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Shape Study of Wear Debris in Oil-Lubricated System with Neural Network

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Abstract : The wear debris is fall off the moving surfaces in oil-lubricated systems and its morphology is directly related to the damage and failure to the interacting surfaces. The morphology of the wear particles are therefore directly indicative of wear processes occurring in tribological system. The computer image processing and artificial neural network was applied to shape study and identify wear debris generated from the lubricated moving system. In order to describe the characteristics of various wear particles, four representative parameter (50% volumetric diameter, aspect, roundness and reflectivity) from computer image analysis for groups of randomly sampled wear particles, are used as inputs to the network and learned the friction condition of five values (material 3, applied load 1, sliding distance 1). It is shown that identification results depend on the ranges of these shape parameters learned. The three kinds of the wear debris had a different pattern characteristics and recognized the friction condition and materials very well by neural network. We discuss how these approach can be applied to condition diagnosis of the oil-lubricated tribological system.

Key words : Wear, wear debris, computer image analysis, morphology, 50% volumetric diameter, aspect, roundness, reflectivity, neural network

Introduction

The wear debris is produced whenever moving surfaces in oil-lubricated tribological systems interact. Its morphology is directly related to the damage and failure to the interacting surfaces. The study for analysis of wear debris morphology can therefore provide very early recognition and diagnosis of a fault in the lubricated moving system.

Despite the facile method of wear debris analysis by microscopic examination and computer [1-3], it has not been widely accepted in industry because effective use of this method requires expert personnel conducting examination of the wear debris, and the cost is not always effective.

Roylance and Raadnui [4] studied the automatic image analysis of wear debris and the diagnosis of operating condition, but he only described the range of shape parameters of wear debris with various wear mechanism (stable wear, severe wear, abrasive wear, etc..). This is the same as a doctor check one's health with blood test. And ferrography[5,6] put into practical use also requires the experience and feeling of expert personnel knowing well lubricated moving system, in order to decide a fault in a operating condition from the analysis result.

Like this, to apply the quantitative analysis of wear debris occured in oil-lubricated tribological system to the diagnosis of operating condition, it is necessary to establish a processing method of wear debris data with the relation of friction and shape characteristics of wear debris generated in lubricated moving system.

For this, we experimented with pin-on-disk sliding device and attempted observation and analysis of wear debris morphology with image processing and artificial neural network. At first, obtained the four shape parameters (50% volumetric diameter, aspect, roundness and reflectivity) of wear debris processed by computer image analysis. And then we identified wear debris on operating condition from above the four representative shape parameters with neural network widely used for a pattern identification in many fields, The neural network is very effective to solve a problem of the nonlinear relation and is not only potential to acquire characteristics of wear debris, but to explain the interacting of friction.

This study was carried out to diagnose operating condition in oil-lubricated tribological system through the identification of wear debris morphology.

Experiments

Experiment of Lubricated Friction

Fig. 1 show the pin-on-disk type tester used for the experiment of friction and wear that pressed a bearing steel ball on disk specimen. the pin specimen was used 52100 steel (ball bearing steel) with 5.0 mm in diameter and disk specimens were used three kinds of steel with difference hardness, those were 1045 steel (plain carbon steel, 200 Hv), 304 steel (stainless steel,

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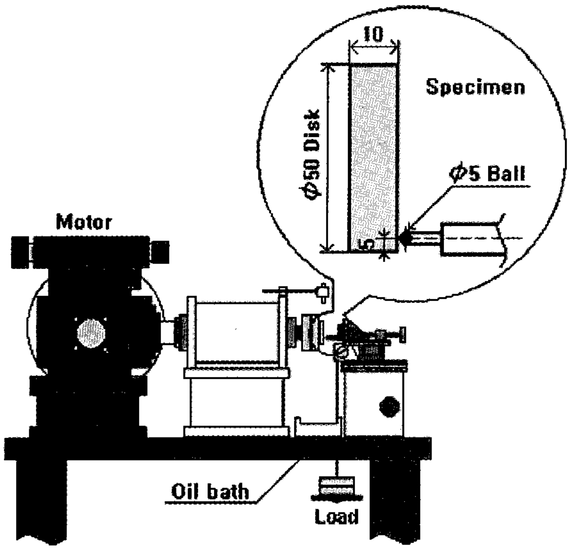

Fig. 1. Schematic diagram of pin-on-disk type tester.

Table 1. Experimental condition

Disk	Load (N)	Sliding distance (m)
1045	9.8, 49, 88.2	78, 156, 234
304	9.8, 49, 88.2	78, 156, 234
52100	9.8, 49, 88.2	78, 156, 234

190 Hv) and 52100 steel (bearing steel, 780 Hv). And dimension of disk was 50 mm in diameter and 10 mm in width and grinded exactly. Lubricant used in this study was added stearic acid (0.1wt.%) to paraffin series base oil(8.2cSt@40°C).

The motor was a speed control motor without a point of contact and was joined with a reduction gear, so all sliding speed was identically 7.23 mm/sec. contact loads was set up to 3 classes of 9.8 N, 49 N and 88.2 N as shown in Table 1. And sliding distance was identically from 0 to 234 m in three kinds of specimen, and was divided according to the early, middle and late stage (0~78 m, 78~156 m and 156~234 m) of the sliding distance by three hours.

In lubricated system, a oil-bath was instituted under contact point of the specimen and oil was supplied on the contact point through a silicon tube by the circulation pump. After oil was well melted in oil-bath, wear debris in oil was taken out through a membrane filter of 0.45 μm (pore size), 47 mm (diameter). The coefficient of friction in a each experimental condition was acquired to a voltage of strain gauge.

Image Analysis of Shape Parameters

Fig. 2 show the image processing system [7] used in order to process data information of wear debris taken from the experiment. The optical microscope of the image processing system equipped two kinds of halogen lamps with transmitted and reflected light and images is saved in a frame grabber of computer through the upper color CCD camera. The frame grabber is 640×480 pixels and the resolvability per pixel is 8-bit (256 gray level) in each R (red), G (green) and B (blue).

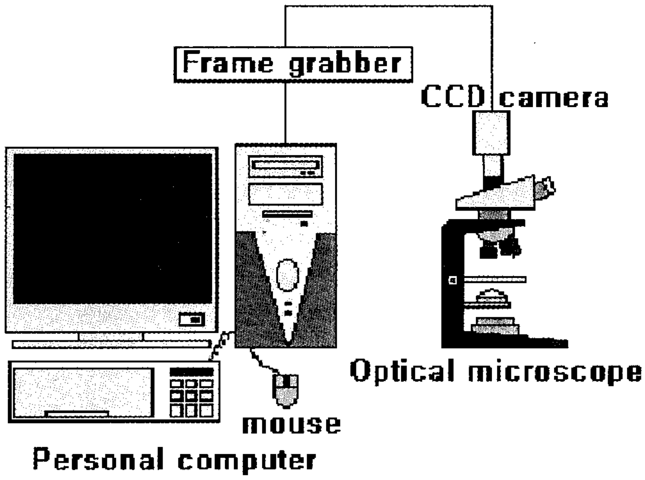

Fig. 2. Schematic diagram of image processing system.

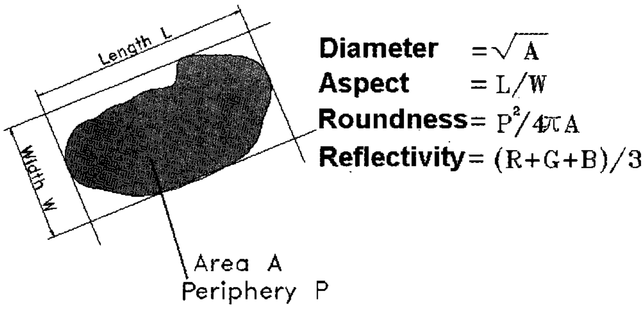

Fig. 3. Shape parameter of wear debris.

The length of a square pixel's side is 0.426 μm. As diameter of a filter in which wear debris exist is 35 mm, the area of one image is 1 over 17,302 in a filter. In all experimental condition, we used an object lens of 40 magnifications and an eye lens of 10 magnifications, and calculated parameters of wear debris more than 10 pixels in 50 filter's random images. The frame grabber was controlled and processed through softwares of C language and assembler.

Fig. 3 show the four shape parameters [7] of a wear debris are defined from data informations (particle periphery, area, the number of particles and particle's color), and these are 50% volumetric diameter, aspect, roundness and reflectivity.

Results and Discussion

Friction Coefficients in Operating Conditions

Fig. 4 show the friction coefficient μ at ending time (9 hours) of experiment in the oil added stearic acid, in case of the 1045 steel and 9.8 N. friction coefficient μ is changed during early stage in 3 hours (0~78 m) but after that time the stable friction is advanced without a large variation.

Fig. 5 shows the friction coefficient μ in base oil and oil added stearic acid for each 3 hours. As for experiment conditions, specimens are 1045 steel, loads are set up 9.8 N, 49 N and 88.2 N, According as loads increase, μ is reduced in two kinds of oil.

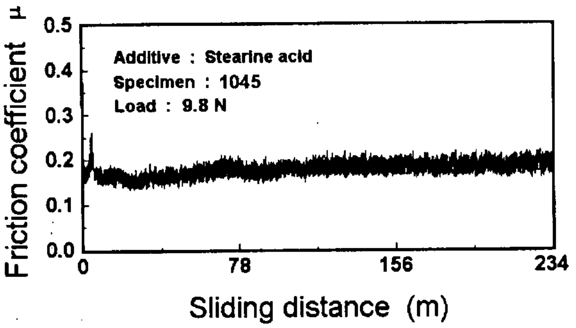

Fig. 4. Wave of friction coefficient.

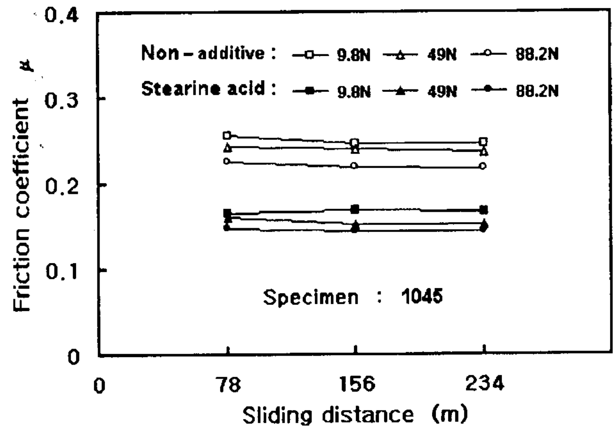

Fig. 5. Effect of sliding distance on the friction coefficient.

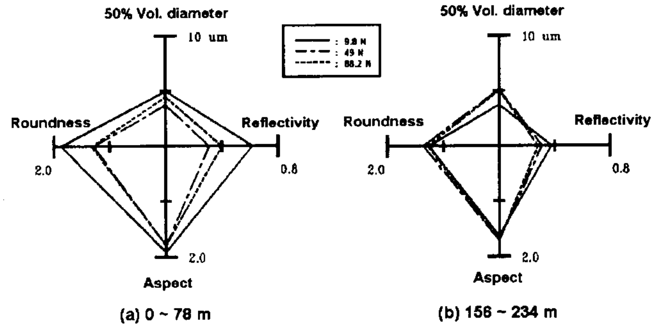

Fig. 6. Diagram of shape parameter values, Specimen: 1045 steel.

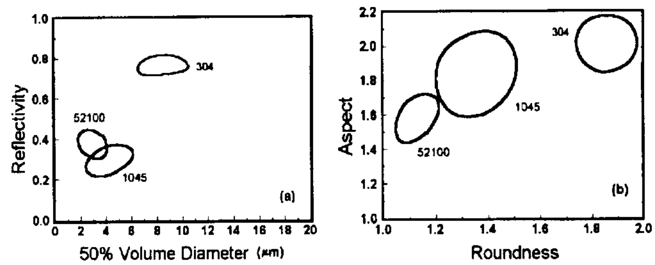

Fig. 7. Average values of shape parameters for specimens in every 100 wear debris, Load: 49 N, Sliding distance: 156~234 m.

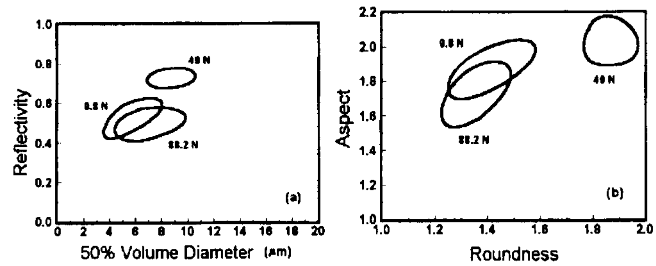

Fig. 8. Average values of shape parameters for applied load in every 100 wear debris, Specimen: 304 steel, Sliding distance: 156~234 m.

This result can be considered that as loads increase, shear strength of the oil molecules are increased and its direction is easy to put about shear direction when oil are put into the contact point of ball and disk specimens. Regardless of loads, oil added stearic acid than base-oil have lower values of friction coefficients. In this case, we consider that the adsorbed film of stearic acid between two surfaces partially prevents the direct contact because the film reduces a breakdown of the boundary layer.

Fig. 6 show the average values of four shape parameters on change of load in the early stage (a) 0~78 m and late stage (b) 156~234 m for 1045 steel. For the load is 9.8 N in (a), the roundness and aspect values are very larger than that of other two load. These describe the shape of wear debris to be very long and complicated. As the sliding distance increase, the reduced reflectivity value shows the processing oxidation and the effect of an adsorbed film. Thus, from the this graph, shape characteristics of wear debris on change of operating condition are easily known.

Distribution of Shape Parameter Values

The operating condition in oil-lubricated system can not decided with a shape parameter value of each wear debris. Therefore, in order to identify obviously the shape characteristic, the property of a small group, namely an average parameter value of all wear debris has to be used.

Fig. 7 show the distribution of average values of four shape parameters, (a) 50% volumetric diameter and reflectivity, (b) aspect and roundness in every 100 wear debris at late stage for three specimens. Considering the shape characteristic, the size of wear particles in the 50% volumetric diameter of 304 steel is larger than that of other two specimens and also the aspect and the roundness is complex and longer. In case of reflectivity, the value of 1045 steel is smallest and the high value for 304 steel is considered as an effect of the element Cr with the corrosive resistance. But the figure of 52100 steel is very small and circular, because 3 shape parameters except for the reflectivity is smaller as compared with other two specimens. In these results, the rate of decision in neural network is expected to be high for materials of all specimens in the lubricated moving system.

Fig. 8 show the distribution of average values in every 100 wear debris of 304 steel for load of 9.8 N, 49 N and 88.2 N in the late stage of sliding distance. In this figure, (a) load of 49 N have high value but 88.2 N have small value in 50% volumetric diameters. According to the increasing load, (b) the roundness

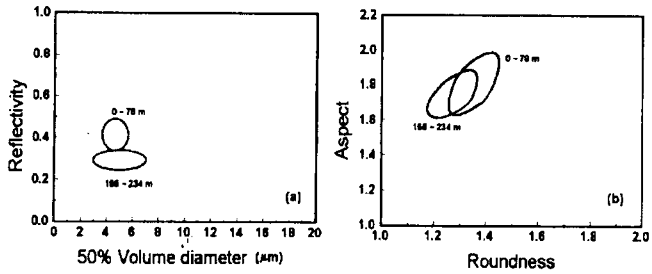

Fig. 9. Average values of shape parameters for sliding distance in every 100 wear debris, Specimen: 1045 steel, Load: 88.2 N.

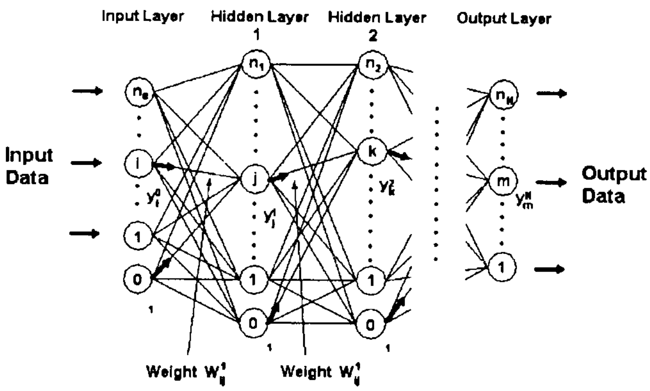

Fig. 10. Diagram of multi-layer neural network.

and aspect are the same a tendency as (a). These results are considered to be a effect of the adhesive wear and the oxidized wear particle by the increase of the contact pressure and to be a consequence of the adsorbed film formed by stearic acid in case of the high load as 88.2N. From the distribution range of these shape parameters, the decision rate of neural network for the load is expected to be very hard because a part of the range is overlapped very much.

Fig. 9 show the distribution diagram of average values for sliding distance in every 100 wear debris for 1045 steel. According as the sliding distance increase, the 50% volumetric diameter show few or no changes, but values of other three shape parameters are reduced. These results are considered because of the oxidation effects and the adsorbed film formed with the transformation of frictional surface and the deterioration of oil with increasing of the sliding distance.

Identification of Wear Debris with Neural Network

Because the four shape parameters are different in every condition of friction, only distribution charts of multi-dimensional shape parameters come hard to identify exactly the shape characteristics of wear debris. Thus, in order to identify the pattern of wear debris for the multi-dimensional inputs, this study presented the possibility of identification of wear debris with the learning and decision of shape parameters by the artificial multi-layer neural network [8,9] that based on the error back propagation.

A neural network is the multi-layer network as shown in Fig. 10. The processing units of each layer is mock neurons, for example, a unit (k) in the second layer outputs a active

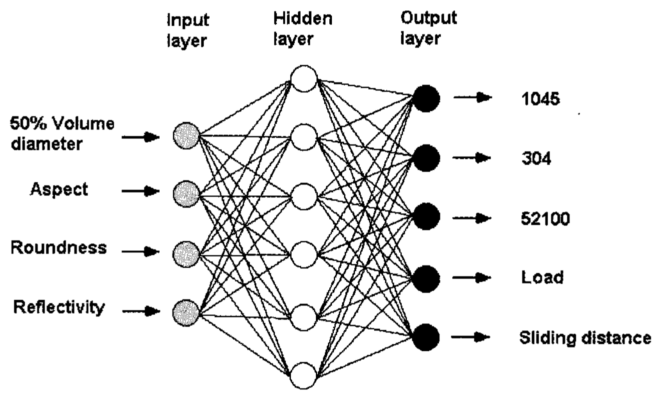

Fig. 11. Construction of neural network.

value to the next layer. The active value of a unit is calculated by $y_k^2 = f(x_k^2)$ of the sigmoid function (f), in this, x_k^2 is the weighted sum of all weight w_{jk}^2 that are the connected strength between a current unit and other input units(y_j^1,j = 0~n^1) in a previous input layer. The network proceeds to learn with the error back propagation method of the supervised learning, and the weight of each unit is modified by the error between a output value and a target value.

As shown Fig. 11, the neural network used to this study was constructed three layers, the hidden layer was one and had 10 units. Input data were four kinds of shape parameter and output data set up 1 severally for three specimens, 0, 0.5 and 1 for 3 conditions of load. And in the sliding distance, output data set up 0 and 1 for data of the early and late distance.

The network learnt with the average values of all wear debris and two classes of small groups in every 100 wear debris. The convergent condition of learning was less than 0.001 for total error or less than 30,000 for learning iteration numbers. The decision criterion was more than 0.7 among 3 output units for specimens, and It was defined that the low load was from 0 to 0.3, the middle load was from 0.3 to 0.7 and the high load was from 0.7 to 1.0 for the load. For the sliding distance, the criterion was that the early distance was from 0 to 0.5 and the late distance was from 0.5 to 1.0.

Table 2, Table 3 and Table 4 show the decision rates of identification results for decision criterions of the materials, the load and the sliding distance by the neural network. Unit numbers in the hidden layer were 10, and the network learnt with learning data of the average value of all wear debris and decided operation conditions with input data of the average value in every 100 wear debris. Considering these results, for

Table 2. Identification result from neural network

Identification of specimen (%)				
		Specimen		
		1045	304	52100
Load	9.8 N	100	96.4	100
	49 N	100	100	100
	88.2 N	100	87.5	100

Learning data: average value of all wear debris

Table 3. Identification result from neural network

Identification of load (%)				
		Applied load		
		9.8 N	49 N	88.2 N
Specimen	1045	100	55.4	75.7
	304	64.3	8.3	54.2
	52100	100	75	100

Learning data: average value of all wear debris

Table 4. Identification result from neural network

Identification of sliding distance (%)			
		Sliding distance	
		078 m	156234 m
Specimen	1045	91.7	83.5
	304	68.7	75.4
	52100	66.6	100

Learning data: average value of all wear debris

Table 5. Identification result from neural network

Identification of specimen (%)				
		Specimen		
		1045	304	52100
Load	9.8 N	100	100	100
	49 N	96.4	100	100
	88.2 N	89.5	91.7	100

Learning data: 2 Classes of small groups in every 100 wear debris

Table 6. Identification result from neural network

Identification of load (%)				
		Applied load		
		9.8 N	49 N	88.2 N
Specimen	1045	100	55.4	78.4
	304	57.1	40.1	64.9
	52100	100	100	100

Learning data: 2 Classes of small groups in every 100 wear debris

the specimen and the sliding distance, the decision rates generally are high but for the load is not high as shown in Fig. 6. It is considered that the shape characteristics does not change simply for the load.

Table 5, Table 6 and Table 7 are the decision results from only learning data of two average values in two classes of small groups in every 100 wear debris, under the same condition as Table 2, Table 3 and Table 4.

From these results, learning and the decision rates with that of 2 classes than average value of all are generally high. After

Table 7. Identification result from neural network

Identification of sliding distance (%)			
		Sliding distance	
		078 m	156234 m
Specimen	1045	79.6	86.3
	304	68.3	77
	52100	100	100

Learning data: 2 Classes of small groups in every 100 wear debris

all, in case the distributive range of parameters is large, it shows that the neural network responds actively for data in the range of its distribution as it is studied with 2 different average data.

In addition to this study, adding the number of wear debris occurred, the volume of a wear debris and the friction coefficient to parameters, we can expect the obvious potential that the network will very well identify wear debris taken from various operating conditions in the oil-lubricated tribological system.

Conclusions

The number of wear debris taken from various operating condition in the oil-lubricated tribological system have been analyzed and identify to determine their shape characteristics with computer image analysis and artificial neural network.

The results show that friction coefficient decrease as the load increases due to adsorbed film between two friction surfaces. It is possible to distinguished the shape characteristics of wear debris on operating conditions on this study with respect to the wear processes from which they generated by computer image analysis. They can be effectively analyzed by using the average in every 100 wear debris.

By the neural network can decide the operating condition in the oil-lubricated tribological system using learning data of all average values for 4 shape parameters. To learn with 2 learning data, the decision rate of the network for operating conditions is improved.

References

1. Kirk, T. B., Panzera, D. R., Anamalay, V. and Xu, Z. L., Computer Image Analysis of Wear Debris for Machine Condition Monitoring and Fault Diagnosis, Wear, 181-183, pp. 717-722, 1995.
2. Thomas, A. D. H., Davies, T. and Luxmoore, A. R., Computer Image Analysis for Identification of Wear Particles, Wear, 142, pp. 213-226, 1991.
3. Roylance, B. J., Albidewi, I. A. and Laghari, M. S., Computer-Aided Vision Engineering-Quantification of Wear Particle Morphology, Lubr. Eng, 50, pp. 111-116, 1993.
4. Roylance, B. J. and Raadnui, S. The Morphological Attributes of Wear Particles-Their Role in Identify ing Wear Mechanisms, Wear, 175, pp. 115-121, 1994.
5. Kirk, T. B., Stachowiak, G. W. and Batchelor, A. W., Fractal

Parameters and Computer Image Analysis applied to Wear Particles isolated by Ferrography, Wear, 145, pp. 347-365, 1991.

6. Roylance, B. J., Pocock, G., Wear Study through Particle Size Distribution: Application of the Weibull Distribution to Ferrography, Wear, 90, pp. 113 -136, 1983.
7. Heung-Sik Park, Tae-Ok Jun, Young-Back Seo, Hyung-Ja Kim, Morphological Analysis of Wear Debris for Lubricated Moving Machine Surfaces by Image Processing, Journal of KSTLE, 12-3, pp. 72-78, 1996.
8. Sugimura, J., Umeda, A. and Yamamoto, Y., Wear Debris Identification with Neural Network, JSME (C), Vol.61, No.509. pp. 4055-4060, 1995.
9. Sugimura, J., Umeda, A. and Yamamoto, Y., Inputs and Outputs of Neural Networks in Identification of Wear Debris, JSME(C), Vol. 63, No. 612, pp. 2839-2844, 1995.