Journal of Production Engineering
Vol.12 No.1

Antic, A., Zeljkovic, M., Hodolic, J., Zivkovic, A.

# MODEL OF CLASSIFICATION SYSTEM OF TOOL WEAR CONDITION WHILE MACHINING BY TURNING

***Abstract:*** *This work deals with a model of a developed fuzzy system for tool wear classification. The system consists of three modules: module for acquisition and data processing, for tool wear classifying and for decision making. In addition, some of the methods of signal processing used for defining the entering fuzzy classifier vector have been given.*
***Key words:*** *Tool monitoring, Signal processing, Vibration signal, Fuzzy system*

## 1. INTRODUCTION

The basic requirements for the automation of the process of scraping in modern production conditions are the reliability of the tool monitoring system and the machining process. The shortcoming of the classical systems for tool wear monitoring is the fact that they work within the given boundaries, which often do not meet the requirements in an adequate way. The development of the modern monitoring systems, which work at real time, make the basis for monitoring the tool state and the machining process in an automatic production. Thus, modern diagnostic and managing systems are required to have a level of automation which can make conditions for managing the quality of a product and the production process, which is often called "intelligent" production system.

The machining process contains several different parameters difficult to measure which, combined with the dynamics of the very process, represent a stochastic and non-stationary process. A great number of parameters influence the very course of the machining process, some of them being: the characteristics of the materials processed, the state of the machining system, vibrations occurring during the machining process and a number of unknown but very influential parameters which together make the creation of an adequate processing model harder. This work deals with defining the model of the classification systems for the state of tool wear with special emphasis on the module for gathering and processing vibration acceleration signals by means of applying discrete wavelet transformation (DWT) on signal decomposing. Distinguishing the adequate characteristics of the fuzzy classifier entering vector for the tool wear classifying is one of the most important functions of the system.

## 2. TOOL WEAR MONITORING PRESENTATION

By developing new technologies and by mutual integration of measuring equipment and other mechatronic elements of a machine, as well as new more flexible managing approaches (open architecture managing system, applying of artificial intelligence algorithms for monitoring and process managing), conditions are met for intelligent processing systems development. [1]

Tool wear is a primary generator of accidental stochastic disturbances with a direct influence on stability, quality and economizing of the machining process. Some estimates show that 20% of the cutting process stoppages belong to the group of those caused by the consequence of the opportune reactions and tool wear discovering.

Getting reliable information about the tool state at real time represents and obligatory condition for identifying the degree of tool wear, which reasonably rises the stability of the machining process quality.

By the mid-80s of the last century several models of wear based on classical mathematical models have been suggested (Bayes` classificatory, the closest neighbors method, linear discriminators, and so on). However, that process was hard to describe by means of classical mathematical models due to its outstanding non - linear and stochastic qualities. Some more intense research on development of tool monitoring systems during the cutting process began in the 90s of the last century by applying a multi sensor approach, i.e. tool wear classifier based on artificial intelligence algorithm, which are in use today as well. The beginning of research in this area assumed that applying of these methods should result in industrially applicable solutions for cutting tools wear monitoring.

Among the most frequently used algorithms are the artificial neural networks (ANN) and fuzzy logics, which are widely applied nowadays and give possibilities for additional research [2].

The reasons for these models being widely applied should be looked for in: the possibility of complex non-linear processes described without sufficient information and burdened with different kinds of disturbance and unwanted noise in signals, usually appearing because of the very stochastic nature of the wearing process and the possibility of brief processing of a larger amount of information at real time. The above mentioned advantages become distinct in problems of the degree of tool wear estimate, where an adequate mathematical wearing model does not exist. In order to increase the quality of the tool wear monitoring system, a number of experimental surveys have been carried out, by using classifying models based on fuzzy logics and recently some hybrid combinations such as Neuro-fuzzy (NF) models and Fuzzy Neural Networks (FNN) appear more often. For this reason distinguishing of a number of different statistical parameters from signals and achieving a group of mutually independent and relevant wearing parameters of satisfactory quality, which are able to fully identify a complex dynamics of cutting tools wear comes as an imperative. The first step is collecting monitoring signals such as forces, vibrations, acoustic emission (AE), temperature and/or engine current etc. The second step is signal processing in order to separate its useful content. The last step is classification, where useful information from the signal are used for current tool state classifying [1].

The vibrating of the cutting tools while machining occurs as a consequence of: chip lamina creating, tools` vibrations, friction on the front and back surface of a tool, wearing of the cutting edge of the tool, the wavy structure of the surface processed and they are also connected to the vibrations caused by conjugated gear action in a kinetic machine chain. Different surveys have shown that tool vibrating occurring during continuous machining is the main reason for the friction between the back surface of a tool and the object being machined. The basic tool vibrating frequency is the resonant system frequency caused by friction on the cutting edge. Vibrations accelerating represent their best measure when appearing at high frequencies. Since the vibrations of cutting tools are the ones of high frequency (over 1 kHz), tool accelerating has been chosen to be a parameter of tool wear monitoring [3].

Applying the value analysis for selecting the identified parameters of the machining process is an important part of parameter adequacy determination. Analyses like this one appear as an adequate response and compensation for following several different and stochastic parameters of the classical systems.

## 3. BASIC DATA ABOUT THE MODEL

Tool wear monitoring system model can basically be regarded through four segments bound together making a whole, represented in the picture 1.

System modules are the following:

- acquisition and data processing module,
- decision-making data classifying module,
- fuzzy decision-making module.

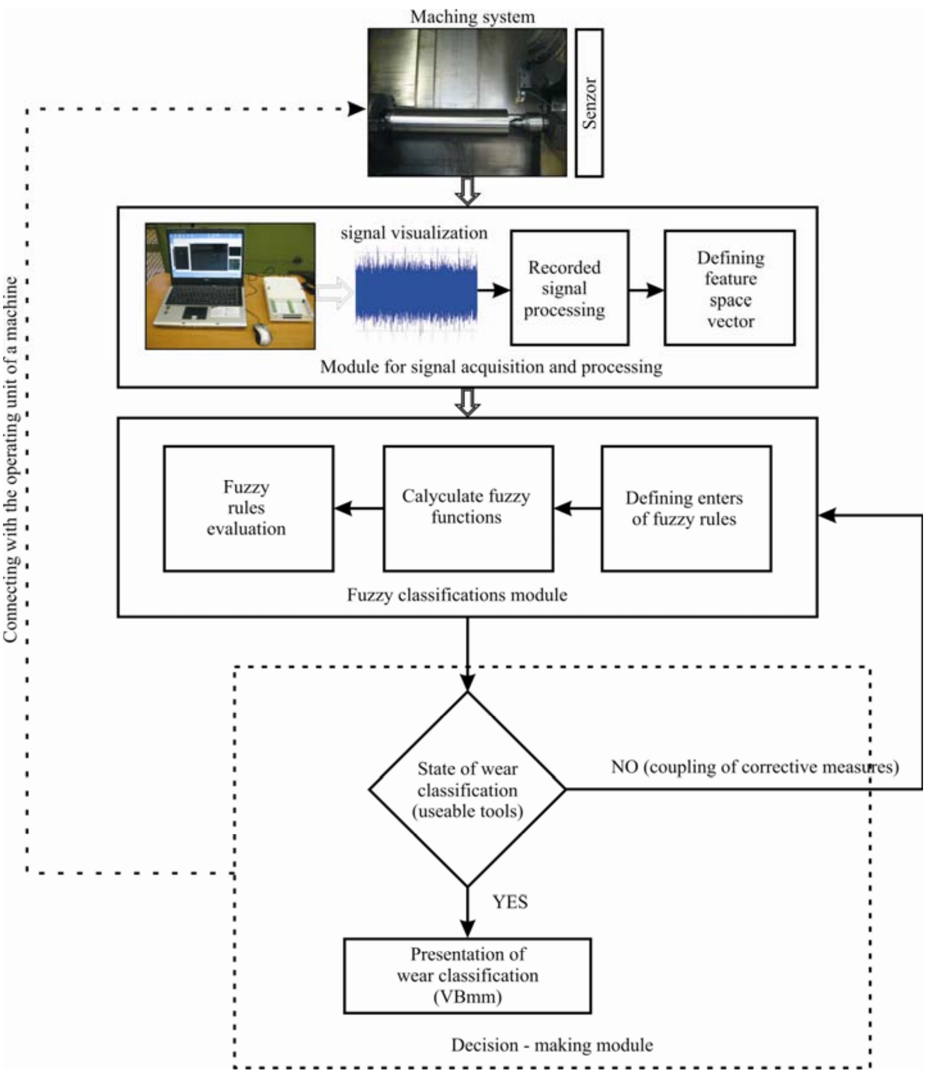


*Fig. 1. Presentation of developed system structure for tool wear classification*

### 3.1 Subsystem for data acquisition and processing

Accelerometer measuring vibration accelerations and mounted on the tool handle makes the sensory part of the data collecting module. The part of the module used for data acquisition, processing and analyzing consists of A/D card NI USB 6281 18bit, 625 kS/s, which receives analogous data from the existing sensor, converts them into digital information and sends them to the entering data base. A software system of the Matlab version R2008b has been used for card managing. The system enables the vital working functions to be defined.

By means of the suggested approach the entering data “vectors” are being additionally filtrated in the training data classifying system module, thus acquiring better results at more complex evaluation concerning more complex processing. The structure of the suggested system can be regarded through two phases. In the first phase, the initial model structure establishing phase, the initial structure of the “classifier” is being established, the parameters of structure for a number of combinations of machining parameters (velocity, depth and motion, characteristics of materials and tools etc) and for each wearing parameter respectively, are being determined. In this part of the classifying system, initializing all parameters is equally non-limited. If the testing shows that system responses could be improved at a higher or lower extent, the initial structure can additionally be improved during the phase of secondary learning i.e. structure stabilizing. Data standardization is being done here, as well. It is essential to go through data standardization in order to get more precise data without disturbances that can occur during sampling. Moreover, different mathematical functions for signal processing at real time can be additionally used and then the measuring data can be transformed into other measuring quantities if necessary. The aim of data selecting and standardization is choosing the most influential and accurate data relevant for the process, on the basis of which fuzzy system will be drilled.

The software system has been projected for information collecting and processing as well as managing hardware components, and thus supervising and classifying tool ware on the basis of given restrictions. The remaining tool validity is determined on the basis of wear trend acquired by simultaneous analysis with the calculated wear and the real state.

Selecting the right kind of filter will depend, in the first place, on the kind of the signal followed, tool characteristics, machines, work piece, machining parameter and other machining conditions. As it follows, the filtering procedure is not uniquely defined and it should be carefully determined for each particular case, regarding the individual characteristics of the process. Thus, the suppression of the parts of the signal which carry vital information about the state of cutting tools will be avoided. According to the literature available, it can be concluded that the lowpass and bandpass filters implemented in the measuring equipment and realized by means of computing processing, i.e. program support in the phase of additional signal filtering, are most frequently applied. Filter selecting will depend on its velocity and the quality of the outgoing signal. It should be mentioned that in literature the right kind of used filter is rarely specified, and that in a large number of works it can be noticed that additional filtering is not mentioned at all, although it has been carried out. Within the research the lowpass FIR (Finite Impulse Response) filter has been used for vibration signals.

The above mentioned forms of filtering can be applied in situations when the frequency range of a signal is of interest a priori and completely defined. There are also situations in which it is not always possible to distinguish properly the range with information about the tools state from the ones representing noise [4]. Concrete examples are the high frequencies of vibration signals and the acoustic emission signal, where elastic waves occur due to the effort in the zones of deforming. The waves occur as a consequence of freeing energy produced by separating molecules in a crystal grid of a material. One of the main advantages of using these kinds of signals follow from the fact that their frequencies are considerably higher (ultrasound area) from the vibration frequency of a machine and the surrounding area. In that way unwanted influences can be directly avoided, as well as the occurring of lower frequency spectrum which is not related to the tool wear. However, a problem occurs in cases when it is necessary to isolate more harmonics which appear because of the plastic deformation and breaking of degraded particles, particles-tools collision and all other disturbances for which it is difficult to determine the area of frequency. It turned out that this kind of disturbance is possible to isolate considerably by applying wavelet transformation method. It is a kind of method based on the signal decomposing procedure after which the partial filtering of its segments follows

### 3.2 Signal processing by means of discreet wavelet transformation

Wavelet transformation is the most frequently used and the most important signal analyzing method in a time-frequent area. Its basic advantage related to methods of frequency area analysis (e.g. Fourier`s transformations) represents a high-quality and simultaneous signal presentation both in a frequency and time areas. In that way, a possibility of signal analysis on the local level is acquired, which is especially important for non-stationary signal processing. This function, while being analyzed, gets a number of different forms related to its width modification. The transformation procedure is based on comparison of wavelet function of a certain width (frequency) defined by a scaling parameter (s) and by parts of signals of the same width in a certain time interval (t – kτ), the scale being inversely defined, considering signal frequency. The record of the continuous wavelet transformation (CWT) in a general form is given in the scheme:

$$\gamma(\tau, s)\frac{1}{\sqrt{|s|}}\int_{-\infty}^{\infty} x(t)\varphi^{*}\left(\frac{t-\tau}{s}\right)dt \qquad (1)$$

Where τ is a translation parameter, s scale parameter, x(t) signal being transformed, γ frequency structure of the signal x(t) at a given time interval k$ and with the s scale, and $ the scaled and translated projection of the original wavelet kτ. When analysis of the whole signal is being carried out with the original function of a given scale, the procedure is being repeated for another scale value, i.e. time interval. If the signal contains a spectral component corresponding to the current scale value, multiplying of the wavelet function and the signal located where the component is existing is relatively high. Wavelet moving in time leads to signal localizing in time, while the scale changing produces information of the signal frequencies in each of the analyzed time intervals. In the low-frequency area signal basis (signal approximation) is determined, while the high-frequency area gives more detailed information.

## 4. WEAR PARAMETERS

### 4.1 Selecting the tool wear defining parameters

A good selection of the best group of wear parameters, which can classify the degree of tool wear with required accuracy during the process of classification, is the last step of the signal processing procedure. Analysis show that in most cases the aim of the process of parameter selection is selection of the optimal number of parameters and only after that the most suitable parameter group, considering the influence of each parameter separately on the degree of tool wear recognizing.

Although it is better to use a larger number of independent parameters as a rule, too many parameters can cause overnoising, for example when neural frameworks are used (overfitting), which are still used by most of the authors at wear process modeling. Overnoising leads to decrease of the general features of the frameworks and consequently worse quality of the system responding.

It can be noticed that the problem of wear parameter analysis and selection has been treated in literature in several ways. Generally, explanation for their particular selection does not exist. They are followed by works in which the analysis of the influence of recorded signals on the wear dynamics was primarily done. On the basis of these observations wear parameters which describe accurately some segments or appearing of wear process were suggested [5]. A group of methods use the so called parameter sequential selection, which imply their mutual independence when tool wear evaluating, while another group is independent when choosing parameter combinations. Generally speaking, as opposed to the combined approach, when the individual parameter selection is concerned, their growth influences less the increase of the model complexity then the increase of additional data analysis. On the other hand, certain situations show that mutual influences of parameters can result in higher degree of correlation with the wear dynamics than in the case of individual approach. Finally, the last group contains the parameters where the wear parameter selection is done depending on their influence on the classifying results. This approach, as well as the individual analysis of wear parameter influence, has been used in this paper, as well.

## 5. CONCLUSION

The presented model of tool wear fuzzy classifier uses the processed signal of vibration acceleration from a sensor allocated on the tool in order to evaluate tool wear. This technique provides an acceptable method for the process of fuzzy modeling on the basis of which are calculated the parameters of membership functions which represent the incoming/outgoing data in the best possible way. Once the model is formed, it can evaluate the degree of tool wear for certain cutting parameters (the ones it has been taught). The model is formed rather rapidly and it can evaluate tool wear on-line. The time needed for the model formation depends on the quantity of entering data, while the model accuracy depends on the data selection

## 6. ACKNOWLEDGMENTS

This paper is a part of research in the framework of the projects: "Research and Development of Roller and Bearing Assemblies Their Components," TR 14048, and the project "Enhancing the quality of processes and products utilizing modern engineering techniques with goal to increase of competitiveness on global market", project TR 14003 part of the technological development program for period from 2008. to 2010., financed by Ministry of science of Republic of Serbia.

## 7. REFERENCES

[1] Sick, B., 2002, On-line and Indirect Tool Wear Monitoring in Turning with Artificial Neural Networks, Mechanical Systems and Signal Processing, No 16(4), 487 – 546., ISSN 0888-3270

[2] Antić A., Hodolič, J., Soković, M., 2006, Development of a Neural-Networks Tool-Wear Monitoring System for a Turning Process, Strojniški vjesnik Journal of Mechanical Engineering, 52(11), 763-776, ISSN 0039-2480

[3] Sharma V.S., Sharma S. K., Sharma A. K., 2007, Cutting tool wear estimation for Turning, Journal Intell Manuf, No 19, 99–108.

[4] Antić A., Petrović, B., Zeljković, M., Dinamika obradnog sistema i njene implikacije na indirektno prepoznavanje stanja reznog alata, 32. Savetovanje proizvodnog mašinstva Srbije, Novi Sad: Fakultet tehničkih nauka, 18-20 septembar, 2008, 341- 346, ISBN 978-86-7892-131-5.

[5] Al-Habaibeh, A., & Gindy, N., , 2001, Self-Learning Algorithm for Automated Design of Condition Monitoring Systems for Milling Operations, The International Journal of Advanced Manufacturing Technology, No 18, pp. 448-459., ISSN 0268-3768

***Authors:*** **Prof. dr Janko Hodolič, Prof. dr Milan Zeljković, M.Sc. Aco Antić**, **M.Sc. Živković Aleksandar,** University of Novi Sad, Faculty of Technical Sciences, Departman for Production Engineering, Trg Dositeja Obradovica 6, 21000 Novi Sad, Serbia, Phone.: +381 21 4852320, Fax: +381 21 454-495. E-mail: hodolic@uns.ac.rs, milanz@uns.ac.rs, antica@uns.ac.rs, acoz@uns.ac.rs,