A simple approach for on-line tool wear monitoring using the analytic hierarchy process

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Abstract: A wide variety of on-line tool condition monitoring techniques have been developed to the present time. Timely decision making for cutting tool indexing needs a proper method for assessment of the state of the tool on-line.

The present work demonstrates a very simple system based on cutting force measurement for determination of the tool condition on-line using the analytic hierarchy process (AHP). The technique shows reasonably close estimation of the tool condition and enables successful on-line tool wear monitoring.

Keywords: machining, turning, tool wear, monitoring, on-line, analytic hierarchy process (AHP)

NOTATION

$\mathbf{A}$	pairwise comparison matrix
C	criterion
P_i	probability
P_X	feed force
P_{XZ}	resultant of feed force and tangential force
P_Y	transverse force
P_Z	tangential force
S_0	feed
t	depth of cut
V_B	average flank wear
V_C	cutting speed
$\boldsymbol{w}$	weight vector
λ_{max}	largest eigenvalue

1 INTRODUCTION

A proper cutting tool condition monitoring (TCM) system is essential for present-day manufacturing by machining. Cutting tools wear out and fail frequently during machining. On-line monitoring of the tool condition helps indexing or replacement of the inserts in time, thereby assuring safe operation of the machine–fixture–tool–work system and saving time, and causes minimum or no damage to the workpiece and the machines.

An appropriate sensory system coupled with a suitable analysis technique is the main component of the on-line tool condition monitoring system.

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Various methods have been reported for on-line assessment of tool condition, both directly and indirectly. Variation in the motor current, dimensional deviation, vibration, cutting forces, acoustic emission, etc., are used for on-line indirect assessment of tool condition. On-line measurement of dimensional deviations of the job, being inconvenient, is not commonly used for tool condition monitoring. In general, it was found that cutting force and acoustic emission (AE) signals are well related to the deteriorating conditions of the tool. Within the tool wear region, it was also reported that cutting force monitoring provides better assessment of the tool conditions than by the AE or any other technique (**1**). Variation of motor current and vibration characteristics are the derived parameters of the cutting forces, and these were reported to be less sensitive and machine dependent (**1**, **2**). More than one sensory system was also tried to give some amount of success (**2**, **3**). Force-based single sensory monitoring systems were found to be quite reliable and accurate (**1**, **2**).

Regarding the signal processing technique as well as the decision-making tool, a number of methods are used for on-line monitoring of the cutting tool. Multivariate time series analyses (**4**, **5**) and multiple regression analyses (**6**, **7**) were used for on-line tool wear estimation during various machining processes. A number of researchers tried on-line tool condition monitoring using self-organizing methods like the group method of data handling (GMDH) (**7**, **8**). Recently, artificial neural networks (ANN) have also been used with some amount of success in this area (**7**–**10**).

The main objective of the present work is to introduce a simple and promising on-line tool condition monitoring (TCM) system using the analytic hierarchy process (AHP)

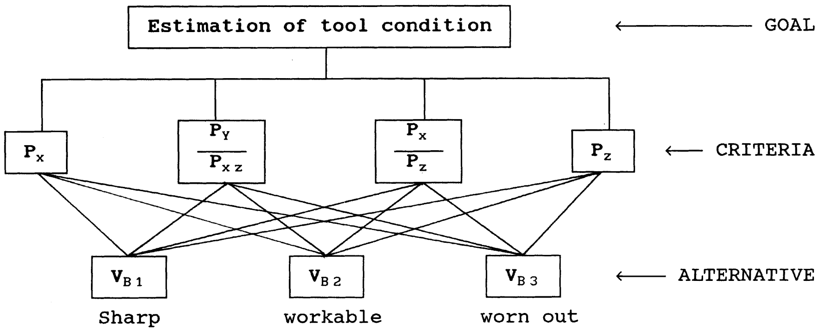

Fig. 1 Hierarchy of the tool condition monitoring system

—a popular and widely used decision-making tool. Cutting force components developed during turning of C25 steel with carbide inserts have been used for on-line monitoring of the state of the tool. The principle, process and the results of the system using the analytic hierarchy process have been presented.

2 THE ANALYTIC HIERARCHY PROCESS (AHP)

The analytic hierarchy process (AHP) (**11**) is a technique to make ranking of a finite number of alternatives based upon a finite number of criteria. The AHP structures any complex discrete multiple-criteria decision-making (MCDM) problem hierarchically. The overall objective of the decision is placed at the top level of the hierarchy and the criteria, subcriteria, if any, and decision alternatives on each descending level (Fig. 1). After structuring the hierarchy, pairwise comparisons among the elements belonging to a level with respect to an element belonging to an immediately higher level are performed in order to derive their local priority weights. The typical form of a pairwise comparison matrix is as follows:

$$\mathbf{A} = \begin{array}{c|cccc} C & E_1 & E_2 & \cdots & E_n \\ \hline E_1 & a_{11} & a_{12} & \cdots & a_{1n} \\ E_2 & a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & & \vdots \\ E_n & a_{n1} & a_{n2} & \cdots & a_{nn} \end{array} \tag{1}$$

where a_{ij} (for $i, j = 1, 2, \ldots, n$) represents the strength of preference of the alternative E_i over E_j with respect to the criterion C, $a_{ji} = 1/a_{ij}$ and $a_{ii} = 1$, for all i and j.

The entries a_{ij} are normally taken from the 1–9 ratio scale (**11**). The semantic interpretation of the numbers are given in Table 1. The matrix **A** is said to be consistent if

$$a_{ij}\, a_{jk} = a_{ik}, \qquad \text{for all } i, j, k = 1, 2, \ldots, n \tag{2}$$

If **A** is consistent it can be expressed as

$$a_{ij} = w_i/w_j, \qquad i, j = 1, 2, \ldots, n \tag{3}$$

where w_i, $i = 1, 2, \ldots, n$, are the priority weights of the alternatives.

If alternative A_1 is 3 times preferable to or dominant over alternative A_2, then $a_{12} = w_1/w_2 = 3$. Furthermore, if the alternative A_2 is 4 times preferable to alternative A_3, then $a_{23} = w_2/w_3 = 4$. From this, it can be inferred that $a_{13} = w_1/w_3 = (w_1/w_2)(w_2/w_3) = 3 \times 4 = 12$, i.e. alternative A_1 is 12 times preferable to alternative A_3. However, 9 is the upper bound of the fundamental 1–9 ratio scale of the AHP. Therefore, this value of a_{13}, which is greater than 9, cannot be taken. In this case, $a_{12}a_{23} \neq a_{13}$. In summary, the above phenomenon violates the general cardinal consistency relation given in equation (2). If all the judgements are consistent, i.e. the matrix entries satisfy the above relation, then the matrix **A** is said to be consistent.

The priority weights of the alternatives can be obtained by solving the eigenvalue problem:

$$\mathbf{A}\boldsymbol{w} = n\boldsymbol{w}, \qquad \text{where } \boldsymbol{w} = (w_1, w_2, \ldots, w_n)^{\mathrm{T}} \tag{4}$$

In reality, the matrix **A** is rarely consistent. In the inconsistent case, the above eigenvalue equation becomes

$$\mathbf{A}\boldsymbol{w} = \lambda_{\max}\boldsymbol{w} \tag{5}$$

where $\lambda_{\max}$ is the largest eigenvalue of the pairwise comparison matrix (PCM) **A**.

Table 1 Semantic interpretation of the ratios in the comparison matrices

Verbal judgement of preference	Numerical rating
Extremely preferred	9
Very strongly to extremely preferred	8
Very strongly preferred	7
Strongly to very strongly preferred	6
Strongly preferred	5
Moderately to strongly preferred	4
Moderately preferred	3
Equally to moderately preferred	2
Equally preferred	1

Note. If alternative E_i has preference strength as any one of the above non-zero numbers compared to E_j, then E_j has the reciprocal value when compared with E_i.

For the inconsistent matrix, the largest eigenvalue, λ_{max}, is always greater than or equal to n. The amount of inconsistency is measured by the consistency index (CI):

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n - 1} \tag{6}$$

The consistency ratio (CR) is found by comparing the consistency index with the index obtained from randomly generated reciprocal matrices whose entries are taken from the scale $(1/9, 1/8, \ldots, 1, \ldots, 8, 9)$. The average consistency index corresponding to the randomly generated matrices is called the random index (RI). The standard values of RIs for various matrix sizes are available (**11**). The ratio of CI to RI is called the consistency ratio (CR). A consistency ratio of 10 per cent or less is generally considered as acceptable (**11**, **12**).

Having obtained λ_{max}, the local weights can be determined by solving the system

$$w_1 = \sum_{j=1}^{n} (a_{ij} w_j)/\lambda_{max}, \qquad i = 1, 2, \ldots, n \tag{7}$$

Alternatively, the principal right eigenvector, $\boldsymbol{w}$, can be directly computed by raising the matrix $\mathbf{A}$ to an increasing power of k and then normalizing the resulting system as

$$\boldsymbol{w} = \lim_{k \to \infty} \frac{\mathbf{A}^k \boldsymbol{e}}{\boldsymbol{e}^{\mathrm{T}} \mathbf{A}^k \boldsymbol{e}} \tag{8}$$

where $\boldsymbol{e}$ is a unit row vector $(1, 1, 1, \ldots, 1)$ and $\boldsymbol{e}^{\mathrm{T}}$ is the transpose of the vector $\boldsymbol{e}$.

It may be noted that the denominator in equation (8) taking $k = 1$ denotes the sum of all the elements of $\mathbf{A}$. One numerical example to illustrate this method is available (**13**). The intuition behind this approach and its interpretation as an averaging process has also been reported (**14**).

If p_j, $j = 1, 2, \ldots, m$, are the weights of the m criteria and q_{ij}, $i = 1, 2, \ldots, n$, are the local weights of n alternatives with respect to the jth criterion, then the global weights of the alternatives are calculated as

$$r_i = \sum_{j=1}^{m} p_j q_{ij}, \qquad i = 1, 2, \ldots, n \tag{9}$$

The AHP is a potential optimization technique to solve a wide variety of real-world problems. Although the AHP is mainly meant for managerial decisions, it can be used to solve problems of other disciplines as well. Some researchers (**15**, **16**) have reported applications of the AHP in more than 40 different fields. The application areas include budgetary fund allocations, transportation, marketing, conflict resolutions, academic planning, environmental planning, facility location, justification of robotic and flexible manufacturing system (FMS) applications, material handling and various other decision-making problems. For algebraic details of the AHP, the reader is referred to reference (**12**). In the present study, the AHP has been introduced for the first time to monitor cutting tool conditions on-line.

3 EXPERIMENTAL INVESTIGATIONS

3.1 Experimental conditions

In the present work, turning tests have been carried out under the machining conditions given in Table 2. The cutting force components P_X, P_Y and P_Z were obtained using a Kistler dynamometer (type 9257B), charge amplifiers and an FFT (fast Fourier transform) analyser (type AD-3524, A and D Company, Japan) and then processed in the frequency range of 0–10 kHz. Each frame of the signal is of 40 ms duration. Five frame averages of the signal were taken for smoothing the signal, which might be affected by several other factors apart from tool wear. Average flank wear, V_B, of the carbide insert P30 was measured at regular intervals under an optical microscope (made by Olympus, Japan). This process was continued beyond the V_B value of 200 μm.

The signals were transferred to an HCL-HP 80386 personal computer via an IEEE-488 interface card. There the average of the force components and the derived parameters were computed. Under varying machining conditions, the monitoring system was tested 89 times.

Cutting speed, V_C, and feed, S_0, were selected considering the normal operating range in the industry. The depth of cut, t, was kept constant because of its insignificant influence on the growth of flank wear, particularly when the machine–fixture–tool–work system has enough strength and rigidity.

3.2 Experimentation

The hierarchical structure of the tool condition monitoring system making use of the analytic hierarchy process

Table 2 Experimental conditions

Machine tool	:	NH22 high-speed precision lathe, Hmt Limited (India) Motor power: 11 kW Speed range: 40–2040 r/min
Cutting tool	:	SNMA 120408, uncoated P30 inserts, Sandvik Asia Limited Tool geometry: −6°, −6°, 6°, 6°, 15°, 75°, 0.8 mm
Tool holder	:	R174.1-2525-12 (Sandvik), overhang 22 mm
Job material	:	Low carbon steel (C25) Composition: C 0.25%, Si 0.18%, S 0.03%, Mn 0.62%, P 0.22% Hardness: HRB 76
Rod size	:	Diameter 150 mm, length 750 mm
Machining conditions	:	Cutting velocity, $V_C = 118$–184 m/min Feed, $S_0 = 0.1$–0.24 mm/rev Depth of cut, $t = 1.5$ mm Environment: dry

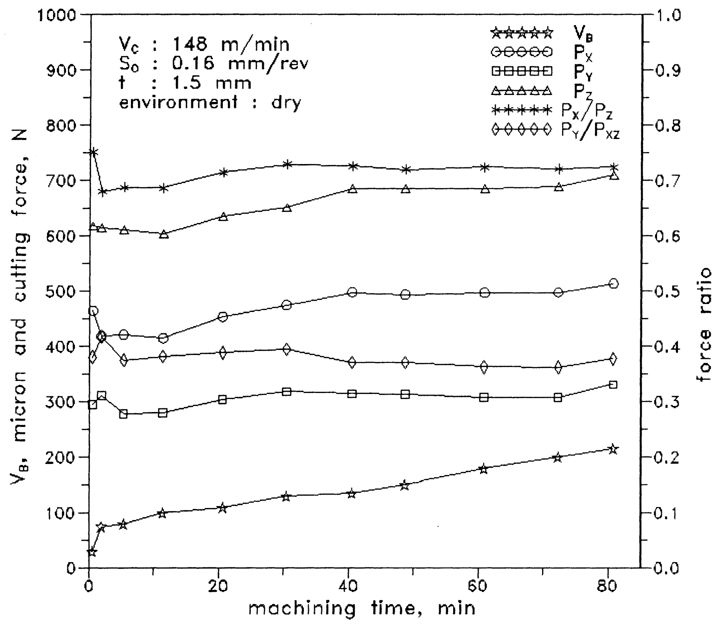

Fig. 2 Growth of flank wear and increase in cutting forces with machining time at the medium speed–feed condition

(AHP) is shown in Fig. 1. To achieve the goal of the system which is the 'estimation of tool condition', four criteria have been selected. These are:

(a) the feed force component, P_X,
(b) the tangential force component, P_Z,
(c) the ratio P_X/P_Z,
(d) the ratio P_Y/P_{XZ}.

Three alternatives considered in the system are:

(a) the sharp tool condition, when $V_B < 100\,\mu m$,
(b) the progressive tool wear region, $100\,\mu m \leqslant V_B \leqslant 200\,\mu m$,
(c) the worn-out tool, $V_B > 200\,\mu m$.

The criteria chosen are used to decide the probable alternative, i.e. the tool condition.

The force parameters show considerable changes with growth of cutting tool wear. Figure 2 shows typical plots of the four criteria and V_B with respect to machining time under a medium speed–feed condition.

The pairwise comparison matrix for the criteria, shown in Table 3, is constructed while viewing the relative changes of each criterion to the growth of flank wear. The changes in the values of the force parameters (criteria) when the tool flank wear is just beyond 200 μm vary from one cutting condition to the other. In the present work, five wear tests have been carried out under different cutting conditions, and it is seen from these experiments that the magnitude of P_X increases by 22–38 per cent, P_Z increases by 10–24 per cent, P_Y/P_{XZ} decreases by 10–22 per cent and P_X/P_Z increases by 6–16 per cent when the average flank wear value of the cutting tool just exceeds 200 μm. A typical plot showing the changes in the selected force parameters corresponding to the medium speed and feed condition is depicted in Fig. 2. According to the changes of the values of the criteria with the growth of tool wear, if they are arranged based upon decreasing sensitivity, the order becomes

$$P_X, P_Z, P_Y/P_{XZ}, P_X/P_Z$$

According to equation (3), all the diagonal elements of the pairwise comparison criteria matrix are 1. Based upon the values above, verbal judgements upon the relationships are perceived to be that P_X is moderately, strongly and equally to moderately preferred over P_Y/P_{XZ}, P_X/P_Z and P_Z respectively when regarding monitoring of the cutting tool conditions, and accordingly the entries taken from the 1–9 scale are inserted in the appropriate positions of the comparison matrix (Table 3). A similar interpretation follows for other comparisons. The components of the principal eigenvector (i.e. the vector corresponding to the largest eigenvalue, λ_{max}) of the matrix give the priority weights of the criteria calculated using equation (7). The consistency ratio (CR) measures the amount of inconsistency present in the matrix.

Table 3 Pairwise comparison matrix for criteria

V_B	P_X	P_Y/P_{XZ}	P_X/P_Z	P_Z	ω
P_X	1	3	5	2	0.4773
P_Y/P_{XZ}	1/3	1	2	1/2	0.1539
P_X/P_Z	1/5	1/2	1	1/4	0.0809
P_Z	1/2	2	4	1	0.2880

$\lambda_{max} = 4.0211$, CR = 0.0078.

Table 4 Pairwise comparison matrices for alternatives in the AHP model for the medium speed–feed cutting condition

Comparison matrices when the criteria value corresponds to tool conditions:

	Sharp				Progressive wear				Worn out			
	(...–466)N				(454–510)N				(510–...)N			
P_X	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	2	5	0.582	1	1/3	1/2	0.163	1	1/3	1/4	0.122
V_{B2}	1/2	1	3	0.309	3	1	2	0.54	3	1	1/2	0.32
V_{B3}	1/5	1/3	1	0.109	2	1/2	1	0.297	4	2	1	0.558
	$\lambda_{max} = 3.0034$					3.0092				3.0183		
	CR = 0.0029					0.0079				0.0157		
	(...–0.375)N				(0.395–0.362)N				(0.365–...)N			
P_Y/P_{XZ}	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	2	3	0.54	1	1/3	1/2	0.168	1	1/2	1/3	0.163
V_{B2}	1/2	1	2	0.297	3	1	1/2	0.349	2	1	1/2	0.237
V_{B3}	1/3	1/2	1	0.163	2	2	1	0.484	3	2	1	0.54
	$\lambda_{max} = 3.0092$					3.1356				3.0092		
	CR = 0.0079					0.1169				0.0079		
	(...–0.715)N				(0.715–0.729)N				(0.724–...)N			
P_X/P_Z	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	3	4	0.625	1	1/4	1/3	0.124	1	1/4	1/5	0.097
V_{B2}	1/3	1	2	0.239	4	1	1/2	0.359	4	1	1/2	0.333
V_{B3}	1/4	1/2	1	0.137	3	2	1	0.517	5	2	1	0.57
	$\lambda_{max} = 3.0183$					3.1078				3.0246		
	CR = 0.0157					0.0929				0.0212		
	(...–630)N				(630–710)N				(710–...)N			
P_Z	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	3	5	0.637	1	1/4	1/2	0.149	1	1/3	1/5	0.105
V_{B2}	1/3	1	3	0.258	4	1	1/2	0.376	3	1	1/3	0.258
V_{B3}	1/5	1/3	1	0.105	2	2	1	0.474	5	3	1	0.637
	$\lambda_{max} = 3.0385$					3.2174				3.0385		
	CR = 0.0332					0.1874				0.0332		

The same procedure has been followed for constructing the pairwise comparison reciprocal matrices for the alternatives with respect to one criterion at a time. The matrices corresponding to the medium speed–feed condition are presented in Table 4. Global weights are determined by equation (9). The largest global weight corresponds to the highest probability of the state of the tool.

The ranges of each of the four criteria ($P_X, P_Z, P_Y/P_{XZ}$ and P_X/P_Z) corresponding to the three tool conditions (sharp, workable and worn out) are determined. For this, 30 patterns in the vicinity of tool engagement, 100 μm and 200 μm, flank wears are used. Generally, the ranges corresponding to the adjacent tool conditions have some overlaps. In the cases of overlapping, the local weights of the alternatives are calculated in the following way.

Firstly, the probability (P_i) of each condition of the tool for the nth set of pattern and the mth criterion parameter is determined:

$$P^m_{n_i} = \frac{|C^m_n - L^m_i|}{B^m_q}, \qquad i = \mathrm{I, II, III};\ q = \mathrm{I{-}II, II{-}III} \tag{10}$$

where

I = sharp tool
II = workable tool
III = worn-out tool
C^m_n = value of the mth criterion for the nth pattern
L^m_i = upper or lower limit of the overlap
B^m_q = overlap between I and II (q = I–II) or II and III (q = II–III) for the mth criterion
$|C^m_n - L^m_i|$ = positive difference between C^m_n and L^m_i

Secondly, the new local weights, w_i, for each criterion

Table 5 Average pairwise comparison matrices for alternatives

Comparison matrices when the criteria value corresponds to tool conditions:	Sharp				Progressive wear				Worn out			
P_X	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	2.333	4.667	0.601	1	0.311	0.5	0.158	1	0.729	0.3	0.179
V_{B2}	0.429	1	2.583	0.281	3.215	1	2	0.548	1.372	1	0.5	0.262
V_{B3}	0.214	0.387	1	0.118	2	0.5	1	0.294	3.333	2	1	0.599
	λ_{max} = 3.0073					3.0053				3.0042		
	CR = 0.0063					0.0046				0.0036		
P_Y/P_{XZ}	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	2	3.333	0.549	1	0.458	0.583	0.203	1	0.625	0.354	0.183
V_{B2}	0.5	1	2.167	0.304	2.183	1	1.5	0.468	1.6	1	0.5	0.28
V_{B3}	0.3	0.462	1	0.151	1.715	0.667	1	0.329	2.825	2	1	0.537
	λ_{max} = 3.0077					3.0030				3.0017		
	CR = 0.0066					0.0026				0.0015		
P_X/P_Z	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	2.5	3.833	0.598	1	0.325	0.611	0.176	1	0.729	0.288	0.176
V_{B2}	0.4	1	1.917	0.258	3.077	1	1.75	0.529	1.372	1	0.5	0.26
V_{B3}	0.261	0.522	1	0.145	1.637	0.571	1	0.295	3.478	2	1	0.564
	λ_{max} = 3.0056					3.0005				3.0063		
	CR = 0.0048					0.0005				0.0054		
P_Z	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω	V_{B1}	V_{B2}	V_{B3}	ω
V_{B1}	1	2.667	4.167	0.61	1	0.394	0.694	0.202	1	0.583	0.308	0.169
V_{B2}	0.375	1	2.389	0.263	2.538	1	1.667	0.502	1.715	1	0.417	0.26
V_{B3}	0.24	0.419	1	0.127	1.441	0.6	1	0.296	3.247	2.398	1	0.576
	λ_{max} = 3.0199					3.0003				3.0062		
	CR = 0.0172					0.0003				0.0054		

were calculated from the equation

$$\begin{aligned} w_i &= P_{\mathrm{I}} w_{i1} + P_{\mathrm{II}} w_{i2}, \qquad i = 1, 2, \ldots, n \ (P_{\mathrm{II}} = 1 - P_{\mathrm{I}}) \\ &\qquad \text{when I and II overlap} \\ &= P_{\mathrm{II}} w_{i1} + P_{\mathrm{III}} w_{i2}, \qquad j = 1, 2, \ldots, n \ (P_{\mathrm{III}} = 1 - P_{\mathrm{II}}) \\ &\qquad \text{when II and III overlap} \end{aligned} \tag{11}$$

These new local weights are used to calculate global weights using equation (9).

In the present study, two considerations regarding the AHP-based tool wear monitoring system have been investigated, and are discussed in the following.

Model 1

First the analytic hierarchy process has been applied to assess cutting tool wear at some particular cutting conditions. For each experimental cutting condition, separate sets of pairwise comparison matrices for the alternatives have been constructed. One such set of alternative matrices is presented in Table 4 corresponding to the medium speed–feed condition.

Model 2

Finally, an AHP model has been investigated to suit a wide range of cutting conditions. For this, the corresponding elements of the sets of pairwise comparison matrices for the alternatives have been averaged to make a set of average comparison matrices for the alternatives (Table 5). The ranges of values of the criteria (force parameters) corresponding to the alternative tool conditions have been found during the wear test under selected cutting conditions (Table 6). Regression analysis is done using these data to find out the ranges of the force parameters for the tool wear conditions within a wide range of cutting conditions. Whenever a particular cutting condition is selected, the ranges of criteria are computed to be used every time to assess the tool wear states during that particular condition of machining.

4 RESULTS AND DISCUSSION

In the present investigation, the AHP-based tool condition monitoring has been studied with two considerations discussed above. Figures 3a to e and Table 6 indicate the

Table 6 Performance of the AHP-based monitoring system

Obsolete tool condition	Cutting condition* (V_C, S_0)	Tool conditions monitored by AHP models (%)†		
		I	II	III
I	(− −)	73.3 (73.3)	26.7 (26.7)	— —
	(+ −)	87.5 (85.7)	12.5 (14.3)	— —
	(− +)	100 (100)	— —	— —
	(+ +)	— (33.3)	— —	100 (66.7)
	(∘ ∘)	60.0 (60.0)	40.0 (40.0)	— —
II	(− −)	12.5 (12.5)	87.5 (87.5)	— —
	(+ −)	12.5 —	12.5 (88.9)	75.0 (11.1)
	(− +)	— —	50.0 (85.7)	50.0 (14.3)
	(+ +)	75.0 (25.0)	25.0 (50.0)	— (25.0)
	(∘ ∘)	27.3 (16.7)	54.5 (58.3)	18.2 (25.0)
III	(− +)	— —	— (20.0)	100 (80.0)
	(+ +)	— —	90.0 —	10.0 (100)
	(∘ ∘)	— —	25.0 (14.3)	75.0 (85.7)

*Levels	−	∘	+
V_C (m/min)	118	148	184
S_0 (mm/rev)	0.1	0.16	0.24

†Numbers within parentheses correspond to individual AHP models, while the general AHP model corresponds to numbers without parentheses.

performance of the AHP-based classification techniques of the state of tool wear. It may be noted that the notations corresponding to model 1 and model 2 used in Figs 3a to e indicate only the state of the tool wear and not the actual tool wear value. The directly measured flank wear is plotted against the machining time. It is seen that the classification technique using model 1 for each selected cutting condition has, in general, higher accuracy than model 2, but the latter is more widely applicable.

At lower cutting speed–feed conditions, the assessment of the state of the cutting tool wear by the AHP has a close match with the actual state of the tool. Only at some points does the AHP system misclassify the cutting tool states, which, perhaps due to variation in forces, results from deep notching occurring beyond the break-in wear region, and built-up edge (BUE) formation in some cases is observed during the experimentation.

Under the high speed–feed condition, the tool–wear–state estimation is found to be less effective. Formation of the built-up edge at the initial stages, small chatter at the initial and later stages of wear and deep notching beyond the break-in wear region may cause undesirable variation in the force components. The considerable changes in the effective principal cutting edge angle due to large flank wear may also cause variation in the forces when the nose radius of the tool is large (0.8 mm for the tool used).

5 CONCLUSION

The following conclusions may be drawn based on the present investigations:

1. A force-based monitoring system is developed to classify the tool wear states using the analytic hierarchy process (AHP).
2. The AHP model for each of the cutting conditions (model 1) shows better results than the AHP model 2, but the latter method is suitable for a wide range of cutting conditions.
3. The misclassifications made by the system may be due to some effects causing variation of the force signals.
4. Except for high cutting speed conditions, the AHP-based monitoring system enables a close estimate of the state of the tools to be made.

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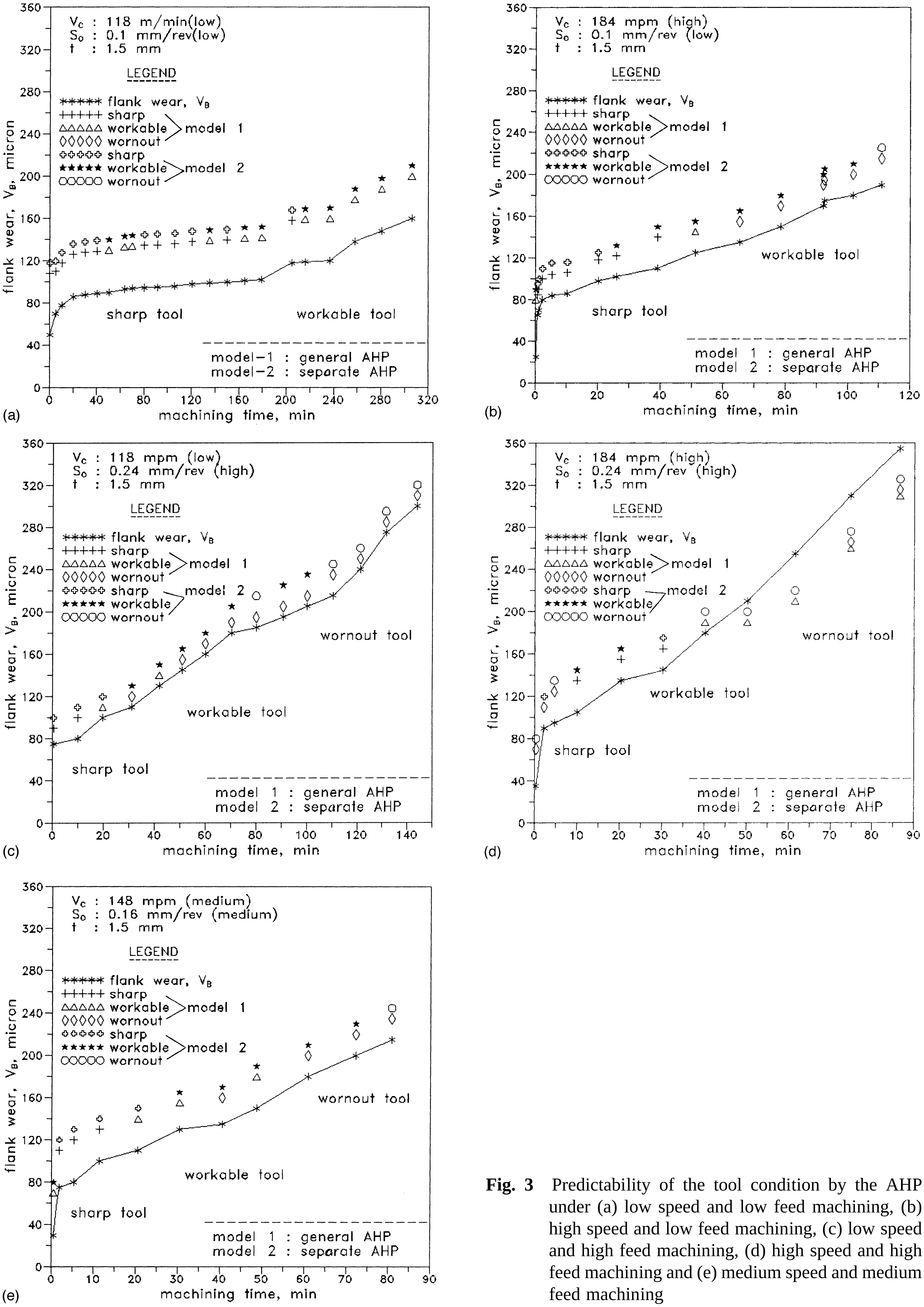

Fig. 3 Predictability of the tool condition by the AHP under (a) low speed and low feed machining, (b) high speed and low feed machining, (c) low speed and high feed machining, (d) high speed and high feed machining and (e) medium speed and medium feed machining

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