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Latest Developments in Condition Monitoring of Machining Operations

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Abstract: The study describes a novel approach for condition monitoring is one of the most important requirements for the automated and unattended manufacturing systems. In the absence of human operators, this monitoring and control has to be performed by sensors and associated decision making systems, able to interpret incoming sensor information for monitoring of machining operation including tool condition monitoring, process control and more recently, advanced topics in machining monitoring sensor related applications. Reviews on tool condition monitoring, sensor technologies, decision making strategies for process monitoring using ANN, FL and GA models are also out lined. Future challenges and trends in sensor based machining operation monitoring are presented.

Key words: Neural network, fuzzy logic, genetic algorithm, milling operation

INTRODUCTION

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 those are 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. Sensor signal features are then fed to and evaluated by cognitive decision making support systems for the final diagnosis. This can be communicated to the human operator or fed to the machine tool numerical controller in order to suggest or execute appropriate adaptive/corrective actions. The sequence of activities in sensor monitoring of machining process conditions can be surmised.

SENSORS AND SENSOR SYSTEMS FOR MACHINING

The measuring techniques for the monitoring of machining operations 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 and has been employed extensively in research laboratories to support the investigations of fundamental measurable phenomena during machining processes.

Motor power and current: Electric drives and spindles provide the mechanical force necessary to remove material from the part. By the measurement of motor related parameters such as motor power or current, both process power and, more recently, measures of the machine tool and drive condition can be realized. The major advantage of motor related parameters to detect malfunctions in the cutting process is that the measurement apparatus does not disturb the machining. The capacity to measure power already exists in the drive controller as part of the drive control loop or can be readily retrofitted and is suitable for use in production environments.

Power and current measurement technology: Retrofit power measurement solutions are an economical monitoring solution for many machining operations. However, the latest modern open control systems allow

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access to internal signals in the numerical controller such as motor power and motor current. Software can be seamlessly integrated into the CNC control and provides the user with a dedicated monitoring interface via the Human Machine Interface (HMI). Over the last decade, this technology has become commonplace in industry. A logical extension of this approach is the adoption of control parameters based on internal control signals. Adaptive Control Optimize (ACO) and Adaptive Control Constraint (ACC) based algorithms have been developed and implemented using both internal control signals and additional sensors (Klocke *et al*., 2008).

Power monitoring signal features: Motor current and power sensing use the motor itself as an indirect sensor of cutting force. Thus, when using sensor systems 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 and uses of current/power monitoring face a number of issues, including (Kettetler, 1999): (1) the amount of spindle power required for material removal may be a very small part of total power, e.g., for small diameter drilling and finish machining; (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 and (4) drive motors are highly dependant on the axis lubrication state, transverse rate and axis condition.

Force and torque: A certain force is required for cutting operation to separate and remove the material. The monitoring of cutting forces in machining for the validation of analytical process models, the detection of tool failure, etc., has been used extensively by researchers (Byrne *et al*., 2004). This is due to the high sensitivity and rapid response of force signals to changes in cutting states. Torque sensors, like force sensors, also consist of a mechanical structure that responds to a deformation but in this case the applied load are torsional. The underlying force measurement technology is often identical but the application of torque sensors and the method of signal transmission from rotating tool holders are different.

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.

Piezoelectric 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. Rotating cutting force dynamometers are also available that contain the force sensing elements capable to measure 3 components of force and torque. The data is transmitted from the rotating part of the sensor to a stator via telemetry. Rotating cutting force dynamometers can operate at speeds of up to 20,000 rpm and have been used for high speed milling of aerospace materials. Developments like the integration of force sensors into the machine structure have taken place over the last 10 years with concepts developed for milling (Byrne *et al*., 1995). Figure 2 shows Arrangement of sensors on the spindle.

Acoustic emission measuring technology and sensors: Piezoelectric sensor technology is particularly suitable for measuring Acoustic Emission (AE) in machining process monitoring (Rogers, 1979). With very wide sensor dynamic bandwidth from 100-900 kHz, AE can detect most of the phenomena in machining, though significant data acquisition and signal processing is required (Rogers, 1979) (Fig. 1). This presents problems for signal

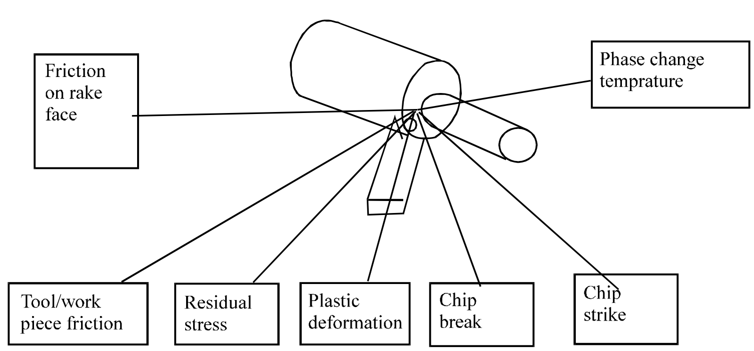

Fig. 1: Sources of AE in machining

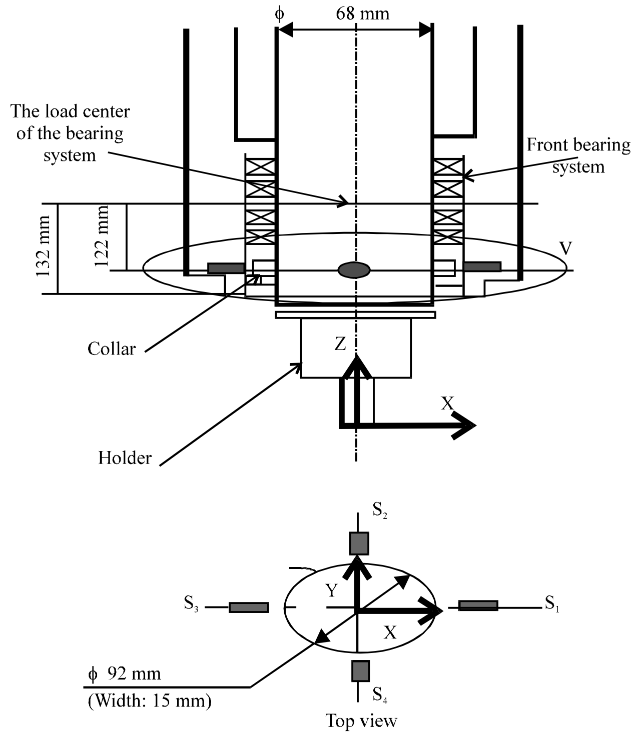

Fig. 2: Arrangement of sensors on the spindle

processing and band pass filters usually provide great flexibility for AE detection by selecting appropriate frequency ranges. The output signal from the AE sensor is fed through a pre amplifier that has a high input impedance and low output impedance. A Root Mean Square (RMS) converter, gain selection unit and filters are also typically contained within the pre amplifier housing. Performed test cuts to detect fracture and/or monitor the condition of small drills using AE features. AE applications by employing simple process-adapted band pass filters, a rectifier and a low pass filter to convert the normally high frequency AE signal to low frequency signals.

AE signal transmission and sensor location: The high frequency and low amplitude nature of AE means that signal transmission via a coupling fluid is possible. By the location of the AE sensor on the coolant supply nozzle, the coolant can be used as transmission path. The signal transmission methods had a distinct advantage for rotating tools such as in milling and drilling. Various other methods of signal transmission from AE sensor to AE coupler/signal processor are common to other sensing applications, including slip rings, inductive coupling and radio frequency transmission. Jemielniak investigated aspects of AE signal processing in machining and proposed that in the machine tool environment the AE signal is repeatedly reflected from the inner surfaces of the structure where the sensor is mounted.

MONITORING SCOPES

Here, a survey of applications related to the main goals of advanced monitoring of machining operations is presented and a summary of viable solutions as a function of the monitoring scopes is reported.

Tool conditions: Kuljanic focus on the application of AE for tool wear estimation in milling using WPD to build an automatic tool wear classification system (Kuljanic *et al*., 2008). Axinte and Gindy try to correlate broaching tool conditions to output signals of multiple sensors: AE, vibration, cutting force and broaching machine hydraulic pressure. In they assess the use of spindle power signal for TCM in milling, drilling and turning: this method is successful for continuous turning and drilling while it shows low sensitivity for discontinuous milling (Axinte and Gindy, 2003). Teti and Baciu (2004) apply an intelligent monitoring system based on audible sound energy for in-process tool state recognition in band sawing of Al alloy and low C steel. A real-time tool breakage monitoring system for milling is presented based on cutting force indirect measurement through feed drive AC motor current, whose sensitivity is sufficient to identify tool breakage (Teti and Baciu, 2004). Ryabov develop an online tool geometry measurement system based on a laser displacement meter. It build up a vision system to detect small diameter tap breaks hardly perceived by indirect in-process monitoring methods as AE, torque and motor current; they propose an online drill wear estimation method based on spindle motor power signal during drilling. Arrazola uses micro-scale thermal imaging to identify effects of steel machinability change on cutting zone temperature and related tool wear mechanisms (Arrazola *et al*., 2008).

End milling cutters are generally used for milling either soft or tough materials. In order to develop monitoring functions, displacement sensors are installed on the spindle unit of a high precision machining center. Figure 3 shows a vertical type-machining center The PCD end-milling cutter having four straight flutes was used. High-pressure coolant jet was employed for cooling and lubrication of the high-speed machining operations. The spindle has constant position preloaded bearings with oil-air lubrication and the maximum rotational speed is 20 000 rpm. Figure 3 shows four eddy-current displacement sensors are installed on the housing in front of the bearings to detect the radial motion of the spindle. The specifications of the sensor are as follows: the diameter is 5.4 mm and the length is 18 mm; measurement range is 1 mm; nominal sensitivity is 0.2 mm V^{-1}; dynamic range is 1.3 kHz; linear sensitivity is ±1% of full scale. Figure 3 shows the sensor locations. The two sensors S_1 and S_3 are aligned opposite in the x-direction and the other two S_2 and S_4 are aligned in the Y-direction.

Chip conditions: Govekar use filtered AE spectrum components for chip form classification. Kim and Ahn propose a method of chip disposal state monitoring in drilling based on spindle motor power features. Apply WPT and spectral estimation of cutting force signals for chip form recognition.

Venuvinod used a variety of sensors to obtain stable clusters of chip form under varying dry cutting conditions through geometric transformations of the control variables: they aimed at recognising chip entanglements, chip size (including continuity) and chip shape. Andreasen and De Chiffre develop and test a laboratory system for automatic chip breaking detection via frequency analysis of cutting forces.

Process conditions: Brophy classify drilling operations as ‘normal’ or ‘abnormal’ (tool breakage or missing tool) using spindle power signals (Brophy *et al*., 2002). Mezentsev *et al*. (2002) develop a method for fault detection in tapping based on torque and radial force; the method allows to identify typical faults of tapping operations: axial misalignment, tap run out, tooth breakage both singly and in a combined way. SFs to identify variable process conditions in Al alloy milling. Pujana report on a new method to assess cutting variables (shear angle, chip thickness, tool vibration amplitude, strain, strain rate) and chip topology by means of high speed photography combined with laser printed square grid patterns on the workpiece at industrial cutting speeds and feeds (Mezentsev *et al*., 2002).

Surface integrity: Azouzi and Guillot apply cutting parameters and two cutting force components for online estimation of surface finish and dimensional deviations. Huang and Chen employ a statistical approach to correlate surface roughness and cutting force in end milling operations. Abouelatta and Madl develop a method of surface roughness prediction in turning based

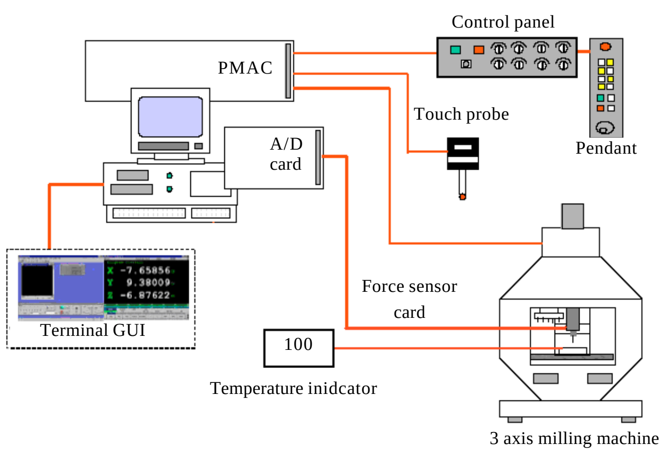

Fig. 3: High speed vertical milling center

on cutting parameters and FFT analysis of tool vibrations. Salgado use singular spectrum analysis to decompose the vibration signals for in-process prediction of surface roughness in turning. Song investigate time series analysis of vibration acceleration signals measured during cutting operations for real-time prediction of surface roughness. Axinte using AE signals backed up by cutting force data, report on process monitoring to detect surface anomalies when abusively broaching and milling difficult-to-machine aerospace materials.

Machine tool state: Verl proposed a system for feed drives wear monitoring based only on signals available in controlled drives: position, speed and motor current. The algorithm compares current characteristic parameters with those detected when the machine is new. Zhou introduced a systematic method to design and implement an integrated intelligent monitoring system, with modular and reconfigurable structure, to monitor power, vibration, temperature and drive and spindle pressure for condition monitoring, fault diagnosis and maintenance planning in flexible manufacturing cells. Saravanan present an analysis of failure frequency and downtime of critical subsystems in a lathe. The highest number of failures took place in electrical and headstock subsystems.

Chatter detection: Chatter can be detected by monitoring the power spectrum of the displacement of a work piece during the machining operation. Kuljanic analyse chatter identification methods used in research and investigate an industrial chatter detection system by comparing several sensors: the best results were given by a multi-sensor system using an axial force sensor and two accelerometers. Berger apply wavelet decomposition of cutting force signals to discriminate between chatter and non chatter states (Berger *et al*., 1998). Govekar use entropy rate of resultant cutting force signals to detect broken chip formation and chatter onset in turning. Kwak and Song develop a method based on AE signals to recognise chatter vibration in grinding (Mezentsev *et al*., 2002). Yoon and Chin apply wavelet transform of cutting force signals for real-time detection of chatter in end milling operations.

DECISION MAKING SUPPORT SYSTEMS AND PARADIGMS

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

Neural networks: Neural Network (NN) is a simplified model of the human brain that assumes that computation is distributed over several highly interconnected processing elements, called neurons or nodes which operate in parallel. NN exhibit characteristics such as mapping capabilities or pattern association, generalization, robustness, fault tolerances and parallel and high speed information processing. It adopts various learning mechanisms of which supervised learning and unsupervised learning methods have to be very popular. NN have been successfully applied to problems in the field of pattern recognition, image processing, data compression, forecasting and optimization (Rajasekaran and Vijayalakshmi, 2003).

Neural network models: NN is a data base processing system consisting of a large number of artificial neurons in an architecture inspired by the structure of the cerebral cortex of the brain. 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 be employed as mapping devices, pattern classifiers or patterns completers. For more information on NN, 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 is used to modify the weight of the connections between neurons.

Supervised learning: In supervised learning, a 'teacher' is assumed to be present during the learning process, i.e., the network aims to minimize the error between the target (desired) output presented by the teacher and the computed output, to achieve better performance (Zurada, 2003). Among supervised learning models, backpropagation (BP) NN which are multiple-layered feedforward (FF) NN, have been very popular for their performance. Training of these NN depends very much on the initial weight values.. This brings the NN to a balance between training and testing errors and enables a notable reduction in the number of hidden nodes. Further supervised NN approaches are also considered here due to their use in decision making during monitoring of machining: probabilistic NN (PNN), recurrent NN (RNN), artificial cellular NN (ACNN), fuzzy logic NN (FLNN) or neurofuzzy systems (NFS) combining NN and FL methods to integrate the benefits of both paradigms.

Unsupervised learning: In unsupervised learning, there is no teacher present to hand over the desired output and the network so that each hidden processing element responds strongly to a different set or closely related group of stimuli. These sets of stimuli represent clusters in the input space which typically stand for distinct real concepts. It is used to perform clustering as the unsupervised classification of objects without providing information about actual classes. Among unsupervised learning paradigms, the Self-Organising Map (SOM) NN has been largely used for their performance.

NN applications to sensor monitoring of machining: The use of Probabilistic NN for automated classification of broaching tool conditions utilizing cutting force data is described in. Trials with short broaching tools that simulate the roughing stage of industrial broaching were carried out to produce square profile slots while detecting cutting force signals. To reproduce real industrial tool failures, where both tool wear and single tooth chipping or breakage may randomly occur, the broaching tools had cutting teeth in different conditions: fresh, worn, chipped tooth, broken tooth. The push-off force Fy was selected as the most sensitive to tool conditions. Tool failure recognition was based on the extraction of a set of N characteristic points from the Fy plot by repetitive selection of local maxima to construct N-elements feature vectors (pattern vectors). Pattern vectors for different tool conditions were used as inputs to a PNN with 4 tool state classes: fresh, worn, chipped, broken. The success rate achieved was as high as 92%. A scheme of the tool failure recognition paradigm is shown in Fig. 4.

Using RNN data processing, accurate flank wear estimations were obtained for the operating conditions adopted in the experimentation. Fractal dimensions were used as input features to a RNN for flank wear land estimation. The development of this estimator comprised four stages: (1) signal representation, (2) signal separation, (3) feature extraction and (4) state estimation (flank wear land). An intelligent multi-sensor chatter detection system for milling using two accelerometers and one axial force sensor embedded in the milling machine was investigated Particular attention was paid to industrial needs: (a) no reduction in machine stiffness; (b) compatibility with pallet and tool changers; (c) no restriction on tools, parts and cutting parameters; (d) robustness against sensing units failures; and (d) independence from cutting conditions and system dynamics. To evaluate the system capability for a broad application range, different test setups with diverse milling machines, toolings, sensor systems and work materials were used. A NN approach was used for decision making, comprising an ACNN applied to acceleration signals and a fuzzy NN for axial force signals. Good levels of NN accuracy were obtained with all single sensor signals (Halgamuge and Glesner, 1984).

To realise the concept of multi-sensor chatter detection (Fig. 5), the NN outputs for each single sensor signal were combined through: (1) linear combination of single sensor chatter indicators; (2) a separate NN for multi-sensor classification; (3) fuzzy logic classification (Sugeno fuzzy model); and (4) statistical inference classification based on conditional probability, i.e., the probability that the system is unstable for a specific combination of single chatter indicators. The accuracy of the first three approaches was very high: 95-96%. But

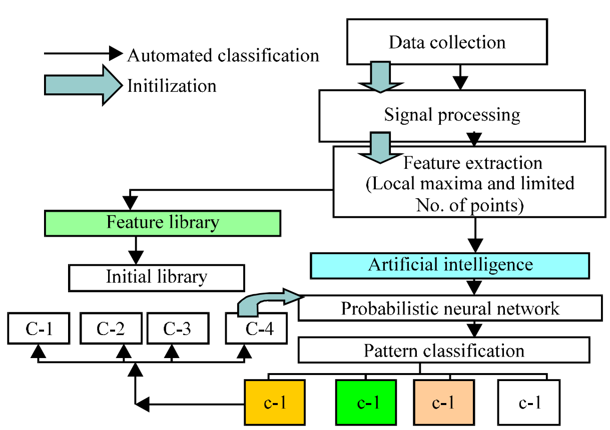

Fig. 4: Schematic of the tool condition recognition system

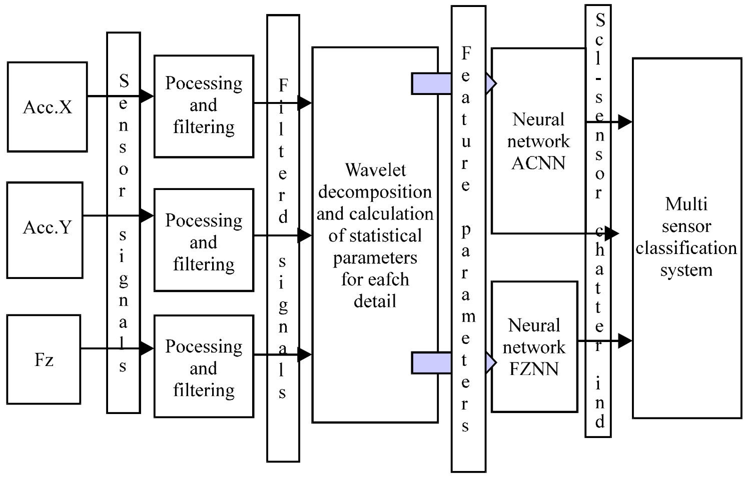

Fig. 5: Outline of the multi-sensor chatter detection system

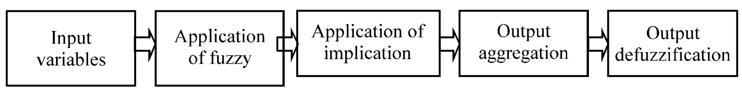

Fig. 6: Fuzzy logic data processing

residual accuracy in case of sensing unit malfunctions dropped notably: 50-75%. The behaviour of the forth approach was quite different: accuracy was slightly lower, 94% but insensitivity to malfunctions was extremely robust: 90-92%. Thus, the statistical inference multi-sensor chatter indicator, combining NN data processing and statistical methods to achieve both high accuracy and high robustness, was assessed as the most suitable for industrial milling applications. Sensor monitoring method, based on spindle motor power sensing and NN processing, was evaluated for chip disposal state detection in drilling. Spindle motor power measurements have the advantage of being easily realised during machining. From them, selected features such as variance/mean, mean absolute deviation, gradient and event count were calculated to form input vectors to a FF BP NN for decision making on chip disposal state.

Fuzzy logic

Fuzzy logic paradigms: Fuzzy Logic (FL) has two different meanings. In a narrow sense, FL is a logical system which is an extension of multivalued logic. But in a wider sense which is in predominant use today, 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 (sometimes 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. A fuzzy inference system calculation comprises the 5 steps illustrated in Fig. 6.

Fuzzy logic applications to sensor monitoring of machining: The application of a Fuzzy Decision Support System, (FDSS ''Fuzzy Flou'') is presented for tool wear estimation during turning using cutting force components measurements. The architecture of the FDSS consists of a knowledge base, an inference engine and a user interface. The knowledge base has two components: the linguistic term base and the fuzzy production rule base. The linguistic term base is divided into fuzzy premises and fuzzy conclusions. Knowledge is represented by a set of if-then rules which specify a relationship between observations (causes) and conclusions (effects). The knowledge base can be created directly from the monitor using the tree view(see below) or can be written in a text editor and loaded into the FDSS. In in-process monitoring during quasi orthogonal cutting of metal alloys was attempted through sensor fusion of frequency features extracted from AE signals through diverse forms of signal analysis. These features were processed by a FL based pattern recognition method to develop a multi-purpose

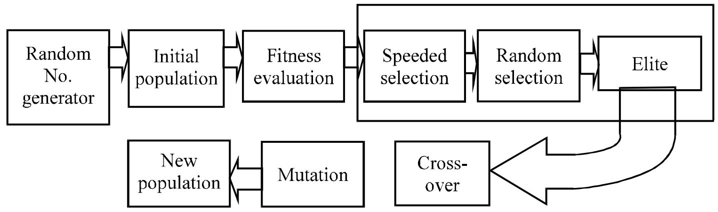

Fig. 7: Structure of genetic algorithms and genetically based operators

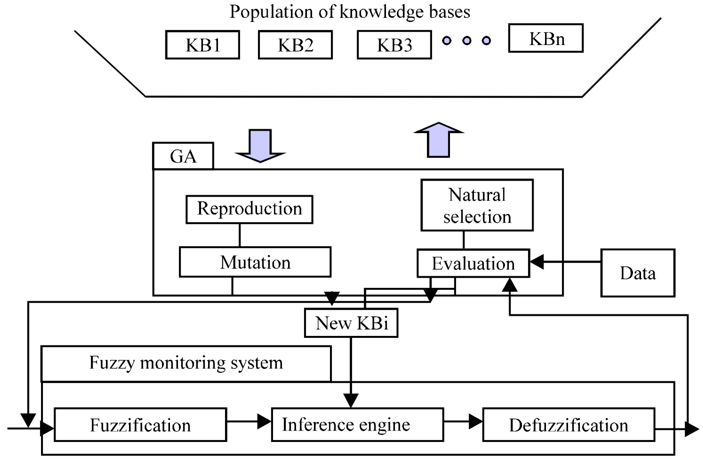

Fig. 8: GA learning process of the FDSS Fuzzy Flou knowledge base

intelligent sensor system for classification of tool wear level and workpiece heat treatment state for two work materials: low C steel and 7075 Al alloy (Teti, 1995).

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. This population of strings evolves by continuously cycling the genetic operators (Achichea *et al*., 2000) (Fig. 7).

In GA are utilized to automatically construct a FL knowledge base (KB) from a set of experimental data on tool wear monitoring during turning without requiring any human expert intervention.

The performance of this FL-GA system is compared with the performance of classical FL and NN systems for application to tool wear estimation. The construction of a FL KB necessitates skills and expertise. The operator has to analyze the dependence of Fc on VB so that the experimental results have to be presented in a conveniently understandable form. This makes FL systems rather difficult for practical implementation in their human manual form. This problem can be solved using a GA to automatically construct the FL KB (Fig. 8). The learning time of the GA method was the shortest among the considered methods, making it very convenient for shop floor use. Moreover, one can specify the maximum complexity level together with how much emphasis the GA must place on accuracy increase versus complexity reduction. There are definite advantages for practical applications since the GA provides more generality to the KB (Achichea *et al*., 2002).

CONCLUSIONS

The novel systems will need to be robust, reconfigurable, reliable, intelligent and inexpensive in order to meet the demands of advanced manufacturing technology. The future enhancement of machining systems and their operation performance will vitally depend upon the development and implementation of innovative sensor monitoring systems. These demands include increasingly small, precision and complex products for applications in biomedicine, transportation, MEMS devices, etc., as well as ubiquitous sensor systems for machine and system monitoring to reduce resource requirements and insure that manufacturing systems operate efficiently with minimal energy consumption and environmental impact. The main reason seems to be the difficult, sophisticated usage of these techniques and methods. One of the main challenges in future machining process monitoring systems is the development of algorithms and paradigms really autonomous from machine tool operators, who are not required to know about methods like neural networks, fuzzy logic etc., with signal feature extraction and decision making performed without intervention of the operator.

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