Prediction of burr formation during face milling using an artificial neural network with optimized cutting conditions

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Abstract: Burrs formed during face milling operations are difficult to characterize because there are several parameters with complex interactions that affect the cutting process. In this paper, a combined artificial intelligence and optimization approach is introduced to predict burr types formed during face milling. The Taguchi method was selected for the optimization and an artificial neural network (ANN) was constructed for the machining of aluminium alloy 6061-T6. For the training of the ANN, the input was non-dimensionalized using the optimized results from the Taguchi method. The resulting ANN output was in agreement with experimental results, validating the proposed scheme.

Keywords: face milling, burr, optimization, cutting parameters, Taguchi method, ANOVA, ANN

1 INTRODUCTION

Burrs are defined as undesirable projections of materials beyond the edge of the workpiece arising because of plastic deformation during machining [**1**]. Burrs can cause many problems during inspection, assembly, and automated manufacturing of precision components. Therefore, it is desirable for precision parts to be burr free.

In general, there are two ways to deal with troublesome burrs. One option is deburring. As mentioned by Gillespie [**2**], burr removal processes are often costly, accounting for up to 30 per cent of the total cost of precision machining parts. Also, deburring processes are hard to generalize because they vary according to manufacturing circumstances. The other choice is burr planning with parameter optimization [**3–6**], which not only prevents the formation of burrs or minimizes their negative influences, but also predicts the types and locations of burrs by designing and analysing manufacturing processes and parameters. For this approach, a careful investigation of process parameters and their interactions is necessary.

When conducting burr research in areas such as burr planning and burr removal, relevant burr formation mechanism(s) need to be understood. Since theoretical approaches are usually not available, researchers have concentrated on experimental studies to identify the effects of machining parameters on burr formation [**7–12**].

Among these, Chern [**9**] investigated exit burrs during face milling on aluminium (Fig. 1). He observed four different types of burr with variations in depth of cut and in-plane exit angle: knife-edge, curl, wave, and secondary. The first three types of burr are primary burrs that have to be removed. The secondary burrs are relatively small burrs that remain after the main portions of the larger primary burrs are cut off. They typically do not pose a problem and therefore do not require deburring.

Several practical applications have demonstrated the need for an optimized set of specific machining parameters. Experimental studies have shown that burrs can be minimized or controlled when adequate machining parameters are selected; however, the results of these studies tend to be limited to certain process parameters, such as range and materials, owing to the complicated interactions among parameters. Recently, the Taguchi method, a widely

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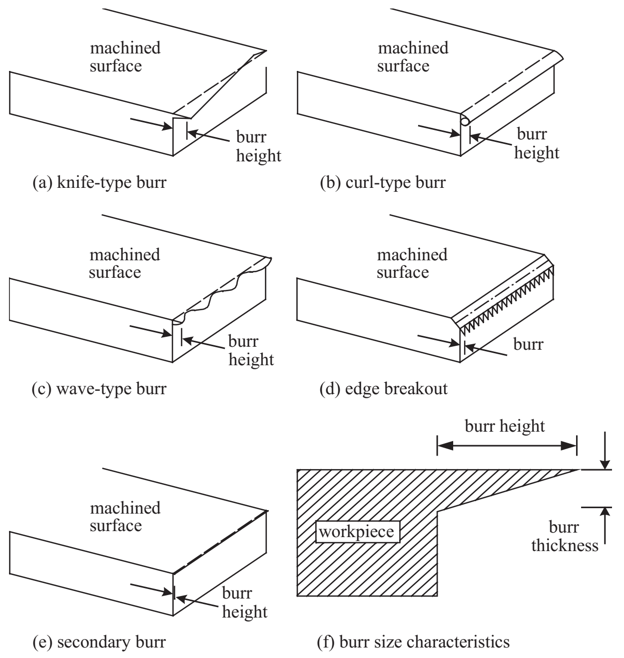


Fig. 1 Exit burr types [**9**]

used systematic optimization application in the design and analysis of experiments, has been successfully introduced in various manufacturing areas including burr formation [**3**, **13**].

In addition to parameter optimization, attention has focused on online prediction and classification methods for burrs generated during the manufacturing process. Tseng and Chiou [**14**] tried to predict burr height by using an artificial neural network (ANN). Although they used the Taguchi method for training selected input and output samples for 'micro-adjustment', their method has inherent problems including the lack of experimental and theoretical verification of parameter selection and the lack of explicit connectivity between the Taguchi method and the ANN. Moreover, it is conceivable that burr height is inappropriate as an absolute measure for the burr formation characteristics of a machined part.

In this study, cutting parameter optimization is performed with respect to burr minimization in face milling, and a subsequent burr-type prediction scheme based on the optimal results is proposed. The Taguchi method was used for the optimization of the experimental parameters for minimum burr heights. For the Taguchi method, parameters based on experimental and theoretical investigations and their ranges were used. After examining performance characteristics in more detail by employing analysis of variance (ANOVA), the optimized results were used to normalize the input vectors of an ANN. The final step of this research was to construct an ANN for the burr-type prediction, as burr types are more effective than simple dimensions including burr heights for the evaluation of edge finishing quality and suitability of deburring [**15**, **16**].

2 TAGUCHI METHOD AND PARAMETER DESIGN

In order to evaluate all the effects of several parameters on performance (e.g. cutting parameters on burr heights), a specially designed experimental process, or design of experiment is needed. One viable approach is the Taguchi method, which evaluates the performance of the parameters in terms of variation.

The first step in the Taguchi method is the selection of design parameters and their levels. The selection process should be such that the parameters efficiently reflect the effects of physical experimental conditions on characteristic values. In addition, the range of parameter levels should be selected to be as wide as possible to ensure stability in parameter design [**17**].

Once the parameters are chosen, the next step is parameter design. The goal of parameter design is to improve quality without controlling or eliminating the causes of variation and to make the product robust against noise factors. In parameter design, robustness can be achieved by reducing the effects of the noise terms through the selection of different design alternatives or by varying the levels of the design parameters for component parts or system elements. Use of an orthogonal array is a widely followed approach in parameter design. An orthogonal array is used to make process improvement decisions with the minimum amount of experimental data, e.g. utilizing a fractional–factorial approach whenever there are several parameters involved. This array indicates a way of conducting the minimal number of experiments that will ultimately yield the full set of variables affecting the output performance.

In parameter design, the index for stability can be expressed in terms of the loss function and the signal-to-noise (S/N) ratio. The loss function is used to indicate the degree of characteristic value deviation from the nominal values. The S/N ratio is a transformation of the repetition data (loss function) and a measure of the variation present. In the design process, a higher S/N ratio is more desirable. A higher S/N ratio implies that characteristic values are close to the nominal outputs in the presence of noise. Three types of S/N ratio are used, depending on the type of characteristic: the nominal the better, the lower the better, and the higher the better. Since this study concerns the minimization of burrs, a lower S/N ratio is better. The loss function and corresponding S/N ratio can be expressed as

$$\text{Loss function} = \frac{1}{n}\sum_{k=1}^{n} y_{ij}^2 \tag{1}$$

$$\text{S/N ratio} = -10\log\left(\frac{1}{n}\sum_{k=1}^{n} y_{ij}^2\right) \tag{2}$$

where n denotes the number of repeated experiments and y_{ij} is the jth experimental value in the ith experiment.

ANOVA can be used to identify the significant control factors that increase the average value of the S/N ratio and subsequently to reduce variations [**18**]. The purpose of ANOVA is to show the significance of each selected parameter to the characteristic value. The total sum S_T of the squared deviations can be expressed as

$$S_T = \sum_{j=1}^{n} (\eta_j - \eta_m)^2 \tag{3}$$

where n is the number of experiments in the orthogonal array, η_j is the jth S/N ratio, and η_m is the mean value of the S/N ratio. The squared deviation S_T can be decomposed into two components: the sum S_i of squared deviations due to each parameter and the sum S_ε of the squared errors. The percent contribution ρ is the percentage of each parameter deviation in the total sum S_T. In addition, the F value, which is the ratio of S_i to S_ε, is used to indicate quantitatively the significance of each parameter compared with the error terms. From the results of ANOVA, a parameter that has very low F and ρ values is insignificant to the characteristic value and can be regarded as an error term with the consideration of other factors such as economical efficiency and workability. The parameter design procedure based on the Taguchi method is summarized in Fig. 2.

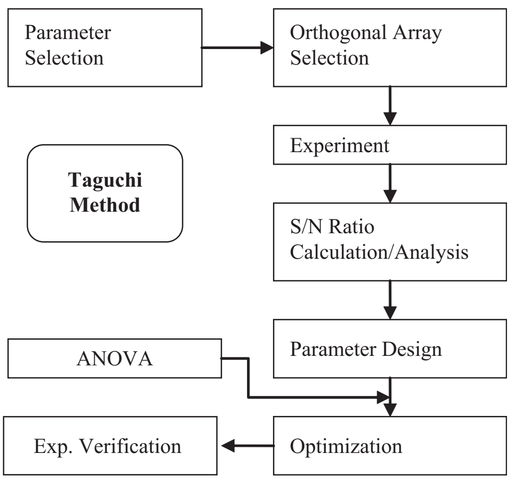


Fig. 2 Optimization using the Taguchi method

A well-designed set of optimized parameter values from the Taguchi method can ensure optimized performance characteristics and reliable reproduction of the desired characteristic values with a minimal range of variation.

3 EXPERIMENTS

3.1 Materials, machine tool, and measurement

Aluminium alloy 6061-T6, an easy-to-machine material which is frequently used in burr research, is selected for the experiments (Table 1).

The experiments were carried out using a Shizuoka sh-40-type vertical milling machine with 2.2 kW (3 hp) main spindle motor on rectangularly shaped workpieces (25 mm × 25 mm × 50 mm) (Fig. 3). The machine allows discrete variation in the spindle speed (75–3600 r/min in 16 steps) and the table linear velocity (15–720 mm/min in 12 steps). The diameter of the face milling cutter was 100 mm, and Korloy grade A30 carbide inserts were used for the aluminium. The radial rake angle and axial rake angle were 0° and 7° respectively. Figure 4 shows the primary and secondary burrs generated during the preliminary experiments. For the measurement of burr

Table 1 Mechanical properties and recommended machining ranges of aluminium alloy 6061-T6

Tensile strength (MPa)	310
Yield stress (MPa)	275
Fracture strain	0.50
Thermal conductivity (W/m K)	222
Recommended machining range*	
Feed (mm/tooth)	0.1–0.4
Cutting speed (D = 100 mm) (r/min)	1270–3185
Depth of cut (mm)	1–5

*Data from the tool company (http://korloy.com).

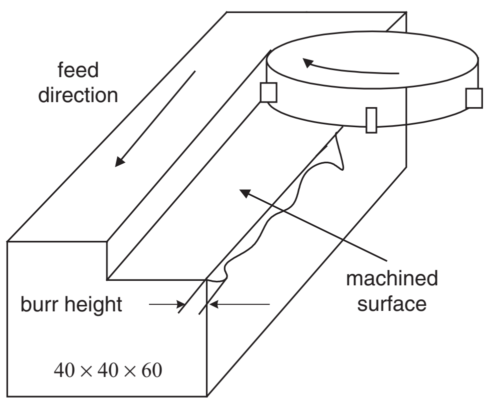
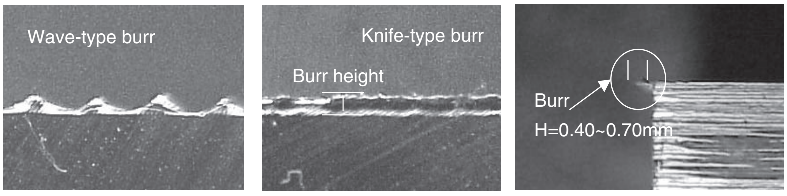
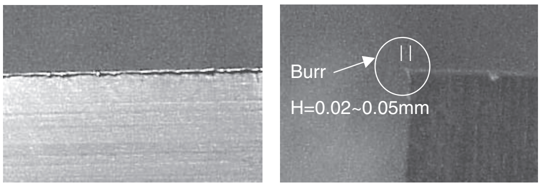


Fig. 3 Schematic diagram of the experiment

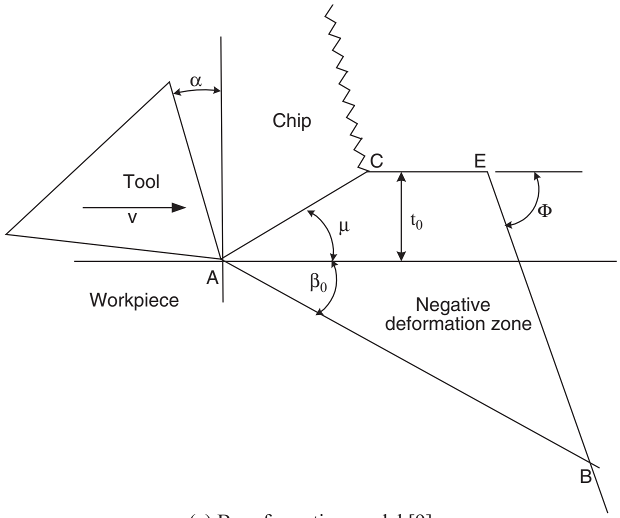


(a) Primary (wave-type) burr (b) primary (knife-type) burr (c) primary burr (side view)

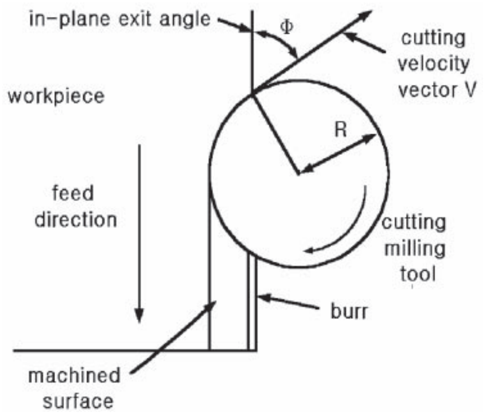


(d) Secondary burr (e) secondary burr (side view)

Fig. 4 Typical burrs generated during the experiments



(a) Burr-formation model [9]



(b) In-plane exit angle in face milling

Fig. 5 Burr formation model [**9**] and in-plane exit angle

heights, an optical microscope with 0.005 mm resolution was used. With the exception of both ends, average values along the workpiece edge were taken for burr height estimation.

Table 2 Selected machining parameters

Cutting variable	Units
In-plane exit angle	deg
Depth of cut	mm
Feed rate	mm/tooth
Cutting speed	r/min

Table 3 Parameter ranges for preliminary experiments

		Range	
Parameter	Initial conditions	Preliminary experiment	Decided
In-plane exit angle (deg)	90	30–150	30–150
Depth of cut (mm)	2.5	0.5–5.5	0.5–4.5
Feed rate (mm/tooth)	0.15	0.05–0.25	0.05–0.2
Cutting speed (r/min)	800	250–3600	300–1100

Table 4 Parameters and their levels

Parameter	Level 1	Level 2	Level 3	Level 4
In-plane exit angle (deg)	30	70	110	150
Depth of cut (mm)	0.5	1.0	1.5	2.0
Feed rate (mm/tooth)	0.05	0.1	0.15	0.2
Cutting speed (r/min)	300	500	700	900

3.2 Selection of cutting parameters

Chern [**9**] derived an equation for the incremental work done for the burr formation in orthogonal cutting, which is

$$\Delta W_{\text{burr}} = \left(\frac{\sigma b v t_0}{12}\right)\left\{\frac{\sin\beta_0(\cot\mu + 0.5\cot\beta_0)}{(\cos\beta_0 - \sin\beta_0\cot\phi)} \times\left[2 + 3\cot\beta_0 - 3\cot(\mu+\beta_0)\right]\right\}\Delta T \tag{4}$$

where t_0 is the depth of cut, β_0 is the initial negative deformation angle, Φ is the in-plane exit angle, v is the cutting speed, μ is the shear angle, σ is the

Table 5 L_{16} orthogonal array and experimental results

Experiment	Parameters: In-plane exit angle (deg)	Depth of cut (mm)	Feed rate (mm/tooth)	Cutting speed (r/min)	Burr type	Average burr height	S/N ratio
1	1	1	1	1	Type 1	0.13	17.72
2	1	2	2	2	Type 1	0.06	24.43
3	1	3	3	3	Type 1	0.12	18.41
4	1	4	4	4	Type 1	0.15	16.47
5	2	1	2	3	Type 1	0.21	13.55
6	2	2	1	4	Type 1	0.08	21.93
7	2	3	4	1	Type 2	0.65	3.74
8	2	4	3	2	Type 1	0.43	7.33
9	3	1	3	4	Type 2	0.60	4.43
10	3	2	4	3	Type 1	0.17	15.39
11	3	3	1	2	Type 1	0.51	5.84
12	3	4	2	1	Type 2	0.72	2.85
13	4	1	4	2	Type 2	0.55	5.19
14	4	2	3	1	Type 2	1.04	−0.34
15	4	3	2	4	Type 2	0.90	0.91
16	4	4	1	3	Type 2	0.80	1.93

maximum normal stress of the negative deformation zone (which is proportional to the yield stress of the workpiece), b is the width of cut, and ΔT is the elapsed time for the incremental tool movement (Fig. 5(a)). Since the negative deformation angle is dependent on the shear angle and the in-plane exit angle [**9**], and the shear angle is determined by the rake angle (α in Fig. 5(a)) and material properties [**19**], it can be stated that

$$\text{Burr formation} \approx (\text{materials function}(v, t_0, \Phi, \text{feed})) \qquad (5)$$

Therefore, for the multipoint cutting (face milling), four cutting parameters (Table 2), which are critically influential to burr generation and size, were selected. Moreover, these parameters have been widely used in previous research [**8–12**]. As illustrated in Fig. 5(b), the in-plane exit angle during face milling is defined as the angle between the cutting velocity and the exit velocity of the cutter at the end of the workpiece. As mentioned above, the in-plane exit angle is a significant factor for determining burr sizes.

3.3 Parameter levels and orthogonal arrays

Before moving on to the designed experiments, preliminary experiments were performed to determine practical machinable ranges and parameter levels. Since the recommended number of levels in practice is typically four to six [**18**], the initial degree of freedom for each parameter was selected as four. During the experiments, one parameter value was varied while the other parameter values remained fixed at the initial conditions.

For the aluminium, experiments were performed relatively thoroughly throughout all the ranges. By varying the cutting speed, corresponding burr heights were gradually reduced as the cutting speed increased. The upper limit was selected as 1100 r/min because only secondary burrs were formed when the cutting speed was above that value. Feed rate experiments had similar tendencies and, considering the recommended feed per tooth value (Table 1), the upper limit for the feed rate was selected. Moreover, most of the determined machining ranges existed inside the recommended machining ranges from the tool company. Tables 3 and 4 show the decided parameter ranges and their levels from the preliminary experiments.

As a result, the $L_{16}(4^4)$ standard orthogonal array (four cutting parameters and four levels) was used in this study. For the given orthogonal arrays, experiments were repeated four times each to acquire a reliable database.

Table 6 Average S/N ratios for each parameter level

Level	Average S/N ratio: In-plane exit angle (deg)	Depth of cut (mm)	Cutting speed (r/min)	Feed rate (mm/tooth)
1	**19.26**	10.23	**11.86**	5.99
2	11.64	**15.36**	10.44	10.70
3	7.13	7.23	7.46	**12.33**
4	1.93	7.15	10.20	10.94

4 OPTIMIZATION OF CUTTING PARAMETERS AND BURR-TYPE PREDICTION

4.1 S/N ratios and ANOVA of experimental results

Experimental results (Table 5) show that primary burrs, which were greater than 0.1 mm in height (Fig. 3),

Table 7 ANOVA results

Parameter	Degrees of freedom $\Phi_i - 1$	Sum of square S_i	Mean square $S_i/(\Phi_i - 1)$	$F = S_i/\ S_\epsilon$	$\rho = (S_i/S_T \times 100)$ (%)
In-plane exit angle (deg)	3	647.63	215.88	21.24	65.54
Depth of cut (mm)	3	178.14	59.38	5.84	18.03
Feed rate (mm/tooth)	3	40.59	13.53	1.33	4.11
Cutting speed (r/min)	3	91.35	30.45	3.00	9.24
ε	3	30.49	10.16		3.09
Total	15	988.18			100

i, parameter; Φ_i, number of the parameter level.

Table 8 Optimal parameters

Parameter	
In-plane exit angle	30°
Depth of cut	1.0 mm
Feed rate	0.05 mm/tooth
Cutting speed	700 r/min

Table 9 Prediction of S/N ratio and experimental verification

Average burr height (mm)	Optimum burr heights (mm)	η_m (dB)	$\overline{\eta_m}$ (dB)	$\hat{\eta}$ (dB)
0.44	0.030 0.031 0.024 0.034	10.0	30.1	30.9

were predominantly formed with an average height of 0.45 mm. Using equations (1) and (2), the average S/N ratios η_m were calculated as 9.99 dB. According to the parameter design procedure, the S/N ratios for each parameter level were computed as well (Table 6). The largest calculated values of each parameter are the optimal cutting conditions. The results also showed the correlation between the level of in-plane exit angle and the performance characteristic.

To study more detailed performance characteristics, ANOVA was performed. Table 7 shows the results of ANOVA using the calculated S/N ratios from Table 6. Consistent with the S/N ratio results, the in-plane exit angle is the most influential parameter with an F value of 21.2 and ρ value of 65.5 per cent. The second most influential parameter is the depth of cut and the other parameters are statistically insignificant because their ρ values are less than 10 per cent. Table 8 shows the selected optimal cutting parameters in this study.

In the final stage of the parameter design, the S/N ratios were estimated and validated with the selected optimal parameters. The estimated S/N ratio with the optimum process levels ($\hat{\eta}$) can be calculated from the equation

$$\hat{\eta} = \eta_m + \sum_{i=1}^{q} (\eta_i - \eta_m) \tag{6}$$

where η_m is the total mean of the S/N ratios, η_i is the mean of the S/N ratios for the optimum level, and q is the number of process parameters. Table 9 shows the verification experiments that were repeated at least four times with the selected optimum conditions. Burr heights were reduced to the point of being negligible in terms of the S/N ratio. Moreover, the average value $\overline{\eta_m}$ with optimum conditions was improved by 20 dB compared with the overall average value η_m. Therefore the optimized parameters reproduce secondary burrs with minimal heights.

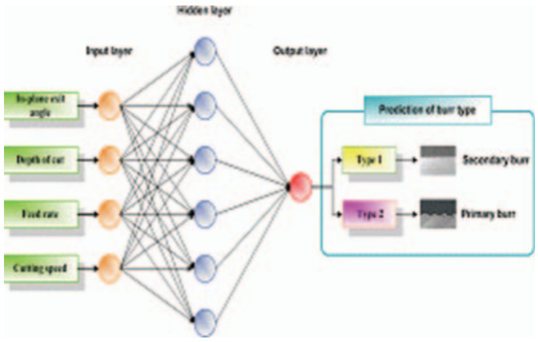


Fig. 6 Architecture of the neural network

4.2 Artificial neural network and non-dimensionalization

An ANN with a back-propagation algorithm was used to predict burr types (type 1, secondary burrs; type 2, primary burrs). Back propagation is a supervised learning technique that compares the responses of the output units with the desired response and re-adjusts the weights in the network so that the next time that the same input is presented to the network the network's response will be closer to the desired response [**20**]. The learning algorithm has become the most popular method [**21**], including in manufacturing applications [**22**, **23**], because of its simplicity and relative power. Figure 6 illustrates the

Table 10 Tendentious non-dimensionalization

Parameter		1	2	3	4	5	6	7
In-plane exit angle (deg)	Range	30	50	70	90	110	130	150
	Dimensionless	0	0.17	0.33	0.5	0.66	0.83	1
	Weight factor	0	0.17	0.33	0.5	0.66	0.83	1
Depth of cut (mm)	Range	0.5	0.75	1.0	1.25	1.5	1.75	2
	Dimensionless	0	0.17	0.33	0.5	0.66	0.83	1
	Weight factor	0	0.05	0.09	0.14	0.18	0.23	0.28
Feed rate (mm/tooth)	Range	0.05	0.075	0.1	0.125	0.15	0.175	0.2
	Dimensionless	0	0.17	0.33	0.5	0.66	0.83	1
	Weight factor	0	0.01	0.02	0.03	0.04	0.05	0.06
Cutting speed (r/min)	Range	300	400	500	600	700	800	900
	Dimensionless	1	0.83	0.66	0.5	0.33	0.17	0
	Weight factor	0.14	0.11	0.09	0.07	0.04	0.02	0

Table 11 Real non-dimensionalization

Parameter		1	2	3	4	5	6	7
In-plane exit angle (deg)	Range	30	50	70	90	110	130	150
	Dimensionless	0	0.17	0.33	0.5	0.66	0.83	1
	Weight factor	0	0.17	0.33	0.5	0.66	0.83	1
Depth of cut (mm)	Range	0.5	0.75	1.0	1.25	1.5	1.75	2
	Dimensionless	0	0.17	0.33	0.5	0.66	0.83	1
	Weight factor	0.09	0.05	0	0.14	0.18	0.23	0.28
Feed rate (mm/tooth)	Range	0.05	0.075	0.1	0.125	0.15	0.175	0.2
	Dimensionless	0	0.17	0.33	0.83	1	0.5	0.66
	Weight factor	0	0.01	0.02	0.05	0.06	0.03	0.04
Cutting speed (r/min)	Range	300	400	500	600	700	800	900
	Dimensionless	1	0.83	0.66	0.5	0	0.17	0.33
	Weight factor	0.14	0.11	0.09	0.07	0	0.02	0.04

Table 12 Learning conditions for training the ANN

Input nodes	Output node	Learning conditions
1. In-plane exit angle 2. Feed rate 3. Depth of cut 4. Cutting speed	Burr type (type 1 × type 2)	1. Number of input nodes, 4 2. Number of output nodes, 1 3. Number of hidden layer nodes, 6 4. Number of sample patterns, 8 5. Initial learning rate, 0.1 6. Error bound, 0.1

Table 13 Leaning dataset (with dimension)

Input parameters				Desired output
In-plane exit angle (deg/min)	Depth of cut (mm)	Feed rate (mm/tooth)	Cutting speed (r)	(burr type (type 1 = 0, type 2 = 1))
30	0.5	0.15	300	0
30	1.0	0.1	500	0
70	0.5	0.1	700	0
70	1.0	0.05	900	0
110	0.5	0.15	900	1
110	1.0	0.2	700	0
150	0.5	0.2	500	1
150	1.0	0.15	300	1

architecture of the ANN with parameter-based (cutting condition) input.

For the effective learning procedure and accurate prediction results of the ANN, the parameter values were non-dimensionalized. For comparison purposes, three different types of input were generated for the ANN.

1. *Inputs with dimensions.*
2. *Non-dimensionalization with fixed direction (tendentious non-dimensionalization).* The non-dimensionalizing factors for the level values of each parameter started at 0 (for the first level) and increased monotonically to 1 (or vice versa). The

Table 14 Learning dataset (tendentious non-dimensionalization)

Input parameters				Desired output
In-plane exit angle (deg)	Depth of cut (mm)	Feed rate (mm/tooth)	Cutting speed (r/min)	(burr type (type 1 = 0, type 2 = 1))
0	0	0	0.14	0
0	0.09	0.02	0.09	0
0.33	0	0.02	0.04	0
0.33	0.09	0	0	0
0.66	0	0.04	0	1
0.66	0.09	0.06	0.04	0
1	0	0.06	0.09	1
1	0.09	0.04	0.14	1

Table 15 Learning dataset (real non-dimensionalization)

Input parameters				Desired output
In-plane exit angle (deg)	Depth of cut (mm)	Feed rate (mm/tooth)	Cutting speed (r/min)	(burr type (type 1 = 0, type 2 = 1))
0	0.09	0	0.14	0
0	0	0.02	0.09	0
0.33	0.09	0.02	0	0
0.33	0	0	0.04	0
0.66	0.09	0.06	0.04	1
0.66	0	0.04	0	0
1	0.09	0.04	0.09	1
1	0	0.06	0.14	1

Table 16 ANN results (with dimensions)

Input parameters				Output	Real type
In-plane exit angle (deg)	Depth of cut (mm)	Feed rate (mm/tooth)	Cutting speed (r/min)	(burr type (type 1 or type 2))	(burr type (type 1 = 0, type 2 = 1))
30	1.5	0.15	700	0.0183	0
30	2.0	0.2	900	0.0178	0
70	1.5	0.2	300	0.6562	1
70	2.0	0.15	500	0.1366	0
110	1.5	0.05	500	0.2521	0
110	2.0	0.1	300	0.8991	1
150	1.5	0.1	900	0.9467	1
150	2.0	0.05	700	0.8872	1

Table 17 ANN results (tendentious non-dimensionalization)

Input parameters				output	Real type
In-plane exit angle (deg)	Depth of cut (mm)	Feed rate (mm/tooth)	Cutting speed (r/min)	(burr type (type 1 or type 2))	(burr type (type 1 = 0, type 2 = 1))
0	0.18	0.04	0.04	0.0002	0
0	0.28	0.06	0	0.0001	0
0.33	0.18	0.06	0.14	0.7656	1
0.33	0.28	0.04	0.09	0.1038	0
0.66	0.18	0	0.09	0.1081	0
0.66	0.28	0.02	0.14	0.9083	1
1	0.18	0.02	0	0.9984	1
1	0.28	0	0.04	0.9685	1

Table 18 ANN results (real non-dimensionalization)

Input parameters				output	Real type
In-plane exit angle (deg)	Depth of cut (mm)	Feed rate (mm/tooth)	Cutting speed (r/min)	(burr type (type 1 or type 2))	(burr type (type 1 = 0, type 2 = 1))
0	0.18	0.06	0	0.0001	0
0	0.28	0.04	0.04	0.0001	0
0.33	0.18	0.04	0.14	0.8489	1
0.33	0.28	0.06	0.09	0.0272	0
0.66	0.18	0	0.09	0.0833	0
0.66	0.28	0.02	0.14	0.9921	1
1	0.18	0.02	0.04	0.9992	1
1	0.28	0	0	0.9591	1

Table 19 Average prediction errors

Input	Error (%)
With dimensions	13
Tendentious dimensionless	7
Real dimensionless	3.9

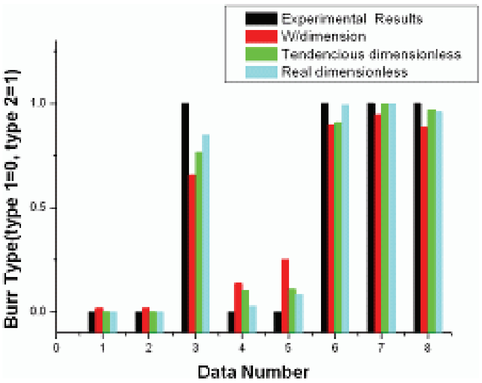


Fig. 7 Comparison of the ANN results

ANOVA results were considered as weight factors. Here, 0 means the smallest burr height (characteristic of secondary burrs) and 1 is the largest (characteristic of primary burrs) (Table 10).

3. *Non-dimensionalization with optimized results (real non-dimensionalization)*. Based on optimized parameter level values and corresponding ANOVA results, the non-dimensionalizing factors and weight factors were assigned accordingly (Table 11).

Table 12 shows the learning conditions of the ANN and Tables 13, 14, and 15 show the learning datasets. Among a total of 48 datasets selected, half were used for learning and the rest were used for the ANN prediction.

After the learning procedures, the input vectors were fed into the ANNs and the burr-type predictions were performed. The prediction results are averaged values after four runs for each condition using different random initial weights. The results are summarized in Tables 16 to 19 and are also plotted against experimental data in Fig. 7, which shows that the dimensionless inputs, particularly the real dimensionless inputs, produce more reliable results in predicting burr types than inputs with dimensions.

5 CONCLUSIONS

In order to predict burr types during face milling, a combined artificial intelligence and optimization approach was introduced. An ANN was constructed for the machining of aluminium alloy 6061-T6. For training the ANN, the input was non-dimensionalized using the optimized results from the Taguchi method. The conclusions are as follows.

1. With thorough parameter selection processes based on experimental and theoretical investigations, the cutting conditions for minimal burr heights can be selected using the Taguchi method.
2. When predicting the burr types, a non-dimensionalized input produces more reliable results than an input with dimensions.
3. With the proposed scheme, a burr-type prediction classifier can be constructed for specific recommended machining ranges.

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APPENDIX

Notation

b	width of cut
F	ratio of S_i to S_ε
S_i	sum of the squared deviations due to each parameter
S_{T}	total sum of the squared deviations
S_ε	sum of the squared errors
t_0	depth of cut
v	cutting speed
β_0	initial negative deformation angle
ΔT	elapsed time for the incremental tool movement
ΔW_{burr}	incremental work done for the burr formation in orthogonal cutting
$\hat{\eta}$	optimum process levels
η_i	mean of the signal-to-noise ratios for the optimum level
η_j	jth signal-to-noise ratio
η_{m}	mean value of the signal-to-noise ratio
$\overline{\eta_{\mathrm{m}}}$	average value with optimum conditions
μ	shear angle
ρ	percentage of each parameter deviation from the total sum (S_{T})
σ	maximum normal stress in the negative deformation zone
Φ	in-plane exit angle