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Condition Monitoring of Tools in CNC Turning

by

Brian Peter Hede

A Doctoral Thesis submitted in partial fulfilment of the requirements
for the award of Doctor of Philosophy (PhD)

Loughborough University

January 2008

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Abstract

The metal cutting industry today is highly automated and, as a step towards Europe's ability to compete on the world market, an increased level of automation can be expected in the future. Therefore, much attention has been paid to the use of automated monitoring systems within the maintenance strategies designed to prevent breakdown. This research focuses on the condition monitoring of cutting tools in CNC turning, using airborne acoustic emission, (AAE). A structured approach for overcoming the problems associated with changing cutting parameters is presented with good results. A reverse and novel approach in estimating gradual tool wear in longitudinal roughing has been made by predicting cutting parameters directly from the acoustics emitted from the process. Using the RMS as a representation of the energy in the signal, where the spectral distributions are working as divisional operators, it has been possible to accurately extract a representation of feed rate, depth of cut and cutting speed from the signal. Using a simplified relationship to estimate tangential cutting force, a virtual force can be calculated and related to a certain amount of flank wear using non-linear regression. Furthermore, this research presents a monitoring solution where disturbances are eliminated by recognising the sound signatures where it, afterwards, is possible to evaluate the reliability of the wear decision. This is done by describing irregularities in the signal, where surface parameters used on a sound waveform, combined in a neural network, has been used to trigger outputs for several defined classes of disturbances. An investigation of the two wear types, flank and crater wear, has been conducted, and is has been concluded, that although crater wear has an effect on the AAE, it is difficult to recognise this. AAE has shown to an efficient tool to detect flank wear, where a direct relationship is shown between the changes in the cutting parameters, tool wear and AAE. This approach has resulted in a precise monitoring solution, where flank wear can be estimated within an error of 10%.
Dedicated to Inge Lise Pedersen
Acknowledgements

This research would not have made it to the state it is, without the help and support from several people, and rest assured, you are all thanked, but the following individuals need special thanks.

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<th>Full Form</th>
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<tbody>
<tr>
<td>AE</td>
<td>Acoustic Emission</td>
</tr>
<tr>
<td>AE RMS</td>
<td>RMS of Structure Borne Acoustic Emission</td>
</tr>
<tr>
<td>AAE</td>
<td>Airborne Acoustic Emission</td>
</tr>
<tr>
<td>AAE RMS</td>
<td>Root Mean Square of Airborne Signal</td>
</tr>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>AR</td>
<td>Autoregressive</td>
</tr>
<tr>
<td>ARD</td>
<td>Automatic Relevance Determination</td>
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<tr>
<td>BUE</td>
<td>Built up Edge</td>
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<tr>
<td>CBM</td>
<td>Condition Based Monitoring</td>
</tr>
<tr>
<td>CBN</td>
<td>Cubic Boron Nitride</td>
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<tr>
<td>CCR</td>
<td>Chip Compression Ratio</td>
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<tr>
<td>CM</td>
<td>Condition Monitoring</td>
</tr>
<tr>
<td>CNC</td>
<td>Computer Numerical Control</td>
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<tr>
<td>CoF</td>
<td>Coefficient of Friction</td>
</tr>
<tr>
<td>CTF</td>
<td>Catastrophic Tool Failure</td>
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<tr>
<td>DSP</td>
<td>Digital Signal Processing</td>
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<tr>
<td>ET</td>
<td>Equivalent Tool Face Model</td>
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<tr>
<td>FFC</td>
<td>Fringe Field Capacitive</td>
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<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
</tr>
<tr>
<td>FMS</td>
<td>Flexible Manufacturing System</td>
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<tr>
<td>FMC</td>
<td>Flexible Manufacturing Cell</td>
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<tr>
<td>FNN</td>
<td>Fuzzy Neural Network</td>
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<td>FWT</td>
<td>Fast Wavelet Transform</td>
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<td>FZ</td>
<td>Flow Zone</td>
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<tr>
<td>HH</td>
<td>Hot Hardness</td>
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<td>HSM</td>
<td>High Speed Machining</td>
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<td>HSS</td>
<td>High Speed Steel</td>
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<tr>
<td>LDF</td>
<td>Linear Discriminator Function</td>
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<tr>
<td>LMS</td>
<td>Least Mean Square</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>MAPE</td>
<td>Mean Absolute Percentage Error</td>
</tr>
<tr>
<td>MLP</td>
<td>Multi-layer Perceptron Network</td>
</tr>
<tr>
<td>MRR</td>
<td>Material Removal Rate, mm(^3)/min</td>
</tr>
<tr>
<td>NN</td>
<td>Neural Network</td>
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<tr>
<td>PDF</td>
<td>Probability Density Function</td>
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<tr>
<td>PDM</td>
<td>Predictive Maintenance</td>
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<tr>
<td>PSD</td>
<td>Power Spectral Density</td>
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<tr>
<td>SF</td>
<td>Surface Finish</td>
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<tr>
<td>SLP</td>
<td>Single Layer Perceptron Network</td>
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<tr>
<td>SNR</td>
<td>Signal to Noise Ratio</td>
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<tr>
<td>SOM</td>
<td>Self Organising Map</td>
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<tr>
<td>SPL</td>
<td>Sound Pressure Level</td>
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<tr>
<td>SVM</td>
<td>Support Vector Machine</td>
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<tr>
<td>TBM</td>
<td>Time Based Maintenance</td>
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<td>TCM</td>
<td>Tool Condition Monitoring</td>
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<td>TDA</td>
<td>Time Domain Averaging</td>
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<tr>
<td>TFD</td>
<td>Time Frequency Difference</td>
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<td>TPM</td>
<td>Total Productive Maintenance</td>
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<tr>
<td>WR</td>
<td>Wear Resistance</td>
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<tr>
<td>WT</td>
<td>Wavelet Transform</td>
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List of Symbols

\[ A \] \quad \text{Attenuated Amplitude}
\[ A_r \] \quad \text{Area of Distribution}
\[ A_s \] \quad \text{Shear Plane Area}
\[ A_0 \] \quad \text{Initial Amplitude}
\[ A_{0u} \] \quad \text{Mean Initial Amplitude}
\[ \bar{A}_u \] \quad \text{Mean Attenuated Amplitude}
\[ a_p \] \quad \text{Depth of Cut}
\[ a_{p\text{pr}} \] \quad \text{Predicted Depth of Cut}
\[ B_0 \] \quad \text{Bonding Ability}
\[ B_r \] \quad \text{Barrier Effect Regarding Chemical Stability}
\[ C \] \quad \text{Constant}
\[ C_1 \] \quad \text{Correction factor for Cutting Speed}
\[ C_2 \] \quad \text{Correction factor for Machining Process}
\[ C_3 \] \quad \text{AE Prediction Constant}
\[ C_5 \] \quad \text{AE Prediction Constant}
\[ C_{l1} \] \quad \text{Constant 1 for Contact Length}
\[ C_{l2} \] \quad \text{Constant 2 for Contact Length}
\[ C_{tn} \] \quad \text{Tool Life Functions}
\[ C_u \] \quad \text{Force/Wear Constant}
\[ C_{vb} \] \quad \text{Force Constant related to Flank Wear}
\[ c_{rc1} \] \quad \text{Chip Ratio Constant}
\[ c_{rc2} \] \quad \text{Chip Ratio Constant}
\[ c_s \] \quad \text{Specific Heat of Workpiece}
\[ c_t \] \quad \text{Thermal Conductivity}
\[ c_m \] \quad \text{Constants}
\[ D \] \quad \text{Diameter}
\[ F \] \quad \text{Resultant Force}
\[ F_c \] \quad \text{Shear Force along Tool Face}
\[ F_f \] \quad \text{Feed Force}
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<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>$F_r$</td>
<td>Radial Force</td>
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<tr>
<td>$F_s$</td>
<td>Shear Force</td>
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<td>$F_i$</td>
<td>Tangentional Cutting Force</td>
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<tr>
<td>$F_{theoretical}$</td>
<td>Theoretical Cutting Force</td>
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<tr>
<td>$F_{virtual}$</td>
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<tr>
<td>$f$</td>
<td>Feed Rate</td>
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<tr>
<td>$f_{pr}$</td>
<td>Predicted Feed Rate</td>
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<tr>
<td>$f_q$</td>
<td>Frequency</td>
</tr>
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<td>$f_s$</td>
<td>Feed Speed</td>
</tr>
<tr>
<td>$f_{spr}$</td>
<td>Predicted Feed Speed</td>
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<tr>
<td>$H$</td>
<td>Tool Hardness</td>
</tr>
<tr>
<td>$H_v$</td>
<td>Hardness, Vickers</td>
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<td>$H_0$</td>
<td>Initial Hardness</td>
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<tr>
<td>$h$</td>
<td>Uncut Chip Thickness</td>
</tr>
<tr>
<td>$h_c$</td>
<td>Deformed Chip Thickness</td>
</tr>
<tr>
<td>$h_m$</td>
<td>Weight of Chip</td>
</tr>
<tr>
<td>$I$</td>
<td>Intensity</td>
</tr>
<tr>
<td>$i_a$</td>
<td>Chip Width</td>
</tr>
<tr>
<td>$K$</td>
<td>Flank Wear Constant</td>
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<tr>
<td>$K_{abrasion}$</td>
<td>Abrasive Wear Constant</td>
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<td>$K_{cw}$</td>
<td>Function of Hardness Ratio</td>
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<tr>
<td>$K_p$</td>
<td>Probability</td>
</tr>
<tr>
<td>$K_t$</td>
<td>Crater Depth</td>
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<td>$K_{cp}$</td>
<td>Predicted Crater Depth</td>
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<tr>
<td>$K_u$</td>
<td>Kurtosis</td>
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<tr>
<td>$k_c$</td>
<td>Specific Energy</td>
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<tr>
<td>$k_{c1.1}$</td>
<td>Initial Specific Energy</td>
</tr>
<tr>
<td>$k_h$</td>
<td>Distance from Cutting Edge to end of Crater</td>
</tr>
<tr>
<td>$L$</td>
<td>Vertical Distance from Inner Microphone to Outer</td>
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<tr>
<td>$L_{mom}$</td>
<td>Left Moment</td>
</tr>
<tr>
<td>$l$</td>
<td>Chip Contact Length</td>
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### Condition Monitoring of Tools in CNC Turning

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<td>Evaluation Length</td>
</tr>
<tr>
<td>( M_{\text{rel}} )</td>
<td>Relative Moment</td>
</tr>
<tr>
<td>( m_c )</td>
<td>Material Constant</td>
</tr>
<tr>
<td>( m_{\text{cr}} )</td>
<td>Material Removal Rate</td>
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<tr>
<td>( N_c )</td>
<td>Normal Force on Tool Face</td>
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<td>( N_s )</td>
<td>Normal Force on Shear Plane</td>
</tr>
<tr>
<td>( n )</td>
<td>Spindle Speed</td>
</tr>
<tr>
<td>( n_1 - n_9 )</td>
<td>AAE RMS Constants</td>
</tr>
<tr>
<td>( n(t) )</td>
<td>Noisy Signal</td>
</tr>
<tr>
<td>( P )</td>
<td>Load</td>
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<td>( P_a )</td>
<td>Workpiece Hardness</td>
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<tr>
<td>( P_c )</td>
<td>Friction Power</td>
</tr>
<tr>
<td>( P_{\text{max}} )</td>
<td>Maximum Peak in the Frequency Domain</td>
</tr>
<tr>
<td>( P_{\mu} )</td>
<td>Friction Power</td>
</tr>
<tr>
<td>( P_s )</td>
<td>Shear Power</td>
</tr>
<tr>
<td>( R )</td>
<td>Force along Tool Face</td>
</tr>
<tr>
<td>( R' )</td>
<td>Force along Shear Plane</td>
</tr>
<tr>
<td>( R_a )</td>
<td>Average Roughness Parameter</td>
</tr>
<tr>
<td>( R_{\text{ai}} )</td>
<td>Ideal Arithmetic Average Surface Roughness</td>
</tr>
<tr>
<td>( R_{\text{hs}} )</td>
<td>High Spot Count</td>
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<td>( R_{\text{kurt}} )</td>
<td>Kurtosis Parameter</td>
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<td>( R_{\text{mom}} )</td>
<td>Right Moment</td>
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<td>( R_p )</td>
<td>Maximum Peak</td>
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<tr>
<td>( R_{pc} )</td>
<td>Peak Count</td>
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<tr>
<td>( R_{sk} )</td>
<td>Skevness Parameter</td>
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<td>( R_{sm} )</td>
<td>Peak Spacing</td>
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<td>( R_t )</td>
<td>Maximum Height Parameter</td>
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<tr>
<td>( R_{\beta} )</td>
<td>Bearing Ratio</td>
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<tr>
<td>( R_{T} )</td>
<td>Non-dimensional Thermal Number</td>
</tr>
<tr>
<td>( R_v )</td>
<td>Maximum Valley</td>
</tr>
<tr>
<td>( R_z )</td>
<td>Peak Parameter</td>
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Condition Monitoring of Tools in CNC Turning

<table>
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<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>$R_{z10}$</td>
<td>Ten Point Height</td>
</tr>
<tr>
<td>$r$</td>
<td>Radius</td>
</tr>
<tr>
<td>$r_e$</td>
<td>Nose Radius</td>
</tr>
<tr>
<td>$r_c$</td>
<td>Chip Compression Ratio</td>
</tr>
<tr>
<td>$r_{\text{low}}$</td>
<td>Lower Cut-off Frequency</td>
</tr>
<tr>
<td>$r_p$</td>
<td>Mean Frequency Range</td>
</tr>
<tr>
<td>$r_{\text{up}}$</td>
<td>Upper Cut-off Frequency</td>
</tr>
<tr>
<td>$S_k$</td>
<td>Skew</td>
</tr>
<tr>
<td>$s(t)$</td>
<td>Pure Cutting Signal</td>
</tr>
<tr>
<td>$T_{\text{int}}$</td>
<td>Temperature at Tool-Chip Interface</td>
</tr>
<tr>
<td>$T_l$</td>
<td>Tool Life</td>
</tr>
<tr>
<td>$T_o$</td>
<td>Toughness</td>
</tr>
<tr>
<td>$T_s$</td>
<td>Shear Plane Temperature, degrees Celsius</td>
</tr>
<tr>
<td>$T_{\text{trans}}$</td>
<td>Unknown Transfer Function from AE RMS to AAE RMS</td>
</tr>
<tr>
<td>$T_0$</td>
<td>Initial Temperature, degrees Celsius</td>
</tr>
<tr>
<td>$t$</td>
<td>Time</td>
</tr>
<tr>
<td>$V$</td>
<td>Volume</td>
</tr>
<tr>
<td>$V_b$</td>
<td>Flank Wear</td>
</tr>
<tr>
<td>$V_{\text{vol}}$</td>
<td>Removed Volume of Workpiece Material</td>
</tr>
<tr>
<td>$v$</td>
<td>Cutting Speed</td>
</tr>
<tr>
<td>$v_c$</td>
<td>Velocity along Chip/Tool Face</td>
</tr>
<tr>
<td>$v_{pr}$</td>
<td>Predicted Cutting Speed</td>
</tr>
<tr>
<td>$v_s$</td>
<td>Velocity along Shear Plane</td>
</tr>
<tr>
<td>$v_{\text{sound}}$</td>
<td>Sound Velocity</td>
</tr>
<tr>
<td>$w$</td>
<td>Wear</td>
</tr>
<tr>
<td>$w_c$</td>
<td>Chip Work Rate</td>
</tr>
<tr>
<td>$w_s$</td>
<td>Shear Work Rate</td>
</tr>
<tr>
<td>$X_{\text{db}}$</td>
<td>Decibel Representation of Sound</td>
</tr>
<tr>
<td>$X_{\text{meas}}$</td>
<td>Measured SPL</td>
</tr>
<tr>
<td>$X_r$</td>
<td>Frequency Amplitude</td>
</tr>
<tr>
<td>$X_{\text{ref}}$</td>
<td>Reference SPL</td>
</tr>
<tr>
<td>Symbol</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-------------</td>
</tr>
<tr>
<td>$x(t)$</td>
<td>Signal including Noise</td>
</tr>
<tr>
<td>$Z$</td>
<td>Horizontal Distance from Outer Microphone to Inner</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Effective Rake Angle</td>
</tr>
<tr>
<td>$\alpha_a$</td>
<td>Attenuation Coefficient</td>
</tr>
<tr>
<td>$\alpha_i$</td>
<td>Rake Angle of Tool Insert</td>
</tr>
<tr>
<td>$\alpha_{sp}$</td>
<td>Spectral Over-subtraction Factor</td>
</tr>
<tr>
<td>$\alpha_t$</td>
<td>Rake Angle of Tool Holder</td>
</tr>
<tr>
<td>$\alpha_0$</td>
<td>Initial Effective Rake Angle</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Friction Angle</td>
</tr>
<tr>
<td>$\beta_w$</td>
<td>Wedge Angle</td>
</tr>
<tr>
<td>$\Delta A$</td>
<td>Burst Attenuated Amplitude</td>
</tr>
<tr>
<td>$\Delta A_0$</td>
<td>Burst Initial Amplitude</td>
</tr>
<tr>
<td>$\Delta E$</td>
<td>Increased Energy</td>
</tr>
<tr>
<td>$\Delta E_{flank}$</td>
<td>Energy Increase caused by Flank Wear</td>
</tr>
<tr>
<td>$\Delta F_{(w)}$</td>
<td>Force Contribution due to Wear</td>
</tr>
<tr>
<td>$\Delta \mu$</td>
<td>Shift</td>
</tr>
<tr>
<td>$\Delta T_c$</td>
<td>Average Temperature Rise at Tool-chip Interface</td>
</tr>
<tr>
<td>$\Delta w$</td>
<td>Progressed Wear</td>
</tr>
<tr>
<td>$\gamma_c$</td>
<td>Clearance Angle</td>
</tr>
<tr>
<td>$\gamma_i$</td>
<td>Inclination Angle</td>
</tr>
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<td>$\kappa$</td>
<td>Entering Angle</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Wavelength</td>
</tr>
<tr>
<td>$\lambda_h$</td>
<td>Plastic Work outside the Shear Zone Coefficient</td>
</tr>
<tr>
<td>$\lambda_{int}$</td>
<td>Temperature Variations Along the Tool-Chip Coefficient</td>
</tr>
<tr>
<td>$\lambda_s$</td>
<td>Heat Conducted into the Workpiece Coefficient</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Mean</td>
</tr>
<tr>
<td>$\mu_f$</td>
<td>Friction Energy</td>
</tr>
<tr>
<td>$\mu_s$</td>
<td>Shear Energy</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Shear Angle</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Density</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Standard Deviation</td>
</tr>
</tbody>
</table>
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$\sigma_f$  Normal Stress on Flank Face
$\theta$  Relief Angle, degrees
$\tau_c$  Normal stress on tool face
$\tau_k$  Shear Strength of Material
$\tau_s$  Shear Stress
$\chi$  Amplification Constant
1 Introduction

Condition monitoring in general is an issue in which companies have developed an interest in order to apply this in their production equipment or products to either extend their life expectancy or to reduce breakdowns. Condition monitoring of cutting tools has become interesting, since the introduction of high speed and numerically controlled machinery in the 1960’s. From this point, it was no longer the machinery which was setting a limitation for the productivity in metal cutting, but the actual tool life. Although there has been an amazing development in the field of metallurgy, where cutting tools have reached an impressive state regarding their ability to resist high cutting speeds, they are still a considerable risk factor when it comes to wear and unexpected breakdowns. From the economic and industrial perspective, a breakdown caused by unattended tool wear can have catastrophic consequences, especially if the machine is a bottleneck machine which is already limiting the production. More and more companies have discovered the fact that, by applying a monitoring scheme in their production, many unexpected breakdowns and failures can be avoided. They are looking towards an increasing degree of automation where manual labour is moved away from production and the degree of unattended production is thereby increased. However, such a situation can also increase the impact of a breakdown.

1.1 Industrial Manufacturing and Trends

Most companies today are using CNC automated equipment for machining, and industrial robots for what used to be manual part-handling, as shown in Figure 1.1.
The reason for this has mainly been to reduce costs, due to the high wages in developed countries compared to manufacturers located in eastern countries, but other benefits are also considerable, such as the automated machinery's repeatability regarding quality. Several condition-monitoring systems have been developed, with the purpose of surveying automated machining processes. Depending on the actual machining process, different principles are used. Condition monitoring of cutting tools is especially related to the metal forming and finishing industries. The metalware industry is the UK's fourth largest manufacturing exporter and accounts for more than 7,000 companies around the UK. Many of the companies are highly advanced and automated, where the machinery consists of CNC centres and automated part-handling systems. The industry is discovering an increased level of automation, which is a step towards Europe's ability to compete on the world market. Through the last decade, much work has been outsourced, whereas the trend in the early nineties was to move production to the eastern European countries, the trend has now changed and companies are moving production to the Far East.

1.2 Production and Manufacturing Systems

Another approach to ensure the efficient use of production capacity has been to develop different manufacturing systems. Many systems have been developed to ensure that the production capacity is used to a maximum. The simplest system to reduce manual labour is the so-called Nagara Machining Cell. The principle of the Nagara Machining Cell is to use one operator to operate as many machines as possible. Normally, the number of machines is three, placed in a u-shape, but will of course vary depending on the
production process. This is a system where the principle is to reduce labour costs by planning the work routine of the operator so the resource will be used efficiently. Today the focus is on systems such as FMS (Flexible Manufacturing System) and FMC (Flexible Manufacturing Cell) in order to ensure the flexibility of the machinery so that it can be adjusted to new product lines, or systems such as LEAN, KAIZEN, TPM, etc. In general, all the systems have been developed with a common goal; to ensure maximum productivity using as few resources as possible in order to cut down production costs. It can be said that the further away from the machinery the employees can be moved, the lower the costs, but another problem arises along with this. Before the introduction of numerically- and fully-automated machining centres, each operator was normally responsible for only one machine. Along with the movement of the manual labour away from the production, the machinery has become more and more unattended. If an undetected failure occurs, unattended machinery can be a risk regarding loss of production time. Previously, if anything unusual happened, the operator was present to stop the machinery. Nowadays, in highly automated and unattended production, there is a big risk that a condition which can lead to a failure or breakdown, will only be discovered when the production line is actually in process of breaking down.

1.3 Condition Monitoring

As mentioned before, several systems have been developed with the purpose of reducing downtime, and some of the more successful have arisen from the TPM philosophy, (Total Productive Maintenance). TPM is an innovative Japanese concept, which can be traced back to 1951, when preventive maintenance was introduced in Japan. TPM is a maintenance philosophy, which involves a defined concept for maintaining production equipment and plants. The overall goals of the program are to increase production and to bring down the downtime of the production equipment. TPM focuses on the maintenance aspects as an important part of the production. In TPM, normal maintenance of the production equipment is not regarded as a non-profit activity and many companies have realised that good maintenance will ensure good productivity. The downtime for the maintenance is normally scheduled as a part of the manufacturing process and in many cases it can be done without conflicting with the planned production, though in some
cases, where the occupancy rate of the production equipment is very high, it can be difficult to find space for maintenance at the right intervals. Different maintenance strategies which should be mentioned are:

**Breakdown maintenance**
Used where equipment failure doesn’t significantly affect the production or generate any significant loss other than repair cost. Basically, the machinery is serviced when it breaks down.

**Preventive maintenance**
Daily/weekly maintenance, (cleaning, inspection, oiling). Emphasis is put on design to retain the healthy condition of equipment and prevent failure through the prevention of deterioration. Here, maintenance involves inspection and equipment condition diagnosis.

**Periodic maintenance (Time-based Maintenance - TBM)**
Time-based maintenance consists of periodically inspecting, servicing and cleaning equipment and replacing parts to prevent sudden failure and process problems.

**Predictive maintenance (PDM)**
This is a method in which the service life of important parts is predicted, based on inspection or diagnosis, in order to use the parts to the limit of their service life. Compared to periodic maintenance, predictive maintenance is condition-based maintenance. It manages trend values by measuring and analyzing data about deterioration and employs a surveillance system designed to monitor conditions through an on-line system.

**1.3.1 Condition-Based Maintenance**
Condition-Based Maintenance is a technique that relates to predictive maintenance. Condition-Based Maintenance, (CBM), actually deals with monitoring the condition of a certain manufacturing process. This is often done in situ, while in operation, and is also referred to as On-Line Monitoring. CBM can be defined as a maintenance process, where the condition of the manufacturing equipment is monitored for early signs of impending failure. Albert and Tsang [1995] state that CBM is used when:
• Failure prevention is not feasible, or how it can be achieved is not yet known, as in cases where the event leading to failure occurs in a predominantly random manner.

• A measurable parameter, which correlates with the onset of failure, has been identified.

• It is possible to identify a value of that parameter which allows action to be taken before full failure occurs.

With the development of intelligent, computer-based machinery and sophisticated sensors, it is now possible to rapidly and accurately sense indicators and thereby predict any instability in the system performance. Using this technology, Condition-Based Maintenance, based on sensing and assessing the current state of the system, emerges as an appropriate and efficient tool for achieving near-zero breakdown time due to process or machine failure, [Cooke and Paulsen 1997]. Implemented CBM systems are expected to save the company up to 20% in production losses and improved quality, [Bengtson 2004]. The equipment performance or parameter monitored by the process may be scheduled on request or set up as a continuous process. A major decision problem in maintenance relates to the issue of scheduled or periodic inspection. Based on the results of previous inspections, new inspection intervals will be defined, and the problem in this process is 'when to look'. The continuous monitoring process is especially interesting, because this can be used to check for early signs of failure. Using continuous monitoring, it is possible to detect gradual wear and, in time, make decisions to either stop or continue the process. This will be controlled by a process variable that relies on sensing methodology.

1.3.2 The Needs for Condition Monitoring in Industry

The arguments for applying a monitoring system for an industrial application have, of course, the financial dimension of either reducing labour costs for having an operator observing a production process, or reducing the downtime due to wear or other unforeseen events which require service. Jetly [1984] estimated, that on-line tool wear sensors can reduce costs by 40% in unattended machining operations. In review, Rehorn
et al. [2004] quote an estimate that the amount of downtime because of tool breakage is in the order of 6.8% to 20%.

In fully-automated production, the on-line detection of tool wear and breakage is seen as essential for the improvement of productivity. It has been predicted, that an accurate and reliable TCM system could result in an increase in the removal rate of 10–50%. A further reduction in downtime due to prediction of upcoming wear is estimated to increase the savings by between 10% and 40%, [Rehorn et al. 2004].

1.3.2.1 Avoiding Breakdown

As mentioned in this chapter, with the fact that the production is becoming more and more unattended, the risk of a catastrophic breakdown is increasing. A breakdown will not only be costly in terms of replacing damaged parts in the machinery, but it will also result in loss of production time, hence increasing the downtime. When speaking of optimizing the production, it is very important to focus on downtime. This time is defined as waste because only the active production time, (up-time), can be used to pay for the large investment. Considering a breakdown, the main costs involved will be:

- Downtime.
- Spare machine parts, tools and tool holders.
- Increased service costs in the form of wages for service/repair time.

Repair time includes preparation time, diagnostic time, correction time and final checkout time, [Sherif2003].

1.3.2.2 Reducing Maintenance Costs

In manufacturing processes that are highly automated, and hence involve large investment, it is normally a necessity that this equipment is exploited to the last second of possible up-time. It is not unusual for the machinery to be running 24 hours per day, where the operators are working in three shifts. Even weekend shifts and flexible vacation periods are becoming more and more common, all with the purpose of keeping the production running. This means that the maintenance and service which companies previously were able to postpone for vacations or weekends, can no longer be carried out in these periods and therefore a normal maintenance or service will result in downtime.
Condition Monitoring of Tools in CNC Turning

according to the planned machine schedule. In order to ensure a maintenance level which is acceptable, and where the interference with the planned production time is held as low as possible, measures such as standard maintenance intervals have been introduced, described above as TBM, (Time-Based Maintenance), where the parts of the production equipment are checked at different intervals. It is of course possible to plan the production to include this, at least to a certain extent, but the fact remains that these intervals might be unnecessary and therefore production time is lost without any gain. This could lead to an extension of the future intervals, which might result in equipment failure. A condition-monitoring system will not remove the need for maintenance or service, but it will indicate the state of the production equipment in time for the production planners to take measures in order to prevent failure in a way that is convenient for the occupancy of the machinery.

1.3.2.3 CM as a Step in Full Automation

The last reason which should be mentioned is the use of CM systems as a tool in fully-automated manufacturing. As mentioned before, automation is necessary for the products to be manufactured at low costs, to ensure that “high wage” European companies are able to compete on the world market. In many manufacturing processes, not only limited to the metal-forming industry, many processes are now supervised by different monitoring systems. CM systems can be used for inspection or monitoring instead of using manual labour and the cost reduction can be of a significant amount.

1.3.3 Human TCM Systems

Previously, all control of the machinery and tools has been carried out manually by the operators. Machining a metal part using a worn tool will usually result in a poor surface finish, which can be discovered by a visual control. The rough surface will indicate rubbing and this will tell the operator that the cutting edge of the tool is worn. This control method is normally limited to checking the state of the finishing tool. The reason for this is that the finishing tool is the last tool in the machining process to remove material, where the depth of cut for this tool usually is between 0.1 to 0.3 mm. Another method of manually checking the tool is by the sound emitted from the machining
process. It is possible for the operator to hear changes in the tool condition and, from experience, he can decide which action to take. Unlike the surface check, this method is normally limited to the roughing tool. The roughing tool is used to remove as much material as possible, often several millimetres with a high MRR, (Material Removal Rate), which results in a significant sound emission if the tool has lost its ability to cut away the material. Other inspections can be carried out using different sensory information, such as the colour of the machined chip or the smell of a hot and burning workpiece, [Burke and Rangwala 1991]. This sensory information is associated with experience, based on memory triggers, upon which a decision is made to stop the machinery or not.

1.4 Research Aim and Objectives

Aim

- The aim in this research is to develop a method to detect gradual tool wear and fracture in a CNC turning process, which can cope with changing cutting parameters and the usual noises in the machining environment, which are normally present during the machining process. It must be reliable enough to be implemented for an industrial application and should be able to work under hostile conditions. This aim has been set from an industrial point of view, where the system should be as easy to implement as possible, as well as being cost-effective.

Objectives

- To develop an analytical model to estimate wear, where both flank and crater wear can be estimated as a function of removed workpiece material, which will reveal the expected dominant wear type.
- To investigate the possible use of AAE to distinguish between flank and crater wear and to investigate the sensitivity of AAE by investigating the relationship between the actual surface roughness profile and the waveform of the acoustics emitted from the process.
- To discard the effect of disturbances, both internal and external, by recognising the sound signature using surface finish parameters on a sound waveform to
describe irregularities and burst disturbances, as well as fracture, in the time signal, where the outcome can be used to evaluate the reliability of the wear decision.

- To overcome the problem of changing cutting parameters, by creating a model where the three parameters depth of cut, feed rate and cutting speed can be predicted from the machining sound, where the time domain signal represents the energy in the cutting signal and the distributions in the frequency domain works as divisional operators.

- To relate the predicted cutting parameters to a virtual cutting force, which can be related to the theoretical cutting force, where a non-linear regression system is relating previous measured wear to the virtual force increment.

- To combine the different models into a multidisciplinary monitoring systems using a combination of on-line AAE sensory signals in order to predict flank wear, with an analytical prediction of the dominant wear type and a on-line system to detect signatures of disturbances, in order to evaluate the reliability of the wear prediction.

1.5 Research Novelty

As stated in the introduction, condition monitoring is a discipline which has attracted much attention. Several methods have been used as well as fusion systems, consisting of multiple sensors. This research is built on the principle of using AAE, (Airborne Acoustic Emission), which is sound in the sonic range. As described in section 1.3.3, different researchers have recognised that operators are capable of detecting changes in the cutting tool by the sound emitted from the process. A few researchers have investigated this field, however, only a few papers exist where the main purpose has been to show the relationship between tool wear and changes in the SPL. However, no structured approach to recognise wear as a function of changing cutting parameters has been presented. As well as for AE, AAE is extremely sensitive to changing cutting parameters, tool wear and disturbances. This research has been conducted only for the condition monitoring of cutting tools in CNC turning, which adds a new dimension to the complexity. CNC machinery is basically a ‘tin can’ or a metal box, where the sound is distorted by
refraction, deflection, destruction and construction of sound waves. Where all previous research has been based on building systems, which uses as many informative signals as possible, this research has been concerned with 'simplifying' the problems in order to fulfil the objective of creating a reliable monitoring system, which is robust enough to be applied in industry. Previous research in similar fields has unsuccessfully been concerned with creating systems which are not affected by changing cutting parameters or which, by a huge amount of training, can cope with some changing parameters. This research has been built on the opposite idea, where the main goal is to recognise the changing cutting parameters in the machining process. This is a novel and reverse approach, where the predicted parameters have been used to create a virtual cutting force, which is basically a scalar representation of the energy in the process, as well as changes in the spectral distributions will reveal how they are distributed with respect to feed rate, depth of cut and cutting speed. Defining ranges across the frequency spectrum, and treating these as separate distributions, it has been possible to build a feature vector, which by simple scalar values can represent the behaviour of the spectral distribution in those ranges. Furthermore, this research has shown that even changing surface finish can be detected in the sonic frequency range. As a novel approach, the time-domain surface finish parameters have been used to describe irregularities in a waveform captured from the sound. The proposed solution consists of a hybrid system, which uses an analytical model to predict tool wear, which later is correlated with the on-line sensory signals as well as the predictions of the virtual cutting force related to tool wear. This research has recognised and pointed out the gaps in the field, where changing cutting parameters and disturbances have been the reasons for the lack of success. Therefore the main purpose has been to identify these problems and work around them, creating a model which can exclude disturbances and non-informative signals from the decision-making process.

1.6 Thesis Outline

This thesis consists of eleven chapters. It is the purpose of this thesis, to take the reader through the process of background information about metal cutting and monitoring systems, to the chapters involving cutting signal analyses. Chapters 2, 3 and 4 will provide some background knowledge, which is the information upon which this research
is built, where chapters 5, 6, 7, 8, 9 and 10 will describe the analyses. An overview of the proposed solution is presented in the introduction in chapter 5. In detail, the thesis is structured as follows:

Chapter 2 will take the reader through the structure of a CNC machine, as well as providing the terminology for the different components as well as cutting parameters, which will be required later. This chapter will continue by explaining the basics of orthogonal metal cutting.

Chapter 3 will give a brief introduction to today’s cutting tools as well as describing different wear types and characteristics for some tool types. The latter part of this chapter will be concerned with describing the analytical prediction of tool wear as well as a review of different monitoring systems and sensing techniques, where the focus will be on the previous lack of success of these systems.

Chapter 4 describes methods which have been used in the different fields of airborne, structure borne and liquid borne acoustic emission, as well as the basics of acoustic emission. Different common pattern recognition techniques are described, which have previously been used in the field of AE monitoring.

Chapter 5 presents an overall picture of the proposed system, and describes the analytical wear-prediction models used to predict flank wear as a function of removed material. This model is used later on to predict the contribution of RMS values as a function of an expected wear increment. They can also be used to predict situations where crater wear will be more pronounced than flank wear, where it has been shown that crater wear is difficult to measure using AAE.

Chapter 6 will briefly explain the different sound signatures which it is necessary to be able to recognise in the cutting process, either in order to detect fracture or to exclude disturbances from the results. The problem with external disturbances is also described.

Chapter 7 will show that a representation in the time-domain can be related to the theoretical energy in the cutting signal. It will explain the development of an AAE RMS model, which is able to predict a level for the AAE RMS as a function of the different cutting parameters. This model is later used in order to double check the wear increment, where the expected AAE RMS can be correlated with the actual measured AAE RMS, indicating either a severe case of crater wear or a fracture.
Chapter 8 shows a feature vector built on surface finish parameters, since they have shown good abilities to detect burst signals in the cutting process. This means that the detection and prediction of wear and disturbances can be separated in two models, using a different set of features.

Chapter 9 will go through an analysis in the frequency domain in order to build a feature vector which can separate the cutting parameters. This chapter will describe how different cutting parameters are changing the spectral range.

Chapter 10 describes a model, which can relate wear to a virtual, calculated cutting force by predicting cutting parameters. The prediction is basically a scalar representation that takes all cutting parameters into account and which can be connected to a certain amount of tool wear by using non-linear regression.

Chapter 11 will summarise the proposed model and conclude this thesis with recommendations for further and future work in this field.


Chapter 2

2 Metal Cutting

This chapter will briefly give an introduction to metal cutting in industry and will also describe some basic theory in metal cutting in order to understand some of the considerations discussed later on. Metal cutting is a subject which has drawn much attention on both the micro- and macro-scale. Looking at metal cutting on the micro-scale, one is concerned with the actual changes in the lattice or dislocations of the material, whereas the macro-scale is concerned with identifying chip flow and the forces involved in the cutting process, which therefore gives a larger picture of the process. Some knowledge of the theory as well as the practical background of metal cutting as a whole is required in order to understand some of the ideas in this thesis, hence the following introductory section, where the historical on production equipment is extracted from Altintas [2000], Stephenson and Agapiou [2006] and Shaw [2005].

2.1 Production Equipment in Metal Cutting Industry

The development of production equipment, such as lathes and milling machines, really became important around the time of the industrial revolution. In 1775, John Wilkinson developed the cannon-boring machine in England, which was later adapted for boring the cylinders for Boulton-Watts steam engines. What is known as the first lathe, being able to possess all the basic features, is credited to Henry Maudsley who, in 1800, introduced the screw-cutting lathe. Later on, in 1818, Eli Whitney invented a milling machine, where work that was normally carried out by skilled manual craftsmen, could be carried out by less skilled operators in a more efficient way. The early development of milling machines virtually all took place in the United States, where they were mainly used to manufacture
Condition Monitoring of Tools in CNC Turning

firearms and farm equipment. With demands for higher productivity, this development of the machinery for metal cutting carried on up to 1952 when John Parson presented a milling machine where the movement in the x and y directions was controlled by punch cards. This gave birth to the NC (Numerically Controlled) milling machines, which could create far more complex shapes than any previously produced by a manually controlled machine. At this time automation had existed on a small scale by using mechanical devices to automate manufacturing tasks. In the 1960s, the introduction of digital computers, combined with the needed power, right size and price, really jumpstarted the industries that were developing automated machinery. Today, almost all metal cutting is controlled by Computer Numerical Control (CNC) and a huge step towards full automation has been taken. One of the most visible parts of today’s automation is the industrial robot, where the advantages of repeatability and higher productivity exceed the disadvantages, such as high capital requirement and decreased flexibility. In industry, there are many types of metal removal principles, all using different techniques but with one common goal: the removal of material from a workpiece. In many cases the workpiece, often referred to as the blank, comes from a deformation process such as rolling or casting and undergoes a series of cutting processes in order to reach the final shape. The metal removal processes can be divided into two groups: grinding and cutting. The metal cutting processes include laser or plasma cutting, boring, drilling, shaping, milling, turning, etc. Looking at metal cutting specifically, the most common types, which are to be found in almost every metal forming company, are drilling, milling and turning. Two ways of metal cutting, which are especially interesting when it comes to the aspect of tool condition monitoring, are milling and turning. These processes are often carried out on very expensive equipment, where preservation of up-time is essential. Also for these two machining types, a breakdown caused by unattended tool wear, can have catastrophic consequences. On the other hand, a tool break in a drilling process will not cause serious problems, regarding repair or realignment of the production equipment, mainly because the forces involved are relatively small.

There are three principle types of machine tools in the metal cutting industry. These are conventional machine tools, production machine tools and CNC machine tools, [Stephenson and Agapiou 2006]. Conventional machine tools are developed for carrying
Condition Monitoring of Tools in CNC Turning

out operations on a variety of parts, where production machine tools are developed for high volume production. These machine tools are normally developed to carry out a repeated operation on a small variety of parts. CNC machine tools in turning and milling centres can be used to produce a large variety of parts. This type of machine is flexible compared to production machine tools, which are normally developed for special purposes. Most of the production equipment today is automated and the conventional machine tools, such as lathes and milling machines, are being equipped with NC control and formed into CNC machining centres, see Figure 2.3.

2.2 CNC Turning

Conventional turning is one of the oldest and most versatile tools. In general, turning is a single point cutting process where the workpiece is rotated and the tool is stationary. The parts and motions involved in conventional turning can be seen in Figure 2.1. In the conventional turning principle, the workpiece is held by a chuck bolted onto the main spindle. This can either be a three-jaw chuck, which is manually fitted to the diameter or a collet chuck. The cutting tool is fixed in a tool holder and pushed through the workpiece with a given feed rate \( f \). Depending on the length of the workpiece, cutting pressure and tool overhang, machining the free end of the workpiece is highly likely to result in some disturbances, such as vibration and deflection of the workpiece.

![Figure 2.1 Conventional turning, [Stephenson and Agapiou 2006].](image)

The conventional turning principle is used in most of the CNC turning centres in industry today, in some cases with the possibility of milling and drilling combined in one
multitasking centre. Broadly, the lathe consists of several different subsystems in each of which failure can occur, see Figure 2.2.

Figure 2.2. The subsystems of a lathe, [Saravanan et al. 2006].

Figure 2.3. A CNC turning centre.

2.2.1 Main Spindle

The spindle is the interface between the machine and the cutting tool. The spindle is the factor which decides the geometric capabilities of the machinery. Worn-out spindle bearings will be reflected in tolerance deviations of the machined part or cause vibrations. There are various spindle types, but on many CNC lathes the box type is often used, where the spindle is driven externally by an electric motor, where the power is transferred by belts. A point which should be mentioned in this chapter is that since the spindle is the interface between the machine and the cutting tool, it is also subjected to the load from
the cutting process. This means that the forces, tangential as well as axial, are transferred to the spindle bearings.

### 2.2.2 Turret

Most CNC lathes are equipped with a tool changing system, referred to as a rotating tooling turret, see Figure 2.4 for a bolt-on turret system. There are primarily two turret types, the VDI-style turret and the bolt-on style turret. The main difference between them is the mounting mechanism of the tool blocks. The VDI type allows a somewhat faster tool change, normally carried out by loosening and tightening one bolt, whereas the bolt-on type is held by four bolts.

![Figure 2.4 CNC Turret [Loveridge].](image)

The turret is basically a magazine of different tools with given index numbers. The turret is based on the carriage of the lathe, which is important when it comes to accuracy. If excessive pressure is put on the cutting tool, the turret will be subjected to torque. For safety reasons, the turret is constructed in such a way, that it will give in if subjected to too much load, which will result in a misalignment. This is normally what happens when a sudden tool break occurs. This will result in a complete change of the tool geometry relative to the workpiece and will affect the diameter accuracy. A realignment of the turret is a complicated and very time-consuming procedure.
2.2.3 Tool Holder

The set-up of the tool holder is one of the factors which can affect machine tool vibrations, such as chatter vibration, but together with the tool insert, it is also considered to be one of the main sources of sound associated with tool wear, [Lu and Kannatey-Asibu 2004]. There are several steps regarding the selection of the tool holder and insert type. These are the selection of the edge clamping system, the type of tool holder, the insert geometry, size and tool material. These selections combined with the cutting data, will in the end determine the result of the cutting process. The main point that should be mentioned here is the ratio of tool overhang. Tool overhang is the portion of a tool that extends beyond the tool block, see Figure 2.6. This is the unsupported portion and its resistance to deflection in the direction of the tangential forces, which decreases with the length, is often the source of chatter vibration, poor surface finish and decreased tool life. The overhang ratio is the ratio between the overhang (l) and the shank diameter/height (d). The chatter instabilities related to tool overhang are a result of the frequency response of the tool clamping system.
2.3 Breakdown from Tool Wear

As mentioned in the introduction, severe damage to the machinery can be caused by unattended tool wear. In order to fully understand the consequences and effects of tool wear, some typical problems that arise from machining with worn tools should be discussed. A few elements of the CNC lathe have been described above but, although these are considered as the primary parts located “around” the cutting zone, there are other parts in the lathe which will be affected when it comes to machining with worn tools. These include especially the spindle motor, the servomotor for the slide/carryage and the bearing system for the slide/carryage, where the extra load will mean decreased life expectancy. Also, energy issues, such as the increased power consumption should be considered, in order to complete the picture. In general, the main considerations regarding the effects of tool wear are:

- Downtime
- Energy consumption
- Life expectancy
- Quality

In this research, only the consequences caused by breakdowns will be addressed.
2.3.1 Tool Breakdown and Major Breakdown

The two types of failure caused by tool wear can be defined as *normal tool failure* and *catastrophic tool failure*. Also two types of breakdown are defined: *breakdown* and *major/catastrophic breakdown*, where the distinction between them is defined by the repair time, hence the influence on the up- and downtime of the machinery.

When a fault is discovered, Figure 2.7 shows a typical decision-making model for the operator. Based on the type of breakdown, either a tool breakdown or a major breakdown, a certain amount of production time will be lost.

![Figure 2.7 Decision-making model.](image)
2.3.1.1 Tool Breakdown

For a tool breakdown where only the cutting edge is breaking, the normal procedure will be to replace the tool insert. In cases where the pressure has been extremely high, or where the process has been stopped automatically by an overload switch, a readjustment of the tool offset can be required. In this case other problems arise, because depending on the offset method, either by an integrated tool setter or a manual measurement, this can require that the first workpiece be machined in single-step mode. Also, if the previous set-up was adjusted based on two overlapping tools, or if a correction has been made in order to compensate for the physical deterioration of the worn tool, a new adjustment is essential, which again is time-consuming. Depending on the encoder system used in the CNC lathe, either absolute or incremental, the machine must be run to its reference point. For an overload switch-off, this normally requires a run to the reference point for all axes, including sub-spindles for multi-spindle lathes etc. For CNC lathes using an automatic bar feeding system, another step will be to manually cut off the machined piece of the metal bar and restart the bar feeder system.

2.3.1.2 Major Breakdown

When it comes to a major breakdown, the repair time consumed can in some cases extend from half a day to several days, all depending on the severity of the damage and also on which parts have been damaged. Generally, a major breakdown caused by a catastrophic tool failure will cause damage to the tool-holder, either the edge clamping system or the entire tool-holder, and in severe cases, the turret or tool post system will need to be realigned. The pressure on the cutting tool in the axial direction will create a torque on the tool block, which in the end can “turn” the turret bolted on the carriage, see Figure 2.8. As for the major breakdown, the considerations mentioned in chapter 2.3.1.1 for tool breakdown also apply in the case of a major breakdown. In rare cases, where huge forces are in play, damage can extend to the chucks when using the three- or four-jaw chuck system. This can happen when the pressure on the workpiece is extremely high and is either dragging or pressing the workpiece out of the jaws.
Figure 2.8 Turret affected by cutting pressure.
2.4 Turning Operations

This research is concerned with external longitudinal roughing for which all the operations and movements will briefly be explained below. In turning there can be said to be four basic movements and four operations, see Figure 2.9.

![Figure 2.9 Basic movements in turning.](image)

Turning is a combination of two movements, a rotation of the workpiece and a movement of the tool through the axis of the workpiece, a combination of which can, in general, be used to create all shapes with rotational symmetry.

- **External Turning**
  
  External turning is the 'outer diameter' machining process. This process has been said to be the most reliable operation when it comes to turning, [Sandvik 1994]. This is due to the fact, that there are no or few limitations or restrictions on the size of the cutting tool and tool holder. Therefore, the cutting process can take place over a larger cross sectional area, thereby reducing the pressure on the tool face.

- **Internal Turning**
  
  Internal turning is known to be very sensitive to vibration. In the internal turning process some consideration should be given to the fact that a tool with a large overhang ratio is used.

- **Cut-Off**
  
  The characteristic for the cut-off, also referred to as the parting process, is that the forces are concentrated on a very small cross sectional area. The machining process is very characteristic, since, in order to maintain a constant cutting speed, the spindle speed is increased along with the movement of the tool along the x-axis.
• **Threading**
On today’s CNC lathes, threading is a standard procedure, where the single-point thread cutting is the feed movement in relation to the rotation of the workpiece. The standard thread, either externally or internally, is made by several passes.

• **Roughing**
Roughing is concerned with removing as much material from the workpiece as possible. This process uses the highest possible depth of cut and feed rate in order to obtain the highest MRR, (Material Removal Rate). Because of the large depth of cut, usually in the range of 2-6 mm, roughing creates a high risk of colliding with the tool holder and/or the shoulder of the uncut workpiece in the event of a catastrophic tool failure, see Figure 2.10.

![Figure 2.10 Risk of collision after a catastrophic tool failure in roughing.](image)

In general roughing, the largest possible nose radius should be selected to obtain the strongest point, [Sandvik 1994]. It is also mentioned as important, that the maximum feed rate \( f \) does not exceed the relative nose radius \( r_e \) given in Table 2.1.

<table>
<thead>
<tr>
<th>( r_e )</th>
<th>0.4</th>
<th>0.8</th>
<th>1.2</th>
<th>1.6</th>
<th>2.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f )</td>
<td>0.12-0.25</td>
<td>0.25-0.5</td>
<td>0.36-0.7</td>
<td>0.5-1.0</td>
<td>0.7-1.6</td>
</tr>
</tbody>
</table>

Table 2.1 Recommended nose radius values in roughing, [Sandvik 1994]

• **Finishing**
The finishing process is usually characterised by low depth of cut and low feed rates. It is concerned with depth of cut in the range of 0.05-2 mm. Therefore the finishing process does not impose as high a risk of a major breakdown as the roughing process. The major issue to address in the finishing process is the surface finish of the workpiece.
2.5 Cutting Factors in Turning

2.5.1 Cutting Speed

Cutting speed in turning is defined as the peripheral surface speed, which means the speed where one point on the surface is passing by the same reference, see Figure 2.11. The cutting speed is an important factor, especially when it comes to tool life. It is a process variable used to optimise the cutting process to the cutting tool and the workpiece material. Too high a cutting speed will accelerate the tool wear; most probably because of damage caused by excessive heat generation and following diffusion wear. When the cutting tool is engaging contact with the workpiece, the workpiece material is lifted up on the tool face, creating a chip, which will eventually break off. In this process, a massive amount of heat is generated because of the friction between the cutting edge and the workpiece material. When the workpiece rotates with a certain spindle speed \( n \) at a given workpiece diameter \( D \), this gives a peripheral speed or surface speed \( v \) described in Equation 2.1.

\[
v = D \cdot \pi \cdot n
\]

Equation 2.1

2.5.2 Constant Cutting Speed

In some cases, a requirement for constant cutting speed will induce changes in the spindle speed. In longitudinal turning, where the diameter is held constant, there are no changes, but in facing, round and angle copying, where the diameter changes, the spindle speed is changed accordingly. On most CNC lathes, a constant cutting speed can be programmed as an option when the cutting tool moves towards the centre.
2.5.3 Material Removal Rate

In some cases it becomes practical to speak of material removal rates, \( MRR \), or actual physical material removal \( V \), especially when it comes to remaining tool life, where a specific volume of material can be expected to be removed from the workpiece, under given cutting parameters, such as cutting speed, feed rate, tool geometry, workpiece material etc. The material removal rate is basically the volume of material removed per time unit, Equation 2.2.

\[
MRR = v \cdot f \cdot a_p
\]

Equation 2.2

2.5.4 Feed Rate and Feed Speed

Feed rate \( f \) is the tool’s movement in the direction of cut, given in mm per revolution, where feed speed \( f_s \) is the axial velocity given in mm per minute. For worn tools, the feed pressure is a result of the feed speed directed on the main cutting edge of the cutting tool and the wear land.
2.5.5 Depth of Cut

The depth of cut relates to the material removal rate. The cutting depth is the distance between the un-cut and cut surface, measured at a right angle to the feed direction, see Figure 2.12.

![Figure 2.12 Cutting depth and feed.](image)

2.5.6 Nose Radius of the Cutting Tool in Turning

The nose of the cutting tool is the part of the tool which is used the most, especially when it comes to finishing or copying, where the depth of cut is normally between 0.1-0.5 mm. The nose radius $r_e$ is measured tangential to the main and secondary cutting edge. In turning, the nose radius is a weak point when it comes to tool life. This is due to the fact, that the nose is a sharp point in the tool's geometry, where the pressure is distributed over a very small cross-sectional area. It has been shown that corner radius has an effect on tool wear, since a larger radius can be used to spread the overall thermal load over a greater region, [Endres and Kountanya 2002].

2.5.7 The Effect of Edge Radius

The edge radius is a micro-scale factor. What used to be stoning of the cutting edge has now been replaced by a preparation on a microscopic scale. The cutting edge is usually prepared in one of three basic ways, either with a honed radius on the corner, a chamfer
which breaks the corner or a land before the actual rake angle, all with the purpose of gaining strength and controlling the direction of the forces.

2.5.8 Entering Angle and its Effect on the Cutting Process

A very important factor in the tool set-up for a turning process is the entering angle $\kappa$. This is the angle between the cutting edge and the feed direction, see Figure 2.13. This angle affects the distribution of the cutting forces and chip formation, as well as chip thickness, and a well-chosen entering angle can be used to maximize the lifetime of the cutting tool. Some of the problems in the metal cutting process arise when the cutting tool is engaging contact with the workpiece. At this point a large momentary force is put on the cutting tool, especially in a turning process using a high entering angle. The large entering angle causes the cutting forces to be distributed over a shorter section of the cutting edge, subjecting the tool to maximum loading and unloading, [Saglam et al. 2007]. The entering angle can give the cutting tool extra strength on entering and exiting the cutting process.

![Figure 2.13 Entering angles.](image)

In turning, the entering angle is normally varied between 45 and 90 degrees, see Figure 2.14, but in some cases, especially related to copying, the angle can be more than 90 degrees in order to machine complicated profiles. An optimum entering angle has been quoted by Saglam et al. [2007] to be between 60 and 75 degrees.
The entering angle plays an important role when it comes to the distribution of the cutting forces. A smaller entering angle can be used to reduce some of the axial forces, which can deflect the cutting tool in longitudinal turning, but on the other hand, a larger radial force could result in a deflection of the workpiece, [Sandvik 1994], see Figure 2.15.

For a heavier cut, or in cases where high material removal rates are required, e.g. in roughing, it is normal to use a tool set-up with a smaller entering angle, rather than 90 degrees. Not only will a smaller entering angle distribute the forces in the axial and radial directions, but the direct force between the cutting edge and the workpiece will be distributed on a longer cutting edge. This is a very important consideration when it comes to wear resistance of the cutting tool.

### 2.5.9 Effective Rake Angle in Practical Turning

The rake angle of the tool holder $\alpha_{tool}$, is often negative, but can also be neutral or positive. Together with the rake angle of the tool insert $\alpha_i$, this constitutes the effective rake angle $\alpha$ and can be expressed as Equation 2.3.

$$
\alpha = \alpha_{tool} + \alpha_i
$$

**Equation 2.3**

### 2.5.10 Inclination Angle in Turning

Oblique cutting is distinguished from orthogonal cutting by an inclination angle $\gamma_i$ of the cutting tool, shown in Figure 2.16, with its clearance angle $\gamma_c$. Because of the tool
geometry of most modern inserts, where the wedge angle $\beta_w$ is often $90^\circ$, the inclination angle tends to be negative. The inclination angle affects the chip flow angle and also the force distribution in oblique cutting.

Figure 2.16 Negative inclination angle (A), Positive inclination angle (B), [Sandvik 1994].

2.5.11 Chip Width and Chip Thickness

The chip width $i_a$, Equation 2.4, is the same as the effective length of the cutting edge, see Figure 2.17. In cases where the entering angle is 90 degrees, the chip width is equivalent to the depth of cut. The chip thickness, see Equation 2.5, is also affected by the changes in the entering angle. A smaller entering angle will result in a thinner chip thickness, where the normal chip thickness for a 90-degree entering angle is equivalent to the feed rate.

Figure 2.17 Chip width and thickness.
2.5.12 Cutting Force in Metal Turning

Dividing the three dimensional cutting force $F$ for a metal turning application into components gives the tangential force $F_t$, the radial force, $F_r$, and the feed force, $F_f$, see Figure 2.18.

\[ F_t = a_p \cdot f \cdot k_c = a_p \cdot f \cdot \frac{k_{cl,1}}{h^n} \cdot C1 \cdot C2 \]

Equation 2.6

A simplified force relationship was described by [Shaw 2005, Saglam et al 2006], where it is assumed that the feed force, as a rule of thumb, can be estimated to be half the tangential force.

2.6 Basics of Metal Cutting

As mentioned before, metal cutting is concerned with the removal of an amount of material from a workpiece or blank. It has developed to a state where demands of high chip removal rates, cutting speeds and exotic workpiece materials, have been making the
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cutting environment very hostile. The basic metal cutting is a chip formation process, where chips are generated and broken off the workpiece, [Shaw 2005]. An important factor in a controlled cutting process is the ability to adjust the cutting conditions to optimise the process, regarding the development of deformation, temperature and forces. In the theory of metal cutting, the orthogonal cutting principle is normally used, such as in turning and milling, because it gives a good approximation of the major cutting edge. An early model of chip formation was proposed by Ernst and Merchant [1941] and was based on a concentrated shear model, using a primary shear zone, which separates the deformed and undeformed metal, see Figure 2.19.

![Figure 2.19 Model of orthogonal cutting.](image)

Other models have been proposed, where the shear zone behaves according to the workpiece material and the geometry of the cutting tool. As can be seen in Figure 2.20a, a soft workpiece material will result in a larger radius in the chip breaking zone, therefore the primary shear zone is distributed over a larger area. Taking the nose radius into consideration, another model is proposed, Figure 2.20b, where the sub surface of the shear zone has a plastic flow [Shaw 2005].
Since it is very difficult to decide which of the models a given process will follow, Figure 2.19 is often used as a good approximation. This is a model of an ideal cutting process, which assumes that the material behaves in a homogeneous fashion. This model is based on the following from Ernst and Merchant [1941].

- The tool is perfectly sharp and there is no contact along the clearance face.
- The shear surface is a plane extending upwards from the cutting edge.
- The cutting edge is a straight line extending perpendicular to the direction of feed and generates a plane surface.
- There is only plain strain, where the chip does not flow to the side.
- The depth of cut remains constant.
- The width of the cutting tool is greater than the workpiece.
- The work moves relative to the tool with a uniform velocity.
- Continuous chip is produced with no built up edge, (BUE).
- The shear and normal stresses along the shear plane and tool are uniform.

### 2.6.1 Two-Dimensional Orthogonal Metal Cutting

Three-dimensional cutting is the most common cutting operation, but the two dimensional model is often used to explain the basics of metal cutting. In orthogonal cutting, the material is removed by the cutting edge, which is perpendicular to the feed direction. The chip is built up around the cutting edge as a layer of workpiece material, deformed by large stresses before it reaches the yield strength of the specific workpiece material. In this process, both elastic and plastic deformation can be observed. Shearing takes place over narrow regions of the primary shear zone, inclined at the shear angle, and the workpiece material is subjected to extensive plastic deformation in the secondary shear zone and over the tool flank. The shear angle depends on the cutting parameters,
cutting tool geometry, frictional conditions on the tool faces and the properties of the workpiece material, [Marinov 2001]. The prediction of the shear angle is one of the fundamental objectives in metal cutting.

2.6.2 Shear Plane and Rake Angle

The shear plane separates the deformed and undeformed workpiece material. Most of the energy in this cutting process is concentrated around this plane, where there is a plastic deformation of the workpiece material at high temperatures. This also means that the chips and the machined surface are undergoing a hardening process, which increases the forces needed for the process. The rake angle $\alpha$, which is the angle between the chip face and a normal to the workpiece material, also plays an important role, see Figure 2.21. This angle determines the shearing angle $\phi$ and also the contact length. A small shear angle means a high shearing force. It is estimated that the rake angle affects the energy required for the cutting process, where a 1-degree increase in rake angle decreases the energy by 1%, [Shaw 2005].

![Figure 2.21 Angles in orthogonal metal cutting [Shaw 2005].](image)

The shear angle is normally obtained by the chip compression ratio, Equation 2.7, where $h$ is the uncut chip thickness and $h_c$ is the deformed.
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\[ r_c = \frac{h}{h} = \frac{AB \sin \phi}{AB \cos (\phi - \alpha)} \qquad \text{Equation 2.7} \]

The shear angle can be defined by Equation 2.8.

\[ \tan \phi = \frac{r_c \cos \alpha}{1 - r_c \sin \alpha} \qquad \text{Equation 2.8} \]

2.6.3 Force Components

There are primarily two forces affecting the free body diagram of the chip. These are: \( \mathbf{R} \) between the tool face and the chip and \( \mathbf{R}' \) along the shear plane between the workpiece and the chip, see Figure 2.22. The force components along the tool face and shear plane are given by Equation 2.9 and Equation 2.10.

Figure 2.22 (a) Composite cutting force circle (b) Free body diagram of chip, [Shaw 2005].

- Shear plane force components consisting of shear force \( F_s \) and normal force on shear plane \( N_s \).

\[ F_s = F_1 \cos \phi - F_1 \sin \phi \]
\[ N_s = F_1 \cos \phi + F_1 \sin \phi \]

- Tool face components consisting of tool/chip force \( F_c \) and the normal force in tool/chip direction \( N_c \).
2.6.4 Tool Face Friction Coefficient

The friction coefficient \( \mu \) for the contact between the chip and the tool face is calculated using the tool face components as in Equation 2.12.

\[
\mu = \frac{F_c}{N_c}
\]

Equation 2.12

In this theory, it is assumed that the chip slides with an average and constant friction coefficient, although in reality, the chip sticks to the rake face for a brief moment, then slides with a constant friction coefficient, [Altintas 2000]. The friction angle \( \beta \) between the rake face and the chip is given by Equation 2.13.

\[
\tan \beta = \mu
\]

Equation 2.13

2.6.5 Tool-Chip Contact Length

Different models have been developed for determining the tool-chip contact length \( l \), and were reviewed by Abukhshim et al. [2004]. Using the knowledge, that the contact length is connected to the chip compression ratio and chip thickness, the contact length was approximated as Equation 2.14. The theoretical contact length with constant depth of cut can be seen from Figure 2.23.
\[ l = h(2.05r_c - 0.55) \]  

Equation 2.14

Figure 2.23 Predicted contact length, using Equation 2.14, as a function of feed rate and effective rake angle.

\[ l = 0.485 + 0.00280 \cdot v \]  

Equation 2.15

Another empirical model is shown as Equation 2.15. The contact length increases with cutting speed. However, the deficiency in this model is that it fails to consider chip thickness and rake angle variations. The theoretical contact length for different cutting speed conditions, using an effective rake angle of 14 degrees, can be seen from Figure 2.24.

Figure 2.24 Predicted contact length, using Equation 2.15, as a function of feed rate and cutting speed. A constant depth of cut of 2 mm.
A model that predicts the contact length from chip thickness, shear and rake angle, where the shear angle can be estimated from the chip compression ratio using the assumption of uniform distribution of normal stress, is shown in Equation 2.16, [Friedman and Lenz 1970, Altintas 2000]. A simulation of the theoretical results is shown in Figure 2.25.

\[ l = \frac{h \sin(\phi + \beta - \alpha)}{\sin \phi \cos \beta} \quad \text{Equation 2.16} \]

As it can be seen, Figure 2.23, Figure 2.24 and Figure 2.25 all show different behaviour. Equation 2.14 is estimating the contact length as a function of the chip compression ratio. Equation 2.15 is showing a linear relationship with the cutting speed, and although several researchers have recognised that there is a relationship between the contact length and the cutting speed, Friedman and Lenz [1970] stated that no regular pattern could be characterised. They mentioned several factors related to the behaviour of the contact length, including tool material, cutting fluid, workpiece material, etc. The interesting part was that they summarized that an increased feed rate increases the contact length, usually in a linear pattern. The cutting geometry also has an effect in that the increased rake angle decreases the contact length. In this chapter, the examples have been calculated using AISI 1040 equivalent Carbon steel as a reference material.

Figure 2.25 Predicted contact length, using Equation 2.16, as a function of feed rate and rake angle. A constant depth of cut of 2 mm is used.

The model described in Equation 2.16 is used in this research since it gives results that correlate with previous research in the field. However, in order to estimate the real influence of feed rate, a comparison is made in Chapter 5.
2.6.6 Normal Stress at the Tool-Chip Interface

Using the assumption that the normal stresses are uniformly distributed, the normal force working on the rake face and the estimated chip contact area $A_c$ can be used, as shown in Equation 2.17.

$$\tau_c = \frac{N_c}{A_c} = \frac{N_c}{l \cdot a_p}$$  \hspace{1cm} \text{Equation 2.17}

2.6.7 Energy Consumption

The energy in the two dimensional cutting model is consumed in different ways.

1. Shear energy along the shear plane $\mu_s$.
2. Friction energy on the tool face $\mu_f$.

The energy varies with the rake angle, where the assumption is, that a 1-degree decrease in rake angle increases the energy by 1%. For a new and completely sharp tool, almost all of the energy is consumed along the shear plane and tool face, however, when the cutting tool wears out, the wear land will cause an increase.

For the energy consumed along the tool face, this is divided between the chip and the cutting tool, with most of it going to the chip. For a typical cutting operation, the energy is distributed as follows [Shaw 2005]:

- 90% of the total energy is distributed to the chip
- 5% of the total energy is distributed to the cutting tool
- 5% of the total energy is distributed to the workpiece

The energy per volume unit can be obtained from Equation 2.18.

\textbf{Shear energy}

$$\mu_s = \frac{F_s v_s}{v \cdot f \cdot a_p}$$  \hspace{1cm} \text{Equation 2.18}

The velocity relation along the shear plane and the direction of work $v_s$ can be expressed as Equation 2.19, [Altintas 2000].

$$v_s = \frac{\cos \alpha}{\cos(\phi - \alpha)} v$$  \hspace{1cm} \text{Equation 2.19}

The velocity along the tool-chip contact $v_c$ is given by Equation 2.20.
The shear power $P_s$ along the shear plane can be calculated using Equation 2.21.

$$P_s = F_s v_s$$  \hspace{1cm} \text{Equation 2.21}

\textbf{Friction energy}

$$\mu_f = \frac{F_c v_c}{v_s f \cdot a_p}$$  \hspace{1cm} \text{Equation 2.22}

The friction power for the tool chip contact $P_c$ can be calculated using Equation 2.23, [Altintas 2000].

$$P_c = F_c v_c$$  \hspace{1cm} \text{Equation 2.23}

### 2.6.8 Specific Energy for Workpiece Material

As mentioned previously, the energy required for the cutting process depends on the rake angle of the tool, but the total energy required also depends on the workpiece material. The specific energy $k_c$, required for machining a unit volume of different materials can be found as initial values $k_{c1,1}$, in Table 2.3, [Fischer et al. 1999]. The specific energy can be calculated using Equation 2.24.

$$k_c = \frac{k_{c1,1}}{h_{mc}} \cdot C1 \cdot C2$$  \hspace{1cm} \text{Equation 2.24}

<table>
<thead>
<tr>
<th>Correction factors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cutting Speed m/min - C1</strong></td>
</tr>
<tr>
<td>10...30</td>
</tr>
<tr>
<td>31...80</td>
</tr>
<tr>
<td>81...400</td>
</tr>
<tr>
<td>401...</td>
</tr>
<tr>
<td><strong>Cutting process - C2</strong></td>
</tr>
<tr>
<td>Milling</td>
</tr>
<tr>
<td>Turning</td>
</tr>
<tr>
<td>Drilling</td>
</tr>
</tbody>
</table>

Table 2.2 Correction factors for cutting speed and process.
Condition Monitoring of Tools in CNC Turning

Conversion of specific energy $k_{cor}$ can be done by using the assumption that a 1-degree increase in rake angle will result in a 1% decrease in specific energy, see Equation 2.25, [Altintas 2000].

$$k_{cor} = k_e \left(1 + \frac{\alpha_0 - \alpha}{100}\right)$$

Equation 2.25

<table>
<thead>
<tr>
<th>Material</th>
<th>$k_{el,l}$ N/mm²</th>
<th>$m_e$</th>
<th>Specific energy $k_e$ in N/mm²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.08</td>
</tr>
<tr>
<td>E295</td>
<td>1500</td>
<td>0.3</td>
<td>3200</td>
</tr>
<tr>
<td>C35, C45</td>
<td>1450</td>
<td>0.27</td>
<td>2870</td>
</tr>
<tr>
<td>C60</td>
<td>1690</td>
<td>0.22</td>
<td>2945</td>
</tr>
<tr>
<td>9S20</td>
<td>1390</td>
<td>0.18</td>
<td>2190</td>
</tr>
<tr>
<td>9SMn28</td>
<td>1310</td>
<td>0.18</td>
<td>2065</td>
</tr>
<tr>
<td>35S20</td>
<td>1420</td>
<td>0.17</td>
<td>2180</td>
</tr>
<tr>
<td>16MnCr5</td>
<td>1400</td>
<td>0.30</td>
<td>2985</td>
</tr>
<tr>
<td>18CrNi8</td>
<td>1450</td>
<td>0.27</td>
<td>2870</td>
</tr>
<tr>
<td>20MnCr5</td>
<td>1465</td>
<td>0.26</td>
<td>2825</td>
</tr>
<tr>
<td>34CrMo4</td>
<td>1550</td>
<td>0.28</td>
<td>3145</td>
</tr>
<tr>
<td>37MnSi5</td>
<td>1580</td>
<td>0.25</td>
<td>2970</td>
</tr>
<tr>
<td>40Mn4</td>
<td>1600</td>
<td>0.26</td>
<td>3085</td>
</tr>
<tr>
<td>42CrMo4</td>
<td>1565</td>
<td>0.26</td>
<td>3020</td>
</tr>
<tr>
<td>50CrV4</td>
<td>1585</td>
<td>0.27</td>
<td>3135</td>
</tr>
<tr>
<td>X210Cr12</td>
<td>1720</td>
<td>0.26</td>
<td>3315</td>
</tr>
<tr>
<td>EN-GJL-200</td>
<td>825</td>
<td>0.33</td>
<td>1900</td>
</tr>
<tr>
<td>EN-GJL-300</td>
<td>900</td>
<td>0.42</td>
<td>2600</td>
</tr>
<tr>
<td>CuZn37</td>
<td>1180</td>
<td>0.15</td>
<td>1725</td>
</tr>
<tr>
<td>CuZn36Pb1.5</td>
<td>835</td>
<td>0.15</td>
<td>1220</td>
</tr>
<tr>
<td>CuZn40Pb2</td>
<td>500</td>
<td>0.32</td>
<td>1120</td>
</tr>
</tbody>
</table>

Values in the table are given for the following rake angles:
- $\alpha_0 = +6^\circ$ for steel
- $\alpha_0 = +2^\circ$ for cast iron
- $\alpha_0 = +8^\circ$ for brass

Table 2.3 Values of specific energy for different materials, [Fischer et al. 1999].
2.6.9 Cutting Force for Orthogonal Steady-State Cutting

The tangential cutting force $F_t$ is estimated from Equation 2.26, [Shaw 2005].

$$F_t = \frac{k_c \cdot v \cdot a_p \cdot f}{v} = k_c \cdot a_p \cdot f$$  
Equation 2.26

The feed force $F_f$ is estimated from Equation 2.27, [Sandvik 1994, Shaw 2005, Saglam et al. 2006].

$$F_f = \frac{F_t}{2}$$  
Equation 2.27

2.6.10 Flow Zone

It is not only the factors around the shear plane that determine the stress and strain; factors along the tool face also have an important influence. The friction is a large factor in the cutting process, especially when it comes to the excessive heat generation between the two sliding metal parts. In the contact zone between the chip and cutting tool, a flow zone FZ is generated, see Figure 2.26, [Sandvik 1994].

![Figure 2.26 Flow zone of molten metal, [Sandvik 1994].](image)

This thin zone consists of molten metal and also serves a purpose in the metal cutting process. The softened metal actually protects the cutting tool by sliding over the surface. A low cutting speed will decrease the temperature, which might lead to increased friction, whereas a high cutting speed will lead to premature tool failure.

2.6.11 Built Up Edge

The flow zone also accounts for other factors, some of them more unwanted than others. Under certain cutting conditions, layers from the flow zone of the workpiece material are built up and hardened on the face of the cutting tool. This is referred to as *built-up edge*, (BUE), and is a factor that can alter the geometry of the cutting tool, as well as removing
its ability to cut away the workpiece material. This is unwanted in the cutting process, not only because of the geometry change, but also because the built-up edge eventually breaks off, and in many cases takes a part of the cutting edge with it. Built-up edge formation reduces machining accuracy, and also affects the surface quality of the workpiece when the material periodically breaks off. When it comes to tool wear, BUE has been said to have an opposing effect, although the breakage of a BUE along with the cutting edge counts for abrasive wear, cutting it actually protects the cutting edge from wear, [Ernst and Merchant 1941]. The formation of a BUE is very much temperature dependant, where the strength decreases with increasing temperature.

2.7 Conclusion of Metal Cutting

This chapter has described the common cutting parameters which are used in the cutting process as well as the practical and theoretical background of metal cutting. The theories which have been covered have mainly concerned simplified orthogonal metal cutting. Although it has been mentioned that most metal cutting is oblique, two-dimensional orthogonal cutting offers a simple way of providing a guideline for describing cutting behaviour.
Chapter 3

3 Tool Wear and Tool Condition Monitoring

This chapter will present some general knowledge about cutting tools, some common types of tool wear and also a brief description of the wear characteristics of the cutting tools currently used in turning, where some analytical considerations are presented. The trend in this work has moved to a point where the researchers recognise that different parameters, besides tool and workpiece material, are influencing the wear models. At the end of this chapter, a general review is presented where promising TCM systems, primarily for turning applications, are reviewed.

3.1 Cutting Tools

The development of today’s cutting tools can be said to have its beginning in the nineteenth century. Along with the industrial revolution, the demands for increased material removal rates became higher, which lead to demands for better cutting tools. In the beginning, the best tool materials available were high-carbon steel and alloy carbon steel. Although the normal workpiece materials at this time were relatively soft, grey-cast iron or bronzes, the tool life expectancy was very short. At this point the carbon steel tools failed because of the heat generation, although the cutting speed was only a fraction of what can be seen in today’s metal cutting. The science of metallurgy moved forward, which lead to a better understanding of heat treatment for alloy steels and therefore, it became possible to improve the tool life at high cutting speeds. After the introduction of High Speed Steel, (HSS), the cutting speed was increased dramatically and by the beginning of the twentieth century the machining time had decreased to a quarter of what it used to be, [Sandvik 1994]. As the twentieth century progressed, developments
continued with the introduction of cast alloys to the cemented carbide tools, which dominated the market during World War Two. At this point, the limitations to increased productivity were no longer found in the tool type, but in the machinery. However, with the developments in technology such as the introduction of numerical controls for high-speed machinery and increasingly automated manufacturing, the demand for increased chip removal rates was again growing by the late 70's. Today's coated cutting tools have reached a high standard, see Figure 3.1, but with the ever-increasing demands for productivity and unmanned production, they are still a liability.

![Coated cutting tools](image)

Figure 3.1 Coated cutting tools, [Sandvik 1994].

In the 1980’s, cemented carbide inserts with a TiC monolayer were introduced, leading to multilayer coatings, such as Al₂O₃. This has expanded in other applications after tool inserts of steel were coated, [Schinltmeister et al. 1984]. Many different tools are available today, for almost all sorts of processes and cutting speeds, see Table 3.1.

<table>
<thead>
<tr>
<th>Tool Material</th>
<th>Cutting Speed (m/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Speed Steels</td>
<td>10 – 60</td>
</tr>
<tr>
<td>Cemented Carbide</td>
<td>30 - 150 or 100 - 250 when coated</td>
</tr>
<tr>
<td>Cermets</td>
<td>150 – 350</td>
</tr>
<tr>
<td>Ceramics</td>
<td>150 – 650</td>
</tr>
<tr>
<td>Cubic Boron Nitride CBN</td>
<td>30 – 310</td>
</tr>
<tr>
<td>Polycrystalline Diamond</td>
<td>200 – 2000</td>
</tr>
</tbody>
</table>

Table 3.1 Cutting speeds for tool materials, [Sandvik 1994].

Figure 3.2 shows the terms used for cutting tools.
3.2 Tool Wear

The wear process in metal cutting follows a certain pattern. As the tool wears, an increase in the cutting forces can be observed. In this process, the friction between the cutting tool and the workpiece plays a big role. Tool wear is a combination of many factors, such as cutting force, material composition, lubrication, coolant and cutting speed. There are different kinds of wear which are related to the cutting speed, [Schintlmeister et al. 1984].

- High speed and feed rate increases the temperatures at the cutting edge. In the chip zone over the rake face, temperatures reach up to 1200°C.
- Wear at lower cutting speeds is caused by galling. As the speed increases, abrasive wear increases and on reaching even higher speeds, the wear becomes dominated by diffusion.

Dimla Snr [2000] described four classes of tool wear:

- Adhesive wear associated with shear plane deformation.
- Abrasive wear resulting from the cutting action of hard particles.
- Diffusion wear occurring at high temperatures.
- Fracture wear, such as chipping due to fatigue.

Schintlmeister et al. [1984] summarise different causes of wear related to the cutting tool, shown in Figure 3.3. After reviewing systems regarding cutting force, Xiaoli et al. [2000]...
state that the cutting force and the tool wear rate are a function of the cutting speed, feed rate, depth of cut and a given wear factor.

Figure 3.3 Causes of tool wear, [Schintmeister et al. 1984].

3.1.1 Wear Types

The following briefly describes the important wear types of cutting tools, giving causes and consequences.

- **Crater Wear**

Crater wear occurs on the rake face or top of the insert, see Figure 3.4. This wear typically occurs when machining steel at elevated cutting speeds. The wear can be caused by a chemical interaction between the hot chip and the workpiece material, or by abrasive particles.

Figure 3.4 Crater wear.
• **Thermal Deformation and Thermal Cracking**

For thermal deformation, see Figure 3.5, heat and pressure can cause the cutting tool’s binder to soften, which results in the movement of the carbide grains.

![Figure 3.5 Thermal deformation and cracking.](image)

• **Nose Wear**

Nose wear is often categorised as a part of flank wear and, moreover, has been said to be related to finish machining, where a smaller depth of cut is in play and where the parameters such as cutting speed and feed rate are in a proportion such that they are not posing an immediate threat of a catastrophic breakdown, [Hede 2004].

• **Depth-of-Cut Notching**

Depth-of-cut notching occurs at the free end of the chip. This is seen when machining with high cutting temperatures, see Figure 3.6.

![Figure 3.6 Depth of cut notching.](image)

• **Built-Up Edge**

Workpiece material is built up on the cutting tool, see Figure 3.7.
Condition Monitoring of Tools in CNC Turning

- **Chipping/Fracturing**
  Interrupted cutting or vibration is often the cause of chipping or fracturing of the tool, see Figure 3.8.

- **Flank Wear**
  This takes place where the tool is in contact with the workpiece at the chip separation point, [Sewailem and Mobarak 1981]. Flank wear, see Figure 3.9, is mainly caused by abrasion, where inclusions and hardness of the workpiece material are playing an important role. Flank wear has been one of the most investigated and used wear types, mainly because it is the easiest to quantify and measure. Flank wear, if left untreated, will result in a poor surface finish, inaccuracy and increased friction. Progressing flank wear is normally associated with an increase in the feed force, [Sewailem and Mobarak 1981]. Tay *et al.* [2002] investigated the topography of the flank surface and the effect increasing flank wear has on the friction mechanism in the chip/tool contact. They used surface parameters such as $R_a$, $R_s$, $R_k$ and $R_ku$ to describe the changing topography of the flank face with progressing flank wear. The increase in these parameters was given as
one of the explanations for the increased sliding friction, along with tool wear. Also, the progressing wear is increasing the wear land on the flank face. Since it has been claimed, that this wear type is the most common in normal machining, it has often been chosen as a failure criterion. In 1977, ISO 3685-1977 suggested the following guidelines, where flank wear is even, an average wear land of 0.3 mm should be used and when the wear land is irregular, scratched, chipped or badly grooved, a maximum of 0.6 mm wear land should be applied, [Lee et al. 1989]. Later on ISO 3685-1993 revised this standard.

Figure 3.9 Flank wear.

3.2 Wear Characteristics of Different Tool Types

In order to use a suitable monitoring strategy for TCM, it is important to know something about the characteristics of the cutting tools used. It has been said, that the lack of success in TCM arises from the fact, that the knowledge regarding the wear mechanisms of the tools used is insufficient, [Dolinsek and Kopac 1999]. This chapter will give a brief description of some of the wear characteristics of common tools used in the metal cutting industry today. Although it has been said that cemented carbide and HSS dominates the tool market, the HSS tools are left out of this section because they are normally found in drills, millers, etc.

3.2.1 Cemented Carbide Tools

Cemented carbide is a powder metallurgical product, and is one of the two tool materials that dominate the industry, where coated and un-coated grades exist. It has been said that the cemented tungsten-carbide tools WC-Co could not stand up to the crater-wear effect in steel, because of the affinity to carbon, [Sandvik 1994]. Other grades that have been developed are the titanium-carbides, which are more stable than tungsten carbides at high
Condition Monitoring of Tools in CNC Turning

temperatures. Also the coating of cemented carbide tools is a very important factor. Dearnley and Trent [1982] investigated the wear mechanism for both coated and uncoated tools with layers of TiC, TiN and Al₂O₃. They concluded that flank and rake-face wear rates were 10 to 100 times less for coated tools. The wear for TiC and TiN coatings were reported to be primarily atomic diffusion and plastic deformation, where the Al₂O₃ wear was observed to be plastic deformation. A classification of the properties is given by Sandvik [1994], see Figure 3.10. The figure shows the Hv, (hardness), Br, (barrier effect regarding chemical reactions), Bo, (bonding ability to insert substrate), CoF, (friction), Vb, (flank wear resistance), KT (crater wear resistance) and To, (toughness).

<table>
<thead>
<tr>
<th></th>
<th>Hv</th>
<th>Br</th>
<th>Bo</th>
<th>CoF</th>
<th>Vb</th>
<th>KT</th>
<th>To</th>
</tr>
</thead>
<tbody>
<tr>
<td>TiC</td>
<td>3000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Al₂O₃</td>
<td>2300</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TiN</td>
<td>2200</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>TiCN</td>
<td></td>
<td></td>
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</tbody>
</table>

Figure 3.10 Main carbide properties, [Sandvik 1994].

Mills [1996] described the properties of cemented carbides regarding their composition. The TiC, NbC and TaC materials were classified as having good chemical and hot-deformation resistance, whereas the WC tools had good thermal shock resistance and hardness properties.

3.2.2 Ceramic Tools

Figure 3.11 Ceramic Al₂O₃ Tools, [Sandvik 1994].
Ceramic tools are hard and very heat resistant. Another benefit is that they do not react with workpiece materials. Neoceramic tool types are now being used as cutting tools, and a huge development is taking place. These types include: $\text{Al}_2\text{O}_3$ and $\text{Al}_2\text{O}_3/\text{CrO}_2$ whisker reinforced, see Figure 3.11. D’Errico et al. [1999] stated that aluminium oxide has a high chemical stability that allows it to work in most environments. A disadvantage is the low resistance of alumina to thermal and mechanical shocks, compared to tungsten carbide. SiAlON or $\text{Si}_3\text{N}_4$ based ceramics were developments which began to be used in cutting tools in the late 1970’s, see Figure 3.12. They have been reported to have good thermal and mechanical properties, but their usage today is mainly in turning nickel-based alloys and grey cast iron at high speeds.

![Figure 3.12 Silicon Nitride Ceramic ($\text{Si}_3\text{N}_4$), [Sandvik 1994].](image)

Vleugels et al. [1995] investigated the influence of ceramics and workpiece composition. In contrast to the chemical resistance, they stated that when machining steel at high speed, chemical dissolution-diffusion wear is limiting tool life. The wear rate of a $\text{Si}_3\text{N}_4$ based cutting tool was reported to be two times higher when machining AISI 1045 steel instead of grey cast iron. However, when machining medium carbon steel, along with turning in hardened steel with modest feed rates, good performance was reported. With SiAlON and YSiAlON cutting tools, chemical interaction becomes the predominant wear mechanism.

Xingzhong et al. [1999] investigated the wear behaviour of Austenitic stainless steel AISI 321 and concluded that, when using $\text{Si}_3\text{N}_4$, the wear of the ceramic is mainly caused by the adhesion peeling-off process. Wayne and Buljan [1989] investigated the thermal shock properties for ceramic tools. They found that thermal shocking promotes micro chipping and depth of cut notch for $\text{Al}_2\text{O}_3$ based tool materials, whereas $\text{Si}_3\text{N}_4$ is able to withstand thermal shock in interrupted cutting. They also concluded, that $\text{Al}_2\text{O}_3$ has a low degree of chemical solubility in Fe and is resistant to crater wear on the rake face,
whereas $Si_3N_4$ and $SiC$ materials are more soluble in $Fe$, which leads to pronounced crater wear.

### 3.2.3 CBN Tools

How wear-resistant a tool is depends on many parameters. For CBN tools, see Figure 3.13, this includes CBN content, grain size, binder material and tool geometry, [Chou and Evans 1996]. The brittle nature of ceramic and CBN tools make them prone to chipping at the cutting edge, while abrasive wear and adhesion may lead to premature tool failure. Lower CBN content tools with a ceramic binder are generally more resistant to abrasive wear due to increased bonding strength, while higher CBN content tools with metallic binders have improved fracture toughness. The CBN tools belong to the ‘Superhard’ category of machining tools, and have been widely used in finishing and ultra precision cutting, [Mamalis et al. 2002].

![Figure 3.13. CBN, (Cubic Boron Nitride), [Sandvik 1994].](image)

The wear mechanism for CBN tools has been reviewed by Mamalis et al. [2002] who stated that CBN tool wear is defined by its polycrystalline line character. The polycrystalline tool edge constantly regenerates. Sandvik [1994] described the characteristics for CBN tools. They should be applied to hard workpiece materials over 48 HRC, where machining with CBN tools in soft materials will cause excessive tool wear.

### 3.2.4 Conclusion of Wear Characteristics

When analysing tool wear, the different wear types can be directly related to the machining process, workpiece and tool material. The properties which seem to be interesting regarding the tool material and coating, when speaking of breakdown monitoring, are the resistance to mechanical and thermal shock and the resistance to
diffusion. The properties of the different tool materials should be taken into account when evaluating results from the wear analysis. It is not only the actual wear that is limiting a cutting tool, but also the entering and exit cycles. It can also be expected that the probability of a breakdown because of mechanical and thermal shocks, which results in fatigue, increases with wear. In this research, different grades of carbon steel are machined and therefore, the wear characteristics with respect to chemical interaction have been taken into consideration for the different tool materials, since the effort has been focused on the abrasive type of wear.

### 3.3 Prediction of Tool Wear

#### 3.3.1 Analytical Prediction of Tool Wear

Before describing methods for on-line prediction of tool wear, a brief summary will be given of attempts for analytical prediction of tool wear. Many of the early mathematical models for tool wear are still used today, although many have been modified to take varying process parameters into account. Following the evolution of the mathematical predictions of tool wear; their constant refinement to take variable process parameters into consideration is probably the most interesting development. Tool wear has normally been defined by the measurement of flank wear because it determines the diametric accuracy. Lee [1986] stated that for a quantification of physical flank wear; a range of 0.15-0.76 mm is adopted. The direct measurement of the physical deterioration has been investigated by numerous researchers and is stated as being the most reliable technique for determining actual tool wear, although others have claimed that the existing metrics are out of date, [Astakhov 2004]. The direct measurement of flank wear has been used in most research for the modelling of tool wear. Tool wear prediction has not only been interesting for tip geometry compensation during ultra precision machining, [Lee and Lee 1999], but is playing an important role for failure prediction and remaining life estimation. Tool life and tool wear have been investigated by a number of researchers starting with F.W Taylor publishing the first tool life equation in 1901, also referred to as the Taylor Equation, see Equation 3.1, where tool life is defined as $T_l$. 
The constants \( c_1 \) and \( c_2 \) can be found from experiments or from published data, all depending on workpiece, tool material and feed rate.

Figure 3.14 Representation of tool life, the Taylor Curve.

Mamalis et al. [2002] stated that different parameters are changing the tool life, but the shape of the \( v - T \) graph remains the same, see Figure 3.14. Taylor’s extended equation, where tool life is described as a function of the three cutting parameters: feed rate, depth of cut and cutting speed, is shown in Equation 3.2.

\[
L = \frac{c_1}{v^{c_2} f^{c_3} a_p^{c_4}}
\]

Equation 3.2

Mamalis et al. [2002] are describing a General Tool Life Equation, where the tool life function, \( TL = f(v) \) is changed and is described by a \( L = f(v) \) function, see Equation 3.3. Instead of the life function, a function for the length of cutting, which directly relates to the tool life, has been obtained. \( c_{11}, c_{12} \) and \( c_{13} \) are life functions for cutting conditions, where \( v \) is the local speed maximum obtained from the \( v - T \) Curve, at points where the cutting speed is increased to \( v_{12} \) and \( v_{23} \). The result of an experiment with 5 different depths of cut is shown in Figure 3.15.
A common way of determining the end of a tool’s life is to set a maximum allowable flank wear, as mentioned in chapter 3.3.1, where it is normally defined as $v_{b\text{max}}$. Jawahir et al. [2000] stated that either flank wear or crater wear can be used as a criterion for tool-life when machining with flat-faced tools, but when it comes to grooved tools, the types of tool wear which reduce tool life become more difficult to determine. The tool wear pattern is influenced by the three-dimensional chip flow and by chip-groove configurations. It was found, that some grooved tools failed long before the major flank wear reached the failure criterion. Jawahir et al. [2000] furthermore stated that there are other wear criteria for grooved tools which are considered to have an influence, see Figure 3.16, and that the variations in chip-groove configurations have made the analytical assessment of tool wear an extremely difficult task. The reason for this is that, even for the same chip-groove configuration, variations in the cutting conditions would alter the chip-groove profile and cause variations in tool-chip contact.

\[
I_{\text{max}} = \frac{C_{11}}{C_{13} - 0.25C_{12}^2}
\]

Equation 3.3

\[
C_{11} = T_{23}(v_{23}^3 + C_{12} \cdot v_{23}^2 + C_{13} \cdot v_{23})
\]

Equation 3.4

\[
C_{12} = -\frac{3}{2}(v_{12} + v_{23})
\]

\[
C_{13} = 3v_{12}v_{23}
\]

Figure 3.15 Experiments with CBN tools with 5 different depths of cut, [Mamalis et al. 2002].
To overcome this problem, the concept of Equivalent Tool Face, (ET), is proposed. The principle of this is to transform a complex grooved tool, into an equivalent flat-faced tool, to facilitate the modelling process. The ET is a model which is iteratively changing the geometry of a grooved tool into a flat-faced tool. Once the effective flat-faced geometry of a grooved tool for a particular set of cutting conditions is established, the predictive theory for flat-faced tools can be utilized for tool wear predictions.

\[ w = K_p \frac{P}{3r} \]

Another wear equation is the so-called Archard equation, see Equation 3.5. Zhao et al. [2002] stated that, in the first Archard wear equation, the wear rate is treated as being independent of the apparent area. Furthermore, the contact stress at the sliding surface is not considered. An analytical model for crater and flank wear for single point turning, was proposed by Usui et al. [1984]. The work was related to the wear of tungsten carbide tools. It was reported to be able to predict wear for a variety of tool shapes and cutting conditions by using the orthogonal cutting data and two wear characteristic constants. The method is a combination of a wear characteristic equation and an energy method developed to predict chip formation and cutting forces. The wear characteristic equation
is built on an Archard type equation for adhesive wear, where changes in the wear volume over the sliding distance are obtained. This model has been reviewed and investigated by Zhao et al. [2002], who built a wear model where the effect of normal stress is considered. Tool reliability has also been investigated as a means of forecasting tool wear and is a statistical descriptor of the tool reliability over time. Wang et al. [2001] proposed a reliability-dependent failure model, to predict the wear of cutting tools subjected to flank wear. In their research, they investigated three reliability models, lognormal distribution, Weibull distribution and the reliability-dependent failure model. They pointed out that the failure model was suitable for describing the reliability of a cutting tool. Regarding the lack of process parameters in the early mathematical predictions of tool wear, recent researchers have carried out several experiments which take different parameters into account. Choudhury and Srinivas [2004] developed a mathematical model which used such factors as the index of diffusion, wear coefficient, the rate of increase of normal load with respect to flank wear and tool hardness. It was shown that the cutting velocity and the index of diffusion are the most significant factors with respect to flank wear, followed by the feed and the depth of cut.

A model based on the three cutting force components, was proposed by Oraby and Hayhurst [2004], see Figure 3.17.

A non-linear regression analysis technique was used to build the tool wear model by using force ratios instead of absolute values of force. An interrelationship between wear
and force ratios was observed and through empirical experiments, two mathematical models were proposed, see Equation 3.6 and Equation 3.7.

\[
R_{xz} = \frac{F_{xz}}{F_y} = 10.79v^{-0.306} f^{-0.393} a_p^{-0.188} t^{-0.160} W^{0.944} \tag{3.6}
\]

\[
T = 78573.35v^{-1.712} f^{-0.714} a_p^{-1.107} + 249.49e^{-78.571(R_f-R_o)} \tag{3.7}
\]

Huang and Liang [2004] used a method where abrasive wear, diffusion wear and adhesive wear were combined in order to describe crater wear in CBN tools. An error of 15% was observed. However, they mentioned that the model and results are valid for continuous turning and in order to model tool wear in interrupted turning, the tool hardness and fracture toughness should be further addressed.

### 3.3.2 Conclusion on Tool Wear Prediction

The previous section has briefly described different tool wear prediction models and this conclusion will summarize some of the considerations concerning these models. As has been mentioned before in this thesis, tool wear is a complex problem, which cannot be considered to be purely mechanical in nature. It is a combination of several factors, which makes it very difficult to suggest a generic approach, since it can be expected that the models proposed would only give guidelines for wear under the exact conditions for which they were developed. The Taylor Approach is commonly used to predict tool wear, which requires that empirical constants must be evaluated. As was expected, no tool prediction models are general, although they are claimed to be. However, they are all built on empirical evaluations of constants that determine the behaviour of the model.

The importance of tool wear prediction in this research is on a lower scale, since the prediction should only give guidelines to the real-time monitoring system with respect to the expected wear progression. Also, the model is only expected to work for a small number of tool/workpiece combinations, in this case carbon steel. From the literature, some important considerations should be mentioned with respect to the models. It has been pointed out by Jawahir et al. [2000], that there is a fundamental difference between the behaviour of models derived with flat faced and grooved tools, and assuming this as a valid conclusion, it can be expected that the behaviour of the model only will be valid for the tool type on which it is based. Where the tool/workpiece hardness is considered,
Huang and Liang [2004] show some good considerations with respect to the general approach. It can be expected that the hardness ratio will affect the wear and an empirical relationship was described in their paper with respect to crater wear. From the literature, the experiments have been carried out under continuous cutting, which is not realistic from an industrial point of view, and therefore, the quantitative wear from interrupted cutting should be considered when evaluating tool wear models.

### 3.4 Tool Condition Monitoring Systems

Different principles of TCM have been developed. This section will describe some of the more promising. It will conclude with a brief critique of the systems and point out their lack of success.

In the field of TCM research, turning processes are often used as the basis, since turning is a simple case of machining. Because the turning tool doesn’t rotate, it is very simple to instrument, which reduces the complexity of designing the system. A Tool Condition Monitoring system is said to serve the following purposes, [Dimla Snr 2000]:

- Provide a system for fault detection in advance for cutting tools.
- Check and safeguard machining process stability.
- Provide the means by which machining tolerance is maintained on the workpiece to acceptable limits by providing a compensatory mechanism for tool wear offsets.
- Machine tool damage avoidance system.

#### 3.4.1 Monitoring Principles

- **Indirect and Direct Monitoring**

Two ways of monitoring are introduced and referred to as direct and indirect monitoring. The indirect method operates by measuring process variables, such as vibrations or acoustics emitted from the process, whilst the direct method measures the physical geometry of the tool. There are pros and cons for both methods, but it can be concluded that the direct method is the most precise due to the fact that the actual wear can be measured, [Shao et al. 2004]. The indirect method involves interpreting signals or process variables from the process, which can be a rather difficult task due to
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disturbances from the process itself. The direct method normally requires that the process be stopped, whereas the indirect method is suitable for in-process monitoring, also referred to as on-line monitoring.

- **On-line and Off-line Monitoring**
The on-line method has the main advantage, of constantly interpreting the incoming sensor signals. Therefore, this is capable of detecting signs of gradual wear. The off-line method is normally implemented using sensor devices to measure the geometry of the cutting edge.

- **Contact and Non-Contact Monitoring**
Contact and non-contact systems are also used. Contact systems need physical contact with the workpiece or the critical parts in the machinery. An example of this is surface measurement using a contact stylus.

### 3.4.2 Previous Reviews of TCM Systems
Several researchers have been reviewing TCM systems and pointing out the key systems and sensing methodologies used to describe tool wear.

Dan and Mathew [1990] reviewed 128 papers and pointed out methodologies including radioactivity analysis, electrical resistance, changing of workpiece size, tool/workpiece distance, acoustic emission, cutting temperature, roughness measurement, optical measurement, vibration and sound, power/motor current and cutting forces. A review of different sensing techniques used for industrial applications to detect tool wear, chipping and the fracture of cutting tools was made by Hoshi [1990]. In 1990 the most common competing techniques were the following:

- Touch sensors.
- Vibration sensors.
- Load sensors.
- Acoustic emission.

Hoshi [1990] reported the success of the different techniques as a percentage of the total numbers of applications reviewed. The review included machining processes, such as drilling, gun drilling, end milling, face milling and single point turning. The results from Hoshi's research can be seen in Figure 3.18.
AE sensing was only successful in 33% of the reviewed applications, but especially for single point turning, interesting information can be extracted from Hoshi’s research. Hoshi reviewed 15 applications with different sensing techniques for single point turning and recorded their success, see Figure 3.19. For use in single point turning, AE-based sensing techniques seem to be the most successful.

With respect to milling and grinding, AE has been reported to be non-useful because of the signal’s discontinuous nature, [Ghosh et al. 2007]. Leem and Dornfeld [1996] reviewed previous techniques for the design and implementation of sensor-based TCM systems, where they mentioned force measurement and AE as the two most popular methods.

Du [1999] listed systems including classification methods of tool wear. Byrne et al. [1995] reviewed the status of research and industrial applications of TCM systems from a total of 188 papers. These included previous review, sensor applications, monitoring
strategies and sensor fusion. Dimla Snr [2000] reviewed a total of 83 papers about sensor methods for condition monitoring, including acoustic emission; tool temperature; cutting forces, both static and dynamic; vibration signature (acceleration signals) and miscellaneous methods, such as ultrasonic and optical measurements, workpiece surface finish quality, workpiece dimensions, stress/strain analysis and spindle motor current. He concluded that vibration measurement and cutting forces were the most widely applicable techniques at that point.

Rehorn et al. [2005] reviewed 107 papers in order to investigate the state and direction of the monitoring systems. He states that the sensors currently available are adequate to extract a significant amount of information about machining process dynamics. This includes force measurement, torques, AE and vibration. The most popular types are the current sensor and drive and spindle power, because they have proved to be reliable, although the majority of the research is concentrated on using cutting force or vibration measurement. AE is mentioned as another interesting area. An interesting observation is the fact that the boundaries between what constitutes mechanical vibrations and AE are not clearly defined. This results in a research overlap of these areas. It is also mentioned, that the areas of sonic emissions and ultrasonic emissions require stricter definitions.

Sick [2002] reviews the literature of TCM in turning based on AI, (Artificial Intelligence). This massive review includes a description of the sensor-based systems and the use of decision-making algorithms, such as fuzzy logic, neural networks, etc. As mentioned, several researchers have been reviewing TCM applications and pointed out the key systems, however, as a supplement to this, the next sub-chapters will briefly explain the principles in some of these systems and also add further research done in the field of TCM systems.

3.4.3 Surface Texture

This technique uses the surface texture of the workpiece as the criterion for tool wear. The technique has been attempted both as an on-line and off-line system. It is said, that the increasing $Ra$, (Average Roughness), is caused by the fact, that the waveform is copied by the shape of the tool tip, [Dong and Wang 1999].
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By experiments, they explained the connection between tool wear and the increase in surface roughness, as shown in Figure 3.20. From my point of view this assumption seems valid however, although it is not mentioned in their paper, it must be expected that this assumption is only valid for finish turning. This is due to the fact, that in the case with the lower depth of cut, only the tool tip is engaged in the workpiece. In roughing the picture changes, where a large portion of the material is removed by the tool flank, where this type of wear will be less recognisable.

Kassim et al. [2000] stated, that a machined surface can be considered as the negative replica of the shape of the cutting tool. Surface roughness is commonly measured mechanically with a stylus device, where the Ra measurement is the most-used descriptor. Ra is commonly adopted in general engineering practice to give a description of the height variations on the surface. It has been estimated, that the surface metrologist has more than 200 parameters that can describe the behaviour of the surface, but there are only a few measurement techniques to obtain the information from the surface, [Jones 1987].

Myshkin et al. [2003] was dealing with surface roughness on the micro scale, and shows a diagram describing various methods regarding the precision of the measurement, see Figure 3.21. Considering this diagram, in cases where surface texture is used to detect...
tool wear, it is my opinion that the stylus method is the most reliable, since it must be expected that there should be a relatively large change in e.g. $R_a$ due to physical changes in the tool tip, which in most cases consist of a radius of 0.4 to 1.2 mm. The contact stylus tracing method is commonly used, where a diamond is drawn across the surface and its vertical movement transformed into electrical signals. Whitehead et al. [1999] described a laser type "stylus", which was developed for measuring dental materials. The laser "stylus" replaces a conventional contact stylus and does not rely on the measurement of scattered laser light.

Figure 3.21 Measurement methods versus precision [Myshkin et al. 2003].

Nowicki and Jarkiewicz [1998] list different in-process measurement methods for surface roughness, but they concluded that the measurement of the successive profile coordinates and calculation of roughness parameters are time consuming, which makes them inadequate as in-process surface roughness measurements for objects moving at high speed. Furthermore, they note that in grinding and turning processes, in-process roughness measurements cannot be based on the surface profile data, because of the limitations of the data-processing rate. They quote the following transmitters as suitable
for in-process measurements: speckle reflectance, pneumatic, ultrasonic, induction or FFC. A Fringe Field Capacitive (FFC) method was proposed for measurements under dynamic conditions, see Figure 3.22.

![Figure 3.22 The FFC method, [Nowicki and Jarkiewicz 1998].](image)

Reasonable results were reported by this method for dry cutting conditions, but coolants will cause disturbance in the measurements. Considering that the data processing equipment has moved forward, it should no longer be expected that this should be the main limitation however, as it was mentioned, the problem with coolant must be regarded as critical for technique.

Schirripa Spagnolo et al. [1997] reviewed surface roughness measured by speckle correlation and compared this method to a conventional stylus method. The principle is that coherent light is used to illuminate a rough surface, where waves scattered from the surface will form a pattern. This will occur as a grain pattern of bright and dark regions, and spatial statistical properties of this speckle image can be related to the surface characteristics. They reported a good correlation between the results from a speckle sensor and those from a mechanical probe. Sensitivity to misalignment, vibration and the necessity of cleaning might limit the use of such a technique for in-process measurements. Although, because of the flexibility, the method offers a possibility of non-contact, in-process, surface roughness measurement, the mechanical stylus technique looks to be the most useful for post-process verification. The proposed technique can be used with success in processes such as turning and grinding. It is of my opinion, that the cleaning and coolant problems in this paper have not been regarded as important as they should. Although it has been mentioned that it could be a limitation, it is my opinion that due to the hostile environment in the turning process, where coolant and chips disturbs the surface constantly, non-mechanical devises will be at high risk of failing, unless the experiments are carried out under ideal conditions. Similar research has been carried out in the field of light-scattering techniques, where the main limitation again should be mentioned to be the practical use under the hostile conditions. Cahill and El Baradie
[2001] used an LED-based, fibre-optic sensor system for the measurement of surface roughness. Scattering with monochromatic, highly coherent light, such as from a laser, has also been attempted. Leonard and Toal [1998] investigated surface roughness measured by a laser speckle contrast system. Yilbas and Hasmi [1999] used a He–Ne laser beam to scan the surface, and a fibre-optic probe was employed to collect the beams reflected from the surface. Whitehouse [1997] describes the use of an ultrasonic method. In this method, waves are projected onto the surface and the scattered waves are picked up using the same principle as for optical scattering. This method was reported to have potential because it is possible to get phase as well as amplitude information, in contrast to optical methods. The drawbacks mentioned are that the high-frequency ultrasonic waves only propagate through air with difficulty and that the directionality of the waves can be poor.

3.4.4 Machine Vision and Optical Measurement

Another attempt in the field of recognizing tool wear has been by using machine vision. The research into machine vision has been concerned with the determination of the physical deterioration of the actual cutting tool, but also a huge effort has been put into recognizing wear from the surface texture of the workpiece. Kassim et al. [2000] concluded that it is more feasible to analyse the machined surface than to look at a certain portion of the cutting tool. Since cutting tools operate directly on the workpiece, the surface texture is directly affected by the operating tool and provides detectable information to recognize the condition of the tool. As mentioned in the previous section, it is my opinion that the surface will only reveal the state of the tool tip, although the effect of flank wear in roughing must be investigated. It is my opinion that with respect to roughing, which this research is concerned about, direct wear-measurement on the cutting tool is the most precise. The indirect surface measurement is made where a light source is used to illuminate the point of interest, an image is captured and processed, features are recognized and a pattern classifier can give an output, [Gonzales and Woods 2004]. Bradley and Wong [2001] used three methods of image analysis to recognize surface texture: image histogram analysis, image frequency domain and image texture domain analysis. All three methods were able to indicate the changes in surface texture due to
increasing tool wear. Mannan et al. [2004] investigated the possibility of detecting tool wear using a fast Hough transform of the image. The images are pre-processed by a Canny edge-detector. Afterwards, a new connectivity-oriented fast Hough transform is used to detect all the line segments. They concluded that this algorithm is fast enough to be implemented for on-line TCM. As mentioned, the most common wear characteristics are known as flank wear and crater wear. Flank wear can be measured directly from images to establish the physical deterioration of a worn tool, whereas crater wear is difficult to quantify. As a critique of the indirect wear measurement, by capturing the workpiece surface, it is my opinion that it will be close to impossible to estimate crater wear directly from the extracted parameters. This is due to the fact that the crater doesn’t limit the tool life in the same sense as nose or flank wear. Devillez et al. [2004] proposed the use of white light interferometry for measurement of craters on cutting tools. Although this technique does not allow in-process crater measurement, the work showed that white light interferometry is a useful tool for measuring the crater wear of cutting tools. In later research, Dawson and Kurfess [2005] proposed the use of white light interferometry and comparison of wear data, with ideal representations of unworn cutting tools. The method uses a previously-developed, three-dimensional, computational metrology technique to compare tool data, see Figure 3.23.

![Figure 3.23 Wear quantification, [Dawson and Kurfess 2005].](image)

Optical and electro-optical methods, which included fibre optic sensors, the use of CCD cameras etc, were reviewed by Dan and Mathew [1990]. The summary of this review was that optical methods can only be used between cutting cycles where the cutting tool is removed from the workpiece. However, using the physical deterioration as a wear
Parameter is claimed to be a precise prediction of wear. Recent research has reported that systems have been developed which can be used for the in-process measurement of the physical deterioration of cutting tools. An approach from 2004, using a CCD vision system, was proposed by Jurkovic et al. [2005], see Figure 3.24. They claimed that the technique can be accomplished in-cycle and that it is especially characterized by its determination of profile depth. Projected laser raster lines are used to determine the profile depth of the tool surface, which can help to define flank and crater wear, the two most dominant wear characteristics.

Figure 3.24: Setup using halogen light and a laser diode, [Jurkovic et al. 2005].

The conclusions were based on tests conducted in the absence of a coolant, where the insert was positioned under the vision system, and where the flank wear and cutting-edge wear images were compared for every 10 min of cutting. Again, most research in this field is made in the absence of coolant, which makes the results non-practical. Although it makes sense to do research without coolant, since the trend in the future will be to limit the use of coolant because of environmental reasons, it has practical limitations. Another issue which must be dealt with is problems with carbon dust or adhesive material stuck on the cutting tool, which again will set a practical limitation for optical methods. It should be stated though, that the optical methods are offering benefits. Li et al. [1999] were using an optical method, which illuminated the surface by a laser and captured the image on a CCD camera. One of the advantages mentioned is that this method is not sensitive to disturbances, such as background noise or vibrations. An ART2 network was used with fuzzy classifiers to detect tool wear from the scattered surface. The method was reported to be able to detect significant tool wear. Pfeifer and Wiegers [2000] created an optimised image by only illuminating the tool face, which would leave only the edges from the actual wear for easier detection of wear. This method is connected with a high
possibility of making false predictions in on-line monitoring, because of disturbances such as chips covering the surface of the tool when machining carbon steel, etc. Overall, the vision and optical systems have been discarded in industry for on-line tool monitoring due to their high cost and variations in illumination [Ghosh et al. 2007].

3.4.5 Power and Force Monitoring

In the machining process for CNC turning, servo drives are pushing the tool through the workpiece during the cutting process and the condition of the cutting tool can be indicated by the dynamic response of the servo motor. The gain and bias parameters can be used to apply a monitoring system. Dan and Mathew [1990] reviewed different monitoring techniques, and described a direct relationship between flank wear in turning and motor current. A method was reviewed where the motor current was measured by using a current transformer. The signal was processed and differentiated and, when tool breakage occurred, the resulting signal was found to drop instantaneously and soon recover to the level prior to the drop. The review concluded that current measurement systems are reliable in monitoring medium and heavy cuts, but the sensitivity is less than systems such as force and vibration sensing. Li et al. [2000] proposed an intelligent Current-Sensor-Based system, which uses the feed force from a current sensor installed on the servomotor of a CNC turning centre. This is proposed as an alternative to measuring the cutting force using dynamometers. Although the dynamometer is one of the most popular methods for monitoring tool wear in an industrial application, its use is not practical due to high cost, negative impact on cutting system rigidity and limitations on stroke length due to the dynamometer wiring harness. The model uses a neuro-fuzzy technique based on the feed motor current to estimate the cutting force. Figure 3.25 represents a schematic diagram.
The experimental results showed that this method is able to detect tool wear, except for light cuts. Li [2001] used the same monitoring technique, but based on TDA, (Time Domain Averaging), with a threshold, for detecting flute breakage in a milling application. With respect to the above mentioned systems, it seems that there is a trend with respect to the current measuring systems, where these are recommended for heavier cuts. The reason for this, should in my opinion be found in the fact, that the proportion of current required to drive the spindles, e.g. where heavy turret systems are placed on the carriage etc., are very high compared to the extra required current to drive the spindle due to tool wear. Li et al. [2000] also applied current measurement for the spindle and feed motor in a drilling application where wavelet transforms and fuzzy techniques were used to monitor tool wear. The continuous and discrete wavelet transforms were used to extract signal features from the two current measurements. Models of the relationships between the current signals and the cutting parameters were used to define the state of the tool. In this monitoring system, the tool breakage detection and tool wear detection are separated. Tool breakage detection is based on wavelet transform, where the detection of tool wear is based on a fuzzy classification method. The proposed system was reported to be successful for the detection of tool wear with a success rate of 85%. What seems interesting in this method, apart from the current measuring technique, is that it is using a decision-making system based on the actual signals and also on an analytical model. The tool wear was related to previous models of flank wear and was estimated from the model as functions of feed and spindle current. The breakage detection was using the sudden

Figure 3.25 Schematic representation of current-sensor system, [Li et al. 2000].
drop and spikes in the wavelet analysis from the spindle and feed current, measured in real-time. Shao et al. [2004] also proposed a system based on the power consumption, but using an updating monitoring threshold of mean cutting power. The system was claimed to be useable for applications with variable cutting conditions. Jemielniak [1999], quoting from a review of TCM systems, claims that current is not a sensitive indicator of power at low loads in three-phase motors. The advantage of power measurement instead of current measurement is that the power is linear. On the other hand, Haber et al. [2004] state that different measurement principles, such as force, power, torque, acoustic-emission, acceleration, velocity and speed, fail to meet the needs of manufacturing industry when it comes to cutting in HSM, (High Speed Machining), but that the dynamometer and the current sensor do meet the requirements. As mentioned before, the dynamometer is commonly used for force measurements and is recognized as a reliable method. Several researchers have investigated the use of force measurement using different methods. Oraby [1995] used a three-component dynamometer and spectral analysis to detect wear. Dimla Snr [2000] investigated the development of a TCM system based on the analytical modelling of online sensor signals using cutting force and vibration, where static force, dynamic force and vibration were compared to the actually measured tool wear. Based on the signal analyses when using the dynamometer and the accelerometer, it was concluded that the signals correlated to the tool wear. Oraby and Hayhurst [2004] performed a test for the determination of tool life based on the measurement of wear and tool-force-ratio variation, using the cutting force components in turning. They found this method to be a good indicator of nose, flank and notch wear. It has been widely established that variations in the cutting force components can be correlated to tool wear, and are more sensitive to chipping and fracture than vibration and motor current, [Cakir and Isik 2005].

The resultant force $F$ is expressed by three orthogonal components, tangential force, feed force and radial force. They mentioned that both tangential and feed forces are sensitive to the tool fracture, but that only the tangential force decreases consistently when the tool breaks.

Another approach to measuring cutting force is by measuring the stress / strain on the tool holder as near to the tool tip as possible.
Scheffer and Heyns [2004] presented a TCM system for interrupted cutting, where resistance strain gauges, which are able to follow the static and dynamic response of a system up to 50 kHz, are used. Feed force sensors have been developed and mounted on the machinery. The sensor consists of two concentric rings with strain gauges mounted as shown in Figure 3.26.

![Feed force sensor mounted on a CNC lathe](image)

Figure 3.26 Feed force sensor mounted on a CNC lathe, [Scheffer and Heyns 2004].

Szecsi [1998] used the axial force to show a relationship between this and flank wear. The flank wear changes the shape of the cutting edge, which again changes the pressing force. This was used to define the condition of the cutting tool. He performed a test where the tool insert was pressed against the workpiece, with the machine stopped, where the axial force was measured using a dynamometric tool holder. After this, he was able to measure the mark left on the workpiece, and hereby calculate a relationship to the axial force as a function of measured flank wear. The modelling included a neural network, to give a wear output from the force and material inputs. In my opinion this is an interesting approach, since he is developing a method to find proportionality between the actual cutting force and the wear land of the tool. Although this is a static approach, the research showed that there is a relationship between the wear land and the axial force.

Sikdar and Chen [2002] quoted cutting forces as one of the two most promising techniques for monitoring tool wear. They stated that flank wear is increasing the cutting forces in all three components: tangential, feed and radial directions. It was stated that the tangential force is the largest while the radial is the smallest. However, when the tool starts to fail, all three forces increase sharply. They pointed out, that a gap in the research
into force monitoring is the lack of universal systems, where previous research has been presenting “heavy” systems, which largely depend on huge amounts of training data.

**3.4.6 Vibration Measurement**

Vibration measurement is a widely-used technique for condition monitoring. Dan and Mathew [1990] reviewed different monitoring systems and concluded that vibration signals vary with tool failure in some frequencies, describing the relationship between the progressing tool wear and changes of vibration. Lim [1995] showed the correlation between flank wear and the acceleration amplitude of vibration.

Dimla Snr [2000] concluded in his review on sensors for tool wear monitoring, that the inter-relationship between vibration signals and cutting forces determines the dynamic nature of the cutting process. He summarises that the static behaviour is determined by cutting forces, where the dynamic behaviour embodies vibration and certain aspects of the dynamic cutting force.

Scheffer and Heyns [2001] used a combination of simultaneous vibration and strain measurements on the tool tip of the cutting tool. A self-organizing map, (SOM), which is a form of neural network based on unsupervised learning, was used to determine tool wear. Almost 100% correct classification of the tool wear data was reported. Normally the vibration is measured by an accelerometer or by an integrated vibration transmitter. The integrated vibration transmitter integrates a shear-mode piezoelectric accelerometer to output the RMS value of the vibration but, in order get precise data from the vibration sensor, it must be placed close to the cutting tool. I can be concluded from their research that the tool holder or fixture will absorb some of the vibrations and therefore work as a damping factor, which can affect the results and that vibration measurement is very sensitive to the method of set-up, as well as the material of both the machine and the workpiece.

Ghani et al. [2002] performed experiments, using an accelerometer in cast iron with alumina ceramic inserts, and they observed that for flank wear, vibrations during cutting decrease as the speed increases, however, at low depth of cut, vibrations remain almost constant with the increase in flank wear. It was not clearly stated in the research how the measurements were obtained with respect to sensor placement. It should normally be
expected that a low depth of cut will result in increased vibrations, since the wave-cutting effect will be higher at a low depth of cut. Dimla [2004] presented an experimental investigation, to identify the characteristic features of the sensor signals, which seems particularly sensitive to cutting conditions as well as to tool wear. He showed that wear progression could be differentiated from the acceleration signals. The tool point vibrations rose rapidly during the primary wear phase but only steadily in the secondary wear phase where the oscillation became significantly damped.

3.4.7 Acoustic Emission

AE, (Acoustic Emission), has been investigated by a number of researchers using different approaches. Weller et al. [1969] were among the pioneers in the investigation of tool wear detection by analysing the sonic vibrations emitted from the process. As a sensing methodology, AE has advantages because of the relationship between the generation of the emission signal, which is generated directly in the cutting zone, and the fracture or tool wear. Dan and Mathew [1990] concluded their review by saying that the AE sensing technique seems to be more sensitive to tool fracture than cutting force and tool vibration measurements. This accords with Dornfeld [1994] who stated that the frequency-range of the AE signal is much higher than the machine vibrations and environmental noise. Using a statistical analysis, Kannatey-Asibu and Dornfeld [1982] also showed the sensitivity of tool wear using AE signals. Dimla Snr [2000] noted that AE is more dependent on the cutting material than on the cutting tool, with its signal reflecting the behaviour of the response from the machine tool set-up. Furthermore, he noted that AE is not a suitable wear indicator in monitoring applications but could be used to detect tool-tip breakage in machining centres. He mentioned as the main drawback, that the AE is sensitive to noise and changes in the cutting conditions, rather than the tool condition itself. Kopac and Sali [2001] showed that cutting conditions, such as feed rate, cutting speed and tool wear, have an influence of the characteristic frequencies that can be measured from Airborne Acoustic Emission. This was previously confirmed by Silva et al. [2000] who carried out experiments using audible AE (sound in the sonic range). They proposed a monitoring system with adaptations for variable cutting conditions. This was based on two neural networks, moderated by an Expert
Condition Monitoring of Tools in CNC Turning

System, based on Taylor's tool life equation. It was shown that it was possible to monitor tool wear with a single machine/tool/material/cutting condition combination, and to identify any inconsistencies between the predictions of the neural networks and engineering practice.

Liang and Dornfeld [1989] presented a signal-processing scheme, which uses an autoregressive time-series to model the acoustic emission generated during cutting. This technique encodes the acoustic emission signal features into a time-varying model parameter vector. It was shown that the parameter vector ignores the change of cutting parameters, but is still sensitive to tool wear. This principle has also been used by Sohyung et al. (2004) and Sun et al. (2004) and referred to as SVM, (Support Vector Machine).

Li [2002] reviewed the use of acoustic emission for cutting processes in turning, including signal classification and correction; processing methodologies, such as time series analysis wavelets and FFT, and finally pattern classification using a fuzzy classifier, a neural network and sensor and data fusion. He concluded that AE signals depend heavily on process parameters and sees the key issue as being how to reduce these effects in intelligent tool wear and fracture monitoring using AE signals.

Dornfeld et al. [2003] discuss the accuracy of AE. AE has been introduced in the field of precision machining, where the actual machining takes place at sub-micrometer to nano-scale dimensions. Figure 3.27 shows a comparison of the level of precision for a conventional and precision machining process. Acoustic emission is a sensitive measurement technique, however as the previous mentioned researchers have mentioned, it is also subject to disturbances. Structureborne acoustic emission is covering a large range of the frequency domain, which means that numerous of noises will be picked up.

In the sonic range up to 20 kHz, Kopac and Sali [2001] used a condenser microphone to capture the airborne signals from the sound pressure at a distance of 0.5 m from the cutting zone. One of the advantages of using this technique, compared to AE sensors and an accelerometer, is that the placement of the microphone can be arbitrary, which is, from my opinion, the main arguments of using AAE, where the signals travel in the air. The characteristics of the signals were extracted by a frequency analysis. In accordance with other researchers and as a critique of AE, Garrett et al. [2001] noted that the use of AE
alone is not a reliable monitoring method due to the fact that it is sensitive to the surrounding environment, parallel machining, chipping, coolant flow, etc. One of the most difficult disturbances to deal with, is disturbance from the process itself where coils of chips are disturbing the signal however, this can also be a problem in vibration monitoring.

AE has also been investigated widely in multi-point machining, such as milling and grinding [Inasaki 1998, Rehorn et al. 2005, Diei and Dornfeld 1987, Hutton and Hu 1999].

Figure 3.27 Sensors versus precision and control parameters Dornfeld et al. [2003].

The milling process has a discontinuous nature and one of the problems with using the signals from this process is the large peak at tooth exit and entry. Another problem is that more than one cutting edge may be active at the same time, which creates several AE sources. Diei and Dornfeld [1987] and Hutton and Hu [1999] used the RMS signals, (Root Mean Square), and concluded that the signal is a periodic signal which can be regarded as a periodic random signal. TDA was used to decompose the signal into a periodic component. Hutton and Hu [1999] concluded that the deviation in the TDA could be used as a characteristic for the AE RMS signal to detect tool wear. The mean TDA describes the dynamic component in AE RMS, and can be related to tool wear.
Abu-Zahra and Yu [2003] used ultrasonic echoes, which were reflected off the cutting edge of tool inserts. This was done by a transducer operating in the pulse/echo mode, first sending pulses at 10 MHz at the tool insert and afterwards receiving the reflected signals. These signals were decomposed into five-layer wavelet packets. The tool has 3 marks defined at nose, flank and a reflection mark. The reflection mark is closest to the transducer, and the reflection from this mark will be the first signal to appear in the echoed signal, afterwards the nose and the flank will reflect echoes, see Figure 3.28. Changes in the time intervals of the echoes can be related to changes in the physical deterioration of the cutting tool.

![Figure 3.28 Ultrasound echo, [Abu-Zahra and Yu 2003].](image)

Yao et al. [1999] used a combination of spindle motor current, feed motor current and AE signals to estimate tool wear. They introduced a new method to estimate tool wear from current measurements by a neural network model with regression technology and fuzzy classification. With respect to the fact that current signals depend on the cutting variables, cutting speed, feed rate and depth of cut, as well as on the tool wear, the NN with fuzzy classification was constructed to detect tool wear over a wide range of cutting conditions. Wavelet transform was used because it was stated that it has a good resolution in both the frequency and time domains. This is synchronous, which means that the components can actually be considered as features of the original signal. Finally, the system was combined using an FNN, (Fuzzy Neural Network), in order to relate the tool wear to the AE signals. The training speed of the FNN is faster than a back-propagation type of neural network. What seemed interesting in this research was the sensor-fusion model, where the different sensory signals each reveal different characteristics and are differently affected by noise. The same approach was previously used by Li et al. [1997], where the tool state was divided into 5 classes, initial, normal, acceptable, severe and
failure. The success rate of wear detection in a drilling process was reported to be 86, 89, 90, 95 and 100% for the failure detection. They also used different ranges in the frequency band of the AE and related these to the different wear states.

Li *et al.* [1999b] presented a drilling breakage system using a discrete wavelet transform, and a simple rule-based breakage algorithm to detect breakage. The characteristics of the tool breakage were observed in the time domain as a sudden drop in the components amplitude and can be used for breakage detection. This philosophy has also been applied in many other systems, but the main drawback is that using only a single descriptor to define wear or breakage can result in misjudgements due to sudden disturbances in the signal.

### 3.4.8 Sensor Fusion and Multiple Sensors

To ensure that a TCM system for an industrial application is reliable, the sensing methodology has often involved a system of multiple sensors. Dimla *et al.* [1997] noted that the use of a single sensor signal in the development of a TCM system fails to recognize the complex and diverse nature of the cutting process. In their review of neural networks in metal cutting, they stated that single sensor models are often unreliable and are generally not capable of recognizing incipient, partial, complete or catastrophic tool failure. In my opinion the fusion models provide a good way of getting better signals while different sensors are affected differently by noise. The multiple sensor system is actually a copy of the human mechanism for recognising multiple inputs. These inputs are given in a way that would make very little or no sense at all if they were given one by one. Dornfeld [1994] wrote that humans are very capable as process monitors because of their high degree of multiple sensory abilities. Under this he mentioned the ability to extract noise-free data, to carry out parallel processing of information and, finally, the ability to learn through training and experience.

Luo *et al.* [2002] reviewed the current sensor technology, the paradigm of multi-sensor fusion, integration and multi-sensor fusion algorithms. The sensor fusion describes the ability to combine or add the output of other sensors for the purpose of giving a more reliable decision.
Ruiz et al. [1993] proposed a sensor system consisting of 4 sensors: AE, a thermocouple, strain gauges and current measurement. This model was the basis for building an automatic feature-extraction system, based on the statistical properties of the descriptors. The system was provided with a neural network to relate the extracted features to tool wear. The system was reported to show good wear estimation. As it can be expected a certain pattern will exist in this system, since there will be a connection between the temperature and cutting forces. Chapter 5 will later describe how the temperature theoretically will change with forces.

Kim and Choi [1996] proposed a multiple-sensor system to improve the reliability of tool breakage signals normally received from a single sensor. In this study, measurements from several sensors: a dynamometer, accelerometer and a gap sensor, were used to detect tool breakage. It was observed that the three parameters used for the monitoring process: the normalized mean cutting force, maximum acceleration and the amplitude of displacement, increased at the same time at tool breakage. Quan et al. [1998] proposed the use of power measurement and acoustic emission, combined with a neural network to recognize on-line tool wear. This method was later used by Haili et al. [2003] where the signals were processed using TFD, (Time Frequency Difference). The interesting parts of both previous research was not as much the processing methods, but that a link is shown between acoustic emission, tool wear and fracture, where the components are showing similar behaviour. Using their results it can therefore be valid to assume that the increased energy from the progressed wear is contained in the acoustic signal.

Bahr et al. [1997] used a combination of a machine vision system and vibration measurement on a CNC lathe. The main idea was to combine a direct and indirect measuring method, where the vibration measurement is concerned with the on-line tool-breakage monitoring process and where the vision system is measuring the actual tool wear between the work cycles. For this method a success rate of 96% was achieved. Initially this is offering a way of double checking the wear between cycles however, as mentioned; the machine vision system is also subjected to disturbance as a result of adhesive wear, carbon dust etc.

Choi et al. [1999] used an approach with an acoustic emission sensor and a built-in force sensor. The recognition process used the characteristics of the actual signals. A burst-AE
signal was used as a triggering signal to inspect the cutting force. A significant drop in cutting force indicated tool breakage. It is mentioned that by using an AE sensor and a built-in force sensor simultaneously, false predictions from the AE sensor caused by chip formation and variations in speed and depth of cut, which can generate AE or force signals similar to those arising from tool breakage, are reduced. Usage of both sensors ensures avoidance of faulty detection of tool breakage and also permits practical usage in a production environment.

Jemielniak et al. [1998] carried out experiments using the same principle, but where the data were fed to a neural network for decision-making. A dynamometer was used for force measurement and the AE sensor was placed on the upper surface of this, so the force and AE were measured at the same point. The result of this sensor placement was inconclusive. Similar to this approach, a dual-mode sensor was introduced, which measured the acoustic emission and the orthogonal force components. This technique was never successful because it used only one installing point, and it appeared that the best place for measuring the cutting force isn’t always the same as for acoustic emission, [Jemielniak 2000].

3.5 TCM Systems in the Industry

To conclude this review of TCM systems, a few commercial developments should briefly be mentioned. Although many methods and theories have been proposed for Tool Condition Monitoring, only a few have been shown to be successful as TCM systems applicable to an industrial environment and have made their way to the market. The systems which will be mentioned in this section are systems which have shown their ability to be applied as on-line monitoring systems.

Investigation has shown that, in spite of expensive lab research, a significant gap exists between theoretical and practical TCM applications, [O’Donnell et al. 2001]. They stated that one of the problems is the variations in the process and mentioned inconsistencies in tool quality, work experience and workpiece properties as reasons. Evaluating the performance of practical applications, Byrne et al. [1995] quoted that 15% of failures for TCM systems are due to the sensor system, 50% due to operator error, 20% due to a defective machine interface, 15% due to the selection of the wrong monitoring strategy.
and 15% due to expectations of no faults. The success of the TCM system is dependent on the sensing methodology, the signal processing and finally the classification of tool wear. They reviewed a total of 1161 installed monitoring applications. This included; acoustic emission (27%), strain (22%), force (17%), current (17%) and others (17%). These systems were applied for the following purposes: tool wear (28%), collision (22%) and breakage (50%). There are different influences, which can affect the operation of a TCM system, as shown in Table 3.2. Byrne et al. [1995] reviewed the development of multiple sensors, the development of intelligent sensors with improved signal processing and decision-making capability and the implementation of sensor systems in open architecture controllers for machine tool control. Later, a review of monitoring systems that actually made it to the market was carried out by Jemielniak [1999]. Six principles for monitoring are mentioned, and can be found as “of the shelf” components. These include: motor/drive power; torque measurement; strain measurement of tool/holder, either by strain sensors or the retro-bolt; vibration measurement and finally acoustic emission.
### 3.5.1 Monitoring Strategies

The most interesting part of the monitoring systems is the actual monitor. There are several universal monitors on the market, which can be fed with signals from different sensors. Depending on the configuration, all these are able to detect collision, breakage and tool wear. What differentiates these monitors is the monitoring strategy. The strategies mainly involve limit and enveloping. Several of the systems on the market are able to combine these strategies. Below, different monitoring strategies are mentioned for treating the digital signals, converted from the monitoring sensors, [Jemielniak 1999].

<table>
<thead>
<tr>
<th>Process</th>
<th>System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tool</td>
<td>Human/Machine</td>
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<tr>
<td></td>
<td>Interface</td>
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<tr>
<td></td>
<td>Tool</td>
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<td></td>
<td>Workpiece</td>
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<tr>
<td></td>
<td>Machine</td>
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<tr>
<td></td>
<td>Environment</td>
</tr>
<tr>
<td>Geometry</td>
<td>Level of user expertise</td>
</tr>
<tr>
<td>Wear</td>
<td>Process visualisation</td>
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<tr>
<td>Tool material/coating</td>
<td>Others</td>
</tr>
<tr>
<td>Cutting conditions</td>
<td>Tool change policy</td>
</tr>
<tr>
<td></td>
<td>Tool resharpening policy</td>
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<tr>
<td>Cutting speed</td>
<td>Workpiece</td>
</tr>
<tr>
<td>Feed rate</td>
<td>Type variation</td>
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<td></td>
<td>Supplier variation</td>
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<td></td>
<td>Batch variation</td>
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<tr>
<td>Depth of cut</td>
<td>Machine</td>
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<tr>
<td>Chip formation</td>
<td>Motor performance variations</td>
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<tr>
<td>Swarf removal</td>
<td>Vibration of machine tool</td>
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<tr>
<td>Depth of hole</td>
<td>Changes of friction in slideways</td>
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<tr>
<td></td>
<td>Bearing performance</td>
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<td>Misalignment of clamping</td>
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<td></td>
<td>Controller cycle time</td>
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<td>Workpiece Hardness</td>
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<td>Dimensional tolerance variation</td>
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<td>Changes of alloy content</td>
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<tr>
<td>Inclusions</td>
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<tr>
<td>Preceding operation</td>
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<td>Casting type (sand or die)</td>
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<td>Coolant</td>
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<td>Changes in concentration</td>
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<td>Variations in pressure</td>
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<tr>
<td>Variations in viscosity</td>
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</tbody>
</table>

Table 3.2 Sources of influences for a TCM system, [O’Donnell et al. 2001]
• Simple Fixed Limits
Using the first machined workpiece as calibration, a limit is set where the upper limit defines the maximum allowable range and a lower limit is used to detect a missing tool.

• Floating Limits
Floating limits track cycle-to-cycle trends every time a workpiece is machined and use this information to adjust the limits in the next machining process.

• Time Defined Limits
A time-displaced fixed limit is used as the time-defined limit. This monitors the rise and fall of the signal over a period, and is easier to adjust to a real monitoring process. This is due to the fact that a signal can sometimes exceed the fixed limit for a brief moment, especially in the entering sequence.

• Part Signature
Every cycle creates its own signature. When the signal rises in steps, these steps are used to draw the part signature, which can be used to track a complex cutting cycle.

• Pattern Recognition
This is used as a tool-breakage strategy, where reference shapes of the signal are stored and compared with the actual signal shape. The advantage of comparing signal shapes rather than amplitudes is that this is more independent of the process parameters.

• Wear Estimator
This uses the relationship between all three cutting force components and requires a three-axis force sensor.

• Dynamic Limits
The monitoring signal is followed by two dynamic limits, above and below the signal. If the dynamic limit is crossed extremely rapidly, tool breakage etc. can be distinguished by comparison with the monitor signal.

3.6 Conclusion of TCM Systems
The literature review of TCM systems has been concentrated on the following systems:

• Surface measurement
• Machine vision
• Force monitoring
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- Power/Current monitoring
- Vibration monitoring
- Acoustic emission
- Sensor fusion

Surface measurement is listed as a technique where the wear can be related to the surface characteristics. It has been mentioned that this is not an efficient technique because of the demanding data-processing requirements. However, with today’s equipment, this should not be the main disadvantage. The main disadvantage is the contact technique, however, different non-contact techniques have been described, but due to sensitivity to misalignment, vibration and the necessity for cleaning, there is a limit to the use of such techniques for in-process measurements. The same disadvantages can be said about the machine vision systems, whether they are used to recognise the actual wear or if the wear measurement is done by relating SF of the workpiece to wear. Another problem that has been mentioned is that crater wear is not measurable using machine vision. The advantage of the optical methods can be said to be that they are not sensitive to disturbances, such as background noise or changing cutting parameters. Current measurement systems are reliable in monitoring medium and heavy cuts, but the sensitivity is less than systems using such methods as force and vibration sensing. Force monitoring is not practical due to high cost and the requirement for a dynamometer wiring harness. Power has the disadvantage that normally such a large proportion of the power is required to drive the spindle or slide, that the increase due to wear can be a small fraction, which makes the system less sensitive to gradual wear. The advantage of power measurement instead of current measurement is that the power is linear. It means that the change in the motor’s power load is proportional to the change in the power. Vibration signals can describe a relationship between the progress of the tool wear and changes of vibration, where the problems are wiring and placement problems as well as structural damping problems. Although AE sensing is more sensitive to tool fracture than cutting force and tool vibration measurements, it is more dependent on the cutting material rather than on the cutting tool. AE is sensitive to noise and changes in the cutting conditions, and the key issue is how to deal with these parameters. Airborne Acoustic Emission offers a way of monitoring tool wear without a wiring harness, however, the
cutting conditions, such as feed rate, cutting speed and tool wear, have an influence on the characteristic frequencies which can be measured. Basically all monitoring techniques offer advantages and disadvantages. Apart from the optical and vision systems, all the principles mentioned here depend on the changing cutting and material parameters. As mentioned above, the key issue is to find an approach which can cope with the changing parameters and disturbances.
Chapter 4

4 Acoustic Emission

The basics of acoustic emission and the signals that are expected in a machining process will briefly be described in this chapter. There have been many attempts at developing TCM systems based on AE, either AE alone or fusion models with other sensors, again combined with different feature extraction and artificial intelligence techniques. Included in the literature review of AE, pre- and post-processing techniques of the AE signals will be pointed out. It should be mentioned here that there is a distinction between AAE, (Airborne Acoustic Emission), and AE, (Acoustic Emission). Although these are distinguished and operate in two completely different frequency ranges, there are some overlapping features enabling parallels to be drawn between the two techniques.

4.1 Acoustic Emission in a Metal Cutting Process

Acoustics is the science of sound, a mechanical wave motion, including its production, transmission, and effects. Low frequencies, referred to as infrasound, or high frequencies, referred to as ultrasound, which cannot be heard by humans, are also categorised as sound. Acoustic Emission (AE) in the metal cutting process is defined as the transient elastic energy, which is spontaneously released when the material is undergoing deformation or fracture Dornfeld [1994]. AE is also referred to as stress wave energy. The machined material's defects release elastic energy due to rapid local stress redistribution as a result of the load. The energy results from growing cracks, rubbed surfaces of cracks or dislocations in the material. The released energy is formed into transient waves, where most of these waves are short-time transient events, (burst signals). The waves can propagate long distances in spheres, in all possible directions.
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The distance of propagation depends on the material and the working environment. Two types of emissions are classified in the metal cutting process. These are defined as burst AE and continuous AE. During the metal cutting, plastic deformation is classified as producing the continuous type of AE signals, whereas fracture of the material is defined as producing a burst type of AE [Inasaki 1998]. A signal detected from a cutting process contains both types of emission [Moriwaki 1983]. Where milling is an interrupted process, containing burst signals from the process itself, the turning process is continuous. Burst signals normally appear from chipping and disturbances in continuous processes. A burst signal is detected when the chip collides with the tool, or because of disturbances in the process, e.g. when coils of workpiece material are wrapped around the workpiece, etc. This signal is essentially different from the real AE signals [Moriwaki 1983]. The burst signal also occurs during tool break or fracture, with significantly large amplitudes.

4.2 Tool Wear and Acoustic Emission

The acoustics emitted from the machining process have a relationship with tool wear. Early research showed that the signals could be used to detect the degree of cutting edge wear [Weller et al. 1969]. Since then, researchers have investigated this relationship and also the causes and behaviour of the acoustics emitted from the process. Along with the progress of tool wear, the wear land increases as well as the cutting force in the feed direction. The cutting edge wears, which creates sliding friction between the nose and the flank of the tool and the surface of the workpiece. This affects the tool and causes vibration. The tool vibrates horizontally away from the feed direction. The vibration causes what can be called an ‘interrupted contact’ with the work piece, which means that the vertical force on the tool varies, similar to self-excited chatter vibration [Kraisheh et al. 1995]. Machining and cutting parameters, such as feed rate, spindle speed, tool overhang and work piece dimensions, also have an effect on the vibrations transmitted [Weller et al. 1969]. The vibrations occur when the system generates a harmonic situation. As the wear progresses, the vibration amplitude increases to the point where the machining process becomes unstable. This condition is normally discovered when the surface roughness of the work piece goes beyond its tolerance or the noise emitted from
the process becomes too high. Weller et al. [1969] showed that increased wear produces a corresponding increase in the amplitude of the vibrations. Moriwaki [1983] carried out experiments, which showed that different tool materials emit acoustic waves of different magnitudes, where the AEs from CBN and ceramic tools have a higher magnitude than when cutting with carbide tools. Also, workpiece material is affecting the AE in the cutting process. Heiple et al. [1994] showed that no signal characteristics changed in the same way for different materials tested. They further concluded that a single change in a particular AE signal characteristic with tool wear, valid for all materials, probably does not exist, although they were of the opinion, that the changes in the signal characteristics would be sufficient to describe tool wear for a given material. Barry and Byrne [2001] investigated the AE from machining hardened steel with various process parameters and compared this to AE from machining soft pearlitic steel. They found that the AE RMS values emitted from hardened steel could be up to two orders of magnitude higher. Moriwaki [1983] also mentioned that there are indications that the AE signal measured at the workpiece and tool side are different. The signal measured on the tool side contains information about the chipping, chip breakage and the contact between the tool and the work piece. The signal measured on the workpiece side, will contain information on plastic deformation and shearing. Silva et al. [2000] reported interesting characteristics of AE arising from variable cutting conditions. With increasing depth of cut, the vibration appeared to reduce, which affected the frequency spectra of the sound. The explanation for this was that an increase in the cutting force leads to the increased stability of the cutting process. The results also showed that, with a variable feed rate, the frequency spectra of the sound showed a sinusoidal behaviour. Diniz et al. [1992] conducted experiments using acoustic emission in finish turning to estimate changes in surface roughness under different cutting conditions. They investigated the relationship between several parameters of acoustic emission, such as zero crossing rate, mean AE RMS, and standard deviation of the AE RMS. One thing that was pointed out was that, not only is flank wear present, in most cases a combination of crater and flank wear is seen. It was pointed out that when it comes to processing the AE signal using AE RMS, these two wear types are cancelling each other out. This can be explained by the fact, that flank wear is increasing the AE RMS, since the sliding friction between the tool and workpiece
will cause an increase in the required energy, whereas crater wear will increase the effective rake angle of the cutting tool, requiring less energy. Effectively this means, that when different wear types are present, the technique which is used must be capable of distinguishing between these types. Chungchoo and Saini [2000] investigated the use of structure-borne acoustic emission in order to investigate the total energy and total entropy of force signals to monitor progressive tool wear. This research is very interesting, because it is drawing good parallels with cutting forces, showing that acoustic emission can be a good estimator of the energy content of the process. They described how different cutting parameters and wear types influenced the results and support other researchers in this field by saying that AE is a method which is highly sensitive to changes in cutting parameters.

4.3 Chatter Instabilities

Chatter vibration is an unfavourable situation, where the tool vibrates with large amplitudes relative to the work piece. Vibrations in machining can be classified into two types: forced vibration and self-excited vibration. Forced vibration is caused by cyclic variations in the cutting force. This is normally in milling processes and processes with interrupted cuts. Self-excited vibration chatter is the dynamic instability, where the cutting tool vibrates relative to the work piece [Kraisheh et al. 1995]. Again, this is divided into two types, regenerative and primary. Regenerative chatter is a simple vibration which comes from the irregularities of the work piece surface. Primary chatter is related to the dynamics of the cutting process and is affected by factors such as friction, changes in cutting forces and the geometry of the cutting tool. This type of vibration is considered to be the most complex to handle in the machining process [Tamg et al. 1994, Dohner et al. 2004]. Hayajneh et al. [1998] add another classification to this; free vibrations during impact or shock, which normally decays under the damping action of the machine tool. Chatter instability for cutting tools, is a mechanism which is reinforced by the variation of the cutting force, which basically varies along with cutting parameters. In order to prevent chatter generation, the transfer function between the cutting force and the variables must be known. According to Hayajneh et al. [1998], the most promising technique has been to use the mechanics of chip formation.
4.4 Transmission of AE Signals

4.4.1 Structure-borne Acoustic Emission

Vibration transferred through the tool and tool holder is referred to as structure-borne acoustic emission. Moriwaki [1983] states, that the AE generated in the cutting process is transmitted to the tool as well as the work piece. The magnitude of the vibration transmitted through the solids is very much dependent on the transmission path and elastic connections, which will work as damping factors. The frequency of structure-borne AE can be measured in the MHz range. Moriwaki also used AE to investigate the possible sources of acoustic emission in the metal cutting environment. When a structure-borne transmission path is used, AE is normally measured in the ultrasonic frequency range, going through a high-pass filter. This is done to eliminate the noise in the lower end of the frequency range. Further, he mentioned, that the normal cut-off values for high and low-pass are 100 kHz and 1 MHz. Two methods of tool wear sensing were investigated to count the number of events and to monitor the averaged level of AE.

1. Correlations were reported between flank wear and the number of counts, where the AE exceeds a predetermined threshold value.
2. The amplitude of averaged AE is used to draw a linear relationship to flank wear.

4.4.2 Airborne Acoustic Emission

Vibrations transmitted from the cutting edge to the surroundings carried by air, is referred to as airborne acoustic emission, and it is what we recognise as sound. The frequency of the airborne signals can be recognised by humans, normally in the range up to 20 kHz. The relationship between the vibrations generating AE and audible sound has been shown by Lu and Kannatey-Asibu [2004], comparing vibration measurement with the sound transmitted from the process. They stated that vibration due to tool displacement is one of the exciting sources for audible sound. Weller et al. [1969] were among the first researchers, to be concerned by building a complete device for the detection of cutting tool wear. The sensing technique used was a high-frequency accelerometer, which detected the structure-borne waves and recorded them on a tape recorder. Using the theory that a worn cutting edge produces high frequency tonal vibration energy, whereas
a sharp one does not, the signals were filtered into high- and low-frequency components. The low-frequency component was in the range 0-4 kHz and the high-frequency one was in the range 4-8 kHz. The ratio of the two frequency components was used to estimate tool wear. Sadat and Raman [1987] used airborne acoustic emission to detect tool flank wear in the frequency range of 2.75-3.75 kHz. They found that these acoustic signals were due to the rubbing action of the tool. Another statement was that the noise outside this frequency range could be identified as gear, bearing, tail stock and carriage movement noise. It is shown that there is a link between the increased forces in the contact area and the sound. Furthermore, an interesting observation in this research was that a significant noise level was observed with increasing tool overhang. This is attributed to the increase in elastic deflection of the tool, which will increase the level of vibration. The principle of using AAE was also proved by Hede [2004], where the sonic frequency range up to 20 kHz, detectable by the human ear, was divided into 12 components by empirical experiments. An algorithm was used to detect the best components to calculate a ratio for tool wear estimation. A fuzzy set was applied to estimate the wear from training data under different cutting and material conditions. Hede [2004] found, that by dividing the frequency range into more components than two, tool wear became easier to detect. This is due to the fact that early wear signs reveal themselves in narrow ranges. As mentioned before, the sonic range up to 20 kHz is detectable by human beings with normal hearing. Other researchers have recognised the fact that the operators are capable of detecting changes in the cutting tool with reasonable accuracy by ear, and have been using the sonic range for tool wear monitoring. Lee [1986] conducted experiments, using a condenser microphone to determine the variations of the characteristic frequency with respect to variable process parameters by measuring the SPL, (sound pressure level). This included cutting speed, feed rate, workpiece material and tool material. Disturbances such as background noise were reported to be concentrated in the lower end of the frequency scale. In the lower frequencies, the sound pressure level was measured and found to be higher than in the range beyond 1 kHz. Jemielniak [2000] stated that the low-frequency components are due to noise and are therefore useless. Kopac and Sali [2001] showed by experiments that the noise from the surroundings is significant in the range up to 2 kHz. The results of Lee [1986] showed
that the characteristic frequency during machining was found between 4 and 6 kHz. He also mentioned that tool overhang plays an important role when using AAE. This is due to the fact that a change in overhang will give another vibration pattern for the cutting tool. It was reported that, by reducing tool overhang, the characteristic frequency falls. By measuring the cutting force and the physical wear of the tool, Lee was creating a relationship between cutting force, sound pressure level and tool wear. Lu and Kannatey-Asibu [2004] compared audible sound to vibration and cutting forces, where the average changes in the spectrum of the sound, were seen around 2.5 kHz. What has been an interesting observation is that, the wear showed a significant increase as a spike in this area. This contradicts Hede [2004], who found that the wear, described as changes in the upper end of the characteristic range, would increase on average over a wide range and not as a spike. Ghosh et al. [2007] used AAE SPL as a measure in milling, and stated that this principle can be considered for an industrial application, because it is easier to mount a microphone than a dynamometer. Although this research concerns milling, it shows a good correlation between tool wear and AAE RMS at the SPL level, but the research is lacking when it comes to conclusions on changing cutting parameters, where it shows a linear trend in the AAE RMS as a function of machining time under one set of cutting conditions.

4.4.2.1 Sound Waves

This sub-chapter basically describes some aspects of the theory of sound waves, which can explain the complexity of sounds associated with a CNC machine.

Sound waves are longitudinal compression waves. This means that the particles vibrate parallel to the direction of the wave's velocity. Airborne Acoustic is measured in terms of amplitudes over a sinusoidal curve. The change in the sound pressure in the air defines the changes in the amplitude. When two or more waves travel through the same medium at the same time, the waves interfere. If the sounds are close to the same frequencies, this can be heard as regular beats. Sound waves lose energy when they travel though the medium. Low-frequency waves travel further than high-frequency waves, because there is less energy transferred to the medium. This also depends on the medium’s temperature. The smallest change which can be heard by humans is about 0.00002 Pa, where the
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pressure change producing pain is in the range of 20 Pa. The properties of sound can be correlated with our physical perception, where frequency is related to the pitch of the sound, and amplitude related to the loudness. Sound can have different characteristics depending on the shape of the waveform, but for tones and non-noise sounds, there is usually a noticeable periodicity. The velocity of sound waves $v_{\text{sound}}$ can be expressed by Equation 4.1.

$$v_{\text{sound}} = \frac{\lambda}{f} = \frac{\lambda}{f_q}$$

Equation 4.1

Sound waves follow the law of superposition, where the existence of one wave does not affect the existence or properties of another wave, even if they are present at the same time. Therefore it is said that waveforms add algebraically.

The inverse square law for sound in space where the intensity is inversely proportional to the squared distance can be seen in Equation 4.2.

$$I \propto \frac{1}{r^2}$$

Equation 4.2

If a plane wave hits a parabolic surface it will reflect back as a circular wave segment and when a waveform is passing by two different media, or from one media to another, refraction occurs, which is accompanied by a change in direction. Another form of refraction is due to temperature deviation. The velocity of sound is greater in warmer air. Sound waves that travel in mediums with different temperature characteristics will be subjected to a form of refraction, due to changes in the wave speed. Interference means a combination or addition of two similar sound waves. Two types of interference exist, *destructive* and *constructive*. Constructive interference is when the waves are in phase resulting in addition, and destructive interference is when the waves are out of phase and cancelling each other out. In the physics of sound one must not forget that the longitudinal wave motion results in an expansion and afterwards contraction. If one sound source at a given period in time is expanding and the other source is contracting, this results in a cancellation of the two sounds at that particular moment. In a CNC lathe, which is often constructed from thin plates of metal, the interference can come from the initial sound waves reflected off the walls of the machine.
4.4.3 Liquid-Borne and Inductive Transmission of AE

Another way of transmitting the AE is through the coolant fluid in metal cutting machines. The AE transmitted from the coolant stream has proved to be successful in turning [Inasaki 1998]. One problem which has been mentioned with this technique is that it requires a bubble-free coolant stream [Byrne et al. 1995].

An inductive, contact-less transmission has also been introduced. The signals are transmitted from the AE sensor to a receiver. This process offers the opportunity for near-process measurement because the sensor can be fitted on the main spindle [Byrne et al. 1995].

4.4.4 Distortion and Disturbances

As already mentioned, the magnitude of the signal received depends very much on the transmission path. Structure-borne stress waves, which propagate from the cutting point to the sensor location, over and through the material, are mainly being distorted by joints and connections, working as damping factors [Iturrospe et al. 2005]. Normally the sensor is mounted near the cutting zone to minimize this effect. For the transmission part, airborne acoustic emissions are not dependent on the structure of the machine or tool holder, but the transmission of the lower frequency signals, can be distorted by resonance in the machining environment or by absorbing factors, where a constant coolant stream at the cutting edge will weaken the signal.

A problem which has been mentioned by numerous researchers is the disturbance of the cutting signal. The captured signal does not contain pure cutting information but contains noise from parallel machining, coolant, chipping, slideways, bearings, hydraulic equipment, etc [Lee 1986].

This has been mentioned as one of the main issues to be solved, along with the variations in the signals due to variable process parameters such as spindle speed, feed rate, material and tool parameters, for AE or AAE to be successful in a real machining environment. The machining environment is very hostile and the disturbances are almost uncontrollable. This implies that the effort in applying a TCM system using AE or AAE, should be put into the area of sensing, pre- and post-processing.
4.5 AE Processing

This chapter will briefly deal with some sensing methodology and signal processing, including both pre-processing and post-processing. Although it has been mentioned that there is a distinction between AAE and AE, the same principles are often used in post-processing.

4.5.1 AE Sensor

The sensing methodology is different depending on whether the desired frequency is in the sonic or ultrasonic range. Piezoelectric AE sensors use the same principle as vibration sensors. AE sensors are designed for the ultrasonic range, above 20 kHz [Li 2002, Jemielniak 1999, Salvan 2004]. Pre-processing is the first step in interpreting the signals from the sensor. The AE sensor is connected to a pre-amplifier or it can be a built in. The signal can then be processed by filters. Since the raw AE signal is at a high frequency, the processing and recording of the signal is very demanding and therefore demodulation techniques are used. A widely-used technique is RMS (Root Mean Square). The low frequency components in ultrasonic AE measurements are considered to be noise and are removed by a high-pass filter. The same can be done at the upper end of the frequency scale [Jemielniak 2000]. The placement of the AE sensor is vital. AE sensors should be placed at least three characteristic wavelengths away from the process being measured, as this allows the emission to be considered as a point source [Jemielniak 2000].

4.5.2 Microphones

Airborne acoustic emission can be captured by microphones. Several types of microphone exist, including carbon, crystal, (piezoelectric), moving coil, capacitor etc. Salvan [2004] noted that the condenser microphone is superior in sensitivity. Condenser microphones have been used in some applications, although the research into AAE is only a very small fraction of AE sensing applications. In the field of wear monitoring of cutting tools, Lee [1986], Hede [2004], Salvan [2004], Kopac and Sali [2001] used condenser microphones in their work. Other fields where these have been used have been in part assembly, where signals from parts mating were detected with condenser microphones [Bright and Moodley 1995]. In laser welding, using a condenser
microphone in the sonic range, diagnostics related to the welding morphology, heat affected zone and depth of penetration were extracted from the signals [Gu and Duley 1996]. This technique has also been used in the wear estimation of ball bearings [Garret et al. 2001, Salvan 2004]. In an aggressive environment, such as metal cutting, there are very few microphones robust enough to operate. The microphone should be placed as close to the cutting zone as possible, but this can create problems because of disturbances from the actual process. Hede [2004] carried out experiments using an omnidirectional microphone to find the best placement, without interfering with the process in a CNC lathe. Three tests were performed; (i) Where the microphone was placed on top of the tool holder; (ii) behind the tool block on the turret, away from the direction of feed, (iii) behind the spindle with the tool moving towards the microphone. It was shown that (i) was subjected to disturbances from chips, etc and (ii) suffered from the problem of not capturing the actual cutting process. However, (iii) showed the best results capturing all the data, unfortunately also the noise.

4.5.2.1 Pickup Patterns

The pickup pattern refers to the direction in which the microphone is sensitive for receiving the signal. There are three main pickup patterns, also referred to as polar patterns, and each of them has advantages and disadvantages.

- Cardioid Pickup Pattern

The cardioid microphone is most sensitive to what is picked up in front of it but is less sensitive to sound from the sides. This microphone is often referred to as having a kidney or unidirectional pickup pattern and is less sensitive to background noise. The advantage of this type of pickup pattern is that it can be directed towards the sound source, leaving out unwanted sounds. Different types of the cardioid pattern exist, such as super cardioid and hyper cardioid.
• **Omnidirectional Pickup Pattern**

The omnidirectional microphone is sensitive to sounds 360 degrees around it, which means that it will be picking up everything, including noise and unwanted sounds. Another issue with this type of microphone is that, even if there are no unwanted sounds to pickup, it will still pick up reverberation.

• **Bidirectional Pickup Pattern**

Bidirectional microphones are equally sensitive to sounds coming from the sides but not from the edges of the microphone.

4.5.3 Signal Processing

To be able to use the AE signals, whether it is AE or audible AAE signals, they must be transformed into something less bulky than the raw signals. The data is transformed into sets of features, referred to as a feature vector. In the monitoring of machining processes, the sensor signals would normally contain noise, but the features must be extracted using data which represent the process characteristics [Silva et al. 2000]. Sitz et al. [2001] described the following techniques used for feature extraction: time-folding representation, auto bi-spectrum, power spectrum, phase spectrum, spectrogram and the AR-model. Li [2002] described other quantifiable methods which have been used for feature extraction, such as ring down count, AE event, rise time and peak amplitude.

• **Time-Folding Representation**

The time-folding representation is used to detect the periodic motion and can reveal the regularity or irregularities of a waveform [Sitz et al. 2001].

• **Power Spectrum and Auto Bi-Spectrum**

The power spectrum is used in the frequency range. Auto bi-spectrum can be used with the power spectrum to identify quadratic phase coupling, but cannot identify amplitude or frequency modulation [Sitz et al. 2001].

• **Spectrogram**

A spectrogram can be used to study the time variability of a sequence of magnitudes [Sitz et al. 2001].
• **AR-Model**

The AR-model, (Autoregressive), is used to describe the variance in time series to a linear approximation. AR parameters and AR residual signals are used as features for monitoring tool wear [Sitz et al. 2001]. Li [2002] claimed that experimental results have found that the power of the AR residual signal of the AE increases with flank wear. This was also shown by Ravindra et al. [1997], where normalized AR parameters were plotted in a two-dimensional diagram. Using a fresh tool, the points were clustered near the origin, but as the tool wear progresses, the point scatters away from the origin. The increase in the magnitude of the AR parameters indicates that the high frequency components are becoming dominant in the signal.

• **Fast Fourier Transform - FFT**

The Fast Fourier Transform was developed to calculate Fourier data in real time, because this algorithm requires less computer power than a normal analysis of the Fourier series. There are different kinds of FFT for special purposes. The goal of the calculation is to calculate $X_r$, which is the strength representation for each frequency. Fourier transform has been shown to be successful in turning and it has been shown that the magnitude of the AE in the frequency domain is sensitive to tool wear [Li 2002], although the Fourier transform’s difficulty in describing the signal in the lower frequency, due to the non-stationary AE signal, is mentioned. One of the main objectives of feature extraction is to provide a compact signal representation while preserving the signal’s sensitivity to tool wear. One problem that has been mentioned when the Fourier transform is being used is that the components generated only represents the strength of each frequency and do not give a time representation of when they occur. Li et al. [1997] also claim that spectral analysis, such as the FFT, is the most commonly used signal-processing technique in TCM systems, but the problem is that it only has a good solution in the frequency domain. This means that it loses signal information in the time domain.

Kamarthi and Pittner [1997] compared the FFT and FWT, (Fast Wavelet Transform), techniques using force and vibration as the sensing methodology. They concluded that FFT seems to have an advantage when used on vibration signals.
• **Ring down Count**
This technique uses the principle of counting the number of times the signal exceeds a threshold. This is done by dividing the signal into time units [Li 2002, Salvan 2004].

• **Signal Rise Time**
This is the time before the signal reaches its peak amplitude from the first threshold [Li 2002]. Ravindra *et al.* [1997] showed the characteristic states for flank wear using different cutting parameters and the signal rise time. The wear characteristics with different cutting speeds were shown using rise time and compared with the physical wear characteristics for the tool.

• **Wavelet Analysis**
Wavelets have been investigated by numerous researchers and there have been attempts to use them as a diagnostic tool in almost all monitoring applications. In the case of wavelet analysis, the basic function consists of the wavelet scale function, and scaled and shifted versions of the mother wavelet. Whilst the FFT only plots each frequency component, the wavelets are able to plot a component’s content and the time occurrence [Salvan 2004]. Wavelets are functions cupped into families. They are generated from the mother wavelet, also referred to as the analyzing wavelet. Different wavelet transforms exist, such as the normal wavelet transform (WT) or the wavelet packet transform. Yao *et al.* [1999] used the wavelet packet transform to identify tool wear and stated that it is suitable to be implemented in real-time monitoring, as the wavelet packet transform only requires a small amount of computation. Li *et al.* [1999] described the discrete wavelet transform as a means of tool breakage detection, where a simple rule-based system is applied to estimate the breakage in drilling.

• **RMS**
As an indicator of tool wear, the RMS values of the AE signals can be used. The general idea behind this is that the RMS energy of the AE signal is expected to be proportional to the work rate of plastic deformation and sliding friction over the wear land of the cutting tools [Trent 1988]. Based on this, RMS has been used in different analytical models of AE content for a cutting process [Kannetey-Asibu and Dornfeld 1981, Sani and Park 1996, Chiou and Liang 2000, Chiou and Liang 2000.b]. The energy rate of the RMS
signal can be expressed as Equation 4.3 and the RMS as Equation 4.4 where $S$ is the
signal as a function of time.
\[
\frac{dE}{dt} \propto (\text{RMS})^2
\]
\[
\text{RMS} = \sqrt{\frac{1}{\Delta t} \int_0^{\Delta t} S^2(t) dt}
\]

Sick [2002] stated that the high-frequency acoustic emission signal should not be
measured, but a low-frequency RMS level of this signal should be used. Ravindra [1997]
showed that there is an increase in RMS during the initial and rapid wear stages. In many
applications, the average RMS values have been used as an identifier of tool wear.
Several statistical functions have also been applied to RMS [Kannatey-Asibu and
Dornfeld 1982]. Jemielniak and Otman [1998] mentioned that the magnitude of the AE
RMS has been considered as a measure of CTF (Catastrophic Tool Failure). The high
amplitude burst signals have been connected to CTF, but they concluded that similar
burst signals can be generated by tool engagement, therefore the AE RMS signal may not
be considered as reliable in e.g. interrupted turning. Hede [2004] showed similar burst
events, which can disturb the signals, generated from chip disturbances in the form of
long unbroken coils wrapped around the work piece. Beggan et al. [1999] described
considerations by other researchers, which claimed that the power of the AE RMS is
directly related to producing plastic deformation and that the AE is proportional to the
square root of the cutting speed. If the RMS signal is heavily distorted by background
noise that cannot be filtered out, Equation 4.5 can be used to obtain a clear signal
\[
\text{RMS} = \sqrt{\text{RMS}_{\text{total}}^2 - \text{RMS}_{\text{noise}}^2}
\]

However, in Kannatey-Asibu and Dornfeld’s work from 1981, which is cited and used by
several researchers, an error was made from the original work in 1974, republished in
Hamstad [1987]. However, this is corrected in Equation 4.5.

- **Statistical Properties of AE**

Several statistical properties have been used to define tool wear signatures, such as
properties of the amplitude distribution, especially expressed by the skewness and
kurtosis. Kannatey-Asibu and Dornfeld [1982] described the use of distribution moments and the beta function as a mean of tool wear estimation using AE. This is originally from the theory of surface metrology, where the basic philosophy is that any practical amplitude distribution could be approximated by this distribution [Whitehouse 1994]. It was shown that the skew and kurtosis of a beta distribution of an RMS acoustic signal are sensitive to both the stick-slip transition for the chip contact at the tool rake face and the progressive tool wear on the flank of the tool.

Jemielniak and Otman [1998] used the same technique for detecting CTF. They concluded that the success rate of detecting tool failure was 80%, although there is a short time delay in the method before CTF is detected.

Farelly et al. [2004] investigated the statistical properties of AE signals for the improvement of TCM systems. This included statistical analysis of the time series amplitude and RMS values. This was carried out for different states of tool wear; where AE amplitudes in the frequency distribution are shown to be distributed with power-law behaviour above a crossover value, see Figure 4.1.

Figure 4.1 Power-law behaviour of the AE signal, [Farelly et al. 2004]

Another technique was to plot the averaged RMS histograms, see Figure 4.2, showing a shift towards lower frequency distribution and skewness. A T-test is proposed to distinguish between the plots for the estimation of tool wear [Heiple et al. 1994].
Farelly et al. [2004] also used the hypotheses that a beta distribution can describe the probability density function related to tool wear. The function has two parameters and can be used for characterization, where the changes in skew and kurtosis can be revealed. However, they concluded that a better approximation should be sought where the reason for this remained inconclusive.

Hede [2004] used simple descriptors, such as the standard deviation and mean of the amplitude distribution. This was able to express a representation in two dimensions. It was shown that the standard deviation of the amplitude distribution changes with changes in the wear land of the cutting tool.

4.6 Feature and Pattern Selection

4.6.1 Feature Extraction and Selection of AE Signals

Ruiz et al. [1993] described the development of an automatic feature extraction system from 4 sensor signals. Only the features with the best discriminating capabilities need to be considered from all the descriptors. This was based on the criterion of discrimination power, where the normalized distance between each class was calculated and evaluated. Not all the features extracted from the process would be appropriate for describing a suitable feature vector because certain features may correspond to noise, be non-informative or simply not relevant for the purpose. Sun et al. [2004] proposed the use of a feature selection system where automatic relevance determination (ARD) and a support vector machine (SVM) are coupled. The experimental results showed that the AE feature-
set selected through this method was more efficient at recognising the tool state over various cutting conditions.

Lee and Landgrebe [1993] described a linear feature-extraction based on decision boundaries. The principle of this technique is to find a set of vectors that represent an observation while reducing the vector dimensionality.

4.6.2 Pattern Classification

An approach using an LDF, (linear discriminator function), was made by Emel and Kannatey-Asibu Jr. [1988]. The LDF is a separation technique used to differentiate between clusters of feature data. Using AE spectral signals, the feature selection techniques considered three classification criteria: the class-mean scatter criterion, the class variance criterion and the Fisher weight criterion. These are also referred to as interclass distance measures. Two classifier designs were discussed, the minimum error and the minimum cost. Experiments showed that the minimum cost design had the highest success rate for detecting a worn tool.

Hede [2004] also used an LDF for separating tool states. Empirical tests showed that for ideal laboratory conditions, a linear relationship could be drawn for the tool states, except when speaking of excessive wear. This was in good correlation with Weller et al. [1969] and Astakhov [2004], who showed a linear relation between the acoustics emitted and flank wear.

4.6.3 Fuzzy Set and Fuzzy Logic

The concept of the fuzzy set can be defined as a generalisation of the classical or crisp set. The crisp set separates individuals into two groups: members that belong in the set and non-members that do not belong in the set. When fuzzy classification is used to detect tool wear, a membership function must be defined for each state of the tool wear using the relevant selected features. Yao et al. [1999] used a fuzzy classification to combine various process parameters, such as spindle current and feed current signals, at different wear states. The model is used to estimate the tool wear as a function of spindle current, feed current and various cutting parameters. This task has been mentioned by
many researchers as being the most difficult task of TCM. This system was combined with a neural network and tool wear was estimated on the basis of AE.

4.6.4 Neural Network

A neural network, (NN), is an attempt at copying the human mechanism of recognition and decision-making. Neural computing was originally presented in the early 1940s. From a period of unpopularity in the 1960's and '70's, neural networks had by the late 1980s again become interesting because of their classification and optimization capabilities, and are widely applied today. NNs have been used in many TCM applications based on the principle of triggering an output from a certain input. Neural networks are especially interesting in the field under consideration here, because tool wear cannot always be regarded as a linear process. This is one of the primary advantages of using NNs, that they are capable of non-linear modelling. Each neuron in a network receives input signals from several other neurons. The connection between the neurons is called a synapse. This will afterwards be passed on to the other neurons through weighted connections. A summation is done over the inputs and an output is triggered. Typically, neural networks have one or more layers of processing elements. Dimla et al. [1997] reviewed NNs used for the detection of tool wear in metal cutting processes. The review showed the trend of using NN for different sensing signals, see Figure 4.3.

![Figure 4.3 The trend in NN used with different sensor signals, as percentage of reviewed applications](Dimla et al. 1997).

A single-layer, feed-forward, perceptron, (SLP), neural network is limited in the range of functions or processes that it can represent, and this is often limited to linear functions or
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linearly separable data. A more powerful network can be achieved by using a three-layer, feed-forward, perceptron network.

Figure 4.4 The NN principles applied in TCM, as percentage of reviewed applications [Dimla et al. 1997].

The survey was based on the following systems: multi-layer perceptron (MLP) type, a Kohonen self-organizing map (KSOM), restricted coulomb energy (RCE) networks, adaptive resonance theory (ART), radial basis functions (RBF), single-category-based classifiers (SCBC) and condensed nearest-neighbour networks (CNNN). Multi-Layer Perceptron, (MLP), is said to be the most popular network architecture in use today, where a back-propagation algorithm, a generalization of the Least Mean Square (LMS) method, is used to train MLP networks. Back-propagation provides a way of using examples of a target function to find the coefficients that make a certain mapping function approximate the target function as closely as possible. They concluded the review by stating that MLP principles have been the most widely applied in TCM, see Figure 4.4.
Chapter 5

5 Wear-quantifying Model

The remaining chapters in this thesis will describe the elements of a combined solution for tool condition monitoring. It is clear that AAE offers possibilities for tool monitoring, where the main advantage is that a condenser microphone is a simple inexpensive sensor solution, which offers great flexibility compared to AE and vibration monitoring. However, there are some other problems arising when using AAE, which are mainly disturbances. The proposed solution has been derived through empirical experiments, whilst bearing in mind the need for a relatively simple system, based on principles from the theory of orthogonal metal cutting. To give an overall picture of the functionality, Figure 5.1 shows a flowchart of the monitoring system. The sound is sampled using a 16-bit device with a 44 kHz sampling rate in order to satisfy the Nyquist rule. The on-line system is basically split into two: a time-domain-based system and a frequency-domain-based system. The time-domain has been proved to handle fracture monitoring and disturbances efficiently, whilst the frequency-domain is used to detect gradual wear. The fracture/disturbance system is built on SF parameters, which are used to describe irregular patterns in the waveform. The gradual wear is predicted by an approach in which the characteristics of the spectral image of the sound, as well as the RMS values from the waveform, are used to predict cutting parameters. This is done in order to calculate a virtual force, where the network is trained with cutting data from a range of feed rates, depths of cut and cutting speeds, using new tools. The network will predict a pattern, where the virtual cutting parameters can be related to a virtual force representing the tool state by a single scalar value in which all cutting parameters are accounted for.
Figure 5.1 Functionality of the proposed monitoring system.

Using a non-linear regression model, the virtual force contribution, which is the difference between the theoretical calculated tangential force and the calculated virtual force, can be correlated with the actual measured flank wear. This research has shown that flank wear is not the only wear present during normal metal cutting. Crater wear occurs on the rake face of the cutting tool. However, AAE is lacking when it comes to monitoring crater wear. Therefore, an analytical model has been developed in order to estimate which type of wear is the most dominant. An analytical wear model, which
estimates flank and crater wear based on previous measurements, is used to estimate a level of wear as a function of removed workpiece material. This wear estimate is used in an AAE RMS model to approximate a level of the AAE RMS as a function of the cutting parameters. The function of this model is to compare the actual measured AAE RMS with the one predicted, within a certain known deviation. Excessive crater wear alters the sound from the worn tool, where AAE RMS decreases with excessive crater wear. Therefore, if the measured AAE RMS is lower than a predicted level, within a certain known deviation, it can be expected that the proportion of crater wear is higher than flank wear. Moreover, since the risk of a catastrophic failure increases with increasing crater-centre distance, this can be used as an indicator of possible upcoming failure. The fracture/disturbance system is basically used either to immediately stop the process in the event of a fracture or to evaluate the tool wear prediction in cases where the system indicates that either internal or external disturbances are taking place, which will invalidate the wear decision. No single parameter can fully describe the problems and therefore, as a good mechatronics approach, several integrated models have been combined into a multi-disciplinary system in order to achieve the main goal, to accommodate the changing cutting parameters, as well as providing a system that is less sensitive to noise and disturbances. Different chapters, see Figure 5.2, will describe the principles behind the system, which can be thought of as a hybrid system, utilising analytical and theoretical models, as well as being combined with on-line, sensory information. This chapter will describe the development of a wear-quantifying model. The first step of recognising tool wear is to understand what to look for, and when to look. The wear-quantifying model, will give an analytical prediction of wear progress. The overall goal of the analytical model is to link the theoretical cutting force, the external parameters in the cutting process, such as tool geometry, and finally workpiece and tool materials. In this research, the wear-quantifying model is used as a means of estimating two wear types: flank wear and crater wear.
5.1 The Principle of the Wear-quantifying Model

Instead of looking at remaining machining time as a wear quantifier, the remaining volumetric left in the tool may be used as a good descriptor for quantifying tool life. In this proposed model, this is done using several factors. The most common wear types are flank, crater and nose wear, where this model considers nose wear as a part of the flank wear. Looking at the flank wear in a turning process, this is normally caused by the frictional contact between the flank face and the workpiece. In longitudinal turning, the flank wear can be controlled by the feed rate, where either reducing or increasing this will have an effect on the flank wear. Some of the controlling factors regarding crater wear, occurring on the rake face of the cutting tool, are material and speed properties. Of course there are many other factors that can affect the wear types, but at least two different types of wear can occur on the cutting tool, and they can be present separately or together.

5.2 Two-Dimensional Tool Wear

Considering these two wear types, a two-dimensional wear model can be claimed to exist, where the wear $w$ is classified by a portion of both elements present at the same time, where $V_b$ represents flank wear and $K_t$ crater wear, Equation 5.1.
A certain amount of tool life is present in a new cutting tool, divided between the tool flank and rake face. All depending on how it is used, the setup and cutting factors, the tool will suffer from wear in different regions. Using the tool flank in longitudinal turning will generate wear on the tool flank as well as the rake face. The rake face is subjected to wear because of the friction from the chip sliding over the face and the abrasive inclusions. When the cutting speed is increased, this will increase the speed with which the abrasive inclusions are passing over the face and the tool face will be subjected to more wear than the flank. On the other hand, if the feed rate is increased, the flank side is subjected to more pressure, which will increase the rate of flank wear but also affect the wear on the rake face.

### 5.3 Flank Wear

As previously mentioned, flank wear is one of the most investigated types of wear. Zhao et al. [2002] proposed a time-based wear model, built on the assumption that the normal stress at the flank face is proportional to the feed force from the cutting process and inverse proportional to the width of cut and wearland, see Equation 5.2.

\[
\sigma_f = \frac{F_f}{A} = \frac{F_f}{i_a V_b}
\]

Relating to the Archard type equations, built on a previous equation by Usui et al. [1984], a wear model defining the wear land as a function of cutting time was expressed as Equation 5.3

\[
V_{b(t)} = K \left( \frac{2v}{i_a^2 \tan \theta} \right)^{\frac{1}{3}} \left( \frac{F_f}{H} \right)^{\frac{1}{3}}
\]

Theoretically, this model represents a function expressed as wear land over cutting time, where the wear land is dependant on the feed force \( F_f \), cutting speed \( v \), width of cut \( i_a \), relief angle \( \theta \) and the tool hardness \( H \). An approximation of \( F_f \) is described in Equation 5.4.
Expressing the removal rate as Equation 5.5, the removed workpiece material as a function of time can be derived as Equation 5.6.

\[
\frac{dV_{\text{vol}}}{dt} = v \cdot f \cdot a_p
\]

\[
V_{\text{vol}(t)} = v \cdot f \cdot a_p \cdot t
\]  

Isolating \( t \) as time given in minutes, then the time as a function of removed volume can be expressed as Equation 5.7.

\[
t = \frac{V_{\text{vol}}}{v \cdot f \cdot a_p}
\]

\( V_{b(\text{vol})} \) can be expressed by Equation 5.8 as a function of the removed workpiece material.

\[
V_{b(\text{vol})} = K \left( \frac{2v}{i_a \tan \theta} \right)^{1/3} \left( \frac{F_f \left( \frac{V_{\text{vol}}}{v \cdot f \cdot a_p \cdot 10^3} \right)}{H} \right)^{1/5}
\]

Inserting \( F_f \), the equation for flank wear, as an expression of removed physical volume and where the removal rate is a function of time, can be defined as Equation 5.9.

\[
V_{b(\text{vol})} = K \left( \frac{2v}{i_a \tan \theta} \right)^{1/3} \left( \frac{a_p \cdot f \cdot k_c}{2} \left( \frac{V_{\text{vol}}}{v \cdot f \cdot a_p \cdot 10^3} \right) \right)^{1/5}
\]

Defining \( k_c \) as Equation 5.10, the expression of flank wear, as a function of removed volume, which incorporates the entering angle and the rake angle through \( K_c \), is shown in Equation 5.11.
\[
k_c = \frac{k_{c1.1}}{h^{m_c}} \cdot C1 \cdot C2 \quad \text{Equation 5.10}
\]

\[
V_{h_{(vd)}} = K\left(\frac{2v}{r^2 \tan \theta}\right)^{\frac{1}{3}} \left(\frac{k_c \cdot V_{vol}}{2 \cdot \nu \cdot 10^3}ight)^{\frac{1}{3}} \quad \text{Equation 5.11}
\]

Figure 5.3 shows the un-scaled predicted flank wear as a function of time, see Equation 5.3. As can be seen, the wear has an inverse relationship with the depth of cut, where the chip width enters the equation as a second order term. The reason for this inverse relationship is that the equation is built on the assumption that the normal stresses on the flank face can be expressed as a function of the feed force and the contact area.

![Flank wear graph](image)

Figure 5.3 Flank wear per time unit as a function of \(a_p\) and \(f\). Carbon steel is used as reference material and the wear constant is set to \(K=1\).

### 5.3.1 Validating the Flank Wear Model

In order to validate the flank wear model, experiments were carried out on a Cincinnati CNC Lathe, following ISO 3685 E, machining carbon steel, as specified in Table 5.1. The tool has a 14 \(\mu\)m thick CVD TiCN- \(\text{Al}_2\text{O}_3\)- TiN coating, and has been stated to be usable for high cutting speeds and dry machining. In order to estimate the wear constant
Condition Monitoring of Tools in CNC Turning

K, a total of 684,370 mm$^3$ of carbon steel was removed at a constant surface speed. Measurements of the flank wear were logged and the wear constant K was calculated for 7 wear measurements, see Table 5.2. Using the average wear constant, Figure 5.4 shows the expected theoretical average and actual measured wear behaviour. As can be seen from Figure 5.4, the predicted wear is overestimated in the range from 0 to 200,000 mm$^3$, and then becomes underestimated when more than 450,000 mm$^3$ of material is removed. Calculating the wear constant K for each measurement also reveals a different constant. The explanation for this could be found in the actual measurement, where a SIP multipurpose optical measurement machine was used. The measurement relies in this case on human assumptions and, for measurements in the micro-range, only small misalignments in the setup could result in deviations. The MAPE of the flank wear experiment was calculated as 74.14%. This is of course an unacceptable error, however, since the experiment is carried out under dry cutting conditions, other researchers have suggested that the thermal softening of the cutting tool should be taken into account.

<table>
<thead>
<tr>
<th>Wear Test Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workpiece material</td>
</tr>
<tr>
<td>Initial diameter</td>
</tr>
<tr>
<td>Cutting length</td>
</tr>
<tr>
<td>Depth of cut</td>
</tr>
<tr>
<td>Cutting speed</td>
</tr>
<tr>
<td>Feed rate</td>
</tr>
</tbody>
</table>

| Tool holder | Sandvik PCLNR 3225P16 |
| Rake angle | -6 degrees |
| Entering angle | 95 degrees |
| Inclination angle | -6 degrees |
| Overhang ratio | 1.5 |

| Tool insert | CNMG120408-PR – GC4015 |
| Rake angle | 20 degrees |
| Effective rake angle | 14 degrees |

Table 5.1 Test data for wear test 1.
In this case, the reason for the poor fit is likely to be that the tool has been abused by being used to cut carbon steel under dry conditions, with a cutting speed that is out of the recommended range, in order to accelerate the wear.

<table>
<thead>
<tr>
<th>Test</th>
<th>$K$</th>
<th>Vol.</th>
<th>$V_b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0098</td>
<td>111734</td>
<td>0.0315</td>
</tr>
<tr>
<td>2</td>
<td>0.0299</td>
<td>216484</td>
<td>0.1200</td>
</tr>
<tr>
<td>3</td>
<td>0.0273</td>
<td>314251</td>
<td>0.1240</td>
</tr>
<tr>
<td>4</td>
<td>0.0265</td>
<td>405035</td>
<td>0.1310</td>
</tr>
<tr>
<td>5</td>
<td>0.0344</td>
<td>488835</td>
<td>0.1810</td>
</tr>
<tr>
<td>6</td>
<td>0.0386</td>
<td>565652</td>
<td>0.2130</td>
</tr>
<tr>
<td>7</td>
<td>0.0381</td>
<td>635486</td>
<td>0.2185</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.02922</strong></td>
<td><strong>640473</strong></td>
<td><strong>0.1896</strong></td>
</tr>
</tbody>
</table>

Table 5.2 Validation of the flank wear model.

![Flankwear, predicted and measured. Tested with carbon steel, a constant depth of cut of 2 mm, constant feed rate of 0.35 mm/r and cutting speed of 242 m/min.](image)

**5.3.2 Thermal Influence on the Flank Wear Behaviour**

This chapter will discuss the need for including the thermal softening in the tool wear model, since it has been described by several researchers [Zhao et al. 2002, Usui et al.].

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1984, Ezugwu et al. 2003] that the thermal properties play an important role when it comes to wear. The thermal softening of the cutting tool influences the wear behaviour. Looking at the hardness factor of the cutting tool \( H \), it has been stated by Zhao et al. [2002] to be exponential, see Equation 5.12.

\[
H(T) = H_0 \exp(-C \cdot T) \tag{5.12}
\]

\( H_0 \) is the initial hardness of the cutting tool, \( T \) is the temperature and \( C \) is a constant.

Encountering the thermal softening in the turning application will result in a different behaviour. Citing Ezugwu et al. [2003], the thermal softening of a WC tool insert will reduce the hardness of this tool by approximately 1300 kg/mm\(^2\) for a temperature range of 0 to 1000° C. Taking this into account for the previous experiment, Figure 5.6 shows the expected values of flank wear as a range.

Looking at this from a practical point of view, many factors will influence the cutting temperature, such as feed rate, depth of cut, thermal conductivity and cutting speed, but the tool wear itself can be expected to make a large contribution to the temperature rise. The heat generation occurs in four different zones in the cutting region, at the primary deformation zone, (shear plane), the secondary deformation zone, the friction zone along the tool-chip interface on the rake face of the cutting tool and finally at the tool-workpiece interface. The latter of these is mainly due to wear, where the increased wear land increases the contact area, which means that for a new tool, only three heat generating zones exist [Dogu et al. 2006].

Several analytical models have been developed, where some only consider the temperature distribution on the shear plane. In the review by Tay [1993], a model classified as the moving heat source method is described, where two heat sources are defined, one at the primary deformation zone and the other at the tool-chip interface.
Figure 5.5 Asperity hardness for tool materials, [Ezugwu et al. 2003].

Figure 5.6 Flank wear prediction with expected thermal softening.
These heat sources are products respectively of the shear force and the velocity along the shear plane, the friction force along the rake face of the cutting tool and the chip velocity. Estimating and measuring temperature is a complex task when models are built on experimental results. Saglam et al. [2006] described a method to estimate the tool-chip interface temperature. The average temperature rise at the tool-chip interface $\Delta T_c$ is described by Equation 5.13.

$$\Delta T_c = \frac{P_a}{m_{cr} \cdot c_s}$$

Equation 5.13

The empirical relationship for temperature measurement in the plastic deformation zone is shown in Equation 5.14, where $\delta$ is estimated as in Equation 5.15.

$$\log \left( \frac{\Delta T_m}{\Delta T_c} \right) = 0.06 - 0.195 \delta \sqrt{\frac{R_f h_w}{l_t}} + 0.5 \log \left( \frac{R_f h_w}{l_t} \right)$$

Equation 5.14

$$\frac{\delta}{h_c} \approx 0.05 - 0.1$$

Equation 5.15

$$T_s = T_0 + \lambda_n (1 - \lambda_s) \frac{F_s \cdot v_z}{MRR_c \cdot c_b}$$

Equation 5.16

Considering the average shear plane temperature $T_s$, Equation 5.16, the estimation can be made using data available for the workpiece material, where $MRR_c$ is the mass removal rate and $c_b$ is the specific heat coefficient of the workpiece. In the shear plane temperature, Equation 5.16, $\lambda_s$ is the fraction of the heat that is conducted into the workpiece. Shaw [2005] describes an estimate of $\lambda_s$ using the empirical Equation 5.17 and Equation 5.18. $\lambda_n$ considers the plastic work done outside the shear zone and a value of 0.7 can be used for carbon steel.

$$\lambda_s = 0.5 - 0.35 \log (R_f \tan \phi_c) \quad 0.04 \leq R_f \tan \phi_c \leq 10$$

Equation 5.17

$$\lambda_s = 0.3 - 0.15 \log (R_f \tan \phi_c) \quad R_f \tan \phi_c \geq 10$$

Equation 5.18

$R_f$, which is a non-dimensional thermal number, is given by Equation 5.19.
The average interface temperature rise at the rake facechip interface $T_{int}$ is given by Equation 5.20, where $\lambda_{int}$ is an empirical correction factor that accounts for temperature variations along the tool-chip contact zone [Saglam et al. 2006].

$$T_{int} = T_s + \lambda_{int} \Delta T_m$$  

Equation 5.20

Figure 5.7 Temperature prediction as a function of increasing tangential cutting force.

Figure 5.7 shows a predicted increase in temperature where the force is increased, but where a constant MRR is used. This can be expected to be equivalent to machining with increasing tool wear. As can be seen from Figure 5.7, the expected temperature increase will be approximately 90° C for an increase in the cutting force of 500 N. To estimate an approximation of the difference in the hardness, where Equation 5.12 is used and the constant is calculated from readings in Figure 5.5 to be 0.000965 for Al$_2$O$_3$ tools, the difference in hardness over a temperature span of 245 °C to 335 °C is found to be 128 kg/mm$^2$. In this calculation it is assumed that the tool temperature will be equal to the interface temperature, which in reality is not the case. However, the temperature increase gives a method of estimating the scenario.
The measured and predicted values of flank wear, when including the softness difference, can be seen in Figure 5.8. The difference between the two predicted wear curves is minimal, and it can be concluded that the temperature difference under normal conditions, will have no significant effect on the reliability of the wear model.

Although the tools used in this research have been classified to be suitable for dry cutting, it is expected that the excessive wear is in some way controlled by the temperature and the “abuse” of the cutting tool. This has been confirmed by other tests, where the material was removed at shorter intervals, where the cutting tool was allowed a cool-off period of 10-20 seconds. In total, 15 test pieces were machined using two tools for comparison. The machining length for each test piece was 70 mm, with a depth of cut of 3 mm, which means that each tool removed a total of 217,602 mm³ workpiece material. The predicted and measured values can be seen in Figure 5.9 and Table 5.3.
Figure 5.9 Predicted and measured flank wear. Machined using a cool-off period, carbon steel, depth of cut of 3 mm, feed rate 0.35 mm/r and cutting speed of 242 m/min.

5.3.3 Conclusion of Flank Wear

Throughout the research, it has been seen that most wear does not fit into the different models, and in case of flank wear, it has been close to impossible to find a model which can be considered generic. Different cutting conditions change the behaviour of the wear and it can be concluded that, although the models accommodate different cutting parameters, the real measured wear shows a significant error. It is assumed that a proportion of this error is caused by the fact that wear in this case is measured based on a human perception. It should also be expected that the different wear models, such as the flank wear model shown in Chapter 5.3, will only give a precise prediction when the experiments are carried out under the same conditions that were used to develop the model. Although it can be seen in Table 5.3 that a part of the model is relatively precise, the under- and over-estimation of wear, as previously described, is a problem at the beginning and at the end of tool life.
Table 5.3 Predicted and measured flank wear.

In this research this problem has been solved by allowing the wear constant $K$ to be a function of the removed workpiece material. This means that the problems with over- and under-estimation are solved; however, it must be expected, that the function of $K(V_{vol})$ will only be valid for the same tool/workpiece combination.

### 5.4 Crater Wear

Moderate crater wear does not normally limit tool life in the same way as flank wear. It has actually been said to increase the effective rake angle of the cutting tool [Stephenson and Agapiou 2006]. However, progressive and excessive crater wear can cause the cutting edge to break, resulting in fracture and catastrophic breakdown. Crater wear is characterised by the depth of the crater, and can be affected by factors such as high
cutting speed and/or temperature or when using tool and workpiece materials which interact chemically.

5.4.1 Contact Length

The tool-chip contact length is described in Chapter 2. As mentioned, different models exist, showing different behaviours. As can be imagined, abrasive crater wear originates from the chip sliding over the rake face of the cutting tool, where the wear contribution is a function of the normal force and tool/workpiece combination. If the wear was found to be uniformly distributed, this would cover the area produced by the tool-chip contact length and chip width. Although experiments have shown that this is not the case, the maximum crater depth can be measured in the area around the crater centre. Using the models shown in Chapter 2, the predicted and real contact length under different cutting conditions has been determined. The tools were investigated using a non-contact surface scanning white light interferometer, where the contact length was measured by the traces on the rake face of the cutting tool, see Figure 5.10. Neglecting any infinitesimal wear, the length was measured for 5 different feed rates, see Table 5.4 and Figure 5.11.

Figure 5.10 Tool-Chip contact length measure by white light interferometry.
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### Table 5.4 Measured contact length with changing feed rate.

<table>
<thead>
<tr>
<th>Feed rate</th>
<th>Test no 1 (v=160)</th>
<th>Test no 2 (v=180)</th>
<th>Test no 3 (v=200)</th>
<th>Test no 4 (v=220)</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.396</td>
<td>0.472</td>
<td>0.4135</td>
<td>0.399</td>
<td>0.4201</td>
</tr>
<tr>
<td>0.2</td>
<td>0.7223</td>
<td>0.8795</td>
<td>0.851</td>
<td>0.8115</td>
<td>0.8161</td>
</tr>
<tr>
<td>0.3</td>
<td>0.955</td>
<td>0.88</td>
<td>0.9005</td>
<td>0.8995</td>
<td>0.9087</td>
</tr>
<tr>
<td>0.4</td>
<td>1.131</td>
<td>1.3219</td>
<td>1.295</td>
<td>1.308</td>
<td>1.264</td>
</tr>
<tr>
<td>0.5</td>
<td>1.334</td>
<td>1.322</td>
<td>1.326</td>
<td>1.391</td>
<td>1.3433</td>
</tr>
</tbody>
</table>

As can be seen from Figure 5.11, the measurement shows the same trend for all 4 tests. Using the average measured contact length, despite it being a function of 4 different cutting speeds, and comparing this with the predicted contact length, using the three models described in Chapter 2, it can be seen that the real contact length is changing with feed rate, as predicted by models 1 and 3.
Increasing the cutting speed does not result in significant changes in the contact length. As can be seen in Table 5.4, there is no clear trend. However, it seems that there is a small decrease in contact length, which is only of a small proportion of the initial length, when measured with a cutting speed of 160 m/min. The MAPE between the cutting speed of 160 m/min and 220 m/min was calculated as 5.44 %, using Equation 5.21, where $l_{160}$ and $l_{220}$ are the contact length measured at 160 and 220 m/min.

$$MAPE_{160-220} = \frac{1}{n} \sum_{f=0.1}^{f_{0.5}} \frac{l_{160}(f) - l_{220}(f)}{l_{160}(f)}$$  \hspace{1cm} \text{Equation 5.21}

The MAPE calculated between the predicted models shown in Figure 5.12 and the average measured contact length, using Equation 5.22, can be seen in Table 5.5. Disregarding model 2, it seems that the models are underestimating the contact length for lower feed rates, when comparing with the real measurements.

$$MAPE = \frac{1}{n} \sum_{f=0.1}^{f_{0.5}} \frac{l_{\text{average}}(f) - l_{\text{predict}}(f)}{l_{\text{average}}(f)}$$  \hspace{1cm} \text{Equation 5.22}
As can be seen from Table 5.5, there is a significant error between the predicted and measured contact lengths. The explanation for this is most probably to be found in the fact that, as for most theory in metal cutting, this is only valid for a given set of conditions. It should also be considered that since the experiments in this research have been carried out under dry cutting, variations should be expected. As described by Friedman and Lenz [1970], one of the important parameters affecting the contact length is the tool material, where the temperature field in the contact zone causes variation in the chip curl. Other factors have also been mentioned, such as workpiece material and coolant type. Introducing the empirical constants $C_{L1}$ and $C_{L2}$, which are valid for this tool/workpiece combination, under the same set of conditions, the contact length can be approximated by Equation 5.23.

$$l = C_{L1} \left( \frac{h \sin(\phi + \beta - \alpha)}{\sin \phi \cos \beta} \right)^{C_{L2}}$$  \hspace{1cm} \text{Equation 5.23}

The coefficients are found by nonlinear regression, using the data in Table 5.4 and Table 5.5. For the tool/workpiece combination, AISI 1045 equivalent and Sandvik CNMG 12 04 08-PR, using feed rate of 0.1 to 0.5 mm/rev and cutting speed from 160 to 220 m/min, the coefficients were calculated as shown in Equation 5.24.
\[ C_{f1} = 1.6474 \]
\[ C_{f2} = 0.6758 \]

Equation 5.24

Figure 5.13 Measured average contact length versus predicted.

Figure 5.13 shows the predicted contact length versus the average measured contact length, using the changes in undeformed chip thickness and shear plane angle shown in Table 5.6. The MAPE between the predicted and measured values was calculated as 7.768%.

<table>
<thead>
<tr>
<th>Feed Rate</th>
<th>( h - \text{mm} )</th>
<th>( \phi - \text{deg} )</th>
<th>( \beta - \text{deg} )</th>
<th>( \alpha - \text{deg} )</th>
<th>( l_{\text{predicted}} - \text{mm} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1 mm/r</td>
<td>0.0996</td>
<td>45.1252</td>
<td>40.5651</td>
<td>14</td>
<td>0.5086</td>
</tr>
<tr>
<td>0.2 mm/r</td>
<td>0.1992</td>
<td>50.5669</td>
<td>40.5651</td>
<td>14</td>
<td>0.7804</td>
</tr>
<tr>
<td>0.3 mm/r</td>
<td>0.2989</td>
<td>53.7798</td>
<td>40.5651</td>
<td>14</td>
<td>1.0042</td>
</tr>
<tr>
<td>0.4 mm/r</td>
<td>0.3985</td>
<td>56.0505</td>
<td>40.5651</td>
<td>14</td>
<td>1.2018</td>
</tr>
<tr>
<td>0.5 mm/r</td>
<td>0.4981</td>
<td>57.7982</td>
<td>40.5651</td>
<td>14</td>
<td>1.3820</td>
</tr>
</tbody>
</table>

Table 5.6 Changes in cutting geometry using different feed rates.

Different wear tests show that the crater development and contact length are related. In most cases, the crater developed in the middle of the cutting edge and the contact length, as shown in Figure 5.14.
5.4.2 Abrasive Crater Wear

El-Gallab and Sklad [2000] described a comprehensive tool wear model for abrasive wear, which depends on the ratio of the hardness of the inclusions in the workpiece to that of the tool. A similar approach was adopted by Huang and Dawson [2005], where the main wear mechanism resulting in volumetric loss is due to abrasion, adhesion and diffusion. They constructed a model that accounts for all three contributions. However, in this case, only the abrasive contribution will be used as a crater wear quantifier, see Equation 5.25.

\[
d\frac{K_t}{t} = K_{\text{abrasion}} K_{\text{cw}} \left( \frac{P_a}{H^n} \right)^{n-1} v_c \cdot k_h \cdot \sigma
\]  

Equation 5.25

In the abrasive contribution, shown in Equation 5.25, the constant \( K_{\text{abrasion}} \) is a constant relating to the abrasive wear contribution. The constant \( K_{\text{cw}} \), which is a known function of the hardness ratio, can be determined from Equation 5.29 [Huang and Liang 2004]. Equation 5.26 expresses the crater wear as a function of time. \( P_a \) and \( H \) is respectively the workpiece and tool hardness, \( \sigma \) is the normal stress and \( k_h \) is the crater front distance.

\[
\int \frac{dK_t}{dt} dt = \int K_{\text{abrasion}} K_{\text{cw}} \left( \frac{P_a}{H^n} \right)^{n-1} v_c \cdot k_h \cdot \sigma \cdot dt
\]  

Equation 5.26

Expressing this as a function of removed material under different cutting conditions, using the isolated \( t \) from Equation 5.7 is used in Equation 5.27.

\[
K_t = K_{\text{abrasion}} K_{\text{cw}} \left( \frac{P_a}{H^n} \right)^{n-1} \left( \frac{V_{\text{vol}}}{v \cdot f \cdot a_p \cdot 10^3} \right) v_c \cdot k_h \cdot \sigma
\]  

Equation 5.27
Inserting the chip velocity over the rake face of the cutting tool, where the normal stress is assumed to be uniform, the crater can be estimated by Equation 5.28.

\[ K_i = K_{ab} \cdot K_{cw} \left( \frac{P_o}{H^n} \right)^{n} \frac{V_{vel}}{V_{r} \cdot f \cdot a_p \cdot 10^3} \left( \frac{\sin \phi}{\sin(\phi - \alpha)} \right) \left( \frac{N_c}{l \cdot i_a} \right) \cdot k_h \]  

Equation 5.28

\[ n = 1.0, \quad K_{cw} = 0.333, \quad \text{when} \quad \frac{H}{P_o} < 0.8 \]  

Equation 5.29

\[ n = 3.5, \quad K_{cw} = 0.189, \quad \text{when} \quad 1.25 > \frac{H}{P_o} > 0.8 \]  

\[ n = 7.0, \quad K_{cw} = 0.416, \quad \text{when} \quad \frac{H}{P_o} > 1.25 \]

5.4.3 Predicting Crater Depth for Constant Parameters

Using 7 measurements, the crater depth was measured. This was done by having a fixed reference on the rake face of the cutting tool and measuring the distance from that reference to the new focal length of each sample. The cutting conditions were kept constant in order to find \( K_{abr} \). The test data can be seen in Table 5.1. The predicted and measured values of the crater wear can be seen in Figure 5.15. Using a calculated mean \( K_{abr} \) for this workpiece/tool combination, shown in Table 5.7, the MAPE was calculated from the data in Table 5.7 to be 13.08%, using Equation 5.30. In the test there was no significant development in \( k_h \) at the beginning, and it was only at the end when changes started to take place. Although \( k_h \) was observed to be in the range of the contact length, it was difficult to estimate if a real crater had developed in that region or if it was due to traces of workpiece material on the rake face.

\[ MAPE_{K_i} = \frac{1}{n} \sum_{k=1}^{n} \frac{K_i(k) - K_{ip}(k)}{K_i(k)} \]  

Equation 5.30

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Table 5.7 Measurement data for crater wear under fixed cutting conditions.

Assuming that the crater will expand to a maximum at the theoretical contact length, which means that \( l \approx k_n \) and that the normal stress is uniformly distributed on the rake face, where the contact length and width of cut is used as the area, Equation 5.28 can be simplified as shown in Equation 5.31.

![Graph](image-url)

Figure 5.15 Measured and predicted crater wear machining carbon steel with constant depth of cut of 2 mm, feed rate of 0.35 mm/r and cutting speed of 242 m/min.
Figure 5.16 Predicted crater wear per time unit as function of feed rate and depth of cut using AISI 1045 carbon steel.

Figure 5.16 shows the predicted time/wear behaviour as a function of feed rate and depth of cut, given per time unit. As can be seen, the crater is predicted to grow when the feed rate is increasing, where the depth of cut has no affect on the crater growth. The depth of cut will naturally change the normal force working on the rake face, as shown in Figure 5.17. However, it can be expected that the increasing chip width will distribute the force over an equivalent area. The crater prediction as a function of feed rate and cutting speed can be seen in Figure 5.18. Although the original model is built as a function of time, as shown in Equation 5.25, it has been rewritten to be a prediction of removed workpiece material. What controls the wear in the model is the time the tool is engaged in the workpiece, as well as the tool/workpiece combination and the normal force.

\[ K_i = K_{\text{abrasion}} K_{\text{cr}} \left( \frac{P_{d,0}^{n-1}}{H^n} \right) \left( \frac{V_{\text{vol}}}{v \cdot f \cdot a_p \cdot 10^3} \right) \frac{\sin \phi}{\cos(\phi - \alpha)} \frac{N_c}{i_a} \]

Equation 5.31
Figure 5.17 Normal forces $N_r$ on the rake face as a function of depth of cut and feed rate with 14 degree rake angle in AISI 1045 equivalent carbon steel.

Usually, tool wear models are given with the tool life as a function of time, which means that the tool will have a shorter life when the cutting speed is increased, which is true. However, in this case, increasing the cutting speed will change the material removal rate, removing the material at a faster rate. Increasing the feed rate and cutting speed will, in the rewritten model, lead to a lower contribution of crater wear, since the tool will be engaged in the workpiece for a shorter time in order to remove the same amount of material, see Figure 5.19. Considering the behaviour in Figure 5.19, there is of course a limit to how far this analogy can be taken, since a very high feed rate, cutting speed or depth of cut would, in theory, result in a near zero wear contribution, but in reality this will not be true. At this point, the predicted behaviour will be assumed to be true when the cutting is carried out within the boundaries of these experiments and when the cutting tool is not abused.
Figure 5.18 Predicted crater wear per time unit as function of feed rate and cutting speed using AISI 1045 carbon steel.

Figure 5.19 Predicted crater depth, as a function of volumetric removal of 684370 mm$^3$ of AISI 1045 carbon steel.
5.4.4 Quantitative Crater Wear

Each amount of material removed can be considered to add to the physical deterioration of the cutting tool. In order to evaluate the proposed model, different cutting tests were carried out under changing cutting parameters. For each entrance and exit, the wear is added up and compared to the predicted solution. The mean $K_{\text{abrasion}}$ from Table 5.7 is maintained, since the experiment used the same tool/workpiece combinations and geometries. The measured and predicted values of $K_r$ can be seen from Figure 5.20 and Table 5.8, where the MAPE is calculated as 3.623%.

![Figure 5.20 Predicted and measured crater depth using changing cutting parameters using carbon steel.](image)

<table>
<thead>
<tr>
<th>Measurement</th>
<th>$K_r$ measured, mm</th>
<th>$K_{sp}$ predicted, mm</th>
<th>Removed, mm$^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0065</td>
<td>0.0074</td>
<td>44745</td>
</tr>
<tr>
<td>2</td>
<td>0.0115</td>
<td>0.0135</td>
<td>107741</td>
</tr>
<tr>
<td>3</td>
<td>0.0156</td>
<td>0.017</td>
<td>184671</td>
</tr>
<tr>
<td>4</td>
<td>0.0190</td>
<td>0.022</td>
<td>270040</td>
</tr>
<tr>
<td>5</td>
<td>0.0230</td>
<td>0.0231</td>
<td>318906</td>
</tr>
<tr>
<td>6</td>
<td>0.0263</td>
<td>0.0251</td>
<td>350306</td>
</tr>
<tr>
<td>7</td>
<td>0.0291</td>
<td>0.0284</td>
<td>393285</td>
</tr>
<tr>
<td>8</td>
<td>0.0322</td>
<td>0.0315</td>
<td>443525</td>
</tr>
<tr>
<td>9</td>
<td>0.0354</td>
<td>0.0331</td>
<td>495531</td>
</tr>
</tbody>
</table>

Table 5.8 Accumulated predicted and measured crater depth.
5.5 Conclusion of Wear-quantifying Model

This chapter has described the use of two empirical tool wear models and shown the different considerations made in conjunction with analytical predictions of tool wear. As has been mentioned, although a certain degree of error must be expected, it has been shown that it is possible to estimate a relative precise wear progression under changing cutting parameters when the constant for the particular tool/workpiece combination is known. The flank wear model has shown an overestimation of wear in the initial stage and afterwards an underestimation. The reason for this probably originates from the exponential development of the flank wear constant $K$. It is suggested that it is replaced with a regression model, approximating $K$ as a function of removed workpiece material.

The crater wear has shown linear characteristics, and therefore the model chosen has been able to describe the development of crater wear using an averaged constant $K_{abrasion}$, where reasonable results have been obtained. The two proposed models are used later on in this research in order to predict the expected dominant wear type, either crater or flank wear, which will assist the on-line monitoring system. It will be shown later that crater wear is difficult to detect using AAE and although it is not directly limiting tool life in the same sense as flank wear, the decreased crater front distance is increasing the risk of a tool fracture.
Chapter 6

6 Sound Signatures

In order to estimate tool wear from airborne acoustic emissions some sound signatures must be identified. In this case, tool fracture and gradual wear are separated in two different models. The way in which tool fracture and gradual wear can be separated relies on fracture having a signature which occurs over a short period in the time domain and which is not as recognisable in the frequency domain, since the fracture itself, including the following amplitude increase or decrease, can be mistaken for being related to other sound signatures. On the other hand, monitoring gradual wear in the time domain is not always efficient because of the fluctuating nature of the signals. It can be done to some extent by exploiting the knowledge of the waveform characteristics as a function of tool wear. The gaps in the research in this field are not only related to the lack of general use of AAE in TCM, which has attracted much less research interest than AE, but to the lack, in both fields, of any organised structure in the relationship between different parameters, such as the cutting parameters themselves but also external parameters, such as disturbances and noise. This chapter will describe the different key elements, which need to be identified in order to predict the state of the actual cutting process for a relevant industrial turning application, in order to exclude disturbances that affect the results.

6.1 Experimental Setup

This research has been conducted on a Cincinnati CNC lathe, machining primarily carbon steel, in order to narrow the research focus. The experimental setup basically consists of a CNC lathe, and a data acquisition system using a normal condenser microphone as the sensor, see Figure 6.1.
A microphone is placed inside the CNC machine; in this case as close to the cutting tool as possible, in order to obtain the best measurements, see Figure 6.2. In reality this placement could be arbitrary, in fact another placement of the microphone would be required since this region is subject to heavy disturbance by chips. However, in the research/analysis case, this is not significant since the data can be excluded or reproduced. This is not the case in an industrial application, where wrong decisions and misinterpretations are likely to have financial consequences. The schematic of the experimental setup can be seen in Figure 6.3. The microphones are studio-quality condenser microphones with a cardioid pick-up pattern, having a frequency response of 20 Hz to 20 kHz. The microphones are Phantom-powered and connected to the amplifiers through shielded XLR cables. The USB-6009 data acquisition is capable of logging four channels simultaneously with a sampling rate of 100 kHz. In this case the sampling rate used for two channels is 44 kHz, in order to capture frequencies up to 20 kHz.
6.2 Key Elements to Identify

The key elements that need to be defined are basically tool wear, both gradual wear and fracture, and noise. Noise includes normal background noise, hydraulic pumps or disturbing parameters such as heavy chip flow, coils of workpiece material wrapped around the workpiece, etc. The sound heard during the machining process contains all these elements, but since humans have a superior auditory system, which can identify different sound signatures and separate these in a multi-dimensional system, this is not
seen as a problem in daily life. In the world of automatic TCM systems it is different. Numerous researchers have mentioned the drawbacks of using AE or AAE, because the sensing methodology is sensitive to things other than pure tool information. As has already been noted, AE, as well as AAE, is sensitive to almost all the parameters in the cutting process.

6.2.1 Tool Wear
To identify tool wear, two elements are required. The signatures of both a normal and of a worn tool must be known. This is actually just a binary representation of tool wear. In between, several states of tool wear exist. Another problem which occurs when classifying tool wear is that the sound signature of the wear cannot be expected to behave similarly under different cutting conditions. The sound coming from the machining process is a product of the energy put into the process, but before it reaches the sensors it goes through a transfer function, which is unknown. Tool wear is described as being flank and/or crater wear, and in contrast to tool fracture, it is a gradual process which slowly alters the features chosen to describe the wear.

6.2.2 Tool Fracture
Progressive and unattended tool wear will result in fracture and the process must be stopped immediately. The signature of a tool fracture in the time-domain will be seen as a sudden burst signal, followed by increased SPL. However, in order to avoid misinterpretations, which will result in unnecessary tool changes or stops, the tool fracture must be identified in a way such that it will not be confused with a process disturbance. Two types of fracture can be defined as:

- Partial Fracture
- Complete Fracture

A partial fracture occurs when only a small portion of the cutting edge breaks off, which is often the case when a built-up edge breaks off.
In this research, a *partial fracture* will be defined as the situation where a tool still retains some of its ability to cut off material without a catastrophic failure immediately resulting. A complete fracture can be seen in Figure 6.5.

**6.2.3 Disturbances**

When using AAE, a major problem in the machining environment is disturbances. Depending on the dynamic range of the microphones and background noise, disturbances...
are picked up along with the cutting signal. Also, disturbances from the process itself are a problem, where long, unbroken coils of metal are wrapped around the workpiece and then hit against the tool, the tool holder or even the microphone, which causes disturbances that will unavoidably cause misjudgements. Burst signals from the chip flow can also result in misinterpretations. This is a phenomenon from real-life machining, which must be identified in order for the signals to be disregarded when they occur.

6.3 In-Process Signatures

Using the time domain in TCM is not a simple task, since time domain parameters are fluctuating. However, the advantage of using a time domain analysis is exactly this point, since sudden changes can be revealed instantly. This research has shown that different parts of the tool monitoring can be successfully conducted in the time domain. Tool wear, at least to a certain extent, fracture and disturbances are revealed in the time domain by irregularities, which cause deviations in a periodic regular waveform. In-process signatures are defined as sound signatures related to the process, which occur between the tool entering and exiting the workpiece.

6.3.1 Tool Entering the Workpiece

It must be considered when and how the tool enters the workpiece. As can be expected, the tool entering will create an array of burst signals, behaving as a function of the actual angle of entry as well as other parameters, such as depth of cut and feed rate. Not only must this behaviour be known in order to exclude the actual tool entering in the monitoring procedure, but also in order to decide when to start the actual monitoring. The different stages of the entering process can be seen in Figure 6.6.
The RMS values of the SPL, see Figure 6.7, show a distinction directly at the point where the tool enters the workpiece, exactly as Figure 6.6 shows on its own. One of the benefits of using RMS values is that it adds power to the higher signal. However, this also reinforces burst disturbances from noise. The tool entering will in some cases create a waveform, which will have some of the characteristics of tool fracture, though this depends on the type of fracture, where the RMS energy will be 'boosted' to a certain level. However, analysis has shown that there are differences which can distinguish this situation. Looking at the RMS values in this example, it can be seen that a difference exists when it comes to tool entering and tool exit. The RMS values immediately drop to a low level when the spindle is stopped and the tool exits the workpiece. However, this is not the case when it comes to the tool entering the workpiece, where the spindle is started at the moment the cutting tool is positioned. Figure 6.7 shows a gradually increasing RMS level from position 100 to 190, followed by a sudden increase in the RMS value at tool entry. This increase is not overly significant because of the spindle noise. Noise from the spindle is a function of spindle speed, which is related to the workpiece diameter when machining with the option of constant cutting speed. Therefore, it should be pointed out that when machining with 'light' parameters, which means low depth of cut and low feed rate, the RMS increase as the tool enters the workpiece might be in a proportion which will be lower than the constant RMS values from the spindle noise.
RMS is an averaged value over a sample length and, although it gives power to higher peaks, the ‘rising edge’, which can be used as a trigger mechanism in order to detect entering, is also averaged out. Defining a trigger mechanism consisting of time domain parameters can be assisted by using the average wavelength parameter which has been shown to be consistent and not largely affected by noise, see Figure 6.8. Using these time-based parameters, a trigger function can be defined, however, one must define a time interval within the rising and falling edge.

Figure 6.7 RMS at tool entering and exit machining carbon steel with 95 degree entering angle using feed rate of 0.2 mm/r, depth of cut of 1 mm and cutting speed of 165 m/min.

Figure 6.8 RSM values at tool entering and exit.
6.3.1.1 Effect of Entering Angles

The different entering angles, which are presented in a normal process, play a role in deciding tool entering. A high entering angle causes a 'shock-like' entering process, gradually decreasing, whereas a lower entering angle allows the tool to engage the workpiece in a smoother way. This all has to do with the instant force, which is affecting the cutting tool exactly at the point of entry, where the chip width and chip thickness determines the amount of material removed. In the previous examples in this chapter, tool entering has been shown with an entering angle of 95 degrees, which means that the effective chip thickness is approximately equivalent to the feed rate.

![Figure 6.9 Time domain signature for tool entering with 60 degree entering angle, 1 mm depth of cut and 0.2 mm/r feed rate.](image)

Figure 6.9 shows a process using a 60-degree tool holder with a diamond-shaped tool insert, where the process is equivalent to Figure 6.6 in chapter 6.3.1.

6.3.2 Tool Fracture

There are different definitions of tool fracture. In the case of a catastrophic fracture, where the tool insert is demolished and removed from the tool holder, and where the depth of cut doesn't exceed the portion of the tool insert which extends from the tool holder, it is fairly easy to distinguish fracture from tool entering. In Figure 6.10 a tool fracture is shown, where the tool insert is torn out of the tool holder during entering. The
fracture takes less than 0.2 second; hence, at a sample rate of 44 kHz, one should allow at least 8800 samples to pass in order to rule out fracture at tool entering.

![Graph showing tool fracture at entering.](image)

*Figure 6.10 Tool fracture at entering.*

### 6.4 Machining Parameters

Machining parameters are related to the cutting process itself. This research is mainly concentrated on the four parameters directly related to the process, which are cutting speed, depth of cut, feed rate and material properties.

#### 6.4.1 Effect of Cutting Speed

Cutting speed is a factor which is directly related to the MRR, where it is entered along with feed rate and depth of cut, as seen in Equation 6.1.

\[
MRR = v \cdot f \cdot a_p
\]

*Equation 6.1*

Cutting speed controls the chip flow over the rake face of the cutting tool as given by Equation 6.2, [Moufki et al. 2006].

\[
v_c = v \frac{\sin \phi}{\cos(\phi - \alpha)}
\]

*Equation 6.2*

This is important, since the secondary zone accounts for the sliding friction over the tool face, where the friction component is controlled by the normal force from the tool/chip contact [Sani and Park 1996]. Different tests have shown that cutting speed changes
influence the results in, what later in this research will be described as, the force components in the frequency range.

6.4.2 Effect of Feed Rate

Feed rate is what is defined as a force component in this research, where the tangential force is regarded as a product of the feed rate, depth of cut and material properties. This is a simple representation of the static cutting force. The feed rate is a proportional factor in the MRR equation, and represents the uncut chip thickness. In this research, both feed speed and feed rate are used, where the effective feed speed is the tool’s velocity through the workpiece, given in mm/min, independent of spindle speed. Parameters, feed rate and depth of cut, change the characteristics of the sound signature. Figure 6.11, shows an alteration of the feed rate from 0.2 mm/r to 0.3 mm/r leading to changes in both the wavelength and the amplitude of the waveform.

![Figure 6.11](image)

Figure 6.11 Time domain signatures with feed rate changes for carbon steel, (a) feed rate 0.2 mm/r and depth of cut of 1 mm, (b) feed rate 0.3 mm/r and depth of cut of 1 mm.

6.4.3 Effect of Depth of Cut

As mentioned above, a relationship between the parameters feed rate and depth of cut exists. However, when it comes to putting numbers to these parameters in the time domain, some problems arise.
Figure 6.12 Time domain signatures with depth of cut changes for carbon steel, (a) feed rate 0.2 mm/r and depth of cut of 1 mm, (b) feed rate 0.2 mm/r and depth of cut of 2.5 mm.

Extracting scalar informative values from waveforms can be a difficult task, because the feed rate and depth of cut components in some cases will have the same signature. In Figure 6.12, a waveform is shown for a machining example where only the depth of cut is changed, which in this case affects the amplitude parameters more than the spacing parameters as in the case of feed rate.

### 6.4.4 Gradual Wear

The main idea of having a TCM system is of course to detect gradual wear and to relate this to an upcoming fracture and reaching a decision about when the tool’s life is at an end. There have been many proposals from researchers in order to detect tool wear, and most of these systems use a method where a decision-making model is learning from measured samples. However, although only two types of gradual wear, flank and crater wear, are defined in this research, this is a very costly and time-consuming procedure, because an infinite number of combinations of cutting parameters, wear types and wear stages exists.

### 6.5 Disturbances

Disturbances are defined as uninformative signals picked up by the sensor, which include noises from the surroundings, parallel machining, noises from the structure of the
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machine, such as spindle noise or hydraulic noise, but also from the process itself, such as disturbances from chips, etc. The internal disturbances are dealt with by excluding the tool-state decision at the moment they occur, since it has proven impossible to filter out many of these disturbances without losing information in the cutting signal. The same principle is used for external disturbances, described in the next chapters.

6.5.1 External Background Noise

One of the considerations in this research, is the effect of disturbances from parallel machining, a drawback which is pointed out earlier in the literature review. The sound from the work environment on the shop floor travels through the air, and although the CNC machine can be thought of as a capsulated ‘tin can’ containing the sensor, it is not well insulated with respect to sound. A measurement was made of how the sound is transferred from the surrounding environment into the machine, using two condenser microphones, placed apart with the distances L and Z, where the schematic can be seen in Figure 6.13.

![Figure 6.13 Sound transfer measurement using two condenser microphones.](image)
6.5.2 Burst Background Noises

The burst background noises encounter signals from hammers, rapid tool-changing systems from neighbouring machinery, punch presses, etc. This type of noise resulted in the following measurement, made from an experiment with a sharp hammering noise, excited 5 metres from the machinery. Figure 6.14 shows the time-domain measurement and the PSD from the respective outside and inside measurements. The experiment was made under a no-load machining process, using the same amplification settings, where a maximum amplitude outside was measured in the range of 6 volts and the same spike inside was measured at 0.8 volts.

This shows a significant damping. However, the burst spike can result in interference with the tool monitoring, since it can be mistaken for a fracture. This attenuation is the reduction of the signals amplitude and its intensity, which for an acoustic wave is dependent on the distance travelled and follows the inverse square law, giving exponential decay. An experiment was carried out where the background noise was kept to a minimum for both microphones, with the purpose of finding the time difference for the sound to travel between them, in order to determine the delay as well as the attenuation. This experiment was carried out using only one outside microphone assuming, in this case, that the sound will be radiated to the front of the machine. Using a cross-correlation analysis from measurements made with the door of the CNC machine closed, the delay is shown graphically in Figure 6.15.
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Figure 6.15 Time delay of the sound radiated from outside to the inside with the door closed.

In Figure 6.15a, the maximum peak occurs after 0.0214 seconds, which means that the waveforms shown in Figure 6.15b and Figure 6.15c correlate after this time-interval. Estimating the directionality of the sound in the CNC machine is a complex task, since the sound is a product of the original sound attenuated in the process of entering the CNC machine, refracted in that process, reflected in the machine, constructed and destructed on its way, through its interaction with other sound waves. A sketch of the complexity is shown in Figure 6.16. In order to be able to show this in a sketch, the problem has been simplified, since the sound radiation is spherical. The behaviour of the sound is of course a product of the acoustic properties of the machine. Dealing with this can be done using
the knowledge of the time delay and attenuation to determine if the noise is coming from
the environment, or from inside the process.

Figure 6.16 Expected behaviour of sound when entering a CNC machine.

The reduced amplitude can be expressed as Equation 6.3, where \( A_0 \) is the amplitude of
the propagating wave at the initial location, in this case at microphone placement 1, and
where \( \alpha_a \) is the attenuation coefficient of the wave travelling in the \( z \) direction.

\[
A = A_0e^{-\alpha_a z} \quad \text{Equation 6.3}
\]

The attenuation coefficient can therefore be calculated using the knowledge of the
respective maximum peak/valley amplitudes from outside and inside the CNC machine,
see Figure 6.17. In this case, where the distance between the two microphones is fixed,
the length \( z \) becomes irrelevant, since the attenuation is just a function of the sound
transfer, including the scattering and absorption effects, between the sounds from the
work environment at the front of the machine, to the sensor pickup in the machine.
Using Equation 6.3, disregarding z, the attenuation coefficient can be calculated from Equation 6.4, using a mean value of three experiments.

\[
\alpha = -\ln\left(\frac{A}{A_0}\right) = -\ln\left(\frac{0.4150 + 0.5468 + 0.5424}{3}\right)\frac{7.682 + 7.684 + 7.681}{3} = 2.7293
\]

Equation 6.4

6.5.3 Detecting Noises from Work Environment during Machining

In order to detect noises coming from outside the CNC machine, the delay calculated in section 6.5.2 of approximately 0.0214 seconds, can be used to determine the direction of the signals. However, during the machining process, other sounds are present in the machine, which will interact with the sound coming from outside and either destroy the signal or construct a new signal by adding the waveforms. Since we are interested in significant burst noises, as shown in Figure 6.14, the expected attenuated signal will be added to the waveform from the machining process. However, since it will be impossible to estimate the phase conditions of that waveform, which can result in destruction or construction of the waveform, the information of the mean absolute maximum amplitude of the cutting process can be used. Since it is not practical to consider every sample in the process, each consideration is divided into intervals. Knowing that the time delay between the two expected spikes is 0.0214 seconds, and using a sample rate of 44 kHz, this interval must be less than 941 samples. As with the detection of noises excited from
the cutting process, where the idea in this research has been to detect the signatures of disturbances in order to exclude decisions of the monitoring process in those periods, the same principle is used for the burst noises. Assuming that the static noise from the work environment is contained in the signal, the burst noise will result in \( \Delta A_0 \) and \( \Delta A \), respectively outside and inside the CNC machine, see Figure 6.18.

\[
\Delta A_0 = A_0 - A_{0\mu}
\]

\[
\Delta A = A - A_{\mu}
\]

Therefore, for the two separated intervals \( t_i \) and \( t_{i+1} \), separated by a time interval of 0.0217 seconds, an increase of \( \Delta A \) inside the machine should be equivalent to the increase \( \Delta A_0 \) outside, as shown in Equation 6.7.

\[
\Delta A_0 e^{-\sigma} = \Delta A
\]

The RMS is adequate when using a mean absolute value to describe burst signals, since it gives power to higher values, in this case the burst disturbances. However, it has been noticed in the experiments, that fundamental differences exist between the signals captured outside and inside the machine, even after scaling the outside signal allowing for
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attenuation. This is due to reverberation in the CNC machine. An experiment was carried out where artificial reverberation was added to the signal captured from the outside microphone after attenuation, see Figure 6.19. The level of the attenuated and transformed signal from the outside microphone is relatively precise, however, when compared with the actual measured and plotted signal from the microphone inside the CNC machine, shown in Figure 6.19a, the span of the RMS increase is narrow. At this point, where it is mainly the spike of the RMS value which is interesting since the signal \( A_0 \) will not be used for modelling the wave \( A \), then the changes in the time intervals \( t, t + \Delta t \) can be used for comparison, in order to detect the burst disturbances and directionality.

![Graphs showing original and attenuated signals with reverberation](image)

Figure 6.19 RMS calculated from burst signals, attenuated and 'reverberated'.

At \( t, t + \Delta t \) a normal level of RMS exists for \( A_0 \). The increase \( \Delta A_0 \) at time \( t \) will be equivalent to \( \Delta A \) at time \( t + \Delta t \) +/- an expected error. Figure 6.20 shows an example of a machining process disturbed by noise from the work environment. The attenuated signal \( A_0 \) is added to the expected level of the RMS of signal \( A \), which can either be calculated as a mean
expected level, or by using a prediction of the AAE RMS described in later chapters. It can be seen from Figure 6.20d that the maximum RMS of signal \( A_0 \) is reached at interval 39, where, for signal \( A \), it reaches its maximum at interval 40, see Figure 6.20c. The error between the two values, \( \Delta A \) and \( \Delta A_0 \), can be calculated as 1.60%.

![Graphs showing RMS peak for a machining process with burst noise from work environment.](image)

**6.6 Conclusion of Sound Signatures**

This chapter has described the different problems which arise in the monitoring process as well as presenting a solution to deal with the external disturbances. Although different filtering techniques have been attempted, none have been successful. With respect to the nature of the disturbances in the machine, where those by coils of workpiece material, are especially unpredictable and chaotic and have been shown to influence the whole frequency spectrum, the best solution has been to recognise these in the time-domain, not for filtering purposes, but in order to evaluate, at a later stage, the tool wear decision made by the system.
Chapter 7

7 Time-Domain Analysis

Tool fracture and disturbances are revealed in the time domain by irregularities which are causing deviations in a periodic regular waveform. The time-domain can also be used as a descriptor of the energy level in the cutting signal. This chapter will describe the development of an AAE RMS prediction model, which will be used to predict the level of AAE RMS with only flank wear present. This is done in order to recognise situations where excessive crater wear is present, since the actual measured AAE RMS in this case will be lower. This chapter will also show that the SPL can be considered as a good representation of the energy in the process, represented by the scalar AAE RMS value, where the AAE RMS is increasing with the wear land.

7.1 Definition of a Regular and Irregular Waveform

It is necessary to explain what is meant by regular and irregular waveforms and how they occur. The regularity has been used to describe the changes in a waveform. This has been seen in the time-folding representation, which can be used to detect regularity in data series, [Sitz et al. 2001].

- A regular waveform is defined when the waveform is periodic.
- An irregular waveform is defined as when the waveform deviates from its periodic cycle and becomes random.

7.1.1 Regular Waveform Emitted from a Machining Process

The waveform produced by the acoustics emitted from the machining process is basically a sampling process which follows a sine curve. A normal machining process will give a
constant acoustic emission. Figure 7.1 shows a regular waveform emitted from a turning process with relative light cutting parameters.

Figure 7.1 Regular and periodic waveform emitted from machining carbon steel with 0.1 mm/r feed rate, 1 mm depth of cut and cutting speed of 165 m/min.

This research has shown that regularities in the sound emitted from the process are closely linked, not only to tool wear, but also to the load which is put on the cutting tool. The regular waveform is defined here as being periodic, as shown in Figure 7.1. Regularities are shown for processes with 'light' cutting parameters, such as feed rate and depth of cut, which indicate that regularity in the waveform is a function of the load on the cutting tool. Auto-correlation analyses have shown these tendencies in practically all samples in this research, supported by an entropy analysis of the time-based waveform. Autocorrelation is a tool which can be used for analysing time domain signals. It shows as a function of the amount of time shift if a signal matches a time-shifted version of itself, which can be said to be a cross-correlation of a signal with itself. The sample autocorrelation is defined as a normalized form of auto-covariance for a time series \( Y \), Equation 7.1.

\[
 r_n = \frac{\text{cov}_n}{\text{var}(Y)} 
\]

Equation 7.1

Figure 7.2 shows the autocorrelation of the waveform shown in Figure 7.1, and it can be seen that a periodic relationship exists, with a correlation factor of more than +/-2 for time lags of approximately 500 samples.
Figure 7.2 Double-sided auto correlation for a machining process of carbon steel with feed rate of 0.1 mm/r, depth of cut of 1 mm and cutting speed of 165 m/min.

7.1.2 Irregular Waveform Emitted from a Machining Process

The irregular waveform is observed with the progress of tool wear or unforeseen events, such as burst signals, from disturbances or actual fracture, but it has also been revealed in this research that load factors are changing the appearance of the time-based waveform. In Figure 7.3, a waveform from a machining process similar to that used in section 7.1.1 is shown, except where the feed rate is changed to 0.4 mm/r. An analysis from this process shows that the more load put on the tool, the more irregular the waveform becomes.
Figure 7.3 Irregular waveform emitted from machining carbon steel with 0.4 mm/r feed rate, 1 mm depth of cut and cutting speed of 165 m/min.

Figure 7.4 Accumulated amplitude distributions for (a) feed rate of 0.1 mm/r, (b) feed rate of 0.4 mm/r. Compared to the regular waveform, the average amplitude over time of an irregular waveform will tend to lie higher, and especially the spreading of the accumulated amplitude distribution will be larger, which can be revealed by simple measures of dispersion, such as the mean and standard deviation, shown in Figure 7.4.
7.2 Putting a Number to Irregularities

Putting a number to the irregularities can be achieved in several ways including the use of measures of dispersion or auto correlation, which gives a description of periodicities in the waveform. The method of calculating entropy can also be used.

7.2.1 Entropy of a Time-based Waveform

Entropy was introduced as a thermodynamic state variable but was promoted as a generic measure of system disorganisation, [Shannon 2001]. This is based on the hypothesis that a noise is a projection into a signal of a system in thermodynamic equilibrium. This means that noise will have the highest entropy value, while periodic sounds are considered as organised, which requires an extra energy to be reproduced in such a form, and therefore will have a considerably lower entropy value, Equation 7.2.

\[ H(x) = -\sum_{i=1}^{N} p(x_i) \log_{10} p(x_i) \]  

Equation 7.2

Entropy has been a major tool in information theory, but is rarely used in signal processing. However, different researchers have reported the use of entropy. Bercher and Vignat [2000] used entropy to estimate changes in PDF, (Probability Density Function). Smith and Player [1991] used the maximum entropy method in order to produce amplitude graphs for ultrasonic surface characterization, where surface parameters were extracted from the images. A method of using entropy to detect speech has been described by Ekstein and Pavelka [2004].
Figure 7.5 shows the entropy calculated under different feed rates and thereby under different tool loads. The energy representation in this signal, is of course a function of the feed rate which, when increased, will cause irregularities in the waveform. The experiments have shown a good correlation with Shannon [2001], as well as Ekstein and Pavelka [2004], where the entropy value increases along with irregularities in the time-based waveform. The trend in the mean entropy is shown in Figure 7.6.

Analysing different tests on an individual basis, it has been shown that the entropy is increasing when the force controlling cutting parameters are increased, such as feed rate.
and depth of cut. However, Figure 7.6 shows a small drop in the mean entropy when the feed rate is increased to 0.3 mm/r using a cutting speed of 200 m/min. This indicates that certain combinations of cutting speed and feed rate create a different harmonic situation, which is supported by calculating the mean entropy as a function of MRR, as shown in Figure 7.7. It can be seen, that the same level of entropy exists for different MRR rates using different cutting parameters. The sensitivity of structure-borne and airborne acoustic emission to machine tool setup and cutting conditions, such as feed rate, cutting speed and tool wear, has been described by numerous researchers, among them Dimla Snr [2000], Kopac and Sali [2001, Silva et al. 2000, Li [2002], Chungchoo and Saini [2000]. The entropy analysis supports the fact, that the acoustics emitted from the machining process are affected by the changing cutting parameters, and it is evident from Figure 7.6 that both feed rate and depth of cut are having a significant influence of the signal emitted. When it comes to cutting speed, Figure 7.6 shows a drop for a certain combination of cutting speed and feed rate, which is in good correlation with Chungchoo and Saini [2000]. They showed that for a certain combination of feed rate and cutting speed, the total energy of the force signals are dropping, crediting this to a drop in cutting forces when increasing the cutting speed.

Figure 7.7 Entropy as a function of MRR.
This observation has been confirmed by others [Seeker et al. 2004, Devillez et al. 2004, Saglam et al. 2007]. It should be mentioned though, that when using airborne acoustic emission, some differences and limitations must be expected, when comparing with
results from structure-borne AE, or vibration monitoring for that matter, because of the sensitivity to noise factors. In this case, the microphone will pick up sounds such as spindle and hydraulic noise, which means that the entropy value will not be a representation of the energy content only, but also represent other parameters.

7.3 Root Mean Square Energy of Cutting Signals

Estimating changes in the sound emitted from a cutting process is a very complex task, especially because of the ‘chaotic’ nature of the process and signals. There are many different parameters which have to be considered in order to build a reliable model. However, in order to show different characteristics of the system under changing parameters, an estimation of AE can be used. There is a fundamental difference between AE transmitted in the structure, and AAE transmitted through the air, as described in Chapter 4. Airborne acoustics are characterized by longitudinal waves, whereas structure-borne AE is normally characterized by Raleigh Waves. Analytical solutions have been established in order to estimate the AE RMS signal from the cutting process, [Chiou and Liang 2000, Chiou and Liang 2000.b]. However, relating AE emitted from the process to AAE is a different task. Many researchers have pointed out the fact that changing parameters in the cutting process will alter the AE or AAE emitted from the process, as well as the necessity of considering the different parameters in the surroundings. To sum up, what is already known is that AE refers to the elastic stress waves generated as a result of the release of strain energy in the material, [Kannatey-Asibu and Dornfeld 1981]. The sources of AE in metal cutting are plastic deformation and fracture, where fracture is related to discontinuous chip formation. The energy used for irrecoverable plastic deformation in the cutting zone is primarily due to the motion of dislocations in the material. By overcoming the drag forces, it releases strain energy and a stress wave produces displacement of the surface, which can be picked up by an AE sensor. As mentioned above, there is a fundamental difference between this and AAE, since the AAE emission can be expected to be a frictional product. However, using the theory of AE emission, where the energy used in the primary and secondary zone is accounted for as well as an added contribution of the energy in the tertiary zone due to wear, an approximation can be made. Claiming that there will be a direct relationship between the
structure-borne waves and the waves transmitted through the air from the same process is an analogy which has certain limitations, but claiming that the energy level used to cut the specific workpiece material will affect the SPL emitted from the process, will at this point be assumed to be valid. However, there are a number of factors which must also be considered before any attempts of drawing parallels are made. Looking at sound emission AAE, these waves will not have free access to the microphone mounted somewhere in the CNC machine. The signal picked up by the sensor, in this case the condenser microphone, will have been affected by parameters from the acoustic properties of the CNC machine, which will influence the reflection of the sound waves and create a 'reverb effect'. Most machinery is built of metal plates, which will have different characteristics. Considering that the AAE RMS can be a representation of the energy in the process, representing the deformation, separation and sliding friction from all the zones, and assuming that the force in the process can be expressed as a simplified model as described earlier, the AAE RMS will therefore contain information about the depth of cut, feed rate and cutting speed parameters as well as the properties of the material. Figure 7.8 shows a plot of the calculated mean AAE RMS values as a function of feed rate and depth of cut when machining carbon steel.

![Figure 7.8 Mean AAE RMS values measured with constant cutting speed v=180 m/min.](image-url)
7.3.1 Predicting AAE RMS from an AE RMS Model

As pointed out, AE and AAE are two different categories of sound, behaving differently and moving in two different media. However, this research is drawing parallels. The AE from the chip-forming process can be estimated using the shear energy method, but since those waves travel in solids, it cannot be assumed that this situation applies to the entire surroundings, just following a simple rule for the refraction of sound from one media to another. In the chip-forming zone, there will be disturbances from the chips and, although this research has been carried out under dry cutting conditions, in reality it can be expected that the coolant will absorb an amount of the sound waves. Experiments have shown that crater wear is decreasing the AAE in some situations, which means that, if a parallel can be drawn from the theory of AE where it is claimed that crater wear is increasing the effective rake angle and so lowering the AE, the AAE is a product of both the shear energy and the sliding friction. Although it can seem to be a minor matter, another consideration when it comes to relating the sound from one media to another is the fact that the media is changing when leaving the chip formation zone, which means that, rather than the sound being released into atmospheric air, it in fact enters a medium made up of a combination of air and coolant molecules. A significant temperature deviation should also be expected in this medium, close to the cutting tool. However, these considerations can be somewhat overestimated when considering the distance the sound must travel, all depending on the sensor placement. However, the decision on the sensor placement when capturing AAE, should take these considerations into account. In order to capture the AAE, which in this model is assumed to be related directly to the release of energy in the primary, secondary and tertiary zones, the sensor placement must be able to give a direct measurement. In AE and vibration measurement, a sensor placement as close to the cutting edge as possible has been stated to be imperative, [Scheffer and Heyns 2001]. However, this is not always practical, [Jemielniak 1999], since wiring and the cutting process itself might cause problems. Although, in order to obtain the best results for this research, the microphone has been placed very close to the cutting zone, this has resulted in practical problems where chips have disturbed the measurements. Under research conditions, this data can naturally be discarded, but in reality, this is a problem that must be considered. In order to understand the effects of the
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changing cutting parameters, it can be useful to look at the analytical prediction of structure-borne waves, AE. Several techniques have been used to analyse AE signals, where RMS is a convenient measure. The RMS is a measure of the energy content in the signal, which can be related to the work rate of the process. Using the theory from orthogonal metal cutting, described in Chapter 2, the cutting forces, rake angle and shear plane angle will affect the chip formation process and will, in a simplified case, represent the friction and shear power in the cutting process. The formation of the chip in the primary shear zone, its motion over the tool face and the sliding in the secondary zone is the main cause of the AE generated. Two distinct sources are identified by Kannatey-Asibu and Dornfeld [1981], where the work in the tertiary zone is disregarded:

- Deformation in the primary zone
- Deformation and sliding friction in the secondary zone

The disregard of the tertiary zone is based on the assumption that a sharp tool is used in the initial stage, where no flank wear exists, however, since this is not the case, this problem must be considered and will be dealt with later on. The resultant force can be calculated using the tangential and feed force components in Equation 7.3.

\[
F = \sqrt{F_t^2 + F_f^2}
\]  
Equation 7.3

The shear force can be expressed as Equation 7.4.

\[
F_s = F_i \cos \phi - F_f \sin \phi
\]  
Equation 7.4

The shear angle can be calculated using the following geometry, Equation 7.5.

\[
\phi = \tan^{-1} \frac{r_c \cos \alpha}{1 - r_c \sin \alpha}
\]  
Equation 7.5

The chip ratio can be calculated using Equation 7.6, where \( h_c \) can be found from experiments measuring the deformed chip thickness. However, an empirical formula is shown by Altintas [2000], Equation 7.7, where lookup tables can be used for specified material data.
\[ r_c = \frac{h}{h_c} \quad \text{Equation 7.6} \]
\[ r_c = c_{rc1} h^{c_{rc2}} \quad \text{Equation 7.7} \]

\( c_{rc1} \) and \( c_{rc2} \) are material constants which can be found in Oxley [1989]. However, in cases where experimental results exist, the approximated deformed chip thickness can be calculated from the following relation in Equation 7.8 [Trent 1984].

\[ h_c = \frac{h_m}{\rho \cdot a_p \cdot l} \quad \text{Equation 7.8} \]

The chip compression ratio, CCR, was said by Astakhov and Shvets [2004], to represent the true plastic deformation in metal cutting. Not only is the CCR important in this case, but it was also mentioned that it could be used to predict the work spent on the deformation in the cutting process.

Assuming that a uniform stress distribution in the shear plane exists, the shear stress can be calculated as Equation 7.9.

\[ \tau_s = \frac{F_s}{A_s} \quad \text{Equation 7.9} \]

The shear plane area is given by the width of cut and uncut chip thickness as Equation 7.10.

\[ A_s = \frac{i_o h}{\sin \phi} \quad \text{Equation 7.10} \]

Chiou and Liang [2000] used Equation 7.11 to estimate the AE RMS emitted from orthogonal machining.

\[ RMS = C_s (\dot{W}_s + \dot{W}_c)^{0.5} \quad \text{Equation 7.11} \]

Considering the primary and secondary shear zone, Equation 7.12 and Equation 7.13 represent the work rates, divided in shear work \( \dot{W}_s \) and chip work \( \dot{W}_c \).
\[ \dot{W}_c = \frac{i_a h \tau_k}{\sin \alpha} \frac{\cos \alpha}{\sin \phi \cos (\phi - \alpha)} v \]  

Equation 7.12

\[ \dot{W}_c = \frac{1}{3} \tau_k i_a (l + 2l_1) \frac{\sin \phi}{\cos (\phi - \alpha)} v \]  

Equation 7.13

The reason for dividing into zones is that sticking and sliding exist in the secondary deformation zone. The distribution of normal stress on the tool face is highest at the tool point in the secondary zone, and zero at the exit point in the secondary zone, where the chip loses contact with the tool. From Saini and Park [1996], the three zones are shown in Figure 7.9.

![Figure 7.9 Cutting zones, Saini and Park [1996].](image)

Using the assumption that the sliding zone is approximately 1.5 times the length of the sticking zone, see Equation 7.14, Chiou and Liang [2000] described the AE RMS values as in Equation 7.15.

\[ l = 1.5 l_1 \]  

Equation 7.14

\[ RMS = C_s \sin \alpha \left[ \tau_{k_a} v \left( \frac{\cos \alpha}{\sin \phi \cos (\phi - \alpha)} + \frac{7}{9} l \frac{\sin \phi}{\cos (\phi - \alpha)} \right) \right]^{0.5} \]  

Equation 7.15

Altintas [2000] stated that the chip-rake face contact length can be predicted as Equation 7.16, where the friction angle in static cutting can be estimated as Equation 7.17. However, in Chapter 5 it is shown that constants found by regression can improve the reliability of the contact length approximation, when practical values are known for certain tool/workpiece combinations.
The RMS model is based on a model from Kannatey-Asibu and Dornfeld [1981], but some problems have been mentioned. Saini and Park [1996] criticise this model for not being able to predict the energy from tools with zero-degree rake angle, as well as it being based on an observation that an increase in rake angle will increase the energy level. This contradicts recent researchers, which claim that the increase of rake angle actually decreases the cutting forces [Saglam et al. 2007], hence less energy is required, which affects the RMS signals. Saini and Park [1996] proposed a model which is not based on the sinusoidal proportionality factor given by Equation 7.18.

\[
RMS = C_3 \left[ \tau_k l_v \left( C_1 \cdot h \frac{\cos \alpha}{\sin \phi \cos (\phi - \alpha)} + C_2 \cdot \left( \frac{2l}{n_{av} + 2} \right) \frac{\sin \phi}{\cos (\phi - \alpha)} \right) \right]^{0.5}
\]

Equation 7.18

\[n_{av} \text{ is a parabolic constant, which can be found by Equation 7.19.}\]

\[n_{av} = \frac{2 \tau_k \cdot a_p \cdot l}{F_r \sin \alpha + F_f \cos \alpha} - 2\]

Equation 7.19

This model represents the theoretical AE RMS values, which are built on static cutting, assuming continuous chip formation. Beggan et al. [1999] also used a modified version of Equation 7.18. However, they assumed a constant chip-tool contact length where the average flank wear is negligible, as well as the shear plane angle, see Equation 7.20.

\[
RMS = C_5 \left[ \tau_k \cdot a_p \cdot l \cdot (C_v \cdot f + C_y) \right]^{0.5} + noise_{rms}
\]

Equation 7.20

This simplification is not useful when it comes to continuous machining with the same cutting tool, since it fails to take the wear into account. Another problem is that it is built on constants only, where the different cutting angles are not accounted for. Claiming that a relationship can be drawn to the audible sound emitted from the process, where it is estimated that the energy put into the system will be divided so a certain amount will be absorbed by the workpiece, chip, tool insert or be absorbed by the coolant and transferred away from the process, a transfer function must exist, which should be considered as a form of up- or down-scaling, see Equation 7.21.
In order to evaluate the model proposed and find the transfer coefficient $T_{\text{trans}}$, tests have been conducted where it has been imperative that the tool insert was kept sharp. The reason for this is to eliminate the expected factor $\Delta E_{\text{flank}}$ due to progressive tool wear, no matter how minor the effect this may impose on the test results. The fact remains that every removed mm$^3$ of workpiece material will induce a certain portion of wear, which will be contained in each of the test results. As one of the main considerations in this research has been to generate a "generic" model, which will accommodate the changing cutting parameters, the fact that the unknown transfer function $T_{\text{trans}}$ might be a function of those parameters must also be considered. Also considering sound, where the SPL is a logarithmic function expressed in Equation 7.22, where $X_{\text{meas}}$ and $X_{\text{ref}}$ respectively refer to the measured values relative to a reference, it should be expected that the AAE emitted from the process follows an exponential function, as well as a function of the different cutting parameters.

$$X_{\text{dB}} = 10 \log \left( \frac{X_{\text{meas}}}{X_{\text{ref}}} \right)$$

Equation 7.22

As shown for the representation of entropy in the time-domain waveform, changing cutting speed is affecting the sound. The same can be shown for the AAE RMS values, both the estimated values from Equation 7.18 and the actual measured AAE RMS values for the same cutting settings. Predicting and showing the actual measured AAE RMS values for two different cutting speeds, as a function of the MRR, see Figure 7.10, it is evident that the analytical model regards the cutting speed to be an important factor, basically because the model is built on the assumption that the energy is released in the deformation process and as a result of the sliding friction over the tool face. Looking at the measured, but un-scaled, RMS values in Figure 7.10b, it can be seen that differences exist between the two graphs, although the trends seem similar.
Figure 7.10a shows a sudden peak between the MRR values of 400,000-500,000 mm³/min, where the peak is shifted between the two different cutting speeds. The same trend can be seen in Figure 7.10b. However, the AAE RMS difference is in a lower proportion than for the predicted values. This indicates that the AAE RMS is more affected by the feed rate and depth of cut parameters. A simplified way of estimating the tangential cutting force is through feed rate, depth of cut and specific energy. Assuming that the total cutting force, see Equation 7.23, in this case of simple longitudinal orthogonal machining, with an initially completely sharp cutting tool, can be represented by a relationship with the tangential force, as described by Shaw [2005]. Equation 7.24, shows that the total approximated orthogonal force can be expressed as Equation 7.25.

\[ F_{\text{tot}} = \sqrt{F_i^2 + F_f^2} \]  

Equation 7.23

\[ F_{\text{tot}} = \sqrt{F_i^2 + \frac{1}{2} F_i^2} \]  

Equation 7.24
Although Sewailen [1980] is using an exponential constant, related to the depth of cut, Seker et al. [2004] shows that a linear approach is a valid approximation when it comes to changes in feed rate, where feed rate is showing a linear relationship with the feed forces. As described by Chungchoo and Saini [2000], as well as Seker et al. [2004], the tangential force is the significant force in the initial stage where no wear exists, therefore at this point; Equation 7.25 will be regarded as a valid assumption. In this consideration the distribution of the cutting forces does not appear as a direct function of the entering angle, however, these parameters are hidden in the factor \( k_c \). Therefore the total force can be expressed as Equation 7.26.

\[
F_{\text{tot}} = \sqrt{\frac{3}{2} \left( a_p \cdot f \cdot k_c \right)^2}
\]

When plotting the measured mean AAE RMS values as a function of the total theoretical cutting force, Figure 7.11 shows that, although AAE RMS is revealing an increasing trend with cutting force, there are some inconsistencies. As well as for entropy level, the RMS is showing a drop for a certain combination of cutting parameters and cutting speeds, supporting the fact that increased cutting speed is lowering the cutting forces at a certain point, hence lowering the energy in the signal, but the problem is that the same RMS levels exist for different combinations of cutting parameters. Furthermore, it should be mentioned here that the experiment shown in Figure 7.11 was carried out using a Sandvik insert with a recommended cutting speed of 165 m/min.
The results of the experiment indicate that the parameters, depth of cut and feed rate, are acting independently, but the AAE RMS is changing behaviour with cutting speed, which means that the transfer function for relating predicted AE RMS to actual AAE RMS, is following a more complex function than expected.

It has now been established that AAE RMS is not just a linear representation of SPL, which was originally thought of as being a representation of the energy content in the signal. However, that idea is true to some extent, but at this point it is valid to assume that the contributions to the signal of the changing cutting parameters, depth of cut, feed rate and cutting speed, are differently weighted. The transfer function $T_{\text{trans}}$ will of course depend on the acoustic properties of each machine's structure, and must therefore be verified experimentally. Assuming that the energy content of the process can be used as a representation of the factors, cutting speed, feed rate and depth of cut, then the transfer function can be expressed as a constant for each of the cutting parameters.

In orthogonal metal cutting, where it is assumed that a 90-degree entering angle is used, the uncut chip thickness will be equivalent to the feed rate, given in mm per revolution. Equation 7.18 can then be expanded to represent the three ‘force varying’ parameters, $f$, $v$ and $ap$, as well as the entering angle $k$, see Equation 7.27.
\[ RMS = C_3 \left[ \tau_k \cdot \frac{a_p}{\sin(\kappa)} \cdot \sqrt{\left( C_1 \cdot \sin(\kappa) \cdot f \cdot \frac{\cos \alpha}{\sin \phi \cos(\phi - \alpha)} + C_2 \cdot \left( \frac{2l}{n_{ac} + 2} \right) \frac{\sin \phi}{\cos(\phi - \alpha)} \right)^0.5} \right] \]

Equation 7.27

Knowing that these parameters have an effect on the sound emitted, where each parameter affects the sound individually, the transfer function must be applied so each cutting parameter is weighted individually, also an exponential behaviour can be expected, depending on the acoustic properties in the CNC machine. The expected AAE RMS for a completely sharp tool is then given as Equation 7.28. The function of the constant \( C_3 \), proposed by Saini and Park [1996], will be replaced by individual constants of which the constants \( C_1 \) and \( C_2 \) have been estimated to be 0.25, which means that the emission from the primary and secondary zone will contribute with equal weights.

\[ AAE_{RMS} = \left[ \tau_k \cdot n_1 \cdot \frac{a_p}{\sin(\kappa)} \cdot n_2 \cdot n_3 \cdot n_4^2 \cdot n_5 \cdot \sin(\kappa) \cdot f \cdot n_6 \cdot \frac{\cos \alpha}{\sin \phi \cos(\phi - \alpha)} + \left( \frac{2l}{n_{ac} + 2} \right) \frac{\sin \phi}{\cos(\phi - \alpha)} \right]^{0.5} \]

Equation 7.28

Using nonlinear regression to solve the constants, \( n_1 - n_6 \), for a set of measured AAE RMS values, the results are shown in Table 7.1.

<table>
<thead>
<tr>
<th>( n_1 )</th>
<th>( n_2 )</th>
<th>( n_3 )</th>
<th>( n_4 )</th>
<th>( n_5 )</th>
<th>( n_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.002134</td>
<td>0.920309</td>
<td>0.002134</td>
<td>0.430383</td>
<td>21.649579</td>
<td>1.860406</td>
</tr>
</tbody>
</table>

Table 7.1 AAE transfer function constants for 1% carbon steel.

Plotting the predicted values for a range of feed rates from 0.1 mm/rev to 0.4 mm/rev, compared with the actual measured mean values for the same range of cutting conditions, can be seen in Figure 7.12. Although a certain error exists in this model, the uncertainties can be estimated by the standard deviation of the real AAE RMS values. Figure 7.13 shows the real fluctuating RMS values, where Figure 7.12 is a graphical representation of the mean AAE RMS values plotted versus the predicted trend. Table 7.2 and Table 7.3 show the mean values and the standard deviation of the real AAE RMS. The absolute and relative percentage error is shown in Table 7.4. A reasonable question to ask is how accurate this model should be in order to assist a tool-monitoring model.
Figure 7.12 Comparison of predicted AAE RMS versus measured real mean AAE RMS.
In the case of predicting tool wear, one is not really interested in a precise prediction of AAE RMS values for a completely sharp tool, but rather in outliers of the AAE RMS after a certain amount of machining time. However, the fluctuating nature of the AAE RMS is introducing a problem. The whole idea of having the AAE RMS prediction model is to compare the expected AAE RMS with the actual measured value, in order to estimate the dominant wear type.

Figure 7.13 Calculated AAE RMS values plotted versus predicted AAE RMS trend.
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<table>
<thead>
<tr>
<th>Mean RMS</th>
<th>ap 1 mm v 165 m/min</th>
<th>ap 2.5 mm v 165 m/min</th>
<th>ap 1 mm v 200 m/min</th>
<th>ap 2.5 mm v 200 m/min</th>
</tr>
</thead>
<tbody>
<tr>
<td>f – mm/rev</td>
<td>0.1</td>
<td>0.043798</td>
<td>0.055335</td>
<td>0.057011</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>0.075609</td>
<td>0.103598</td>
<td>0.095503</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.105444</td>
<td>0.125664</td>
<td>0.091189</td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td>0.147832</td>
<td>0.227160</td>
<td>0.133395</td>
</tr>
</tbody>
</table>

Table 7.2 Real AAE RMS mean values.

<table>
<thead>
<tr>
<th>Std.dev RMS</th>
<th>ap 1 mm v 165 m/min</th>
<th>ap 2.5 mm v 165 m/min</th>
<th>ap 1 mm v 200 m/min</th>
<th>ap 2.5 mm v 200 m/min</th>
</tr>
</thead>
<tbody>
<tr>
<td>f – mm/rev</td>
<td>0.1</td>
<td>0.002869</td>
<td>0.003780</td>
<td>0.004779</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>0.007332</td>
<td>0.010260</td>
<td>0.007655</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.011729</td>
<td>0.011986</td>
<td>0.006494</td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td>0.01865</td>
<td>0.021037</td>
<td>0.017983</td>
</tr>
</tbody>
</table>

Table 7.3 Real AAE RMS standard deviation.

<table>
<thead>
<tr>
<th>Error</th>
<th>ap 1 mm v 165 m/min</th>
<th>ap 2.5 mm v 165 m/min</th>
<th>ap 1 mm v 200 m/min</th>
<th>ap 2.5 mm v 200 m/min</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δε10⁻³</td>
<td>re %</td>
<td>Δε10⁻³</td>
<td>re %</td>
</tr>
<tr>
<td>0.1</td>
<td>9.152</td>
<td>21</td>
<td>22.57</td>
<td>41</td>
</tr>
<tr>
<td>0.2</td>
<td>2.188</td>
<td>3</td>
<td>10.86</td>
<td>10</td>
</tr>
<tr>
<td>0.3</td>
<td>0.305</td>
<td>0</td>
<td>29.01</td>
<td>23</td>
</tr>
<tr>
<td>0.4</td>
<td>6.679</td>
<td>5</td>
<td>19.48</td>
<td>9</td>
</tr>
</tbody>
</table>

Table 7.4 Absolute and relative percentage errors for measured and predicted RMS.
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2.5 times the standard deviation of the measured AAE RMS values from Figure 7.13, shown in Table 7.3, have been added and subtracted from the predicted mean AAE RMS level in Figure 7.14 and Figure 7.15. In order to show that the value of the AAE RMS can be expected to lie within 2.5 times the known standard deviation, which will account for the fluctuations in the AAE RMS signal, a different set of measurements have been

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Figure 7.14 Expected and real AAE RMS with known standard deviations for 1% carbon steel and \( v = 165 \) m/min, (a) \( a_p = 1 \) mm, (b) \( a_p = 2.5 \) mm.

Figure 7.15 Expected and real AAE RMS with known standard deviations for 1% carbon steel and \( v = 200 \) m/min, (a) \( a_p = 1 \) mm, (b) \( a_p = 2.5 \) mm.
shown in Figure 7.14 and Figure 7.15, where it can be seen that the majority of the measurements are lying within the known standard deviation for a given feed rate, depth of cut and cutting speed. As described previously, RMS is a method which is widely used for quantifying the magnitude of a signal. However, the accuracy of this depends on the sampling rate and the sampling window size, [Fan and Bollen 2004]. The sampling window size determines at which frequencies the RMS output is obtained. If the sampling window is increased, it means that more frequencies are available to ensure a correct magnitude of the RMS signal. In this case, where the signals are used to monitor tool fracture, there are some special requirements for the window size. A complete tool fracture is shown to happen in less than 0.2 seconds; however, a time window of this size will decrease the sensitivity of the system. The previous analyses in this chapter have been carried out with a window size of 0.0227 seconds, but the larger window size exhibits less fluctuating behaviour, as it can be seen from Figure 7.16a to Figure 7.16d.

![Figure 7.16 AAE RMS standard deviation as a function of window size.](image)

### 7.3.3 Incorporating Progressive Wear in the AAE RMS Model

As shown in Equation 7.21, progressive wear will add an extra contribution to the energy consumed in the cutting process. This contribution is mainly due to increased wear land on the flank face of the cutting tool, shown in Equation 7.29.
\[ \Delta \dot{E} = \Delta \dot{E}_{\text{flank}} \]

### 7.3.4 AAE RMS with Increasing Flank Wear

In order to estimate an AAE RMS level when accounting for progressive flank wear, it can be helpful to look at Figure 7.11, where the AAE RMS is a function of the cutting force for the recommended cutting speed, is increasing linearly with the feed rate. Knowing that AAE RMS values are increasing with cutting force, it is valid to assume that this increase will add an extra contribution as a result of increased flank wear. Sewailem [1980] indicated that the wear increment with respect to the tangential cutting force varies linearly with the wear land. This means that the tangential force can be related to a certain portion of the flank wear, see Equation 7.30.

\[
F_t(V_b) = \left( a_p \cdot f \cdot \left( \frac{k_{c_c,1}}{(\sin k \cdot f)} \right)^{mc} \cdot C1 \cdot C2 \left( 1 + \frac{\alpha_0 - \alpha}{100} \right) \right) + \Delta F(V_b) \quad \text{Equation 7.30}
\]

Using the knowledge that the force varies linearly with the wear land, the wear contributions have been described by Sewailem [1980] as Equation 7.31.

\[
\Delta F(V_b) = C_u \cdot a_p \cdot V_b \quad \text{Equation 7.31}
\]

In this case, \( V_b \) is the wear land on the flank face and \( C_u \) is a coefficient found by experiment. The wear land can be estimated analytically as a function of the removed work material under different cutting conditions. Therefore Equation 7.31 can be expanded to include the wear land in millimetres, and using the tangential force and knowledge of the cutting speed, \( \Delta \dot{E}_{\text{flank}} \) can be calculated using Equation 7.32.
Knowing that \( C_u \) is a constant depending on the emission contribution from flank wear, where \( C_u \) is chosen as the material constant \( k_c \), the expected increase in power can be expressed as Equation 7.32, where the expected AAE RMS contribution for the wear can be described as Equation 7.33.

\[
\Delta E_{\text{flank}} = C_u \cdot a_p \cdot K \left( \frac{2V}{i_a^2 \tan \theta} \right) \left( \frac{k_c \cdot V_{\text{vol}}}{2 \cdot V \cdot 10^3} \right)^{\frac{1}{3}} \cdot v \cdot f
\]

Equation 7.32

\[
\Delta AAERMS_{\text{wear}} = n7 \cdot v \cdot n8 \cdot k_c \cdot a_p \cdot K \left( \frac{2V}{i_a^2 \tan \theta} \right) \left( \frac{k_c \cdot V_{\text{vol}}}{2 \cdot V \cdot 10^3} \right)^{\frac{1}{3}} \cdot n9 \cdot f
\]

Equation 7.33

The complete AAE RMS signal, Equation 7.34, can be described as the nominal acoustic emission and the added acoustic emission from wear, [Chiou and Liang 2000].

\[
AAERMS = AAERMS_{\text{sharp}} + \Delta AAERMS_{\text{wear}}
\]

Equation 7.34

### 7.3.5 Combined AAE RMS Model

Knowing that \( C_u \) is a constant depending on the emission contribution from flank wear, where \( C_u \) is chosen as the material constant \( k_c \), the expected increase in power can be expressed as Equation 7.32, where the expected AAE RMS contribution for the wear can be described as Equation 7.33.

\[
\Delta E_{\text{flank}} = C_u \cdot a_p \cdot K \left( \frac{2V}{i_a^2 \tan \theta} \right) \left( \frac{k_c \cdot V_{\text{vol}}}{2 \cdot V \cdot 10^3} \right)^{\frac{1}{3}} \cdot v \cdot f
\]

Equation 7.32

\[
\Delta AAERMS_{\text{wear}} = n7 \cdot v \cdot n8 \cdot k_c \cdot a_p \cdot K \left( \frac{2V}{i_a^2 \tan \theta} \right) \left( \frac{k_c \cdot V_{\text{vol}}}{2 \cdot V \cdot 10^3} \right)^{\frac{1}{3}} \cdot n9 \cdot f
\]

Equation 7.33

The complete AAE RMS signal, Equation 7.34, can be described as the nominal acoustic emission and the added acoustic emission from wear, [Chiou and Liang 2000].

\[
AAERMS = AAERMS_{\text{sharp}} + \Delta AAERMS_{\text{wear}}
\]

Equation 7.34

### 7.3.6 Validating the AAE RMS Model

In this case, when linking the cutting force to an emission of energy, using the assumption that the AAE RMS is representing this, it can be shown that different AAE RMS values exist for the different states of tool wear. Different tests have been carried out in order to reveal the significance of flank wear being present along with changing cutting parameters. Using different stages of measured flank wear along with the initial constants from Table 7.1, the constants for the wear contribution in Equation 7.33 can be seen in Table 7.5.

<table>
<thead>
<tr>
<th>( n7 )</th>
<th>( n8 )</th>
<th>( n9 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00039703</td>
<td>0.00030455</td>
<td>0.00043219</td>
</tr>
</tbody>
</table>

Table 7.5 AAE RMS constants for wear contribution in carbon steel.
Figure 7.17 AAE RMS from three different stages of flank wear in carbon steel using constant depth of cut of 1 mm and cutting speed of 165 m/min measured at 4 points, (a) Mean AAE RMS, (b) Standard deviation of the AAE RMS.

From Figure 7.17 it can be seen that there is a distinction of the AAE RMS values when it comes to flank wear. Figure 7.18 shows the AAE RMS values, both measured and predicted, for two different stages of flank wear with no, or insignificant, crater wear present.
Figure 7.18 AAE RMS measured for 4 points and predicted for two stages of flank wear using a depth of cut of 1 mm and cutting speed of 165 m/min, (a) $V_b = 0.0705$ mm, (b) $V_b = 0.1082$ mm.

7.3.6.1 AAE RMS Fluctuations

One of the major problems dealt with by monitoring systems is the fact that noise and changing parameters are disturbing the process. Especially when monitoring in the time domain, using AE or AAE, small disturbances can have severe impacts on the AAE RMS signal and heavy fluctuations are seen. The previous chapters have all been presented using real-time, non-filtered data, which has been done from the point of view that a filtered signal, where frequency information has been removed, isn’t a complete representation of the true process. However, in this case, where the AAE RMS should be seen as a representation of the energy in the process, represented by a scalar amplitude level, fluctuations can be removed under certain circumstances. Figure 7.19a and Figure 7.19b show real AAE RMS values with their corresponding filtered values, after being subjected to a third-order Butterworth filter, see Figure 7.19c and Figure 7.19d. As can be seen, the filtered values represent the trend of the AAE RMS with steady values.
This method actually decreases the sensitivity of the RMS parameter, which is the argument for dealing with time-domain-based parameters in the first place. However, it has been shown that it actually increases the reliability of the TCM system. The filter is useful not only when it comes to predicting AAE RMS, but also when real-time fractures occur. When a fracture occurs there is a sudden burst increase in the non-filtered AAE RMS followed by rather fluctuating behaviour. Using the third-order Butterworth filter, the AAE RMS maintains a steady behaviour at the new increased level of AAE RMS after the fracture. Figure 7.20 shows an example of a filtered fracture. The response-time of the filter should be taken into account, see Figure 7.20. In this example, the Butterworth filter is designed as a third-order filter, where the response can be improved by increasing the filter order, although this will increase the computational time. The conclusion on the fluctuating behaviour of the time domain signal is that there is a trade-off between a responsive, but fluctuating, TCM system and one which is less responsive, but more stable.
Figure 7.20 Filter response time from tool fracture using a third order butterworth filter.

### 7.4 Flank Wear and AAE RMS with Changing Parameters

Evaluating tool wear directly from the RMS values, as well as comparing the predicted and measured values of the AAE RMS, can only be done when the noise from the spindle system can be estimated and subtracted from the results. This disregarding of the effect of the spindle noise is a lack in the previous research in this area. Sadat and Raman [1987] mentioned the noise as being everything, apart from what can be measured in the 2-3.75 kHz range, where the sound in that specific range was expected to be due to rubbing and tool wear. Later in this thesis, it is shown that spindle noise has a fundamental frequency at 5 kHz. However, this is only valid in the case where the experiments are carried out under the same acoustic conditions. Silva et al. [2000] suggested that the unpredictable shop environment should be coped with by using stronger recognition systems, but it must be stated here that in the time-domain, the AAE RMS is expected to be a representation of the energy in the process as well containing a representation of all noises. Therefore, instead of putting the effort into better recognition systems or artificial intelligence, the signal must be separated so it can be assumed to contain only pure cutting data. The spindle noise has been shown to be one of the main disturbances coming from the process itself, as well as coils of metal wrapped around the workpiece. In order to show the response of flank wear, several tests have been carried out.
Figure 7.21 RMS versus flank wear and spindle speed in carbon steel, $f_s=240$ mm/min, (a) shows the curve of machining incl. spindle noise at 5 measured points, (b) shows the spindle speed for the 5 measured points.

Figure 7.21 and Figure 7.22 show a wear test under constant cutting speed and depth of cut, but where the feed is varying. The corresponding data from the experiments can be seen in Table 7.6 and Table 7.7. The feed speed is used in order to control the tool’s velocity relative to the cutting speed, since it has been shown that the sound is a combination of the noise expected from the sliding over the rake face, as well as receiving a contribution from the tertiary zone. Therefore, regardless of the spindle speed, the velocity in the feed direction is kept constant.

| $V_b$ mm | 0   | 0.0695 | 0.0780 | 0.1040 | 0.1550 |
| Rpm     | 1142 | 1194   | 1459   | 1382   | 1142   |
| D mm    | 46   | 44     | 36     | 38     | 46     |
| RMS     | 0.1914 | 0.2082 | 0.2401 | 0.2372 | 0.2226 |

Table 7.6 RMS data for flank wear test using a constant feed speed of 240 mm/min
As can be seen from Figure 7.21 and Figure 7.22, the RMS value is heavily increased at the point where the spindle speed is increased. The experiments have been carried out using the same workpiece material, but with a mixed combination of diameters. The spindle RMS under no-load conditions can be calculated at different intervals by fitting a polynomial through the data points, using non-linear regression, as shown in Equation 7.35.

\[ RMS_{\text{spindle}} = \chi(a \cdot n^2 + b \cdot n + c) \]  

Equation 7.35
For a reference signal with no amplification, where $\chi$ is the amplification constant depending on the properties and amplification settings, the polynomial constants for the spindle RMS were calculated as Equation 7.36.

$$RMS_{spindle} = \chi(7.9943 \cdot 10^{-8} \cdot n^2 - 8.0853 \cdot 10^{-5} \cdot n + 0.07151)$$

Equation 7.36

The actual measured and fitted non-amplified RMS values, for a no-load spindle run and at different speed intervals, can be seen in Figure 7.23. Referring to Figure 7.21a, the expected behaviour of the RMS would be slightly exponential, or close to linear as illustrated in Figure 7.24.

![Figure 7.23 Measured and fitted RMS values during varying no-load spindle speeds.](image)

Based on the difference in the amplification settings and conditions between the experiment establishing the RMS level for the spindle noise and the flank wear experiment, a constant $\chi$ can be calculated using the relationship between the reference and the no-load spindle run, see Equation 7.37.

$$\frac{RMS_{N Wol\times1000}}{RMS_{Ref\times1000}} = \chi$$

Equation 7.37

The RMS difference in Figure 7.24, between $V_b=0$ and $V_b=0.1550$, is due to the increased flank wear, since the two experiments were performed during the same overrun and with the same spindle speed. Figure 7.27 shows an image of the actual flank wear. At this point, only a small amount of adhesive wear was found on the rake face of the cutting tool.
Condition Monitoring of Tools in CNC Turning

Figure 7.24 The expected and actual behaviour of RMS versus flank wear in carbon steel with a cutting speed of 165 m/min, feed speed of 240 mm/min and depth of cut of 1.0 mm. The deterioration resulted in a measurable diametric deviation as shown in Figure 7.28. The incremental RMS contribution for the noise-free data, or for data where the noise is constant, can be calculated as shown in Equation 7.38.

$$\Delta RMS_{\text{wear}} = RMS(V_{\text{bn}}) - RMS(V_{\text{bn}})$$

Equation 7.38

Dealing with the noise can be achieved by subtracting the RMS values from the expected spindle noise, using the relation shown in Equation 7.39.

$$RMS = \sqrt{RMS_{\text{signal}}^2 - RMS_{\text{spindle}}^2}$$

Equation 7.39

Subtracting the spindle noise, using an amplification constant $\chi=1.10$ to estimate the RMS noise contribution, the corrected RMS values can be seen in Figure 7.25 and Figure 7.26, with their corresponding values in Table 7.8 and Table 7.9.

Figure 7.25 Corrected RMS signal versus flank wear for a depth of cut of 1.0 mm, feed speed of 240 mm/min and cutting speed of 165 m/min.
Condition Monitoring of Tools in CNC Turning

<table>
<thead>
<tr>
<th>$V_b$ mm</th>
<th>0</th>
<th>0.0695</th>
<th>0.0780</th>
<th>0.1040</th>
<th>0.1550</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rpm</td>
<td>1142</td>
<td>1194</td>
<td>1459</td>
<td>1382</td>
<td>1142</td>
</tr>
<tr>
<td>RMSsignal</td>
<td>0.1914</td>
<td>0.2082</td>
<td>0.2401</td>
<td>0.2372</td>
<td>0.2226</td>
</tr>
<tr>
<td>RMSnoise</td>
<td>0.0834</td>
<td>0.0889</td>
<td>0.1237</td>
<td>0.1125</td>
<td>0.0834</td>
</tr>
<tr>
<td>RMS${\text{corrected}}$</td>
<td>0.1680</td>
<td>0.1837</td>
<td>0.1978</td>
<td>0.2024</td>
<td>0.2027</td>
</tr>
</tbody>
</table>

Table 7.8 Corrected RMS for constant feed speed of 240 mm/min.

![Graph](image)

Figure 7.26 Corrected RMS signal versus flank wear with a feed speed of 360 mm/min, cutting speed of 165 m/min and depth of cut of 1.0 mm.

<table>
<thead>
<tr>
<th>$V_b$ mm</th>
<th>0</th>
<th>0.0780</th>
<th>0.0820</th>
<th>0.1040</th>
<th>0.1645</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rpm</td>
<td>1251</td>
<td>1459</td>
<td>1194</td>
<td>1382</td>
<td>1251</td>
</tr>
<tr>
<td>RMSsignal</td>
<td>0.2489</td>
<td>0.2715</td>
<td>0.2553</td>
<td>0.2684</td>
<td>0.2653</td>
</tr>
<tr>
<td>RMSnoise</td>
<td>0.0955</td>
<td>0.1237</td>
<td>0.0889</td>
<td>0.0955</td>
<td>0.1032</td>
</tr>
<tr>
<td>RMS${\text{corrected}}$</td>
<td>0.2257</td>
<td>0.2349</td>
<td>0.2358</td>
<td>0.2381</td>
<td>0.2436</td>
</tr>
</tbody>
</table>

Table 7.9 Corrected RMS for constant feed speed of 360 mm/min.
Figure 7.27 Flank wear at tool midlife.

Figure 7.28 Deviation due to tool deterioration.
7.5 Conclusion of Time-Domain Analysis

This chapter has described how a time-based waveform shows irregularities when the tool load is increased, as well as when the cutting tool wears out. It is shown that the AAE RMS signal can be used to represent the cutting process, with respect to the different cutting parameters, where an analytical model is expanded to include emission from a wear contribution, where empirical constants are used to describe a transfer function from AE RMS to AAE RMS. Furthermore the problem with spindle noise has been addressed, and a solution to the subtraction of spindle noise by subtracting the predicted spindle AAE RMS has been proposed and verified.
Chapter 8

8 Recognising Sound Signatures

Knowing that the sound emitted from the process is a product of the energy, and that a dull tool requires more energy to remove material, which normally leaves the workpiece with a poor surface finish, a novel technique is used where SF parameters are used to detect wear and fracture directly from the sound. In order to do this, the following chapters will provide some specific information on surface roughness related to metal cutting. Parallels will be drawn between physical surface finish and the sound emitted from the process. Furthermore it will be shown that the surface finish parameters can be used to describe irregularities on the machined surface, as well as the same parameters being used to describe irregularities of the sound emitted from the process. It has been possible to build a model which can recognise burst disturbances and signatures by using common SF parameters.

8.1 Brief Description of Cutting Energy and Surface Finish

A machinist operating machinery, such as a lathe or similar, would definitely state that there is a clear link between the acoustics emitted from the machining process and the final surface finish of the machined workpiece. This phenomenon has also been recognised by many researchers, [Dornfeld 1994, Weller et al. 1969, Beggan et al. 1999]. It is known that surface finish parameters obtained from measuring the workpiece can be used for inspecting and describing quality as well as it has been linked to tool wear. Although the waveform is generated by a totally different subject, such as a structure or
airborne acoustic emission source, the common parameters are able to describe irregularities and this chapter will outline a few considerations to illuminate the basics behind this idea. Tool wear basically creates rubbing, which will leave a poor surface finish on the machined workpiece. The interesting part is that both the waveform from the sound emitted and the surface finish left on the workpiece become irregular when the tool wears. Thus, the surface finish parameters developed to describe the irregularity of the physical surface waveform, either in the sense of amplitude or spacing deviations, should be able to describe the irregularity of the sound waveform emitted from the machining process. There is of course a limit to how far this analogy can be extended, although Beggan et al. [1999], investigating the field of structure-borne AE and surface finish, found that there is a close relationship between the AE and the actual measured surface finish.

8.2 Surface Metrology

Surface metrology is the measurement of the deviations of a workpiece from its intended shape, [Whitehouse 1994]. It is widely known, that tool wear creates a poor surface on a machined workpiece and that the surface finish parameters can also be applied in the estimation of tool wear. In manufacturing, it appears that the finish on the machined surface is sensitive to any changes in the manufacturing process; therefore the assumption that measurement of the surface could be used to control the process seems logical. The principle was that, if the surface parameter measured at the process remained constant from workpiece to workpiece, then the process was under control. Any change in the surface parameters should initiate a review of the process parameters, [Whitehouse 1997]. Surface finish is normally concerned with measuring the physical deviations of the workpiece. Three recognised sources of deviations have been identified in the field of surface characterisation.

- Roughness
- Waviness
- Errors of form
These three descriptors can be used to describe the waveform of a surface, and its deviations from a nominal or intended shape. Combined, the first two, roughness and waviness, are normally referred to as surface texture.

### 8.3 Surface Characterisation

- **Surface Roughness**

Roughness is probably the best-known deviation. It is normally described as the average height of the irregularities on the surface. Roughness can be said to be caused by the material removal process, where the workpiece is left with the negative of the tool tip. The theoretical maximum peak height, $R_p$, can be calculated from Equation 8.1, [Sandvik 1994].

$$R_p = \frac{f^2}{8r_e}$$

*Equation 8.1*

According to Wang and Feng [2002], the ideal arithmetic average surface roughness $R_{ai}$ can be estimated using Equation 8.2.

$$R_{ai} = \frac{f^2}{32r}$$

*Equation 8.2*

- **Waviness**

Waviness is of a longer wavelength than roughness and is normally caused by vibrations. The waviness is said to represent an important symptom of machine tool behaviour and, from a manufacturing point of view, this measurement is the most important, [Whitehouse 1994]. Waviness is intermediate in length between roughness and form errors.

- **Errors of Form**

Errors of form are relatively easy to detect. They can be defined, as the deviation from an original shape and are normally broken down into Euclidean shapes such as circles or planes. Errors of form are long wavelengths, where polynomials can be fitted to match intended geometrical shapes. They are normally related to machining or slideway errors.
8.4 A Brief Review of Research Related to Metal Cutting

Characterising a surface and relating this to tool wear, has been attempted by many different methods. Whitehouse [1997] shows how the power spectral density can be used to identify problems in turning through the use of a power spectrum plot of the surface. As the tool wears, a significant change occurs in the spectrum. Whitehouse shows that the ratio of the harmonic amplitudes in the power spectrum increases as the wear progresses. This was explained as being due to the imposition on the surface from the wear scars on the tool. Using optical diffraction, Rakels and Hingle [1986] investigated the information obtained about the surface. Three components are mentioned, where it is assumed that the surface profile consists of a periodic, a random and a tool-scar component. The periodic component is a function of the tool shape and feed rate, whereas the random component is caused by machine vibrations. Beggan et al. [1999] used the assumption, that AE can be directly related to the surface finish. They carried out experiments, based on the RMS values of the AE signal, and related these to the measurements of the surface profile. A good correlation was shown in the experiments. Petropoulos et al. [2004] presented a study investigating the roughness and waviness. They mentioned that different types of tool wear will cause irregularities of the surface texture, which cannot be handled by all surface parameters. They listed a table, where the parameters used in the test were marked for their ability to distinguish between 1; irregular and regular surface and 2; particular irregularities. It was shown that parameters such as $R_a$, $R_t$ and $R_{sm}$ could be used to distinguish between irregular and regular surfaces, where $R_{sk}$ and $R_{ku}$ also are effective for particular irregularities. Lou et al. [1998] proposed a regression system based on simple surface parameters, such as average roughness and root mean square. The system is just a mathematical model, but its simplicity makes it appear promising. Other researchers have been concentrating on finding mathematical relationships, normally using feed rate and cutting speed as process variables. Puertas Arbizu and Perez [2003] and Sahin and Motorcu [2005] proposed mathematical systems to estimate surface finish based on feed rate and cutting speed. It has been shown that the surface finish is dependent on these parameters, as well as on tool wear, but it was concluded that for surface roughness, the models rarely fit the real-life problems.
Statistical functions have been proposed for the purpose of tool monitoring. Whitehouse and Zheng [1992] described and compared the properties of two space-frequency functions: the ambiguity function and the Wigner distribution. Another model related to tool wear, which has been used recently, is the Beta distribution, [Farrelly et al. 2004, Whitehouse 1994, Whitehouse 1997]. Interesting research was carried out by Wang and Feng [2002], which proposed an empirical model based on the same principle as the Taylor tool life equation, where the surface finish is claimed to be affected by a number of parameters, all exponentially weighted by constants, see Equation 8.3. This is a constant $C$, tool hardness $P_a$, feed rate $f$, entering angle $\kappa$, depth of cut $a_p$, cutting speed $v$ and temperature $t$.

$$R_a = C P_a^{c_1} f^{c_2} \kappa^{c_3} a_p^{c_4} v^{c_5} t^{c_6}$$  \text{Equation 8.3}

Using non-linear regression, the constants were found for this empirical model and good correlation was reported. It is interesting that this model shows a relationship to surface roughness, using the cutting parameters pointed out to affect the AE and AAE. Furthermore they concluded that further research will include the nose radius effect missing in their empirical model.

### 8.5 Common Surface Parameters

This chapter describes some of the basic parameters used in surface metrology. These parameters are widely used to identify deviations in a metal cutting process. Although $R_a$ is the most used surface parameter in the industry to characterise surface roughness, it is not a descriptor that can reveal much about the actual surface, since surfaces with the same $R_a$ can be very different. The parameters used in the following are standard parameters and can be found in almost all the literature on surface metrology, [Dagnall 1996, Whitehouse 1994].
Figure 8.1 Surface profile with parameter indications.

- **Peak Spacing** $R_{sm}$
  The peak spacing will reveal the average spacing between the waveform peaks at the mean line. This is calculated from the highest point on the waveform, between an upwards and downwards crossing, see Figure 8.1 and Equation 8.4.

$$R_{sm} = \sum_{i=1}^{n} s_i = \frac{S1 + S2 + ... + Sn}{n}$$  

**Equation 8.4**

- **Zero Crossings** $R_{zc}$
  The zero crossing is basically another description of the peak spacing. It describes how many times the signal crosses the mean line.

- **Peak Count** $R_{pc}$
  Peak count is a number related to the count of peaks in a profile. For the purpose of calculating $R_{pc}$, a "peak" is defined relative to an upper and lower threshold. This is referred to as the peak count threshold. This distance is defined as the lower and upper threshold from the mean line. The main idea is that a peak must cross above the upper threshold and below the lower threshold, in order to be counted, see Figure 8.1. The peak count over the evaluation length is shown in Equation 8.5.

$$R_{pc} = \frac{\sum_{i=0}^{l_{peak}}}{l_{e}}$$  

**Equation 8.5**
• **High Spot Count** \( R_{hsc} \)

The high spot count is the number of complete profile peaks projecting above the mean line. This method can also be applied using a threshold or slice-level value. The peak must cross the threshold and return again, as shown in Figure 8.1.

• **Peak Parameter** \( R_z \)

The peak parameter describes the average difference in the peak/valley of the profile length or, using a fixed number of \( n \), is also sometimes referred to as the 5- or 10-point height, see Figure 8.1 and Equation 8.6.

\[
R_z = \frac{(r_1 + r_2 + ... + r_n)}{n} - \left( \frac{r_1 + r_2 + ... + r_n}{n} \right)
\]

Equation 8.6

• **Height Parameter** \( R_p \) and \( R_v \)

\( R_p \), (peak), and \( R_v \), (valley), are used to describe the maximum distance to either a valley or peak from the mean line, or it is used to describe the distance from the peak to the valley over a sampling length, see Figure 8.1.

• **Average Roughness** \( R_a \)

This parameter normally serves as a common surface measurement. It is well known and describes the average surface profile over a sampling length.

\[
R_a = \frac{1}{L} \int_0^L |y(x)| \, dx
\]

Equation 8.7

• **Skewness** \( R_{sk} \)

The skewness parameter \( R_{sk} \) describes the symmetry of the profile about the mean line, and will distinguish between asymmetric profiles.

\[
R_{sk} = \frac{1}{R_y^3} \left[ \frac{1}{Lr} \int_0^L Z^3(x) \, dx \right]
\]

Equation 8.8

• **Kurtosis** \( R_{ku} \)

The kurtosis describes the sharpness of the surface profile.

\[
R_{ku} = \frac{1}{R_y^4} \left[ \frac{1}{Lr} \int_0^L Z^4(x) \, dx \right]
\]

Equation 8.9

• **Bearing Ratio** \( R_{lp} \)

This is the length of the surface expressed as a percentage, below a set reference line.
8.6 Correlating the Physical Surface with Wear and AAE

Experiments have been carried out with the purpose of investigating the possibility of relating airborne acoustic emission, in the sonic range up to 20 kHz, directly to the produced surface finish, as well as to detect the extent to which changes in surface finish and tool wear can be correlated with irregularities in the AAE time domain waveform.

8.6.1 Surface Analysis

In order to reveal the changes in the surface, 8 parameters were selected for the experiment. $R_a$, $R_{ku}$, $R_v$, $R_p$, $R_z$, $R_{lp}$, $R_{sm}$ and $R_{z/0}$ were calculated. Those calculations were plotted in Figure 8.3a to Figure 8.3h, showing the trend in the physical surface as a function of the workpiece material removed. A third-degree polynomial was fitted through the data using non-linear regression. This function represents the trend of the surface parameters where, for most of these parameters, there is a clear trend. As shown in Figure 8.3a, the $R_a$ plot shows non-linear behaviour. This can be explained by the fact, that a new tool has a 'wear in' phase. $R_a$ starts at the initial value when the cutting tool is new, then gradually decreases and remains at this value for a certain period. After this stage, the wear becomes predominant, affecting the surface. It has also been seen that $R_a$ is elevated in stages, which can be explained by wear, such as built-up edge, which increases the roughness until the edge breaks off and leaves the tool with a new cutting edge. The Kurtosis factor $R_{ku}$ describes the spikiness of the amplitude distribution for each calculated sample. It can be derived from the $R_{ku}$ plot in Figure 8.3b. If this trend is decreasing, it means that the surface is changing from being spiky to becoming more bumpy as the tool wear progresses. The measurements showed a weak increasing trend in the $R_v$ and $R_p$ values. However, the deviation of the real values is in a proportion such that these parameters have been regarded as non-informative. This of course also affects the parameter $R_z$, which is the added valley and peak values over one sample length. $R_{lp}$, shown in Figure 8.3f, and is calculated with the bearing line set from the reference line of the first calculated sample. $R_{lp}$ is increasing in the wear-in phase, which means that a higher percentage of the evaluation length consists of peaks set from the bearing line. The $R_{sm}$ parameter in Figure 8.3g shows that the wear-in phase exhibits a decreasing trend, revealing that the surface is getting spikier in this phase and, as the wear progresses, the
surface is getting bumpier, supported by a decreasing $R_{h}$. In industry $R_{a}$ has been recognised as a good descriptor of surface quality. However, it has been mentioned that completely different surfaces can have the same $R_{a}$ value since it is an average descriptor.

The trend in the surface and AAE $R_{a}$ measurements is shown in Figure 8.2a, where the development in flank wear, is shown in Figure 8.2b. In this figure, $R_{a}$ is calculated on both the physical surface and the parameter is used on the sound waveform. It can be seen that the development of flank wear increases the surface $R_{a}$, as well as the AAE $R_{a}$ emitted from the process.

![Figure 8.2 Trend in average roughness and flank wear as function of material removed, (a) trend for physical surface $R_{a}$ and AAE $R_{a}$, (b) flank wear.](image)

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Figure 8.3 Trend in physical surface roughness as a function of removed material.

8.6.2 AAE Irregularities Described by SF Parameters

From the above, the initial conclusion is that sound in the sonic range can be used as an indicator of when changes in the surface roughness are taking place, which leads to the
question of how comparable the parameters from the physical waveform are with the parameters calculated from the AAE waveform, and to what extent these parameters can be used to distinguish between a normal working tool, fracture and disturbances. This experiment has shown an interesting trend in some of the SF parameters calculated on the waveform of the sound emitted. Figure 8.4 shows a selection of 8 parameters, which have been compared with corresponding parameters in Figure 8.3. Comparing Figure 8.3a and Figure 8.4a, it can be seen that a similar behaviour exists when it comes to the average roughness. This analysis supports the theory that a worn cutting tool releases more energy due to rubbing. An increase in $R_{10}$, see Figure 8.3h and Figure 8.4h, shows that the peak-to-valley heights are increasing, for both the physical surface and the AAE, although the max peak and valley parameters have been shown to be non-informative in the case of the physical surface measurement. The average peak spacing has shown a decreasing trend in the AAE analysis, see Figure 8.4g, which reveals a change in the frequency content of the signal.

All the above have shown a good correlation between a selection of common SF parameters measuring the surface of a machined part, while logging the acoustics emitted from the process and afterwards subjecting this waveform to the same analysis. The primary goal is to establish a relationship between these parameters, in order to determine different sound signatures, fracture or wear. As has been mentioned, building a feature vector of time-domain parameters in order to detect gradual wear can be difficult, since they are affected by disturbances. Whereas the AAE RMS model in Chapter 7.3.5 is a function of the cutting parameters built in order to estimate a certain outcome, other time-domain features may not be as easily related to the cutting parameters.
Figure 8.4 Parameters calculated from the AAE waveform.
8.6.3 Wear Detection from AAE using SF Parameters

This section will show the response of gradual tool wear using SF parameters. Different tests have been made in which flank and crater wear were recorded and plotted against the selected SF parameters, see Figure 8.5. As can be seen from Figure 8.5, the plots, a, d, f and h, are showing similar characteristics to their corresponding parameters in Figure 8.4, where the parameters were plotted as a function of removed workpiece material, which means that the obvious can be proved, that the cutting tool wears as a function of removed workpiece material, where a portion of the increased energy required to do the cutting is lead through the surroundings by the air, changing the characteristics of the SPL. Therefore an array of SF parameters, shown in Figure 8.5, should initially be adequate to estimate gradual tool wear. However, there have been other difficulties associated with this, which should be dealt with. As Figure 8.5 shows, there is a clear pattern in some of the parameters when they are plotted as a function of flank wear. The difficulty in using time-based parameters has been to separate the different wear types from each other, as described in Chapter 5. Different wear types show a different pattern when it comes to building a feature-vector of parameters. Flank and nose wear show the same characteristics, but in cases with significant crater wear, the pattern is changing. It would normally be expected, that the AAE level would increase as a function of crater growth, since the friction coefficient on the rake face changes and the sliding would require a substantial energy increase. Although this trend can be seen for a minor amount of crater wear, excessive crater wear shows a decreasing trend of the AAE level.
As can be seen in Figure 8.6, these graphs show a different behaviour despite the machining process, at the time where the AAE was logged, being conducted with the same cutting parameters. Therefore, the parameter will be a function of both flank and crater wear, which means that direct wear detection using SF parameters is not feasible. However, some parameters have been shown to be useful when it comes to separating the two wear types: crater and flank wear. This inability to use both AE and AAE has previously been put down to one type of wear cancelling the other out.
Figure 8.6 AAE SF parameters versus flank wear, with excessive crater wear.

Figure 8.7 shows the wear curve belonging to the results shown in Figure 8.5. It can be seen that the flank wear is increasing over the whole period, with a large jump at measurement 4-5, as well as the crater wear starting to show a significant increase. In Figure 8.5a and h, with flank wear of 0.1710 mm, minor changes in the AAE are seen, but not in the order which would be expected with the sudden increase in wear. This is expected to be because both flank and crater wear are increasing at the same time.
Figure 8.7 Wear curve for tool with larger proportion of flank than crater wear, (a) wear curve for crater wear, (b) wear curve for flank wear.

Figure 8.8 Wear curve for tool with larger proportion of crater than flank wear, (a) wear curve for crater wear, (b) wear curve for flank wear.

Figure 8.8 shows the wear curve belonging to the results in Figure 8.6, where the crater wear is being accelerated by high cutting speed, but changed back to the original settings during the AAE and wear measurements. The crater wear is in this case growing ‘immediately’, and it can be seen from Figure 8.6 that the AAE is exhibiting a decreasing trend until the flank wear reaches 0.0902 mm, where the combined wear types will emit
an increasing level of AAE. The flank wear measurement at $V_b=0.14$ mm in Figure 8.8b, is starting to show a decreasing trend afterwards, which can be correlated with the lower level of AAE emitted, see Figure 8.6.

### 8.6.4 Detection of In-process Disturbances

As mentioned in Chapter 6, there are several in-process parameters which must be detected in order to determine tool entering and to exclude noise and burst signals. The disturbances are mainly coming from the chips, where coils of metal continue to be wrapped around the workpiece, or where the chip flow is affecting the microphone. Section 4.5.3 has described different techniques, which have been used in the field of tool monitoring using AE, where time-folding and ringdown-count are similar to some of the techniques described in this chapter. Small changes in the machine setup and cutting conditions have an impact on the time-domain parameters, which makes them less feasible when it comes to gradual wear detection, unless their approximate value can be estimated as a function of the cutting parameters. However, experiments have shown that a feature vector built on an array of time-based parameters has been very efficient in detecting in-process disturbances, as well as fracture. Some of the disturbances can be thought of as clicking. Figure 8.9 shows a range of SF parameters calculated for a machining process, where burst signals occur as a result of chips hitting the steel plates and microphone in the CNC machine. When it comes to the process of tool entering, Figure 8.9e, g, h show fluctuating behaviour during spindle start and at the exact moment when entering occurs, but afterwards, in the actual cutting process, they show stable behaviour. This principle is the same for the parameter shown in Figure 8.9j. However, the fluctuating behaviour is seen during machining, as well as a sudden boost in the values. Detecting in-process disturbances are only relevant when the machining process has actually started and not during spindle start, see Figure 8.9, in the time interval between 0 and 2.5 seconds. The amplitude parameters $R_p$ and $R_{210}$, shown in Figure 8.9c and Figure 8.9i are good indicators of burst disturbances. As can be seen, the difference between those two is that $R_{210}$ is an averaged form of showing a peak-valley relationship, where $R_p$ immediately considers burst signals, which makes it very responsive but somewhat more unstable. As described, a peak count can be used for defining a
threshold, which the peaks must exceed in order to exclude minor burst signals. This will cause another problem though, since a minor fracture of the cutting edge, caused by a BUE breaking off and taking a bit of the tool along with it, will result in a smaller increase of the amplitude parameters, which might lie within the threshold. Therefore, it is necessary to separate the detection of in-process disturbances and fracture. The relationship of the time-domain parameters, used for the in-process disturbance feature vector, was tested with a feed-forward, back-propagation, neural network. The purpose of this was mainly to show, that small chip disturbances can be detected. The feature vector $\vec{F}$ consists of the parameters shown previously, see Equation 8.10.

$$\vec{F} = [AAE_{ra} \ AAE_{rp} \ AAE_{rv} \ AAE_{rku} \ AAE_{rsk} \ AAE_{rkm} \ AAE_{rp} \ AAE_{r10} \ AAE_{rzero} \ AAE_{rq}]$$

Equation 8.10

Using 10 inputs and defining an output vector, shown in Equation 8.11, consisting of 3 outputs, the weights were calculated using different training data.

$$\vec{O} = [Out_{slide\_pos} \ Out_{chip\_Burst} \ Out_{entered}]$$

Equation 8.11

A simulation was made, where the output is defined between 0 and 1, defining the strength of the decision, where 0 is defined as no output and 1 is an absolute output, see Figure 8.10. With the feature vector from Equation 8.10 and limited training, the network was clearly able to detect the different disturbances in the process. Although slide positioning and spindle start-up show similar characteristics to the chip/burst disturbances, the network is able to separate them.
Figure 8.9 Turning process with entering and in-process disturbances.
8.6.5 Detection of Cutting Edge Fracture

Unfortunately, fracture shows similar characteristics to the spindle-start, slide-positioning and chip/burst disturbances. The technique of making sure that fracture monitoring is only carried out when entering has been triggered and an in-process flag has been set, has at this time been proved to be sufficiently reliable to distinguish between ‘fracture’ and ‘spindle-start’ signatures. In this case a fracture is defined, as a catastrophic fracture, where most of the insert is removed. This increases the risk of a tool/workpiece collision in cases where the depth of cut is of a certain proportion. Figure 8.11 shows a turning process with a complete catastrophic tool fracture, where the insert is torn out of the tool holder. The complete network has been designed using a total of 5 outputs, shown in Equation 8.12, as well as the feature vector from Equation 8.10.
Figure 8.11 Turning process with catastrophic tool fracture.
Condition Monitoring of Tools in CNC Turning

Figure 8.12 Neural network decisions for a fracture, (a) Sound waveform with fracture, (b) decision for slide positioning, (c) decision for chip/burst disturbances, (d) decision for tool entering, (e) decision for tool fracture.

\[ \bar{O} = [\text{Out}_{\text{Slide\_pos}} \text{ Out}_{\text{Chip\_burst}} \text{ Out}_{\text{Spindle\_run}} \text{ Out}_{\text{entered}} \text{ Out}_{\text{fracture}} ] \] Equation 8.12

The trained network can be seen in Figure 8.13 with its input and outputs. Different tests have been conducted in order to evaluate the function of the network. As can be seen from Figure 8.12, the network is capable of distinguishing between the different signatures: slide positioning and chip/burst disturbances as well as entering and fracture. Also investigated was the detection of the free, no-load, running spindle. However, this seems to be a more complicated task, since the signatures overlaps, and the network was continuously making false predictions. Another observation in these experiments was the results of the output type of the neural network. Two different networks have been created, with a Boolean a real output type, where the latter was defined as a range of 0 or 1. The Boolean type wasn’t always able to detect the chip/burst disturbances. However,
when changing this to a real type, the network was able to give an output, which, in most cases, was proportional to the actual chip/burst signal.

Figure 8.13 Trained network for in-process disturbances and fracture.
8.7 Conclusion of Recognising Sound Signatures

This chapter has described the connection between surface finish, tool wear and AAE. It has been shown that AAE is, to a certain extent, able to describe the changing trend in the surface roughness. This has been shown by an analysis where the trend in the physical surface roughness and the $R_a$ from the AAE waveform has been compared with the trend in the actual flank wear. The roughness is showing an increasing trend with the wear. This means that the tool rubbing, which is decreasing the surface quality, is represented in the AAE waveform. However, it has been concluded that SF parameters are less efficient for describing gradual wear. Although it has been possible to compare trends, it has been more difficult to describe a function which directly can relate the parameters to gradual wear. The limited extent is due to the fact that a certain trend develops over a relative long sample period, which decreases the sensitivity of the gradual wear detection.

When it comes to describing burst irregularities, SF parameters have been shown to have good abilities. A model has been established, using a Neural Network to relate a range of SF parameters to in-process disturbances. It can be concluded that the output of the network has been sufficiently stable to be used to monitor the disturbances in real-time.
Chapter 9

9 Frequency-Domain Analysis

As has been mentioned, the SPL is to be thought of as a representation of the energy content in the process, in this case just released to the surroundings by air. It has been established that the SPL and behaviour are products of wear, but unfortunately also of changing cutting parameters. It has also been established that the two most common wear types, flank and crater wear, can cancel each other out, which means that the product of the AAE will be lower than that which could be expected using the previously derived analytical model. However, the time-domain can successfully be used to detect fracture and disturbances, but the frequency-domain has been shown to be successful when it comes to detecting gradual tool wear. As with the time-domain parameters, the parameters calculated in the frequency-domain are also affected by changing cutting parameters. The approach in this research has been to identify cutting parameters from the machining sound. Where the RMS of the SPL can be thought of as a representation of the energy in the signal, the features calculated in the frequency-domain are working as divisional operators. It has been shown in Chapter 7, that, for different combinations of cutting parameters, the same RMS level can exist. However, when this level is compared with the features in the frequency-domain, where changes in feed rate and depth of cut are showing different characteristics, it is possible to separate the cutting parameters.

9.1 Dependencies of Cutting Parameters

In order to validate the dependencies of cutting parameters in different ranges of the frequency domain, with respect to the behaviour of the sound, several experiments have
been carried out. As pointed out earlier in this thesis, a metal cutting process consists of many parameters, which in some way are related, but when changed separately they behave in a manner which is not always obvious. It should be mentioned that the sound picked up by the sensor also depends on the acoustic properties of the machine, as well as the dynamic structure of the tooling system. From an examination of the same parameters used when evaluating RMS values, it can be seen that the behaviour in the frequency-domain is not just following a similar ‘simple’ amplitude change. As well as for the AAE RMS analysis, four basic parameters are pointed out, which are the normal parameters machinists on the shop floor are dealing with:

- Workpiece material
- Feed rate
- Cutting speed
- Depth of cut

There are other parameters which also affect this process, such as rake angle, entering angle, tool overhang, cutting geometry, etc. It should again be emphasized, that dealing with tool monitoring is not a simple task, because of the complex relationship between these parameters, but dealing with this in AAE monitoring, the difficulty is given an extra dimension. In tool monitoring using vibration or structure-borne AE, where the properties are measured in the actual structure itself, the difficulties consist in getting the sensor close enough to the tool and in avoiding damping factors within the structure or from bolt connections; the problem is largely contained in the structure of the machine. This is not the case when it comes to condition monitoring using AAE, where an apparently chaotic condition can be observed, with interference of waves resulting in the construction and destruction of sounds, beats and pulses, as well as reverberation, echoes and background noises.

### 9.1.1 Effect of Feed Rate

The feed rate is a parameter that directly affects the cutting forces and is directly related to the material removal rate; therefore it is easy to understand the effect on the process when this parameter is changed. The estimated cutting force with respect to feed rate has
a linear relationship with the depth of cut when evaluating Equation 9.1, which is a general formula widely used, [Sandvik 1994].

\[ F_i = a_p \cdot f \cdot k_c \]  

Equation 9.1

Several analyses in this research have shown that both feed change and change of cutting depth are the main factors affecting the AAE emitted from the process. This chapter will be dealing with the explanation of these, along with the changes of other cutting parameters. The AAE released from the cutting process is a product of energy, consisting of energy used in the shear zone and for the sliding friction over the tool face. This is the energy released following the theory of orthogonal metal cutting using a completely sharp tool. However, in practice, the tertiary component, which will be a product of the energy used on the tool flank, must be considered as well. Observations under different cutting conditions have revealed certain behaviour in the frequency domain that is linked to changing feed speeds. Using Figure 9.1 as the initial reference, it can be seen that the amplitude around 7.5 kHz is increasing from an initial max peak value of 0.0257 to 0.0808 along with the increase in the feed rate, when comparing to Figure 9.2. These tests are made with the same specification, where only the feed speed through the workpiece, the feed rate, is changed, making it the only difference between them. The same behaviour can be observed when analysing Figure 9.3 and comparing the initial value of 0.0931 with the amplitude of 0.1515 in Figure 9.4. From these tests it can be concluded that the feed rate changes are affecting the amplitudes in the range of 7-7.5 kHz. Repeating the experiments and increasing the depth of cut, adds to the frequency content in the ‘feed’ range. An interesting observation was that when the depth of cut was increased, another range in the frequency-domain was also affected, indicating that, although the cutting parameters are affecting the sound in different combinations, they are also having independent characteristics of their own in the frequency-domain.
9.1.2 Effect of Depth of Cut

Figure 9.5, shows a total of 8 cuts made to the same specification by using 2 constant depths and where the feed rate is varied. In good correlation with other experiments, it can be observed that the increasing feed rate is increasing the maximum amplitude around 7.5 kHz. Repeating the same experimental setup and feed pattern but with an
increased depth of cut, it was shown that the boost in cutting forces due to a relatively larger chip width, is adding to the frequency produced in this range.

![Graph](image1)

**Figure 9.3** Frequency/feed test with a cutting speed of 180 m/min, depth of cut of 1.0 mm, spindlespeed of 1194 rpm and feed rate of 0.2 mm/r.

![Graph](image2)

**Figure 9.4** Frequency/feed test with a cutting speed of 180 m/min, depth of cut of 1.0 mm, spindlespeed of 1194 rpm and feed rate of 0.3 mm/r.

Interestingly enough, it is shown that the higher frequency range is experiencing an addition to the frequency contents when the forces are increased, whereas the contents of the lower frequency range are decreasing. Unfortunately there is not always a clear pattern for the frequency content's behaviour, which can be partially explained by noises,
which fail to reveal any information concerning the process itself. Such noises can be expected from the chip flow, where discontinued chips under high velocity are hitting the structure of the CNC machine, or it can be noises from the spindle under load conditions. It can be observed that changes in the ‘depth’ range of the frequency domain are around 3kHz, of course depending on the machine setup and the acoustic properties.

Figure 9.5 Frequency analysis with a sample rate of 44 kHz and cutting speed of 165 m/min, (a) depth of cut of 1.0 mm, (b) depth of cut of 2.5 mm.
9.1.3 Effect of Cutting Speed

Figure 9.6, shows a similar process to the one in Figure 9.5 that was carried out with a cutting speed of 200 m/min instead of 165 m/min, which in this case does not only change the chip flow but also the MRR since the experiment uses a feed rate depending on the spindle speed. Apparent changes can be observed with respect to the MaxPeak parameter in the two frequency ranges. Feed rate, cutting speed and depth of cut, exhibit a linear relationship with respect to MRR, where halving the cutting speed while doubling the feed rate will maintain the same rate.

Figure 9.6 Frequency analysis with a sample rate of 44 kHz and cutting speed of 200 m/min, (a) depth of cut of 1.0 mm, (b) depth of cut of 2.5 mm.
What is interesting is that, although the MRR is increasing, which ideally should require more energy, and although feed rate, depth of cut and material parameters are an expression of the tangential cutting force, where the increasing cutting speed will be a factor for the power, shown in Equation 9.2, the amplitude in the 'feed' and 'depth' range is decreasing.

\[ P_c = v \cdot f \cdot a_p \cdot k_c \]  

Equation 9.2

This leads to the conclusion that, as well as for the entropy calculated as a function of MRR in Chapter 7.2.1, a certain combination of 'force parameters', in this case feed rate and depth of cut, combined with the increasing cutting speed, shows an opposite trend to the one expected with the increase of feed and depth of cut only. The same phenomenon was reported by Kopac and Sali [2001]. It is shown in Equation 2.20 that the deformed chips slides on the rake face of the cutting tool, with a speed determined by a geometrical relationship between rake angle, shear plane angle and cutting speed. The power spent on both friction and shear deformation, \( P_{total} \), can be calculated as the sum of Equation 2.21 and Equation 2.23, shown in Equation 9.3.

\[ P_{total} = P_f + P_c \]  

Equation 9.3

Since the cutting speed is entering the power as a linear factor, the drop of SPL for a certain combination of speed versus force is indicating that a flow zone might be playing a role, see Sandvik [1994] and section 2.6.10. This theory can be backed up by experiments which have shown that what this thesis refers to as the force parameters - feed rate and depth of cut - are in most cases increasing the SPL. This also occurs when they are presented in different combinations without increasing the cutting speed. If this theory is true, another complexity is added to the problem, namely the workpiece material itself, where an almost infinite number exist, all having different properties. It has also been observed that increasing or changing the cutting speed shifts the lower range of the frequency-domain. Also, another problem is the noise from the spindle system. Either a small diameter workpiece, or a high cutting speed, will require a substantial increase in spindle speed, which has been shown to affect the frequency analysis.
9.2 The Effect of Spindle Noise in the Monitoring Process

In the cutting process, the many disturbing factors must be pointed out and eliminated, if the signal is to be regarded as a representation of the true process. All depending on sensor placement, the noise from the spindle is playing an important role. As well as for vibration and AE monitoring, [Scheffer and Heyns 2001, Jemielniak 1999], the sensor placement capturing the AAE signals is vital in order to obtain decent results. As mentioned, for the use of AE and vibration, one is dealing with problems such as connections and joints, which are acting as damping factors. In AAE the problem is, as pointed out before, that the signal captured is not just a representation of the energy used for the process, but it contains all the noise in the CNC machine. The noise from the spindle is not just the noise from the bearings, but also from the motor, hydraulics and the surrounding mechanisms. However, since there are no noticeable changes, this noise is treated as static. Yet the spindle noise itself is very characteristic and the fluctuation of the spindle speed results in different sounds when machining different diameters.

9.2.1 Analysis of Spindle Speed Changes in the Time-Domain

In order to explain the effect of varying spindle speed, Figure 9.7 shows the different waveform characteristics resulting from spindle noise. Looking at the changes of spindle speed in the time-domain, the problems that will be caused by machining a very small diameter using the option of constant surface speed can be appreciated. As can be seen in Figure 9.7, the wavelength is changing and the amplitude increasing.

9.2.2 Spindle Speed under No-Load Condition

The analysis of spindle speed, under a no-load condition in the frequency domain, shows that major changes in the PSD plot happen in a narrow band, see Figure 9.8, However, it is also revealed that other parts of the frequency spectrum are affected. Since it is expected that tool wear will induce changes in the frequency domain as drops or spikes in different ranges, and since it remains uncertain if varying spindle speed will affect these ranges, a relationship must be established. Looking at Figure 9.8, it seems that for a spindle speed of 1000 rpm and upwards, an offset is applied to each plot. However, when machining at a lower rpm, such as the 500 rpm shown in Figure 9.8, it seems that other
factors are influencing the results. These have been shown to be the result of other noises, such as the hydraulic system, because at this point, the spindle noise is in such a proportion that it does not exceed the noise from the hydraulic system and the surroundings. A correlation coefficient analysis, see Table 9.1, shows the relationship between the different PSD plots in Figure 9.8.

Figure 9.7 Varying spindle speed logged in time-domain.
Figure 9.8 PSD plot of 6 different spindle speeds.

<table>
<thead>
<tr>
<th>PSD Spindle Speed</th>
<th>Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>500 rpm – 1000 rpm</td>
<td>0.1346</td>
</tr>
<tr>
<td>1000 rpm – 1500 rpm</td>
<td>0.9816</td>
</tr>
<tr>
<td>1500 rpm – 2000 rpm</td>
<td>0.9858</td>
</tr>
<tr>
<td>2000 rpm – 2500 rpm</td>
<td>0.9781</td>
</tr>
<tr>
<td>2500 rpm – 3000 rpm</td>
<td>0.9313</td>
</tr>
</tbody>
</table>

Table 9.1 Correlation analysis of changing spindle speed under no-load.

As pointed out earlier in this chapter, different ranges in the frequency domain are revealing changes in the cutting process. The effect of spindle speed noise in the cutting process can be explained by showing a PSD plot when machining a workpiece using two different diameters, where the cutting speed, feed rate and depth of cut remain constant, see Figure 9.9. As the figure shows, the speed change from 971 to 2491 rpm shows characteristic changes in the frequency-range around 5 kHz. The same pattern can be seen in Figure 9.10, where the feed rate is reduced, and a high amplitude level around 5 kHz for the high spindle speed can be observed. The opposite is seen with a lower spindle speed, where the amplitude is at a low level. Comparing the ‘feed’ range at 7.5 kHz, Figure 9.9 shows an almost similar level in this exact range, meaning that the proportion
of feed rate is higher than spindle noise, where the opposite effect is shown in Figure 9.10.

Figure 9.9 PSD analysis for feed rate of 0.4 mm/r, with a cutting speed of 180 m/min and depth of cut of 0.5 mm.

Figure 9.10 PSD analysis for feed rate of 0.1 mm/r, with a cutting speed of 180 m/min and depth of cut of 0.5 mm.

As Figure 9.9 and Figure 9.10 show, the dominant frequency range related to the changes in feed rate is found around 7.5 kHz in this case, and it is revealed that increased spindle
speed is inducing an increase in the amplitudes across the frequency range, but especially around 5 kHz. The purpose of Figure 9.11 is to show that, when machining with low feed rate or depth of cut, the spindle noise might actually exceed the process signal across the frequency range in cases where the force is not proportional to the spindle speed. Figure 9.11 shows the plot of a 1000-rpm spindle run under a no-load condition, and the equivalent cutting process with low depth of cut and feed rate, as well as the plot of a 3000-rpm spindle run under a no-load condition. It is evident that an increase in spindle speed will affect the visibility of both the feed and depth components, shown in the range of 2.5 and 7.5 kHz. A situation like this is not unusual. Machining a thin diameter workpiece will result in an automatic increase of spindle speed in order to accommodate the selected cutting speed.

Figure 9.11 Frequency analysis of spindle noise under load and no-load conditions with a cutting speed of 180 m/min, feed rate of 0.1 mm/r and depth of cut of 0.5 mm.

**9.2.3 Filtering of Spindle Noise**

Since it is difficult to estimate exactly how fluctuating spindle noise is influencing the signal, especially in the frequency domain, filtering is necessary. In this case where it is not a static noise, but rather dynamic, which is blended in the range of the informative signals, an adaptive method of filtering is preferred. However, due to the acoustic properties in the CNC machine, this method has been unsuccessful. Different filtering
methods have been attempted, but the problem is that, although spindle noise is concentrated mainly around a fundamental frequency of 5 kHz, the noise is also affecting other regions in the frequency domain, where the filtering processes have been shown to affect the actual tool information in the signal.

### 9.2.3.1 Static Spectral Subtraction

Since it is not possible to use a filtering method, e.g. by microphone arrays, where the noisy signal can be subtracted from the process signal, because the two sources cannot be isolated, a static method has been chosen. Spectral subtraction is a popular method of subtracting noisy signals, which, due to its simplicity, has been successfully applied in hands-free communication. It is applied to signals which are disturbed by additive noise, with slow varying spectral characteristics, [Gülzow 2003]. Boll [1979] described a noise-suppressing spectral estimator, where a windowed signal consists of a noise signal $n(t)$ and a pure signal $s(t)$, where the sum given in Equation 9.4.

$$x(t) = s(t) + n(t) \quad \text{Equation 9.4}$$

The pure signal can be obtained by spectral subtraction, shown in Equation 9.5.

$$S(e^{j\omega}) = X(e^{j\omega}) - N(e^{j\omega}) \quad \text{Equation 9.5}$$

Berouti et al. [1979] described a power spectral subtraction, see Equation 9.6, using an over-subtraction factor. Since the noise estimate cannot be obtained directly, the estimate of $N$ is calculated during periods of silence.

$$|S(e^{j\omega})|^2 = |X(e^{j\omega})|^2 - \alpha_{sp} |N(e^{j\omega})|^2 \quad \text{Equation 9.6}$$

In this research, where the changing spindle speed is a disturbing factor, and since it is either changing with cutting speed or as a result of the diameter or x-position of the cutting tool, it will be possible to use a static model, where stored knowledge of the spectral distribution across the frequency band is known.
Figure 9.12 Static spectral subtraction of signals machined with a feed rate of 0.2 mm/r and depth of cut of 0.5 mm, where the waveform is subtracted the static signal of the spindle noise.

Figure 9.12 shows a 512-point windowed PSD plot of two identical machining processes, but where the spindle speed is changed from 1000 rpm to 2000 rpm. The feed speed of the tool is changed in this process, which affects the 'feed' range. However, the lower frequency band is heavily disturbed. Using spectral subtraction, where static data is available for an average spectral distribution for different no-load spindle speeds, it is possible to reconstruct the signal, so it will match the spindle speed at the time of training, or it will be possible to train the system using only the cutting data, leaving out the estimation of spindle noise.

Figure 9.13 Static spindle noise, no-load spindle run.
Using the spectral data in Figure 9.13, with the notation of \( n_{1000} \) and \( n_{2000} \), an estimation of the 1000 rpm signal in Figure 9.12, can be achieved by subtraction and addition of frequency content, see Equation 9.7.

\[
\text{FFT}(x_{1000 \text{rpm}}) = \text{FFT}(s_{2000 \text{rpm}}) - \text{FFT}(n_{2000 \text{rpm}}) + \text{FFT}(n_{1000 \text{rpm}})
\]

Equation 9.7

In Berouti et al. [1979] the noise is estimated during non-speech using an over-subtraction factor as shown in Equation 9.6. This noise is averaged from several frames of “silence”. Since there is no correlation between the signal and noise for a short-term signal, the processed spectrum may be negative; therefore Equation 9.8 will apply when using Equation 9.5.

\[
S(e^{j\omega}) = \begin{cases} 
S(e^{j\omega}), S(e^{j\omega}) > 0 \\
0, otherwise
\end{cases}
\]

Equation 9.8

As can be expected from the example in Figure 9.11, processes with small diameters, which results in higher spindle speed, will be at risk of ending with the result \( S(e^{j\omega}) = 0 \), since the noise is at a larger proportion than the machining sound. Berouti et al. [1979] suggested a spectral floor parameter, which means that the spectral components are prevented from descending below a lower bound. In this case, where the FFT\((n(t))\) is known in the form of an average spectral distribution for different spindle speeds, it will be possible to set a spectral floor in cases where \( S(e^{j\omega}) = 0 \).

### 9.2.4 Effect of Tool Wear in the Frequency-Domain

Different wear analyses have shown that mainly two ranges are affected by wear. As can be seen in Figure 9.14, the three ranges show different behaviours, which is at 3 kHz, 7.5 kHz and 15 kHz. There is a shift towards a lower pitch, exactly as can be seen when machining with increased depth of cut or increasing the feed pressure.
Filtering out the unwanted or uninformative frequencies, the ranges which are expected to provide information about the state of the cutting tool are shown in Figure 9.15. At this point, the tool state is classified as midlife, where a maximum allowable flank wear is estimated to be 0.3 mm. Although a movement can be seen, the changes in the frequency spectrum are still relatively small. However, the physical effects can be noticed on the workpiece, in the form of poor surface finish and a diametric deviation. At this point the time-domain-based RMS has increased by 17.12 %, as shown earlier in section 7.4. Using the frequency domain to monitor gradual wear on its own has been shown to give a sort of ‘binary’ representation of wear, where excessive wear in the end of the tool life becomes easy recognisable in the frequency-domain, but where less wear should be supported by the AAE RMS in order to describe gradual wear.
9.3 Recognising Changes in the Frequency Domain

Based on several analyses of the frequency spectrum, a model has been built in order to evaluate changing parameters. As mentioned, little research has been carried out using AAE in the audible range, therefore only a few papers have been available describing changes in the frequency domain. Kopac and Sali [2001] analysed the frequency domain under different cutting conditions, where they related the amplitudes directly to flank wear. They concluded that AAE is a technique which can be successfully implemented in machining, where the parameters, apart from feed rate, are having small variations. As has been mentioned in the literature review, changing cutting parameters and noise are blamed for the lack of success when it comes to AE and AAE monitoring. The effort in this research has been put into building as generic a model as possible in order to cope with the changing parameters. As can be seen in Figure 9.16a to Figure 9.16b, the amplitude changes with increasing depth of cut and, when increasing the feed rate along with the depth of cut, a shift towards a lower pitch can be observed. As has been pointed out, narrow, distinct ranges exist, affected by the different cutting parameters, depth of cut, cutting speed and feed rate. Since it is not practical to store information on spectral distributions for all possible parameters, a feature vector must be built to represent the changes as a scalar value. Some problems arise when trying to classify the descriptors from the feed rate.
Feed rate is given as mm per revolution, and since different diameters will change the surface speed and the spindle speed, the feed speed at which the cutting tool is moved through the workpiece changes. Although the forces should, theoretically, remain constant, experiments have shown that the acoustics emitted from this process are different. In order to classify the feed range, it is necessary to introduce the feed speed, which is the actual speed of the tool, see Equation 9.9.
\[ f_s = f \cdot n \]  

Equation 9.9

In good correlation with Kopac and Sali [2001], the feed rate increases the amplitude in a narrow band. However, the combination of cutting parameters has been shown to change the shape of the graph as well as shifting the pitch.

Looking at Figure 9.17a and Figure 9.17b, where carbon steel is machined with a constant spindle speed and feed rate at an initial start diameter of 40 mm, the cutting speed is varying throughout the cuts, from 126 to 116 m/min for the three cuts in Figure 9.17a, with a speed of 1000 rpm, and from 163 to 151 m/min for the three cuts in Figure 9.17b, with a speed of 1300 rpm. It can be seen, that the range of \(~7.5\) kHz is increasing, from a maximum of \(-15\) dB in Figure 9.17a to a maximum of \(-10\) dB in Figure 9.17b, despite the feed rate being kept constant. This is due to the changes in spindle speed, where the actual feed speed is changed from 200 mm/min to 260 mm/min, when the spindle speed is changed from 1000 to 1300 rpm. Further tests were made using the same amplification settings, where the feed rate is changed to 0.3 mm/rev and where the
diameter is reduced 6 mm to an initial start diameter of 34 mm. This alters the cutting speed, from an initial speed of 107 to 97 m/min for 1000 rpm, and from 139 to 127 m/min for 1300 rpm, and where the feed speed is respectively 300 mm/min in Figure 9.18a and 390 mm/min in Figure 9.18b. In this case, an increase in the amplitudes was expected. However, the tests showed an actual decrease, which could most probably be explained by the relationship of the cutting speed and the feed speed.

![Figure 9.18 Frequency analysis - constant spindle speed and feed rate of 0.3 mm/r, (a) 1000 rpm, (b) 1300 rpm.](image)

Figure 9.19 shows a closer analysis of the ‘feed range’, from 6 to 9 kHz. It seems that the increased feed speed is shifting the ‘moment’ of the graphs if an axis is placed at 7.25 kHz. Supporting earlier research in similar fields, several analyses in this research have shown that feed rate and feed speed are the most easily recognised parameters.
Figure 9.19 Linear analysis of frequency range 6-9 kHz with constant spindle speed.

9.4 Defining Frequency Ranges

When it comes to changes regarding depth of cut, no obvious pattern exists. As can be seen in Figure 9.20, different changes and patterns can be observed at the lower end of the frequency band.
Looking across the frequency spectrum, different ranges can be defined. In this thesis, the feed and depth of cut ranges have been referred to as the ‘force’ ranges. Each range can then be defined at a fundamental frequency, which will serve as a centreline for that specific range, having a lower and upper bound, see Figure 9.21. Several ranges have been shown to be informative in the process, whereas others disclose no information on the cutting process, see Figure 9.22.
If the components in the PSD can be thought of as a function of the frequency $f_q$, within the lower and upper cut-off frequencies, it can be represented by a new variable shown in Equation 9.10, where area of the spectral components can be defined by Equation 9.11.

$$Y(f_q) = \frac{r_{up}}{r_{low}} PSD(f_q)$$  \hspace{1cm} \text{Equation 9.10}$$

$$A_r = \int_{r_{low}}^{r_{up}} Y(f_q) df_q$$  \hspace{1cm} \text{Equation 9.11}$$
9.4.1 Initial Definition of Frequency Ranges

In order to build a model which can recognise features and estimate cutting parameters, 4 initial ranges are defined as shown in Figure 9.22, where these ranges are initially chosen from an analysis of a selection of machining processes in order to determine which of the ranges is the dominant one.

<table>
<thead>
<tr>
<th>Range</th>
<th>( f_\text{low}, \text{Hz} )</th>
<th>( f_\text{low}, \text{Hz} )</th>
<th>( f_\text{up}, \text{Hz} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>3000</td>
<td>2000</td>
<td>4000</td>
</tr>
<tr>
<td>R2</td>
<td>5000</td>
<td>4000</td>
<td>6000</td>
</tr>
<tr>
<td>R3</td>
<td>7250</td>
<td>6000</td>
<td>8500</td>
</tr>
<tr>
<td>R4</td>
<td>15000</td>
<td>14000</td>
<td>16000</td>
</tr>
</tbody>
</table>

Table 9.2 Initial definition of ranges in the frequency domain.

This is basically band-pass filtering, as shown in the Simulink model in Figure 9.23, where the lower and higher cut-off frequencies are shown in Table 9.2, as respectively \( f_\text{low} \) and \( f_\text{up} \).

Figure 9.23 Bandpass filtering in order to obtain data for R1-R4.

The filtering used a third order Butterworth band-pass filter, with the respective low and high cut-off frequencies shown in Figure 9.23. Figure 9.24 shows the spectrogram of a machining process, filtered according to the ranges selected in Table 9.2. Please note that...
it can be expected that these ranges will vary from machine to machine because of variations in the machines' structures and acoustic properties.

Figure 9.24: Machining process filtered in ranges from R1-R4.

### 9.4.2 Skew and Kurtosis of Frequency Ranges

As can be seen from Figure 9.20 and Figure 9.21, there is a shift in the signal when the machining parameters are changing. Figure 9.25 shows a bar plot of the selected frequency range. The PSD window is in this case selected to be 1024 samples in order to obtain a more detailed plot. In Figure 9.25 it can be seen that there is a different skew to the histogram, where Figure 9.25b shows a lesser positive skew than Figure 9.25a. The symmetry in the distribution can be represented mathematically by the skew factor, shown in Equation 9.12, where \( Y(f_q) \) is the amplitude as a function of the frequency, \( \mu \) is the mean frequency and \( \sigma \) is the standard deviation.

\[
S_k = \frac{\sum_{i=1}^{N} (Y(f_q) - \mu)^3}{(N-1)\sigma^3}
\]

Equation 9.12
Figure 9.25 Frequency range 1.5-3.5 kHz for two processes in carbon steel with feed rate of 0.2 mm/r, spindle speed of 1000 rpm, (a) depth of cut of 0.5 mm, (b) depth of cut of 1.5 mm.

Observing the PSD, where the amplitude is thought of as the ‘frequency’ or ‘hits in each bin’, $\mu$ will represent a mean value of the frequency $f_q$ in Hz, Equation 9.13.

$$\mu = \frac{\sum_{f_q=\text{row}}^{\text{rup}} f_q Y(f_q)}{\sum_{f_q=\text{row}}^{\text{rup}} Y(f_q)}$$

Equation 9.13

The standard deviation will then be given by Equation 9.14, where the amplitude $Y(f_q)$ with respect to Equation 9.10 represents the number of observations of a given frequency $f_q$.

$$\sigma = \sqrt{\frac{\sum_{f_q=\text{row}}^{\text{rup}} Y(f_q)(f_q - \mu)^2}{\sum_{f_q=\text{row}}^{\text{rup}} Y(f_q) - 1}}$$

Equation 9.14

The kurtosis, Equation 9.15, describes the size of the distribution tails, where distributions with relatively large tails are referred to as *leptokurtic* distributions, having a high probability around the mean, and distributions with relatively small tails are referred to as *platykurtic distributions*, having a lower probability around the mean.

$$K_u = \frac{\sum_{f_q=\text{row}}^{\text{rup}} (Y(f_q) - \mu)^4}{(\sum_{f_q=\text{row}}^{\text{rup}} Y(f_q) - 1)^4} - 3$$

Equation 9.15
9.4.3 Maximum Peak

The maximum peak, Equation 9.16, defines the highest peak in each selected range.

\[ P_{\text{max}} = \max_{f_q = \text{rlow}}(Y(f_q)) \]

Equation 9.16

9.4.4 Relative Moment

As has been mentioned, the idea of looking in narrow ranges is to be able to represent the behaviour of the spectral distribution as a simple scalar. It has been observed, that the distribution shifts under different cutting parameters. By calculating a right and left moment, using the centre \( r_{\mu} \), it is possible to determine how the distribution is shifting, according to a fixed reference point in the range, see Figure 9.26. This is similar to the skewness, but where the skewness describes the distribution's skew with reference in its own centre point.

\[ M_{\text{rel}} = \frac{L_{\text{mom}}}{R_{\text{mom}}} = \frac{\frac{ru_{p}}{2} \int_{f_{=\text{rlow}}}^{ru_{p}} Y(f_q) df_q}{\frac{ru_{p} + 1}{2} \int_{f_{=\text{rlow}}}^{ru_{p}} Y(f_q) df_q} \]

Equation 9.17

In the example in Figure 9.26, there are some characteristic differences. The fundamental difference between the two processes is the depth of cut, as well as a minor difference in cutting speed. The diameter was 34 mm for the process machined with a depth of cut of 1.5 mm and 31 mm for the process machined with a depth of cut of 1.0 mm. This means a minor change in the surface speed, from 107 m/min to 97 m/min, which in this case is neglected. Figure 9.26 shows the data calculated in that particular frequency range, and it can be seen that the skew and kurtosis of the process with the lower depth of cut is close to the normal distribution. Furthermore, the central tendency of the distribution is close to the chosen centreline of the frequency range.
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Figure 9.26 Calculation of the relative moment for two different machining processes with constant spindle speed of 1000 rpm and feed rate of 0.3 mm/r.

These characteristics indicate that symmetry is supported by the relative moment, calculated from $r_\mu$ at 7250 Hz, where this value is lower when compared with the other process having the opposite characteristics regarding skew, kurtosis and central tendency. Figure 9.27 shows the distribution of the 6-8.5 kHz range, when machining with stepwise increasing feed rate. In this case, there is almost a linear trend across the selected features, where the distribution is shifting to the left, becoming a positive skewed distribution.

Figure 9.27 Calculation of features in the 6-8.5 kHz range using different feed rates, constant cutting speed of 180 m/min, depth of cut of 0.5 mm.
9.4.5 Shift

The shift $\Delta \mu$, Equation 9.18, from the intended centreline $r_\mu$, can be calculated using the knowledge of the mean or central tendency of the distribution, $\mu$. This will reveal the shift of the distribution with respect to a fixed point in the frequency-range.

Equation 9.18

$$
\Delta \mu = r_\mu - \mu = r_\mu - \frac{\sum_{f_q=\text{low}}^{\text{up}} f_q}{\sum_{f_q=\text{low}}^{\text{up}} Y(f_q)}
$$

9.4.6 Changing Feed Rate

As has been described before, the changing feed rate seems to be predominant around 7.5 kHz, which has been referred to as the feed range. One of the main ideas behind pointing out different ranges is to avoid 'too much' filtering, as well as simplifying the feature extraction. Feed changes have been observed to affect the $\sim 7.5$ kHz range with a somewhat linear pattern. The same linearity with respect to feed rate has been shown before for the RMS values in the time domain. The spectral analyses are shown in Figure 9.28 to Figure 9.31, for all selected frequency ranges with constant depth of cut, but for 4 different feed rates. The corresponding values calculated from the features can be found in Table 9.3. As can be seen in Figure 9.32 column R3, there seems to be a constant linear trend for most of these features. The increasing skew reveals a left shift, and the increasing MaxPeak and moments around the centre show that more frequency content is added to this range. The mean of the distribution is decreasing, showing a shift to the left supporting the skew but where the distribution is still dominated by having most of the area to the right, as shown by the relative moment. From Figure 9.28 and Figure 9.31, it can be seen that the difference between the amplitudes is relatively small, where the difference is in a larger proportion in Figure 9.29 and Figure 9.30. The behaviour of the features with respect to changing feed rate is represented graphically in Figure 9.32.
Figure 9.28 Spectral distribution for range 1 in 1% carbon steel with a depth of cut of 0.5 mm and a cutting speed of 180 m/min.

Figure 9.29 Spectral distribution for range 2 in 1% carbon steel with a depth of cut of 0.5 mm and a cutting speed of 180 m/min.
Figure 9.30 Spectral distribution for range 3 in 1% carbon steel with a depth of cut of 0.5 mm and a cutting speed of 180 m/min.

Figure 9.31 Spectral distribution for range 4 in 1% carbon steel with a depth of cut of 0.5 mm and a cutting speed of 180 m/min.
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#### Features Range 1 to 4 – \(a_p=0.5\) mm – \(v=180\) m/min

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<th>(R)</th>
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<th>(f=0.2) mm/r</th>
<th>(f=0.3) mm/r</th>
<th>(f=0.4) mm/r</th>
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</table>

Table 9.3 Feature values for R1-R4 – varying feed rate.
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Figure 9.32 Features for R1-R4 with respect to feed response – Constant $a_p=0.5$mm.
9.4.7 Changing Depth of Cut

Figure 9.33 to Figure 9.36 show the spectral distribution for the four frequency ranges R1 to R4, where the corresponding features calculated for varying depths of cut are shown in Table 9.4. In this research, depth of cut is referred to as one of the force parameters, where a simplification of the tangential cutting force is a product of the feed rate, depth of cut and cutting material, see Chapter 2.5.12. As well as for feed rate, the most characteristic change in the spectral range is found in R3, where the proportion is relatively large, see Figure 9.35. A good characterisation is of course, that the behaviour is predictable, where the amplitudes increase or decrease as a function of feed rate. Figure 9.33 shows the spectral range R1, and it can be seen that there is no obvious pattern in this range. The same is seen in Figure 9.34, which means that other parameters are affecting this range more than the depth of cut, which decreases the SNR, meaning that it would be difficult to distinguish or separate the parameters using only information from those ranges. Each different cutting parameter on its own does not just affect a range; rather they affect the ranges in different combinations, where the features in different ranges will be able to describe the process and the behaviour of the sound.
Figure 9.33 Spectral distribution for range 1 in 1\% carbon steel with a feed rate of 0.2 mm/r and a cutting speed of 180 m/min.

Figure 9.34 Spectral distribution for range 2 in 1\% carbon steel with a feed rate of 0.2 mm/r and a cutting speed of 180 m/min.
Figure 9.35 Spectral distribution for range 3 in 1% carbon steel with a feed rate of 0.2 mm/r and a cutting speed of 180 m/min.

Figure 9.36 Spectral distribution for range 4 in 1% carbon steel with a feed rate of 0.2 mm/r and a cutting speed of 180 m/min.
<table>
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<th>Features Range 1 to 4 – $f=0.2$ mm – $v=180$ m/min</th>
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<th>$a_p=1.0$ mm</th>
<th>$a_p=1.5$ mm</th>
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</table>

Table 9.4 Feature values for R1-R4 – varying depth of cut.
Figure 9.37 Features for R1-R4 with respect to feed response – Constant $f=0.2\text{mm/r}$.
9.4.8 Features versus the ‘Force Parameters’

It has been described that the energy content in the cutting process is assumed to be represented through the SPL, which has been confirmed by analysis in this research. It has been shown in section 9.4.6, that the features calculated in the frequency domain show a linear behaviour with respect to feed rate. The simplified formula for the tangential cutting force, Equation 9.19, shows that depth of cut and feed rate have a linear relationship with the properties of the workpiece material, see Chapter 2.5.12.

\[ F_i = a_p \cdot f \cdot kc \]  
Equation 9.19

The main idea of calculating features which can separate the different components in the machining sound is to calculate a virtual cutting force, which, together with the real AAE RMS, is a representation the ‘force’ in the signal. The feed rate and depth of cut are the two most important factors affecting the sound emitted from the process. It has been difficult to directly recognise an obvious pattern in the features when they are plotted alone. However, Figure 9.38 to Figure 9.41 show the calculated features as a function of both feed rate and depth of cut when machining carbon steel. It can be seen from most of these figures that there is a linear relationship when it comes to feed rate, as has been pointed out, but combined with the depth of cut, the values of the features are varying in different manners. This supports earlier research, as described by Silva et al. [2000], where a certain combination of parameters with increased depth of cut leads to an increased stability, which in this case will create a different harmonic situation. A part of the variation in the results can of course be attributed to noise, since the analysis has been carried out with unfiltered cutting data in order to preserve as much of the informative cutting signal as possible. It has previously been described, that range R3, from 6000 to 8500 Hz, seems to be affected the most when it comes to changing the force relating cutting parameters, and, as can be seen from Figure 9.40, there is a pattern in the parameters.
Figure 9.38 Features of R1, shown as a function of depth of cut and feed rate.

Figure 9.39 Features of R2, shown as a function of depth of cut and feed rate.
Condition Monitoring of Tools in CNC Turning

Figure 9.40 Features of R3, shown as a function of depth of cut and feed rate.

Figure 9.41 Features of R4, shown as a function of depth of cut and feed rate.
9.4.9 Effect of Cutting Speed

Chapter 9.1.3 described that, although cutting speed is a factor in the formula for the power required for the process, increasing cutting speed seemed to decrease the frequency content in certain ranges under different combinations. Analysed tests are shown in Figure 9.42 to Figure 9.45, where the features are plotted using two different cutting speeds. It is obvious throughout the frequency analysis, that the ranges R1 and R3 are the ranges which are most affected by changes in cutting speed, depth of cut and feed rate. However, it is uncertain how those spectral ranges are affected under combinations of the cutting parameters, and since it must be expected that this is a function of the acoustic properties in the CNC machine and the behaviour of the dynamic system of the cutting tool, this can be expected to change from machine to machine. In this research neural networks have been used in order to find dependencies in the data, where no obvious pattern exists.

Figure 9.42 Features for R1 calculated using various depths of cut and cutting speeds.
Figure 9.43 Features for R2 calculated using various depths of cut and cutting speeds.
Figure 9.44 Features for R3 calculated using various depths of cut and cutting speeds.
Figure 9.45 Features for R4 calculated using various depths of cut and cutting speeds.
9.5 Classification of cutting parameters

It has been shown that changes in the cutting parameters affect the SPL and the time domain parameters, such as RMS, as well as the frequency domain. Previous research has been based on building systems that can cope with changing cutting parameters, where the effort has been put into systems depending on massive amounts of training, whereas the overall goal in this research has been to build a system which can recognise those changes on its own. In this chapter an output matrix is defined as Equation 9.20.

\[
\overline{\text{Out}}_{\text{cut}} = \begin{bmatrix} f_{pr} & a_{pr} & v_{pr} \end{bmatrix} \quad \text{Equation 9.20}
\]

This matrix represents predicted values of the feed rate, depth of cut and the cutting speed. The feature vector for the cutting parameter estimation is given by Equation 9.21.

\[
\overline{F}_{\text{cut}} = [K_u, S_k, \mu, \sigma, L_{mom}, R_{mom}, M_{rel}, P_{max}, \Delta\mu, AAERMS] \quad \text{Equation 9.21}
\]

The trained network can be seen in Figure 9.46. The network was trained using both Matlab® and EasyNN®, in order to double-check the output of the queries. A hybrid model is used in this case, where the frequency parameters are mixed with the AAE RMS. One of the challenges has been to overcome the problem of changing cutting speed, which causes the AAE RMS to decrease as described in Chapter 7.3. Using the combination of features from the frequency domain, which describes the changes in the spectral distribution, combined with the AAE RMS, which is representing a scalar value for the energy in the process, a stable network has been created using only features from range R3.
Figure 9.46 Trained feed forward back-propagation network to estimate $f$, $a_p$, and $v$. 
9.5.1 Functionality of the Neural Network

The training in this example was carried out by using 4 different feed rates, given in mm/r, two different depths of cut and two different cutting speeds, where the test was to simulate the network in order to estimate the errors. The data was organised as shown in Equation 9.22.

\[
\begin{bmatrix}
    f \\
    a_p \\
    v
\end{bmatrix} =
\begin{bmatrix}
    0.1 & 0.2 & 0.3 & 0.4 \\
    1 & 1 & 1 & 1 \\
    165 & 165 & 165 & 165
\end{bmatrix}
\begin{bmatrix}
    0.1 & 0.2 & 0.3 & 0.4 \\
    2.5 & 2.5 & 2.5 & 2.5 \\
    165 & 165 & 165 & 165
\end{bmatrix}
\begin{bmatrix}
    0.1 & 0.2 & 0.3 & 0.4 \\
    1 & 1 & 1 & 1 \\
    200 & 200 & 200 & 200
\end{bmatrix}
\begin{bmatrix}
    0.1 & 0.2 & 0.3 & 0.4 \\
    2.5 & 2.5 & 2.5 & 2.5 \\
    200 & 200 & 200 & 200
\end{bmatrix}
\]

Equation 9.22

Figure 9.47 Actual and predicted values from a trained network using feed rate.

The simulation of the network showed some minor errors. However, these were mainly connected to the prediction of feed rate, see Figure 9.47. An array of different parameters, which in this case consisted of samples machined with feed rates from 0.1 to 0.4 mm/rev, depth of cut from 1 and 2.5 mm and two different cutting speeds of 165 and 200 m/min, was calculated and fed to the network. The percentage error was plotted for each sample,
shown in Figure 9.48. The mean absolute percentage error, (MAPE), can be calculated using Equation 9.23 where $Y_i$ is the true value and $Y_{pr}$ is the predicted. As can be seen in Figure 9.48, the errors are relatively low, where the MAPEs are 2.17% for feed predictions, 0.0116% for depth of cut and 0.497% for cutting speed predictions.

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{Y_i - Y_{pr}}{Y_i}$$

Equation 9.23

Figure 9.48 Percentage errors for simulated model using feed rate.

Section 9.3 describes the introduction of the feed speed as being necessary, since a constant cutting speed will result in different spindle speeds when machining various diameters. This results in a different AAE, which can be attributed to an expected increase in feed pressure in the tertiary zone. Although the cutting speed is kept constant, the feed speed of the tool is a function of the spindle speed, where a different behaviour than that theoretically expected has been observed. Theoretically, all experiments in orthogonal metal cutting should be made using a cutting tool with no flank wear, but since wear progresses immediately, a contribution from the tertiary zone must be expected. The amended output vector is shown in Equation 9.24, where $f_{s\ pr}$ is the predicted feed speed, $a_{p\ pr}$ is the predicted depth of cut and $v_{pr}$ the predicted cutting speed.

$$\overline{Out_{cut}} = \begin{bmatrix} f_{s\ pr} & a_{p\ pr} & v_{pr} \end{bmatrix}$$

Equation 9.24

The pattern of the predicted values, when simulating with data taken at the exact feed rates, depths of cut and cutting speeds, can be seen in Figure 9.49. Introducing the feed speed reduced the MAPE for the feed prediction to 1.86%. However, the errors for the depth of cut and cutting speed were slightly increased, see Figure 9.50.
Figure 9.49 Actual and predicted values from a trained network using feed speed.

Figure 9.50 Percentage errors for simulated model using \( f_s \), \( a_p \) and \( v \).

These errors were expected, since this example only incorporated one of the ranges across the frequency band.

### 9.5.2 Classification Using all Ranges R1-R4

Using features for all the chosen ranges of the frequency band, where the AAE RMS represents the energy content of the process, a complete feature vector can be expressed. The features representing the spectral properties, described in section 9.3, are basically...
working as divisional operators, separating feed rate and depth of cut from the cutting signal. Another input parameter that must be introduced is the material parameter $k_c$, which represents the material properties, also referred to as specific energy, as well as the tool setup, rake angle and entering angle, see section 2.6.8. Combining the network, it is clear that dependencies exist between the input features and outputs. The predictions of a simulation of all four ranges using the network in Figure 9.53, sketched with the purpose of showing its complexity, can be seen in Figure 9.51. The error curve and MAPE errors are shown in Figure 9.52, where it can be seen that the actual error is minimal. This is of course simulated under ideal conditions using a noise-free signal, matching the conditions of the training set.

Figure 9.51 Actual and predicted values from a trained network using all ranges.
Figure 9.52 Percentage errors for simulated model using all ranges R1-R4.
Figure 9.53 Neural network for ranges R1-R4.
9.6 Conclusion of the Frequency-Domain Analysis

This chapter has presented the analysis of the behaviour in the frequency domain. In addition, the importance of spindle-noise in the frequency domain has been pointed out. A spectral subtraction method is suggested, in order to exclude the effect of spindle noise during machining. Although this model shows some inconsistencies, since the spindle noise must be assumed to be static, where a stored image of the spectral distribution of average spindle noise is subtracted from a fluctuating dynamic signal, reliable and acceptable results have been obtained. This has provided a method of dealing with this in-process disturbance in the frequency domain. It has been shown that the frequency domain is affected by cutting parameters, as was the time-domain. Another conclusion is the frequency domain’s sensitivity to tool wear. It has been seen that minor gradual tool wear changes the spectral distribution. However, this is in a low proportion. Therefore, the frequency domain is inadequate for directly describing gradual wear. However, when combined with the time-domain-based AAE RMS, which represents the energy by a single scalar value, it is possible to predict the cutting parameters from a machining sound.
Chapter 10

10 Virtual Force Model

Previously in this thesis, in Chapter 5, the Wear-quantifying Model has been dealing with developing an analytical tool wear model, which is able to predict the progress of wear as a function of the volume of workpiece material removed. Chapter 6 has briefly described the different sound signatures in the machining process, which involves tool entering, fracture, wear and disturbances. In Chapter 7, the focus has been on RMS as a function of changing cutting parameters, as well as a representation of the energy content of the cutting process. Chapter 8 describes the use of SF parameters to detect fracture and burst disturbances as a separate system, without involving the actual monitoring system. Chapter 9 describes features which can be used to identify changes in the spectral distribution in selected frequency ranges.

This chapter will create the last link between these chapters, in order to develop a hybrid monitoring model, which consists of an online-sensor system, using a combination of time- and frequency-domain parameters to detect gradual wear, using a virtual, calculated, theoretical, tangential cutting force, combined with an analytical model for tool wear prediction.

10.1 Brief Summary of Cutting Forces and Tool Wear

This chapter will briefly summarise the foregoing review of tool condition monitoring systems that use force, as well as adding some additional information, which will be connected to the next chapters. Referring to section 3.4.5, where it has been concluded that force monitoring is one of the successful techniques used for tool monitoring, Sikdar and Chen [2000] showed that all three cutting components increase as a result of flank
wear. Xiaoli et al. [2004] have cited similar research, where it was later stated that the tangential and feed forces were found to be a sensitive measure of tool wear. However, the feed force is heavily dependent on the change in feed rate. Different techniques have been used in this field, cited by Xiaoli et al. [2004]. The ratio of cutting forces has been used, where the feed force to the tangential component was found to be a sensitive measure. It has been stated that the magnitudes of the cutting forces are not appropriate for monitoring because of their fluctuating nature. Dividing the forces into static and dynamic components, where the static component is used to identify flank wear and the dynamic fluctuation is indicating crater wear, due to the increased adhesion effect over the crater creating unstable or interrupted machining on the rake face, it was possible to get an indication of crater wear. Xiaoli et al. [2004] mentioned that crater wear is difficult to recognise, since the static forces do not increase appreciably.

10.2 Virtual Cutting Force and Tool Wear

For a completely sharp cutting tool, a certain amount of AAE RMS can be estimated using Equation 7.28. As shown in Chapter 7.3.3, progressing wear increases the AAE RMS, where an increase can be estimated by Equation 7.33. At the exact point \( w = 0 \), it is possible to estimate a theoretical tangential cutting force, incorporating the known parameters \( a_p, f, k_c, \alpha \) and \( \kappa \), as shown in Equation 10.1.

\[
F_t = a_p \cdot f \cdot \left( \frac{k_{c_1} \cdot 1}{(\sin k \cdot f)_{mc}} \cdot C1 \cdot C2 \right) \left( 1 + \frac{\alpha_0 - \alpha}{100} \right) \quad w = 0
\]

Equation 10.1

Since this research has not been involved with the actual force measurements, but is only using the terminology from orthogonal metal cutting, the forces are referred to as theoretical and virtual cutting forces.

The cutting force is said to vary linearly with the wear land, [Sewailum 1980], and after a certain point of machining, the wear will have progressed to \( \Delta w \), where the theoretical force can be represented as Equation 10.2, where \( \Delta F \) is the increased force due to wear.

\[
F_t(w>0) = F_t(w=0) + \Delta F(\Delta w)
\]

Equation 10.2

Since the RMS described by Chiou and Liang [2000], see Equation 7.11, is representing the virtual cutting force, where the shear and tool/chip forces can be found from the
geometrical relationship between the feed and the tangential force as shown in section 2.6.3, then the increased theoretical force can be related to increased RMS as described in section 7.3.3, using Equation 10.3.

\[
AAERMS = AAERMS_{w=0} + \Delta AAERMS_{\Delta w}
\]

Equation 10.3

Referring to Chapter 9, where a classification of cutting parameters was made, and an output vector was defined to contain the three cutting parameters, see Equation 9.24, an output will exist for two cases; see Equation 10.4 and Equation 10.5.

\[
Out_{(w=0)} = \left[ f_s^{pr(w=0)} a_p^{pr(w=0)} v_{pr(w=0)} \right] \approx \begin{bmatrix} f \cdot n \ a_p \ v \end{bmatrix} \quad w = 0
\]

Equation 10.4

\[
Out_{(w>0)} = \left[ f_s^{pr(w>0)} a_p^{pr(w>0)} v_{pr(w>0)} \right] \quad w > 0
\]

Equation 10.5

Using the predicted values for those two cases, a virtual force can be calculated knowing the specific energy of the workpiece material, which is an input factor for the network. In an ideal case for \( w=0 \), the theoretical cutting force in Equation 10.1 is equal to the virtual force calculated from the predicted parameters \( f_p \) and \( a_p \), see Equation 10.6.

\[
F_t = \left( \frac{f_p^{pr(w=0)}}{n} \right) \cdot a_p^{pr(w=0)} \cdot k_c \quad w = 0
\]

Equation 10.6

In the case of \( w>0 \), the predicted output will be different, since the network will be unable to relate the features to the right output values for \( a_p \) and \( f \). This means that the network, in cases of higher feed pressure due to increased wear land in the tertiary zone, will correlate with the increased AAE RMS with spectral changes in the feed range R3, and correspond with a higher prediction of the feed speed. Therefore the virtual force with progressed wear \( \Delta w \) can be expressed as in Equation 10.7.

\[
F_t(\Delta w) = \left( \frac{f_p^{pr(w>0)}}{n} \right) \cdot a_p^{pr(w>0)} \cdot k_c
\]

Equation 10.7

In this research, where the tool wear is the main objective, and as the cutting force is expected to vary linearly with the wear land, the incremental wear can be found as a subtraction of the initial theoretical cutting force from the virtual force, as given by Equation 10.8.
\[ \Delta F_{r(w)} = F_{r(\Delta w)} - F_{r} \quad \text{Equation 10.8} \]

Since the wear is expected to be flank wear, this can be related to an equation for the wear land using an empirical constant found by experiment, where slight crater wear is neglected and where excessive crater wear is treated separately. The reason for this is that excessive crater wear shows different characteristics and therefore has been difficult to combine as part of a generic model. Assuming that the wear land is proportional to the increase in force, the force can be calculated using Equation 10.9.

\[ \Delta F_i (w) = C_{vb} \cdot a_p \cdot V_b \quad \text{Equation 10.9} \]

### 10.2.1 Predicting Virtual Cutting Force

Experiments were carried out in order to validate the estimation of the virtual cutting forces, not in order to relate these to the actual cutting force of the system, but to build a regression model which can estimate flank wear as a function of the incremental virtual force contribution. The interesting aspect of this method is that the system does not rely on a true prediction, but rather a false one, where it is the error of the network that will predict the force increment. Four measurements were taken in order to evaluate the principle, where the mean features were calculated during machining and recorded. The flank wear measurements can be seen in Figure 10.1 and Table 10.1. A neural network was trained for machining processes with a feed speed from 200 mm/min to 400 mm/min, using a new tool, where the small amount of wear occurring during training was neglected.

<table>
<thead>
<tr>
<th>Flank wear ( V_b )</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>mm</td>
<td>0</td>
<td>0.062</td>
<td>0.110</td>
<td>0.122</td>
<td>0.151</td>
</tr>
</tbody>
</table>

Table 10.1 Flank wear measurements.
In this case, it was only necessary to train the network to recognise different feed speeds, therefore the depth of cut and cutting speed were kept constant. The tests were made while machining carbon steel, using a constant depth of cut of 1.0 mm, a constant feed speed of 240 mm/min and a cutting speed of 165 m/min. Using the features described in section 9.5, including the AAE RMS corrected for spindle speed, the network was able to predict output values as shown in Table 10.2.

<table>
<thead>
<tr>
<th>Wear $V_b$</th>
<th>$f_{spr}$</th>
<th>$a_p$</th>
<th>$v_{pr}$</th>
<th>rpm</th>
<th>$f$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>235.3</td>
<td>0.983</td>
<td>164.3</td>
<td>1194</td>
<td>0.197</td>
</tr>
<tr>
<td>0.062</td>
<td>262.4</td>
<td>0.999</td>
<td>166.3</td>
<td>1194</td>
<td>0.220</td>
</tr>
<tr>
<td>0.110</td>
<td>300.3</td>
<td>1.003</td>
<td>165.0</td>
<td>1251</td>
<td>0.240</td>
</tr>
<tr>
<td>0.122</td>
<td>317.3</td>
<td>0.100</td>
<td>164.1</td>
<td>1251</td>
<td>0.254</td>
</tr>
<tr>
<td>0.151</td>
<td>359.0</td>
<td>0.978</td>
<td>169.4</td>
<td>1313</td>
<td>0.273</td>
</tr>
</tbody>
</table>

Table 10.2 Predicted cutting parameters.

The feed speed can be converted back to a virtual feed rate given in mm/rpm, since it is possible to calculate the spindle speed from the cutting speed. This means that the basic cutting parameters can be estimated virtually. Using a corrected $k_c$ of 2495 N/mm² for carbon steel, with an effective rake angle of 14 degrees and an entering angle of 95 degrees, the theoretical and the virtual cutting forces can be calculated as in Table 10.3.
Using Equation 10.9, where the constant can be found as shown in Equation 10.10, an approximation of the flank wear can be found, and a virtual wear curve, valid for this tool/workpiece combination, can be plotted as a function of $\Delta F_f(w)$. The constant $C_{vb}$, calculated for the different wear contributions, can be seen in Table 10.4.

$$\frac{\Delta F_f(w)}{a_p \cdot V_b} = C_{vb}$$

Equation 10.10

<table>
<thead>
<tr>
<th>Test</th>
<th>$V_b$</th>
<th>$\Delta F_f(w)$</th>
<th>$a_p$</th>
<th>$C_{vb}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.062</td>
<td>46.3</td>
<td>1.000</td>
<td>745.7</td>
</tr>
<tr>
<td>2</td>
<td>0.110</td>
<td>121.8</td>
<td>1.000</td>
<td>1106.9</td>
</tr>
<tr>
<td>3</td>
<td>0.122</td>
<td>153.8</td>
<td>1.000</td>
<td>1260.3</td>
</tr>
<tr>
<td>4</td>
<td>0.151</td>
<td>211.3</td>
<td>1.000</td>
<td>1399.3</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>1128.0</strong></td>
</tr>
</tbody>
</table>

Table 10.4 Calculation of constant $C_{vb}$.

The calculated virtual force contribution, from the predicted cutting parameters, can be plotted as a function of the actual measured flank wear, as shown in Figure 10.2. As has been mentioned, the interesting part in this method is to train the neural network to predict a linear behaviour between the cutting parameters. Although there is no obvious linear relationship in the features, except under certain circumstances as shown in Chapter 9.5, this method has provided a relatively simple way of showing a close to linear relationship between the sound and tool wear as a function of changing cutting parameters. A regression model can predict the tool wear, as a function of $\Delta F_f(w)$, where either a linear or non-linear model can be fitted through the data points, see Figure 10.3.

The coefficients of the models are shown in Equation 10.11 and Equation 10.12.
Figure 10.2 Virtual force contribution as a function of measured flank wear.

Figure 10.3 Predicted Flank Wear as a function of the virtual force contribution.

For this tool/workpiece combination, the non-linear fit seems to offer a better prediction, where the MAPE can be calculated to be 2.21% for the non-linear model and 5.86% for the linear fit. The coefficients used for the two models can be seen in Figure 10.3. The model is able to estimate a combination of feed speed and depth of cut, which gives a relatively precise approximation of flank wear. The predicted and real parameters of a test carried out with varying feed speed can be seen in Table 10.5 and Table 10.6. The purpose was to investigate the prediction with the effect of the wear in the tertiary zone,
while increasing the feed pressure. The predicted and measured wear can be seen in Figure 10.4, where the MAPE was calculated as 8.57%.

\[ V_b = -1.447 \cdot 10^{-6} \Delta F_t(w)^2 + 9.212 \cdot 10^{-4} \Delta F_t(w) + 0.0189 \]  
\[ V_b = 6.478 \cdot 10^{-4} \Delta F_t(w) + 2.222 \cdot 10^{-2} \]

<table>
<thead>
<tr>
<th>Test</th>
<th>Wear</th>
<th>( f_s )</th>
<th>( a_p )</th>
<th>( \text{rpm} )</th>
<th>( v )</th>
<th>( f_{s_{pr}}, \text{mm/min} )</th>
<th>( a_{p_{pr}}, \text{mm} )</th>
<th>( v_{pr}, \text{m/min} )</th>
<th>( f_{pr}, \text{mm/rpm} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0695</td>
<td>240</td>
<td>1.0</td>
<td>1194</td>
<td>165</td>
<td>259.3</td>
<td>1.095</td>
<td>164.4</td>
<td>0.2172</td>
</tr>
<tr>
<td>2</td>
<td>0.0780</td>
<td>240</td>
<td>1.0</td>
<td>1459</td>
<td>165</td>
<td>276.6</td>
<td>0.996</td>
<td>165.7</td>
<td>0.1896</td>
</tr>
<tr>
<td>3</td>
<td>0.0780</td>
<td>360</td>
<td>1.0</td>
<td>1459</td>
<td>165</td>
<td>412.1</td>
<td>1.044</td>
<td>172.9</td>
<td>0.2825</td>
</tr>
<tr>
<td>4</td>
<td>0.1040</td>
<td>240</td>
<td>1.0</td>
<td>1382</td>
<td>165</td>
<td>302.2</td>
<td>0.991</td>
<td>165.2</td>
<td>0.2187</td>
</tr>
<tr>
<td>5</td>
<td>0.1040</td>
<td>360</td>
<td>1.0</td>
<td>1382</td>
<td>165</td>
<td>410.9</td>
<td>1.192</td>
<td>166.3</td>
<td>0.2973</td>
</tr>
<tr>
<td>6</td>
<td>0.1550</td>
<td>240</td>
<td>1.0</td>
<td>1142</td>
<td>165</td>
<td>349.1</td>
<td>1.070</td>
<td>164.6</td>
<td>0.3057</td>
</tr>
<tr>
<td>7</td>
<td>0.1645</td>
<td>360</td>
<td>1.0</td>
<td>1251</td>
<td>165</td>
<td>512.2</td>
<td>0.957</td>
<td>167.3</td>
<td>0.4095</td>
</tr>
</tbody>
</table>

Table 10.5 Real and predicted cutting parameters tested with varying feed speed.

<table>
<thead>
<tr>
<th>Test</th>
<th>( F_t ), ( w=0 )</th>
<th>( F_{\Delta w} ), ( w&gt;0 )</th>
<th>( \Delta F_t(w) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>501.3</td>
<td>541.9</td>
<td>40.6</td>
</tr>
<tr>
<td>2</td>
<td>410.3</td>
<td>472.9</td>
<td>62.7</td>
</tr>
<tr>
<td>3</td>
<td>615.4</td>
<td>704.8</td>
<td>89.4</td>
</tr>
<tr>
<td>4</td>
<td>433.1</td>
<td>545.7</td>
<td>112.4</td>
</tr>
<tr>
<td>5</td>
<td>649.7</td>
<td>741.8</td>
<td>92.1</td>
</tr>
<tr>
<td>6</td>
<td>524.1</td>
<td>762.7</td>
<td>238.6</td>
</tr>
<tr>
<td>7</td>
<td>717.7</td>
<td>1021.6</td>
<td>303.9</td>
</tr>
</tbody>
</table>

Table 10.6 Theoretical and virtual forces calculated with varying feed speed.
10.3 Conclusion of Virtual Cutting Force

This chapter has described the last link in the proposed monitoring solution, the Virtual Force Model. As has been mentioned, the virtual and theoretical cutting forces described in this research have not been measured physically, since they are only representing a means of describing tool wear as a single scalar value using the virtual force contribution. This is a novel approach for estimating tool wear. Experiments have shown a good correlation between the actual measured wear and that predicted. It is obvious that tool wear is changing the sound characteristics, where flank wear shows a rather linear trend regarding the SPL. However, as mentioned above, changes in, and certain combinations of, the cutting parameters are also changing the pattern. This chapter has shown that the model gives good results, where, relying on the purity of the cutting signal with respect to disturbances, a prediction of flank wear can be made within an error of 10%.
Chapter 11

11 Conclusion

The objectives in this research were to develop a method to detect gradual tool wear and fracture in a CNC turning process. The method should be able to cope with changing cutting parameters and the usual noises of the machining environment and be sufficiently reliable to be implemented as an industrial application. The gaps in the field have been pointed out, where changing cutting parameters and disturbances are the reasons for the lack of success. The main purpose was to identify and address these problems by creating a model which can exclude disturbances and non-informative signals from the decision-making process. This research has presented an organised way of recognising changing parameters. To summarise the work in this research, the schematic of the proposed solution is shown in Figure 11.1. As an integrated system, the chapters in this thesis have each described their contribution to this solution, where gradual wear and fracture are monitored and disturbances are excluded from the results. Each model provides information for the final decision model evaluated by a rule-based system. The on-line sensory information is divided into two domains, the time domain and the frequency domain, where the time domain is used to detect fracture and disturbances. The frequency-domain is used to evaluate sound signatures, in order to predict the cutting parameters in the process. These parameters are used to relate a virtual force contribution to a certain proportion of flank wear. This solution uses two analytical models in order to detect crater wear. An AAE RMS model compares the real measured AAE RMS.
Figure 11.1 Overall functionality of the proposed system.
This solution has provided a means of detecting crater wear, where it has been difficult to detect actual crater wear by the sound in the sonic range, since more than one wear type is present at the same time. Listed below are the conclusions of the previous work in TCM using AE or AAE:

- The most commonly occurring wear types in the metal cutting process are flank wear and crater wear.
- The previously proposed solutions for TCM systems using AE, or the few AAE systems available, have been unable to successfully detect tool wear under changing cutting parameters.
- The lack of success in this field has been pointed out to be due to changing cutting parameters and disturbances, such as external disturbances from parallel machining.
- The focus in previous research has been on developing different decision-making or signal-processing systems, in order to minimise the effect of changing parameters.

With respect to the work in this research, the conclusions based on the observations and proposed models are:

- Flank wear is the easiest wear type to recognise using AAE, since the SPL has an almost linear behaviour with the wear land. When it comes to crater wear, it has not been possible to directly recognise and distinguish crater wear by AAE. The reason for this is expected to be that when two or more wear types are present at the same time, they are able to cancel each other out, which results in the problem that no distinct signature exists for each wear type. It has been observed that when machining with excessive crater wear, the AAE RMS seems lower than would normally be expected. However, although it is noticeable, the trend is not always as clear as described by research in the field of AE. This research has proposed the use of an analytical AAE RMS prediction model to estimate a certain level of RMS which can represent the expected level with only flank wear present. This approach has made it possible to detect inconsistencies in the SPL which can be attributed to excessive crater wear.
• The information from the AAE RMS model can be related to information from the analytical crater prediction, which is able to give a binary TCM model with respect to crater wear. If inconsistencies between the expected AAE RMS and the measured AAE RMS exist, and the predicted crater wear is exceeding a certain threshold, then the analytical prediction, assisted by the on-line sensory information, can be assumed to be valid and measures can be taken to stop the process. It has been observed that, unlike flank wear, crater wear does not limit the process since no real geometrical deviations have been observed when machining with cratered tools. However, the crater is increasing the risk of a fracture when the crater front distance is decreasing.

• Cutting parameters are changing the SPL. However, when the parameters are changed in certain combinations, this change is not always linear. An almost linear change in the AAE RMS is seen from changes in the feed rate, but when changing the depth of cut, the AAE RMS behaves differently. Representing the energy in the cutting signal by AAE RMS and relating spectral changes to the different cutting parameters, depth of cut, feed rate and cutting speed, has provided a novel approach to dealing with this problem. A common way of dealing with changing parameters in previous research has been to train systems with different tool states and changing cutting parameters. The approach in this research requires a minimal training effort, using only a new tool. The system is then trained under different combinations of feed speed, depth of cut and cutting speed. This approach will create a linear relationship between the parameters and the sound, which can be related to tool wear through a non-linear regression model.

• External disturbances have been excluded from the decision-making process by a noise-detection system. In this research, different approaches to filtering noises have also been attempted. However, these have proved unsuccessful. The explanation for this may be found in the complexity of the acoustic properties in the CNC machine. At this point it should also be concluded that, although AAE is offering a good means of TCM, the airborne signal contains less information from
the cutting process compared to that expected from an AE signal, and therefore the filtering is often removing useful information.

- Internal disturbances are also excluded from the decision-making process since it has not been possible to remove these by filtering. These signals are of such a chaotic nature that all attempts at removing them have failed. However, as a novel approach, they can be detected and the decision of the tool state can be excluded at that point. The author is of the opinion that this approach is the most reliable one currently available.

- Surface finish parameters have been correlated with tool wear and disturbances, and it is shown that, although SF parameters are offering a means of detecting wear, they are more efficient in describing irregularities, such as burst signals and disturbances. It is shown that surface finish parameters can be used to detect changes in the sound and that a comparison has been made between the physical surface and the sound logged from the machining process. It can be concluded that, although the physical surface and the waveform are showing the same trend, revealing a relationship, where the sound can be used as an indicator of a poor surface, the method has not proved reliable.

- A reliable flank wear detection system has been presented, where the errors are seen in the range of 10%. It has been shown that the sound is a good estimator of the cutting process, although it must be remembered that it only contains a fraction of the cutting information of structure-borne AE. It should be concluded, that the main AAE contribution can be expected from the sliding and rubbing in the tertiary zone, and not so much from the plastic work. However, it has been concluded that, since the crater is lowering the AAE RMS and since it has been seen that the AAE RMS with a flat-faced tool with lower rake angle is decreasing the energy content in the signal for the same parameters, the plastic work is also contained in the signal.

- Overall TCM by AAE is offering a flexible method of monitoring tool wear, where the main benefits are the simplicity of the system and its great cost efficiency.
11.1 Contributions to Knowledge

This research has contributed to knowledge by presenting a structured way of recognising tool wear and fracture, considering changing cutting parameters and noises in the process.

- An analytical tool wear model has been presented and discussed, where both flank and crater wear can be predicted as a function of removed workpiece material. The model considers different parameters, such as cutting parameters as well as geometrical and tool material parameters. The functionality of this model has been to assist an on-line wear prediction, where the expected dominant wear type can be estimated analytically.

- The use of AAE as a mean of tool condition monitoring in order to detect gradual wear has been investigated. A comprehensive investigation of the influence of different cutting parameters has been discussed, and a model which can cope with the problems has been derived from this. The difference between flank and crater wear, with respect to the visibility of the two wear types when using AAE, has been investigated, where the crater wear has shown to be less recognisable using AAE compared to flank wear.

- The relationship between flank wear, physical surface roughness and AAE, specifically the SPL, have been investigated and an analysis that directly draws parallels between the surface and sound waveform has been discussed. It has been shown that there is a link between the actual sound and the irregularities on the surface of the machined workpiece.

- It has been shown that surface finish parameters can be used to describe irregularities in a sound waveform, and a model has been proposed, where sound signatures with respect to defined disturbances have been recognised. In order to build a reliable system, the disturbances are recognised in order to evaluate the reliability of the wear decision, where decisions made at the moment where any disturbances occur are discarded.

- A noise evaluating system have been presented which regards external noises from parallel machining etc. This system is using the known attenuation and time delay of the sound between two microphones to predict the directionality of the noise, and then to evaluate if the noise can be considered external, which must be
excluded from the wear/fracture evaluation, or if it is an internal which must be considered in the wear/fracture evaluation.

- A model of AAE RMS has been established which can predict an expected level of AAE RMS with progressed flank wear. This model is used as a guideline to estimate a level of the sound with no crater wear present, where a known standard deviation of previous AAE RMS is used to spot outliers. This model is working as an empiric transfer function of the expected AE RMS from the primary and secondary zones, to the AAE RMS including the tertiary zone.

- A link is created between a theoretical cutting force and a virtual cutting force. The virtual cutting force is composed of cutting parameters predicted from the sound by a neural network. Different features are presented which are able to be used in the neural network to precisely predict cutting parameters. A close relationship between the cutting force and the behaviour of the SPL have been proved, and it has been established that flank wear is showing the same sound characteristics as increased feed force.

- A non-linear regression system is presented to relate virtual force, predicted from the sound, to a certain amount of flank wear. This system has shown to be able to predict a level of flank wear within an error of 10%.

- A hybrid system consisting of analytical, on-line and neural prediction systems have been combined in order to fulfil the aim of creating a monitoring system which should be able to regard changing cutting parameters as well as noises in the machining process.

11.2 Future Work

This research has been carried out using a Mechatronics approach, which is mainly to integrate different fields into an application. However, it has been seen throughout the research that almost every part offers the possibility of future work in order to improve the reliability of the proposed system.
11.2.1 Analytical Tool Wear Model
The analytical model was developed with the purpose of predicting progressing tool wear, where a wear constant is based on previous measured values and changing cutting parameters are changing the quantifiable tool wear. It has been seen that this model offers reasonable reliability but, as is to be expected with most models, they only work under a given set of conditions. This analytical model can be explored and improved in conjunction with a reliability model which can account for thermal fatigue, etc.

11.2.2 Force Monitoring and Crater Wear Detection
A virtual model is proposed in this research. However, the actual link to physical force monitoring has not been investigated. Xiaoli et al. [2004] proposed the use of the cutting force ratio. Dividing the forces into static and dynamic components, where the static component is used to identify flank wear and the dynamic fluctuation is indicating crater wear, due to increased adhesion effect over the crater creating unstable or interrupted machining on the rake face, it was possible to get an indication of crater wear. A better way of determining crater wear must be sought, where the actual dynamic and static forces can be correlated with the behaviour of the AAE.

11.2.3 Noise Filtering
It is the author's opinion that some noises cannot be filtered, which includes coils of workpiece material wrapped around the workpiece. Therefore, a noise-suppressing system is proposed, excluding the results when noises are detected. However, a better way of filtering or subtracting external signals and spindle noise from the measurements can be sought. It is shown that this requires an investigation of the acoustic properties inside the CNC machine, where a DSP application or similar could be used to model negative replicas of the noises, subtracting them from the actual cutting signal. However, due to the complex nature of the acoustics in the machine, this is a demanding task requiring further work.
References


Condition Monitoring of Tools in CNC Turning


Wolfson School of Mechanical and Manufacturing Engineering, Loughborough University. M.Sc.


