On-line tool wear estimation in CNC turning operations

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ABSTRACT

In order to prevent tool breakage and resultant decrease in productivity in unmanned turning operations, many researchers have attempted to develop tool wear estimation and classification models. These include neural network models, fuzzy logic models and working scenario for quantitative models. The worn tools need to be replaced before their wear exceeds the allowed limits. Normally, cutting forces, $AE_{rms}$ and cutting conditions including cutting speed, feed rate, rake angle and depth of cut are employed as inputs in these models. In the recent past, however, many researches have focused on flank wear prediction and off-line tool wear prediction systems. Additionally, the accuracy of tool wear prediction for these models needs to be increased. Therefore, in this research, a new on-line tool wear estimation system having higher accuracy for estimating the length of flank wear and the maximum depth of crater wear in CNC turning operations is developed.

Initially, quantitative models for predicting mean forces, mean $AE_{rms}$, and average tool flank wear width as well as a model for estimating a number of chip fracture occurring during the sampling period were developed. Employing these models, a computer program (a working scenario for such models) for tool flank and crater wear estimation was adapted. However, experimental results indicated that the average accuracy of flank and crater wear prediction by these models is about 60-70%. Hence, a new fuzzy neural network model for flank and crater wear estimation was developed in order to increase the accuracy of tool wear prediction. This fuzzy neural network model employs cutting forces, $AE_{rms}$, the derivatives of cutting forces, the derivatives of $AE_{rms}$ and cutting conditions as inputs. Experimental results showed that this fuzzy neural network model
can estimate flank and crater wear accurately. Hence, it was used in the on-line system for estimating tool wear. Due to the fact that tip fracture, or chipping at the major cutting edge, or both on tool inserts cause greater forces and $AE_{\text{rms}}$ signals, tool inserts having these defects could be detected from the significant increase in force signals. The detection of chipping and fracturing at tool cutting edges was also incorporated in the tool wear estimation system developed by the author. In the present research, the derivatives of cutting forces, the total energy and the total entropy of cutting forces, were also introduced as new parameters for monitoring tool flank and crater wear. The total energy of forces was also used as an input of the fuzzy neural network model.

Experimental results indicated the new on-line tool wear estimation system can estimate flank and crater wear accurately and eliminates tool wear estimation error due to a variation in actual cutting tool geometry. The computational time for this tool wear estimation was about 16 seconds. However, it decreased to 8 seconds for the subsequent flank and crater wear estimation during turning operation.
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\[ \Delta F_r : \text{increase in feed force (N)} \]
\[ \Delta F_r : \text{increase in radial force (N)} \]
\[ \alpha : \text{rake angle (degrees)} \]
\[ \alpha_n : \text{normal rake angle for fresh tool (degrees)} \]
\[ \alpha_{nm} : \text{normal rake angle for worn tool (degrees)} \]
\[ \alpha_e : \text{effective rake angle (degrees)} \]
\[ \beta : \text{friction angle (degrees)} \]
\[ \phi : \text{shear angle (degrees)} \]
\[ \phi_n : \text{normal shear angle (degrees)} \]
\[ \phi_e : \text{effective shear angle (degrees)} \]
\[ \eta_e : \text{chip flow angle (degrees)} \]
\[ \mu : \text{coefficient of friction} \]
\[ \sigma_n : \text{normal stress on rake face (MPa)} \]
\[ \sigma_{n_{\text{max}}} : \text{maximum normal stress at the cutting edge (MPa)} \]
\[ \sigma_{\text{fw}} : \text{normal stress on flank wear land (MPa)} \]
\[ \tau_s : \text{shear stress (MPa)} \]
\[ \tau_{s_{\text{max}}} : \text{maximum shear stress (MPa)} \]
\[ A_1, A_2, A_3 : \text{constant} \]
\[ A_{k(n)} : \text{Finite Fourier Transforms} \]
\[ A_{\text{sm}} : \text{shear plane area for worn tool (mm}^2)\]
\[ C_1 : \text{proportionality constant} \]
\[ C_2, C_3, C_4, C_5 : \text{signal attenuation constants} \]
<table>
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<th>Description</th>
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<td>$C_a$</td>
<td>clearance angle (degrees)</td>
</tr>
<tr>
<td>$C_s$</td>
<td>side cutting edge angle (degrees)</td>
</tr>
<tr>
<td>$CF_{freq}$</td>
<td>average frequency for chip fracture (Hz)</td>
</tr>
<tr>
<td>$E$</td>
<td>Young's Modulus (MPa)</td>
</tr>
<tr>
<td>$E_{cb}$</td>
<td>strain energy released during fracture (N·mm)</td>
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<td>$F_t$</td>
<td>friction force (N)</td>
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<td>$K$</td>
<td>the shear yield stress of work material (MPa)</td>
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<td>$N$</td>
<td>number of chip fracture</td>
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<td>$N_B$</td>
<td>total normal force on flank wear at nose cutting edge region (N)</td>
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<td>$N_{sp}$</td>
<td>number of samples</td>
</tr>
<tr>
<td>$N_t$</td>
<td>normal force (N)</td>
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<td>$P(i)$</td>
<td>frequency whose magnitude is higher than threshold (Hz)</td>
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<td>$P_{Fc}(i)$</td>
<td>probability of a value of PSD of energy consumption $U_{Fc}$ at event $i$</td>
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<tr>
<td>$P_{Fr}(i)$</td>
<td>probability of a value of PSD of energy consumption $U_{Fr}$ at event $i$</td>
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<td>$P_{Fr}(i)$</td>
<td>probability of a value of PSD of energy consumption $U_{Fr}$ at event $i$</td>
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<td>PSD</td>
<td>power spectrum density</td>
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\[ S_{Fc} : \] the entropy consumption per unit time calculated from \( F_c \) signal

\[ S_{Ff} : \] the entropy consumption per unit time calculated from \( F_f \) signal

\[ S_{Fr} : \] the entropy consumption per unit time calculated from \( F_r \) signal

\[ S_{total} : \] the total entropy consumption per unit time

\[ U_{Fc} : \] the energy consumption per unit time calculated from \( F_c \) signal (Nm/s)

\[ U_{Ff} : \] the energy consumption per unit time calculated from \( F_f \) signal (Nm/s)

\[ U_{Fr} : \] the energy consumption per unit time calculated from \( F_r \) signal (Nm/s)

\[ U_{total} : \] the total energy consumption per unit time (Nm/min)

\[ U_{Fc}' : \] power spectrum density of \( U_{Fc} \) (Nm/min)

\[ U_{Ff}' : \] power spectrum density of \( U_{Ff} \) (Nm/min)

\[ U_{Fr}' : \] power spectrum density of \( U_{Fr} \) (Nm/min)

\[ U_{totalF} : \] the total energy of force signals (Nm/min)

\[ U_{Fce} : \] the expected value of \( U_{Fc} \) (Nm/min)

\[ U_{Ffe} : \] the expected value of \( U_{Ff} \) (Nm/min)

\[ U_{Fre} : \] the expected value of \( U_{Fr} \) (Nm/min)

\[ V : \] cutting speed (m/min)

\[ V_{Fc} : \] chip velocity in \( F_c \) direction (m/min)

\[ V_{Ff} : \] chip velocity in \( F_f \) direction (m/min)

\[ V_{Fr} : \] chip velocity in \( F_r \) direction (m/min)

\[ W : \] average flank wear width (mm)

\[ W_{cr} : \] maximum depth of crater wear (mm)

\[ W_k(j) : \] window selected
\( W_p \) : distance on flank wear land (mm)

\( b \) : depth of cut for fresh tool (mm)

\( b_m \) : depth of cut for worn tool (mm)

\( f \) : feed rate (mm/rev)

\( f_{sp} \) : sampling frequency (Hz)

\( i \) : angle of inclination (degree)

\( r \) : nose tool radius for fresh tool (mm)

\( r_m \) : nose tool radius for worn tool (mm)

\( l_m \) : total cutting edge length for worn tool (mm)

\( l_p \) : distance on tool rake face (mm)

\( l_{st} \) : sticking chip-tool contact length (mm)

\( l_t \) : total chip-tool contact length (mm)

\( w(i) \) : normalized magnitude of P(i)
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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

In order to enhance productivity, modern factories usually employ an unmanned machining system for production of their products. One of the essential functions of this unmanned machining system is the ability to change worn or damaged tools automatically [1]. It was reported that 6.8% of the downtime of machining centers was spent for changing the failed tools [2]. Normally, tool change strategies are based on the estimation of tool life from past tool wear data [1] such as tool wear rate which is a function of cutting conditions and cutting time [3-8]. However, in instances, when a fixed time tool replacement strategy is adopted, some tools may fail before they are replaced and some tools still have significant life left. In order to use tools to the fullest extent, automatic on-line tool wear estimation with indirect measurement of tool wear in turning operations is preferred.

Due to the fact that catastrophic tool failure as well as large chipping at the cutting edge of a tool can be detected by using force and AE_{rms} signals [9-11], estimation of flank and crater wear has become an important area of research in machining operations. In the recent past, artificial neural networks have been used for development of tool wear estimation models. These models have been developed for both estimating [12-15] and classifying [16-21] tool wear in turning operations. However, very few of these models have been employed in on-line systems [12, 16, 19, 20]. In these neural network
models, cutting forces, $AE_{rms}$ and cutting conditions including speed, feed, rake angle and depth of cut have been usually used as input [12-14, 16-18, 21].

Although these neural network models have a high accuracy for estimating as well as classifying tool wear, they do not consider some phenomena which usually occur during turning and can result in tool wear estimation and classification error. These phenomena include tool failure, chipping at the cutting edge and variation in signals. It was reported that forces and $AE_{rms}$ changed significantly when catastrophic tool failure as well as chipping at the cutting edge occurred [9, 10, 22]. Lucca and Seo [23] observed the ± 5% variation in cutting and thrust forces for the repeat of cutting of a tool insert with no change in edge profile. Additionally, a variation in geometry of received fresh tool inserts make dissimilar in forces and $AE_{rms}$. This variation in signals results in inaccurate tool wear estimation.

Since previous on-line tool wear estimation systems have some limitations including less accuracy for predicting tool wear as well as long computational time, therefore, a new on-line tool wear estimation system which can be used in the industry and have a higher accuracy for flank and crater wear predictions needs to be built. To archive this aim, a research was taken with objectives detailed below.

1.2 THESIS OBJECTIVES

The research work described in this thesis is devoted to the development of an on-line tool wear estimation system in CNC turning operations. The research objectives are as follows:
1. To investigate the geometry of tool-chip contact area on a tool rake face for fresh tools and the geometry of flank and crater wear for worn tools. These results will be employed in objectives 2 and 3.

2. To develop a quantitative model for predicting mean three-forces (cutting, feed and radial) for fresh and worn tools in oblique turning operations.

3. To develop a quantitative model for estimating a mean \( AE_{rms} \) for fresh as well as worn tools in oblique cutting.

4. To develop a computer program for estimating flank and crater wear, employing the quantitative models developed in the second and third objectives for prediction of wear.

5. To develop a new technique that can detect the occurrence of chip fracture as well as estimate the number of chip fractures occurring during a sampling period.

6. To develop new parameters (derivatives of force signals) for monitoring progressive tool wear in order to enhance the capability of forces for tool wear monitoring.

7. To develop a neural network model for detecting the occurrence of fracture at the tool tip and chipping at the major cutting edge during turning operations.

8. To examine the variability of force and \( AE_{rms} \) signals at the beginning of cutting as well as during cutting with different tool inserts having the same specification.

9. To develop a fuzzy-neural network model for estimating flank and crater wear. This model can also eliminate an effect of the variation in mean signals resulting in tool wear estimation error.
10. To develop an on-line tool wear estimation system for CNC turning operations.

1.3 THESIS ORGANIZATION

The thesis is organized into 7 chapters. An outline of each chapter is given below.

Chapter 1 highlights the significance of the research project and describes the objectives to be achieved. It also includes an outline of the thesis.

Chapter 2 summarizes the major knowledge employed in this thesis for development of on-line tool wear estimation system. The relevant knowledge includes forms of tool wear occurring during metal cutting, force models, $AE_{rms}$ models, tool condition monitoring, and tool wear estimation and classification.

Chapter 3 proposes a new on-line tool wear estimation system. A structure of this on-line system and the function of each section are also explained.

Chapter 4 presents development of new models as well as technique which need to be used in the new algorithm proposed in Chapter 3. These models and technique include (i) quantitative force and $AE_{rms}$ models for fresh as well as worn tools, (ii) a new technique for estimating number of chip fracture events which occur during the signal sampling period, (iii) a neural network model for detecting tool tip fracture and chipping at the major cutting region, (iv) quantitative models for flank wear estimation, and (v) fuzzy neural network model for estimating the average width of flank wear and
the maximum depth of crater wear. This chapter also introduces some new parameters such as the total energy and the total entropy of forces for monitoring cutting tool condition.

Chapter 5 details experiments done in this thesis for verifying new models and a new technique as well as testing new parameters developed in Chapter 4.

Chapter 6 discusses experimental results from experiments explained in Chapter 5.

Chapter 7 presents concluding remarks and summaries the research in this thesis. Suggestions for future work are also provided.
CHAPTER 2

LITERATURE SURVEY

In order to develop an on-line tool wear estimation system in CNC turning operations which can be used in the real world, knowledge of several areas is required. This knowledge can be grouped into five independent areas: (i) forms of tool wear, (ii) force models, (iii) $A_E_{rms}$ models, (iv) tool condition monitoring, including signals employed for indirect tool wear monitoring, and (v) tool wear estimation and classification including quantitative and neural network models. The relevant literature for these five areas is reviewed in the following sections:

2.1 FORMS OF TOOL WEAR OCCURRING DURING METAL CUTTING

Progressive tool wear including flank and crater wear of cutting tool is a combination of many types of wear such as adhesive, abrasive, diffusion, and fracture wear [24]. The tool wear processes generally occur in combination with the predominant wear mode which is dependent on cutting conditions, workpiece materials, tool materials and tool insert geometries. For example, when cutting with high speeds crater wear on tools consists of adhesive and abrasive wear zones. In turning operations, normally, adhesive wear is caused by the fracture of welded asperity junctions between the two metals in tool-chip interface as well as tool-workpiece interface in the cutting zone while abrasive wear results from the cutting action of hard particles. Diffusion wear usually occurs at high temperatures, and chipping due to fatigue is a cause of fracture wear [24].
As shown in Figure 2.1, there are seven types of wear which could be observed on worn tool inserts [1]. These are (i) major flank wear, (ii) minor flank wear, (iii) notch wear at major cutting region, (iv) notch wear at minor cutting region, (v) crater wear, (vi) chipping, and (vii) tip breakage. Flank, nose and crater wear are progressive wear while chipping and tip breakage occur from fracture at the cutting edge and nose of the tool respectively.

Figure 2.1 Seven types of wear on cutting tool inserts

2.2 QUANTITATIVE FORCE MODELS

Normally, ‘thin-zone’ and ‘thick-zone’ models (Figure 2.2) are employed for studying the mechanics of metal cutting [25]. However, the thin-zone model is likely to be more useful for the development of a force model. This is because most evidence indicates that a thin shear plane is approached at higher speed, and the thin-zone model leads to a
simpler mathematical treatment than does the thick-zone model [25]. Based on these reasons, therefore, only force models developed by using thin-zone model are considered and employed for developing the force model in this thesis. It should be noted that since a flat rake face insert and cutting processes under steady-state metal removal are employed and considered in the present thesis, only the literature of a cutting force model relating to these criteria is reviewed.

In this section, force models for four cases of metal cutting are reviewed. These are: (i) orthogonal cutting, (ii) oblique cutting with single cutting region, (iii) oblique cutting with two cutting regions and (iv) oblique cutting with three cutting regions. These four cutting cases are shown in Figure 2.3.
(a) Orthogonal cutting

(b) Oblique cutting with single cutting region

(c) Plan view of oblique cutting with two cutting regions

(d) Plan view of oblique cutting with three cutting regions

Figure 2.3 Four cases of orthogonal and oblique cutting
2.2.1 Force Models for Orthogonal Cutting

In 1944, Merchant [26] presented the first relation between force components in orthogonal cutting by using a mathematical analysis of the geometry and mechanics of the metal-cutting processes. It should be noted that an estimation of forces in metal cutting was not presented in this work. Based on Merchant’s study [26], however, quantitative models for predicting force components in orthogonal cutting have been developed. Details for each cutting force model are summarized and presented next.

2.2.1.1 Force Models for Orthogonal Cutting with Fresh Tools

The first quantitative model for estimating forces in orthogonal cutting was proposed by Merchant [27]. Merchant’s force model was developed based on the following assumptions: (i) The tool tip is sharp and no rubbing or ploughing occurs at the cutting edge, (ii) The deformation is two-dimensional (no side spread), (iii) stresses on the shear plane have uniform distribution, and (iv) Resultant force on the chip applied at the shear plane is equal, opposite and collinear to the force applied to the chip at the tool chip interface. As a result, Merchant’s cutting forces are functions of shear stress, undeformed chip thickness, width of cut, shear angle, friction angle and rake angle. Assuming the minimum-energy principle applied in metal cutting, the relationship between friction, shear and rake angle was expressed. However, later researchers [28-30] found that this relationship is inaccurate and further relationships have been introduced.
The later observation indicated that the radius of the tool cutting edge varies from 0.005 mm to 0.03 mm for new high speed steel tools [31]. For an edge radius large compared with the undeformed chip thickness, it was suggested that the force acting on the cutting tool edge cannot be neglected [32]. In such a case, the ploughing force needs to be considered. Boothroyd [32] also explained that this ploughing (or plowing) force consisted of two forces - force acting on tool edge and friction force on tool flank face caused by a contact between the tool and the new workpiece surface over a small area of the tool flank.

Effects of a ploughing process on metal cutting were presented by Albrecht in 1960 and 1961 [33-34]. In these researches, it was found that ploughing process occurring due to tool edge causes higher cutting and thrust forces. A force diagram occurring due to the ploughing process was also presented in his work [33]. Albrecht explained that the ploughing process also occurs due to a built-up edge [33] and is similar to the ploughing process due to tool edge. The ploughing process due to the built-up edge also causes forces to increase. Additionally, it was observed that the built-up edge makes a chip up-curl radius to decrease [34] which results in shorter tool-chip contact length.

Two recent force models for orthogonal cutting considering the radius of the tool cutting edge were presented by Waldorf et al. [35]. Both models predict forces based on theories of elastic-plastic deformation. A similarity between these models is that both models focus on the flow of workpiece material around the cutting edge. However, the first model assumes that a separation point exists on the rounded cutting edge while the second model includes a stable build-up adhered to the edge and assumes a separation point at the outer extreme of the build-up. In the experiment, a large edge radius was
employed for cutting. Comparing predicted forces from the first and the second models with measured forces, results suggested that a stable built-up should adhere to the cutting edge. Hence, a workpiece material separation point is not located on the tool. As a result, the second force model is more realistic than the first model.

2.2.1.2 Force Models for Orthogonal Cutting with Worn Tools

Flank and crater wear cause a change in the geometry of cutting tools, resulting in a change in the magnitude of the cutting forces. It was found that the contact area between the tool flank wear land and the new surface of the workpiece consists of two zones – plastic and elastic contact zones [36]. However, some researchers assume the contact area between flank and workpiece to be fully plastic [37].

In 1992, Mesquita et al. [38] proposed a model for predicting cutting forces for worn tools having both flank and crater wear. This model is built by using the following basis: (i) as the flank wear grows, the normal and shear stresses on the tool-flank contact area cause increases in the horizontal and vertical forces respectively, (ii) it was assumed that crater wear results in an increase in the side rake angle only which causes a change in the forces on the shear plane and the tool rake face, and (iii) the ploughing force due to the cutting edge radius results in higher horizontal force. However, the purpose of Mesquita et al.'s work is to employ this force model to determine the dynamic shear stress in metal cutting. Experimental results showed a good agreement between the shear stress values on the shear plane estimated by predicted forces and measured forces.
Another recent model for prediction of cutting forces on fresh tool as well as tool having flank wear (Figure 2.4) was presented by Arcona and Dow [39]. This model has been developed for precision machining. Therefore, the ploughing process at the tool edge and the elastic deformation of workpiece (spring back) influence the forces significantly. Hence, Arcona and Dow’s model [39] estimates cutting and thrust forces generated due to the plastic deformation on the shear zone, the friction on tool rake face, the ploughing at the cutting edge, the friction on workpiece-flank wear land contact area, and the elastic deformation of workpiece. Their experimental results indicated a close agreement between the estimated and the measured cutting forces. However, it was also found that a large difference between predicted and actual thrust forces always occurred for cutting with high uncut chip area [39]. Additionally, a new relationship between the shear angle and the coefficient of friction was also introduced [39].

Figure 2.4 Arcona and Dow’s model [39]
2.2.2 Force Models for Oblique Cutting

The first relationship between force components in oblique cutting was also introduced by Merchant and Ohio [26]. As with orthogonal cutting, this relation between force components in oblique cutting was derived by using a mathematical analysis of the geometry and the mechanics of the metal-cutting processes. A few years later, a further investigation in the mechanics of three-dimensional (oblique) cutting operations was presented by Shaw, Cook and Smith [40]. In this work, it was found that the angle between the direction of chip flow and the normal to the cutting edge was found to be approximately equal to the inclination angle for ordinary friction conditions, but this angle becomes progressively greater than the inclination angle as the friction decreases [40]. It was also observed that the direction of the force component along the tool rake face deviates considerably from the chip flow direction, particularly for larger values of the inclination angle [40].

Many researchers have attempted to develop quantitative models for predicting the three forces in oblique turning operations. Research began with models for the cutting with a single edge cutting tool. However, the current research focus is on force models for the cutting edge having several cutting regions (major, nose and minor cutting regions). Details for each force model are presented next:
2.2.2.1 Force Models for Oblique Cutting with Fresh Tools

- Cutting with a Single Cutting Region

The mechanics of oblique cutting with a single cutting region is the simplest case of three-dimensional cutting. Normally, rake angle, shear angle, velocity relationships, chip flow, and force and stress relationships are the areas studied. Oblique cutting in this case is presented in Figure 2.3(b).

A well known force model for oblique cutting was introduced by Armarego and Brown [25]. To derive relations for the three components of force in terms of stress on the shear plane, the first, third and fourth assumptions in Merchant’s model [27] need to be used. It should be noted that the forces in the direction of cutting as well as normal to the direction of cutting and the machined surface are approximated from the orthogonal theory by taking the inclination angle equal to zero and the rake angle equal to the normal rake angle. Armarego and Brown [25] also used mathematical analysis and chip flow direction approximated by using Stabler’s rule for deriving a relationship between the normal shear angle, the normal friction angle and the normal rake angle. A more recent relationship between these angles was introduced by Shamoto and Altintas in 1999 [41].

Further development of Armarego and Brown’s force model [25] was presented by Lin et al. [42]. They started with a prediction of forces in orthogonal cutting by using the orthogonal (plane strain) machining theory and workpiece material properties including flow stress and thermal properties. For oblique cutting, they assumed that the cutting
force component and the force component normal to the cutting direction and the
machined surface can be predicted from the orthogonal cutting by taking (i) inclination
angle = ‘0’ and (ii) rake angle = normal rake angle. Then, using the value of the
inclination angle, the force component (F_R) normal to F_C and F_T can be predicted from
F_C and F_T. Employing the side cutting edge angle, forces in the three directions (cutting,
feed and radial) can be expressed in terms of F_C, F_T and F_R. It should be noted that a
significant difference between measured and predicted forces was observed in the
experimental results.

In the research of Lin et al [42], the shear flow stress on the shear plane which
influences the shear force needs to be estimated from a correlation between shear flow
stress, uniaxial flow stress at “uniaxial strain = 1”, strain at shear plane and strain
hardening index. The uniaxial flow stress and strain hardening index can be determined
from a graph of flow stress and strain hardening index versus velocity-modified
temperature which can be expressed in term of the material properties, cutting
conditions, uniaxial strain rate, and constants in the velocity-modified temperature
equation.

As mentioned above, a chip-flow direction needs to be known for estimating the normal
shear angle, the normal friction angle, and the normal rake angle. Therefore, the tool-
chip direction has been studied by many researchers. For example, in 1951, Stabler [43]
found that a chip-flow angle equals to the angle of inclination. However, experimental
evidences in his later research [44] led Stabler to suggest that the magnitude of chip-
flow angle is between 0.9 and 1.0 of the angle of inclination. But, for low speeds, the
chip-flow angle approaches the angle of inclination. In Stabler’s work [43-44], work
material and cutting conditions were varied for studying a chip-flow angle, however the
influence of rake angle on a chip-flow angle was not investigated.

- **Cutting with Two Cutting Regions**

A sharp tool, as shown in Figure 2.3(c), is usually employed for studying oblique
turning with two cutting regions. A force model for two cutting regions (sharp tool) was
proposed in 1978 by Usui, Hirota and Masuko [45]. Their model estimated the cutting,
feed and radial forces in turning operations by using the energy method. In their
research, mathematical equations for estimating shear plane area were developed based
on a realistic geometry of the shear plane. However, this model was based on three
major assumptions: (i) the relation between effective shear angle and effective rake
angle is same as the relation between shear angle and rake angle in orthogonal cutting
under equivalent cutting conditions, (ii) the shear stress on the shear plane is a function
of the effective rake angle and this relation is assumed to be the same as for orthogonal
cutting at equivalent cutting conditions, and (iii) the friction force in orthogonal cutting
with unit width of cut and undeformed chip thickness is assumed to act upon the unit
width of the tool face at the location of the same undeformed chip thickness (feed) in
the plane containing cutting velocity and chip velocity, although this plane is not
perpendicular to the tool face. However, the influence of speed and feed rate on the
shear stress in the shear plane was not considered by Usui, Hirota and Masuko in their
model [45]. Employing the third assumption for oblique cutting, the friction force was
predicted from sticking friction on the projected area of an uncut-chip area on the tool
rake face. Additionally, an effect of chip flow angle, cutting conditions, and inclination
angle on the three forces were also investigated. Experimental results indicated that the
measured forces were greater than the predicted forces. This may be because the sliding friction on the tool-chip contact occurring next to the projection area was neglected.

Hu et al. [46] proposed another force model which was a modification of Lin et al.'s model [42] for oblique cutting with two straight cutting regions. Hu et al. [46] employed the concept of equivalent cutting edge for simplifying two straight cutting regions to a single cutting region (Figure 2.5). As a result of using the concept of equivalent cutting edge, inclination angle, side cutting edge angle, normal rake angle and chip flow angle need to be modified before being used for estimating forces. In this model, Colwell's model [47] was employed for determining the equivalent cutting edge. For predicting forces, the flow stress and thermal properties of the work material need to be known. Then, assuming that the normal rake angle equals the rake angle, Hu et al. [46] used a method for calculating the flow stress and thermal properties such as specific heat and thermal conductivity in orthogonal cutting [42] to estimate the flow stress and thermal properties of the workpiece in oblique cutting.

Hu et al. [46] presented an analysis of metal cutting wherein they replaced the actual cutting edge by an equivalent cutting edge. The use of the equivalent cutting edge resulted in a cutting edge having shorter length. However, this resulted in a simpler analysis of the metal cutting operation. Figure 2.5 also shows that the length of the minor cutting region depends on the feed while length of major cutting region depends on the depth of cut. For small feed and large depth of cut, the shear plane area estimated from the equivalent cutting edge is similar to the actual shear plane area. However, the difference between actual and estimated shear plane area increases for large feed rate and small depth of cut.
In 1978, Usui and Hirota [48] proposed a model for predicting cutting, feed and radial forces in oblique turning operation with three cutting regions (Figure 2.3d). This model was developed based on Usui, Hirota and Masuko’s model [45]. The three assumptions employed in the earlier model [45] were also used in Usui and Hirota’s model [48]. The friction force was predicted from sticking friction on the projection of the chip area on the tool rake face. This model also investigates the influence of the three cutting regions (major, nose and minor cutting regions) on the shear plane area. The influence of cutting conditions, tool geometry on the three forces (cutting, feed and radial) was also investigated in their research.
Other force models for the three cutting regions were developed by Young et al. [49], Arsecularatne et al. [50], and Arsecularatne et al. [51]. These models represent further development of the model of Hu et al. [46]. These models still predict forces by using the concept of equivalent cutting edge (Figure 2.6). The major improvement in these models is a modification of chip flow direction.

Figure 2.6 indicates that the equivalent cutting edge is the shorter than the actual cutting edge length. As with the case of two cutting regions, the shear plane area estimated from the equivalent cutting edge is similar to the actual shear plane area for small feed as well as nose radius, and large depth of cut. However, the difference between actual
and estimated shear plane areas increases for large feed rate as well as nose radius and small depth of cut.

2.2.2.2 Force Models for Oblique Cutting with Worn Tools

In the last two decades, force models for worn tools have been studied for both single and multi-cutting regions. One of the more recent force models for worn tools having flank wear was presented by Elanayar and Shin in 1996 [52]. This model was developed for three-dimensional cutting. In this work, Elanayar and Shin [52] proposes that shear force on a shear zone is the vector resultant of the shearing and ploughing components. A force normal to the shear plane is also introduced with a similar concept. However, shear and normal forces on the shear zone are estimated by using the predictive machining theory developed by Oxley [53]. It is also assumed that ploughing forces in cutting and thrust directions are caused by friction and indentation processes on flank wear land only. Elanayar and Shin [52] also employed this force model to isolate the ploughing forces due to flank wear from the measured forces and then develop a model for the indentation process. For a carbide insert, experimental results indicate that the magnitude of the indentation force is approximately 50 percent of the friction force on the flank wear land. In a ceramic case, however, the ploughing force due to the indentation process is similar to the ploughing force by the friction process on the wear land [52].
2.3 QUANTITATIVE $\text{AE}_{\text{rms}}$ MODELS

Acoustic emission (AE) refers to the elastic stress waves generated as a result of the strain energy released from a rearrangement of the material’s internal structure [54]. In metal cutting processes, AE is generated by many distinct sources including (i) deformation in the primary zone (shear zone), (ii) deformation and sliding friction in the secondary zone (chip-rake face contact), (iii) deformation and sliding friction in the tertiary zone (flank-workpiece contact), and (iv) breaking of chips and their impact on the cutting tool or workpiece. These sources of AE in turning are illustrated in Figure 2.7.

![Diagram showing energy sources of AE signal during metal cutting](Image)

**Figure 2.7** Energy sources of AE signal during metal cutting [69]
Since the 1980s, acoustic emission in metal cutting has been studied in two ways: raw AE signal and root mean square of AE signal ($AE_{rms}$). In this thesis, only $AE_{rms}$ models developed for turning operations under steady-state cutting conditions have been considered and reviewed.

Since AE is defined in terms of the transient elastic energy spontaneously released in materials undergoing deformation or fracture or both [55], the AE signal depends on basic mechanisms including dislocation motion, twining, grain boundary sliding, and vacancy coalescence [56]. In most crystalline materials, dislocation motion is the major mechanism of plastic deformation. Therefore, AE relates strongly to the grain size, dislocation density and distribution of second phase particles in materials [56]. Using a proportional relation between $RMS^2$ and the energy expenditure during the time interval, Dornfeld and Kannatey-Asibu [56] proposed the first model for prediction of $AE_{rms}$ in orthogonal turning operations in 1980. Employing a correlation between the average strain rate and the average dislocation velocity [57] as well as a correlation between the shear strain rate and cutting parameters [56], Dornfeld and Kannatey-Asibu’s model estimates $AE_{rms}$ from cutting and material parameters including material shear strength, volume of participating material (including material undergoing deformation in both the primary and secondary shear zones), chip thickness ratio, cutting speed, shear plane spacing, rake angle, and shear angle [56]. It was suggested that a suitable approximation of the volume of the participating material is the volume of the slip-line field for orthogonal cutting without built up edge as proposed by Lee and Shaffer [29].
Results of Dornfeld and Kannatey-Asibu’s experiment indicated that the proportionality between calculated strain rate and the square of measured AE_{rms} agreed with Dornfeld and Kannatey-Asibu’s equation [56]. Dornfeld and Kannatey-Asibu expected (i) AE_{rms} to be strongly influenced by cutting speed due to an influence of cutting velocity on the strain rate, and (ii) AE_{rms} should increase with decrease in feed rate due to influence of feed on the strain rate observed by Kececioglu [58]. Their experimental results agreed with the first expectation but disagreed with the second expectation. The results showed that AE_{rms} was constant with change in feed at the lowest velocity and AE_{rms} decreased slightly with change in feed at higher speed. The reason for these phenomena was that an increase in feed made the tool-chip contact length to rise which generated an additional AE signal. However, this additional signal nullified the effect of increase in the shear zone thickness (which caused the AE signal to drop) as feed rate increased [56]. Experimental results also indicated that the tool rake angle did not affect AE_{rms}. This is because, as rake angle increased, the effect of Cos(\alpha) causing AE_{rms} to decline was nullified by a decrease in the shear zone thickness and the additional AE signal from longer tool-chip contact length [56].

Employing a proportionality relation between the energy rate and RMS\textsuperscript{2} as well as a correlation between work rate, applied stress, strain rate and volume of material being deformed, Kannatey-Asibu and Dornfeld introduced a new AE_{rms} model for predicting AE_{rms} [54]. This model estimated AE_{rms} from the work rate in the shear zone and tool-chip zone. As with Dornfeld and Kannatey-Asibu’s model, only a proportionality constant is used in this model. Three assumptions are employed to evaluate the theoretical AE_{rms} values. These are (i) the length of the sticking zone is approximately one-half the measured contact length [59], (ii) at the high strain rates involved, the shear
stress is constant [60], and (iii) the shear zone thickness is constant. Comparison between theoretical $A E_{rms}$ and measured $A E_{rms}$ indicated that the proportionality constant was rake-angle-dependent. Therefore, they modified their model by multiplying the proportionality constant by $\sin(\alpha)$ [54]. Experimental results also showed that a small AE signal was generated from the sliding zone on the tool rake face. This is because of the lack of bulk deformation of sliding friction [54].

A further refinement of the $A E_{rms}$ model was proposed by Lan and Dornfeld in 1986 [61]. This model was developed by considering the work rate in the shear zone, tool-chip interface zone and flank-workpiece interface zone. Unlike Kannatey-Asibu and Dornfeld’s model, Lan and Dornfeld’s model employs two types of constants: a proportionality constant and a factor of signal attenuation. The proportionality constant employed in this model is influenced by tool geometry, instrumentation gain, etc [61]. Three factors of signal attenuation used in such a model correspond to signal transmission losses during travel from the shear zone, tool-chip interface zone and wear zone to the transducer on the tool shank [61]. The factors of signal attenuation for tool-chip contact and flank wear were assumed to be “1”. The factor of signal attenuation for shear zone was between 0.2-0.25 as found by the experimental tests [62].

Lan and Dornfeld’s experiment results [61] indicate that the $A E_{rms}$ did not change significantly with different feed rate and width of cut. However, it was observed that $A E_{rms}$ was sensitive to variation in Brinell hardness. In their test, the occurrence of chip fracture was found to result in $A E_{rms}$ significantly. They also suggested that the actual measured rate of chip fracture could be calculated from the average number of chips produced per unit of time.
For three-dimensional machining, the radius of the nose of the tool, the direction of chip flow (no longer perpendicular to the cutting edge), and plastic flow in three-dimensional cutting need to be concerned for development of the analytical model [61]. Since no cutting tool is perfectly sharp, the ploughing force due to a tool edge [63] can result in increase in specific cutting energy [61]. The effect of this ploughing force becomes important for small undeformed chip thickness [61].

Due to the fact that the model coefficients in the diamond machining test of Pan and Dornfeld [64] did not validate Kannatey-Asibu and Dornfeld's equation [54] completely, Teti and Dornfeld introduced another $AE_{rms}$ model for fresh tools in orthogonal cutting processes [65]. Using graphs of measured $AE_{rms}$ vs cutting speed, feed rate as well as depth of cut, the model ('power function model') was developed by statistical technique. Cutting speed, feed rate and depth of cut were employed as variables for their model. The coefficients and offset value of this power function model depended on the workpiece material.

Another $AE_{rms}$ model was developed by Rangwala and Dornfeld [66]. Four major assumptions were employed for model development. These are (i) AE is generated only by dislocation damping associated with plastic deformation in the primary and secondary shear zones, (ii) the entire contact length is a sticking zone, (iii) the secondary zone thickness equals the primary zone thickness, and (iv) the shear zone thickness remains constant with feed rate and cutting velocity. In their experiment, they used controlled contact length tools for studying $AE_{rms}$. Their experimental results indicated that for small tool-chip contact length, the measured $AE_{rms}$ agrees with the
predicted $AE_{rms}$ generated due to plastic deformation alone [66]. However, for long chip-contact lengths, the increase in $AE_{rms}$ is attributed to increased sliding activity at the tool-chip interface [66].

Effects of a built-up edge on acoustic emission in orthogonal cutting were studied by Hutton and Qinghuan in 1990 [67]. Based on the characteristics of a built-up edge such as life-cycle and stability, the built-up edge was classified as immature, periodic or developed [67]. Each type of built-up edge influenced $AE_{rms}$ differently. The influence of built-up edge on $AE_{rms}$ could be observed both in time and frequency domains.

Integrating the effect of built-up edge into $AE_{rms}$ model, Hutton and Qinghuan [67] suggested that the original rake angle should be replaced by actual rake angle. This actual rake angle is larger than the original rake angle due to the geometry of the built-up edge. The actual rake angle also results in a change in the shear angle. Hutton and Qinghuan [67] introduced a modified model for predicted $AE_{rms}$. However, this model estimates $AE_{rms}$ from the primary shear zone only. Hutton and Qinghuan also commented that the term ‘$\sin(\alpha)$’ in Kannatey-Asibu and Dornfeld’s model [54] will make the predicted $AE_{rms}$ to be “0” for zero rake angle. This predicted $AE_{rms}$ is not true. However, the Sine of rake angle still appears in the model modified by Hutton and Qinghuan [67].

Carolan et al. [68] proposed a schematic representation of the effect of the crater floor position on rake angle for both negative and positive cutters as shown in Figure 2.8. Their experimental results indicated that rake angle changes due to crater wear or by excessive flank wear. The wear on the tool rake face can give rise to either increase or decrease in effective rake angle, depending on the position of the floor of the crater. For
a tool insert having both crater and flank wear, it appeared that the change in rake angle had a larger effect on $AE_{rms}$ [68]. It was also found that the initial value of rake angle as well as its direction of change was important in its effect on $AE$ [68]. Caronlan et al. [68] also mentioned that different material responds differently in the shear plane angle to a change in the rake angle due to their different flow stress characteristics with temperature, strain and strain rate. Although their work was related to face milling, their schematic can be used for turning.

Figure 2.8 Effect of crater wear on tool rake face [68]
Another recent $AE_{rms}$ model was introduced by Saini and Park [69]. This $AE_{rms}$ model was developed for predicting mean $AE_{rms}$ in orthogonal cutting processes. A further improvement in Saini and Park’s research [69] is a consideration of the realistic stress distributions on the tool rake face. In their work, Zorev stress distribution model [59] was employed for estimating the energy consumption in tool-chip zone. Lengths of sticking and sliding zones on the tool rake face were expressed in terms of a parabolic constant in Zorev’s model [59]. This constant can be predicted from measured cutting and tangential forces. Experimental results of Lee et al. [70] indicated that stress distributions on the tool rake face for an aluminium workpiece is dissimilar to Zorev’s model [59]. Hence, Saini and Park’s $AE_{rms}$ model [69] is not suitable for some workpiece materials such as aluminium.

2.4 TOOL CONDITION MONITORING

In recent times, many researchers have attempted to develop techniques or methods for monitoring tool wear. Dan and Mathew [1] proposed that tool wear sensing could be classified into two major categories – direct and indirect. The direct sensing method refers to the measurement of the actual tool wear while the indirect sensing method refers to the measurement of a parameter correlated with tool wear [1]. However, the indirect methods are more appreciated because they do not interrupt the cutting processes.

Dimla Snr [24] suggested that sensor selection for the development of tool condition monitoring systems has to consider the robustness, reliability and applicability of the
sensor signals. Additionally, the sensors should conform to the following criteria: (i) ease of use, (ii) high signal to noise ratio, (iii) consistency in wear sensitivity and (iv) minimal peripheral instruments for harnessing.

2.4.1 Signals for Tool Wear Monitoring in Turing Operations

It has been reported that cutting forces [71, 72], acoustic emission [20, 71, 73, 74], ultrasound [75, 76], sound [77, 78], tool vibration [79-82], cutting temperature [83-92], and tribo emf [85, 86, 93-95] have been employed for indirect tool wear monitoring. In the present thesis, however, only research pertaining to tool wear monitoring employing cutting forces and acoustic emission signals will be reviewed. This is because these signals will be used in the new on-line tool wear estimation system developed in this thesis. The details of each signal including sources and a correlation with tool wear are as follows:

- Tool Wear Monitoring using Cutting Forces

In turning operations, cutting forces can be measured by both mechanical transducers (i.e. hydraulic pressure cells and pneumatic devices) and electrical transducers (i.e. strain gauges and transducer tubes). Both static and dynamic cutting forces have been used for monitoring tool wear [9, 14, 71, 96, 97]. A change in these forces, especially cutting force, has often been used to detect tool wear in the laboratory [1]. Compared with vibration and power measurement, it was reported that force sensing methods are more sensitive [98]. In recent times, force signals can be measured by using a force
transducer employing a piezo-electric element. This sensor measures the forces in cutting, feed and radial directions.

As mentioned earlier, both static and dynamic cutting forces can be used for monitoring tool wear. Normally, static of forces (or mean forces) has been used for monitoring tool wear. Some experimental results [99-104] indicated that tool wear influences feed and radial forces more than main cutting force. However, it was also found that feed force is insensitive to crater wear [105, 106]. Additionally, it was reported that the forces increase with feed rate as well as depth of cut and decrease with cutting speed [32, 107]. At low speed, however, a built-up edge occurs on tool inserts for a steel workpiece [108, 109]. This built-up edge results in a more negative rake angle and more ploughing force, which cause cutting forces to rise. Hence, forces follow the trend: increase at low cutting speed and then decrease at high speed.

The dynamic cutting forces are generally considered in a frequency domain for tool wear monitoring [24]. Experimental results indicated that the power spectra of dynamic cutting forces in some frequency bands increased as tool wear developed [106]. Similar results were also found by other researchers [97, 110, 111]. In Lee et al.'s experimentation [97], the feed and tangential dynamic force bore a good relationship to flank wear. Research conducted by Yao and Fang [110, 111] also showed two distinct frequency bands (a low frequency band 0.5-1 kHz and a higher frequency band 2.6-3.5 kHz) in all three force components associated with a wear rate mechanism. However, it should be noted that the dynamic cutting forces are also influenced by other parameters including chatter vibration [24].
Sometimes, derivatives of the dynamic cutting force were employed for monitoring tool flank wear. Examples of these derivatives are energy quanta and entropy [112, 113]. Both parameters are determined from power spectra of the input, transformation and output energy of cutting processes [114]. Cutting conditions including speed, feed rate and depth of cut were found to influence the energy quanta and the entropy of both the input and the output energies. However, only the energy quanta and the entropy of output energy were affected by flank wear, while the energy quanta and the entropy of input energy seemed to remain unaffected by wear [112].

It should be noted that some derivatives of force signals have often been employed to detect tool fracture [1, 22]. However, they are not reviewed in detail in this thesis.

The ratio of feed force to cutting force has also been used for tool flank wear monitoring. Shi and Ramalingam [72] conducted machining tests to investigate the feasibility of using different force components for on-line tool condition monitoring, and observed that this force ratio showed sensitivity to flank wear but was insensitive to change in process parameters such as cutting speed and depth of cut.

- **Tool Wear Monitoring using Acoustic Emission**

As mentioned earlier (Section 2.3), acoustic emission (AE) in turning operations is generated from several sources including deformation in shear zone, friction between chip and tool rake face, friction between flank face and tool rake face, chip fracture and chip impingement on tool as well as workpiece [54, 56]. Acoustic emission, root mean square of acoustic emission (AE_{rms}) and their derivatives have been employed for
monitoring and estimating tool wear in turning operations [20, 71, 73, 74]. In turning operations, other signals such as vibrations and noise are also generated. However, AE signals have been observed to remain unaffected by ambient vibrations and noise if acoustic emission measurements are conducted at the end of the tool shank [115].

It was found that the amplitude level of AE increased almost in proportion to the cutting speed during cutting carbon steels and depends strongly on the tool flank wear, while hardly not affected by the feed and depth of cut [73]. An increasing AE power within the 400-700 kHz range was found to be associated with progressive tool wear [116]. Other researchers also concluded that the magnitude of the AE signal amplitude increased at frequencies of about 120, 170 and 210 kHz with an increase in the flank wear land [73]. Similar results were also observed by Ravindra et al. [117].

Skew and kurtosis for a short window of the signal are derivatives of AE signals employed for monitoring tool wear developed on tool inserts [20]. In the research of Niu et al. [19], however, transient AE signals were separated by using a wavelet packet transform first, and then skew, kurtosis, frequency band power for each transient AE signal were determined. The reason for the use of this wavelet packets transform is that the wavelet transform can separate the AE signal caused by chip fracture, tool breakage or tool wear from the collected AE signal [19].

Influences of tool wear and cutting conditions on normalized autoregressive (AR) parameters and power of AR residual of raw AE signal were investigated by Ravindra et al. [117]. Experimental results showed that power of the residual signal increased with tool wear. Additionally, the ratios of normalized AR parameters (A2:A1 and
A3:A1) were affected by the growth of flank wear. The results also showed that the normalized AR parameters provided a higher percentage of correct tool wear classification than powers of residual and raw AE signal.

The influence of both flank and crater wear on AE_{rms} has been investigated by several researchers [21, 74, 118]. Lan and Dornfeld [61] found that chip fracture also caused peaks in AE_{rms} signals.

Kannatey-Asibu and Dornfeld [74] employed a beta (β)-distribution to characterize the AE_{rms} regarding the degree of tool wear. This β-distribution function including their parameters can be estimated by using the equations introduced by Whitehouse [119]. Experimental results indicated that skew and kurtosis of the β-distribution function of AE_{rms} were influenced by the magnitude of flank wear. Due to the fact that the magnitude of AE_{rms} signal may not be considered as a reliable measure of catastrophic tool failures, parameters of the β-distribution function of AE_{rms} signal (r and s) and skew as well as kurtosis of the β-distribution of AE_{rms} signals were also employed for detecting catastrophic tool failure [10, 11]. Experimental results showed that these parameters have a good sensitivity to the tool breakage and chipping.

Another derivative of AE_{rms} is parameters of autoregressive (AR) time series analysis of AE_{rms} signal. These AR parameters were introduced in 1989 by Liang and Dornfeld [120]. Using a stochastic gradient algorithm, AR time-series modeling of the acoustic emission RMS signal has been implemented under a variety of experimental conditions of orthogonal cutting operations. It was observed that there is a strong correlation between the flank wear and the values of the model parameters. However, the
autoregressive model parameters do not vary significantly with different cutting conditions [120]. Therefore, this technique can be used for detecting worn tool in turning operations.

2.4.2 Multi-sensor Approaches

In order to increase the accuracy of tool wear monitoring in turning operations, multi-sensor systems have been used [20, 121]. There are two possible ways to achieve a multi-sensor approach: (i) each sensor is used to measure different variables and (ii) different sensors are employed to measure the same variable at a different gain [122]. Niu et al. [20] suggested that force and $AE_{rms}$ are often used as signals for multi-sensor system for monitoring progressive tool wear. This is because the use of multi-sensors provide more complete information of the machining process compared with the use of a single-sensor [20]. A major advantage of using AE and force sensors is that the AE sensor provides information relating to microscopic phenomena (e.g. stress waves resulting from the plastic and friction in the cutting zone) while the force sensor provides macroscopic information (e.g. vibrations) [121]. Therefore, a broad spectrum and complementary information about tool wear states are provided by both signals together. Successful use of AE and force sensors for monitoring tool fracture was reported by Youn, Yang and Park [71].

2.4.3 Intelligent Sensors

In order to enhance the capabilities of sensors for tool condition monitoring, intelligent sensors have been developed. Compared to conventional sensors, special functions ,
including (i) self-calibration, (ii) signal processing, (iii) decision making, (iv) fusion ability and (v) learning capability, have been incorporated in the intelligent sensors [122]. For developing intelligent sensors having such special functions, a combination of conventional sensors, signal processing and feature extraction methods as well as implementation strategies needs to be integrated into the sensors or sensor systems [122].

Use of neural network for integrating information from multiple sensors is an example of intelligent sensor systems developed by previous researchers [121]. In their research, neural networks were employed to integrate information from acoustic emission and force sensors in order to recognize the occurrence of tool wear in turning operations. Another example of an intelligent sensor system is the system developed by Niu, Wong and Hong [20]. Similar to the first example, force and acoustic emission sensors were employed in the intelligent system. The information from both sensors was processed by ART2 neural network for recognizing tool flank wear states. The experimental results indicated that both intelligent sensor systems were successful in monitoring tool wear in turning operations [20, 121].

2.5 TOOL WEAR ESTIMATION AND CLASSIFICATION

In order to predict tool wear in turning operations, many researchers have attempted to develop models including quantitative models, pattern recognition, statistical and neural network models for predicting the width of flank wear and the depth of crater wear in both orthogonal and oblique cutting operations. These tool wear models can be classified into two groups – estimation model and classification model. A result of an
estimation model is an exact size of tool wear while a result of a classification model is a range of tool wear size. Earlier models were for off-line tool wear prediction. However, later models are developed for on-line tool wear prediction systems. These tool wear estimation and classification models (for both on-line and off-line systems) are summarized and discussed next.

2.5.1 Tool Wear Estimation by Quantitative Models

A conventional method of tool wear prediction is to estimate the size of flank and crater wear by using the wear rate of the tool insert on the flank face and tool rake face respectively. The wear volume of the cutting tool depends strongly on cutting distance (which can be expressed in term of cutting velocity and cutting time [3]), absolute temperature of the wear land and normal stress on the worn surface. Examples of crater wear model developed based on this correlation are: (i) Usui and Shirakashi’s model [4], (ii) Suh’s model [5], (iii) Kramer and Suh’s model [6], and (iv) Usui, Shirakashi and Kitagawa’s model [3]. Examples of flank wear model modified using such correlation are the model of Kitagawa et al. [7] and the model of Maekawa et al. [8]. However, the prediction of flank and crater wear by using the wear rate has significant inaccuracies compared with tool wear estimation by indirect tool wear measurement which employed a change in signals (i.e. forces, $AE_{ms}$ and ultrasound wave) influenced by tool wear.

Another type of quantitative model for tool wear estimation was developed by using a correlation between signals (such as forces, temperature and ultrasound wave) collected by sensors and the magnitude of tool wear. An example for this type of quantitative
model is the model of Barlier et al. [123] which estimates flank wear by using the increase in tool temperature due to greater energy consumption on the flank workpiece zone. However, this model is not suitable for use in the industry. This is because a thermocouple needs to be inserted in the cutting tool, which requires more manpower, time, equipment and money. If the tool temperature is measured by indirect temperature measurement, this equation can be employed in real manufacturing processes.

Another example is Chryssolouris, Guillot and Domroese's model [124] as shown in Figure 2.9. This model employs predicted forces, predicted temperature in shear and tool-rake face zones, and wear rate, for flank and crater wear estimation. This procedure was developed for predicting tool wear in two cases. Case I: In an operation when crater wear does not significantly influence cutting forces, flank wear is estimated by using force model. Case II: In an operation when crater wear significantly influences cutting forces, crater wear is predicted first based on a correlation between wear rate, cutting time, normal stress on rake face and crater temperature. Then, employing this depth of crater wear, flank wear is estimated by force model in the same way as in Case I.

Previous researchers [61, 125] have attempted to develop quantitative models for $AE_{rms}$ prediction for a worn tool. These models predict mean $AE_{rms}$ from acoustic emission sources including plastic deformation in shear zone, tool-chip zone and workpiece-flank face zone. Using the $AE_{rms}$ measured in the turning operation and substituting in these models, flank wear can be predicted.
2.5.2 Tool Wear Estimation and Classification by Neural Network Models

Artificial neural networks have been employed in machining operations for tool wear estimation and classification since the 1980s. Unlike quantitative models (analytical models) providing explicit models with a deep physical understanding, neural network models provide implicit models captured within the weight matrices of the net [126]. Neural networks have a good accuracy for pattern recognition and facilitating quantitative prediction. Currently, neural network models learn from prior experimental
data but not from a prior analytical insights as yet [126]. From the literature, it was found that both supervised and unsupervised neural networks have been employed for tool wear estimation and classification.

The application of neural network for tool wear monitoring can be grouped into two categories. The first group is for tool wear estimation [12-15, 17, 18, 21, 127-129] and the second group is for tool wear classification (or tool wear state recognition) [16, 19, 20]. Generally, the accuracy of tool wear classification is higher than the accuracy of tool wear estimation. The accuracy for tool wear classification was observed up to 100% for training data [16].

![Figure 2.10 Architecture of backpropagation neural network](image-url)

**Figure 2.10 Architecture of backpropagation neural network**
It was found that previous researchers [12-14, 21] usually selected backpropagation neural network architecture (Figure 2.10) which is a supervised neural network for model development. However, in case of unsupervised neural network [19, 20], ART2 neural network architecture has been usually selected for developing the tool wear model. Mean force, mean $AE_{rms}$, and derivatives of AE (such as band power, skew as well as kurtosis of AE and decomposing results of AE by wavelet packet transformation) have usually been used as inputs of the neural networks.

Image data have also been used as inputs in some neural network models [130]. Since image data from a video recorder is an example of direct tool wear monitoring, the neural network which uses this image data as its input should have a higher accuracy for tool wear prediction compared to the network employing force or $AE_{rms}$ as the inputs. However, the use of a video recorder for recording image data in the research of Teshima et al. [130] is for direct tool wear measurement which interrupts the cutting process. It is possible to integrate the video recorder in a turning machine and record the tool wear image automatically when the turning machine stops for changing the workpiece or the tool is retraced to start another cut. In this way, this method will not interrupt the cutting processes.

Previous experimental results showed that a number of input units, hidden units and hidden layers influenced the accuracy of tool wear estimation and classification [16, 21]. A large number of inputs and hidden units did not provide the highest accuracy, but the model having a suitable number of inputs and hidden units provided the highest accuracy of tool wear estimation [16]. The accuracy of flank wear prediction was found to increase if one more hidden layer was added into the backpropagation neural
network [21]. However, such an addition of a hidden layer would be likely to increase the processing time for an output.

The accuracy of the neural networks was usually greater than 90% for the training data [13, 14, 16, 21]. However, only some researchers [21] have tested their neural network model with the testing data. This testing data can be (i) the data collected under different cutting conditions used for training data or (ii) repetition of the training data. It is recommended that both types of testing data should be used for testing the accuracy of the neural network model. Since the neural network model is trained by using the training data, the accuracy of tool wear prediction employing training data is usually better than using testing data.

Currently many new neural network architectures have been developed. These new architectures cannot only increase the accuracy of neural network but also decrease the training time of the model. However, each architecture is suitable for different proposes. Hence, the neural network architecture needs to be selected correctly (matching with a problem type).

2.5.3 Tool Wear Estimation and Classification by Miscellaneous Models

Not only quantitative and neural network models but also other models can be used for estimating as well as classifying tool wear occurring on the cutting tool in turning operations. Examples of these models are:

- Flank Wear Estimation by Using Control Theory [131]
- Flank Wear Estimation by Statistical Model using Ultrasonic Echo Signal [76]
- Tool Life Prediction by Statistical Method using Cutting Force Ratio [132]
- Tool Wear Measurement using Stereo Imaging [133]
- Classification of Tool Wear States using Pattern Recognition [134]
- Tool Wear Classification using the Analytic Hierarchy Process [135]
- Tool Wear Classification by Fuzzy Pattern Recognition [136]

Since this thesis does not employ such models for flank and crater wear prediction, as well as due to the limitation of space, details for such models will not be reviewed in the present chapter.

2.6 SUMMARY OF THE LITERATURE WORK

This chapter presents the literature survey of several areas related to the present research. It was found that some important phenomena such as (i) tool failure, (ii) chipping at cutting edge, and (iii) variation in force and AE_{rms} signals at the start of cut were not considered in the development of tool wear estimation model. These phenomena can significantly influence the estimation of tool wear. Additionally, previous researchers have usually focused on the estimation of flank wear and off-line tool wear prediction systems. Therefore, a new on-line tool wear estimation system having higher accuracy for computing the length of flank wear and the maximum depth of crater wear in CNC turning operations needs to be developed.
CHAPTER 3

PROPOSED ON-LINE TOOL WEAR ESTIMATION SYSTEM

As indicated in literature survey, several researchers have attempted to develop on-line tool wear estimation and classification models [12-16, 18-21]. However, these models predicted only flank wear developed on tool inserts and did not take into consideration crater wear as being an important aspect of tool life. An on-line monitoring system which can estimate both the flank and crater wear needs to be developed.

In order to develop an on-line tool flank and crater wear estimation system in CNC turning operations, several new models and computer programs need to be adapted and then integrated together. A new on-line tool wear estimation system proposed by the author is presented in Figure 3.1. This new system consists of four major parts: (i) user interface, (ii) signal collection, (iii) tip fracture and chipping at cutting edge detection, and (iv) tool wear estimation model. The details of each part will be explained later in the following sections.
3.1 User Interface

The user interface part of the new on-line system (shown in Figure 3.1) will allow machine operators to enter necessary information including cutting conditions, initial size of flank wear and initial size of crater wear. The computer will then estimate forces and $AE_{rms}$ for fresh tool as well as other parameters used in the third and fourth sections such as shear stress on shear plane, shear and normal stresses on tool rake face. Another major function of this section is to display the estimated tool flank and crater wear to the user. In this thesis, the user interface section was developed by using MatLab V 5.1.
3.2 Signal Collection

Using Visual C++ 5.0 and the PC30D driver developed by Eagle Technology Inc., an executable file for sampling three-force as well as $AE_{rms}$ signals was built. In the on-line system, the MatLab program calls and uses this file for its function. When operators want to know the estimated flank and crater wear, this executable file will collect 16,000 samples of force and $AE_{rms}$ data through the PC30D card. The data will then be saved on the computer hard-disk for the further processing.

3.3 Detection of Tip Fracture and Chipping at Cutting Edge

Tip fracture and chipping at major cutting region causes a significant increase in $AE_{rms}$ and force signals. This increase in signals can result in tool wear estimation error, if they are employed as inputs of tool wear estimation model. Hence, tip fracture and chipping at the major cutting region on inserts need to be detected. The proposed system will alert operators about the fracture and the chipping, and the tool wear will not be estimated for this case.

In this research, the tip fracture and chipping at cutting edge including nose as well as major cutting regions can be detected by using a neural network model developed by employing significant increase in feed and radial forces due to occurrence of such chipping and tip fractures. More details of this model are presented in Chapter 4.
3.4 Flank and Crater Wear Estimation

In this research, two tool wear estimation models were developed for predicting flank and crater wear in turning operations. The first model is the computer program employing mathematical equations developed in this research to predict tool wear. The second model is fuzzy neural network model using 36 basic as well as derived parameters influenced by tool wear or affecting tool wear rate as inputs. Only one of the above two tool wear models, having the higher accuracy for flank and crater wear prediction, will be selected for further development of computer program for on-line tool wear estimation system.
CHAPTER 4

DEVELOPMENT OF NEW MODELS, PARAMETERS AND TECHNIQUE

In order to develop an on-line tool wear estimation in CNC turning operations proposed in Chapter 3, several new models, parameters and technique need to be developed and then be employed by the on-line system. These include:

- Quantitative model for predicting forces in turning operations
- Quantitative model for predicting $A_{E_{rms}}$ in turning operations
- Quantitative models for estimating flank wear
- A computer program employing above models for flank and crater prediction
- Detection and estimation of chip fracture events
- New parameters for monitoring tool wear
- Fuzzy Neural Network for flank and crater wear estimation
- Neural network model for chipping at major cutting region and tool tip fracture detection

The details for each model, parameter and technique are presented in the following sections. An algorithm for the on-line system is also given in this chapter.

4.1 FORCE AND $A_{E_{rms}}$ MODELS

Since the 1950s, several force models [26, 39, 45, 48, 137-139] as well as $A_{E_{rms}}$ models [54, 56, 61] for both orthogonal and oblique cutting operations have been developed.
However, a few models have been adopted in order to predict cutting forces [39, 124] and $AE_{rms}$ [61] for both fresh and worn tools.

Figure 4.1 A section of tool inserts for five different cases
During turning operations, both flank and crater develop on tool inserts. However, it was observed that usually flank wear develops first and then crater wear develops later. Therefore, sometimes, only flank wear is observed on tool inserts (Figure 4.1b). For tool insert having both flank and crater wear, the shape of cutting edge is as shown in Figures 4.1(c-e).

4.1.1 Influence of Tool Wear on Tool Geometry

In the present research, uniform wear rate along the length of the cutting edge (major, minor and nose cutting regions) is assumed. Hence, the shape of worn tools will be as shown in Figure 4.2 and is named as “ideal worn tool”. As the wear rate along the cutting edge is considered uniform, the shape of nose cutting region for worn tools will be similar to the shape of nose cutting region for fresh tools. However, due to the flank wear, the radius of the nose of worn tools is smaller than the radius of the nose of fresh tools. Using a Nikon V12 projector to observe the shape of worn tools, it was found that the shape of worn tools was similar to the shape of ideal worn tool. Thus, the assumption of ideal worn tool is reasonable.

A development of flank wear on the cutting edge causes a change in tool insert geometry (Figure 4.2). An occurrence of flank wear results in larger contact area on the flank face. Larger friction on this flank wear land causes forces and $AE_{rms}$ to increase. In oblique cutting with three cutting regions (major, minor and nose cutting regions), however, the flank wear also reduces the length of nose cutting region due to the decrease in nose radius. Therefore, a new nose radius relation needs to be developed. The new nose radius can be expressed as Equation (4.1).
Flank wear also results in a decrease in depth of cut. Hence, in the present research, a new depth of cut relation also needs to be developed. This new depth of cut can be shown as the following equation.

\[
\begin{align*}
    r_m &= r - \frac{W \cdot \sin(C_a - \alpha_n)}{\cos(\alpha_n) \cdot \sin(90 - C_a - 2\alpha_n)} \\
    b_m &= b - \frac{W \cdot \sin(C_a - \alpha_n)}{\cos(\alpha_n) \cdot \sin(90 - C_a - 2\alpha_n)}
    \end{align*}
\] (4.1)

Figure 4.2 The tool geometry of fresh and ideal worn tools

It has been observed that no significant change in shear angle and friction angle occurs when flank wear land size increases [140]. Hence, for this research, it will be assumed that the shear and friction angles are not influenced by flank wear.
Occurrence of crater wear causes a change in tool rake face geometry. It has been suggested that crater wear also influences cutting forces [124, 129, 141] as well as $AE_{rms}$ [61, 68]. Hence, the effect of crater wears needs to be included in the quantitative force and $AE_{rms}$ models. Assuming that the most significant effect of crater wear is to change the rake angle [124, 142], the modified normal rake angle [124] can be expressed as:

$$\alpha_{nm} = \alpha_n + 90 - \cos^{-1}\left[\frac{W_{cr}}{l_t} \right]$$

$$\left[\frac{0.25 + (W_{cr} / l_t)^2}{\sqrt{0.25 + (W_{cr} / l_t)^2}}\right]$$

(4.3)

The coefficient of friction on the rake face can be assumed to remain unaffected by crater wear [124]. Additionally, shear angle is also assumed to be not significantly dependent upon crater wear [124].

The shape of tool cutting edge changes due to large flank and crater wear developed during turning operation. A typical shape of such a worn cutting edge is shown in Figure 4.1(e). The curve at the cutting edge causes ploughing processes which can result in higher forces and $AE_{rms}$.

During the experiment, it was observed that tool inserts having both flank and crater wear usually were similar to the tool shown in Figures 4.1(c-d). A few worn tools had shape as in Figure 4.1(e). This was because the tools usually broke before the large wear at cutting edge developed (more details in Chapter 6). Hence, it is reasonable to assume that the shape of worn tools shown in Figure 4.1(c) represents worn tools developed in the turning operations. As a result, the effect of ploughing process by the new cutting edge surface on the deteriorated cutting edge is neglected.
4.1.2 Influence of Chip Fracture

Previous researchers [143, 144] observed that flank and crater wear cause an increase in chip breakability, rendering the chip easy to fracture. It was observed that chip fracture influences the magnitude of the AE$_{rms}$ signal significantly [61].

**Figure 4.3 The hitting of chip on tool holder caused chip fracture**

In oblique cutting, a chip fracture is caused by the impact of the chip on the tool holder for a large chip up-curl radius (Figure 4.3), and by the impact of the chip on tool flank face for a small chip up-curl radius. A complete chip breaking cycle normally consists of (i) initial stage of chip curling, (ii) chip impacts on the tool holder or tool flank face, (iii) chip starts to slide on tool holder or flank face, and (iv) chip fracture occurs. As the chip slides on tool holder (or sometimes tool flank face), the bending moment at chip root increases. If the chip strain caused by this bending moment is greater than the ultimate strain of chip material, the chip will be break [145]. In this research, the AE
signal generated from the chip fracture process is assumed to be produced from a dislocation motion occurring during chip fracture [146].

![Figure 4.4 Bending stress in chip causing chip fracture](image)

The fracture of a chip is similar to the failure of a torsion spring (Figure 4.4). Hence, the chip is broken by the bending stress. In fact, chips start to break by the tensile stress at the outer side of the curl as shown in Figure 4.4. The chip bending generates both tensile and compressive stresses in the chip. However, the chip breaking always occurs due to tensile stress. Thus, the strain energy released during chip fracture can be estimated by the strain energy released of single-edge crack mode "I".

An investigation of the chip collected during experiments indicated that the chip was broken at the notch between chip segmentations. Hence, it can be assumed that the total area of chip fracture equals the shear plane area. Not much literature is available wherein chip material mechanical properties have been investigated. Therefore, the shear stress on fracture area will be assumed to be equal to shear stress on shear plane. Since the shear stress on the shear plane is the maximum shearing stress, the shear stress on fracture area also equals the maximum shear stress due to the assumption mentioned earlier.
Considering the chip as a slab having a cross sectional area equal to the chip fracture area (Figure 4.5), and applying Griffith's elastic strain energy release equation [147-149], a total strain energy released during fracture was developed in this thesis. This total strain energy released during fracture can be expressed as Equation (4.4).

\[ E_{cb} = 4\pi(t_{s\text{max}})^2(A_{sm})^2 / (l_m \times E) \]  

(4.4)

Figure 4.5 Bending stress distribution in both chip and slab that have an equivalent cross-section area

The additional AE signal generated by chip fracture will also be proportional to the strain energy. If the number of chip fracture events (N) occurring in a sampling period is known, the average strain energy released from chip fractures is:
4.1.3 Shear and Normal Stresses

Arsecuralatne [150] reviewed stress distributions on tool-chip contact area estimated by many methods including photoelastic, split tool, and experimental slip-line field technique. It was observed that the pattern of stress distributions on tool rake face depends on the workpiece material. The stress distributions on the rake face of a split carbide tool, observed by Usui and Shirakashi [151], was found to be similar to Zorev's model [59] which is shown in Figure 4.6. The work material used by Usui and Shirakashi [151] and that used in the present research is AISI 1045 steel. Hence, in the present research, the stress distribution on the tool rake face is assumed to be similar to that used by Zorev (Equations 4.6 and 4.7).

\[
E_{c_{ba}} = \frac{4\pi \cdot f_{sp} \cdot N \cdot (\tau_{s_{max}})^2 \cdot (A_{sm})^2}{I_m \cdot N_{sp} \cdot E} \tag{4.5}
\]

\[
\sigma_n = \sigma_{n_{max}} \left(1 - \left(\frac{l_p}{l_t}\right)^{A_{11}}\right) \tag{4.6}
\]

\[
\tau_s = \mu \sigma_n \quad \text{at low } \sigma_n
\]
\[
= \tau_{s_{max}} \quad \text{at high } \sigma_n \tag{4.7}
\]

The stress distributions on the flank face have been considered in a number of ways by different researchers. For example, Zhou et al. [37] assumed that normal and shear stresses have uniform distribution. In the first one-third of flank wear from the cutting edge, however, Chandrasekaran and Nagarajan [152] found that the normal stress on the flank face decreased sharply (following a power law) while the shear stress dropped
insignificantly. However, both stresses remain constant for the rest of flank wear. In this research, the distributions of normal and shear stresses along the flank face, shown in Figure 4.6, were assumed as:

\[ \sigma_n = \sigma_{n \text{max}} (1 - A_2 (W_p)^{A_3}) \]  \hspace{1cm} (4.8)

\[ \tau_s = \tau_{s \text{max}} \]  \hspace{1cm} (4.9)

**Figure 4.6 Assumed stress distribution on rake face and flank face**

*(section X-X of Figure 4.2)*

As shown in Figure 4.6, the maximum normal and shear stresses on the rake face are assumed to be equal to the maximum normal and shear stresses on the flank face respectively. Previous research indicated that both normal and shear stresses are influenced by many parameters including yield stress of workpiece, rake angle, and cutting speed [3, 153, 154]. Black [155] suggested that the shear stress is composed of a
temperature-dependent part and a temperature-independent part ($\tau_s = \tau_d + \tau_{id}$). The temperature-dependent part is a function of cutting temperature which in turn is a function of cutting conditions. The temperature-independent part is a function of material properties and some cutting conditions.

Hsu [154] and Usui et al. [3] studied the influence of cutting speed, which strongly influences cutting temperature, on shear and normal stresses on the rake face. In their experiment, it was observed that cutting velocity had little effect on normal stress. Hence, in the present research, normal stress will be assumed to remain constant with no influence of cutting speed or temperature. Based on the maximum normal stress in orthogonal cutting developed by Chandrasekaran and Kapok [153], the maximum normal stress on the rake face of the tool for oblique cutting can be modified and expressed as Equation (4.10). In this equation, the maximum normal stress is a function of yield stress of the workpiece and normal rake angle only.

$$\sigma_{n\text{max}} = 2K(1.3 - \frac{\alpha_n}{180})$$

(4.10)

Due to significant influence of cutting conditions, especially cutting speed (through cutting temperature) on the magnitude of maximum shear stress, the shear stress model which is a function of cutting conditions needs to be developed. Hu et al [46] suggested that the cutting force in oblique cutting can be approximated from the cutting force in orthogonal cutting which employs the value of normal rake angle as the value of rake angle. Substituting cutting conditions, cutting geometry and measured cutting force of oblique cutting into the cutting force equation developed by Armarego and Brown [25], shear stress on the shear plane of AISI 1045 steel workpiece used in the test can be
estimated. Using regression technique, the shear stress model which is a function of cutting conditions and shear strength of the workpiece material can be built. Employing an assumption shown in Figure 4.6 (shear stress on shear plane equals to maximum shear stress at the cutting edge) in this research, the maximum shear stress as well as shear stress on the shear plane will be approximated by using this regression model ($\tau_s = \text{Constant} + a_1V + a_2f + a_3\alpha$).

4.1.4 Development of New Force and $AE_{rms}$ Models

4.1.4.1 Force Model

Using a minimum energy method [45, 48], Zorev's stress distributions on rake face [59], average chip velocity on rake face estimated by slip-line field analysis [156-158] and chip flow direction [159] as well as assuming a perfect sharp cutting edge, a new force model for oblique cutting has been developed in the present research. This force model can be expressed as Equations (4.11) – (4.15). This force model can be employed for predicting cutting, feed and radial forces for (i) fresh tool, (ii) worn tool with flank wear, and (iii) worn tool with flank and crater wear.

$$F_t = \left[ \tau_{s_{\text{max}}} \cdot l_m \cdot l_{\text{st}} \right] + \left[ l_m \cdot \mu \cdot \sigma_{\text{nmax}} \int_{l_{\text{st}}}^{l_t} \left( 1 - \left( \frac{l_p}{l_t} \right)^{A_1} \right) dl_p \right]$$  (4.11)
\[ F_c = \frac{1}{\cos(\phi_e - \alpha_e)} \left\{ \tau_{\text{smax}} \cdot A_{\text{sm}} \cdot \cos \alpha_e \right\} + \frac{2}{3} \tau_{\text{smax}} \cdot l_m \cdot l_{st} \cdot \sin \phi_e \right\} + \left\{ l_m \cdot \mu \cdot \sigma_{\text{nmax}} \cdot \sin \phi_e \cdot \int_{l_{st}}^{l_t} \left( 1 - \left( \frac{I_p}{I_t} \right)^{A_1} \right) dl \right\} + \tau_{\text{smax}} \cdot W \cdot l_m \]  

(4.12)

\[(F_c)_{\text{umin}} = N_t \cdot \cos \alpha_{nm} \cdot \cos i + (F_t)_{\text{umin}} \cdot \sin \alpha_e \]  

(4.13)

\[ F_f = -N_t \cdot \sin \alpha_{nm} + F_t \cdot \cos \eta_c \cdot \cos \alpha_{nm} + F_A \]  

(4.14)

\[ F_r = -N_t \cdot \cos \alpha_{nm} \cdot \sin i + F_t \cdot \sin \eta_c \cdot \cos i - F_t \cdot \cos \eta_c \cdot \sin \alpha_{nm} \cdot \sin i + F_B \]  

(4.15)

Where

\[
\mu = \frac{\tau_{\text{smax}}}{\sigma_{\text{nmax}} (1 - l_{st}^A_1)}
\]  

(4.16)

\[ l_m = \left[ \left( \frac{b}{\cos C_s} \right) - r \right] + \left( \frac{\pi}{2} \cdot r_m \right) + \frac{f}{2}\]  

(4.17)

\[ F_A = -N_c \sin C_s + N_{Bf} + N_A \cos C_s \]  

(4.18)

\[ F_B = N_c \cos C_s + N_{Br} + N_A \sin C_s \]  

(4.19)

The parameters, \( F_A \) and \( F_B \), in Equations (4.18) and (4.19) are forces on flank wear land in feed and radial directions respectively (Figure 4.7). Both \( F_A \) and \( F_B \) are the result of
normal forces acting on the flank face in the major cutting region \( (N_A) \), nose cutting region \( (N_B) \) and minor cutting region \( (N_C) \). A diagram of these forces \( (F_A, F_B, N_A, N_B \text{ and } N_C) \), introduced by the author, is shown in Figure 4.7. The normal force on the flank face in the nose cutting region is separated to 2 terms: forces in the feed and radial directions \( (N_{Br} \text{ and } N_{Br}) \). Assuming that the constant \( A_2 \) in Equation (4.8) equals 1 and the constant \( A_3 \) in Equation (4.8) equals the constant \( A_1 \) in Equation (4.6), and the widths of flank wear on major, nose and minor cutting regions are the same, forces \( (N_A, N_{Br}, N_{Br} \text{ and } N_C) \) can be estimated by the following equations:

\[
N_A = \sigma_{n\text{max}} \int_0^W (1 - W_p A_1) dW_p \cdot \left( \frac{b}{\cos C_s} - r \right) \quad (4.20)
\]

\[
N_{Br} = \sigma_{n\text{max}} \int_0^W (1 - W_p A_1) dW_p \cdot \frac{\pi \cdot r m}{180} \sum_{i=1}^{90} \cos(C_s + (i - \frac{1}{2})) \quad (4.21)
\]

\[
N_{Br} = \sigma_{n\text{max}} \int_0^W (1 - W_p A_1) dW_p \cdot \frac{\pi \cdot r m}{180} \sum_{i=1}^{90} \sin(C_s + (i - \frac{1}{2})) \quad (4.22)
\]

\[
N_C = \sigma_{n\text{max}} \int_0^W (1 - W_p A_1) dW_p \cdot \left( \frac{f}{2} \right) \quad (4.23)
\]

In this research, the nose cutting region is separated into 90 elements as shown in Figure 4.8 and forces \( (N_{Br} \text{ and } N_{Br}) \) in Equations (4.21) and (4.22) are then predicted from a summation of normal force acting on these 90 elements. Additionally, the relationship
between shear plane angle, friction angle and rake angle in oblique cutting is assumed to follow Merchant's relationship \( (\phi = \pi/4 - (\beta - \alpha)/2) \).

\[ \text{Figure 4.7 A diagram of } F_A, F_B, N_A, N_B \text{ and } N_C \text{ forces acting on tool insert} \]

It should be noted that angle \( \lambda \) shown in Figure 4.7 encompasses nose cutting region and minor cutting region [37] and angle \( \phi \) is used for integration from 0 to \( \lambda \). Both angles will be used later in Section 4.2.1. An equation for estimating the value of angle \( \lambda \) will also be expressed in the same section.
4.1.4.2 $AE_{rms}$ Model

Kannatey-Asibu and Dornfeld [54] have developed a quantitative model for predicting $AE_{rms}$ in orthogonal cutting operations by using the energy consumed in various zones. However, for the present research, a new model for prediction of $AE_{rms}$ in oblique cutting has been developed by using the energy consumed in the shear zone, tool-chip zone, tool-workpiece zone and chip fracture. Using the same assumptions employed for force model development, the new $AE_{rms}$ model was developed in this thesis. This $AE_{rms}$ model can be expressed as:
Where $A_1$ can be estimated from the following equation

$$F_n = l_t \cdot l_m \cdot \sigma_{n max} (1 - \frac{l_t}{A_1 + 1})$$

(4.25)

It should be noted that the above $AE_{rms}$ model is suitable for AISI 1045 steel workpiece material. This is because the stress distributions on the tool rake face for this material follow the Zorev's stress distributions [70, 151].

Although both the force model (Section 4.1.4.1) and $AE_{rms}$ model (Section 4.1.4.2) have been developed for AISI 1045 steel workpiece material, these models can be simply supplied for other workpiece materials by replacing Zorev's stress distribution model with the stress distribution model applicable to the particular workpiece material.

4.2 QUANTITATIVE MODEL FOR TOOL WEAR ESTIMATION

As mentioned in Section 4.1, flank wear always develops on tool inserts; however, such worn tools usually have crater wear as well. Quantitative models for predicting flank wear can be developed from the cutting force model and $AE_{rms}$ model developed in the
previous section. For worn tools having both flank and crater wear, however, a computer algorithm including several quantitative flank wear models needs to be used for estimating tool wear. The details of flank wear model and the computer algorithm for predicting flank and crater wear are presented in the following sections.

4.2.1 Flank Wear Model

In the present research, two new flank wear models have been developed. The first model predicts the width of flank wear by using the increase in feed and radial forces while the second model estimates the flank wear by employing the increase in $AE_{rms}$ signal.

The first flank wear model is developed based on a relationship between increase in feed and radial forces and increase in normal stress on flank face (wear land). Incorporating the reduction of total cutting edge length due to flank wear, the relationship between the increase in feed and radial forces and the increase in normal stress on flank face can be expressed as Equation (4.26):

\[
\sigma_{n\text{max}} \left[ 1 - A_2 (W_p)^{A_3} \right] dW_p = \left[ \frac{\left( \Delta F_r \cos C_S + \Delta F_f \sin C_S \right) + \frac{1}{\lambda} \int_0^\pi \cos \phi d\phi}{\int_0^\pi \sin \phi d\phi} \right] \left( \frac{b_m \cos C_S - r_m}{\cos C_S} \right) + \frac{\lambda}{\int_0^\pi \cos \phi d\phi} \right] \] (4.26)
Assuming $A_2 = 1$ and $A_3 = A_1$ and rearranging the various terms, the flank wear model can be expressed as Equation (4.27):

$$W[\sigma_{n\max} - \frac{1}{A_1 + 1} W^{A_1}] = \left( A_1 + 1 \right) \frac{1}{\sin \lambda} \left( \frac{\Delta F_f \cos C_S + \Delta F_r \sin C_S}{\Delta F_r \cos C_S - \Delta F_f \sin C_S} \right) \frac{1}{(1 - \cos \lambda)}$$

(4.27)

Where

$$\Delta F_f = F_{f,m} - F_{f,p}$$

(4.28)

$$\Delta F_r = F_{r,m} - F_{r,p}$$

(4.29)

The predicted feed ($F_{f,p}$) and radial forces ($F_{r,p}$), shown in Equations (4.28) and (4.29), can be estimated from the force models (Equations 4.13 and 4.15) explained earlier. Additionally, the definitions of angles $\lambda$ and $\theta$ used in Equation (4.26) are shown in Figure 4.7. Zhou et al. [37] developed a relation for angle $\lambda$ for both fresh and worn tools. This equation (4.30) will also be employed in the flank wear model (Equation 4.27) for assessment of $\lambda$.

$$\lambda \approx \frac{\pi}{2} + \arctan\left(\frac{f}{2r_m}\right)$$

(4.30)
The flank wear of the tool in turning operations can also be predicted by using the $\text{AE}_{\text{rms}}$ signal. The progressive tool flank wear can be estimated by using a quantitative flank wear model developed based on the $\text{AE}_{\text{rms}}$ model (Equation 4.24). This flank wear model can be expressed as:

$$
\text{w} = \left( \text{AE}_{\text{rms}} \right)^2 - C_1^2 \left[ \frac{C_2 \tau_{\text{s max}} A_{\text{sm}}}{\mu_{\text{m}} \sigma_{\text{n max}}} \int_{\text{lst}} \left[ 1 - \left( \frac{l_{\text{p}}}{l_{\text{t}}} \right)^{A_{\text{t}}} \right] \text{d}l_{\text{p}} \right] + \left( \frac{2}{3} \right) \tau_{\text{s max}} l_{\text{st}} l_{\text{m}} \left( \cos \phi_e - \alpha_e \right) \left( \cos \phi_e - \alpha_e \right) + \frac{C_3 V}{\cos \phi_e} \sin \phi_e$$

(4.31)

**4.2.2 Computer Algorithm for Tool Wear Estimation**

A computer algorithm, shown in Figure 4.9, is developed for estimating both flank and crater wear of tool inserts. In this research, it will be assumed that crater wear causes a change in the tool rake face geometry only. Feed and radial forces were found not to be influenced significantly by the change in rake angle [45, 48]. Hence, Equation (4.27) can be used for flank wear estimation for both worn tool having both flank and crater wear and worn tool with flank wear only. This computer algorithm will start with the prediction of flank wear by employing Equation (4.27). Then, depth of crater wear can be predicted by using Equations (4.31) and (4.3) respectively.
Figure 4.9 A computer algorithm for flank and crater wear estimation
4.3 NEW PARAMETERS FOR MONITORING TOOL WEAR

(THE TOTAL ENERGY AND THE TOTAL ENTROPY OF FORCES)

Since 1980s, many models including neural network models [12, 13, 16, 18, 19, 21, 121] have been developed to monitor, classify and estimate tool wear in turning operations. The cutting forces and acoustic emission (AE) signals have been usually used as the inputs for these models. However, temperature, vibration signals, chatter frequencies and the energy quanta can be also employed to monitor tool wear since the previous researchers observed that they correlate with the tool flank wear [112, 113, 123, 160-162]. The accuracy and reliability of tool wear monitoring will increase if two or more signals are used in the tool condition monitoring.

The present research will employ force and $AE_{rms}$ sensors for monitoring the tool wear. In order to develop additional parameters for monitoring progressive tool wear in oblique turning operations and keeping sensing costs as low as possible, the new parameters should be derivatives of force or $AE_{rms}$ signals. Two new parameters - the total energy and the total entropy of force signals were therefore developed for monitoring of tool wear. Employing these new parameters along with forces and $AE_{rms}$, tool wear can be monitored using multi-parameter approach without the increase in sensor costs.

4.3.1 Development of New Parameters

Due to the fact that force signals (composed of cutting, feed and radial force signals) are generated from energy consumption on shear plane, rake face and flank face, the energy
consumption per unit time calculated from these force signals can represent the total energy consumed during oblique cutting processes. The energy consumption per unit time by cutting, feed and radial forces as well as the total energy consumption per unit time in turning operations can be expressed as:

\[ U_{FC} = F_c \times V_{Fc} \] (4.32)

\[ U_{Ff} = F_f \times V_{Ff} \] (4.33)

\[ U_{Fr} = F_r \times V_{Fr} \] (4.34)

\[ U_{\text{total}} = U_{FC} + U_{Ff} + U_{Fr} \] (4.35)

Based on Parseval's theory reviewed by Kay and Marple [163], the energy of the periodic signal determined in time domain equals to the energy determined in frequency domain. For example, an area under curve of Figure 4.10 equals to the power of this particular periodic signal. However, sometimes, the frequency distribution shown in Figure 4.10 can be displayed by peaks at each frequency as shown in Figure 4.11. The frequency distribution shown in Figure 4.10 can be estimated by the power spectrum density methods (PSD) [164].

One PSD technique is Welch method which is a procedure for an application of the Fast Fourier Transform (FFT) algorithm to estimate power spectrum density [165]. Advantages of this method are a reduction in the number of computations and in lower required core storage. The amplitude for each frequency estimated by Welch method can be expressed as Equation (4.36).
Figure 4.10 The frequency distribution estimated by PSD

\[ P(f_n) = \frac{L}{UK} \sum_{k=1}^{K} |A_k(n)|^2 \] (4.36)

Where
\[ U = \frac{1}{L} \sum_{j=0}^{L-1} W^2(j) \]  \hspace{1cm} (4.37)

\[ f_n = \frac{n}{L} \quad n = 0, 1, 2, \ldots, \frac{L}{2} \]  \hspace{1cm} (4.38)

And, Finite Fourier Transforms, \( A_k(n) \), can be written as:

\[ A_k(n) = \frac{1}{L} \sum_{j=0}^{L-1} X_k(j) W(j) e^{-2 \pi i n j / L} \]  \hspace{1cm} (4.39)

Generally, the frequency and the probability are considered same [166]. However, frequency is usually defined for the event that already happened, but probability is defined for the event that has not occurred [167]. Applying probability theory for frequency domain, the expected value of energy consumption per unit time can be expressed as:

\[ U_{F_{\text{ce}}} = \sum_{i=1}^{N} [P_{F_{\text{c}}}(i) \times \hat{U}_{F_{\text{c}}}(i)] \]  \hspace{1cm} (4.40)

\[ U_{F_{\text{fe}}} = \sum_{i=1}^{N} [P_{F_{r}}(i) \times \hat{U}_{F_{r}}(i)] \]  \hspace{1cm} (4.41)

\[ U_{F_{\text{re}}} = \sum_{i=1}^{N} [P_{F_{r}}(i) \times \hat{U}_{F_{r}}(i)] \]  \hspace{1cm} (4.42)
Since the sum of probability $p(i)$ must be equal to 1 [167, 168], the probability $P_{Fc}(i)$, $P_{Ff}(i)$ and $P_{Fr}(i)$ can be determined by using the method presented by Fu, Mori and Yokomichi [168]. These probabilities (or frequencies) can be expressed as:

$$p_{Fc}(i) = \frac{\hat{U}_{Fc}(i)}{N} \sum_{i=1}^{\hat{U}_{Fc}(i)}$$ (4.43)

$$p_{Ff}(i) = \frac{\hat{U}_{Ff}(i)}{N} \sum_{i=1}^{\hat{U}_{Ff}(i)}$$ (4.44)

$$p_{Fr}(i) = \frac{\hat{U}_{Fr}(i)}{N} \sum_{i=1}^{\hat{U}_{Fr}(i)}$$ (4.45)

Using equation (4.35), the total energy of force signals can be written as:

$$U_{totalF} = U_{Fce} + U_{Ffe} + U_{Fre}$$ (4.46)

The entropy of probability $p(i)$ defined by Fu et al. [168] represents the distribution pattern of signals in frequency domain. The experimental results of Fu et al. [168] showed that the frequency distribution of different vibration signals gave the dissimilar value of the entropy of signals. Using the definition of entropy, the entropy of cutting, feed and radial forces can be expressed as:
\[ S_{Fc} = -\sum_{i=1}^{N} [p_{Fc}(i) \times \ln p_{Fc}(i)] \] (4.47)

\[ S_{Ff} = -\sum_{i=1}^{N} [p_{Ff}(i) \times \ln p_{Ff}(i)] \] (4.48)

\[ S_{Fr} = -\sum_{i=1}^{N} [p_{Fr}(i) \times \ln p_{Fr}(i)] \] (4.49)

Since the uncertainty (or entropy) of two independent events A and B taken together should be the sum of the uncertainty (or entropy) of A and B [169], the total entropy of force signals can be expressed as:

\[ S_{total} = S_{Fc} + S_{Ff} + S_{Fr} \] (4.50)

### 4.4 A NEW TECHNIQUE FOR DETECTION AND ESTIMATION OF NUMBER OF CHIP FRACTURE EVENTS

Several quantitative models predicting \( A_{E_{rms}} \) signals have been developed by using a correlation between \( A_{E_{rms}} \), tool wear and cutting conditions [54, 56, 66, 67, 170-172]. These quantitative models predict the \( A_{E_{rms}} \) based on the energy consumed in the shear zone, the tool-chip interface zone, and tool flank-workpiece interface zone in metal cutting operations. However, these quantitative models did not integrate the strain energy generated by chip fracture which can influence the magnitude of \( A_{E_{rms}} \) [54].
In order to increase the accuracy of $AE_{rms}$ predictions, the energy from chip fracture need to be incorporated in the quantitative $AE_{rms}$ model which was developed in the present research. But a major problem is the unknown number of chip fracture events occurring during a sampling period. Therefore, in this section, a technique that can detect and count chip fracture events in a turning operation is proposed.

![AErms Signal for Oblique Cutting with Chip Fracture](image)

Figure 4.12 The $AE_{rms}$ signal for oblique cutting with chip fracture

Previous researchers [173, 174] employed a threshold in frequency domain of cutting force for chip fracture detection. However, the number of chip fracture events cannot be counted by the above techniques. This is because chip fractures influence only the magnitude of peaks while number of peaks which are above the threshold in the frequency domain do not relate to number of chip fractures.

The previous researchers [144] found that the development of flank and crater wears causes a smaller chip up-curl radius which can result in an increase in chip-breakability.
In oblique turning operations, the fracture of chips is caused by the impact of the chip on the tool holder (Figures 4.3) or on tool flank face. Lan and Dornfeld [61] observed that chip fracture instances could be detected in the plotted AE_rms. The similar result was also found in the present research as shown in Figure 4.12. Hence, in this thesis, a technique for counting and detection of chip fracture events was developed by using the correlation between chip breakage and peaks of AE_rms signal. Employing the proposed method, a computer program that can estimate the number of chip fracture instances is developed.

4.4.1 Chip Fracture Detection

Andreasen and De Chiffre [173, 174] employed frequency analysis of cutting force to detect chip fracture. Their method used thresholds for detection of chip breakage occurrence. However, the magnitude of cutting force for the frequency range 0 - 1.250 kHz is influenced not only by chip breakage but also by tool wear and cutting conditions. These influences can result in peaks of signal at low, medium and high frequency bands and may cause detection errors.

Experimental results in Lan and Dornfeld's research [61] indicated that the chip fracture results in peaks in the AE_rms signal. These peaks cause larger variation of AE_rms signal which produces a higher ratio of standard deviation (SD) to mean of AE_rms. Using this influence of chip fracture on a ratio of SD to mean of AE_rms, a new technique to detect the occurrence of chip fracture has been developed in this thesis. Unlike Andreasen and De Chiffre's model [173, 174] where frequency domain was employed for detecting
chip fracture, the present technique detects the occurrence of chip fracture by using the ratio of SD to mean of $AE_{rms}$.

### 4.4.2 Estimation of the Number of Chip Fractures

Using a suitable running average filter, chip fracture events can be observed from the peaks of filtered $AE_{rms}$ (Figure 4.13). These peaks of filtered $AE_{rms}$ in time domain cause an increase in magnitude of filtered $AE_{rms}$ spectrum in the frequency domain of the same signal especially in low frequency zone (less than 250 Hz). Thus, in this research, the number of chip fractures will be estimated by the frequency analysis of the filtered $AE_{rms}$.

**Figure 4.13 $AE_{rms}$ with 20-point running average filter**
Employing PSD function (Welch method [165]), the frequency distribution of filtered $AE_{rms}$ can be shown as in Figure 4.14. The threshold shown in this figure is employed to classify the peaks due to chip fracture from the others. Using this basis, a suitable value of this threshold was determined later from experimental results. An expected frequency for chip fracture can be estimated using the following equation.

$$CF_{freq} = \sum_{i=1}^{n} [w(i) \cdot P(i)]$$  \hspace{1cm} (4.51)

Where $P(i)$ : the frequency whose magnitude is higher than the threshold

$w(i)$ : the normalized magnitude of $P(i)$ which is greater than the threshold

$CF_{freq}$ : the average frequency for chip fracture
4.5 FUZZY NEURAL NETWORK MODEL FOR ESTIMATING TOOL WEAR

In recent past, several neural network models have been developed and employed for predicting tool wear in turning operations [12-16, 18-21]. These neural network models usually use forces, $A_{E_{rms}}$ and cutting conditions including cutting speed, feed rate, rake angle and depth of cut as the inputs. However, experimental results in Chapter 6 indicate that at the start of cut the cutting forces (cutting, feed and radial forces) and $A_{E_{rms}}$ for different fresh tools having the same specification can vary up to $\pm 16\%$, $\pm 23\%$, $\pm 21\%$ and $\pm 18\%$ respectively. Such variations in cutting forces and $A_{E_{rms}}$ when employed for tool wear estimation by neural network can result in incorrect estimation of tool wear. These variations in mean forces and $A_{E_{rms}}$ have not been considered in previous neural network models [12-16, 18-21]. In order to eliminate tool wear estimation error due to the mean signal variation, a new fuzzy neural network model is developed.

This Fuzzy Neural Network (FNN) model can be separated into four subsections as shown in Figure 4.15. The first section of the FNN model classifies tool wear by using fuzzy logic. The second part is employed to normalize the inputs for the neural network. The third section of the FNN model is developed to estimate the maximum depth of crater wear and the average width of flank wear by using the Modified Least Square Backpropagation (MLSB) neural network [175] which has relatively high accuracy and consumes less training time compared to other neural networks such as conventional backpropagation neural network and least square backpropagation neural network [175]. The fourth section of the FNN model is used to adjust the results of the third part.
in order to eliminate the effect of the variation in force and $AE_{rms}$ signals generated by different cutting tools having the same specifications.

### 4.5.1 Fuzzy Neural Network

As indicated above, the new fuzzy neural network model (Figure 4.15) consists of 4 sections: Tool Wear Classification (fuzzy logic), Input Normalization, Tool Wear Estimation (MLSB neural network), and Tool Wear Adjustment (fuzzy logic). The details of each section are presented as follows.

![Figure 4.15 The architecture of the proposed fuzzy neural network model](image-url)
Tool Wear Classification Using Fuzzy Logic

For predicting the occurrence of flank wear, crater wear, chip fracture and cutting edge deterioration, the first section of Figure 4.15 is developed by using fuzzy logic. In this research, 32 fuzzy rules divided into four groups are developed to predict these four results. Although the flank wear growth is significantly influenced by temperatures generated at tool-chip interface, tool-workpiece interface, and in shear zone, however, the purpose of these fuzzy rules is not to predict the magnitude of either the flank wear or crater wear. These rules are simply designed to indicate that the flank or crater wear growth has initiated or not on a new tool after it began the turning operation. The estimation of wear magnitudes at later stage in fact is carried out by using $AE_{\text{rms}}$ and force signals only. Recent research [158] indicates that for a fresh tool, the temperature on the cutting edge is nearly similar to the maximum temperature in shear zone. The maximum temperature on rake face of tool, however, will be influenced by the energy consumption in the tool-chip interface zone. The energy consumptions in both shear and tool-chip interface zones can be expressed in terms of material properties and cutting conditions. It will be assumed that tool material removal due to wear on rake and flank face occurs since the start of turning. The rate of these material removals is strongly influenced by temperatures and applied normal stress on these faces [4]. However, some duration of cutting time is also required for stabilizing cutting temperature [176] as well as burning any work material adhered to the tool during initial stage of low temperatures at the beginning of cut [107]. Hence, the initiation of flank wear can be predicted by using energy consumption in shear zone and the duration of cutting time (the first fuzzy rule group). The second group predicts the initiation of crater wear by employing the friction energy on rake face and the duration of cutting time. Chip
fracture is indicated by using the third group of fuzzy rule which employs size of flank and crater wear, ratio of standard deviation and the average of $AE_{rms}$ and cutting time. The last fuzzy rule group is built based on a correlation between cutting edge deterioration, average width of flank wear, maximum depth of crater wear and cutting time. The details of fuzzy members and fuzzy rules employed in this research have been presented in Section 6.5.2 of Chapter 6.

In the present research, the probability of occurrence of each event - chip fracture, cutting edge deterioration, flank wear and crater wear is presented by a number having a value between 0 and 1. The value '0' means no occurrence of these events. The value '1' means these events happen. The value '0.5' means such events may or may not occur.

It should be noted that the fuzzy members and fuzzy rules used in both tool wear classification and tool wear adjustment sections are conventional fuzzy logic. These fuzzy members and rules were developed based on a method presented by Berkan and Trubatch [177].

- Inputs Normalization

The inputs, which are less than 0 and greater than 1, need to be normalized between 0 and 1 [13, 17]. This is to prevent infinite value of sigmoid function output for a large value of input summation. The normalized value for each parameter can be determined by dividing this value by two times the maximum value for the whole data set for the
same parameter. The purpose of this step is to force the normalized value to the middle of the range of 0 and 1.

- **Tool Wear Estimation Using the MLSB Neural Network**

The basis of MLSB neural network algorithm developed by Li et al. [175] is to adjust both the connecting weights and outputs of the hidden layer based on least square backpropagation algorithm. A set of 'required' outputs of the hidden layer is added to the input sets through a feedback path to accelerate the convergence speed of neural network. This concept has also been employed for accelerating the convergence speed of neural network employed in the present model. Compared to the conventional backpropagation neural network, the modified neural network uses fewer training iterations as well as shorter training time and has a higher accuracy [175].

The input layer was constructed based on 36 inputs including basic and derived parameters (Table 4.1). Experimental results in Section 6.3 and previous experimental results [13, 127, 132, 178, 179] indicated that several of these parameters including three forces, $AE_{rms}$, the total energy of forces, the ratio of forces, and skew as well as kurtosis of some force bands are influenced by flank and crater wear.

Rao and Shin’s results [180] and results in Section 6.3 showed that the frequency distribution pattern of force signals is influenced by cutting conditions and tool wear. Hence, change in tool wear and cutting conditions causes a change in skew and kurtosis of force distribution in fixed frequency band. Hence, it is for this reason the skew and kurtosis of some force bands are selected as inputs.
Previous researchers [48, 171, 180] and results in Sections 6.3 and 6.4 indicated that forces, $AE_{\text{rms}}$, the total energy of forces are influenced by cutting conditions, chip fracture, cutting edge deterioration, and flank as well as crater wears. Therefore, basic parameters as well as the occurrence of chip fracture, cutting edge deterioration, flank wear and crater wear also need to be used as inputs.

The number of hidden units leading to minimum error can be estimated by using several techniques including the Hirose’s method [181], the Sensitivity Analysis method [182] and the Pruning method [182]. In the present research, the technique employed by Hirose et al. [181] was selected for finding the suitable number of hidden units. This is because such a technique can be integrated in the computer program for training MLSB neural network. However, the number of hidden units has to be less than the upper bound for the required number of hidden units (twice the number of input units plus one) [183].

Table 4.1: Input units employed in the new fuzzy neural network model

<table>
<thead>
<tr>
<th>1. Bias (0.5)</th>
<th>2. Cutting force (Fc)</th>
<th>3. Feed force (Ff)</th>
<th>4. Radial force (Fr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5. $AE_{\text{rms}}$</td>
<td>6. SD/ mean of $AE_{\text{rms}}$</td>
<td>7. Speed</td>
<td>8. Feed rate</td>
</tr>
<tr>
<td>33. Skew of $F_f$ (420-620 kHz)</td>
<td>34. Kurtosis of $F_f$ (420-620 kHz)</td>
<td>35. Skew of $F_f$ (820-1020 kHz)</td>
<td>36. Kurtosis of $Fr$ (820-1020 kHz)</td>
</tr>
</tbody>
</table>
Since most real world problems may have linear components, hence it is difficult to estimate an accurate result by using a non-linear activation function for all hidden units. Therefore, one of the hidden units should always be a linear function \([184]\). As a result, the activation functions of hidden units in this research comprise of both linear and non-linear functions. A simple linear function \((y = x)\) is applied for one hidden unit. The remaining hidden units employ the sigmoid function as their activation function.

A single hidden layer many a times cannot provide the satisfactory results. Hence, more layers are required in order to increase the estimation accuracy of neural network. This is because networks with large number of layers, as well as fewer units in the early layers, may generalize better than shallow networks with many units in each layer \([185]\). One technique that can produce a long and narrow network is to train and then trim a network with the fewest possible units. Thereafter, extra layers can be inserted to enable the network to relearn the solution \([182]\).

The output layer of both MLSB neural networks in the model (Figure 4.15) consists of estimated average width of flank wear as well as maximum depth of crater wear. These layers employ the sigmoid function as the activation function. It should be noted that the estimated tool wear should be negative if force and AE\(_{rms}\) signals for testing data of a fresh tool are lower than the signals for the training data. However, in this case, the estimated values are 0 because the output of sigmoid function is between 0 and 1. Hence, all of crater wear sizes have to be increased by 0.5 and all of flank wear sizes have to be divided by 10 and then added with 0.5 before training the neural network in order to force the results into the active range of the sigmoid function. The purpose of this step is to force the normalized value to the middle of the range of 0 and 1. Since the
output of MLSB neural network is the normalized value, flank and crater wear need to be adjusted to the actual size before input to the tool wear Adjustment section.

- **Adjustment of MLSB Results Using Fuzzy Logic**

As mentioned earlier, the variation in magnitude of mean forces and $AE_{rms}$ generated at the start of cut during turning with different new tools using the same cutting conditions causes the error in tool wear estimations. The fourth part (fuzzy logic section), shown in Figure 4.15, is used for adjusting the results from the MLSB neural networks. The basic idea is to adjust the current tool wear using the initial tool wear. The current width of flank wear as well as depth of crater wear of the worn tool are estimated by using the submodel B of the fuzzy neural network model. The initial tool wear, which is the error due to the variation in mean forces and $AE_{rms}$ at the beginning of machining, is predicted by employing submodel A. In this research, ten fuzzy rules were developed to alter the flank and crater wear by using a correlation between the results of submodels A and B. The details of fuzzy members and fuzzy rules used in this section are presented in Section 6.5.2.

### 4.6 DETECTION OF TIP FRACTURE AND CHIPPING AT THE CUTTING EDGE USING NEURAL NETWORK MODEL

In Section 6.5.1, the mean feed and radial force signals have been observed to increase significantly when tip fracture as well as chipping at major cutting region occur. However, the cutting force was found to change slightly for a few seconds before regaining the previous value. This was also observed in the previous research [9]. $AE_{rms}$
was found to increase when chipping or fracture occurs, but the level of $AE_{\text{rms}}$ signal drops to the previous value as the cutting time elapses. This increase in signals, especially feed and radial forces, can result in incorrect tool wear estimation if these forces and $AE_{\text{rms}}$ are employed as inputs of tool wear prediction models developed by using the neural network model proposed in Section 4.5 or by using the quantitative models (Section 4.2). Unlike tip fracture or chipping at the cutting edge, the tool breakage, however, causes an instant increase followed by a small drop of all three-force components [9].

The experimental results presented in Section 6.5 of Chapter 6 also indicated chipping at the cutting edge including nose as well as major cutting regions and tip fracture in about one third of the tools used. The complete rapture of the cutting edge was usually observed on worn tools with high wear. In this research, only tool with chipping of cutting edge and fracture tip is considered. This is because they are observed in many used tools and cause an increase in force signals resulting in incorrect tool wear estimation. Therefore, a new neural network model, which can detect (i) chipping on cutting edge including nose and major cutting regions, and (ii) small tip fracture is introduced (Figure 4.16).

4.6.1 Model Development

The new neural network model for detecting tip fracture and chipping at the cutting edge (Figure 4.16) was developed by using a correlation between a significant increase in feed as well as radial forces and the occurrence of tip fracture as well as cutting edge chipping. Modified least-square backpropagation neural network (MLSB) architecture
is selected for the neural network development. This is because MLSB requires a
short training time and has high accuracy compared with conventional backpropagation
neural network [175].

The inputs of the neural network model (Figure 4.16) consist of six parameters: (i)
measured feed force at the start of cut, (ii) measured radial force at the start of cut, (iii)
current measured feed force, (iv) current measured radial force, (v) predicted feed force
for fresh tool by quantitative force model, and (vi) predicted radial force for fresh tool
by quantitative force model. In previous research, the inputs which are less than ‘0’ and
greater than ‘1’ have been normalized between ‘0’ and ‘1’ [13, 17]. This was to prevent
infinite value of the sigmoid function output for a large value of input summation. The
same criterion will also be used for the present model. The normalized value for each
parameter was obtained by dividing the forces by 1000.

For this research, the number of hidden units in each layer leading to minimum error
has been estimated by using the Hirose’s method [181]. A major advantage of this
method is that it can be integrated in the computer program for training MLSB neural
network. Employing the Sietsma and Dow approach [182], the second and third hidden
layer can be added if required for increasing an accuracy of the neural network model.

As discussed in Section 4.5, one of the hidden units should always be a linear function
[184]. This is because most real world problems may have a linear component, and it is
difficult to predict an accurate result by using a non-linear activation function for all
hidden units [184]. In this thesis, as a result, the activation functions of the hidden units
comprise of both linear and non-linear functions. A simple linear function \( y = x \) is
applied for one hidden unit. The remaining hidden units employ the sigmoid function as their activation function.

The proposed neural network model has single output which has only two values, either ‘0’ or ‘1’. The value ‘1’ represents an occurrence of tip fracture and/ or chipping at the major cutting region influencing the mean forces and $A_{rms}$. The value ‘0’ represents (i) no tip fracture, (ii) no chipping at the major cutting region, (iii) small tip fracture which does not influence forces and $A_{rms}$ and/ or (iv) small chipping at the major cutting region which does not lead to increase the signals.

![Diagram](image)

**Figure 4.16 MLSB neural network model for detecting chip fracture and chipping at major cutting region**

Since predicted as well as measured mean feed and radial forces for fresh tool need to be used for detecting an occurrence of chipping at major cutting region, tip fracture or
both at the start of cut, a quantitative model (Equations 4.11-4.15) for estimating feed and radial forces has to be employed. Due to the fact that these equations were developed for predicting mean cutting forces for worn tools having flank and crater wear, to apply such equations for fresh tools, three forces ($F_P$, $F_A$ and $F_B$) need to be set to zero. Furthermore, the modified normal rake angle ($\alpha_{nm}$), the modified shear plane area ($A_{sm}$) and the modified total cutting edge length ($l_m$) for worn tools need to be equal to the normal rake angle ($\alpha_n$), the shear plane area ($A_s$) and the total cutting edge length ($l$) respectively.

4.7 ON-LINE TOOL WEAR ESTIMATION SYSTEM

As mentioned in Chapter 3, the on-line tool wear estimation (Figure 4.17) will be developed by using the models, technique and parameters developed in Sections 4.1 – 4.6. Experimental results in Chapter 6 indicated that the accuracy of tool wear estimation by the fuzzy neural network model (Figure 4.15) was higher than the accuracy of tool wear prediction by the computer algorithm using quantitative models (Figure 4.9). Hence, in this on-line system, hence, the fuzzy neural network model (Figure 4.15) will be employed for predicting flank and crater wear.

This algorithm starts with collecting 16,000 samples of forces and $A E_{rms}$ at about 15 seconds after the start of turning. These data will be saved into the computer hard-disk and used later by the Submodel ‘A’ (Figure 4.15). After collecting signals, the computer will estimate cutting, feed and radial forces as well as $A E_{rms}$ for the fresh tool. These will be used as inputs of the neural network model for detecting chipping at major cutting region and fracture at tool tip. Then, weights for input layer, hidden layer and
output layer of the fuzzy neural network model (Figure 4.15) will be estimated. Employing the 16,000 samples recorded earlier and the weights of the fuzzy neural network model, the initial flank and crater wear which is a small error due to the variation in mean forces and $AE_{\text{rms}}$ at the beginning of cut will be predicted. These values will be used later for adjusting flank and crater wear.

By pressing the enter-button, another 16,000 samples of forces and $AE_{\text{rms}}$ will be collected and then the current flank and crater wear will be estimated. Before estimation process, however, the chipping at the major cutting region and the fracture at the tool tip need to be detected by the neural network model in Figure 4.16. This neural network model employs mean forces, mean $AE_{\text{rms}}$, cutting conditions, predicted forces for fresh tool, and predicted $AE_{\text{rms}}$ for fresh tool as inputs. If chipping or fracturing occurs, the flank and crater wear will be not estimated and operator will be suggested to change the tool insert. Otherwise, the current flank and crater wear will be predicted by the submodel 'B' of the fuzzy neural network model (Figure 4.15). Employing the initial flank and crater wear as well as the current flank and crater wear, and then, the actual values of the current flank and crater wear will be determined by the tool wear adjustment part of the fuzzy neural network model (Figure 4.15). These values will be then shown on the screen (Figure 4.17). After finishing tool wear estimation, operator will be asked to exit program or to continue to predict tool wear prediction.
Figure 4.17 Algorithm for on-line tool wear estimation
In order to develop an on-line system for estimating flank and crater wear in CNC turning operations, several models have been developed in Chapter 4. Experimentation is necessary to investigate some phenomena occurring during oblique metal cutting, to validate the models developed in Chapter 4 and to test the on-line system. Hence, large number of experiments was carried out. These experiments have been grouped into seven lots of experiments. The experimental setup and the specific details for each test are presented in the following sections.

5.1 EXPERIMENTAL SETUP

The experimental setup which was employed in this thesis is shown in Figure 5.1. A piezo-electric transducer, PAC 1151 (150 kHz resonant frequency), was used to collect the AE signal in the turning operations. The sensor was placed on the ground and the finished end of tool holder which was mounted on a 3D Kistler 9272 dynamometer which in turn was rigidly bolted on the CNC turret through a specially designed bracket. Unless mentioned otherwise, 4000 samples per signal for each cut were collected by using a 16-channel A/D converter with a sampling rate of 2.5 kHz for each signal. Then, all signal samples were synchronously digitized. These accumulated signal samples were stored on the hard disk of an IBM compatible computer. Mean forces and AE_{rms} were calculated later from these samples using Microsoft Excel ®.
5.2 EXPERIMENTAL DESIGN

As mentioned above, seven lots of experiments were designed for observing some phenomena occurring during metal cutting processes and for verifying the models developed earlier. The sequence of these experiments is based on the order of experimental data employed to develop the on-line tool wear estimation system. It starts with experiments for verifying tool wear estimation models, incorporating quantitative models as well as fuzzy neural network model, and then an experiment for testing the on-line system. The details for each experiment are as follows:
- **Experiment 1**

This experiment was designed to investigate the tool-chip contact area of fresh tools and the geometry of flank as well as crater wear of worn tools. The first half of this experiment aims to the investigation of tool-chip interface area while the remainder was for observing the geometry of the progressive flank and crater wear of tool. In order to examine the geometry of chip tool contact area, fresh tools were employed for turning at three sets of cutting conditions:

1. Speed = 160 m/min; feed rate = 0.1, 0.2 and 0.3 mm/rev; rake angle = 5 degrees and depth of cut = 1mm
2. Speed = 80, 120, 160 m/min; feed rate = 0.3 mm/rev; rake angle = 5 degrees and depth of cut = 1mm
3. Speed = 160 m/min; feed rate = 0.3 mm/rev; rake angle = -5, 0, 5 degrees and depth of cut = 1mm

It should be noted that the variation of depth of cut was neglected in this experiment. This is because the depth of cut does not affect the tool-chip contact length significantly.

The tool-chip contact area, as shown in Figure 5.2, could be observed by using the Leica DMRM microscope. Since this microscope could record the image of the tool-chip contact area as a computer file (jpeg format), the chip flow angle, sticking zone color, and sliding zone color were measured or observed later from this photograph.
The boundary of each zone of tool-chip contact on line A-C can be observed clearly from the roughness profile recorded by SURFCOM 550AD. Such profile also provided the tool-chip contact length along the line A-C. The images of tool face by the Leica DMRM microscope were used for estimating the average chip flow angle. The tool-chip contact length along line A-C was then divided by cosine of flow angle to estimate the tool-chip contact length in chip flow direction.

Figure 5.2 Geometry of tool-chip contact area

In this experiment, due to a difference in the values of chip flow angle at opposite sides of the cutting edge, the average value \( \{90° - (\text{angle } '1' + \text{angle } '2')/2\} \) was used as the chip flow angle (Figure 5.2). In order to investigate the roughness of the sticking and
the sliding zones of the tool-chip interface area, the profile of the tool rake face needs to be measured along the line A-C by using a surface roughness analyzer (SURFCOM 550AD). This line A-C was chosen for the trace because it passes through the centre of the tool-chip contact area. The recommended vertical and horizontal magnifications are 10000 and 100 respectively.

For investigating the geometry of flank and crater wear on worn tools, fresh K420 tool inserts were used for turning under the following cutting conditions: speed 160 m/min; feed rate 0.3 mm/rev; rake angle -5, 0 and 5 degrees; and depth of cut 1 mm. For each cutting condition, three fresh tools were used for cutting with a turning time of 3, 6 and 9 minutes respectively. The average width of flank wear could be measured by an optical profile projector. The maximum depth of crater wear could be detected by using a surface roughness analyzer (SURFCOM 550AD). A technique which can show the profile of crater wear and detect the maximum depth of crater wear is described as follows:

1. Using the minor cutting region of tool inserts as a datum (the position of the cutting edge can be found exactly by moving a stylus in a direction perpendicular to the trace line, and when the stylus reaches the cutting edge, this is immediately indicated on the an indicator of SURFCOM).

2. Moving the SURFCOM 550AD stylus on each trace line, a profile of the crater wear of each trace line was plotted (the distance between each trace on the rake face is 0.2 mm as shown in Figure 5.3).

3. From the recorded crater wear profiles, the maximum depth of crater wear can be determined.
The recommended vertical and horizontal magnifications for this case are 1000 and 20 respectively. However, for small crater wear a greater vertical magnification may be required.

It should be noted that the tool holder CSBPR-2525M12 has a 5° rake angle. No modifications were done in the tool holder to employ a 5° rake angle on tool insert during cutting. However, the bottom faces of two tool holders and two tool holder brackets were ground in order to achieve 0° and −5° rake angles during turning.

Figure 5.3 Trace on rake face of worn tools
To record the signals of the three forces (cutting, feed and radial) as well as $AE_{rms}$ for tool inserts having different tool wear, seven tool inserts including a fresh tool and six worn tools were employed for cutting under the cutting conditions shown in Table 5.1. The preliminary test indicates that during up to 50 minutes of turning time, only flank wear develops on the tool insert (K420) if the turning is carried out with the following conditions: 160 m/min cutting speed; 0.1 mm/rev feed rate; -5 degrees rake angle and 1 mm depth of cut. Thus, three worn tools with different flank wear were made using the above cutting conditions with a turning time of 15, 30 and 45 minutes respectively. Three other fresh tools were used to generate both the flank and crater wear on them with cutting conditions: 160 m/min cutting velocity; 0.3 mm/rev feed rate; -5 degrees rake angle and 1 mm depth of cut with cutting times of 10, 20 and 30 minutes respectively. The details of the flank and crater wear on these six tool inserts are given in Table 5.2. The sizes of flank as well as crater wear were measured by the same technique as used in Experiment 1. Using a 16-channel A/D converter, three forces and $AE_{rms}$ were collected at the sampling rate of 2.5 kHz for a duration of six seconds and synchronously digitized. All signal samples were stored on the hard disk of an IBM compatible computer for analysis at a later stage.

It should be noted that the variation of depth of cut was neglected in this experiment. This is because the depth of cut does not affect $AE_{rms}$ significantly.
Table 5.1 The cutting conditions of Experiment 2

<table>
<thead>
<tr>
<th>Tool insert</th>
<th>Tool holder</th>
<th>Work piece material</th>
<th>Cutting speed (m/min)</th>
<th>Feed rate (mm/rev)</th>
<th>Depth of cut (mm)</th>
<th>Rake angle (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fresh Tool/ worn Tool</td>
<td>Kennametal K420 (SPUN 12 03 08)</td>
<td>Ken. CSBPR-2525M12</td>
<td>60-160</td>
<td>0.1-0.3</td>
<td>1</td>
<td>-5.0 and 5</td>
</tr>
</tbody>
</table>

Table 5.2 The details of fresh and worn tool used in Experiment 2

<table>
<thead>
<tr>
<th>Width of flank wear (mm)</th>
<th>Depth of crater wear (mm)</th>
<th>Cutting Conditions</th>
<th>Cutting time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fresh tool</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Worn tool</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 1</td>
<td>0.085</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>Case 2</td>
<td>0.141</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>Case 3</td>
<td>0.163</td>
<td>0</td>
<td>A</td>
</tr>
<tr>
<td>Case 4</td>
<td>0.115</td>
<td>0.025</td>
<td>B</td>
</tr>
<tr>
<td>Case 5</td>
<td>0.131</td>
<td>0.065</td>
<td>B</td>
</tr>
<tr>
<td>Case 6</td>
<td>0.177</td>
<td>0.045</td>
<td>B</td>
</tr>
</tbody>
</table>

Note: A : cutting speed 160 m/min, feed rate 0.1 mm/rev, rake angle -5 degrees and depth of cut 1 mm
B : cutting speed 160 m/min, feed rate 0.3 mm/rev, rake angle -5 degrees and depth of cut 1 mm

In order to estimate forces and \( AE_{rms} \) by using Equations (4.11) to (4.15) and (4.24) respectively, the length of tool-chip contact needs to be known. The tool-chip contact length can be simply estimated by dividing the length of line A-C by the Cosine of the chip flow angle. Thus the estimated tool-chip contact length is located on line A-B in Figure 5.2. Since this method is simple and provides a fairly accurate value for tool-chip contact length, hence no significant error on shear and normal stress distributions is expected.

For turning during which chip fracture occurs, chip fracture frequency needs to be estimated. During the test, chip samples are collected during a cutting time of 5 seconds. Then, the number of chips is counted. An average chip fracture per unit time can be calculated by dividing number of chips by the cutting time of 5 seconds. The reciprocal
of the average chip fracture per unit time is the average chip fracture frequency. It should be noted that data on cutting forces and $AE_{rms}$ have to be collected during this cutting time of 5 seconds. The number of chip fractures during the sampling period is the production of the average chip fracture per unit time multiplied by the duration of sampling period.

The experimental data collected in this experiment were used for three main purposes: (i) validating new quantitative force and $AE_{rms}$ models, (ii) verifying new parameters – the total energy and entropy of forces, and (iii) training the fuzzy neural network model.

![Graphs showing frequency distribution of energy consumption](image)

Figure 5.4 The frequency distribution of energy consumption for fresh tool at 160 m/min, 0.1 mm/rev and -5 degrees

Since the total energy and the total entropy of forces are derivatives of force signals, a specific MatLab (version 5.1) program was developed for estimating the frequency
distribution of energy of cutting, feed and radial force signals (Figure 5.4). An estimation of the energy amplitude by Power Spectrum Density (PSD) function (Welch method) was also employed in this program. Since the Welch method is based on Fast Fourier Transform (FFT), the number of samples which specifies the FFT length that is used by PSD should be a power of 2 for the fastest execution [186]. The number of samples used for each signal in the PSD function was 2048 ($2^{11}$). The code of this MatLab program is shown in the Appendix B.

It should be noted that the phenomena such as chip fracture, development of tool wear, and cutting edge deterioration occurring in each cutting condition needs to be observed and recorded for developing fuzzy members and fuzzy rules of tool wear classification section in the fuzzy neural network model.

- **Experiment 3**

In order to verify the effect of chip fracture on the $AE_{rms}$ generated, a number of turning tests were conducted on a CNC Hitachi Seiki (Hitec-Turn 20 SII) lathe. The cutting conditions employed for turning with fresh and worn tools are presented in Table 5.3. Using a 16-channel A/D converter, $AE_{rms}$ and three force signals were collected at the sampling rates of 2.5 and 7.5 kHz for duration of six seconds and synchronously digitized. All signal samples were stored on the hard disk of an IBM compatible computer for analysis at a later stage. It should be noted that the estimation of energy amplitude by the PSD function (Welch method) was also employed for estimating the frequency distribution of filtered $AE_{rms}$. 
• Experiment 4

In order to determine the variation in mean forces and $A_{E_{rms}}$ for different fresh tool inserts, four fresh cutting tools were employed for turning with the following cutting conditions: speed 60-160 m/min; feed rate 0.1-0.3 mm/rev; rake angle -5, 0 and 5 degrees; and depth of cut 1 mm. The three force and $A_{E_{rms}}$ signals were collected for a duration of 1.6 seconds at the same sampling rate as that used in Experiment 2 after about 15 seconds of turning with each tool after engagement with the workpiece. This pause of 15 seconds allows stabilizing the cutting action as well as the mean cutting temperature of the workpiece [176]. The results of this experiment were also employed for developing the Tool Wear Adjustment section in the Fuzzy Neural Network part.

Table 5.3 The cutting conditions of Experiment 3

<table>
<thead>
<tr>
<th>Fresh Tool</th>
<th>Worn Tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tool insert</td>
<td>Ken. K420 (SPUN 12 03 08)</td>
</tr>
<tr>
<td>Tool holder</td>
<td>Ken. CSBPR-2525M12</td>
</tr>
<tr>
<td>Tool wear</td>
<td>-</td>
</tr>
<tr>
<td>Work piece material</td>
<td>AISI 1045 steel</td>
</tr>
<tr>
<td>Cutting speed (m/min)</td>
<td>60-160</td>
</tr>
<tr>
<td>Feed rate (mm/rev)</td>
<td>0.1</td>
</tr>
<tr>
<td>Depth of cut (mm)</td>
<td>1</td>
</tr>
<tr>
<td>Rake angle (degree)</td>
<td>-5</td>
</tr>
<tr>
<td>Sampling frequency (kHz)</td>
<td>2.5 and 7.5</td>
</tr>
</tbody>
</table>

• Experiment 5

For finding the cause of variation in the average cutting, feed and radial forces and the mean $A_{E_{rms}}$, the geometry of cutting tool inserts (Figure 5.5) needs to be examined. Eight new tools were selected at random and their measurements obtained by using the optical profile projector.
In order to examine the variation in mean forces and $AE_{rms}$ for different worn tool inserts and to obtain the data for verification of the fuzzy neural network model (Figure 4.15 in Section 4.5.1), the above four signals were collected using the following conditions: speed 160 m/min; feed rate 0.1-0.3 mm/rev; rake angle -5, 0 and 5 degrees; and depth of cut 1 mm. For each cutting condition, twelve fresh K420 inserts were employed for turning. Sixteen thousand samples of three forces and $AE_{rms}$ were collected at the following cutting times: 15 seconds, 2, 4, 6, 8 and 10 minutes, with the same sampling frequency as that used in Experiment 2. After cutting with each insert for 10 minutes, the turning process was stopped, and then their flank as well as crater wear were measured with the optical profile projector and the surface roughness analyzer respectively as detailed in Experiment 1. During flank wear measurement using the profile projector, tool tip fractures or chipping on major cutting region were also recorded.
During the experimentation, it was observed that some tools were fractured and chipped. Hence, the data recorded in this experiment was also employed for studying the influence of tool tip fracture and major cutting region chipping on force and $AE_{rms}$ signals.

For examining the influence of tool tip and major cutting region chipping on the force and $AE_{rms}$ signals, the used tool inserts were classified into three categories. The first category is worn tool inserts without tip fracture, or chipping at the major cutting region, or both tip fracture and chipping at cutting edge. The second category is tool inserts having small tip fracture, or chipping at cutting edge, or both tip fracture and chipping at the cutting edge which have insignificant influence cutting forces and $AE_{rms}$. The last category is tool inserts with tip fracture, or chipping at the major cutting region, or both tip fracture as well as chipping at cutting edge causing significant increase in force and $AE_{rms}$.

- **Experiment 7**

This experiment was designed to test the performance of the computer program for on-line tool wear estimation, developed in this project. This program collected three force and $AE_{rms}$ signals and then estimated the flank and crater wear by using Fuzzy Neural Network. The computational time for predicting tool wear (from commencement of signal collection to display of results) was also recorded. The cutting conditions for testing this program were: speed 160 m/min; feed 0.1-0.3 mm/rev; depth of cut 1 mm and rake angle -5 degrees.
In order to develop a new on-line tool wear estimation system for CNC turning operations, new models and parameters were developed and then used for the on-line system. For verification of these models and parameters, seven experiments mentioned in Chapter 5 were designed and performed. In this chapter, such experimental results are analyzed. Reasons for the important phenomena observed are also explained in this chapter. The chapter starts with force and AE<sub>rms</sub> models, followed by tool wear estimation by using quantitative models, new parameters for monitoring tool wear, chip fracture detection, tool wear estimation by fuzzy neural network model, tip fracture and chipping detection, and finally on-line tool wear estimation. The details are presented in the following sections.

6.1 QUANTITATIVE FORCE AND AE<sub>rms</sub> MODELS

This section presents a discussion of forces as well as AE<sub>rms</sub> signals for fresh and worn tools as predicted by the models developed in Chapter 4. Causes of differences in the measured and predicted values are also investigated and explained. Tool-chip contact area, chip fracture and tool wear geometry influencing forces and AE<sub>rms</sub> are also discussed in this section.
6.1.1 Tool-Chip Interfacing Area

In oblique turning operations with a flat face tool insert, the geometry of the tool-chip contact area (Figure 6.1) was found to depend on many parameters including (i) cutting speed, (ii) feed rate and (iii) rake angle. Two parameters which can represent this geometry are chip flow direction and total contact length on tool rake face. A simple way to estimate the tool-chip contact area is to multiply the total cutting edge length by the total contact length on the tool rake face. This tool-chip contact length along line A-B (Figure 5.2) equals the length of contact area measured on line A-C divided by the Cosine of the chip flow angle.

As shown in Figure 5.2, the chip flow angle can be taken as 90° - an average value of the angle ‘1’ and angle ‘2’. Employing the results of Experiment 1, the values of chip flow angle, angle ‘1’ and angle ‘2’ for a variety of cutting conditions are presented in Table 6.1.

Table 6.1 Chip flow angle of fresh tool for oblique cutting

<table>
<thead>
<tr>
<th>Cutting conditions</th>
<th>Angle ‘1’ (degree)</th>
<th>Angle ‘2’ (degree)</th>
<th>Chip flow angle (degree)</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>160 m/min, 0.1 mm/rev, 5 degrees</td>
<td>38</td>
<td>79</td>
<td>32.75</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min, 0.2 mm/rev, 5 degrees</td>
<td>49</td>
<td>71</td>
<td>30</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min, 0.3 mm/rev, 5 degrees</td>
<td>79</td>
<td>76.5</td>
<td>30</td>
<td>BU</td>
</tr>
<tr>
<td>120 m/min, 0.3 mm/rev, 5 degrees</td>
<td>71</td>
<td>49</td>
<td>71</td>
<td>BU</td>
</tr>
<tr>
<td>80 m/min, 0.3 mm/rev, 5 degrees</td>
<td>57</td>
<td>71</td>
<td>71</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min, 0.3 mm/rev, -5 degrees</td>
<td>57</td>
<td>71</td>
<td>27.5</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min, 0.3 mm/rev, 0 degree</td>
<td>51.5</td>
<td>75</td>
<td>26.75</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min, 0.3 mm/rev, 5 degrees</td>
<td>51.5</td>
<td>75</td>
<td>26.75</td>
<td>BU</td>
</tr>
</tbody>
</table>

Note: CH - Chipping at major cutting region observed
      CHS - Small chipping at major cutting region observed
      BU - Built-up edge observed
      BUS - Small built-up edge observed
      CW - Crater wear observed
The results in Table 6.1 indicate that the chip flow angle depends on the cutting conditions. A similar observation has also been reported by a previous researcher [159]. An example of tool-chip interface area is shown in Figure 6.1. For some cutting conditions, however, angle ‘1’ cannot be measured because of small tool-chip contact area (Figure 6.1a) or unclear contact area due to serious chipping at the major cutting region (Figure 6.1d).

Earlier, the chip flow angle was reported to be equal to the angle of inclination ‘i’ for oblique cutting with a single cutting region [187]. However, both the nose and minor cutting regions influence chip flow direction [159]. This can result in a chip flow angle greater than the 15-degree inclination angle (Table 6.1).

Previous researchers [109] indicated that friction occurring on this contact area consists of sticking and sliding friction caused by high and low normal stresses respectively. Both frictions cause three regions of the contact area: (i) sticking region, (ii) transition region (mixing between sticking and sliding), and (iii) sliding region [109]. Hsu [154] mentioned that the bright contact zone was the sliding area and the dark contact zone was the sticking area. In the present research, all three regions were observed on the tool rake face (Figures 6.1a and b).
(a) speed 160 m/min, feed 0.1 mm/rev and rake angle 5 degrees

(b) speed 160 m/min, feed 0.2 mm/rev and rake angle 5 degrees

Figure 6.1 Tool-chip interface area
(c) speed 160 m/min, feed 0.3 mm/rev and rake angle 0 degrees

(d) speed 80 m/min, feed 0.3 mm/rev and rake angle 5 degrees

Figure 6.1 Tool-chip interface area (Continued)
These results are similar to the results of previous researches [188, 189] which found that shear stress distribution on tool rake face for workpiece 1045 steel has three zones (sticking, transition and sliding zones). The previous results also showed that the ratios of sliding/total contact length and transition/total contact length are about 3/10 and 2/10 respectively [188, 189]. It was also found that the shear stress in the transition zone drops significantly (from about 200 MPa to about 50 MPa). Hence, if Zorev’s model is employed for this stress distribution, the sliding zone of Zorev’s model should include the transition zone of the actual stress distribution.

To examine the roughness of these regions, the profile of the used tool rake face needs to be recorded by using a surface roughness analyzer. This profile was examined along the line A-C (Figure 5.2). Experimental results indicated that the profile of the sliding region is smoother than the other regions including the original surface of the tool. It was also found that compared to other regions the profile of the sticking region had relatively large asperities (Figure 6.2).

The lengths of sticking, transition and sliding zones measured on the line A-C (Figure 5.2) are shown in Table 6.2. From this table, it is found that the ratio of (sliding plus transition length) to total contact length varies from about 1/3 to 1/2. It is assumed that this ratio for line A-B is also between 1/3 and 1/2. Hence, in this thesis, the value ‘5/12’ (the medium value) is employed as the ratio of sliding to total contact length for Zorev’s model.
Figure 6.2 A profile of tool rake face on line A-C for Figure 6.1(b)

Table 6.2 Sticking and sliding lengths of tool-chip contact area

(on line A-C in Figure 5.2)

<table>
<thead>
<tr>
<th>Cutting conditions</th>
<th>Sliding length (mm)</th>
<th>Transition length (mm)</th>
<th>Sticking length (mm)</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>160 m/min. 0.1 mm/rev, 5 degrees</td>
<td>0.130</td>
<td>0.118</td>
<td>0.448</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min. 0.2 mm/rev, 5 degrees</td>
<td>0.251</td>
<td>0.125</td>
<td>0.730</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min. 0.3 mm/rev, 5 degrees</td>
<td>0.289</td>
<td>0.244</td>
<td>0.644</td>
<td>BU</td>
</tr>
<tr>
<td>80 m/min. 0.3 mm/rev, 5 degrees</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>CH</td>
</tr>
<tr>
<td>120 m/min. 0.3 mm/rev, 5 degrees</td>
<td>0.22</td>
<td>0.2</td>
<td>0.53</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min. 0.3 mm/rev, 5 degrees</td>
<td>0.289</td>
<td>0.244</td>
<td>0.644</td>
<td>BU</td>
</tr>
<tr>
<td>160 m/min. 0.3 mm/rev, -5 degrees</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>CHS, CW</td>
</tr>
<tr>
<td>160 m/min. 0.3 mm/rev, 0 degree</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>BUS, CW</td>
</tr>
<tr>
<td>160 m/min. 0.3 mm/rev, 5 degrees</td>
<td>0.289</td>
<td>0.244</td>
<td>0.644</td>
<td>BU</td>
</tr>
</tbody>
</table>

Note: CH - Chipping at major cutting region observed
CHS - Small chipping at major cutting region observed
BU - Built-up edge observed
BUS - Small built-up edge observed
CW - Crater wear observed
In Figure 6.1(c), crater wear was observed on the tool rake face. This is confirmed by the profile of the tool rake face. The lengths of sticking, transition and sliding zones were not measured for a tool having such wear (Table 6.2). It should be noted that the lengths of sticking, transition and sliding zones for the tool in Figure 6.1(d) were also not measured due to unclear mark of tool-chip contact area on the tool rake face. This unclear mark may occur due to chipping at the cutting edge resulting in very small tool-chip contact area.

6.1.2 Shear Stress in Shear Zone Prediction

Using experimental data for fresh tools (Experiment 2), the shear stress on the shear plane can be estimated from the cutting force model as mentioned in Section 4.1.3. Employing these estimated shear stresses, the constants in the regression model suggested in Section 4.1.3 (Chapter 4) for predicting the shear stress on the shear plane of AISI 1045 can be estimated. This regression model can be expressed as:

\[
\tau_s = 1000.51 - 0.2745 \cdot V - 991.6104 \cdot f + 19.1307 \cdot \alpha
\]  
(6.1)

Examples of estimated shear stresses on shear zone from the cutting force model and from Equation (6.1) are presented in Figure 6.3. This figure indicates that the estimated shear stress by Equation (6.1) closely agrees with the estimated shear stress from cutting force model for small feed as well as low cutting speed. However, the difference between both estimated shear stresses ranges up to 14% at larger feeds and high speeds.
6.1.3 Forces and $AE_{rms}$ Estimation for Fresh Tools

Examples of three measured cutting forces (cutting force, feed force and radial force) for the fresh tool in Experiment 1 are shown in Figures 6.4 to 6.6. For medium and large feed rate, the mean measured cutting forces appear to increase when the feed rate increases. Cutting forces also increase when the cutting speed or rake angle declines. Similar results have also been observed by Brandt [107].

Lin et al. [42] observed that during oblique turning the shear stress of the workpiece material at low temperature is larger than the shear stress at higher temperature. Brandt [107] and Leshock & Shin [190] explained that the cutting temperature is a function of cutting conditions such as feed rate, depth of cut and cutting speed. They observed that the cutting temperature rises while cutting speed, feed rate or depth of cut increases.
Consequently, shear stress decreases when cutting speed, feed rate or depth of cut becomes larger. This is why cutting forces decrease as cutting speed increases. As the feed rate or depth of cut rises, however, the decrease in shear stress did not result in a decrease in forces. This is because the decrease in forces due to lower shear stress was nullified by the increase in forces causing by greater shear plane area due to larger feed or depth of cut.

For a feed rate of 0.1 mm/rev, however, cutting, feed and radial forces were found to increase as cutting speed rose in the range 80 to 140 m/min. A possible reason for this phenomenon is increase in flow stress of the material for some range of temperature. Macgregor and Fisher [191] observed that the flow stress of the SAE 1045, related to the average shear stress in the shear zone, normally decreased with the velocity-modified temperature influenced by cutting conditions including cutting speed. However, within the range of about 440K to 560K, the flow stress increased as the temperature rose. This increase in flow stress with greater velocity-modified temperature can result in larger forces with increase in cutting speed.

A comparison between measured forces and those predicted by using Equations (4.13), (4.14) and (4.15) is shown in Figures 6.7 and 6.8. In both cases, it was found that the predicted values of the three forces agree with the measured values. However, a small difference between predicted and measured forces can be observed. A reason for this difference is a small dissimilarity between real and specified tool geometry as observed in Table 6.9 in Section 6.5. The specified tool geometry was used for estimating cutting forces while the real forces related to the size of shear plane which depended on the
actual tool geometry. Therefore, this dissimilarity in tool geometry can result in a small difference between estimated and recorded forces.

Figure 6.4 Mean measured cutting forces for fresh tool

Figure 6.5 Mean measured feed forces for fresh tool
Figure 6.6 Mean measured radial forces for fresh tool

Another reason for this small disparity between measured and predicted forces is the difference between true stress distribution (having 3 stress zones) and Zorev’s stress distribution model (having 2 stress zones) adopted for development of Equations 4.13 to 4.15. This difference in real and assumed stress distributions can result in the dissimilarity in friction energy on the tool rake face which is one energy source of cutting forces. Another possible reason is a difference between the actual and estimated shear stress in the shear zone predicted from Equation 6.1.
Figure 6.7 Predicted and mean measured forces for fresh tool

Figure 6.8 Predicted and mean measured forces for fresh tool
The influence of the cutting conditions including cutting speed, feed and rake angle on \( A_{\text{E rms}} \) developed during turning with a new tool is shown in Figure 6.9. In this graph, it is observed that the mean \( A_{\text{E rms}} \) rises with higher cutting velocity. The mean \( A_{\text{E rms}} \) also rises with decreasing rake angle. However, the \( A_{\text{E rms}} \) was not found to be very sensitive to feed rate. Similar results were also observed by other researchers [54, 171] for orthogonal cutting processes.

Mean \( A_{\text{E rms}} \) increases with higher cutting speed because the strain rate on the shear plane is proportional to the dislocation formation rate [56] which is a source of AE signal, and is influenced by the cutting speed [56, 192]. The feed rate does not affect the \( A_{\text{E rms}} \) signals (Figure 6.9) because higher feed during the turning operation decreases the dislocation movement in the shear zone, resulting in lower acoustic emissions from this source. However, the increased tool-chip rubbing, caused by larger contact length at higher feeds, results in additional acoustic emission which nullifies the decrease of \( A_{\text{E rms}} \) in the shear zone [21, 56].

A higher rake angle causes the shear plane angle to increase [45], resulting in smaller shear plane area. However, a larger rake angle decreases the total contact length between the tool and the chip on the rake face [193] and thus reduces the interface area between the tool and the chip. Both the reduction of shear plane area and interface area on rake face result in lower AE signal for the 5-degree rake tool (Figure 6.9).
Figure 6.9 Mean measured $A_{E_{rms}}$ versus cutting speed

In the $A_{E_{rms}}$ model (Equation 4.24), the constants $C_2$, $C_3$ and $C_4$ are signal attenuation constants which depend on signal transmission losses between AE sources and the AE transducer located at the end of the tool holder. In a previous research, the magnitude of $C_2$ was found to be between 0.2-0.25 [61, 62] while $C_3$ and $C_4$ were assumed to be 1.0 [61]. This assumption for constants $C_3$ and $C_4$ is incorrect. In fact, they should be less than 1.0. This is because only part of the AE signal generated from the plastic deformation in the tool-chip contact zone and from the workpiece-flank contact zone is transmitted to the transducer via the cutting tool and the tool holder. Some of this signal is transmitted to the workpiece and the chip. Additionally, these constants should also include loss of AE signal due to transfer of signal from the tool holder to the socket.

An additional AE signal loss comes from the band pass filter employed in the AE amplifier. For example, a 100-300 kHz band pass filter was used in the tests and the AE
transducer could detect the signal in 10-700 kHz frequency range. As a result, the AE signals in 10-100 kHz and 300-700 kHz frequency bands were not included in the calculation of $\text{AE}_{\text{rms}}$. Hence, the magnitudes of constants $C_2$, $C_3$, and $C_4$ also depend on AE signal loss due to the band pass filter.

The constant $C_5$ corresponds to signal transmission losses between the chip breaking area and the transducer. As with constants $C_2$, $C_3$ and $C_4$, the magnitude of $C_5$ should be less than 1.0. The magnitude of proportionality constant $C_1$ depends on the setting of the AE gain. In this thesis, 40 dB was used as the AE gain. Therefore, the best way for evaluating constants $C_1$, $C_2$, $C_3$, $C_4$ and $C_5$ is from the experimental results. Three different tool holders were used in order to provide different rake angles in turning operations. Hence, the values of constants $C_1$ to $C_5$ are average values for the three tool holders employed during the tests.

Assuming $C_1 = 1.0$ [69] and using the results in Experiment 2 as well as the SAS® software, the constants $C_1$, $C_2$, $C_3$, $C_4$, and $C_5$ in Equation (4.24) can be estimated. These constants $C_2$, $C_3$, $C_4$ and $C_5$ were found to be 0.0000066, 0.0001536, 0.000106 and 0.00000113 respectively. Using these constants in Equation (4.24), the $\text{AE}_{\text{rms}}$ was estimated from cutting conditions, material properties, and the number of chip fractures. These predicted values of $\text{AE}_{\text{rms}}$ and those measured in the experiment for a fresh tool insert are plotted in Figures 6.10 and 6.11.
Figure 6.10 A comparison between predicted and mean measured $AE_{rms}$ for fresh tool

Figure 6.11 A comparison between predicted and mean measured $AE_{rms}$ for fresh tool
Figures 6.10 and 6.11 indicate that the predicted $AE_{rms}$ closely agrees with the measured values. In both figures, however, a small disparity between measured and predicted $AE_{rms}$ can be observed. Possible reasons for this disparity are (i) difference between real and assumed stress distributions on the tool rake face, (ii) dissimilarity between actual and estimated magnitude of shear stress on the shear plane, and (iii) difference between the actual and specified geometries of the tool insert.

### 6.1.4 Flank and Crater Wear Geometry

Results of Experiment 1 indicated that a maximum depth of crater wear was usually found on the third trace line (0.6 mm from the datum). The shape of this crater wear is similar to an arc of a circle (Figures 4.1c and 4.1d). The shape of flank wear and notch are also similar to the wear shown in Figure 2.1. Normally, it was observed that the shape of worn tools on the third trace line is similar to Figures 4.1(c) and (d). A few worn tools were observed to have a shape shown in Figure 4.1(e). This is because worn tools usually broke due to large flank and crater wear before the shape of cutting edge became as shown in Figure 4.1(e).

The shape of the cutting edge, shown in Figure 4.1(e), is a result of significant wear at the cutting edge. The geometry of the deteriorated cutting edge was found to look like a semi circle (Figure 6.12). For worn tools having cutting edge deterioration, large flank and crater wear were always observed.

The first, second, fourth and fifth trace lines resembled the shapes of worn tools are as shown in Figures 4.1(c) and (d). This means that the wear rate at the cutting edge of
these four trace lines was less than the wear rate at the third line. Due to the fact that the crater wear rate is influenced by the tool rake face temperature, the temperature distribution on tool-chip contact area is one reason for the different wear rate at each trace line. The maximum depth of crater wear usually was observed on the third trace line. This is possibly because the third trace passes through the area having the highest temperature on the tool rake face.

As mentioned above, the shapes of worn tools observed in this thesis are usually as shown in Figure 4.1(c) and 4.1(d). Therefore, the assumption for the shape of worn tool in Figure 4.1(c) to represent the shape of all worn tools having flank and crater wear appears to be reasonable.

Figure 6.12 The geometry of cutting edge deterioration and crater wear on the third trace line (0.6 mm from the datum)
In the experiments, it was found that the tool insert usually broke if an insert having large flank and crater wear was allowed to continue to do turning. A major reason for this phenomenon is the greater stress concentration occurring at the neck between both flank and crater wear. This greater stress concentration results from two main causes: (i) an increase in cutting forces due to ploughing force at the deteriorated cutting edge and forces at flank wear land and (ii) a decrease in tool cross section area between flank and crater wear due to wear development.

6.1.5 Chip Fracture

In oblique turning operations, chip fracture can occur due to many causes including impact of chip on workpiece for orthogonal cutting, or impact of chip on tool flank face due to the use of insert with chip breaker. During this research, however, chip fracture occurred from the impact of the chip on tool holders (Figures 4.3 and 6.13) or the impact of the chip on tool flank face due to relatively smaller chip up-curl radius caused by flank and crater wear. Using a Nikon V12 profile projector to examine the fractured chips, it was found that chips broke at a neck between notches as shown in Figure 6.14. A major cause for the fracturing of the chip at the neck is the high stress concentration in the chip due to a relatively small cross section area.

The experimental results indicated that chips were usually unbroken (ribbon chips and turbular chips) when cutting with a fresh tool, but chips easily fractured when worn tools were employed. Such fractures occurred due to an impact of the chip on the tool holder (for large chip up-curl radius) or on the tool flank face (for small chip up-curl radius). This is because the flank wear increases chip breakability via a reduction of
effective rake angle and an increase in the temperature difference due to larger thickness of chips [144, 194]. At the same time, crater wear also increases chip breakability through the increase in chip up-curl, which decreases the up-curl radius [144]. However, chip breakability is also influenced by cutting conditions which affect the chip flow direction through the radius of up-curl and the radius of side-curl [143, 144]. As a result, chips easily fractured at low cutting velocity.

Figure 6.13 Chip fracture during turning operations on lathe machine

The fractured chips collected during the experiments could be classified in 10 categories: (i) Tubular chips - large diameter, (ii) Tubular chips - snarled, (iii) Ribbon chips - long, (iv) Ribbon chips - snarled, (v) Cork-screw chips - broken long, (vi) Cork-screw chips - medium, (vii) Cork-screw chips - short, (viii) Arc chips - side curl, (ix) Toothed-edge chips - long, and (x) Toothed-edge chips - short. These chip shapes were grouped based on the chip shape classification presented in a Machining Handbook [195]. From the results in Table 6.3, it was confirmed that flank and crater wear cause chip curling resulting in chip fracture.
It should be noted that little material concerning properties of chip is available in the literature. However, its properties such as shear and normal strength are different from the properties of workpiece. This is because a chip is a deformed fragment of the workpiece.

Table 6.3 Example of chips collected during the Experimentation

<table>
<thead>
<tr>
<th>Speed (m/min)</th>
<th>Cutting conditions</th>
<th>Rake angle (degree)</th>
<th>Flank wear (mm)</th>
<th>Crater wear (mm)</th>
<th>Chip pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>160</td>
<td>0.1</td>
<td>-5</td>
<td>0.177</td>
<td>0.045</td>
<td>ii, iv, vi</td>
</tr>
<tr>
<td>160</td>
<td>0.3</td>
<td>-5</td>
<td>0.177</td>
<td>0.045</td>
<td>viii, ix, x</td>
</tr>
<tr>
<td>160</td>
<td>0.1</td>
<td>0</td>
<td>0.177</td>
<td>0.045</td>
<td>iv, vi, vii</td>
</tr>
<tr>
<td>100</td>
<td>0.3</td>
<td>-5</td>
<td>0.177</td>
<td>0.045</td>
<td>vii, ix, x</td>
</tr>
<tr>
<td>100</td>
<td>0.3</td>
<td>5</td>
<td>0.177</td>
<td>0.045</td>
<td>iii, vi, vii, ix</td>
</tr>
</tbody>
</table>

6.1.6 Prediction of Forces and $AE_{rms}$ for Worn Tools

In the present research, influences of flank and crater wear on the three forces (cutting, feed and radial forces) as well as $AE_{rms}$ can be observed from the results of Experiment
2. Figure 6.15 shows that forces increase while flank wear increases, and forces decrease with larger crater wear. There is a significant effect of flank and crater wear on the force signals. The reason for this rise of forces with higher flank wear is shear and normal stress on the wear land. Shear stress on the flank face causes an increase in cutting force, and normal stress on the flank face causes an increase in feed and radial forces. One major effect of crater wear on the tool geometry is that the rake angle becomes more positive value. This more positive rake angle results in lower normal and shear stresses on tool rake face. Hence, these three forces decrease with development of crater wear.

However, it should be noted that flank wear also indirectly affects the force and $AE_{\text{rms}}$ signals through cutting temperature. Olberts [194] found that a drop in tool-chip interface temperature (up to 100 F) occurred as the wear land increased from zero to 0.005 inch. When the wear land further increased to 0.010 inch, the interface temperature rose slightly. Similar results were also observed in Muraka, Barrow and Hinduja's research [196]. A reason for the drop in the tool-chip temperature is extensive conduction of heat away from the tool flank by the rubbing workpiece shoulder [196]. This drop in the temperature on the tool rake face can result in a change in the friction coefficient on the tool rake face. This change in the friction coefficient influences both force and $AE_{\text{rms}}$ signals via energy consumption on the sliding zone of the tool rake face.

When both flank and crater wear develop on the tool insert, the cutting action becomes more complex. In some cases, it was observed that force signals did not increase much for large flank wear because of the effect of crater wear. As mentioned earlier, cutting
edge deterioration was found for tool inserts having large flank and crater wear. A ploughing force acting on the new surface of the cutting edge (due to cutting edge deterioration) causes forces to increase (case 5 in Figure 6.15).

A comparison between the measured forces and those predicted by Equations (4.13) to (4.15) for worn tools is shown in Figures 6.16 to 6.18. For a feed rate of 0.1 mm/rev, experimental results indicate that at lower speed there is a close agreement between the predicted and measured values (Figure 6.16). However, at larger speeds the measured values of forces are slightly higher than the predicted ones. For feed rates of 0.2 and 0.3 mm/rev, it was found that the predicted forces agree well with the measured values for all cutting speeds (Figures 6.17-6.18).

The variation of $AE_{rms}$ with cutting speed for six worn tools is shown in Figure 6.19. The mean $AE_{rms}$ increases with higher cutting speed and larger flank wear and decreases with larger crater wear. The higher $AE_{rms}$ for larger flank wear appears to have been caused by an increase in energy consumption due to rubbing or friction at the interface between the workpiece and the tool.

The $AE_{rms}$ predicted by Equation (4.24) and that measured in the Experiment 2 for a worn tool is shown in Figures 6.20 to 6.22. The results indicate that the predicted $AE_{rms}$ agrees closely with the measured $AE_{rms}$ for the worn tool.
130

feed = 0.3 mm/rev and rake angle = 5 deg

- fresh (FW = 0 mm, CW = 0 mm)
- case 1 (FW = 0.085 mm, CW = 0 mm)
- case 2 (FW = 0.141 mm, CW = 0 mm)
- case 3 (FW = 0.163 mm, CW = 0 mm)
- case 4 (FW = 0.115 mm, CW = 0.025 mm)
- case 5 (FW = 0.131 mm, CW = 0.065 mm)
- case 6 (FW = 0.177 mm, CW = 0.045 mm)

Note: Cutting edge deterioration was observed in Case 5

Figure 6.15 Mean measured cutting forces for worn tool

Figure 6.16 Predicted and mean measured forces for worn tool having flank wear
Feed rate = 0.2 mm/rev, rake angle = 0 degree and depth of cut = 1 mm

Figure 6.17 Predicted and mean measured forces for worn tool having flank and crater wear

Feed rate = 0.3 mm/rev, rake angle = -5 degrees and depth of cut = 1 mm

Figure 6.18 Predicted and mean measured forces for worn tool having flank and crater wear (cutting edge deterioration)
At lower cutting speeds and small feed rate (Figure 6.20), a built-up edge developed during the turning operation due to low temperature on shear plane and tool-chip contact. This built-up edge appears to change the geometry of cutting tool. A ploughing process occurring due to built-up edge and friction between the built-up edge and new workpiece surface cause an increase in $AE_{rms}$. Similar results were found by Hutton and Yu [67].
**Figure 6.20** Predicted and mean measured $AE_{rms}$ for worn tool having flank wear

**Figure 6.21** Predicted and mean measured $AE_{rms}$ for worn tool having flank and crater wear
Feed rate = 0.3 mm/rev. rake angle = -5 degrees, depth of cut = 1 mm. FW = 0.131 mm and CW = 0.065 mm

Figure 6.22 Predicted and mean measured $AE_{rms}$ for worn tool having flank and crater wear (cutting edge deterioration)

During the growth of wear on the tool, it has been assumed that the width of major, nose and minor flank wear grows uniformly. However, the observations indicate no development of minor flank wear when the major flank wear is small. This therefore possibly results in lower $AE_{rms}$ compared to the predicted $AE_{rms}$ for small flank wear values. However, at larger values of flank wear, the difference between the major and minor flank wear width is small and hence the predicted and measured $AE_{rms}$ values have a close agreement.
6.2 FLANK AND CRATER WEAR ESTIMATION BY QUANTITATIVE MODELS

As mentioned earlier, the average width of tool wear for a worn tool having only flank wear can be estimated by using both Equations 4.27 and 4.31. However, for tools having flank and crater wear, both of these can be estimated by employing Equations (4.3), (4.27) and (4.31) respectively as detailed in the computer program developed in Section 4.2.3 (Figure 4.9). Table 6.4 shows a comparison between measured and predicted tool wear.

The results in Table 6.4 indicate that Equations 4.27 and 4.31 estimate the average width of flank wear fairly accurately. However, a small difference between the estimated and measured values is also observed. A dissimilarity between the actual and specified geometry of tool inserts is one cause of this difference in values. This is because both equations employed an increase in mean forces and $AE_{rms}$ to estimate flank wear. However, such a value also included a difference in the value between estimated and actual signals of the fresh tool. As a result, a predicted flank wear will be greater than a real size if the actual forces and $AE_{rms}$ for fresh tool exceed their predicted values. On the other hand, the estimated flank wear is smaller than the actual in case of smaller measured forces and $AE_{rms}$ of fresh tool compared with their predicted values.

As small flank wear develops, the temperature on the tool rake face decreases significantly [194, 196]. This decrease in tool rake face temperature can result in the development of a built-up layer on the rake face (near the cutting edge). This built-up
layer causes greater forces and $AE_{rms}$ which in turn cause prediction of higher flank wear. This is another possible reason for the difference between measured and predicted wear for tools having only flank wear.

The sizes of flank and crater wear estimated by employing the computer algorithm shown in Figure 4.9 are also presented in Table 6.4. The average accuracy of wear estimation for tools having both flank and crater wear is slightly lower compared with the accuracy of flank wear estimation in case of tools having only flank wear. The geometry of crater wear, in fact, increases the positive rake angle of tool resulting in a difference in the pattern of shear and normal stress distributions between rake face having crater wear and rake face with no wear. In the absence of relevant data, however, the change in stress distributions due to the crater wear was assumed to be the same as with the change due to an increase in rake angle. This assumption is one possible cause of the inaccuracy.

### Table 6.4 Measured and estimated tool wear

(speed = 160 m/min, feed = 0.3 mm/rev, rake angle = 0 degree)

<table>
<thead>
<tr>
<th>Insert number</th>
<th>Mea. flank Wear (mm)</th>
<th>Mea. crater wear (mm)</th>
<th>Est. flank wear (mm)</th>
<th>Est. crater wear (mm)</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.004</td>
<td>-</td>
<td>Equation 4.27</td>
</tr>
<tr>
<td>2</td>
<td>0.085</td>
<td>0</td>
<td>0.013</td>
<td>-</td>
<td>Equation 4.31</td>
</tr>
<tr>
<td>3</td>
<td>0.141</td>
<td>0</td>
<td>0.066</td>
<td>-</td>
<td>Equation 4.27</td>
</tr>
<tr>
<td>4</td>
<td>0.163</td>
<td>0</td>
<td>0.126</td>
<td>-</td>
<td>Equation 4.31</td>
</tr>
<tr>
<td>5</td>
<td>0.115</td>
<td>0.025</td>
<td>0.135</td>
<td>0.037</td>
<td>Figure 4.9</td>
</tr>
<tr>
<td>6</td>
<td>0.131</td>
<td>0.065</td>
<td>0.144</td>
<td>0.088</td>
<td>Figure 4.9</td>
</tr>
<tr>
<td>7</td>
<td>0.177</td>
<td>0.045</td>
<td>0.193</td>
<td>0.041</td>
<td>Figure 4.9</td>
</tr>
</tbody>
</table>
6.3 NEW PARAMETERS FOR TOOL WEAR MONITORING

6.3.1 The Frequency Distribution of Energy of Force Signals

The frequency distributions of the three energies determined from cutting, feed and radial forces by using the PSD method are shown in Figure 6.23. These frequency distributions were estimated by using the specific program developed earlier (Computer program in Appendix B). An examination of Figure 6.23 indicates that the mean amplitude of frequency distribution for energy consumption of cutting force is highest. Furthermore, the examination also indicates that frequency distribution patterns of these three-energy consumption are different.

Figure 6.23 The frequency distribution of energy consumption for fresh tool at 160 m/min, 0.1 mm/rev and -5 degrees
6.3.2 The Influence of Cutting Conditions on the Total Energy and the Total Entropy of Forces

Figures 6.24 and 6.25 show the influence of cutting conditions on the total energy of force signals. The total energy of all the three forces was observed to increase with larger feed rate. Below cutting velocity of 140 m/min, the total energy of forces increases as cutting speed rises. However, the total energy of forces does not appear to vary much when cutting speed is above 140 m/min.

![Figure 6.24 The total energy of force signals versus cutting conditions](image)

Figure 6.24 The total energy of force signals versus cutting conditions
Figure 6.25 The total energy of force signals versus cutting conditions

The term of feed rate does not appear in Equations (4.32)-(4.35); however, it affects the total energy of forces through force signals. Larger feed rate results in greater shear plane area, so more energy (higher forces) will be consumed during cutting process. Therefore, the total energy of forces increases with larger feed rate as shown in Figure 6.24.

The total energy of force signals is influenced directly by 4 factors: cutting velocity and three forces (cutting, feed and radial forces). The increase of the total energy of forces is related to the rise in cutting velocity (Equations 4.32, 4.33 and 4.34). However, cutting forces decrease with greater cutting speed (Figure 6.26) due to lower shear stresses on the shear plane. Thus, cutting speed has a dual effect on the total energy of forces. For example, in Figure 6.24 at cutting speed below 140 m/min, the effect of the increase of cutting velocity was higher than the effect of the decrease in three forces; so, the total
energy grows with high cutting speed. On the other hand, at cutting speed above 140 m/min, the effect of lower forces was stronger than the effect of higher velocity; so, the total energy of force signals appears to slightly fall.

The influence of rake angle on the total energy of forces is presented in Figure 6.25. Previous researchers [48] indicated that the higher rake angle decreases the shear plane area and hence cutting forces will drop. Thus, the total energy of forces should decrease as rake angle increases.

Figure 6.26 Mean cutting force versus cutting conditions
Figure 6.27 Mean cutting force versus cutting conditions

Figure 6.28 The total entropy of force signals versus cutting conditions
The experimental results in Figure 6.25 indicate that the total energy of forces for 5 degrees rake was the lowest for all cutting velocities; however, the total energy of forces for 0 and -5 degrees rake were similar for all cutting speeds. This is because of the similar cutting forces for 0 and -5 degree rake angles (Figure 6.27).

The effect of cutting conditions on the total entropy of force signals is shown in Figures 6.28 and 6.29. An investigation of both figures indicates that the cutting conditions do not affect to the total entropy of forces. Although the magnitude of PSD of these energies change with different cutting conditions, the pattern of normalized amplitude does not vary much resulting in similar total entropy of forces for various cutting conditions.
The results indicate that the cutting conditions affect the total energy and the total entropy of forces in different ways. These effects can be summarized and shown in Table 6.5.

Table 6.5 The comparison of the effect of cutting conditions on mean cutting forces, mean $AE_{\text{rms}}$, total energy of forces and total entropy of forces

<table>
<thead>
<tr>
<th>Cutting conditions</th>
<th>Cutting force</th>
<th>Feed force</th>
<th>Radial force</th>
<th>$AE_{\text{rms}}$</th>
<th>Total energy of force signals</th>
<th>Total entropy of force signals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase in:</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>Inc</td>
<td>Inc (below 140 m/min)</td>
<td>NS</td>
</tr>
<tr>
<td>- Cutting velocity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Dec (above 140 m/min)</td>
<td>NS</td>
</tr>
<tr>
<td>- Feed rate</td>
<td>Inc</td>
<td>Inc</td>
<td>Inc</td>
<td>NS</td>
<td>Inc</td>
<td>NS</td>
</tr>
<tr>
<td>- Rake angle</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>should Dec</td>
<td>NS</td>
</tr>
</tbody>
</table>

Note: Inc = increase, Dec = decrease, NS = not sensitive

6.3.3 The Tool Wear and the New Parameters

The total energy of forces increases when flank wear grows (Figures 6.30 and 6.31). However, flank wear does not affect to the total entropy of forces as shown in Figures 6.32 and 6.33. The higher energy consumption due to the friction between tool insert and workpiece on flank wear land is a reason for this increase in total energy of forces as flank wear grows.

An examination of Figure 6.30 indicates that the total energy of cutting forces for tool with flank wear only (case 3) is higher than the total energy of forces for tool with both the flank and crater wear (case 6). It appears that the crater wear of the tool reduces the magnitude of the total energy. However, particular shapes of crater wear can increase the total energy of forces. For example the total energy of cutting force for case 5 is higher than case 2 at the same cutting conditions (Figure 6.31).
Figures 6.32 and 6.33 indicate that the total entropy of force signals is not influenced by both flank and crater wear. The possible reason is that the progressive tool wear changes only the magnitude of the energy consumption in the frequency domain, while the pattern of the normalized amplitude does not vary much.

Note: Cutting edge deterioration was observed in Case 5

**Figure 6.30 The total energy of force signals versus tool wear**
Note: Cutting edge deterioration was observed in Case 5

**Figure 6.31 The total energy of force signals versus tool wear**

Note: Cutting edge deterioration was observed in Case 5

**Figure 6.32 The total entropy of force signals versus tool wear**
Note: Cutting edge deterioration was observed in Case 5

**Figure 6.33** The total entropy of force signals versus tool wear

Figures 6.34 and 6.35 show typical geometry of worn tools (cases 4 to 6) during cutting tests. Main difference between worn tools of cases 4 and 6 and worn tool in case 5 is that the flank wear of tool in case 5 deteriorates the cutting edge, while flank wear of tool in cases 4 and 6 does not damage the cutting edge.

**Figure 6.34** Worn tool geometry during turning (cases 4 and 6)
Figure 6.35 Worn tool geometry during turning (case 5)

Usually, the energy consumption during metal cutting decreases with the occurrence of crater wear due to increase in effective rake angle [38, 68, 171] as well as decrease in tool-chip interfacing area on rake face [197]. Consequently, reduced cutting forces and $AEm$ are generated as the crater wear grows.

Table 6.6 The effect of tool wear on mean cutting forces, mean $AEm$, total energy of forces and total entropy of forces

<table>
<thead>
<tr>
<th>Tool wear</th>
<th>Cutting force</th>
<th>Feed force</th>
<th>Radial force</th>
<th>$AEm$</th>
<th>Total energy of force signal</th>
<th>Total entropy of force signal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase in:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Flank wear (case 1-3)</td>
<td>Inc</td>
<td>Inc</td>
<td>Inc</td>
<td>Inc</td>
<td>Inc</td>
<td>NS</td>
</tr>
<tr>
<td>- Crater wear (case 4, 6)</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>NS</td>
</tr>
<tr>
<td>- Crater wear (case 5) for zero and positive rake angle</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>Dec</td>
<td>NS</td>
</tr>
<tr>
<td>- Crater wear (case 5) for negative rake angle</td>
<td>Inc</td>
<td>Inc</td>
<td>Inc</td>
<td>Inc</td>
<td>Inc</td>
<td>NS</td>
</tr>
</tbody>
</table>

Note: Inc = increase, Dec = decrease, NS = not sensitive

However, in some specific cases, the occurrence of crater wear increases the level of $AEm$ signal such as in Figure 6.35(a). This Figure shows that the flank wear extends
into crater region resulting in higher negative rake angle [68] which causes the effective rake angle to be come more negative resulting in higher $AE_{rms}$. Table 6.6 summarizes the trends observed in the present research for mean forces, mean $AE_{rms}$, total energy and total entropy of forces when tool wear grows.

6.3.4 Chip Fracture and the New Parameters

During the experimentation, the chip fracture was found to occur at some cutting conditions especially when turning with worn tools with both flank and crater wear at low velocity as also observed by previous researchers [143, 144]. Flank wear increases chip breakability via reduction of effective rake angle [144] which changes chip flow direction and reduces the chip-up curl radius. Another reason of increase in chip breakability with flank wear is the behavior of chip as a thermal bi-metallic spring. The greater temperature difference between upper and lower side of chip, caused by energy consumption on flank wear land, results in the chip to curl to a smaller radius due to higher thermal stresses [144].

The crater wear increases chip breakability through the increase of chip up-curl (decrease of up-curl radius) [144]. When chip radius is reduced, it will have a greater tendency to hit the tool holder resulting in chip fracture.

In present research, forces and $AE_{rms}$ signals were filtered with 140 kHz low pass filter and 100-300 kHz band pass filters respectively. Typical feed force and $AE_{rms}$ signals with chip fracture are shown in Figures 6.36 and 6.37. Figures 6.38 and 6.39 show $AE_{rms}$ signals with no chip fracture. An examination of these Figures indicates that chip
fracture affected $AE_{rms}$ signal, but it did not influence the feed force in time domain. However, it had a small effect on feed force in frequency domain. Figures 6.40 and 6.41 indicate that the magnitude of cutting and radial forces is not influenced by chip breaking. This is because the chip fracture causes forces to peak in some frequencies only. This influence of chip breaking on both cutting and radial forces is also similar to that on feed force (Figure 6.36). Similar results for influence of chip fracture on $AE_{rms}$ and forces were also found in Lan and Dornfeld's experiment [61].

The occurrence of chip fracture can be easily detected through $AE_{rms}$ signal in frequency domain [117, 198] as well as time domain [61] because the released strain energy due to chip breaking influences the amplitude of AE signal significantly. However, chip breaking can also be detected via force signals in frequency domain [162, 173], but it cannot be identified in time domain (Figure 6.36). This is because the energy consumed to break the chip is very small compared with the energy on the shear zone, tool rake face and flank wear land.
Figure 6.36 The feed force signal of worn tool with chip fracture (flank wear = 0.141 mm)

Figure 6.37 The $A_{E_{rms}}$ signal of worn tool with chip fracture (flank wear = 0.141 mm)
Speed = 160 m/min, feed = 1 mm/rev and rake angle = 5 deg

Figure 6.38 The $A_{E_{rms}}$ signal of fresh tool without chip fracture

Speed = 160 m/min, feed = 0.3 mm/rev and rake angle = -5 deg

Figure 6.39 The $A_{E_{rms}}$ signal of worn tool without chip fracture (flank wear = 0.141 mm)
Figure 6.40 The cutting force signal of worn tool with chip fracture (flank wear = 0.141 mm)

Figure 6.41 The radial force signal of worn tool with chip fracture (flank wear = 0.141 mm)
6.3.5 Radial to Feed Force Ratio and Tool Wear

Experimental results of this research indicate that the radial-feed force ratio (Fr/Ff) for fresh tools is normally below 0.8. However, the Fr/Ff ratio observed by authors was about 1 or higher for worn tools (Table 6.7). The reason for this difference in Fr/Ff values is possibly due to greater sensitivity of radial force to a changed tool insert shape resulting from flank wear or crater wear compared to feed force.

Table 6.7 The radial to feed force ratio of fresh and worn tools for a depth of cut 1 mm

<table>
<thead>
<tr>
<th>Cutting conditions</th>
<th>Fresh tool</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Worn tool</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
<th>Case 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>60 m/min, 0.1 mm/rev and -5 degrees</td>
<td>0.64</td>
<td>0.62</td>
<td>1.30</td>
<td>1.17</td>
<td>1.26</td>
<td>1.01</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>120 m/min, 0.1 mm/rev and -5 degrees</td>
<td>0.66</td>
<td>1.11</td>
<td>1.16</td>
<td>0.86</td>
<td>1.14</td>
<td>0.94</td>
<td>0.88</td>
<td></td>
</tr>
<tr>
<td>160 m/min, 0.1 mm/rev and -5 degrees</td>
<td>0.53</td>
<td>1.07</td>
<td>1.01</td>
<td>0.79</td>
<td>1.07</td>
<td>0.89</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td>60 m/min, 0.3 mm/rev and -5 degrees</td>
<td>1.03</td>
<td>1.25</td>
<td>1.25</td>
<td>1.08</td>
<td>1.36</td>
<td>1.21</td>
<td>1.39</td>
<td></td>
</tr>
<tr>
<td>120 m/min, 0.3 mm/rev and -5 degrees</td>
<td>0.76</td>
<td>1.11</td>
<td>1.05</td>
<td>0.94</td>
<td>1.26</td>
<td>1.10</td>
<td>1.28</td>
<td></td>
</tr>
<tr>
<td>160 m/min, 0.3 mm/rev and -5 degrees</td>
<td>0.66</td>
<td>1.12</td>
<td>0.99</td>
<td>0.92</td>
<td>1.57</td>
<td>1.05</td>
<td>1.22</td>
<td></td>
</tr>
<tr>
<td>60 m/min, 0.1 mm/rev and 5 degrees</td>
<td>0.76</td>
<td>0.66</td>
<td>1.14</td>
<td>1.16</td>
<td>1.20</td>
<td>1.27</td>
<td>1.48</td>
<td></td>
</tr>
<tr>
<td>120 m/min, 0.1 mm/rev and 5 degrees</td>
<td>0.72</td>
<td>1.46</td>
<td>1.55</td>
<td>0.98</td>
<td>1.06</td>
<td>1.12</td>
<td>1.37</td>
<td></td>
</tr>
<tr>
<td>160 m/min, 0.1 mm/rev and 5 degrees</td>
<td>0.77</td>
<td>1.47</td>
<td>1.40</td>
<td>0.93</td>
<td>0.99</td>
<td>0.98</td>
<td>1.30</td>
<td></td>
</tr>
</tbody>
</table>

With this particular geometry of tool holder (Kennametal CSBPR-2525M12) and tool insert (Kennametal K420) for a depth of cut 1 mm, it was found that the length of major cutting region is smaller than the length of nose cutting region, and the minor cutting region has significant length compared with the length of major cutting region. Due to this, the normal stress on the wear land influences the level of forces in the radial direction more than in the feed direction.

The effect of crater wear on the geometry of tool rake face was examined by previous researchers [38, 68, 171] who indicated that crater wear causes a change in the rake
angle. The experimental results of Usui and Hirota [48] show that the changes in the rake angle have greater influence on radial force compared to feed force. Hence, crater wear influences radial force more than feed force. An examination of the Table 6.7 thus indicates that the ratio of radial and feed force can be used as a criterion to separate fresh tool from worn tool.

6.4 DETECTION AND ESTIMATION OF CHIP FRACTURE

As explained in Section 4.4, chip fracture causes a peak in AE\text{rms} signal. During turning for each cutting condition, however, an investigation of sampled chips indicated that there was a variation in chip geometry and chip size. This variation also results in a non-uniform chip breaking period which can be observed in the AE\text{rms} signal as well. Collected chips were found to be of three types: arc, short screw and medium screw - the shapes suggested by Fang and Jawahir [199].

6.4.1 The Signal Sampling Frequency and Chip Fracture

As mentioned in experiment section, two different sampling frequencies of 2.5 and 7.5 kHz were employed for signal collection (Figures 6.42 and 6.43). The experimental results indicate that peaks of AE\text{rms}, representing chip fracture events can be observed in signals with 2.5 kHz as well as 7.5 kHz sampling frequency. Chip fracture events indicated by peaks in AE\text{rms} signal is confirmed by comparing time between peaks of AE\text{rms} with the time consumed for cutting that produces chips having length similar to the sampled chip. This comparison will be discussed in the following sections (AE\text{rms} filtering & Estimation of average chip fracture frequency).
speed = 140 m/min, feed = 0.1 mm/rev, rake angle = -5 degrees, depth of cut = 1 mm, sampling frequency = 2.5 kHz and sampling period = 0.6 sec

Figure 6.42 $AE_{rms}$ with sampling frequency 2.5 kHz

---

speed = 140 m/min, feed = 0.1 mm/rev, rake angle = -5 degrees, depth of cut = 1 mm, sampling frequency = 7.5 KHz and sampling period = 0.6 sec

Figure 6.43 $AE_{rms}$ with sampling frequency 7.5 kHz
Figure 6.43 indicates sharp peaks and drops in $AE_{\text{rms}}$ collected at high sampling frequency. Such peaks and drops in $AE_{\text{rms}}$ were caused by minor fracture in tool cutting edge observed after the cut. Similar observations have also been made by previous researchers in raw AE signal [200, 201].

### 6.4.2 $AE_{\text{rms}}$ Filtering

In the present research, four different running average filters (10, 20, 50 and 100-point running average) were used to filter the sampled $AE_{\text{rms}}$ signal (Figures 6.44, 6.45 and 6.46). These running average filters were selected because they can make the $AE_{\text{rms}}$ variation in trend significantly clear. The experimental results indicate that the 20-point running average filter is the most suitable for filtering the sampled $AE_{\text{rms}}$ signal. It was also found that the mean and standard deviation (SD) of time spans between consecutive peaks of filtered $AE_{\text{rms}}$ in Figure 6.45 (mean = 0.0171 & SD = 0.013) was close to the mean and SD of chip production time for sampled chips in Figure 6.48 (mean = 0.0192 & SD = 0.011). Hence, the number of chip fracture can be counted directly from the plotted $AE_{\text{rms}}$ with a suitable running average filter.
Figure 6.44 $AE_{\text{rms}}$ with 10-point running average filter

Figure 6.45 $AE_{\text{rms}}$ with 20-point running average filter
speed = 80 m/min, feed = 0.1 mm/rev, rake angle = -5 degrees and depth of cut = 1 mm

6.4.3 Chip Fracture Detection

The experimental results, shown in Section 6.3, indicate that the $AE_{\text{rms}}$ of turning process with chip fracture has a higher SD value compared to the $AE_{\text{rms}}$ of turning process without chip fracture. This phenomenon is caused by increase in the band width of $AE_{\text{rms}}$ due to peaks of $AE_{\text{rms}}$ which are caused by the chip fracture. A small change in mean value of $AE_{\text{rms}}$ also occurs. Hence, the change in value of SD of $AE_{\text{rms}}$ over mean of $AE_{\text{rms}}$ can be used as the index to detect the occurrence of chip fracture. Table 6.8 shows the comparison between SD over mean of $AE_{\text{rms}}$ of oblique cutting with chip fracture and without chip fracture. The experimental results indicate that normally chip breakages will be observed if SD over mean of $AE_{\text{rms}}$ is higher than 0.012.

Figure 6.46 $AE_{\text{rms}}$ with 50-point running average filter
Table 6.8 Examples of the comparison between SD/mean of \( \text{AE}_{\text{rms}} \) with and without chip fracture

<table>
<thead>
<tr>
<th>Cutting conditions</th>
<th>Flank wear (mm)</th>
<th>Crater wear (mm)</th>
<th>SD/mean of ( \text{AE}_{\text{rms}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turning without chip breakages</td>
<td>0</td>
<td>0</td>
<td>0.010</td>
</tr>
<tr>
<td>120 m/min, 0.1 mm/rev, 5 deg rake</td>
<td>0</td>
<td>0</td>
<td>0.011</td>
</tr>
<tr>
<td>140 m/min, 0.1 mm/rev, 5 deg rake</td>
<td>0</td>
<td>0</td>
<td>0.009</td>
</tr>
<tr>
<td>Turning with chip breakages</td>
<td>0.131</td>
<td>0.065</td>
<td>0.020</td>
</tr>
<tr>
<td>120 m/min, 0.1 mm/rev, 5 deg rake</td>
<td>0.131</td>
<td>0.065</td>
<td>0.017</td>
</tr>
<tr>
<td>140 m/min, 0.1 mm/rev, 5 deg rake</td>
<td>0.131</td>
<td>0.065</td>
<td>0.013</td>
</tr>
</tbody>
</table>

6.4.4 Estimation of Average Chip Fracture Frequency

As explained earlier (\( \text{AE}_{\text{rms}} \) filtering), the number of chip breakages occurring during sampling period can be counted directly from the plot of filtered \( \text{AE}_{\text{rms}} \) with the 20-point running average filter. However, this number of chip fracture events can also be estimated by the expected frequency of filtered \( \text{AE}_{\text{rms}} \) in the frequency domain (Equation 4.51). In this research, three \( \text{AE}_{\text{rms}} \) thresholds were employed to estimate the number of chip fracture events. These thresholds are 1/3, 1/2 and 3/4 of maximum \( \text{AE}_{\text{rms}} \) in frequency band 20 to 250 kHz. It was found that the most suitable threshold is 1/3 of maximum \( \text{AE}_{\text{rms}} \).

Figures 6.47 and 6.48 show the cutting time used to produce sample fractured chips and the cutting time estimated by using the expected frequency (Equation 4.51). The comparison between average chip production time determined from chip fracture frequency, estimated by Equation 4.51, and calculated from the bar chart (Figures 6.47 and 6.48) indicates a minor difference between the two. Hence, the expected frequency can be used to predict the number of chip breakages which occurs during the sampling period.
Figure 6.47 The histogram of chip production for worn tool

Figure 6.48 The histogram of chip production for worn tool
6.5 FUZZY NEURAL NETWORK FOR TOOL WEAR ESTIMATION

6.5.1 Variation in Mean Force and AE_{rms} Signals

Figures 6.49 to 6.52 show the variation of mean AE_{rms} and three forces at the beginning of cut for four new K420 inserts (Experiment 4). The experimental results indicated a variation in mean AE_{rms} up to ±17.64 percent for fresh tool number 1-4 (Figure 6.49). However, up to ±20.63 percent variation in mean AE_{rms} was observed for some other cutting conditions. The results also showed ±11.11 percent variation in mean cutting force (Figure 6.50). Variations of ±19.03% and ±17.7% in mean feed and radial forces respectively were also observed for different cutting tools (Figures 6.51 and 6.52). Since significant variations in mean AE_{rms}; cutting forces; feed forces and radial forces were observed, more experiment of Experiment 4 (inserts 5-8) need to be done in order to confirm the variations in force and AE_{rms} signals. Experimental results in Figures 6.49-6.52 indicated that the variations in mean AE_{rms}; cutting forces; feed forces and radial forces for inserts 5-8 are similar to the variations in these signals for inserts 1-4. Such variations in mean AE_{rms} and mean forces can result in significant error in tool wear prediction. Two possible errors can creep in estimation of tool wear: case 1, estimated tool wear size smaller than the actual size, and case 2, the predicted size larger than the real size.
Figure 6.49 Variation in mean $AE_{rms}$ for eight different fresh tools

Figure 6.50 Variation in mean cutting force for eight different fresh tools
Figure 6.51 Variation in mean feed force for eight different fresh tools

Figure 6.52 Variation in mean radial force for eight different fresh tools
Dornfeld and Asibu indicated that AE signal is strongly dependent on the rate of deformation (strain rate), the applied stress, and the volume of the participating material [56]. During the turning operation, the shear strain rate increases as cutting velocity rises [192]. As expected, therefore, $AE_{rms}$ increases with larger speed (Figure 6.49). However, the cutting, feed and radial forces (Figures 6.50 to 6.52) decrease as speed rises. This phenomenon is caused by reduction in normal as well as shear stresses of the workpiece material due to higher temperature in the shear zone, which results from an increase in cutting velocity (Section 6.1).

Table 6.9 The measurement of tool insert geometry

<table>
<thead>
<tr>
<th>Tool insert:</th>
<th>$r_1$ (mm)</th>
<th>$r_2$ (mm)</th>
<th>nose radius (mm)</th>
<th>angle 'a' (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Insert 1</td>
<td>0.804</td>
<td>0.772</td>
<td>0.788</td>
<td>1.2</td>
</tr>
<tr>
<td>- Insert 2</td>
<td>0.741</td>
<td>0.866</td>
<td>0.804</td>
<td>2.2</td>
</tr>
<tr>
<td>- Insert 3</td>
<td>0.793</td>
<td>0.816</td>
<td>0.805</td>
<td>1.3</td>
</tr>
<tr>
<td>- Insert 4</td>
<td>0.871</td>
<td>0.782</td>
<td>0.827</td>
<td>1.0</td>
</tr>
<tr>
<td>- Insert 5</td>
<td>0.849</td>
<td>0.897</td>
<td>0.873</td>
<td>1.1</td>
</tr>
<tr>
<td>- Insert 6</td>
<td>0.794</td>
<td>0.799</td>
<td>0.797</td>
<td>1.4</td>
</tr>
<tr>
<td>- Insert 7</td>
<td>0.819</td>
<td>0.856</td>
<td>0.838</td>
<td>0.7</td>
</tr>
<tr>
<td>- Insert 8</td>
<td>0.839</td>
<td>0.797</td>
<td>0.818</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Experimental measurements (Experiment 5) indicated variations in the geometry of the fresh cutting tool insert (Table 6.9). These variations include nose radius ($r$) and side cutting edge angle ($a$) as shown in Figure 5.5(b). Since shear plane area, total cutting edge length, tool-chip interface area, and chip flow angle depend on tool insert geometry and cutting conditions [13, 159] and (results in Section 6.1), a variation in tool insert geometry results in a diversity in these parameters. Previous researchers observed that shear plane temperature is influenced by the shear plane area [202]. The shear plane temperature affects the shear stress of workpiece material through the shear strain rate [203]. Hence, a variation in tool geometry results in a variety of shear plane area, total cutting edge length, chip flow direction and shear stress. Because the magnitude of
forces and $\text{AE}_{\text{rms}}$ strongly depends on these parameters [48] and (results in Section 6.1),
a variation in insert geometry is one significant cause of a deviation in force and $\text{AE}_{\text{rms}}$
signals.

![Graph showing variation in mean $\text{AE}_{\text{rms}}$ versus cutting time with specific conditions: speed = 160 m/min, feed = 0.3 mm/rev, rake = -5 degrees and depth of cut = 1 mm.](image)

**Figure 6.53 Variation in mean $\text{AE}_{\text{rms}}$ versus cutting time**
speed = 160 m/min, feed = 0.3 mm/rev, rake = -5 degrees and 
depth of cut = 1 mm

Figure 6.54 Variation in mean cutting force versus time
speed = 160 m/min, feed = 0.3 mm/rev, rake = -5 degrees and depth of cut = 1 mm

Figure 6.55 Variation in mean feed force versus cutting time
Figure 6.56 Variation in mean radial force versus cutting time
The $\text{AE}_{\text{rms}}$ and three forces versus cutting time for twelve tool inserts are presented in Figures 6.53 to 6.56 (Experiment 6). The results indicate that there is a significant difference in mean cutting and feed forces as well as $\text{AE}_{\text{rms}}$ at the beginning of machining for different tools. At the commencement of the cutting operation, all inserts are new. However, flank and crater wear starts to develop as cutting time elapses. Measurement of both flank and crater wear on various tool inserts after 10 minutes of cutting also showed a significant difference in magnitude of respective wear which resulted in variation in three forces and $\text{AE}_{\text{rms}}$ for different tool inserts (Figures 6.53 to 6.56). Possible causes of the difference in mean forces and $\text{AE}_{\text{rms}}$ for different tool insert are (i) difference in cutting tool insert geometry (ii) difference in chip fracture rate (iii) different tool wear rate resulting in different tool wear size, (iv) small fracture in tip, (v) chipping at major cutting region and (vi) built up layer on rake face. The detail of each cause will be discussed later.

When flank and crater wear grow, a reduction in total cutting edge length due to flank wear and increase in normal rake angle due to crater wear causes the $\text{AE}_{\text{rms}}$ signal to decrease. At the same time, however, the strain energy released from the interfacing area between flank face and workpiece and from chip fracture results increased $\text{AE}_{\text{rms}}$ and hence the trend of $\text{AE}_{\text{rms}}$ is in Figure 6.53.

Figures 6.54 to 6.56 indicate that the mean cutting, feed and radial forces increased with cutting time. Kuljanic [204] reported that flank wear land develops after a few seconds from the starting of cut. The normal stress on this flank wear land results in the increase in feed and radial forces, and the shear stress on the same wear land causes the higher cutting force. At the same time, however, the decrease in energy consumption on tool
rake face due to crater wear slightly hinders the forces to rise. The effect of crater wear results in reduction of negative rake angle which causes drop in normal stress on the rake face. Therefore, the trend of three forces seen in Figures 6.54-6.56.

Table 6.10 Size of flank and crater wear measured after 10 minutes of cutting

(for speed = 160 m/min, feed = 0.2 mm/rev, rake angle = -5 degrees and depth of cut = 1 mm)

<table>
<thead>
<tr>
<th>Tool insert</th>
<th>Flank wear (mm)</th>
<th>Crater wear (mm)</th>
<th>Built - up layer/ built-up edge/ chipping and cutting edge deterioration</th>
</tr>
</thead>
<tbody>
<tr>
<td>insert 1</td>
<td>0.111</td>
<td>0.03</td>
<td>Co</td>
</tr>
<tr>
<td>insert 2</td>
<td>0.147</td>
<td>0.025</td>
<td>F, Cn, Cc, Co, Bu</td>
</tr>
<tr>
<td>insert 3</td>
<td>0.147</td>
<td>0.032</td>
<td></td>
</tr>
<tr>
<td>insert 4</td>
<td>0.122</td>
<td>0.05</td>
<td>De</td>
</tr>
<tr>
<td>insert 5</td>
<td>0.121</td>
<td>0</td>
<td>Cos</td>
</tr>
<tr>
<td>insert 6</td>
<td>0.051</td>
<td>0</td>
<td>Cos</td>
</tr>
<tr>
<td>insert 7</td>
<td>0.081</td>
<td>0.005</td>
<td>Cos, Buc</td>
</tr>
<tr>
<td>insert 8</td>
<td>0.066</td>
<td>0.006</td>
<td>Buc</td>
</tr>
<tr>
<td>insert 9</td>
<td>0.077</td>
<td>0.011</td>
<td>De, Co</td>
</tr>
<tr>
<td>insert 10</td>
<td>0.084</td>
<td>0.016</td>
<td>Bu, Cns, Fs</td>
</tr>
<tr>
<td>insert 11</td>
<td>0.073</td>
<td>0.01</td>
<td>De, Co</td>
</tr>
<tr>
<td>insert 12</td>
<td>0.075</td>
<td>0.012</td>
<td>De, Co</td>
</tr>
</tbody>
</table>

Note: F Fracture at tip
Fs Small Fracture at tip
Cc Chipping on major cutting region
Ccs Small chipping on major cutting region
Co Chipping on tool edge (not cutting edge)
Cos Small chipping on tool edge (not cutting edge)
Cn Chipping on nose cutting region
Cns Small chipping on nose cutting region
De Cutting edge deterioration
Bu Built-up layer on tool rake face
Buc Small built-up layer behind crater wear
Bue Small built-up edge between cutting edge and crater wear

Tay [202] explained that the temperature on rake face is influenced by many parameters including chip tool contact area and cutting conditions. Different cutting tool geometry including cutting edge length observed for new inserts will thus result in dissimilar temperature variation on tool rake face if different tools are employed. Usui, Shirakashi and Kitagawa [3] observed that the crater wear rate of tool insert is a function of several factors including normal stress on rake face, the temperature on rake face and the chip sliding distance. Therefore, different cutting tools will have dissimilar crater wear rates
Additionally, variation in wear rate resulting in different wear size (Table 6.10) was observed. This phenomenon is caused by the difference in shear stress due to the dissimilar shear zone temperatures.

Using a surface roughness analyzer and an optical profile projector, the built-up layer were observed on some worn tools (Table 6.10). No such built-up layer was observed on the flank face of any of tools used in this research. Measurements carried out on built-up layer on rake face of tool insert number 5 (Table 6.10) by using a surface roughness analyzer indicated its height equal to 24 \( \mu \text{m} \). After measurements, an unsuccessful attempt was made to dislodge the built-up layer by using a sharp edge knife. Built-up edges have been observed to form during machining of steel at relatively low cutting speeds. The temperature at the rake face has been found to drop in the crater wear zone when the flank wear growth reaches to values of about 0.025 mm [194], resulting in an environment similar to that caused by low cutting speeds. Therefore, it appears that built-up layers observed on the rake face of some inserts were formed during cutting operations. Due to formation of such built-up layers on the rake face of tool, the growth of significant crater wear will be hindered or would be very small. Hence, the crater wear of such tools in this research was assumed to be negligible. This built-up layer causes the negative rake angle to increase resulting in higher forces and \( AE_{\text{rms}} \). A small built-up layer was also observed behind crater wear area and on crater wear surface for some inserts (Table 6.10). On few inserts having large crater wear, a small adhering material was found on a surface of crater.

Chip Fracture has been observed to influence the magnitude of \( AE_{\text{rms}} \) (results in Sections 6.3 and 6.4). The impact of chip on tool holder which causes the chip to
fracture is the result of chip flow direction which depends on tool geometry, cutting conditions, flank wear and crater wear (results in Section 6.4). Different tool geometry as well as wear sizes observed in the present research can be attributed to the variation in chip flow direction resulting in different chip fracture rate. This phenomenon results in different values of mean $AE_{rms}$ as shown in Figure 6.53.

Employing the optical profile projector, an examination of worn tools revealed (i) a small fracture of tool tip of some inserts, (ii) chipping at cutting edge as well as the tool edge, and (iii) both the fracture and chipping of cutting edge as well as tool edge of inserts. Tool chipping near the cutting edge was possibly caused by the impacting of the chip coiled around the workpiece. However, this tool chipping does not influence the cutting edge and cutting action. A fractured edge on nose radius and major cutting regions causes greater forces due to more contact area at the tip. $AE_{rms}$ and forces for tool with a small fractured tool tip are presented in Figures 6.57 and 6.58. The experimental results show that forces increase significantly for cutting duration between 4 and 6 minutes (Figure 6.58). However, after 6 minutes, the trend of the three forces did not change much. A possible cause of this phenomenon is the occurrence of tool tip fracture during this time. The increase in $AE_{rms}$ is also observed; however, it was found to drop after 6 minutes of cutting time.

Relatively higher energy consumption due to larger tool-work contact area resulted by tool tip fracture appears to be the main reason for increase in cutting, feed and radial forces. The geometry of fractured tip also alters (i) tool geometry including side cutting angle, (ii) end cutting edge angle, (iii) depth of cut, and (iv) chip flow direction. Since the three forces are influenced differently by tool geometry and cutting conditions [45,
48], the trend for each force will differ and depend on the particular fractured tip geometry.

**Figure 6.57** $A E_{\text{rms}}$ for small tool tip fracture

**Figure 6.58** Forces for small tool tip fracture
6.5.2 Tool Wear Estimation Using Fuzzy Neural Network Model

As explained in Chapter 4, the fuzzy neural network model developed in this research consists of 4 sections: Tool Wear Classification (fuzzy logic), Input Normalization, Tool Wear Estimation (MLSB neural network), and Tool Wear Adjustment (fuzzy logic). Fuzzy members and fuzzy rules of the first and the fourth sections were developed from the experimental results observed in Experiments 1 to 3. In this thesis, however, the fuzzy members were adapted based on a simple membership function such as trapezoidal and triangular membership functions. A summary of these fuzzy members and rules is presented as follows:

Table 6.11 Fuzzy member of estimated shear energy on shear plane

<table>
<thead>
<tr>
<th>Est. shear energy (N*m/s)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>40,000</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>50,000</td>
<td>0.75</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>60,000</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>70,000</td>
<td>0.25</td>
<td>0.75</td>
<td>0</td>
</tr>
<tr>
<td>80,000</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>120,000</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>130,000</td>
<td>0</td>
<td>0.75</td>
<td>0.25</td>
</tr>
<tr>
<td>140,000</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>150,000</td>
<td>0</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>160,000</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>200,000</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.12 Fuzzy member of estimated friction energy on rake face

<table>
<thead>
<tr>
<th>Est. friction energy (N*m/s)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1,500</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2,000</td>
<td>0.75</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>2,500</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>3,000</td>
<td>0.25</td>
<td>0.75</td>
<td>0</td>
</tr>
<tr>
<td>3,500</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>7,000</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>7,750</td>
<td>0</td>
<td>0.75</td>
<td>0.25</td>
</tr>
<tr>
<td>8,500</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>9,250</td>
<td>0</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>10,000</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>13,000</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 6.13 Fuzzy member of cutting time

<table>
<thead>
<tr>
<th>Cutting time (min)</th>
<th>Short</th>
<th>Medium</th>
<th>Long</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1.25</td>
<td>0.75</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>1.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>1.75</td>
<td>0.25</td>
<td>0.75</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>40</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>45</td>
<td>0</td>
<td>0.75</td>
<td>0.25</td>
</tr>
<tr>
<td>50</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>55</td>
<td>0</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>60</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>80</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.14 Fuzzy member of SD/mean of $A_{Erms}$

<table>
<thead>
<tr>
<th>SD/ mean of $A_{Erms}$</th>
<th>Abnormal (low)</th>
<th>Normal</th>
<th>Abnormal (high)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.005</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.0055</td>
<td>0.75</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>0.006</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>0.0065</td>
<td>0.25</td>
<td>0.75</td>
<td>0</td>
</tr>
<tr>
<td>0.007</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0.012</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0.0125</td>
<td>0</td>
<td>0.75</td>
<td>0.25</td>
</tr>
<tr>
<td>0.013</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>0.0135</td>
<td>0</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>0.014</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0.019</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.15 Fuzzy member of previous flank wear

<table>
<thead>
<tr>
<th>Previous flank wear (mm)</th>
<th>No wear</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
</tr>
</thead>
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</table>
Table 6.16 Fuzzy member of previous crater wear

<table>
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<th>Previous crater wear (mm)</th>
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<th>Medium</th>
<th>Large</th>
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Table 6.17 Fuzzy member of delta time

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<th>Delta time (min)</th>
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<th>Medium</th>
<th>Long</th>
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<tr>
<td>0.625</td>
<td>0.75</td>
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<td>0</td>
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<tr>
<td>0.75</td>
<td>0.5</td>
<td>0.5</td>
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<tr>
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<td>0.25</td>
<td>0.75</td>
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<td>0</td>
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Table 6.18 Fuzzy member of cutting speed

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Table 6.19 Fuzzy member of degree of flank wear

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<th>Degree of flank wear</th>
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<th>Yes</th>
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<tbody>
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</tr>
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<td>0.75</td>
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<tr>
<td>0.25</td>
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<tr>
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Table 6.20 Fuzzy member of degree of crater wear

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<th>Yes</th>
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<tbody>
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</tr>
<tr>
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<td>0.75</td>
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<td>0</td>
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<tr>
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</tr>
<tr>
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<td>0.75</td>
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<td>1</td>
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<td>0.75</td>
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Table 6.21 Fuzzy member of degree of chip fracture

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Table 6.22 Fuzzy member of degree of cutting edge deterioration

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Table 6.23 Fuzzy rules for an occurrence of flank wear

<table>
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<th>Rule No.</th>
<th>Description</th>
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<tbody>
<tr>
<td>1.</td>
<td>Degree of Flank wear is Yes if Shear energy is Low and Cutting time is Medium or Long</td>
</tr>
<tr>
<td>2.</td>
<td>Degree of Flank wear is Yes if Shear energy is Medium and Cutting time is Medium or Long</td>
</tr>
<tr>
<td>3.</td>
<td>Degree of Flank wear is Yes if Shear energy is High and Cutting time is Short, Medium or Long</td>
</tr>
<tr>
<td>4.</td>
<td>Degree of Flank wear is Maybe if Shear energy is Medium and Cutting time is Short</td>
</tr>
<tr>
<td>5.</td>
<td>Degree of Flank wear is No if Shear energy is Low and Cutting time is Short</td>
</tr>
</tbody>
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Table 6.24 Fuzzy rules for an occurrence of crater wear

<table>
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<th>Rule No.</th>
<th>Description</th>
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<td>1.</td>
<td>Degree of Crater wear is Yes if Friction energy is Low and Cutting time is Long</td>
</tr>
<tr>
<td>2.</td>
<td>Degree of Crater wear is Yes if Friction energy is Medium and Cutting time is Medium or Long</td>
</tr>
<tr>
<td>3.</td>
<td>Degree of Crater wear is Yes if Friction energy is High and Cutting time is Medium or Long</td>
</tr>
<tr>
<td>4.</td>
<td>Degree of Crater wear is Maybe if Friction energy is High or Medium and Cutting time is Short</td>
</tr>
<tr>
<td>5.</td>
<td>Degree of Crater wear is Maybe if Friction energy is Low and Cutting time is Medium</td>
</tr>
<tr>
<td>6.</td>
<td>Degree of Crater wear is No if Friction energy is Low and Cutting time is Short</td>
</tr>
</tbody>
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Table 6.25 Fuzzy rules for an occurrence of chip fracture

<table>
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<th>Rule No.</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>1.</td>
<td>Degree of Chip fracture is Yes if SD/mean of $AE_{rms}$ is Abnormal (low), Normal or Abnormal (high) and Previous flank wear is Medium or Large and Previous crater wear is Medium or Large and Friction energy is Low, Medium or High and Delta time is Short, Medium or Long</td>
</tr>
<tr>
<td>2.</td>
<td>Degree of Chip fracture is Yes if SD/mean of $AE_{rms}$ is Abnormal (low), Normal, or Abnormal (high) and Previous flank wear is Small or Medium and Previous crater wear is Small and Friction energy is Medium or High and Delta time is Medium or Large</td>
</tr>
<tr>
<td>3.</td>
<td>Degree of Chip fracture is Yes if SD/mean of $AE_{rms}$ is Abnormal (high) and Previous flank wear is No wear and Previous crater wear is No wear and Cutting speed is Low</td>
</tr>
<tr>
<td>4.</td>
<td>Degree of Chip fracture is Maybe if SD/mean of $AE_{rms}$ is Abnormal (low), Normal or Abnormal (high) and Previous flank wear is Small or Medium and Previous crater wear is Small and Friction energy is Medium or High and Delta time is Short or Medium</td>
</tr>
<tr>
<td>5.</td>
<td>Degree of Chip fracture is Maybe if SD/mean of $AE_{rms}$ is Abnormal (low), Normal or Abnormal (high) and Previous flank wear is Small or Medium and Previous crater wear is Small and Friction energy is Low and Delta time is Long or Medium</td>
</tr>
<tr>
<td>6.</td>
<td>Degree of Chip fracture is Maybe if SD/mean of $AE_{rms}$ is Abnormal (low), Normal or Abnormal (high) and Previous flank wear is Small or Medium and Previous crater wear is Small and Friction energy is Medium or High and Delta time is Short</td>
</tr>
<tr>
<td>7.</td>
<td>Degree of Chip fracture is Maybe if SD/mean of $AE_{rms}$ is Abnormal (high) and Previous flank wear is No wear and Previous crater wear is No wear and Cutting speed is Medium or High</td>
</tr>
<tr>
<td>8.</td>
<td>Degree of Chip fracture is Maybe if SD/mean of $AE_{rms}$ is Abnormal (low) or Normal and Previous flank wear is Small or Medium and Previous crater wear is Small and Friction energy is Low and Delta time is Short</td>
</tr>
<tr>
<td>9.</td>
<td>Degree of Chip fracture is Maybe if SD/mean of $AE_{rms}$ is Abnormal (low) or Normal and Previous flank wear is No wear and Previous crater wear is No wear and Cutting speed is Low, Medium or High</td>
</tr>
</tbody>
</table>
### Table 6.26 Fuzzy rules for an occurrence of cutting edge deterioration

<table>
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<th>Rule No.</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Degree of Cutting edge deterioration is Yes if Previous flank wear is Medium or Large and Previous crater wear is Large</td>
</tr>
<tr>
<td>2.</td>
<td>Degree of Cutting edge deterioration is Yes if Previous flank wear is Medium or Large and Previous crater wear is Medium and Friction energy is Low and Delta time is Long</td>
</tr>
<tr>
<td>3.</td>
<td>Degree of Cutting edge deterioration is Yes if Previous flank wear is Medium or Large and Previous crater wear is Medium and Friction energy is Medium and Delta time is Medium or Long</td>
</tr>
<tr>
<td>4.</td>
<td>Degree of Cutting edge deterioration is Yes if Previous flank wear is Medium or Large and Previous crater wear is Medium and Friction energy is High and Delta time is Short, Medium or Long</td>
</tr>
<tr>
<td>5.</td>
<td>Degree of Cutting edge deterioration is Maybe if Previous flank wear is Medium or Large and Previous crater wear is Medium and Friction energy is Low and Delta time is Long</td>
</tr>
<tr>
<td>6.</td>
<td>Degree of Cutting edge deterioration is Maybe if Previous flank wear is Medium or Large and Previous crater wear is Small and Friction energy is High and Delta time is Medium or Long</td>
</tr>
<tr>
<td>7.</td>
<td>Degree of Cutting edge deterioration is Maybe if Previous flank wear is Medium or Large and Previous crater wear is Small and Friction energy is Medium and Delta time is Long</td>
</tr>
<tr>
<td>8.</td>
<td>Degree of Cutting edge deterioration is Maybe if Previous flank wear is No wear and Previous crater wear is No wear and Friction energy is High and Delta time is Long</td>
</tr>
<tr>
<td>9.</td>
<td>Degree of Cutting edge deterioration is No if Previous flank wear is Small, Medium or Large and Previous crater wear is Small and Friction energy is Medium and Delta time is Short or Medium</td>
</tr>
<tr>
<td>10.</td>
<td>Degree of Cutting edge deterioration is No if Previous flank wear is Small, Medium or Large and Previous crater wear is Small and Friction energy is Low and Delta time is Short, Medium or Long</td>
</tr>
<tr>
<td>11.</td>
<td>Degree of Cutting edge deterioration is No if Previous flank wear is No wear and Previous crater wear is No wear and Friction energy is Low, Medium or High and Delta time is Short and Medium</td>
</tr>
<tr>
<td>12.</td>
<td>Degree of Cutting edge deterioration is No if Previous flank wear is No wear and Previous crater wear is No wear and Friction energy is Low and Medium and Delta time is Long</td>
</tr>
</tbody>
</table>

Tables 6.23 to 6.26 were developed for detecting the occurrence of flank wear, crater wear, chip fracture and cutting edge deterioration. As mentioned earlier in Section 4.5.1, the occurrence of these is predicted based on a correlation between each event, cutting conditions (speed, feed and rake angle) and turning time.

In MatLab program, it should be noted that these 32 fuzzy rules (for all four groups) need to be enhanced to 256 fuzzy rules. This is because of the limitation of fuzzy logic toolbox which cannot employ both ‘and’ and ‘or’ in one rule. For example, the first rule in Table 6.23 is enhanced to two rules: 'Degree of Flank wear is Yes if Shear energy is
Low and Cutting time is Medium’ and ‘Degree of Flank wear is Yes if Shear energy is Low and Cutting time is long’.

Table 6.27 Fuzzy member of initial flank wear

<table>
<thead>
<tr>
<th>Initial flank wear</th>
<th>Negative</th>
<th>Small</th>
<th>Positive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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</tr>
<tr>
<td>-0.16</td>
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<td>0</td>
</tr>
<tr>
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<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>-0.085</td>
<td>0.25</td>
<td>0.75</td>
<td>0</td>
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<td>0.5</td>
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</tr>
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</tr>
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</tr>
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<td>1</td>
</tr>
<tr>
<td>0.085</td>
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</tr>
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<td>0.16</td>
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</tbody>
</table>

* Note: The initial flank wear, which is the error due to the variation in mean forces and AErms, can be both positive and negative values. This depends on the difference between measured forces as well as AErms and those for training data.
### Table 6.28 Fuzzy member of initial crater wear

<table>
<thead>
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<th>Initial crater wear</th>
<th>Negative</th>
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<th>Positive</th>
</tr>
</thead>
<tbody>
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<tr>
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</tr>
</tbody>
</table>

* Note: The initial crater wear, which is the error due to the variation in mean forces and AE RMS, can be both positive and negative values. This depends on the difference between measured forces as well as AE RMS and those for training data.

### Table 6.29 Fuzzy member of flank wear adjustment

<table>
<thead>
<tr>
<th>Flank wear adjustment</th>
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<th>Positive</th>
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<tbody>
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<td>Medium</td>
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<td>1</td>
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<td>0.75</td>
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</table>

* Note: Since the error in flank wear prediction due to the variation in signals can be both positive and negative values, positive and negative values for flank wear adjustment (for eliminating this error) are required.
Table 6.30 Fuzzy member of crater wear adjustment

<table>
<thead>
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<th>Crater wear adjustment</th>
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<th>Positive</th>
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</thead>
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<td>High</td>
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<tr>
<td>0.045</td>
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<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

* Note: Since the error in crater wear prediction due to the variation in signals can be both positive and negative values, positive and negative values for crater wear adjustment (for eliminating this error) are required.

Table 6.31 Fuzzy rules for flank wear adjustment

<table>
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<tr>
<th>Rule No.</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>1.</td>
<td>Flank wear adjustment is Low if Initial flank wear is Small</td>
</tr>
<tr>
<td>2.</td>
<td>Flank wear adjustment is Positive medium if Initial flank wear is Negative medium</td>
</tr>
<tr>
<td>3.</td>
<td>Flank wear adjustment is Positive high if Initial flank wear is Negative large</td>
</tr>
<tr>
<td>4.</td>
<td>Flank wear adjustment is Negative medium if Initial flank wear is Positive medium</td>
</tr>
<tr>
<td>5.</td>
<td>Flank wear adjustment is Negative high if Initial flank wear is Positive Large</td>
</tr>
</tbody>
</table>

Table 6.32 Fuzzy rules for crater wear adjustment

<table>
<thead>
<tr>
<th>Rule No.</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Crater wear adjustment is Low if Initial crater wear is Small</td>
</tr>
<tr>
<td>2.</td>
<td>Crater wear adjustment is Positive medium if Initial crater wear is Negative medium</td>
</tr>
<tr>
<td>3.</td>
<td>Crater wear adjustment is Positive high if Initial crater wear is Negative large</td>
</tr>
<tr>
<td>4.</td>
<td>Crater wear adjustment is Negative medium if Initial crater wear is Positive medium</td>
</tr>
<tr>
<td>5.</td>
<td>Crater wear adjustment is Negative high if Initial crater wear is Positive Large</td>
</tr>
</tbody>
</table>
Tables 6.31 and 6.32 were developed for adjusting the size of flank wear and crater wear. As mentioned in Section 4.5.1, these adjustments were developed based on the correlation between the real, initial and predicted size of tool wear.

In order to train MLSB neural network model, results in Experiment 2 need to be used as training data. Employing training method mentioned in Section 4.5, a 36-40-2 structure was found to be the best architecture. The average tool wear estimation error of this structure was less than 2% and the training time was lower than 1 minute. Employing the same data for training MLSB neural network with two hidden layers, it was found that the 36-40-29-2 was the best structure. Using a MLSB neural network with the 36-40-29-2 structure, the average tool wear prediction error was about 1.4%. The accuracy of tool wear estimation for the 36-40-29-2 structure increased only by 0.6% compared with the best result of the single hidden layer. However, the computational time for the 36-40-29-2 structure increased by about 40% compared with 36-40-2 structure. Hence, one hidden layer structure (36-40-2) was selected for developing the on-line fuzzy neural network model due to shorter computational time as well as high accuracy in prediction of flank and crater wear.
speed = 160 m/min. feed rate = 0.2 mm/rev. depth of cut = 1 mm and rake angle = 0 degree

Figure 6.59 Measured and estimated tool wear using training data

Figure 6.60 Measured and estimated tool wear using testing data (selected insert)
Typical examples of flank and crater wear estimated by using the Fuzzy Neural Network are presented in Figure 6.59. Figure 6.59 shows a comparison between the measured wear and the estimated wear using training data (Experiment 2). The results indicate that the flank and crater wear predicted by model closely agree with the values of measured tool wear. Employing testing data (Experiment 6), the flank and crater wear predicted by the proposed model are shown in Figure 6.60. A comparison of the predicted flank and crater wear with the measured wear in testing data indicates a higher error compared to that in Figure 6.59. However, the result shows that this fuzzy neural network still has a high accuracy to estimate the average width of flank wear and the maximum depth of crater wear.

As mentioned earlier, the worn tools for training data were prepared by using the following cutting conditions: (i) 160 m/min, 0.1 mm/rev and −5 degrees and (ii) 160 m/min, 0.3 mm/rev and −5 degrees. The negative 5 degrees rake was used to minimize or eliminate crater wear development on insert for small feed rate (0.1 mm/rev). For large feed (0.3 mm/rev), however, the crater wear was found to develop on tool rake face. If these tools are employed with zero or positive rake angle, the real contact geometry between flank face and workpiece is as shown in Figure 6.61(a) for the tools employed for training data while the contact geometry for testing tools for the same rake angle is as shown in Figure 6.61(b). This difference in flank-workpiece geometry can result in small errors in flank and crater wear estimation for testing data.

In order to maintain a constant cutting velocity, the rotary speed of the workpiece was increased as its diameter got reduced. The vibrations at the spindle bearing have been found to be influenced by many parameters including geometry of bearing, radial
moment of inertia of the spindle and angular velocity of spindle [205]. Hence, workpiece angular velocity variations result in different vibrations at spindle bearing. Since workpiece bar is held in chuck fitted in spindle bearing, the vibrations at workpiece are also induced by the bearing vibrations. Tounsi and Otho [206] observed that tool-work vibration influences the force dynamic including the oscillation frequency. This frequency distribution directly affects the values of derived parameters including skew and kurtosis of frequency bands of forces as well as the total energy of forces. Therefore, a variation in workpiece diameters may influence the tool wear estimation by the proposed fuzzy neural network model.

![Diagram](image)

(a) Training worn tool  
(b) Testing worn tool

Figure 6.61 Flank-workpiece contact geometry of worn tools for 0 degree rake angle

Minor fractures on cutting edges of a number of tool inserts were also observed after cutting. The higher forces (Figure 6.58) caused due to edge fractures will result in
estimated flank wear which will be greater than the measured values for such tools. However, the estimated crater wear for this case may be greater or smaller than the actual crater wear based on the testing data.

It should be noted that the accuracy of the tool wear classification (first part) affects the accuracy of the third and fourth parts significantly (Figure 4.15). This is because the influence of flank and crater wear on force and $AE_{rms}$ signals depends on the shape of worn tools. For example, the $AE_{rms}$ and forces decrease as crater wear develops. This is because crater wear increases effective rake angle (results in Section 6.3). However, a large crater wear with destroyed cutting edge results in decreased effective rake angle which make forces and $AE_{rms}$ to increase with the growth of crater wear (results in Section 6.3).

**6.6 TIP FRACTURE AND CHIPPING AT THE CUTTING EDGE DETECTION**

The experimental results in Section 6.5 (Figures 6.57 and 6.58) indicated that small tip fracture as well as chipping at cutting edge result in significant increase in force and $AE_{rms}$. The increase in signals causes tool wear estimation error for fuzzy neural network model. Hence, tool insert having tip fracture, chipping at cutting edge, and both tip fracture as well as chipping at cutting edge needs to be detected.

**6.6.1 Influence of Chipping and Fracture on Forces and $AE_{rms}$**

An examination of used tool inserts with an optical profile projector indicated that a large number of inserts have tip fracture and chipping at cutting edge as well as near
cutting edge. However, the experimental results indicated that tool chipping near the cutting edge does not influence the cutting forces and $AE_{rms}$. This is because such chipping of the tool is away from tool-chip contact area. A fracture at nose and major cutting regions causes the forces and $AE_{rms}$ to increase due to ploughing and more friction at chipping and fracture area. The results also showed that a very small tip fracture and/or chipping at cutting edge do not lead to increased forces and $AE_{rms}$.

The trends of signals for worn tools spanning three categories are shown in Figures 6.62 to 6.65. Due to the use of small feed, flank and crater wear of inserts 9 to 12 in Figures 6.62-6.65 were small. Hence, no significant effect was observed on $AE_{rms}$ as well as forces magnitude. Any significant change in magnitude of cutting forces was caused due to fracture and chipping. Due to no fracture or chipping on insert '9', there is insignificant increase in cutting forces for this insert. The trend of signals for insert '10' indicates that small tip fracture and small chipping at major cutting region do not influence forces. However, a very small increase in $AE_{rms}$ was observed. Insert '11' is the cutting tool insert where tip fractured at the start of cut. Forces for this case are very high at the beginning of cut and then they decrease. However, on insert '12', the tip fracture and chipping at major cutting region occurred when significant time elapsed after the start of cut. Forces for this insert increase after the fracture and chipping developed on cutting edge. However, after a few seconds of chipping and fracture, the trend of forces begins to drop. This is because the chipped and fractured surface of tool tip becomes smoother. The experimental results also indicate that tool tip fracture and chipping at major cutting region (inserts 11 and 12) influence $AE_{rms}$ insignificantly compared with cutting forces.
Relatively higher energy consumption due to ploughing and more friction at chipping and fracture area is a cause of increase in force and $AE_{\text{rms}}$ signals significantly after the occurrence of tool tip fracture and chipping at major cutting region. The trend of forces decreased after cutting time of 4 minutes for insert ‘12’ (Figure 6.63-65). For insert 11, cutting force remained unchange for the first two minutes and then it tended to drop as cutting time progressed (Figure 6.63). However, the trend of feed and radial forces decreased after cutting time of 15 seconds (Figures 6.64-6.65). This is may be because of rounding of edge of fracture and chipping areas due to the friction when cutting time elapsed.

Figure 6.62 Mean $AE_{\text{rms}}$ versus cutting time (selected inserts)
speed = 160 m/min. feed = 0.1 mm/rev. rake angle = 5 degrees and depth of cut = 1 mm

Figure 6.63 Mean cutting force versus cutting time (selected inserts)

(speed = 160 m/min. feed = 0.1 mm/rev. rake angle = 5 degrees and depth of cut = 1 mm)

Figure 6.64 Mean feed force versus cutting time (selected inserts)
Employing experimental data in Figure 6.65, three trends of the mean radial force for the different categories are clarified and shown in Figure 6.66. A predicted radial force for fresh tool estimated by Equation 4.15 is also presented in this figure. Line ‘A’ is the trend of mean radial force for the second category (insert having small tool tip fracture or chipping at major cutting region). However, the trend of mean radial force for insert with no fracture or chipping (the first category) was also observed to be similar to line ‘A’. Lines ‘B’ and ‘C’ show the trends of mean radial force for an insert of the third category. Line ‘B’ shows the trend of force for tip fracture, cutting edge chipping or both tip fracture and chipping at cutting edge after about 2 minutes from beginning of the cut. Line ‘C’ is the trend of both forces for tip fracture, chipping at major cutting
region, or both tip fracture and cutting edge chipping to occur at the start of the cut. It should be noted that the trend of the feed force for each category was similar to the trend of the radial force but their magnitudes are different.

Eighty percent of tool inserts in each category were selected at random, and the mean feed and radial forces for these inserts were employed as training data for the neural network model. The mean feed and radial forces for the remaining used tool inserts were used as testing data for testing the accuracy of the model.

In order to train and test the neural network model for detecting chipping on cutting edge and small fracture (Figure 4.16), the measured feed and radial forces need to be used as current measured feed force and radial force units. The measured feed and radial forces at the cutting times of 4 and 6 minutes (points ‘a’ and ‘b’) were selected and used for training neural network for tool inserts in the first and the second category. Feed and radial forces at before and after the occurrence of tip fracture and cutting edge chipping

![Figure 6.66 Trend of mean radial force for the three categories of worn tools](image)

**Figure 6.66 Trend of mean radial force for the three categories of worn tools**
(points 'c' and 'd') were employed for training the network of inserts in the third category (line 'B'). In the case of inserts in the third category where signals have the trend as line 'C', feed and radial forces at the cutting times of 15 seconds and 2 minutes (points 'e' and 'f') were employed to train the neural network model.

6.6.3 Detection of Chipping on Cutting Edge and Small Fracture

Training data from the experiment were employed for training a single hidden layer MLSB neural network with a 7-9-1 structure. This architecture was found to be the best in 7 structures tested (Figures 6.67 and 6.68). The training time for this structure was less than 1 minute, and the training error observed was zero (Figure 6.67). The experimental results indicated that the accuracy of the neural network model was about 93.5% for the data tested (Figure 6.68). This is a fairly high accuracy for detecting tip fracture and chipping at major cutting region.

Figure 6.67 An average training error for 7-n-1 structure (training data)
6.7 ON-LINE TOOL WEAR ESTIMATION

As mentioned in Chapter 3, the tool wear estimation section of on-line tool wear estimation model will be selected from the computer algorithm (Figure 4.9) employing quantitative models or the fuzzy neural network model (Figure 4.15). Using data from Experiment 2, it was found that the fuzzy neural network model provides a better accuracy for tool flank and crater wear estimation compared with the results from the computer algorithm using quantitative model. Hence, in this thesis, the fuzzy neural network model was selected for estimating flank and crater wear in the on-line system. A schematic diagram and a flow chart of the on-line tool wear estimation system developed in this research are shown in Figures 6.69 and 6.70 respectively.

Due to the use of the fuzzy neural network model to predict tool wear in the on-line tool wear estimation model, the accuracy of the on-line model is the same as the accuracy of
the fuzzy neural network model. However, the computational time of the on-line system will be longer than the fuzzy neural network model. This is because the on-line tool wear estimation model also integrates other models and systems in order to develop the on-line system.

Figure 6.69 A schematic diagram of on-line tool wear estimation system
Figure 6.70 A flow chart of on-line tool wear estimation system

(repeat Figure 4.17)
An on-line fuzzy neural network algorithm was tested on an IBM PC Pentium III (500MHz), and it was found that the computation time for tool wear estimation was about 16 seconds. The tool wear classification section (fuzzy logic model) was observed to consume the longest calculation time. Flank and crater wear prediction every minute in cutting operation appears to be reasonable. Hence, sixteen seconds of computation time is satisfactory. However, the computation time can be further reduced if this on-line fuzzy neural network program is developed using C++ programs and computers with faster processing speeds are employed. It should be noted that if the operator selects to continue tool wear monitoring, the computational time for flank and crater wear estimation reduces to about 8 seconds. This is because in this loop, the on-line system is not required to calculate the weights again for fuzzy neural network model (Figure 4.15) and for neural network model (Figure 4.16).

The accuracy of estimated flank and crater wear by the on-line fuzzy neural network algorithm proposed in this research can also be increased by using a new set of training data. It is suggested that the training data for worn tools be obtained from CNC turning operations where flank and crater wear are allowed to progressively grow. However, such an approach will require significant time for data collection.
CHAPTER 7

CONCLUSIONS AND FUTURE WORK

7.1 CONCLUSIONS

This study has outlined the development of a new on-line tool wear estimation system for predicting flank and crater wear in CNC turning operations. Owing to insufficient knowledge related to this system, further research has to be done in this thesis. And yet, the following conclusions can be drawn from the present research.

• Tool-Chip Rake Contact Area and Tool Wear Geometry

Results of Experiment 1 indicate that the geometry of the tool-chip contact area depends on the cutting conditions, especially feed rate. The length of the sticking zone is about 7/12 of the total contact length. In this experiment, it was also found that the deterioration of cutting edge occurs in direct relation with large flank and crater wear development on the tool inserts, resulting in a malformation of the cutting edge to an approximately semi-circular shape.

• Quantitative Force and AE_{rms} Models

In this thesis, new quantitative models were developed for predicting mean forces (cutting, feed and radial forces) and AE_{rms} for both fresh as well as worn tools. The conclusions for this section can be summarized as follows:
Force model:

- The new force model can predict mean cutting, feed and radial forces accurately for both fresh and worn tools.

- When flank wear develops on the tool, forces increase due to frictional energy consumption between the flank face and the new surface of workpiece. This energy can be estimated by shear and normal stresses acting on the flank wear land. However, a decrease in total cutting edge length due to flank wear results in smaller shear plane area hindering increase in forces.

- It was observed that cutting, feed and radial forces are influenced insignificantly by chip fracture.

$AE_{rms}$ models:

- A new $AE_{rms}$ model can estimate $AE_{rms}$ accurately for both fresh and worn tools.

- The flank-workpiece contact area causes an increase in $AE_{rms}$ signal. However, this increase is slightly hindered by a smaller cutting edge length due to occurrence of flank wear.

- The strain energy released from chip fracture results in significant peaks in $AE_{rms}$ signal.

- Tool Wear Estimation using Quantitative Models

A computer program integrating the force and $AE_{rms}$ quantitative models for predicting flank and crater wear was developed in this thesis. The experimental results indicate
that this computer program can estimate the average width of flank wear and a maximum depth of crater wear with reasonable accuracy. This program was observed to take a long calculation time. This is because the new computer program employed a large number of equations and many calculation loops for minimizing the error in flank and crater wear sizes. However, this calculation time could be further reduced if a faster computer was used and/or if the computer program is developed in C++.

- **New Parameters for Tool Wear Monitoring**

In the present research, the total energy and the total energy of forces were introduced as new parameters to monitor tool wear. The total energy of forces was observed to increase with the higher cutting speed and feed rate, and smaller rake angle. It also increases with flank wear growth. However, the total entropy of force signals is not found to be sensitive to cutting conditions or progressive tool wear. It was also found that the total energy and the total entropy of force signals are not sensitive to chip fracture.

- **Chip Fracture Detection and Estimation**

By using a correlation between energy released from chip fracture and peaks in \( AE_{rms} \), a new technique that can detect the occurrence of chip fracture and also estimate the number of chip fracture was developed. The results showed that the proposed technique is successful in detecting chip fracture as well as estimating the number of chip fractures.
• Tool Wear Estimation using Fuzzy Neural Network Model

Research was also done to develop a new fuzzy neural network model for estimation of tool wear in CNC turning operations that can eliminate tool wear estimation error due to variation in mean forces and $AE_{rms}$ at the start of a cut for different inserts having the same specification. Experimental results indicated that this fuzzy neural network model estimates the average width of flank wear and the maximum depth of crater wear accurately. Experimental results also showed that this new fuzzy neural network uses less time for training the model due to the use of MLSB neural network.

• Detection of Tip Fracture and Chipping at Major Cutting Region

In order to alert machine operators to an occurrence of tip fracture, chipping at major cutting region, or both, which can result in incorrect flank and crater wear estimation, a new neural network model for detecting these occurrences was developed. Important findings from the present research can be listed as follows:

- Tool tip fracture and chipping at major cutting region results in significant increase in forces. However, they have only a small effect on $AE_{rms}$.

- The experimental results indicate that the new neural network model has a high accuracy rate for detecting the occurrence of tip fracture or chipping at the cutting edge or both tip fracture and cutting edge chipping.
• **On-line Tool Wear Estimation in CNC Turning Operations**

The on-line tool wear estimation system developed in this study can predict the average flank wear width and the maximum depth of crater wear accurately, needing only about 16 seconds of computational time. However, the computational time will be less for subsequent tool wear estimations. The computational time could be further reduced if the computer program for this on-line system is developed based on the Visual C++ software, and if faster processing speeds are used.

7.2 **SUGGESTIONS FOR FURTHER RESEARCH**

During literature survey and development of models for this research, a lack of published research material has been noticed in many areas. Some of these areas have been investigated and studied in this thesis. Further research in this area is summarized below.

• **Stress Distributions on Crater Wear Land**

Many models for stress distributions on the tool rake face of fresh tools have been introduced by researchers. These models were developed based on experimental results by using split-tool analysis and photoelastic technique. However, such models were developed for orthogonal cutting of fresh tools. No model for oblique cutting or for worn tools especially tool having crater wear has been developed. Therefore, it is suggested that the stress distributions for both cases should be studied deeply.
• *A New Allowance Limit for Flank and Crater Wear*

Large flank and crater wear could result in catastrophic tool failure (results of Experiment 1). One cause of this failure is greater stress acting on the tool tip due to the occurrence of large flank as well as crater wear. Some machining handbooks suggest an allowance limit of flank and crater wear, but sometimes tool inserts break before this limit is reached. Hence, a new allowance limit for both flank and crater wear needs to be established. One possible method for finding the new limit is to develop a new model based on a correlation between stresses acting on the tool insert, cutting conditions, workpiece material properties, and the geometry of flank and crater wear.

• *Future Development for An On-line Tool Wear Estimation System*

The on-line tool wear estimation system developed in this research can predict flank and crater wear accurately. However, it will not estimate both types of wear if fracturing and chipping occur on tool cutting edges. In order to enhance the performance of this on-line system, a future tool wear estimation system should able to predict tool flank and crater wear despite small tip fracture and chipping at the major cutting region. Additionally, a prediction of catastrophic tool failure needs to be integrated into the on-line tool wear estimation system for alerting machine operators before the failure occurs.
REFERENCES


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APPENDICES
APPENDIX A

Appendix A contains the results of Experiments 1 to 7 which were also discussed in the 'Results and Discussion' chapter. These results were saved in the format of Microsoft Excel® and Microsoft Word® file. These computer files are contained in the CDROM attached with this thesis. The details of each computer files are presented in Table A1.

Table A1 Details of the computer files contained the experimental results

<table>
<thead>
<tr>
<th>No.</th>
<th>File name</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Result 1</td>
<td>Scan photos of chip-tool contact area and its trace line</td>
</tr>
<tr>
<td>2.</td>
<td>Result 2</td>
<td>Cutting forces, AErms, the total energy of forces, and the total entropy of forces for different cutting conditions and tool wear</td>
</tr>
<tr>
<td>3.</td>
<td>Result 3</td>
<td>Forces and AErms of sampling frequency 2.5 and 7.5 kHz for studying the influence of chip fracture on the signals</td>
</tr>
<tr>
<td>4.</td>
<td>Result 4</td>
<td>Force and AErms signals for different fresh tools having the same specification at the start of the cut</td>
</tr>
<tr>
<td>5.</td>
<td>Result 5</td>
<td>Tool geometries of different fresh tools having the same specification</td>
</tr>
<tr>
<td>6.</td>
<td>Result 6</td>
<td>Force and AErms signals for different tool inserts having the same specification at cutting time 15 seconds, 2, 4, 6, 8 and 10 minutes</td>
</tr>
<tr>
<td>7.</td>
<td>Result 7</td>
<td>Forces and AErms for worn tools recorded in order to test the performance of the proposed on-line tool wear estimation system</td>
</tr>
</tbody>
</table>
APPENDIX B

In order to develop an on-line tool wear estimation system, many computer programs need to be developed and then integrated together. In the present research, these computer programs were adapted by using MatLab and Microsoft Visual C++ computer software version 5 and 4 respectively. The listings of all computer programs used in the proposed on-line tool wear estimation system are presented in this appendix. The objectives of each algorithm are shown in Table B1.

Table B1 Computer program employed in this thesis

<table>
<thead>
<tr>
<th>No.</th>
<th>File name</th>
<th>Note/ Function of the file</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Online_system.m</td>
<td>This file is the main computer program for on-line tool wear estimation in CNC turning operations.</td>
</tr>
<tr>
<td>2.</td>
<td>Collect.c</td>
<td>This file is complied by Visual C++ and then the compiled file (executable file) will be called by Matlab program for collecting the raw data of force and AErms signals</td>
</tr>
<tr>
<td>3.</td>
<td>Inputdata.m</td>
<td>Invites operators to input cutting conditions and calculates some basic parameters for quantitative force and AErms models</td>
</tr>
<tr>
<td>4.</td>
<td>Ltotal.m</td>
<td>Estimates total and sticking contact lengths on tool rake face</td>
</tr>
<tr>
<td>5.</td>
<td>Npower.m</td>
<td>Calculates ‘n’ value of Zorev’s model</td>
</tr>
<tr>
<td>6.</td>
<td>AErms_Fresh.m</td>
<td>Predicts AErms for fresh tools</td>
</tr>
<tr>
<td>7.</td>
<td>Force_Fresh.m</td>
<td>Predicts forces for fresh tools</td>
</tr>
<tr>
<td>8.</td>
<td>InputMLSB.m</td>
<td>Creates an input matrix used as input of MLSB NN</td>
</tr>
<tr>
<td>9.</td>
<td>Input_Fuzzy.m</td>
<td>Detects an occurrence of flank wear, crater wear, chip fracture and destroyed cutting edge</td>
</tr>
</tbody>
</table>
Table B1 Computer program employed in this thesis (continued)

<table>
<thead>
<tr>
<th>No.</th>
<th>File name</th>
<th>Note/ Function of the file</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.</td>
<td>Weights_FC.m</td>
<td>Prepares weights for the neural network model detecting the fracturing and chipping</td>
</tr>
<tr>
<td>11.</td>
<td>Fracture_Chipping.m</td>
<td>Checks tip fracture and chipping at major cutting edge by neural network mode</td>
</tr>
<tr>
<td>12.</td>
<td>Weights_TW.m</td>
<td>Prepares weights for neural network for tool wear estimations</td>
</tr>
<tr>
<td>13.</td>
<td>TW_Initial.m</td>
<td>Estimates flank and crater wears by using online system</td>
</tr>
<tr>
<td>14.</td>
<td>TW_Estimation.m</td>
<td>Estimates flank and crater wears by using online system</td>
</tr>
<tr>
<td>15.</td>
<td>TWadjfuzzy.m</td>
<td>Determines values for correcting estimated tool wear</td>
</tr>
<tr>
<td>16.</td>
<td>DFW.fis</td>
<td>Fuzzy rules for detecting occurrence of flank wear</td>
</tr>
<tr>
<td>17.</td>
<td>DCW.fis</td>
<td>Fuzzy rules for detecting occurrence of crater wear</td>
</tr>
<tr>
<td>18.</td>
<td>DCF.fis</td>
<td>Fuzzy rules for detecting occurrence of chip fracture</td>
</tr>
<tr>
<td>19.</td>
<td>DDCE.fis</td>
<td>Fuzzy rules for detecting occurrence of destroyed cutting edge</td>
</tr>
<tr>
<td>20.</td>
<td>TWadj.fis</td>
<td>Fuzzy rules for adjusting estimated tool flank and crater wear</td>
</tr>
</tbody>
</table>
FILE - ONLINE_SYSTEM.M

clc;
clear all;
Inputdata; % Asking operators to enter input information
AErrms_fresh; % Estimating AErrms for fresh tool
Force_fresh; % Estimating forces for fresh tool
% ...
Preparing weights for both neural network model ...
Weights_FC; % Setting weights of NN for fracturing and chipping detection
Weights_TW; % Setting weights of NN for tool wear estimation
% ...
Estimating flank and crater wear for fresh tool ...
% Note: These are error values for tool wear estimation and they are used for adjusting the actual tool wear later.
%
time = 0; % default time elapsed (sec)
Del_time = 0;
informationGo = input(' Press any key when the turning starts ');
tic; % To start counting turning time
InputMLSB;
Const_Ff = Ff; % Ff at start of cut
Const_Fr = Fr; % Fr at start of cut
Fracture_Chipping;
if FC < 0.5 % No tip fracture and/or major cutting edge chipping
    TW_Initial;
    Rept = 1;
else
    disp(' Can not estimate flank and crater wear due to an occurrence of tip fracture or major cutting edge chipping');
    Rept = 0;
end
while Rept == 1
    informationGo = input(' Press any key for starting tool wear estimation ');
    InputMLSB;
    Fracture_Chipping;
    if FC < 0.5 % No tip fracture and/or major cutting edge chipping
        TW_Estimation;
        TWadjfuzzy;
        Rept = input(' Do you want to estimate new tool wear ? [ '1' for 'Yes' and '0' for 'No' ] '); % There is fracture and/or major cutting edge chipping
    else
        disp(' Can not estimate flank and crater wear due to an occurrence of tip fracture or major cutting edge chipping');
        Rept = 0;
    end
end
disp(' Thank you for using our program ');
FILE - COLLECT.C

/*
* File - Collect.c
*
* 32 bit A/D input
*
* To capture 12,000 samples from four A/D channels using polled IO.
* The sampling frequency is set to 2500 Hz per channel (10 kHz)
* The data is dumped to C:\ rawdata.txt.
*
* Main functions employed:
*
*   EDR_ADInBin
*   EDR_ADInBinBackground
*   EDR_BackgroundADInStatus
*   EDR_SetADClockmilliHz
*   EDR_MaxADInThroughputHz
*   EDR_SetADTransferMode
*   EDR_ADInBinToVoltageBlock
*   EDR_SetADChanListLen
*   EDR_AddToADChanList
*   EDR_SetCTInputFreqHZ (See page 136 or 139 in PC30 manual)
*
* Boards supported: All boards with A/D channels.
*
* (c)2000 Modified by C. Chungchoo (based on David Tinker's structure)
*/

#include "C:\Eagle Tech\edr.h" /* driver functions */
#include <windows.h>
#include <stdio.h>
#include <stdlib.h>
#include <conio.h>

#define BUFSIZE 120001 /* number of samples to take */

int bh; /* our board handle */
unsigned short bin[BUFSIZE]; /* buffer for binary data */
int uvolts[BUFSIZE]; /* buffer for voltages */
int freq=100001; /* sampling frequency */

void printerror(int r); /* displays error message and exits */
void quit(int c); /* release our board handle and exit */

void main(int argc,char *argv[])
{
    int baseaddr;
    int boardtype;
    int numad;
    int t,i,num,b;
    int bg;
    char s[80];
    FILE *f;

    printf("A/D input program by I/O mode \n\n");
/* Display boards and ask user to select board number */
printf("Boards installed:\n");
for (t=0,i=1; i<=8; i++)
    if (EDR_GetBoardType(i, &boardtype) == EDR_OK) {
        EDR_GetBase(i, &b);
        EDR_StrBoardType(boardtype, s);
        printf("%d - %s(%X)\n", i, s, b);
        t++;
    }
if (t==0) {
    printf("No boards are installed. Run control panel and choose Eagle "
            "board setup.\n");
    return;
}
printf("Select board number or enter 0 to quit: ");
bh=getch();
printf(" %c\n", bh);
bh='0';
if ((bh<1) || (bh>t)) return;
EDR_GetBoardType(bh, &boardtype);

/* check that the board has some A/D channels */
EDR_GetADInType(bh,0,&t); /* get the type of AD inputs */
umad=EDR_NumADInputs(boardtype, t);
if (numad==0) {
    printf("This board does not have any A/D channels\n");
    quit(1);
}

/* Ask the user to choose a transfer mode */
printf("A/D Transfer modes supported by this board and demo:\n");
for (i=0,t=EDR_POLLED; t<EDR_STREAM; t++)
    if (((t!=EDR_STREAM) && (EDR_ValidADTransferMode(bh, t)))) {
        EDR_StrTransferMode(t, s);
        i=i;
    }
if (i=0) {
    printf("(None)\n");
    quit(1);
}
printf("Using I/O mode ");
t = 1-'O';
getch();
printf("\n");
if ((t<EDR_POLLED) || (t>=EDR_STREAM)) exit(1);

/* set the transfer mode */
i=EDR_SetADTransferMode(bh, t);
if (i<0) printerror(i);
EDR_StrTransferMode(t, s);
printf("Using %s\n", s);

/* background mode */
bg = 0; /* background mode is not used */

/* make sure freq is not too high for this board */
if (freq>EDR_MaxADInThroughputHz(boardtype))
    freq=EDR_MaxADInThroughputHz(boardtype);
/* set the sampling frequency */
printf("Setting A/D sampling frequency to %d Hz\n",freq);
t=EDR_SetADClockmilliHz(bh,freq*1000);
if (t<0) printerror(t);

/* add four A/D channels to the channel list */
EDR_SetADChanListLen(bh,0); /* make sure it is empty */
for (i=0; i<4; i++) EDR_AddToADChanList(bh,i); /* put in 4 channels */

/* sample the data */
printf("Taking %d samples\n",BUFSIZE);
if (!bg) {
EDR_SetADKeyAbort(bh,1);
num=EDR_ADInBin(bh,BUFSIZE,bin);
if (num<0) printerror(num);
}
printf("Got %d samples\nDumping data as text to C:\ RAWDATA.TXT\n",num);

/* convert binary data to voltages and dump to file */
EDR_ADInBinToVoltageBlock(bh,uvolts,bin,num,0);
f=fopen("C:\ rawdata.txt","w+");
if (!f) {
printf("Unable to open rawdata.txt\n");
quit(1);
}
fprintf(f,"Sample Channel Hex Voltage\n");
fprintf(f,"--------- ---- ---------\n");
for (i=0; i<num; i++)
fprintf(f, "%6d %7d %03X %.6f\n",i,bin[i],
(float)(uvolts[i])/1000000.0);
fclose(f);

printf("\n\nPress a key to exit\n");
getch();
}

void printerror(int r)
/* displays error msg and exits */
{
char s[80];
EDR_StrError(r,s); /* convert error number into a string */
printf("%s (%d)\n",s,r);
quit(1);
}

void quit(int c)
/* release our board handle and exit */
{
EDR_StopBackgroundADIn(bh);
EDR_FreeBoardHandle(bh);
exit(c);
}
% This file was developed for asking cutting conditions for calculating some parameters
% in order to estimate forces (Fc, Ff and Fr), AErms and their derivatives.

% ... Input cutting conditions ...
% f = input('feed rate (mm/rev) : '); % Feed rate (mm/rev)
s = input('cutting speed (m/min) : '); % Cutting speed (m/min)
Asl = input('side rake angle (degree) : '); % Rake angle (degrees)
disp('');
%
% ... Calculation of tool geometry ...
% b = 1; % Depth of cut (mm)
r = 0.8; % Nose radius (mm)
Ab1 = 5; % Back rake angle (degrees)
Cs1 = 15; % Side cutting edge angle (degrees)
Ab = Ab1*pi/180;
As = As1*pi/180;
Cs = Cs1*pi/180;
i = atan(tan(As)*cos(Cs)-tan(As)*sin(Cs)); % Angle of inclination
An = atan((tan(As)*cos(Cs))+(tan(As)*sin(Cs))*cos(i)); % Normal rake angle
Nc = atan(((f/2)+r)/(b/cos(Cs))); % Chip flow angle
Ae = asin(sin(i)*cos(An)*sin(On-An)); % Effective rake angle
rt = (0.325+(f-0.1)/4)+(0.000325*(s-80))+(0.00025*(As)); % Chip thickness ratio
On = rt*cos(An)/(1-rt*sin(An));
Ns = atan((tan(i)*cos(On-An)-tan(Nc)*sin(On))/cos(i)); % Total cutting length
Oe = asin(cos(Ns)*cos(Ae)*sin(On)/(cos(Nc)*cos(An))); % Merchant's relationship
l = (b/cos(Cs))-r+(pi*r2)+f/2; % Area of shear plane (mm^2)
AS = (2/3)*f*l/(sin(On));
Be = (pi/2)+Ae-(2*Oe); % Coefficient of friction

% ... Shear and normal stresses of workpiece material ...
% k = 570; % Yield stress (MPa)
NSmax = 2*k*(1.3-Ae); % Normal stress (MPa)
TSmax = 1000-(0.2745*s)-(991.6104*f)+(19.1307*As1); % Shear stress (MPa)

% ... Call function Ltotal for estimating total and sticking contact lengths ....
% Ltotal;
%
% ... Call function for predicting n value of Zorev's stress distribution ....
% Npower;
%
% ... Coefficient of friction ...
% u = TSmax/NSmax*(1-(lst/lt)^n); % Coefficient of friction
FILE - LTOTAL.M

% This M-file calculates the total and sticking contact lengths on the tool rack face.

\[
\begin{align*}
\text{It} &= \frac{f}{rt} \times (1 - \tan(Ae) + rt \times \sec(Ae)) ; \\
\text{lst} &= \frac{7}{12} \times \text{lt} ;
\end{align*}
\]

% Total contact length
% Sticking contact length
FILE - NPOWER.M

% This M-file predicts the 'n' value in the stress distribution equations.

\[ F_{nn} = F_c \cos(A_e) \]

\[ n = \frac{(F_{nn} - A_S N_{\text{max}} + A_S N_{\text{max}} \cdot l_t)}{(-F_{nn} + A_S N_{\text{max}})} \]

Note: From the experimental results, it was found that 'n' value is between 0.76 to 1.17. Hence for a simple calculation, 'n' can be assumed to be "1".
% The functions of this M-file is to estimate AErms for fresh tools in oblique turning operations.

% Note: 1. Although the AErms model developed in Chapter 4 can predict mean AErms for both fresh
% and worn tools, only AErms for fresh tools is employed in the on-line tool wear estimation
% system. Therefore, this M-file estimates AErms for fresh tool only.

% 2. Inputdata.m needs to be called first.

Wp = TSmax*AS*cos(Ae)*s/cos(Oe-Ae); % Energy on shear plane
% func = '(1-(x/lt)\n)';
% funcint = int(func,lst,lt)
funcint =
1615717558608981/4503599627370496*(n*4503599627370496^n*lt^n+4503599627370496^n*lt^n-
1615717558608981^n)/(n+1)/(4503599627370496^n)/(lt^n)-538572519536327/2251799813685248*
(n*2251799813685248^n*lt^n+2251799813685248^n*lt^n-
538572519536327^n)/(2251799813685248^n)/(lt^n)/(n+1);  
Wr1 = u*NSmax*funcint*l*s*sin(Oe)/cos(Oe-Ae);  
Wr2 = TSmax*l*1*(2/3)*s*sin(Oe)/cos(Oe-Ae);  
% Energy on tool rake face
Wr = Wr1+Wr2;
k1 = 0.0000066;
k2 = 0.0001536;
AErms_pre = sqrt(k1*Wp+k2*Wr);
disp('Estimated AErms (V) : '); disp(AErms);
FILE – FORCE_FRESH.M

% The function of this M-file is to calculate three cutting forces for fresh tools during oblique cutting.
% Note: 1. Although the force model developed in Chapter 4 can predict the three forces for both fresh and worn tools, only three forces for fresh tools are employed in the on-line tool wear estimation system. Therefore, this M-file estimates cutting, feed and radial forces for fresh tool only.
% 2. Inputdata.m needs to be called first.

Intterm = (lt-lst)-(1/(lt)^n)*(1/(n+1))*(((lt)^n(n+1)))+((lst)^n(n+1))); 
Ft = (TSmax*l*lst)+(l*u*NSmax*Intterm); 
FH = (1/cos(Oe-Ae))*((TSmax*AS*cos(Ae))+((0.667*TSmax*l*lst*sin(Oe))+l*u*NSmax*sin(Oe)*Intterm)); 
Nt = (FH-Ft*sin(Ae))/(cos(An)*cos(i)); 
FV = (-Nt)*sin(An)+Ft*cos(Nc)*cos(An); 
FT = (-Nt)*cos(An)*sin(i)+Ft*sin(Nc)*cos(i)-Ft*cos(Nc)*sin(Nc)*sin(i); 
Fc_pre = FH; % Cutting force (N) 
Ff_pre = FV; % Feed force (N) 
Fr_pre = FT; % Radial force (N) 
disp('Estimated cutting force (N) : '); disp(Fc_pre); 
disp('Estimated feed force (N) : '); disp(Ff_pre); 
disp('Estimated radial force (N) : '); disp(Fr_pre);
FILE - INPUTMLSBM.M

assert(0) % Sampling data and then setting input matrix of MLSB neural network
assert(0)

return dos = dos('Collect.exe'); % Calling Collect.exe for sampling the raw data

% ... Reading sampling data from data file ...
fid = fopen('rawdata.txt');
A = fscanf(fid,'%g %g',[4 inf]);
A = A';
fclose(fid);

% ... Finding average value of AErms and forces ...
N = 4000;
AA1 = A(1:N,1)*1000;
Fc = mean(AA1);
Sdfc = std(AA1);

AA2 = A(1:N,2)*1000;
Ff = mean(AA2);
Sdff = std(AA2);

AA3 = A(1:N,3)*1000;
Fr = mean(AA3);
Sdfr = std(AA3);

AA4 = A(1:N,4);
Mae = mean(AA4);
AErms=Mae;
Sdae = std(AA4);

% ... Define default values for signal processing ...
N = 2048;
% N = number of rows = sample per channel =>(2A k)
% Sampling frequency is 10 kHz/ 4 channels => 2500 Hz/ channel
dt = 1/2500;
Ws = 1/dt;

% ... PSD of cutting forces ...
% % Cutting velocity (m/s) --- get s from Input_conditions.m
% Velocity in Fc direction
ss = s/60;
Vfc = ss;
A1 = A(1:N,1)*1000*Vfc;
F1 = psd(A1,N,Ws,N,0);
Fp1 = F1(1:(N/2));

% Chip velocity --- get Oe and Ae from Input_conditions.m
% Velocity in Ff direction
Vc = ss*sin(Oe)/cos(Oe-Ae);
Vff = Vc*cos(Ae);
A2 = A(1:N,2)*1000*Vff;
F2 = psd(A2,N,Ws,N,0);
Fp2 = F2(1:(N/2));
%
% => Radial force column @ N samples
%
Vfr = Vc*sin(Ae)*cos((pi/2)-Cs-Nc); % Velocity in Fr direction
A3 = A(1:N,3)*1000*Vfr;
F3 = psd(A3,N,Ws,N,0);
Fp3 = F3(1:(N/2));
%
% => Total energy of cutting forces ...
%
% => The energy of cutting force signals
%
df = 1/(N*dt);
PT1 = 0;
for i = 1:(N/2)
    PT1 = PT1 + abs(Fp1(i));
end
Gf1 = 0;
for i = 1:(N/2)
    Gf1 = Gf1 + (abs(Fp1(i))^2)/(PT1);
end
%
% => The energy of feed force signals
%
PT2 = 0;
for i = 1:(N/2)
    PT2 = PT2 + abs(Fp2(i));
end
Gf2 = 0;
for i = 1:(N/2)
    Gf2 = Gf2 + (abs(Fp2(i))^2)/(PT2);
end
%
% => The energy of radial force signals
%
PT3 = 0;
for i = 1:(N/2)
    PT3 = PT3 + abs(Fp3(i));
end
if Vfr == 0
    PT3 = 1;
end
Gf3 = 0;
for i = 1:(N/2)
    Gf3 = Gf3 + (abs(Fp3(i))^2)/(PT3);
end
%
% => The total energy of force signals
%
Gf = (Gf1) + (Gf2) + (Gf3);
%
% ... Fuzzy logic model ...
%
OFW = 0.5; % default value for occurrence of flank wear
OCW = 0.5; % default value for occurrence of crater wear
OCF = 0.5; % default value for occurrence of chip fracture
ODCE = 0.5; % default value for occurrence of destroyed cutting edge
Input_fuzzy;  % Predicting OFW, OCW, OCF and ODCE
  % ... Skewness and kurtosis of forces ...
  %
  % => The skew and kurtosis of PSD(Fc) at band 50-250 Hz, 550-750 Hz and 950-1150 Hz
  %
  Skfcl = skewness(Fp1(20:220));
  Skfc2 = skewness(Fp1(420:620));
  Skfc3 = skewness(Fp1(820:1020));
  Kufcl = kurtosis(Fp1(20:220));
  Kufc2 = kurtosis(Fp1(420:620));
  Kufc3 = kurtosis(Fp1(820:1020));
  %
  % => The skew and kurtosis of PSD(Ff) at band 50-250 Hz, 550-750 Hz and 950-1150 Hz
  %
  Skff1 = skewness(Fp2(20:220));
  Skff2 = skewness(Fp2(420:620));
  Skff3 = skewness(Fp2(820:1020));
  Kuff1 = kurtosis(Fp2(20:220));
  Kuff2 = kurtosis(Fp2(420:620));
  Kuff3 = kurtosis(Fp2(820:1020));
  %
  % => The skew and kurtosis of PSD(Fc) at band 50-250 Hz, 550-750 Hz and 950-1150 Hz
  %
  Skfr1 = skewness(Fp3(20:220));
  Skfr2 = skewness(Fp3(420:620));
  Skfr3 = skewness(Fp3(820:1020));
  Kufr1 = kurtosis(Fp3(20:220));
  Kufr2 = kurtosis(Fp3(420:620));
  Kufr3 = kurtosis(Fp3(820:1020));
  %
  % => Normalization of input units and setting input units
  %
  XX(1,1) = 0.5;  % Bias
  XX(1,2) = s/180;  % Normalized speed
  XX(1,3) = f*2.5;  % Normalized feed
  XX(1,4) = (Asl+10)/20;  % Normalized rake angle
  XX(1,5) = b/2;  % Normalized depth of cut
  XX(1,6) = Fc/1000;  % Normalized cutting force
  XX(1,7) = Ff/1000;  % Normalized feed force
  XX(1,8) = Fr/1000;  % Normalized radial force
  XX(1,9) = Ff/Fc;  % Normalized Ff/Fc
  XX(1,10) = Fr/Fc;  % Normalized Fr/Fc
  XX(1,11) = 0.5*(Fr/Ff);  % Normalized Fr/Ff
  XX(1,12) = Gf/(10^10);  % Normalized total energy of forces
  XX(1,13) = AErms/4;  % Normalized AErms
  XX(1,14) = Sdae/Mae;  % Normalized SD/ mean of AErms
  XX(1,15) = (OFW+0.5)/2;  % Normalized OFW
  XX(1,16) = (OCW+0.5)/2;  % Normalized OCW
  XX(1,17) = (OCF+0.5)/2;  % Normalized OCF
  XX(1,18) = (ODCE+0.5)/2;  % Normalized ODCE
  XX(1,19) = Skfcl;  % Skewness of Fc 20-220 Hz
  XX(1,20) = Skfc2;  % Skewness of Fc 420-620 Hz
  XX(1,21) = Skfc3;  % Skewness of Fc 820-1020 Hz
  XX(1,22) = Kufcl;  % Kurtosis of Fc 20-220 Hz
  XX(1,23) = Kufc2;  % Kurtosis of Fc 420-620 Hz
  XX(1,24) = Kufc3;  % Kurtosis of Fc 820-1020 Hz
  XX(1,25) = Skff1;  % Skewness of Ff 20-220 Hz
  XX(1,26) = Skff2;  % Skewness of Ff 420-620 Hz
  %
XX(1,27) = Skfr3;
XX(1,28) = Kuff1;
XX(1,29) = Kuff2;
XX(1,30) = Kuff3;
XX(1,31) = Skfr1;
XX(1,32) = Skfr2;
XX(1,33) = Skfr3;
XX(1,34) = Kufr1;
XX(1,35) = Kufr2;
XX(1,36) = Kufr3.

disp(XX);

Skewness of Ff 820-1020 Hz
Kurtosis of Ff 20-220 Hz
Kurtosis of Ff 420-620 Hz
Kurtosis of Ff 820-1020 Hz
Skewness of Fr 20-220 Hz
Skewness of Fr 420-620 Hz
Kurtosis of Fr 20-220 Hz
Kurtosis of Fr 420-620 Hz
Kurtosis of Fr 820-1020 Hz
FILE – INPUT_FUZZY.M

% Fuzzy logic model to:
% 1. Detect occurrence of flank wear
% 2. Detect occurrence of crater wear
% 3. Detect occurrence of chip fracture
% 4. Detect occurrence of cutting edge deterioration
%

% Note: Inputdata.m and InputMLSB.m needs to be called first.

% ... Input parameters ...

Cutting_time = time/60; % Getting value from InputMLSB.m then converting to minute
Shear_energy = Wp; % Getting Wp from AErms_Fresh.m
Friction_energy = Wr; % Getting Wr from AErms_Fresh.m
SDMean = Sdae/Mae; % Getting Sdae and Mae from InputMLSB.m
PFW = 0; % Previous value of flank wear
PCW = 0; % Previous value of crater wear
Del_time = Del_time + Cutting_time;
Cutting_speed = s; % Getting s from Input_conditions.m

% ... Occurrence of flank wear ...
% fis = readfis ('DFW');
Inputvector = [Cutting_time Shear_energy];
Outputvector = evalfis(Inputvector, fis);
OFW = Outputvector;

% ... Occurrence of crater wear ...
% fis = readfis ('DCW');
Inputvector = [Friction_energy Cutting_time];
Outputvector = evalfis(Inputvector, fis);
OCW = Outputvector;

% ... Occurrence of chip fracture ...
% fis = readfis ('DCF');
Inputvector = [Friction_energy SDMean PFW PCW Del_time Cutting_speed];
Outputvector = evalfis(Inputvector, fis);
OCF = Outputvector;

% ... Occurrence of destroyed cutting edge ...
% fis = readfis ('DDCE');
Inputvector = [Friction_energy PFW PCW Del_time];
Outputvector = evalfis(Inputvector, fis);
ODCE = Outputvector;
% This M-File was developed for preparing weights of MLSB NN for tip fracture and major cutting edge chipping.

% ... Training pair, input unit, hidden unit and output unit ...

NTP = 172; % Number of training pairs [12 inserts x 3 feeds x 3 rake angles x 2 (before and after fracturing and chipping) x 80%]
NIN = 7; % Number of input units including bias
NHD = 9; % Number of hidden units
NOP = 1; % Number of output units

% ... Training data ...

fid = fopen('C:\........\FC_traindata.txt');
B = fscanf(fid,'%g %g',[8 172]);
B = B';
fclose(fid);

% ### Section 1 ###

% Initialization

% ... Form input data X = [NTP x NIN] ...

for r=1:NTP
    for c=1:NIN
        X(r,c) = B(r,c);
    end
end

% ... Set initial weights ...

% W1(NIN,NHD) => weights from input units to hidden units
% For example Wx(1,1) => weight from X1 to HD1
W1=1*randn(NIN,NHD); % => i=1:NIN and j=1:NHD (for first train)

% W2(NHD,NOP) => weights from hidden units to output units
W2=1*randn(NHD,NOP); % => j=1:NHD and k=1:NOP (for first train)

% ... Set the initial desired output R ...

% size of matrix R = A but A = [0.5 A1]
% where A1 = X*W1 ->[NTP x NIN]*[NIN x NHD]=[NTP x NHD]
% And A is [NTP x NHD+1]. Hence, R = [NTP x NHD+1] and W2 has to be added a first row to % - take care constant 0.5 -> W2n

for r = 1:NTP
    for c = 1:NHD
        R1(r,c) = 0;
    end
W2c = 1*randn(1,NOP);
W2n = [W2c;W2];

% ... Form the input matrix Xr -> Xr = [X R1] ...
% 
Xr = [X R1];
for r = 1:NTP
    Rc(r,1) = 0.5;
end
R = [Rc R1];

% ### Section 2 ###
% Optimization of Output layer weight
%
%
% ... Propagate the given input matrix Xr through the network and get
% the outputs of the hidden layer and the output layer ...
%
% Since Xr -> [NTP x (NIN+NHD)], Wr should be [(NIN+NHD) x NHD]
% Wr is a [(NIN+NHD) x NHD] or = [W1 W] where W1 is a [NIN x NHD]
for r = 1:NIN
    for c = 1:NHD
        Wr(r,c) = W1(r,c);
    end
end
for r = NIN+1 : NIN+NHD
    for c = 1:NHD
        Wr(r,c) = 1;
    end
end
% -> A1 = 1/(1+exp(-(Xr*Wr)));
IA1=Xr*Wr;
for r=1:NTP
    for c=1:NHD
        A1(r,c)=1/(1+exp(-IA1(r,c)));
    end
end

countloop = 1;
while countloop < 3
    for r=1:NTP
        Ac(r,1)=0.5;
    end
    A = [Ac A1];
% where Ac = [0.5] -> bias
% 
% -> Y = 1/(1+exp(-(A*W2n)));
IY = A*W2n;
for r=1:NTP
    for c=1:NOP
        Y(r,c)=1/(1+exp(-IY(r,c)));
    end
end
%
% ... Get the 'designed' weighted sums of output neurons by inverse
% activation function ...
% Inverse function of sigmoid function is x = -ln(1/y -1) { y = 1/(1+e^x) }
% for r=1:NTP
    for c=1:2
\[ T(r,c) = B(r,(NIN+c)) \]
end

\% \rightarrow S = -\log((1/T)-1)
for \( r=1:NTP \)
for \( c=1:2 \)
\[ S(r,c) = -\log((1/T(r,c))-1); \]
end
end

% \% ... Compute the optimal weights of output layer ...
% \% \textcolor{red}{W2n=Als;}
% \%

% \% ... Determine the 'required' output of the hidden layer ... 
% \% \rightarrow dT1*V-(S-A*W2n) = minimal and R = A+[0.0 dT1] 
% 
% ST = S-(A*W2n);
for \( r = 1:NHD \)
for \( c=1 NOP \)
\[ V(r,c) = W2n(r+1,c); \]
end
end
% \% \% where \( Tc = [0.0] \) for bias 
% \%

% \% \% ... Normalise the 'desired' output of the hidden layer ...
% \%
% \% \% -> To determine \( ak, bk \) and \( gk \)
% 
% for \( r = 1:NTP \)
for \( c = 1:NHD \)
\[ R1(r,c) = R(r,(c+1)); \]
end
end

for \( c = 1:NHD \)
\[ rjk(c) = 0; \]
for \( r = 1:NTP \)
\[ rjk(c) = rjk(c)+R1(r,c); \]
end
\[ ak(c) = rjk(c)/NTP; \]
end
for \( c = 1:NHD \)
for \( r = 1:NTP \)
\[ R1r(r) = R1(r,c); \]
end
\[ bk(c) = \max(R1r); \]
end
for \( c = 1:NHD \)
for \( r = 1:NTP \)
\[ R1r(r) = R1(r,c); \]
end
\[ gk(c) = \min(R1r); \]
end
% \% \% -> define element of \( C(k,k) \)
% for r = 1:NHD
% for c = 1:NHD
% if r == c
%   kk = [0.5 (bk(c)-ak(c)) (ak(c)-gk(c))];
%   Ckk(r,c) = 2*max(kk);
% else
%   Ckk(r,c) = 0;
% end
% end
% % -> define element of C(0,0)
% C00 = 1;
% % -> define element of C(k,0)
% for r = 1:NHD
% for c = 1:1
%   Ck0(r,c) = 0;
% end
% end
% % -> define element of C(0,k)
% for r = 1:1
% for c = 1:NHD
%   ok = [0.5 (bk(c)-ak(c)) (ak(c)-gk(c))];
%   C0k(r,c) = 2*(ak(c)-max(ok));
% end
% end
% Cl = [C 0 0  C0k];
% C2 = [Ck0 Ckk];
% C = [Cl; C2];
% % ... Construct inverse C ...
% % Ci00 = C00;
% Ci0k = C0k;
% for r = 1:1
% for c = 1:NHD
%   Ci0k(r,c) = -C0k(r,c)/Ckk(c,c); % Ci0k=-C0k/Ckk;
% end
% end
% for r = 1:NHD
% for c = 1:NHD
%   if r == c
%     Cikk(r,c) = 1/Ckk(r,c);
%   else
%     Cikk(r,c) = 0;
%   end
% end
% end
% Ci1 = [Ci00 Ci0k];
% Ci2 = [Cik0 Cikk];
% Cinv = [Ci1; Ci2];
% % % ... To transform R to a matrix with elements between 0 and 1
% %
Rtr = R*Cinv;
R = Rtr;
Wtr = C*W2n;
W2n = Wtr;

% ### Section 3 ###
% Optimization of the hidden layer weights
%

% ... Determine the 'desired' weighted sum of the hidden neurons ...
%
for r = 1:NTP
    for c = 1:NHD
        Rl(r,c) = R(r,(c+1));
    end
end
% -> QR = -log((l/Rl)-l)
for r = 1:NTP
    for c = 1:NHD
        if Rl(r,c) == 1;  
            Rl(r,c) = Rl(r,c)-0.0001;
        end
        if Rl(r,c) == 0;  
            Rl(r,c) = Rl(r,c)+0.0001;
        end
        QR(r,c) = -log((l/Rl(r,c))-l);
    end
end
% ...
% ... Form the input matrix Xr of the hidden layer ...
%
Xr = [X Rl];  
% Xr = [NTP x (NIN + NHD)]
%
% ... Compute the optimal weights Wr of hidden layer ...
%
Wr=Xr\QR;

% ### Section 4 ###
% Repeat step 2-3 until a certain error tolerance is satisfied
%
countloop = countloop+1;
end
%
% ... Weights of NN for fracturing and chipping detection ...
%
Wrfc = Wr;
W2nfc = W2n;
% This MATLAB program was developed for detecting tip fracture and major cutting edge chipping by Neural Network model with 7-9-1 structure.

% MLSB neural network model ...

NIN = 7;  % Number of input units including bias
NHD = 9;  % Number of hidden units including bias.
NOP = 1;  % Number of output units (flank and crater wear)

% Xr = [1 x (NIN + (NHD-1))] = [X R1]
% Wr fc= [(NIN+(NHD-1)) (NHD-1)]
% W2nfc= [NHD NOP]

% ... Set Input matrix ...

XX = [0.5 Const_Ff Const_Fr Ff_pre Fr_pre Ff Fr];

% Detection of tip fracture and chipping at major cutting edge

NTP = 1;  % Number of pair = 1 for estimation tool wear
for r = 1:NTP
    for c = 1:NHD
        RR1(r,c)=0;
    end
end
XXr = [XX RR1];  % Xr = [NTP x (NIN + NHD)] and X from InputMLSB.m
IIA1 = XXr*Wrfc;
for r = 1:NTP
    for c = 1:NHD
        AAA1(r,c) = 1/(1+exp(-IIA1(r,c)));
    end
end
RR1 = AAA1;
XXr = [XX RR1];
for r = 1:NTP
    AAc(r,1) = 0.5;
end
IIA1 = XXr*Wrfc;
for r = 1:NTP
    for c = 1:NHD
        AAA1(r,c) = 1/(1+exp(-IIA1(r,c)));
    end
end
AAA = [AAAc AAA1];

% where Ac = [0.5] -> bias
% -> Y = 1/(1+exp(-(A*W2nfc)));
IIY = AAA*W2nfc;
for r = 1:NTP
    for c = 1:NOP
        YY(r,c) = 1/(1+exp(-IIY(r,c)));
    end
end
FC = (sqrt((real(YY(1)))^2+(imag(YY(1)))^2));
if FC <= 0.5
    Disp(' No fracturing or chipping on tool insert ');
else
    Disp(' There is fracturing or chipping or both on tool insert ');
end
% This M-File was developed for preparing weights of MLSB NN for tool wear estimation.

% ... Training pair, input unit, hidden unit and output unit ...

NTP = 378;  % Number of training pairs
NIN = 36;    % Number of input units including bias
NHD = 40;    % Number of hidden units including bias
NOP = 2;     % Number of output units

% ... Training data ...

fid = fopen('C:\......\Traindata_test.txt');
B = fscanf(fid,'%g %g',[38 378]);  % 38 is the number of input units + output units
B = B';
fclose(fid);

% ### Section 1 ###
% Initialization

% ... Form input data X = [NTP x NIN]

for r=1:NTP
    for c=1:NIN
        X(r,c) = B(r,c);
    end
end

% ... Set initial weights ...

% W1(NIN,NHD) => weights from input units to hidden units
% For example Wx(1,1) => weight from XI to HD1
W1=1*randn(NIN,NHD);  % => i=1:NIN and j=1:NHD (for first train)
% W2(NHD,NOP) => weights from hidden units to output units
W2=1*randn(NHD,NOP);  % => j=1:NHD and k=1:NOP (for first train)

% ... Set the initial desired output R ...

% size of matrix R = A but A = [0.5 A1]
% where A1 = X*W1 -> [NTP x NIN]*[NIN x NHD]=[NTP x NHD]
% And A is [NTP x NHD+1]. Hence, R = [NTP x NHD+1] and W2 has to be added a
% - first row to take care constant 0.5 -> W2n
for r = 1:NTP
    for c = 1:NHD
        R1(r,c) = 0;
    end
end
W2c = 1*randn(1,NOP);
W2n = [W2c;W2];
% ... Form the input matrix Xr -> Xr = [X R1] ...
%
Xr = [X R1];
for r = 1:NTP
    Rc(r,1) = 0.5;
end
R = [Rc R1];
%
% ### Section 2 ###
% Optimization of Output layer weight
%
% ... Propagate the given input matrix Xr through the network and get
% the outputs of the hidden layer and the output layer ...
%
% Since Xr -> [NTP x (NIN+NHD)], Wr should be [(NIN+NHD) x NHD]
% Wr is a [(NIN+NHD) x NHD] or = [W1 W]' where W1 is a [NIN x NHD]
for r = 1:NIN
    for c = 1:NHD
        Wr(r,c) = W1(r,c);
    end
end
for r = NIN+1 : NIN+NHD
    for c = 1:NHD
        Wr(r,c) = 1;
    end
end
% -> A1 = l/(l+exp(-(Xr*Wr))); % A1 = [NTP, NHD]
IA1 = Xr*Wr;
for r=1:NTP
    for c=1:NHD
        A1(r,c)= 1/(1+exp(-IA1(r,c)));  
    end
end
countloop = 1;
while countloop < 3
    for r=1:NTP
        Ac(r,1)=0.5;
    end
A = [Ac A1]; % where Ac = [0.5] -> bias
% -> Y = l/(l+exp(-(A*W2n)));  
IY = A*W2n;
for r=1:NTP
    for c=1:NOP
        Y(r,c)= 1/(1+exp(-IY(r,c)));  
    end
end
%
% ... Get the 'designed' weighted sums of output neurons by inverse
% activation function ...
% Inverse function of sigmoid function is x = -ln(1/y -1)  \{ y = 1/(1+e^-x) \}
%
for r=1:NTP
    for c=1:2
        T(r,c)=B(r,(NIN+c));
    end
end
% -> S = -log((1/T)-1)
for r=1:NTP
  for c=1:2
    S(r,c)=-log((1/T(r,c))-1);
  end
end
%
% ... Compute the optimal weights of output layer ...
%
W2n=A'S;
%
% ... Determine the 'required' output of the hidden layer ...
% -> dT1*V -(S-A*W2n) = minimal and R = A+[0.0 dT1]
ST = S-(A*W2n);
for r = 1 :NHD
  for c = 1:NOP
    V(r,c) = W2n(r+1,c);
  end
end
%
% -> dT1*V-ST = min --- dT1=ST*pinv(V)
for r = 1:NTP
  Tc(r,1) = 0.0;
end
R = A + [Tc dT1]; % where Tc = [0.0] for bias
%
% ... Normalise the 'desired' output of the hidden layer ...
%
% -> To detemine ak, bk and gk
%
for r = 1:NTP
  for c = 1:NHD
    Rl(r,c) = R(r,(c+1));
  end
end
for c = 1:NHD
  rjk(c) = 0;
  for r = 1:NTP
    rjk(c) = rjk(c)+Rl(r,c);
  end
  ak(c) = rjk(c)/NTP;
end
for c = 1:NHD
  for r = 1:NTP
    R1r(r) = R1(r,c);
  end
  bk(c) = max(R1r);
end
for c = 1:NHD
  for r = 1:NTP
    R1r(r) = R1(r,c);
  end
  gk(c) = min(R1r);
end
%
% -> define element of C(k,k)
%
for r = 1:NHD
  for c = 1:NHD
if r == c
    kk = [0.5 (bk(c)-ak(c)) (ak(c)-gk(c))];
    Ckk(r,c) = 2*max(kk);
else
    Ckk(r,c) = 0;
end
end
end
%
% -> define element of \( C(0,0) \)
% C00 = 1;
%
% -> define element of \( C(k,0) \)
% for r = 1:NHD
% for c = 1:1
%    Ck0(r,c) = 0;
% end
% end
%
% -> define element of \( C(0,k) \)
% for r = 1:1
% for c = 1:NHD
%    ok = [0.5 (bk(c)-ak(c)) (ak(c)-gk(c))];
%    C0k(r,c) = 2*(ak(c)-max(ok));
% end
end
C1 = [C00 C0k];
C2 = [Ck0 Ckk];
C = [C1; C2];
%
% ... Construct inverse C ... 
%
Ci00 = C00;
Ci0k = C0k;
for r = 1:1
    for c = 1:NHD
        Ci0k(r,c) = -C0k(r,c)/Ckk(c,c);  % \( Ci0k = -C0k/Ckk; \)
    end
end
for r = 1:NHD
    for c = 1:NHD
        if r == c
            Cikk(r,c) = 1/Ckk(r,c);
        else
            Cikk(r,c) = 0;
        end
    end
end
Ci1 = [Ci00 Ci0k];
Ci2 = [Ck0 Cikk];
Cinv = [Ci1; Ci2];
%
% ... To transform \( R \) to a matrix with elements between 0 and 1 
%
Rtr = R*Cinv;
R = Rtr;
Wtr = C*W2n;
W2n = Wtr;

% % ### Section 3 ###
% Optimization of hidden layer weights
%

% ... Determining the 'desired' weighted sum of the hidden neurons ...
%
for r = 1:NTP
    for c = 1:NHD
        R1(r,c) = R(r,(c+1));
    end
end
% -> QR = -log((1/R l)-1)
for r = 1:NTP
    for c = 1:NHD
        if R1(r,c) == 1;
            R1(r,c) = R1(r,c)-0.0001;
        end
        if R1(r,c) == 0;
            R1(r,c) = R1(r,c)+0.0001;
        end
        QR(r,c) = -log((1/R1(r,c))-1);
    end
end
%
% ... Form the input matrix 'Xr' of the hidden layer ...
%
Xr = [X R1]; % Xr = [NTP x (NIN + NHD)]
%
% ... Compute the optimal weights 'Wr' of hidden layer ...
%
Wr=Xr\QR;

% % ### Section 4 ###
% Repeat step 2-3 until a certain error tolerance is satisfied
%
countloop = countloop+1;
end
%
% ... Weights of MLSB NN for tool wear estimation ...
%
Wrtw = Wr;
W2ntw = W2n;
FILE - TW_INITIAL.M

%  This MATLAB program was developed for estimating tool flank and crater wear by using Fuzzy Neural Network model with 36-40-2 structure.

%  Number of input units including bias
NIN = 36;
%  Number of hidden units including bias.
NHD = 40;
%  Number of output units (flank and crater wear)
NOP = 2;

%  Xr = [1 x (NIN + {NHD-1})] = [X R1]
%  Wrtw = [(NIN+{NHD-1}) (NHD-1)]
%  W2ntw = [NHD NOP]

IFW = 0;
ICW = 0;
NTP = 1;
for r = 1:NTP
    for c = 1:NHD
        RR1(r,c)=0;
    end
end
XXr = [XX RR1];  %  Xr = [NTP x (NIN + NHD)] and X from InputMLSB.m
IIA1 = XXr*Wrtw;
for r = 1:NTP
    for c = 1:NHD
        AAA1(r,c) = 1/(1+exp(-IIA1(r,c)));
    end
end
RR1 = AAA1;
XXr = [XX RR1];
for r = 1:NTP
    AAAc(r,1) = 0.5;
end
IIA1 = XXr*Wrtw;
for r = 1:NTP
    for c = 1:NHD
        AAA1(r,c) = 1/(1+exp(-IIA1(r,c)));
    end
end
AAA = [AAAc AAA1];  %  where Ac = [0.5] -> bias

%  Y = 1/(1+exp(-A*W2ntw));
IIY = AAA*W2ntw;
for r = 1:NTP
    for c = 1NOP
        YY(r,c) = 1/(1+exp(-IIY(r,c)));
    end
end
IFW = (sqrt((real(YY(1)))^2+(imag(YY(1)))^2))*10 - 0.5;  %  Eliminate the adding value 0.5
ICW = (sqrt((real(YY(2)))^2+(imag(YY(2)))^2))*10 - 0.5;  %  Eliminate the adding value 0.5
disp(' Initial flank wear (mm) : '); disp(IFW);
disp(' Initial crater wear (mm) : '); disp(ICW);
FILE – TW_ESTIMATION.M

% This MATLAB program was developed for estimating tool flank and crater wear by using Fuzzy Neural Network model with 36-40-2 structure.

NIN = 36; % Number of input units including bias
NHD = 40; % Number of hidden units including bias.
NOP = 2; % Number of output units (flank and crater wear)

time = toc;
NTP = 1; % Number of pairs (1 for estimation tool wear)

for r = 1:NTP
    for c = 1:NHD
        RRl(r,c)=0;
    end
end

XXr = [XX RRl]; % Xr = [NTP x (NIN + NHD)] and X from InputMLSB.m
IIA1 = XXr*Wrtw;
for r = 1:NTP
    for c = 1:NHD
        AAA1(r,c) = 1/(1+exp(-IIA1(r,c)));
    end
end

RRl = AAA1;
XXr = [XX RRl];
for r = 1:NTP
    Ac(r,l) = 0.5;
end

IIA1 = XXr*Wrtw;
for r = 1:NTP
    for c = 1:NHD
        AAA1(r,c) = 1/(1+exp(-IIA1(r,c)));
    end
end

AAA = [AAAc AAA1]; % where Ac = [0.5] -> bias

IIY = AAA*W2ntw;
for r = 1:NTP
    for c = 1:NOP
        Y(r,c) = 1/(1+exp(-IIY(r,c)));
    end
end

CFW = (sqrt((real(YY(1)))^2+(imag(YY(1)))^2))*10 - 0.5; % Corrected flank wear
CCW = (sqrt((real(YY(2)))^2+(imag(YY(2)))^2))*10 - 0.5; % Corrected crater wear
disp('Estimated flank wear (mm) : '); disp(CFW);
disp('Estimated crater wear (mm) : '); disp(CCW);
%
%... Displaying tool wear estimation result ...
%
TWadjfuzzy;
RFW = CFW - FWadj; % Note: get FWadj from TWadjfuzzy.m
\begin{verbatim}
RCW = CCW - CWadj;  \hspace{1cm} % Note: get CWadj from TWadjfuzzy.m
if RFW < 0;
    RFW = 0;
end
if RCW < 0;
    RCW = 0;
end
disp(' Real Length of flank wear (mm) : ') ; disp(RFW);
disp(' Real Maximum depth of crater wear (mm) : ') ; disp(RCW);
\end{verbatim}
FILE – TWADJFUZZY.M

% ..............................................................................................................................................
% ..............................................................................................................................................
% Fuzzy logic model for adjusting tool wear
% ..............................................................................................................................................

fis = readfis ('TWadj');
Inputvector = [IFW ICW];         % Getting both values from TW_estimation.m
Outputvector = evalfis(Inputvector, fis);
FWadj = Outputvector(1,1);         % Adjusting flank wear length (mm)
CWadj = Outputvector(1,2);         % Adjusting crater wear depth (mm)
FILE - DFW.FIS

[System]
Name='DFW'
Type='mamdani'
NumInputs=2
NumOutputs=1
NumRules=8
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Cutting_time'
Range=[0 80]
NumMFs=3
MF1='Short': trapmf,[0 0 12]
MF2='Medium': trapmf,[1 2 40 60]
MF3='Long': trapmf,[40 60 80 80]

[Input2]
Name='Shear_energy'
Range=[0 200000]
NumMFs=3
MF1='Low': trapmf,[0 0 40000 80000]
MF2='Medium': trapmf,[40000 80000 120000 160000]
MF3='High': trapmf,[120000 160000 200000 200000]

[Output1]
Name='DFW'
Range=[-0.5 1.5]
NumMFs=3
MF1='No': trimf,[0.5 0 0.5]
MF2='Maybe': trimf,[0 0.5 1]
MF3='Yes': trimf,[0.5 1 1.5]

[Rules]
3 1, 3 (1) : 1
2 2, 3 (1) : 1
3 2, 3 (1) : 1
1 3, 3 (1) : 1
2 3, 3 (1) : 1
3 3, 3 (1) : 1
1 1, 1 (1) : 1
1 2, 2 (1) : 1
FILE - DCW.FIS

[System]
Name='DCW'
Type='mamdani'
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='Friction_energy'
Range=[0 50000]
NumMFs=3
MF1='Low':trapmf,[0 0 10000 20000]
MF2='Medium':trapmf,[10000 20000 30000 40000]
MF3='High':trapmf,[30000 40000 50000 50000]

[Input2]
Name='Cutting_time'
Range=[0 80]
NumMFs=3
MF1='Short':trapmf,[0 0 1 2]
MF2='Medium':trapmf,[1 2 40 60]
MF3='Long':trapmf,[40 60 80 80]

[Output1]
Name='DCW'
Range=[-0.5 1.5]
NumMFs=3
MF1='No':trimf,[-0.5 0 0.5]
MF2='Maybe':trimf,[0 0.5 1]
MF3='Yes':trimf,[0.5 1 1.5]

[Rules]
1 3, 3 (1) : 1
2 2, 3 (1) : 1
2 3, 3 (1) : 1
3 2, 3 (1) : 1
3 3, 3 (1) : 1
2 1, 2 (1) : 1
3 1, 2 (1) : 1
1 2, 2 (1) : 1
1 1, 1 (1) : 1
FILE - DCF.FIS

[System]
Name='DCF'
Type='mamdani'
NumInputs=6
NumOutputs=1
NumRules=193
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input 1]
Name='Friction_energy'
Range=[0 50000]
NumMFs=3
MF1='Low': 'trapmf', [0 0 10000 20000]
MF2='Medium': 'trapmf', [10000 20000 30000 40000]
MF3='High': 'trapmf', [30000 40000 50000 50000]

[Input 2]
Name='SD/mean'
Range=[0 0.019]
NumMFs=3
MF1='Abnormal_low': 'trapmf', [0 0 0.005 0.007]
MF2='Normal': 'trapmf', [0.005 0.007 0.012 0.014]
MF3='Abnormal_high': 'trapmf', [0.012 0.014 0.019 0.019]

[Input 3]
Name='PFW'
Range=[0 0.3]
NumMFs=4
MF1='Nowear': 'trapmf', [0 0 0 0.025]
MF2='Small': 'trapmf', [0 0.05 0.1 0.15]
MF3='Medium': 'trapmf', [0.1 0.15 0.2 0.25]
MF4='Large': 'trapmf', [0.2 0.25 0.3 0.3]

[Input 4]
Name='PCW'
Range=[0 0.06]
NumMFs=4
MF1='Nowear': 'trapmf', [0 0 0 0.005]
MF2='Small': 'trapmf', [0 0.01 0.02 0.03]
MF3='Medium': 'trapmf', [0.02 0.03 0.04 0.05]
MF4='Large': 'trapmf', [0.04 0.05 0.06 0.06]

[Input 5]
Name='Delt'
Range=[0 8]
NumMFs=3
MF1='Short': 'trapmf', [0 0 0.5 1]
MF2='Medium': 'trapmf', [0.5 1 3 3.5]
MF3='Long': 'trapmf', [3 3.5 8 8]

[Input 6]
Name='Cutting_speed'
Range=[60 160]
NumMFs=3
MF1='Low':'trapmf',[60 60 80 100]
MF2='Medium':'trapmf',[80 100 120 140]
MF3='High':'trapmf',[120 140 160 160]

[Output 1]
Name='DCF'
Range=[-0.5 1.5]
NumMFs=3
MF1='No':'trimf',[-0.5 0 0.5]
MF2='Maybe':'trimf',[0 0.5 1]
MF3='Yes':'trimf',[0.5 1 1.5]

[Rules]
1 1 2 2 1 0, 1 (1) : 1
1 2 2 2 1 0, 1 (1) : 1
1 1 3 2 1 0, 1 (1) : 1
1 2 3 2 1 0, 1 (1) : 1
2 1 2 2 1 0, 2 (1) : 1
2 2 2 2 1 0, 2 (1) : 1
2 3 2 2 1 0, 2 (1) : 1
2 1 3 2 1 0, 2 (1) : 1
2 2 3 2 1 0, 2 (1) : 1
2 3 3 2 1 0, 2 (1) : 1
3 1 2 2 1 0, 2 (1) : 1
3 2 2 2 1 0, 2 (1) : 1
3 3 2 2 1 0, 2 (1) : 1
3 1 3 2 1 0, 2 (1) : 1
3 2 3 2 1 0, 2 (1) : 1
3 1 2 2 2 0, 2 (1) : 1
3 2 2 2 2 0, 2 (1) : 1
3 3 2 2 2 0, 2 (1) : 1
2 1 3 2 2 0, 2 (1) : 1
2 2 3 2 2 0, 2 (1) : 1
2 3 3 2 2 0, 2 (1) : 1
3 1 2 2 2 0, 2 (1) : 1
3 2 2 2 2 0, 2 (1) : 1
3 3 2 2 2 0, 2 (1) : 1
3 1 2 2 2 0, 2 (1) : 1
3 2 2 2 2 0, 2 (1) : 1
3 3 2 2 2 0, 2 (1) : 1
1 1 2 2 2 0, 2 (1) : 1
1 2 2 2 2 0, 2 (1) : 1
1 2 3 3 1 0, 3 (1) : 1
1 2 3 3 2 0, 3 (1) : 1
1 2 3 3 3 0, 3 (1) : 1
1 1 3 4 1 0, 3 (1) : 1
1 1 3 4 2 0, 3 (1) : 1
2 3 4 3 0, 3 (1) : 1
2 3 4 3 1, 3 (1) : 1
2 3 4 3 2, 3 (1) : 1
2 3 4 3 3, 3 (1) : 1
2 3 4 4 1, 3 (1) : 1
2 3 4 4 2, 3 (1) : 1
2 3 4 4 3, 3 (1) : 1
3 1 3 3 1, 3 (1) : 1
3 1 3 3 2, 3 (1) : 1
3 1 3 3 3, 3 (1) : 1
3 1 3 4 0, 3 (1) : 1
3 1 3 4 1, 3 (1) : 1
3 1 3 4 2, 3 (1) : 1
3 1 3 4 3, 3 (1) : 1
3 1 4 3 1, 3 (1) : 1
3 1 4 3 2, 3 (1) : 1
3 1 4 3 3, 3 (1) : 1
3 1 4 4 0, 3 (1) : 1
3 1 4 4 1, 3 (1) : 1
3 1 4 4 2, 3 (1) : 1
3 1 4 4 3, 3 (1) : 1
3 2 3 3 1, 3 (1) : 1
3 2 3 3 2, 3 (1) : 1
3 2 3 3 3, 3 (1) : 1
3 2 3 4 0, 3 (1) : 1
3 2 3 4 1, 3 (1) : 1
3 2 3 4 2, 3 (1) : 1
3 2 3 4 3, 3 (1) : 1
3 2 4 3 1, 3 (1) : 1
3 2 4 3 2, 3 (1) : 1
3 2 4 3 3, 3 (1) : 1
3 2 4 4 0, 3 (1) : 1
3 2 4 4 1, 3 (1) : 1
3 2 4 4 2, 3 (1) : 1
3 2 4 4 3, 3 (1) : 1
3 3 3 3 0, 3 (1) : 1
3 3 3 3 1, 3 (1) : 1
3 3 3 3 2, 3 (1) : 1
3 3 3 3 3, 3 (1) : 1
3 3 3 4 0, 3 (1) : 1
3 3 3 4 1, 3 (1) : 1
3 3 3 4 2, 3 (1) : 1
3 3 3 4 3, 3 (1) : 1
3 3 4 3 1, 3 (1) : 1
3 3 4 3 2, 3 (1) : 1
3 3 4 3 3, 3 (1) : 1
3 3 4 4 0, 3 (1) : 1
3 3 4 4 1, 3 (1) : 1
3 3 4 4 2, 3 (1) : 1
3 3 4 4 3, 3 (1) : 1
2 1 2 2 0, 3 (1) : 1
2 1 2 2 1, 3 (1) : 1
2 1 2 2 2, 3 (1) : 1
2 1 3 2 0, 3 (1) : 1
2 1 3 2 1, 3 (1) : 1
2 1 3 2 2, 3 (1) : 1
2 2 2 2 0, 3 (1) : 1
2 2 2 2 1, 3 (1) : 1
2 2 2 2 2, 3 (1) : 1
2 2 3 2 0, 3 (1) : 1
2 2 3 2 1, 3 (1) : 1
2 2 3 2 2, 3 (1) : 1
2 3 2 2 0, 3 (1) : 1
2 3 2 2 1, 3 (1) : 1
2 3 2 2 2, 3 (1) : 1
2 3 2 3 0, 3 (1) : 1
2 3 2 3 1, 3 (1) : 1
2 3 2 3 2, 3 (1) : 1
2 3 2 3 3, 3 (1) : 1
3 1 2 2 0, 3 (1) : 1
3 1 2 2 1, 3 (1) : 1
3 1 2 2 2, 3 (1) : 1
3 1 2 2 3, 3 (1) : 1
3 1 2 3 0, 3 (1) : 1
3 1 2 3 1, 3 (1) : 1
3 1 2 3 2, 3 (1) : 1
3 1 2 3 3, 3 (1) : 1
3 2 2 2 0, 3 (1) : 1
3 2 2 2 1, 3 (1) : 1
3 2 2 2 2, 3 (1) : 1
3 2 2 2 3, 3 (1) : 1
A41

322230,3 (1): 1
323220,3 (1): 1
323230,3 (1): 1
332220,3 (1): 1
332230,3 (1): 1
333220,3 (1): 1
333230,3 (1): 1
212210,2 (1): 1
213210,2 (1): 1
222210,2 (1): 1
223210,2 (1): 1
232210,2 (1): 1
233210,2 (1): 1
312210,2 (1): 1
313210,2 (1): 1
322210,2 (1): 1
323210,2 (1): 1
332210,2 (1): 1
333210,2 (1): 1
011101,1 (1): 1
011102,1 (1): 1
011103,1 (1): 1
021101,1 (1): 1
021102,1 (1): 1
021103,1 (1): 1
031102,2 (1): 1
031103,2 (1): 1
031101,3 (1): 1
FILE – DDCE.FIS

[System]
Name=’DDCE’
Type=’mamdani’
NumInputs=4
NumOutputs=1
NumRules=46
AndMethod=’min’
OrMethod=’max’
ImpMethod=’min’
AggMethod=’max’
DefuzzMethod=’centroid’

[Input 1]
Name=’Friction_energy’
Range=[0 50000]
NumMFs=3
MF1=’Low’:’trapmf’,[0 0 10000 20000]
MF2=’Medium’:’trapmf’,[10000 20000 30000 40000]
MF3=’High’:’trapmf’,[30000 40000 50000 50000]

[Input 2]
Name=’PFW’
Range=[0 0.3]
NumMFs=4
MF1=’Nowear’:’trapmf’,[0 0 0 0.025]
MF2=’Small’:’trapmf’,[0 0.05 0.1 0.15]
MF3=’Medium’:’trapmf’,[0.1 0.15 0.2 0.25]
MF4=’Large’:’trapmf’,[0.2 0.25 0.3 0.3]

[Input 3]
Name=’PCW’
Range=[0 0.06]
NumMFs=4
MF1=’Nowear’:’trapmf’,[0 0 0 0.005]
MF2=’Small’:’trapmf’,[0 0.01 0.02 0.03]
MF3=’Medium’:’trapmf’,[0.02 0.03 0.04 0.05]
MF4=’Large’:’trapmf’,[0.04 0.05 0.06 0.06]

[Input 4]
Name=’Delt’
Range=[0 8]
NumMFs=3
MF1=’Short’:’trapmf’,[0 0.5 1]
MF2=’Medium’:’trapmf’,[0.5 3 3.5]
MF3=’Long’:’trapmf’,[3 3.5 8 8]

[Output 1]
Name=’DDCE’
Range=[-0.5 1.5]
NumMFs=3
MF1=’No’:’trimf’,[-0.5 0 0.5]
MF2=’Maybe’:’trimf’,[0 0.5 1]
MF3=’Yes’:’trimf’,[0.5 1 1.5]

[Rules]
0 3 4 0, 3 (1) : 1
0 4 4 0, 3 (1): 1
1 3 3 3, 3 (1): 1
1 4 3 3, 3 (1): 1
2 3 3 2, 3 (1): 1
2 4 3 2, 3 (1): 1
2 3 3 3, 3 (1): 1
2 4 3 3, 3 (1): 1
3 3 3 1, 3 (1): 1
3 4 3 1, 3 (1): 1
3 3 3 2, 3 (1): 1
3 4 3 2, 3 (1): 1
3 3 3 3, 3 (1): 1
3 4 3 3, 3 (1): 1
1 3 3 3, 2 (1): 1
1 4 3 3, 2 (1): 1
3 3 2 2, 2 (1): 1
3 4 2 2, 2 (1): 1
3 3 2 3, 2 (1): 1
3 4 2 3, 2 (1): 1
2 3 2 3, 2 (1): 1
2 4 2 3, 2 (1): 1
2 2 2 1, 1 (1): 1
2 3 2 1, 1 (1): 1
2 4 2 1, 1 (1): 1
2 2 2 2, 1 (1): 1
2 3 2 2, 1 (1): 1
2 4 2 2, 1 (1): 1
1 2 2 1, 1 (1): 1
1 3 2 1, 1 (1): 1
1 4 2 1, 1 (1): 1
1 2 2 2, 1 (1): 1
1 3 2 2, 1 (1): 1
1 4 2 2, 1 (1): 1
1 2 2 3, 1 (1): 1
1 3 2 3, 1 (1): 1
1 4 2 3, 1 (1): 1
1 1 1 1, 1 (1): 1
2 1 1 1, 1 (1): 1
3 1 1 1, 1 (1): 1
1 1 1 2, 1 (1): 1
2 1 1 2, 1 (1): 1
3 1 1 2, 1 (1): 1
3 1 1 3, 2 (1): 1
1 1 1 3, 1 (1): 1
2 1 1 3, 1 (1): 1
FILE - TWADJ.FIS

[System]
Name='TWadj'
Type='mamdani'
NumInputs=2
NumOutputs=2
NumRules=10
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input 1]
Name='TFW'
Range=[-0.16 0.16]
NumMFs=5
MF1='Nlarge': 'trapmf',[-0.16 -0.14 -0.1 -0.08]
MF2='Nmedium': 'trapmf',[-0.1 -0.08 -0.04 -0.02]
MF3='small': 'trapmf',[-0.04 -0.02 0.02 0.04]
MF4='Pmedium': 'trapmf',[0.02 0.04 0.08 0.1]
MF5='Plarge': 'trapmf',[0.08 0.1 0.14 0.16]

[Input 2]
Name='ICW'
Range=[-0.04 0.04]
NumMFs=5
MF1='Nlarge': 'trapmf',[-0.04 -0.035 -0.025 -0.02]
MF2='Nmedium': 'trapmf',[-0.025 -0.02 -0.01 -0.005]
MF3='small': 'trapmf',[-0.01 -0.005 0.005 0.01]
MF4='Pmedium': 'trapmf',[0.005 0.01 0.02 0.025]
MF5='Plarge': 'trapmf',[0.02 0.025 0.035 0.04]

[Output 1]
Name='FWadj'
Range=[-0.18 0.18]
NumMFs=5
MF1='Nhigh': 'trimf',[-0.18 -0.12 -0.06]
MF2='Nmedium': 'trimf',[-0.12 -0.06 0]
MF3='low': 'trimf',[-0.06 0 0.06]
MF4='Pmedium': 'trimf',[0 0.06 0.12]
MF5='Phigh': 'trimf',[0.06 0.12 0.18]

[Output 2]
Name='CWadj'
Range=[-0.045 0.045]
NumMFs=5
MF1='Nhigh': 'trimf',[-0.045 -0.03 -0.015]
MF2='Nmedium': 'trimf',[-0.03 -0.015 0]
MF3='low': 'trimf',[-0.015 0 0.015]
MF4='Pmedium': 'trimf',[0 0.015 0.03]
MF5='Phigh': 'trimf',[0.015 0.03 0.045]

[Rules]
3 0, 3 0 (1) : 1
2 0, 4 0 (1) : 1
1 0, 5 0 (1) : 1