Evaluation of critical wear transition loads of MMCs by rule based fuzzy modelling

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Received 4 May 1995; accepted 13 December 1995

The evaluation of critical transition loads in a wear system of metal matrix composites (MMCs) was attempted with the aid of the wear knowledge established using fuzzy rule based modelling. The model presumes that the membership function of the inputs and the rule base are proper. The membership function of the output is adjusted to minimise the error between the predicted output and the experimental results. The influencing parameters considered in this paper include particle size, composite hardness and particle volume fraction. The method shows its unique advantage to model the wear of the complex system with metal matrix composites.

Keywords: critical wear transition load; rule based fuzzy modelling; metal matrix composites

1. Introduction

In a wear system of metal matrix composites (MMCs), when an applied load reaches a critical value, a transition from mild wear to severe wear occurs [1–3]. This load, called a critical wear transition load, is associated with many variables such as material properties, counterparts and working conditions. From material point of view, for example, parameters such as particle volume fraction (f_v), particle size (d) and composite hardness (H) may all affect the wear transitional behaviour [2,3]. The high transition load from mild to severe wear and the low wear rate in mild wear are main characteristics of MMCs as high wear resistance materials [1–4]. Although extensive work has been done in this area, the understanding of the mechanisms of the transition is very limited and its prediction is particularly difficult. For instance, Zhang and Alpas [2] pointed out that the decrease of the flow strength of the metal matrix induced by the temperature rise during sliding was the cause of the wear transition. However, Wang and Rack [1] suggested that it is crack initiation and propagation at the subsurface that bring about the transition. A mechanism of delamination [5] which postulates that delamination at the subsurface is caused by the formation of voids and initiation and propagation of cracks was also used to explain the transitional behaviour. It is known that the addition of the ceramic particles into the metal matrix can increase the hardness and enhance the shear strength of the composites, and larger particles are more effective than smaller ones to enhance the shear strength under sliding.

On the other hand, the contribution of individual parameters to wear and the interactions between them are very complex. Some parameters such as hardness of the composite and size of the reinforcement are vague. Conventional methods show their weakness to evaluate properly the wear behaviour when many factors are involved [4], the development of a novel method therefore becomes essential.

The fuzzy set theory, first introduced by Zadeh [6], provides an effective method to tackle a process associated with a large number of variables with vague interactions. Though earlier applications were mainly in the area of sociology, medicine, psychology and management, recent successful studies on various engineering problems, such as fuzzy plasticity [7], roughness prediction [8], ball bearing wear [9,10], tool wear recognition [11,12], design techniques [13], fuzzy advisory systems for grinding [14–17] and general applications in complex systems [18], have demonstrated the feasibility of this approach to study the complex wear systems with MMCs.

The purpose of this paper is to propose a fuzzy mathematical method to study the transition from mild wear to severe wear for a number of MMCs with an aluminium matrix and ceramic reinforcements. Wear data is first established by a series of experiments and the rule based fuzzy modelling is then used to evaluate the critical transition loads.

2. Experimental database

The objectives of the wear tests were to obtain the critical transition loads (or pressures) of some typical MMCs and to gain sufficient wear knowledge for a fuzzy analysis. Experiments were carried out on a pin-on-disk wear machine [3] at a sliding speed of 1 m/s at a dry sliding condition with about 70% relative humidity at room temperature. The applied pressure varied between 1 and 5 MPa. The disk was made of a low carbon steel with a Vickers hardness of 450. The pin materials were 6061 Al alloy reinforced with respectively 10 and 20% (volume fraction) angular alumina (Al_2O_3) particles, 10 and 20% SiC particles (Duralcon materials) and 20% spherical alumina particles (Comral). The material properties such as particle size and composite hardness were measured before wear tests. Although these parameters are fuzzy-like, the average values can be obtained. To give a general information on these material characteristics, wear transition loads (pressure σ_c) and some main material parameters are listed in table 1. The transition loads are the average values from three repeated measurements. Only the mean particle size, d, and average Vickers hardness values, H_v, are given in this table. To understand the fuzzy characteristics of the particle size, fig. 1 shows the distribution of the particle

Table 1
Wear transition load (pressure) and material parameters

Parameter	Particle				
	SiC	SiC	Al_2O_3 (angular)	Al_2O_3 (angular)	Al_2O_3 (spherical)
f_v (%)	10	20	10	20	20
$d(\mu m)$	1.8	1.8	4.5	8.8	18.7
H (kgf/mm^2)	130	155	130	145	136
σ_c (MPa)	0.5	0.75	1.0	2.5	4.0

size for the Comral composite with 20% spherical alumina. Reinforcements in the Duralcon composites also show similar size distributions.

3. Rule based fuzzy modelling

3.1. BASIC STRUCTURE

The basic architecture of the rule based modelling for the prediction of the critical transition load is illustrated in fig. 2. It consists of four parts: fuzzification of the input, rule base, fuzzy inference engine and defuzzification of the output. The fuzzification process is to obtain a grade of the membership by sensing an input value on its membership function, see fig. 3, where VS means "very small", S "small", M "medium", B "big" and VB "very big". For instance, as shown in fig. 3a, giving an input data $X_{10} = 6$, the grade of membership of SMALL is 0.75,

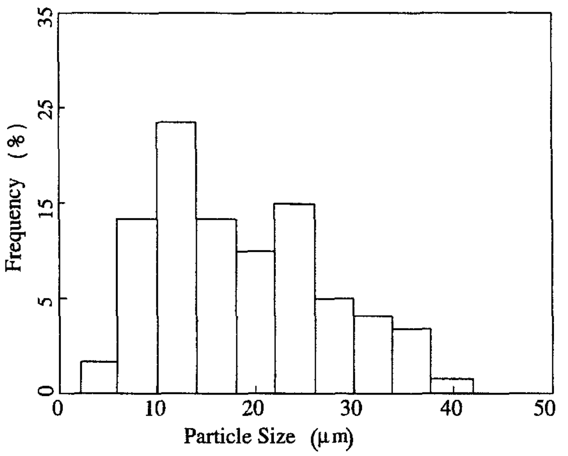

Fig. 1. The relative percentage frequency distribution of the particle in Comral composite.

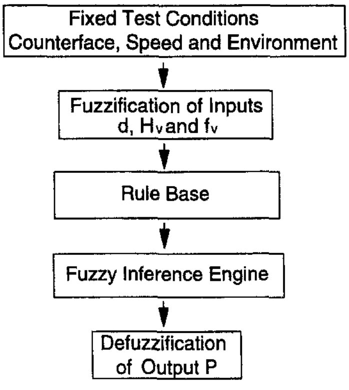

Fig. 2. The architecture of the rule based fuzzy modelling.

which means that a particle size of 6 μm belongs to the linguistic variable "small" to a degree of 0.75. Similarly, giving input value $X_{20} = 140$ in fig. 3b, and $X_{30} = 15$ in fig. 3c, the grades of corresponding membership are 0.5 S & 0.5 M and 0.5 VS & 0.5 S, respectively. The function of defuzzification is to produce a nonfuzzy value on its output axis by calculating the results with different rules. A typical defuzzification method is by centre-of-area (COA) [20], which will be described in subsection 3.4. Rule base is given by a finite set of conditional sentences, in the form of "***IF A Then B***", where A and B are fuzzy sets in forms of linguistic variables, for example, "small", "high" and so on. The function of the inference engine is to determine the rules which apply to the given condition and to obtain the level of certainty.

The rule base is essential for the prediction of the critical transition load. It is established based on the sufficient experience of the wear behaviour. As shown in table 2, 12 fuzzy rules are selected to represent the input–output relationship. The rule base covers the most possible combinations of the fuzzy sets. We presume that the rules are proper and the number of the rules are complete (to a certain degree based on our experimental results available). The rule base applies three parameters as input and one output. Taken the sixth rule as an example, it is given as:

"*If d is medium AND H_v is medium AND f_v is small THEN P is medium*".

3.2. MEMBERSHIP FUNCTION OF THE INPUTS

The membership function of the fuzzy sets associated with the linguistic variables for the three inputs are shown in fig. 3. The ranges of each input are: particle size: 0–20 μm, hardness: 110–180 kgf/mm^2 and particle volume fraction: 5–55%. The shape and location of each linguistic variable of the three inputs are presumed to be proper. After operation by the rule base shown in table 2, linguistic variables of the output are obtained. Thus the only thing needed to do is to adjust the shape

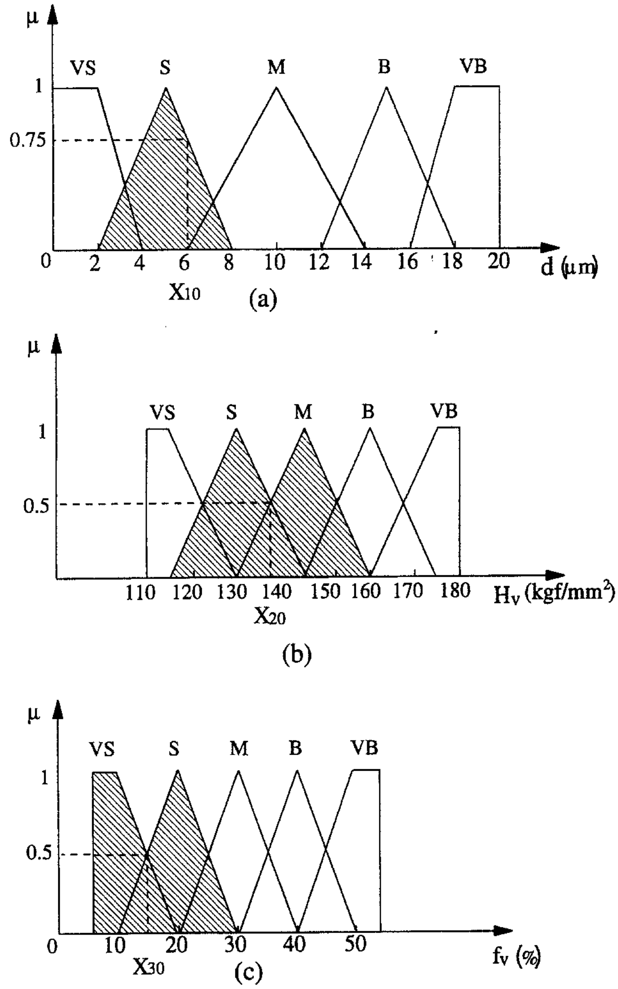

Fig. 3. Membership function of the input parameters; (a) particle size d; (b) composite hardness H_v and (c) particle volume fraction f_v.

and location of the membership function of the output in order to minimise the performance criteria Q which is the distance between the measured output and calculated output by using the rule based fuzzy modelling.

3.3. INFERENCE ENGINE AND ADJUSTMENT OF THE MEMBERSHIP FUNCTION OF THE OUTPUT

According to the rule base the output is obtained in linguistic variables. The grade of the membership of the output is calculated by the minimising operation, i.e.

Table 2
Rule base on the input d, H_v, f_v and output P

Rule No.	Input d	Input H_v	Input f_v	Output P
1	VS	S	VS	VS
2	VS	M	S	VS
3	VS	B	S	S
4	S	S	VS	S
5	S	M	S	M
6	M	M	S	M
7	B	M	S	M
8	M	B	B	B
9	B	B	S	B
10	VB	M	S	B
11	M	B	M	VB
12	VB	B	B	VB

$$h_j = A_1(X_{10}) \wedge A_2(X_{20}) \wedge A_3(X_{30}), \tag{1}$$

where $A_i(X_{i0})$ is the grade of the membership of the ith input with its input value X_{10}. The symbol $\wedge$ stands for the *MIN* operation of the active rules. The value of h_j indicates the active rules for producing the output y. An example for the grade of the output membership when the fourth and fifth rules are active is illustrated in fig. 3, in which $A_1(X_{10}) = 0.75$ S, $A_2(X_{20}) = 0.5$ S & 0.5 M and $A_3(X_{30}) = 0.5$ VS & 0.5 S. Thus the grade of the output membership h, according to the selected rule base in table 2 and fuzzy operation by eq. (1), is 0.5 S & 0.5 M.

The shape and location of the membership function of the output has to be adjusted referring to the definition of the membership function of the inputs and rule base. This adjustment is also based on the experience on the problem and has to minimise a given performance criteria Q [18]. By considering these factors, the range of the transition load is adjusted to be 0–5 MPa. The locations of centre-of-area of the output for different linguistic variables are $C_1 = 0.5$; $C_2 = 1$; $C_3 = 2.5$; $C_4 = 4$; $C_5 = 4.5$.

3.4. DEFUZZIFICATION OF THE OUTPUT

The output linguistic variables obtained from the rule base need to defuzzify to a crisp output value that best presents the membership function of an inferred fuzzy rule. The output value inferred from all the fuzzy rules is calculated according to the method of centre-of-area [20], i.e.

$$y = \left(\sum_{j=1}^{n} h_j y_j\right) \Big/ \sum_{j=1}^{n} h_j, \tag{2}$$

where h_j is the grade of membership function of the output obtained by rule j, n is the number of the active rules for the output and y_j is the centre of the area of the corresponding output membership function. If only one rule is active, the crisp value of the output y is the coordinate value at the output axis corresponding to the apex because the symmetrical triangular shape is used in the present work. An example to obtain the defuzzified value of the output, using eq. (2) and the data of set 6 in table 3, is given by

$$y = \frac{0.5 \times 1.0 + 0.5 \times 2.5}{0.5 + 0.5} = 1.75\,. \tag{3}$$

3.5. EXAMPLES

Numerical example of input values and the prediction of the critical transition loads of given composites are illustrated in table 3. The predicted results of five composites and their input values are listed in the first five rows. The difference exists only on that associated with 20% SiC–Al composite, for which the predicted result is 0.88 MPa while the experimental result is 0.75 MPa. For other composites, exactly the same values as the experimental are obtained. The corresponding output of the other three random inputs of the material parameters are calculated and listed in the last three rows in this table. By using the present method, the critical transition load of this kind of metal matrix composites in such a wear system can be evaluated. By comparing the evaluated results and some experimental results in table 1, it can be seen that the present fuzzy modelling shows it unique advantage. If more input parameters are involved, this advantage becomes more prominent.

4. Concluding remarks

Rule based fuzzy modelling for evaluation of the critical transition load is presented in this paper. The material parameters such as particle size, composite hard-

Table 3
Numerical example of the inputs d, H_v, f_v and output P

No.	Input d	Input H_v	Input f_v	Output P	Active rules
1	1.8	130	10	0.5	1
2	1.8	155	20	0.88	2 & 3
3	4.5	130	10	1.0	4
4	8.8	145	20	2.5	6
5	18.7	136	20	4.0	10
6	6	140	15	1.75	4 & 5
7	15	150	20	3.25	9
8	10	170	30	4.5	11

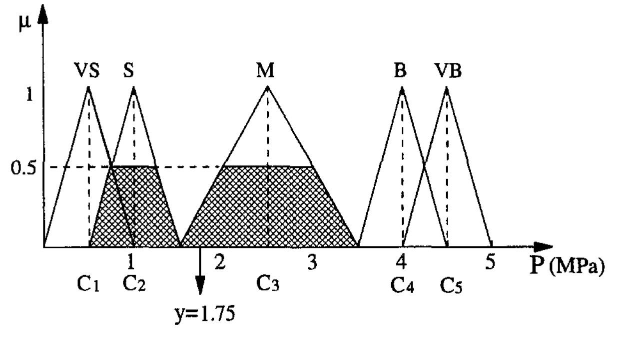

Fig. 4. Membership function of the transition load P as an output.

ness and particle volume fraction are used as input and the transition load as output. The model presumes the membership function of the inputs and the rule base being proper, and the membership function of the output is adjusted to minimise the error between the predicted output and the experimental results. The method shows its simplicity and unique advantage to model such a complex system as wear of metal matrix composites.

Acknowledgement

The authors would like to thank the Australian Research Council for the continuing support of this work and Comalco Research Centre in Melbourne for supplying the composites for testing. ZFZ is supported by an EMSS scholarship.

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