Investigation of CNC Turning Tool Wearing using Image Processes

Nukman Bin Yusoff, Abdulaziz S. Alaboodi, Osama I. Alsultan

Abstract—Tool wear affects both spacemen dimensional precision and surface quality. Therefore, the prediction of tool wear amount during machining processes is very important in order to obtain high precision parts, which is reducing the manual fit operations, and production cost. Image processing analysis has been used to investigate tool wearing. One of the most common methods for image processing is texture analysis. That is the gray level co-occurrence matrix (GLCM), which have large number of texture features. In this paper, the relationship between GLCM texture features and the cutting tool wear in CNC turning operations has been investigated. Cutting tool wear has been represented by the machining time. A vision system has been employed to capture images for specimens with various machining time for the same cutting tool then images will analyzed by MATLAB functions codes, to calculate the texture features. Results showed that four texture features have good correlations with the machining time of the cutting tool.

***Index Terms*—CNC, GLCM, Tool Wearing, texture features, vision system, Image processing.**

I. INTRODUCTION

MACHINE vision is utilized to recuperate the essential information about a scene from its two-dimensional projections [1]. In machine vision, information recovery is usually attained a computer processor, but the processor can be thought of as a human doing utilizing equivalent processing, such as measuring wear from the tool. Compared to a human, machine based vision processing has many advantages, such as repeatability, which is being applied in many applications in the industry.

The main components of any machine vision system are Camera, lighting, grabber, object and processor. These components allow the system to capture the 2D projection of the object image, and extract the required information.

The camera and lens are usually modeled with a perspective projection [2]. Due to the effort that has been made to enhance visual system artificially, it was a logical step to apply the advancement in computers to this job [3]. Surface texture is an important feature of an image. It is classified as qualitative properties of surfaces that corresponds to brightness value and pixel locations. Due to the complexity and the high variety of texture, the unique definition of texture and accepted computational representation are not existing [4]. One of the definitions of texture is defined by Pichler et al. [5] as an optical pattern that contains a large number of elements, each visible to some degree. Besides that, Coggins and Jain [6] have compiled a catalogue of texture definitions in the computer vision literature.

One of the texture features classification is to divide them into four categories as statistical texture, structural texture, model based texture, and transform-based texture [7]. The most widely used technique in the industry is the statistical texture for quality grading or classification. Model-based and transform-based texture might also be used. [8]. Statistical methods analyze the latitudinal distribution of gray color values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. The defining of local feature depends on the number of pixels. Statistical approaches can also be subdivided into one, two, or higher-order pixels.

Texture feature has been introduced into a wide range of applications such as metal surface analysis, textiles characterization, cell recognition and counting, ultrasonic images processing, and food qualities evaluation [9, 10]. In the field of surface roughness, Gadelmawla [11] used the GLCM to characterize and to evaluate surface roughness of machined products. Texture features utilized fuzzy neural network (FNN) approaches to establish relationship between actual surface roughness and texture features of the surface image by many researchers [12-15]. In the medical fields, Tsai and Kojima [16] used the texture features of ultrasonic images to classify the heart disease. In food industry, Chandraratne et al. [17] investigated the usefulness of raw meat surface characteristics in predicting cooked meat tenderness. The gray level co-occurrence matrix (GLCM) is a texture feature that used widely in industry with high accuracy.

The use of machine vision in the determination of tool wear is being widely spread and appears in literature, and dates back thirty years [22]. Many texture descriptors were used for tool wear monitoring using computer vision. For example, Kassim et al. [23, 24] used both fractal analysis and Hough transform for tool wear monitoring of machined surfaces. In addition, Peng-Yang et al. [25] used the Wavelet Packet for the same purpose. Kerr et al. [26] have introduced a comprehensive review of tool wear monitoring using computer vision. The authors employed GLCM texture features to monitor tool wear and reported that only the Inertia and Entropy statistics gave the expected monotonic trends with wear and only in a particular GLCM search direction. Volkan et al.

Manuscript Received on December 2014.

Dr. Nukman Bin Yusoff, Department of Mechanical Engineering, faculty of Engineering , University of Malaya, 50603 Kuala Lumpur, Malaysia.

Dr. Abdulaziz S. Alaboodi, Department of Mechanical Engineering, Qassim University, PO Box 6677 Buraydah 51452, Qassim, Saudi Arabia.

Eng. Osama I. Alsultan, Department of Mechanical Technology, Buraydah College of Technology, Buraydah, Qassim, Saudi Arabia.

[27] introduced a computer vision-based approach in drilling tool condition monitoring by capturing images and applying a Canny edge detector to extract tool features from the acquired images. In order to obtain a measure of tool wear, a tool condition measure called deviation from linearity DEFROL was developed to monitor drilling tool flank wear.

The objective of this paper is to study the relationship between GLCM texture features and the cutting tool wear in CNC turning operations. The relationship Outcome might help to predict the cutting tool wear at any time using computer vision.

II. EXPERIMENTAL WORKS

The used cutting tool for turning operations had tips of commercial type CNMG 120408 EN-TM. It was used for 8 hours to produce 20 specimens as mentioned. To study the effect of machining time on the cutting tool using image texture features, it was required to capture an image for the cutting tool after machining each specimen. Horizontal and vertical scratches marked on the side face of the cutting tool using a height Vernier to prepare it for imaging. The marks used to help in positioning cutting tool in a microscope to capture images of cutting tool's side and top face.

Twenty cylindrical specimens with 50 mm diameter were prepared and machined using a face turning operation to study the effect of wear on both cutting tools and specimens. It is required to decide the required time to be used for the cutting tool and to calculate the required machining time for each face. By using the cutting tool for 8 hours, it produce 20 specimens. Hence, the required machining time for each specimen can be calculated using equation (1).

$$t_s = \frac{t_t \times 60}{n} \tag{1}$$

Where t_s: machining time required for each specimen (in min), t_t: machining time for the cutting tool (in min), and n: number of specimens to be machined by the cutting tool. As a result, each specimen will be machined for 24 minutes. The to the machining time for each face (t_f) can be calculated using equation (2).

$$t_f = \frac{1}{f \times s} \tag{2}$$

where: t_f: machining time required for each face (in min), l: length of cut; i.e. diameter/2 (in mm), and f: feed (mm/rev); s: speed (rev/min). Then the length of machined part in each specimen can be calculated using equation (3).

$$l_m = \frac{t_s}{t_f \times d_c} \tag{3}$$

where: l_m: length of machined part (in min), t_s: machining time required for each specimen (in min), t_f: machining time required for each face (in min), and d_c: depth of cut (in min). The total length of each specimen can be calculated using equation (4):

$$l_t = l_m + h_s + l_f \tag{4}$$

where: l_t: Total length of raw specimen (in min), l_m: length of machined part (in min), h_s: Height of specimen after machining (in min), and l_f: length of finishing part (in min). Excel sheet has been created to automate this process of calculating the dimensions of row specimens based on different machining parameters. The calculated length of each specimen was 87.6 mm. Therefore, a steel bar with 50 mm diameter (Steel 70 type) was used as a raw material to produce 20 specimens with a length of 87.6 mm for each specimen. These specimens, then, were machined using a CNC machine as discussed in the following section.

A CNC turning machine was used to produce the required specimens and to reduce the length of each specimen from 87.6 mm to 20 mm using the cutting conditions shown for the cutting process in Table I. A finishing process was used to finish the face of each specimen using the cutting conditions shown for the finishing process in Table II. Figure 1 shows an image for the three samples among of twenty specimens machined by the CNC machine.

Table I

Cutting Conditions for the Cutting Process and Finishing Process for Each Specimen

Cutting Process			Finishing Process		
Feed (f_c)	0.3	mm/rev	Feed (f_c)	0.3	mm/rev
Speed (s_c)	200	rpm	Speed (s_c)	200	rpm
Depth of cut (dc_c)	1	mm	Depth of cut (dc_c)	1	mm

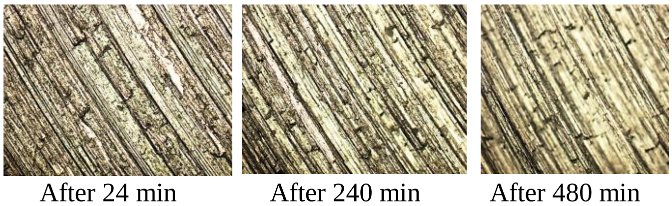

Fig. 1. Captured images for specimens after 24, 240 and 480 minutes

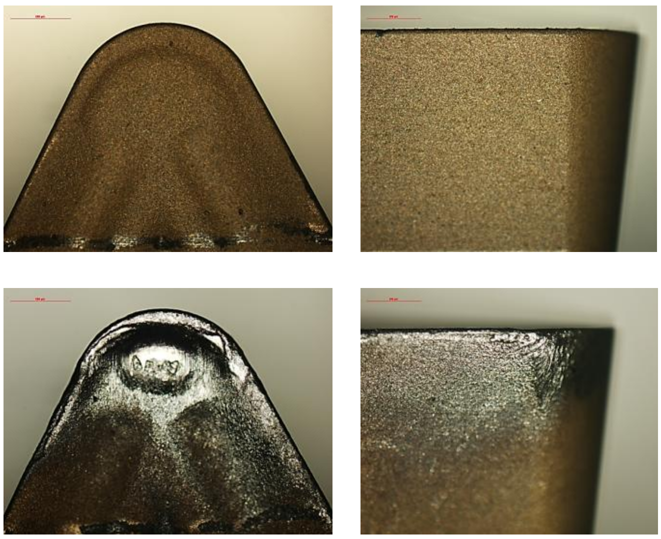

Fig. 2. Captured images for tool at 0 min (top) and 480 min (bottom)

A Nikon microscope with CCD camera system was used to capture images for both machined specimens and cutting tool. The microscope was connected to a PC computer.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

A Capturing image software called NIS is provided with the Nikon vision system was used to capture images for machined specimens and the cutting tool after each machining process. The NIS software enables to capture images with different sizes. However, for this work all images were capture at size 1280 * 960 pixels. Figure 1 shows the captured images for the cutting tool after different machining process. Furthermore, all specimens were captured at a magnification of 50X. Figure 2 shows the top and side view of cutting toll at before cutting and after 480 minutes of cutting.

Table II
Calculated Values of the Image Texture Features for Specimens for Sample Numper 1, 10 and 20

	Samples No.		
GLCM Texture Features	1	10	20
Contrast (CON):	652.3633	372.2996	78.8312
Dissimilarity (DIS):	17.9126	12.8985	5.7827
Homogeneity HOM / Inverse Difference Moment (IDM):	0.0913	0.1264	0.2161
Similarity (SIM):	0.1563	0.199	0.3
Angular Second Moment (ASM):	1.73E-04	2.03E-04	3.03E-04
Entropy (ENT):	9.7391	9.4186	8.6207
Mean (Sum Mean) (μ):	153.4268	158.484	165.1608
Variance and Standard Deviation (VAR & SD):	4.19E+03	4.32E+03	3.12E+03
Correlation (COR):	2.20E-04	2.22E-04	3.16E-04
Maximum probability (MaxP):	0.0088	0.0064	0.0016
Cluster Shade (CSH):	-1.79E+05	-4.17E+05	-5.31E+05
Cluster Prominence (CPR):	4.83E+08	5.20E+08	3.39E+08
Triangular Symmetry (TS) / Diagonal Variance (DgVAR)	23.6337	21.2615	16.4711
Diagonal Moment (DM):	7.50E+04	5.96E+04	2.82E+04
Second Diagonal Moment (SDM):	1.37E+03	983.1616	448.9933
Coefficient of Variation (CVAR):	27.3098	27.2625	18.893
Sum Average (SAVE):	306.8992	317.0148	330.3757
Sum Entropy (SENT):	6.1045	6.0915	6.0196
Sum Variance (SVAR):	1.07E+05	1.14E+05	1.18E+05
Difference Average (DAVE):	18.9126	13.8985	6.7827
Difference Entropy (DENT):	3.8853	3.5595	2.7725
Difference Variance (DVAR):	555.8164	311.4484	60.6042
Mean Correlation 1 (MCOR1):	-0.2016	-0.2561	-0.3822
Mean Correlation2 (MCOR2):	0.9517	0.9736	0.9931

Image Processing Toolbox is a collection of functions that extend the capability of the MATLAB software. The toolbox supports with a variety of range for the image processing operations. By using the image processing in MATAB toolbox then using another MATLAB codes to calculate the texture of the specimens images. The vision system was used to capture two images for each specimen at different areas. To avoid varying illumination conditions, which may affect the values of texture features, the microscope light was adjusted to constant light intensity while capturing all images through all tests. After applying the MATLAB functions, the texture features were calculated and listed as shown in tables Table II. It shows the calculated texture features for the specimens' number 1, 10 and 20 as samples of 20 specimens under investigation in this work. Equations of correlation had extracted for the texture features using the plotted graphs as in figures 3, 4, and 5. Twenty-one more graphs was generated (not presented here) then the highly correlation feature with machining time are selected and presented as follows:

$$\begin{aligned} DVAR &= -0.9596\, M_t + 511.41 \\ CON &= -1.1126\, M_t + 600.82 \\ DM &= -95.027\, M_t + 77532 \\ DIS &= -0.0242\, M_t + 17.304 \\ SDM &= -1.8892\, M_t + 1340.7 \end{aligned}$$

Where M_t is the machining time in min. From these equations, the tool wear (machining time) can be calculated using one of the following equations:

$$M_t = \frac{DVAR - 511.41}{-0.9596}$$

$$M_t = \frac{CON - 600.82}{-1.1126}$$

$$M_t = \frac{DM - 77532}{-95.027}$$

$$M_t = \frac{DIS - 17.304}{-0.0242}$$

$$M_t = \frac{SDM - 1340.7}{-1.8892}$$

Figure 6 shows the twenty-four texture features sorted according to their correlation coefficients with the machining time. It is appears that the first six features have correlation coefficient greater than 0.9.

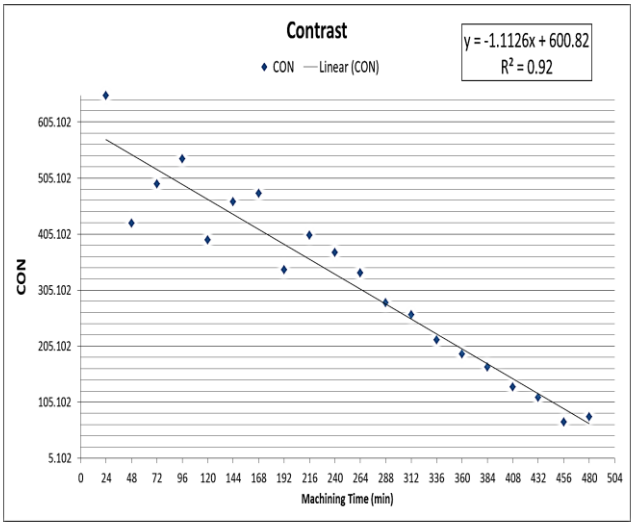

Fig. 3. Relationship between CON and the tool machining time

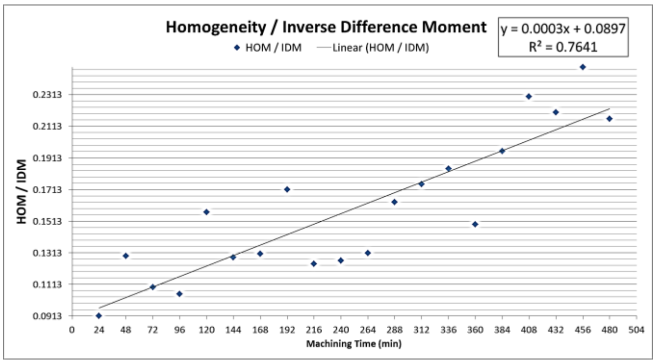

Fig. 4. Relationship between HOM / IDM and the tool machining time

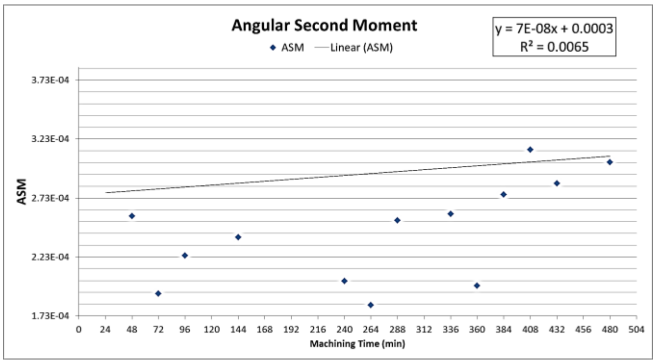

Fig. 5. Relationship between ASM and the tool machining time

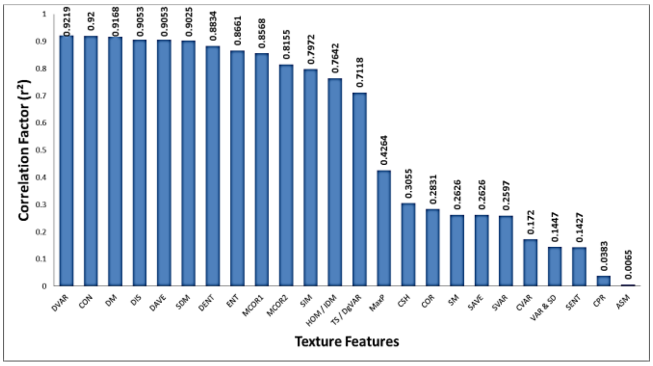

Fig. 6. Texture features sorted according to their correlation coefficients with the machining time

III. CONCLUSION

This paper investigates the relationship between the cutting tool wear, represented by machining time, and image texture features. A vision system was employed to capture images for specimens produced by CNC turning machine using various machining time. A MATLAB codes was used to calculate twenty four GLCM texture features for the captured images.

Six texture features (DVAR, CON, DM, DIS, DAVE, and SDM) are highly correlated with the machining time of the cutting tool (correlation coefficient greater than 0.9). Therefore, these texture features could be used to predict the tool wear.

REFERENCES

1. R. Jain, R. Kasturi, and B. G. Schunck. Machine Vision. McGraw-Hill, Inc., 1995.
2. D. A. Forsyth and J. Ponce. Computer Vision. Pearson Education, Inc., 2003.
3. Parker, J.R. Algorithms for image processing and computer vision, John Wiley & Sons. Inc, 1997.
4. Patel, D., Hannah, I. and Davies, E.R. Foreign object detection via texture analysis, In: Proceedings of the 12th IAPR International Conference on Computer Vision & Image Processing, vol. 1, no. 9-13, 1994, pp 586-588.
5. Pichler, O., Teuner, A. and Hosticka B.J. A comparison of texture extraction using adaptive Gabor filtering, pyramidal and tree structured wavelet transforms, Pattern Recognition, 1996, 29(5), 733-742.
6. Coggins, J.M. and Jain, A.K. A spatial filtering approach to texture analysis, Pattern Recognition Letters, 1985, 3, 195–203.
7. Zheng, C., Sun, D.W. and Zheng, L. Recent applications of image texture for evaluation of food qualities – a review, Trends in Food Science & Technology, 2006, 17(3), 113–128.
8. Bharati, M.H., Liu, J.J. and MacGregor, J.F. Image texture analysis: methods and comparisons, Chemometrics and Intelligence Laboratory Systems, 2004, 72, 57–71.
9. Park, B., Lawrence, K.C., Windham, W.R., Chen, Y.R. and Chao, K. Discriminant analysis of dual-wavelength spectral images for classifying poultry carcasses, Computers and Electronics in Agriculture, 2002, 33, 219-231.
10. Quevedo, R., Carlos, L.G., Aguilera, J.M. and Cadoche, L. Description of food surface and microstructural changes using fractal image texture analysis, Journal of food engineering, 2002, 53, 361-371.
11. Gadelmawla, E.S. A vision system for surface roughness characterization using the gray level co-occurrence Matrix, NDT&E International, 2004, 37, 577–588.
12. Ho, S.Y., Lee, K.C., Chen, S.S. and Ho, S.J. Accurate estimation of surface roughness from texture features of the surface image using an adaptive neuro-fuzzy inference system, Precision Engineering, 2005, 29, 95–100.
13. Lee, B.Y. and Tarng, Y.S. Surface roughness inspection by computer vision in turning operations, Int. J. Machine Tools Manufacture, 2001, 41, 1251–63.
14. Lee, B.Y., Juan, H. and Yu, S.F. A study of computer vision for measuring surface roughness in the turning process, Int. J. Adv. Manufacturing Technol., 2002, 19, 295–302.
15. Ho, S.Y., Lee, K.C., Chen, S.S. and Ho, S.J. Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system, Int J Machine Tools Manufacture, 2002, 42, 1441–1446.
16. [38] Tsai, D.Y. and Kojima, K. Measurements of texture features of medical images and its application to computer-aided diagnosis in cardiomyopathy, Measurement, 37(3), 2005, 284–292.
17. Chandraratne, M.R., Samarasinghe, S., Kulasiri, D. and Bickerstaffe, R. Prediction of lamb tenderness using image surface texture features, Journal of Food Engineering, 2005, 28, 1-8.
18. Day, D.D. and Rogers, D. Fourier-based texture measures with application to the analysis of the cell structure of baked products, Digital Signal Processing, 1996, 6, 138–144.

19. Paliwal, J., Visen, N.S., Jayas, D.S. and White, N.D.G. Cereal grain and dockage identification using machine vision, Biosystems Engineering, 2003, 85, 51–57.
20. Kondo, N., Ahmad, U., Monta, M. and Murasc, H. Machine vision based quality evaluation of Iyokan orange fruit using neural networks, Computers and Electronics in Agriculture, 2000, 29, 135–147.
21. Thybo, A.K., Szczypiński, P.M., Karlsson, A.H., Dønstrup, S., Stødkilde-Jørgensen, H.S. and Andersen, H.J. Prediction of sensory texture quality attributes of cooked potatoes by NMR imaging (MRI) of raw potatoes in combination with different image analysis methods, Journal of Food Engineering, 2004, 61, 91–100.
22. Andrew Otieno, Chandhana Pedapati, Xiaonan Wan, Haiyan Zhang. Imaging and Wear Analysis of Micro-tools Using Machine Vision, Proceedings of the International Conference on Engineering & Technology (IJME-Intertech), October 19-21, 2006, Kean University, IT 301: Paper # 071.
23. Kassim, A.A., Zhu Mian, Mannan, M. A. Texture Analysis using fractals for tool wear monitoring. IEEE, 2002, 3, 105-108.
24. Kassim, A.A., Zhu Mian, Mannan, M. A. Connectivity oriented fast Hough transform for tool wear monitoring. Pattern Recognition, 2004, 37, 1925-1933.
25. Peng-Yang Li, Chong-Yang Hao, Shuang-Wu Zhu. Machining tools wear condition detection based on wavelet packet. Proceedings of the Sixth International Conference on Machine Learning and Cybernetics, Hong Kong, 19-22 August 2007, pp 1559-1564.
26. David Kerr, James Pengilley, Robert Garwood, Assessment and visualisation of machine tool wear using computer vision. International Journal of Advanced Manufacturing Technology, 2006, 28(7-8), 781–791.
27. Volkan Atli A., Urhan O., Ertürk S., and Sönmez M. A computer vision-based fast approach to drilling tool condition monitoring. Proc. IMechE Part B: J. Engineering Manufacture, 2006, 220, pp. 1409-1415.

AUTHORS PROFILE

Dr. Nukman Bin Yusoff, Associate Professor in the Department of Mechanical Engineering, University of Malaya (UM), Malaysia. Appointed as HOD of Engineering Design & Manufacture in 2007 and actively doing research in the field of Laser Materials Processing, CAD/CAM, CNC and Manufacturing Process and Management. He acquired his PhD from Loughborough University in 2009 and Master in Engineering Science, MSc. (Mechatronics) from DeMontFort University, Leicester United Kingdom in 1998. He acquired his first degree in CAD/CAM from University of Central England in Birmingham. Since then he has been teaching undergraduate in the field of CAD/CAM and Manufacturing degrees and graduate level teaching since 2007. He published many papers in the field of manufacturing and articles in different international, regional and national journals, conference proceedings and bulletins and co-author of two technical books.

Dr. Abdulaziz S. Alaboodi, Associate Professor in the Mechanical Department at Engineering College, Qassim University. Earned his PhD degree in Mechanical Engineering from KFUPM, Saudi Arabia. He has been teaching undergraduate at QU in the field of Mechanical Design and Manufacturing since 2007. He published more than twenty papers and articles in different international and national journals, conference proceedings.

Eng. Osama I. Alsultan, Graduate student at Engineering College at Malay University, Malaysia. In addition, Lecturer at Buraydah College of Technology.