一、中文摘要

本研究在於探討使用碳化鈷刀具設計
車削參數，以使生產率極大化或生產成本極
小化。首先削削參數與切削性能之間關係，
使用多項式神經網路來加以建構，然後再引
用最佳化演算法來搜尋最佳切削參數。

關鍵詞：切削性能，切削參數，最佳化。

ABSTRACT

In the literature, several optimization
studies of cutting parameters for turning
operations have been documented [2–4]. To
determine the optimal cutting parameters,
reliable mathematical models have to be
formulated to associate the cutting parameters
with cutting performance. In this paper, a
polynomial network [5] is used to construct the
relationships between the cutting parameters
(cutting speed, feedrate, and depth of cut) and
cutting performance (surface roughness,
cutting force, and tool life). The polynomial
network is a self-organizing adaptive modeling
tool [6] with an ability to construct the
relationships between input variables and
output feature spaces. 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 optimal cutting
parameters are subject 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 [7], is used to solve the
optimal cutting parameters. This optimization
method has been considered to be an excellent
approach for handling constrained optimization
problems.

2. POLYNOMIAL NETWORKS

Polynomial networks proposed by
Ivakhnenko are group method of data handling
(GMDH) techniques [8]. The polynomial
network is composed of a number of
polynomial functional nodes and grouped into
several layers. Then, the network structure is
determined by using an algorithm for synthesis
of polynomial networks (ASPEN) [9].
2.1 Polynomial Functional Nodes

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

\[ y_0 = w_0 + \sum_{i=1}^{m} w_i x_i + \sum_{i=1}^{m} \sum_{j=1}^{m} w_{ij} x_i x_j + \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{m} w_{ijk} x_i x_j x_k + \ldots \]  

(1)

where \( x_i, x_j, x_k \) are the inputs, \( y_0 \) is the output, and \( w_0, w_i, w_{ij}, w_{ijk} \) are the coefficients of the polynomial functional 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 algorithm for synthesis of polynomial networks (ASPN), called predicted squared error (PSE) criterion [9], is used to determine an optimal network structure. The PSE criterion is composed of two terms, that is:

\[ \text{PSE} = \text{FSE} + \text{KP} \]  

(5)

where \( \text{FSE} \) is the average squared error of the network for fitting the training data and \( \text{KP} \) is the complex penalty of the network that can be expressed as:

\[ \text{KP} = \text{CPM} \frac{2\sigma_p^2 K}{N} \]  

(6)

where \( \text{CPM} \) is the complex penalty multiplier, \( K \) is the number of coefficients in the network, and \( \sigma_p^2 \) 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 less 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 machining of S45C steel bars. The feasible space of the cutting parameters were selected by varying cutting speed \( u \) in the range of 135 to 285 m/min, feedrate \( f \) in the range of 0.08 to 0.32 mm/rev, depth of cut \( d \) in the range of 0.6 to 1.6 mm. Each of these cutting parameters was set at three levels that are listed in Tab. 1.

The average surface roughness \( R_a \) measured by a profile meter is selected to evaluate machining performance in this study. 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. Tool life is defined as the period of cutting time that the average flank wear land \( V_B \) of the tool is equal to 0.3 mm or the maximum flank wear land \( V_{B_{max}} \) 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, and cutting force, tool life) corresponding to cutting parameter combinations is also listed in Tab. 1.

3.2 Machining Model for Turning Operations

Based on the experimental data listed in Tab. 1, a three-layer polynomial network for predicting cutting performance is synthesized. Figs. 1,2,3 show the developed polynomial network for predicting surface roughness, cutting force, and tool life, respectively. The error between the predicted and measured surface roughness, cutting force, and tool life for the experimental data listed in Tab. 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

4.1 Maximizing Production Rate

Basically, maximizing production rate is equivalent to minimizing 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, that is, part handling time, machine time, and tool change time. In multistage turning, the total production cycle time $T_p$ for one part can be expressed as:

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

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

4.2 Minimizing Production Cost

During a turning operation, minimizing production cost can be considered as minimizing the total cost per part. The total cost per part is composed of four items, that is, 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:

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

where $C_h$ is the cost rate for the part handling; $C_{mr}$ is the cost rate for the rough machining; $C_{mf}$ is the cost rate for the finish machining; $C_c$ is the cost rate for the tool change; $C_{tr}$ is the tool cost for the rough machining; $C_{tf}$ is the tool cost for the finish machining; $N_{tr}$ is 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 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 $x$ which can minimize the objective function $f(x)$ subject 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 state-of-the-art in nonlinear programming methods. The basic concept is that the approximation function instead of the original nonlinear function is used for optimization.

5.2 Case Study

Fig. 4 shows the geometric drawing of a part and the shading area is removed by multistage turning operations. As shown in Fig. 4, 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.

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 $T_p$ subject to:

135 m/min $\leq$ cutting speed $v \leq 285$ m/min,
0.08 mm/rev $\leq$ feedrate $f$ for rough turning $\leq 0.32$ mm/rev,
0.08 mm/rev $\leq$ feedrate $f$ 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 $\leq 1.5 \mu m$.

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, feedrate 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, feedrate 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 $\mu$m.

5.2.2 Example 2

The problem for minimizing production cost can be expressed as: minimizing the total cost per part $C_p$ subject to the same conditions as shown in Example 5.2.1.

In this example, the various cost rates for the multistage turning operations are given as: the cost rate for the part handling $C_h = 0.003$ $$/sec$; the cost rate for the rough machining $C_{mr} = 0.0028$ $$/sec$; the cost rate for the finish machining $C_{mf} = 0.003$ $$/sec$; the cost rate for the tool change $C_c = 0.003$ $$/sec$; 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, feedrate 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, feedrate 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 $\mu$m.

5. 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.

6. REFERENCES


Table 1. Experimental cutting parameters and cutting performance.

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<th>d (mm)</th>
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Fig. 1. Polynomial networks for predicting surface roughness.

Fig. 2. Polynomial networks for predicting cutting force.

Fig. 3. Polynomial networks for predicting tool life.

Fig. 4. Geometrical drawing of a part.