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Parameter estimation of cutting tool temperature nonlinear model using PSO algorithm*

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Abstract: In cutting tool temperature experiment, a large number of related data could be available. In order to define the relationship among the experiment data, the nonlinear regressive curve of cutting tool temperature must be constructed based on the data. This paper proposes the Particle Swarm Optimization (PSO) algorithm for estimating the parameters such a curve. The PSO algorithm is an evolutional method based on a very simple concept. Comparison of PSO results with those of GA and LS methods showed that the PSO algorithm is more effective for estimating the parameters of the above curve.

Key words: Particle Swarm Optimization (PSO), Cutting tool, Parameter estimation, Temperature nonlinear model
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INTRODUCTION

In modern metal cutting theory, research on cutting tool is one of the major concerns. To understand the characteristics of a new cutting tool, many experiments (such as cutting force experiment, cutting temperature experiment, anti-striking experiment, etc.) should be conducted to obtain an enormous amount of experiment data. The development of a proper cutting tool temperature model is a very difficult task due to the large number of interrelated parameters (cutting speed, feed, depth of cut, cutting tool wear, physical and chemical characteristics of machined part, cutting tool coating type, etc.) affecting the cutting tool. Therefore proper methods for extracting the general relationships among cutting tool parameters are required to develop an analytical model of cutting tool.

In fact, system modeling is aimed at minimizing the error between the actual value and the model's output value. Two mostly commonly adopted ones for modeling using experiment data are least square (LS) and maximum likelihood (ML) methods implemented recursively using measured input and output data (Yin *et al.*, 2003; Aso *et al.*, 2002), but are essentially local search techniques that search for the optimum by gradient methods. They often fail in the search for global minimum if the objective function is not differential or linear in model parameters. Therefore effective method for parameter estimation of nonlinear model should be investigated.

Particle Swarm Optimization (PSO) is a population-based computation technique introduced first by Kennedy and Eberthart (1995). The underlying motivation for the development of PSO algorithm was animal social behavior such as flocking, schooling, and swarming. Some of the attractive features of the PSO include the ease of implementation and the fact that no gradient information is required. It was widely used to solve optimization problems (Ray and Liew, 2001; Yu *et al.*, 2003; Eberthart and Shi, 2001; Shi and Eberhart, 1998). In fact, system modeling can be

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converted to an optimization problem (Guo *et al.*, 1998). In this work, the cutting temperature experiment of P05 horny alloy steel tool with 38CrNi3Mo is first investigated. Then PSO algorithm is used to estimate the parameters of temperature nonlinear model of P05 based on the experiment data. The results and conclusions are given at the end.

P05 CUTTING TEMPERATURE EMPIRICAL MODEL

One of the most commonly used cutting temperature empirical models for P05 is given as follows (Zhou *et al.*, 1998):

$$T_{\mathrm{r}} = k a_{\mathrm{p}}^{x} f^{y} v^{z} \tag{1}$$

where T_{r} is the output of temperature model, k is a coefficient depending on the machined material, a_{p} is the depth of cut (mm), f is the cutting feed rate (mm/rev), v is the cutting speed (m/min). x, y, z are coefficients depending on the cutting machining type and cutting tool material.

This work aims at estimating the coefficients k, x, y, z using the PSO algorithm based on experiment related data. The goal of model parameter estimation is to minimize the error between model simulation output temperature T_{r} and actual temperature T. The optimal goal objective function f_{itness} can be written as follows

$$f_{\mathrm{itness}} = \sum_{i=1}^{n} [T(i) - T_{\mathrm{r}}(i)]^2 \tag{2}$$

where $n>0$ is the number of experiment data.

DESCRIPTION OF THE METAL CUTTING SYSTEM

In order to develop the cutting tool temperature model, experiment results were used. The experiment metal cutting system is illustrated in Fig.1, where the cutting tool is P05 horny alloy steel, the metal of workpiece is 38CrNi3Mo. The available experiment related data are listed in Table 1.

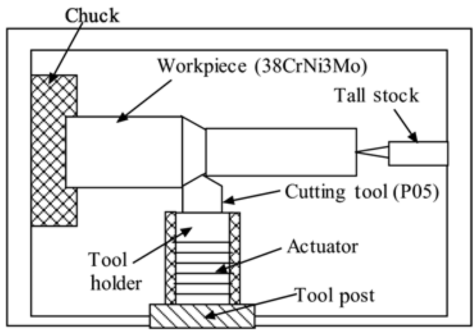

Fig.1 Metal cutting system

Table 1 Experiment data on P05

No.	a_{p} (mm)	f (mm/rev)	v (m/min)	$T(i)$ (°C)
1	1.00	0.1	0.0600	740.24
2	1.41	0.2	0.0600	793.80
3	2.00	0.4	0.0600	854.80
4	1.41	0.1	0.0948	819.42
5	2.00	0.2	0.0948	870.00
6	1.00	0.4	0.0948	904.80
7	2.00	0.1	0.1500	879.60
8	1.00	0.2	0.1500	911.10
9	1.41	0.4	0.1500	974.10

DESCRIPTION OF THE PARTICLE SWARM OPTIMIZATION

Introduction to the particle swarm optimization algorithm

PSO is similar to evolutionary computation techniques in that a population of potential solutions to the optimal problem under consideration is used to probe the search space. Each potential solution is also assigned a randomized velocity, and the potential solutions, called particles, correspond to individuals. Each particle in PSO flies in the D-dimensional problem space with a velocity dynamically adjusted according to the flying experiences of its individuals and their colleagues. The location of the ith particle is represented as $X_i=[x_{i1}, x_{i2}, \ldots, x_{iD}]$, where $x_{id} \in [l_d, u_d]$, $d \in [1, D]$, l_d, u_d are the lower and upper bounds for the dth dimension, respectively. The best previous position (which gives the best fitness value) of the ith particle is recorded and represented as $P_i=[p_{i1}, p_{i2}, \ldots,$

p_{iD}], which is also called P_{best}. The index of the best particle among all the particles in the population is represented by the symbol g. The location P_g is denoted as g_{best}. The velocity of the ith particle is represented as V_i=[v_{i1}, v_{i2}, …, v_{iD}], and is clamped to a maximum velocity $V_{\max}$=[$v_{\max 1}$, $v_{\max 2}$, …, $v_{\max D}$], which is specified by the user. The particle swarm optimization concept consists of, at each time step, regulating the velocity and location of each particle toward its P_{best} and g_{best} locations according to the Eqs.(3a) and (3b), respectively:

$$v_{id}^{n+1} = wv_{id}^{n} + c_1 r_1^{\,n}(p_{id}^{n} - x_{id}^{n}) + c_2 r_2^{\,n}(p_{gd}^{n} - x_{id}^{n}) \quad (3a)$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \quad (3b)$$

where w is inertia weigh; c_1, c_2 are two positive constants, called cognitive and social parameter respectively; d=1, 2, …, D; i=1, 2, …, m, and m is the size of the swarm; r_1, r_2 are random numbers, uniformly distributed in [0,1]; and n=1, 2, …, N, denotes the iteration number, N is the maximum allowable iteration number.

ALGORITHM FOR PARAMETERS ESTIMATION WITH PSO

The process for implementing PSO for model parameter estimation is as follows:

Step 1: Initialize related parameters, including the size of swarm m, the inertia weight w, the acceleration constants c_1 and c_2, the maximum velocity $V_{\max}$, the stop criterion and the initial position and velocity of each particle.

Step 2: Evaluate the desired fitness function values for current each particle.

Step 3: Compare the evaluated fitness value of each particle with its P_{best}. If current value is better than P_{best}, then set the current location as the P_{best} location. Furthermore, if current value is better than g_{best}, then reset g_{best} to the current index in the particle array.

Step 4: Change the velocity and location of the particle according to Eqs.(3a) and (3b), respectively.

Step 5: Loop to Step 2 until a stop criterion is met. The criterion usually is a sufficiently good fitness value or a predefined maximum number of generations $G_{\max}$.

CASE STUDY: PSO ALGORITHM FOR PARAMERS ESTIMATION OF P05 TEMPERATURE NONLINEAR MODEL

Based on the experiment data shown in Table 1, the PSO algorithm is used to estimate the parameters k, x, y, z in Eq.(1). The parameters of PSO algorithm are selected as: w=1.2~0.1, which means that w starts from 1.2 and gradually decreases to 0.1; m=20, c_1=0.5, c_2=0.5. The number of estimated parameters equals 4, therefore D is selected as 4.

The estimated parameters are obtained: k=470.3, x=0.0324, y=0.0828, z=0.159. Therefore the cutting temperature nonlinear model of P05 can be written as:

$$T_{\mathrm{r}} = 470.3 a_{\mathrm{p}}^{\ 0.0324} f^{\,0.0828} v^{0.159} \quad (4)$$

The residual standard deviation defined as in Eq.(5) is an index of modeling performance

$$S = \sqrt{\sum_{i=1}^{n} [T_{\mathrm{r}}(i) - T(i)]^2 / (n-2)} \quad (5)$$

where n is the number of sample data. In the PSO-based estimation algorithm, the residual standard deviation S equals 5.129. The corresponding regressive curve of the temperature nonlinear model is illustrated in Fig.2. The surface of the identified temperature nonlinear model based on the PSO algorithm is illustrated in Fig.3 with the cutting speed v being constant.

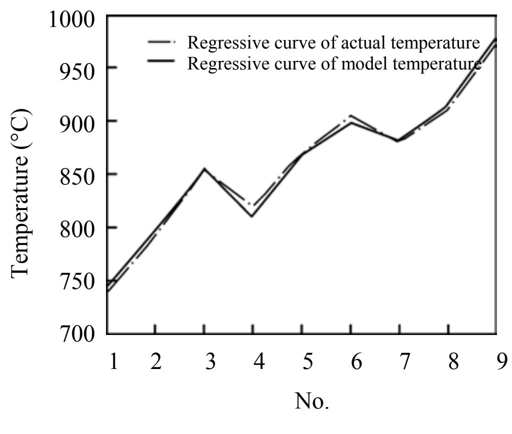

Fig.2 Regressive curve of the temperature nonlinear model

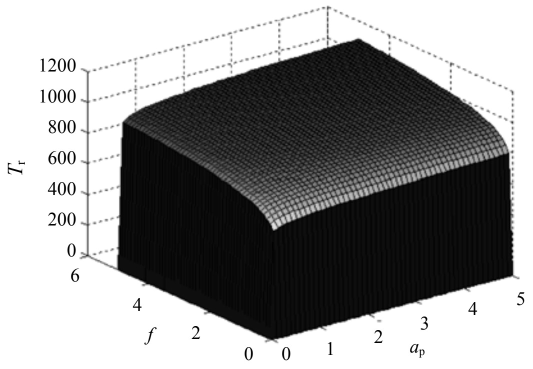

Fig.3 Surface of the identified temperature nonlinear model based on the PSO algorithm (*v*=60 mm)

Use of LS method (Zhou *et al.*, 1998) yielded the model below:

$$T_r = 467 a_p^{0.033} f^{0.083} v^{0.16} \tag{6}$$

where the residual standard deviation S=5.695.

Using GA (Genetic Algorithm) (Zhou *et al.*, 1998), the model is obtained as follows:

$$T_r = 471 a_p^{0.0301} f^{0.083} v^{0.159} \tag{7}$$

where the residual standard deviation S=5.187.

From the above results, it can be seen that PSO algorithm is very simple and improves the precision of the temperature nonlinear model compared with the LS and GA methods. PSO algorithm can rapidly estimate the parameters of the nonlinear model.

SUMMARY

In this paper the PSO algorithm for estimating the parameters of P05 cutting temperature nonlinear model is proposed. The results showed that the PSO algorithm is an effective approach to parameters estimation in nonlinear model. This work showed that PSO is certainly a promising candidate for system modeling.

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