NIMIA-SC2001 - 2001 NATO Advanced Study Institute on Neural Networks
for Instrumentation, Measurement, and Related Industrial Applications: Study Cases
Crema, Italy, 9-20 October 2001

Artificial Neural Networks Applications in Tribology – A Survey

Laurentiu FRANGU and Minodora RIPA,
University "Dunarea de Jos" of Galati, Romania

Abstract – *The paper deals with the potential of the artificial neural networks in the field of tribology. Their properties of learning and nonlinear behavior make them useful to model complex nonlinear processes, better than the analytical methods. The neural structures, considered appropriate for such models, are presented. The applications found in the referenced papers mainly consist of prediction and classification. They present some common points, specific to the field: wear processes and particles, friction parameters, faults in mechanical structures. The results obtained by the authors, in their interdisciplinary research are described, proving that neural networks are an useful tool during the design stage as well as the running stage.*

Keywords - ***neural networks, tribology, prediction, classification***

I. INTRODUCTION

In the field of mechanical engineering - in general and of tribology – in particular case, very complex and highly nonlinear phenomena are involved. This is the reason why analytical models are difficult, even impossible to obtain. However, the improvement of performances of mechanical equipment requires accurate modeling and prediction of the friction and wear processes. Artificial Neural Networks (ANN) are good candidates to such models, due to their capabilities of nonlinear behavior, learning from experimental data and generalization.

Two main functions of ANN are useful in tribological applications:

– the continuous approximation of a multivariable function, used for modeling of processes;

– classification, that is a discrete approximation of functions, used for recognition of the operation conditions of machinery.

The former function is usually obtainable by feed-forward NN, called Multi Layer Perceptron (MLP). The latter may be obtained using self-organizing NN, as Kohonen and Adaptive Resonance Theory (ART). MLP equally may be used for classification if adding a supplementary discriminator of the output values. Both functions are already applied in the field of tribology and machinery and presented in several recent papers.

This work aims at evaluating the usefulness of ANN in such applications, as it is reflected in above mentioned papers. It contains a first chapter as introduction, a second chapter dedicated to the main ANN structures, chapters three and four dealing, respectively, with modeling and classification applications and a conclusions part.

II. DESCRIPTION OF ARTIFICIAL NEURAL NETWORK STRUCTURES

II.1. Multi Layer Perceptron

Figure 1 shows an example of a MLP type neural network. Its basic structure is composed of layers, namely the input layer, hidden layers and output layer. The input layer accepts data from the external world, the output layer generates outputs to the external world. There may be one or more hidden layers. Each layer consists of a number of nodes (neurons, cells, processing elements). As shown in figure 1, each processing element may have several input paths but only one output. The inputs of a neuron may come from the external world (in the input layer) or from the outputs of other neurons (in the hidden and output layer). Each neuron sums its input signals, modified by the interconnection weights. The sum, modified by an activation function (frequently a sigmoidal function), is the output of the neuron.

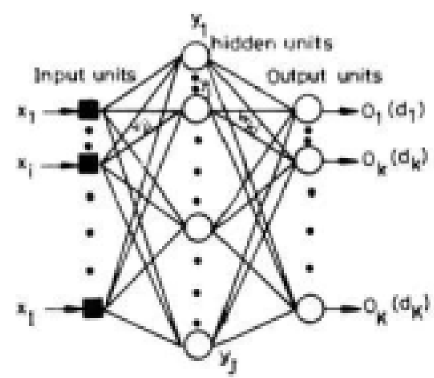

Fig. 1 Example of a neural network [1]

The information propagates from the input layer to the output layer, through connections existing only between elements in adjacent layers. In order to prevent saturation of the activation function the data used for train the NN are generally normalized.

The learning procedure starts with computing of each output O_k, for a specified input vector, X. Then the error between the computed output O_k and the desired one, d_k is used to modify the weights of the neurons in order to decrease this error. The procedure is repeatedly applied for all input vector sets, in order to minimize the global approximation error of the network. This is the back-propagation learning algorithm. It has many versions, aiming at minimizing the learning time and at a good convergence.

II.2 Kohonen self-organizing neural network

The network consists of output units, typically arranged in a two-dimensional plane, with weights between each unit and input units. When an input vector is fed to the network, only one output unit, which has the best-matching weight. i.e. the weight vector is the closest to the input vector, is selected as a 'winner'. After learning, units in the network have modified weights such that neighboring units have similar weight vectors. Hence similar inputs are linked with winner units that are located close to each other, while winner units for different inputs are located far away in the network. Thus the feature map is created and inputs to the network are automatically classified on the map. The advantage of the feature map is that the weight of each output unit directly shows a corresponding input vector itself.

The main property of the Kohonen network is the unsupervised learning. That permits to divide the input vectors set in clusters without prior knowledge about their similarities.

II.3. Adaptive Resonance Theory Network (ART)

The ART network is shown schematically in figure 2. It has two layers: the first is the input/comparison layer and the second is the output/recognition layer. These layers are connected together with extensive use of feedback from the output layer to the input layer along with the feed forward connections. Associated with each connection, the ART network has feed forward weights (w_{ji}s) from the input layer to the output layer and feed back weights (t_{ij}s), from the output layer to the input layer. Between the input and output layers there is also a reset circuit which is actually responsible for comparing the evaluated Euclidean distance (making use of the current inputs and the most recent weights) to a vigilance threshold that determines whether the pattern under consideration pertains to one of the already generated clusters or a new cluster must be created.

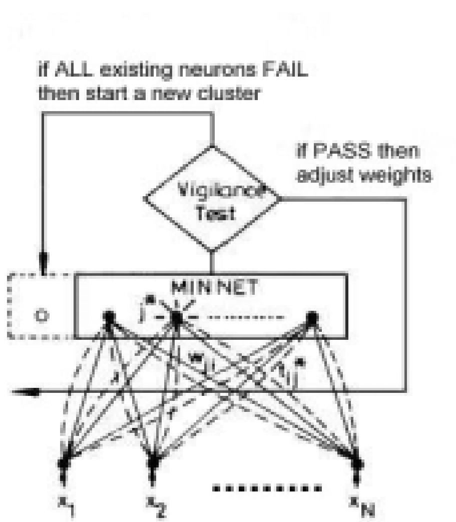

Fig. 2 The configuration of ART network [18]

Although the structure is different with respect to the Kohonen network, their main functions are similar: unsupervised clustering of the input space, based on experimental data. They are useful in pattern classification applications.

III. MODELING AND PREDICTION

The MLP network is suitable for modeling of the processes. It offers a continuous approximation of a multivariable function, that is not analytically obtainable, but it is properly described by the experimental data set. Usually, the purpose of the model is the one-step ahead prediction, i.e. to determine the value of the output function at the moment t+1, knowing the present and the previous values of the output and inputs (t is integer). This ability is used in applications such as tool wear or lubricant wear prediction. There are also applications where the current time is not one of the variables, such as the model of the pressure distribution in a rectangular gas bearing.

The paper [1] presents an ANN that models a simple mechanical system involving friction and wear, according to three standard experiments: rub-shoe, pin-on-disk and four balls models. The input variables are: speed, load, viscosity, sliding distance, friction coefficient and temperature. The output functions are the wear volume (μm^3) and the wear rate (m^3/m).

The purpose of this model is to predict the life time of the friction elements for given operating conditions (even without carrying on a real experiment), or to perform accelerated-life testing, on more complex mechanical systems. A feed-forward NN is trained on the basis of experimental data to output the current wear volume or the current wear rate. On different data set the output yielded by the NN is compared to the recorded one, in order to validate the model (fig. 3).

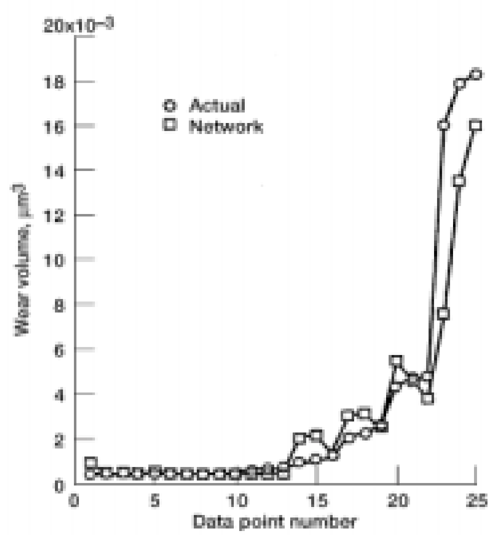

Fig. 3 Comparison between actual and predicted data [3]

The focus of this work was the evaluation of the performance of different network dimensions [1], including recurrent network that filters the input data. As a general result the models prove to be good approximations of the wear volume or rate.

Papers [2] and [3] present other related results of the same research group.

A similar problem is solved in [4]. The prediction of the linear wear (mm) is performed by a MLP network, the considered inputs being: load, velocity, relative humidity and sliding distance.

The papers [5], [6], [7] proposed by another group of authors, deal with the same problem of the wear volume prediction, but in fretting experiments. The main changes concern the dimension of the network, including the number of the relevant inputs (fig. 4). Two interesting aspects presented in the paper [7] have to be mentioned: the friction coefficient is no longer considered as fixed input with previously known value, but as a variable, which has to be modeled by the network. The authors consider that studying the relevance of various parameters of the tribological behavior of the system will help to understand the relation between tribological proprieties and material parameters in fibber composites. This is a challenging start to using NN for knowledge extraction.

The authors of the paper [8] make use of a MLP to model the tool wear in a face milling process. The input vector contains forces, feed rate, eccentricity and the work piece geometry. The output is the average flank wear. Different number of neurons in the hidden layer are tested but the results seem to be very close one to each other (very small error). A specific element for the cutting process is that the cutting force itself evolves along with the tool wear. Not only the cutting force influences the tool wear but also an inverse influence exists.

The influence of the cutting force on the tool is separately evaluated outside the network. In order to validate the neural model, its output is compared to previously identified analytical models; the neural model proves to be better.

The authors of paper [9] apply the same type of ANN to model the turning process. The input vector contains three forces, cutting velocity and feed (mm/rev). The output is the average flank wear of the cutting tool. The model is closed to the real process, excepting for large feed rates, when the error increases due to the unstable associated phenomena.

In paper [10] a MLP is used to predict some parameters of the surface topography, after a specified wear time: RMS, skewness and kurtosis. These parameters further specify the statistical properties of the worn surface, which is subject of a surface reconstruction.

The articles [11] and [12] deal with the estimation of the tool wear in micro-machining. Paper [11] concerns analytical estimations of the cutting forces. A very interesting application, based on the neural model, is developed in the paper [12]. The authors propose a periodic inspection device, to evaluate the tool condition, in order to preserve the quality of the manufacturing. The inspection is executed as it follows: at the specified sampling periods, the tool moves from the workpiece to a test piece and cuts a slot, then comes back to the workpiece (fig. 5). During the test, the cutting forces are measured and they become input data to the neural model previously learned. The output of the network (Neural-Network-based Periodic Tool Inspector-N^{2}PTI) is the estimation of the tool wear. It permits to decide when to bring

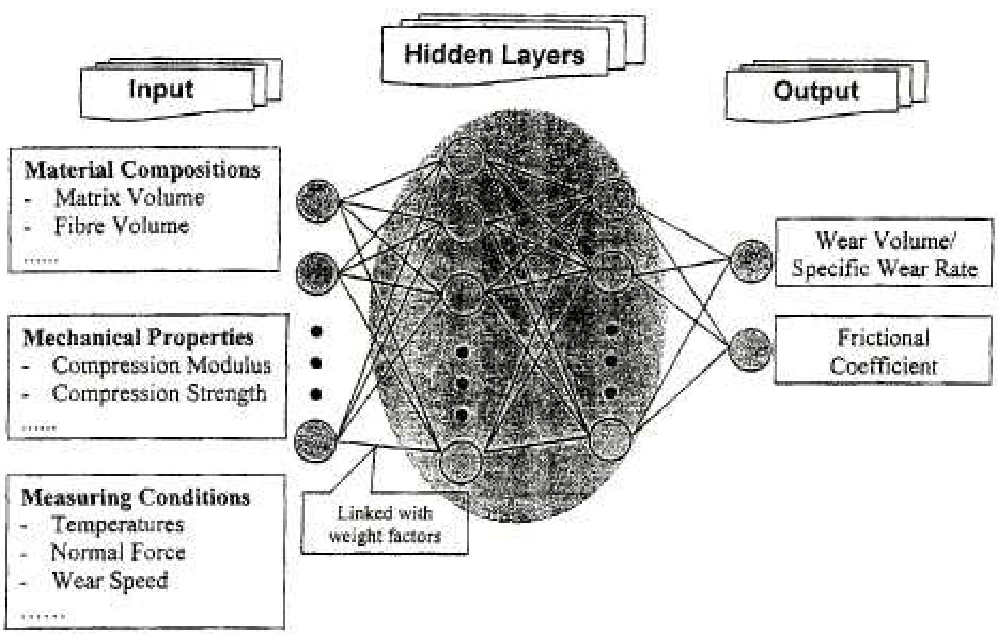

Fig. 4 Construction of ANN [7]

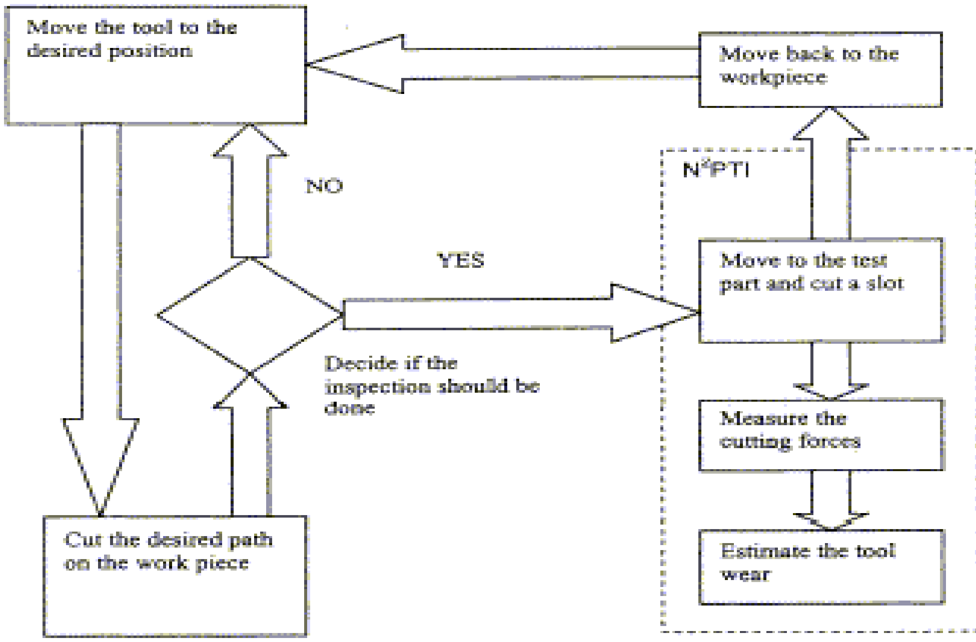

Fig. 5 Operation of the N^{2}PTI [12]

a new tool, being in a better condition. This is a typical diagnose application .

An original contribution of the authors is the comparison between more variants of network implementation. Concerning the structure, they used the classical MLP, with backpropagation training rule, as well as a probabilistic neural network (PNN). This kind of network (described in [12]) has four layers: input, pattern, summation and output. One neuron is assigned to the pattern layer for each training case. After training, pattern and summation layer neurons create the output. For each class there is one summation neuron. Training is very fast; however, the size of the network depends on the number of training cases. If there are many training cases, a large network will be established. In the paper [12] the basic version of PNN is used, having a single scaling parameter. The authors compare the advantages of the MLP to the PNN. They establish, based on experimental data, that backpropagation learning is 10 times longer than the training of PNN, but the average estimation error is 2 to 5 times better. Another contribution of the authors is the comparison between three encoding methods, that is the selection of the parameters fed to the network input. The concerned methods are:

- force-variation-based encoding (the inputs are the differences between the maximum and minimum values of the forces, in each period);
- segmental-average-based encoding (10 samples per period are presented to the network, for each cutting force);
- wavelet-transformation-based encoding (16 normalized parameters, provided by the wavelet transformation, are presented to the network).

The study of the authors found the wavelet transformation as better estimating the forces and the wear, but requiring more time and costly resources. At the other end, the force-variation-based encoding is simply to implement, but provides the worst estimate.

Two other papers deal with neural models, having to predict variables similar to wear. Paper [13] presents an application concerning the degradation of the physical properties of the lubrication oil, during its lifetime. Properties such as viscosity, flash point, water content, insoluble rating, are sampled during the life of the oil. The MLP network is trained to associate the age of the oil (as output) to its properties (inputs). The result is the ability of the network to predict the moment when each property of the oil reaches a certain value, considered unacceptable (called by the authors the "rejection time").

Paper [14] presents a neural network approach to modeling the abrasive flow machining process. This is a manufacturing process, involving the same phenomena and variables as those presented so far (for typical wear processes). Consequently, the models are similar. The authors trained a MLP to model the material removal rate and the quality of the obtained surface (surface finish). The four inputs are the flow speed, the abrasive concentration, the abrasive mesh size and the number of abrasive cycles. The integral of the material removal rate provides the material loss, so the effects may be predicted on-line, in order to control the abrasive flow machining process. The idea of using the model for on-line control is important for fabrication processes, that need good prediction of the critical parameters or variables. The same network may be used to study the possible effects of the process, prior to performing the real experiment. The validation of the neural model proved that better results are obtained, with respect to previously identified multivariable regression models.

Finally, a neural model application that does not imply prediction as function of time, is contained in paper [15]. The studied process is the pressure distribution in a rectangular gas bearing. The inputs of the network are: a dimensionless normalized distance (along the width of the bearing), the supply pressure, the gap width between the two plates and a form factor of the plates. The first two variables are more relevant for the pressure value (correlation coefficient 0.8) than the last two (correlation coefficient 0.05). The same network models the load-carrying capacity of the gas bearing, more accurately than the theoretical model derived by Kassab from the Navier-Stokes model. This is due to the highly nonlinearity of the process, difficult to catch in a simple analytical model.

VI. RECOGNITION OF FAULTS IN BEARINGS, MACHINERY AND IN MATERIAL STRUCTURE

Classification is the oldest application of the neural networks. This ability is useful in a mechanical environment, mainly to recognize the faults, as part of a diagnose effort. As presented in chapter II, the networks containing neurons with threshold activation function in the output layer are suitable for classification problems. However, linear or sigmoidal activation functions are also suitable for this purpose, if the output value is considered as a probability density function, subject of a further threshold discrimination. The training of the network may be supervised or unsupervised (clustering). As a consequence, both MLP and self-organizing maps may be used in a classification problem.

Paper [16] presents the ability of a Kohonen network to classify 4 types of bearing faults and their combinations. They are: outer bearing race defect, inner bearing race defect, ball defect and train defect. The source of information is the vibration transducer. At each sampling moment, a narrow horizon Fourier analysis provides the spectral components, that are fed as inputs of the network. This one recognizes the bearing vibration signatures. The training is supervised, requiring short time.

Paper [17] introduces an application of MLP to fault classification of a rotor-bearing system. The inputs still are spectral components of the vibration signals, whereas the meaning of the outputs of the MLP is that of probability density function of the fault signatures. The outputs are used to discriminate four faults (rotor with mass unbalance, rotor with bearing cap loose, rotor with misalignment and play in spider coupling). The network does not offer a quantification of the fault, once it is recognized, but manages to recognize even combinations of faults. The authors mention that the influence of the training parameters (in a backpropagation procedure) on the classification abilities have to be investigated further.

Paper [18] contains a very complex and rigorous analysis of the classification of faults, localized in ball bearings. It uses both MLP and self organizing network (ART2) to recognize two main faults. The process information, provided by piezo-electric accelerometers, is subject of the Fourier analysis, that computes the spectrum components. These are then compressed in 8 significant descriptors, fed as inputs of the network. The meaning of the output, normalized between 0.1 and 0.9, is that of a scalar description of the possible defects of the bearing. The value 0.1 corresponds to a normal bearing, 0.6 to a ball defect and 0.9 to an outer race defect. The MLP is trained in a supervised procedure, whereas the ART network performs a clustering process. Both networks performed a 100% reliable recognition of the defect bearings (on the presented data sets). MLP distinguished the possible states of the defect bearings, for diagnose purposes, with a rate of success of 95%. The ART2 network was less accurate in recognizing different defects, but it was 100 times faster in training.

The last three papers have a common element: they deal with the classification of the wear conditions. Paper [19] indicates a MLP network as a proper classifier of the sliding conditions, in a pin-on-disk sliding experiment. The information considered relevant is the shape of the wear particles, studied at the microscope and compressed in 4 descriptors that are the network inputs. The 5 outputs of the network are normalized (0 to 1). Three of them represent the type of lubricant, whereas the remaining two represent the low- or high-load conditions of the process. After a supervised training, the network is able to recognize the mentioned sliding conditions. In order to make use of image information (copying the human abilities, of image processing and pattern recognition), the same paper proposes a self-organizing network to classify the surface images. The inputs are two textural parameters, extracted from the image of the wear particles (rather distinct to the worn surfaces than similar). After the unsupervised training, a Kohonen network is able to recognize the above mentioned sliding conditions.

Paper [20] also deals with the wear debris classification, in order to detect the phase of the wear process of the lubricated sliding surfaces. The shape of the particles, studied by microscopy, are described by Fourier descriptors, compressed in 16 histogram parameters, fed as inputs to the MLP network. The single output of the network is able to point to the wear stage (initial or final), by classifying the shape of the wear debris.

The papers [21] and [22] present MLP networks that classify wear particles, in terms of wear mode. The authors created a powerful software for managing the classification possibilities of the networks. The inputs are Fourier descriptors in one example, to classify the shape of the particles, or elements of the co-occurrence matrix of the gray image (the texture), in other example, to discriminate the worn surfaces in "smooth" and "rough". Other examples of MLP networks that classify wear particles, based on image analysis and Fourier descriptors, appear in paper [23].

V. CONCLUSIONS

The purpose of this study was to assess the potential of using neural networks to predict the performance and life of mechanical systems. The mentioned papers, as well as many others, not listed here, succeeded to model tribological processes, making use of ANN. In general, their conclusions indicate ANN as a good modeling method, due to the learning, generalization and nonlinear behavior properties.

The main functions performed by the ANNs are prediction (model) and classification. The purpose of the prediction may be the diagnose (prediction of the lifetime), accelerated life-time testing, on-line control of manufacturing processes that involve wear and prediction of the main properties of the mechanical systems, during the conceptual design stage. The classification is useful for diagnose purposes: recognition of the conditions of operation and recognition of the faults. Usually, the result will have a cost- and time-saving effect. Different technologies, variables and sources of information are subject of the modeling process. Some of the ANN inputs require more previous processing, like Fourier analysis, filtering and image processing.

The most popular ANNs are MLP - for prediction and classification, and self-organizing maps - Kohonen, ART, for classification. Their properties and the diversity of the difficult mechanical processes suggest that new applications of the ANN in tribology will appear in the near future.

REFERENCES

[1]. S. P. Jones, R. Jansen and R.L. Fusaro, "Preliminary investigation of neural network techniques to predict tribological properties", *Tribology Transactions,* vol. 40, no. 2, pp. 312-320, 1997.

[2]. S. P. Jones, R. Jansen and R.L. Fusaro. (2000, Dec.). Tribological Application of ANN. GRNN NASA. [On line]. Available: http://www.grc.nasa.gov/WWW/spacemech/neural.html

[3]. R. L. Fusaro. (1998, Apr.). Feasibility of Using Neural Network Models to Accelerate the Testing of Mechanical Systems. NASA Research Center. [On line]. Available: http://www.lerc.nasa.gov/Other_Groups/RT1997/5000/5930fusaro.htm

[4]. P. Gimondo et al., "Neural Networks for Predicting Tribological Experimental Results" in *Proc. World Tribology Congress*, Vienna, 2001 (paper no. on CD)

[5]. K. Velten, R. Reinicke, and K. Friedrich, "Wear volume prediction with artificial neural networks", *Tribology International*, vol. 33, no.10, pp. 731-736, 2000.

[6]. K. Velten, R. Reinicke, and K. Friedrich, "Neuronale Netze zur Vorhersage und Analyse des Verschleissverhaltens polymerer Gleitwerkstoffe", *Mat.-wiss. u. Werkstofftech.,* vol. 31, pp. 712-714, 2000.

[7]. Z. Zhang et al., "Wear Prediction of Polymer Composites using Artificial Neural Networks", in *Proc. CMSE/1*, 2001, pp. 203-206

[8]. S.C. Lin and R.J. Lin, "Tool wear monitoring in face milling using force signals", *Wear*, vol. 198, no.1-2, pp. 136-142, 1996.

[9]. S. Das et al., "Evaluation of wear of turning carbide inserts using neural networks", *Int. J. Mach. Tools Manufact.,* vol. 36, no. 7, pp. 789-797, 1996.

[10].Y. Ao, Q.J. Wang and P. Chen, "Simulating the Worn Surface in a Wear Process" in *Proc. World Tribology Congress*, Vienna, 2001 (paper no. on CD)

[11].I.N. Tansel et al., "Tool wear estimation in micro-machining. - Part I: tool usage-cutting force relationship", *Int. J. Mach. Tools Manufact.,* vol. 40, no. 4, pp. 599-608, March 2000.

[12].I.N. Tansel et al., "Tool wear estimation in micro-machining. - Part II: neural-network-based periodic inspector for non-metals", *Int. J. Mach. Tools Manufact.*, vol. 40, no. 4, pp. 609-620, March 2000.

[13].A.N. Sinha, P.S. Mukherjee and A. De, "Assessment of useful life of lubricants using artificial neural network", *Ind. Lubric. and Tribology,* vol. 52, no.3, pp. 105-109, 2000.

[14].R.K. Jain, V.K. Jain and P.K. Kalra, "Modelling of abrasive flow machining process: a neural network approach", *Wear,* vol. 231, no.2, pp. 242-248, 1999.

[15].M. Karkoub and A. Elkamel, "Modelling pressure distribution in a rectangular gas bearing using neural networks", *Tribology International,* vol.30, nr. 2, pp. 139-150, 1997.

[16].D. Aiordachioaie, R. Teodorescu and G. Puscasu, "Fault Detection in Electrical Machines with Neural Networks" in *Proc. ELECTROMOTION'95 Symposium,* Cluj-Napoca, Romania, 1995.

[17].N.S. Vyas and D. Satishkumar, "Artificial neural network design for fault identification in a rotor-bearing system", *Mechanism and Machine Theory*, vol. 36, no. 2, pp.157-175, 2001.

[18].M. Subrahmanyam and C. Sujatha, "Using neural networks for the diagnosis of localized defects in ball bearings", *Tribology International,* vol. 30, no.10, pp. 739-752, 1997.

[19].Umeda, J. Sugimura and Y. Yamamoto, "Characterization of wear particles and their relations with sliding conditions", *Wear,* vol. 216, no.2, pp. 220-228, 1998.

[20].N.K. Myshkin et al., "Classification of wear debris using a neural network", *Wear,* vol. 203-204, pp. 658-662, 1997.

[21].K. Xu and A.R. Luxmoore, "An integrated system for automatic wear particle analysis", *Wear*, vol. 208, no.1-2, pp. 184-193, 1997.

[22].K. Xu, A.R. Luxmoore and F. Deravi, "Comparison of Shape Features for the Classification of Wear Particles", *Eng. Applic. of Artificial Intelligence*, vol. 10, no. 5, pp.485-493, Oct. 1997.

[23].H.S. Hundal et al., "Particle shape characterization using image analysis and neural networks", *Powder Technology*, vol. 91, no. 3, pp. 217-227, May 1997.