Computer Aided Flank Wear Measurement in End Milling Cutting Tool

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ABSTRACT
Flank wear width is generally recognized as the key indicator for tool life. In the experiments of this study, nine tools made of HSS and stainless steel 316L as work piece with three spindle speeds (550,930 and 1100) rpm and three redial depth of cut (1.5,2 and 2.25)mm were used. The cutting tool wear was measured using optical microscope and vision system based on a proposed algorithm. Maximum and minimum percentage errors in the flank wear width were (8.250% and 0.645 %) respectively. The numerical method used was by a multiple linear and polynomial regression model and developed a polynomial model, especially to predict the flank wear using MATLAB software. Maximum and minimum percentage errors were found (14% and 0.322 %) respectively.
Keywords: tool wear, flank wear, microscope ,regression model.

INTRODUCTION
Tool wear is the change of shape of the tool from its original shape, loss of tool material and influences cutting power, machining quality, tool life and machining costs. When tool wear reaches a certain value, increasing cutting force, vibration and rise of cutting temperature cause surface integrity deterioration and dimensional error. The methods to measure tool wear can be largely divided into direct and indirect measuring methods. The direct measuring method measures the cutting edge of the tool using a machine vision system and optical microscope. The indirect measuring method measures the degree of tool wear by processing the signals generated in the cutting process with the use of signal of cutting force, spindle torque,…etc. This method has a problem of accuracy depending upon signal processing and analysis [1].The use of direct optical microscope and vision system to measure wear in end milling tool give more accuracy.

Tool Wear Measurement
Microscope and Vision System
Wang et al (2005) [2] used image processing with median filtering, histogram, edge operation morphology operation and on-line flank wear measurement of insert cutter milling tool after finding critical area and find reference line. David K et al (2005) [3] used the digital image processing techniques in the analysis of images of wear on milling insert cutter tools manual measurement, histogram analysis and thresholding of variance with off-line process. Ali abbar (2011)[4] suggested an image processing method for measurement of spur gear data which generated accurate and efficient model and provided a substantial saving in time and cost of product. Chen Zhang,et al.(2013) [5] used gray level value difference threshold, Image rotation,

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Sub-pixel Sobel edge detection, reference line computation, detect the bottom edge of the tool wear region and the measure flank wear by off-line process and use Fiber optical light in end milling tool.

Numerical Regression Model

The regression model is a purpose of mathematical and statistical operations for the analysis of experimental data and the fitting of mathematical model to get a smooth fitting curve of data values to these data by estimating the unknown parameters of the model to find equations of approximation [6]. Jaharah Ghani, et al (2013) [7] and Abbas F. Ibrahim,et al (2014) used first order multiple linear regression model ,but Amri Lajis, et al (2008) [9] and Skali kalidass, et al (2012) [10] used second order multiple polynomial regression model.

Flank Wear Forms

On general lines for milling operation the standard ISO 8688-2 describes the main wear patterns in end milling tool and localizations, as shown in Figure (1) [11].

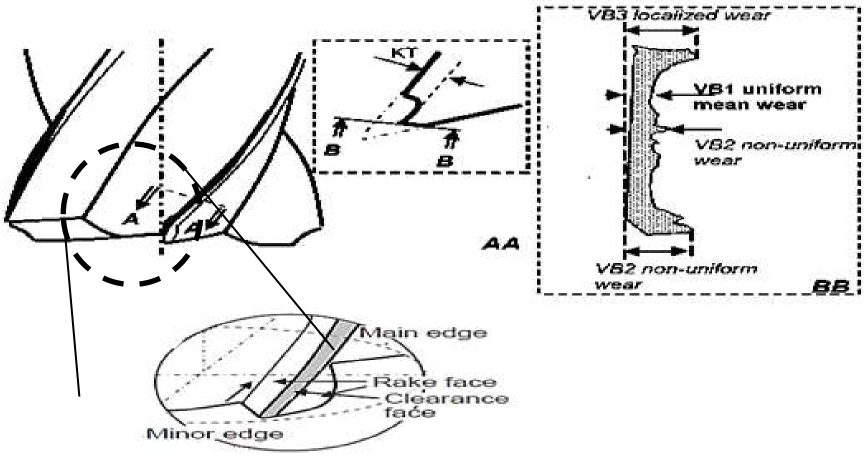


Figure (1) Type wear in end milling tools [11]

The Flank wear (VB) is defined as the loss of particles along the cutting edge, that occurs on the clearance and rake faces as shown in Figure (1), being measured in the clearance face of end milling [11].

- **Uniform Flank Wear (VB1):** Wear land which is normally of constant width and extends over those edges as shown in Figure (1) [11].
- **Non-uniform Flank Wear (VB2):** Irregular wear in several zones of the cutting edge as shown in Figure (1) [11].
- **Localized Flank Wear (VB3):** Wear is usually found in specific points. One type that is placed just in the depth of cuts line, the notch wear (VBN) is shown in Figure (1) [11].

Experimental Work

Machine Used

The experimental work has been achieved using universal milling (KNUTH) model (MF1). It has the specification listed in the Table (1).

Table (1) Specification of machine used.

Spindle speed	(80-4500) rpm	Travel –z	370mm
Feed rate	(27-816)mm/min	Motor main drive	3hp
Travel- x	670mm	Travel –y	290mm

Workpiece Material

Stainless steel (316L) workpieces with a hardness of HV 170 (Kg/mm^2) are used, the chemical composition are given in Table (2).

Table (2) Chemical composition of workpiece material.

Materia	C %	Si %	Mn %	P %	Co %	Cr%	Mo %	Ni%	V %	AL %	Cu %	Fe %
Weight	0.008	0.29	1.68	0.02	0.23	18.5	2.08	11.7	0.07	0.006	0.32	Bal

Cutting Tools

Nine tools with 4-flute types of end milling cutting tools are used with the geometry properties listed in Table (3).

Table (3) Geometry Properties of Cutting Tools Machining Conditions

Cutting tool	Material	Mill diameter (mm)	Shank diameter(mm)	Flute length (mm)	Overall Length (mm)
4-flute	HSS Coated(TiN)	18	18	23	92

Spindle speed: Three spindle speeds (550,930 and 1100) rpm are used. The cutting speed is mostly determined by the material to be cut as listed in Table (4).

Table (4) Conversion from rotational speed to cutting speed

spindle speed (r.p.m)	Convert law	Cutting Speed (m/min)
550	$Vc = \frac{\pi DN}{1000}$	31
930		53
1100		62

Feed rate: - The feed rate depends on speed, depth of cut, desired finish and many other variables. In this work (50) mm/min was used.

Depth of cut: - The depth depends on all the machine conditions, in this work an axial depth of a_a= 2mm and three radial depth a_r (1.5, 2, 2.25) mm were used.

Dry cutting: - without using cooling fluids that reduces tool wear.

Down Cut Milling:- Causes an increase in material removal with increased temperature and increased wear compared with up cut milling.

Tool Wear Measurement by Microscope

The following steps are achieved in order to measure the flank wear region:

1. The cutting process starts due to down milling using the end milling cutting tool.
2. The cutting conditions are selected as mentioned above.
3. The flank wear was measured using micro scale and optical microscope, as shown in Figures (2) and (3), for different machining times .

The test is repeated for other spindle speeds listed in table (5).

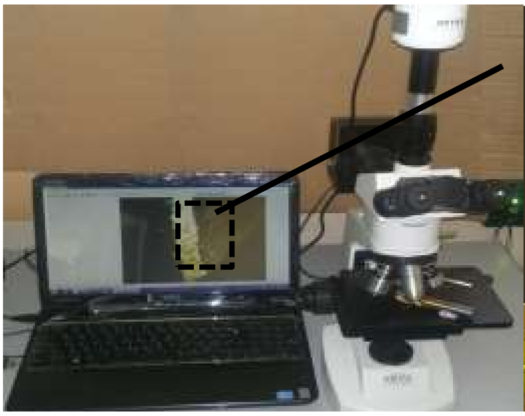


Figure (2) optical microscope used

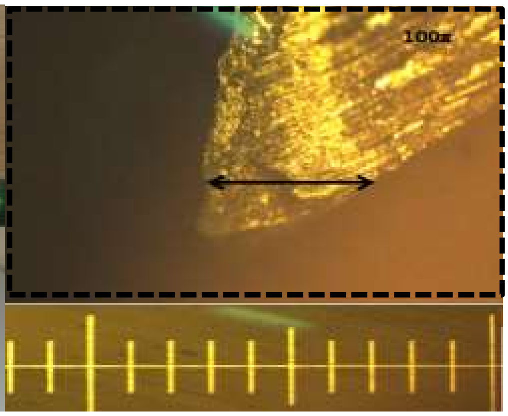


Figure (3) wear using micro scale for tool(5) after 69min machining time

Table (5) The machining parameters used in this work

Tool No.	Cutting speed Vc (m/min)	Radial depth of cut a_r (mm)	Axial depth of cut a_a (mm)	Feed rate f (mm/min)	Machining Timet (min)
1	31	1.5	2	50	69
2	31	2	2	50	56
3	31	2.25	2	50	52
4	53	1.5	2	50	51
5	53	2	2	50	47
6	53	2.25	2	50	40
7	62	1.5	2	50	40
8	62	2	2	50	35
9	62	2.25	2	50	30

Tool Wear Measurement with Vision System

Experimental Set-up of the Proposed Vision System

The vision system used in the experiments was mounted on a working fixture, the system consists of the following elements:

- **FINE color CCD** camera with a resolution of 576 × 704 pixels with focal CCTV lens (18 – 120) mm.
- Digital Video Recorder (DVR) and Software of CCD camera for capturing image and change brightness.
- Laptop equipped MATLAB program as an image processing software.
- Ring of LED illumination source with adjustable switch.

The cutting tool is fixed in front of the camera so the image plane coincides with the major clearance face of the cutting tool. The images are then cropped to a resolution of 250 × 200 pixels to minimize the algorithm operation time. The elements of system set-up are shown in Figures (4) and (5).

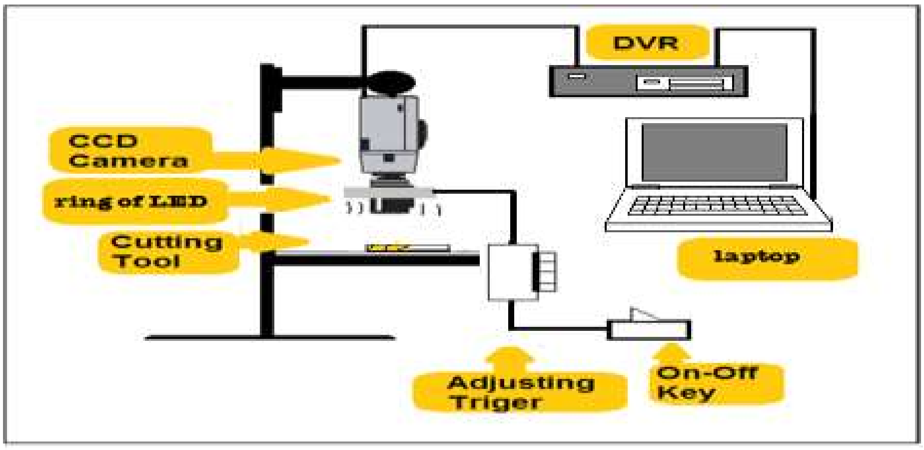


Figure (4) Diagram showing the elements of the vision based system

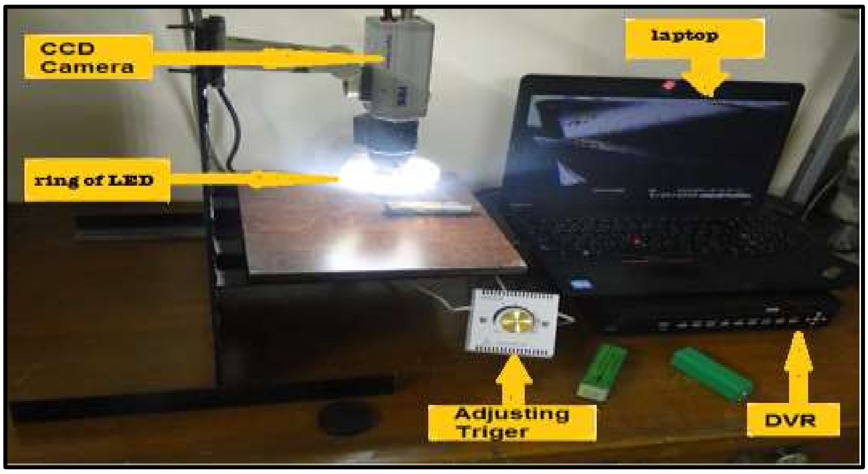


Figure (5) Experimental set-up of the vision based system

Illumination

In vision system; everything depends on image capture, and it depends at most on the illumination. The robust algorithms can be prepared to solve large problems of inadequacy on these fronts and care with acquisition with eraser, more reliable algorithms can be produced [12]. The dominant illumination method LED variable is used by (R. Schmitt et al (2012) [13] and Chen Zhang, et al.(2013) [5]) Light Emitting Diodes (LED) reacts instantly over a wide range of illumination. The most advantageous lighting system in industrial image processing is the LED light due to monochromatic nature, low cost, light weight, flexible, inexpensive operation, long life and less heat generation. They are used as ring light or array of lights. From experimental work to achieve the explanation of wear region with minimum reflection occurs with putting a light source in the same direction of camera and change the light intensity using adjusting trigger as shown in figures (4) and (5). For more explain wear region using brightness adjusting in camera setting to produce unsatisfactory results as shown in figure (6). It was found a brightness of 30% gives clear wear rejoin for edges.

(a) (b) (c)

Figure (6) Cropped milling tool images with a) brightness 30%b) brightness70% c) brightness125%

Camera Calibration

The camera is calibrated using two standard gauge blocks each with 1.5 and 3mm in width as presented in figure (7) and take 1.5mm to find calibration factor for y and 3mm for x. The gauge block was positioned near the wear area on the cutting tool clearance face. The width of the gauge (in pixels) is calculated using a camera calibration toolbox in MATLAB program and the calibration factors was calculated using the following equations [14].

$$Px=\frac{actual\ (standard)\ width\ of\ the\ block}{no.of\ \ pixels\ for\ gauge\ block\ width} \quad \text{….. (1)}$$

$$Py=\frac{actual\ (standard)\ length\ of\ the\ block}{no.of\ \ pixels\ for\ gauge\ block\ length} \quad \text{….. (2)}$$

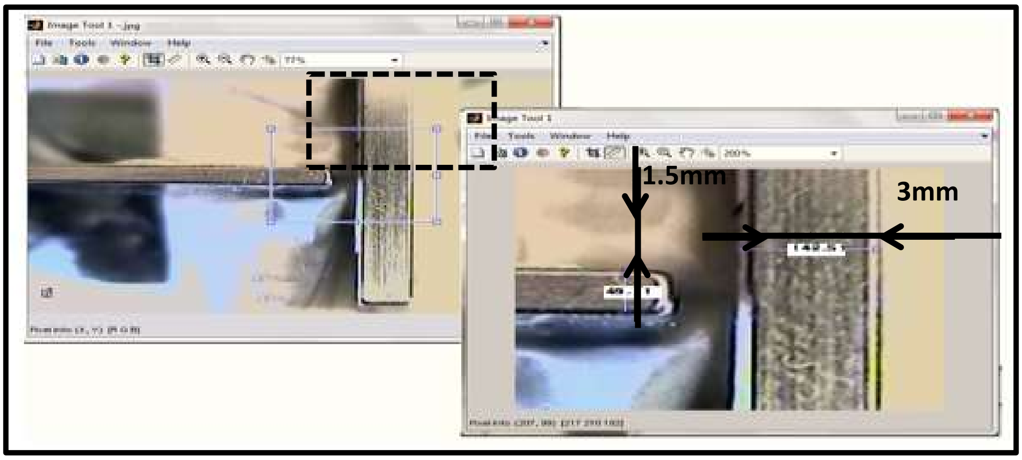


Figure (7) Camera calibration using

The Proposed Algorithm

The Proposed algorithm is briefly illustrated in the flowchart shown in Figure (8) which consists of the following steps:

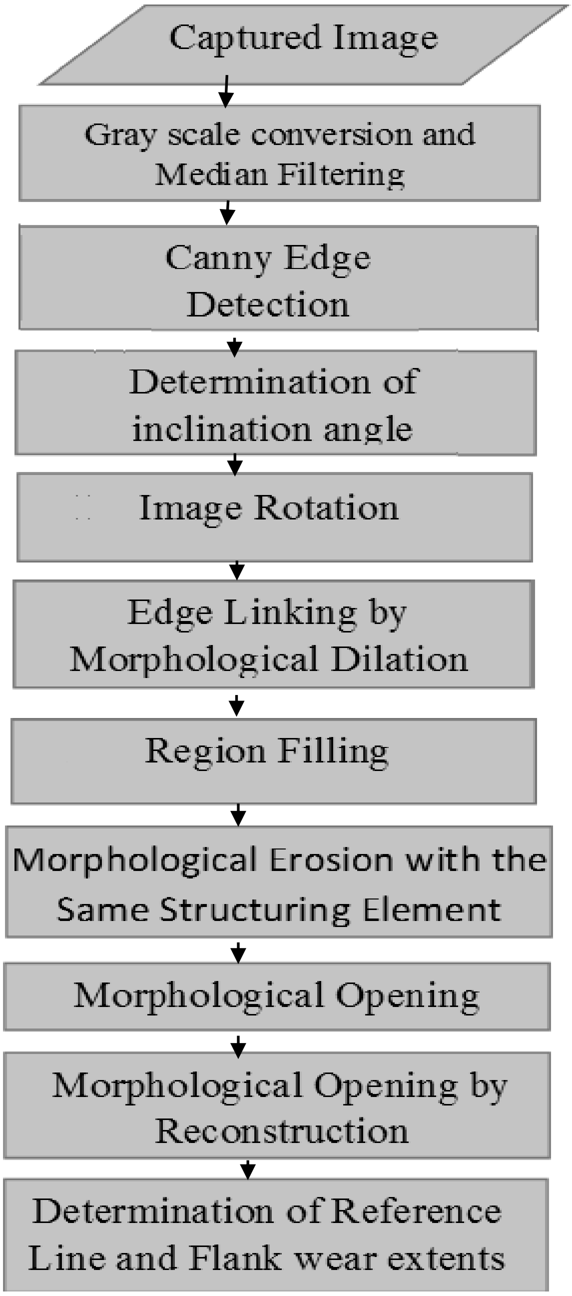
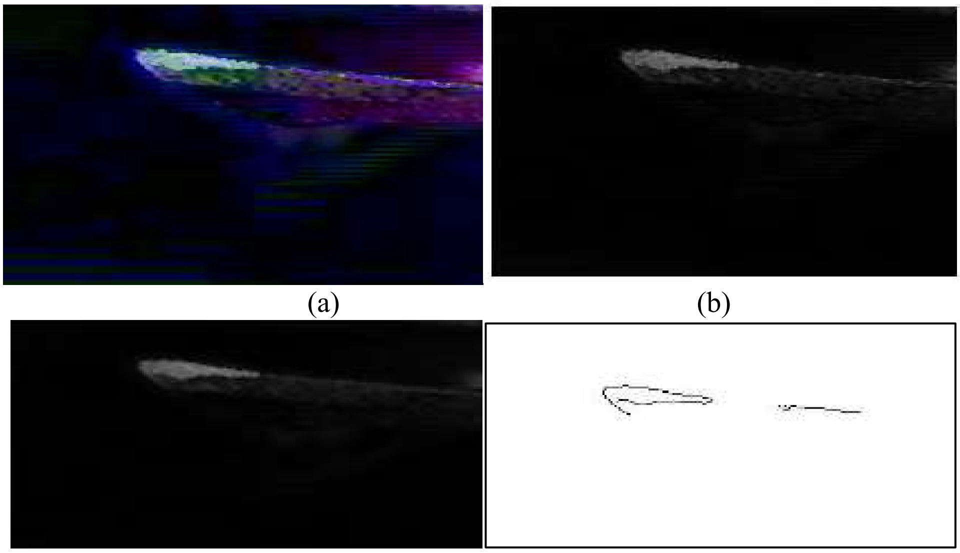


Figure (8) The proposed algorithm of image process

Step 1: Convert the captured colored image to a gray scale image as shown in figure (9 a) to reduce the algorithm operation time as shown in Figure (9 b).
Step 2: Use median filtering to reduce the noise introduced in the image without any distortion edges as shown in Figure (9 c).
Step 3: Segmented image using the Canny edge detection as shown in Figure (9 d).



(a) (b)

(c) (d)

Figure (9) a) Captured color image for tool no.5 b) Gray scale image c) Median filtered image d) using Canny edge detection

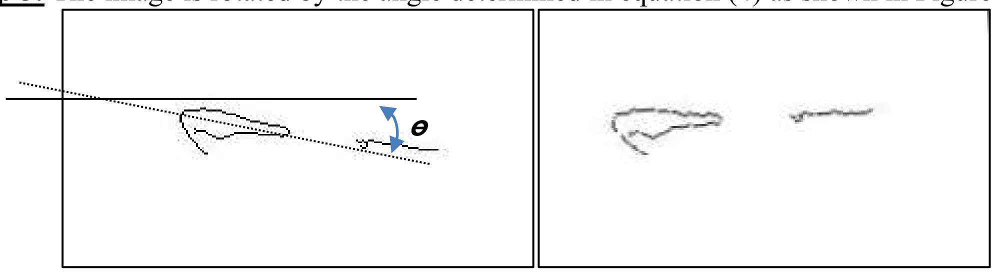
Step 4: using linear regression analysis to find cutting edge pixels fit line and the angle of the inclination of the fitting line in order to get a proper determination of wear land in the subsequent steps. The slope of the inclination was determined by least square fit of a straight line by using equation (3).

$$a_1 = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum x_i^2 - \left(\sum x_i\right)^2} \quad \ldots\ldots (3)$$

The inclination angle found by the inverse tangent of the slope

$$\boldsymbol{\theta} = \tan^{-1}(a_1) \quad \ldots\ldots.. (4)$$

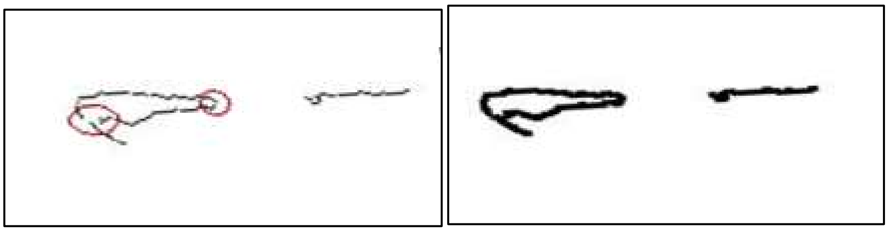
Step 5: The image is rotated by the angle determined in equation (4) as shown in Figure (10).



(a) (b)

Figure (10): Image of tool no.5 a) before rotation, b) after rotation.

Step 6: The wear region in some experimented images has some discontinuities due to the noise as shown in Figure (11a). These discontinuities cause problems in the subsequent steps so edge complete of wear region contour is required. A morphological dilation with 3 × 3 square structuring element (8-connectivety) was used to complete the interrupted contour as shown in Figure (11 b).



(a) (b)

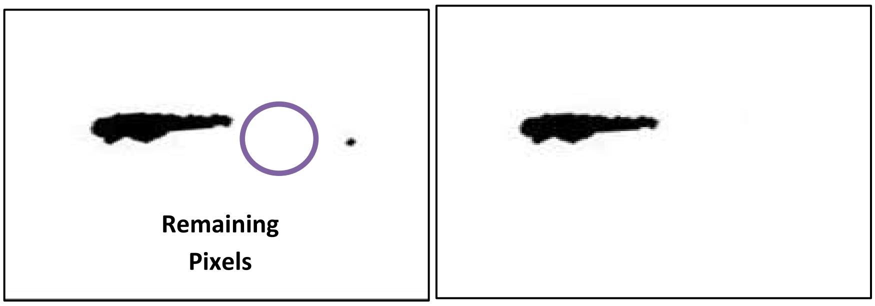
Figure (11) Zoomed image of tool no.5 a) discontinuities in contour b) after morphological dilation

Step 7: Apply region filling to fill the pixels inside the wear area, if the wear region contour is not closed. This operation will fail and corrupt the image as shown in Figure (12 a).
Step 8: morphological erosion with the same structuring element using 3 × 3 square 8-connectivity connection to remove pixels added by dilation process as shown in Figure (12 b).

(a) (b)

Figure (12) Zoomed image of tool no.5 a) after region filling b) after performing morphological erosion

Step 9: Apply morphological opening with disk 4-connectivity structuring element to remove the cutting edge line pixels in order to extract the flank wear land only, as shown in Figure (13a).
Step 10: Some pixels of the cutting edge lines remain which cause inaccuracy in determining flank wear land width. Morphological opening by reconstruction is applied to remove the pixels in un wear region as shown in Figure (13b).



(a) (b)

Figure (13) a) Remaining pixels after opening. b) after remove remaining pixels

Step 11: The top edge of tool wear region should be a straight line, but there are many small saw-teeth shape along this edge actually after the tool is working for some time, as shown in Figure (13).

To ensure the accuracy of the proposed algorithm, boundary extraction is applied to the image in step 10 and then this boundary is superimposed to the captured image rotated with inclination angle determined in step 4 as shown in Figure (14).

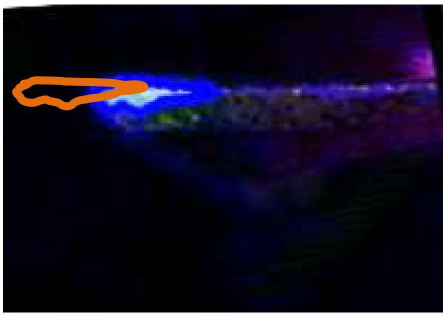


Figure (14) Superimposed boundary of tool no.5

Prediction Process

Used regression mathematical (RM) models for predicting tool flank wear which is taken as output parameter measured during the milling process, while cutting speed and depth of cut are taken as input parameters. Presented in terms 1st and 2nd order equations as shown in the follow equation:

$$y_i = a_0 + a_1 x_i + a_2 x_{ii} \quad \text{…………(5)}$$

$$y_i = a_0 + a_1 x_i + a_2 x_{ii} + a_3 x_i^2 + a_4 x_i x_{ii} + a_5 x_{ii}^2 \quad \text{…………(6)}$$

Where y_i=flank wear (output) (mm).

x_i=cutting speed (input) (m/min).

x_{ii}=Radial depth of cut (input)(mm)

$a_0, a_1, a_2, a_3, a_4, a_5$=regression coefficients to be determined.

Results and Conclusions

Flank Wear Measurements

First, the calibration factors are computed according to equations (1) and (2) by using the procedure described in section (6-3). The wear land parameters including width, length and area are determined and then substituted in the following equations to convert image unit (pixels) to actual unit (mm).

$$\mathrm{VB\ (mm)} = \mathrm{Px}\left(\frac{\mathrm{mm}}{\mathrm{pixel}}\right) * \mathrm{VB\ (pixels)} \quad \text{…..(7)}$$

$$\mathrm{VL\ (mm)} = \mathrm{Py}\left(\frac{\mathrm{mm}}{\mathrm{pixel}}\right) * \mathrm{VL\ (pixels)} \quad \text{…..(8)}$$

$$\mathrm{VA\ (mm)} = \mathrm{VB\ (mm)} * \mathrm{VL(mm)} \quad \text{…..(9)}$$

$$\mathrm{VBB} = \sum_{i=0}^{Vl} \mathrm{VB} / \mathrm{VL} \quad \text{…..(10)}$$

Where VB is wear width.

VL is the wear land length.

VBB is the mean wear width.

VA is the flank wear area.

The experimental results are listed in table (6) and shown in Figure (15). The percentage error and mean absolute percentage error are calculated by using the following equations.

$$Error_{percent} = \frac{|True\ value - Measure\ value|}{True\ value} * 100 \quad \text{……(11)}$$

$$Mean_{error} = \frac{\sum_1^9 |Sum\ of\ percentage\ error|}{\sum_1^9 Total\ number\ of\ trial} \quad \text{…….(12)}$$

Table (6) The flank wear measurements

Tool No.	VB_{max} (mm) (microscope)	VB_{max} (mm)	percentage Error %	VBB (mm)	VA (mm^2)
1	0.30	0.308	-2.666	0.160	0.288
2	0.30	0.310	-3.333	0.172	0.313
3	0.35	0.369	-5.428	0.191	0.291
4	0.28	0.277	1.071	0.188	0.330
5	0.40	0.367	8.25	0.260	0.453
6	0.34	0.358	-5.294	0.231	0.419
7	0.28	0.290	-3.571	0.235	0.346
8	0.30	0.298	0.666	0.165	0.386
9	0.31	0.312	-0.645	0.189	0.391

Figure (15) shows as comparison between microscope and vision measurement and shows that max correlation occurs in tools no 4 ,8 and 9 and minimum correlation in tool no.5 and so that maximum percentage error occurs in tool no.5 with 8.250% and minimum percentage error in tool no.4 ,8 and 9 with 1.07 %, 0.66% and -0.645% respectively. The mean absolute percentage error is 3.436 %. The error source is an uneven reflection from the flank wear land edges. The result are shown in figure (15).

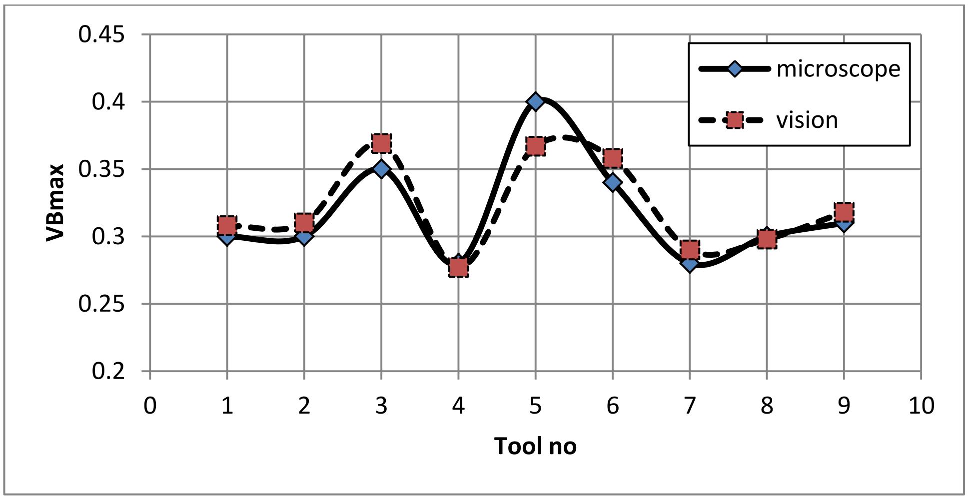


Figure (15) Comparison between microscope and vision measurement

Prediction of Flank Wear

Regression mathematical (RM) models are adopted for predicting tool flank wear firstly, by use of multiple linear regression model with flank wear output parameters measured and using cutting speed and axial depth input parameters and then use multiple polynomial regression using to generate mathematical model according to equations (5) and (6) respectively. So the limits of the working ranges of all process parameters selected are listed in table (7) to simplify the process.

Table (7) Process parameters and their levels

Process parameters	Units	Notation	Limits		
			+1	0	-1
Cutting speed	m/min	$V(x_1)$	31	53	62
Radial depth of cut	mm	$a_r\ (x_2)$	1.5	2	2.25

A well planned design of experiment with three levels and two parameters are selected for first order and second order models used for fitting these models by using MATLAB software.

The mathematical regression model is given between the input and output parameter. According to equation (13) and (14), the symbol X_1 and X_2 refer to cutting speed and radial depth of cut as an input and Y is refer to tool wear as an output. The multiple linear regression model is a first order equation and a second order for multiple Polynomial regression models. The first and second order models for two selected parameters are given in the following equations:

$$Y=0.3294+0.0133X_1-0.0208X_2 \quad \dots \dots\dots(13)$$

$$Y=0.3444+0.015X_1-0.025X_2-0.0217X_1^2-0.0217X_2^2-0.0075X_1X_2 \quad \dots\dots(14)$$

Multiple Polynomial regression models in equation (14) are developed to final model in equation (15) which is used to predict the tool wear. The final mathematical model for tool wear after development for more accuracy is given by:

$$Y=0.3444+0.015X_1-0.025X_2-0.0217X_1^2-0.0217X_2^2 \quad \dots\dots (15)$$

The overall cutting conditions and flank wear measurement and prediction are listed in table (8).

Table (8) Experimental, predicted and error values

Tool No.	X_1	X_2	VBmax (microscope) (mm)	Multiple linear regression model	Multiple polynomial regression model	Percentage Error %	
						Using multiple linear (RM)	Using Multiple Polynomial (RM)
1	+1	+1	0.30	0.321	0.291	-7	3
2	+1	0	0.30	0.342	0.337	-14	-10
3	+1	-1	0.35	0.363	0.341	-3.714	2.571
4	0	+1	0.28	0.308	0.297	-10	-3.571
5	0	0	0.40	0.329	0.344	17.75	14
6	0	-1	0.34	0.350	0.347	-2.941	-2.058
7	-1	+1	0.28	0.295	0.261	-5.357	6.785
8	-1	0	0.30	0.316	0.307	-5.333	-2.333
9	-1	-1	0.31	0.336	0.311	-8.387	-0.322

$$Mean_{error\ \text{line}} = \frac{\sum_1^9 |Sum\ of\ percentage\ error|}{\sum_1^9 Total\ number\ of\ trial} = \frac{|7+14+3.714+10\text{…………}+8.387.|}{9} = 8.275\%$$

$$Mean_{error\ \text{poly}} = \frac{\sum_1^9 |Sum\ of\ percentage\ error|}{\sum_1^9 Total\ number\ of\ trial} = 4.960\ \%$$

From table (6) and Figure (16) shown a correlation between microscope and linear and polynomial model.

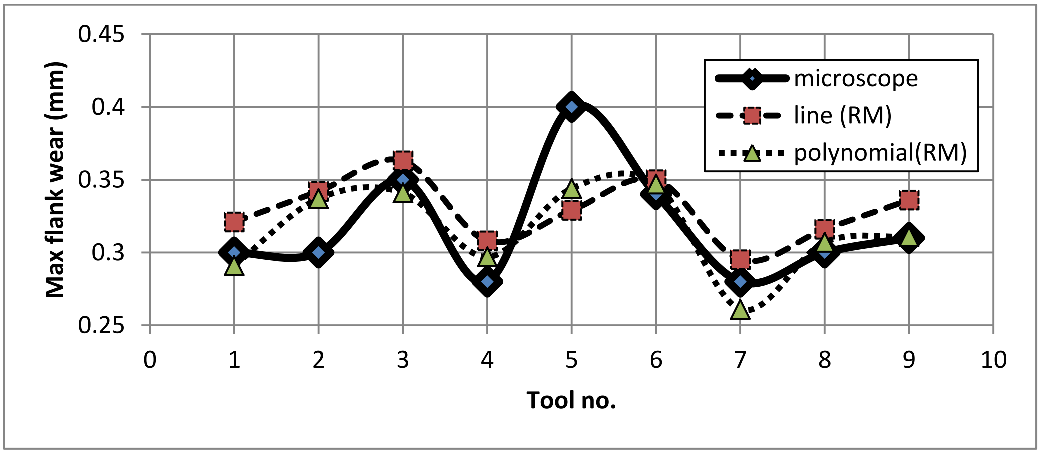


Figure (16) Comparison between microscope, line (RM) and polynomial (RM) for flank wear

From table (8) and Figure (17) the maximum percentage Error in multiple linear regressions is 17.75% in tool no.5 and minimum percentage error is 2.941% in tool no.6. While in multiple polynomial regression maximum percentage error is 14% in tool no.5 and minimum is 2.058% and the mean absolute percentage error **for** multiple linear regressions is 8.275%**.** While in multiple polynomial regression is 4.960%, that show multiple polynomial regression model has more accuracy and reliable than multiple linear regression in tool life prediction model. This point was also noted by the researchers (Amri Lajis,et al 2008)[9].

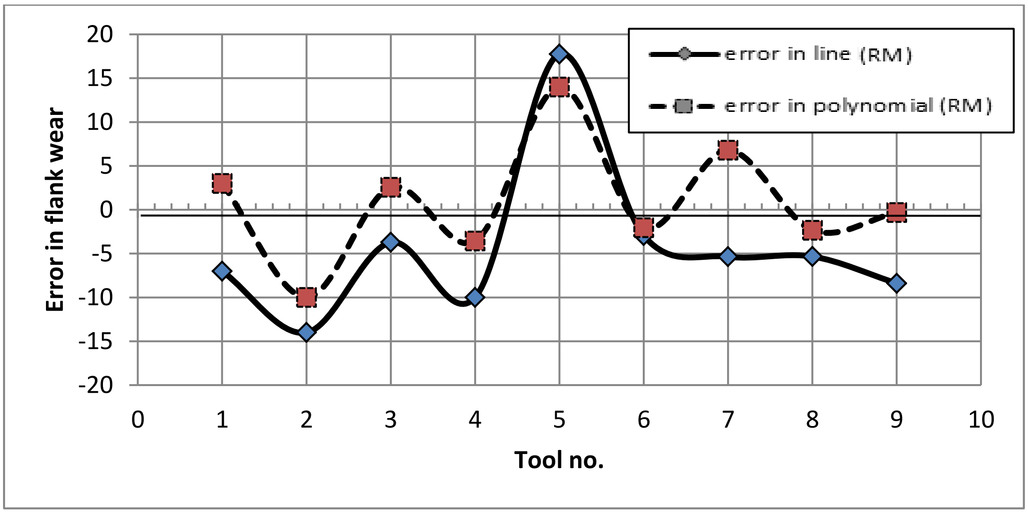


Figure (17) Comparison between error in linear (RM) and polynomial (RM) for flank wear prediction

CONCLUSION

In this work, the results that are obtained from the experimental work include the following points:

- The use of low intensity illumination sources LED light is critical to prevent light reflection in flank wear land edges and enhance the image capturing.

- The cutting speed effect on the tool wear is more dominant than other machining parameters such as feed rate and depth of cut.
- Maximum and minimum flank wear errors between microscope and vision system are (8.25%) and (0.645%) respectively .
- The proposed algorithm uses MATLAB to compute the number of pixels in two dimensions, and converts it to millimeter units leading to measure the object dimension from edge to edge with low error and using inexpensive equipment.
- Determining flank wear area by image processing show maximum area(0.453) mm^2 at speed (53m/min), feed 50mm and depth of cut(2mm) and minimum (0.288) mm^2 at speed(31 m/min), feed (50mm) and depth of cut(1.5mm).
- Using multiple polynomial regression gives good results and powerful method to predict the flank wear in the numerical experiments with maximum and minimum flank wear error with microscope are (14%) and (0.322%) respectively.

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