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Multi-Objective Optimization for Milling Operations using Genetic Algorithms under Various Constraints

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Abstract

In this paper, the parameter optimization problem for face-milling operations is studied. A multi-objective mathematical model is developed with the purpose to minimize the unit production cost and total machining time while maximize the profit rate. The unwanted material is removed by one finishing pass and at least one roughing passes depending on the total depth of cut. Maximum and minimum allowable cutting speeds, feed rates and depths of cut, as well as tool life, surface roughness, cutting force and cutting power consumption are constraints of the model. Optimal values of objective function and corresponding machining parameters are found by Genetic Algorithms. An example is presented to illustrate the model and solution method.

Keywords: face-milling operation; multi-objective optimization; machining parameter; genetic algorithms

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1. Introduction

In today's manufacturing environment, many large companies in metal-cutting industries are making use of advanced manufacturing and management technologies to reduce production cost and increase profit. Machining parameter optimization plays an important role in meeting these requirements and it is an essential part of a Computer Aided Design/Computer Aided Process Planning/Computer Aided Manufacturing (CAD/CAPP/CAM) system. Machining parameter optimization usually involves the optimal selection of cutting speed, feed rate, depth of cut, and the number of passes. In practice, machining parameters are in most cases selected from machining database or handbooks. The cutting regimes given in such a way may not be the optimal values [1]. Single-objective optimization problems have been intensively studied using dynamic programming [2], geometric programming [3], linear programming [4], and some other techniques [5-6]. With the ever-increasing need for lowering cost and increasing production rate, several different and competing objectives have to be simultaneously optimized [7-9]. Multi-objective optimization problems have been studied since the early 1960s, especially during the past decade. The solutions for a multi-objective optimization problem may not meet all single objective functions and the obtained parameters cannot be simply compared with each other, and therefore the solutions are called non-dominated [10]. The existing models and processes for multi-objective optimization problems are usually complex and do not consider all practical constraints.

From a literature review, it can be known that machining parameter optimization has been performed mainly for turning process. Milling is a machining process of cutting material away by feeding a workpiece against a rotating cutter with multiple teeth. The machined surface may be a flat, angular, or curved one, or any combination of them, and thus milling is the most versatile machining process compared to the others such as turning, grinding, and reaming. In face milling, the cutter is mounted on a spindle rotating perpendicular to the machining surface. The cutting action of the many teeth on the periphery and face of the cutter forms the milled surface, providing a fast method of material removal. In this paper, the unit production cost, unit machining time and profit rate are optimized simultaneously for face-milling operations. A variety of realistic machining conditions and quality specifications are considered as constraints. The model is solved by Genetic Algorithms (GAs). An example is given to illustrate the model and solution procedure.

2. Model Development

Machining optimization models are mathematical programming models formulated from realistic machining processes. These models have objective functions based on certain economic criterion and subject to various practical constrains from machining conditions. In this section, a multi-objective machining optimizing model to minimize unit production cost and unit machining time as well as to maximize profit rate is proposed for multi-pass face-milling operations in single-tool applications. The total depth of material to be removed, including one finish pass and multiple rough passes, is cut with the same tool. Multi-pass machining operations are governed by complicated machining conditions.

2.1. *Objective function*

For a face-milling process, unit machining time TC (min) is comprised of actual machining time t_m (min), machine idle time t_l (min), and tool replacement time t_R (min). Dividing a milling process into one finish pass and n rough passes, actual machining time $t_m = \frac{\pi D L_{ts}}{1000 V_s f_s Z} + \sum_{i=1}^{n} \frac{\pi D L_{tr}}{1000 V_{ri} f_{ri} Z}$, where D (mm) is the diameter of the cutter; L_{ts} (mm) is the finish cutting travel length, $L_{ts} = L + 0.5(D - \sqrt{D^2 - B^2}) + 3$; L_{tr} (mm) is the rough cutting travel length, $L_{tr} = L + D + 3$; L (mm) and B (mm) are respectively the length and width of the workpiece; Z is the tooth number of the cutter; V_s (m/min) and f_s (mm/tooth) are respectively cutting speed and feed rate for the finish pass; V_{ri} (m/min) and f_{ri} (mm/tooth) are respectively cutting speed and feed rate for the i-th rough pass. Machine idle time t_l is defined as $t_l = t_p + t_i$ [2], where t_p (min) is preparation time, and t_i (min) is idle tool motion time. Therefore, $t_l = t_P + n(h_1 L_{tr} + h_2) + (h_1 L_{ts} + h_2)$, where h_1 (min/mm) is tool travel time and h_2 (min) is tool approach/depart time. Tool replacement time t_R can be given by $t_R = t_e Z \frac{t_m}{T}$, where t_e (min) is tool exchange time, T (min) is tool life. Then the objective function to minimize unit machining time can be written as

Minimize:

$$TC = t_m + t_l + t_R = t_s + \sum_{i=1}^{n} t_{ri} + t_p \, , \qquad (1)$$

where

$$t_s = (1 + \frac{t_e Z}{T_s}) \frac{\pi D L_{ts}}{1000 V_s f_s Z} + (h_1 L_{ts} + h_2) \, , \qquad (2)$$

$$t_{ri} = (1 + \frac{t_e Z}{T_{ri}}) \frac{\pi D L_{tr}}{1000 V_{ri} f_{ri} Z} + (h_1 L_{tr} + h_2) \, . \qquad (3)$$

Similarly, unit production cost UC (\$) is comprised of actual machining cost *CM*, machine idle cost *CI*, tool replacement cost *CR*, and tool cost *CT*, if material cost is not considered. *CM* is based on actual machining time t_m and labor cost, k_0 (\$/min), including overhead, then $CM = k_0 t_m$. The machine idle cost CI is defined as $CI = k_0 t_l$. Tool replacement cost *CR* and tool cost *CT* can be respectively given by $CR = k_0 t_R$ and $CT = k_t Z \frac{t_m}{T}$, where k_t (\$) is tool cost. Then

$$UC = CM + CI + CR + CT = UC_s + \sum_{i=1}^{n} UC_{ri} + k_0 t_p \, , \qquad (4)$$

where

$$UC_s = \left(k_0 + \frac{k_t Z}{T_s} + \frac{k_0 t_e Z}{T_s} \right) \frac{\pi D L_{ts}}{1000 V_s f_s Z} + k_0 (h_1 L_{ts} + h_2) \, , \qquad (5)$$

$$UC_{ri} = \left(k_0 + \frac{k_t Z}{T_{ri}} + \frac{k_0 t_e Z}{T_{ri}} \right) \frac{\pi D L_{tr}}{1000 V_{ri} f_{ri} Z} + k_0 (h_1 L_{tr} + h_2) \, . \qquad (6)$$

The profit rate in face-milling process can be determined by [11]

$$P_t = \frac{S_p - UC - C_{mat}}{TC} \, , \qquad (7)$$

where S_p denotes the unit sale price of the product (\$), C_{mat} represents the cost of raw material (\$).

2.2. *Constraints*

For given cutting conditions, there exist reasonable ranges of cutting speed, feed rate, and depth of cut, for either a finish or a rough pass:

$$V_{s,\min} \le V_s \le V_{s,\max} \, , \; f_{s,\min} \le f_s \le f_{s,\max} \, , d_{s,\min} \le d_s \le d_{s,\max} \, , \qquad (8)$$

$$V_{r,\min} \le V_{ri} \le V_{r,\max} \, , \; f_{r,\min} \le f_{ri} \le f_{r,\max} \, , d_{r,\min} \le d_{ri} \le d_{r,\max} \, . \qquad (9)$$

Tool lives in face-milling can be given by

$$T_s^l = \frac{C_v K_v D^{q_v}}{V_s d_s^{x_v} f_s^{y_v} B^{s_v} Z^{p_v}} \, , \; T_{ri}^l = \frac{C_v K_v D^{q_v}}{V_{ri} d_{ri}^{x_v} f_{ri}^{y_v} B^{s_v} Z^{p_v}} \, , \qquad (10)$$

where C_v, K_v, q_v, p_v, x_v, y_v, and s_v are constants; T_s and T_{ri} are tool lives (mm) in finish machining and rough machining, respectively. In this paper, we assume the tool lives are identical in finish and rough machining operations and require the same tool replacement time, i.e. $T_s = T_{ri} = T$. Surface finish requirements can by given by

$$f_s \le \sqrt{r_e R_{s,\max} / 0.0321} \, , \; f_{ri} \le \sqrt{r_e R_{r,\max} / 0.0321} \, , \qquad (11)$$

where r_e is cutter nose radius (mm); $R_{s,\max}$ and $R_{r,\max}$ are surface roughness requirements (mm) for finish machining and rough machining, respectively. Cutting force constraints can be written as

$$F = \frac{C_f K_f B^{s_f} Z^{p_f} d_s^{x_f} f_s^{y_f}}{D^{q_f}} \le F_{\max} \, ,$$

$$F = \frac{C_f K_f B^{s_f} Z^{p_f} d_{ri}^{x_f} f_{ri}^{y_f}}{D^{q_f}} \le F_{\max} \, , \qquad (12)$$

where C_f, K_f, x_f, y_f, p_f, q_f and s_f are constants; $F_{\max}$ is maximum available cutting force (kgf). Cutting power can be derived by multiplying cutting force and cutting speed,

$$P = \frac{FV_s}{6120\eta} = \frac{C_f K_f B^{s_f} Z^{p_f} V_s d_s^{x_f} f_s^{y_f}}{6120\eta D^{q_f}} \le P_{\max},$$

$$P = \frac{FV_{ri}}{6120\eta} = \frac{C_f K_f B^{s_f} Z^{p_f} V_{ri} d_{ri}^{x_f} f_{ri}^{y_f}}{6120\eta D^{q_f}} \le P_{\max}, \quad (13)$$

where η is the efficiency of the machine tool and $P_{\max}$ is the maximum power (kW). The total depth of cut d_t can be expressed as

$$d_t = d_s + \sum_{i=1}^{n} d_{ri}. \quad (14)$$

In the model, V_s, f_s, d_s, V_{ri}, f_{ri}, d_{ri}, and n are decision variables.

3. Solution Method

The primary objectives in solving the machining parameter optimization problems are reliability, accuracy of results, and efficient computation. The selection of a suitable solution method for the optimization problem depends on the problem itself. The form and complexity of the objective functions and constraints influence the solution procedure to be applied. The solution approaches themselves have characteristics that affect their efficiency and accuracy. In this paper, the values of optimal unit production cost, optimal unit machining time, optimal profit rate and corresponding machining parameters are found by GAs as evolutionary algorithms are becoming more popular in engineering design due to their effectiveness, particularly in obtaining global optimal solutions.

3.1. *Solution procedure statement*

Genetic Algorithms is a particular class of evolutionary algorithms that make use of techniques motivated by evolutionary biology such as selection, mutation, and crossover. When solving the multi-objective optimization model using GAs, decision variables V_s, f_s, d_s, V_{ri}, f_{ri}, d_{ri} are represented by binary numbers and these numbers are aligned in a long binary string which is called a chromosome. The population size in this research is 100. The fitness function consists of the sum of the unit production cost, unit machining time and profit rate using different weight coefficients for each objective function: $fit = w_1 UC + w_2 TC + w_3 Pt$, where the values of weight coefficients can be decided based on the practical situation, and w_1+w_2+w_3=1. Crossover is the operation to exchange some part of two chromosomes to generate new offspring (crossover rate is 80% in this paper). This operation is important for exploring the whole search space rapidly. Mutation operation randomly alters each bit of a binary string after crossover with a small probability (mutation rate is 0.05 in this work) to provide a small uncertainty to the new chromosome. In the paper 20% chromosomes with best fitness values are kept within the population to avoid losing the best strings, and the rest chromosomes apply to a crossover or mutation operation during each reproduction cycle. The same population size is maintained during the evolution process. After crossover and mutation, a new generation forms and the values of objective functions and machining parameters are calculated. After a certain number of generations (2000 iterations in this research), the GA should converge to the best chromosome, which represents the optimal or near-optimal solution to the problem. Fig. 1 shows the diagram of the proposed genetic algorithm.

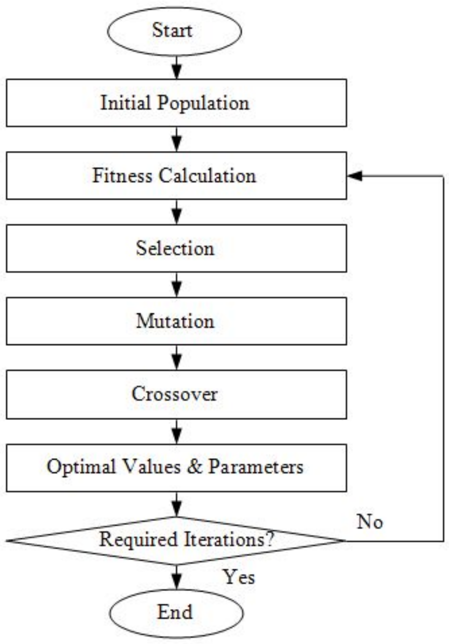

Fig. 1. GA flow chart

In this work, weight coefficients are respectively given by w_1 =0.6, w_2 =0.2, w_3 =0.2. Based on a given value of the total depth of cut and the feasible ranges of rough and finish cutting passes, possible numbers of total passes can be calculated. The algorithm computes for each case and compares the results for an optimal pass number.

We assume that the unwanted material should be cut off with one finish pass and *n* rough passes ($n \geq 1$). Therefore, the total number of cutting passes is $N=n+1$. The total depth of cut considered in this paper is 2.0mm$\leq d_t$ <8mm.

When n=1, there are 5 decision variables: V_s , V_r , f_s , f_r , d_s ($d_r = d_t - d_s$). When n=2, there are 8 decision variables: V_s , V_{r1} , V_{r2} , f_s , f_{r1} , f_{r2} , d_s , d_{r2} ($d_{r1} = d_t - d_s - d_{r2}$).

3.2. *GA implementation for n=1*

We select n =1 as an example to explain how to use the genetic algorithm for solving solutions of the problem.

3.2.1. *Determination of the string length*

Before the initial population is generated, the total length of a binary string which represents cutting parameters in the given order needs to be determined based on the domain and precision of the decision variables.

(i) Cutting speed of the finish pass, V_s : The parameter constraint is 50.0 $\leq V_s \leq$ 300.0. The domain of the variable is [50.0, 300.0] and the required precision is one place after the decimal point. The required number of bits for a binary variable can be calculated by $2^{L_1 - 1} < 300.0 \times 10^1 \leq 2^{L_1} - 1$. Therefore, the length of a binary string for V_s is L_1 =12.

(ii) Cutting speed of the rough pass, V_r : The domain of the variable is [50.0, 300.0] and the required precision is one place after the decimal point. Similarly, the length of a binary string for V_r is L_2 =12.

(iii) Feed rate of the finish pass, f_s : The domain of the variable is [0.10, 0.60] and the required precision is two places after the decimal point. Therefore, we have $2^{L_3 - 1} < 0.60 \times 10^2 \leq 2^{L_3} - 1$. The length of a binary string for f_s is L_3 =6.

(iv) Feed rate of the rough pass, f_r : The domain of the variable is [0.10, 0.60] and the required precision is two places after the decimal point. Therefore, we have $2^{L_4 - 1} < 0.60 \times 10^2 \leq 2^{L_4} - 1$. The length of a binary string for f_r is L_4 =6.

(v) Depth of cut for the finish pass, d_s : The domain of the variable d_s is [0.50, 2.00] and the required precision is two places after the decimal point. The required number of bits for a binary varible is computed by $2^{L_5 - 1} < 2.00 \times 10^2 \leq 2^{L_5} - 1$. The length of a binary string for d_s is L_5 =8.

Therefore, the total length of a chromosome is $L=L_1+L_2+L_3+L_4+L_5$=44.

3.2.2. *Fitness calculation*

Chromosomes in a population evolve based on their fitness values. In this paper, unit production cost and unit machining time are to be minimized while profit rate is to be maximized. Therefore, profit rate should be converted to the following form in the fitness function

$$P = \frac{1}{P_t} . \quad (15)$$

The fitness function is formed as follows:

$$fit = w_1 UC + w_2 TC + w_3 P . \quad (16)$$

The objective functions with large values may dominate contribution of other objectives. To avoid this, Equation (16) is replaced with Equation (17),

$$fit = w_1 \frac{UC}{UC_{\max}} + w_2 \frac{TC}{TC_{\max}} + w_3 \frac{P}{P_{\max}} . \quad (17)$$

The fitness value is the sum of the three items and should be minimized. Therefore, a chromosome with a lower fitness value has a higher probability of being selected to survive.

3.2.3. *Crossover*

To avoid losing the best strings, 20% chromosomes with best fitness values in a population are selected to directly enter the new population. Crossover operations are performed on the rest 80% chromosomes. An integer from the range [1, 43] is randomly generated as the crossover point. Offspring is generated by exchanging the right parts of the two parent chromosomes. The new chromosomes through crossover are required to meet all constraints to the model.

3.2.4. *Mutation*

Mutation rate is a probability to alter one gene (one bit of a chromosome). The mutation rate should be very low. Here the probability of mutation is set as 0.05. After crossover, a number r from [0, 1] is randomly produced and is compared with 0.05. If $r \le 0.05$, do mutation on that bit, changing zero to 1 or 1 to zero. During mutation operations, the created chromosomes are also required to meet all constraints. If some chromosomes do not, we keep creating new ones until the required number of satisfied chromosomes are generated.

4. Case Study and Analysis

The face-milling example given in Table 1 [11] is considered in this paper. Cemented carbide cutting tools are used to machine a gray cast iron workpiece (190HB). The same example was used to illustrate a solution approach [12].

Table 1. Data for the given example.

L=240mm, D=160mm, r_e=1mm, B=100mm, Z=16
k_o=0.5\$/min, k_t=2.5\$, t_e=1.5min, t_p=0.75min, S_p=25\$, C_{ma}=0.5\$
$h_1=7\times10^{-4}$(min/mm), h_2=0.3(min)
V_{max}=300m/min, V_{min}=50m/min, f_{max}=0.6mm/tooth, f_{min}=0.1mm/tooth, $d_{s,max}$=2mm, $d_{s,min}$=0.5mm, $d_{r,max}$=4mm, $d_{r,min}$=1mm
T=240min, $R_{s,max}$=0.0025mm, $R_{r,max}$=0.025mm, F_{max}=815.77kgf, P_{max}=10kW, η=0.8
C_v=445, l=0.32, x_v=0.15, y_v=0.35, p_v=0, q_v=0.2, s_v=0.2, K_v=1.0
C_f=54.5, x_f=0.9, y_f=0.74, s_f=1.0, p_f=1.0, q_f=1.0, K_f=1.0

The optimization model was solved by the proposed GA approach with MATLAB programming for d_t = 2.0, 2.5, 4.0, 6.0 and 8.0 mm. Table 2 shows the optimal solutions and corresponding parameters by one computation for each d_t . The average values of unit production cost, unit machining time and profit rate after 20 repeats are given in Table 3.

The results in Table 2 show that two rough passes and one finish pass are required when the total depth of cut is d_t = 8.0mm, with unit production cost of 1.3604\$/piece, unit machining time of 2.6296min, and profit rate of 8.7997\$/min. According to Ref. 12, the unit production cost is 1.70\$/piece, unit machining time is 3.14 min, and profit rate is 7.25\$/min. By comparison, the proposed optimization method reduces the unit production cost by 19.98% and the unit machining time by 16.25%, and increases the profit rate by 17.61%. The proposed method also presents better results than other methods in the literature [7].

Table 2. Optimal solutions and corresponding parameters by one computation.

d_t [mm]	2.0	2.5	4.0	6.0	8.0
d_s [mm]	0.7118	1.2412	1.0941	0.8353	1.1000
d_{r1} [mm]	1.2882	1.2588	2.9059	1.4113	2.9705
d_{r2} [mm]	—	—	—	3.7534	3.9295
f_s [mm/tooth]	0.2778	0.2556	0.2492	0.2810	0.2619
f_{r1} [mm/tooth]	0.5683	0.5286	0.4810	0.3063	0.5127
f_{r2} [mm/tooth]	—	—	—	0.3937	0.5683
V_s [m/min]	227.1673	235.1038	272.1612	268.5592	259.4017
V_{r1} [m/min]	241.0867	265.4457	235.3480	204.5788	288.1563
V_{r2} [m/min]	—	—	—	182.2955	266.5446
N	2	2	2	3	3
UC [\$/piece]	1.0939	1.1001	1.0929	1.4440	1.3604
TC [min]	2.1049	2.1144	2.1042	2.7669	2.6296
P_t [\$/min]	11.1198	11.0671	11.1240	8.3327	8.7997

Table 3. Optimal solutions after 20 computations.

d_t [mm]	2.0	2.5	4.0	6.0	8.0
N	2	2	2	3	3
UC [\$/piece]	1.0781	1.0848	1.0806	1.3978	1.3922
TC [min]	2.0808	2.0916	2.0850	2.6922	2.6810
P_t [\$/min]	11.2573	11.1964	11.2334	8.5830	8.6217

Our research demonstrates that GA operators have influence on the results of the objective functions. Tables 4-6 respectively show the variation of unit production cost, unit machining time, and profit rate with the change of crossover and mutation rates in our computational range, when the total depth of cut is d_t=6mm and the tool replacement time is T=240min. The optimal unit production cost, unit machining time, and profit rate respectively take the best values of 1.3893\$/piece, 2.6767min, and 8.6355\$/min, all at the condition of crossover rate=0.75 and mutation rate=0.04.

Table 4. Unit production cost under various values of GA operators (d_t=6mm, T=240min)

Mutation Rate \ Crossover Rate	0.6	0.75	0.8
0.03	1.4064	1.3987	1.3981
0.04	1.3934	1.3893	1.3974
0.05	1.3927	1.3939	1.3978

Table 5. Unit machining time under various values of GA operators (d_t=6mm, T=240min)

Mutation Rate \ Crossover Rate	0.6	0.75	0.8
0.03	2.7042	2.6918	2.6911
0.04	2.6840	2.6767	2.6896
0.05	2.6816	2.6840	2.6922

Table 6. Profit rate under various values of GA operators (d_t=6mm, T=240min)

Mutation Rate \ Crossover Rate	0.6	0.75	0.8
0.03	8.5421	8.5837	8.5859
0.04	8.6099	8.6355	8.5910
0.05	8.6185	8.6095	8.5830

The objective function and some of the constraint functions in the optimization model are non-linear, using GA seems simpler than using conventional nonlinear optimization methods. Using those methods may require model linearization and approximation, and sometimes, with slow convergence.

5. Conclusions

The multi-objective optimization of machining parameters for face-milling operations was studied in this paper. Unit production cost, unit machining time, and unit profit rate were optimized simultaneously by Genetic Algorithms. The method presented in this paper can also be used in other machining operations such as grinding and drilling and some non-traditional machining processes. In addition, other objectives such as surface quality and tool life can also be optimized using the proposed method. These may form our future work in the area of machining parameter optimization. As well, Simulated Annealing (SA) and other meta-heuristics may be used to solve these problems.

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