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A Review of Machining Monitoring System Based On Artificial Intelligence Process Models

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Abstract: *This paper follows a recent update of the literature on machining monitoring systems. The paper reviews the past contributions in these areas and provides an up-to-date comprehensive survey of methodology overview, sensor technologies, signal processing, decision making strategies for process monitoring and integrated workpiece quality evaluation. Tool wear measuring technique using vision system as well. Application examples including sensor systems are reported. Future challenges and trends in sensor based machining operation monitoring are presented.*
Key words**:** *monitoring systems, machining operations*

I. INTRODUCTION

Manufacturing enterprises currently have to cope with growing demands for increased product quality, greater product variability, shorter product life-cycles, reduced cost, and global competition [1, 2, 3]. A key issue for an unattended and automated machining system is the development of reliable and robust monitoring systems. Machining problems, such as cutter breakage, excessive wear, chatter and collision, impede production consistency and quality.

The complex interactions between machines, tools, workpieces, fluids, measurement systems, material, humans and the environment in cutting operations requires that sensors be employed to insure efficient production and protect workers and the environment.

Loss due to disturbance could be prevented, or at least limited, using an in-process tool condition monitoring (TCM) system. An accurate and reliable TCM system could increase savings between 10% and 40% [4]. Now there are additional requirements for increased flexibility. Specifically, sensor systems must be able to be interfaced with open system architecture controllers for machines and systems must be designed to accommodate needs of so called “reconfigurable” systems

The typical machining process monitoring system operates according to the following rationale. In the cutting region there are several process variables, such as cutting forces, vibrations, acoustic emission, noise, temperature, surface finish, etc., that are influenced by the cutting tool state and the material removal process conditions. The variables that is prospectively effective for machining process monitoring can be measured by the application of appropriate physical sensors. Signals detected by these sensors are subjected to analogue and digital signal conditioning and processing with the aim to generate functional signal features correlated (at least potentially) with tool state and/ or process conditions

The measuring techniques for the monitoring of machining systems have traditionally been categorized into two approaches: direct and indirect.

In the direct approach the actual quantity of the variable, e.g. tool wear, is measured. Examples of direct measurement in this case are the use of cameras for visual inspection, radioactive isotopes, laser beams, and electrical resistance. Many direct methods can only be used as laboratory techniques. This is largely due to the practical limitations caused by access problems during machining, illumination and the use of cutting fluid. However, direct measurement has a high degree of accuracy [5].

Through indirect measurement approaches, auxiliary quantities can be measured. The actual quantity is subsequently deduced via empirically determined correlations. Indirect methods are less accurate than direct ones but are also less complex and more suitable for practical applications. In contrast to the traditional detection of tool conditions, the approach is that machining processes are being continuously monitored via sensing devices to quantify the process performance or provide information for process optimization.
A tool condition monitoring system can therefore be viewed [6] as serving the following purposes:

1. advanced fault detection system for cutting and machine tool,
2. check and safeguard machining process stability,
3. means by which machining tolerance is maintained on the workpiece to acceptable limits by providing a compensatory mechanism for tool wear offsets, and
4. machine tool damage avoidance system.

II. METHODOLOGY OVERVIEW

According to the literature, a generic methodology for developing an intelligent monitoring system for machining is composed of six key issues:

1. Sensors: The cutting process can be characterized by a variety of physical quantities. Appropriate sensors such as dynamometers, AE sensors, accelerometers, current/ power sensors, etc., transform a physical quantity into the corresponding electrical signals. It is important to take into account the reliability of each sensor, the cost, its intrusive nature, and its application in order to select the most appropriate sensor system for a given monitoring purpose. Frequency of sensor usage related to machine monitoring systems is presented in [7]
2. Signal processing: Signal processing can be more or less complex, consisting in amplifying and filtering (with analogical low-pass, band-pass, or high-pass filters) the signals. Sample frequency limitations of acquisition boards must be taken into account to avoid aliasing. In addition, digital signal processing through digital filters and signal segmentation operations has to be considered to be able to acquire the part of the signal which is of interest.
3. Feature generation: The sensor signal has to be transformed into features that could describe the signal adequately. Many different features from the time domain, frequency domain and wavelet domain can be used for this purpose.
4. Feature selection/extraction: In order to develop robust and reliable models for monitoring, it is necessary to use the most meaningful features which best describe the machining process. Feature selection and feature extraction are two methods which allow the most useful sensory features to be defined.
5. Process knowledge model

(a) Design of experiments: Experimental runs in machining for modeling purposes are both economically costly and time-consuming, so an effective design of experiments is to enable monitoring systems to be applied in industry.

(b) AI technique: Monitoring systems require reliable models which are able to learn complex non- linear relationships between process performance variables and process variables in machining. An adequate selection of the AI technique is crucial to develop reliable machining models. This selection depends mainly on the number of experimental samples, the stochastic nature of the process, the desired model accuracy, and the explicit or implicit nature of the model.

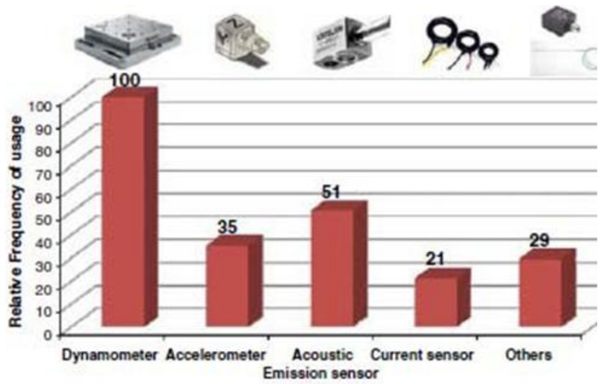


Fig .1 Frequency of sensor usage related to machine monitoring systems [7]

III. MOTOR POWER AND CURRENT MEASUREMENT TECHNOLOGY

When using an indirect sensor system based on motor current or power, it is crucial that the relationship between input current/power and output force/torque is linear and understood.

The signal features [6]:

1 the amount of spindle power required for material removal may be a very small part of total power
2 the spindle motor power is proportional to the resultant cutting force, the least wear sensitive parameter;
3 temperature rises inherent in electrical motors influence power consumption;
4 drive motors are highly dependent on the axis lubrication state, transverse rate and axis condition.

IV. FORCE AND TORQUE MEASUREMENT TECHNOLOGY

Force and torque sensors generally employ sensing elements that convert the applied force or torsional load into deformation of an elastic element. The two main sensor types used are piezoelectric based and strain based sensors Direct force measurement using piezoelectric sensors is possible when the force transducer is mounted in line with the force path. In cases where more measurement flexibility is required, multi-component force transducers have been developed and are used extensively in lab based applications Strain gauge force transducers, consisting of a structure that deforms under a force, offer reasonably high frequency response and long-term stability. The total cutting force could be obtained by the summation of the static and dynamic forces. Experimental setup with 3 component dynamometer acoustic emission sensor and 3 –component accelerometer for machining process monitoring is in Fig 2 [8].

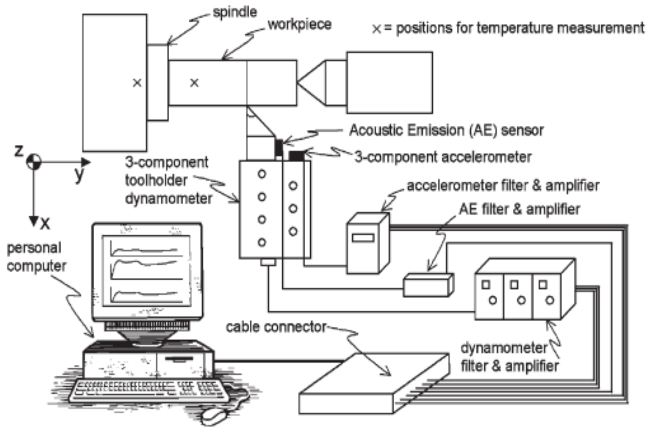


Fig. 2 Monitoring setup [8]

V. ACOUSTIC EMISSION MEASURING TECHNOLOGY AND SENSORS

Piezoelectric sensor technology is particularly suitable for measuring acoustic emission (AE) in machining process monitoring. With very wide sensor dynamic bandwidth from 100 to 900 kHz, AE can detect most of the phenomena in machining, though significant data acquisition and signal processing is required [6] (Fig. 3) The capacitance principle can also be used for detecting AE, as the capacitance of two parallel plates changes with the distance between plates. The accuracy of this AE detection method is higher than many other techniques and capacitance based AE sensors are used for calibrating other AE sensors. However, capacitance type displacement sensors for AE are very sensitive to sensor position and surface mounting.

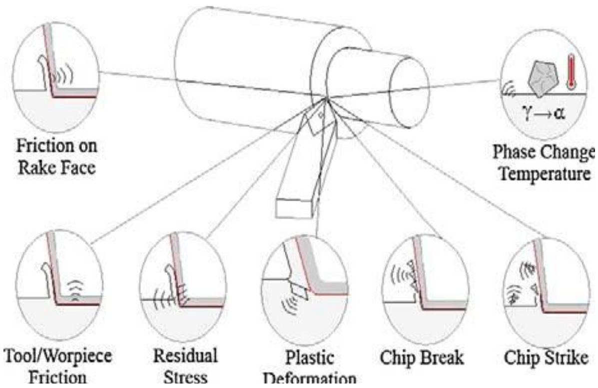


Fig. 3 Sources of AE in machining [6].

During metal cutting the workpiece undergoes considerable plastic deformation as the tool pushes through it. Within the deformation zones (dislocation movements) strain energy is released as the bonds between the metal atoms are disturbed. This released energy is commonly referred to as acoustic emission. Other sources of AE include phase transformations, friction mechanisms (tool-workpiece contact) and crack formation or extension fracture

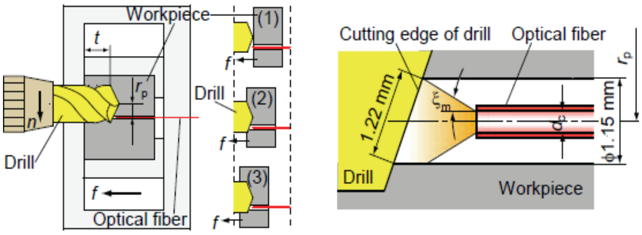
VI. VIBRATION

A large variety of sensing principles are used for sensing vibration. However, piezoelectric transduction is the most common type in vibration sensing of machining operations. Vibrations that occur during metal cutting can be divided into two groups:
(i) dependant and
(ii) independent of the cutting process
As in many applications using machine vision, object illumination notably impacts the process and for industrial applications can lead to process unreliability [9].

VII. THE CUTTING TEMPERATURE

The resultant high temperatures around the cutting tool edges has a direct controlling influence on the rate and mode of cutting tool wear, the friction between chip and cutting tool, and also that between the cutting tool and the newly formed surface. As the temperature distribution is not uniform, knowing the exact amount of heat transferred via the tool is not straight forward. For practical applications such as on-line TCM, remote thermocouple sensing appear to be the only worthy way to measure the workpiece-tool temperature but a direct measurement of the tooltip or rake face temperature distribution cannot be obtained. Past attempts at measuring the cutting edge temperature have proven exceptionally difficult due to lack of direct access to the cutting zone [10].

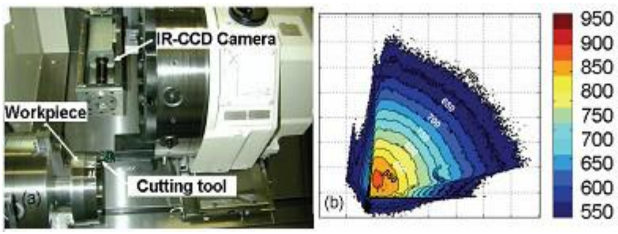
The cutting temperature is measured using a two-color pyrometer with an optical fiber. The fundamental structure is indicated in Figure 4 and the detail of temperature measurement condition is in Figure 4. In Figure 4(a), which is the top view of the cutting point, the optical fiber is inserted into the fine hole in the workpiece and is fixed to the bed of the lathe at the point where the distance between the cutting edge of drill and the incidence face of the fiber is 1mm. The distance of 1 mm is maintained constantly while the drilling is performed. The feed rate is given by the movement of the workpiece, but the optical fiber has no contact with the workpiece and is at a state of geostationary.



(a) Optical fiber setting (b) Detail of temperature measurement

Fig, 4 Arangement of optical fiber in drilling process and target area of temperature measurement [11]

A typical IR-CCD, described in [12], is shown in Figure 5 (a). It consists of a near infrared (NIR), high resolution (4.5 m), silicon-based, CCD camera with an observation area of 3.5 mm by 2.5 mm. Temperature measurements are restricted to the range of 500ºC to 1000ºC and are made with no coolant. A calculation of the uncertainty, which considers only a black body calibration source and assumes an emissivity higher than 0.5 for the tool insert, shows the maximum error to be less than 5%. The temperature distribution map for machining stainless steel at 220 m/min, [12], is given in Figure 5 (b)



Fig, 5 (a) IR-CCD measurement arrangement [12]. showing the (b) temperature maps (ºC) for machining SS2541 machined with an S6 insert at a cutting speed of 200 m/min and a feed of 0.15 mm.

A data acquisition system records the timing of the thermal and visible spectrum images, along with analog data such as cutting forces [13].

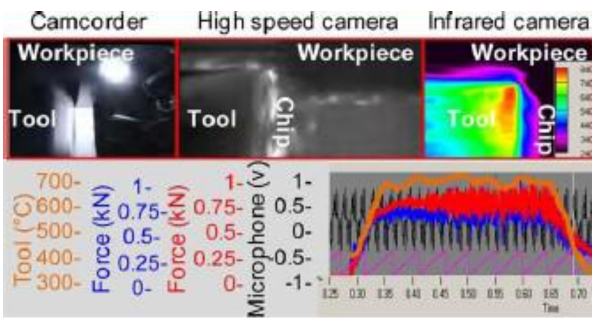


Fig. 6 Output parameters from dual spectrum equipment after orthogonal tests [13]

True temperature at any given location in the tool and corresponding cutting forces are played back in a synchronized manner. Fig. 6 shows an example of (i) a standard camcorder image, (ii) the visible spectrum image captured at 30,000 frames per second and 33 ms integration time, yielding 256 -128 pixel size, and (iii) the spectral radiance maps acquired at 300 frames per second and 19 ms integration time, from 3.8 mm to 5.1 mm in wavelength with 160 -120 pixel size.

VIII. INTEGRATED WORKPIECE QUALITY EVALUATIONS

Finally, was looked at the ability to integrate evaluation of the workpiece quality into cutting performance. This remains an elusive goal due to many challenges. The first challenge is defining workpiece quality quantitatively over the range of processes and parts manufactured (for example, subsurface damage in machining, or surface roughness).

Second, measuring or somehow assessing the quality elements of the workpiece as part of the production environment (for example, surface roughness that is dependent on so many independent variables in the process such as tool condition). Finally, it is not clear how to incorporate this information in some way into the machine and process control scheme.

The closest system relating to workpiece quality evaluation is the “workpiece monitoring” bar which, is hardly seen in practice in industry. But, this important piece is needed for much of the advancements in cutting performance reviewed above (open architecture adaptive control and reconfigurable systems, for example). This is one area where modeling is not easily applied. The challenge is integration of independent, reliable and capable sub-systems with the goal of assessing the product quality.

IX. TOOL WEAR MEASURING TECHNIQUE USING VISION SYSTEM

The presented system [14] is characterized by its measurement flexibility, high spatial resolution and good accuracy. The system consists of a light source to illuminate the tool, CCD camera, laser diode (used in conjunction with profile deepness assessment) with linear projector, grabber for capturing the picture, and a PC.

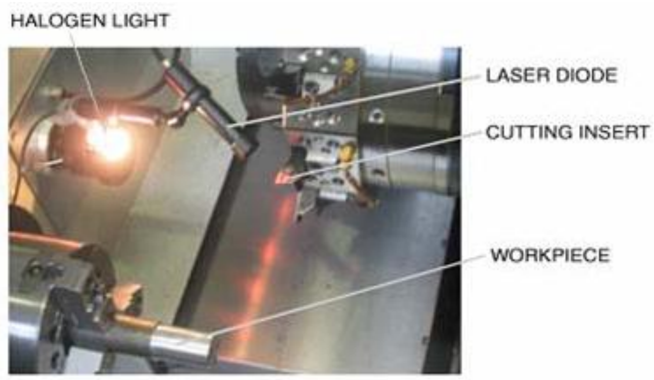


Fig. 7 Measurement set mounted on a machine tool

The technique is specially characterized by its determination of profile deepness with the help of projected laser raster lines on a tool surface. So it has advantage comparing with other techniques, which can measure only 2D profiles. With the technique presented in this paper a 3D image of relief surface can be obtained without having need to employ a very complicated measuring system.

For on-line tool wear monitoring using geometric descriptors from digital images LDA (linear discriminant analysis) shows that three out of the nine descriptors provide the 98.63% of the necessary information to carry out the classification, which are eccentricity, extent and solidity [15]. The result obtained using a finite mixture model approach shows the presence of three clusters using these descriptors, which correspond with low, medium and high wear level. A monitoring approach is performed using the tool wear evolution for each insert along machining and the discriminant analysis. This evolution represents the probability of belonging to each one of the wear classes (low, medium and high). The estimate of the wear level allows to replace the tool when the wear level is located at the end of the M class (medium), preventing that the tool enters into the H class (high) Fig 8.

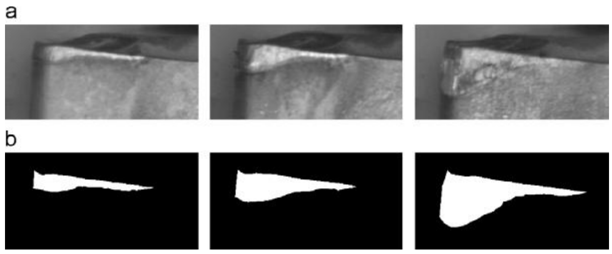


Fig 8 (a) First image in series shoving three wear levels: (b) segmented images with the worn region in white [15]

X. MONITORING OF CRATER WEAR IN TURNING USING ULTRASONIC TECHNIQUE

The ultrasonic probe of 10MHz having 10mm diameteris used to transmit/receive (T/Rprobe) the ultrasonic signal in to the uncoated carbide insert (CTC2135). The tool-transducer configuration as shown in Fig. 9, is favorable to measure the crater wear.

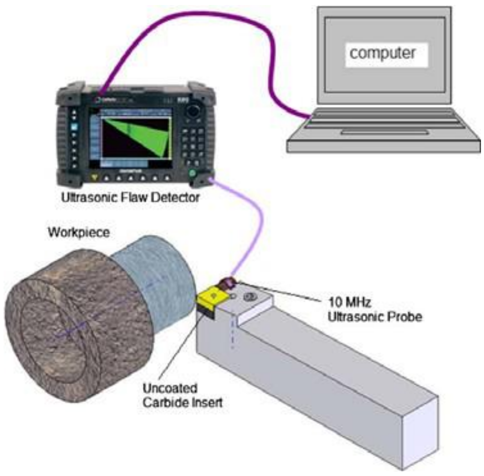


Fig. 9 Online setup forcraterwear monitoring [16]

The ultrasonic waves transmitted through the insert are reflected back from the side flank. The maximum energy is received in this condition because, the surface of the side flank acts as a flat reflector
The total amount of reflected ultrasonic energy decreases with gradual wear due to scattering of ultrasound waves. The increase in crater depth increases the scattering and this energy loss can be correlated with crater depth.

XI. DECISION MAKING SUPPORT SYSTEMS

In monitoring and control activities in modern manufacturing systems, the computing methods employed intelligent sensors and sensorial systems. A number of schemes, techniques and paradigms have been used to develop decision making support systems functional on machining process conditions based on sensor signals data features. The most frequently employed for the purpose of sensor monitoring in machining, including neural networks, fuzzy logic, genetic algorithms and hybrid systems able to synergically combine the capabilities of the various cognitive methods

Neural network

An artificial neural network (NN) is a computational model of the human brain that assumes that computation is distributed over several simple interconnected processing elements, called neurons or nodes, which operate in parallel. A NN provides a mapping through which points in the input space are associated with corresponding points in an output space on the basis of designated attribute values, of which class membership can be one. NN can capture domain knowledge from examples, do not archive knowledge in an explicit form such as rules or databases, can readily handle both continuous and discrete data, and have a good generalisation capability Knowledge is built into a NN by training. Some NN can be trained by feeding them with typical input patterns and expected output patterns. The error between actual and expected outputs issued to modify the weight of the connections between neurons. This method is known as supervised training.

Fuzzy logic

Fuzzy logic is a logical system, which is an extension of multivalve logic. But in a wider sense, FL is almost synonymous with the theory of fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. A fuzzy set defines a mapping between elements in the input space (some times referred to as the universe of discourse) and values in the interval [0, 1]. A membership function is a curve that defines how each point in the input space is mapped to a membership value (degree of membership or truth degree) between 0 and 1. The membership function can be any arbitrary curve, the shape of which can be defined as a function suitable from the point of view of simplicity, convenience, speed and efficiency.

Other methods (genetic algorithms, hybrid systems, etc.)

Genetic algorithms (GA) belong to a branch of computer science called "natural computation" where programmers, inspired by phenomena in the biological world, create models of these systems on a computer. This technique can solve complex problems by imitating Darwinian theories of evolution on a computer. The first step in the use of a GA is building a computer model to represent a given problem. Interacting variables in the problem are first combined and encoded into a series of binary strings (rows of ones and zeros) to form numerical "chromosomes". The computer randomly generates an entire "population" of these chromosomes and ranks them based on a "fitness function" which determines how well they solve the problem. Those strings which are deemed the "fittest" are allowed to "survive" and "reproduce" with other chromosome strings, through genetic operators such as "crossover" and ‘‘mutation", to create "offspring" chromosomes [6, 17]
Figure 10 shows the AI approaches applied in machining monitoring systems according to the references found in the research platform *ISI*-Web of knowledge from 2002 to 2007.

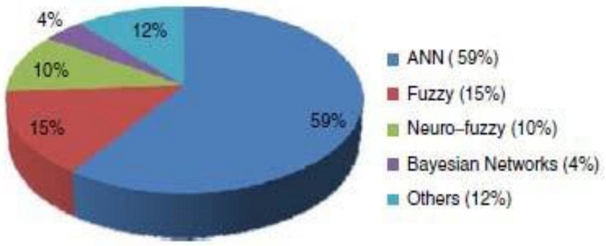


Fig. 10 Frequency of usage AI approaches applied in machining monitoring systems according to the references found in the research platform *ISI-Web of knowledge* from 2002 to 2007

XII. INTELLIGENT SENSOR MONITORING

Intelligent sensor monitoring systems including, abilities for self-calibration and self diagnostics, signal conditioning, and decision making. Recommended measures [6]:

1 more applied research in intelligent sensor monitoring applications to manufacturing,
2 development of high performance equipment, 3 efforts towards standardisation,
4 promotion with industry,
5 robust pattern recognition paradigms; and
6 training and formation of skilled operators in intelligent sensor monitoring.

XIII. CONCLUSIONS

Many machining monitoring systems based on in process models have been developed in the past for optimising, predicting or controlling machining processes. All research works present different methodologies without showing clear guidelines or key issues for the development of intelligent machining systems.

The paper has reviewed: (1) methodology for monitoring overview (2) the different sensor systems applied to the monitoring of machining processes, (3) tool wear measuring technique, (4) decision making support systems, (5) the DoE required to model a machining operation with minimum experimental data and (6) the main characteristics of several AI techniques to facilitate their application/selection.

Cutting forces (static and dynamic), AE and vibration (acceleration) are considered the most widely applicable parameters. Advances and increased sophistication in instrumentation technology employed for measuring these parameters make them viable, practical, cost effective, robust, and easy to mount and have the quick response time needed to indicate changes for on-line monitoring of machining process.

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