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General Strategies in Developing Alloy Steel Fuzzy Model for Machinability Data Selection of Turning Process

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ABSTRAK

Beberapa fuzzy model untuk pemilihan data "machinability" bagi proses turning "alloy steel" telah dicadangkan dalam kertas kerja ini. Pemilihan data "machinability" merupakan suatu tugas yang penting, dan, biasanya ia dilaksanakan oleh para jurumesin yang mahir. Oleh sebab itu, fuzzy model telah dicadangkan untuk meramal data "machinability", iaitu kelajuan memotong dan kadar suapan yang optima. Kesemua fuzzy model yang dicadangkan dalam kertas kerja ini adalah berdasarkan perhubungan di antara dua input (kekerasan bahan kerja dan kedalaman pemotongan) dan dua-output (kelajuan memotong dan kadar suapan). Tiga strategik yang umum bagi pembentukan model fuzzy telah dibentang dan dirunding dalam kertas kerja ini. Objektif bagi implikasi strategik-strategik ini adalah untuk memudahkan proses pembentukan fuzzy model. Data "machinability" (kelajuan memotong dan kedalaman pemotongan) yang diramal oleh fuzzy model telah dibandingkan dengan data yang diperoleh daripada "Machining Data Handbook" (Metcut Research Associate 1980). Kolerasi yang baik telah dikemukakan melalui perbandingan tersebut.

ABSTRACT

In this paper, several fuzzy models have been proposed for machinability data selection of turning process of alloy steel. The selection of the machinability data is a crucial task, and normally done by the skilled machinists. Thus, fuzzy models have been suggested for predicting the optimum machinability data, which are cutting speed and feed rate. These fuzzy models are developed based on the relationship of two-input (material hardness and depth of cut) and two-output (cutting speed and feed rate). A few general strategies in developing fuzzy models are presented and discussed in this paper. Generally, there are three different strategies that are suggested in this paper. The objective of implementing these strategies is to simplify the process of fuzzy model development. The predicted cutting speed and feed rate are compared with the data obtained from the Machining Data Handbook (Metcut Research Associate 1980) and a good correlation has been shown throughout the comparison.

Keywords: Fuzzy model, machinability data selection, general strategies

INTRODUCTION

Performing a good machining practice in turning process requires the proper selection of machinability data such as cutting tools, cutting speed and feed rate. The selection of machinability data is always a crucial task with respect to the complexity of the machining process. Therefore, the task is normally performed by those skilled and experienced machinists who will make the decision based on their experience and intuition (Wong *et al.* 1999). Through experience gained over the years, skilled machinists possess certain empirical rules and guiding principles for choosing the optimum

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machinability data. Machinability data directly influences the machining process, and also the manufacturing cost. Without the presence of skilled machinists, the manufacturer may face difficulty when undergoing the machining process. Hence, there is a necessity for extracting their knowledge into a model, so that a normal machining operator will be able to perform a good machining practice. But the machinability data selection cannot be easily formulated into any mathematical model (Ali *et al.* 2001). Thus, the fuzzy logic concept is introduced as a tool to describe the strategy and action of the skilled machinist when selecting the machinability data (Metcut Research Associate 1980).

The most widely used source of machinability data is the Machining Data Handbook (Metcut Research Associate 1980), and these data are obtained from laboratory and industry experiments. The data in the handbook is grouped according to the types of material, then being separated into different types of processes. The handbook recommends the suitable cutting speed and feed rate according to the hardness of the work-piece material and depth of cut. According to the "Machining Data Handbook" (Metcut Research Associate 1980), it is very difficult to recommend the optimum machining parameters due to the reason of imprecise information of those variables, which will influence the performance of the machining. Therefore, the recommended machinability data from the handbook should be always considered as a good starting point.

Fuzzy systems are suitable for describing very complex systems where it is very difficult to give a mathematical description. The fuzzy models have the ability to represent vague and imprecise information. The computational procedures of fuzzy logic are classified into "soft computing" techniques, which can be directly utilized in intelligent control (Russo and Jain 2001).

Generally, fuzzy systems possess three main components, which are Fuzzification, Inference Mechanism and Defuzzification. Firstly, the input of the fuzzy system is translated into linguistic form. Then, the translated input will undergo the inference mechanism (consists of predefined rules) to produce the output. The generated output (in linguistic form) will be transformed into numerical form. Consequently, the fuzzy systems are suitable for describing the relationship between system input and desired system output.

The beauty of the fuzzy logic has inspired the interest of many researchers to apply it in the machining process. One of the first fuzzy logic models for machining data selection was suggested by El Baradie (1997). The work describes the development stages of a fuzzy logic model for metal cutting. The model was developed based on the relationship of a given material hardness and the recommended cutting speed. The predicted output was verified by using Fuzzy Knowledge Builder. The fuzzy model, which was suggested by El Baradie (1997), is based on single-input-single-output relationship, where depth of cut was considered as a discrete parameter. The work was then further extended by Wong *et al.* (1997) and the new fuzzy models for machinability data selection of turning process of Carbon Steel have been developed. The new models incorporated depth of cut as one of the input parameters. In other words, these models have the relationship of 2-input-1-output. Wong *et al.* (1997) introduced another fuzzy model with the relationship of single-input-single-output for predicting the feed rate and material hardness was the input of the model. The predicted outputs were then compared with the data obtained from the "Machining Data Handbook" (Metcut Research Associate 1980), and a good correlation has been shown.

Similar types of fuzzy models (cutting speed and feed rate) for machinability data selection of turning process of alloy steel have been developed by Tan *et al.* (2002). Both of the models were developed based on the relationship between 2-inputs and 1-output for a given work-piece material and cutting tool. This indicates the capabilities of such similar models in representing machinability data relationship for different work-piece material and cutting tools.

Chen *et al.* (1995) have introduced a fuzzy expert system for the design of machining operations. This fuzzy-based modular system comprised a few modules, which enable the system to select the commercial cutter and optimum cutting conditions. Furthermore, it consists of a learning module that has the capability of self-improvement. An online fuzzy expert system for machinability data selection has been proposed by Wong *et al.* (2003). It was developed by using object-oriented programming, dynamic link library (DLL) and ActiveX Control. Besides that, Wong *et al.* (2000) also worked on the optimization of fuzzy rules for the fuzzy expert system. The optimization process was carried out based on the Genetic Algorithm approach to obtain the optimum fuzzy rules. It replaces the tedious process of trial and error for obtaining the better combination of fuzzy rules (Wong *et al.* 2000).

Arezoo *et al.* (2000) have developed a knowledge-based expert system for the selection of cutting tools and cutting conditions of machining operations. The developed system possesses the features of analyzing and optimizing the cutting conditions (feed speed and depth of cut) selection.

This paper describes the development of two-input and two-output fuzzy models for turning process of alloy steel with different cutting tools. Three general strategies are presented for the development of new fuzzy models based on a reference model. The general strategies may be considered the recommended approach in fuzzy model development. Comparative studies have been carried out to determine the best approach.

MACHINABILITY DATA

Machinability data plays an important role in the efficient utilization of machine tools and significantly influences the overall manufacturing costs. Machinability data consists of the selection of appropriate cutting tools and machining parameters, which include cutting speed, feed rate and depth of cut (Wong *et al.* 1997) . The increase of cutting speed or feed rate results in an increase of temperature on the tool face. At low cutting speed, increases in tool-face temperature tend to reduce friction at the chip-tool interface and hence prevent the formation of built-up edge. At high cutting speed, increase in tool-face temperature tends to increase the rate of crater wear (Boothroyal 1984); therefore, proper selection of the cutting parameters is very important for efficient utilization of the machine tool and thus significantly influences the overall manufacturing cost. On the other hand, the proper selection of cutting parameters is important for performing a good machining practice. In general, the first step in establishing the cutting conditions is to select the depth of cut. The depth of cut will be limited by (Oberg *et al.* 2000):

- The amount of metal being machined from the work piece.
- The power available on the machine tool
- The rigidity of the work piece and cutting tool

The second step is to select the feed rate, and the third step is to select the cutting speed. Even though the recommended cutting speed and feed rate can be obtained from the handbook, experience in machining a certain material may form the best basis for adjusting the given cutting speed to a particular job (Tan *et al.* 2002).

DEVELOPMENT OF FUZZY MODELS

The present fuzzy models are developed based on the relationship of two inputs (work-piece hardness and depth of cut) and two outputs (cutting speed and feed rate). Each model handles different cutting tools and they are:

- High Speed Steel
- Cast Alloy
- Carbide Tool (Brazed)
- Carbide Tool (Throw-Away)

Then, the fuzzy rules of respective models are further divided into two sets, which are represented by R_1 and R_2 to yield cutting speed and feed rate, respectively. The development of the preset fuzzy models is based on the recommended approach, where three suggested strategies are implemented for fuzzy model development. Each strategy is used to develop four fuzzy models for the cutting tools that are mentioned above.

General Strategies for the Development of Fuzzy Models

A fuzzy model comprises 3 main elements, which are the input membership functions (work-piece hardness and depth of cut), the fuzzy rules, and the output membership functions (cutting speed and feed rate). Tedious trial and error work needs to be carried out in order to obtain optimum sets of the membership functions and the fuzzy rules. In order to design similar fuzzy models based on a reference model, the designer can repeat the entire development process. This can be as tedious as developing a fuzzy model for a new system, where input and output membership functions and fuzzy rules have to be redetermined. This strategy is defined as strategy one in Table 1. Wong *et al.* (1999) have suggested a strategy to simplify the process of fuzzy model development, where the fuzzy rules are fixed, and input and output fuzzy membership functions are altered. Besides that, Wong *et al.* (1999) have also suggested fixing the input and output membership functions and alter the fuzzy rules. Throughout the general strategies in Table 1, the input and output membership functions may be fixed or altered based on trial and error or according to a predefined pattern. The fuzzy rules may also be fixed or altered based on intuition. For the first strategy in Table 1, the input and output membership functions were altered based on trial and error and the fuzzy rules were altered based on intuition. The process of trial and error is based on the previous experience of fuzzy model development and the intuition is based on the general rules of thumb. For the second strategy, the input membership functions are fixed, the fuzzy rules are altered based on intuition, and the output membership functions were altered according to the predefined equations. Similarly, for the third strategy, the input membership functions and fuzzy rules are fixed, and the output membership functions are altered according to predefined equations. The major difference among these three strategies is that the input membership functions and the fuzzy rules are either fixed or altered accordingly.

Implementation of the General Strategies

Initially, the fuzzy models were developed with the equal–sided fuzzy sets of input (material hardness and depth of cut) and output (cutting speed and feed rate) membership functions. Then, the first strategy is applied to yield better results, where the input and output membership functions were altered based on trial-and-error, which was according to the experience gained through the development of previous fuzzy models (Tan *et al.* 2002). *Figs. 1* and *2* show the material hardness (first input) and depth

TABLE 1
General strategies for development of fuzzy models

Strategy	Input membership functions	Fuzzy Rules	Output membership functions
1st	Altered based on trial and error	Altered based on intuition	Altered based on trial and error
2nd	Fixed	Altered based on intuition	Altered according to equation
3rd	Fixed	Fixed	Altered according to equation

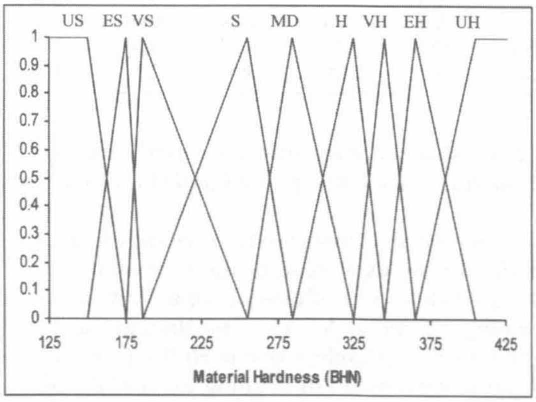

Fig. 1: Material hardness membership functions (cast alloy fuzzy model)

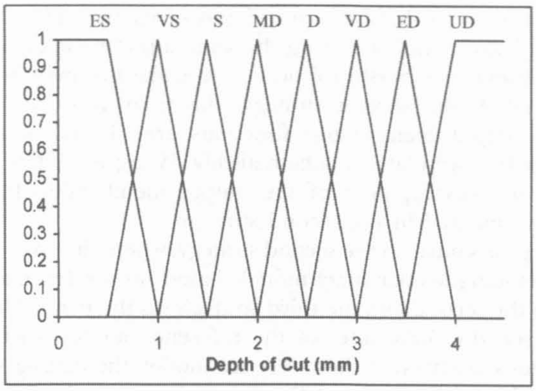

Fig. 2: Depth of cut membership functions (cast alloy fuzzy model)

of cut (second input) membership functions of cast alloy fuzzy models, which were developed based on the first strategy. The terms used in the figures are explained in Table A1 of the appendix. Besides that, in order to yield better results, the fuzzy rules were also altered based on intuition, and the intuition was based on the general rules of thumb, which are:

- Harder material hardness, slower cutting speed and slower feed rate
- Softer material hardness, faster cutting speed and faster feed rate

TABLE 2
Cutting speed fuzzy rules of cast alloy fuzzy model

Material Hardness	Depth of cut							
	ES	VS	S	MD	D	VD	ED	UD
US	UF	UF	EF	EF	VVF	VVF	VF	VF
ES	UF	EF	EF	VVF	VF	VF	F	F
VS	VVF	F	F	QF	SF	SF	F	MD
S	VF	F	QF	QF	F	F	SS	SS
MD	F	SS	SS	QS	QS	SF	VS	VS
H	MD	QS	S	S	VS	VS	VS	VVS
VH	S	VS	VS	VVS	VVS	VVS	VVS	ES
EH	VVS	VVS	VVS	ES	ES	US	US	US
UH	ES	ES	ES	ES	US	US	US	US

- Deeper depth of cut, slower cutting speed and faster feed rate
- Shallower depth of cut, faster cutting speed and slower feed rate

The fuzzy rules of the cast alloy fuzzy model were shown in Table 3 (refer to Tables A1 and A2 in appendix for the expression of the fuzzy rules).

The first strategy is a tedious way of developing a fuzzy model. In order to simplify the process of developing a fuzzy model, a second strategy was considered. The second strategy illustrates the process in developing related fuzzy models based on a reference fuzzy model. This is particularly useful in defining the new membership functions. Cast alloy fuzzy model is chosen as the reference fuzzy model through the arbitrary way. Then, the other fuzzy models, which are high speed steel and carbide tool (brazed and throw-away), were developed based on the reference model by adopting the second strategy. The input (material hardness and depth of cut) membership functions were fixed and all of the fuzzy models are using the same input membership functions of the reference model. These membership functions are like the membership functions of reference models. With the second strategy, the fuzzy rules are altered based on intuition and the output membership functions are altered according to specific patterns which may be formulated mathematically. Wong *et al.* (1999) have suggested two equations for the development of the output membership function, and these equations were implemented in the second strategy.

The third strategy is similar to the second strategy, where, it serves as a recommended procedure for developing similar fuzzy models based on a reference model. The only difference between the second and the third strategies is the fuzzy rules are fixed for the third strategy. It used the fuzzy rules of the reference model (cast alloy). The input membership functions are fixed as the reference model; the cutting speed membership functions are altered according to predefined equations, and the feed rate membership functions remained as the membership functions in the second strategy.

Fuzzy Membership Functions

Designing the membership function is a crucial task where the designer has to define the appropriate fuzzy sets. For the second and third strategies, both of the input (material hardness and depth of cut) membership functions are fixed. This is because, according to "Machining Data Handbook" (Metcut Research Associate 1980), all the recommended cutting speed and feed rate are under the same range of material hardness and depth of cut; therefore, it is not necessary to change them. On the other hand, the output membership functions (cutting speed and feed rate) were altered according to the predefined equations, and they will change according to a specific pattern. The development of the output membership functions is based on two equations designed by Wong *et al.* (1999). The first equation is:

$$M_{\text{new}} = M_{\text{new, min}} + \left(\frac{M_{\text{std}} - M_{\text{std, min}}}{M_{\text{std, max}} - M_{\text{std, max}}} \right)^{n} \times \left(M_{\text{new, min}} - M_{\text{new, min}} \right) \tag{1}$$

where, M_{new} is the new value of output membership function, and it is yielded from the reference fuzzy model, which is the Cast Alloy fuzzy model. The $M_{new,max}$, $M_{new,min}$, $M_{std,max}$, and $M_{std,min}$, are the maximum and minimum values of the new and standard membership functions, respectively. The pattern of the yielded membership function is determined by the exponential value, n. For the case $n = 1$, a linear proportional relationship is defined. But this relationship may not be suitable for other membership functions. Therefore, in order to obtain a better correlation, the value of n is obtained from the second equation, which is:

$$n = \begin{cases} x - \left(\dfrac{M_{\text{std}} - M_{\text{std, min}}}{\left(M_{\text{std, max}} - M_{\text{std, min}} \right) \times R} \right)^{P_1} \times (x - y), \\ \_M_{\text{std}} \leq M_{\text{std, min}} + \left(M_{\text{std, max}} - M_{\text{std, min}} \right) \times R \\ 1 - \dfrac{M_{\text{std, min}} + \left(M_{\text{std, max}} - M_{\text{std, min}} \right) - M_{\text{std}}}{\left(M_{\text{std, max}} - M_{\text{std, min}} \right) \times (1 - R)^{P_2} \times (1 - y)}, \\ \_M_{\text{std}} > M_{\text{std, min}} + \left(M_{\text{std, max}} - M_{\text{std, min}} \right) \times R \end{cases} \tag{2}$$

The value of n will be equal to x at the minimum M_{std} value and gradually decrease to y when M_{std} is at the required ratio of the range, R. The changing pattern of n is dependent on the constant value of P_1. Proportionally, for the maximum value of M_{std}, the n value will gradually increase to unity, and its pattern will change according to the constant value of P_2.

The value of n is the most influential factor for the development of the new membership functions. In this paper (referred to the second and third strategies in Table 1), the value of parameters in Equations 1 and 2 are showed in Table 3, and they are only applied on the development of cutting speed membership functions. For feed rate membership functions, the value of $n = 1$. This is because, according to "Machining Data Handbook" (Metcut Research Associate 1980), the increase of material hardness does not have much effect on the feed rate, hence it can be defined in relationship of linear proportional. The parameters in Table 3 are fixed for all of the fuzzy models, which developed under the respective strategy. The determinations of the value of these parameters were based on trial and error.

The cutting speed and feed rate membership functions of high speed steel fuzzy models, developed by the second strategy are illustrated in *Figs. 3* and *4*, respectively (the expressions of these figures are shown in Table A2 in appendix).

TABLE 3
The parameters of Equations 1 and 2

Strategy	n	x	y	P_1	P_2	R
2nd	variable	0.8	1.25	5	0.7	0.45
3rd	variable	0.9	0.8	4.5	0.7	0.45

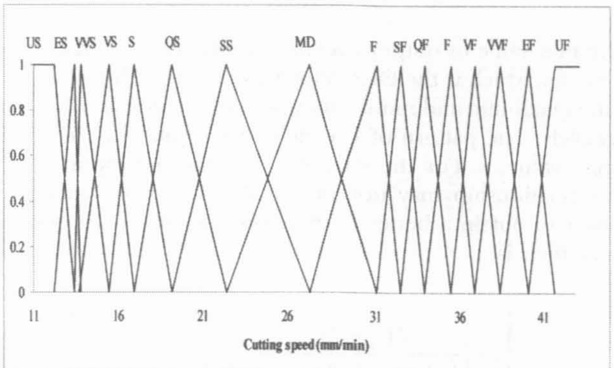

Fig. 3: Cutting speed membership functions (high speed steel fuzzy model)

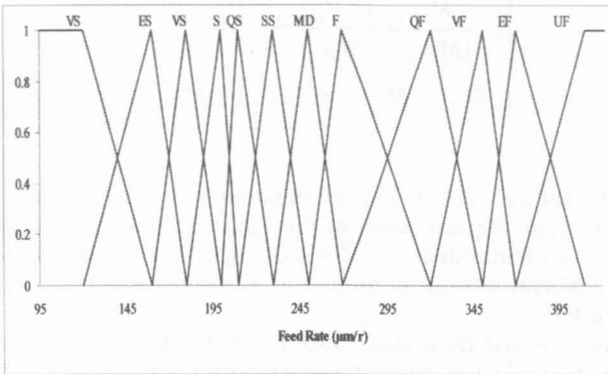

Fig. 4: Feed rate membership functions (high speed steel fuzzy model)

Fuzzy Rules

Developing the best fuzzy rules is always a difficult task for most of the fuzzy designers. This is because there are too many possible sets of rules for each model. This situation would be more complicated when the inputs and/or outputs were increased. In this paper, the fuzzy rules were constructed for each of the fuzzy models based on the authors' intuition and general rules of thumb. Then fine-tuning, which is based on intuition, has been conducted for better results. Therefore, all the fuzzy models consist of their own fine-tuned fuzzy rules for the first and second of the strategies. The fuzzy rules of the third strategy are based on the reference model, which are cast alloy fuzzy models. The developments of the fuzzy rules are based on some suggested rules of thumb. The following statements are the main suggested rules of thumb:

- Harder work-piece material without varying depth of cut requires slower cutting speed and slower feed rate
- Softer work-piece material without varying depth of cut requires faster cutting speed and faster feed rate
- Deeper depth of cut without varying hardness requires slower cutting speed and faster feed rate
- Shallower depth of cut without varying hardness requires faster cutting speed and slower feed rate
- Harder work-piece material and deeper depth of cut require slower cutting and faster feed rate
- Harder work-piece material and shallower depth of cut require slower cutting speed and slower feed rate
- Softer work-piece material and deeper depth of cut requires faster cutting speed and faster feed rate
- Softer work-piece material and shallower depth of cut requires faster cutting speed and slower feed rate

RESULTS AND DISCUSSION

The predicted outputs (cutting speed and feed rate) for all of the strategies are compared with the standard data from "Machining Data Handbook" (Metcut Research Associate 1980). The mean absolute percentage errors of predicted cutting speed and feed rate for respective fuzzy models developed by the first, second and third strategies are shown in Tables 4, 5 and 6.

TABLE 4
Results summary of fuzzy model (referred to first strategy)

Cutting tool type (1st strategy)	Mean Absolute Percentage Error, %	
	Cutting Speed	Feed Rate
High Speed Steel	3.70	2.11
Cast Alloy	3.13	2.82
Carbide Tool (Brazed)	3.20	3.21
Carbide Tool (Throw-Away)	3.16	3.21
Average	3.30	2.84

TABLE 5
Results summary of fuzzy model (referred to second strategy)

Cutting tool type (2nd strategy)	Mean Absolute Percentage Error, %	
	Cutting Speed	Feed Rate
High Speed Steel	4.45	2.48
Cast Alloy	3.13	2.82
Carbide Tool (Brazed)	3.38	4.00
Carbide Tool (Throw-Away)	3.19	4.00
Average	3.54	3.33

TABLE 6
Results summary of fuzzy model (referred to third strategy)

Cutting tool type (3rd strategy)	Mean Absolute Percentage Error, %	
	Cutting Speed	Feed Rate
High Speed Steel	5.64	2.48
Cast Alloy	3.13	2.82
Carbide Tool (Brazed)	4.93	4.00
Carbide Tool (Throw-Away)	4.76	4.00
Average	4.62	3.33

The maximum value of the mean absolute percentage errors of cutting speed and feed rate are 3.7% and 3.21%, respectively, and the average of the mean absolute percentage errors are 3.30% and 2.84%, respectively (Table 4). The average of the mean absolute percentage error of cutting speed and feed rate are 3.54% and 4.62%, respectively (Tables 5 and 6). These results show that the fuzzy model developed by using the first strategy will gain the best results. But this strategy is the most tedious way of fuzzy model development; where much trial and error work needs to be done. Hence, the second strategy was introduced by fixing one of the input membership functions. This is to reduce the trial and error work from the first strategy. Based on the results in Table 5 (refer to the second strategy), the average percentage error is slightly higher compared to the results in Table 4 (refer to the first strategy). In spite of this, the second strategy is still preferred strategy compared to the first strategy due to the systematic way of designing the membership functions. The membership functions are derived automatically based on a reference model in a pre-defined pattern through implementation of Equations 1 and 2. Equations 1 and 2 have incorporated linear and non-linear pattern change. By using Equations 1 and 2, the designer only requires to alter the maximum and minimum value of the membership function in Equation 1 and also the parameters for value n in Equation 2 instead of the tedious trial and error way. When compared to the second and the third strategies, the third strategy is better than the second strategy due to the elimination of the process of altering the fuzzy rules; hence less effort and time are required for developing a related fuzzy model. The development of the output membership functions (cutting speed) of the third strategy are similar to the second strategy, which is by applying Equations 1 and 2. As the number of the fixed elements (refer to input and output membership functions or fuzzy rules) is increased, the effort required for fuzzy model development was reduced.

Fig. 5 illustrates the difference between predicted cutting speeds of the high speed steel fuzzy model (by first, second and third strategy, respectively) and the data from the "Machining Data Handbook" (Metcut Research Associate 1980) with 1 mm depth of cut. Other fuzzy models also have the similar pattern of deviation for the same depth of cut by both of the strategies.

CONCLUSION

Throughout the comparisons, a good correlation has been shown between the fuzzy models (developed both strategies) and the "Machining Data Handbook" (Metcut Research Associate 1980). Since there is not much difference among the average mean percentage error of fuzzy models that developed with the first, second and third

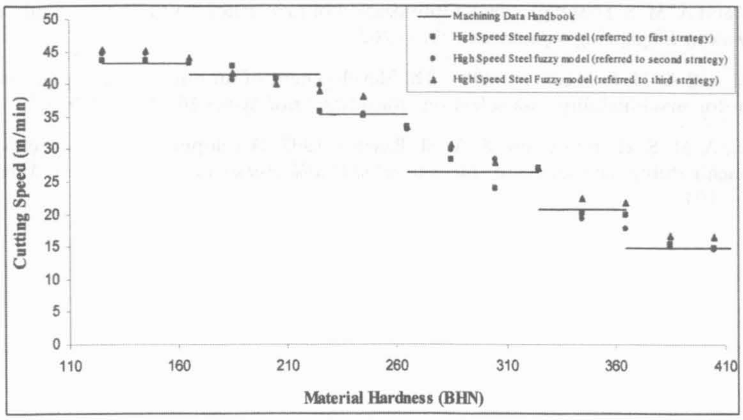

Fig. 5: Graph cutting speed Vs material hardness of high speed steel fuzzy model for 1mm depth of cut

strategies, it is advisable to develop the fuzzy model by using the third strategy rather than the first and second strategies. This is because it is easier for the designer to construct the output membership function based on Equations 1 and 2, and also the fixture of the fuzzy rules. Anyhow, the ideal case will be the generalization strategy, where the input and output membership functions, and also the fuzzy rules are fixed. The generalization comes with the hope to develop one fuzzy model for handling all different cutting tools. Generalization becomes a difficult task when the number of machining parameters increases. Furthermore, most of the machining parameters are interrelated.

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APPENDIX

TABLE A1
Expression for the input membership functions

Input 1 (Work-piece Hardness)		Input 2 (Depth of cut)	
Abbreviation	Expression	Abbreviation	Expression
US	Ultimately Soft	ES	Extremely Shallow
ES	Extremely Soft	VS	Very Shallow
VS	Very Soft	S	Shallow
S	Soft	MD	Medium
MD	Medium	D	Deep
H	Hard	VD	Very Deep
VH	Very Hard	ED	Extremely Deep
EH	Extremely Hard	UD	Ultimately Deep
UH	Ultimately Hard		

TABLE A2
Expression for the output membership functions

Output 1 (Cutting Speed)		Output 2 (Feed Rate)	
Abbreviation	Expression	Abbreviation	Expression
US	Ultimately Slow	US	Ultimately Slow
ES	Extremely Slow	ES	Extremely Slow
VVS	Very Very Slow	VS	Very slow
VS	Very Slow	S	Slow
S	Slow	QS	Quite Slow
QS	Quite Slow	SS	Slightly slow
SS	Slightly Slow	MD	Medium
MD	Medium	F	Fast
F	Fast	QF	Quite Fast
SF	Slightly Fast	VF	Very Fast
QF	Quite Fast	EF	Extremely Fast
F	Fast	UF	Ultimately Fast
VF	Very Fast		
VVF	Very Very Fast		
EF	Extremely Fast		
UF	Ultimately Fast		