Optimization of Multi-Pass Turning Operations Using Genetic Algorithms

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Abstract

Cutting operations are one of the most popular machining operations in the industrial manufacturing systems. These operations consist of two stages, namely roughing and finishing. In the finishing stage, machining parameters including cutting speed, feed rate and depth of cut are to be determined. In rouging stage, in addition to these parameters, the number of rough cut passes should be decided. This paper proposes a non-linear constrained mathematical programming model for determination of the aforementioned parameters. An optimization technique based on genetic algorithms (GA) is proposed to simultaneously optimize the multi-pass roughing and single-pass finishing parameters. An illustrative example adopted from the literature is solved through the proposed algorithm to show the efficiency and effectiveness of the proposed method.

Keywords: Multi-pass turning, Constraints, Optimization, Cutting parameters, Genetic Algorithms

Nomenclature

UC	Unit production cost except material cost ($/piece)
C_M	Cutting cost by actual time in cut ($/piece)
C_I	Machine idle cost due to loading and unloading operations and tool idle motion time ($/piece)
C_R	Tool replacement cost ($/piece)
C_T	Tool cost ($/piece)
V_r, V_s	Cutting speeds in rough and finish machining (m/min)
V_{rL}, V_{rU}	Lower and upper bound of cutting speed in rough machining (m/min)
V_{sL}, V_{sU}	Lower and upper bound of cutting speed in finish machining (m/min)
f_r, f_s	Feed rates in rough and finish machining (mm/rev)
f_{rL}, f_{rU}	Lower and upper bound of feed rate in rough machining (mm/rev)
f_{sL}, f_{sU}	Lower and upper bound of feed rate in finish machining (mm/rev)
d_r, d_s	Depth of cut for each passes of rough and finish machining (mm)
d_{rL}, d_{rU}	Lower and upper bound of depth of cut in rough machining (mm)
d_{sL}, d_{sU}	Lower and upper bound of depth of cut in finish machining (mm)
n	Number of rough cuts (an integer)
d_t	Depth of material to be removed (mm)
D, L	Diameter and length of work-piece (mm)
k_o	Direct labor cost + overhead ($/min)
k_t	Cutting edge cost ($/edge)

t_{mr}, t_{ms}, t_m Rough, finish and actual machining times (min)

t_e, t_r Tool exchange and tool replacement times (min)

h_1, h_2 Constants related to tool travel and approach/departure time (min)

T, T_r, T_s Tool life, expected tool life for rough machining, expected tool life for finish machining (min)

T_p Tool life of weighted combination of T_r and T_s (min),

T_L, T_U Upper and lower bounds for too life (min),

p, q, r, C_o Constants of tool life equation,

F_r, F_s Cutting forces during rough and finish machining (kgf),

F_U Maximum allowable cutting force (kgf),

k_1, μ, ν Constants of cutting force equation,

P_r, P_s Cutting power during rough and finish machining (kW),

P_U Maximum allowable cutting power (kW),

λ, υ Constants related to expression of stable cutting region,

SC Limit of stable cutting region constraint,

R Nose radius of cutting tool (mm),

SR_U Maximum allowable surface roughness (mm),

Q_r, Q_s Chip-tool interface rough and finish machining temperatures (C°),

Q_U Maximum allowable chip-tool interface temperatures (C°),

$k_2, \tau, \varphi, \delta$ Constants related to equation of chip-tool interface temperature,

k_3, k_4, k_5 Constants for roughing and finishing parameter relations $k_3, k_4, k_5 \geq 1$.

1. Introduction

To survive in today's competitive manufacturing environment, production of products with a good quality in a shorter time and with lower cost is essential. The selection of optimal cutting parameters is a very important issue for every machining process. To ensure the quality of machined surfaces and reduce the machining costs and time, it is inevitable to optimally select the machining parameters like the number of passes, depth of cut for each pass, feed rate and cutting speed. In manufacturing processes, the most commonly used optimization criteria is the unit production cost function, which has been dealt by many researchers. Other important criteria are such as surface quality, material removal rate, and tool life. In this paper unit production cost function is considered as the objective function to be optimized and an optimization technique based on genetic algorithms is proposed for solving the machining optimization problems concerning the multi-pass turning operations. Machining optimization problem is investigated in two modes, single-pass and multi-pass. However, mostly multi-pass mode is preferred over single-pass mode because of economic reasons. This optimization problem has been attempted by many researchers. However, early studies were limited to single-pass mode without consideration of regular constraints which gave a subnormal face to the problem. Shin and Joo [1] developed a mathematical model for multi-pass turning operations. Their model is frequently benchmarked and extended in other studies. They provided a numerical example and proposed an approach for solving it that combined the Fibonacci search and dynamic programming. Afterwards, Gupta et al. [2] solved the same problem in two steps. The first step of their approach is to calculate the minimum production cost for the roughing and finishing operations for the various depths of cut. The second step is to determine the optimal combination of depth of cut for roughing and the finishing operation. Their approach determines a production cost, which is substantially less than when using Shin and Joo's method. Alberti and Perrone [3] suggested a multi-objective possibilistic programming model in which the optimal solution is obtained using a genetic algorithm. They compared their results with the results obtained by Gupta et al. [2] for the same examples. Although their results were never worse than those obtained by Gupta et al., in two of the six examples their solutions showed a very tiny violation of the cutting force constraint. Chen and Tsai [4] extended the multi-

pass turning operation model of Shin and Joo [1] by adding seven more constraints. They also proposed an approach combining the simulated annealing algorithm and a pattern search technique for solving the extended model. Onwubolu and Kumalo [5] proposed a technique based on a genetic algorithm to determine the optimal machining parameters for the extended model of Chen and Tsai. They arrived at an even lower production cost than that obtained by Chen and Tsai [4]. However, the optimal value obtained by Onwubolu and Kumalo was argued impractical by Chen and Chen [6]. They pointed out that Onwubolu and Kumalo did not limit the number of rough cuts to an integer value. For the same problem, Vijayakumar et al. [7] proposed an ant colony optimization method and claimed that their ant colony-based approach found an even better solution with less runs than either the approach of Chen and Tsai or the GA-based approach of Onwubolu and Kumalo. However, their solution was later proven to be invalid [8]. In this paper an optimization technique based on genetic algorithm has been adopted to optimize the multi-pass turning operations, subject to several constraints provided by the machining model of Chen and Tsai [4]. Hereafter, the paper is organized as follows. Section 2 describes the mathematical formulation of the attempted problem. Section 3 briefly describes the proposed hybrid genetic algorithm. An illustrative example is solved and discussed in Section 4 to show the applicability and validity of the formulated model.

2. Multi-Pass Turning Model

The main objective of the present optimization cutting model is to determine the optimal machining parameters including cutting speed, feed rate, depth of cut and number of rough cuts in order to minimize the unit production cost and simultaneously achieve an acceptable surface finish, without violating any imposed cutting constraint. The mathematical model used by Chen and Tsai [4] is adopted in this work for determining the optimal machining parameters mentioned above.

2.1. Cost function

The unit production cost, UC, except material cost, for the multi-pass turning operations problem consists of four basic cost components [1].

1. Machining cost by actual time in cutting operation, CM.
2. Machine idle cost due to loading and unloading operations and idle tool motion, CI.
3. Tool replacement cost, CR.
4. Tool cost, CT.

Chen and Tsai [4] considered all the four basic cost components discussed by Shin and Joo [1]. The present work considers these basic cost components because they seem to be adequate in modeling the multi-pass turning operations problem.
These components are now summarized. For more details, see Chen and Tsai [4].

2.1.1. Machining cost

The cutting process is divided into multi-pass roughing and finishing [1]. The machining cost, *C*M, is expressed as:

$$C_M = k_0 \left[\frac{\pi DL}{1000 V_r f_r} \left(\frac{d_t - d_s}{d_r} \right) + \frac{\pi DL}{1000 V_s f_s} \right]. \tag{1}$$

2.1.2. Machine idle cost

The machine idle cost is divided in a constant term due to loading and unloading operations and a variable term due to idle tool motion [1] expressed as:

$$C_I = k_0 \left[t_c + \left(h_1 L + h_2 \right) \left(\frac{d_t - d_s}{d_r} + 1 \right) \right]. \tag{2}$$

2.1.3. Tool replacement cost

The Taylor tool-life equation is used as given in Armarego and Brown [9]:

$$T = \frac{C_0}{V^p f^q d^r}. \tag{3}$$

Owing to the different machining conditions, the wear rate of tools usually differs between roughing and finishing. The tool life in such a case can be expressed as in [1]:

$$T_p = \theta T_r + (1-\theta) T_s, \tag{4}$$

Where

$$T_r = \frac{C_o}{V_r^p f_r^q d_r^r}, T_s = \frac{C_o}{V_s^p f_s^q d_s^r}. \tag{5}$$

The tool replacement time can be written in terms of tool life (T_p), time required to exchange a tool (t_e) and cutting time [1]. It can be formulated as:

$$C_R = k_o \frac{t_e}{T_p}\left[\frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_s}{d_r}\right) + \frac{\pi DL}{1000 V_s f_s}\right]. \tag{6}$$

2.1.4. Tool cost

The tool cost can be formulated as follows:

$$C_T = \frac{k_t}{T_p}\left[\frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_s}{d_r}\right) + \frac{\pi DL}{1000 V_s f_s}\right]. \tag{7}$$

2.1.5. Unit production cost

Using equations (1), (2), (6) and (7), the unit production cost, UC, is defined as:

$$\begin{aligned} UC = C_M + C_I + C_R + C_T &= k_o\left[\frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_s}{d_r}\right) + \frac{\pi DL}{1000 V_s f_s}\right] \\ &+ k_o\left[t_c + \left(h_1 L + h_2\right)\left(\frac{d_t - d_s}{d_r} + 1\right)\right] + k_o \frac{t_e}{T_p}\left[\frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_s}{d_r}\right) + \frac{\pi DL}{1000 V_s f_s}\right] \\ &+ \frac{k_t}{T_p}\left[\frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_s}{d_r}\right) + \frac{\pi DL}{1000 V_s f_s}\right]. \end{aligned} \tag{8}$$

2.2. Surface quality function

The surface quality function is described as [10]:

$$R_a = k v_s^{x_1} f_s^{x_2} d_s^{x_3} \tag{9}$$

where x_1, x_2, x_3 and k are the constants relevant to a specific tool–workpiece combination. Since reaching an ideal surface finish is not necessarily required in industry, so in this paper the surface quality function is treated as a constraint and therefore constraint satisfaction method is adopted in here.

2.3. Cutting condition constraints

Several cutting constraints are considered during roughing and finishing operations as follows:

1. Parameter bounds
2. Tool-life constraint

3. Cutting force constraint
4. Power constraints
5. Surface finish constraints
6. Stable cutting region constraint
7. Chip-tool interface temperature constraint
8. Surface finish constraint (for finishing stage only)
9. Roughing and finishing parameter relations.
10. Depth of cut equality constraint.

2.4. Final cutting model

The optimization model for multi-pass turning operations is formulated as:

$$F(X) = Min \text{ UC} \tag{10}$$

Subject to

Roughing:

$$V_{rL} \le V_r \le V_{rU} \tag{11}$$

$$f_{rL} \le f_r \le f_{rU} \tag{12}$$

$$d_{rL} \le d_r \le d_{rU} \tag{13}$$

$$T_{rL} \le T_r \le T_{rU} \tag{14}$$

$$F_r = k_1 (f_r)^{\mu} (d_r)^{\nu} \le F_U \tag{15}$$

$$P_r = \frac{F_r V_r}{6120\eta} \le P_U \tag{16}$$

$$Q_r = k_2 (V_r)^{\tau} (f_r)^{\phi} (d_r)^{\delta} \le Q_u \tag{17}$$

$$V_r^{\lambda} f_r d_r^{\nu} \ge SC \tag{18}$$

Finishing:

$$V_{sL} \le V_s \le V_{sU} \tag{19}$$

$$f_{sL} \le f_s \le f_{sU} \tag{20}$$

$$d_{sL} \le d_s \le d_{sU} \tag{21}$$

$$T_{sL} \le T_s \le T_{sU} \tag{22}$$

$$F_s = k_1 (f_s)^{\mu} (d_s)^{\nu} \le F_U \tag{23}$$

$$P_s = \frac{F_s V_s}{6120\eta} \le P_U \tag{24}$$

$$Q_s = k_2 (V_s)^{\tau} (f_s)^{\phi} (d_s)^{\delta} \le Q_u \tag{25}$$

$$V_s^{\lambda} f_s d_s^{\upsilon} \ge SC \tag{26}$$

$$\frac{f_s^2}{8R} \le SR_U \tag{27}$$

Relations:

$$V_s \ge k_3 V_r \tag{28}$$

$$f_r \ge k_4 f_s \tag{29}$$

$$d_r \ge k_5 d_s \tag{30}$$

Moreover, the overall depths of cut in rough passes plus depth of finish cut must be equal to the total depth of material to be removed:

$$n d_r + d_s = d_t \tag{31}$$

As a result, the number of rough passes can be expressed as:

$$n = \frac{d_t - d_s}{d_r} \tag{32}$$

It is to be noted that number of cuts (n) must be an integer value.
The cutting force constraint of equation (15) and the power constraint of equation (16) follow the formulation of Shin and Joo [1]. The chip-tool interface constraint of equation (17) follows the formulation of Hati and Rao [11]. The stable cutting region constraint of equation (18) follows the formulation of Narang and Fischer [12].

3. Genetic Algorithms

Genetic algorithms are a family of computational models that has been proposed by Holland in 1975 in the light of Darwin's theory of evolution. These algorithms encode a potential solution to a specific problem on a simple data structure (chromosome) and apply genetic operators to these structures so as to preserve critical information. An implementation of a genetic algorithm begins with a population of (typically random) chromosomes. One then evaluates these structures and allocates reproductive opportunities in such a way that those chromosomes which represent a better solution to the target problem are given more chances to ''reproduce'' than those chromosomes which are inferior solutions. The ''goodness'' of a solution is typically measured through a fitness function [10].

3.1 Representation of solutions

The optimization problem modeled in previous section has three independent variables for roughing process (V_s, f_s, d_s) and three independent variables for finishing process (V_r, f_r, d_r). These 6 variables are represented respectively with (x_1, x_2, x_3) and (x_4, x_5, x_6) genes in binary mode.

3.2 Scaling function

The scaling function converts raw fitness scores returned by the fitness function to values in a range that is suitable for the selection function. The proposed genetic algorithm uses rank function for scaling function. Rank function scales the raw scores based on the rank of each individual, rather than its score. The rank of an individual is its

position in the sorted scores. The rank of the fittest individual is 1, the next fittest is 2, and so on. Rank fitness scaling removes the effect of the spread of the raw scores.

3.3 Crossover

The proposed genetic algorithm uses scattered function for crossover, which creates a random binary vector, then selects the genes from the first parent wherever the vector is 1, and the genes from the second parent wherever the vector is 0, and combines the genes to form the child.

3.4 Mutation

Mutation brings unexpected features to the children that do not exist in parents. Each gene is chosen for mutation with a probability of p_m which is a GA parameter.

The proposed genetic algorithm uses uniform function for mutation, which is a two-step process. First, the algorithm selects a fraction of the vector entries of an individual for mutation, where each entry has the same probability as the mutation rate of being mutated. In the second step, the algorithm replaces each selected entry by a random number selected uniformly from the range for that entry.

3.5 Selection

The selection function chooses parents for the next generation based on their scaled values from the fitness scaling function. In the proposed algorithm, remainder function is used which assigns parents deterministically from the integer part of each individual's scaled value and then uses roulette selection on the remaining fractional part.

3.6 Implementation

The elements of the proposed genetic algorithm have been implemented in the genetic algorithm toolbox of the MATLAB Software and run on a Pentium 4 PC with 3.0 GHz Intel Processor and 2 GB of RAM. The values set for different parameters of the genetic algorithm are shown in Table 1.

Table 1 Parameters of the GA

Parameter	Value
Population size	100
Elite count	4
Crossover probability (%)	25
Mutation probability (%)	1

4. Illustrative Example and Discussion

An illustrative example has been adopted from [4] to demonstrate the performance of the proposed approach. Table 2 shows the data of the illustrative example.

Table 2 Cutting model data of Chen and Tsai [4]

Parameter/ constraint	Value	Parameter/ constraint	Value	Parameter/ constraint	Value	Parameter/ constraint	Value
D	50 mm	L	300 mm	C_0	$6*10^{11}$	d_t	6 mm
V_{rU}	500 m/min	V_{rL}	50 m/min	V_{sU}	500 m/min	V_{sL}	50 m/min
f_{rU}	0.9 mm/rev	f_{rL}	0.1 mm/rev	f_{sU}	0.9 mm/rev	f_{sL}	0.1 mm/rev
d_{rU}	3.0	d_{rL}	1.0	d_{sU}	3.0	d_{sL}	1.0
p	5	q	1.75	r	0.75	η	0.85
k_0	0.5 $/min	k_1	108	k_2	132	k_3	1.0
k_4	2.5	k_5	1.0	k_t	2.5 $/edge	θ	0.8
$T_{\min}$	25 min	$T_{\max}$	45 min	$F_{\max}$	200 kg.f	$P_{\max}$	5 KW

μ	0.75	ν	0.95	SR_U	10 μm	R	1.2 mm
λ	2	υ	-1	SC	140	Q_u	1000 $°C$
τ	0.4	ϕ	0.2	δ	0.105	t_c	0.75 min/piece
h_1	$7*10^{-4}$	h_2	0.3	t_p	0.75 min/piece	t_e	1.5 mm/edge

This example problem is a well-known test case in this issue and is frequently benchmarked by other researchers to evaluate the efficiency of their proposed algorithms.

Table 3 shows a comparison of the minimum unit production cost UC achieved by the proposed genetic algorithm and other optimization methods reported in the literature including SA/PS [4], GA [6], ACO [7] and PSO [13]. Although ACO-based approach of Vijayakumar [7] achieves a UC value equal to 1.8450, but it strongly violates the cutting force constraint and the power constraint both in the rough pass so their solution is invalid. GA-based technique of Onwubolu and Kumalo [6] arrives at a UC value of 1.761 but their optimal value is also strongly affected by many constraint violations [13].

The proposed GA insures a 6.26% UC reduction in comparison with the PSO and 7.23% UC reduction in comparison with the SA/PS approach adopted by Chen and Tsai [4]. Table 4 illustrates the optimal cutting parameters obtained by the proposed GA.

Table 3 Optimum UC obtained by various techniques

Method	Proposed GA	PSO	ACO	GA	SA/PS
Optimum UC	2.1298	2.2721	1.8450	1.761	2.2959

Table 4 Optimal cutting parameters obtained by proposed GA

Cutting parameters	V_r	V_s	f_r	f_s	d_r	d_s
Optimal values obtained by proposed GA	109.663	169.986	0.566	0.226	3.0	3.0

5. Conclusions

In this paper, an optimization technique based on genetic algorithm is applied to solve the machining optimization problem concerning the multi-pass turning operation. The unit production cost is considered as an objective function to be optimized based on a famous mathematical model which is subject to several practical constraints including depth of cut equality constraint. Then a well-known illustrative example has been adopted from literature to demonstrate the applicability of the proposed GA. Comparing the results obtained by the proposed GA with other traditional and non-traditional techniques clarifies that the proposed GA overcomes other methods proposed by other researchers. For future research, the proposed technique can be modified to multi-objective constrained optimization problems in turning and also other machining problems, such as milling and grinding operations.

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