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IN-PROCESS EVALUATION OF THE OVERALL MACHINING PERFORMANCE IN FINISH-TURNING VIA A SINGLE DATA SOURCE

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ABSTRACT

As a different approach to the condition monitoring of machining processes by sensor fusion, which has been of great interest over the recent time, this paper presents a novel approach of utilising a single data source to evaluate in-process the overall machining performance in finish turning. The overall machining performance includes the variations of machining performance (chip breakability, surface roughness, dimensional accuracy and cutting forces) with progressive tool wear of various types of tool wear (major flank, crater and minor flank wear). The 3-D cutting force measured by a tool dynamometer, perhaps the most reliable data source available for machining processes, is fully utilised through the combination of multivariate time series models and neural network techniques. Dispersion analysis based on the established multivariate time series model of 3-D cutting force is introduced to single out signal features corresponding to particular types of tool wear, and four dispersion patterns along with others are used to train the neural network to quantify the complex interrelationship between machining performance (chip breakability, dimensional accuracy and surface roughness) and progressive tool wear for cutting tools with different chip control geometry. The approach has demonstrated to be a simple yet effective means in on-line monitoring of the overall machining performance for finish-turning operations.

1. INTRODUCTION

Effective in-process estimation of the machining performance is the prerequisite for effective control of machining process in automated machining systems, particularly in finish-turning operations where the surface quality and dimensional accuracy of a finished product take their final form. In general, the machining performance in finish-turning can be characterised by surface roughness, chip breakability, dimensional accuracy, cutting forces and various types of tool wear at major flank, minor flank and rake face. It may change significantly primarily due to the progressive tool wear formed at different tool faces.

Since the present knowledge of machining process and traditional modelling techniques are inadequate to quantify the complex interrelationship between the varying machining performance and progressive tool wear, the neural network technique provides an attractive yet feasible alternative to tackle the problem. Recently, neural networks have been applied to problems associated with machining processes, such as tool wear estimation [1-3], analysis of cutting dynamics [4] and process optimisation [5]. An early work has shown that using neural networks is an effective method for assessing chip forming patterns and surface roughness with tool wear progression for a flat-faced tool [6].

Time series methods have demonstrated to be effective to describe quantitatively the complex machining process and have found a number of applications in machining process monitoring and control [7-10]. However, some types of complex interrelationship, such as varying machining performance with progressive tool wear, can not be found by time series method alone. Dispersion analysis [7, 11-12] based on the multivariate time series models of three-dimensional (3-D) cutting forces has demonstrated to be an effective way to quantitatively discriminate among various modes of process variations [12,13]. Dispersion analysis has been used in previous work [13] to estimate multiple types of tool wear including major flank, crater and minor flank wear, and to extract key features to train neural networks and to assess chip forming patterns and surface roughness with tool wear progression [6].

In condition monitoring of complex processes and systems, monitoring a single variable by proper combining information from several data sources has been known as sensor fusion [1-3, 14]. Although synthesising information from several sensors may provide more reliable estimates of the process variable, it increases the complexity as well as the cost of the monitoring system. The unique feature of the method presented in this paper is that a single but perhaps the most reliable sensor is fully utilised to evaluate the overall machining performance in-process.

With the aid of neural networks an on-line monitoring strategy has been developed by using 3-D cutting force signal to evaluate in-process the overall machining performance including the variations of surface roughness, chip breakability, dimensional accuracy and cutting force with progressive tool wear of various types (major flank, crater and minor flank wear). The 3-D cutting force measured through a single sensor (tool dynamometer), is fully utilised to form a simplified yet multi-functional monitoring system.

2. EXPERIMENT AND MACHINING CONDITIONS

Three types of cutting tools were used to conduct a series of machining experiments to study the patterns of progressive tool wear and the corresponding patterns of surface roughness, chip breakability, dimensional accuracy and cutting forces. The experiments were conducted under typical finish-turning conditions, as shown in Table 1. The cutting conditions are arranged into two groups, one for training the neural networks and the other for testing. For training the neural networks, the degrade tool tests [15] were adopted to shorten the expensive and time-consuming tool wear experiments by using softer tool material for

TABLE 1 MACHINING CONDITIONS USED FOR TRAINING AND TESTING NEURAL NETWORKS

Machine Tool	Colchester Mascot 1600 (9.3kW)
Work Material	AISI4140 (BHN=300) : C 0.4% Mn 0.8% Mo 0.2% Cr 0.9%
Tool Inserts	i) TNMA160408F flat-faced ii) TNMG160408 groove-style iii) TNMG160408 obstruction-style
Tool Material	For training : carbide SECO 883 For testing : carbide SECO 883 and carbide P10
Tool Geometry	0°, 5°, -6°, 90°, 60°, 0.8
Cutting Conditions for Training	Cutting Speed : 115m/min 145m/min 180m/min Feed : 0.06mm/rev 0.1mm/rev 0.15mm/rev Depth of Cut : 0.5mm 1.0mm
Cutting Conditions for Testing	Cutting Speed : 100 - 200 m/min Feed : 0.06 - 0.20 mm/rev Depth of Cut : 0.25 - 1.5 mm

harder workpieces.

A tool dynamometer (Kistler 9257A) was used to measure the 3-D cutting force, i.e., main cutting force F_z, feed force F_x and thrust force F_y. Scanning electron microscope (SEM), stereo microscope with camera attachment and surface measuring instrument (Surfcom 550AD) were jointly used to measure various tool wear parameters. A portable surface measuring instrument was used to assess the surface roughness in terms of the arithmetic mean deviation R_a by taking the average from four measurements around the periphery but along the same circle of workpiece. Dimensional accuracy ΔD was assessed by using a coordinate measuring machine (CMM) in terms of the error on the workpiece diameter. A fuzzy membership rating system [16-17] was introduced to quantify the chip breakability within a range (0, 1) according to the chip shape/size produced. The membership value is assigned in such a way that the larger the membership value is, the better the chip breakability.

3. Multivariate Time Series Model for Progressive Tool Wear Patterns

To estimate multiple types of tool wear, trivariate time series model ARV(n) was developed to based on the 3-D cutting forces,

$$\begin{bmatrix} F_x(t) \\ F_y(t) \\ F_z(t) \end{bmatrix} = \sum_{k=1}^{n} \begin{bmatrix} \phi_{xx}^{(k)} & \phi_{xy}^{(k)} & \phi_{xz}^{(k)} \\ \phi_{yx}^{(k)} & \phi_{yy}^{(k)} & \phi_{yz}^{(k)} \\ \phi_{zx}^{(k)} & \phi_{zy}^{(k)} & \phi_{zz}^{(k)} \end{bmatrix} \begin{bmatrix} F_x(t-k) \\ F_y(t-k) \\ F_z(t-k) \end{bmatrix} + \begin{bmatrix} a_x(t) \\ a_y(t) \\ a_z(t) \end{bmatrix} \quad (1)$$

where the elements of the matrix $\phi^{(k)}$ are the autoregressive coefficients which describe the instantaneous dynamics of the machining process and $[a_x(t), a_y(t), a_z(t)]^T$ the independent random variables. The model order n can be determined by the F-test [7] or AIC method [18].

Based on the multivariate time series model, the dispersion analysis can be introduced to single out features in the signals corresponding to particular types of tool wear. As the calculation of dispersion (d_i) is directly related to the eigenvalues (λ_i) of each time series of the ARV(n) model, the dispersion percentage (D_i) can be introduced to quantify the contribution of each eigenvalue to the variation (γ_o) of the time series concerned, as shown below :

$$D_i = \frac{d_i}{\gamma_o} = (g_i \sum_{k=1}^{n} \frac{\sigma_a g_k}{1-\lambda_i \lambda_k}) / \gamma_o$$

(i=1, 2, ..., n for each time series) (2)

where d_i is the dispersion value and σ_a the covariance of the random variables, and g_i is calculated as follows :

$$g_i = \frac{\lambda_i^{n-1}}{\prod_{k=1, k\neq i}^{n} (\lambda_i - \lambda_k)} \quad (3)$$

Particularly, the eigenvalues appearing in complex conjugate pairs contribute to the oscillating variations of the machining process. The most interesting findings, as shown in Fig. 1, are the close interrelationship existing among (i) various types of forces acting on different tool faces; (ii) various types of wear formed at different tool faces; and (iii) various modes of dispersion patterns of 3-D cutting force. From Fig. 1, it was also found that all LF (low frequency) dispersions are related to the normal forces and HF (high frequency) to the tangential forces.

Earlier work [12-13] has consistently shown that two dominant percentage dispersions, D_i(LF) in low frequency related to the idle frequency of machine-tool and D_i(HF) in high frequency related to the natural frequency of the tool/tool-holder/dynamometer system, exhibit patterns agreeable with that of the wear rate patterns of major flank wear VB, crater depth KT and minor flank wear VB'. The general trends found from this work between the progressive patterns of tool wear rates and dispersion patterns are shown in Fig. 2.

4. NEURAL NETWORKS FOR MODELLING THE OVERALL MACHINING PERFORMANCE

As it is difficult to develop the interrelationship between the variations of machining performance and progressive tool wear by using multivariate time series model alone, neural networks were employed to take the advantage that the complex mechanisms involved can be quantified based on the observed data. In addition, once a neural network is trained off-line, it can be readily implemented into an on-line monitoring system. Applying neural network in this paper starts with learning the mapping between inputs (tool wear progression along with others) and outputs (chip breakability, dimensional accuracy and surface roughness) by using the given input-output data sets.

Once the mapping from the inputs to outputs has been learned, the neural networks will be capable of predicting outputs for any inputs which were ever not previously presented to the system. Back-propagation (BP) algorithm is a learning strategy which trains the input-output relation through a multi-layered feed-forward neural network [19-20].

In applying neural networks for the problem in question, it is vital to select appropriate inputs. They must be sensitive to the particular types of tool wear, which are the dominant factors influencing the chip breakability, dimensional accuracy and surface

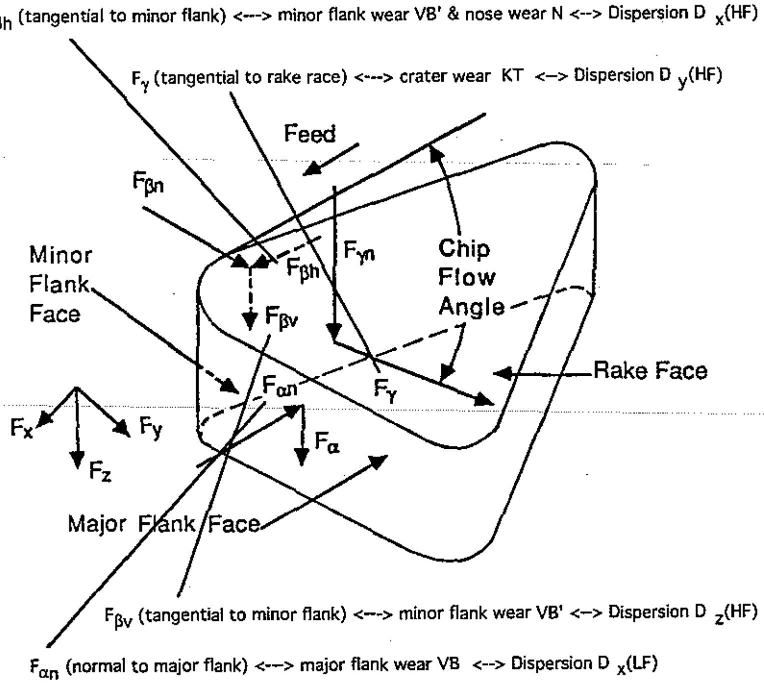

FIG. 1 INTERRELATIONSHIP BETWEEN VARIOUS TYPES OF FORCES/WEAR AT DIFFERENT TOOL FACES AND THE FOUR DISPERSION PATTERNS RECOGNISED FROM 3-D CUTTING FORCE

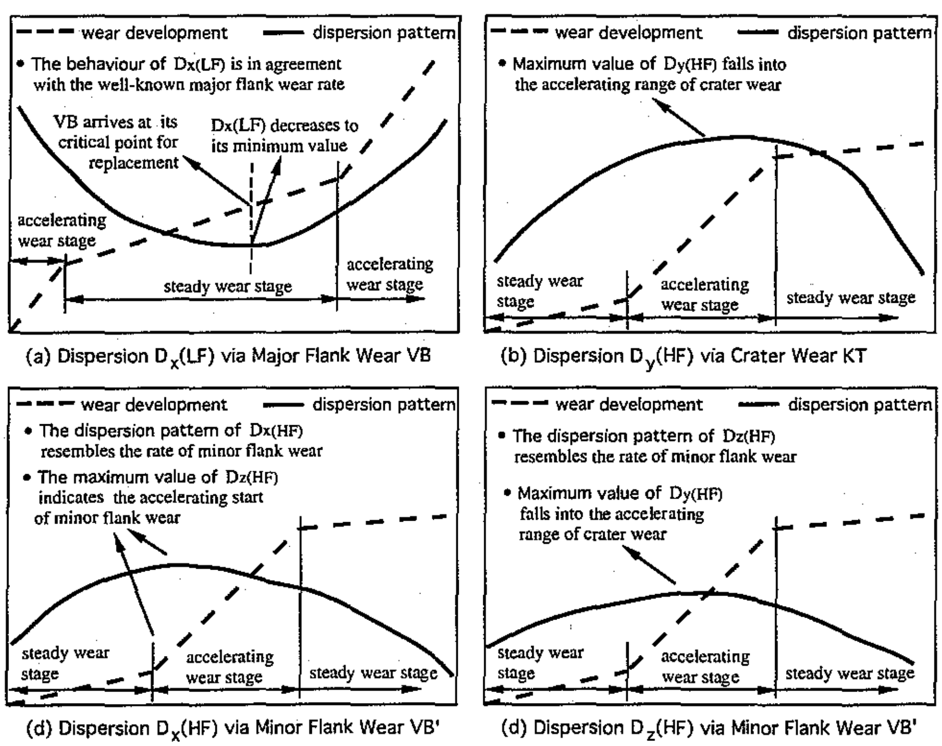

FIG. 2 FOUR DISPERSION PATTERNS RELEVANT TO THE PROGRESSIVE TOOL WEAR

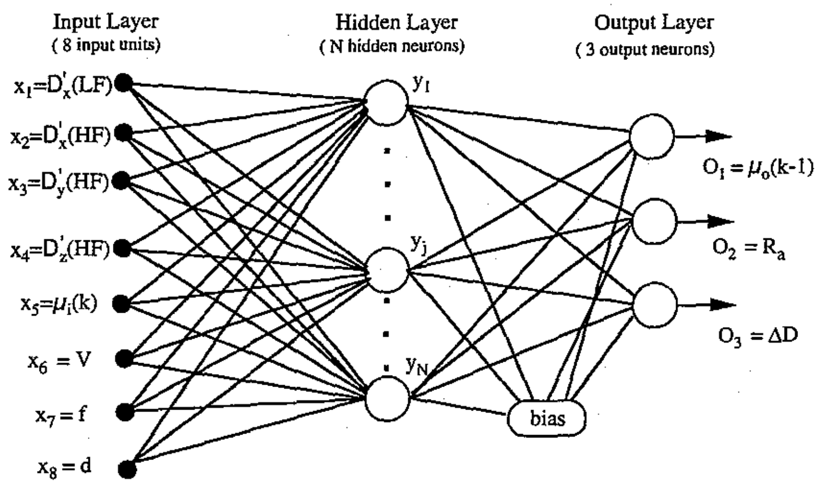

FIG. 3 THE STRUCTURE OF A 3-LAYER BP NEURAL NETWORK

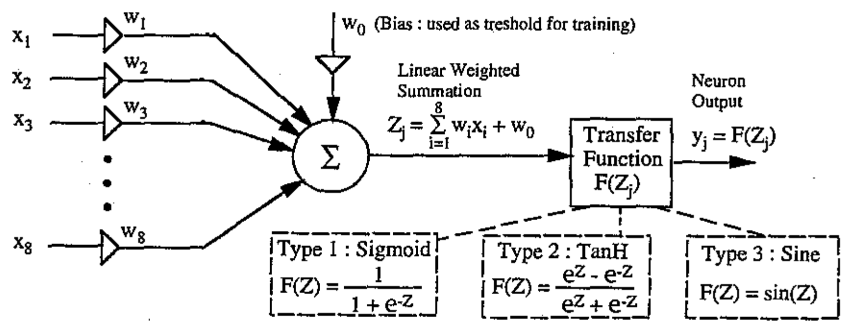

FIG. 4 ALGORITHM OF A PERCEPTRON NEURON IN BP NEURAL NETWORK

roughness. In this work, 8 features were selected to construct a three-layer BP neural network for predicting 3 process outputs, i.e., chip breakability $\mu_o(k-1)$, surface roughness R_a and dimensional accuracy ΔD, as shown in Fig. 3. The first four input features are dispersion patterns which are related to the overall tool wear at different tool faces. The fifth input feature is the chip breakability $\mu_i(k)$. Based on the assumption that no sudden change in chip breakability will occur as tool wear normally progresses gradually, it is reasonable to use the output of chip breakability from the neural network at previous time interval $\mu_o(k-1)$ as the value of current input $\mu_i(k)$, that is

$$\mu_i(k) = \mu_o(k-1) \quad \text{for } k = 1, 2, \ldots \tag{4}$$

where the initial value $\mu_i(0)$ is predicted from the established chip breakability database for unworn tool inserts. Three important machining process parameters, cutting speed, feed rate and depth of cut, were chosen as input features as well due to their close relationship with overall tool wear progression, chip breakability, surface roughness and dimensional accuracy.

The function of and the algorithm associated with a perception neuron, such as the one in hidden layer or output layer, used in this work are shown in Fig. 4.

As the aim of using neural networks is to predict the evolving patterns of chip breakability, dimensional accuracy and surface roughness with different progressive stage of tool wear, the input data should be presented to the neural networks by group, as shown in Table 2 for three representative groups of input-output data.

As no prior knowledge about how many hidden neurons and which transfer function would produce the best performance for the problem in question, a trial-and-error approach has to be used in this work to train the neural network with three common transfer functions (Sigmoid, TanH and Sine) and different number of neurons in the hidden layer (maximum to 16). From the training process, it was found impossible to achieve the expected accuracy by using a single neural network structure for all three types of cutting tools. Therefore, a neural network structure was used for each type of tool insert based on the minimum RMS error generated during the training process. Shown in Table 3 are the neural network structures from the results of training for three different types of cutting tools. A neural computing software, NeuralWorks Professional II was used for training. Once such neural networks are established off-line, the corresponding non-linear functions and the identified weights can be readily implemented into an on-line monitoring system.

5. SYSTEM INTEGRATION AND PERFORMANCE TESTING

By integrating all the algorithms developed for evaluating the different aspects of overall machining performance including major flank, crater and minor flank wear, and the variations of surface roughness, chip breakability, dimensional accuracy and cutting force with progressive tool wear for different types of tool inserts, a single sensor based in-process monitoring system is schematically shown in Fig. 5.

In order to test the performance of the established monitoring system, a series of machining experiments were conducted under the conditions which were not previously presented to the training of neural networks. Shown in Fig. 6 (a soft flat-faced tool) and Fig. 7 (a hard grooved tool) are two sets of representative results for in-process evaluating the overall machining performance (the 3-D cutting force which can be directly obtained from the tool dynamometer is not included). As seen, the deviation of the neural network outputs from the actual experimental results is small therefore the system would be effective in evaluating the overall machining performance for finish-turning conditions.

TABLE 2 THREE REPRESENTATIVE GROUPS OF INPUT-OUTPUT DATA FOR TRAINING NEURAL NETWORKS

Input Features to Neural Networks								Outputs		
D_x'(LF) min^{-1}	D_x'(HF) min^{-1}	D_y'(HF) min^{-1}	D_z'(HF) min^{-1}	$\mu_i(k)$	Speed m/min	Feed mm/rev	Depth of Cut mm	$\mu_o(k)$	R_a μm	ΔD μm
• Group 1 : flat-faced tool										
-4.91	3.22	1.50	1.47	0.25	115	0.1	0.5	0.25	1.09	0
-3.89	2.52	1.31	1.15	0.25	115	0.1	0.5	0.30	1.14	15
-3.03	1.92	1.14	0.87	0.30	115	0.1	0.5	0.32	1.23	38
-1.15	0.62	0.78	0.27	0.32	115	0.1	0.5	0.35	1.32	60
0.73	-0.68	0.42	-0.33	0.35	115	0.1	0.5	0.41	1.78	105
2.61	-1.98	0.06	-0.93	0.41	115	0.1	0.5	0.58	1.99	168
4.49	-3.28	-0.30	-1.53	0.58	115	0.1	0.5	0.51	2.35	209
6.05	-4.36	-0.59	-2.04	0.51	115	0.1	0.5	0.46	2.50	243
7.78	-5.62	-0.95	-2.61	0.46	115	0.1	0.5	0.42	2.68	273
• Group 2 : groove-style tool										
-1.75	2.64	1.32	2.64	0.47	115	0.1	0.5	0.47	0.88	0
-1.51	2.39	1.16	2.42	0.47	115	0.1	0.5	0.48	1.02	14
-1.26	1.99	0.90	2.12	0.48	115	0.1	0.5	0.49	1.09	35
-0.77	1.17	0.38	1.50	0.49	115	0.1	0.5	0.51	1.21	65
-0.28	0.36	-0.14	0.89	0.51	115	0.1	0.5	0.53	1.84	109
0.21	-0.46	-0.66	0.27	0.53	115	0.1	0.5	0.54	2.07	153
0.70	-1.28	-1.18	-0.35	0.54	115	0.1	0.5	0.46	2.25	186
1.19	-2.09	-1.70	-0.96	0.46	115	0.1	0.5	0.43	2.43	228
1.68	-2.91	-2.22	-1.58	0.43	115	0.1	0.5	0.43	2.55	247
• Group 3 : obstruction-style tool										
-2.56	1.72	1.69	1.86	0.62	115	0.1	0.5	0.62	0.95	0
-2.33	1.60	1.54	1.72	0.62	115	0.1	0.5	0.60	1.06	12
-1.94	1.38	1.30	1.48	0.60	115	0.1	0.5	0.58	1.15	31
-1.17	0.95	0.80	1.00	0.58	115	0.1	0.5	0.54	1.29	57
-0.32	0.48	0.26	0.47	0.54	115	0.1	0.5	0.50	1.95	84
0.37	0.09	-0.19	0.04	0.50	115	0.1	0.5	0.48	2.05	121
1.14	-0.34	-0.69	-0.44	0.48	115	0.1	0.5	0.45	2.19	161
1.91	-0.77	-1.18	-0.92	0.45	115	0.1	0.5	0.41	2.47	201
2.83	-1.29	-1.77	-1.50	0.41	115	0.1	0.5	0.40	2.62	235

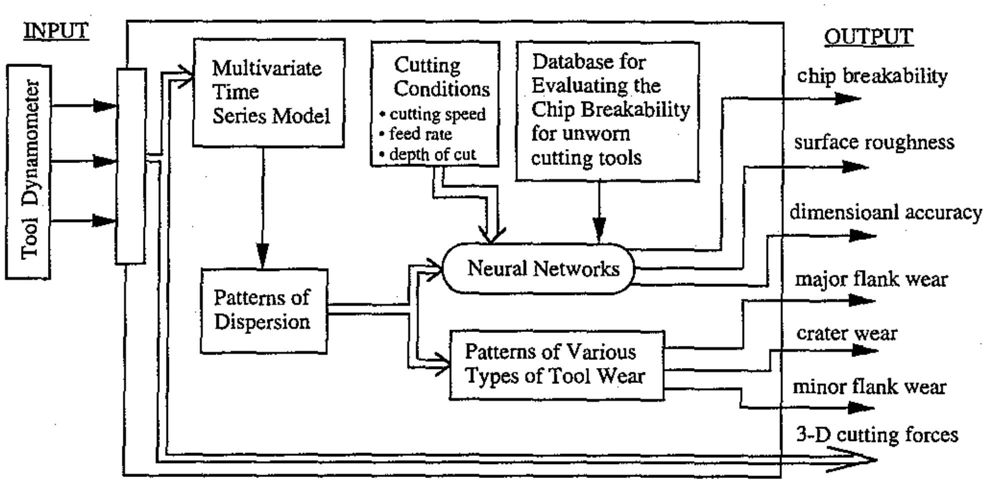

FIG. 5 A SINGLE SENSOR BASED MULTI-FUNCTIONAL MONITORING SYSTEM FOR IN-PROCESS EVALUATING THE OVERALL MACHINING PERFORMANCE

TABLE 3 NEURAL NETWORKS ESTABLISHED FOR DIFFERENT TOOL INSERTS

Tool Inserts	Neural Network Structure			Transfer Function	RMS Errors
	Input	Hidden Neurons	Output		
flat-faced	8	14	3	TanH	0.013
groove-style	8	14	3	TanH	0.015
obstruction-style	8	15	3	Sigmoid	0.024

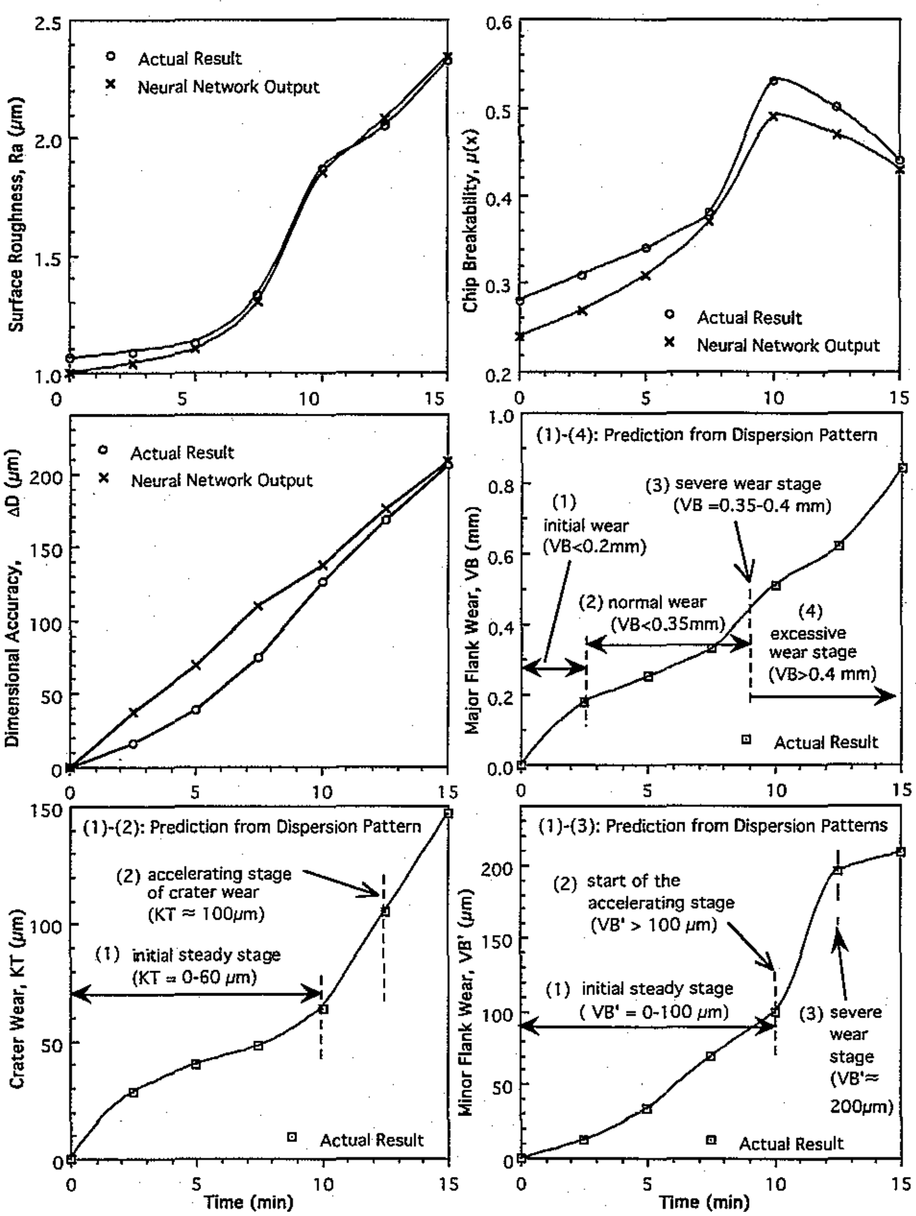

FIG. 6 A REPRESENTATIVE EXAMPLE OF THE TESTING RESULTS OF THE OVERALL MACHINING PERFORMANCE FOR A SOFT FLAT-FACED TOOL (V = 140m/min, f = 0.12mm/rev, d = 0.5mm, Tool Grade = SECO 883)

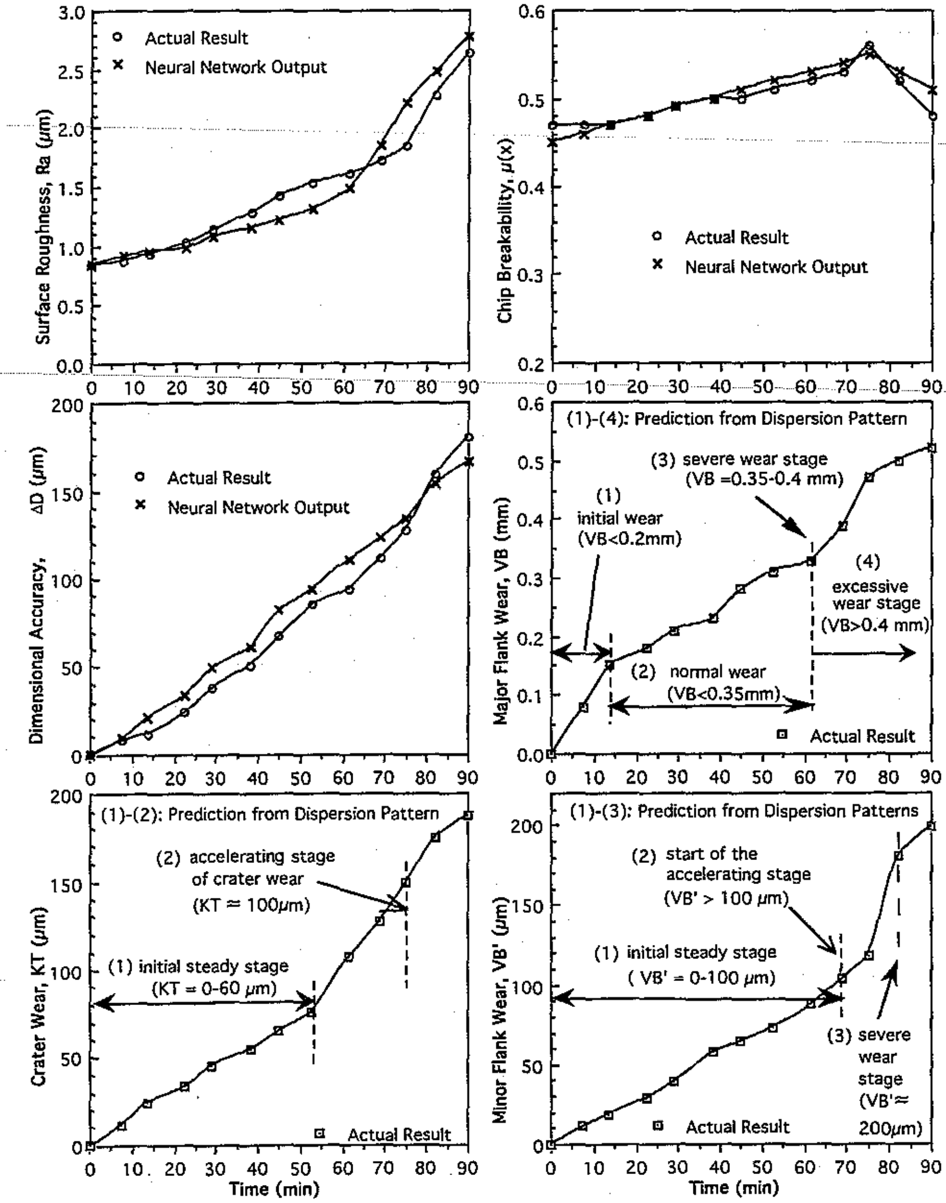

FIG. 7 A REPRESENTATIVE EXAMPLE OF THE TESTING RESULTS OF THE OVERALL MACHINING PERFORMANCE FOR A HARD GROOVE-STYLE TOOL (V = 170m/min, f = 0.10mm/rev, d = 0.5mm, Tool Grade = ISO P10)

6. CONCLUDING REMARKS

As contrasted to the more recently popular approach of sensor fusion, this paper presents a approach by using a single yet perhaps the most reliable sensor to evaluate in-process the overall machining performance through a novel combination of multivariate time series analysis and neural network techniques. How to fully utilise the single data source, i.e., 3-D cutting force, to achieve the on-line evaluation of overall machining performance including various types of tool wear, and cutting forces, chip breakability, dimensional accuracy and surface roughness with progressive tool wear, has been illustrated. The results show that a reasonable effectiveness was achieved under the selected cutting conditions for three cutting tools of different chip control geometry. Therefore, the approach described in this paper may serve as an attractive alternative to sensor fusion in developing on-line assessment strategy for automated machining systems.

However, the major drawback of the back-propagation (BP) neural networks used in this work is that the learning algorithm is based on a "supervised" strategy which needs desired output patterns in each case. It is not economic to conduct extensive experiments to find the target patterns for numerous combinations of work materials and tool configurations/geometry. Therefore, a strategy of "learning by self-organising" should be developed to replace currently used "learning by being shown". The significance of a self-organising neural network is its ability to adapt to the environments where rules may change unpredictably, that is, the ability to adapt through direct confrontation with its "experiences" without a teacher to "supervise".

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