Summary and Conclusion

A mechanics-based model has been developed and utilized in this paper for analyzing steady-state filament/workpiece contact during concentric brushing of a cylindrical workpiece. The analysis enables one to compute the response of filament/workpiece reaction force, filament torque, and filament stress associated with a specified brush geometry, filament composition, and brush operating condition. This, in turn, provides a basis for determining the power requirement for driving the brush, as well as the anticipated brush life and/or operating conditions that can lead to fiber damage or rapid/excessive wear of brush honing tools.

All brush response parameters (i.e., force, stress, and torque) exhibit large gradients at small brush penetration depths which, as a matter of practical importance, corresponds to the brush/workpiece engagement that is customarily used in brush honing applications. This finding suggests that although normal wear of the abrasive cluster can lead to a relatively small reduction of brush/workpiece engagement, brush performance may be significantly altered by such wear. Thus, it is conjectured that an improved consistency of honing tool machining performance can be obtained by employing greater brush/workpiece engagement during the brushing process. Specific recommendations for improved brush performance, however, must be made within the context of the overall design of the brushing tool. Further research in this area can lead to the improved design and performance of brush honing tools. However, this research must also be accompanied by an improved understanding of material removal mechanics issues which, at present, remain unexplored for brush honing tools.

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In-process Evaluation of the Overall Machining Performance in Finish-Turning via Single Data Source

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Sensor fusion often uses multiple sensors to evaluate a single quantity. The work presented in this paper attempts to use information from a single sensor to estimate overall machining performance (characterized by cutting forces, chip breakability, surface roughness, and dimensional deviation due to tool wear). In particular, the performance is aimed at reflecting the in-process changes of the above-named quantities with respect to tool wear progression (major flank, crater and minor flank wear). 3-D cutting force measured by a tool dynamometer is fully utilized by aggregating multivariate time series models and neural network techniques. Dispersion analysis is used to extract signal features which correlate well with progressive tool wear. The results have shown the effectiveness of the proposed method which also has the obvious merit of simplicity.

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Table 1 Experimental set-up and conditions used

Machine Tool	Colchester Mascot 1600 (9.3kW)
Sensor Used	3-component tool dynamometer (Kistler 9257A)
Work Material	AISI4140 (BHN=300): C 0.4, Mn 0.8, Mo 0.2, Cr 0.9
Tool Inserts	i) TNMA332F flat-faced ii) TNMG332 groove-style iii) TNMG332 obstruction-style
Tool Material	Carbide SECO 883 and Carbide P10 (for testing only)
Tool Geometry	0°, 5°, -6°, 90°, 60°, 0.8
Training Conditions	Cutting Speed, V (m/min): 115 145 180 Feed, f (mm/rev): 0.06 0.10 0.15 Depth of Cut, d (mm): 0.5 1.0
Testing Conditions	V=100-200m/min, f=0.06-0.2mm/rev, d=0.25-1.5mm

1 Introduction and Experimental Set-up

In condition monitoring of complex processes, the method of combining information from several sensors has been known as sensor fusion (Dornfeld, 1990). Although fusing information from several sensors may provide more reliable estimates, the complexity and cost may increase as a result. This paper presents an investigation into the feasibility of using a single sensor to estimate multiple indices, built upon the authors' previous work on multivariate time series (ARV) analysis and neural network modeling (Yao and Fang 1992, 1993). The new ideas of this work can be described as (i) in fundamental, presenting an approach to using a single sensor to monitor multiple indices as a contrast to the currently popular sensor-fusion method, thus having the obvious merit of simplicity; (ii) in methodology, developing a new way to integrate ARV models with neural networks for on-line prediction of machining performance during tool wear progression; and (iii) in particular, contributing to better understanding of the dynamic and complex relationship between wear formation and the forces acting on different tool faces as a result of process variations. In addition to this, the experimental conditions have been extended to include different types of tool chip breakers, as shown in Table 1.

2 Multivariate Time Series Modeling for Progressive Tool Wear Estimation

To estimate multiple types of tool wear, trivariate time series model ARV(n) was first developed based on experimental data of 3-D cutting force, that is,

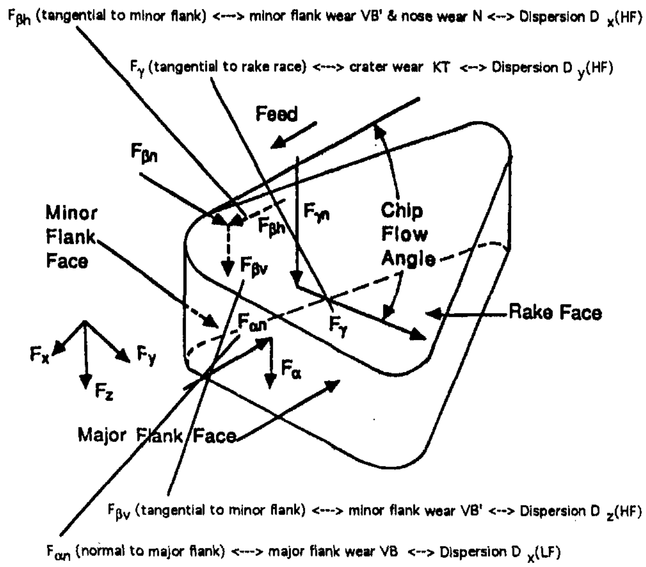

Fig. 1 Interrelationship between forces, wear and dispersions

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

where the elements of the matrix $\phi^{(k)}$ are the autoregressive coefficients which describe the instantaneous dynamics of the machining process, $[a_x(t), a_y(t), a_z(t)]^T$ is the independent random variable matrix, and n is the model order. In this work, $n = 11$ was found to be adequate for all three types of tools under various cutting conditions. Then, ARV dispersion analysis was used to single out the features which can be effectively correlated with progressive tool wear.

Figure 1 is a direct and dynamic reflection of the interaction between the cutting tool and the workpiece on three different tool faces, for example, F_α and $F_{\alpha n}$ are resulted from the interaction between major flank and workpiece in feed direction; F_γ and $F_{\gamma n}$ from that between rake face and chip flow; and F_β, $F_{\beta h}$ and $F_{\beta v}$ from that between minor flank and workpiece in both feed and cutting directions. This force model shows the close interrelationships existing among (i) forces acting on different tool faces; (ii) wear formed at different tool faces; and (iii) dispersion patterns of 3-D cutting force.. This can be summarized that the LF (low frequency) dispersion is related to the normal force and HF (high frequency) dispersions to the tangential forces. These forces can in turn be related to various types of wear, i.e., major flank wear VB, crater depth KT and minor flank wear VB'. Based on this physical analysis, these types of wear are then plotted against the corresponding dispersions as seen in Fig. 2. It can be clearly seen that dispersion patterns correlate well with the development of wear, which is obtained from actual measurements. It should be pointed out that, although the actual values of dispersions and wear may vary from one condition to another, the patterns of correlation shown in Fig. 2 are consistent under all experimental conditions.

3 Neural Network Modeling

In this work, back-propagation (BP) algorithm is used, which trains the input-output relation through a multi-layered feed-forward neural network by using the experimentally obtained data. After the mapping from inputs to outputs has been trained, the network is capable of predicting outputs for any inputs that were not previously presented. In this work, 8 input features were selected to construct a 3-layer BP neural network for predicting 3 process outputs (surface roughness, chip breakability and dimensional deviation due to tool wear). The first four input features are derivatives of force dispersion patterns, i.e. D_x'(LF), D_x'(HF), D_y'(HF) and D_z'(HF). The reason for choosing derivatives is because only development trends, instead of individual values, of disper-

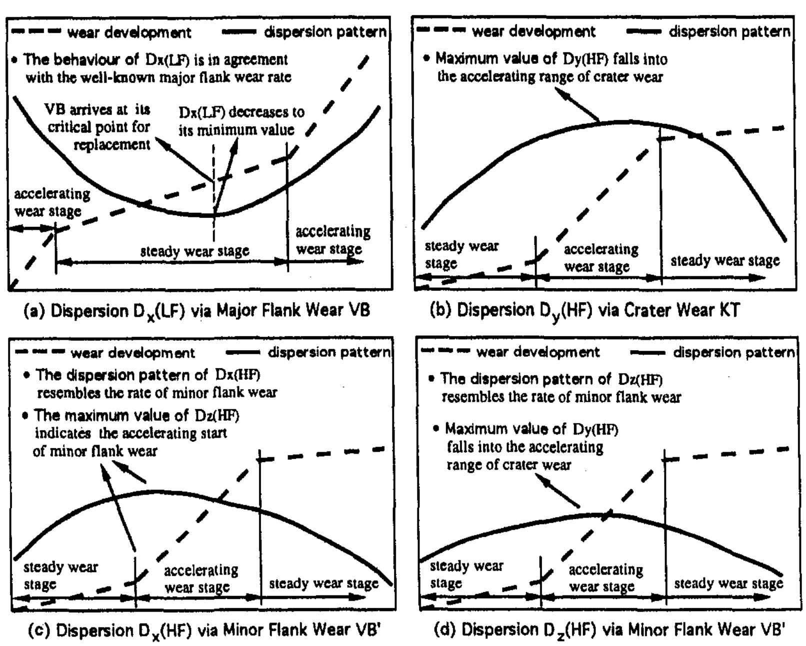

Fig. 2 Four dispersion patterns with respect to progressive tool wear

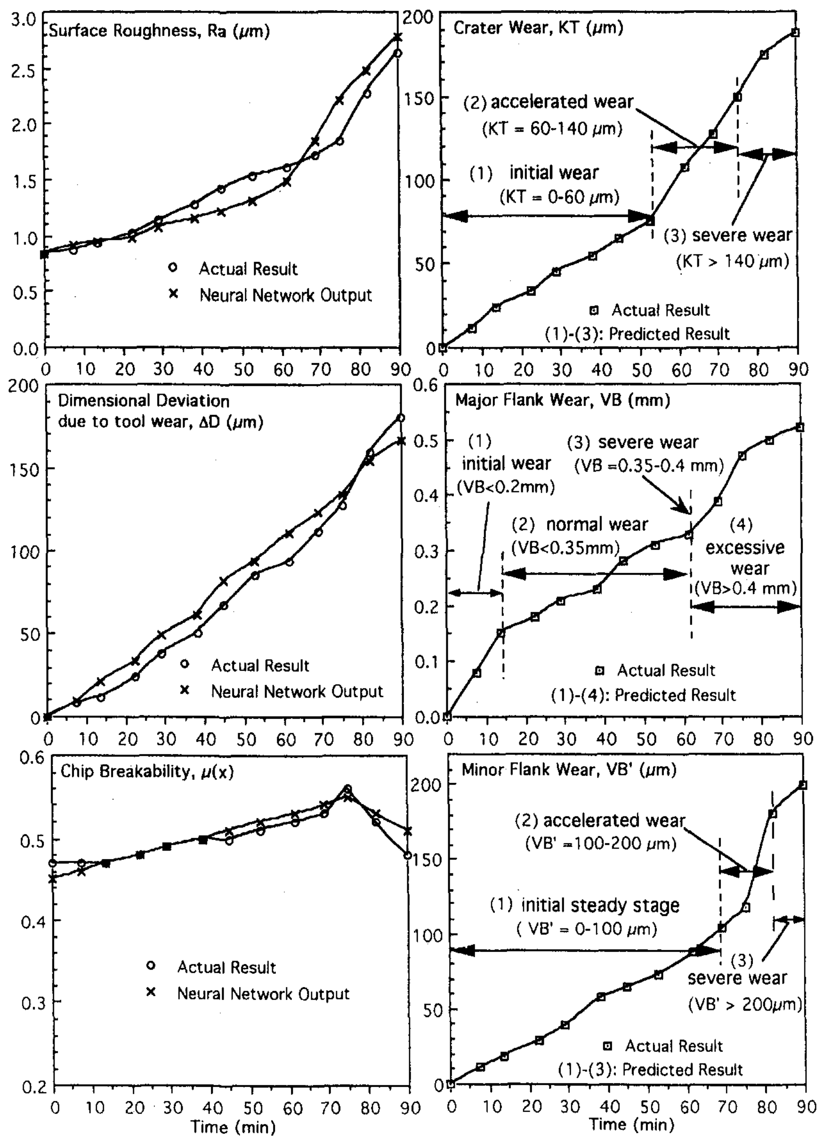

Fig. 3 A representative testing result (V = 170m/min, f = 0.10 mm/rev, d = 0.5 mm, grooved tool with grade P10)

sions, are related to progressive tool wear. The fifth input feature is the chip breakability quantified in numerical value $\mu_i(k)$ (Fang and Jawahir, 1993). By assuming that no sudden changes in chip breakability can occur as tool wear always develops gradually, the output of chip breakability at previous time interval $\mu_o(k-1)$ is used as the current input $\mu_i(k)$. Three most important process parameters, i.e., cutting speed, feed and depth of cut, were chosen as the rest of input features. Their intimate relationship with overall machining performance justifies the choice.

4 Performance Testing

In order to test the performance of the proposed method, machining experiments were conducted under nine conditions different from those used in training. Shown in Fig. 3 is a representative set of results using a grooved tool. As seen, there are reasonable agreements between the values predicted by the neural net and those measured from the actual tests. Progressive tool wear is predicted based on ARV dispersion patterns and assessed in terms of different wear stages, e.g. four stages for major flank wear, i.e. (1) initial, (2) normal, (3) severe and (4) excessive.

To ascertain the statistical soundness of the method developed, two representative testing results from 9 different conditions are given in Fig. 4 for surface roughness and major flank wear. In general, the deviations of the predicted outputs from the actual testing results are reasonably small therefore the method would be effective in evaluating the overall machining performance.

5 Concluding Remarks

As contrasted to the approach of sensor fusion, this paper presents an approach of using a single sensor to evaluate overall machining performance. It is achieved by combining multivariate time series analysis and neural network techniques. The results show that the method is reasonably effective under the selected cutting conditions for all three different tools. It should be pointed out that this paper does not attempt to demonstrate that the proposed method is superior to sensor fusion. Instead, it is aimed at showing that the method is effective as evident

(a) Testing Results for Surface Roughness

TEST	Errors (%) of Surface Roughness R_a (μm) at the Different Cutting Times													Average Errors
	t=0	t=Δt	t=2Δt	t=3Δt	t=4Δt	t=5Δt	t=6Δt	t=7Δt	t=8Δt	t=9Δt	t=10Δt	t=11Δt	t=12Δt	
TEST 1 (Δt≈2.5')	5.7	5.5	2.7	2.3	1.1	1.5	0.5							2.8%
TEST 2 (Δt=6'-9')	0	4.6	2.2	3.9	4.4	10	14	14	7.5	7.6	19	8.8	5.7	7.8%
TEST 3 (Δt≈2.5')	8.0	4.2	2.8	4.5	3.2	2.9	10							5.1%
TEST 4 (Δt≈2.5')	14	8.0	6.2	2.1	9.3	5.8	5.5							7.3%
TEST 5 (Δt≈2')	11	3.4	10	8.9	8.1	7.5								8.2%
TEST 6 (Δt≈2.5')	13	8.6	11	5.2	7.2	6.8	6.5							8.3%
TEST 7 (Δt≈2.5')	11	7.4	6.9	7.7	4.2	3.0								6.7%
TEST 8 (Δt≈2')	7.5	5.9	8.0	11	6.2	5.4								7.3%
TEST 9 (Δt≈7.5')	9.2	6.8	7.0	7.3	2.5	2.3	2.0	4.7	6.0	7.7	8.7	6.2		5.9%

(b) Testing Results for Major Flank Wear

TEST	Comparison of Major Flank Wear VB (mm) at the Different Cutting Times													
		t=0	t=Δt	t=2Δt	t=3Δt	t=4Δt	t=5Δt	t=6Δt	t=7Δt	t=8Δt	t=9Δt	t=10Δt	t=11Δt	t=12Δt
TEST 1 (Δt≈2.5')	predicted	i.w.	i.w.	n.w.	n.w.	s.w.	e.w.	e.w.						
	actual	0	0.18	0.25	0.33	0.51	0.62	0.84						
TEST 2 (Δt=6'-9')	predicted	i.w.	i.w.	i.w.	n.w.	n.w.	n.w.	n.w.	n.w.	s.w.	e.w.	e.w.	e.w.	e.w.
	actual	0	0.08	0.15	0.18	0.21	0.23	0.28	0.31	0.33	0.39	0.47	0.50	0.52
TEST 3 (Δt≈2.5')	predicted	i.w.	i.w.	n.w.	n.w.	s.w.	e.w.	e.w.						
	actual	0	0.17	0.23	0.30	0.48	0.57	0.80						
TEST 4 (Δt≈2.5')	predicted	i.w.	i.w.	n.w.	n.w.	s.w.	e.w.	e.w.						
	actual	0	0.15	0.20	0.28	0.46	0.52	0.74						
TEST 5 (Δt≈2')	predicted	i.w.	i.w.	n.w.	n.w.	s.w.	e.w.							
	actual	0	0.19	0.27	0.34	0.39	0.54							
TEST 6 (Δt≈2.5')	predicted	i.w.	i.w.	n.w.	n.w.	s.w.	e.w.	e.w.						
	actual	0	0.21	0.28	0.38	0.50	0.60	0.84						
TEST 7 (Δt≈2.5')	predicted	i.w.	i.w.	n.w.	n.w.	n.w.	s.w.							
	actual	0	0.18	0.30	0.37	0.44	0.56							
TEST 8 (Δt≈2')	predicted	i.w.	i.w.	n.w.	n.w.	s.w.	e.w.	e.w.						
	actual	0	0.15	0.19	0.26	0.46	0.50	0.65						
TEST 9 (Δt≈7.5')	predicted	i.w.	i.w.	i.w.	i.w.	n.w.	n.w.	n.w.	n.w.	n.w.	s.w.	e.w.	e.w.	
	actual	0	0.10	0.14	0.19	0.21	0.24	0.26	0.29	0.31	0.36	0.42	0.49	

• i.w.=initial wear (<0.2mm), n.w.=normal wear (<0.35mm), s.w.=severe wear (0.35-0.4mm), e.w.=excessive wear (>0.4mm)
• Highlighted squares indicate that the actual testing results are not fallen into the predicted tool wear stages.

Fig. 4 Two representative results of statistical performance testing

in the experimental investigation, while it has the obvious advantage of simplicity.

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