Determination of Optimal Cutting Condition for Desired Surface Finish in Face Milling Process Using Non-Conventional Computational Methods

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Abstract. CNC (Computer Numerical Control) milling process is one of the common metal removal operation used in industries because of its ability to remove material faster with reasonably good surface quality. Surface roughness is the most important attributes of the manufactured component in finish machining process. To obtain required surface finish the selection of optimal cutting condition so as to minimize the total production time is aimed in this work. In contrast to structured conventional/traditional algorithm, this paper discusses the use of three non-conventional optimization methods viz., Particle Swarm Optimization (PSO), Teaching Learning Based Optimization (TLBO), and Fuzzy set based optimization to solve optimization problem. To demonstrate the procedure and performance of the approach illustrative examples are discussed. The algorithms are coded in Matlab® and computational efforts, accuracy of result, effectiveness of algorithm are compared.

Keywords: Finish milling, fuzzy set, optimization, PSO, TLBO.

1 Introduction

Optimization of machining parameters is an important step for the selection of cutting conditions in CNC machining being used in today's automated manufacturing system. Among several CNC machining process, face milling is one of the commonly used metal removal operations for machining casted components due to its ability to remove material faster with reasonable good surface quality. For optimizing the process, number of researchers used various conventional and non-conventional optimization techniques both for single or multi pass machining problems. The conventional methods of optimization such as graphical techniques, constrained optimization strategy, dynamic programming, branch and bound algorithm, etc., have been used for the optimization of cutting parameters [1,2]. These techniques are found to be ineffective since they either result in local minima, or take long time to converge on a reasonable result. Mukherjee and Ray [3] mentioned that the determination of optimal cutting conditions through cost–effective mathematical models is a complex research for long time and the techniques for process modeling and optimization have undergone substantial development and expansion. In recent past, the researchers have used soft computing techniques as they are being preferred to physics-based models for predicting the performance of machining processes. Chandrasekaran et al. [4] have reviewed nearly 20 years of research work in the area of metal cutting processes with the application of soft computing methods. The use of major soft computing tools such as neural networks, fuzzy sets, genetic algorithms, simulated annealing, ant colony optimization, and particle swarm optimization in performance prediction and optimization of four common machining process viz., turning, milling, drilling, and grinding is aimed in their work.

Wang [5] employed an optimization strategy for single pass end milling on CNC machine tools considering many practical constraints for optimization of minimum production time per component. Shunmugam et al. [6] used GA for optimization of multi pass face milling process to minimize minimum production cost. The machining parameters such as cutting speed, feed per tooth, depth of cut, and number of passes are optimized. Baek et al. [7] developed a method for optimization of a face milling process using a surface roughness model. Rao et al. [8] carried out the optimization of multi pass milling using three non-conventional optimization algorithms namely artificial bee colony (ABC), particle swarm optimization (PSO) and simulated annealing (SA). From the review of literatures, most of the researchers used soft computing based optimization methods and found good results over conventional optimization approach. The literature related to milling optimization is mainly concerned with single objective only, mostly of minimization of production time or cost. Also the fuzzy set based optimization, teaching learning based optimization is not attempted earlier in optimizing milling process.

In the present work, the determination of optimal cutting condition to achieve desired surface finish in a face milling process for minimizing the total production time is attempted. Three non-conventional optimization methods, viz., PSO, TLBO and Fuzzy set based optimization are employed to solve the problem. The accuracy of the results, computational effort, and efficiency of algorithm are found advantageous in comparison with conventional optimization techniques.

2 Mathematical Formulation

In CNC milling, the desired surface roughness is aimed in finish pass during which the depth of cut remains constant. The surface roughness mainly depends on selected cutting conditions viz., cutting velocity and feed per tooth. In this work, an optimization model proposed by Singh et al. [9] to minimize the total production time is used. The total production time composed of: (i) Actual machining time (Tm), (ii) Work piece loading and unloading time (Tl/u), (iii) Cutter change time (Ttc) and (iv) Machine preparation time (Tp) to produce batch of components. Thus the total production time being sum of all above is expressed as:

$$P_t = T_m + T_{l/u} + T_{tc} + T_p \quad (1)$$

$$P_t = \frac{\pi DL}{1000Vf_z z} + T_{l/u} + t_c \frac{\pi DL}{1000Vf_z z} \times \left[\frac{Vd^{x_v} f_z^{y_z} W^{t_v} z^{p_v}}{C_v K_v D^{q_v}} \right]^{1/m} + \frac{t_s}{B_s} \quad (2)$$

The objective is to minimize P_t.

Machining Constraints.

The practical constraints imposed during the process are mainly due to: (i) parameter bounds and (ii) operating constraints. The parameter bounds are expressed as:

$$V_{\min} \le V \le V_{\max} \text{ and } (f_z)_{\min} \le f_z \le (f_z)_{\max} \quad (3)$$

Operating constraints namely cutting force, and cutting power constraints are considered in this modeling. The cutting force constraint aims to prevent chatter as well as to limit deflection of cutter which would otherwise lead to produce poor surface finish and dimensional deviation. The peripheral cutting force during face milling is given by [10].

$$P_z = \frac{C_F K_F W^{t_F} z^{p_F} d^{x_F} f_z^{y_F}}{D^{q_F}} = C_1 d^{x_F} f_z^{y_F} \quad (4)$$

where C_F and K_F are constants, t_F,p_F,x_F,y_F and qF are exponents and

$C_1 = \frac{C_F K_F W^{t_F} z^{p_F}}{D^{q_F}}$ hence, $P_z \le P_{z(\max)}$.

Surface finish is affected by various parameters such as cutting speed, feed, depth of cut, tool geometry, etc. The empirical relation based on dominating parameters is expressed as [10]

$$R_a = 0.0321 \frac{f_z^2}{r} \quad (5)$$

where, r is the cutter tooth nose-radius. Hence the surface finish constraint satisfies if $R_a \le R_{(\max)}$. Combining cutting force and surface finish constraints, the variable bounds for feed are obtained as:

$$f_{z(\min)} \le f_z \le \min \left\{ f_{z(\max)}, \sqrt{\frac{R_{\max} r}{0.0321}}, \left[\frac{Pz}{C_1 d^{x_F}} \right]^{1/y_F} \right\} \quad (6)$$

The cutting power during machining process should not exceed the maximum power (P_{max}) available at the machine tool spindle. It is given by

$$P = \frac{C_P K_P W^{t_P} z^{p_P} V d^{x_P} f_z^{y_P}}{D^{q_P}} = C_2 V d^{x_P} f_z^{y_P} \tag{7}$$

where C_P and K_P are constants, t_P,p_P,x_P,y_P and q_P are exponents and $C_2 = \frac{C_P K_P W^{t_P} z^{p_P}}{D^{q_P}}$.

Hence, $P \le P_{(max)}$. This imposes the variable bounds for cutting speed as:

$$V_{min} \le V \le \min\left\{ V_{max}, \frac{P}{C_2 d^{x_P} f_z^{y_P}}, \right\} \tag{8}$$

3 Solving by Non-Conventional Optimization Methods

A. Particle Swarm Optimization Method

PSO is a population based stochastic optimization technique inspired by social behavior of bird or fish schooling, developed by Eberhart and Kenedy [11] in 1995. Similar to the behavior of birds a group of random particles (solutions) is initialized and searches for global optimum solution by updating generations. For n-dimensional space the position and velocity of ith particle in the search space is initialized as and respectively. The objective function value is considered as fitness value of each particle. The best solution of each particle (pbest) and the current global best (gbest) are stored. The new coordinates of the particle are updated in every generation according to the following relation:

$$v_{ij}(t+1) = w.v_{ij}(t) + c_1 r_1 (pbest_{ij}(t) - x_{ij}(t)) + c_2 r_2 (gbest_{ij}(t) - x_{ij}(t)) \tag{9}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{10}$$

j=1,2,3,…….n

where c_1 and c_2 are learning factors and r is a random number between (0,1) and w is the inertia weight for the present velocity.

Number of particles, particle co-ordinate range, learning factors, inertia weights and termination criteria are important PSO parameters. The algorithm effectiveness is mainly depends on proper selection of these values.

An Example.

Consider a finish pass milling process at a constant depth of cut of 1.5 mm to obtain desired surface finish of 2.0 µm. The length (l) and width (w) of the work piece is 300 mm and 150 mm respectively. The cutter size (D) is 160 mm. The length of travel by the cutter (L) is considered as (L + D) and is 460 mm. A work material of grey cast iron is machined with cutter made of cemented carbide. The other parameters remain constant as shown in Table 1.

Table 1. Numerical data of the example problem.

Process : Face Milling	
Cutting speed range (V)	50 – 300 m/min
Table feed range (f_z)	0.1 – 0.6 mm/tooth
Number of teeth (z)	16 Nos
Tool change time (t_c)	5 min
M/c preparation time (t_s)	15 min
Loading and unloading time ($T_{l/u}$)	1.5 min
Batch size (Bs)	150 Nos.
Constants and exponents	
Tool life: $C_v = 445$, $K_v = 1.0$, $m = 0.32$, $x_v = 0.15$, $y_v = 0.35$, $p_v = 0$, $q_v = 0.2$, $t_v = 0.2$	
Cutting Force: $C_F = 534.6$, $K_F = 1.0$, $t_F = 1$, $p_F = 1.0$, $x_F = 0.9$, $y_F = 0.74$, $q_F = 1.0$	
Cutting Power: $C_P = 0.5346$, $K_P = 1.0$, $t_P = 1.0$, $p_P = 0$, $x_P = 0.9$, $y_P = 0.74$, $q_P = 1.0$	

PSO was performed for desired surface roughness value of 2.0 µm. Ten particles are considered as initial population and the particle's co-ordinates are randomized in the solution space. In subsequent iterations all swarms move towards optimum and it is reached in 8th iterations. The optimum parameters are 180.9 m/min and 0.137 mm/tooth for V and f_z respectively. The total production time obtained is 2.2061 min. The algorithm was coded in Matlab® and run on a Pentium 4 PC.

B. Teaching-Learning-Based Optimization (TLBO) Method

In solving machining optimization problems 'nature-inspired' heuristic optimization techniques are becoming popular and proven to be better than conventional optimization methods. However, the applications of these algorithms are effective for specific kind of problem and the selection of optimal controlling parameters found to be difficult. Rao et al. [12] proposed a new optimization technique known as "Teaching-Learning-Based-Optimization (TLBO)" based on philosophy of the teaching-learning process. TLBO being population based method has a 'group of learners' learns both from the teacher in 'Teacher phase' as well as through interaction between them in 'Learner phase'. They have applied this technique for different benchmark design optimization problems and shows better performance with less computational effort. This technique is applied here for obtaining optimal cutting parameters for finish milling process in which 'initial randomized solution' considered as 'number of learners', 'best solution of the iteration' as 'teacher of the iteration' and 'decision variables' as 'courses or subjects offered' by them in the process of learning.

Steps in the TLBO.

The optimization methodology based on TLBO [12] consists of following steps:

Step 1: Randomize initial population (n=number of learners) and the termination criteria (i.e., number of generation).

Step 2: In teacher phase, first calculate mean of each decision variables (V & f_z) of the optimization problem and identify mean row vector (i.e., MD = [V,f_z]). The new mean (M_new,D) is the best solution of the iteration and will act as a teacher.

Step 3: Now update the current solution by adding the 'difference of the means' to it. The difference between the means is given by Eq. 11.

$$Diff_D = r(M\_new_D - t_f \times M_D) \tag{11}$$

where r is a random number in the range [0,1] and t_f is teacher factor which is either 1 or 2. The new solution is accepted if it gives better function value otherwise not.

Step 4: In learner phase, select any two learners (data sets) and evaluate its function

values. Based on their function values the new data set (X_{new}) is calculated. If P_{t_1} and P_{t_2} are the two function values,

$$\begin{aligned} X_{new} &= X_{old} + r(X_1 - X_2) \;\; if \;\; P_{t_1} < P_{t_2} \\ and \;\; X_{new} &= X_{old} + r(X_2 - X_1) \;\; if \;\; P_{t_2} < P_{t_1} \end{aligned} \tag{12}$$

Accept X_{new} if it gives better function value otherwise not.

Step 5: Continue from Step 2 till the termination criteria is met.

An Example.

For the illustrated problem stated in previous section the optimum cutting condition obtained by TLBO is (180.9, 0.137) and the total production time at optimal cutting condition is 2.2061 min and the solution is converged in three iterations. Table 2 shows iteration wise result of the problem. Number of problems having depth of cut from 1.5 mm to 2.5 mm for different values of surface roughness are tested and results are better than PSO.

Table 2. Iteration wise result.

Input data (d,Ra): 1.5 mm, 2.0 µm		
Iteration No.	Optimum cutting parameters (V (m/min) and f_z (mm/tooth))	P_t (min)
1	177.9, 0.137	2.2172
2	180.7, 0.137	2.2073
3	180.9, 0.137	2.2061

C. Fuzzy Set Based Optimization Method

Prof. Zadeh introduced fuzzy set theory in 1965 and it has been applied to a number of engineering problems. Its applications include: (i) use of fuzzy set operations in decision making, (ii) use of fuzzy arithmetic wherein physical variables are considered as fuzzy numbers and (iii) use of fuzzy logic in modeling and control problems. Recently, Chandrasekaran et al. [13] have developed a fuzzy rule based optimization procedure for solving general optimization problems, which can provide an approximate and multiple solutions. They used fuzzy set theory as a general optimization tool for optimizing multi pass turning process and the method is applied here to obtain optimum cutting condition.

Steps in the Fuzzy Set Optimization.

The proposed optimization strategy using fuzzy logic consists of the following steps:

Step 1: The search domain is divided into a number of cells with the decision variables fuzzified into a number of fuzzy sub-sets. Membership grade 1 is allotted to centroids of the cell and 0 to the boundaries of the cell. A linear membership function is considered for the fuzzy subset.

Step 2: Machining is performed at each cell centroids and evaluate the function values at cell centroids. Now, decide the minimum ($P_{t_{\min}}$) and maximum ($P_{t_{\max}}$) values. Fuzzyify them into n number of overlapping fuzzy sets as shown in Figure 5. If $P_{t_{\min}}$ and $P_{t_{\max}}$ are the variable bounds then for i-th fuzzy subset of the fuzzified variable, the value at the vertex corresponding to the membership grade 1 is given by:

$$\text{value at the vertex} = P_{t_{\min}} + \frac{P_{t_{\min}} - P_{t_{\min}}}{n-1}\left(i-1\right) \tag{13}$$

The right and left limits of the fuzzy subset (vertices corresponding to 0 membership grades) are given by

$$right\lim it = P_{t_{\min}} + \frac{P_{t_{\max}} - P_{t_{\min}}}{n-1} i \quad \text{and}$$

$$left\lim it = P_{t_{\min}} + \frac{P_{t_{\max}} - P_{t_{\min}}}{n-1}(i-2) \tag{14}$$

The first fuzzy subset does not have a left vertex (0 membership grade) and last fuzzy subset does not have a right vertex (0 membership grade). Now, for each cell, the consequent part of the rule is the output of fuzzy subset at cell centroids and the strength of the rule is the membership grade of the fuzzy subset. A typical rule has the following form: "**If *V* is high and f_z is high, then P_t is very low**"

Step 3: Based on the rule base, desired objective and constraints the cell having the highest strength of the rule is selected and the search refined (starts with Step 1) in it. This identifies the optimum zone in which there is no significant variation in function value but provides number of optimal cutting conditions.

An Example.

Consider a finish pass milling process having depth of cut of 1.5 mm to obtain maximum desired surface roughness value of 2.0 µm. The linguistic sub division of search domain satisfying the constraints for this problem is as shown in Figure 1. The size of the search domain varies with problem in order to satisfy required constraints. Machining is performed at each of cell centroids and results are shown in Table 3.

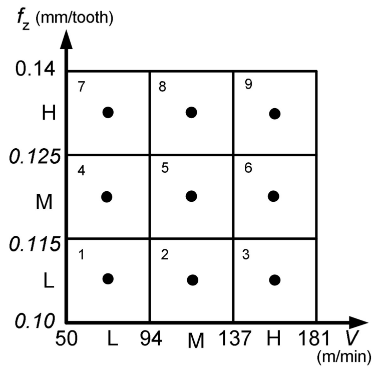

Fig. 1. Linguistic division of search domain

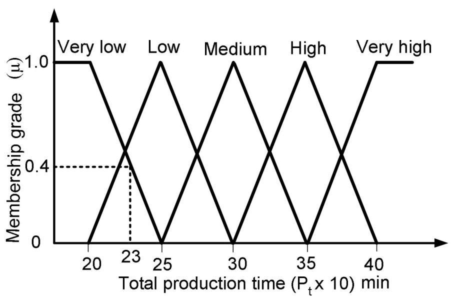

Fig. 2. Fuzzification of output variable.

Choosing $P_{t_{\min}}$ =2.0 and $P_{t_{\max}}$ =4.0 the output variable is fuzzified into 5 fuzzy subsets as shown in Figure 2. Table 4 depicts the rule base along with strength of the rules. As the problem objective is to minimize the function value, the rule 9 corresponds to cell 9 with the cutting condition of cell centroid (159.1, 0.132) having higher strength (membership grade) at low function value of 2.312, is fired. Thus, the search domain is reduced to $137 \le V \le 181$ and $0.125 \le f_z \le 0.14$.

Table 3. Function values at centroids of each cell.

Input data (d,R_a): 1.5 mm, 2.0 μm			
Cell No.	Cell centroids V (m/min), f_z (mm/tooth)		Total Production time (P_t) (min)
1	(71.8,0.106)	(low-low)	3.498
2	(115.5,0.106)	(medium-low)	2.788
3	(159.1,0.106)	(high-low)	2.473
4	(71.8,0.119)	(low-medium)	3.301
5	(115.5, 0.119)	(medium-medium)	2.670
6	(159.1,0.119)	(high-medium)	2.384
7	(71.8, 0.132)	(low-high)	3.141
8	(115.5,0.132)	(medium-high)	2.570
9	(159.1,0.132)	(high-high)	2.312

Table 4. Fuzzy rule base with membership strength.

Cell No	*Cutting speed (V)*	*Feed (f_z)*	*Total production time (P_t)*	*Membership grade*
1	Low	Low	High	1.0
2	Medium	Low	Low	0.4
3	High	Low	Low	1.0
4	Low	Medium	Medium	0.4
5	Medium	Medium	Low	0.6
6	High	Medium	Very Low	0.2
7	Low	High	Medium	0.8
8	Medium	High	Low	0.8
9	**High**	**High**	**Very Low**	**0.4**

The new search is now initiated in the identified search domain, dividing it into 4 cells with the fuzzy sub-set being 'low' and 'high'. This provides new domain: $159.1 \le V \le 180.9$ and $0.13 \le f_z \le 0.14$. The function value has no significant variation which is in the range between 2.2 and 2.3. Thus, with the given range of cutting speed and feed rate, the fuzzy set based optimization provides the following solution.

$$159.1 \le V \le 180.9, \quad 0.13 \le f_z \le 0.14 \tag{15}$$

With small variation in time the fuzzy set based optimization provides multiple numbers of solutions.

A number of other problems having depth of cut varying from 1.5 mm to 2.5 mm for different values of desired surface roughness are tested. The optimum zone provides multiple solutions to the problem. The function value and surface roughness produced in optimum fuzzy domain do not vary significantly.

4 Results and Discussion

Table 5 shows the comparison of the results obtained by three optimization methods. Based on computational results presented herein, it may be concluded that the proposed non-conventional optimization methods are advantageous and can be applied to machining optimization problem. PSO algorithm being a random search obtains optimal or near optimal global solution with 10 or less number of iterations. It requires proper selection of controlling parameters and algorithm effectiveness mainly depends on it. TLBO takes less number of iterations in reaching global optimum solution. Though the result obtained by both techniques is very close. Of the two, TLBO provides marginally better result than PSO. Fuzzy set based optimization technique provides multiple numbers of solutions having feasibility for alternative selection of optimum cutting condition. It may be noted that the optimal solution obtained by PSO and TLBO for different problems are within the optimum fuzzy domain. The linguistic subdivision of the domain provides an optimum zone in the solution space range, in which the objective function value does not change drastically. The feasibility of incorporating an expert knowledge is one of the main advantages of this method.

Table 5. Comparison of results.

Desirable surface finish R_a(μm)	For 1.5 mm depth of cut Optimum cutting parameters (V, f_Z), Minimum production time (P_t)and Number of iterations (i)		
	PSO (V,f_z):P_t:i	TLBO (V,f_z):P_t:i	Fuzzy set (V; f_z; P_t)
2.0	(180.9,0.137):2.2061:8	(180.9,0.137):2.2061:3	$159.1 \le V \le 180.9; 0.13 \le f_z \le$ C $2.2 \le P_t \le 2.3$
2.5	(166.7,0.150):2.1894:8	(166.7,0.150):2.1893:3	$157 \le V \le 167; 0.14 \le f_z \le 0.15$ $P_t = 2.2$
3.0	(156.3,0.167):2.1743:7	(156.3,0.167):2.1742:2	$147.4 \le V \le 156.8; 0.16 \le f_z \le$ ($P_t = 2.2$
4.5	(134.3,0.205):2.1401:9	(134.3,0.205):2.1400:4	$127.2 \le V \le 134.5; 0.19 \le f_z \le$ ($2.1 \le P_t \le 2.2$
5.0	(129.2,0.216):2.1313:7	(129.2,0.216):2.1310:3	$122.6 \le V \le 129.2; 0.21 \le f_z \le$ C $2.1 \le P_t \le 2.2$

In general the result shows that the total production time per component reduces as the maximum allowable surface finish increases. Figure 3 shows the result of total production time Vs desired surface roughness for different values depth of cut. From the graph it is evident that the production time decreases as depth of cut decreases. However in finish machining process depth of cut remains constant. Among the other two influencing parameters i.e., feed and cutting velocity, feed is constrained mainly due to desired surface roughness value while cutting velocity by cutting power. Since the cutting power is the function feed, depth of cut and cutting velocity, the increased depth of cut proportionately decreases optimum cutting velocity while feed remains fixed due to surface roughness criterion.

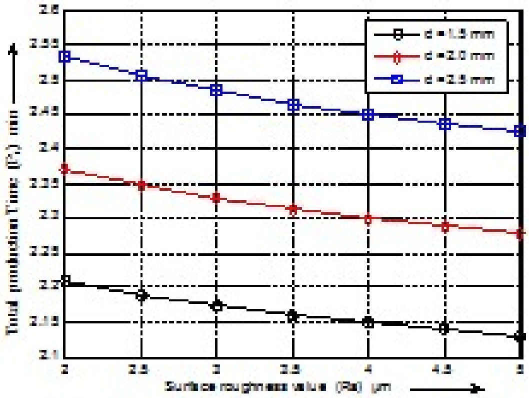

Fig. 3. Variation of 'Ra' Vs 'P_t'.

5 Conclusions

In this work, CNC milling process is optimized to minimize total production time and so as to obtain desired surface finish value of the components produced. Cutting speed and feed per tooth as decision variables and practical constraints such as cutting force, cutting power, surface roughness, and variable bounds of the decision variables are considered in model formulation. Three non-conventional optimization methods viz., PSO, TLBO, and Fuzzy set based optimization are employed to solve the problem. The solution methodology is presented with an illustrated example and numbers of problems are solved.

Both PSO and TLBO provide better solution accuracy with less computational effort compared with conventional optimization techniques. Of the two, TLBO provides marginally better result than PSO with less number of iterations. PSO need proper selection of controlling parameters and effectiveness of algorithm is mainly depends on it. While TLBO is free from such algorithm parameters and found easy to implement it. Fuzzy set optimization is based on linguistic subdivision of the domain providing a 'range of optimal solution' in which the objective function value does not change drastically. Thus the procedure provides multiple numbers of optimal solutions having feasibility for alternative selection. Source codes for all three methods are written in MATLAB 7.2 and computational time takes less than a second in Pentium-IV with RAM 512. The code can be used for other finish machining process as well as for multi pass machining with necessary modification

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