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ORIGINAL ARTICLE

Optimization techniques for machining operations: a retrospective research based on various mathematical models

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Abstract Simulated annealing, genetic algorithm, and particle swarm optimization techniques have been used for exploring optimal machining parameters for single pass turning operation, multi-pass turning operation, and surface grinding operation. The behavior of optimization techniques are studied based on various mathematical models. The objective functions of the various mathematical models are distinctly different from each other. The most affecting machining parameters are considered as cutting speed, feed, and depth of cut. Physical constraints are speed, feed, depth of cut, power limitation, surface roughness, temperature, and cutting force.

Keywords Machining parameters · Three mathematical models · Optimization techniques

1 Introduction

In today's manufacturing environment, to ensure the quality of the machining products, to reduce the machining costs, and to increase the machining effectiveness, it is very important to select the machining parameters when the machine tools are selected in computer numerical controlled (CNC) machining. The main objective in machining is to produce products with low cost but with high quality. Cost consciousness with respect to the metal cutting process is an essential element in efficient manufacturing. So, it is essential to analyze the metal cutting operations to operate at economic conditions.

Due to high capital cost and machining cost of CNC machines, there is an economic need to operate machines as efficiently as possible in order to obtain the required payback. The success of the machining operation mainly depends on the selection of machining parameters such as cutting speed, feed, and depth of cut. A process planner selects the machining parameters based on his experience and from the available handbooks. But these parameters do not yield optimal values and cannot minimize production cost. Conventional methods of determining optimal machining parameters require the use of large numbers of mathematical formulas that are developed from experimental data. But any set of experiments usually contains systematic and random errors. Since the optimization process is a decision making process, the results obtained should enhance the objectives.

Agapiou [1] has investigated the optimization problem for multi-stage machining systems. This literature proposed Nelder-Mead simplex method for optimization. Here, the author utilized the idle time to the full extent at all machining stations, with the intension of improving tool life and, thus, achieving the cost reduction. Later, the author developed a combined objective of cost and time using weighted coefficient method. Y. C. Shin et al. [2] have presented a model for multi-pass turning, and dynamic programming was used for selection of depth of cut for individual passes. X. M. Wen et al. [3] have developed a micro-computer-based optimization technique to optimize grinding condition viz wheel speed, work piece speed,

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depth of dressing, and lead of dressing and employed combined objective function model with a weighted approach. The quadratic programming was used to solve the surface grinding optimization problem, subjected to constraints such as thermal damage, wheel wear parameters, machine tool stiffness, and either surface finish or production rate. Bob White et al. [4] have added the quality cost of the part as an important element to the machining cost. This model determines the effect of surface roughness on the production cost. Chen et al. [5] have developed an optimization model for a continuous profile using simulated annealing approach. In this machining model, straight turning, taper turning, and circular turning were simultaneously considered. P. K. Kee [6] has studied the development of constraint optimization analysis and strategies for selecting the optimum cutting conditions for multi-pass rough turning operations in CNC, and conventional lathe was outlined and discussed. Bhaskara Reddy et al. [7] have used genetic algorithm to select optimal depth of cut to achieve minimum production cost in multi-pass turning operations. M. C. Chen et al. [8] have developed an optimization model for a continuous profile using simulated annealing approach. In this machining model, straight turning, taper turning, and circular turning were simultaneously considered. Cheol Lee W. et al. [9] have developed a framework of modeling, the complex grinding processes, and finding optimal process condition. Evolution strategies were proposed for the optimization of grinding process. James Kennedy et.al. [10] have developed particle swarm optimization which is a population-based search procedure that could yield global optimum solution. Y. V. Hui et al. [11] have developed a time dynamic economic model for a single pass turning operation. This literature provided a quality machining economical model for turning to investigate the trade-off between quality cost and other cost factors. G. C. Onwubolu et al. [12] implemented genetic algorithm for the determination of the cutting variables in multi-pass machining operations. The depth of cut constrained for the multi-pass turning was not considered. K. Choudhri et al. [13] have also suggested genetic algorithm to find the optimum machining conditions in turning. In this work, two objective functions, namely unit production time and unit production cost, were optimized after satisfying few practical constraints. Suresh et al. [14] have used genetic algorithm to obtain required surface roughness based on the available mathematical model. Saravanan et al. [15] have applied genetic algorithm for the model found in an adopted literature and showed that genetic algorithm performs better than the quadratic programming technique. Vijayakumar et al. [16] have applied ant colony algorithm to find optimal machining parameters for multi-pass turning operation and also found that the proposed algorithm outperformed the adopted genetic algorithm. Anne Venugopal et al. [17] have used genetic algorithm for the optimization of the grinding of silicon carbide with diamond wheels to obtain maximum metal removal rate using surface grinding machine. Surface finish and surface damage were considered as constraints. Structural ceramics, such as silicon nitride and silicon carbide, are now being increasingly used in bearings, valves, rotors, and other applications where a close dimensional tolerance is required. They are also very sensitive to the forces when introduced to machining. Gopal et al. [18] have used available mathematical model for solving optimization problem for silicon carbide grinding with diamond wheels. Saravanan et al. [19] have developed a new model based on genetic algorithm and simulated annealing for optimizing machining parameters for turning operation. Franci Cus et al. [20] have used genetic algorithm to reduce the production cost and time. This paper presented a new methodology for continuous improvement of cutting condition with genetic algorithm. Experimental results show that the proposed genetic algorithm-based procedure is both effective and efficient. N. Baskar et al. [21] have developed a model based on simulated annealing algorithm for optimization of surface grinding processes. Researchers have also developed number of constraints equations applicable for grinding processes in which many process variables are involved. Zhang Li Ping et al. [22] have used particle swarm optimization technique to find out optimal choice of machining parameters. The constriction factor, velocity constraint, and population size have significant impact on the performance of particle swarm optimization. Increasing population size can improve the solution quality, although the computational time may be longer. Ramon Quiza Sardinas et al. [23] have also used genetic algorithm for multi-objective optimization problem. The two conflicting objectives are to increase tool life and decrease operation time. Indrajit Mukherjee et al. [24] have done a review of various optimization techniques. Rong-Tsu Wang et al. [25] have used geometric programming principle to develop a solution method that is able to derive the interval unit production cost with interval parameters. A pair of two level machining problems is formulated to calculate the upper bound and lower bound of unit production cost. The results indicated that the cost interval contains more information for making decision. Lee [26] made a robustness analysis with the available mathematical model for grinding process to maximize material removal rate.

Most of the researchers have used traditional as well as non-traditional optimization techniques for solving machining problems. Traditional techniques such as geometric programming, dynamic programming, and branch-and-bound technique has difficulty solving these problems and they are able to obtain only local optimal solution, which are not efficient when the practical search space is too large. More number of practical constraints and the number of pass makes the problem more complicated. Researchers have also used non-traditional techniques such as simulated annealing, genetic algorithm, and particle swarm optimization for solving machining problems.

In this paper, an attempt has been made to find an algorithm that is robust and versatile in nature. This is done by testing the behavior of three different algorithms viz, simulated annealing, genetic algorithm, and particle swarm optimization in various mathematical models.

2 Proposed methodology

Non-traditional search and optimization methods are becoming very popular in engineering optimization problems. These techniques mimic the process of natural evolution by adopting the method of survival of the fittest among a structured solution by information exchange. The various non-traditional optimization methods used in this work are as follows

1. Simulated annealing algorithm (SA)
2. Genetic algorithm (GA)
3. Particle swarm optimization (PSO)

2.1 Simulated annealing algorithm

Simulated annealing algorithm (SA) is a non-traditional optimization technique based on random numbers for the evaluation of the objective function that gives global optimum solution. Even though, it requires a large number of evaluations to find the optimum solution, it can find the global optimum solution with high probability even for ill-conditioned function with number of local minima. Simulated annealing algorithm resembles the cooling process of molten metals through annealing. At high temperature, the atoms in the molten metal can move freely, but as the temperature is reduced, the movement of the atoms gets restricted. The atoms start to get ordered, and finally form crystals having minimum possible energy. If the temperature is reduced at very faster rate, the crystalline state may not be achieved but may end in polycrystalline state with higher energy state. The temperature needs to be reduced at a slower rate to achieve absolute minimum energy state, and this process is called as annealing in metallurgical parlance. The good features of simulated annealing algorithm are:

1. The quality of the final solution is not affected by the initial values.
2. Global optimum solution can be obtained, thus optimum values are escaped from local optimum solution.
3. The discrete nature of the objective function and the constraint does not affect the continuity of the functions.
4. The convergence is not influenced by the convexity status of the feasible space.

2.1.1 Algorithm of SA

Step 1 Choose an initial point $x_,^{(o)}$ a termination criterion ϵ. Set T as a sufficiently high value, number of iterations to be performed at a particular temperature *n*, and set t=0.

Step 2 Calculate a neighboring point $x^{(t+1)} = N\left(x^{(t)}\right)$. Usually, a random point in the neighborhood is created.

Step 3 If $\Delta E = E\left(x^{(t+1)}\right) - E\left(x^{(t)}\right) < 0$, set t=t+1; else, create a random number (r) in the range (0, 1). If $r \leq \exp(-\Delta E/T)$, set t=t+1; else, go to Step 2.

Step 4 If $\left(x^{(t+1)} - x^{(t)}\right| < \epsilon$ and T is small, terminate. Else, go to step 2. End.

2.1.2 Parameters of SA

Number of iteration performed	1,000
Population	100
Initial temperature	500°C
Decrement factor	0.999

2.2 Genetic algorithm

Genetic algorithm (GA) mimics the principles of natural genetics and natural selection to constitute search and optimization procedures. Genetic algorithms are computerized search and optimization algorithms based on the mechanics of natural genetics and natural selection. In order to solve a problem using GA, the variables are coded in to some string structure. The length of the string is usually determined according to the desired solution accuracy. For example, if 4 bits are used to code each variable in a two variable function optimization problem, the strings [0000 0000] and [1111 1111] would represent the points $\left(x_1^L, x_2^L\right)^T \left(x_1^U, x_2^U\right)^T$, respectively, because the sub strings (0000) and (1111) have the minimum and maximum decoded values. The population is then operated by three main operators—reproduction, cross-over, and mutation to create a new population of points. The new population is further evaluated and tested for termination.

2.2.1 Algorithm of GA

Step 1: Choose a coding to represent problem parameters, a selection operator, cross-over, and a mutation operator. Choose a population size *n*, cross-over probability P_c, and a mutation probability P_m. Initialize a random population of string 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 cross-over on random pairs of string.

Step 6: Perform bit wise mutation.

Step 7: Evaluate string in the new population. Increment $t = t + 1$ and go to Step 3. End.

2.2.2 Parameters of GA

Number of iteration performed	1,000
Population	100
Cross-over probability	0.80
Mutation probability	0.05

2.3 Particle swarm optimization

Particle swarm optimization simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird, which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. It is called as "particle". All of the particles have fitness values, which are evaluated by the fitness function to be optimized and have velocities, which direct the flying of the particles. The particles are "flown" through the problem space by following the current optimum particles. After finding the two best values, the particles update its velocity and positions with the following equations:

$$\mathrm{V}[] = \mathrm{c}_1{*}\mathrm{rand}(){*}(\mathrm{pbest}[] - \mathrm{present}[]) + \mathrm{c}_2{*}\mathrm{rand}(){*}(\mathrm{gbest}[] - \mathrm{present}[])$$

$$\mathrm{New\,v}[] = \mathrm{V}[] + \mathrm{present}[]$$

V [] is the particle velocity, present is the current particle, pbest and gbest are defined as stated before, rand () is the random number between 0 and 1, and c_1, c_2 are learning factors usually varies from 1 to 4. PSO is a population-based optimization tool. The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as cross-over and mutation. In PSO, the potential solutions called particles are flown through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space, which are associated with the best solution (fitness) it has achieved so far. The fitness value is also stored. This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighbor of the particle. This location is called as *lbest*. When a particle takes all the particle toward its pbest and lbest locations, acceleration is weighted by random term, with separate random numbers being generated for acceleration toward pbest and lbest locations. One of the reasons that PSO is attractive is that there are few parameters to adjust. There are two key steps when applying PSO to optimization problems; the representation of the solution and the fitness function. One of the advantages of PSO is that it takes real number as particles. The searching is a repeat process and the stop criteria are that when the maximum iteration is reached or the minimum error condition is satisfied. The various parameters in PSO are number of particles, dimension of particles and range of particles, learning factor, stop condition, and global vs local version.

2.3.1 Algorithm of PSO

Step 1: Initialize a population of *n* particle randomly.

Step 2: Calculate fitness value for each particle. If the fitness value is better than the best fitness value (pbest) in history, set current value as the new pbest.

Step 3: Choose particle with the best fitness value of all the particles as the gbest.

Step 4: For each particle, calculate particle velocity according to the equation. $v[] = v + c_1{*}rand(){*}(pbest[] - present[]) + c_2{*}rand(){*}(gbest[] - present[])$ where, $present[] = present[] + v[]$ *v[]* is the particle velocity, *present[]* is the current particle (solution), *rand()* is a random number between (0,1), and c_1, c_2 are learning factors (range between 1 to 4).

Step 5: Particle velocities on each dimension are clamped to a maximum velocity V_{max}. If the sum of acceleration would cause the velocity on that dimension to exceed V_{max} (specified by the user), the velocity on the dimension is limited to V_{max}.

Step 6: Terminate if maximum number of iterations is reached. Else, go to Step 2.

Step 7: End.

2.3.2 Parameters of PSO

Number of iteration performed	1,000
Population	100
Learning factor c_1	2
Learning factor c_2	2

3 Single pass turning operation

3.1 Mathematical model

The mathematical model proposed by Agapiou [1] is considered in this work. This work is concerned with the optimal selection of machining parameters such as cutting speed, feed rate, and depth of cut. Since these parameters strongly affect the cost, time, productivity, and quality of the machined parts, determining the optimal machining parameters is an essential step in machining operation. The objective is a combined objective function that includes minimum production time and minimum production cost.

3.2 Formulation of objective function

The values for the machining parameters like L, D, v_{min}, v_{max}, etc. are obtained from the knowledge of the machine limitations and from the handbooks. The tool material is tungsten carbide, and the work piece material is high carbon steel. The values of machining parameters for single pass turning operation are shown in Table 1.

3.2.1 Production cost

The production cost per component for a machining operation consists of the sum of the costs for tooling, machining, tool changing time; handling time, and quick return time. Tool changing cost for each part is calculated based on the machining time of the part to the tool life. This is because a single tool may be used to machine several parts before it needs to be replaced by a sharp one.

Production cost is given by:

$$c_u = C_o.\, t_m + (t_m/T)C_o.\, t_{cs} + C_t + C_o(t_h + t_R) \quad (1)$$

The machining time per pass in turning is given by:

$$t_m = (\pi DL)/(1000\, vf) \quad (2)$$

Tool life is given by:

$$T = \left(K/v\, f^{al}\ d^{a2}\right)^{(1/a_3)} \quad (3)$$

3.2.2 Production time

The total time required to produce a part is the sum of the times necessary for machining, tool changing, tool quick return time, and work piece handling time that includes loading and unloading of work piece in the machine. This is given by:

$$t_u = t_m + t_{cs}(t_m/T) + t_h + t_R \quad (4)$$

3.2.3 Combined objective function

The objective function consists of the combination of the production time and the production cost using different weight coefficients for each criterion.

$$\mu(v, f, d) = w_1.\, c_u + w_2.\lambda.t_u \quad (5)$$

where, w_1 and w_2 are the weight coefficients, which indicates the relative importance of the production time and production cost. It has been assumed that these weight coefficients should satisfy the condition given below. When both weight coefficients w_1 and w_2 are set equal to 0.5, the objective functions moves closer to the higher profit rate.

$$w_1 + w_2 = 1, 0 \leq w_1 \leq 1 \text{ and } 0 \leq w_2 \leq 1 \quad (6)$$

The optimum function is normalized through the use of a constant multiplier

$$\lambda = c_{u\,min}/t_{u\,min} \quad (7)$$

where, $c_{u\ min}$ and $t_{u\ min}$ are the minimum production cost and minimum production time, respectively, under the defined process constraints.

3.3 Machining parameters

Although there are many machining parameters which affect the machining operation, cutting speed, feed, and depth of cut have the greatest effect on the success of a

Table 1 Values of machining parameters

Parameters	Values	Parameters	Values
L	203 MM	F_{max}	1,100 N
D	152 mm	SR_{max}	8 µm
v_{min}	30 m/min	HP_{max}	5 KW
v_{max}	200 m/min	t_{max}	500°C
f_{min}	0.254 mm/rev	a_1	0.29
f_{max}	0.762 mm/rev	a_2	0.35
d_{min}	2.0 mm	a_3	0.25
d_{max}	5.0 mm	K	193.3
t_{cs}	0.5 min/edge	C_o	0.1/min
t_R	0.13 min/pass	C_t	0.5/edge

machining operation. Therefore, only these machining parameters are considered in this work. Moreover, these machining parameters also considered as the practical constraints.

3.3.1 Cutting speed

When compared to depth of cut and feed rate, cutting speed has a greater effect on tool life. Certain combinations of speed, feed, and depth of cut are usually selected for easy chip removal, which are directly proportional to the type of tool and work piece material.

Thus, the range of cutting speed can be written as:

$$v_{\min} \leq v \leq v_{\max} \tag{8}$$

3.3.2 Feed

By increasing the feed and decreasing the cutting speed, it is always possible to obtain much higher metal removal rates without reducing tool life. Thus, the range of feed can be written as:

$$\mathrm{f}_{\min} \leq \mathrm{f} \leq \mathrm{f}_{\max} \tag{9}$$

3.3.3 Depth of cut

Selection of depth of cut should counter balance between the tool life and metal removal rate to obtain highest permissible level of depth of cut. Thus, the range of depth of depth of cut can be written as:

$$\mathrm{d}_{\min} \leq \mathrm{d} \leq \mathrm{d}_{\max} \tag{10}$$

3.4 Physical constraints

There are always many constraints that exist in the actual cutting condition for the optimization of the objective function. For a given pass, an optimum cutting speed, feed, and depth of cut is chosen and, thus, balancing the conflict between the metal removal rate and tool life. The following constraints are considered in optimizing the machining parameters. On satisfying these constraints, the optimum machining parameters are arrived.

1. Parameter constraints

$$\mathrm{v}_{\min} \leq \mathrm{v} \leq \mathrm{v}_{\max}, \ \mathrm{f}_{\min} \leq \mathrm{f} \leq \mathrm{f}_{\max} \ \& \ \mathrm{d}_{\min} \leq \mathrm{d} \leq \mathrm{d}_{\max}, \tag{11}$$

2. Power constraint

$$0.0373\, \mathrm{v}^{0.91}\, \mathrm{f}^{0.78}\, \mathrm{d}^{0.75} \leq \mathrm{HP}_{\max} \tag{12}$$

3. Surface finish constraint

$$14785\, \mathrm{v}^{-1.52}\mathrm{f}^{1.004}\mathrm{d}^{0.25} \leq \mathrm{SR}_{\max} \tag{13}$$

4. Temperature constraint

$$74.96\, \mathrm{v}^{0.4}\, \mathrm{f}^{0.2}\, \mathrm{d}^{0.105} - 17.8 \leq \mathrm{T}_{\max} \tag{14}$$

5. Cutting force constraint

$$844\, \mathrm{v}^{-0.1013}\, \mathrm{f}^{0.725}\, \mathrm{d}^{0.75} \leq \mathrm{F}_{\max} \tag{15}$$

3.5 Computational result of SA

The number of iterations performed is 1,000 for a population of 100. Initial temperature is set at 500°C and the decrement factor is 0.999. Figure 1 shows the number of iteration vs combined objective function (COF). From Fig. 1, it is evident that the minimum COF is observed at the 94th iteration.

3.6 Results of SA

The minimized COF value and corresponding machining parameters values of cutting speed, feed, and depth of cut are given below in Table 2.

3.7 Computational result of GA

The number of iterations performed is 1,000 for a population of 100.Cross-over probability is 0.80 and mutation probability is 0.05. From Fig. 2, it is evident that the minimum COF is observed at the 74th iteration.

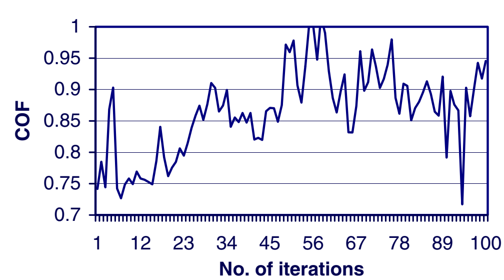

Fig. 1 Number of iterations vs COF

Table 2 Results of SA

Machining parameters		
v	f	d
m/min	mm/rev	mm
125.2850	0.6503	2.0535
Objective function		
t_u	c_u	COF
min	\$/piece	\$/piece
2.9936	0.7994	0.7170

Table 3 Results of GA

Machining parameters		
v	f	d
m/min	mm/rev	mm
148.4848	0.6056	2.2082
Objective function		
t_u	c_u	COF
min	\$/piece	\$/piece
2.8181	0.7818	0.6896

3.8 Results of GA

The minimized COF value and corresponding machining parameters values of cutting speed, feed, and depth of cut are given below in Table 3.

3.9 Computational result of PSO

The number of iterations performed is 1,000 with a population size of 100. From Fig. 3, it is evident that the minimum COF is obtained at 46th iteration. The COF is gradually decreasing up to the 46th iteration. Then the COF is constant for further iterations.

3.10 Results of PSO

The optimum COF value and corresponding machining parameters values of cutting speed, feed, and depth of cut are given below in Table 4.

4 Multi-pass turning operation

4.1 Formulation of objective function

The mathematical model proposed by Bhaskara Reddy et al. [7] is considered in this work. Total production cost is taken as the objective function. The values for the machining parameters like L, D, V_{min}, V_{max}, etc. are obtained from the knowledge of the machine limitations and from the handbooks for the given work piece material and tool material. Table 5 shows the values of machining parameters for multi-pass turning operation.

4.1.1 Production cost

The total production cost model for multi-pass turning with the constraints of available speed and feed ranges, surface finish, maximum cutting force, and maximum cutting power of the machine tool is taken from Shin and Joo (2). Taylor's tool life equation is expressed as

$$T = C/V^x\, S^y\, d^z \tag{16}$$

The total production cost, U_t, is the sum of the cost for the finish pass and rough passes and is given by:

$$U_t = U_r + \sum_{i=1}^{n} U_{ri} + A_4 \tag{17}$$

where, A_4 represents the cost of tool preparation and is given by:

$$A_4 = k_1\, t_p \tag{18}$$

The cost for a single finish pass is given as:

$$U_r = A_1 sf^{(y/x-1)}\, df^{(z/x)} + A_2 \tag{19}$$

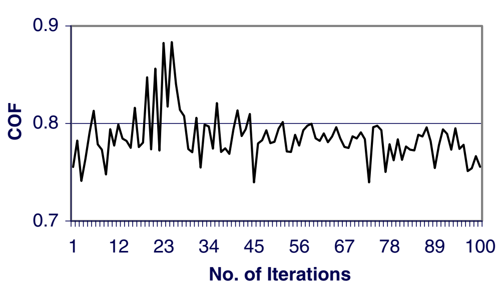

Fig. 2 Number of iterations vs COF

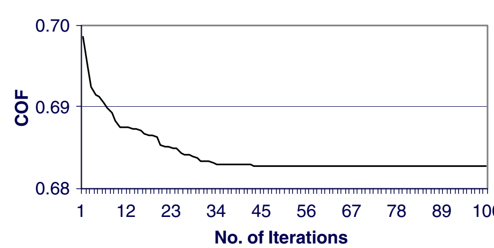

Fig. 3 Number of iterations vs COF

Table 4 Results of PSO

Machining parameters		
v	f	d
m/min	mm/rev	mm
148.2490	0.7620	2.0000
Objective function		
t_u	c_u	COF
min	\$/piece	\$/piece
2.7743	0.7774	0.6828

where,

$$A1 = (\pi D L k_1/1000 T_R)\,[T_f/C]^{(1/x)}(T_f + A_3(T_e + k_t/k_1)) \tag{20}$$

$$A_3 = T_f/T_R \tag{21}$$

The second term, A2 in Eq. 19, represents the cost corresponding to idle tool motion, such as tool travel and tool approach/depart time, being expressed as:

$$A_2 = k_1(h_1 L + h_2) \tag{22}$$

4.2 Physical constraints

The following constraints are considered in optimizing the machining parameters. On satisfying these constraints, the optimum machining parameters are arrived.

1. Speed, feed, and depth of cut constraints:

$$v_{min} \le v \le v_{max},\ s_{min} \le s \le s_{max} \text{ and } d_{min} \le d \le d_{max}, \tag{23}$$

Table 5 Values of machining parameters

Parameters	Values	Parameters	Values
L	300 MM	F_{max}	1962 N
D	50 mm	r	1.2 mm
v_{min}	50 m/min	HP_{max}	5 KW
v_{max}	500 m/min	T_{min}	25 min
s_{min}	0.1 mm/rev	T_{max}	45 min
s_{max}	0.9 mm/rev	a_2	0.255
$d_{r\ min}$	1.0 mm	a_4	0.375
$d_{r\ max}$	3.0 mm	K_1	108
t_{cs}	1.5 min/edge	C	6×10^{11}
t_R	0.75 min/pass	a_1	0.249
x	5	h_1	7×10^{-4}
y and z	1.75 and 0.75	h_2	0.3

The minimization of cost function Eq. 19 is carried out under the following constraints. For a given machining operation, the ranges of parameter value are chosen for a selected machine and are expressed in terms of lower and upper bounds. The minimum and maximum speed limits using the tool life is

$$C^{(1/x)} \Big/ \left(T_R^{(1+x)} V_{max}\right) \le s_f^{(y/x)}\, df^{(d/f)} \le C^{(1/x)} \Big/ T_R^{(1+x)} V_{min} \tag{24}$$

The minimum or maximum depth of cut constraints is expressed as:

$$d_{f.min} \le d_f \le d_{f.max} \tag{25}$$

The minimum and maximum feed constraint is:

$$s_{min} \le s_f \le s_{max} \tag{26}$$

The surface finish constraint is expressed in terms of the nose radius of the tool and the peak-to-valley height for surface roughness as:

$$s_f \le (8 r R_f)^{1/2} \tag{27}$$

Making use of the constraint in Eq. 27, the constraint in Eq. 26 may be expressed as:

$$s_{min} \le s_f \le \min\left(s_{max}(8 r R_f)^{1/2}\right) \tag{28}$$

The cutting force constraint is used to prevent chatter and to limit the deflection of the work piece or cutting tool that result in dimensional error. Neglecting the effect of cutting speed, this constraint is expressed by:

$$k_1\, s_f^{\mu}\, d_f^{v} \le F_{max} \tag{29}$$

During machining, the cutting power should not exceed the maximum power of the machining tool. On eliminating Vf using the tool-life equation Eq. 16. the constraint is expressed as:

$$s_f^{(\mu - y/x)}\, d_f^{(v - z/x)} \le 6120\eta\, T_R^{(1/x)} P_{max} \Big/ k_1 C^{(1/x)} \tag{30}$$

For finish pass turning, the objective function given by Eq. 19 is optimized, considering the constraints in Eqs. 24,

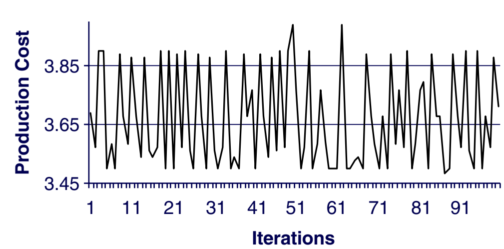

Fig. 4 Number of iterations vs production cost

Table 6 Production cost for various depth of cut

S. No	n	d_t	d_r	d_f	u_t
1	2	6.0	2.50	1.00	2.386
2	3	8.0	2.40	0.80	2.933
3	3	8.5	2.90	0.80	2.892
4	3	9.0	2.84	0.48	3.008
5	4	9.5	2.27	0.42	3.415
6	4	10.0	2.40	0.40	3.483

Table 7 Production cost for various depth of cut

S. No	n	d_t	d_{r1}	d_{r2}	d_{r3}	d_f	u_t
1	2	6.0	2.50	2.30	–	1.2	2.372
2	3	8.0	2.30	2.30	2.20	1.2	2.913
3	3	8.5	2.70	2.50	2.10	1.2	2.983
4	3	9.0	2.90	2.60	2.30	1.2	3.053
5	4	9.5	3.00	2.70	2.60	1.2	3.123
6	4	10.0	3.00	2.90	2.90	1.2	3.193

25, 28, 29, and 30. The cost of one rough pass may be stated similarly to the cost for the finish pass

$$U_{ri} = A_1 {s_{ri}}^{(y/x-1)}\, d_r^{(z/x)} + A_2 \tag{31}$$

For rough pass turning, the constraints in Eqs. 24, 29, and 30 remain the same except for subscript r (rough) instead of f (finish). The constraint in Eq. 28 is modified using Rr in place of Rf. In Eq. 25, $d_{f\ min}$ and $d_{f\ max}$ are used as the lower and upper limits of the depth of cut. In addition to the above constraints, the following is used to account for the total stock to be removed.

$$d_t = d_r + \sum_{i=1}^{n} dr \tag{32}$$

The trial number of rough passes is calculated based on the maximum depth of cut allowed in the roughing operation and depth of cut for the finish pass within its range. Thus, the trial number of rough passes is:

$$n = (d_t - d_f)/(d_r)_{max} \tag{33}$$

4.3 Machining parameters

4.3.1 Depth of cut

The selection of maximum depth of cut is dependent on (1) tool material, (2) cutting force, (3) available horse power, (4) stability of the tool work machine, (5) dimensional

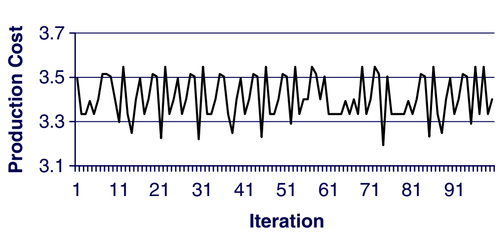

Fig. 5 Number of iterations vs productions cost

accuracy, and (6) surface finish required. Thus, the range of depth of depth of cut can be written as:

$$d_{min} \le d \le d_{max} \tag{34}$$

4.3.2 Feed

The production rate and the spindle speed are greatly affected by the maximum allowable feed. It also has a significant effect on tool life. Thus, the range of feed can be written as:

$$s_{min} \le s \le s_{max} \tag{35}$$

4.3.3 Cutting speed

Every machine has minimum cutting speed and minimum cutting speed that should be maintained to avoid failure of cutting tools due to built-up edge formation. From these two minimum values, the higher value is taken as the minimum cutting speed. Allowable maximum cutting speed is available from the machine. Thus, the range of cutting speed can be written as:

$$v_{min} \le v \le v_{max} \tag{36}$$

4.4 Computational result of SA

The number of iterations performed is 1,000 for a population of 100. Initial temperature is set at 500°C and the decrement factor is 0.999. Figure 4 show the number of iteration vs production. From Fig. 1, it is evident that the minimum cost is observed at the 87th iteration. Table 6 shows the optimum production cost for various depth of cut.

4.5 Results of SA

Table 6 shows the optimal results of various depth of cut. The depth of cut varies from 6 mm to 10 mm. The number

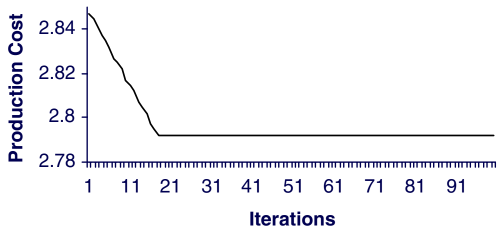

Fig. 6 Number of iterations vs production cost

of passes of rough depth of cut, finish depth of cut, and total production cost are also displayed in the table.

4.6 Computational result of GA

The number of iterations performed is 1,000 for a population of 100. Cross-over probability is 0.80 and mutation probability is 0.05. From Fig. 5, it is evident that the minimum cost is observed at the 74th iteration. Table 7 shows the optimum production cost for various depth of cut.

4.7 Result of GA

Table 7 shows the optimal results of various depth of cut. The depth of cut varies from 6 mm to 10 mm. The number of passes of rough depth of cut, finish depth of cut, and total production cost are also displayed in the table.

4.8 Computational result of PSO

The number of iterations performed is 1,000 with a population size of 100. From Fig. 6, it is evident that the minimum cost is obtained at 18th iteration. The cost is gradually decreasing up to the 18th iteration. Then, the cost is constant for further iterations. Table 8 shows the optimum production cost for various depth of cut.

4.9 Result of PSO

Table 8 shows the optimal results of various depth of cut. The depth of cut varies from 6 mm to 10 mm. The number of passes of rough depth of cut, finish depth of cut, and total production cost are also displayed in the table.

5 Surface grinding

5.1 Mathematical model

The mathematical model proposed by Anne Venugopal et al. [17] is considered in this work. This work is concerned with the optimal selection of machining parameters such as feed rate and depth of cut. Since these parameters strongly affect the cost, time, productivity, and quality of the machined parts, determining the optimal machining parameters is an essential step in machining operation. Maximizing the material removal rate is the objective function of the proposed model. Table 9 shows the machining parameter values for surface grinding.

5.2 Objective function

Material removal rate is the objective function of the proposed model. It is the rate at which the material is removed from the work piece during the machining process.

$$\mathrm{MRR} = \mathrm{f}, \mathrm{d} \tag{37}$$

5.3 Machining parameters

5.3.1 Feed

The maximum allowable feed greatly affects the production rate. It has a significant effect on tool life. By increasing the feed and decreasing the cutting speed, it is always possible to obtain much higher metal removal rates without reducing tool life. Surface finish determines the maximum feed in finish operation. Thus, the range of feed can be written as:

$$\mathrm{f}_{\min} \leq \mathrm{f} \leq \mathrm{f}_{\max} \tag{38}$$

Table 8 Production cost for various depth of cut

S. No	n	d_t	d_r	d_f	u_t
1	2	6.0	2.80	0.40	2.156
2	3	8.0	2.53	0.41	2.708
3	3	8.5	2.70	0.40	2.716
4	3	9.0	2.86	0.42	2.725
5	3	9.5	3.00	0.50	2.745
6	3	10.0	3.00	1.00	2.792

Table 9 Values of machining parameters

Parameters	values	Parameters	Values
f_{min}	5 M/MIN	R_{min}	50
f_{max}	15 m/min	R_{max}	100
d_{min}	5 µm	$R_{a\ min}$	0.155 µm
d_{max}	30 µm	$R_{a\ max}$	0.4 µm
M_{min}	120	$\%D_{min}$	1.5
M_{max}	500	$\%D_{max}$	4.0

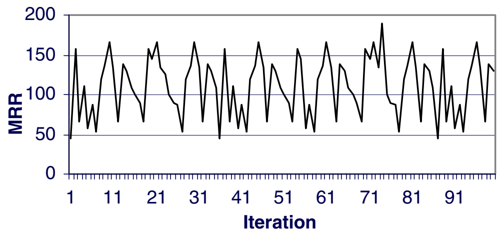

Fig. 7 Number of iterations vs MRR

5.3.2 Depth of cut

By changing the depth of cut, tool life is less affected. So, there should be a counter balance between the tool life and metal removal rate to obtain highest permissible level of depth of cut. The selection of maximum depth of cut is dependent on (1) tool material, (2) cutting force, (3) available horsepower, (4) stability of the tool work machine, (5) dimensional accuracy, and (6) surface finish required. Thus, the range of depth of depth of cut can be written as:

$$d_{min} \leq d \leq d_{max} \tag{39}$$

5.4 Physical constraints

1. Feed: optimum feed must be in the range determined by the minimum and maximum feed rates of the machine and can be written as:

$$f_{min} \leq f \leq f_{max} \tag{40}$$

2. Depth of cut: optimum depth of cut must be in the range determined by the minimum and maximum depth of cut of the machine and can be written as:

$$d_{min} \leq d \leq d_{max} \tag{41}$$

Table 10 Results of SA at various R_a values and 2% area of surface damage (%D)

R_a	f	d	MRR
0.175	5.85	8.09	47.40
0.200	7.04	9.77	68.83
0.225	8.27	11.70	96.87
0.250	9.63	13.46	129.72
0.275	10.92	15.62	170.73
0.300	12.22	17.60	215.18
0.325	13.80	19.94	275.35
0.350	14.23	20.91	317.91
0.375	14.71	21.92	328.91
0.400	15.00	22.92	343.92

Table 11 Results of SA at various surface damage values (%D) and R_a=0.25

%D	f	d	MRR
1.50	12.44	6.53	81.37
1.75	10.81	9.66	104.57
2.00	9.64	13.48	130.04
2.25	8.66	17.97	155.68
2.50	7.85	24.14	189.58
2.75	7.31	29.42	215.37
3.00	7.25	29.88	216.95
3.25	7.25	29.98	217.67
3.50	7.25	29.98	217.67
3.75	7.25	29.98	217.67
4.00	7.26	29.96	217.70

3. Grain size: grain size is the size of the abrasive grain in the grinding wheel which should be within the given range.

$$M_{min} \leq M \leq M_{max} \tag{42}$$

4. Grain density: grain density is the closeness of packing of abrasive grains on the grinding wheel which should be within the given range

$$R_{min} \leq R \leq R_{max} \tag{43}$$

5. Surface roughness: it refers to the smoothness of machined surface which should be within the range is given by:

$$R_a = 0.36(d)^{0.1843}(f)^{0.5253}(M)^{-0.2866}(R)^{-0.2444} \leq R_{amax} \tag{44}$$

6. Surface damage: surface damage should be within the range is given by:

$$\%D = 24.44(d)^{0.2857}(f)^{-0.3}(M)^{-0.4140} \leq D_{max} \tag{45}$$

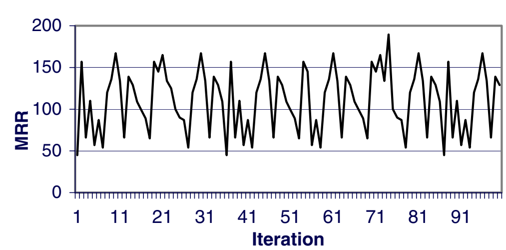

Fig. 8 Number of iterations vs MRR

Table 12 Results of GA at various R_a values and D=2%

R_a	f	d	MRR
0.175	5.82	7.96	46.37
0.200	7.20	9.03	65.03
0.225	8.46	10.74	90.96
0.250	9.71	12.69	123.38
0.275	11.21	14.40	161.55
0.300	12.58	16.51	207.85
0.325	14.42	17.45	251.74
0.350	14.66	20.26	297.25
0.375	14.98	20.95	314.08
0.400	14.80	22.84	338.30

5.5 Computational results of SA

The number of iterations performed is 1,000 for a population of 100. Initial temperature is set at 500°C and the decrement factor is 0.999. Figure 7 shows the number of iteration vs material removal rate (MRR) and it is evident that the maximum MRR is observed at the 74th iteration.

5.6 Results of SA

Table 10 shows the optimal MRR values obtained by SA for various surface roughness values. The surface roughness values are varied from 0.175 to 0.4 µm.

From Table 10, it is evident that the surface roughness is directly proportional to material removal rate.

Table 11 shows the optimal MRR values obtained by SA for various surface damage values. The surface damage values are varied from 1.5% to 4%.

Table 13 Results of GA at various surface damage values (%D) and R_a=0.25

%D	f	d	MRR
1.50	12.39	6.45	79.99
1.75	10.69	9.47	101.27
2.00	9.71	12.69	123.38
2.25	8.80	16.70	147.12
2.50	8.01	22.42	179.80
2.75	7.38	28.34	209.19
3.00	7.21	29.92	216.01
3.25	7.21	29.92	216.01
3.50	7.21	29.92	216.01
3.75	7.21	29.92	216.01
4.00	7.21	29.92	216.01

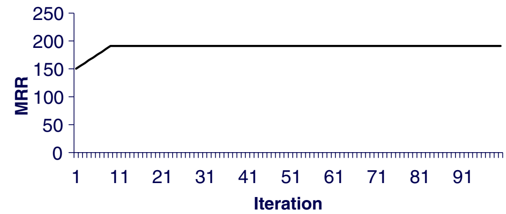

Fig. 9 Number of iterations vs MRR

From Table 11, it is evident that the percentage of surface damage directly proportional to MRR.

5.7 Computational result of GA

The number of iterations performed is 1,000 for a population of 100.Cross-over probability is 0.80 and mutation probability is 0.05. From Fig. 8, it is evident that the minimum cost is observed at the 76th iteration.

5.8 Results of GA

Table 12 shows the optimal MRR values obtained by GA for various surface roughness values. The surface roughness values are varied from 0.175 to 0.4 µm.

From Table 12, it is evident that the surface roughness is directly proportional to material removal rate.

Table 13 shows the optimal MRR values obtained by GA for various surface damage values. The surface damage values are varied from 1.5% to 4%.

From Table 13, it is evident that the percentage of surface damage directly proportional to material removal rate.

5.9 Computational result of PSO

The number of iterations performed is 1,000 with a population size of 100. From Fig. 9, it is evident that the

Table 14 Results of PSO at various R_a values and 2% area of surface damage (%D)

R_a	f	d	MRR
0.175	5.85	8.09	47.40
0.200	7.04	9.77	68.83
0.225	8.27	11.70	96.87
0.250	9.63	13.46	129.72
0.275	10.92	15.62	170.73
0.300	12.22	17.60	215.18
0.325	13.80	19.94	275.35
0.350	14.23	20.91	317.91
0.375	14.71	21.92	328.91
0.400	15.00	22.92	343.92

Table 15 Results of PSO at various surface damage values (%D) and R_a=0.25

%D	f	d	MRR
1.50	12.44	6.53	81.37
1.75	10.81	9.66	104.57
2.00	9.64	13.48	130.04
2.25	8.66	17.97	155.68
2.50	7.85	24.14	189.58
2.75	7.31	29.42	215.37
3.00	7.25	29.98	216.95
3.25	7.25	29.98	217.67
3.50	7.25	29.98	217.67
3.75	7.25	29.98	217.67
4.00	7.26	29.96	217.70

MRR is gradually increasing up to the ninth iteration and remain constant for further iterations.

5.10 Results of PSO

Table 14 shows the optimal MRR values obtained by PSO for various surface roughness values. The surface roughness values are varied from 0.175 to 0.4 µm.

From Table 14, it is evident that the surface roughness is directly proportional to material removal rate.

Table 15 shows the optimal MRR values obtained by PSO for various surface damage values.

From Table 15, it is evident that the percentage of surface damage directly proportional to material removal rate. The surface damage values are varied from 1.5% to 4% with an increment of 0.25%. As the surface damage value increases, the MRR also gradually increases up to 3%. After that, there is small deviation in the value of MRR with respect to percentage of surface damage.

6 Results and discussions

In this work, MATLAB software is used for coding all the proposed algorithms. The number of iterations performed is 1,000 with a population size of 100 in all the cases.

Table 16 Computational time

Algorithm	In seconds		
	Single pass	Multi-pass	Grinding
PSO	11	12	4
GA	15	15	6
SA	12	13	5

Table 17 Results of various algorithms

Algorithm	COF
PSO	0.6827
GA	0.6896
SA	0.7170
NMS [[1]]	0.7415

Table 16 shows the computational time for execution of single run in a Core 2 Duo processor computer.

6.1 Single pass turning operation

Table 17 shows the best results obtained in particle swarm optimization, simulated annealing algorithm, and Nelder–Mead simplex method.

From Table 17, it is evident that PSO performed better than other optimization techniques. Also, all the non-traditional optimization techniques yielded better result than the result available in literature [1]. Figure 10 shows the comparison of results obtained by the proposed algorithms.

6.2 Multi-pass turning operation

Table 18 shows the best results obtained in particle swarm optimization and simulated annealing algorithm.

From Table 18, it is evident that PSO performed better than other optimization techniques. Figure 11 shows the comparison of results obtained by the proposed algorithms.

6.3 Surface grinding operation

Table 19 shows the best results obtained in particle swarm optimization and simulated annealing algorithm

From Table 19, it is evident that PSO performed better than other optimization techniques. Figure 12 shows the comparison of results obtained by the proposed algorithms.

7 Conclusion

In this work, the three different mathematical models of machining operations are considered for optimization.

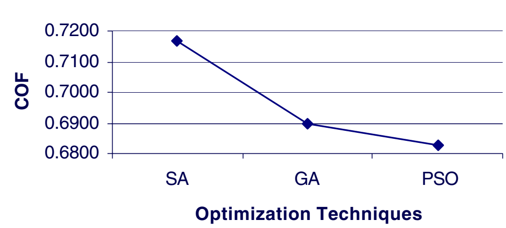

Fig. 10 Comparisons of results (minimization problem)

Table 18 Results of various algorithms

Algorithm	Production cost
PSO	2.792
GA [[7]]	3.193
SA	3.483

Table 19 Results of various algorithms

Algorithm	MRR
PSO	191.01
GA [[17]]	179.80
SA	189.58

These mathematical models have different objective function and constraint equations. In the first model, the objective function is to minimize the combined objective function and the machining parameters are cutting speed, feed, and depth of cut. In the second model, the objective function is to minimize the total production cost for multi-pass turning operation and the machining parameters are number of passes, cutting speed, feed and depth of cut. In the third model, the objective function is to maximize the material removal rate, and the machining parameters are feed and depth of cut. The non-traditional optimization techniques such as simulated annealing, genetic algorithm, and particle swarm optimization are used to optimize machining parameters.

PSO technique has yielded best result among the other two techniques. In single pass turning operation, the result of PSO is 4.7% and 1% better than GA and SA, respectively. In multi-pass turning operation, the result of PSO is 12.5% and 19.8% better than GA and SA, respectively. In grinding operation, the result of PSO is 6.2% and 1% better than GA and SA, respectively. The following points were observed as a sort of conclusion of this present work.

1 Particle swarm optimization has proved to be the best among the other non-traditional optimization techniques simulated annealing and genetic algorithm.
2 Particle swarm optimization technique tends to converge to the global optimal solution at a faster rate.
3 All the computational time is less than half a minute and hence computational cost is not going to be a affecting parameter in obtaining the required objective function.
4 Since all the proposed techniques can obtain a global optimum solution within a reasonable execution time on a personal computer, the algorithms can be used on online systems for the selection of optimal machining parameters.
5 The software is completely generalized and problem independent, so that it can be easily modified to optimize any machining operation under various economic criteria and numerous practical constraints.
6 Moreover, all the non-traditional techniques can be easily used to implement for other engineering applications.

7.1 Scope for future work

In this work, the combination of total production time and total production cost are taken as the objective function with some practical constraints. But metal machining is a complex phenomena, and inclusion of many other machining parameters and constraints that may enhance the end result.

8 Nomenclature

Single pass turning operation

v	Cutting speed, m/min
f	Feed rate, mm/rev.
d	Depth of cut, mm
c_u	Production cost, $/piece
t_u	Production time, min
t_m	Machining time, min

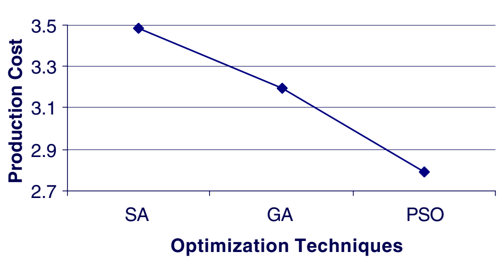

Fig. 11 Comparisons of results (minimization problem)

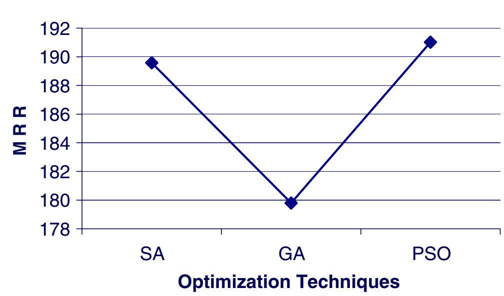

Fig. 12 Comparisons of results (maximization problem)

t_{cs}	Tool change time, min/edge
t_h	Loading and unloading time, min/piece
t_R	Quick return time, min/pass
w_1	Weight coefficient for cost
w_2	Weight coefficient for time
λ	Constant multiplier
c_o	Operating cost, min
c_t	Tool cost per cutting edge, $/edge
$c_{u\ min}$	Minimum production cost, $/piece
$t_{u\ min}$	Minimum production time, min
D	Outside diameter, mm
L	Length of the part, mm
T	Tool life, min
COF	Combined objective function, $/piece
K, a_1, a_2, a_3	Empirical constants

Multi-pass turning operation

D	Depth of cut (mm)
d_t	Total stock (mm)
A_1, A_2, A_3, A_4	Constants
C	Taylor's tool life constant
D	Diameter of work piece (mm)
F	Cutting force (N)
h_1, h_2	Constants pertaining to tool travel
k_1	Overhead cost ($/min)
k_t	Cost of cutting edge ($)
k_f	Constant used in cutting force and power equation
L	Length of work piece (mm)
M	Assumed number of divisions of the depth of cut ranges in rough or finish passes
n	Assumed maximum number of rough passes
P	Cutting power (kW)
R	Nose radius of tool (mm)
R	Surface roughness height (μm)
S	feed (mm/rev)
t_e	Time required to exchange tool (min/cutting edge)
t_p	Preparation time for loading and unloading of tool (min)
T	Tool life (min)
T_R	Tool replacement time (min)
U	Cost of each pass ($/piece)
U_t	Total production cost ($/piece)
V	Cutting speed (m/min)
μ,γ	Exponents of feed and depth of cut in force equation
ή	Cutting power efficiency of a machine tool
f	finish pass
i	ith rough pass
j	jth value of depth of cut
min	Minimum value
max	Maximum value
o	Optimal value of a parameter
r	Rough pass

Grinding operation

d	Depth of cut, μm
f	Feed, m/min
M	Grain size, mm
R	Grain density, mm
D	Surface damage
R_a	Surface roughness, μm
MRR	Material removal rate, mm^3/min
d_{max}	Max.depth of cut, μm
d_{min}	Min. depth of cut, μm
f_{max}	Max. feed, m/min
f_{min}	Min. feed, m/min
M_{max}	Max.grain size
M_{min}	Min. grain size
R_{max}	Grain density
R_{min}	Grain density
$R_{a\ max}$	Max. surface roughness
$R_{a\ min}$	Min. surface roughness
D_{max}	Max. surface damage
D_{min}	Min. surface damage

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