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ORIGINAL ARTICLE

Optimization of machining parameters on temperature rise in end milling of Al 6063 using response surface methodology and genetic algorithm

P. S. Sivasakthivel · R. Sudhakaran

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Abstract This present study focused on the effect of machining parameters such as helix angle of cutter, spindle speed, feed rate, axial and radial depth of cut on temperature rise in end milling. A prediction model of the temperature rise was developed using response surface methodology. The experiments were conducted on Al 6063 by high-speed steel end mill cutter based on central composite rotatable designs consisting of 32 experiments. The temperature rise was measured using K-type thermocouple. The adequacy of the model was verified using analysis of variance. The given model is utilized to analyze direct and interaction effect of the machining parameters with temperature rise. The optimization of machining process parameters to obtain minimum temperature rise was done using genetic algorithms. A source code using C language was developed to do the optimization. The obtained optimal machining parameters gave a value of 0.173 °C for minimum temperature rise.

Keywords Response surface · Analysis of variance · Cutting temperature · Mathematical model · Genetic algorithm

1 Introduction

In end milling operation, heat energy is generated at the tool chip interface in deforming chip and overcoming friction between the tool and work piece. The power utilized during end milling is mostly converted into heat energy near the cutting edge of the tool. The heat energy produces high temperature in the deformation zones and surrounding regions of the chip, tool and work piece. This temperature rise propagates tool wear, degrades the work piece quality and increases the tooling cost. The temperature rise affects the work material properties, as moderate temperature rise induces residual stress in the machined surface, while high temperature rise may leave a hardened layer on the machined surface [1]. The cutting tool which possesses high hardness at room temperature cannot retain the hardness at high temperature during milling. Hence, temperature rise on the rake face of the tool have a strong influence on tool life [2]. As temperature in this area increases, the tool softens and wears more rapidly, the tool material diffuses into chip and leads to tool failure and the work piece material adhere to the tools, which causes rapid wear. The softening of the tool due to high temperature rise propagates wear rapidly. Therefore, determining the critical value of the temperature becomes important for the reduction of tool wear. Temperature rise on the relief face of the tool affect the surface finish and metallurgical state of the machined surface. Cutting temperature is an important factor that influences tool wear and surface finish in the machining performance. The temperature at the tool cutting edge is affected by properties of work piece material, cutting condition of the machine tool, tool geometry and many other variables.

The measurement of cutting temperatures is more difficult because the temperature is a scalar field which varies throughout the system and cannot be uniquely described by values at a point. The most widely used method to measure cutting temperatures is tool-work thermocouple, which measures average interfacial temperature at tool work piece interface [3]. The thermocouple can be embedded in the tool or work piece to measure the temperature accurately with less effort. Smart and Trent [4] measured the cutting temperature by inserting thermocouple in the hole drilled in the work piece. Thermocouples are conductive, operate over a

P. S. Sivasakthivel (✉)
School of Mechanical Engineering, SASTRA University,
Thanjavur - 613401, Tamil Nadu, India
e-mail: sakthi_2011@mech.sastra.edu

R. Sudhakaran
Department of Mechanical Engineering, SNS College of
Engineering, Coimbatore - 641107, Tamil Nadu, India
e-mail: absudha@yahoo.com

wide temperature range, rugged and inexpensive [5]. This measurement by thermocouple is very useful to study the effects of the cutting parameters on the temperature. An understanding of cutting temperatures at tool work piece interface provides insight into the effects of cutting parameters on the temperature. A cost-effective application is required for end milling operation to understand the relationship between temperature rise and performance measures (tool wear and surface finish). Hence, an effective model is essential to predict the cutting temperature becomes necessary.

The current study takes into account the temperature rise for analysis to understand its effect on performance measures, to determine its predictive model from machining parameters and to optimize temperature rise by using response surface methodology and genetic algorithm. The literature survey pertaining to the work of other researchers is given below. Zakaria and ElGomayel [6] examined the reliability of monitoring tool wear by measuring the cutting temperature. They measured the on-line cutting temperature using the tool-work piece thermocouple technique. They concluded that the thermal voltage signal is very sensitive to the cutting conditions and increases with the increase in tool wear. Mathew [7] presented a method to describe the relationship between the log of the tool wear rates and the reciprocal of the absolute temperatures achieved at the tool/chip interface. Cutting temperatures was predicted by considering the dynamic flow stress and temperature properties of the work material when machining plain carbon steels. Maekawa et al. [8] developed a method to study the effect of cutting temperature and tool wear on high-speed turning operation of Inconel 718 and milling operation of Ti–6Al–6V–2Sn alloy. They investigated the temperature and wear of cutting tools by means of cutting experiments and numerical analysis by varying the cutting speed. A numerical model had been proposed to validate the temperature measurement. Lazoglu and Altintas [2] proposed a numerical model based on the finite difference method to predict tool and chip temperature fields in continuous machining and time varying milling processes. They found that the model results are in satisfactory agreement with experimental temperature measurements. Choudhury and Bartarya [9] proposed an empirical relation between the cutting zone temperature and input variables such as cutting speed, feed and depth of cut in turning process by employing design of experiments and artificial neural networks. They compared the predicted values with the experimental values and determined their closeness with the experimental values.

Dessoly et al. [10] developed a model based on the moving heat source theory of conduction. They analyzed the heat transfer and temperature distribution in rotary tool turning of hardened 52100 steel (58 HRC). This model was experimentally verified for different cutting conditions. Palanisamy et al. [1] estimated tool–chip interface temperatures for different machining conditions by using Oxley's energy partition function and also analyzed the thermal effect on the cutting force using Rapier's equation. They concluded that the maximum temperature in the tool increases with the increase in the cutting speed. Haci et al. [11] presented the modeling of the tool/chip interface temperature distribution during orthogonal metal cutting and found that the proposed model data have better agreement with the experimental results. Weinert et al. [12] described the influences of the material properties and the process conditions on the cutting temperatures while drilling polymer materials. They concluded that high tool temperatures lead to melting and thermal damage of the material in the peripheral zone of the drilled hole. Geerdes and Alvardo [13] presented a finite element technique combined with artificial neural network to predict the temperature in a hot strip mill. This hybrid computing technique helps in predicting cutting tool temperature with more accuracy and has less dependency on experimental data. Zhang and Liu [14] presented a one-dimensional transient temperature distribution in monolayer coated tools. They provided data for selecting appropriate coating of materials to reduce temperature within coated tools.

Kadirgama et al. [15] proposed a first-order temperature model using the response surface methodology to determine the temperature distribution on cutting tool when machining hastelloy C-22HS with carbide coated cutting tool. The first-order model indicates that the cutting conditions such as feed rate, axial depth of cut and cutting speed plays an important role in determining temperature at the cutting zone. They verified the experimental results by applying finite element analysis. Suhail et al. [16] employed the Taguchi technique to optimize the cutting parameters using work surface temperature and surface roughness as performance measure. They concluded that work piece surface temperature can be sensed and used effectively as an in-process signal for optimizing cutting parameters. Liu et al. [17] applied the particle swarm optimization technique to develop nonlinear curve for determining cutting temperature. Liu and Wang [18] used the modified genetic algorithm for the optimization of milling parameters. They concluded that the simulation and experimental results showed an improvement in performance. Reddy and Rao [19] applied genetic algorithm to optimize the machining parameters such as radial rake angle, nose radius, cutting speed and feed rate to obtain minimum surface roughness in end milling operation. Palanisamy et al. [20] employed the genetic algorithm technique to minimize the machining time and cutting force, to increase productivity and tool life and obtain better surface finish. The result of the work shows how a complex optimization problem can be handled by genetic algorithm and the result converges very quickly. Venkatesan et al. [21] proposed a genetic algorithm based artificial neural network model for developing a model between the process parameters and tool performance in the turning process. They concluded that genetic algorithm-based ANN model can provide accurate results in less time. Bharathi Raja and Baskar [22] applied genetic algorithm for the mathematical models of different machining operation and concluded that the genetic algorithm is effective in converging equation to give optimum solution.

The literature indicated above reveals that not much work has been reported on prediction and optimization of temperature rise in metal cutting. The tool geometry helix angle of the cutting tool has been included in the machining parameters during the prediction which has not been concentrated by other researchers. In this work, the main objective is to develop a model based on response surface methodology to the cutting temperature rise in terms of machining parameters such as helix angle of cutting tool, spindle speed, feed rate, axial and radial depth of cut. Furthermore, the statistical model developed was utilized to optimize the machining parameters to obtain minimum temperature rise using genetic algorithm. During milling, the maximum cutting temperature rise is measured using K-type thermocouple. The mathematical model helped us to study the direct and interaction effect of each parameter.

2 Experimental design

Response surface methodology is the most effective method to analyze the results obtained from factorial experiments. It is an effective tool for modeling and analyzing the engineering problems. It provides more information with less number of experimentation. It is an experimental strategy for exploring the limits of the input parameters and developing empirical statistical model for the measured response, by approximating the relationship existing between the response and input process parameters. The limit of the process parameters has to be defined in response surface methodology and the initial experimentation was done to identify the machining parameters that affect the temperature rise and to explore the range of the selected machining parameters. In the present work, helix angle of cutting tool, spindle speed, feed rate, axial and radial depth of cut have been considered as the machining parameters. The response temperature rise T can be expressed as a function of process parameters helix angle (α), spindle speed (N), feed rate (Z), axial (X) and radial depth of cut (Y).

$$\text{Temperature rise, } T = \phi\,(\alpha_{iu}, N_{iu}, Z_{iu}, X_{iu}, Y_{iu}) + e_u \qquad (1)$$

where ϕ is the response surface, e_u is the residual, u is the number of observations in the factorial experiment and iu represents level of the ith factor in the uth observation.

When the mathematical form of ϕ is unknown, this function can be approximated satisfactorily within the experimental region by polynomials in terms of the process parameter variable. Box and Hunter [23] proposed the central composite rotatable design for fitting a second-order response surface based on the criterion of rotatability. The selected design plan chosen consists of 32 experiments. It has five factors—five levels central composite rotatable design consisting of 32 sets of coded conditions (Table 1). The design for the above said experiment comprises of a ½ replication of 2^5 (=16) factorial design plus six center points and ten star points. These correspond to first 16 rows, the last six rows and rows from 17 to 26, respectively, in the design plan as shown in Table 2.

For ½ replicate, the extra point included to form a central composite design, α, becomes $2^{(k-1)/4}=2$. The upper limit of the parameter is coded as 2, lower limit as −2 and the coded values for intermediate values were calculated from the following relationship [24]:

$$X_i = \frac{2(2X - (X_{\max} + X_{\min}))}{(X_{\max} - X_{\min})} \qquad (2)$$

where

X_i required coded value of a variable X
X any value of the variable from $X_{\min}$ to $X_{\max}$
$X_{\min}$ lower limit of the variable
$X_{\max}$ upper limit of the variable

The intermediate values coded as −1, 0 and 1.

3 Experimental details

The experiments were conducted on a HAAS vertical machining center: model tool room mill with high-speed steel end mill cutter under dry condition. The work piece material was Aluminium alloy (Al 6063) commonly available machinable metal which finds application in automobile and valve industries. The dimension of the work piece specimen was 32× 32 mm in cross section and 40 mm in length. The temperature was measured by using K-type thermocouple and the observations are tabulated to obtain the mathematical model (Table 2). A 1-mm hole was drilled in the work piece specimen at 4 mm below the machining surface. A K-type thermocouple was inserted into the hole and the initial temperature was noted using the digital thermometer. During machining, the maximum temperature was measured, the difference between the maximum and initial temperature gave the temperature rise.

4 Development of mathematical model

The general form of a quadratic polynomial which gives the relation between response surface y and the process variable x under investigation is given by

Table 1 Parameters and levels in milling

Parameter	Units	Factor levels				
		−2	−1	0	1	2
Helix angle (α)	°	30	35	40	45	50
Spindle speed (N)	rpm	2,000	2,500	3,000	3,500	4,000
Feed rate (Z)	mm/rev	0.02	0.03	0.04	0.05	0.06
Axial depth of cut (X)	mm	1.5	2	2.5	3	3.5
Radial depth of cut (Y)	mm	1.5	2	2.5	3	3.5

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i<j} b_{ij} x_{ij} \tag{3}$$

Where b_0 is a constant, b_i is the linear term coefficient, b_{ii} is the quadratic term coefficient and b_{ij} is the interaction term coefficient.

Table 2 Experimental design—central composite design matrix

S. no.	Control factors					Temperature rise (°)		
	α	N	Z	X	Y	Observed value	Predicted value	% Error
01	−1	−1	−1	−1	1	30.5	29.90	1.96
02	1	−1	−1	−1	−1	20.2	20.06	0.65
03	−1	1	−1	−1	−1	37.9	37.10	2.08
04	1	1	−1	−1	1	17.1	17.22	−0.73
05	−1	−1	1	−1	−1	36.9	35.81	2.95
06	1	−1	1	−1	1	27.5	27.57	−0.27
07	−1	1	1	−1	1	43.1	42.22	1.92
08	1	1	1	−1	−1	31.2	31.08	0.36
09	−1	−1	−1	1	−1	44.8	44.66	0.31
10	1	−1	−1	1	1	26.1	26.57	−1.83
11	−1	1	−1	1	1	40.3	39.87	1.06
12	1	1	−1	1	−1	28.5	28.23	0.92
13	−1	−1	1	1	1	34.7	34.76	−0.19
14	1	−1	1	1	−1	18.3	18.28	0.07
15	−1	1	1	1	−1	37.4	36.73	1.79
16	1	1	1	1	1	34.1	33.79	0.90
17	−2	0	0	0	0	59.3	60.96	−2.80
18	2	0	0	0	0	36.9	36.39	1.36
19	0	−2	0	0	0	23.9	23.99	−0.41
20	0	2	0	0	0	30.1	31.16	−3.54
21	0	0	−2	0	0	17.9	18.36	−2.58
22	0	0	2	0	0	21.5	22.53	−4.79
23	0	0	0	−2	0	17.1	17.71	−3.57
24	0	0	0	2	0	23.6	23.18	1.77
25	0	0	0	0	−2	28.1	29.28	−4.20
26	0	0	0	0	2	29.3	29.28	0.06
27	0	0	0	0	0	21.2	20.44	3.55
28	0	0	0	0	0	20.6	20.44	0.74
29	0	0	0	0	0	20.4	20.44	−0.22
30	0	0	0	0	0	20.3	20.44	−0.71
31	0	0	0	0	0	20.1	20.44	−1.72
32	0	0	0	0	0	20.6	20.44	0.74

The values of the coefficients of the polynomials were calculated by multiple regression method. A statistical software QA Six Sigma DOE PC IV was used to calculate the values of these coefficients. The second-order mathematical model was developed by neglecting the insignificant coefficients of the temperature rise (T).

$$\begin{aligned}\text{Temperature rise(T)} = {} & 20.446 - 6.142\alpha + 1.792\mathrm{N} + 1.042\mathrm{Z} \\ & + 1.367\mathrm{X} + 7.059\alpha^2 + 1.784\mathrm{N}^2 \\ & - 2.209\mathrm{Y}^2 + 0.437\alpha\mathrm{N} + 1.287\alpha\mathrm{Z} \\ & + 0.937\alpha\mathrm{Y} + 1.638\mathrm{NZ} - 3.013\mathrm{ZX} \\ & + 2.062\mathrm{ZY} + 0.887\mathrm{XY} \qquad (4)\end{aligned}$$

where

α helix angle (°)
N cutting speed (rpm)
Z deed rate (mm/rev)
X axial depth of cut (mm)
Y radial depth of cut (mm)

The adequacy of the model was tested using the analysis of variance (ANOVA) technique (Table 3). The calculated F ratio of the model does not exceed the standard value, and the calculated R ratio of the model exceeds the standard value for a desired 95 % level of confidence. Table 3 shows that the model is adequate, and that the error between the experimental and predicted values is less than 5 %.

5 Genetic algorithm

Genetic algorithm is a computerized search and optimization algorithm based on the mechanics of natural genetics and natural selection. According to the concept of survival of the fittest, the fittest individuals of any population have the highest probability to reproduce and survive to the next generation, thus improving successive generations. However, inferior individuals also have meager chances to survive and reproduce. Genetic algorithm is a population-based search technique used to solve both linear and nonlinear problems by exploring all regions of the stated space and range [25, 26]. The data processed by genetic algorithm includes a set of strings or chromosomes with an infinite length in which each bit is called an allele (or a gene). A selected number of strings are called population and the population at a given time is known as generation. Generations of the initial population of strings are randomly based since the binary alphabet offers the maximum number of schemata per bit of information of any coding. A binary encoding scheme is traditionally used to represent the chromosomes using either zeros or ones. Thereafter, the fitness value (objective function value) of each member is computed. The population is then operated by the three main operators namely, reproduction, crossover and mutation to create a new population. The new population is further evaluated and tested for determination. The completion of an iteration of these operators is known as generation in the parlance of genetic algorithm. The current population is checked for acceptability or solution. The iteration is stopped after the completion of maximum number of generations or on the attainment of the best results.

The steps involved in the genetic algorithm are described below:

Step 1 Choose a coding to represent problem parameters, a selection operator, a crossover operator, and a mutation operator. Choose a population size n, a crossover probability p_c, and mutation probability p_m. Initialize a random population of strings of size l. Choose a maximum allowable generation number t_{max}. Set t=0.
Step 2 Evaluate each string in the population.
Step 3 If t _ $t$max or other termination criteria is satisfied, terminate.
Step 4 Perform reproduction on the population.
Step 5 Perform crossover on pair of strings with probability p_c.
Step 6 Perform mutation on strings with probability p_m.
Step 7 Evaluate strings in the new population. Set=t+1 and go to step 3

5.1 Objective function

The objective in this study is to minimize average temperature rise. The mathematical model developed in the chapter can be utilized to obtain optimum combination of machining parameters such as helix angle (α), spindle speed (N), feed rate (Z), axial depth of cut (X) and radial depth of cut (Y) to minimize machining performance.

Table 3 Adequacy of the model

Response	Factors *df*	Lack of fit *df*	Pure error	*F* ratio		*R* ratio		Whether model is adequate
				model	standard	model	Standard	
Temperature rise	17	11	6	4.006	5.07	89.13	4.1	Adequate

The objective is to minimize the following functions such as:

$$\begin{aligned}\text{Minimize, Temperature rise, T} = {} & 20.446 - 6.142\alpha + 1.792\mathrm{N} \\ & + 1.042\mathrm{Z} + 1.367\mathrm{X} + 7.059\alpha^2 \\ & + 1.784\mathrm{N}^2 - 2.209\mathrm{Y}^2 + 0.437\alpha\mathrm{N} \\ & + 1.287\alpha\mathrm{Z} + 0.937\alpha\mathrm{Y} + 1.638\mathrm{NZ} \\ & - 3.013\mathrm{ZX} + 2.062\mathrm{ZY} + 0.887\mathrm{XY}\end{aligned} \tag{5}$$

Subject to $-2 \leq \alpha$, N, Z, X, $\mathrm{Y} \leq 2$

5.2 Coding

In order to use genetic algorithm to solve the above problem, machining parameters (α, N, Z, X and Y) are first coded in some string structures. Binary-coded strings having 1's and 0's are primarily used. The length of the string is usually determined according to the desired solution accuracy. In this study 8 bits are chosen for the machining parameters (α, N, Z, X and Y). The strings (00000000) and (11111111) would represent the point's lower and upper limits of the process variables and thereby making a total string length of 40. With the coding, the solution accuracy obtained in the given interval for α, N, Z, X and Y are 0.078430°, 7.84314 rpm, 1.5686×10^{-4} mm/rev, 0.00784 mm and 0.00784 mm, respectively, as shown in Table 4.

5.3 Fitness function

Genetic algorithm mimics the "survival of the fittest" principle. So, naturally they are suitable to solve maximization problems [25, 26]. Maximization problems are usually transformed to minimization problems by some suitable transformation. A fitness function, $F(x)$, is derived from the given objective function, $f(x)$, and is used in successive genetic operations. For maximization problems, fitness function can be considered the same as the objective function. The minimization problem is an equivalent maximization problem such that the optimum point remains unchanged. A number of such transformations are possible. The transformation does not alter the location of the minimum, but converts a minimization problem to an equivalent maximization problem. The fitness function value of the string is known as the string's fitness. The operation of genetic algorithms begins with a population of random strings representing design or decision variables. Thereafter, each string is then operated by three main operators—reproduction, crossover and mutation—to create a new population of points. The new population is further evaluated and tested for termination. If the termination criterion is not met, the population is iteratively operated by the above three operators and evaluated. This procedure is continued until the termination criterion is met. One cycle of these generation and the subsequent evaluation procedure is known as a generations in genetic algorithms.

5.4 Reproduction

Reproduction is the first operator applied on a population. In this process, individual strings are copied into a separate string called the 'mating pool' according to their fitness values, i.e., the strings with a higher value have a higher probability of contributing one or more offspring in the next generation. Reproduction operator is also known as selection operator. A reproduction operator can be implemented in algorithmic form in a number of ways. The easiest way is to create a biased roulette wheel where each current string in the population has a roulette wheel-slot-size in proportion to its fitness. In this way, more highly fit strings have higher numbers of offspring in the succeeding generation. Once the string has been selected for reproduction, an extra replica of the string is made. The string is then entered into the mating pool; a tentative new population is created for further genetic operator action. In reproduction, good strings in a population are probabilistically assigned a large number of copies and a mating pool is formed which ensures that there is no new strings formed in the reproduction phase [25, 26].

5.5 Crossover

After reproduction, the population is enriched with good strings from the previous generation but does not have any

Table 4 Solution accuracy for the machining parameters

Machining parameters	Limits	Code	Decode	Range	Accuracy
Helix angle (α)	30–50°	00000000 11111111	0 255	20	20/255=0.07843
Spindle speed (N)	2,000–4,000 rpm	00000000 11111111	0 255	2,000	2,000/255=7.84314
Feed rate (Z)	0.02–0.06 mm/rev	00000000 11111111	0 255	0.04	$0.04/255=1.5686\times10^{-4}$
Axial depth of cut (Y)	1.5–3.5 mm	00000000 11111111	0 255	2	2/255=0.00784

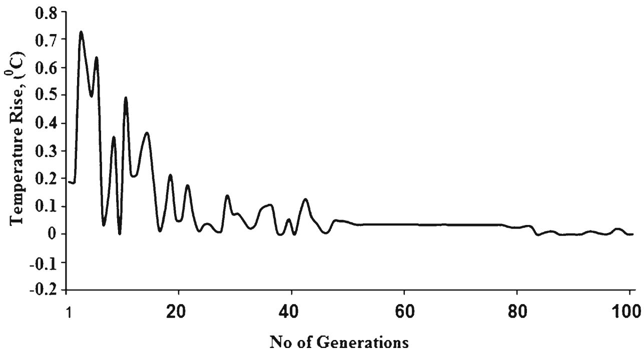

Fig. 1 Variation of fitness value with no of generations for temperature rise

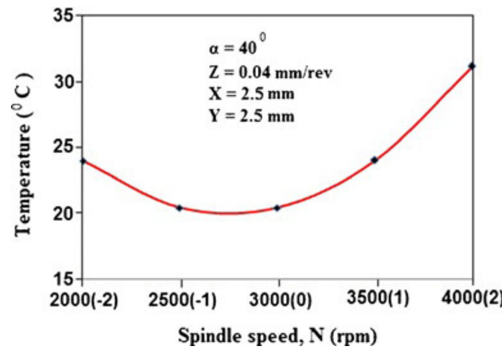

Fig. 3 Direct effect of spindle speed

new string. A crossover operator is applied to the population to hopefully create better strings. The total number of participative strings in crossover is controlled by the crossover probability, which is the ratio of total strings selected for mating and the population size. The crossover operator is mainly responsible for the search aspects of genetic algorithm. In most crossover operators, two strings are picked from the mating pool at random and some portions of the strings are exchanged between the strings [25, 26]. In crossover a random number is generated between 1 and 8. If the random number is 5, the bits after the fifth position are exchanged as given in the following example.

Example :	String 1	–	1100**1111**
	String 2	–	0101**0100**
	Crossover probability	–	0.9
	New string(offspring 1)	–	1100**0111**
	New string(offspring 2)	–	0101**1100**

The two strings participating in the crossover operation are known as the parent strings, and the resulting strings are known as children strings.

5.6 Mutation

Mutation, as in the case of simple genetic algorithm, is the occasional random alteration of the value of a string position. This means changing 0 to 1 or vice versa on a bit-by-bit basis and with a small mutation probability of 0 to 0.1. The need for mutation is to maintain diversity in the population [25, 26].

Example :	String 1	–	**11000111**
	String 2	–	**01011100**
	Mutation probability	–	0.01
	New string(offspring 1)	–	**01000111**
	New string(offspring 2)	–	**01011100**

After applying the genetic algorithm operators, a new set of population is created. Then, they are decoded and objective function values are calculated. This completes one generation of genetic algorithm. Such iterations are continued till the termination criterion is achieved. The above process is simulated by a computer program developed by using C language with a population size of 100, iterated for 100 generations and crossover and mutation probability are selected to be 0.9 and 0.01, respectively.

5.7 Results of genetic algorithm

Figure 2 shows the results obtained by running the C program for minimizing temperature rise. The initial variation in the curve is due to the search for optimum solution. In Fig. 1, it is evident that the minimum temperature rise occurs at the 40th generation and the value is 0.173 °C.

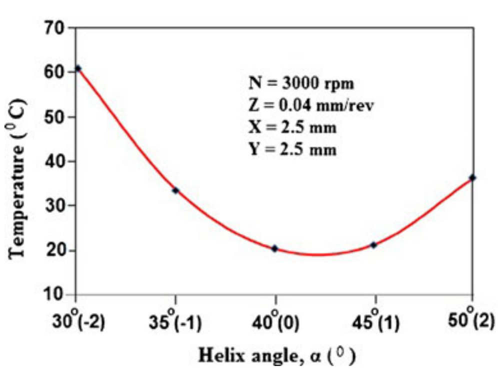

Fig. 2 Direct effect of helix angle

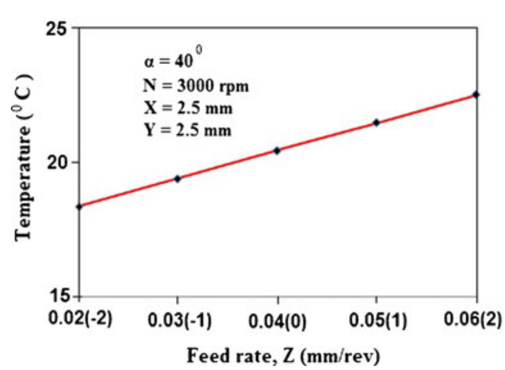

Fig. 4 Direct effect of feed rate

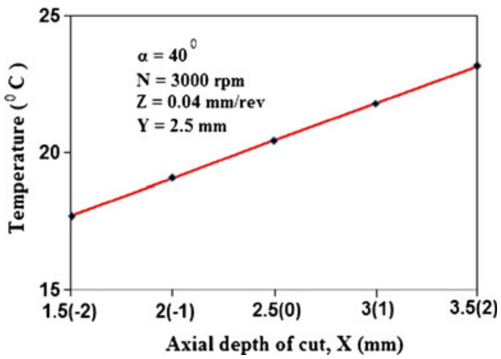

Fig. 5 Direct effect of axial depth of cut

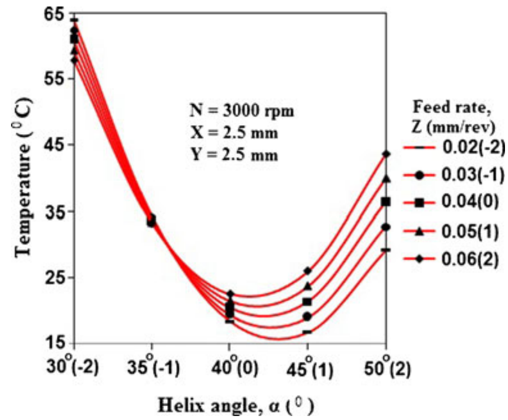

Fig. 7 Interaction effect of helix angle and feed rate

The optimum values of the machining parameters are given as

Helix angle	–	42°
Spindle speed	–	2, 870 rpm
Feed rate	–	0.03 mm/rev
Axial depth of cut	–	1.7 mm
Radial depth of cut	–	3.4 mm

6 Results and discussion

In the present investigation, 32 experiments were conducted with varying machining conditions such as helix angle, spindle speed, feed rate, axial depth of cut and radial depth of cut. A mathematical model was developed to predict the temperature rise during end milling. The direct and interaction effect of these machining parameters on temperature rise were calculated and presented in a graphical form for further investigation. Insignificant variables such as radial depth of cut (Y) and insignificant interaction factors such as αX, NX and NY have been neglected since their contribution is minimal in the temperature rise. The trends plotted in the direct and interaction effects helps us to analyze the cause and effect of the machining parameters on temperature rise during end milling.

6.1 Direct effect of variables

In this work, the effects of helix angle, spindle speed, feed rate, axial depth of cut and radial depth of cut on temperature rise were experimentally investigated and plotted. Figures 2, 3, 4 and 5 show that the helix angle, spindle speed, feed rate and axial depth of cut have a significant effect on temperature rise.

Figure 2 depicts the direct effect of helix angle on temperature rise. This figure illustrates that the increase in helix angle resulted in a decrease in temperature rise, and it is minimal at the helix angle range of 40–45°. Decreasing the helix angle increases the rake or relief angle of the cutting tool. This reduction in relief angle increases the peak cutting temperature by reducing the area through which heat can diffuse from the cutting tool [27].

Figure 3 presents the direct effect of spindle speed on temperature rise. In this figure, it is evident that the increase in spindle speed increases the temperature rise and it is minimal at the speed range of 2,500–3,000 rpm. Increasing

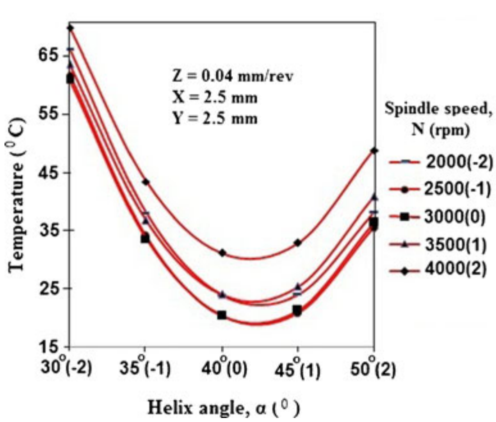

Fig. 6 Interaction effect of helix angle and spindle speed

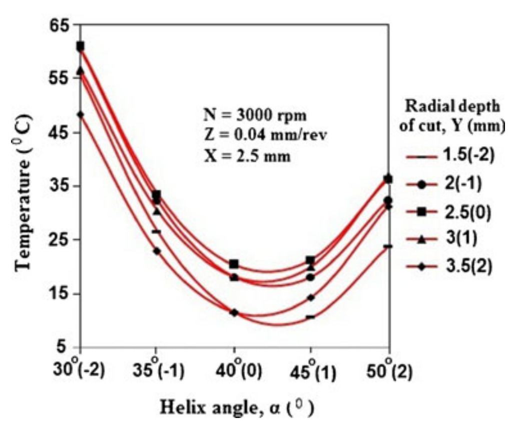

Fig. 8 Interaction effect of helix angle and radial depth of cut

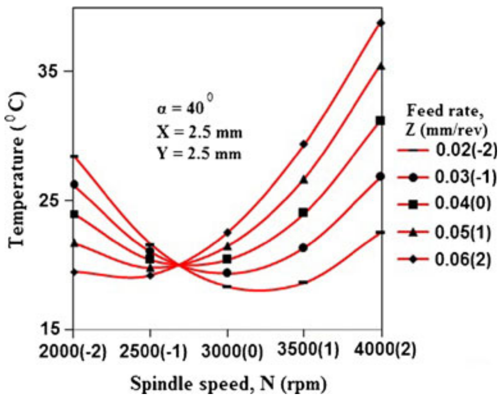

Fig. 9 Interaction effect of spindle speed and feed rate

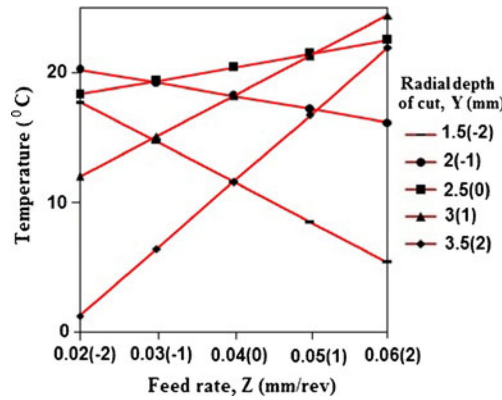

Fig. 11 Interaction effect of feed rate and radial depth of cut

the spindle speed increases the rate at which energy dissipated through plastic deformation and friction. Thus, the rate of heat generation in the cutting zone increases resulted in a high cutting temperature [28]. An increasing cutting speed results in increasing the cutting temperature rise to a point where atomic diffusion between the tool and work piece material takes place, which in turn propagates the tool wear. The temperature rise slightly increases with decreasing spindle speed from 2,500 to 2,000 rpm; this may be due to the adhesion of work material on the tool, which results in more friction.

Figure 4 shows the direct effect of feed rate on temperature rise. This figure indicates that the increase in feed rate increases the temperature rise. Increasing the feed rate also increases the rate of heat generation in the cutting zone. Tool chip interface increases with the square root of the cutting speed and the third root of the feed rate [5]. Chip melting is observed when machining aluminum Al 6063 at higher feed rate.

Figure 5 represents the direct effect of axial depth of cut on temperature rise. The figure makes it clear that the increase in axial depth of cut increases the temperature rise. Increase in depth of cut causes larger amount of work piece materials to be removed, which increases the cutting temperature. At lower depths of cut, less amounts of work piece material adhere on the flank of the tool than at lager depths of cut. This adhesion of work piece material on the tool flank causes an increase in temperature rise.

6.2 Interaction effect of variables

A strong interaction was observed between various process parameters for temperature rise. The graph between these most significant process parameter interactions was plotted. The following conclusion can be made from these interaction plots.

The interaction effect of helix angle and spindle speed, helix angle and feed rate and helix angle and radial depth of cut on temperature rise is shown in Figs. 6, 7 and 8. These figures show that the increase in helix angle resulted in a decrease of temperature rise from 30 °C to 40 °C and in between 45 °C and 50 °C, there is a slight increase in temperature rise. The threshold value lies between helix angle of 40° and 45°, which gave a minimum temperature rise. The increase in helix angle reduces the rake angle, which in turn reduces friction between the area of contact

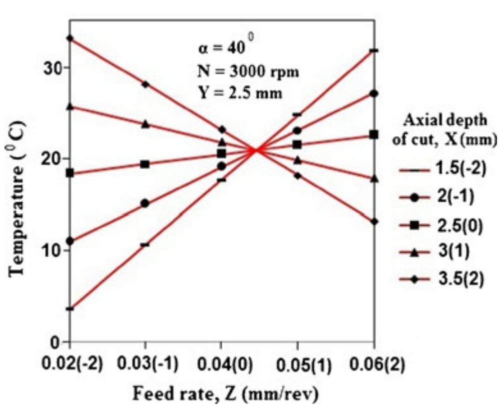

Fig. 10 Interaction effect of feed rate and axial depth of cut

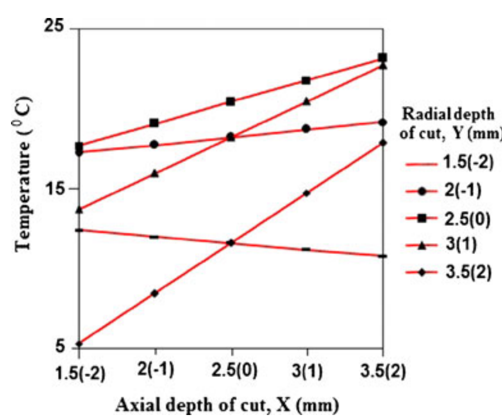

Fig. 12 Interaction effect of axial and radial depth of cut

of tool and work piece. The trend for helix angle is same for all the levels of spindle speed, feed rate and radial depth of cut. The increase in feed rate resulted in the decrease of temperature for the level of 30° of helix angle, whereas the trend gets completely reversed for the other levels of helix angle (35–50°) as shown in Fig. 7. The interaction effect of spindle speed and feed rate on temperature rise is depicted in Fig. 9, which shows that the increases in spindle speed resulted in a decrease in temperature rise from 2,000 to 3,000 rpm, increase in temperature from 3,500 to 4,000 rpm, and optimal in between 3,000 and 3,500 rpm for the change of levels of feed rate from 0.02 to 0.04 mm/rev. The interaction effect of feed rate and axial depth of cut, and the radial depth of cut on temperature rise are shown in Figs. 10 and 11, respectively. Figure 10 indicates that temperature rise increases with increase in feed rate for the levels of axial depth of cut between 1.5 and 2.5 mm. The trend gets reversed for the levels of axial depth of cut between 2.5 and 3.5 mm, where the temperature rise decreases with the increase in feed rate. In Fig. 11, it is clear that temperature rise increases with increase in feed rate for the levels of radial depth of cut between 3.5 and 2.5 mm. The trend gets reversed for radial depth of cut between 2 and 1.5 mm, where temperature rise decreases with increase in feed rate. The interaction effect of axial and radial depth of cut on temperature rise is shown in Fig. 12, which reveals that as the axial depth of cut increases, the temperature rise increases for all levels of radial depth of cut.

7 Conclusion

The following conclusions derived from the prediction of tool wear from the various machining parameters:

- The helix angle is the most significant parameter which reduces peak temperature rise. The temperature rise is minimal between 40° and 45° helix angles.
- The increase in spindle speed, feed rate and axial depth of cut increases cutting temperature.
- The radial depth of cut does not have a significant effect on temperature rise.
- The interactions between the process parameters on temperature were analyzed, and a significant interaction were observed between feed rate and axial depth of cut.
- It is realized from the study that the error percentage of the developed model is less than 5 %.
- The genetic algorithm has been employed to optimize the machining parameters to obtain the minimum temperature rise. The optimal combination of machining parameters for minimum temperature of 0.173 °C was found to be 42°, 2,870 rpm, 0.03 mm/rev, 1.7 mm and 3.4 mm for helix angle, spindle speed, feed rate, axial and radial depth of cut, respectively.

References

1. Palanisamy P, Rajendran I, Shanmugasundaram S, Saravanan R (2008) Prediction of cutting forcer and temperature rise in end-milling operation. Proc Inst Mech Eng B J Eng Manuf 220 (10):1577–1587. doi:10.1243/09544054JEM542, 2006
2. Lazoglu I, Altintas Y (2002) Prediction of tool and chip temperature in continuous and interrupted machining. Int J Mach Tool Manuf 42:1011–1022
3. Leshock CE, Shin YC (1997) Investigation of cutting temperature in turning by a tool-work thermocouple technique. ASME J Manuf Sci Eng 119:502–508
4. Smart EF, Trent EM (1975) Temperature distributions in tools used for cutting iron, titanium and nickel. Int J Prod Res 13:265–290
5. Shaw MC (1984) Metal cutting principles. Oxford University Press, London
6. Zakaria AA, ElGomayel JI (1975) On the reliability of the cutting temperature for monitoring tool wear. Int J Mach Tool Design Res 15:195–208
7. Mathew P (1989) Use of predicted cutting temperatures in determining tool performance. Int J Mach Tool Manuf 29:481–497
8. Maekawa K, Kitagawa T, Kubo A (1997) Temperature and wear of cutting tools in high speed machining of Inconel 718 and Ti–6Al–6V–2Sn. Wear 202(2):142–148
9. Choudhury SK, Bartarya G (2003) Role of temperature and surface finish in predicting tool wear using neural network and design of experiments. Int J Mach Tool Manuf 43:747–753
10. Dessoly, Melkote SN, Espalier C (2004) Modeling and verification of cutting tool temperatures in rotary tool turning of hardened steel. Int J Mach Tool Manuf 44:1463–1470
11. Haci S, Faruk U, Suleyman Y (2006) Investigation of the effect of rake angle and approaching angle on main cutting force and tool tip temperature. Int J Mach Tool Manuf 46:132–141
12. Weinert K, Brinkel F, Kempmann C, Pantke K (2007) The dependency of material properties and process conditions on the cutting temperatures when drilling polymers. Prod Eng Res Dev 1:381–387. doi:10.1007/s11740-007-0015-y
13. Geerdes WM, Alvardo MAT (2008) An application of physics based and artificial neural network-based hybrid temperature prediction scheme in a hot strip mill. J Manuf Sci Eng 130:014501
14. Zhang S, Liu ZQ (2008) An analytical model for transient temperature distributions in coated carbide cutting tools. Int Commun Heat Mass Transfer 35:1311–1315
15. Kadirgama K, Noor MM, Rahman MM, Harun WSW, Haron CHC (2009) Finite element analysis and statistical method to determine temperature distribution on cutting tool in end-milling. Eur J Sci Res 25(2):250–256
16. Suhail AH, Ismail N, Wong SV, Abdul Jalil NA (2010) Optimization of cutting parameters based on surface roughness and assistance of work piece surface temperature in turning process. Am J Eng Appl Sci 3(1): 102–108, ISSN 1941-7020
17. Liu YJ, Zhang JM, Wang SQ (2005) Parameter estimation of cutting tool temperature nonlinear model using PSO algorithm. J Zhejiang Univ (Sci) 6A(10):1026–1029
18. Liu YM, Wang CJ (1999) A modified genetic algorithm based optimisation of milling parameters. Int J Adv Manuf Technol 15:796–799
19. Reddy NSK, Venkateswara Rao P (2006) Selection of an optimal parametric combination for achieving a better surface finish in dry milling using genetic algorithms. Int J Adv Manuf Technol 28:463–473. doi:10.1007/s00170-004-2381-3
20. Palanisamy P, Rajendran I, Shanmugasundaram S (2007) Optimization of machining parameters using genetic algorithm and experimental validation for end-milling operations. Int J Adv Manuf Technol. doi:10.1007/s00170-009-2104-x

21. Venkatesan D, Kannan K, Saravanan R (2009) A genetic algorithm-based artificial neural network model for the optimization of machining processes. Neural Comput & Applic 18:135–140
22. Bharathi Raja S, Baskar N (2010) Optimization techniques for machining operations: a retrospective research based on various mathematical models. Int J Adv Manuf Technol 48:1075–1090. doi:10.1007/s00170-009-2351-x
23. Cochran WG, Cox GM (1963) Experimental design. Asia Publishing House, India
24. Montgomery DC (1976) Design and analysis of experiments. John Wiley and Sons, New York
25. Goldberg DE (1989) Genetic algorithms in search, optimization and machine learning. Addison-Wesley Pub, New York
26. Deb K (1995) Optimization for engineering design: algorithms and examples. Prentice-Hall, New Delhi
27. Donaldson C, Lecain GH, Goold VC (1957) Tool design. Tata McGraw-Hill, New Delhi
28. Stephenson DA, Agapiou JS (2006) Metal cutting theory and practice. Taylor & Francis, New York