World Applied Sciences Journal 6 (1): 64-69, 2009
ISSN 1818-4952

Optimization of Machining Parameters to Minimize Tool Deflection in the End Milling Operation Using Genetic Algorithm

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Abstract: Optimization of cutting parameters is valuable in terms of providing high precision and efficient machining. One of the effects of cutting force in the end milling operation with low diameter tool (during metal cutting) is tool deflection. Assuming that machining errors mostly arise from tool deflection, attempt was made to optimize machining parameters using Genetic Algorithm (GA) so as to minimize tool deflection. In contrast to other optimizations in which machining time and cost are defined as the objective functions, our algorithm considers tool deflection as the objective function while surface roughness and tool life are the constraints. In order to verify accuracy of optimization, results were compared with those calculable based on the theoretical relationships, in terms of agreement to those obtained experimentally. The obtained results indicate that the optimized parameters are capable of machining the workpiece more accurately with better surface finish.

Key words: Genetic algorithm . End milling . Tool deflection

INTRODUCTION

This paper reports on a new error compensation approach focused on machining parameters induced errors in machined surface with low diameter tools. The determination of optimal cutting parameters such as axial depth of cut, radial depth of cut and feed rate, which are applicable for assigned cutting tools, is one of the vital modules in process planning of metal parts, since the accuracy of machined surface plays an important role in increasing productivity and competitiveness [1]. One of the purposes of this paper is to investigate the optimal cutting parameters to minimize tool deflection for error compensation on the machined surface while maintaining material removal rate and stability of the cutting process. The main parameters in machining affecting tool deflection and surface finish are axial depth of cut, radial depth of cut and feed rate. The optimal cutting parameters are subjected to an objective function of tool deflection with the feasible range of cutting parameters. The user of the machine tool must know how to choose cutting parameters in order to minimize cutting time, cutting force and produce better surface finish (surface roughness) under stable conditions. Normally, feed rate, axial depth of cut and radial depth of cut immersion are chosen according to the technical guide. But these parameters are strongly dependent on the static and dynamic properties of the tool. In order to obtain better surface roughness, the proper setting of cutting parameters is crucial before the process takes place.

This study introduces a developed computer algorithm to optimize the cutting parameters to minimize tool deflection and increase tool life and surface roughness for a constant material removal rate. The system is mainly based on a powerful artificial intelligence (AI) tool, called genetic algorithms (GA). The use of the impact and the power of AI techniques have been reflected on the performance of the optimization system. The methodology of the developed optimization system is illustrated by practical examples throughout the study. Optimization of the machining parameters increases the product quality to a great extent [2, 3].

MODELING

In the milling process, material is removed from a work piece by a rotating cutting tool. Milling process can be modeled as cutting simultaneously with a number of single-point cutting tools. A model coordinate system of end milling is illustrated in Fig. 1. The cutter is assumed to have z number of teeth and 30 (Deg) helix angle.

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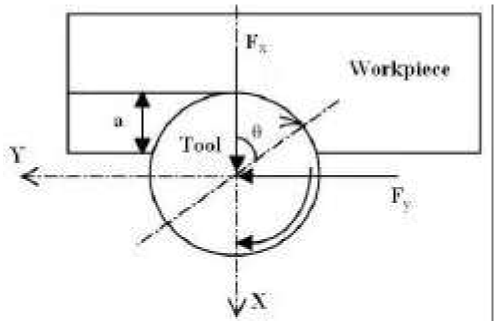


Fig. 1: Model coordinate system

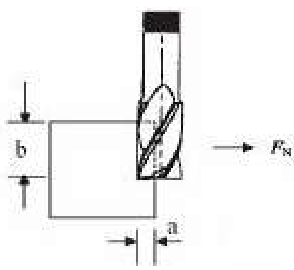


Fig. 2: Axial and radial depth of cut

Determination of cutting force

Conventional cutting force model: Tlusty and McNeil's cutting force model [4] was developed for Conventional end-milling operations in 1975. It was based on the following three assumptions:

Assumption 1: The tangential cutting force, F_t (N), is proportional to the cutting area (It is tangent to tool's edge).

$$F_t = K_m bh \tag{1}$$

Assumption 2: The radial cutting force, F_r (N), is proportional to the tangential cutting force (It is vertical to tool's edge).

$$F_r = P_f F_t \tag{2}$$

Assumption 3: The chip thickness, h (mm), can be expressed by the following expression:

$$h = f_t \sin\theta \tag{3}$$

The coordinate system of the model, axial depth, b(mm) and radial depth, a(mm) of cut is presented in Fig. 1 and Fig. 2, respectively.

For a certain tool cutting angle θ (Rad), the chip thickness, h, is not a constant but a function of Z_c (The coordinate perpendicular to the x-y plane) because of the tool helix angle β (Rad).

$$dF_t = Kh(z_c)\, dz_c$$

Where

$$Z_c = Z_c(\theta)$$

$$dz_c = (r/\tan\beta)\, d\theta$$

The expressions Eq. (1) and Eq. (2) can be rewritten as:

$$dF_t = 2(F_u / f_t)h(\theta)d\theta$$
$$dF_r = 2(F_u / f_t)P_f h(\theta)d\theta$$

The expressions for the cutting force model were derived as:

$$F_x = F_u \begin{bmatrix} (\theta_e - \theta_s) - P_f(\sin^2\theta_e - \sin^2\theta_s) \\ - 0.5(\sin^2\theta_e - \sin^2\theta_s) \end{bmatrix} \tag{4}$$

$$F_x = - F_u \begin{bmatrix} P_f(\theta_e - \theta_s) + (\sin 2\theta_e - \sin 2\theta_s) \\ - 0.5P_f(\sin 2\theta_e - \sin 2\theta_s) \end{bmatrix} \tag{5}$$

Where, F_u is unit force (N) and $F_u = K_m r f_t/\tan\beta/2$, F_x is normal direction cutting force (N), F_y is feed direction cutting force (N), r is tool radius(mm), K_m is material coefficient (N mm^{-1}), f_t is feed per tooth(mm tooth^{-1}), θ_s is integrating start angle (Rad), θ_e is integrating end angle (Rad), also according to the experimental data, the proportional factor P_f was usually selected as 0.3.

OPTIMIZATION

Working principle of GA: The genetic algorithm (GA) is a population-based search optimization technique. In general, the fittest individuals of any population tend to reproduce and survive to the next generation, thus improving successive generations. However, inferior individuals can, by chance, survive and also reproduce. Genetic algorithms have been shown to solve linear and nonlinear problems by exploring all regions of the state space and exponentially exploiting promising areas through mutation, crossover and selection operations applied to individuals in the population. The use of a genetic algorithm requires the determination of six fundamental issues, chromosome representation, selection function, the genetic operators making up the reproduction function, the creation of the initial population, termination criteria and the evaluation function [2]. The range of cutting parameters is given in Table 1.

Table 1: Cutting parameters for experimental

Diameter of tool (mm)	Cutting speed (m min^{-1})	Feed rate (mm min^{-1})	Axial depth of cut (mm)	Radial depth of cut (mm)
3	23.56	8,16,25,40,50	1.5	1.5
3	23.56	8,16,25,40,50	3.0	1.5
3	23.56	8,16,25,40,50	4.5	1.5
3	23.56	8,16,25,40,50	5.0	1.5

Implementation of GA

Coding: In order to use GAs to solve the problem, variables (in this study a, b and ft) are first coded in some string structures. Binary-coded strings having ones and zeros are primarily used. The length of the string is usually determined according to the desired solution accuracy. In order to solve this problem using GA, binary coding is chosen to represent the variables f, b and a. In the calculation here, 8 bits are chosen for f, b and a and thereby making a total string length of 24. With the coding, the solution accuracy obtained in the given interval for ft, b and a are 0.001 mm $tooth^{-1}$, 0.01 mm and 0.01 mm, respectively.

Fitness function: GAs mimic the "survival of the fittest" principle. So, naturally they are suitable to solve maximization problems. Maximization problems are usually transformed to minimization problems by some suitable transformation. A fitness function, F(x), is derived from the 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 fitness function often used is

$$F(x)\frac{1}{(1\_f(x))} \qquad (6)$$

Where F(x) is the fitness function and f(x) is the objective function.

The independent variables for optimal cutting parameters have been identified as the following: Tool diameters and length, spindle speed and feed per tooth [2].

Genetic operators

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. 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 for further genetic operator action.

Crossover: After reproduction, the population is enriched with good strings from the previous generation but does not have any 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 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 GA. In order to perform crossover, a random number is generated between 1 and 7. If the random number is 5, the bits after the 5th position are exchanged as given below in the following example.

Example:
String 1_11001101
String 2_01110100
Crossover probability = 0.9
New string (offspring 1)-11001100
New string (offspring 2)-01110101

Mutation: Mutation, as in the case of simple GA, 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 0.001 to 0.05.

The need for mutation is to keep diversity in the population.

Example:
String 1 -11001101
String 2 -01110100
Mutation probability =0.001
New string (offspring 1)-01001101
New string (offspring 2)-01110110

Table 2: Speciation of tool

Mill diameter (D1), Shank diameter (D2)	Flute (C,N)	Flute length (L1)	Overall length (L2)
3mm, 6mm (HSS)	4 (9.05, 0.95)	11 mm	56 mm

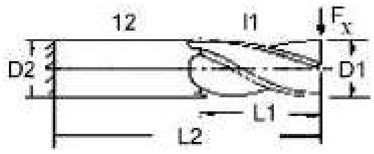


Fig. 3: Loading and boundary conditions of the end mill [5]

After applying the GA operators, a new set of population is created. Then, they are decoded and objective function values are calculated. This completes one generation of GA. Such iterations are continued till the termination criterion is achieved. The above process is simulated by a computer program with a population size of 25, iterated for 200 generations and crossover and mutation probability are selected to be 0.9 and 0.001, respectively.

Objective function

Deflection analysis of end mills: The main objective of the static analysis is to determine the deflection of end mills under milling forces. For static deflection analysis of end mills, the tool holder is assumed to be rigid and the cantilever beam model is used. However, the holder and clamping stiffness can also be included in the analysis if they are known. End mill deflections can be approximated using the beam model. The loading and boundary conditions of the end mill used in the model are shown in Fig. 3, where D1 is the mill diameter, D2 is the shank diameter, L1 is the flute length, L2 is the overall length, Fx is the point load.

Modeling and FEA can be unpractical and time consuming for each tool configuration in a virtual machining environment. Therefore, simplified equations are generated to predict deflections of tools for given geometric parameters and density. The static characteristics of end mills can easily be

$$f(x) = deflection_{\max} = C\frac{F_x}{E}\left[\frac{L1^3}{D1^4} + \frac{(L2^3 - L1^3)}{D2^4}\right]^N \qquad (7)$$

Where Fx is the applied force and E is the modulus of elasticity (MPa) of the tool material. The geometric properties of the end mill are in mm. The constant C is 9.05, 8.30 and 7.93 and constant N is 0.950, 0.965 and 0.974 for 4-flute, 3-flute and 2-flute cutters, respectively, Kivanc and Budak [5]. These parameters for this investigation is given in the Table 2.

CONSTRAINTS

This section shows optimizing the machining parameters for minimizing tool deflection by using genetic algorithm. In this problem, the objective function is minimizing tool deflection in end milling operation.

In practice, possible ranges for cutting speed and feed rate are limited by the following constraints:

- Surface finish requirements; for the milling process the surface roughness range is 0.8 to 6.3 µm.
- Tool life; minimum expected tool life for an HSS tool is 60 to 120 min.
- Maximum cutting force permitted by the rigidity of the tool; maximum cutting force is limited to 500 N.
- Amplitude of vibration at the work piece holder; for stable cutting the maximum amplitude of vibration is limited to 2 µm.
- Maximum heat generated by cutting
- Available feed rates and spindle speeds on the machine tool

Excessive heat generation can be overcome by the use of efficient coolants. Also, modern NC and CNC machines are not faced with the last constraint since they provide all possible feed rates and spindle speed within an acceptable range. Therefore, the first four constraints are considered in this work.

Surface roughness: R_a is the most commonly used parameter to describe the average surface roughness and is defined as an integral of the absolute value of the roughness profile measured over an evaluation length, Tolouei-Rad and Bidhendi [6]:

$$R_a = (1/l)\int_0^l |Z(x)|dx \qquad (8)$$

Where, Z(x) is the area of the each peak and l is the length of workpiece that has machined. The average roughness is the total area of the peaks and valleys divided by the evaluation length; it is expressed in µm (thousandths of a millimeter). The arithmetic value of surface roughness in end milling can be represented by:

$$R_a = 318(f_t^2)/(4d) \qquad (9)$$

Where f_t is feed per tooth (mm tooth^{-1}) and d cutter diameter (mm).

Tool life: Tool life T_L(min) can be defined as a tool's useful life until it no longer produces satisfactory parts.

Table 3: GA results values for the optimized cutting parameters for minimizing tool deflection

Diameter of end mill	Feed rate	Axial depth of cut	Radial depth of cut
3 mm (HSS)	22 (mm min^{-1})	2.925 (mm)	1.42 (mm)

Table 4: GA results values for the optimized cutting parameters for minimizing tool deflection in practice

Diameter of end mill	Feed rate	Axial depth of cut	Radial depth of cut
3 mm (HSS)	20 (mm min^{-1})	3 (mm)	1.5 (mm)

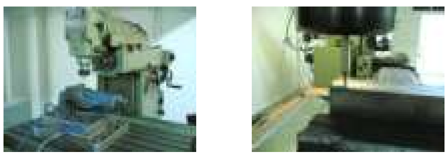


Fig. 4: Experimental (end milling)

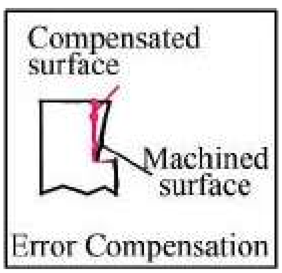


Fig. 5: Error compensation (perpendicularly)

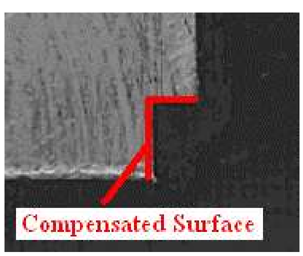


Fig. 6: Compensated surface (perpendicularly) by using GA results in Table 4

When the wear reaches a certain value the tool is not capable of further cutting unless it is resharpened. This is because increased bluntness of the cutting edge causes an increase in cutting forces and as a result tool temperature also increases. Consequently both dimensional accuracy and surface finish of the machined piece suffer, ultimately leading to the production of rejects. Life of the tool is affected by various parameters such as cutting speed, feed, depth of cut, chip thickness, tool geometry and cutting fluid. A corrected empirical formula for the practical tool life T_L(min) of a cutting tool to be used in end milling operations has been proposed by Tolouei-Rad and Bidhendi [6]:

$$T_L = (\frac{60}{Q})\left[\frac{C(G/5)^g}{V(A)^w}\right]^{\frac{1}{m}} \quad (13)$$

Where m is 0.15 for HSS tools, while it reaches a maximum of 0.30 for the carbide tools, C is 33.98 for HSS tools and 100.05 for the carbide tools, Q is the contact proportion of cutting edge with workpiece per revolution, G is slenderness ratio that G=b/ft and A is chip cross-sectional area that A=b.ft, g=0.14 and w=0.28, Tolouei-Rad and Bidhendi [6].

Cutting force: The cutting force equations derived from the model in the x and y directions are given by equations 4 and 5.

MATERIALS AND METHODS

The milling operation was carried out on Universal milling machine on steel AISI 1045 workpiece material using two HSS tools. The purpose of the experiment is to validate the optimized parameters during an end milling operation. The experimental setup is shown in Fig. 4. The test conditions are selected conform to Machinery's Handbook and limitations of milling machine they are given in Table 1.

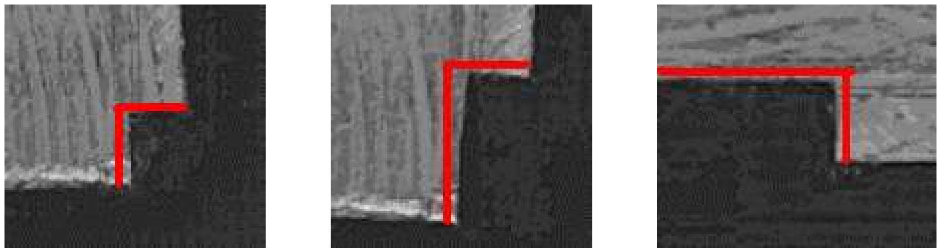
Optimization has been performed using GA to decide the best possible combination of feed rate, axial depth of cut and radial depth of cut by satisfying constraints including tool deflection, cutting force, tool life and surface roughness. Figure 5 shows the effect of tool deflection on the machined surface. In this work, error of tool deflection on the machined surface has been compensated by using genetic algorithm.

The ranges of cutting parameters are given in Table 1. In this table, feed rates and depths of cut are changed but the cutting speed is considered constantly, because the cutting speed has less effect on the cutting force and tool deflection. Table 3 shows the GA results for optimized cutting parameters in the x direction for machining of mild steel material (AISI1045), but because of the limitation of milling machine, Table 4 has been used for cutting operation. Table 5 shows the comparison of GA results and measured parameters for optimized machining parameters for machining of mild steel material. The good agreement between the GA results and measured parameters clearly demonstrates the accuracy and effectiveness of the model presented and program developed.

Table 5: Comparison of GA results and experimental values for the optimized cutting parameters

Cutting speed ($m\ min^{-1}$)	Feed rate ($mm\ min^{-1}$)	Axial depth of cut (mm)	Radial depth of cut (mm)	GA results 1	GA results 2	GA results 3	Measured values 1	Measured values 2	Measured values 3
23.56	25	3	1.5	1.6	0.0531	19	2	0.056	10

1: Roughness (µm); 2: Tool deflection (mm); 3: Cutting force Fx(N)



(a) (b) (c)

Fig. 7: Effect of tool deflection on the machined surface without using GA results
(a), b=3mm, a =1.5 mm, cutting speed= 23.56($m\ min^{-1}$), feed rate=16($mm\ min^{-1}$)
(b), b=3mm, a =1.5 mm, cutting speed = 23.56($m\ min^{-1}$), feed rate =40($mm\ min^{-1}$)
(c), b=3mm, a =1.5 mm cutting speed = 23.56($m\ min^{-1}$), feed rate =50($mm\ min^{-1}$)

Figure 6 is shown that in practice with optimized cutting parameters (Table 4) effect of tool deflection on the machined surface has been reduced. This Figure is shown, compensated surface (perpendicularly) by using GA results (Table 4).

Metal cutting has been performed by other the cutting parameters (Table 1). Figure 7 is shown effect of tool deflection on the machined surface without using GA results.

CONCLUSIONS

Machining parameters are typically adjusted according to the instructions in the tools catalogues and/or handbooks without regard to the roughness requirements and geometrical tolerances of the surface to be machined. Incorrect adjustment of the machining parameters, feed rate and depth of cut lead to tool deflection and consequently reduced surface quality. With increasing feed rate and depth of cut, the tool deflection is increased. Optimization of machining parameters using Genetic Algorithm led to minimal machining errors. By defining maximum surface roughness of 6.3 µm as the constraint, surface roughness of 1.6µm was obtained with the optimized parameters. With the GA-based optimization system developed in this work, it would be possible to increase machining accuracy (surface roughness and geometrical tolerances) by using optimal cutting parameters.

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