Optimal Cutting Parameters for Turning Operations with Costs of Quality and Tool Wear Compensation

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Abstract

The process design of turning operations involves the determination of suitable values for the different process parameters such as cutting speed, feed rate and depth of cut, with the objective of optimizing the economics of the process. This paper provides a new mathematical model that takes into consideration costs of quality and tool wear compensation in the determination of the optimal cutting conditions for the turning operation of multiple similar parts. Based on that model, an optimization approach is proposed. An illustrative example is presented to demonstrate the characteristics of the optimal solutions.

Keywords
Turning, Taguchi's loss function, tool wear compensation.

1. Introduction
In today's highly competitive market conditions, it becomes crucial to maintain high quality products while keeping manufacturing costs as low as possible. In order to achieve that, manufacturing processes have to be appropriately designed by selecting optimized process parameters. Traditionally, manufacturing process design is conducted with an emphasis on minimizing the manufacturing costs; while quality issues are dealt with separately. With the introduction of Taguchi's loss function [1], it became possible to represent deviations from target quality levels by equivalent costs of quality that can be integrated into the process design economic models. Such integration facilitates the simultaneous consideration of both manufacturing economies and quality requirements.

In metal cutting processes, various optimization techniques have been proposed for determining the optimum process design [2]. Generally, the process design parameters in metal cutting processes are relatively few such as cutting speed, feed rate and depth of cut; however, their optimization remains a challenge due to several other factors related to processing conditions and shape complexities [3]. Furthermore, as indicated in [4], the difference in machining geometry for various types of machining processes necessitates a unique treatment and analysis for each type of process. This paper is concerned with the optimization of the turning process.

In the literature, the traditional economic models that have been proposed for the turning process take into consideration different cost elements including direct and indirect machining costs and tool regrinding and replacement costs [5, 6]. Maheshwari et al. [7] provided one of the early attempts of integrating quality into the process parameter selection. They used Taguchi method for selecting the process parameters that result in reducing the variation in surface roughness. Later, Maheshwari [8] introduced a mathematical model that utilizes Taguchi's loss function to represent quality losses for both dimensional accuracy and surface finish.

A special attention has been given to the determination of the optimal tool regrinding and replacement policies [9-11]. However, most of the traditional models have not taken into consideration quality measures until recently when this issue was addressed by Hui and Leung [12]. They developed a mathematical model to guide the optimal selection of tool regrinding and replacement decisions in a single pass turning process. In their model, tool life is represented as a random variable with known probability distribution function. The Taguchi's loss function is used to represent the cost associated with deviation from quality target for a generic quality characteristic. They demonstrated how that model can be used to optimize the tool regrinding and replacement decisions.

Hui et al. [3] extended the previous work in [12] by specifying two types of quality costs. The first is associated with deviation from a target surface roughness value, and the second represents losses due to deviations from the target workpiece diameter. They demonstrated how the developed model can be used to optimize the process parameters when machining, tool and quality costs are simultaneously considered. Al-Ahmari [13] proposed an optimization approach via simulation for determining optimal process parameters. He utilized a mathematical model similar to [3] and built a simulation model to represent the process parameters selection decisions when the tool life is defined as a random variable. The main benefit of using simulation is that it overcomes the complexities in the mathematical model when stochastic tool life is assumed.

This paper considers an integrated economic model that takes into consideration quality losses in the form of Taguchi's loss function for both dimensional accuracy and surface roughness for a turning operation in which multiple parts are to be sequentially produced. The main difference that distinguishes this work from what has been proposed in the literature is the consideration of tool wear compensation as a parameter that can be adjusted in order to achieve better dimensional accuracy that would minimize the quality loss costs. Furthermore, the developed model utilizes simple empirical formulas that take the form of extended Taylor type equations for representing tool wear and surface roughness. The rest of this paper is organized as follows. In section 2, the problem description and assumptions are provided, followed by the developed mathematical model in section 3. Based on the mathematical model, an optimization approach is developed in section 4, followed by a demonstrative example in section 5. The conclusions are provided in section 6.

2. Problem Description and Assumptions

This paper is concerned with a turning operation in which identical parts are to be produced successively with a single tool. The machining economics problem under consideration involves decisions related to the determination of cutting parameters and the policy to be used for tool regrinding and replacement. In the literature, tool life has been treated as a random variable in order to be able to represent the situations in which unexpected tool breakage occurs. Such a representation has been employed in [3] to represent costs associated with tool replacement decisions as well as quality loss costs. However, there are practical concerns on how to determine a suitable probability distribution function that can be a valid representation of the tool life for a specific tool, workpiece material and cutting conditions. Moreover, the complexity of the mathematical formulas that result from such a representation is relatively high which complicates the analysis and optimization. Therefore, we opt to neglect any random effect that would result in tool breakage in the developed model. The following is a list of the assumptions considered in the current study concerning the tool life.

(1) The tool life is governed by the amount of flank wear for which a threshold value is specified, beyond which tool regrinding has to be made
(2) After regrinding, the tool is assumed to restore its original condition
(3) Any unexpected breakage of the tool is neglected
(4) The criteria used to decide a tool replacement is based solely on the number of times a regrinding is conducted
(5) Cutting is conducted using sharp edge tools

3. Mathematical Model

In the proposed model, there is a set of decision variables whose values are to be selected so that the objective of maximizing the profit per unit time is achieved. The decision variables include the traditional variables that are commonly known in machining problems which are the feed rate and the cutting speed. In addition, a tool wear compensation decision variable is considered in the developed model. The tool wear compensation variable is an addition to the depth of cut at the beginning of the processing of each part so that the expected drift in the part's diameter due to tool wear during the process is compensated and the losses that will be incurred due to drifting from the target diameter are mitigated. Table 1 lists the different decision variables used in the model.

The cutting speed and feed rate are assumed to be fixed for all parts processed. Meanwhile, the tool wear compensation varies from one part to another. The depth of cut for part i, denoted d_i, is dependent on the tool wear compensation δ_i. If D_o denotes the initial workpiece diameter and D denotes the final product target diameter, the depth of cut is evaluated as follows.

$$d_i = \frac{(D_o - D)}{2} + \delta_i \quad (1)$$

Table 1. Decision variables in the developed model

Symbol	Meaning
V	Cutting speed (m/min)
f	Feed rate (mm/rev)
N	Number of parts to be processed before tool regrinding is made
δ_i	Tool wear compensation (mm) for part i where $i = 1, \dots, N$

3.1 Cutting time

The mean cutting diameter is estimated as $\overline{D}_i = (D_o - d_i)$. If L denotes the required final part length, the cutting time for part i is evaluated as follows.

$$t_{c,i} = \frac{\pi \overline{D}_i L}{1000 V f} \ \text{min.} \quad (2)$$

The cumulative cutting time needed to finish cutting of n parts is calculated as follows.

$$T_n = \sum_{i=1}^{n} t_{c,i} \ \text{min.} \quad (3)$$

3.2 Tool wear and drift in workpiece diameter

As indicated by Al-Hossainy et al. [14], the flank wear (w) can be empirically estimated in the form of an extended Taylor type formula with the inclusion of machining time. This formula is represented as follows.

$$w = k_w V^{\propto_w} f^{\beta_w} d^{\gamma_w} t^{\sigma_w} \quad (4)$$

Where k_w, $\propto_w$, β_w, γ_w and σ_w are constants whose values are determined empirically using regression analysis. The variable t represents the length of time in minutes spent in cutting under the cutting conditions specified by the cutting speed V, the feed rate f, and the initially adjusted depth of cut d. Since the depth of cut changes from one part to another due to adjustments for tool wear compensation as indicated by equation (1), the value of t in equation (4) needs to be properly adjusted to ensure the continuity of tool wear value from one part to another. Accordingly, the tool wear w_i measured while processing part i after t minutes is expressed as follows.

$$w_i = k_w V^{\propto_w} f^{\beta_w} d_i^{\gamma_w} (t_{w,i} + t)^{\sigma_w} \quad \text{for } \ 0 \leq t \leq \ t_{c,i} \quad (5)$$

Where $t_{w,i}$ is the equivalent time that could have been spent in processing part i to result in the same amount of tool wear that is reached at the end of processing part $i-1$. Let W_i be the tool wear reached at the end of processing part i, i.e. $W_i = k_w V^{\propto_w} f^{\beta_w} d_i^{\gamma_w} (t_{w,i} + t_{c,i})^{\sigma_w}$. The value of $t_{w,i}$ can be estimated using equation (4) as follows.

$$t_{w,i} = \left(\frac{1}{k_w} V^{-\propto_w} f^{-\beta_w} d_i^{-\gamma_w} W_{i-1} \right)^{1/\sigma_w} \quad (6)$$

Since the process is assumed to start with a new or reground tool, it should be W_0= 0 and $t_{w,0} = 0$. Accordingly, the cumulative tool wear measured at the end of processing n parts is defined by $W_n = k_w V^{\propto_w} f^{\beta_w} d_n^{\gamma_w} (t_{w,n} + t_{c,n})^{\sigma_w}$. The length of the tool regrinding time interval can be determined by setting a specific value for the flank wear ($\widehat{W}$) near and below which the regrinding is to be conducted. This condition is interpreted into an equivalent number of parts ($\widehat{N}$) to be produced before a tool regrinding is required as follows.

$$\widehat{N} = \underset{i=1,2\dots}{\operatorname{argmin}} \left(\widehat{W} - W_i \right) \quad \text{for } \ \widehat{W} - W_i \geq 0 \quad (7)$$

The value of $\widehat{N}$ in equation (7) is equivalent to a tool regrinding time interval of $T_{\widehat{N}}$ which is determined using equation (3). In addition, the amount of tool wear in the flank can be used to estimate the amount of drift that occurs to the workpiece diameter during the process. The drift, denoted Δ_i for part i, with a clearance angle θ, is estimated as follows.

$$\Delta_i = 2(w_i - W_{i-1}) \tan(\theta) \qquad \text{for } 0 \le t \le t_{c,i} \tag{8}$$

3.3 Surface roughness

As shown by Al-Hossainy et al. [14], the surface roughness of the machined part (Φ) can be estimated empirically using Taylor type extended formula as follows.

$$\Phi = k_r V^{\propto_r} f^{\beta_r} d^{\gamma_r} t^{\sigma_r} \tag{9}$$

Where k_r, $\propto_r$, β_r, γ_r and σ_r are constants whose values are determined empirically using regression analysis. Traditionally, surface roughness is approximated in the literature [15, 16] as a function of both the feed rate f and the change that occurs to the geometry of the tool due to tool wear. The assumption made here is consistent with the literature in the point that tool wear has a major impact on the surface roughness. Since the tool wear is related to the length of time spent in cutting as well as the other machining parameters as indicated in equation (4), the relationship given in equation (9) can be seen as an encapsulation of those factors. The variable t which represents the time spent in cutting is treated in a similar manner as was done for the tool wear in equation (5). Accordingly, the surface roughness obtained for part i is expressed as follows.

$$\Phi_i = k_r V^{\propto_r} f^{\beta_r} d_i^{\gamma_r} (t_{w,i} + t)^{\sigma_r} \quad \text{for } 0 \le t \le t_{c,i} \tag{10}$$

3.4 Cutting force

The cutting force is necessary to estimate the maximum power needed for the process which is bounded by the capabilities of the machine used. The cutting force can be estimated empirically as indicated in [14] as follows.

$$F = k_c V^{\propto_c} f^{\beta_c} d^{\gamma_c} t^{\sigma_c} \tag{11}$$

Similarly, the cutting force for a specific part is given as follows.

$$F_i = k_c V^{\propto_c} f^{\beta_c} d_i^{\gamma_c} \left(t_{w,i} + t\right)^{\sigma_c} \quad \text{for } 0 \le t \le t_{c,i} \tag{12}$$

3.5 Economic objective

In addition to the cutting task, the turning operation under investigation involves additional tasks that include loading/unloading of workpiece material and finished part, and tool regrinding. Similar to the traditional machining economics model, there are some parameters that need to be considered. These parameters are included in table 2.

Table 2. Machining economics parameters

Symbol	Meaning
C_h	Labor cost for loading/unloading per unit time ($/min)
C_w	Labor cost for manning machine per unit time ($/min)
C_z	Cost of machine per unit time in-cut time ($/min)
C_g	Cost of regrinding a tool ($)
p	Revenue per final part ($)
t_h	loading and unloading time for a workpiece (min)

Based on the relationships provided earlier in this paper, the profit per tool regrinding cycle for the studied process, denoted P, is expressed as follows.

$$\mathrm{P} = E - (DC + GC + QC) \tag{13}$$

Where E is the total earnings, DC is the direct labor and machine cost, GC is the tool regrinding cost and QC is the quality losses. All these measures are evaluated for a single tool regrinding cycle. The first three terms are evaluated as follows.

$$E = Np \tag{14}$$

$$DC = NC_h t_h + (C_w + C_z)T_N \tag{15}$$

$$GC = C_g \tag{16}$$

In order to evaluate the quality losses, QC, Taguchi's loss function is used. In the studied problem, there are two types of quality losses: Losses due to deviation from target diameter and losses due to deviation from target surface roughness. In Taguchi's loss function, the square value of the difference between the actual and the target values is multiplied by a loss factor whose value is estimated from market and consumer cost measures. In the studied problem, two types of loss factors are defined: the loss factor for the deviation from the target diameter (ℓ_d), and the loss factor for the deviation from the target surface roughness (ℓ_r). Accordingly, if R denotes the target surface roughness, the total quality loss for a single tool regrinding cycle is evaluated as follows.

$$QC = \sum_{i=1}^{N} \ell_d \int_{T_{i-1}}^{T_i} (2\delta_i - \Delta_i)^2 dt + \sum_{i=1}^{N} \ell_r \int_{T_{i-1}}^{T_i} (\Phi_i - R)^2 dt \tag{17}$$

3.6 Working conditions and constraints

There is a set of constraints which define the ranges of the cutting parameters within which all empirical formulas are constructed. If the cutting parameters are assigned values outside these ranges, the empirical formulas may not be valid. These constraints are presented as follows.

$$f_{min} \le f \le f_{max} \tag{18}$$

$$V_{min} \le V \le V_{max} \tag{19}$$

$$d_{min} \le d_i \le d_{max} \qquad \forall i = 1, \dots, N \tag{20}$$

Table 3. Specification limits for final parts

Symbol	Meaning
D_{LSL}	Lower specification limit for final part diameter
D_{USL}	Upper specification limit for final part diameter
R_{USL}	Maximum allowable surface roughness

Furthermore, the specification limits define the ranges for acceptable part diameters and surface roughness. The required specifications of the final parts are listed in table 3. The following two constraints represent these quality limits.

$$D_{LSL} \le D - 2\delta_i + \Delta_i \le D_{USL} \qquad \forall i = 1, \dots, N \quad \text{at } t = 0 \text{ and } t = t_{c,i} \tag{21}$$

$$\Phi_i \le R_{USL} \qquad \forall i = 1, \dots, N \quad \text{at} \quad t = t_{c,i} \tag{22}$$

The power consumed during the process should not exceed the maximum power available by the machine, denoted $\mathbb{P}_{max}$. This constraint is expressed as follows.

$$V.F_i \le \mathbb{P}_{max} \qquad \forall i = 1, \dots, N \quad \text{at} \quad t = t_{c,i} \tag{23}$$

In addition, the number of parts to be processed before a tool grinding is to be conducted is limited by the upper bound defined in equation (7), which is represented by the following constraint.

$$N \le \hat{N} \tag{24}$$

The objective function which is traditionally taken as the maximization of profit per unit time is expressed as follows.

$$\text{Max. } Z = \frac{P}{Nt_h + T_N} \quad (25)$$

This objective function, along with the constraints given by the relationships (18) to (24), forms a non-linear programming model. In the next section, an optimization approach based on that model is presented.

4. Proposed Optimization Approach

As shown in the previous section, there are two types of decisions to be conducted for the studied problem. The first is of a discrete nature as it is concerned with the determination of the number of parts N to be processed in every tool regrinding cycle. The second type of decision is related to the determination of the continuous process parameters V, f and δ_i. Since the determination of the value of N is a prerequisite for the evaluations that are required for the objective function and the constraints, it is inevitable for any optimization approach to construct and solve subproblems that are defined using fixed values of N, while an outer loop is used for suggesting those values.

The proposed optimization approach is a simple sequential search technique that starts with an initial value for N=1 and increments this value by one until a stopping criterion is satisfied. At each value of N, the underlying non-linear programming model is constructed and solved to determine the best process parameters. There are two stopping criteria employed. The first is a simple one that stops the algorithm when an infeasible non-linear programming model is encountered. The main source of infeasibility is due to not satisfying constraint (24). The second stopping criteria is based on evaluating the quality of the solution obtained at a given value of N with respect to its neighboring solutions obtained at $N-1$ and $N+1$. If the percentage differences in the values of Z at these points are minor (less than 2%) with sign changes, this indicates that a local optimum is obtained and the algorithm may stop at this point. For the subproblems that are formed at each value of N, their non-linear programming models can be solved using traditional constrained non-linear programming algorithms. Several commercial packages are available for dealing with such problems.

5. An Illustrative Example

In this section, an illustrative example is presented to demonstrate the optimization approach and to investigate some properties of the optimal solutions. Most of the parameters considered in the illustrative example are based on the example presented in [3] and the experimental results presented in [14]. Table 4 lists the numerical values used for the different parameters.

Table 4. Numerical values for the parameters of the illustrative example

Category	Numerical values
Dimensions of the workpiece	D_o= 98 mm, D=100 mm, L=35 mm
Specifications for workpiece	D_{USL}= 98.1 mm, D_{USL}= 97.9 mm, R= 2.5 μm, R_{USL}= 10 μm
Revenue rate, and Labor and machining costs	p= 37.5 , C_h= \$0.5 /min, C_w= \$0.5 /min, C_z= \$2 /min, C_g= \$20
Part loading and unloading time	t_h= 2 min
Quality loss costs	ℓ_d = \$125 /mm^2, ℓ_r = \$0.0075 /μm^2
Tool wear limit	$\widehat{W}$= 0.4mm
Tool clearance angle	θ = 15°

Table 5 shows the different values of the constants used in the empirical formulas, along with the working ranges for the process parameters in which these empirical formulas are defined.

Table 5. Constants for formulas and working ranges for process parameters

Category	Numerical values
Tool wear empirical constants	k_w = 8.2961×10^{-5}, $\propto_w$= 2.747, β_w= 1.473, γ_w= 1.261, σ_w= 0.43
Surface roughness empirical constants	k_r = 11.619, $\propto_r$= 0.261, β_r= 0.565, γ_r= 0.565, σ_r= 0.08887
Cutting force empirical constants	k_c = 173226.613, $\propto_c$= -0.992, β_c= 1.016, γ_c= 1.033, σ_c= 0.03877

Working ranges for empirical formulas	f_{min}= 0.08 mm/rev, f_{max}= 0.28 mm/rev V_{min}= 32 m/min, V_{max}= 70 m/min d_{min}= 0.5 mm, d_{max}= 1.5 mm $\mathbb{P}_{max}$ = 15 Kw

The required calculations in the mathematical model are conducted on a spreadsheet using Microsoft Excel®. The optimization of the non-linear programming models generated at different values of N is conducted using the Generalized Reduced Gradient (GRG) nonlinear solver [17]. The running time of the solver is found to be less than 3 seconds in all runs on a dual-core Intel CPU with a clock speed of 1.86 GHz and a RAM size of 2 GB. Table 6 shows the detailed results for the different process parameters and measures for N from 1 to 7.

Table 6. Summary of results for the illustrative example

N	***V***	***F***	***Z***	**Part (*i*)**	δ_i	**Maximum** Φ_i	**Initial diameter**	**Final diameter**
1	70	0.0898	3.01	1	0.050	9.203	97.90	98.07
2	67.64	0.0873	5.47	1	0.050	9.025	97.90	98.06
				2	0.050	9.599	97.90	97.96
3	63.14	0.0856	5.96	1	0.050	8.840	97.90	98.03
				2	0.039	9.449	97.92	97.97
				3	0.050	9.756	97.90	97.93
4	60.12	0.0845	6.08	1	0.048	8.719	97.90	98.02
				2	0.036	9.326	97.93	97.97
				3	0.040	9.657	97.92	97.95
				4	0.050	9.870	97.90	97.92
5	57.87	0.0836	6.09	1	0.044	8.640	97.91	98.02
				2	0.033	9.236	97.93	97.97
				3	0.037	9.566	97.93	97.95
				4	0.041	9.797	97.92	97.94
				5	0.050	9.959	97.90	97.92
6	56.32	0.0823	6.04	1	0.042	8.543	97.92	98.01
				2	0.032	9.129	97.94	97.97
				3	0.035	9.456	97.93	97.96
				4	0.038	9.689	97.92	97.94
				5	0.041	9.872	97.92	97.94
				6	0.050	10.000	97.90	97.92
7	55.23	0.0804	5.94	1	0.039	8.438	97.92	98.01
				2	0.029	9.014	97.94	97.97
				3	0.033	9.337	97.93	97.96
				4	0.036	9.568	97.93	97.95
				5	0.038	9.750	97.92	97.94
				6	0.040	9.900	97.92	97.93
				7	0.050	10.00	97.90	97.91

The results in table 6 show that there is a tendency to reduce the cutting speed and feed rate as the number of parts increases. This can be attributed to the impact that these two cutting parameters have on the dimensional accuracy and surface roughness, in addition to the tool wear. As shown in section 3 and as suggested by the empirical constants provided in table 5, increasing both parameters results in higher tool wear and therefore lower dimensional accuracy. This characteristic also exists in the case of surface roughness. Therefore, reducing the values of cutting speed and feed rate helps in reducing the quality losses as the number of parts increases.

Meanwhile, the selection of the tool wear compensation amount δ_i tends to start with relatively higher value for the first part, then its value decreases for the following parts up to an intermediate point at which its value starts to increase until reaching the final part. The higher values at the beginning are attributed to the fact that the tool wear at the beginning of using a new or reground tool increases with a higher rate until it reaches a steady state. Therefore, higher tool wear compensation at the first part is required to maintain a relatively even distribution around the target diameter value. For the succeeding parts, two opposing economic factors are the reason for the resulting pattern. The first is related to minimizing the cutting time to increase the profit per unit time, which forces the tool wear compensation amount to decrease. While the second factor is related to reducing quality related costs which force the tool wear compensation to increase.

Regarding the objective value Z, it is shown in figure 1 that its value increases with the increase of number of parts until it reaches its peak point. Then, the profit per unit time steadily decreases with the increase of number of parts. It is expected that at a larger number of parts an infeasible case will be encountered due to not satisfying constraint (24) as indicated earlier. According to the stopping criteria specified by the proposed optimization approach, the search for an optimal solution will stop at N=6. The optimal number of parts in the studied case is N=5.

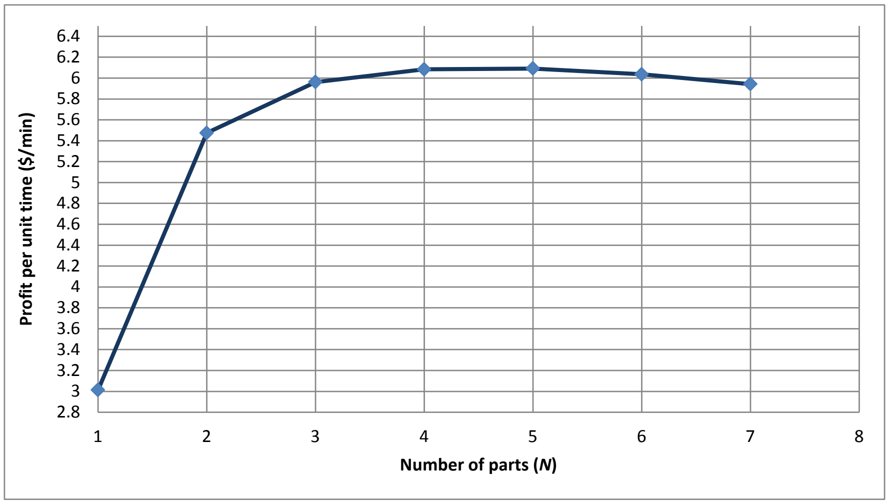

Figure 1: Optimal profit per unit time values obtained at different values of N for the illustrative example

6. Conclusions

In this paper, a new mathematical model is proposed for a turning operation in which multiple parts are produced successively. In this model, the tool wear compensation is taken into consideration and represented as a decision variable whose value is to be determined for each part. Losses due to deviations from target diameter and surface roughness are taken into consideration in the model in addition to the traditional cost elements defined for the machining processes. A non-linear programming model is formulated for the studied problem and an optimization approach is proposed. An example is presented to illustrate characteristics of the optimal solutions and demonstrates the capability of the proposed optimization approach.

Compared to similar models in the literature which have addressed quality costs in the form of Taguchi's loss function and studied the tool regrinding policies, the proposed model is simpler and more practical. The developed model avoids the complexities that result from considering unexpected tool breakage. Such a consideration requires a valid tool life probability distribution function which could be difficult to obtain practically. Instead, empirical formulas that relate tool wear, surface roughness and other measures to the main process parameters along with the cutting time provide an easy way to capture the complex relationships and to facilitate analysis, optimization and computational efforts.

References

1. Taguchi, G., 1986, Introduction to Quality Engineering, Asian Productivity Organization, Tokyo.
2. Mukherjee, I. and Ray, P.K., 2006, "A review of optimization techniques in metal cutting processes," Computers and Industrial Engineering, 50, 15-34.
3. Hui, Y.V., Leung, L.C. and Linn, R., 2001, "Optimal machining conditions with costs of quality and tool maintenance for turning," International Journal of Production Research, 39(4), 647-665.

4. Chang, T.C. and Wysk, R.A., 1985, An Introduction to Automated Process Planning Systems, Prentice-Hall International Series in Industrial and Systems Engineering.
5. Davis, R.P., Wysk, R.A., and Agee, M.H., 1978, “Characteristics of machining parameter optimization models,” Applied Mathematics Modeling, 2(2), 275-279.
6. Lambert, B.K. and Walvekar, A.G., 1978, “Optimization of multi-pass machining operations,” International Journal of Production Research, 16(2), 259-265.
7. Maheshwari, S.K., Misra, V. and Mehta, N.K., 1991, “A new approach to parameter selection: Integration of quality,” Computers and Industrial Engineering, 21(1-4), 57-62.
8. Maheshwari, S.K., 2007, “Optimizing meal cutting cost by integration of cost of quality using Taguchi’s loss function,” Academy of Information and Management Sciences Journal, 10(1), 2007, 65-74.
9. Taha, H., 1966, “A policy for determining the optimal cycle length for a cutting tool,” Journal of Industrial Engineering, 17, 157-162.
10. Kindall, L.A., and Bayoumi, A., 1988, “Automatic tool-war monitoring and tool changing using intelligent supervisory control,” International Journal of Production Research, 26(10), 1619-1628.
11. Schall, S.O., and Chandra, J., 1990, “Optimal tool inspection intervals using a process control approach,” International Journal of Production Research, 25(5), 841-851.
12. Hui, Y.V., and Leung, L.C., 1994, “Optimal economic tool regrinding with Taguchi’s quality loss function,” The Engineering Economist, 39(4), 313-331.
13. Al-Ahmari, A.M., 2010, “Solving stochastic machining economics problem using simulation optimization approach,” Journal of King Saud University, 22(1), 29-40.
14. El-Hossainy, T.M., El-Zoghby, A.A., Badr, M.A., Maalawi, K.Y. and Nasr, M.F., 2010, “Cutting parameter optimization when machining different materials,” Materials and Manufacturing Processes, 25, 1101-1114.
15. Chang, T.C. and Wysk, R.A., 1985, An Introduction to Automated Process Planning Systems, Prentice-Hall International Series in Industrial and Systems engineering.
16. Goller, J.A. and Barrow, G., 1985, “The prediction of surface finish in turning operations,” Proceedings of the Twenty sixth International Machine Tool design and Research Conference, 26, 229-237.
17. Generalized Reduced Gradient (GRG) Nonlinear Solver, March 2012, http://www.solver.com