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 processes 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, cannot 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

<table>
<thead>
<tr>
<th>Machine Tool</th>
<th>Colchester Mascot 1600 (9.3kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Work Material</td>
<td>AISI 4140 (BHN=300) : C 0.4% Mn 0.8% Mo 0.2% Cr 0.9%</td>
</tr>
<tr>
<td>Tool Inserts</td>
<td>i) TNMA160408 flat-faced</td>
</tr>
<tr>
<td></td>
<td>ii) TNMC160408 groove-style</td>
</tr>
<tr>
<td></td>
<td>iii) TNMG160408 obstruction-style</td>
</tr>
<tr>
<td>Tool Material</td>
<td>For training: carbide SECO 853</td>
</tr>
<tr>
<td></td>
<td>For testing: carbide SECO 853 and carbide P10</td>
</tr>
<tr>
<td>Tool Geometry</td>
<td>(0°, 30°, 60°, 90°, 60°, 0.8)</td>
</tr>
<tr>
<td>Cutting Conditions</td>
<td>Cutting Speed: 115m/min</td>
</tr>
<tr>
<td></td>
<td>145m/min</td>
</tr>
<tr>
<td></td>
<td>180m/min</td>
</tr>
<tr>
<td>for Training</td>
<td>Feed:</td>
</tr>
<tr>
<td></td>
<td>0.06mm/rev</td>
</tr>
<tr>
<td></td>
<td>0.15mm/rev</td>
</tr>
<tr>
<td>for Testing</td>
<td>Depth of Cut:</td>
</tr>
<tr>
<td></td>
<td>0.5mm</td>
</tr>
<tr>
<td></td>
<td>1.0mm</td>
</tr>
<tr>
<td>Cutting Conditions</td>
<td>Cutting Speed: 100-200 m/min</td>
</tr>
<tr>
<td>for Testing</td>
<td>Feed:</td>
</tr>
<tr>
<td></td>
<td>0.05-0.20 mm/rev</td>
</tr>
<tr>
<td></td>
<td>Depth of Cut:</td>
</tr>
<tr>
<td></td>
<td>0.25-1.5 mm</td>
</tr>
</tbody>
</table>

where \( d_i \) is the dispersion value and \( \sigma_i \) the covariance of the random variables, and \( g_i \) is calculated as follows:

\[
\sigma_i = \frac{1}{\prod_{k=1}^{n} (\lambda_k - \lambda)}
\]

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, \( D(LF) \) in low frequency related to the idle frequency of machine-tool and \( D(HF) \) 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 roughness.
FIG. 1 INTERRELATIONSHIP BETWEEN VARIOUS TYPES OF FORCES/WEAR AT DIFFERENT TOOL FACES AND THE FOUR DISPERSION PATTERNS RECOGNISED FROM 3-D CUTTING FORCE

--- wear development --- dispersion pattern
• The behaviour of Dx(LF) is in agreement with the well-known major flank wear rate
Dx(LF) decreases to its minimum value
stably wear stage
accelerating wear stage
(a) Dispersion Dx(LF) via Major Flank Wear VB

--- wear development --- dispersion pattern
• Maximum value of Dy(HF) falls into the accelerating range of crater wear

(b) Dispersion Dy(HF) via Crater Wear KT

--- wear development --- dispersion pattern
• The dispersion pattern of Dz(HF) resembles the rate of minor flank wear
• The maximum value of Dz(HF) indicates the accelerating start of minor flank wear

(c) Dispersion Dz(HF) via Minor Flank Wear VB

--- wear development --- dispersion pattern
• The dispersion pattern of Dz(HF) resembles the rate of minor flank wear
• Maximum value of Dz(HF) falls into the accelerating range of crater wear

(d) Dispersion Dz(HF) via Minor Flank Wear VB

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

<table>
<thead>
<tr>
<th>Input Features to Neural Networks</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_x'(LF)$</td>
<td>$D_y'(HF)$</td>
</tr>
<tr>
<td>min$^{-1}$</td>
<td>min$^{-1}$</td>
</tr>
</tbody>
</table>

- **Group 1**: flat-faced tool
  - $-4.91$ $3.22$ $1.50$ $1.47$ $0.25$ $115$ $0.1$ $0.5$ $0.25$ $1.09$ $0$
  - $-3.89$ $2.52$ $1.31$ $1.15$ $0.25$ $115$ $0.1$ $0.5$ $0.30$ $1.14$ $15$
  - $-3.03$ $1.92$ $0.87$ $0.67$ $0.30$ $115$ $0.1$ $0.5$ $0.22$ $1.23$ $38$

- **Group 2**: groove-style tool
  - $-1.15$ $0.62$ $0.12$ $0.27$ $0.32$ $115$ $0.1$ $0.5$ $0.35$ $1.32$ $60$
  - $0.73$ $-0.68$ $0.42$ $-0.33$ $0.35$ $115$ $0.1$ $0.5$ $0.41$ $1.78$ $105$
  - $2.61$ $-1.98$ $0.06$ $-0.93$ $0.41$ $115$ $0.1$ $0.5$ $0.58$ $1.99$ $168$

- **Group 3**: obstruction-style tool
  - $6.05$ $-4.36$ $2.52$ $1.31$ $1.15$ $0.25$ $115$ $0.1$ $0.5$ $0.51$ $2.35$ $209$
  - $7.78$ $-5.62$ $-0.95$ $-2.61$ $0.46$ $115$ $0.1$ $0.5$ $0.46$ $2.50$ $243$
  - $2.26$ $-1.80$ $1.92$ $0.90$ $0.38$ $115$ $0.1$ $0.5$ $0.48$ $1.84$ $109$

**INPUT**
- Multivariate Cutting Database for chip breakability
- Tool Conditioner

**OUTPUT**
- Surface roughness
- Dimensional accuracy
- Major flank wear
- Crater wear
- Minor flank wear
- 3-D cutting forces

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

<table>
<thead>
<tr>
<th>Tool Inserts</th>
<th>Neural Network Structure</th>
<th>Transfer Function</th>
<th>RMS Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>flat-faced</td>
<td>8</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>groove-style</td>
<td>8</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>obstruction-style</td>
<td>8</td>
<td>15</td>
<td>3</td>
</tr>
</tbody>
</table>

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

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6. CONCLUDING REMARKS

As contrasted to the more recently popular approach of sensor fusion, this paper presents an 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, 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".

S.M. Wu Symposium

Volume I, 1994
References


