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CUTTING TOOL CONDITION SYSTEM FOR TURNING OPERATION

Saurav Singh
Research Scholar, Glocal University, UP, India.
sauravsibgh09@gmail.com

Anuraag Rai
Supervisor / Guide, Glocal University, UP, India.
anuraagrai2006@gmail.com

Sharad S. Mulik
Co-Guide, (Dean Academics & Professor), Department of Mech. Engg., RMD Sinhgad School of Engineering, Pune-411058, Maharashtra, India.
sharadmulik@gmail.com

Abstract

Our Research "Cutting Tool Condition System for Turning Operation" is a Cutting tool wear monitoring in machining operations has been an active area of research for nearly last two decades. Cutting tool wear plays an important role in deciding economic strategies, product quality, tooling cost, tool-changing cost, rejection of products and productivity. Metal cutting processes are in general non-linear and stochastic in nature. It is therefore difficult to represent them as a mathematical model and they usually require simplifying assumptions. As a result, such models are not capable of representing real metal cutting process. For an automated industry, all the machining input parameters (cutting speed, feed rate, depth of cut) are controllable except cutting tool condition. Major problem in the machining process is cutting tool wear prediction. In this research work an attempt has been made to develop neural network models using sensors' signals to predict the health of a cutting tool. Properties of signals from the sensors depend on many factors such as machining conditions (cutting conditions), workpiece material, and cutting tool geometry. Apart from the complexity of the process, signals from the sensors are disturbed for many reasons: outbreak at cutting edges, chatter (i.e. self-exited vibrations), sensor non-linearity, noise of digitizers, crosstalk effects between sensor's channels, etc. Cutting tool wear sensing techniques are broadly classified into two categories: direct and indirect. Direct methods are those that utilize effect caused directly by tool wear, and measured by using optical microscope, radioactive, or camera vision. However, direct methods of measuring tool wear have not been easily adaptable for shop floor applications. They are not suitable for on-line condition monitoring. However, they can be easily applied to off-line measurements which require more time. Indirect tool sensing techniques generally employ one or more of the responses of a machining process like temperature, cutting force, vibration, surface finish, acoustic emission, motor current and so on.

Key: Cutting, Tool, Condition, System, Turning, Operation.

Introduction

Condition monitoring Condition monitoring and diagnostics of machines is a subject of increased importance in the course of progressive automation. It is essential in order to ensure operation within design consideration and anticipate problems in time, so as to prevent catastrophic failures.

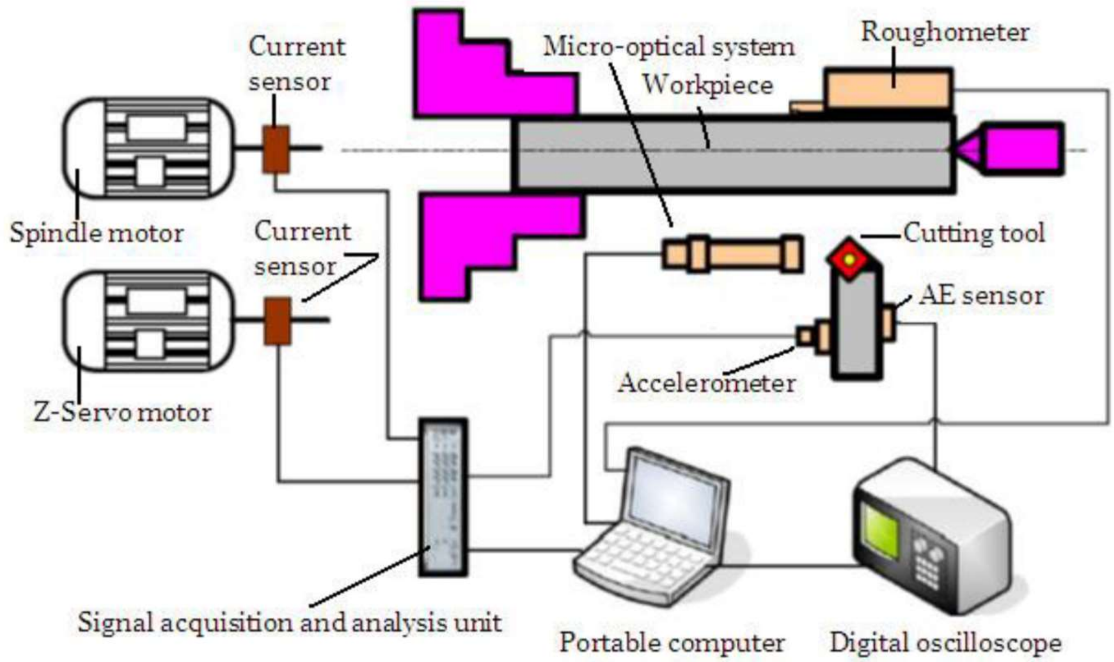

Fig.1: Cutting Tool Condition System for Turning Operation Process.

It is concerned with extracting information from cutting tools and machine tools to indicate their conditions, and to enable them to be operated smoothly throughout their serviceable life. Manufacturing industries mainly pertaining to computer integrated manufacturing system, robot controlled machining system, have undergone tremendous changes in the past three decades. Today customer demands high quality products for lowest possible price. In order to meet such demands and to face global competition, modern industries are aiming towards achieving high dimensional accuracy. Manufacturers are focusing on the technical aspects of, how to achieve uninterrupted automated machining for longer duration with least human supervision. Cutting tool wear condition monitoring is one such important aspect that needs to be looked into in automated cutting processes and unmanned factories. In a metal cutting operation, a major hurdle in realizing total automation is cutting tool state prediction and consequently maintenance.

Objectives of the Thesis

In actual metal cutting experiments, the tool wear geometry generated is not uniform hence its dimensions have to be averaged out. Artificially created worn out tool may also have thermal defects like micro-cracks and thermal residual stresses [1][3]. The concept of artificially creating flank wear on the tool can be applied for non-uniform shape and size provided they are mathematically representable. However, while interpreting the captured signals, this difference should be kept in mind. Therefore, for purpose of algorithm development and calibration it was decided to artificially create the uniform flank wear of the desired averaged dimension on the tool using EDM machine. This created wear is well defined shape and easy to measure (using USB port microscope). In this thesis two sets of sensors (strain gauge and accelerometers) were used to monitor the cutting tool condition. These were placed very close to cutting tool tip.

Literature survey

The vast amount of literature in this field suggests that a variety of process parameters in the metal cutting environment can be tapped and used to predict the cutting tool-state. In this chapter, following typical methods are discussed along with their correlation to tool wear during experimentation.

• Acoustic emission (AE),
• Cutting forces (static and dynamic),
• Vibration signature (accelerometer signals),
• Cutting tool temperature,
• Miscellaneous method such as ultrasonic, optical measurements, work piece surface finish measurements, work piece dimensions, stress/strain analysis, spindle motor current and so on.

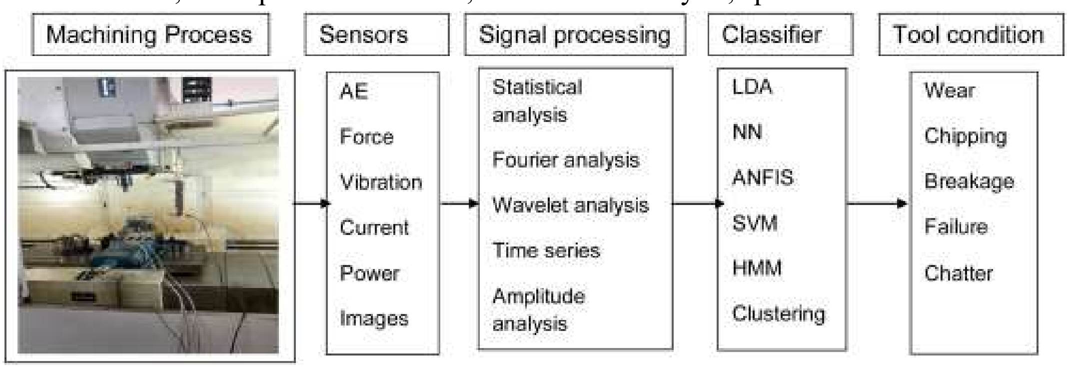

Fig.2: Cutting Tool Condition System for Turning Operation Method.

The tool tip/ cutting edges temperature

Metal cutting generates a significant amount of heat. 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. Frictional behaviour on the tool faces is thought to affect the geometry of the cutting process by some mechanism not completely understood. Two metallic surfaces in sliding contact would normally experience dry friction commonly referred to as Coulomb friction. In metal cutting, the coefficient of friction is independent of sliding speed and area of contact. Force is therefore required for the continual shearing of the tips of the asperities or hills.

This required force (or load) is proportional to the frictional force in dry sliding. The coefficient of friction between tool and chip varies considerably due to changes in cutting speed and rake angle resulting in high pressures. In the meantime, the real area of contact would approach unity thereby giving rise to high frictional forces that eventually lead to high temperatures and render sliding at the interfaces almost impossible. Removal of the generated heat is through the chip, workpiece and/or tool. A

Artificial Neural Network

Artificial Neural Networks technology is of a relatively old origin and enormous studies are available which relate to vibrations and dynamics of machinery. Most of the work has been carried out in the last few decades. Mayes [6][1] applied ANN for on-line vibration monitoring of large turbo-generators. The investigations focused on data processing and the use of the neural networks were discussed. Elkordy et al. [6][2] investigated the applicability of ANN for vibration signature analysis of a five-store steel structure. The primary investigations showed that ANNs have considerable potential to assess structural damage.

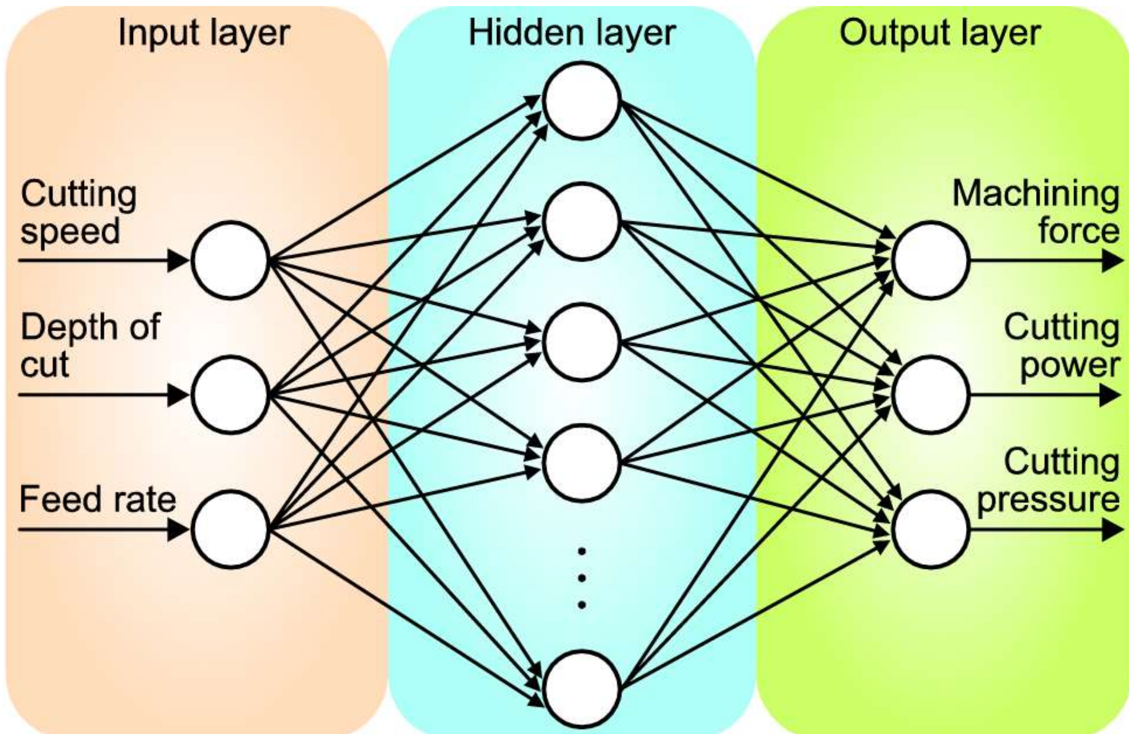

Fig.3: Cutting Tool Condition System for Turning Operation ANN

Creation of artificial flank wear

In the present work, the DNMG inserts are used which already have built-in chip breaking groove. So, during actual cutting, it is not possible to introduce crater wear. As mentioned earlier only two types of tool damage namely flank wear (nose wear also included in this case) and chipping were studied. In actual machining experiments, the wear generated geometry is not uniform hence its dimensions have to be averaged. However in the present case, uniform flank wear was artificially created having the desired dimension. It was done using EDM machine as discussed in the following paragraph. While creating artificial flank wear, the following important cutting tool geometrical parameters were taken into consideration namely, rake angle, clearance angle, length of the flank wear and radial wear length.

Experimental setup

Now-a-days, high speed machining is popular to increase the production rate as well as to reduce the production cost. Selection of an appropriate machine is also an important task. All the experiments are carried out on a CNC GILDMEISTER CTX 400 Serie 2 turning center. One of the main objectives of the research work is to monitor the condition / health of the cutting tool. While concentrating on cutting tool, it is assumed that the condition of the machine and its components is good in all other aspects such as foundation of the machine, rigidity of the machine components (such as bed, spindle, tail stock, etc.) and so on. All the components of the machine tool should function properly and should not vibrate by applying external dynamic load. Hence, the above said CNC turning center is chosen. The experimental set up The experiments are conducted on EN-8 steel (workpiece) using DNMG 150608 insert with Seco tool holder PDJNR 2020 K15 without cutting fluid (dry machining).

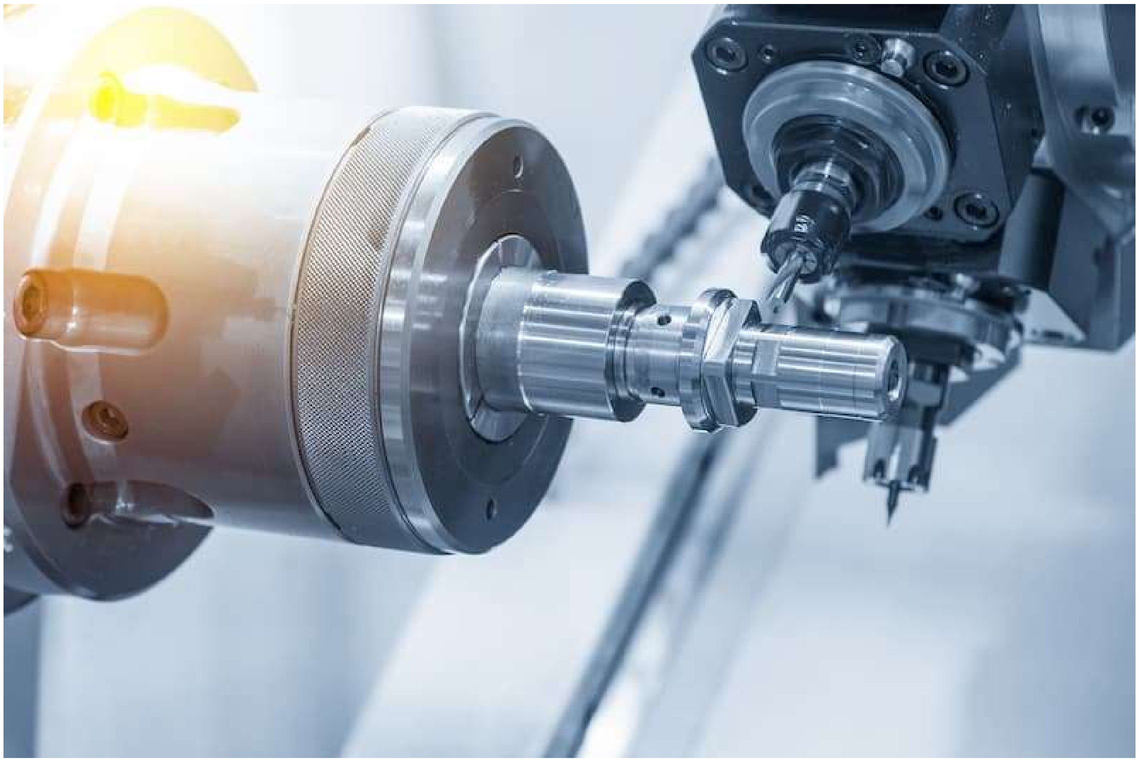

Fig.4: Cutting Tool Condition System for Turning Operation

Instrumentation

System There are two basic configurations of tool and process condition monitoring systems: compact and modular. Montronix, Brank-amp, Bruel and Kajer, Nordmann and Kistler produce the former. In such a system, the core element is the monitor. The monitors are universal, i.e. they can be fed with signals from different types of sensors. The signals generated by the sensors and conditioned by amplifiers are sent to the monitor, which is directly connected to the machine control (PLC/CNC). Only Kistler, which is basically a producer of excellent force, stress, vibration, AE sensors offer one universal monitor and also output of the sensor can be fed to the computer through DAQ card which is supplied by National Instruments (LabVIEW),

Activation function

It defines the output of a neuron in terms of activity level at its input. It limits the amplitude of output of the neuron and introduces non-linearity in the network. These are sometimes referred to as squashing functions as they are used to limit the output in the definite small range irrespective of values of the input. Activation functions for the hidden units are required to introduce non-linearity into the network. Without non-linearity, hidden units would not make nets more powerful than just plain perceptrons (which do not have any hidden units, just input and output units). Almost any nonlinear function does the job, although for back propagation learning, it must be differentiable and it helps if the function is bounded; the sigmoidal functions such as logistic and tanh are the most common choices.

Data Acquisition,

Storage and Display A computer code has been developed in LabVIEW for data acquisition, data storage and display. This program has the following adjustable features:

(i) Scan rate (set at 25000 samples/s).

(ii) Number of data points to be read before each display (set at 4096 data points).

(iii) Device and Channel numbers from which to acquire data (set at Device No. 1 and Channel No. 1).

(iv) Frequency range (set at 10000 Hz). A Hanning window is then applied to the acquired time domain signal.

Fast Fourier Transform (FFT) of the time signal is carried out and the FFT is displayed in 'real' time along with the time domain signal on the front panel. Provision is also made on the front panel for the user to select the desired frequency range for FFT display. Option is provided for logging the time domain data and frequency domain data into the hard disc at any desired instant of time.

Network Training and Testing

The neural network architecture, number of layers, nodes, transfer function and training pattern chosen in the present study We have conducted 27 experiments with different combinations of machining conditions. On taking flank wear levels of 0, 0.2, 0.3, 0.4 and 0.5 mm as a parameter, the total number of experiments becomes 135(=27x5) as shown in. Out of these, 110 experiments with different machining conditions have been selected for training and remaining 25 experiments are reserved for testing. Additionally, training algorithms, number of nodes, transfer functions and number of layers are varied to study the behaviour of networks and to arrive at an optimum configuration.

Results

Development of ANN models for tool failure prediction have been described in this chapter. Frequency domain and statistical input based ANNs have been developed. Probabilistic Networks based on Bayes' Rule have also been developed. Experimental data of measured acceleration, g and micro strain are utilized to train the network models. Trained models are used in predicting flank wear and chipping failure for various different cutting conditions. The developed prediction system is found to be capable of accurate in predicting tool failure - both flank wear and chipping, for the range it has been trained. All data, experimentally obtained and collected from the sensors, have been used to create ANN models. On the basis of prediction accuracy, these models can be extended and extrapolate for other machining conditions

Conclusions

The development of practical and reliable condition monitoring methods for detecting flank wear and chipping failure in turning operation is essential for realization of intelligent and flexible manufacturing systems. In this thesis, the problem of detection of flank wear and chipping failure in turning operation has been studied using vibration and strain measurement methods. Based on the findings of this thesis, following conclusions are drawn:

• An artificial wear can be created in a controlled manner by using EDM process, which emulates the real flank wear and chipped off cutting edge where machining responses are similar to actual flank wear and chipped off cutting edge.

• Vibration and strain monitoring during turning operation can be useful for predicting flank wear as well as chipping failure. For this purpose, four statistical moments are estimated using time domain data and then they are used in ANN analysis as the input data. Four layer ANN response then can be used to classify the flank wear at different levels. Frequency domain analysis has also been carried out and features were fed in to six layer ANN.

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