CHAPTER 3

EXPERIMENTAL SET-UP AND PROCEDURE

3.1 GENERAL

Tool wear monitoring continuous to be a major area of concern in machining. In order to produce quality products at reasonable cost tool condition monitoring becomes an important study for all the researchers. To monitor the tool wear during machining process an experimental study has been carried out using acoustic emission technique (AET). Further these experimental results are used to train Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference system (ANFIS). The details of the experimental setup, procedure, AET, ANN and ANFIS are discussed in this chapter.

3.2 EXPERIMENTAL SET-UP

Figure 3.1 shows the schematic of the experimental setup developed in this research work. A Banka make, 5.0 HP, all – geared centre lathe was used for machining. C45 steel of 270 BHN was used as the work material. TK35- CNMG 12 04 08 carbide coated cutting tool insert and PCLNR – 16 16 K12 Tool holder were used. The tool was coated with one layer of TiC and TiN, and thirteen layers of AlON using chemical vapour deposition (CVD) process for better stress propagation of AE signal. 100 kHz to 2 MHz range acoustic emission (AE) sensors were used to capture the signals due to crater wear. A vibration probe and an analyzer were used to measure and store the vibration during the metal cutting operation.
Figure 3.2 shows the pictorial view of the experimental setup. Pre - Amplifiers, power supply unit and digital oscilloscope were used to amplify the raw signal from the acoustic emission sensors. The signals were stored in the computer for further analysis. Lathe tool dynamometer, force probe were used to measure the cutting forces. An ammeter was used to measure the electrical current consumed by the motor fitted in the experimental setup.

Figure 3.1 Schematic of the single point cutting tool wear monitoring using acoustic emission techniques
3.2.1 Lathe Details

The specification of the all geared centre lathe used in this research work is given in Table 3.1.

Table 3.1 Specification of centre lathe

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Make</td>
<td>BANKA</td>
</tr>
<tr>
<td>2</td>
<td>Power</td>
<td>5 HP, 3 Phase</td>
</tr>
<tr>
<td>3</td>
<td>Length of bed</td>
<td>1370 mm</td>
</tr>
<tr>
<td>4</td>
<td>Width of bed</td>
<td>240 mm</td>
</tr>
<tr>
<td>5</td>
<td>Height of centre</td>
<td>175 mm</td>
</tr>
<tr>
<td>6</td>
<td>Admit between centre</td>
<td>700 mm</td>
</tr>
<tr>
<td>7</td>
<td>Hole through spindle</td>
<td>40 mm</td>
</tr>
<tr>
<td>8</td>
<td>Swing over bed</td>
<td>350 mm</td>
</tr>
<tr>
<td>9</td>
<td>Speed of motor</td>
<td>1440 rpm</td>
</tr>
</tbody>
</table>
3.2.2 Work Material

A harder and frequently used work material was selected to make the research work as application oriented. The harder material was selected to have the faster tool wear rate which would reduce the number of observations required. Keeping these points in mind C45 steel of 270 BHN was chosen as the work material. Also, the important properties of work material are given in Table 3.2.

Table 3.2 Properties of work material

<table>
<thead>
<tr>
<th>1. Chemical properties (Compositions - % of wt.)</th>
<th>Carbon (C) %</th>
<th>Silicon (Si) %</th>
<th>Manganese (Mn) %</th>
<th>Sulphur (S) %</th>
<th>Phosphorus (P) %</th>
<th>Nickel (Ni) %</th>
<th>Chromium (Cr) %</th>
<th>Molybdenum (Mo) %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon (C) %</td>
<td>0.42 - 0.50</td>
<td>&lt; 0.40</td>
<td>&lt; 0.45</td>
<td>&lt; 0.045</td>
<td>&lt; 0.045</td>
<td>&lt; 0.040</td>
<td>&lt; 0.040</td>
<td>&lt; 0.10</td>
</tr>
</tbody>
</table>

2. Mechanical Properties

- Tensile Strength, Ultimate: 800 MPa
- Tensile Strength, Yield: 400 MPa
- Elongation at break: 15 %
- Reduction in area: 16 %
- Modulus of elasticity: 210 GPa
- Hardness: 270 GPa

3. Physical Properties

- Density: 7850 Kg/m³
- Appearance and order: Odorless gray metallic solid. Available in ingots, mill products, castings, sponge, chips, briquettes and other irregular shapes.

4. Thermal Properties

- Specific Heat: 500 J/kg - k
- Thermal Conductivity: 46 W/m – k
- Melting point: 1813 K (1540°C)
- Maximum service temperature, Air: 673 K (400°C)
3.2.3  Cutting Tool and Tool Holder

The coated carbide tool was selected based on its wider application in the machining industries. To have faster wear, rough turning grade of TK35 CVD coated carbide CNMG 12 04 08 – 05 tool insert was chosen. All the tools are commercially available inserts, supplied by Van Moppes Diamond tools, India. The pictorial view of the tool inserts is shown in Figure 3.3 and its nomenclature and specification are presented in Table 3.3.

![Figure 3.3 Cutting inserts used for the experiment](image)

Further the tool holder is designed to introduce additional properties to the cutting action, such as

- Angular approach – direction of tool travel.
- Spring loading – deflection of the tool bit away from the material when excessive load is applied.
- Variable over hang – the tool bit may be extended or retracted as the job requires.
- Rigidity – the tool holder can be sized according to the work to be performed.
- Avoid direct cutting fluid or coolant to the work area.
Table 3.3 Specification of cutting tool inserts

<table>
<thead>
<tr>
<th>Nomenclature of the cutting tool inserts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Back rake</td>
</tr>
<tr>
<td>-5°</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cutting tool designation</td>
<td>Coated carbide: TK 35 – CNMG 12 04 08 – 05</td>
</tr>
<tr>
<td>C</td>
<td>N</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>Shape symbol</td>
</tr>
<tr>
<td>2</td>
<td>Relief angle symbol</td>
</tr>
<tr>
<td>3</td>
<td>Tolerance symbol</td>
</tr>
<tr>
<td>4</td>
<td>Hole/chip breaker symbol</td>
</tr>
<tr>
<td>5</td>
<td>Edge length symbol (ISO)</td>
</tr>
<tr>
<td>6</td>
<td>Thickness symbol</td>
</tr>
<tr>
<td>7</td>
<td>Corner radius symbol</td>
</tr>
<tr>
<td>8</td>
<td>Manufacturer option</td>
</tr>
</tbody>
</table>

Coating details

i) Material | Three layers of Titanium Carbide (TiC), Titanium Nitrate (TiN) and Aluminum Oxynitride (AlON) |
ii) No. of layers | Tic and TiN, each single layer and AlON thirteen layers |
iii) Coating process | Chemical Vapour Deposition (CVD) process |
iv) Coating thickness | 8 μm |

Pictorial view of the tool holder used for machining is given in Figure 3.4.

**Figure 3.4** Pictorial view of the tool holder with tool used
3.2.4 Selection of AE Sensor and Pre - Amplifier

The acoustic emission (AE) sensor and pre – amplifier with filters 100 kHz to 2 MHz range is selected for the experimental work. The sensor and preamplifiers are shown in Figure 3.5 and its specification is given in Table 3.4.

Figure 3.5 Photographs of AE sensor and Pre-amplifier (100 kHz to 2 MHz)

Table 3.4 Specification of the AE sensor - 100 kHz to 2 MHz range and Pre-amplifier

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE Sensor - 100 kHz to 2 MHz range</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>Model</td>
<td>FAC 500</td>
</tr>
<tr>
<td>2.</td>
<td>Make</td>
<td>Physical Acoustic Corporation</td>
</tr>
<tr>
<td>3.</td>
<td>Sl.No.</td>
<td>142587</td>
</tr>
<tr>
<td>4.</td>
<td>Sensor Element</td>
<td>Piezo – electric crystal</td>
</tr>
<tr>
<td>5.</td>
<td>Operating Frequency Range</td>
<td>100 kHz – 2 MHz</td>
</tr>
<tr>
<td>Pre Amplifier</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>Make</td>
<td>Physical Acoustic Corporation</td>
</tr>
<tr>
<td>7.</td>
<td>Model</td>
<td>160 B; Gain :40 dB - 60 dB</td>
</tr>
<tr>
<td>8.</td>
<td>Operating Voltage</td>
<td>+15 V</td>
</tr>
<tr>
<td>9.</td>
<td>Filter</td>
<td>125 kHz - High Pass</td>
</tr>
</tbody>
</table>
Mechanically induced noises have very little energy and the peak in the range of 20 kHz to 50 kHz. Electrical noise pick up is higher with operating frequency. To a great extent this type of noise can be covered by filtering out acoustic signal below 100 kHz and above 2 MHz and it will eliminate the mechanically and electrically induced noises. Furthermore, second attenuation in most of the engineering materials is low in this region of 100 kHz to 2 MHz. Therefore, sensors can be placed at some distance away from the source without the loss of signal strength. Further, the AE signal frequency due to tool wear lie between 100 kHz and 2 MHz with significant effect above 200 kHz. Thus, the AE sensors and pre – amplifiers with filters to monitor crater wear are selected as the AE Sensor of 100 kHz to 2 MHz range.

3.2.5 Filters

Filter is used to control the unwanted signals from the pre - amplifier and the filtered signal is passed through the digital oscilloscope. The pictorial view of the filter is shown in Figure 3.6 and the specification is shown in Table 3.5.

Figure 3.6 Pictorial view of the Filter used in this work
### Table 3.5 Filter specification

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Make</td>
<td>KISTLER Corporation</td>
</tr>
<tr>
<td>2.</td>
<td>Model</td>
<td>1801 – 100 H</td>
</tr>
<tr>
<td>3.</td>
<td>Operating Voltage</td>
<td>15 V</td>
</tr>
<tr>
<td>4.</td>
<td>Filter width pass</td>
<td>100 kHz High Band</td>
</tr>
</tbody>
</table>

#### 3.2.6 Couplant

In this work Epoxy resin was used as the couplant because of its better adherence to the sensor shoe and the surface of the tool holder and also because of its easier availability. The use of couplants in between the sensor and the component surface is essential for efficient detection of acoustic emission.

#### 3.2.7 Digital Storage Oscilloscope

The signal generated due to tool wear were captured and stored in the digital storage oscilloscope model 1450. In this model, up to 20 waveforms can be stored. This features two identical input channels with a maximum sensitivity of 2 m V/ div. This 1450 provides a combination of digital storage and real time facilities and caters to measurements from DC to 20 MHz with a flicker free display. The digital method of storage provides many advantages, notably, the facilities for storing a waveform indefinitely and for pre – trigger viewing. The time base ranges from 0.5 μs/div to 0.2
sec/div in NORMAL mode with additional ranges down to 50 s/div in STORE mode. An AX10 facility expands the upper limit to 50 ns/div.

Cursor, vertical datum and horizontal datum are available on either trace for convenience in making measurements on the traces. This also has both RS423 serial and IEEE parallel interfaces which enables the instrument to send stored data to an external controller (e.g. computer) and if required receive new data for display. The Pictorial view of the digital storage oscilloscope is shown in Figure 3.7. Also, the specification of this oscilloscope is presented in the Table 3.6. The details of signal storing procedure “Auto arm” and signal transfer communication software “Auto DASP” are discussed below.

Figure 3.7 Pictorial view of the digital storage oscilloscope
Table 3.6 Specification of the digital storage oscilloscope

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Make</td>
<td>L&amp;T OS 1450, 20 MHz dual trace and Digital facilities</td>
</tr>
<tr>
<td>2.</td>
<td>Storage size</td>
<td>1024 8 bits per channel</td>
</tr>
<tr>
<td>3.</td>
<td>Vertical resolution</td>
<td>1 in 256 approximately 28.5 steps/div.</td>
</tr>
<tr>
<td>4.</td>
<td>Horizontal resolution</td>
<td>1 in 1024 approximately 100 samples/div.</td>
</tr>
<tr>
<td>5.</td>
<td>Sample rate</td>
<td>2 MHz (0.5 μs) reducing in proportion with time base</td>
</tr>
<tr>
<td>6.</td>
<td>Waveform storage</td>
<td>Up to 20 waveforms can be stored</td>
</tr>
<tr>
<td>7.</td>
<td>Auto arm and save</td>
<td>Up to 20 wave forms can be successively captured and saved in backup memory.</td>
</tr>
</tbody>
</table>

Using this software the AE signals stored in the oscilloscope due to wear are transferred to a computer through RS423 serial interface for analysis at later stage. The pictorial view of the AE signal stored in the oscilloscope and transferred to computer is shown in Figure 3.8.

![Figure 3.8](image)

Figure 3.8 Pictorial view of AE signal stored in oscilloscope and transferred into computer
3.2.8 Profile Projector

The profile projector was used to measure the wear land of flank wear and the propagation of crater wear extent along the rake surface. The specification of the profile projector is given in the Table 3.7.

**Table 3.7 Specification of the profile projector**

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Work stage size</td>
<td>200 x 160 mm</td>
</tr>
<tr>
<td>2.</td>
<td>Measuring traverse</td>
<td>Longitudinal – 50 mm and Transverse – 40 mm</td>
</tr>
<tr>
<td>3.</td>
<td>Reading accuracy</td>
<td>0.001 mm</td>
</tr>
<tr>
<td>4.</td>
<td>Diameter of object Glass plate</td>
<td>105 mm</td>
</tr>
<tr>
<td>5.</td>
<td>Magnification of projection lenses</td>
<td>10x, 25x, 50x and 100x</td>
</tr>
</tbody>
</table>

3.2.9 Surface Roughness Measuring Instrument

Surface roughness measuring instrument was used to measure the maximum crater depth. The specification of the Surfcorder is shown in Table 3.8.

**Table 3.8 Specification of the surfcorder**

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Model</td>
<td>Surfcorder model SE – 40 G, Kosaka Laboratory, Japan</td>
</tr>
<tr>
<td>2.</td>
<td>Measuring Parameters</td>
<td>All surface roughness parameters</td>
</tr>
<tr>
<td>3.</td>
<td>Measuring Magnification</td>
<td>100, 200, 500, 1000, 2000, 5000, 10000, 20000, 50000, 100000</td>
</tr>
<tr>
<td>4.</td>
<td>Stylus</td>
<td>R5 ( \mu ) m made of diamond</td>
</tr>
<tr>
<td>5.</td>
<td>Drive speed</td>
<td>0.1, 0.5 mm/sec (at measurement) 0.1, 0.5, 2 mm/sec (at returning)</td>
</tr>
<tr>
<td>6.</td>
<td>Measuring Length</td>
<td>Setting between 0.2 and 30 mm</td>
</tr>
<tr>
<td>7.</td>
<td>Data display/Printing</td>
<td>LCD display and thermal printer</td>
</tr>
</tbody>
</table>
3.2.10 Tool Dynamometer

Tool dynamometer was used to measure the cutting forces at different speed, feed, and the depth of cut for different materials. The components of cutting forces in orthogonal cutting are the axial, perpendicular and vertical components (X, Y, Z directions). The unit is provided with a strain gauge bridge balance with power supply and digital indicator. This instrument comprises independent DC excitation supply for feeding strain gauge bridges, signal processing system to process and compute respective force values for direct independent display in kgf units. The lathe tool dynamometer output was connected to the digital display unit. The photograph of the lathe tool dynamometer along with its display meter is shown in Figure 3.9.

Figure 3.9 Pictorial view of the lathe tool dynamometer

The specification of the lathe tool dynamometer display meter and sensor are given in the Table 3.9.
### Table 3.9 Specification of the lathe tool dynamometer

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Lathe tool dynamometer</strong></td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>Capacity</td>
<td>500 kgs</td>
</tr>
<tr>
<td>2.</td>
<td>Excitation voltage</td>
<td>10 to 12 v DC</td>
</tr>
<tr>
<td>3.</td>
<td>Operating temperature</td>
<td>+5 to 55°C</td>
</tr>
<tr>
<td>4.</td>
<td>Non-linearity</td>
<td>1% max</td>
</tr>
<tr>
<td>5.</td>
<td>Electrical connections</td>
<td>Three meters of shielded cable with suitable connectors</td>
</tr>
<tr>
<td></td>
<td><strong>Display meter</strong></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>Type</td>
<td>Independent for X, Y, Z force selector switch type</td>
</tr>
<tr>
<td>7.</td>
<td>Display</td>
<td>3 ½ digits LED display</td>
</tr>
<tr>
<td>8.</td>
<td>Polarity indication</td>
<td>Automatic indication</td>
</tr>
<tr>
<td></td>
<td><strong>Lathe tool dynamometer sensor (strain gauge type)</strong></td>
<td></td>
</tr>
<tr>
<td>9.</td>
<td>Capacity in X, Y, Z Direction</td>
<td>500 kgs</td>
</tr>
<tr>
<td>10.</td>
<td>Bridge resistance</td>
<td>350 Ohms</td>
</tr>
<tr>
<td>11.</td>
<td>Excitation voltage</td>
<td>10 to 12 v DC</td>
</tr>
<tr>
<td>12.</td>
<td>Operating Temperature</td>
<td>+10 to 50°C</td>
</tr>
<tr>
<td>13.</td>
<td>Non-linearity</td>
<td>1% Max</td>
</tr>
<tr>
<td>14.</td>
<td>Mounting</td>
<td>Dynamometer mounting on the Lathe is same as that of the tool holder mounting on the tool post</td>
</tr>
</tbody>
</table>
3.2.11 Vibration Signature Analysis

Vibration is produced by cyclic variation in the dynamic components of the cutting forces. Usually, these vibrational motions start as small chatter responsible for the serrations on the finished surface and chip thickness irregularities, and progress to what has come to be commonly termed as vibration. Mechanical vibrations generally result from periodic wave motions. The nature of the vibration signal arising from the metal cutting process is such that it incorporates facets of free, forced, periodic and random types of vibration. Vibration is the physical movement or oscillation of a mechanical part about a reference position.

Since vibration is transmitted as an AC signal, there are four unit modifiers that may be used to condition the signal. These modifiers have a direct impact on the measurement value. If the wrong modifier is used, the measurement could be either too high, or too low, thus causing possible maintenance action to be, or not to be, accomplished erroneously. The schematic amplitude frequency curve of the vibration signal is shown in Figure 3.10.

![Schematic of amplitude frequency curve](image)

Figure 3.10 Schematic of amplitude frequency curve
Peak to Peak is the distance from the top of the positive peak to the bottom of the negative peak. Peak is the measurement from the zero line to the top of the positive peak. Average value is 0.637 times of peak value. Root Mean Square (RMS) value is 0.707 times of peak value.

The power of the acceleration signal obtained by spectral analysis is a linear function of tool wear. Moreover, the power or acceleration could be used on-line to monitor the tool wear. Hence, the vibration pick up was measured hand held on tool holder vertically to sense vertical tool vibration. The pictorial view of the vibration analyzer and its pick up is shown in Figure 3.11.

![Figure 3.11 Pictorial view of vibration analyzer](image)

The specification of the vibration analyzer used to measure the acceleration due to tool vibration is given in Table 3.10.
Table 3.10 Specification of vibration analyzer

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Analog section</strong></td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>Number of channel</td>
<td>1</td>
</tr>
<tr>
<td>2.</td>
<td>Input</td>
<td>Accelerometer connector</td>
</tr>
<tr>
<td>3.</td>
<td>Filters</td>
<td>Butter worth type filters</td>
</tr>
<tr>
<td>4.</td>
<td>High pass filter</td>
<td>3, 10 Hz</td>
</tr>
<tr>
<td>6.</td>
<td>Measurement</td>
<td>Acceleration, Velocity and Displacement</td>
</tr>
<tr>
<td></td>
<td><strong>Measurement Range</strong></td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>Acceleration</td>
<td>0-316 m/s²</td>
</tr>
<tr>
<td>8.</td>
<td>Velocity</td>
<td>0-1000 mm/s</td>
</tr>
<tr>
<td>9.</td>
<td>Displacement</td>
<td>0-28.3 mm</td>
</tr>
<tr>
<td></td>
<td><strong>Display characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>10.</td>
<td>Acceleration</td>
<td>Effective value (RMS) Equivalent peak value (EQ PEAK)</td>
</tr>
<tr>
<td>11.</td>
<td>Velocity</td>
<td>Effective value (RMS)</td>
</tr>
<tr>
<td>12.</td>
<td>Displacement</td>
<td>Equivalent peak to peak value (EQP-P)</td>
</tr>
<tr>
<td></td>
<td><strong>Memory section</strong></td>
<td></td>
</tr>
<tr>
<td>13.</td>
<td>Max. memory capacity</td>
<td>500 data</td>
</tr>
<tr>
<td>14.</td>
<td>Dimensions</td>
<td>Approximately 21.5 (Length) x 12.4 (width) x 4.3 (Height) cm</td>
</tr>
<tr>
<td>15.</td>
<td>Weight</td>
<td>Approximately 700 gms.</td>
</tr>
</tbody>
</table>

3.2.12 Ammeter

0 – 20 A ranges Ammeter is used for measuring the electric current. The pictorial view of the ammeter is shown in Figure 3.12. The ammeter provides an overview of the entire electrical system. The level of current
being drawn and the supply current are clearly displayed, and the shunt – a measurement resistor can be inserted into the measurement point in a matter of seconds. The fine connecting cable that runs from the shunt to the gauge is easy to lay without taking up much space.

![Ammeter](image)

**Figure 3.12 Pictorial view of the ammeter**

The specification of the ammeter is given below

- 140 mm installation diameter
- 90° display angle
- Operating voltage 50 V – 300 V
- Current consumption less than100 mA
- Moving Iron type meter
- Frequency range 50 Hz to 60 Hz
- Horizontal position will give the highest accuracy
- Zero adjusting screw provided
Figure 3.13 Cause and effect diagram

Figure 3.13 also depicts the different parameters that affect the machining quality of C45 steel and the following parameters are selected for the present work (Table 3.11). The recommended cutting speed range 80-160 m/min for the selected combination of work and cutting tool material.

Table 3.11 Parameters selected for the present work

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Description</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Cutting speed</td>
<td>88, 96, 100, 104, 112 m/min</td>
</tr>
<tr>
<td>2.</td>
<td>Feed</td>
<td>0.102 mm/rev</td>
</tr>
<tr>
<td>3.</td>
<td>Depth of cut</td>
<td>1.5 mm</td>
</tr>
<tr>
<td>4.</td>
<td>Coolant</td>
<td>No coolant (Dry condition)</td>
</tr>
</tbody>
</table>

3.3 EXPERIMENTAL PROCEDURE

Tool condition monitoring using Acoustic Emission Technique (AET) is a suitable method for on-line monitoring of tool wear, mainly for the crater wear. In order to study the single point cutting tool failure during
machining of a workpiece in a lathe, an experimental setup has been
developed. The experimental procedure followed in this research work is
explained below. The research work carried out in this thesis can be classified
into the following seven (7) modes.

1. Verification of Acoustic Emission (AE) Sensor Frequency
   Range.

2. Tool Condition Monitoring for Crater wear.

3. Tool condition monitoring for Flank wear.

4. Repeatability Verification of Tool Wear.

5. Tool Breakage through Acoustic Emission Technique.

6. Tool wear monitoring using Artificial Neural Network.

7. Tool wear monitoring using Adaptive Neuro Fuzzy Inference
   System.

3.3.1 Verification of Acoustic Emission (AE) Sensor Frequency Range

The schematic of the experimental setup is shown in Figure 3.1. The
Acoustic Emission (AE) sensor was positioned on the left side surface of
the tool holder to sense AE signal due to crater wear. The signal was filtered
and amplified and stored in a digital storage oscilloscope for further analysis
in the computer using ‘AUTO DASP” software. The experimental procedure
is given below:

1) The work piece was turned to clean the surface for rust and to
get roundness before the start of the experiment.
2) The cutting conditions were set as cutting speed 100 m/min, feed 0.102 mm/rev, depth of cut 1.5 mm and machined for dry cutting condition.

3) The machine was run for one minute and at the same time the Oscilloscope was also switched on to capture the AE signal.

4) Tool was removed from the tool holder and cleaned with carbon tetrachloride in order to ensure that no work piece material or other foreign materials are adhering to the tool.

5) The AE wave stored in the oscilloscope was transferred to a computer through the RS423 serial interface for further studies.

6) Again the tool was fitted to the tool holder and the experiment was repeated three times and average values were noted for further analysis.

The above said experiment was repeated using two different acoustic emission (AE) sensors of frequency range 125 kHz to 250 kHz and 100 kHz to 2 MHz by selecting suitable combination of AE sensors and preamplifiers with filters. These two ranges of AE signals were captured for the same cutting conditions.

3.3.2 Tool Condition Monitoring for Crater Wear

The workpiece was cleaned and fitted on the lathe. Also the cutting tool along with the tool holder was fixed. The AE sensors for crater wear were placed in the respective positions, as explained, after cleaning the surface and applying the Couplants. The sensors were fixed by using epoxy resin couplant. These sensors output signals were fed to the digital storage
oscilloscope via pre – amplifier and filter. The stored signals were processed off – line through a computer using ‘AUTODASP’ software. The detailed procedure for the experimental work carried out is given below:

1. The machine was set to the selected cutting condition.

2. The oscilloscopes were set in ‘Auto Arm’ mode to receive and store 15 frames of signals automatically. As the machining interval was decided for 30 seconds duration, each signal frame was timed for 2 seconds duration.

3. The machine was started and simultaneously the oscilloscopes were armed to capture the AE signals generated due to crater wear.

4. The machine was stopped at the end of 30 second and the AE signal generated due to crater wear was stored in the oscilloscope for further analysis.

5. The tool was taken out from the tool holder and it was cleaned with carbon tetrachloride.

6. The extent of crater wear propagation was also noted using the profile projector.

7. Then, the crater wear was measured in the Surfcorder. The entire region of crater wear propagation was scanned to measure the maximum crater depth using a vernier micrometer. The surface roughness parameter chosen was Ry which is the sum of Rp + Rv, Where Rp is the distance between the highest peak and the mean line within the measuring length and Rv is the distance between the lowest valley and the mean line.
Figure 3.14 shows the crater wear profiles observed along the side cutting edge at various stages of wear.

8. AE signals stored in the oscilloscopes due to crater wear was transferred to a computer through RS423 serial interface for analysis at a later stage. This pictorial view is shown in Figure 3.8.

9. The tool was again fixed to the tool holder with the same cutting edge in cutting position.

10. The step from 1 to 9 was repeated for next observation.

11. Like this, 40 observations were noted, which meant that the experiment was carried out for 20 minutes and 600 AE waveforms of each 2 seconds duration were captured separately for the crater wear. The captured signals were processed using ‘AUTO DASP’ software.

Figure 3.14 Crater wear profiles
3.3.3 Tool Condition Monitoring for Flank Wear

The experimental procedure for crater wear and flank wear are similar. The only difference is the position of AE sensor for flank wear is on the side surface of the tool holder. The results during studies on flank wear are discussed in the next chapter.

3.3.4 Repeatability Verification of Tool Wear

The results and findings on tool condition monitoring using AET experimental work were verified for their repeatability by carrying out the same experimental work with same conditions for 10 minutes. During this repeated experiment 300 AE wave forms for each 2 seconds duration were captured for crater wear. The experiment was repeated for 15 times and average values were noted for further study. The observations are verified for the repeatability of TCM through AET.

The effect of cutting speed on acoustic emission response in tool condition monitoring was studied experimentally. The cutting conditions selected for the initial experimental work, were kept constant, except the cutting speed. The cutting speed of 100 m/min, selected for the initial experiment, was varied within ±10% and thus, four different cutting speeds viz., 88 m/min, 96 m/min, 104 m/min and 112 m/min are selected. The experiments were conducted for four different cutting speeds. The crater wear and the corresponding AE parameters were noted. The experiment was repeated for three times and average values were used for further analysis.

3.3.5 Tool Breakage through Acoustic Emission Technique

The suitability and applicability of Acoustic Emission Technique (AET) in the tool wear monitoring are discussed in the earlier sections. In
this phase of research work, the AE response to tool breakage was experimentally studied. The experimental set-up, procedure and conditions were all similar in TCM and additionally the following procedure is followed.

i) Crater wear monitoring set-up was retained.

ii) The approach angle was set at $90^0$ to accelerate the tool breakage.

iii) The AE signal generated due to tool conditions were stored at the interval of 30 seconds and the tool was inspected for any breakage instead of crater wear measurement.

iv) The experiment was continued till the breakage of the tool and the AE signal captured during tool breakage was considered for further analysis.

The photograph of the broken tool is shown in Figure 3.15. An Artificial Neural Network is characterized by, its pattern of connections between the neurons (called its architecture). It is a method of determining the weights on the connections (called its training or learning, algorithm), and its activation function.

![Figure 3.15 Pictorial view of the broken tool](image)
3.3.6 Tool Wear Monitoring Using Artificial Neural Network

The network function is determined largely by the connections between elements. Therefore, a neural network can be trained to perform a particular function by adjusting the values of the connections (weight) between the elements. Commonly neural networks are adjusted or trained, so that a particular input leads to a specific target output. Figure 3.16 shows the basic operation of a neural network. The network weight is adjusted based on a comparison of the output and the target, until the network output matches the measured value.

![Figure 3.16 Basic operation of neural network](image)

Figure 3.16 Basic operation of neural network

Figure 3.17 shows a neuron with a single scalar input with no bias. The scalar input \( p \), is transmitted through a connection that multiplies its strength by the scalar weight \( w \), to form the product \( wp \), again a scalar. Here the weighted input \( wp \) is the only argument of the activation function \( f \) and \( n \) is the net input, which produces the scalar output \( a \).

![Figure 3.17 Single input neuron without bias](image)

Neuron without bias \( a = f(wp) \)

Figure 3.17 Single input neuron without bias
Figure 3.18 shows a neuron with a scalar input, with scalar bias. The bias is much like a weight, except that it has a constant input of 1. The activation function net input $n$, again a scalar, is the sum of the weighted input $wp$ and the bias $b$, this sum is the argument of the activation function $f$. Here $f$ is an activation function, typically a step function or a sigmoid function, that takes the argument $n$ and produces the output $a$. Here $w$ and $b$ are both adjustable parameters of the neuron.

The central idea of neural network is that such parameters ($w$ and $b$) can be adjusted so that the network exhibits some desired or interesting behaviour. Thus, we can train the network to do a particular job by adjusting the weight or bias parameters, or perhaps the network itself will adjust these parameters (weight and bias) to achieve the desired target.

Figure 3.19 shows the Artificial Neural Network (ANN) training algorithm. The step involved in training is given below.
Figure 3.19 Flowchart of ANN training algorithm

1. **Start**

2. Initialize weights and randomized initial weight between -0.5 and +0.5 and offset (1)

3. Present input (Average value, RMS value, Area and Time)

4. Calculate actual output of hidden units and output units

5. Adjust weights by \( w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji}(t) \) where

   \[
   \Delta p w_{ji}(t) = \eta \delta_{pj} o_{pl}
   \]

   If the unit \( j \) is an output unit, then \( \delta_{pj} = (t_{pj} - o_{pj})f_j(n_{et_{pj}}) \)

   If unit \( i \) is an internal hidden unit, then \( \delta_{pj} = (n_{et_{oi}}) \varepsilon \delta_{ok} w_{ki} \)

6. Change the training pattern

7. Training pattern: end

8. Increment the number of iteration

9. Iteration: Limit the number

10. **End**
Training Algorithm

Step 1: The weights are initialized randomly between -0.5 and +0.5.

Step 2: While stopping condition is false do steps 3-12.

Step 3: Initialize the error and sum of mean squared error (E)

\[ e_k(0) = 0, \text{for}(k = 1, 2, 3, \ldots, p) \]
\[ E = 0 \] (3.1)

Step 4: For each training pair do steps 5-11

Step 5: Compute the output signals for the hidden units

\[ z_j = 1, 2, 3, \ldots, m. \]

\[ z_{\text{in}_j}(s) = w_{oj} + \sum_{i=1}^{n} x_i w_{ij} \] (3.2)

\[ z_j(s) = f(z_{\text{in}_j}(s)) = \frac{2}{1 + e^{-z_{\text{in}_j}(s)}} - 1 \] (3.3)

Step 6: Compute the output signal for the output units

\[ y_k = 1, 2, 3, \ldots, p. \]

\[ y_{\text{in}_k}(s) = v_{oj} + \sum_{k=1}^{p} z_j(s) v_{jk}, \] (3.4)

\[ y_k(s) = f(y_{\text{in}_k}(s)) = \frac{2}{1 + e^{-y_{\text{in}_k}(s)}} - 1 \] (3.5)

Step 7: Compute the error and sum of mean squared error (E)

for \((k = 1, 2, 3 \ldots p)\)

\[ e_k(s) = t_k(s) - y_k(s), \] (3.6)
\[ E_{\text{new}} = E_{\text{old}} + [e_k(s)]^2 \]  
\[ \text{(3.7)} \]

Step 8: Compute the error gradient and the change in weight for the output neurons, for \( k = 1,2,3,\ldots,p \) and for \( j = 1,2,3,\ldots,m \)

\[ \hat{e}_k = e_k(s)f'(y_{\text{in}_k}(s)) \]  
\[ \text{(3.8)} \]

\[ \Delta v_{jk} = \alpha \hat{e}_k z_j(s) + \eta \Delta v_{jk} \text{(old)} \]  
\[ \text{(3.9)} \]

Step 9: Compute the error gradient and the change in weight for the hidden neurons, for \( j = 1,2,3,\ldots,m \) and for \( i = 1,2,3,\ldots,n \)

\[ \hat{e}_j = \left( \sum_{k=1}^{p} \hat{e}_k v_{jk} \right) f'(z_{\text{in}_j}(s)) \]  
\[ \text{(3.10)} \]

\[ \Delta w_{ij} = \alpha \hat{e}_j x_i(s) + \eta \Delta w_{ij} \text{(old)} \]  
\[ \text{(3.11)} \]

Step 10: Each output unit \( Y_k, k=1,2,3,\ldots,p \), update its bias and weight, for \( j = 0,1,2,\ldots,m \) as

\[ v_{jk} \text{(new)} = \Delta v_{jk} + v_{jk} \text{(old)} \]  
\[ \text{(3.12)} \]

Step 11: Each hidden unit \( Z_j, j=1,2,3,\ldots,m \), update its bias and weight, for \( i = 0,1,2,\ldots,n \) as

\[ w_{ij} \text{(new)} = \Delta w_{ij} + w_{ij} \text{(old)} \]  
\[ \text{(3.13)} \]

Step 12: Test for stopping condition.

An artificial neural network is composed of neurons with a deterministic activation function. The neural network, trained by adjusting the
numerical value of the weights, will contain the non-linearity of the desired mapping, such that difficulties in the mathematical modeling can be avoided. The back propagation training algorithm is used to adjust the numerical values of the weights and the internal threshold of each neuron. The network is trained by, initially selecting small random weights and internal threshold and then presenting all training data. Weights and thresholds are adjusted after every training example and presented to the network, until the weight converges or the error is reduced to an acceptable value. Figure 3.20 shows the structure of BPN Network for analysis of the wear performance.

Figure 3.20  Structure of back propagation network for analyzing of the crater wear

The input (first) layer serves only as distribution points; they perform no input summation. The input signal is simply passed to the weights on their outputs. Each neuron in the subsequent layer produces output signals according to the activation function used. A neuron is associated with the set of weights that connects to its input. This network is considered to consist of three layers. The input or distribution layer is designated as layer 0, the second layer called hidden layer is denoted as layer 1 and the output layer as layer 2.
The activation function used in the BPN is the sigmoidal function. Training is generally commenced with randomly chosen weight values. Typically, the weights chosen are small (between -1 and +1 or -0.5 and +0.5), since larger weight magnitudes may drive the output of layer 1 neurons to saturation, requiring more time to come out of the saturated state. The learning begins with the feed forward recall phase.

The input parameters used in this network $x_i$ are average value, RMS value, Area and Time. The weight function used between the input layer and hidden layer is $W_{ij}$. The net weighted input along with the bias signal $V_{oj}$ is given as the functional parameter $Z_{ij}$ for hidden layer.

$$z_{ij} = v_{oj} + \sum x_i W_{ij} \text{ and } z_j = f(z_{ij})$$ \tag{3.14}

Output of the hidden layer neurons $z_j$ are calculated using the sigmoidal function. This output values are given as the input parameter for the output layer. The net weighted input $Z_j V_{jk}$ along with the bias is given as the functional parameter for the output layer. The final output value which is the crater wear is calculated using the sigmoidal activation function.

3.3.7 Tool Wear Monitoring Using Adaptive Neuro Fuzzy Inference System

The fuzzy inference system under consideration has two inputs $x$ and $y$, and one output $z$. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno’s type.

**Rule 1:** If $x$ is $A_1$ and $y$ is $B_1$, then $f_1 = p_1 x + q_1 y + r_1$

**Rule 2:** If $x$ is $A_2$ and $y$ is $B_2$, then $f_2 = p_2 x + q_2 y + r_2$
Then the Type-3 fuzzy reasoning is illustrated in Figure 3.21, and the corresponding equivalent ANFIS architecture (Type-3 ANFIS) is shown in Figure 3.22. The node functions in the same layer are of the same function family as described below:

\[
f_2 = p_1 x + q_1 y + r_1 \\
f_2 = p_2 x + q_2 y + r_2
\]

Figure 3.21 Type-3 fuzzy reasoning

\[
f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2
\]

\[
f = \overline{w}_1 f_1 + \overline{w}_2 f_2 \quad (3.15)
\]
Layer 1: Every node $i$ in this layer is a square node with a node function

$$O_i^1 = \mu_{A_i}(x)$$

(3.16)

where $x$ is the input to node $i$ and $A_i$ is the linguistic label (small, large, etc.) associated with this node function. In other words, $O_i^1$ is the membership function of $A_i$, and it specifies the degree to which the given $x$ satisfies the quantifier $A_i$. Usually $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{A_i}(x) = \frac{1}{1 + \left(\frac{x-c_i}{a_i}\right)^{2b_i}}$$

(3.17)

or

$$\mu_{A_i}(x) = \exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\}$$

(3.18)
where \( \{a_i, b_i, c_i\} \) is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label \( A_i \).

**Layer 2:** Every node in this layer is a circle node labeled \( \Pi \) which multiplies the incoming signals and sends the product out. For instance,

\[
\mathbf{w}_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i=1,2
\]  

(3.19)

Each node output represents the firing strength of a rule.

**Layer 3:** Every node in this layer is a circle node labeled \( N \). The \( i \)th node calculates the ratio of the \( i \)th rule’s firing strength to the sum of all rules’ firing strengths

\[
\overline{\mathbf{w}}_i = \frac{\mathbf{w}_i}{\mathbf{w}_1 + \mathbf{w}_2}, \quad i=1,2
\]  

(3.20)

For convenience, outputs of this layer will be called normalized firing strengths.

**Layer 4:** Every node \( i \) in this layer is a square node with a node function

\[
\mathbf{O}_i^4 = \overline{\mathbf{w}}_i \mathbf{f}_i = \overline{\mathbf{w}}_i (p_ix + q_iy + r_i)
\]  

(3.21)

where \( \overline{\mathbf{w}}_i \) is the output of layer 3, and \( \{p_i, q_i, r_i\} \) is the parameter set. Parameters in this layer will be referred to as consequent parameters.

**Layer 5:** The single node in this layer is a circle node labelled \( \Sigma \) that computes the overall output as the summation of all incoming signals, i.e. the overall output is,
\[ O_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \] (3.22)

Three inputs, Type-3 ANFIS with twenty seven rules are shown in Figure 3.23. Three membership functions are associated with each input and so the input space is partitioned into twenty seven fuzzy subspaces, each of which is governed by fuzzy if-then rules. The premise part of a rule delineates a fuzzy subspace, while the consequent part specifies the output within this fuzzy subspace.

Figure 3.23 ANFIS Structure

The type-3 ANFIS architecture is proposed, it is observed that given the values of premise parameters, the overall output can be expressed as a linear combinations of the consequent parameters. More precisely, the output \( f \) can be rewritten as
\[ f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \]  \hspace{1cm} (4.23)

\[ f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \]  \hspace{1cm} (4.24)

\[ = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1) r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2) r_2 \]  \hspace{1cm} (4.25)

This is linear in the consequent parameters \((p_1, q_1, r_1, p_2, q_2, r_2)\). As a result, we have

\[ S = \text{set of total parameters} \]
\[ S_1 = \text{set of premise parameters} \]
\[ S_2 = \text{set of consequent parameters} \]

In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent.

The Network diagram of the proposed wear prediction system is shown in Figure 3.23. The proposed ANFIS based Crater wear Performance Predication System (ACPPS) is developed using MATLAB 7.0.4 version. For this case, the input variables are Average Value, RMS Value and Area. By trial and error, initially, the system was developed with three different types of Membership Functions such as Gaussian type, bell-shaped type and triangular type for each input variable of which bell-shaped type membership function yields the best results. Suitable linguistic variables such as SMALL (S), MEDIUM (M) and LARGE (L) are assigned to fuzzy sets of Average Value, RMS Value and Area. The output variable is Wear. The initial and tuned membership functions are shown in Figure 3.24.
Figure 3.24  Membership function (a) Before and (b) After tuning

The system architecture of this three and four input system are shown in Figures 3.25 and 3.26 respectively.

Figure 3.25  Structure of ANFIS for analysis of crater wear for three inputs
3.4 SUMMARY

The experimental studies were carried out to find the suitable sensors to monitor the crater wear individually without any combined effect for C45 steel using coated carbide inserts. Further about 1200 AE waveforms due to crater wear are analyzed and a suitable method was studied for the on–line monitoring using acoustic emission technique (AET). This finding was verified experimentally for its repeatability. The effect of different cutting speed on AE response in monitoring tool wear is also experimentally studied. Finally, tool breakage and the AE response and the relative sensitivity of AET with other tool wear monitoring techniques like measurement of motor current, cutting force and acceleration due to tool vibration were also studied. The results obtained for the combination of wear and the AE parameters were carefully noted. The effectiveness of the intelligent techniques like Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) for analyzing the status of crater wear of the cutting tool was studied. The results obtained during the above wear measurement method’s are discussed in the next chapter.

Figure 3.26 Structure of ANFIS for analysis of crater wear for four inputs