ISSN: 0128-7680
Pertanika J. Sci. & Technol. Supplement **9(2)**: 209-218 (2001)

Fuzzy Rules Optimization in Fuzzy Expert System for Machinability Data Selection: Genetic Algorithms Approach

S.V. Wong & A.M.S Hamouda
Department of Mechanical & Manufacturing Engineering
Faculty of Engineering, Universiti Putra Malaysia
43400 Serdang, Malaysia

ABSTRACT

Machinability data selection is complex and cannot be easily formulated by any mathematical model to meet design specification. Fuzzy logic is a good approach to solve such problems. Fuzzy rules optimization is always a problems for a complex fuzzy rules from more than 10 thousand combinations. (Wong *et al.* 1997) developed fuzzy models for machinability data selection. There are more than 2 x 10^{29} possible sets of rules for each model. Situation would be more complicated if futher increase the number of inputs and/or outputs. The fuzzy rules were selected by trial and error and intuition in reference (Wong *et al.* 1997). Genetic optimization is suggested in this paper to futher optimizing the fuzzy rules optimization with genetic algorithms has been developed. Weighted centroid method is used for output defuzzification to save processing time. Comparisons between the results of the new models and the previously published literatures are made.

Keywords: Fuzzy rules optimization, genetic algorithm, fuzzy expert system, machinability data

INTRODUCTION

Machinability is a loosely defined term; it is expressed as the time of tool life, power required for cutting, cost of removing a deformed amount of material, or surface condition obtained. (Ostwald and Munoz 1997) stated that Machinability is not a precise term, but a word that implies several concepts. 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 the appropriate cutting tools and machining parameters, which includes cutting speed, feed rate and depth of cut. It is usually a crucial step in machining process. Machinability data constitutes a critical link between computer-aided design (CAD) and computer-aided manufacturing (CAM). Normally a skill-machining operator will decided the cutting tool type, cutting speed and feed rate based on his intuition and experience. The operator will start machining a part with intial cutting speed and feed rate which they think are most likely to be the optimum values. There is never any precise mathematical model for the data selection (Oberg *et al.* 1988). The most widely used source of machinability data is the Machining Data Handbook published by (Metcut Research Associates 1980).

A throughout review of the information obtained from the literatures and from industry has indicated that the recommended speeds and feeds for any machining operation may vary considerably. The optimum performance or efficiency of any machining operation included factors in addition to the proper selection of speeds and feeds. Variables such as part configuration, condition of the machine, type of fixture, dimensiol tolerance and surface roughness all affect performance. Because the effects of these variables on tool life are not always precisely known, it become difficult to recommend optimum conditions for a machining operation. Therefore the recommendations for speeds, feeds and other parameters presented in the handbook are nominal recommendations and should be considered only as good starting points (Metcut Research Associates 1980).

Efforts have been done to predict and optimize the machining operations as in references (Sing and Raman 1992; Fang and Jawahir 1994; Liu *et al.* 1995; Rangwala and Dornfeld 1989). Very recently, (Wong et al. 1997) has developed a fuzzy based expert system for machining data selection. They describe the development stages of a fuzzy logic model for metal cutting. The system is based on the relationship that exists for any specific material between its hardness (input 1), depth of cut (input 2) and the corresponding recommended cutting speed (output). The model has been has been applied to data extracted from the Machining Data Handbook (Metcut Research Associates 1980), and good correlation was obtained between the handbook and that predicted using fuzzy logic model.

The fuzzy rules used in (Wong et al 1997) were chosen based on trial and error with the help from intuition.

Fuzzy rules design is never an easy task especially subjected to complex real world problems. Fuzzy it-then rules were derived from human experts in most fuzzy based system. Each fuzzy model described in reference (Wong *et al.* 1997) will have more than 2×10^{29} possible sets of fuzzy rules. A simple two-inputs-one-outputs possible combinations. Although applying common sense and expert knowledge would normally narrow down the scope, but the selected fuzzy rules are normally not the best fit.

Recently, several approaches were suggested for generating the fuzzy rules from numerical data automatically. (Wang and Mendel 1992) have described a general method to generate fuzzy rules from numerical data. (Jang 1992) and (Berenji and Khedkar 1992) have proposed self-learning method for adjusting membership functions of fuzzy sets in fuzzy it-then rules. To the authors' knowledge, automatically generating fuzzy rules will lose one of the most important features in fuzzy logic. The beauty of fuzzy logic is describing the system in linguistics term. This enables the design of such system with more human-like reasoning, especially with the fuzzy it-then rules. (Karr 1991) adjusted fuzzy membership functions, and (Normura *et al.* 1992) determined fuzzy partition of input spaces by genetic algorithms. (Ishibuchi *et al.* 1995) described the selection of fuzzy rules for classification problems using GA.

In this paper, the authors use the genetic algorithm approach in fuzzy rules design. The genetic algorithm approach in fuzzy rules design. The genetic optimization replaces the tedious process of trial and error for better combination of fuzzy rules. The development stages of the optimization object-oriented library are described. The results of the optimized fuzzy rules are shown and discussed. Comparisons are made between the new rules with results from references (Wong *et al.* 1997) and (Wong and Hamouda 1998).

MACHINING VARIABLES

(Vaughn 1958) studied a series of variables involved in traditional machining. According to Vaughn, the rate at which metal can be machined is affected by size and type of machine, power available, cutting toll used, material to be cut, speed, feed and rate of cut. The major independent variable, those can be changed directly, in the cutting process are (Kalpakjian 1980):-

- Tool Material, coating and condition
- Tool Shape, surface finish, and sharpness
- Cutting parameters, such as speed, feed and depth of cut
- Use of cutting fluid
- The characteristics of the machine tool, such as its stiffness and damping
- Workholding, fixturing, etc

Effect of Speed, Feed and Depth of Cut

The cutting conditions that determine the rate of metal removal are the cutting speed, the feed rate, and the depth of cut. These cutting conditions and the nature of the material to be cut determine the power required. The cutting conditions must be adjusted to stay within the power available on the machine tool to be used.

The cutting conditions must also be considered in relation to the tool life. Tool life can be defined as the length of time that a cutting tool will cut before it must be replaced. It should be understood that the cutting conditions and tool life are related (Oberg *et al.* 1988).

In 1907, F.W. Taylor conducted a classic study on machining steels, an approximate relationship was established. The relationship is shown in Equation (1).

$$VT^n = C \tag{1}$$

Where

T is the cutting time (min) that it takes to develop a flank wear land of certain dimension.

V is cutting speed (m min^{-1})

n is an exponent that depends on cutting conditions

C is a constant parameter, sometimes called the Tylor constant, which can represent the cutting speed for 1 min tool life.

For the each combination of workpiece and tool materials and each cutting condition has it own n dan C. Both are determined through experiments.

Cutting speed is the most significant process variable in tool life, however, depth of cut and feed rate are also important. Similar trends occur for the feed and depth of cut and so the tool life may be expressed as:-

$$T = \frac{K}{V^{1/n} f^{1/n_1} d^{1/n_2}} \tag{2}$$

Where

T is the tool life (min)

V is the cutting speed (m min^{-1})

f is the feed (mm rev^{-1})

d is the depth of cut (mm)

K is a constant for a given tool work combination and tool work combination and tool geometry

$1/n$ is exponent of the speed

$1/n_1$ is exponent of the feed

$1/n_1$ is exponent of the depth of cut

Equation (2) is the simplified extension of the Taylor equation. Equation (2) has been suggested by a number of researchers (Fang and Jawahir 1994). The values of the exponents $1/n$, $1/n$l and $1/n_2$ as well as K will depend on the failure criteria.

The theory in this section has shown the importance of selecting proper speed, feed and depth of cut. With increasing the parameters, tool life is reduced. On the other hand, if speed, feed and depth of cut are low, tool life is long but the material removal rate is low.

While it is difficult to predict accurately the best machining operation, data from the handbook usually represents a good starting point from which to proceed to optimum by progress change. The machining data handbook (Metcut Research Associates 1980) is a very comprehensive source of such data. The work piece material used in the present study are wrought carbon steels (low carbon 1005-1025).

Fuzzy Models

Wong *et al.* suggested four separate fuzzy rules for four different types of tool in reference (Wong *et al.* 1997). They are high-speed steel tool and coated carbide tool. Wrought carbon steel is chosen as the work-piece material. Hardness of workpiece material and depth of cut are the inputs and cutting speed is the output of the fuzzy models. Table 1 and Table 2 show the inputs fuzzy expression and output fuzzy expression respectively.

TABLE 1
Inputs fuzzy expressions and notations

1st Input (Material Hardness)		2nd Input (Depth of Cut)	
Abbreviation	Expression	Abbreviation	Expression
VS	Very Soft	VS	Very Shallow
S	Soft	S	Shallow
MD	Medium	MD	Medium
H	Hard	D	Deep
VH	Very Hard	VD	Very Deep

TABLE 2
Output fuzzy expressions and notations

Abbreviation	Expression
EVS	Extremely Very Slow
ES	Extremely Slow
VVS	Very Very Slow
VS	Very Slow
S	Slow
QS	Quite Slow
AS	A bit Slow
MD	Medium
AF	A bit Fast
QF	Quite Fast
F	Fast
VF	Very Fast
VVF	Very Very Fast
EF	Extremely Fast
EVF	Extremely Very Fast

Table 3 show the range of the fuzzy input membership functions and the output membership functions. All membership functions (both inputs and output for all models) are in isosceles triangle shape and well distributed. Four fuzzy models with different fuzzy rules among themselves are developed through intuition with trial and errors. Fundamental knowledge of the relationship, which if harder the material and deeper the depth of cut then slower the cutting speed, is applied.

Fuzzy Set Handing

A simplified fuzzy set handling class (FSH class) has been developed and incorporated into the optimization process described in this paper. The FSH class is developed using C++ programming language. The members of the FSH store the property of a fuzzy shape and it's properties. The simplified FSH class can only handle triangle and truncated triangle fuzzy shapes. Some common operations like truncation and truly degree calculation are included.

All the fuzzy calculation described in this paper is based on Max-Min Inference Method. In order to save, Defuzzification method has been used. Max-Min Inferene Method and Union Centroid Output Defuzzification were applied in (Wong *et al.* 1997). The use of Weighted Centroid Output Defuzzification has proven to be insignificant in the output results but it has significantly saved the processing time (Wong and Hamouda 1998).

Genetic Optimizatin Algorithm

Major operations of GA depend on random choice. A random number generator class is developed. It consists of 3 main functions. They are to generate a random real number from 0 to 1, to generate a random number from a user given start to a user given end integer value, and to give green or red light for a user given probability.

Genetic Optimization of fuzzy rules have been carried out with the help of an object-oriented genetic optimization library (GOL), developed by the authors. It consists of several useful and inter-connected classes. To evaluate the fuzzy result, FSH class has to be included.

The GOL uses bit-wise interpretation, which means, the length of a particular allele is expressed in term of bit. If an allele carries a possible value from 0 to 7 (or 8 possible features), the length of the allele is 3. The fuzzy models consist of 5 fuzzy sets for all inputs and 15 fuzzy possibilities each. Thus, the total number of possible fuzzy rules combination will be $15^{25} = 2.525 \times 10^{29}$. For initialization, 25 alleles are required and the length of each allele will be 4 bits to cope with 15 possible values. Index representations in Table 2 and Table 3 are used. The population consists of 80 sets of fuzzy rules. The crossover probability and the mutation probability are set as 0.6 and 0.009 respectively. The initial individuals of the population are required. The fuzzy rules from reference (Wong *et al.*, 1997) are assigned as one of the initial individuals. The rest of the rules are generated automatically and randomly. Basically, in a population, it consists of certain fixed- number of individual has it's own chromosome, which consists of certain fixed-number of alleles. The genetic optimization processes are repeated for 10000 generations.

Fitness Calculation

Calculation of an individual's fitness involves extracting data from the individual's chromosome, translating the value of all alleles and assigning the represented fuzzy rules into the FSH class. Then fuzzy operations are performed with the predetermined inputs (work piece material and depth of cut) to yield the output (cutting speed). Calculation of absolute error percentage compare to the result from Machining Data Handbook (Metcut Research Associates 1980) is carried out. The number of predetermined sets of inputs is 80. The operations above iterate until finished assessing all the predetermined sets of inputs. The mean of all individual absolute error percentage is calculated. The mean of absolute error percentage is a suitable fitness representation of the particular individual (chromosome) in the population. Orientation of fitness consideration in the developed GOL is higher value of the fitness the better. To cope with this scenario, the fitness is obtained through equation (3).

$$Fitness = K - \frac{\sum_{i=0}^{n} (abs\_error\%)_i}{n+1} - \sum \text{error\_factor} \tag{3}$$

The value of i in equation 3 is the numbering of the predetermined inputs starts from 0. Thus, value n is the predetermined inputs , which equals to 79 in this case. Error factor is for rules violation penalty. Refer to section "Pattern Violation Penalties" for description of rules violation. The value K is an arbitary selected positive value. It must be foreseen to be more than the achievable maximum summation of the absolute error percentage mean and the error factors. K is defined as 1000 for purpose of this study. Generally, lower mean absolute error.

TABLE 4
Results summary

	Mean Absolute Error Percentage			
	40 Checking Points		80 Checking Points	
Tool Material	Union Centroid (Wong, *et al.*, 1997)	Weighted Centroid (Wong and Hamouda, 1998)	Weighted Centroid	Weighted Centroid with Genetic Optimization
High-Speed Steel	4.208	4.068	5.812	4.946
Uncoated Brazed Carbide	3.330	3.138	4.194	3.866
Uncoated Indexable Carbide	3.836	3.790	5.759	4.511
Coated Carbide	2.950	2.971	3.081	2.946

percentage, higher fitness value and nearer to K. For the final consideration of the fitness in the competition of reproduction selection, equation (4) is employed.

$$F\ Fitness_i = Fitness_i - \min(Fitness_0 \ldots Fitness_n) \tag{4}$$

$F\ Fitness_i$ is the final fitness value for a particular individual $_i$ of the population. $Fitness_i$ is the value calculated from the Equation 3 for individual i. min $(Fitness_0 \ldots Fitness_n)$ is a function which will yield the minimum value from $Fitness_0$ to $Fitness_n$. The value n is the size of the population.

Pattern Violation Penalties

The Genetic Optimization Class allows control of fuzzy rules pattern, means, the designer can provide his/her expert knowledge in specifying the relationship between the inputs and the outputs. For the purpose of his study, the authors have included four general constraints for the fuzzy rules, which are:-

- harder the workpiece material, faster cutting speed
- softer the workpiece material, slower cutting speed
- shallower the depth of cut, faster cutting speed
- deeper the depth of cut, slower cutting speed

Each violation will cause a penalty value of 25 in the summation of error factor in Equation (3). Thus, more number of violations will cause lower fitness. Pattern validation is carried out during the assignment of fuzzy rules in to the FHS class from the value of alleles.

RESULT AND DISCUSSION

The genetic optimization algorithm is being used to find better fuzzy rules. In this study 40 different checking points (sets of inputs as mentioned) are used for comparison to the result from the Machining Data Handbook (Metcut Research Associates 1980). Thus, the mean absolute error percentage for different tool types is obtained through validation of 40 checking points. For every single checking point, a particular value of material hardness and value of depth of cut were provided as the inputs. Calculations were carried out to yeild the output. The output value is then compared. Union centroid defuzzification and weighted centroid defuzzification are used in references (Wong et al. 1997; Wong and Hamouda 1998), respectively. The mean absolute error percentages are 4.2%, 3.3%, 3.8% and 3.0% for high-speed steel tool, uncoated barzed carbide tool, uncoated indexable carbide tool and coated carbide tool respectively with union centroid defuzzification. Meanwhile, 4.1%, 3.1%, 3.8% and 3.0% with weighted centroid defuzzification. In order to yield better result, the density of the checking points is increased from 40 to 80. Machining Data Handbook (Metcut Research Associates 1980) only provides recommended cutting speed for 1mm, 4mm, 8mm and 16mm depth of cut. The additional testing points are obtained with linear interpolation by assuming linear relationship between cutting speed and depth of cut at the particular region. As usual, summation of absolute error will increase when the system is subjected to more checking points for validation. Table 4 show the changes of mean absolute error percentage from the union centroid defuzzification with 80 sets of testing point.

TABLE 5
Optimized fuzzy rules for high-speed steel fuzzy model (with abbreviation indication)

Material Hardness	Depth Of Cut				
	VS	S	MD	D	VD
VS	VVF	MD	AS	QS	VS
S	QF	AS	S	S	VVS
MD	QF	QS	S	S	VVS
H	QF	S	VS	VVS	EVS
VH	QS	VVS	VVS	EVS	EVS

TABLE 6
Optimized fuzzy rules for uncoated brazed carbide fuzzy model (with abbreviation indication)

Material Hardness	Depth Of Cut				
	VS	S	MD	D	VD
VS	EVF	MD	QS	S	VVS
S	VVF	MD	S	VS	VVS
MD	QF	AS	S	VS	VVS
H	QF	S	VS	ES	EVS
VH	AF	VS	VS	ES	EVS

TABLE 7
Optimized fuzzy rules for uncoated indexable carbide fuzzy model (with abbreviation indication)

Material Hardness	Depth Of Cut				
	VS	S	MD	D	VD
VS	EVF	MD	QS	S	VS
S	F	QS	QS	VS	VVS
MD	F	S	S	VVS	VVS
H	QF	S	VS	VVS	EVS
VH	MD	VS	VVS	ES	EVS

TABLE 8
Optimized fuzzy rules for uncoated carbide fuzzy model (with abbreviation indication)

Material Hardness	Depth Of Cut				
	VS	S	MD	D	VD
VS	EVF	MD	AS	QS	VS
S	EF	QS	S	VS	VVS
MD	F	S	S	VS	VVS
H	AF	S	VS	VVS	ES
VH	MD	VS	ES	ES	EVS

Fig. 1 shows the genetic optimized results of high speed steel fuzzy model in graphical form. Note that all interpolated checking points are not included for display in Figure 1. Improvements are reported for all the fuzzy models. The percentage of improvement ranges from 4.3% to 21.7%. The corresponding fuzzy rules are shown in Table 5, 6, 7 dan 8. The authors set the maximum number of generations to be 10, 000. Better result might be obtained by allowing more generations to be reproduced. Results show that the high-speed steel fuzzy model stands the highest mean absolute error percentage, which is near to 5%. A study of the optimization algorithms is carried out based on the worse set of data, the high-speed steel fuzzy model. Majority of huge deviations occurs with 1mm depth of cut and shown in Figure 1. The deviations are believed that the system tends to cope with interpolated values in the region (between 1-mm depth of cut and 4-mm depth of cut). According to the authors' knowledge, increasing the density of interpolated checking points in the above mentioned region could yield better result. Without considering the interpolated checking points, similar improvements achieved as well. For example, the high speed steel fuzzy model improves from 4.1% of mean absolute error to 3.9% in the 130th generation with the fuzzy rules showed in Table 5.

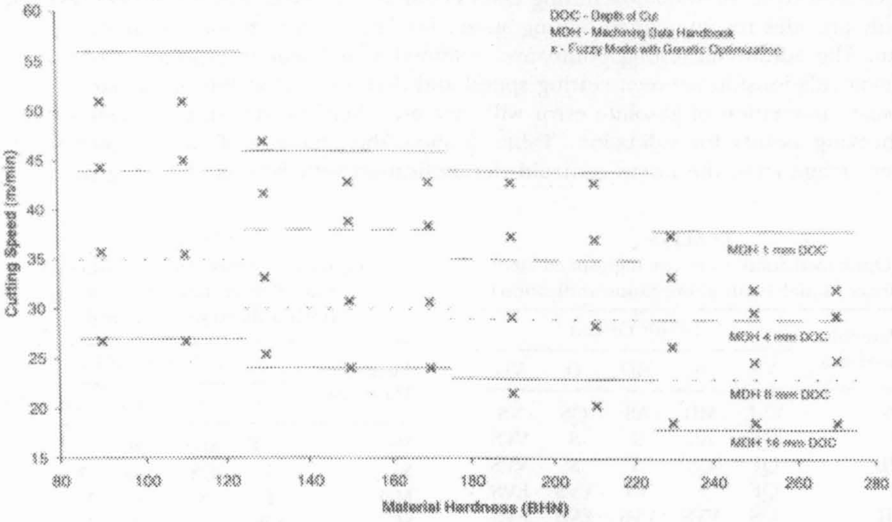

Fig. 1. Cutting speed against material hardness for high-speed steel model

All the results mentioned above are bound to the constraints described in section "Pattern Violation Penalties". Capability of constraint application in GOL is very useful for fuzzy designer. A fuzzy designer. A fuzzy designer can apply his expert knowledge to control the fuzzy relationship between the inputs and the outputs. To show its efficiency and effectiveness, the constraints are discarded for the optimization algorithm for high-speed steel fuzzy models. Better fuzzy rules recommended, which improved of the mean absolute error percentage from 5.8% to 3.7%.

CONCLUSION

Four improved fuzzy models have been suggested for four different types of cutting tool. The models are validated with previous literatures and Machining Data Handbook.

More complicated relationship among cutting speed, workpiece hardness and depth of cut are suggested.

Several related C++ classes handling genetic optimization are developed, grouped under Genetic Optimization Library (GOL). It has been proved the success of the GOL working with HSF class to search better fuzzy rules. Effect of varying checking point density is show. Generally, higher density will cause greater mean absolute error percentage. Both initial and higher checking point density demonstrates improvement under genetic optimization. GOL can be used to handle more complicated problems and scenario.

The Genetic Optimization is a novel method to search the best-fit solution. It is good tool for fuzzy designer when designing the fuzzy rules. The designer does not need to conduct trial and error tests, which is a tedious task. One's expert knowledge can be incorporated into the genetic optimization algorithms, which is one of the most important features provided by fuzzy logic system.

The genetic optimization can be used to find the possible loophole in one's expert knowledge in designing the fuzzy rules. More complicated relationship in cutting machinability data could be developed with the help from the genetic optimization. The GOL can help the development of the Fuzzy Expert System on Machining Data Selection, which covers all the perform a lot of trial and error tests to get the satisfactory fuzzy rules combinations. In addition, the designer's expert knowledge of machinability data relationships can be validated through the optimization process.

REFERENCES

BERENJI, H.R. and P. KHEDKAR. 1992. Learning and tuning fuzzy logic controllers through reinforcements. IEEE *Transactions on Neural Network* **3** (**5**): 724-740.

FANG, X.D and I.S JAWAHIR. 1994. Predicting total machining performance in finish turning using integrated fuzzy-set models of the machinability parameters. *Int. J. Pro. Res.* **32** (**4**): 833-849.

ISHIBUCHI, H., K. NOZAKI, N. YAMAMOTO, and H. TANAKA. 1995. Selecting fuzzy if-then rules for classification problems using genetic algorithms. IEEE *Transactions on Fuzzy System* **3** (**3**): 260-270.

JANG, J.S.R. 1992. Self-learning fuzzy controllers based on temporal back propagation. IEEE *Transactions on Neural Network.* **3** (**5**): 714-723.

KARR, C.L. 1991. Design of an adaptive fuzzy logic controller using genetic algorithms. In *Proc. Fourth Int Conf. Genetic Algorithms. San Diago,* July 13-16: 450-457.

LIU T. I., X.M YANG and G.J. KALAMBUR. 1995. Design for machining using expert system and fuzzy logic approach. *J. of Materials Engineering and Performance* **4**(**5**): 599-609.

METCUT RESEARCH ASSOCIATES INC. 1980. *Machining Data Handbook.* 3rd edn. Vols. 1 and 2. Cinaconnate.

NOMURA, H., I. HAYASHI and N. WAKAMI. 1992. A selftuning method of fuzzy reasoning by genetic algorithms. In *Proc. Int. Fuzzy Ssytem Int.*

OBERG, E., F.D. JONES and H.LL HORTON. 1988. *Machinery's Handbook.* 23rd Edition. New York: Industrial Pree Inc.

OSTWALD P.F. and J. MUNOZ. 1997. *Manufacturing Processes and System.* John Wiley & Son Press.

RANGWALA, S.S. and D.A. DORNFELD. 1989. Learning and optimization of machining operations using computing abilities of neural network. IEEE *Transactions on System for Machining Problems.* ASTME Technical Paper. No. 164.

SING, R. and S. RAMAN. 1992. Metex- An expert system for machining planning. *Int. J. Prod. Res.* **30**: 1501-1516.

VAUGHN, R.L. 1958. A Theoretical Approach to the Solution of Machining Problems. ASTME Technical Paper. No. 164.

WANG, L.X. and J.M. MENDEL. 1992. Generating fuzzy rules by learning from examples. IEEE *Transactions on Systems, Man and Cybernetics* **22 (6)**: 1414-1427.

WONG, S.V., A.M.S. HAMOUDA and M.A. EL BARADIE. 1997. Development of a fuzzy based expert system for cutting data selection. *International Journal of Flexible Automation and Integrated Manufacturing* **5** (**1** & **2**): 79-104.

WONG, S.V. and A.M.S HAMOUDA. 1998. A fuzzy logic based expert system for machinability data-on-demand on the internet. In *Advances in Material Processing and Technology '98*, ed. A.M.S Hamouda. et al. p. 1048-1058. Kuala Lumpur, August 24-28.