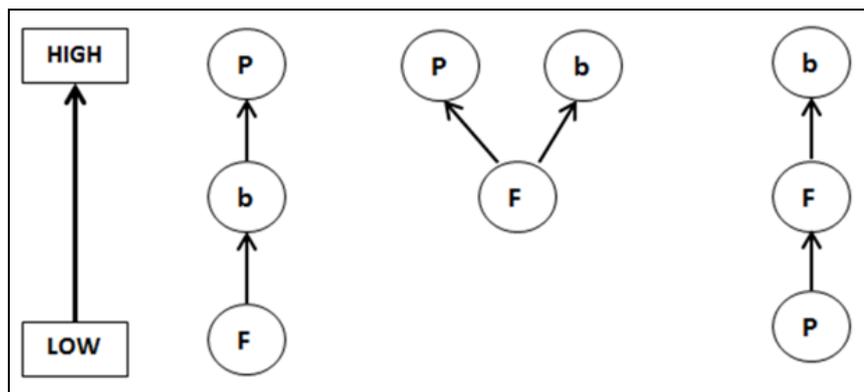


Figure 2: Different preferences of machining features of various consumers

The adjacent matrix presents relation amid each machining feature in the form of a matrix as shown below:

$$PG_m = [pg_{qr}]_{N \times N} \quad (q, r = 1, 2, 3, \dots, m, \dots, N) \quad (2)$$

Where m is the number of consumers, N is the number of features and pg_{qr} specifies the dominances of q over r in an $N \times N$.

$$PG_1 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad PG_2 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad PG_3 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix}$$

Dominance matrices (D^n) for different PGs are computed with adjacency matrices. The dominance matrix recognizes the best preferred Machining Feature (MF) over the other features. The dominance matrix is computed using equation (3).

$$D^n = PG_n^1 + PG_n^2 + \dots + PG_n^{M-1} \quad (3)$$

Where m value taken as '4' then:

$$D^1 = PG_1^1 + PG_1^2 + PG_1^3$$

Also

$$d_m^n = \sum_{j=1}^M pg_{ij}$$

Weights of machining features are computed using equation (4) (Rao et al., 2016)

$$W_m = rir_m / \sum_{m=1}^M rir_m \dots \dots \dots (4)$$

The weights for P,b & F are computed as 0.368,0.421 & 0.210 respectively.

$$W_m = (0.368, 0.421, 0.210)$$

3. EXPERIMENTATION

The experiments were conducted on a CNC milling machine with two spindle velocity levels, four orbital velocity levels, two axial cutting depth levels, and 10 mm and 8 mm diameter milling cutters. In Table 1, process factors with unique levels were shown. Helical milling tests on AISI D2 steel with carbide end mill cutters were conducted according to Taguchi's orthogonal array of L8. AISI D2 steel is a Cold Work Steel with High Carbon and High Chromium Content. Because of the 0.90 percent Vanadium inclusion, the quality has high wear resistance and hardness. It is typically supplied in the Annealed condition, with a hardness of 57-59 HRC. The experimentally measured cutting force and power consumption data are tabulated in Table.1.

Based on the research done in the ScienceDirect scientific articles database, when searching for the terms "ANT", "actor-network theory", and "energy" in papers titles, abstracts, and keywords, 21 articles published between 1999 and 2020 where found. Thus, seven articles

were chosen (Table 1), based on the magazines' impact factor in which those papers were published.

Table 1: Experimental measured force and power consumption

Exp. No.	Cutter Diameter in mm	Spindle speed (n _c) in rpm	Orbital speed(n _o) in rpm	Axial cutting depth (a _p) in mm	Cutting Forces F _{ex} (N)	Power Consumption P _{ex} (watts)
1	10	3000	200	0.3	1050	3508
2	10	3000	150	0.2	780	2011
3	10	2000	100	0.2	600	1059
4	10	2000	50	0.3	575	886
5	8	3000	200	0.2	510	1617
6	8	3000	150	0.3	500	1691
7	8	2000	100	0.3	490	931
8	8	2000	50	0.2	470	569

As it was mentioned in Figure 3, tests are carried out on a linear three-axis CNC vertical machining centre with a table specification scale of 950 X 650 mm DMC-75V. On the machine table, a KISTLER 9257B style force dynamometer is placed and a wattmeter is used to measure cutting forces and power consumption online, respectively. For every experiment, a new mill cutter is used and cutting forces data is acquired.



Figure 3: Experimental setup

The geometry of the chip has gained importance, as researchers have shown that the optimization of a machining process often relies on chip formation. The geometry of the chip leads to the numerical calculation of cutting forces and consumption of power/energy (Vara Prasad, Rao and Murthy, 2020). In helical milling, the chip height increases from 0 to 180 degrees of cutter rotation. That's why the maximum value of the cutting forces is taken for all the experiments to estimate cutting force coefficients. From the experimental results, it was observed that cutting forces decreased as the axial depth of cut decreased. Similar kinds of

cutting force values are also seen in earlier studies carried out on helical milling by (Sonawane and Joshi, 2010), (Liu, Wang and Dargusch, 2012) and (Sultan and Okafor, 2016).

4. RESULTS AND DISCUSSION

4.1. Estimation of machining features using Mechanistic model

The size and shape of a chip for 180 degrees rotation of the cutter were shown in Figure. 4. Side edge depth of the chip (b) at different angles was estimated using equation (5). Chip geometry for the eight experiments at 90° was given in Table 2.

$$b(\theta_i) = d_a - \frac{d_a}{\pi} \cos^{-1} \left(\frac{e - R_c \cos(\theta_i)}{\sqrt{e^2 + R_c^2 - 2R_c e \cos(\theta_i)}} \right) \quad (5)$$

Where d_a is axial depth of cut, e is eccentricity; R_c is the radius of mill cutter

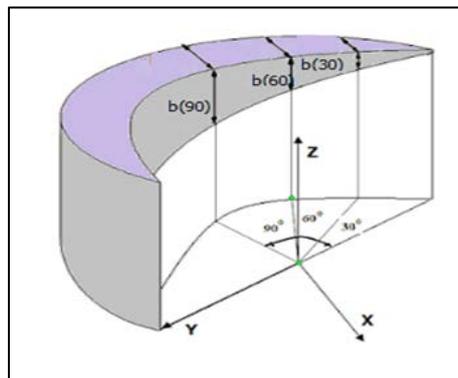


Figure 4: Chip geometry

4.2. Estimation of Cutting Forces Coefficients with mechanistic model

The cutting forces were associated with two types of force coefficients Figure.5 shows the cutting forces in linear models described by shear or cutting components (F_c) and edge or ploughing force components (F_e). Figure 5 demonstrates the cutter being engaged with the workpiece, the width of the workpiece and the cutting angles are shown, and the cutting forces seen here are the same as on the workpiece. The cutting forces were expressed in terms of the force coefficients as presented in the equations (6-8). Shear force coefficients were represented with K_c the ploughing or edge force coefficients were represented with K_e (Vara Prasad, Rao & Murthy, 2020) in all axial directions.

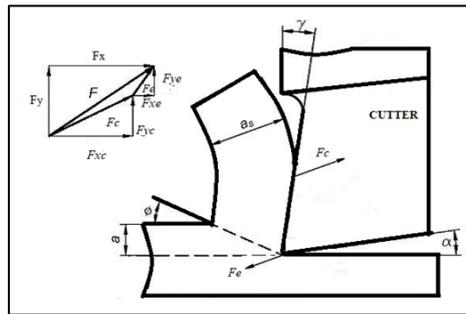


Figure 5: Cutting force components involved in machining

$$F = F_c + F_e = K_c ab + K_e b \quad (6)$$

Where a is uncut chip thickness and b is the width of cut. The shear or cutting force coefficients and ploughing or edge force coefficients are estimated as follows:

$$K_c = \frac{F_c}{ab} \quad (7)$$

$$K_e = \frac{F_e}{b} \quad (8)$$

As the cutting force is a function of the depth of cut or uncut chip thickness, the cutting force components and ploughing force components were estimated using the zero uncut chip thickness method (Popovic, Tanovic and Ehmann, 2017; Vara Prasad, Rao and Murthy, 2020). The intercept value is used to estimate end or ploughing force coefficients using the equations (7, 8).

Equations (9) were used to estimate cutting forces in all axial directions with respect to the chip geometry at 90° of cutter rotation. Sample calculation for estimation of cutting forces was given below for 90° of cutter rotation:

$$\begin{aligned} F &= K_c \cdot b(\Theta) \cdot h(\Theta) + K_e \cdot b(\Theta) \quad (9) \\ &= 6934.12 * b(90^\circ) * h(90^\circ) + 1166.6 * b(90^\circ) = 1320 \text{ N} \end{aligned}$$

During the machining process, power consumption can be measured easily with a suitable measuring instrument. But, it is difficult to measure power consumption with respect to chip geometry as it varies. In the present study, power consumption is estimated using the cutting forces which are estimated in the previous section and cutting velocities in all axial directions (X, Y and Z) using the equations (10)-(13).

$$P = \sum FV \quad (10)$$

$$V_T = V_C + V_O \quad (11)$$

$$V_{TX} = V_T \sin(\theta^i) \quad (12)$$

$$V_{TY} = V_T \cos(\theta^i) \quad (13)$$

Table 2: Machining features estimated using a mechanistic approach

S.No	Cutter radius (Rc) mm	Spindle speed (N) rpm	Orbital speed (nc) rpm	Axial cutting depth(ap) mm	Height of the chip(b _θ) mm	Cutting force (F _m) N	Power consumption (P _m) W
1	10	3000	200	0.3	0.221	1320	3701
2	10	3000	150	0.2	0.136	750	2100
3	10	2000	100	0.2	0.128	581	986
4	10	2000	50	0.3	0.205	542	890
5	8	3000	200	0.2	0.137	455	1512
6	8	3000	150	0.3	0.195	356	1632
7	8	2000	100	0.3	0.199	345	895
8	8	2000	50	0.2	0.139	463	542

Chip geometry at 90° of tool rotation was estimated using the equations (9), the corresponding cutting forces in all axial directions at the same angles and power consumption were also estimated shown in Table 2 using the equations (6) & (10) respectively and are found to be in good agreement compared to experimental results. The comparison of cutting forces, power consumption estimated from the mechanistic approach and experimentations is presented in Figure 6 and Figure 7 respectively.

The estimated data of all outcomes were analysed by the Taguchi method using smaller, better characteristics. Optimal process factors were found independently and the corresponding optimal outcomes were forecasted using the Taguchi approach. Optimum parameters and predicted optimal values of three outcomes were given in Table 3.

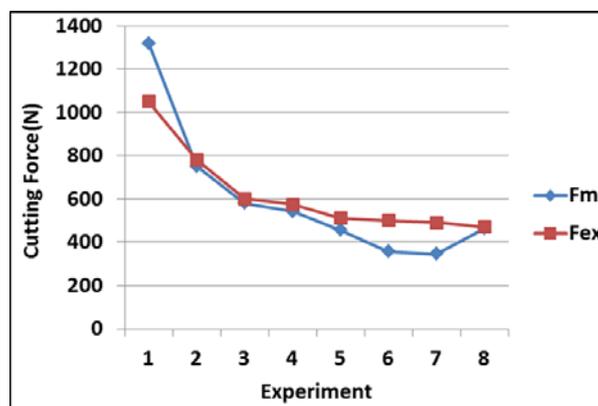


Figure 6: Cutting forces comparison plot

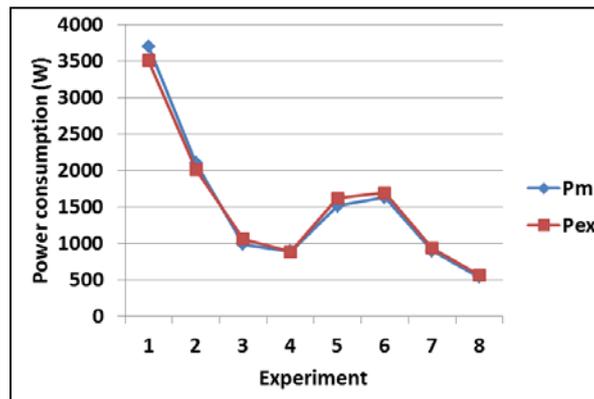


Figure 7: Power consumption comparison plot

Table 3: Optimum levels of process factors and corresponding predicted outcomes

Sl.No	Outputs	Optimal factors				Predicted values
		D	nc	no	ap	
1	F(N)	8	3000	150	0.3	329
2	P(W)	8	2000	50	0.2	489
3	b (mm)	10	2000	100	0.2	0.13

4.3. Preference scale construction

The preference scale for every outcome was governed by using equation (14). In the determination of the scale, PS value was considered amid 0 and 9 based on the suitable levels (Kuttolamadom et al., 2017).

$$PS = A \log \frac{X_i}{X_i'} \quad (14)$$

Where X_i is the value of attribute response, X_i' is the minimum acceptable value of machining features and A is constant. The calculated A values are -8.9, -17.8 and -41.4 for minimum power consumption, minimum cutting forces and minimum chip geometry.

Utility values of all outcomes computed using the following equation (15)

$$U = PS * W \quad (15)$$

Where PS is the preference scale factor and W represents the weights of responses. Formerly the weights for P,b and F were found as 0.368, 0.421 and 0.210 respectively.

Table 4: Estimated utility values of the response

Exp.No	Force utility	Power utility	Chip width utility	Total utility
1	0.000	0.000	0.368	0.368
2	0.484	0.799	3.671	4.954
3	0.912	1.719	3.671	6.302
4	0.981	1.975	0.000	2.956
5	1.177	1.112	3.110	5.398

6	1.209	1.047	0.036	2.292
7	1.242	1.904	0.036	3.182
8	1.310	2.611	3.110	7.030

The individual utility and total utility values of machining features for each experiment as a sum of each outcome utility were presented in Table 4. If the all the responses are given same weightage, it is observed that total utility value obtained 6.892 which is the highest shown in Table 5 and by comparison the total utility value is found to be high for same set of process parameters. Figure 8 represents the optimization of total utility values using Taguchi approach.

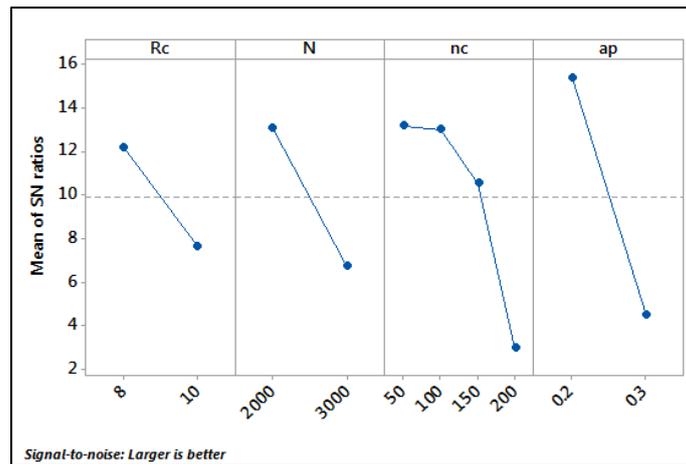


Figure 8: Optimization of Total utility by Taguchi

Table 5: Estimated utility values of the response with equal weightage

Exp.No	Force utility	Power utility	Chip width utility	Total utility
1	0.000	0.000	0.289	0.289
2	0.759	0.716	2.878	4.352
3	1.429	1.540	2.878	5.847
4	1.537	1.770	0.000	3.307
5	1.844	0.996	2.438	5.277
6	1.894	0.938	0.028	2.861
7	1.946	1.706	0.028	3.680
8	2.052	2.339	2.438	6.829

Hence from the multi optimization approach GTMA, the highest total utility process parameters are considered as best suitable i.e., spindle speed 2000 rpm, axial depth of cut 0.2 mm, orbital speed 50 rpm during helical milling of AISI D2 steel.

4.4. FEM simulation for validation

In the present study, ThirdWave AdvantEdge software was used to predict cutting forces, Power consumption and chip geometry. The software was with a dynamic explicit Lagrangian finite element solver along with continuous meshing and adaptive meshing

techniques to simulate the machining operation (Nahm, Ishikawa and Inoue, 2013). In the simulation, the size of the workpiece was taken as 50 mm length, 50 mm width and 10mm height. During the simulation, the tool is assumed to be rigid due to its relatively high elastic modulus.

As per the Johnson-Cook material model, the simulation considered the mechanical and physical properties which are commonly available in the material library of software. The workpiece is assumed to be plastic and the flow of metal during the chip formation is in ductile/plastics behavior. Plastic flow stress during the chip formation is estimated using the following equation (16). Material constants of the Johnson-Cook model for AISI D2 steel are provided in Table 6.

$$\sigma_f = [A + B (\epsilon)^n] \left[1 + C \ln \left(\frac{\epsilon^0}{\epsilon_0^0} \right) \right] \left[1 - \left(\frac{T - T_{room}}{T_{melt} - T_{room}} \right)^m \right] \quad (16)$$

Table 6: Material constants of Johnson-Cook model for AISI D2 steel

A (M Pa)	B (M Pa)	C	n	m	Damage property value
1.766	904	0.012	0.312	3.38	1.17

Table 7: Simulation parameters

Maximum element size of the workpiece	2 mm	Minimum element size of the workpiece	0.15 mm
Mesh grading for the workpiece	0.5	Minimum element edge length (Chip bulk)	0.05152 mm
Minimum element edge length (Cutter edge)	0.0394 mm	Maximum tool element size	1 mm
Minimum tool element size	0.1 mm	Mesh grading for the tool	0.5

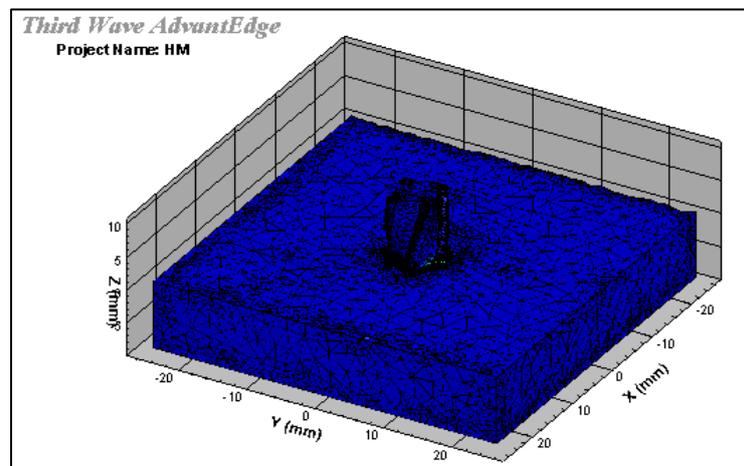


Figure 9: Geometrical designation of workpiece and cutter

For simulation as per the basic principle of finite element analysis, the workpiece and tool are meshed with certain grading in elements. AdvantEdge employs an adaptive meshing method, which continuously remeshes the tool, workpiece and the formed chip, whenever the

cutting zone elements change their initial shape. Hence, Advantedge software provides ease of meshing in simulation of complex geometry.

The meshing and simulation parameters are provided in Table 7. The workpiece material was set to AISI D2 Steel. As shown in Figure. 9, bottom surface of the workpiece was fully restricted of movement in all directions and the mill cutter was restricted of movement at its top in the Z-axis direction. The rotating cutter was defined to move in a helical path into the workpiece with a given orbital speed and axial depth of cut to accomplish relative motion between the cutter and workpiece.

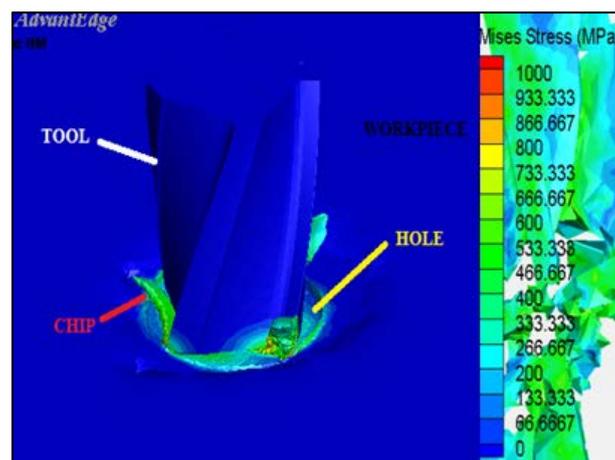


Figure 10: Simulation of helical milling for the first experiment

As per Table 1, process parameters were defined and simulation was carried out for the optimal process parameters experiments. Figure 10 shows the simulation of helical milling for the working conditions, spindle speed of 2000 rpm, the orbital speed of 50 rpm axial depth of 0.2 mm for the 8 mm diameter mill cutter. Stresses induced in the workpiece shearing zone and chip were also shown in Figure. 10. To measure the chip geometry in ThirdWave Advantedge software there is a tool named “measure distance”, hence chip geometry is also validated with aid of FEM along with other responses.

Table 8: Comparison to Estimated vs FEM values of responses

Sl.No	Outputs	Optimal factors				Estimated values	FEM Predicted values
		D	nc	no	ap		
1	F(N)	8	2000	50	0.2	463	452
2	P (W)	8	2000	50	0.2	542	498
3	b (mm)	8	2000	50	0.2	0.139	0.128

The FEM outputs predicted values in comparison to the mechanistic model approach estimated values of responses are tabulated in Table 8.

5. CONCLUSIONS

In the present study, experimental measurement of cutting forces and power consumption is done. As the literature revealed chip geometry plays a significant role in optimization of machining operation, a mechanistic approach was used to model chip geometry, cutting force and power consumption with respect to tool rotation. The process parameters are optimized with GTMA approach for better machining performance. The following conclusions were drawn from this study:

- a) Chip geometry at 90° of cutter rotation was estimated using the mechanistic approach and also estimated with numerical simulation. It was observed that the chip geometry i.e., depth of the chip increased with respect to cutter rotation.
- b) Multi optimization approach GTMA the highest total utility of 7.030, process parameters are considered as best suitable i.e., spindle speed 2000 rpm, orbital speed 50 rpm, axial depth of cut 0.2 mm during helical milling of AISI D2 steel.
- c) At 2000 rpm of spindle speed, 50 rpm of orbital speed and 0.2 mm of depth of cut, lower cutting forces and power consumption were obtained as 0.139 mm, 463 N and 542 W respectively for 8 mm diameter mill cutter at 90° of cutter rotation.
- d) The estimated and simulated responses were compared with the experimental values and are found under an acceptable agreement among them. As FEM simulation takes much time for prediction of responses, these kinds of mechanistic models with simple calculations can be considered for the prediction of responses quickly and also accurately.

Finally, the FEM simulations are performed for the optimized process parameters for validating the outcomes. It was observed that there is a strong closeness between simulated and semi-analytical estimated values of all the responses. The study has a further scope of application of ultrasonic vibration-assisted helical milling of a variety of difficult to cut materials.

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