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Cutting-parameter selection for maximizing production rate or minimizing production cost in multistage turning operations

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Abstract

In this paper, an investigation of optimal cutting parameters for maximizing production rate or minimizing production cost in multistage turning operations is reported. A machining model is constructed based on a polynomial network. The polynomial network can learn the relationships between cutting parameters (cutting speed, feed rate, and depth of cut) and cutting performance (surface roughness, cutting force, and tool life) through a self-organizing adaptive modeling technique. Once the geometric model for machined parts and various time and cost components of the turning operation are given, an optimization algorithm using a sequential quadratic programming method is then applied to the polynomial network for determining optimal cutting parameters. The optimal cutting parameters are subjected to an objective function of maximum production rate or minimum production cost with the constraints of a permissible limit of surface roughness and cutting force and a feasible range of cutting parameters. © 2000 Published by Elsevier Science S.A.

Keywords: Optimization; Minimum production cost; Maximum production rate; Turning

1. Introduction

Turning is a widely used machining process in manufacturing. Therefore, an optimal selection of cutting parameters to satisfy an economic objective within the constraints of multistage turning operations is a very important task. The original study of machining economics is credited to Gilbert [1]. Two economic objectives have been considered, i.e., maximum production rate and minimum production cost. In the literature, several optimization studies of cutting parameters for turning operations have been documented [2–5]. To determine the optimal cutting parameters, reliable mathematical models have to be formulated to associate the cutting parameters with cutting performance. However, it is also well known that reliable mathematical models are not easy to obtain. In recent years, the use of adaptive learning tools to associate the cutting parameters with cutting performance is gradually gaining reputation as a reliable, effective modeling technique [6–8]. In this paper, a polynomial network [9] is used to construct the relationships between the cutting parameters (cutting speed, feed rate, and depth of cut) and cutting performance (surface roughness, cutting force, and tool life). The polynomial network is a self-organizing adaptive modeling tool [10] with the ability to construct the relationships between input variables and output feature spaces. A comparison between the polynomial network and a back-propagation network has shown that the polynomial network has higher prediction accuracy and fewer internal network connections [11]. The best network structure, number of layers, and functional node types can be determined by using an algorithm for synthesis of polynomial networks (ASPNs) [12].

Once the reliable model for turning operations has been constructed, an optimization algorithm is then applied to the model for determining optimal cutting parameters. The geometric model for machined parts and various time and cost components of the multistage turning operation are also given in the optimization process. The optimal cutting parameters are subjected to an objective function of either maximum production rate or minimum production cost with the constraints of a permissible limit of surface roughness and cutting force. In this paper, an optimization algorithm, called a sequential quadratic programming method, is used to solve the optimal cutting parameters. This is because the sequential quadratic programming method represents the state-of-the-art in non-linear programming methods [13,14].

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This optimization method has been considered to be an excellent approach for handling constrained optimization problems.

The paper is organized in the following manner. Polynomial networks are introduced first. The use of polynomial networks to construct a machining model is given next. Machining economic objectives such as maximum production rate or minimum production cost are described. Finally, optimization algorithms are applied to the machining economic objectives to solve optimal cutting parameters with the constraints of cutting parameters and cutting performance.

2. Polynomial networks

The polynomial networks proposed by Ivakhnenko [15] are a group method of data handling (GMDH) techniques. The polynomial network is composed of a number of polynomial functional nodes grouped into several layers. Then, the network structure is determined by using an ASPN.

2.1. Polynomial functional nodes

The general polynomial function known as the Ivakhnenko polynomial in a polynomial functional node can be expressed as

$$y_0 = w_0 + \sum_{i=1}^{m} w_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} w_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} w_{ijk} x_i x_j x_k + \cdots \tag{1}$$

where x_i, x_j, x_k are the inputs, y_0 the output, and w_0, w_i, w_{ij}, w_{ijk} are the coefficients of the polynomial functional node.

In this study, several types of polynomial functional nodes are used in the polynomial network for the modeling of turning operations, and are explained as follows:

1. *Normalizer and unitizer*. A normalizer transforms the original input into the normalized input. On the other hand, a unitizer converts the output of the network to the real output. The polynomial equation of the normalizer and unitizer can be expressed as:

   $$y_1 = w_0 + w_1 x_1 \tag{2}$$

   where x_1 is the input of the node, y_1 the output of the node, and w_0, w_1 are the coefficients of the node.
2. *Single, double, and triple nodes*. The single, double and triple nodes have one, two, and three inputs, respectively. The polynomial equations for the single, double and triple nodes are limited to the third degree with possible cross-terms for one, two, and three inputs. For example, the polynomial equation of the double node can be expressed as

   $$y_1 = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1^2 + w_4 x_2^2 + w_5 x_1 x_2 + w_6 x_1^3 + w_7 x_2^3 \tag{3}$$

   where x_1, x_2 are the inputs to the node, y_1 the output of the node, and $w_0, w_1, w_2, \ldots, w_7$ are the coefficients of the double node.
3. *White node*. The white node is used to summarize all linear-weighted inputs plus a constant, i.e.,

   $$y_1 = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3 + \cdots + w_n x_n \tag{4}$$

   where $x_1, x_2, x_3, \ldots, x_n$ are the inputs to the node, y_1 the output of the node, and $w_0, w_1, w_2, \ldots, w_n$ are the coefficients of the white node.

2.2. Synthesis of polynomial networks

To build a polynomial network, training data with the information of inputs and outputs is required first. Then, an ASPN, called the predicted squared error (PSE) criterion [12], is used to determine an optimal network structure. The PSE criterion is composed of two terms, i.e.,

$$\mathrm{PSE} = \mathrm{FSE} + \mathrm{KP} \tag{5}$$

where FSE is the average squared error of the network for fitting the training data and KP is the complex penalty of the network that can be expressed as

$$\mathrm{KP} = \mathrm{CPM}\,\frac{2\sigma_{\mathrm{P}}^2 K}{N} \tag{6}$$

where CPM is the complex penalty multiplier, K the number of coefficients in the network, and σ_{P}^2 is a prior estimate of the model error variance, also equal to a prior estimate of FSE.

The best network is the network with the minimum value of PSE. Therefore, the principle of the PSE criterion is to select a network as accurate but as least complex as possible.

3. Building of a machining model using polynomial networks

Experimental data with regard to different cutting parameters and cutting performance are required to train the polynomial networks for constructing a machining model. In this section, turning experiments and cutting performance are discussed first. Then, a machining model is obtained by using the polynomial networks.

3.1. Turning experiments and performance measure

A number of turning experiments were carried out on an engine lathe using tungsten carbides with the grade of P-10 for the machining of S45C steel bars. The feasible space of the cutting parameters was selected by varying cutting speed in the range 135–285 m/min, feed rate in the range

Table 1
Experimental cutting parameters and cutting performance

v (m/min)	f (mm/rev)	d (mm)	R_a (μm)	F (N)	T (s)
135	0.08	0.6	1.24	263.0	2645
135	0.20	0.6	5.34	403.0	2379
135	0.32	0.6	9.49	550.0	2233
135	0.08	1.1	1.68	454.0	2604
135	0.20	1.1	1.92	704.0	2060
135	0.32	1.1	4.06	889.0	1870
135	0.08	1.6	1.86	628.0	2563
135	0.20	1.6	4.12	924.0	2032
135	0.32	1.6	9.44	1198.0	1733
210	0.08	0.6	2.61	212.0	1605
210	0.20	0.6	4.51	389.0	1198
210	0.32	0.6	11.05	502.0	802
210	0.08	1.1	1.01	377.0	1350
210	0.20	1.1	2.75	622.0	1059
210	0.32	1.1	7.49	853.8	734
210	0.08	1.6	2.64	593.0	1310
210	0.20	1.6	6.06	952.0	1031
210	0.32	1.6	14.37	1169.7	602
285	0.08	0.6	0.56	203.0	860
285	0.20	0.6	2.84	363.8	847
285	0.32	0.6	9.70	464.2	216
285	0.08	1.1	0.91	335.0	854
285	0.20	1.1	2.74	573.1	846
285	0.32	1.1	6.12	812.7	212
285	0.08	1.6	1.25	443.0	840
285	0.20	1.6	4.18	856.8	765
285	0.32	1.6	10.17	1099.3	203

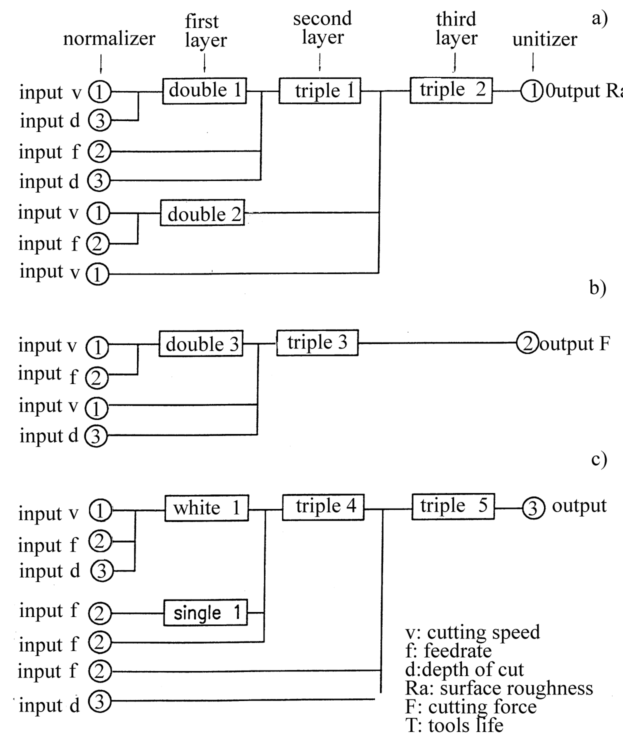

Fig. 1. Polynomial networks for predicting cutting performance: (a) surface roughness; (b) cutting force; and (c) tool life.

0.08–0.32 mm/rev, depth of cut in the range 0.6–1.6 mm. Each of these cutting parameters was set at three levels that are listed in Table 1. Hence, 27 turning experiments were performed based on the cutting parameter combinations.

The machined surface roughness was measured by a profile meter (3D-Hommelewerk). The average surface roughness R_a, which is the most widely used surface finish parameter in industry, is selected in this study. It is the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured within the sampling length of 8 mm. The cutting force acting on the cutting tool in the X, Y, and Z directions was measured by a three-component piezo-electric dynamometer (Kistler 5257A) under the tool holder. The resultant cutting force is then calculated to evaluate machining performance in this study. Tool life is defined as the period of cutting time until the average flank wear land V_B of the tool is equal to 0.3 mm or until the maximum flank wear land V_{Bmax} is equal to 0.6 mm. In the experiments, the flank wear land was measured by using an optical tool microscope (Isoma). The cutting performance (surface roughness, cutting force, and tool life) corresponding to 27 turning experiments is also listed in Table 1.

3.2. Machining model for turning operations

A three-layer polynomial network for predicting cutting performance is synthesized based on the experimental data listed in Table 1. Fig. 1 shows the developed polynomial networks for predicting surface roughness, cutting force, and tool life. All of the polynomial equations used in the networks (Fig. 1) are listed in Appendix A. The error between the predicted and measured surface roughness, cutting force, and tool life for the experimental data listed in Table 1 is less than 10%. Therefore, the developed networks have a reasonable accuracy for the modeling of turning operations.

4. Economics of multistage turning operations

In this section, mathematical equations are derived for the calculation of the economics of multistage turning operations. Based on the mathematical equations, the production rate and production cost in multistage production can be calculated.

4.1. Maximizing production rate

Basically, maximizing the production rate is equivalent to minimizing the cutting time per part. Therefore, the objective is to complete the production order as quickly as possible. The total production cycle time for one part is composed of three items, i.e., part handling time, machining time, and tool change time. In multistage turning, the total production cycle time T_p for one part can be expressed as

$$T_p = T_h + (T_{mr} + T_{mf}) + T_c N_c \tag{7}$$

where T_h is the part handling time including loading time and unloading time, T_{mr} the rough machining time, T_{mf} the finish machining time, T_c the tool change time, and N_c is the number of tool changes.

4.2. Minimizing production cost

During a turning operation, minimizing the production cost can be considered as minimizing the total cost per part. The total cost per part is composed of four items, i.e., part handling cost, machining cost, tool change cost, and tool cost. In multistage turning, the total cost of producing one part C_p can be expressed as

$$C_p = C_h T_h + (C_{mr} T_{mr} + C_{mf} T_{mf}) + C_c T_c N_c + (C_{tr} N_{tr} + C_{tf} N_{tf}) \tag{8}$$

where C_h is the cost rate for the part handling, C_{mr} the cost rate for the rough machining, C_{mf} the cost rate for the finish machining, C_c the cost rate for the tool change, C_{tr} the cost for the rough machining tool, C_{tf} the cost for the finish machining tool, N_{tr} the number of rough machining tools per part, and N_{tf} is the number of finish machining tools per part.

5. Optimization of multistage turning operations

The use of an optimization algorithm called the sequential quadratic programming method to maximize the production rate (Eq. (7)) and minimize the production cost (Eq. (8)) will be discussed in this section.

5.1. Sequential quadratic programming method

Basically, parametric optimization is used to solve a set of design variables, x_i, $i = 1, 2, \ldots, n$, contained in the vector $\mathbf{x}$ which can minimize the objective function $\mathbf{f}(\mathbf{x})$ subjected to equality and inequality constraints and the upper and lower bounds of the design variables (x_i, $i = 1, 2, \ldots, n$). The sequential quadratic programming method represents the state-of-the-art in non-linear programming methods. The basic concept is quite simple. The approximation function instead of the original non-linear function is used for optimization. First, a second order Taylor series approximation of the objective function and constraints functions with respect to the design variables (x_i, $i = 1, 2, \ldots, n$) is constructed. The search direction vector $\mathbf{s}$ for optimization can be determined by the matrix of the second derivatives of the approximation function. Once the search direction vector $\mathbf{s}$ is chosen, an optimal scalar step length parameter α is calculated through the quadratic interpolation. Therefore, the design vector $\mathbf{x}_{k+1}$ during iteration can be expressed as:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{s}_k \tag{9}$$

where k is the iteration number.

In other words, the sequential quadratic programming method consists of three main stages, i.e.: (1) find the search direction vector $\mathbf{s}$; (2) find the scalar step length parameter α; (3) test for convergence to the optimum and terminate if convergence is achieved.

The detailed description of the mathematical equations of the sequential quadratic programming method is found in [13,14].

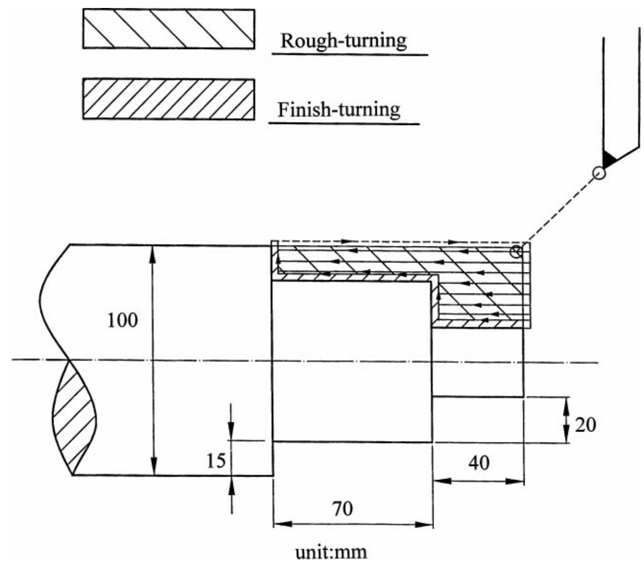

Fig. 2. Geometrical drawing of a part.

5.2. Case study

Fig. 2 shows the geometric drawing of a part, where the shading area is removed by multistage turning operations. As shown in Fig. 2, multiple repetitive rough turning cycles are performed first. Then, a finish turning cycle is executed to obtain better surface roughness. Two examples are presented to illustrate the optimization approach developed in this study. The flow chart for the optimization of multistage turning operations is shown in Fig. 3.

5.2.1. Example 1

The problem for maximizing the production rate of the part can be expressed as minimizing the total production cycle time T_p subjected to: 135 m/min$\leq$cutting speed $v\leq$285 m/min; 0.08 mm/rev$\leq$feed rate f for rough turning$\leq$0.32 mm/rev; 0.08 mm/rev$\leq$feed rate f for finish turning$\leq$0.16 mm/rev; 0.6 mm$\leq$depth of cut d for rough turning $\leq$1.6 mm; 0.6 mm$\leq$depth of cut d for finish turning$\leq$1.0 mm; cutting force F for rough turning$\leq$1000 N; surface roughness R_a for finish turning$\leq$1.5 μm.

The optimization results are listed as follows: the minimum total production cycle time T_p=11.28 min, cutting speed for rough turning v=285 m/min, feed rate for rough turning f=0.27 mm/rev, depth of cut for rough turning d=1.59 mm, cutting speed for finish turning v=285 m/min, feed rate for finish turning f=0.13 mm/rev, depth of

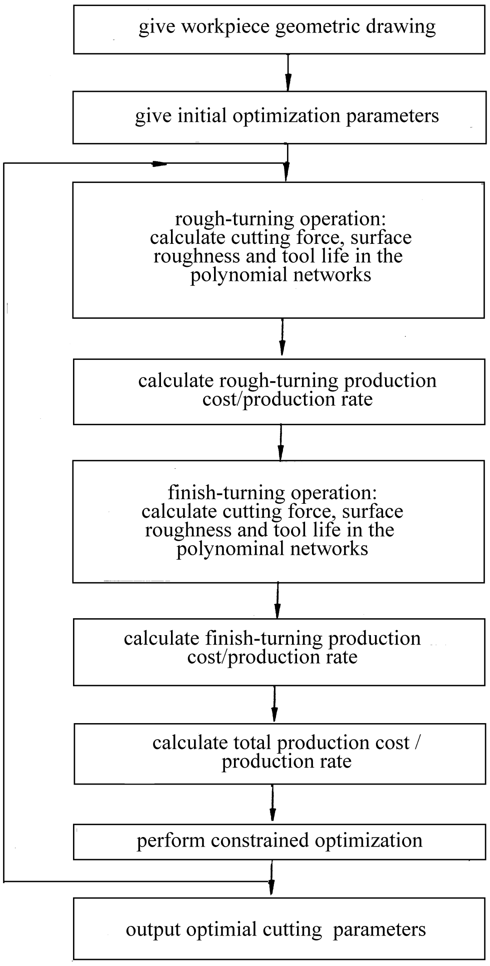

Fig. 3. Flow chart for the optimization of multistage turning operations.

cut for finish turning d=0.95 mm, and surface roughness R_a of the part=1.4 μm.

5.2.2. Example 2

The problem for minimizing production cost can be expressed as minimizing the total cost per part C_p subjected to the same conditions as shown in Section 5.2.1.

In this example, the various cost rates [16] for the multistage turning operations are given as: the cost rate for the part handling C_h=0.003 \$/s, the cost rate for the rough machining C_{mr}=0.0028 \$/s, the cost rate for the finish machining C_{mf}=0.003 \$/s, the cost rate for the tool change C_c=0.003 \$/s, the tool cost for rough machining C_{tr}=2.1 \$/piece, the tool cost for finish machining C_{tf}=2.0 \$/piece.

The optimization results are listed as follows: the total cost per part C_p=\$3.02, cutting speed for rough turning v=285 m/min, feed rate for rough turning f=0.26 mm/rev, depth of cut for rough turning d=1.6 mm, cutting speed for finish turning v=285 m/min, feed rate for finish turning f=0.13 mm/rev, depth of cut for finish turning d=0.95 mm, and surface roughness R_a of the part=1.4 μm.

6. Conclusions

In this work, optimal selection of cutting parameters considering the economics of multistage turning operations has been reported. Polynomial networks have been used to construct the machining model for multistage turning operations. The sequential quadratic programming method is then applied to the networks for searching optimal cutting parameters with maximizing the production rate or minimizing production cost. Practical examples in multistage turning operations are presented to illustrate the approach proposed by this study.

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Appendix A.

1. Normalizer:
   - 1.1. $y_1 = -3.37 + 0.016x_1$
   - 1.2. $y_1 = -2 + 10x_1$
   - 1.3. $y_1 = -2.64 + 2.4x_1$
2. Unitizer:
   - 2.1. $y_1 = 4.82 + 3.72x_1$
   - 2.2. $y_2 = 623 + 289x_1$
   - 2.3. $y_3 = 1310 + 757x_1$
3. Single node:
   - 3.1. $y_1 = 0.0586 - 0.368x_1 - 0.0608x_1^2$
4. Double node:
   - 4.1. $y_1 = -0.166 + 0.0839x_2 - 0.282x_1^2 + 0.455x_2^2 + 0.0488x_1x_2$
   - 4.2. $y_1 = 0.846x_2 - 0.28x_1^2 + 0.278x_2^2 + 0.0783x_1x_2$
   - 4.3. $y_1 = 0.0904 - 0.138x_1 + 0.644x_2 - 0.0236x_1^2 - 0.0703x_2^2 + 0.0206x_1x_2$
5. Triple node:
   - 5.1. $y_1 = -0.485 + 0.445x_1 + 0.808x_2 + 0.0635x_1^2 + 0.276x_2^2 + 0.149x_3^3 + 0.611x_1x_2 - 0.116x_2x_3 + 0.467x_1x_2x_3 + 1.33x_1^3$
   - 5.2. $y_1 = -0.0565 + 0.89x_1 - 0.0777x_2 - 0.0695x_3 - 0.133x_1^2 - 0.23x_2^2 + 0.044x_3^2 + 0.346x_1x_2 - 0.313x_1x_3 + 0.32x_2x_3 + 0.0937x_1x_2x_3 + 0.00794x_1^3 + 0.146x_2^3$
   - 5.3. $y_1 = 0.953x_1 + 0.727x_3 + 0.297x_1x_3 + 0.042x_1x_2x_3 + 0.0679x_1^3$
   - 5.4. $y_1 = -0.258 + 0.975x_1 + 0.102x_2 + 0.0564x_3 + 0.408x_1^2 - 1.54x_1x_2 - 0.274x_1x_3 - 0.26x_1x_2x_3 - 0.0427x_1^3$
   - 5.5. $y_1 = -0.0293 + x_1 - 0.0188x_3 + 0.0304x_3^2 - 0.0253x_2x_3 - 0.0395x_1x_2x_3$
6. White node:
   - 6.1. $y_1 = -0.883x_1 - 0.368x_2 - 0.104x_3$

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