POLISH ACADEMY OF SCIENCES - COMMITTEE OF MATERIALS SCIENCE
SILESIAN UNIVERSITY OF TECHNOLOGY OF GLIWICE
INSTITUTE OF ENGINEERING MATERIALS AND BIOMATERIALS
ASSOCIATION OF ALUMNI OF SILESIAN UNIVERSITY OF TECHNOLOGY
Conference Proceedings
12th INTERNATIONAL SCIENTIFIC CONFERENCE
ACHIEVEMENTS IN MECHANICAL & MATERIALS ENGINEERING

Tool condition monitoring system

A. Stoić, P. Raos

Mechanical Engineering Faculty ,
Trg I. B. Mažuranić 18, HR 35000 Slavonski Brod, Croatia

On line sensing of cutting process has been used to detect tool failure indirectly, measuring acoustic emission, force, sound, vibration, etc. In these indirect methods, the signal magnitude, root mean square value, or magnitudes of the power spectrum, among others, are reported. These values indicate necessity for tool change typically via threshold. To make decision logic works safely and with minimal faults, the control system has to be well trained. The system training results shows influence of cutting speed, feed rate, nose radius of cutting tool on noise and forces during turning. The measurements were performed on 40 CrMnMo 7 steel, when CBN were used as cutting material during dry cutting. The results showed that a high possibility in terms of tool wear monitoring exists, especially for a large-scale production.

1. INTRODUCTION

Considerable research has been done in the area of tool monitoring due to the fact that tool failure represents about 20% of machine tool down–time and that tool wear negatively impacts the work quality in the context of dimensions, finish, and surface integrity. The monitoring tasks are performed through of three main parts: sensing of the process, signal processing and monitoring decision-making. There is no a fault free alarms during the detection of the cutting process abnormalities (wear, breakage, chipping). The monitoring decision-making has to make possible the transformation between the monitoring indices and the process conditions [1]. Research and development in the machining process monitoring and control has not met the requirements necessary for industry adoption. Commercial realization of these technologies is still quite limited after some thirty years of research efforts.

2. OBJECT OF THE MONITORING

Very important decision what has to be done before performing of monitoring tasks is selection of suitable monitoring object (cutting effects – fig.1) and number of influencing parameters. With increasing of the number of monitored parameters decrease the portion of randomly appeared disturbances on chosen cutting effect within sensing and increase the reliability of monitoring model but also indirectly sampling number.

Objects (effects) of the tool wear monitoring as well as applied sensors are widely and significantly different [2]. Early attempts found that the feed and radial forces are more sensitive to tool wear than the cutting force [3, 4]. The radial force component was reported to be the most sensitive to nose wear, with the feed force and the radial force components affected by flank wear [5]. Similarly, flank wear was observed to correlate with the feed and cutting force components [6]. Force ratios can also be used to predict tool wear since they present a certain pattern as the tool wears. The feed force to cutting force ratio was found to be sensitive to flank wear [6].

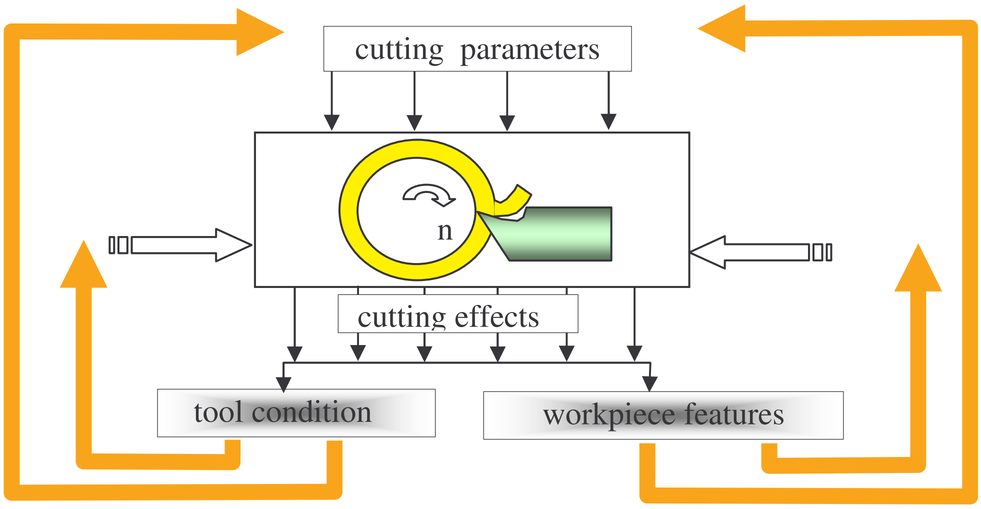

Figure 1. Disturbances on monitoring model

3. DECISION MAKING TECHNIQUES

In unattended manufacturing worn tools must be changed on statistical basis, e.g. with reference to the shortest life expectancy of any tool in a lot. In process sensing techniques allowing for the optimal utilization of the tool life, though highly desirable, are to date not fully developed. In fact, the availability of decision making systems being reliable, accurate, economical, and relatively easy to apply represents one of the major obstacles for the further development of the sensing systems. The basic idea is to detect a change in the parameter in comparison with an independent sequence. Then it can be proposed a statistic hypothesis test to verify the change of the parameter. In the case of a Gaussian sequence a change in the mean leads to the next sufficient statistic:

$$S = \frac{\mu_1 - \mu_0}{\sigma^2}\left(y_i - \frac{\mu_1 + \mu_0}{2}\right) \tag{1}$$

This change detection algorithm is one of the oldest and most well known algorithms for continuous inspection, and is called Shewhart control chart. This algorithm can be rewritten as:

$$\left|\bar{y} - \mu_0 \geq k\frac{\sigma}{\sqrt{N}}\right|; k = \frac{(e)}{MSE} \tag{2}$$

The right side of this equation is the so-called control limit where e and MSE are the residual and the mean square error of a linear regression, calculated dynamically for a sliding window of workpieces. The linear regression protects the decision-making system against fast variations of the property under diagnosis. When an abrupt change happens, the parameter *k* grows rapidly and reveals a change in some insert of the corresponding group. Then the parameter *k* exceeds its normal value. An appropriate choice of the threshold for the parameter *k* lets to detect a fault in every group. To avoid false alarms the threshold must be exceeded several times consecutively. Tool failure shown in figure 2 falls to the lot of one tenth of the second. There are three prominent force peaks that reference to the tool wear. Within these three moments PI is close to zero and parameter *k* exceeds its normal value and pays attention to the tool damage.

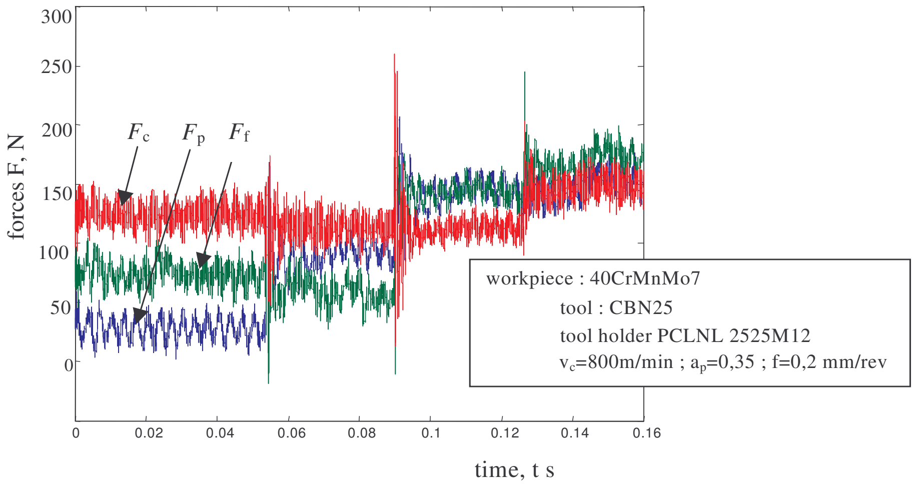

Figure 2. Cutting forces sensing results

4. DECISION MAKING PROCEDURE

In many cases, the changes in sensing features may result from changing cutting conditions also making it difficult to define a set of signal processing routines that would isolate the tool wear changes independently. This has significant implications for a tool wear monitoring system probably resulting in a monitoring system that is specific to a small working set of conditions.

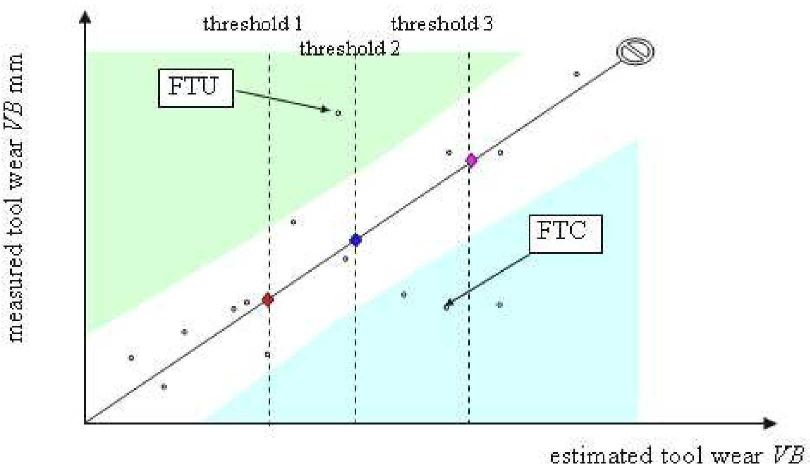

Figure 3. Decision logic supervising

One way in which the faults in decision-making could be reduced is the introduction of an external supervisor, which uses appropriate knowledge about the cutting process to remove illogical decisions. An appropriate knowledge in the case of tool wear could be generated by Taylor's tool life equation $v_c T^m = C$ that provides a relationship between cutting speed v_c tool life T and two parameters m and C dependent on tool and workpiece materials. From experience gained in the experiments described here and from the analysis of other wear curves Taylor's tool life equation can give estimates within ± 35% [7] of the actual tool life (Figure 3). Threshold criterion for certain tool $Tr_{Ti} = \text{training score}_{Ti}\,(0{,}33 \cdot \xi_{\text{global}} + 0{,}67 \cdot \xi_{Ti})$, where Ti – is the tested tool and ξ- is ratio coefficient.

The results in accordance with these equations can produce faults in prediction of tool life called as FTC and FTU (where FTC is fault tool change and FTU is fault tool use). In order for such rules to be used the Taylor parameters m and C, as well as K_{ad} wear coefficient for the workpiece and tool material have to be known.

5. CONCLUSIONS

Paper describes an application of tool wear diagnosis, based on statistical signal processing. Experimental data obtained during training period have allowed defining statistical behavior of the variables for non-fault conditions, tool wear and breakage. Automatic interpretation of SPC control charts using the PI and variance ratio methods, for different processes, was a part of computer-integrated logic for tool wear control model. There was also pay attention on decision when the observed signal are of out of SPC control charts limits. The goal of the control model is to optimize the lifetime of the tool, while ensuring dimensional tolerance in the product.

REFERENCES

1. R. Du; M. A. Elbestawi and S. M. Wu: Automated monitoring of manufacturing processes, Part 2: applications, ASME Journal of Engineering for Industry , 117, 1995., pp 133-141.
2. J. Kopač; A. Stoić; S. Šali; I. Samardžić: The relation between the sound pressure and tool vibrations during the turning process, Proceedings of 8th International Scientific Conference on Production Engineering, Ed. R. Cebalo & H. Schulz, Brijuni-Croatia, 2002., pp. I 081-I 091.
3. L. Gould: Sensing Tool and Drive Element Condition in Machine Tools, Sensors, 1988., pp. 5-13.
4. P.M., Lister: On Line Measure of Tool Wear," Ph.D. Dissertation, Manufacturing and Machine Tools Division, Department of Mechanical Engineering, UMIST, Manchester, UK, 1993.
5. S.E. Oraby and D.R. Hayhurst: Development of Models for Tool Wear Force Relationship in Metal Cutting, International Journal of Machine Tools and Manufacture, Vol. 33, No. 2, pp. 125–138, 1991.
6. Y. Yao, X.D. Fang, and G. Arndt: Comprehensive Tool Wear Estimation in Finish–Machining Via Multivariate Time–Series Analysis of 3–D Cutting Forces, Annals of the CIRP, Vol. 39/1, pp. 57–60, 1990.
7. M. Sabourine and A. Mitchie: Modelling and classification of shape using a kohonen associative memory with selective multiresolution, Neural Networks 6, 1993. pp 275-283.