Journal of Achievements in Materials and Manufacturing Engineering
VOLUME 21
ISSUE 2
April
2007

Determination of machining parameters in HSM through TSK-FLC

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Received 12.10.2006; accepted in revised form 15.11.2006

Analysis and modelling

ABSTRACT

Purpose: The optimal setting of machining parameters that may be realized via a suitable model/controller is an important concern to fulfill the overall objectives in machining.
Design/methodology/approach: The present paper proposes an approach for determination of optimal setting of machining parameters in high speed climb milling operation through an TSK-type fuzzy logic controller (TSK-FLC). A novel approach is proposed here which combines the techniques of linear regression (LR) and genetic algorithm (GA) to utilize the advantages of each other, in order to develop an efficient FLC for high-speed milling.
Findings: Modeling of manufacturing process enables generating of manufacturing data and knowledge representation in machining process. Comparisons of results with real experimental data as well as those obtained by other common methods of modeling show the effectiveness of the FLC.
Research limitations/implications: The design approach of fuzzy logic controller uses experimental data for learning. The shape of fuzzy subsets as well as the structure(s) of rule consequent functions are the important concern for optimal knowledgebase (KB) of a FLC. Use of the advantages of both LR and GA makes it possible to achieve optimal KB of FLC.
Practical implications: Use of developed FLC results in improved productivity and efficiency of machining process via the setting of optimal values of cutting parameters and the possiblilty to develop automatic manufacturing system by online determination of machining parameters.
Originality/value: The paper describes a method for desiging a FLC for manufacturing process by a combination of LR and GA, which leads to eliminate a long regression function as required in standard linear regression method.
Keywords: Artificial intelligence methods; TSK-type FLC; High-speed milling; Surface roughness

1. Introduction

In automobile and aerospace industries, there is an immense need of good surface finish and dimensional precision of a machined part, as the key factors that are owing to the advantage of improved functional performance of the component. With the introduction of new technologies such as high speed machining, it is possible to achieve these requirements in an efficient way. However, in high-speed milling (HSM) there are four primary machining parameters (cutting speed, feed per tooth, axial depth of cut, and radial depth of cut) whose optimal values greatly influence to attain a desired surface roughness on the machined surface. In past literatures, it has been found that several methods were adopted by various researches to construct suitable model(s) for milling operation [1-8]. An investigation is made to improve the surface finish of stamping dies in high speed milling by proper selection of cutting tools such as coated carbide tool and PCBN (polycrystalline cubic born nitride) through extensive experimental studies [9].

However, due to complexity as well as non-linear interaction among the machining parameters, it is very difficult to develop an efficient model using conventional approaches. Thus, the techniques to build a model/controller based on example data are growing interest in recent years. However, due to several factors as well as inherent human error, some of the data samples those are observed/measured though experimentation may be contaminated with noisiness and these cannot be recognized or identified before hand. In contrast, each sample in the training data set effects the construction of model. Therefore, the model developed based on the example data where some of them affected with noisiness may not be able to make an accurate prediction. In the past literatures, it has been observed that the models that are developed base on example data, do not consider the intrinsic noisiness associated to the measured data samples. One of the primary objectives of this work is also to incorporate this aspect of noisy data in building a model/controller.

In the present work, an TSK (Takagi-Sugeno-Kang)-type FLC is constructed in order to determine an optimal setting of machining parameters in high-speed climb milling to obtain a desired surface roughness on workpiece. The performance of a FLC depends mainly on its KB, which consists of rule base (RB) and input variables' membership function distributions (MFDs). In this an approach adopted which combines the techniques of LR and GA to utilize the advantages of each other in order to develop an efficient KB of FLC to determine the optimal machining parameters in high-speed climb milling [10].

The effectiveness of the TSK-FLC is verified through experimental data. Later results of the TSK-FLC are compared with conventional modelling method such as standard regression equation based on design of experiment technique to analysis its superior prediction capability.

2. TSK-type FLC

The TSK-type FLC is based on the fuzzy rule-based system [11, 12]. The TSK model has the following form of fuzzy rules:

If x_1 is A^r_1 and x_2 is A^r_2 and…and x_n is A^r_n, then $y = f^r(x_1,\ldots, x_n)$.

where $A^r_{1}, \ldots, A^r_n$ are fuzzy subsets of the input variables $x_1, \ldots, x_n$, respectively of the r^{th} rule. The output function of r^{th} is considered as a polynomial function in the form

$$y = \sum_{j=1}^{K_r} a^r_j f^r_j(x_1,\ldots,x_n) \tag{1}$$

where a^r_j are the function coefficients of the corresponding r^{th} rule consequent and $f^r_j(x_1,\ldots,x_n)$ are the sub-functions characterized by the input variable(s) and the associated exponential parameter(s).

The overall output of the TSK-FLC can be obtained for the input tuple $(x_1, x_2, \ldots, x_n)$ using the following empirical expression.

$$Y = \frac{\sum_{r=1}^{R}\left(\prod_{v=1}^{n}\mu^r_v(x_v)\right)\sum_{j=1}^{K_r} a^r_j f^r_j(x_1,\ldots,x_n)}{\sum_{r=1}^{R}\left(\prod_{v=1}^{n}\mu^r_v(x_1,\ldots,x_n)\right)} \tag{2}$$

where n is the number of input variables that occur in the rule premise, R is the number of rules in the rule base. $\prod_{v=1}^{n}\mu^r_v(x_1,\ldots, x_n)$ is the membership function value for the input variable x_v. $\prod$ is the product representing a conjunction.

3. Design of KB of TSK-FLC using a combined LR & GA approach

The output of an TSK-type fuzzy rule is expressed by a linear combination of the input variables. A typical TSK-type fuzzy rule used to design the RB in order to model the input-output relationship in high speed milling looks as follows:

If cutting speed (v_1) is Low (L) AND feed per tooth (v_2) is Low (L) AND axial depth of cut (v_3) is Low (L) AND radial depth of cut (v_4) is Low (L) THEN surface roughness is

$$y = c_1 v_1^{p_1} + c_2 v_2^{p_2} + c_3 v_3^{p_3} + c_4 v_4^{p_4}, \tag{3}$$

where c_1, c_2, c_3, and c_4 are the function coefficients, and p_1, p_2, p_3 and p_4 are the exponential parameters of the respective input variables.

The input variables of the FLC are assumed to have semi-trapezoidal MFDs as shown in Figure 1. Each input variable is considered to have two fuzzy subsets that are characterized by the linguistics terms Low L and H, hence there could be a total of 2x2x2x2=16 rules in the RB of the FLC. A semi-trapezoidal MFD is defined by two parameters b1 and d1.

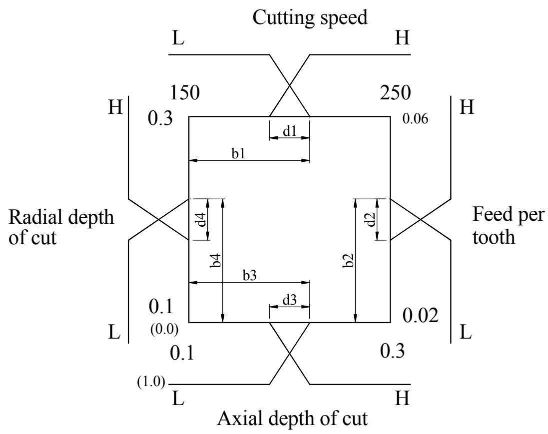

Fig. 1. Membership function distributions of the input variables

The performance of a fuzzy model mainly depends on the RB with the proper values of related function coefficients and the variable's exponential parameters in the rule consequents, and the optimised MFDs of the input variables.

In this work, an approach is utilized which combines LR technique and GA to determine the function coefficients as well as the exponential parameters of input variables of the rule consequents [10]. The GA is used to find values of exponential parameters of input variables and optimize the MFDs simultaneously. On the other hand LR method is combined with

TSK-FLC in order to determine the function coefficients of the selected rule consequents in the framework of GA [13].

A GA works iteratively by successively applying the three GA-operators (population size (Ps), crossover probability (Cp) and mutation probability (Mp)) until the specified termination criterion of certain fitness value is achieved [14]. As, a GA is computationally expensive the GA-based optimisation is carried out off-line. During optimization of MFDs, the variations of parameters (b1, d1) for cutting speed, (b2, d2) for feed per tooth, and (b3, d3) for axial depth of cut and (b4, d4) for radial depth of cut as shown in Figure 1 are taken carefully. The values of the exponential terms of the input variables in the rule-consequents are endorsed to diverge in the range of 0 to 1 during GA-based optimization.

4. Experimentation of HSM

The input-output data samples are measured though an experimentation conducted in a HSM centre with vertical-spindle (Deckel Maho DMU 50 Evolution) [15]. W-Nr. 1.2344 hardened steel of 50-54 HRC was used as the workpiece material. A cutting tool of KOBELCO series MIRACLE: (Al, Ti) N coated micro grain carbide, two flute ball end mill VC2SBR0300 of diameter 6 mm was used for the machining operation. The effective roughness of the machined surface was measured using a Taylor-Hobson Form Taylsurf Series 2 profile rugosimeter. In order to determine the surface roughness value, a total evaluation length of 4.8 mm (6x0.8 mm), a nominally 2 micron stylus tip with a 0.8 Gaussian cut-off filter and a bandwidth ratio of 300:1 were considered. A stylus speed of 0.5 mm/sec was used in conjunction with a 0.8 mN static force with a stylus cone angle of 90˚. The average value of six different successive readings is considered as the effective roughness value. Using the above experimental methodology 81 different input-output data samples as shown in Figure 2 are measured in order to construct the fuzzy model and another 10 data samples to validate the model performance for the climb milling operation.

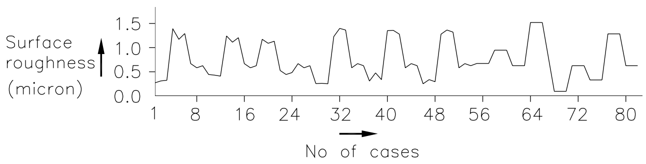

Fig. 2. Experimental training data samples of 81 cases

5. Results and discussion

In order to determine the optimal values of the function coefficients and exponential parameters of rule consequents, 81 experimental data as discussed in Section 4, are used in GA-based optimization. In order to have a better reliability of the FLC, the performance of the FLC is to be uniformed throughout the entire input space. To achieve such kind of consistancy of results from an FLC in every region of the input space, the errors of all training data samples should have an equal importance for minimizing the GA-fitness value. Thus, The fitness value of a GA solution is estimated based on the percentage error of each training data sample. The error is the deviation of the result (surface roughness) of the FLC from that of the desired one. Since the error may be positive or negative, the absolute value of the error is considered in determining the average percentage error as a fitness value of GA solution.

The optimal setting of GA parameters those are obtained through parametric study are Ps=250; Cp= 0.92 and Mp=0.01. The optimised values of the parameters related to MFDs of the input variables as obtained after GA-based optimization process are b1= 20.9971; d1=3.53861; b2=0.01615; d2=0.00541; b3=0.08113; d3=0.04682; b4=0.05303; d4=0.00782.

The regression equation obtained using factorial design method based on the same experimental data used to develop the TSK-fuzzy model, is expressed by the following empirical expression [15].

$$R_{reg\_equn} = 0.683042 - 1.34515\, V_4 - 2.49037\, V_3 + 3.40813\, V_2$$
$$- 0.00250345\, V_1 + 0.00672575\, V_4 V_1 + 14.6044\, V_3^2$$
$$- 17.0406\, V_3 V_2 + 0.0057915\, V_3 V_1 \quad (4)$$

Table 1 shows the comparative results of TSK-FLC and the standard regression equation (as described in Equation (4)) with real experimental data. In Table 1, $R_{experimental}$, R_{TSK_model} and R_{reg_equ} reprent the experimenal value, output obtained by FLC and standard regression equation, respectively. Error I and Error II are the absolute values of deviations of results (in percentage) of the TSK-FLC and standard regression equation from those obtained using experimentation, respectively, to predict surface roughness in high speed climb milling. It has been observed that for almost all cases, the TSK-FLC performs far better than the model developed using standard regression equation. This is obvious, because this model is described by a single regression equation, which is derived by a conventional regression method alone. Therefore, it may not be able to determine the optimal values of function coefficients for a given structure of regression function with fixed values of exponential parameters of input variables. Moreover such this regression equation is complex. On the other hand, a TSK-FLC comprises of several (simpler) regression functions as the consequents of its rules. The function coefficients are obtained by a weighted linear regression method while the input variable's exponential parameters are optimised using GA. Since a GA has a strong search power capability, it is possible to obtain the structures of rule consequent functions with the optimal values of exponential parameters of input variables. Finally, a suitable combination of these rule consequents based on the fuzzy logic concept gives results that show supremacy over others obtained using conventional method in order to predict the output for a given set of input parameters. Thus, the developed TSK-FLC based on the proposed approach of a combination of LR and GA is much more reliable and efficient to determine the optimal values of machining parameters in high-speed (climb milling) milling namely, cutting speed, feed per tooth, axial depth of cut and radial depth of cut to achieve a desired surface roughness.

Table 1.
Comparision of results

No of casess	V1 (m/min)	V2 (mm)	V3 (mm)	V4 (mm)	$R_{experimental}$ (micron)	R_{TSK_model}	Percentage Error-I	R_{reg_equ}	Percentage Error-II
1	150	0.02	0.1	0.1	0.21673	0.21186	2.247	0.29186	34.700
2	150	0.02	0.1	0.3	0.24766	0.24160	2.446	0.22460	9.311
3	150	0.02	0.3	0.1	1.11283	1.12381	0.986	1.06772	4.054
4	150	0.02	0.3	0.3	0.93807	0.91283	2.690	1.00046	6.650
5	150	0.06	0.1	0.1	0.35369	0.34812	1.574	0.36002	1.790
6	150	0.06	0.1	0.3	0.34434	0.33957	1.385	0.29276	14.98
7	150	0.06	0.3	0.1	0.99341	1.00015	0.678	0.99956	0.620
8	150	0.06	0.3	0.3	0.89143	0.88092	1.179	0.93230	4.580
9	250	0.02	0.1	0.1	0.20214	0.20643	2.123	0.16668	17.540
10	250	0.02	0.1	0.3	0.20844	0.21843	4.792	0.23394	12.200
11	250	0.02	0.3	0.1	0.98330	0.93406	5.007	1.05837	7.630
12	250	0.02	0.3	0.3	1.11840	1.11938	0.087	1.12563	0.650
13	250	0.06	0.1	0.1	0.24439	0.24938	2.041	0.23485	3.904
14	250	0.06	0.1	0.3	0.38016	0.40013	5.253	0.30210	20.530
15	250	0.06	0.3	0.1	1.08217	1.06120	1.937	0.99021	8.498
16	250	0.06	0.3	0.3	1.08790	1.10155	1.254	1.05747	2.797

6. Conclusions

In the present work, an TSK-type FLC is designed to determine the machining parameters of high speed climb milling operation to obtain a desired surface roughness on hardened steel. In order to design a suitable FLC, a combined approach of GA and weighted LR is adopted. The performance of the FLC is judged by a comparative study of its results with the experimental data as well as that obtained by regression equation obtained using factorial design. Both the FLC and regression equation are learned with the same experimental data. From this study, it is revealed that the FLC outperforms than conventional regression equation and the designed FLC may be adopted for developning automatic manufacturing system for climb milling operation.

Acknowledgements

Author is grateful to the director of CMERI, India for his support to carry out this research work.

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