MODELING OF TOOL WEAR WHEN TURNING OF TI-6AL-4V TITANIUM ALLOY

by

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ABSTRACT

Difficult-to-cut materials are widely used particularly in the aerospace and automotive industries. However, the high cost of processing these materials limits the use of their improved mechanical properties. Tool life is one of the most important factors in machining operations of such materials and it is mainly affected by cutting conditions including the cutting speed, feed, depth of cut and cooling environment along with the generated temperature and cutting forces. In addition, the modern industry is moving towards automating the manufacturing processes. Therefore, tool life monitoring is important to achieve an efficient manufacturing process. In this study, a tool wear prediction model during the turning of Titanium alloys is studied. It is based on the monitoring of tool performance in controlled machining tests with measurements of cutting forces and vibration under different combinations of cutting parameters (cutting speed, feed rate, depth of cut and coolant). The influence of cutting parameters on the tool life was studied experimentally by performing more than 300 cutting tests. A prediction model was then developed to predict tool wear. The basic steps used in generating the model adopted in the development of the prediction model are: collection of data; analysis, pre-processing and feature extraction of the data, design of the prediction model, training of the model and finally testing the model to validate the results and its ability to predict tool wear. In this work, tool wear prediction was developed using three different modeling methods: Feed-forward Back-Propagation Neural Network, Regression Analysis and Gaussian Mixture Regression (GMR). Comparing the predicted tool wear values with the measured ones showed reasonable agreement. Neural Network modeling yielded the least prediction error with prediction accuracy of 90.876% which is 2.702% and 1.23% higher than the prediction accuracy of the GMR and regression models respectively.

Search Terms: Titanium alloys, Turning process, Tool wear, Neural Network, Regression Analysis, Gaussians Mixture Regression.

Table of Contents

List of Tables

List of Figures

1 Introduction

This chapter provides a general review about turning processes and their parameters as well as tool materials and cutting fluids. In addition, machinability of difficult to cut materials and tool wear are discussed.

1.1 Manufacturing Process

Manufacturing process can be defined as the process of converting raw materials into products, including the product design, selection of raw materials and the sequence of the manufacturing procedure [1]. In today's highly competitive market, the quality of manufactured products must be assured in all manufacturing stages [2]. This has increased the demand for efficient manufacturing processes with optimum manufacturing cost, high quality and environmental sustainability considerations [3]. There are two main concepts in modern manufacturing: machining automation and advanced engineering materials.

Automation of manufacturing process could be the ideal solution to today's development revolution in terms of the new materials, cutting tools, and machining equipment. Automation will help in achieving an economical implementation of resources in the manufacturing process (materials, labor, energy, etc.) without compromising the high levels of quality and productivity. In addition, the change in market demands and product specification requires faster production rates and consistency and uniformity of the manufactured parts [1]. Achieving these requires changing the tool just at the right time to get these benefits [4][5].

The other main issue of modern manufacturing is the use of new advanced engineering materials. New industrial applications require materials with modified properties for products' particular requirements with reliable and economical manufacturing processes. Such advanced engineering materials are used in aerospace, electronics, medical applications and others industries [6][7]. The modified properties will improve the quality of these materials and help meet certain mechanical, electrical, or chemical requirements. Typical properties of interest include: tensile strength, hardness, thermal, conductivity, and corrosion and wear resistance [6][8][9]. Despite of all the advantages of the advanced engineering materials, they are difficult to cut and result in a high cost of processing require high cost processing.

1.2 Turning Process

Metal cutting is one of the most extensively used manufacturing processes, and its technology continues to advance in parallel with the developments in material science. In the metal cutting process, a sharp cutting tool removes material from surface of a work-piece to achieve the desired product. The most common types of cutting process are: turning, milling, and drilling [2].

Turning is the process of removing material from the outer diameter of the work-piece. In the turning process, the single point cutting tool is moving with a certain velocity while the work-piece is rotating. It is used mainly to produces work-pieces with conical, curved, or grooved shapes [1]. The turning process is illustrated in Figure 1.1.

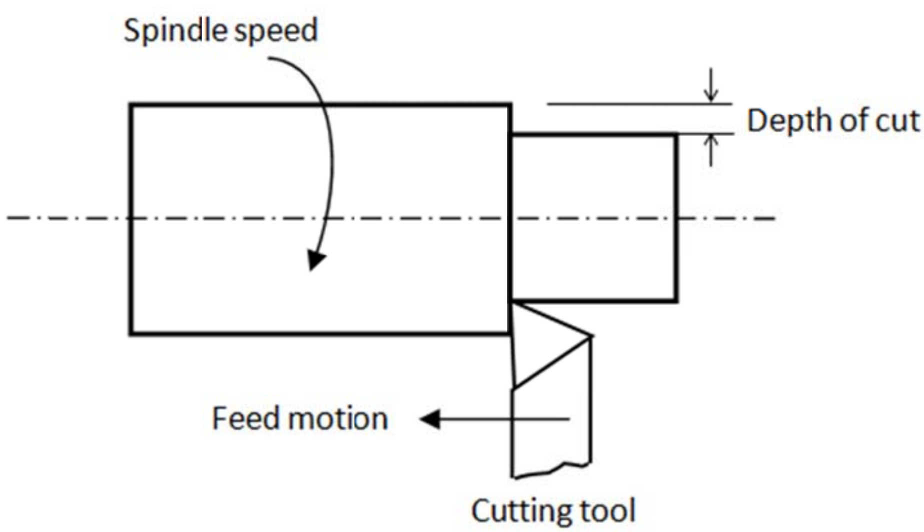

Figure 1.1: An illustration of the turning process and its parameters

The turning processes are carried out on a lathe machine and the automatic turning process is performed by the CNC (Computer Numerical Control) lathe machine.

The typical cutting tool used in the CNC machine has a replaceable cutting edge (tool insert).

1.2.1 Cutting Parameters in Turning

The cutting parameters of the turning operation include the cutting speed, feed rate and depth of cut. Cutting speed is the speed of the work-piece material measured in meters per minute. Feed is the rate at which the cutting tool is traveling in millimeters per each spindle revolution. The depth of cut is the amount of material removed from the work-piece measured in millimeters. The selection of these parameters influences cutting forces, power consumption, surface roughness of the work-piece and cutting tool life. Cutting parameters are usually selected based on the work-piece material, tool material, and tool geometry. Optimization of cutting conditions will minimize the machining cost and improve the quality of the product [6][10].

1.2.2 Cutting Forces in Turning:

Figure 1.2 [2] shows the three forces acting on the cutting tool in the turning process. The cutting force (Fc) is main force in the turning process and it acts downward on the cutting tool. The thrust force (Ft) or feed force acts in the direction of the feed motion of the cutting tool. The radial force (Fr) acts in the radial direction.

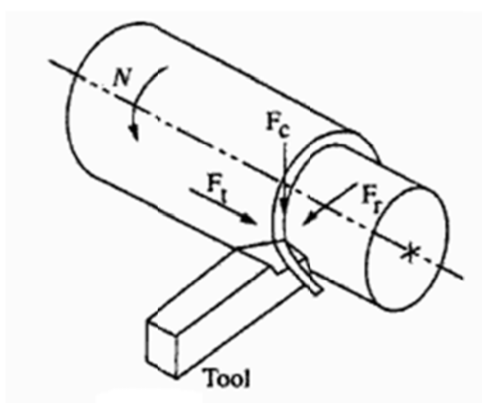

Figure 1.2: The cutting forces acting on a tool during turning process [2]

1.2.3 Cutting Tool

The cutting tool used in the turning process is a single point tool that has one cutting edge to remove material from the work-piece. Different cutting tool materials are used for different machining applications. In order to produce good quality parts, the cutting tool material should be harder than the work material and it should have the ability to withstand the increased cutting temperature, forces and speeds. Many efforts have been made to develop new cutting tool materials to withstand these tough cutting conditions [6].

During machining, the cutting tools are subjected to high temperature and stresses. Thus their material must have certain properties such as hardness, toughness and chemical stability [1]. Other significant characteristics are wear resistance and having acceptable tool life before replacement of the cutting insert is required. Tool wear will be much more rapid at elevated temperatures because of the reduction in hardness of the cutting tool [6].

One of the oldest tool materials is carbon steel [1] but its use today is very limited. It has low hardness and low wear resistance which make it unsuitable for current applications. In industry today, there are many types of tool materials such as high speed steel, ceramics, cemented carbides and diamond.

High-speed steels have high toughness and good wear resistance which make them suitable for relatively higher cutting speeds applications. Cemented carbides could be considered the most important tool materials today. They have high hardness and wear resistance over wide range of temperatures [1] but low toughness. Diamond is the hardest material and is used in general as a coating material [1].

1.3 Tool Wear

Cutting tools are subjected to extremely severe conditions of very high stress and high temperature. Tool wear occurs during the cutting action due to the interactions between the cutting tool and work-piece and results in the failure of the cutting tool. When the tool wear reaches certain level value, the tool has to be replaced to achieve the required shape, dimension and surface finish. Effects of tool wear include the increasing of cutting forces and temperatures which adversely affects the quality of the machined part and its dimensional accuracy [5]. Moreover, it deteriorates the surface finish and influences the shape of the parts produced. In addition, tool wear lowers the component quality and efficiency of the production process which leads to an increase in the cost.

The huge industrial demand of machining requires optimization of high cutting speed, depth of cut, feed rate and cutting fluids in order to have a long tool life and minimize tool wear. Also, cutting tool material with the correct application for the type of work-piece material has to be used to guarantee a reduced wear rate.

Tool wear can be defined as the gradual wearing away of the cutting edge material or the change of its shape resulting from the continuous use of the tool in cutting [1]. Tool wear is usually measured by the amount of deterioration in the tool material on the cutting surface. There are two basic types of tool wear: flank wear and carter wear, which are in the two surfaces where the cutting edge of the tool is in contact with the work-piece material and the produced chip. The two basic types of wear are shown in Figure 1.3 [1].

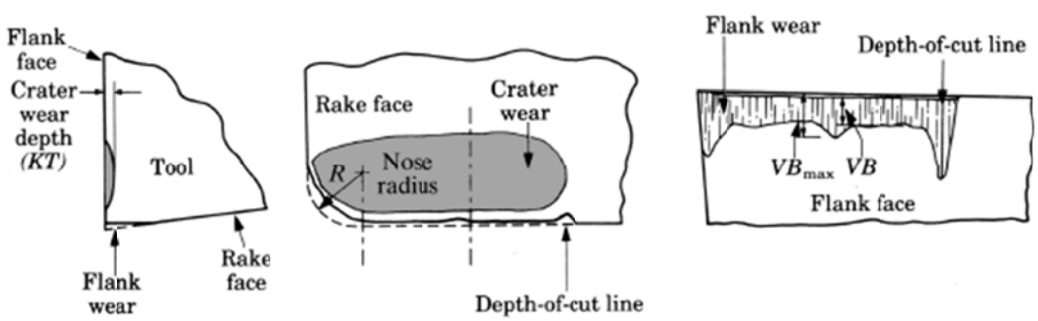

Figure 1.3: The two basic types of tool wear: flank and carter wear [1]

Flank wear occurs on the flank face of the tool [1]. It is caused by the friction between the new surface of the work-piece and the tool flank face. It results in poor surface finish and an increase in cutting force, temperature and vibration. Flank wear can be measured using the average (VB) and maximum wear land size (VB_{max}). Flank wear is considered as an important index of cutting tool performance [11] and thus is widely researched and modeled to avoid its influence on the work-piece.

Crater wear occurs on the rake face of the cutting tool. It is caused by the friction between the produced chip and rake face of the cutting tool. The crater wear depth (KT) is usually used as a measurement of crater wear in the rake face. Crater wear causes a weakened cutting edge and poor surface finish and may cause breakage of the cutting tool.

1.4 Cutting Fluids

The aim of any cutting process is to achieve the required accuracy and quality good surface finish of the produced work-piece as well as to have a longer tool life. However during the cutting process, heat is generated due to the friction at the tool edge. This heat can be reduced by using a cutting fluid.

Many materials can be machined by dry machining without using a cutting fluid. However the use of cutting fluid can improve the machining operation. The high temperature generated in the cutting zone of titanium alloys will cause rapid tool wear [7]. The use of a cutting fluid will reduce friction and wear and thus improve tool life and surface finish. In addition, it will cool the work-piece and the cutting zone [6][7] and hence reduce cutting forces and energy consumption.

Four types of cutting fluids are commonly used: oils, emulsion, semisynthetics and synthetics [1]. Oils are very effective in the reduction of friction and tool wear but have low thermal conductivity and low specific heat. Moreover, it is usually difficult and costly to remove oils from the work-piece.

Emulsions are mixture of two immiscible liquids such as oil and water and are also known as water-based coolants [1]. The water gives high cooling capacity so emulsions are used in high speed machining. Water-base coolants are considered more efficient than oil in high speed cutting of titanium alloys [7].

Synthetic solutions contain no mineral oil and are formulated using inorganic and other chemicals dissolved in water [1]. Semi Synthetic solutions contain small amounts of emulsifiable oils.

There are three basic methods of applying cutting fluids: flood cooling, mist cooling and high pressure system minimal quantity lubrication. Flooding is the most common method wherein a large volume of fluid is applied to the cutting interface.

Applying this method guarantees very good cooling and chip removal by applying the nozzle to the tool surface.

In the mist application, cutting fluid is applied at a high pressure in the form of a mist. The amount of lubricant used by this method is lower than that of flood cooling. The third method is the Minimal Quantity Lubrication (MQL). The amount of lubricant used by MQL is very small.

Coolant is considered an important way to improve the machining process of titanium alloys whether standard coolant or cryogenic cooling is used [8].

Cutting fluids play a significant role in machining process and can impact the tool life and the quality of produced work. However, environmental liability and the operators' health have become major concerns. Operators may be exposed to many hazards caused by the cutting fluids such as chemical fumes or skin damage [6]. Other issues in using the cutting fluids that concern the environment are the disposal of the used cutting fluids and the cleaning of the turning machine and the work-piece. Also cutting fluids may affect the work-piece material and the cutting tool. This can be minimized by using Minimal Quantity Lubrication method [6] which will reduce the machining cost as well as reducing environmental pollution.

1.5 Thesis Objectives and Contribution

The ultimate objective of this work is to enhance the efficiency of the machining process and the machined surface quality when machining titanium alloy as a difficult-to-cut material, while taking into consideration the economic feasibility of the process. The main objective is to develop an online tool wear monitoring system that will contribute to developing modeling of tool wear while machining titanium alloy, and selection of proper machining parameters to maximize tool life.

The first phase of the work is to generate a database of cutting performance during machining of titanium alloys while varying the cutting parameters: depth of cut, feed, cutting speed, and cutting coolant. The experimental work consists of turning tests with a dynamometer and an accelerometer to measure the cutting force and vibration during the turning process of titanium alloy. Measurements of tool wear and surface roughness after each cut are also recorded.

Data collected by sensors will be analyzed and used along with different cutting conditions to develop a tool wear prediction model. Modeling techniques used are Artificial Neural Network, Gaussian Mixture Regression and Regression Analysis. The predicted tool wear by each model will be compared to the measured wear and the performance of the different modeling techniques will be compared. The specific objectives of this project are:

1. Develop an experimental set up that will suit the selected tested monitoring strategies of cutting forces and vibration.
2. Develop test matrices to cover the required range of cutting conditions using design of experiments.
3. Collect experimental data that can be used to evaluate the effectiveness of the used sensors to measure cutting force and vibration.
4. Analyze the experimental data of the different sensors and extract the significant information related to tool wear.
5. Quantify the coolant strategies to be used as input to the prediction model of tool wear.

6. Use Artificial Neural Network, Gaussian Mixture Regression and Regression Analysis to find the correlation between monitoring strategy output and machining process parameters and tool wear.
7. Compare the different modeling techniques to determine the most accurate technique to predict tool wear while machining titanium alloy.

2 Literature review

2.1 Introduction

This chapter provides a brief literature review on machinability of titanium alloys and different sensors and techniques used to correlate the tool wear to the machining parameters and measured signal. In addition, the implemented prediction methods of tool wear such as the Artificial Neural Network and Regression Analysis are reviewed.

2.2 Literature Review

Metal cutting is one of the most extensively used manufacturing processes, and its technology continues to advance in parallel with the developments in material science. The productivity and accuracy of the metal removal operations depend on machining process parameters, cutting conditions and cutting tool geometry as well as the work-piece material and material of the tool. An important aspect in manufacturing and machining process is to obtain the desired final dimensions and surface finish quality [12].

The relative ease with which a material can be machined is referred to as its machinability [6]. There is no exact definition of this term but machinability is generally assessed in terms of particular process responses such as tool life, surface finish and power required to cut [1][6][12]. The tool life obtained is considered to be the most important factor in machinability [1].

Rapid progress in the science and technology of materials has resulted in the development of a wide range of advanced engineering materials. These materials are customized to attain special characteristics of the required applications such as high strength-to-weight ratio, high strength at elevated temperatures, excellent wear resistance etc. An example of these materials is titanium-based alloy. Although these materials are being used in a wide variety of engineering applications (e.g. aerospace, medical, petroleum), they are considered difficult-to-cut and their properties impose a lot of constraints on their machinability and their machinability imposes a lot of constraints due to their properties[7][8][13].

Lack of appropriate machining technology is the major constraint to taking advantage of advanced materials and there is a great need for reliable and cost effective machining processes. One way of achieving this cost-effectiveness in machining advanced material is by elongating tool life by reducing replacements of tools and the resources used in the machining process. Tool wear causes degradation of the shape and efficiency of the tool cutting edge and this influences the surface quality and dimensional accuracy of the finished product.

Titanium and its alloys have been increasingly used in a wide range of applications such as aerospace, automotive, and medical industries. Titanium is extensively used due to its superior properties of low density, high strength to weight ratio, good temperature resistance and corrosion resistance [6]. These properties harden its machinability so it is classified as a “difficult-to-cut” material [6][8][14].

Short tool life is the main challenge while machining titanium alloys [8]. This has limited the cutting tools to coated carbide and ceramics tools [6][7] and prevents the use of high cutting speeds [8]. The poor machinability of titanium alloys is due to their low thermal conductivity which increases the temperature at the cutting tool and the work-piece creating a very high temperature cutting zone [7]. Additionally, the interface between titanium chips and cutting tools is usually quite small, which results in high cutting zone stresses. There is also a strong tendency for titanium chips to pressure-weld to cutting tools [8].

The literature reported several ways to improve and ensure efficient and economic cutting of titanium. Some studies are presented below such as the use of an alternate cutting tool, the use of cryogenic cooling and liquid nitrogen (LN2).

Ezugwu [6] has addressed some of the implemented techniques to improve the machining of difficult-to-cut aerospace superalloys. One of the techniques is the use of rotary tooling in which movement of the cutting tool ensures that the cutting edge will be involved in machining for a very short period and then will rest for some period. This will improve heat transfer and reduce the heat in the cutting zone. The proper application of a rotary cutting tool showed improved machining especially for difficult-to-cut materials, and increased tool life. However using rotary tools generates severe chatter and increase errors in machined surfaces.

Ezugwu also reported on the delivery of the coolant at high pressure to reduce the temperature generated at the tool-work-piece and tool-chip interfaces when cutting at higher speed conditions - and consequently elongate tool life - by minimizing the friction and lowering component forces. The effect of using high pressure coolant depends mainly on tool type. For example when machining Inconel 718 or titanium with coated carbide tools, results showed improvement in tool life while ceramic tools showed lower tool life. This could be a result of high compressive stresses on the cutting edge that accelerate notching and/or tool fracture during machining.

Another way to improve machining processes is the use of modern machining techniques. Chinmaya et al. [8] studied the ability of Laser Assisted Machining(LAM) and hybrid machining to elongate tool life and improve the material removal rate while machining titanium alloy. LAM is based on localized heating and lowering the cutting forces during machining. Results indicated a reduction in the specific cutting energy and improvement of surface roughness compared to conventional machining. Laser-assisted machining improved the cutting of titanium for the cutting speed range of 60-107 m/min. In addition, improvement in surface roughness was reported.

Liquid Nitrogen (LN2) has been widely investigated as a cryogenic coolant for machining titanium and its alloys [6][13][14]. LN2 was proven to be a good lubricant and its ability to reduce tool wear and improve tool life were reported. LN2 is considered as a coolant in the metal cutting process because of its low viscosity and the fact that it does not adhere to metal surfaces easily due to its non-wetting tendency [14]. In addition it is considered to be environmentally friendly since it evaporates quickly into the air. The effectiveness of cooling will be enhanced when LN2 is released exactly to the chip-tool interface.

Ezugwu [6] presented the use of cryogenic cooling by directing a jet of liquefied gases under pressure into the cutting zone. When turning titanium alloy, Ti-6Al-4V, with cemented carbide using LN2, an improvement in tool performance was shown. Temperatures generated at the cutting interface and tool wear rates were lower than those achieved by dry machining.

Hong et al. [14] studied the effect of LN2 on the friction between the chip and the tool while machining Ti-6Al-4V. The reduction of the coefficient of friction was used to evaluate the effectiveness of LN2, along with the chip microstructure. The normal and frictional forces on the tool rake were determined from the cutting forces which were measured experimentally by a three-dimensional dynamometer. Cutting tests were performed for both dry and cryogenic cutting by LN2. An increase in the cutting force was noted while using LN2 cryogenic cooling which was explained by the lower temperature that makes the work material harder. On the other hand this decreased the feed force and frictional force of the chip acting on the tool during the cutting process.

In another study, Hong et al [13] tried to find the most effective approach of applying cryogenic cooling that will yield to the longest tool life while using minimum amounts of liquid nitrogen (LN2). Different cryogenic cooling strategies used in Ti-6Al-4V machining were compared to develop an economical cryogenic cooling approach using micro-nozzles that inject focused LN2 into the chip-tool interface, at the tip of the cutting tool where the highest temperature is. In addition, an auxiliary nozzle sprays LN2 onto the flank at the cutting edge to further reduce the cutting temperature. The test's findings showed an increase in tool life and the author believes it yields the best tool life compared with any machining method from current known sources such as LN2 flooding.

Ezugwua et al. [9] studied the correlation between cutting parameters and process parameters of high-speed turning of nickel-based alloy (Inconel 718). An Artificial Neural Network (ANN) model was introduced with cutting conditions as inputs, namely cutting speed, feed rate, cutting time and coolant pressure. The output parameters are component forces, power consumption, machined surface roughness, tool wear measured as average and maximum flank wear and nose wear. The study showed that the cutting speed has an influence on the surface roughness, cutting forces, power consumption and flank wear. When cutting speed increased, surface roughness, tool wear and power consumption increased significantly. The cutting force also increased and led to a rise in the temperature at the cutting zone and softening of the work-piece material. In addition, increasing the feed rate showed a reduction in the surface roughness value but an increase in forces and power consumption. A reduction in cutting force and power consumption was also noticed with the increase in coolant pressure.

Another common approach to ensure effective machining processes is implementing a Tool Condition Monitoring system (TCM). Based on acquisition systems of in-process signals, the supervision of tool wear will help to exchange the cutting tool at the right time and avoid excessive tool wear or tool breakage.

Various approaches have been taken to monitor tool wear using signal processing techniques. Generally the development of a TCM consists of three main stages: selection of the sensors, extraction of significant information from the sensors signals, and finally the correlation between the processed information and the amount of tool wear.

Kannan et al. [15] presented an energy based analytical model for predicting the tool wear during orthogonal cutting of particulate metal matrix composites(PMMCs) which are considered difficult-to-cut material. The model accounted for the particulate size effect, cutting conditions, material and cutting tool hardness and cutting tool geometry.

A developed energy method was utilized by Kishawy et al. [16] to predict the forces generated during machining. The effect of process parameters on the generated forces was included. Cutting experiments were carried out for different feeds on different matrix materials and volume fractions. The predicted cutting force was compared to the experimentally measured forces; the results indicated a very good match.

Kishawy et al. [11] derived an analytical model to predict tool wear during bar turning of PMMCs. The model accounted for the effects of particulate size and volume fraction on tool life during turning with different nose radii tool. The results of the flank wear model showed match between the proposed model and the measured wear values.

One of the most important elements of tool condition monitoring systems is the set of sensors used to collect signals. Sensing methodologies may include force, power, sound, vibration and acoustic emission. Different signal analysis and feature extraction techniques are used to analyze the most useful information for determining the tool condition. Methods based on signals measured from a single sensor have been used. Alternatively, multiple sensors have been combined to build sensor fusion systems. The use of multiple sensors enhances the performance of tool wear monitoring systems, as each sensor signal may contain different information related to tool wear. Below is a brief review of some of the implemented sensing methods.

A significant amount of research has been based on the measurement of cutting forces since it has direct effect on the machining accuracy and surface finish [4][17][18]. Cutting forces can be measured by mounting a dynamometer or force transducer on the tool [1].

Choudhury and Ratch [4] showed that tool flank wear can be estimated by calculating the tangential cutting force coefficient from the average X and Y forces during the milling process. A number of milling experiments were carried out with different values of speed, feed and depth of cut and cutting force measurements using a dynamometer. The effects of cutting conditions on the tangential cutting force coefficient were investigated and the results indicated that flank wear can be estimated using the tangential cutting force coefficient and cutting parameters.

Zhang et al. [17] studied tool wear and cutting forces during end milling of Inconel 718 with a coated cemented carbide cutting tool. Milling experiments were performed with measurements of cutting forces using Kistler 9257A dynamometer. The cutting tests were interrupted at the specified cutting intervals and the tool wear was measured with a professional handheld digital microscope. The 0.3 mm average flank wear criterion was used to determine the effective tool life. The obtained results proved that the cutting forces are very sensitive to the increase in flank wear. Increasing the tool wear will increase the tool-workpiece contact area and hence increase the cutting forces.

Lee et al. [5] presented an experimental study of tool failure using the dynamic component of the tangential cutting force. The results indicated a good correlation between tangential cutting force and tool flank wear. Also, the cutting force increased as the tool wear increased.

Kannan et al. [18] studied the generated forces during cutting metal matrix composites (MMCs) and found that they can be correlated to the average dislocation density in the matrix. The forces were measured using a three component piezoelectric dynamometer. In addition, microstructural change analysis using TEM showed that the change in microstructure is due to cutting conditions, material composition, and particulate size and volume fraction.

Another effective important signal in cutting processes is the vibration signal collected through an accelerometer. An accelerometer can be used to measure the frequency and amplitude of vibration within the machine structure, spindle, tool and work-piece. The occurrence of vibration affects the surface finish and tool life.

Haddadi et al. [19] studied the effect of the tool edge condition on tool vibration parameters experimentally in the frequency domain. The results obtained indicated that the spectrums associated with worn tools contain more energy than sharp tools within 0 to 3.5 KHz. Also it was observed that the spectrum of the vibration signal is not sensitive to varying the tool rake angle.

Upadhyay et al. [20] used vibration signals for in-process prediction of surface roughness during turning of Ti-6Al-4V alloy. Turning experiments were conducted with measurements of vibration using a tri-axial Kistler accelerometer. Different values of cutting speed, feed rate and depth of cut were used. Multiple regression and Neural Network models were developed using cutting parameters and vibration signals for prediction of surface roughness. The results of both models showed a good predictive ability. The vibration signal alone was found to be insufficient input to the prediction models.

Salgado et al. [21] studied the applicability of singular spectrum analysis (SSA) to signal processing for tool condition monitoring systems development using vibration. The vibration signals were measured using two accelerometers in the longitudinal and transverse directions. The tool wear was predicted using multilayer Neural Network trained with the features extracted from the SSA-processed vibration signals. Singular spectrum analysis depends on dividing the signal in the time series into a set of independent additive time series. In this study, decomposed vibration signals were interpreted into two signals: the trend signal representing the signal's local mean, and the detrended or noise signal representing the difference between the original signal and the trend. The results showed that information about the tool flank wear is mostly contained in high-frequency detrended signals.

Acoustic emission signals are also used in establishing tool condition monitoring systems. Li [22] has conducted a review on using acoustic emissions (AE) and found that it can be successfully used to estimate tool wear. Different signal processing techniques were used to extract the relevant features of AE signal to tool wear including time series analysis, Fourier Transform, Gabor Transform and Wavelet Transform.

Arul et al. [23] used AE sensing to study the effect of drilling parameters on thrust force and flank wear while machining glass fiber reinforced plastic composites material. AE emitted from the work-piece during drilling was measured with a Kistler wide band piezoelectric sensor. Also Kistler two-component dynamometer was used to measure the thrust cutting force. It was found that the thrust force is affected by the feed rate more significantly compared to the cutting speed. Moreover, results showed that RMS values of the measured AE signal can be correlated to the flank wear.

Pai and Rao [24] presented a tool monitoring technique based on the analysis of acoustic emission in face milling. The acoustic emission signal parameters (ring down count and RMS voltage) were correlated with the tool status in face milling of steel using one, two, and three inserts. It has been shown that these signal parameters can be used to monitor the tool condition effectively.

Signals measured by deferent sensors are used to develop a model of machining process such as prediction of tool wear or surface roughness. Applied signal analysis techniques include – but are not limited to - frequency domain analysis [5][19][22][31][35], Principle Component Analysis (PCA) [3][28], and stepwise regression [36]. Signal analysis is an important step that helps in selecting the significant features of collected signals to be used in the model.

Some of the techniques used in modeling machining process are Artificial Neural Network (ANN), Fuzzy Logic, Polynomial Classifier and Regression Analysis (RA). Neural Network is widely used in modeling the machining process [3][25]-[30][32].

Ghosh et al. [25] presented an ANN model using sensor fusion for tool condition monitoring in a face milling. Sensors for the following measurements were used: cutting forces, spindle motor current and supply voltage, spindle vibration, acoustic emission and machining sound signal. Signal processing and feature extractions from the sensors signal are important steps to extract the relevant tool wear data from the measured signal. Cutting parameters along with the extracted features were used as input to the Neural Network model to predict flank wear. The feed-forward back-propagation Neural Network was used to model the flank wear. Results showed that fusion of multiple sensors can predict tool wear better than using a single sensor. The best prediction results were obtained from sensor fusion based on cutting force and voltage and current of spindle motor.

D'Addona et al [26] proposed a tool wear prediction model based on Neural Networks. Four main steps were applied to generate the Neural Network: collection of input-output dataset, dataset pre-processing, NN training, and finally performance evaluation of NN. The input-output dataset was collected by performing machining tests with different cutting speed values and a constant feed rate and depth of cut. Cutting speed and cutting time were used as inputs to the Neural Network while the output was the tool wear. Results showed a good correlation between the experimental and predicted tool wear.

Zain et al. [27] developed a surface roughness prediction model since that is considered an important performance measurement of machining processes. Two modeling methods were applied individually: Artificial Neural Network and regression analysis. The developed Neural Network model was the feed-forward back-propagation Neural Network. It consisted of the input layer that includes the cutting conditions, two hidden layers, and one output layer to predict surface roughness. The experimental data was divided for the training and testing of the Neural Network with a ratio of 70%: 30%. The results showed that the predicted value of surface roughness by the ANN and regression was less than the measured value by about 1.05% and 1.57% respectively.

Segreto et al. [28] applied a sensor fusion artificial Neural Networks for tool state classification during turning of Inconel 718 nickel base alloy. The multiple sensor monitoring system compromised measurements of cutting force, acoustic emission and vibration signal. Turning tests were carried out with different cutting speeds and feed rates using different fresh and worn uncoated carbide inserts. The collected signals were analyzed using Principal Component Analysis (PCA) to extract the significant signal features that would be used as input variables to the Neural Network.

Szecsi [29] presented a method to monitor tool condition on CNC lathes using an Artificial Neural Network. The method was based on plastic deformation theory by analyzing the axial force generated while pressing of the cutting edge of an insert into the work-piece when the cutting process is stopped. ANN Artificial Neural Network was used to analyze the experimental data and examine the correlation between axial pressing force and flank wear. Results showed that there is a close relationship between the axial force and the flank wear of the cutting tool.

Rao and Srikant [30] applied Artificial Intelligence techniques to estimate tool condition and the tool wear value online by measuring radial cutting force. The flank wear was estimated using three AI techniques: Fuzzy Logic, Neural Network, and neuro-fuzzy. The neuro-fuzzy model produced the best results.

Deiab et al. [3] presented a novel approach to model and predict cutting tool wear using statistical signal analysis, pattern recognition, and sensor fusion while machining mild steel using coated carbide inserts. Tool wear was predicted using Artificial Neural Network (ANN) and Polynomial Classifiers (PC). Measurements of force and acoustic emission were used as input to the network along with cutting conditions parameters. The pattern recognition used was based on two methods: Artificial Neural Networks and Polynomial Classifiers (PC). It was proved that PC had significantly reduced the required training time compared to that of ANN without compromising the prediction accuracy. The predicted results were compared with the measured tool wear and showed a good match.

Wang et al. [31] presented a Gaussian Mixture Regression (GMR) based model to predict tool wear while machining titanium alloy. A number of milling experiments were conducted with titanium alloy Ti-6Al-4V as work piece and measurements of cutting force by a piezoelectric dynamometer. Machining parameters were kept constant. An optical microscope was used to measure the length of wear after every cutting pass. Features extracted from the measured cutting force signal by frequency harmonic method were used as input variables to generate a GMR model to predict tool wear. The performance of the GMR model was compared with other models such as the back propagation Neural Network model and radial basis network based on the same training and test data. The results showed that the GMR method is more accurate than the other applied methods.

Korkut et al. [32] used artificial Neural Network (ANN) and Regression Analysis (RA) to predict temperature at the tool-chip interface in machining since it has a direct influence in the cutting tool wear. The ANN used is the back-propagation network with inputs of cutting conditions and cutting forces. The output of the network is the interface temperature. The data used was obtained from a previous experimental study. In addition, the same input variables set were used to generate a regression model to investigate the relation between the variables and tool-chip interface temperature. Results showed that the Artificial Neural Network and regression analysis models can be used for prediction of interface temperature with regression being more accurate.

Ghani et al. [33] presents a model for predicting the cutting tool wear using regression analysis. The regression model is based on cutting force signals measured experimentally while machining of titanium alloy using a Kistler dynamometer.

Gokulachandran et al. [34], developed two tool life prediction models using regression and fuzzy logic methods. A multiple regression model was used to build a relation between tool wear and process parameters (spindle speed, feed, and depth of cut). The Taguchi approach was used to design the experiments and to select the factors to be included in the model and their levels. Different fuzzy rules were used with triangular, Gaussian and trapezoidal functions. The Gaussian function gave the least error. The predicted tool wear by each model was compared to the experimentally measured value and it was found that the results obtained by the fuzzy model were more accurate.

Kuo [35] proposed a tool prediction system using a Fuzzy Neural Network (FNN) model. It was based on integrating the two technologies of the Neural Network and fuzzy logic. Tool wear was measured experimentally by carrying out turning experiments with measurements of cutting force, vibration and acoustic emission. The measured signals were analyzed using time series analyzer and frequency analyzer by Fast Fourier Transform to extract the significant features of tool wear. These features were used as input to the FNN model to estimate the tool wear. In addition, a multi regression model and a NN model were also developed to predict the tool wear. The results obtained by FNN were found to be better compared with the other methods.

Shanableh and Assaleh [36] proposed a stepwise regression as a dimensionality reduction method to solve the practical problem of large feature set expanded by polynomial expansion technique. Stepwise is a regression technique in which the independent (predictor) variables set that best describes the dependent variable is selected. Since the best features are selected, training of the polynomial classifier network is easier. The method was tested on two applications related to image and video based recognition. Results showed classification rate is higher than the standard polynomial classifier but the computational complexity is relatively higher.

It can be seen from the above review that prediction of tool wear in metal cutting is an important field of study. Developing an online tool monitoring system is widely implemented to monitor the cutting tool status and maximize its utilization without affecting the required accuracy and surface roughness. Sensor fusion is considered more effective than single sensor but is economically infeasible especially for industrial applications.

The intention of this work is to experimentally investigate the machinability of a difficult-to-cut material: titanium alloys used in the aerospace and automotive industries. The main objective of this work is to study the influence of cutting conditions in the tool wear in the turning process of titanium alloys. Cutting forces and vibration measurements will be implemented to develop a reliable and effective TCM system and predict tool wear.

3 Experimental work

3.1 Introduction

This chapter discusses the procedure used to create the tool monitoring system. The objectives of the study are set and the experimental set up, equipment and machine used, work-piece and cutting tool inserts are discussed.

The experimental work consists of controlled machining tests with force and vibration measurements, as well as tool wear and surface roughness. Experimental tests were carried out using fresh inserts and a test matrix was created to cover all possible combinations of machining parameters namely cutting speed, feed rate, depth-of-cut and coolant strategy.

The system design and arguments for the choices made according to the Design of Experiment technique (DOE) are described here. The basic requirements to develop the system are to measure force, vibration and the wear of the tool and send the results to a system that analyzes the information to create a tool condition monitoring system.

3.2 Design of Experiment (DOE)

Design of Experiment (DOE) is a scientific approach used to determine the impact of a certain process factors on the output of the process. DOE process can be divided into three main stages as follows [37].:

1. Planning stage

The planning stage is the most important stage, where the experimentation parameters and set up are selected. This stage includes the following: defining the problem, setting the objectives of the experiment, selecting the cutting parameters and their levels and establishing the measurement system and experiment matrix.

2. Conducting stage

This stage includes conducting the experiments, collecting the sensors' signals, measuring tool wear and surface roughness and collecting the chip samples.

3. Analyzing stage

In this stage, the experimental tests are analyzed to interpret results. Also, validation experiments may be conducted to confirm the results.

3.3 Planning of Experiments

For the current study, the stages of DOE [37] have been implemented according to the following steps:

1. Identify the problem: machinability of difficult-to-cut material and the need to monitor tool wear to achieve the required efficiency.
2. Determine the objective: establish a tool condition monitoring system to optimize the change of tool insert. Also study the effect of cutting parameters on tool wear and cutting forces and vibration signal.
3. Identify the process factors to be studied: cutting parameters (cutting speed, feed rate, depth of cut and coolant), cutting force and vibration signal.
4. Select the cutting condition parameters and all possible combinations to set the cutting matrix suitable to the work-piece and cutting insert material selected.
5. Conduct the experiments: establish the experimental setup, carry out the tests and collect the experimental data.
6. Analyze the data using the appropriate analysis techniques and interpret the results.

3.3.1 Work-piece material

The material chosen for machining test was Titanium alloy, Ti-6Al-4V. Titanium is difficult to machine due to its characteristics of high tensile strength, low density, high corrosion resistance, ability to withstand extreme temperatures and low weight ratio [6][7][8]. The Titanium bars used have an initial diameter of 100 mm with chemical composition of Aluminum, Al 6% and Vanadium, V4%.

3.3.2 Cutting Tool material

Since Titanium is considered as difficult-to-cut material [1][6][7][8], the tool material used should be capable of high speed machining and with dry cutting conditions. In the present study, cemented carbide inserts were used to machine the Titanium and perform the turning experiments. They are generally used for high speed machining of titanium alloys [6]. The inserts are the commercial 16 mm Sandvik triangular tool; TCMT 16 T3 08-MM (1105) [39].

3.3.3 Range of cutting conditions investigated

Using the tool insert manufacturer's guidelines [39], a cutting range was selected according to the maximum and minimum values of the feed rate, depth of cut and the work-piece type. The cutting parameters levels were selected based on tool material and work-piece material and by studying different research papers. Depth of cut was kept fixed as many researchers indicated that the depth of cut has negligible effect on tool wear compared to the cutting speed and feed rate.

The tests were conducted at feed rates of 100, 150, 200 mm/rev and a fixed depth of cut 0.8 mm. The experiments were carried out under cutting condition of dry, mist, flood and cryogenic cooling with liquid nitrogen (LN). The cutting speeds selected in the experiment were 100,125 and 150 m/min. Cutting conditions employed in the machining trials are listed in Table 3.1.

Table 3.1: Cutting process variables and their levels

Cutting Parameter	Unit	Levels			
		1	2	3	4
Cutting speed, *v*	m/min	100	125	150	-
Feed rate, *f*	mm/rev	0.1	0.15	0.2	-
Depth of cut, *d*	mm	0.8	-	-	-
Coolant, *c*	-	Dry	Flood	Mist	LN

All possible combinations of machining parameters - cutting speed, feed rate, and depth of cut and coolant strategy - are to be varied in order to insure all possible machining scenarios (total of 36 experiments). The test matrix is shown in Table **3.2**.

Table 3.2: Test matrix with the experimental conditions

Experiment	*v*	*c*	*d*	*f*	Experiment	*v*	*c*	*d*	*f*
1	1	1	1	1	19	2	3	1	1
2	1	1	1	2	20	2	3	1	2
3	1	1	1	3	21	2	3	1	3
4	1	2	1	1	22	2	4	1	1
5	1	2	1	2	23	2	4	1	2
6	1	2	1	3	24	2	4	1	3
7	1	3	1	1	25	3	1	1	1
8	1	3	1	2	26	3	1	1	2
9	1	3	1	3	27	3	1	1	3
10	1	4	1	1	28	3	2	1	1
11	1	4	1	2	29	3	2	1	2
12	1	4	1	3	30	3	2	1	3
13	2	1	1	1	31	3	3	1	1
14	2	1	1	2	32	3	3	1	2
15	2	1	1	3	33	3	3	1	3
16	2	2	1	1	34	3	4	1	1
17	2	2	1	2	35	3	4	1	2
18	2	2	1	3	36	3	4	1	3

3.4 Experimental Setup

The basic configuration of the experimental measuring setup is shown in Figure 3.1. It contains a CNC lathe equipped with sensors for measuring cutting force and vibration. Machining tests were conducted on a CNC lathe that has a continuously variable spindle speed. The sensors implemented were the dynamometer and accelerometer to measure cutting forces and vibration.

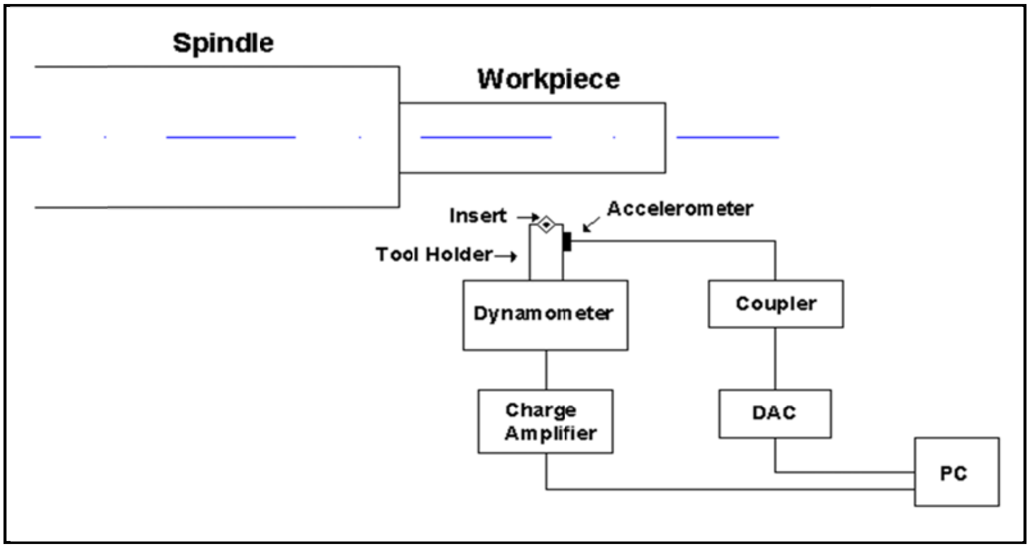

Figure 3.1: Basic configuration of the experimental measuring setup

3.5 Collection of Input/Output dataset

3.5.1 Measurement of Force

The Kistler dynamometer (3 components 9251A Kistler quartz force sensor) [40] was mounted on the tool post to measure the cutting forces in the CNC lathe machine at a sampling rate of 0.8 kHz. The measured force signals were in the three force directions: tangential/cutting force (Fy), axial/feed force (Fx) and radial/thrust force (Fz). The force signals were then passed through the integrated multichannel charge amplifier (3×1 channel Kistler 5070A charge amplifier) which converts the electrical charge signals of the sensor into voltages exactly proportional to the three components. The cutting force signals were continuously recorded using the data acquisition software DynoWare Type 2825A-02 [40].

3.5.2 Measurement of Vibration

The Triaxial accelerometer (KISTLER 8765A250m5) was mounted on the tool holder to measure vibration in three orthogonal axes. The accelerometer has a sensitivity of 20g/mv. The vibration signals were then passed through an amplifier and collected using a data acquisition board (National Instruments PCI-6132) at a sampling rate of 50 kHz. The MatLab software [47] was used to collect and save the vibration data.

3.5.3 Measurement of Tool Wear and Surface Roughness

Tool wear measurements were taken using a tool maker's microscope equipped with graduated scale in mm. The surface roughness of the machined surface was measured using the portable Surface Roughness Tester "Mitutoyo" which reports the roughness average.

3.5.4 Experimental procedure

Interrupted turning cuts were carried out at fixed cutting conditions with fresh tool inserts. The measured parameter to represent the progress of wear was tool flank wear VB. The cutting test run was periodically interrupted and the insert was taken out to measure tool wear just after the force and vibration signals had been recorded. Generally test cuts lasted for 10 seconds at the beginning of each test run and as the test progressed, the duration of each test was systematically increased. The turning operation of a test was stopped when the VB reached 0.3 mm. The 0.3mm VB is the standard recommended criteria in defining a tool life endpoint by the ISO 368 [41].

The surface roughness of the machined surface was measured after each cutting test. Readings were taken at three different locations and the average value was recorded. Also, chip samples of each cut were collected. The obtained data were analyzed in order to investigate the relation between the tool wear and the sensor signals.

3.5.5 Output of the experiments

More than 300 cutting tests were performed within the defined 36 experiments. The output of these tests were the following:

1. Cutting time where the cutting tool is removing material.
2. Cutting forces in the three directions.
3. Vibration signal in the three directions.
4. Tool wear, VB in mm.
5. Surface roughness after the cut, Ra in µm.
6. The collected chip samples produced while cutting.

4 Modeling methods

4.1 Introduction

The basic steps used in creating a model of tool wear are: collection of data, analysis and pre-processing of the data, design of the network or model, and testing of the prediction model. In this chapter a basic review of different tool wear prediction modeling methods is presented. Modeling methods include: Neural Network, Regression Analysis by polynomial expansion and Gaussians Mixtures Regression (GMR). In addition Stepwise Regression Analysis is discussed as a dimensionality reduction technique.

4.2 Artificial Neural Networks (ANNs)

4.2.1 Introduction to ANN

The human brain consists of a network of over a hundred billion interconnected neurons that can process small amounts of information and then activate other neurons to continue the process [42]. Artificial Neural Networks (ANNs) are based on the idea of human brain with the neurons as processing elements and weighted connections. They are used in problem solving and process modeling in a way similar to human brain functionality [43]. They are currently being used in many fields of engineering and machining [9], business, finance and medicine [10].

Neurons are connected to each other with weighted inputs and outputs in which the weight of each input represents its strength. The weighted inputs are then added and the output of the neuron is passed through an activation function to be amplified. Modeling of a complex process requires the use of many neurons instead of using a single neuron [44]. Figure 4.1 illustrates the architecture of a neuron with the arrowheads pointing toward the direction of information flow. In the figure $x_1, x_2, ..., x_n$ are the inputs to the neuron and $w_1, w_2, ..., w_n$ are the weights. The weighted sum of the inputs is computed as $\sum_{i=1}^{n} w_i x_i$ and then will be passed through the activation function to produce the output of the neuron. Examples of the activation function are threshold and sigmoid functions.

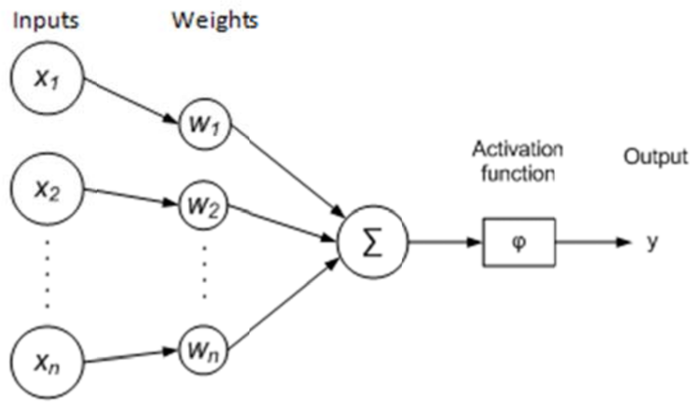

Figure 4.1: The architecture of a neuron

Multilayer Neural Networks are probably the most used Neural Network models [43]. The basic structure of a multilayer Neural Network consists of three main layers: an input layer, a hidden layer and an output layer. The number of neurons in the input and output layers are determined according to the available number of inputs to the network and the number of outputs required from the network. However, the number of neurons in the hidden layers can be changed until the required output is achieved. The input signals$\{x_1, x_2, ..., x_n\}$ will propagate in the forward direction in the layers of the network so it is called a feed-forward Neural Network. An example of a multilayer Neural Network is shown in Figure 4.2 with a direction of flow from the input layer to the output layer.

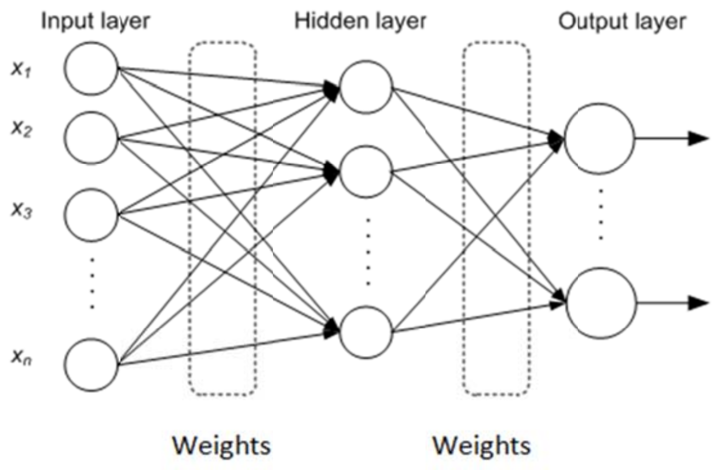

Figure 4.2: Architecture of multilayer Neural Network

4.2.2 Training and Validating of Neural Networks

One of the most important features of Neural Networks is their ability to learn from the input data. This makes them able to improve their response and process unknown input data to produce the required output [43].

Connections between the neurons are assigned certain weights which determine the output of the Neural Network. These weights are assigned in the training process by initially assuming random numbers and then adjusting them in the validation process depending on the Neural Network performance. The process of adjustment of the weights is repeated until the Neural Network output is within an acceptable rate of error [42]. The desired input-output relationship is determined during this training process of the Neural Network.

There are a number of learning algorithms to train Neural Networks that can be categorized as supervised training and unsupervised training [42]. In the supervised training method, the Neural Network is fed with sample of input data along with the output to be predicted by the network. The training may take several iterations until the predicted output matches the actual output within an acceptable error. Each iteration is basically altering the connection weights. This is the most common Neural Network training method. In the unsupervised training the output is not fed while training the Neural Network. It depends on identifying some features of the input and then classifying the inputs to several groups.

After training the network, testing (validation) is applied with another set of data. From the available data, a testing data set is used to test the network to verify that the network can produce the required output. Usually the data is divided randomly into two sets allocated for training and testing. A typical partitioning is done with a ratio of 75% and 25% of the entire data for training and testing respectively [43].

4.2.3 Neural Network Architecture

The most common Neural Network architecture is the feed-forward back-propagation Neural Network which can be applied to many different tasks [42]. The feed-forward implies that the neurons are connected foreword to the next layer as it processes without any backward connections. The back-propagation term is related to the training process of Neural Network [42]. The back-propagation is considered as a supervised training algorithm since the output is fed to the network. In the feed-forward back-propagation Neural Network, the input data is applied in the input layer, propagate through the hidden layers and then to the output layer. Then, an error signal is computed by comparing the generated output to the desired output. The computed error signal is transmitted backward from the output layer to the neurons in the last hidden layer that is connected to the output layer [43].

Each neuron in the hidden layer that is connected to the output layer receives a weighted portion of the total error signal depending on its earlier weight in generating the output signal. This process propagates backward through the layers of the network. The total error and the connection weights are updated. The process of feeding the input signal with the new weights and transmitting back the error signal to update the connection weights is repeated until the network error is reduced to an acceptable value.

4.2.4 Neural Network for Tool Wear Prediction

Figure 4.3 shows the architecture of the Neural Network used in the current study to predict the tool wear. It is a multilayer feed-forward back-propagation Neural Network consisting of three layers: an input layer, a hidden layer and an output layer. The inputs to the network are: cutting speed (v), feed rate (f), depth of cut (d), coolant (c), cutting forces (F), and vibration (V). The output of the Neural Network is the tool wear.

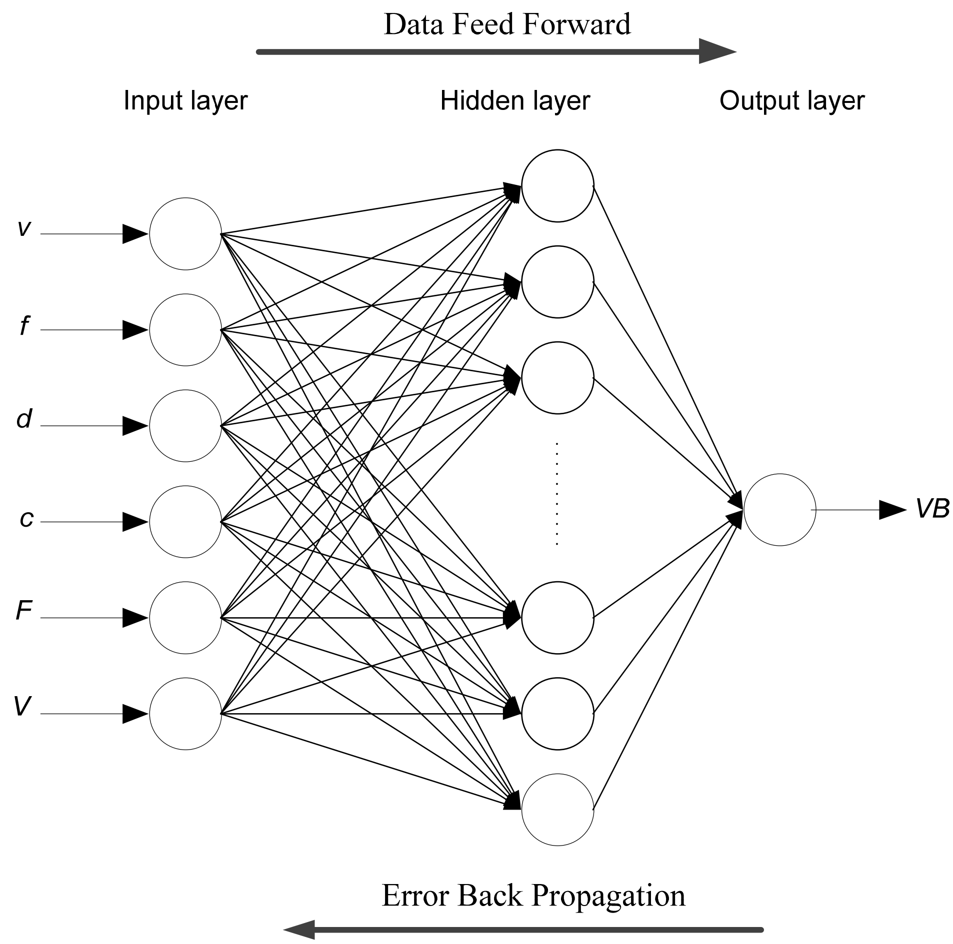

Figure 4.3: Neural Network used in training and predicting tool wear

4.3 Regression Analysis

4.3.1 Introduction to Regression Analysis

Regression analysis is a simple method for investigating the functional relationships among variables expressed in the form of an equation or a model connecting the dependent variable and one or more independent variables [45]. It is commonly used to predict values of one variable (response) when given values of the other independent variables (regressors).

Assuming Y is the dependent variable and X is the independent variables, the regression model will relate Y to a function of X and β formalized as $Y = f(X, \beta)$, where β represents a set of unknown parameters to be determined from the data, called the regression parameters or coefficients. The concept of regression analysis is to find the best relationship between Y and X that allows for prediction of the response values, given the regressor values [45]. This is mainly accomplished by determining the regression parameters (β) given the values of the independent variables (X) and their known response value (Y).

If there is only one independent variable that explains Y, the regression analysis is called a single regression but the analysis is termed multiple regression if more than one variable is required to describe Y in the regression model. In the multiple regression case, Y and X of the model are vectors of response and independent variables respectively.

4.3.2 Linear Regression Model

In the linear regression model, the dependent variable is assumed to be a linear function of the independent variables. The simple linear regression model can be written as:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \qquad (4.1)$$

where k is the number of parameters to be estimated in the linear regression model and ε is the random term introduced to account for any disturbance or error. The primary objective of the regression analysis is to estimate the regression coefficients that minimize the error. The most popular method is the least squares method which minimizes the sum of squares of the error of each observation data point. Assuming there is n number of observations in the data to be analyzed, the errors can be written as [45]:

$$\varepsilon_i = y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \cdots - \beta_k x_{ik}, \quad i = 1,2, \dots, n \qquad (4.2)$$

The sum of squares of these errors is [45]:

$$S(\beta_0, \beta_1, \dots, \beta_k) = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \dots \dots - \beta_k x_{ik})^2 \quad (4.3)$$

If the function f is nonlinear as a function of x (i.e. the relationship between the X and Y is nonlinear), a general nonlinear regression model could be written as:

$$Y = \beta_1 f(X_1) + \beta_2 f(X_2) + \cdots + \beta_k f(X_k) \qquad (4.4)$$

4.3.3 *Prediction by Regression*

Assuming we have k independent variables x_1, x_2, …, x_k and n observation y_1, y_2, …, y_n, a general linear regression model can be constructed in matrix form as:

$$y = \boldsymbol{X}\beta + \boldsymbol{\varepsilon} \qquad (4.6)$$

Where:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad \boldsymbol{X} = \begin{bmatrix} 1 & x_{11} & x_{21} & \cdots & x_{k1} \\ 1 & x_{12} & x_{22} & \cdots & x_{k2} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{1n} & x_{2n} & \cdots & x_{kn} \end{bmatrix}, \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix}, \quad \boldsymbol{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

The estimated values of the regression parameters, $\boldsymbol{\beta}$, can be determined as

$$(\mathbf{X}^{\mathrm{T}}\mathbf{X})\boldsymbol{\beta} = \mathbf{X}^{\mathrm{T}}\mathbf{y} \quad \rightarrow \quad \boldsymbol{\beta} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{y} \qquad (4.7)$$

Knowing the regression parameters, $\boldsymbol{\beta}$, it is possible to predict the dependent variable, y and this can be used to predict tool wear.

4.3.4 *Selection of Variables*

Selection of variables is an important issue in multiple regression analysis where a subset of X that best predicts Y is found. There are some procedures that are used to select variables to be included in the regression equation. The best regression equation will be computed by adding or deleting variables from the equation depending on its performance [46]. Examples of techniques used to choose significant explanatory variables are forward selection, backward elimination and stepwise selection [46].

In the forward selection procedure, the modeling equation starts with no variables, then each added variable will be tested using a specified criterion. Another variable that improves the model will be added and this will be repeated until there are no more variables that improve the model. On the other hand, in the backward elimination procedure, modeling will start with an equation that contains all the variables, then deletion of each variable will be tested. The process will be repeated until no further deletion of variables improves the model.

The stepwise method is similar to the forward selection procedure but at each step, the deletion of the variables will be checked for model improvement [46].

Variables are added and removed from the model based on their statistical significance in the regression model. The stepwise procedure begins with an initial model and then compares the performance of larger and smaller models. At each step, a specified statistic is computed to test models with and without the tested variable [45].

4.3.5 Power Transformation of Variables

A standard assumption of the regression analysis is that the relationship between the dependent variable and independent variables is linear but this is not usually the case. Analyzing the variables before implementing the regression analysis is important to get the model that best describes the data. It is common practice to use a transformed form of the variables to fit the linear regression model [46]. Transformations of the variables are applied to achieve the linearity of the regression model or to stabilize the error variance [46]. Since the literature suggests that the relation between the tool wear and cutting process parameters is nonlinear, an appropriate transformation of the variables can make the relationship between the transformed variables and tool wear linear.

Some of the transformations implemented are the logarithmic transformation [27], square root transformation, and power transformation. In the power transformation the variables are raised to a defined power and the new transformed variable matrix is used in the regression model instead of the original variables. Raising the independent variables matrix to a power of 2 is discussed and used in this study. The predictor matrix X ($n \times k$; k columns of independent variables and n observations) is expanded into a quadratic design matrix D to be used in the regression analysis. A full quadratic model D of n columns matrix X contains the following order of terms [47]:

1. The constant term.
2. The linear terms of X in order of: 1, 2, ..., k.
3. The products terms of X in order of: (1,2), (1,3), .., (1,k), (2, 3), .., (k-1, k).

4. The squared terms of X in order of: 1, 2, ..., k.

Rewriting equation 4.6, X will be transformed to the matrix D according to the following:

$$y = \boldsymbol{D}\beta + \boldsymbol{\varepsilon} \qquad (4.8)$$

where:

$$\boldsymbol{D} = \begin{bmatrix} 1 & x_{11} & x_{21} & \cdots & x_{k1} & x_{11}x_{21} & \cdots & x_{11}x_{(k-1)1} & {x_{11}}^2 & \cdots & {x_{k1}}^2 \\ 1 & x_{12} & x_{22} & \cdots & x_{k2} & x_{12}x_{22} & \cdots & x_{12}x_{(k-1)2} & {x_{12}}^2 & \cdots & {x_{k2}}^2 \\ \vdots & \vdots & \vdots & & \vdots & \vdots & & \vdots & & & \vdots \\ 1 & x_{1n} & x_{2n} & \cdots & x_{kn} & x_{1n}x_{2n} & \cdots & x_{1n}x_{(k-1)n} & {x_{1n}}^2 & & {x_{kn}}^2 \end{bmatrix}$$

Training set of data will be used to compute the regression parameters and then predict the dependent variable (tool wear).

4.4 Gaussian Mixture Regression

Gaussian Mixture Models (GMMs) are among the most common methods used in clustering [48]. Clustering is a process in which a data set is divided into number of groups combining similar data points. GMMs have been widely applied to data analysis, pattern recognition, signal processing, image processing and learning and modeling [48][49][50]. GMM is basically a probability density function formed by combining a number of Gaussian components. The GMM algorithm described in [48] is summarized below.

A Gaussian mixture model is a weighted sum of k-component Gaussian densities as given by the equation:

$$p(x_t|\Theta_i) = \sum_{i=1}^{k} \alpha_i p_i(x_t|\theta_i) \qquad (4.9)$$

where x is a d-dimensional data vector and $\alpha_i(i = 1,2,...,k)$ are the mixture weights or coefficients of the k components that must sum to one. The $p(x|\theta_i)$ are the component Gaussian densities (for i = 1,2,…,k) in the form of:

$$p(x|\theta) = \frac{1}{(2\pi)^{d/2}\sqrt{|\Sigma|}} \exp\left(-\frac{(x-\mu)^T\Sigma^{-1}(x-\mu)}{2}\right) \ , \ \theta = (\mu, \Sigma) \qquad (4.10)$$

The parameters of each Gaussian component are the mean μ, and the covariance ∑. The resulting density function of the n-vectors of features X ={x_1, x_2, . . . , x_n} is:

$$p(X|\Theta) = \prod_{t=1}^{n} p(x_t|\Theta) = L(\Theta|X) \ , \ \ \Theta = (\alpha_i, \theta_i) \qquad (4.11)$$

The parameters that best match the Gaussian distribution are estimated by maximizing the likelihood function L(Θ|X). The commonly used strategy is the Expectation-Maximization (EM) algorithm [49]. EM algorithm is performed by taking the objective function Q such that:

$$Q = \sum_{t=1}^{n} \sum_{i=1}^{k} w_{it} \log[\alpha_i p_i(x_t|\theta_i)] \qquad (4.12)$$

where w_{it} is the probability for individual k classes and is constrained to sum to one.

$$w_{it} = \frac{\alpha_i p_i(x_t|\theta_i)}{\sum_{s=1}^{k} \alpha_s p_s(x_t|\theta_s)} \qquad (4.13)$$

An iteration of the EM algorithm consists of the E step and M-step. Iterations of EM will stop when the value of log-likelihood cannot be increased and the best model parameters are provided. The E-step involves computing expected classes w_{it} of all data points. In the M-step, the mixture new weights, means and covariance are re-estimated by the following formulas:

$$\alpha_i^{new} = \frac{1}{n} \sum_{t=1}^{n} w_{it} \qquad (4.14)$$

$$\mu_i^{new} = \frac{\sum_{t=1}^{n} w_{it} x_t}{\sum_{t=1}^{n} w_{it}} \qquad (4.15)$$

$$\textstyle\sum_i^{new} = \frac{\sum_{t=1}^{n} w_{it} (x_t - \mu_i^{new})(x_t - \mu_i^{new})^T}{\sum_{t=1}^{n} w_{it}} \qquad (4.16)$$

4.4.1 GMR Modeling

GMM can be used to estimate a response variable for a given independent input variables by fitting the data to a Gaussian Mixture Regression (GMR) model. GMR model is developed using number of Gaussian mixture models to represent the joint density of the data and then compute regression functions from each GMM model [31]. The GMR algorithm [31] can be described as follows.

Given the data set (X,Y) of size n, where x is the input independent variables and y is the response output, the relationship between X and Y can be described by k-components GMM models with a joint probability density function of [31]

$$f_{XY}(x, y) = \sum_{i=1}^{k} \alpha_i p_i(x, y: \mu_i, \textstyle\sum_i) \qquad (4.17)$$

where $\mu_i = \begin{bmatrix} \mu_{ix} \\ \mu_{iy} \end{bmatrix}$ is the mean, $\sum_i = \begin{bmatrix} \sum_{iXX} & \sum_{iXY} \\ \sum_{iYX} & \sum_{iYY} \end{bmatrix}$ is the variance of each Gaussian component and α_i are the priors. The global GMR function can be written as follows:

$$f_{X|Y}(x|y) = \sum_{i=1}^{k} w_i p_i(y: m_i(x), \sigma_i^2) \qquad (4.18)$$

with mixing weights w_i, mean $m_i(x)$ and variance σ_i^2 that can be described by the following formulas:

$$w_i = \frac{\alpha_i p_i(x: \mu_{iX}, \sum_{iX})}{\sum_{i=1}^{k} \alpha_i p_i(x: \mu_{iX}, \sum_{iX})} \qquad (4.19)$$

$$m_i(x) = \mu_{iY} + \sum\nolimits_{iYX} \sum\nolimits_{iX}^{-1} (x - \mu_{ix}) \qquad (4.20)$$

$$\sigma_i^2 = \sum\nolimits_{iYY} - \sum\nolimits_{iYX} \sum\nolimits_{iX}^{-1} \sum_{iXY} \qquad (4.21)$$

Again, the parameters $\theta_i = (\alpha_i, \mu_i, \sum_i)$, of the Gaussian distribution are estimated by maximizing the likelihood function using the iterative procedure of EM algorithm by computing posterior probability $p(i|x_i)$ in the E-step and updating the mixture parameters in M-step according to the following formula:

$$p(i|X) = \frac{\alpha_i p_i(X: \mu_i, \sum_i)}{p(X, \theta)} \tag{4.22}$$

$$\alpha_i^{new} = \frac{\alpha_i^{old}\, p_i(X: \mu_i, \sum_i)}{\sum_{i=1}^{k} \alpha_i^{old}\, p_i(X: \mu_i, \sum_i)} = \frac{1}{n}\sum_{i=1}^{n} p(i|x_i) \tag{4.23}$$

$$\mu_i = \frac{1}{\alpha_i n}\sum_{i=1}^{n} p(i|x_i)\, x_i \tag{4.24}$$

$$\sum\nolimits_i = \frac{1}{\alpha_i n}\sum_{i=1}^{n} p(i|x_i)\, [(x_i - m_i)(x_i - m_i)^T] \tag{4.25}$$

4.5 Description of Statistical Features

In this study the measured cutting forces and vibration will be represented by extracted statistical features. These statistics will be used in the input variables vector to the modeling of the tool wear. Features selected are the commonly used statistics of maximum, mean, standard deviation, variance, skewness and kurtosis. For a given signal x of N data points, these features can be computed as follow:

Mean $\bar{x}$:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4.26}$$

Standard deviation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i - \bar{x})^2} \tag{4.27}$$

Skewness:

$$\text{skewness} = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \bar{x})^3}{\sigma^3} \qquad (4.28)$$

Kurtosis:

$$\text{kurtosis} = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \bar{x})^4}{\sigma^4} \qquad (4.29)$$

4.6 Measurements of Prediction Model Goodness

After fitting the data, the predicting model should be evaluated. Error can be defined as the difference between the real response and the predicted one. Assuming that y is the measured value of n observation and mean $\bar{y}$, and $\hat{y}$ is the predicted or fitted value, the accuracy of the model can be measured using different statistics such as these described below.

The sum of squares error (SSE) is a measure of the difference between the data and predicted model. A small SSE value indicates a good fit of the model to the data. SSE can be represented by:

$$\text{SSE} = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (4.30)$$

Another measure to quantify the difference between the real value and predicted one is the root mean squared error (RMSE). It is basically the square root of the SSE divided by the number of observation, n.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad (4.31)$$

Relative error (RE) indicates how large the error is relative to the correct value, y. It provides a comparison of the error to the size of the measurement and can be computed by:

$$\mathrm{RE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} y_i^2}} \times 100 \qquad (4.32)$$

The coefficient of determination (R^2) is a number between 0 and 1 that demonstrates the goodness of the model where 1.0 indicates that a regression line fits the data well.

$$R^2 = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}} \quad , \qquad \mathrm{SST} = \sum_{i=1}^{n}(y_i - \bar{y})^2 \qquad (4.33)$$

Where SST is the total sum of squares error computed as the sum of the squared differences of each data point from the mean $\bar{y}$.

5 Data analysis and results

5.1 Introduction

In this chapter the results for the developed tool wear monitoring system in turning of Titanium Alloy are presented. A total of 319 experiments were conducted with different combinations of cutting conditions: cutting speed, feed rate, depth of cut and coolant.

Using the gathered data, various graphs were plotted to analyze the relation between the cutting conditions and the measured force and vibration. Also tool wear performance was observed for the various cutting conditions. The collected data was processed to acquire the features to be used as input to the model of predicting the tool wear. Modeling methods used were Neural Network, Regression Analysis and Gaussian Mixture Regression.

5.2 Tool Wear Monitoring System

An illustration of tool wear monitoring system stages is shown in Figure 5.1. The first step is to decide on the cutting conditions of the turning process. The second step is to select the sensor to acquire the data signals during the turning process (force and vibration sensors). The collected signals from the sensors are processed for feature extraction. The extracted features will then be used as inputs to the prediction model with the cutting conditions to train the prediction model in the training phase and to predict tool wear in the prediction mode.

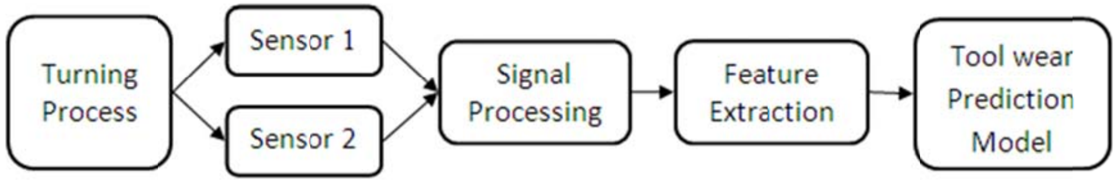

Figure 5.1: An illustration of tool wear monitoring system stages

5.3 Signal Correction and Pre-processing

Before using the measured force and vibration signal, the signal in which the real cutting happened had to be obtained. The attached sensors were initiated to measure for some additional time before and after the cutting to insure that the whole signal was recorded. Figure 5.2 below shows an example of force signal before signal correction. The corrected force signal is shown in Figure 5.3.

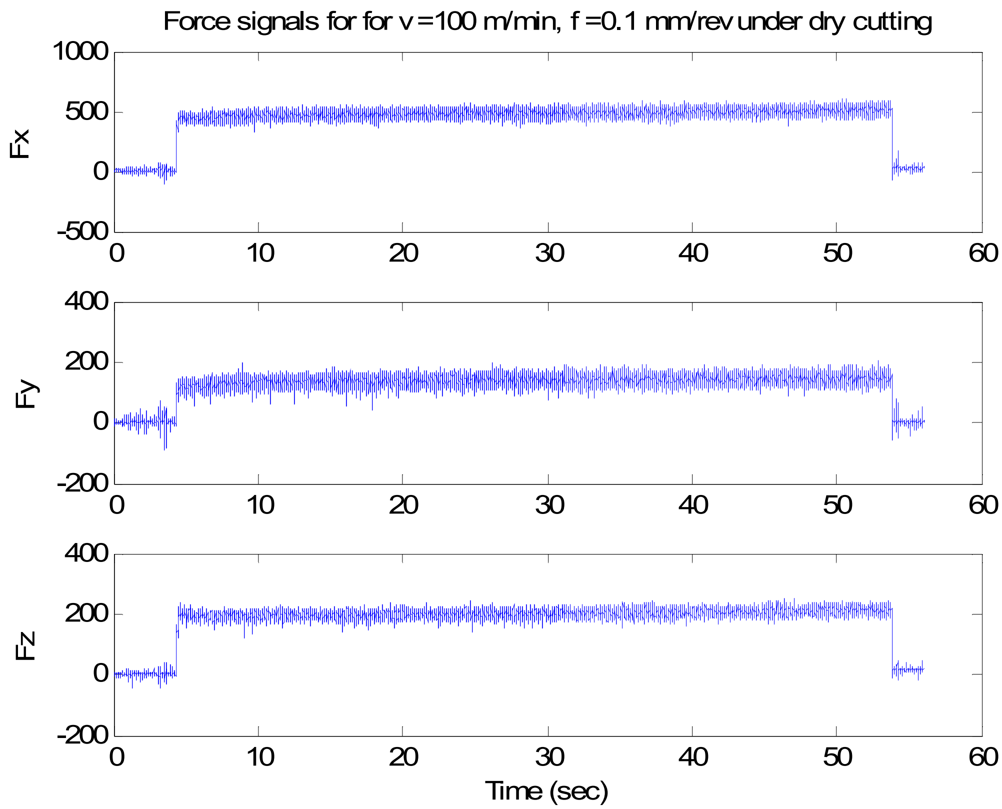

Figure 5.2: Original measured cutting force signal (N) for v =100 m/min, f =0.1 mm/rev under dry cutting.

5.4 Experimental Results

The results of the experiments conducted consist of the cutting time, measured tool wear in VB and surface roughness for the different speed, feed rate, depth of cut, and coolant for each experiment. Results of measured signals, cutting forces, and vibration, were analyzed via MatLab software [47].

Values of tool wear increased when the cutting time increased. Also the tool wear increased when the cutting speed increased for the same feed rate, depth of cut and coolant. In a similar way, the tool wear increased when the feed rate increased for the same cutting speed, depth of cut and coolant. The effect of coolant can also be observed. The tool wear is higher during the dry cutting and lower for the flood or mist cutting. These observations are discussed in detail later in this chapter.

Figure 5.3 and Figure 5.4 show examples of the measured cutting forces and vibration signals for the turning test of 100 m/min cutting speed, 0.1 mm/rev feed rate and depth of cut of 0.8 mm under dry cutting. The values of force and vibration are considerably changed when the tool starts or stops cutting. It can also be seen that the cutting forces increased with the cutting time.

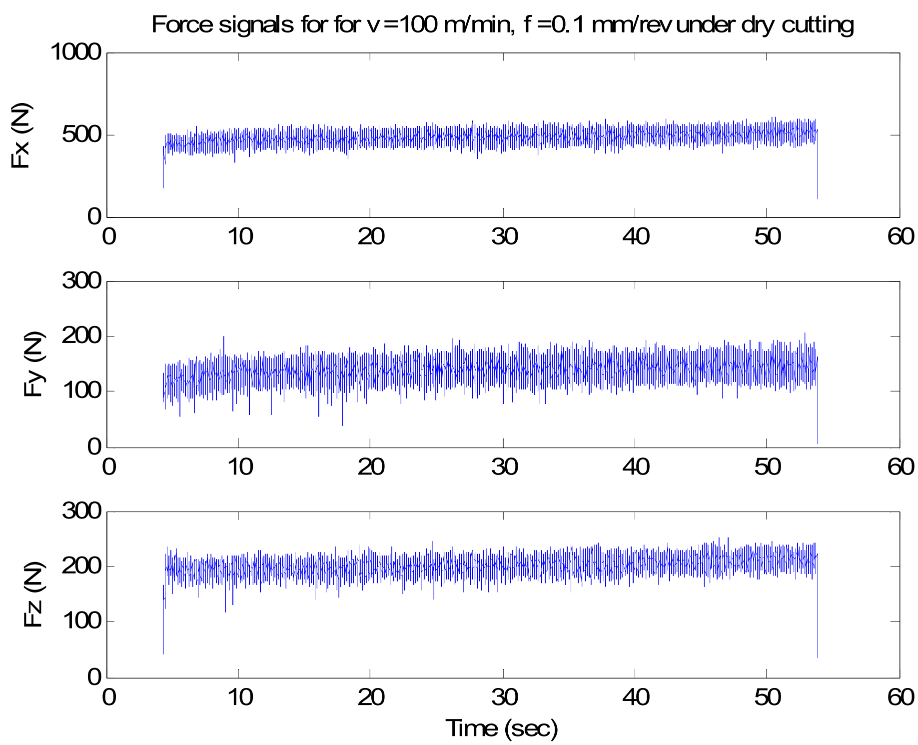

Figure 5.3: Measured cutting force signals for v =100 m/min, f =0.1 mm/rev under dry cutting

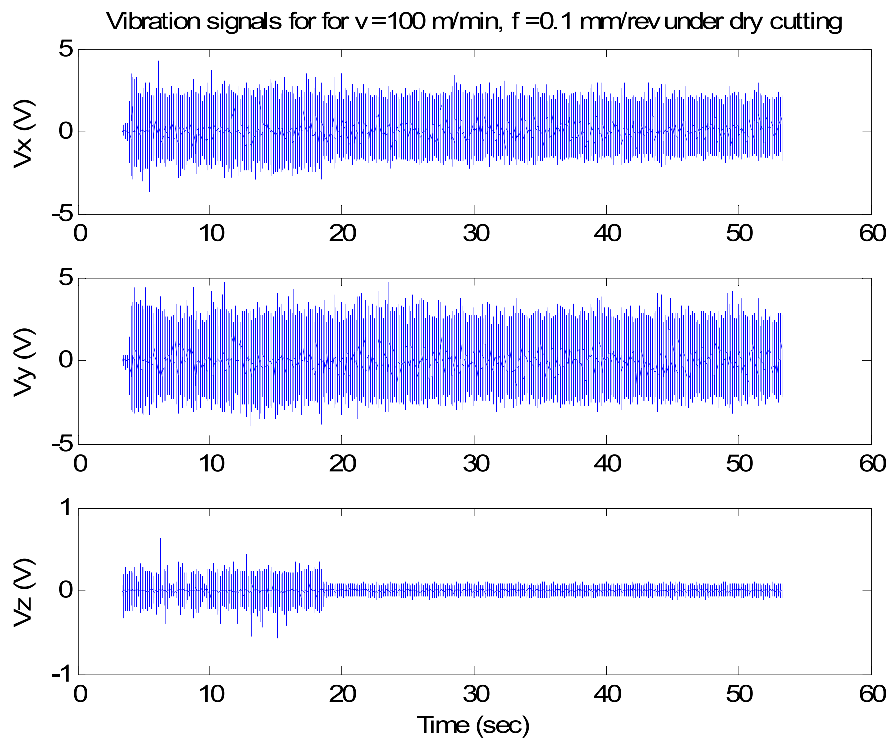

Figure 5.4: Measured vibration signals for v =100 m/min, f =0.1 mm/rev under dry cutting

5.4.1 Cutting Forces

A significant amount of tool wear research has been based on the measurement of cutting forces [4][5][17][18]. Knowledge of the cutting forces is important as they have a direct influence on the generation of heat, and thus on tool wear [53][12]. Also they have a direct effect on the machining accuracy and surface finish.

There are three cutting forces which act on a single point tool (Fx, Fy and Fz) as illustrated in Figure 1.2. Fx is the thrust force (feed force) acting in the X direction, Fy is the cutting force acting downward on the Y direction and Fz is the radial force acting in the Z direction. The cutting forces were measured using 3-component dynamometer structure (3 components 9251A Kistler force sensor, multi-channel charge amplifier type 5070 and data acquisition software DynoWare).

It can be observed from Figure 5.3 that the measured thrust force (Fx) has the highest values among the other cutting forces. Additionally, the cutting force (Fy) is generally lower than both the thrust (Fx) and radial forces (Fz).

The maximum value of the cutting force signal (Fx) was considered as the analysis criteria of the cutting forces. The maximum value of the cutting force signal (Fx) measured during turning process under different cutting speeds and feed rates were plotted for the different coolant conditions used. Results are shown in Figure 5.5 for dry cutting, Figure 5.6 for mist cutting, Figure 5.7 for flood cutting and Figure 5.8 for the LN cutting environment.

It can be seen that the total cutting time varies in cutting tests with different cutting speeds and feed rates. This is because the 0.3 mm average flank wear criterion was used to determine the effective tool life. So the turning operation of a test was stopped when the VB reaches 0.3 mm. Generally, it took a longer time to reach the 0.3 mm VB at a lower cutting speed and feed rate. For example, the cutting time for 100m/min cutting speed and 0.1 mm/rev feed rate under mist cutting was 120 seconds. For the same feed rate, the cutting times were 55 and 45 seconds for cutting speeds of 125 and 150 mm/min respectively. In addition, the cutting time was longer when using cutting fluid hence it elongates tool life.

Figure 5.5 shows the cutting force signal (Fx) with machining time under dry cutting at different cutting speed and feed rate. Cutting forces increased when the cutting speed increased. The cutting force reached around 2000N when the speed was 150m/min while it was in the range of 1000N under 100m/min cutting speed. This can be explained by the increase of tool wear as the cutting speed increases and consequently increasing the cutting forces. In addition, the increase in tool wear enlarges the contact area between the cutting tool and the work-piece and hence increases the cutting forces [12]. It can also be seen that increasing the feed rate showed an increase in the cutting forces for the same cutting speed. This is consistent with the results reported in [9].

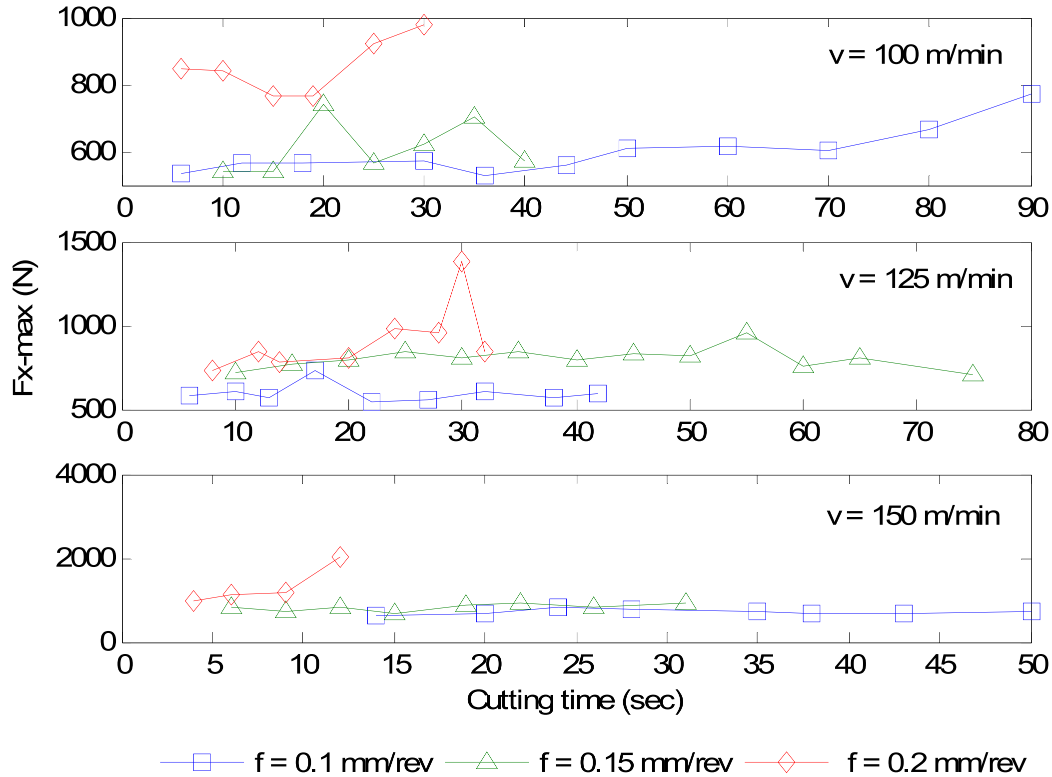

Figure 5.5: Cutting force signal (Fx) with machining time under dry cutting at different cutting speeds (v) and feed rates (f)

The same can also be observed from the plots for other coolant strategies, i.e. the cutting forces increased as the cutting speed and feed rate increased whether using mist, flood, or LN cutting. However, the cutting forces are higher for the dry cutting compared to other coolant environments. This can be attributed to the use of coolant which reduces the friction at the tool-chip and tool work-piece interfaces and thus reduces the cutting forces generated during machining [6]. Moreover, the cutting fluid acts as a lubricant and reduces the tool temperatures and decreases the cutting forces [7]. Cutting forces are almost the same under mist and flood environments for the same cutting speed and feed rate while they are lower under LN cooling. The LN cooling has a higher capacity to decrease the cutting temperatures and lubricate the cutting zone.

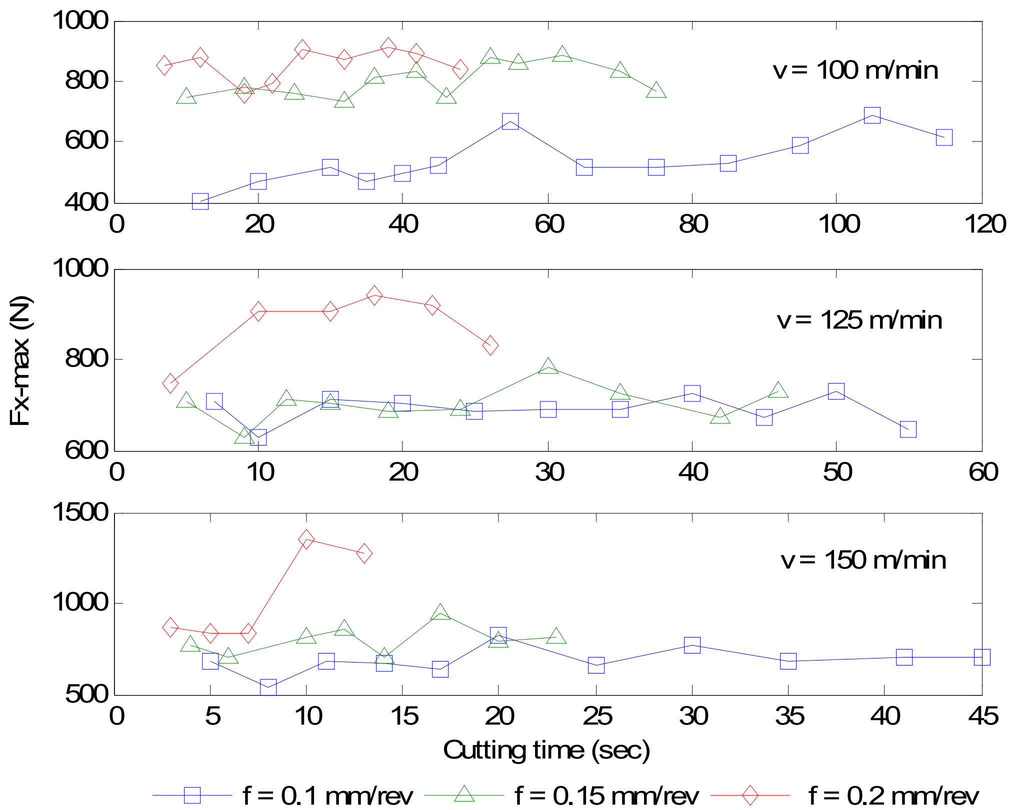

Figure 5.6: Cutting force signal (Fx) with machining time under mist cutting at different cutting speeds (v) and feed rates (f)

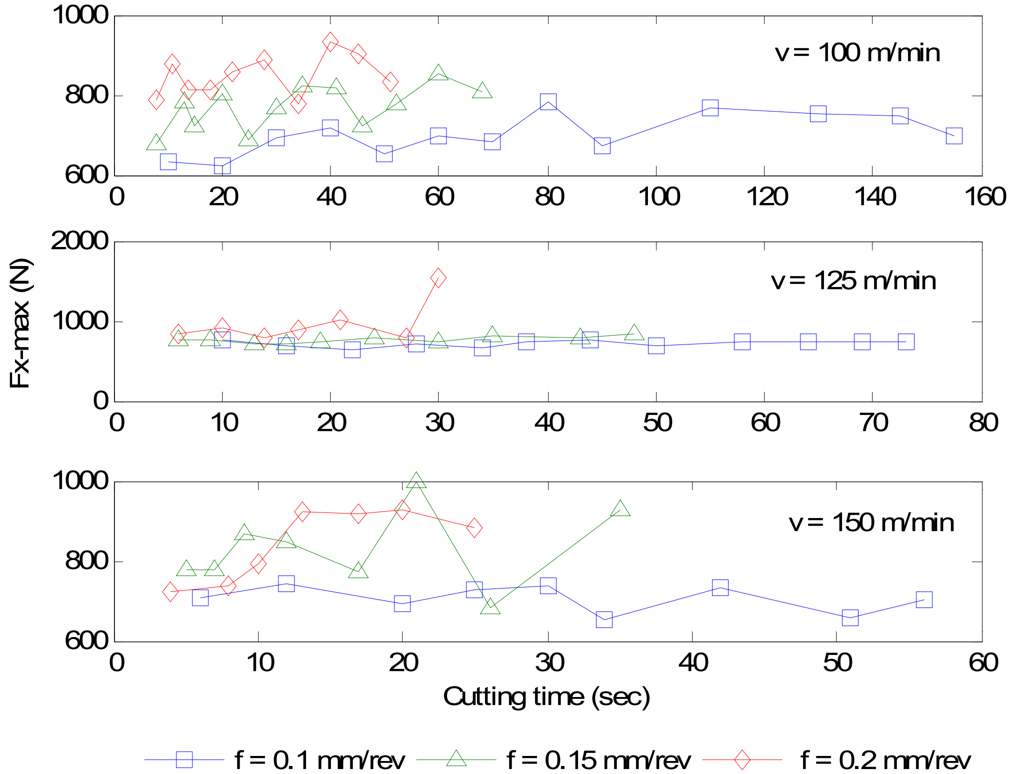

Figure 5.7: Cutting force signal (Fx) with machining time under flood cutting at different cutting speeds (v) and feed rates (f)

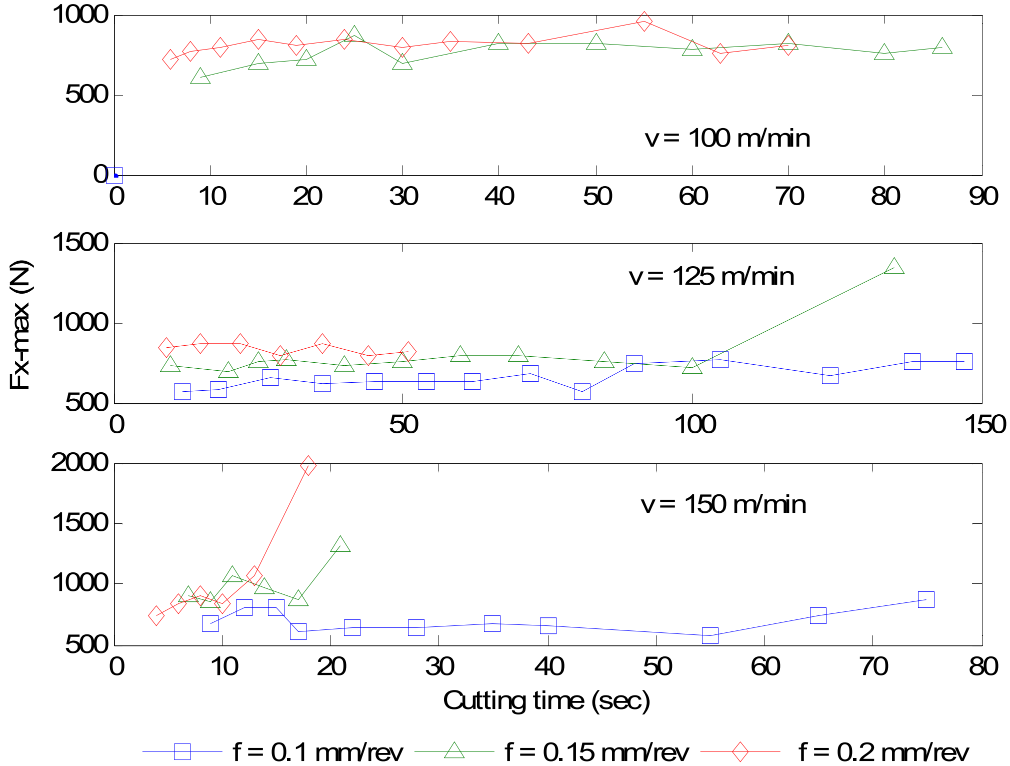

Figure 5.8: Cutting force signal (Fx) with machining time under LN cutting at different cutting speeds (v) and feed rates (f)

5.4.2 Vibration Signals

Figure 5.4 shows an example of the vibration signals measured during the turning process for v =100 m/min and f =0.1 mm/rev under dry cutting conditions. The vibration signal in the x-direction had the highest amplitude and the vibration in z-direction was generally lower than that in the x and y directions. The high vibration in the x-direction is related to the high cutting force in the x- direction that increases the vibration.

The maximum values of the measured vibration signal (Vx) were plotted for the different coolant conditions and with different cutting speeds and feed rates. Results are shown in Figure 5.9 for dry cutting, Figure 5.10 for mist cutting, Figure 5.11 for flood cutting and Figure 5.12 for the LN cutting environment.

The total cutting time varied in cutting tests with different cutting speeds and feed rates since the criterion of 0.3 mm average flank wear was used to determine the effective tool life and stop the turning test. The wear rate was faster with higher cutting speeds and feed rates consequently the total cutting time was shorter. Also, the cutting fluids reduced the wear rate therefore the total cutting time under dry cutting was less than that of mist, flood, and LN coolant. In addition, the tool wear rate was the slowest with the LN coolant.

The plotted figures show that the vibration amplitude decreased as the cutting speed increased under all coolant conditions. In addition, vibration amplitude for the dry cutting was higher than that with flood, mist or LN coolant. This can attributed to the high cutting forces in the machining of titanium especially under dry cutting [5] which increase the vibration. Also the presence of vibration increases with higher tool wear at higher speed [8].

Additionally, the vibration plots show that increasing the feed rate led to an increase in the vibration signal amplitude. This can be noticed on the plots of all coolants and is consistent with and agrees with results reported in other research [20].

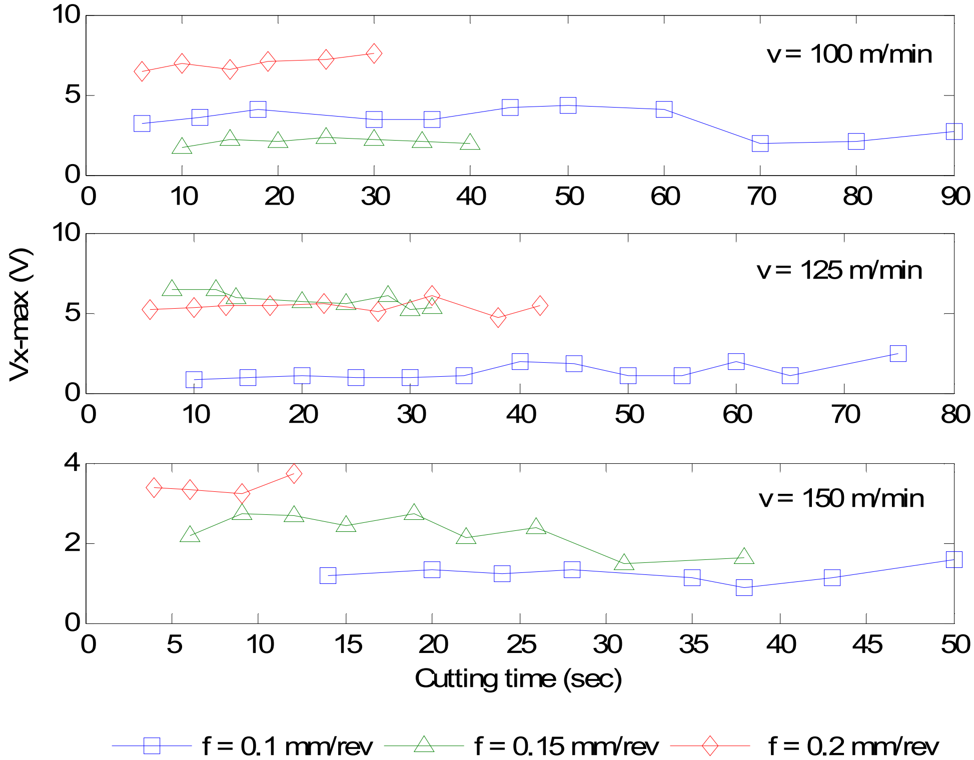

Figure 5.9: Vibration signal (Vx) with machining time under dry cutting at different speeds (v) and feed rates (f)

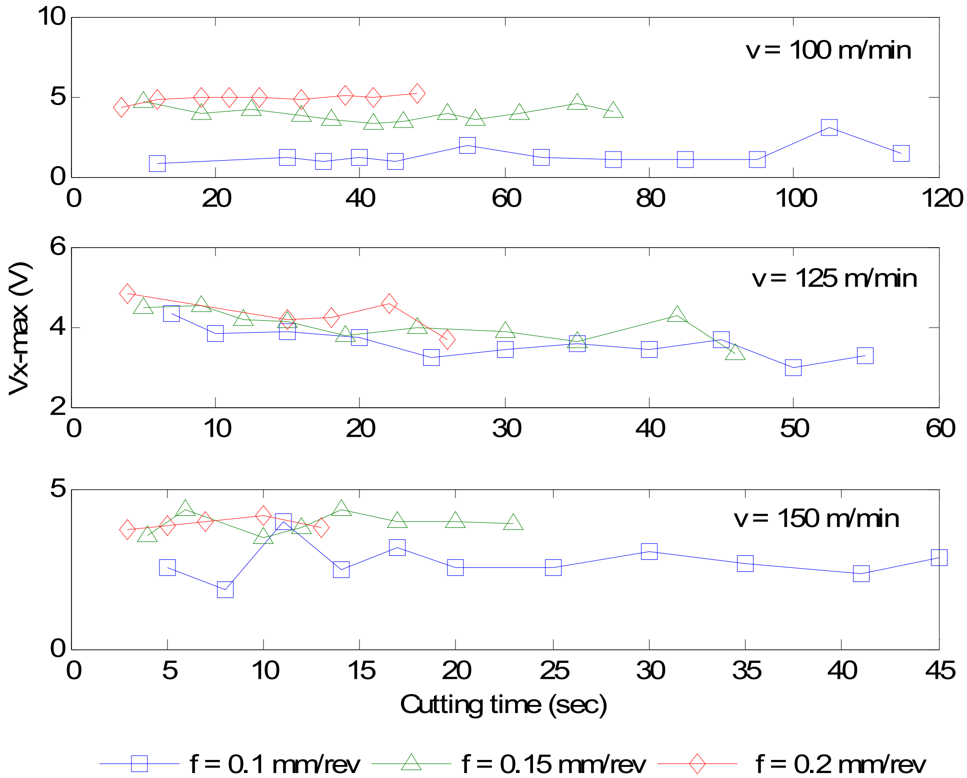

Figure 5.10: Vibration signal (Vx) with machining time under mist cutting at different speeds (v) and feed rates (f)

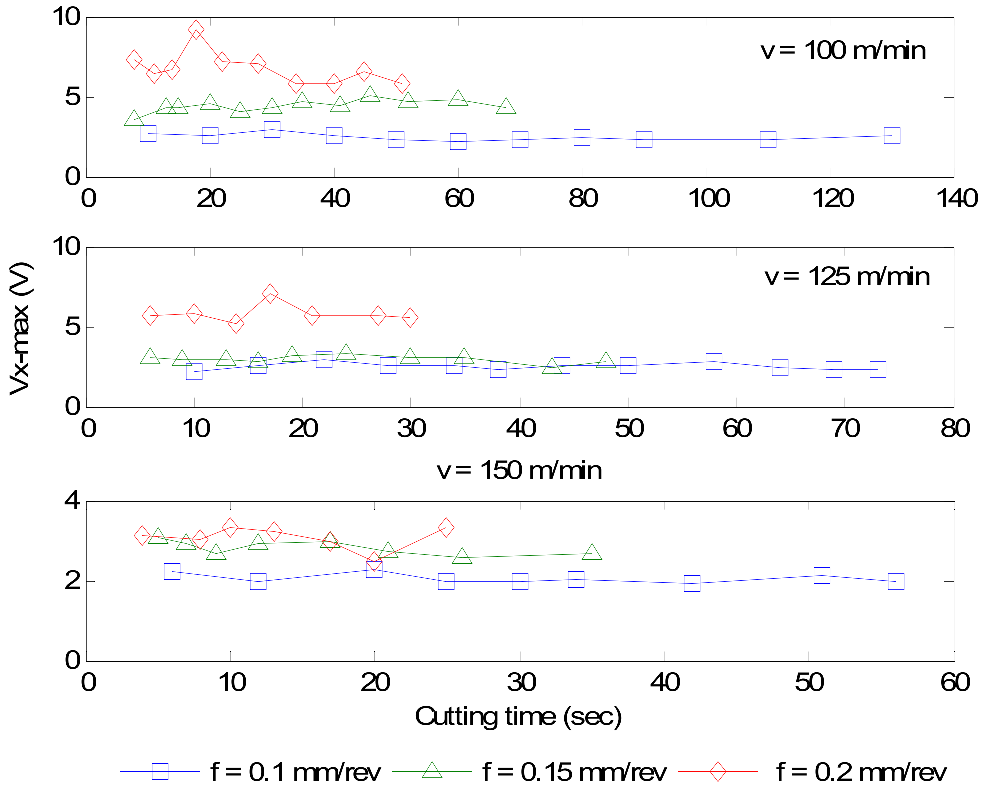

Figure 5.11: Vibration signal (Vx) with machining time under flood cutting at different cutting speeds (v) and feed rates (f)

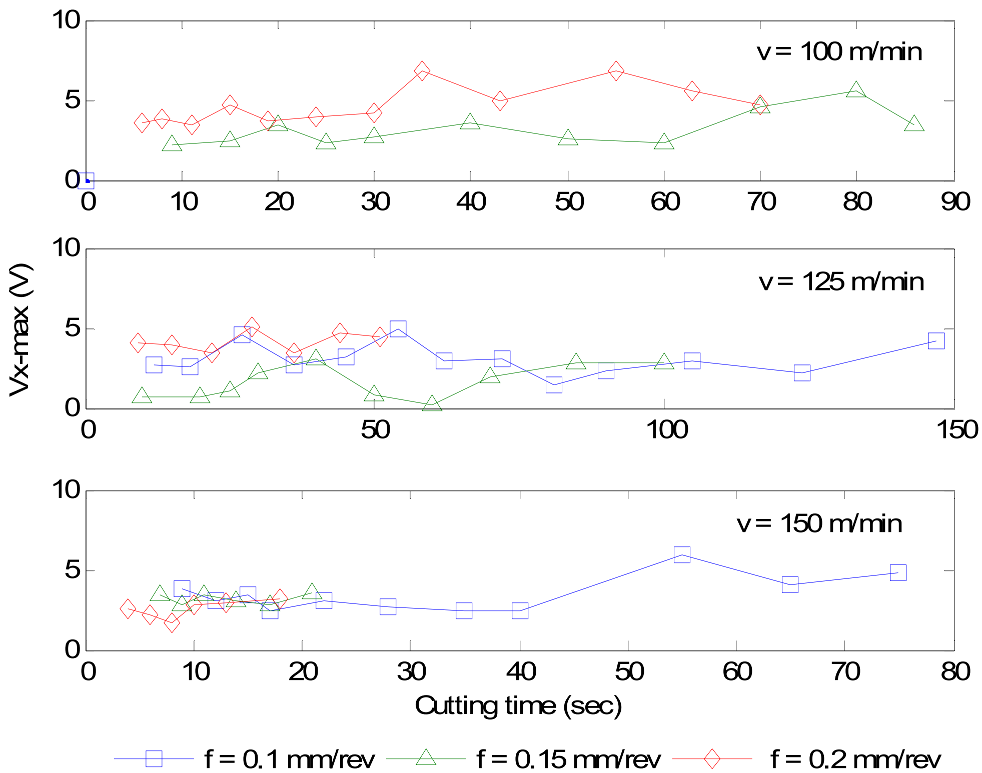

Figure 5.12: Vibration signal (Vx) with machining time under LN cutting at different cutting speeds (v) and feed rates (f)

5.4.3 Tool Wear

The progression of flank wear at different cutting speeds and feed rates was plotted for the different coolant conditions. Results are shown in Figure 5.13 for dry cutting, Figure 5.14 for mist cutting, Figure 5.15 for flood cutting and Figure 5.16 for the LN cutting environment.

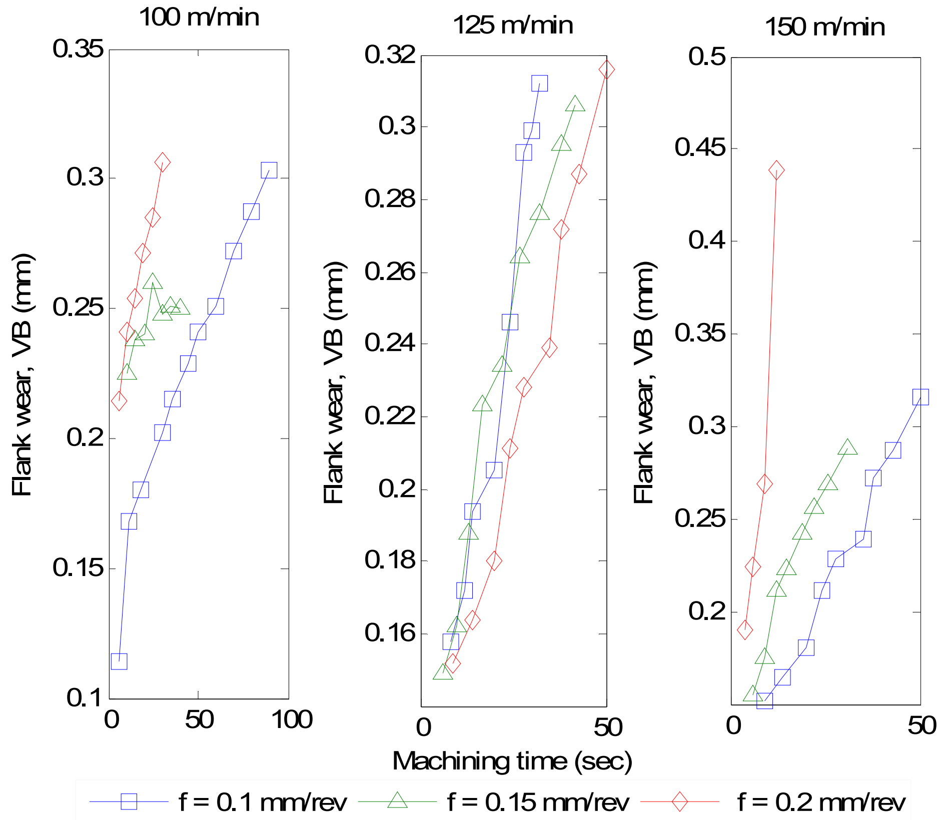

Figure 5.13: Growth of tool wear with machining time under dry cutting at different cutting speeds (v) and feed rates (f)

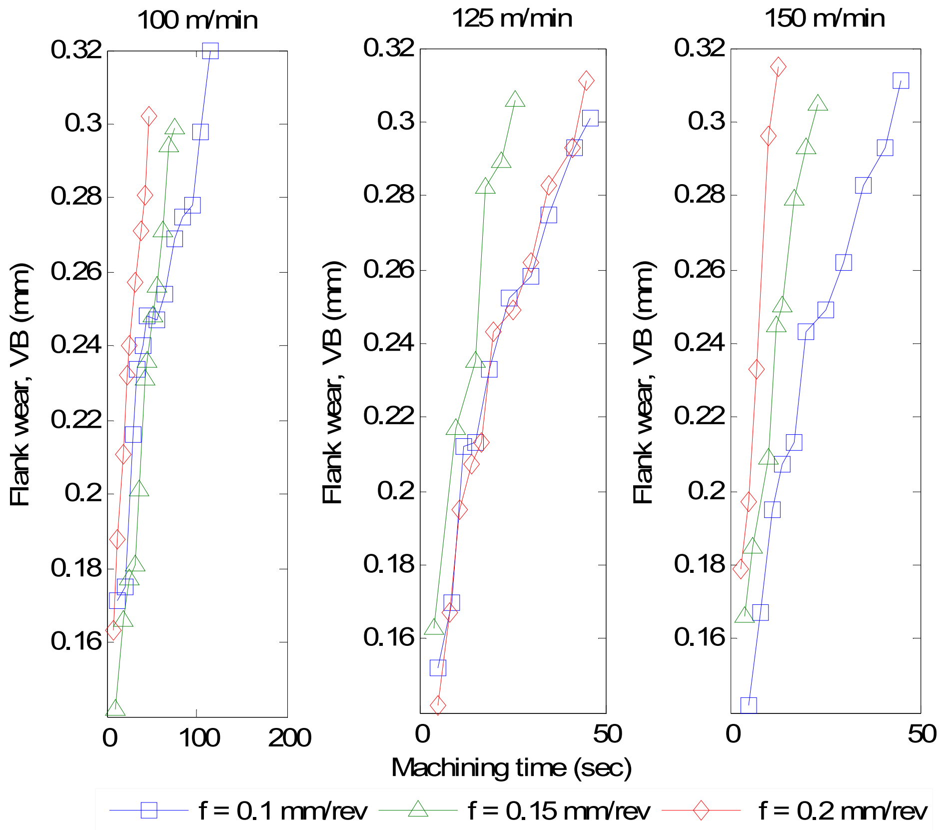

Figure 5.14: Growth of tool wear with machining time under mist cutting at different cutting speeds (v) and feed rates (f)

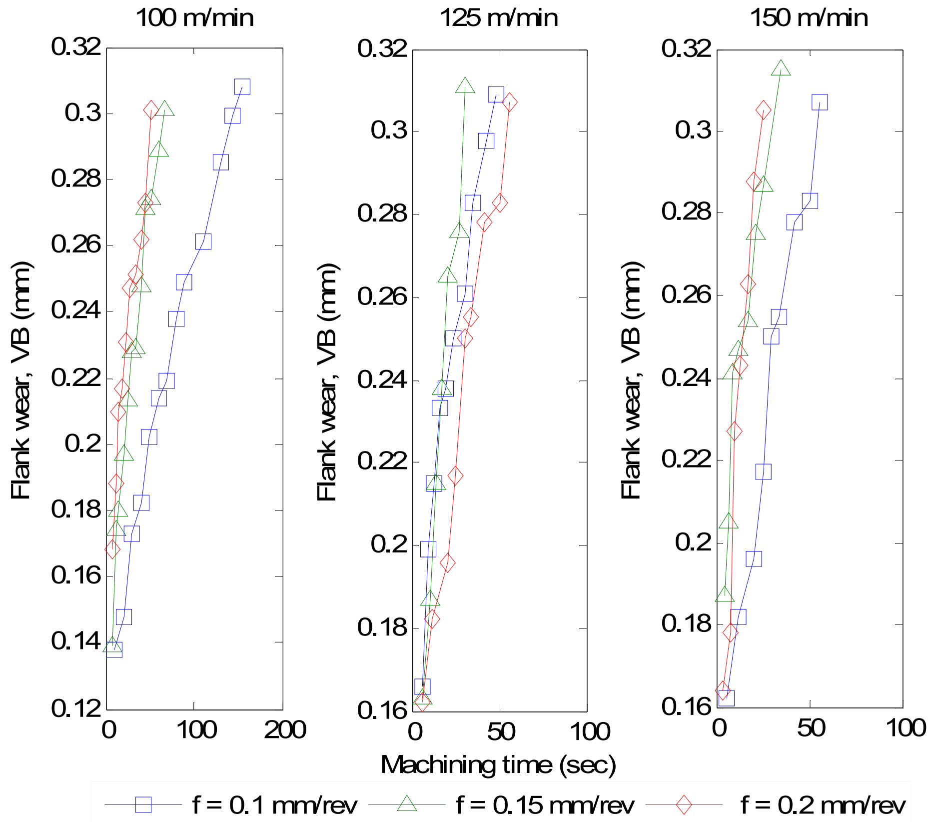

Figure 5.15: Growth of tool wear with machining time under flood cutting at different cutting speeds (v) and feed rates (f)

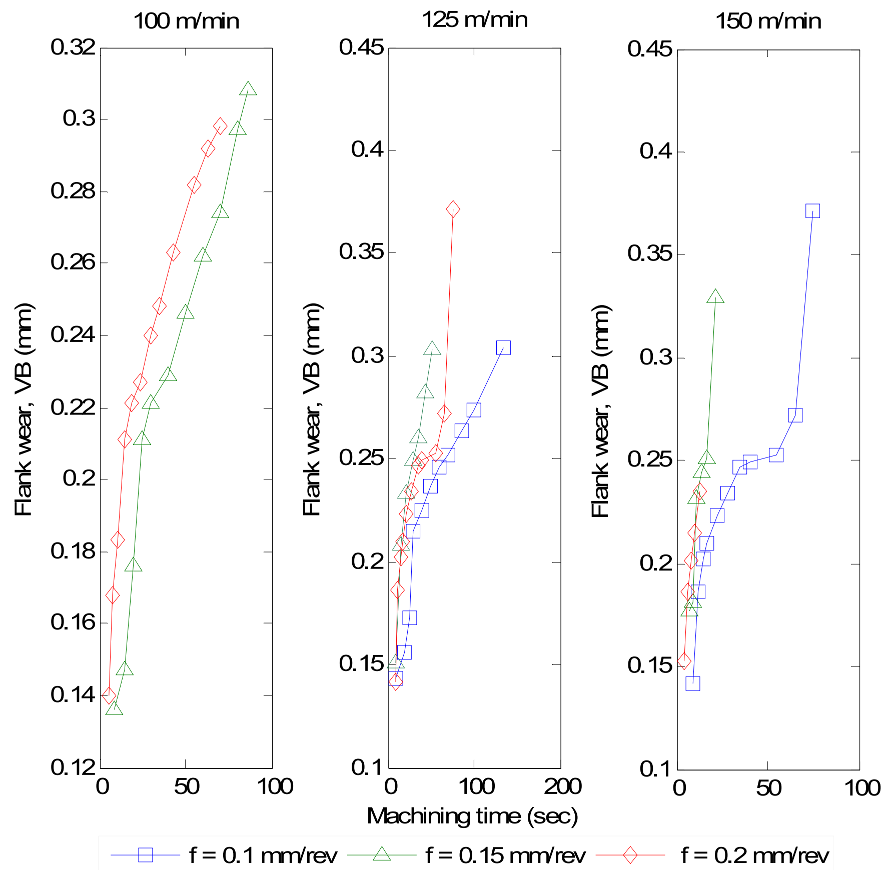

Figure 5.16: Growth of tool wear with machining time under LN cutting at different cutting speeds (v) and feed rates (f)

Wear rate was more rapid at higher cutting speeds and feed rates especially when cutting under dry condition. Also it can be observed that higher feed rate tend to increase the tool wear since titanium alloys are sensitive to changes in feed rate [7][13]. Increasing cutting speed and feed rate increases cutting temperature, which leads to rapid tool failure [8].

Cutting speed had the most influence on tool life [7][13]. Cutting speeds for Titanium alloy are usually limited to ensure good tool life [6]. It can be seen that tool life is shorter at higher cutting speeds as indicated in the literature [8][7][10][11].

Cutting at higher speed conditions increased the temperature generated at the tool-work-piece and tool-chip interfaces [6]. The low thermal conductivity of titanium alloys leads to an increase in the temperature at the cutting zone which promotes rapid tool wear [6][7][8]. So, overcoming the short tool life is a primary challenge when machining titanium because it prevents the use of high cutting speeds [8].

The tool wear rate was higher in dry machining compared to mist, flood and LN coolant machining. The improvements in tool life can also be attributed to the use of coolants. The use of coolant is considered an important way of improving the machining of titanium alloys [8][13][14] and to minimize the effect of high temperature at the cutting tool [7] and thus improve the tool life.

Liquid nitrogen (LN) has been investigated widely and proven to be an efficient way of improving tool life when machining titanium alloys [6][14]. The current results show that cryogenic cooling by LN can enhance tool life. For example, the tool life with a cutting speed of 100 m/min and feed rate of 0.2 mm/rev was 30 sec in dry cutting conditions, 48 sec in mist conditions, 51 sec for flood and 70 sec in LN cutting conditions based on the 0.3 VB criteria.

Another example is when cutting with a cutting speed of 125 m/min and a feed rate of 0.15 mm/rev, the tool life was 32 sec for dry, 46 sec for mist cutting, 48 sec for flood and 135 sec under LN cutting. It can be seen that for the same cutting conditions the tool life is longer with cryogenic cooling.

Some advantages of LN over other coolants are that LN has low viscosity and it does not adhere to metal surfaces easily [14]. Also it enhances the chemical stability of the work-piece and the cutting tool [13] and evaporates quickly into the air [14].

5.5 Signal Processing and Features Extraction:

After acquiring the force and vibration signals during the turning process, the next step was to extract features from these signals that demonstrate an effective trend towards the tool wear. The extracted features were then used as inputs to the prediction model along with cutting parameters to predict tool wear.

Many signal processing methods have been used to analyze signals and extract the features [3][21][22] for testing or monitoring. The methods applied in the current analysis were the Principal Component Analysis (PCA) and Stepwise Regression Analysis.

There were a total of 319 experimental turning tests. The statistical features considered in this study are the common statistics of maximum, standard deviation, variance, skewness and kurtosis for the cutting force and vibration signals at the three axis. The matrix generated has a size of 319-by-15. Descriptions of statistical features are provided in section 4.5.

5.5.1 Features extraction by Principal Component Analysis

Principal Component Analysis (PCA) is a dimensionality reduction technique used to represent data according to the maximum variance direction(s) [3]. A description of the Principal Component Analysis algorithm can be found in [54].

Features extraction by Principal Component Analysis was used to extract the relevant information from the collected force and vibration signal that showed an effective trend towards the measured tool wear. This reduced representation was used instead of the full size as input to the Neural Network and other tool wear prediction models.

PCA on force and vibration data was performed using the MatLab built-in command (princomp) [47]. The function returns the principal component coefficients and scores. Coefficients are a 319-by-319 matrix, each column containing coefficients for one principal component, and the columns are in order of decreasing component variance. The scores are the data formed by transforming the original data into the space of the principal components. Component Scores contains the coordinates of the original data in the new coordinate system defined by the principal components.

5.5.1.1 PCA of Force Signal

A plot of the first two columns of scores is shown in Figure 5.17. It shows the ratings data projected onto the first two principal components. The MatLab command "Gname" was used to graphically identify points far from the concentrate points [47]. These points represent experimental test numbers that have different results from the rest of the experiments. The experiments data identified by these points were eliminated when obtaining the variance explained by each component to get a better representation of the experimental data and its effect on tool wear.

The percent of variance explained by each principle component is plotted in Figure 5.18. The first and second components represent 91.38% and 3.79% of the variance respectively. These are the maximum force in the X and Y directions respectively. The component of maximum force at the X direction accounted for the most of the variance, so this component was considered an essential input to the tool monitoring system.

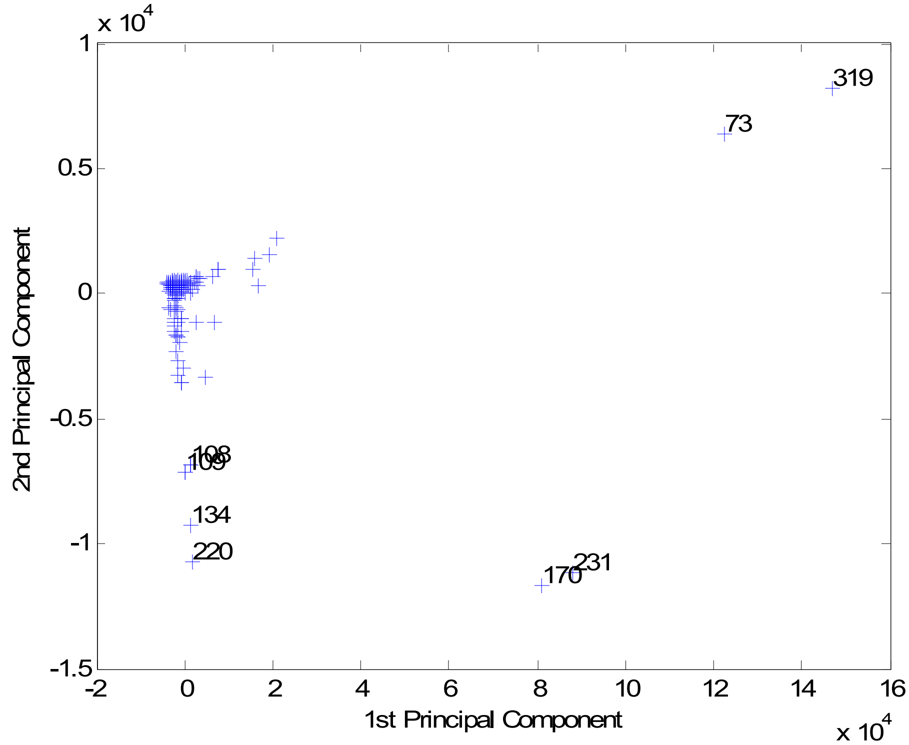

Figure 5.17: First two principal components of force signal.

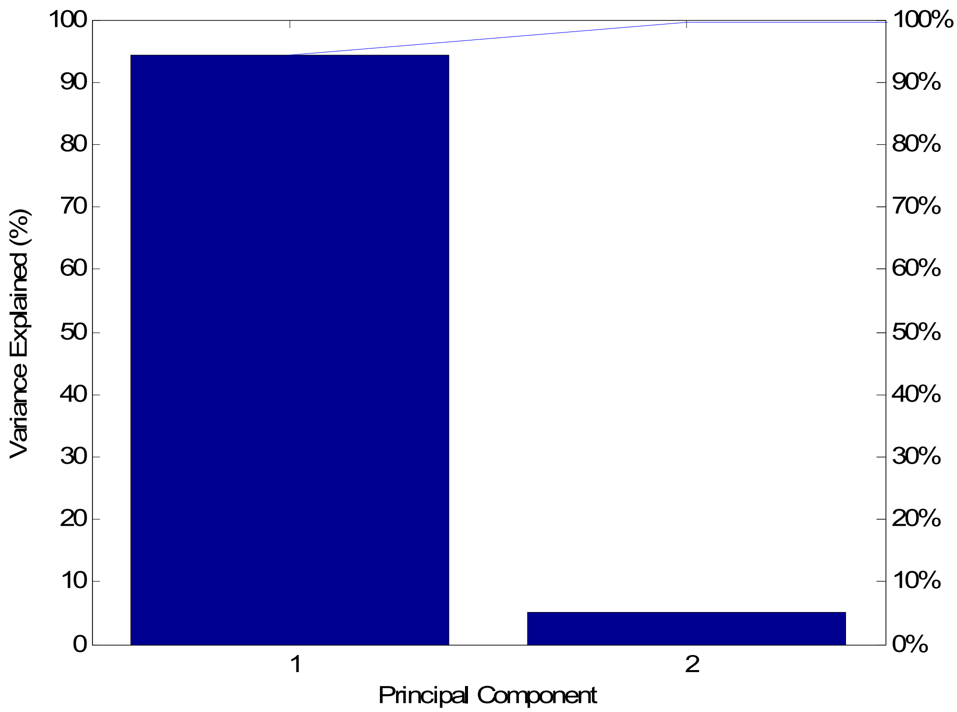

Figure 5.18: The percent of variance explained by each principle component for force signal**.**

5.5.1.2 PCA of Vibration Signal

In a similar way, the PCA of the vibration signal was computed. The first two columns of scores are shown in Figure 5.19 and the variance explained by each principle component is plotted in Figure 5.20. The first and second components represent 94.36% and 5.18% of the variance respectively. These are the maximum vibration in the X and Y direction respectively.

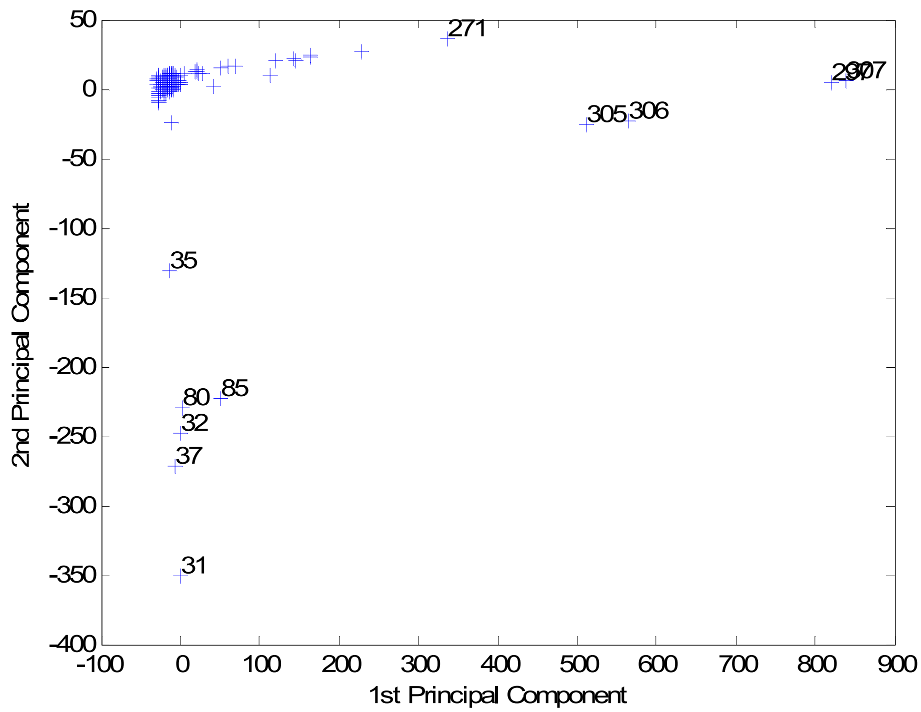

Figure 5.19: First two principal components of vibration signal.

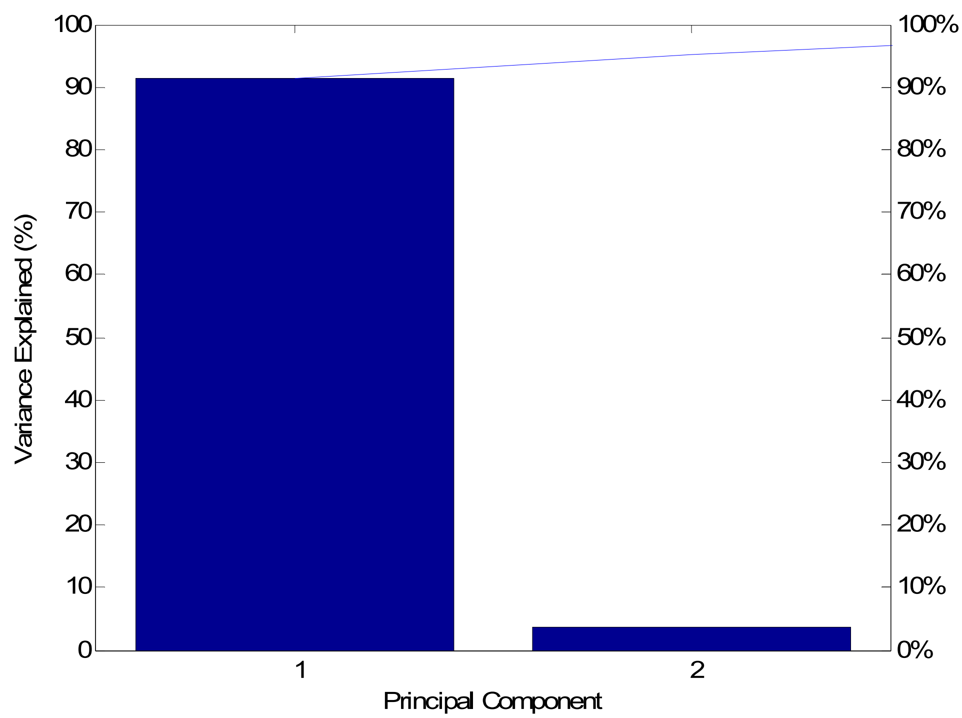

Figure 5.20: The percent of variance explained by each principle component for vibration signal.

As a result of performing PCA on the force and vibration signal independently, the maximum value of force and vibration signal at the X direction accounted for more than 90% of the variance in each of the signal, so these components were considered an essential input to the tool monitoring system.

5.5.2 Feature dimensionality reduction by Stepwise Regression

Stepwise multi-linear regression method was performed to find the estimated coefficients that best describe the tool wear. Please refer to section 4.3.4 for the technique algorithm. The MatLab function stepwisefit(X,y) [47] was used to carry out the stepwise regression algorithm. The stepwise regression model represents the response variable Y as a function of the predictor variables represented by the columns of the matrix X. In this work, X is the variable matrix that includes all the 35 variables (cutting parameters and all the statistical features extracted from the force and vibration signals at the three axis X, Y, and Z) and y is the measured tool wear value.

Since there are many variables, stepwise regression technique was used to create a subset of these variables that best described the tool wear. The result of running the MatLab command of stepwise showing the procedure of adding and removing variables is available in Appendix A.

A total of 14 variables were specified as significant variables to include in the model of the tool wear. These were cutting time, cutting speed, feed rate, coolant, forces value of X-maximum, Z-standard deviation, X-variance, Y-skewness and Y-kurtosis), and vibration value of X-maximum, Y-standard deviation, X-skewness, Y-skewness and Z-skewness). This variables subset was considered as the input to the tool wear prediction model.

5.6 Inputs/Output to the Tool Wear Prediction Model:

The inputs to the network were: cutting time, cutting speed, feed rate, depth of cut, coolant, force and vibration. The force and vibration were represented by different statistical features of the measured force and vibration signals determined in sections 5.5.1 and 5.5.2 above. The output was tool flank wear measured in VB.

One of the primary inputs to the structured tool wear model is the coolant strategy. Four different strategies were used in this experimental work: dry, flood, mist and cryogenic cooling using liquid Nitrogen. The mist and flood coolant are basically oil emulsion formulated by mixing oil (Aquatex 3180) and water at a ratio of 1:40.

A search for fluid properties revealed that the properties of many used cutting fluids are not available (i.e. viscosity and specific heat). In this research, the property of density was used to represent the coolant as an input to the Neural Network. The density of each coolant is shown in Table 5.1 below [52]. For dry cutting, density of air at room temperature was used. For mist and flood cutting, the density was calculated using the concept of composite. The density of a solution is determined as the sum of the weighted densities of the components of the solution. The density of coolant is the volume contribution percentage of water multiplied by the density of water plus the volume percentage of oil multiplied by its density.

Table 5.1: Density of different coolant strategies used

Coolant	**Density (kg/m^3)**
Dry, air at 25 °C	1.184
Flood	997.317
Mist	897.437
LN	808.607

5.7 Neural Network for Tool Wear Prediction

The collected sensors signal along with process parameters were used with Artificial Neural Networks to develop an online tool wear monitoring system and predict tool life.

5.7.1 Feed-Forward Back-Propagation Neural Network (FFBPNN)

The feed-forward network was trained using back-propagation method with different properties to investigate the optimum network properties. The performance of Neural Network was compared to the experimental data.

The Feed-Forward Neural Networks (FFBPNN) type is widely used in tool monitoring applications. FFBPNN consists of three main layers: the input layer, the hidden layer, and the output layer. The hidden layer consists of number of interconnected groups of neurons and the input information moves in forward direction through the hidden layer to the output layer.

The FFBPNN used contained initially 30 neurons in the hidden layer with TRAINLM learning function and TANSIG transfer function. These network properties were found to be the optimum ones for this study. The input data was divided randomly to have 75% of the data for training the network and the other and 25% for testing the network. Predicted and measured tool flank wear values were compared and results showed good matching.

For the first trial, the inputs to the network were taken as time, cutting speed, feed rate, depth of cut, and the maximum values of force and vibration in the X direction. The network's output and the absolute error between measured and predicted tool wear is plotted in Figure 5.21. A comparison between the predicted and measured tool flank wear value results showed good matching. The training time was 1.0181 second and the mean of the absolute error was 0.0183.

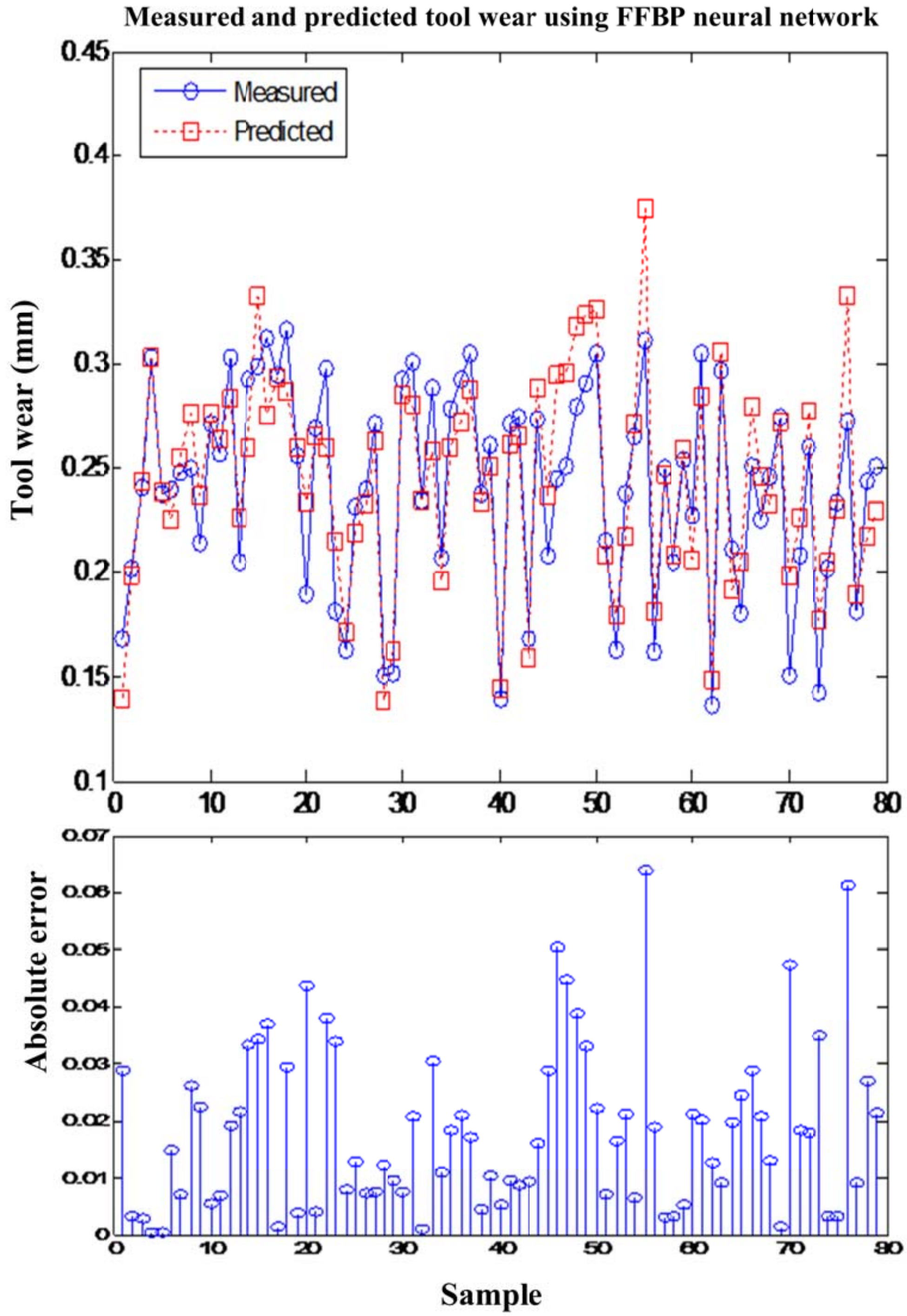

Figure 5.21: Simulation of the feed-forward back-propagation network and the absolute error between measured and predicted tool wear for trial 1.

In the second trial, the maximum force and vibration values in the Y direction were added to the input vector. Therefore the inputs to the network were taken as time, cutting speed, feed rate, depth of cut, and the maximum values of force and vibration in the X and Y directions. The network's output and the absolute error between measured and predicted tool wear is shown in Figure 5.22. The training time was 1.3075 second and the mean of the absolute error was 0.0168.

In another run of the network, the maximum and standard deviation of force and vibration values in the Y and Z direction were added as inputs. Therefore the inputs to the network were taken as time, cutting speed, feed rate, depth of cut, the maximum values of force and vibration in the X, Y and Z direction and standard deviation of force and vibration in the X, Y and Z direction. The number of neurons in the hidden layer was increased to 50. The training time was 2.6016 second and the mean of the absolute error is 0.0240. The network's output and the prediction error is shown in Figure 5.23.

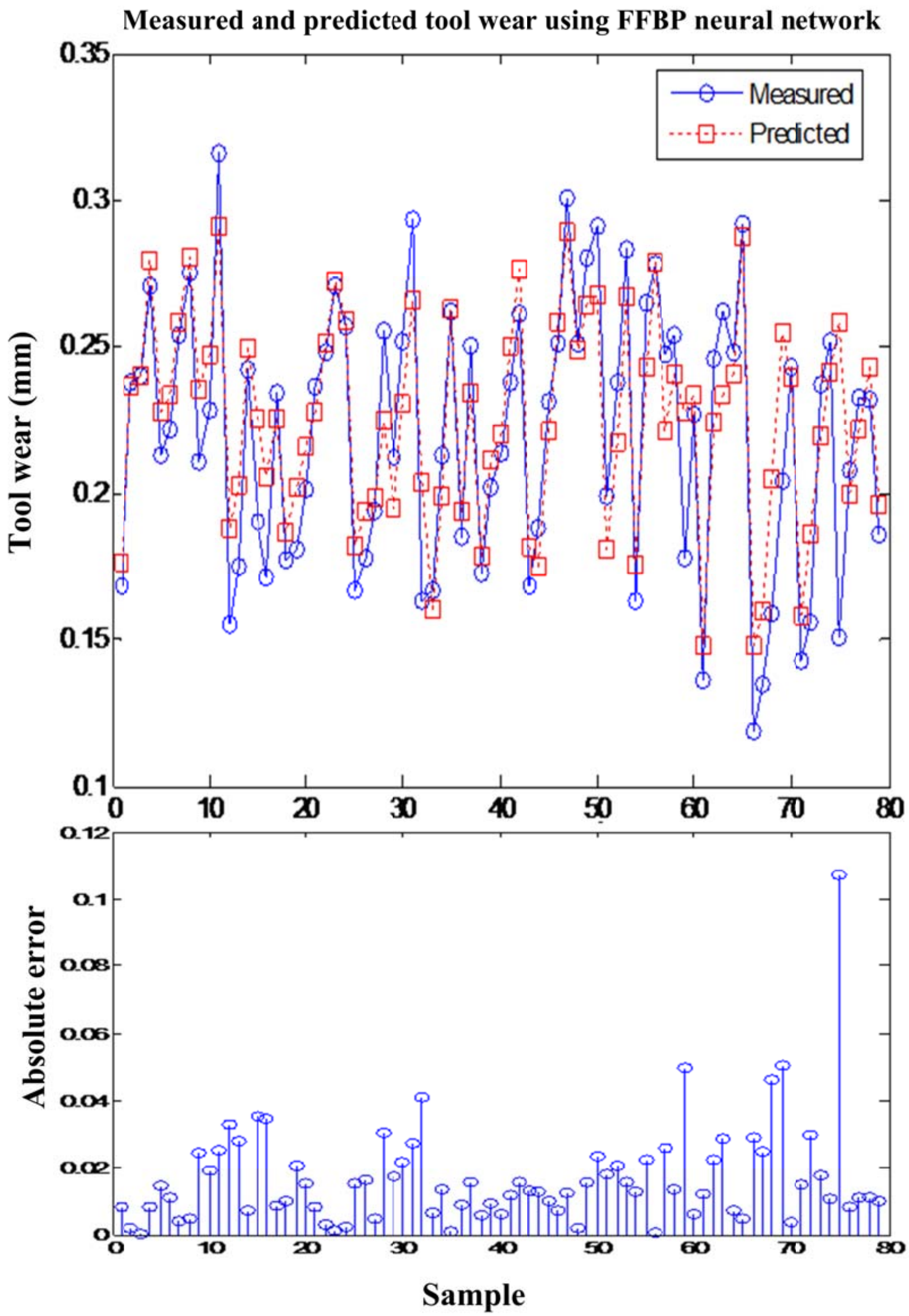

Figure 5.22: Simulation of the feed-forward back-propagation network and the absolute error between measured and predicted tool wear for trial 2.

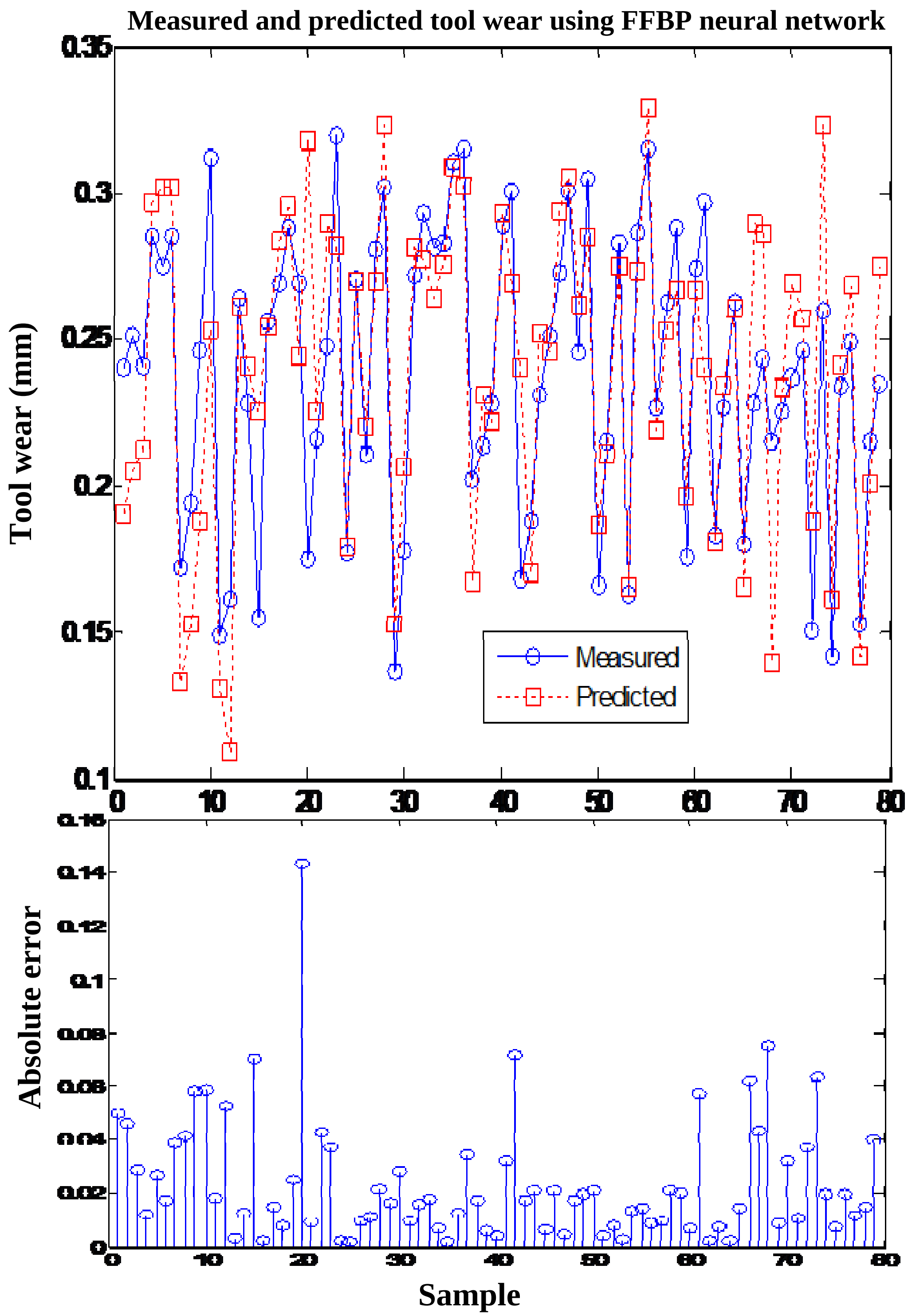

Figure 5.23: Simulation of the feed-forward back-propagation network and the absolute error between measured and predicted tool wear for trial 3

In addition, the FFBPNN was run with all the variables as input. These included the cutting parameters (time, cutting speed, feed rate, depth of cut) and the statistical features of the force and vibration signals (maximum, standard deviation, variance, skewness and kurtosis for the signals at the three axes axis X, Y, and Z). The number of neurons in the hidden layer was set to 100. The training time was 51.1223 seconds and the mean of the absolute error was 0.0343. The network's output and the prediction error is shown in Figure 5.24. Increasing the number of input variables required a longer training time.

The Neural Network was tested with a larger number of neurons in the hidden layer (150). This resulted in lower mean error to 0.0299 but a longer training time of 91.7451 seconds.

Finally, the FFBPNN, with 50 neurons in the hidden layer, was run with all the variables from the stepwise regression analysis (cutting time, cutting speed, feed rate, coolant, forces value of X-maximum, Z-standard deviation, X-variance, Y-skewness and Y-kurtosis), and vibration value of X-maximum, Y-standard deviation, X-skewness, Y-skewness and Z-skewness). The training time was 3.4506 seconds and the mean of the absolute error was 0.0223. The network's output and the prediction error is shown in Figure 5.25. Increasing the number of neurons in the hidden layer to 100 resulted in a lower mean error of 0.0164 with a training time of 9.6224 seconds.

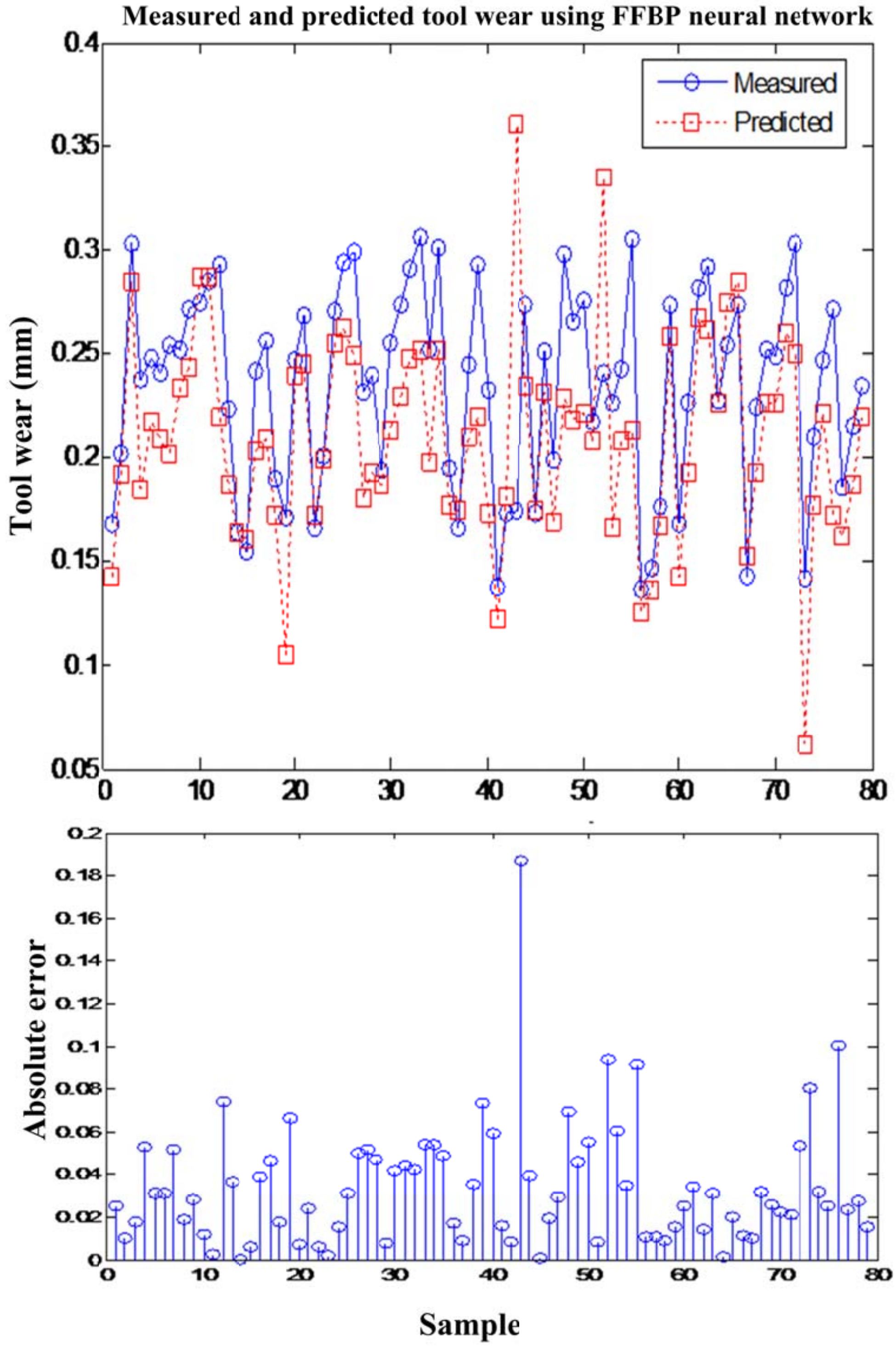

Figure 5.24: Simulation of the feed-forward back-propagation network and the absolute error between measured and predicted tool wear for trial 4

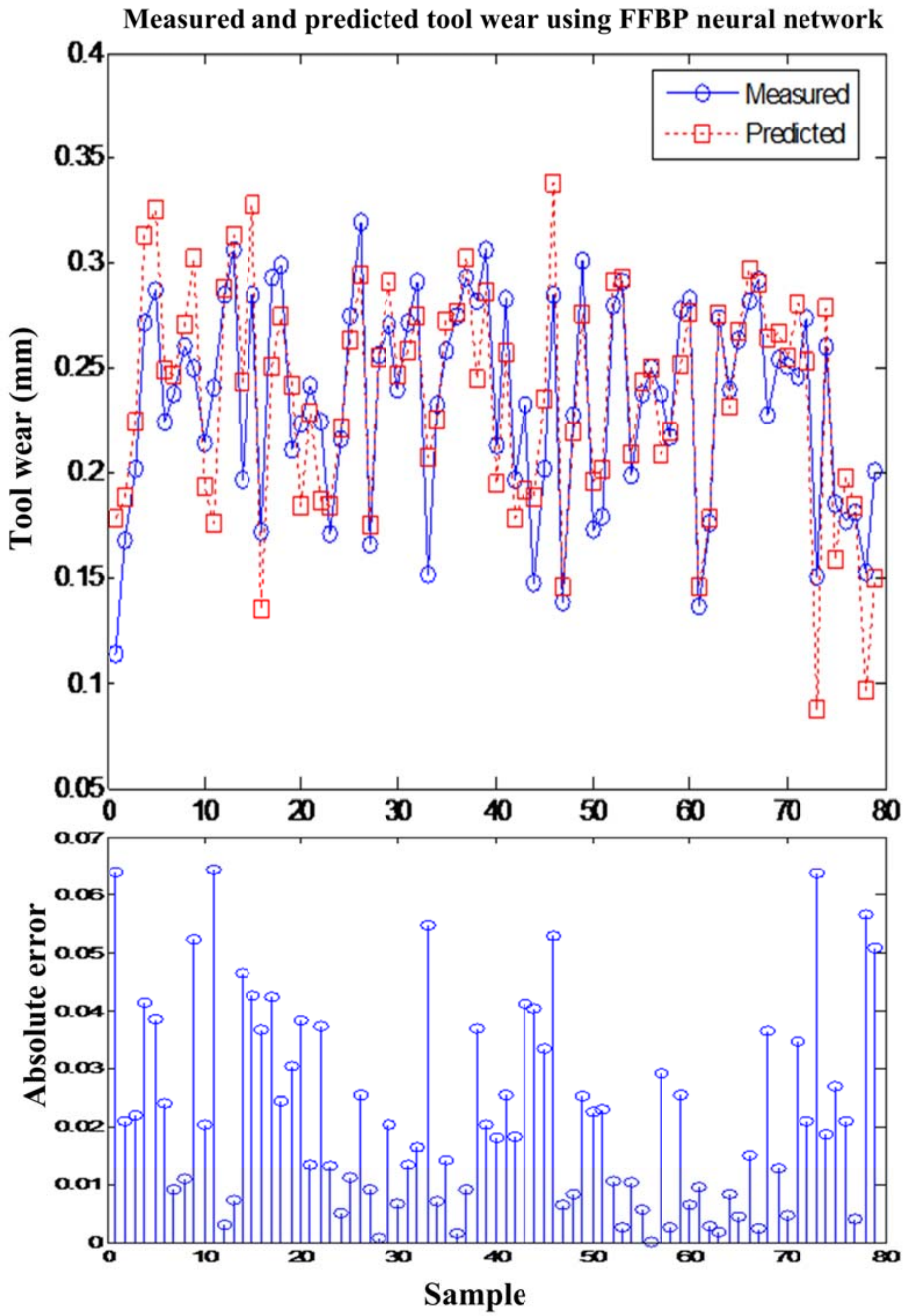

Figure 5.25: Simulation of the feed-forward back-propagation network and the absolute error between measured and predicted tool wear for trial 5

5.8 Tool Wear Prediction by Regression

Regression Analysis was applied to predict tool wear. The regression analysis model and its algorithm are described in section 4.3. The MatLab function x2fx [47] was used to convert predictor matrix X to a design matrix for regression analysis to estimate the tool wear. The design matrix selected was the quadratic model with constant, linear, interaction, and squared terms.

A linear regression model was developed to relate the tool flank wear with the different variables. The input data was divided randomly to have 75% of the data for training the network and the other 25% for testing the network. The coefficients matrix was computed in the training step and then used to predict the tool wear for the testing data set.

For the first trial, the predictor matrix X was taken as all the 35 collected variables. It was transformed to a quadratic design matrix and used to predict tool wear. The measured and predicted tool wear using regression analysis with quadratic polynomial expansion is shown in Figure 5.26. The mean of the absolute error was 0.0828.

The regression model then was run with the variables identified by the stepwise regression analysis (cutting time, cutting speed, feed rate, coolant, forces value of X-maximum, Z- standard deviation, X- variance, Y- skewness and Y- kurtosis), and vibration value of X-maximum, Y- standard deviation, X- skewness, Y- skewness and Z-skewness). The measured and predicted tool wear using regression analysis with quadratic polynomial expansion is shown in Figure 5.27. The mean of the absolute error was 0.0212.

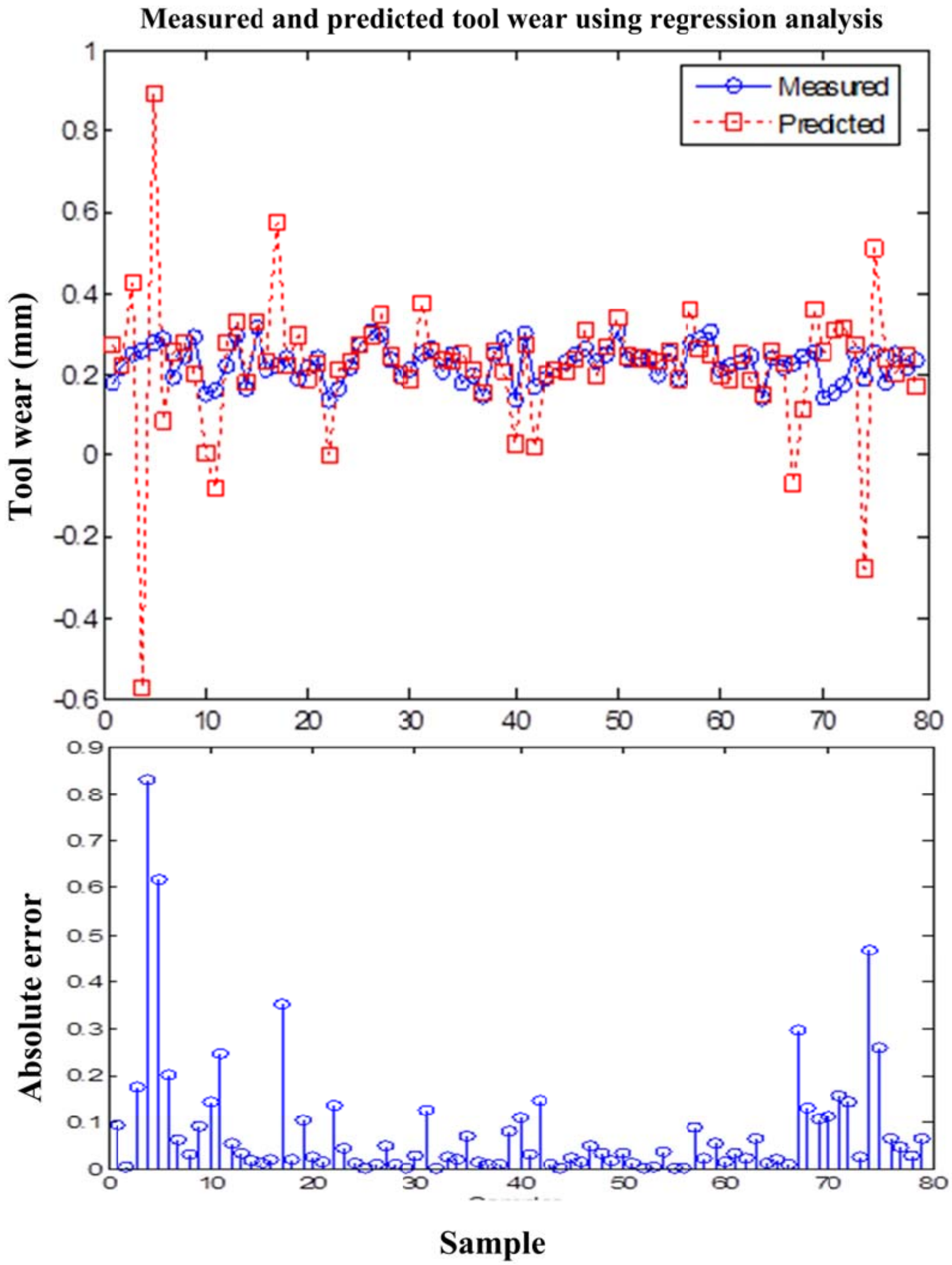

Figure 5.26: Measured and predicted tool wear using regression analysis with quadratic polynomial expansion in trial 1

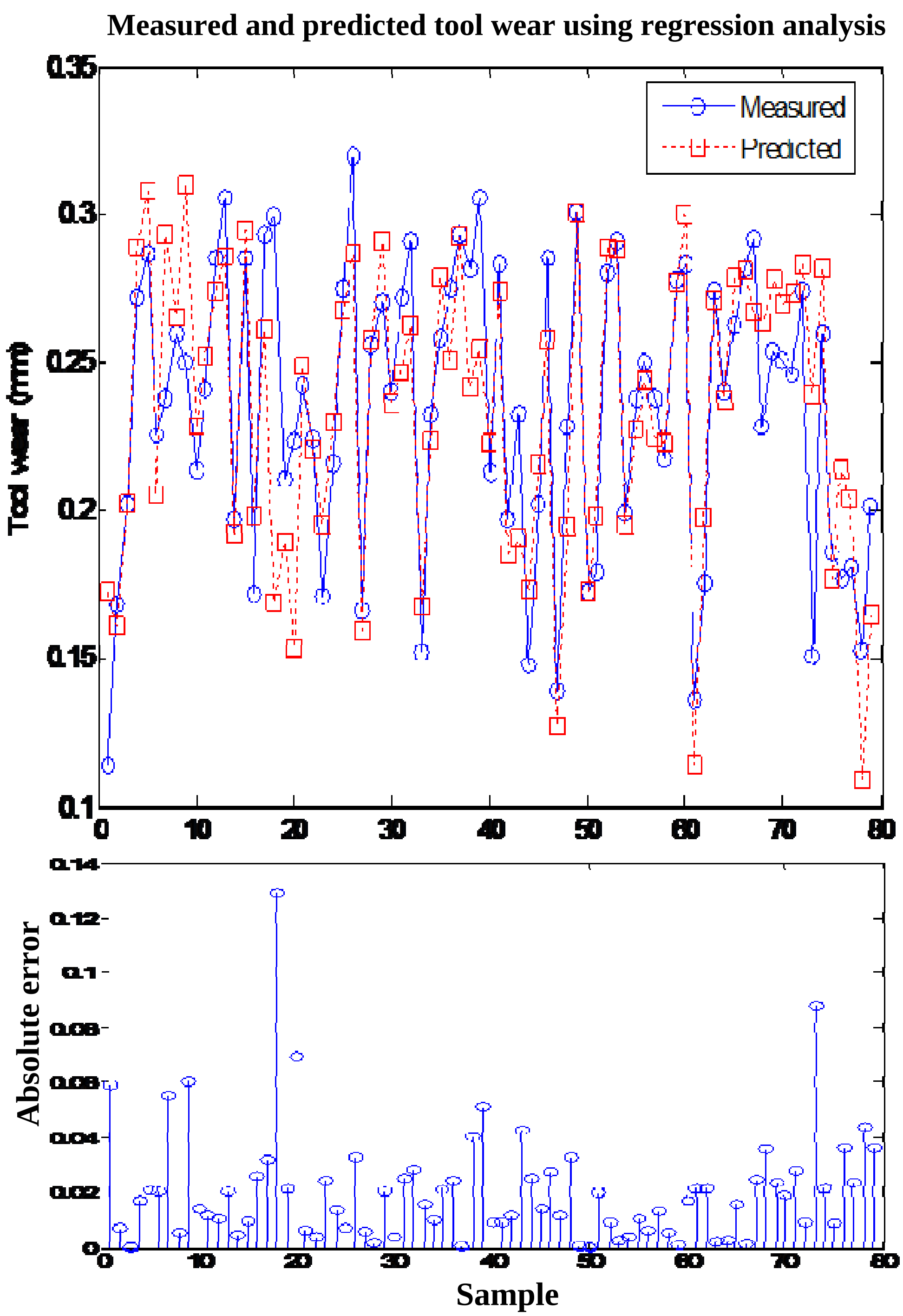

Figure 5.27: Measured and predicted tool wear using regression analysis with quadratic polynomial expansion in trial 2.

5.9 Tool Wear Prediction by GMR

The Gaussian Mixture Regression (GMR) model was used to estimate the tool wear based on cutting parameters and features extracted from force and vibration signals. Please refer to section 4.4 for a description of the GMR technique. The GMR model is built by the combination of the Gaussian mixture models initialized using k-means clustering algorithm and trained by Expectation-Maximization (EM) algorithm. The MatLab code obtained from [55] was modified to fit the current application and predict tool wear.

K-means clustering algorithm was used to estimate the models initial parameters (priors, μ, and $\sum$). Priors are the prior probabilities of the k-GMM components. μ represents the means, the centers, of the k-GMM components. $\sum$ represents the covariance matrices of the K GMM components. These parameters were modified by the Expectation-Maximization (EM) algorithm where the model is trained by feeding the training data. Training data was 75% of the total data set with the input variables and corresponding measured tool wear values. Gaussian Mixture Regression (GMR) was performed given the input data of the testing data set. The GMR algorithm computes the expected tool wear depending on the learnt GMM parameters.

For the first GMR run, the number of the Gaussian mixture was selected as 5 and the input was taken as the entire 35 variables of cutting parameters and features extracted from force and vibration. The mean absolute error between the measured and predicted tool wear was found to be 0.0243. The measured and predicted tool wear using GMR is shown in Figure 5.28.

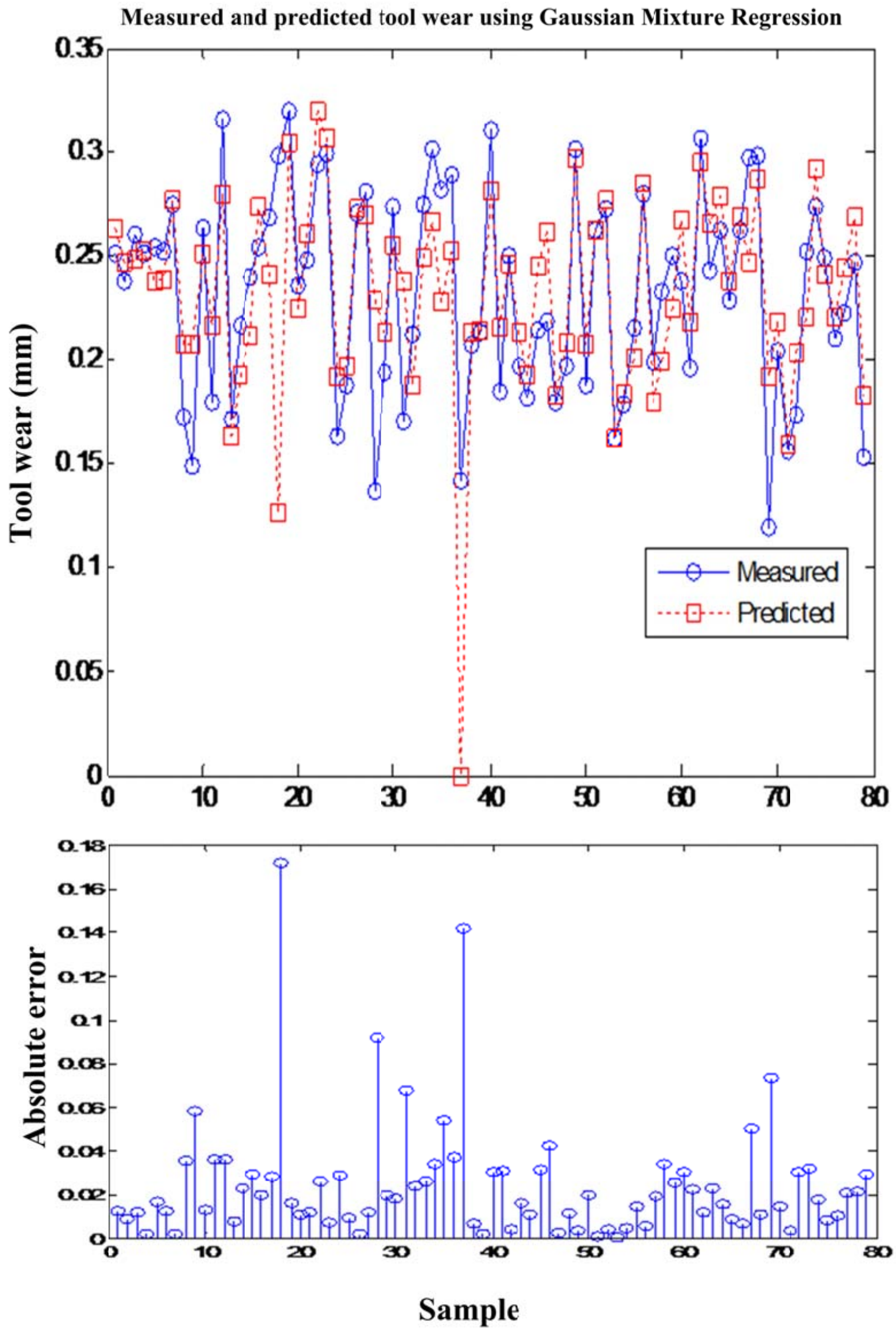

Figure 5.28: Measured and predicted tool wear using GMR in trial 1

The input then was taken as the cutting parameters and maximum value of force and vibration in the X-direction. The mean absolute error between the measured and predicted tool wear was found to be 0.0267. The measured and predicted tool wear using GMR is shown in Figure 5.29.

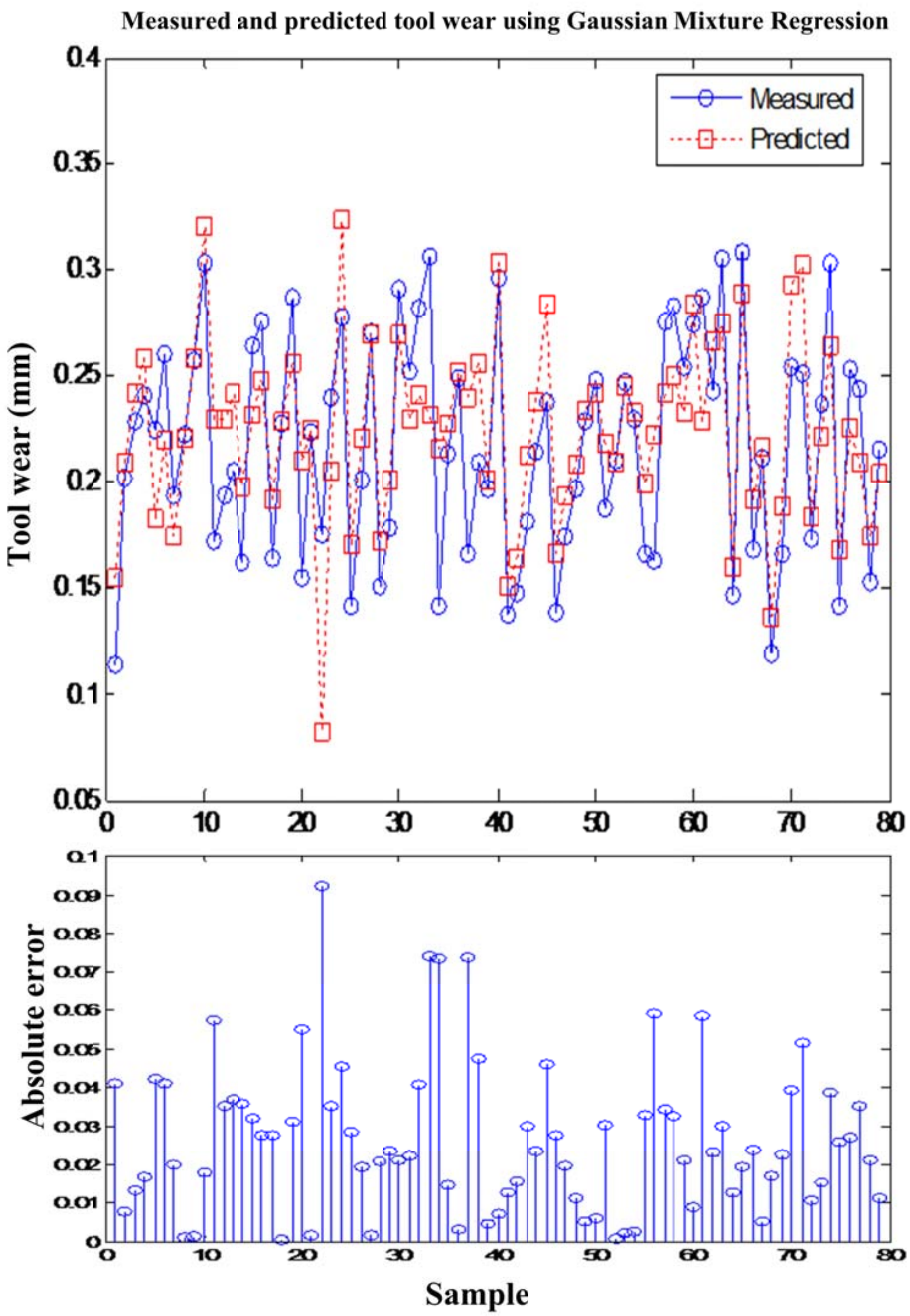

Figure 5.29: Measured and predicted tool wear using GMR in trial 2

The maximum values of force and vibration in the Y direction were added to the input. The mean absolute error between the measured and predicted tool wear was found to be 0.0181. The measured and predicted tool wear using GMR is shown in Figure 5.30.

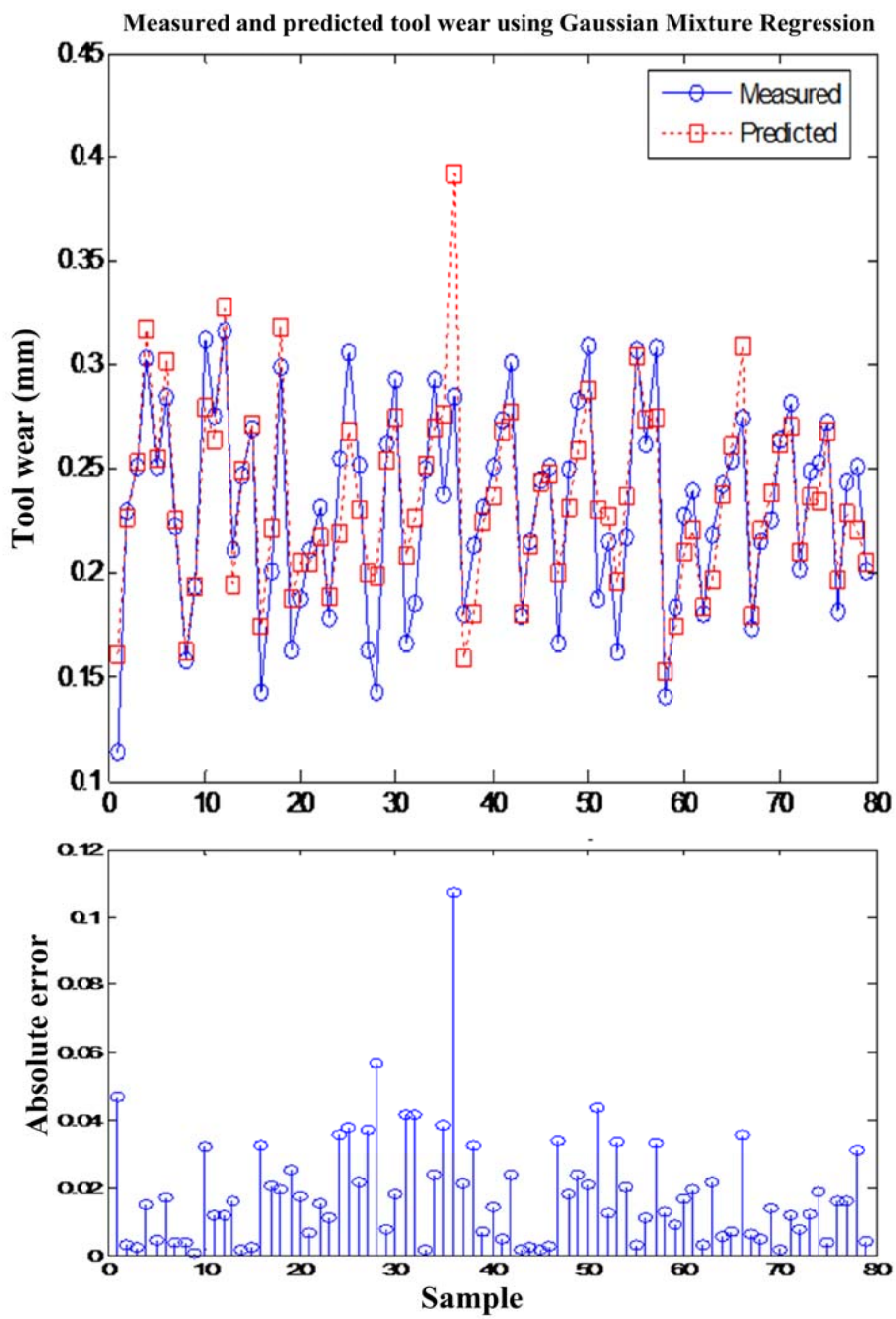

Figure 5.30: Measured and predicted tool wear using GMR in trial 3

The GMR model also was run with the variables identified by the stepwise regression analysis (cutting time, cutting speed, feed rate, coolant, forces values (X-maximum, Z-standard deviation, X-variance, Y-skewness and Y-kurtosis), and vibration values (X-maximum, Y-standard deviation, X-skewness, Y-skewness and Z-skewness). The mean absolute error between the measured and predicted tool wear was found to be 0.0228. The measured and predicted tool wear using GMR is shown in Figure 5.31.

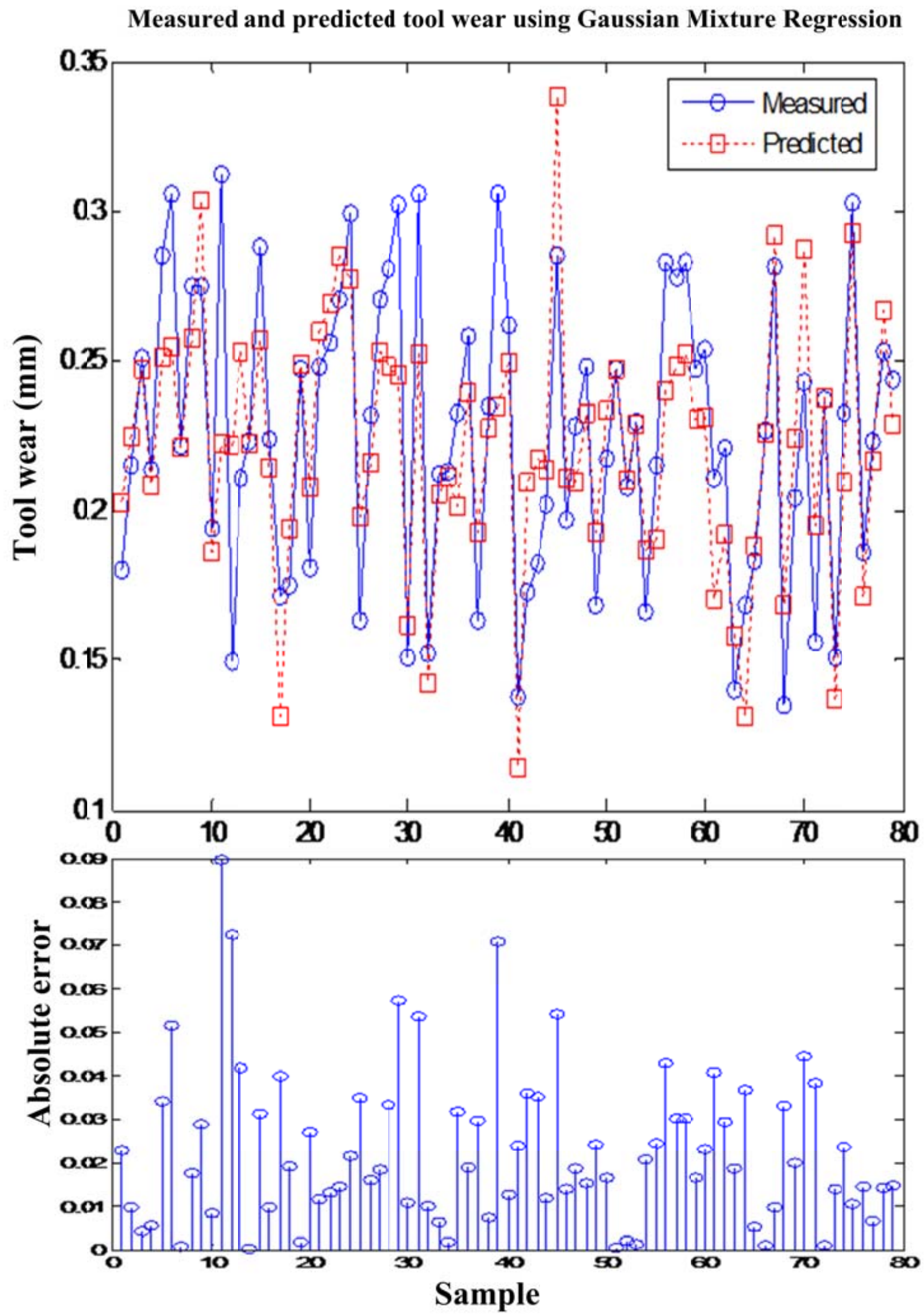

Figure 5.31: Measured and predicted tool wear using GMR in trial 4

5.10 Tool Wear Prediction Models Validation

The validation of the different implemented tool wear prediction models was performed by repeated random sub-sampling validation method. The data was randomly divided into training and validation (testing) data subsets. The model was fitted using the training data and then tested using the validation data. The process was repeated and the results were averaged over the different iterations.

The data set used as input to the different tool prediction models was grouped into five main subsets. Machining parameters (cutting time, cutting speed, depth of cut, feed rate, and the coolant) were considered main inputs to all data sets. The statistical features extracted from force and vibration signals were taken from the variables identified by PCA and stepwise regression analysis as effective parameters of tool wear.

For each data subset, evaluation of the three selected models - Neural Network, Regression and GMR - were repeated 25 times and the obtained test results were averaged. The data used comprised a total of 317 observation points from different cutting tests. The subsets were generated in such a way that 75% (238 data points) of the data was used for training and 25% (79 data points) for the testing. Results are discussed in the models comparison section below.

Data set 1 contained a total of seven variables; machining parameters, and the maximum values of force and vibration in the X direction. The maximum values of force and vibration in the X direction had the highest percentage in the Principal Component Analysis performed. Figure 5.32 shows a sample of the measured and predicted tool wear using this data set for the different predicting models.

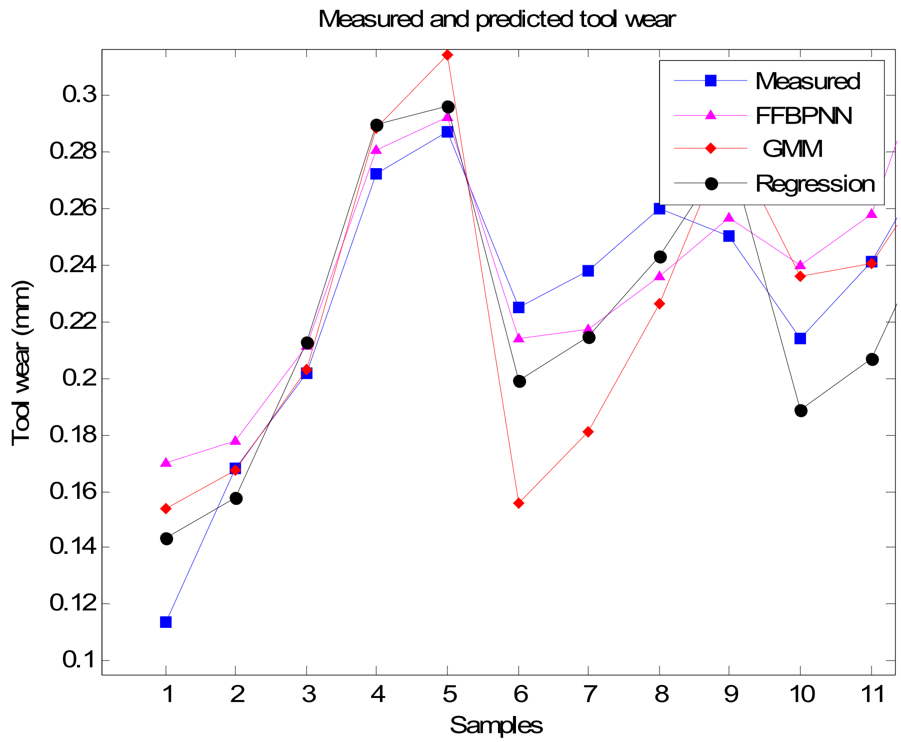

Figure 5.32: Measured and predicted tool wear using data set 1

Data set 2 contained a total of nine variables; machining parameters, and the maximum values of force and vibration in the X and Y directions. These were the features resulted from the Principal Component Analysis performed. Figure 5.33 shows a sample of the measured and predicted tool wear using this data set.

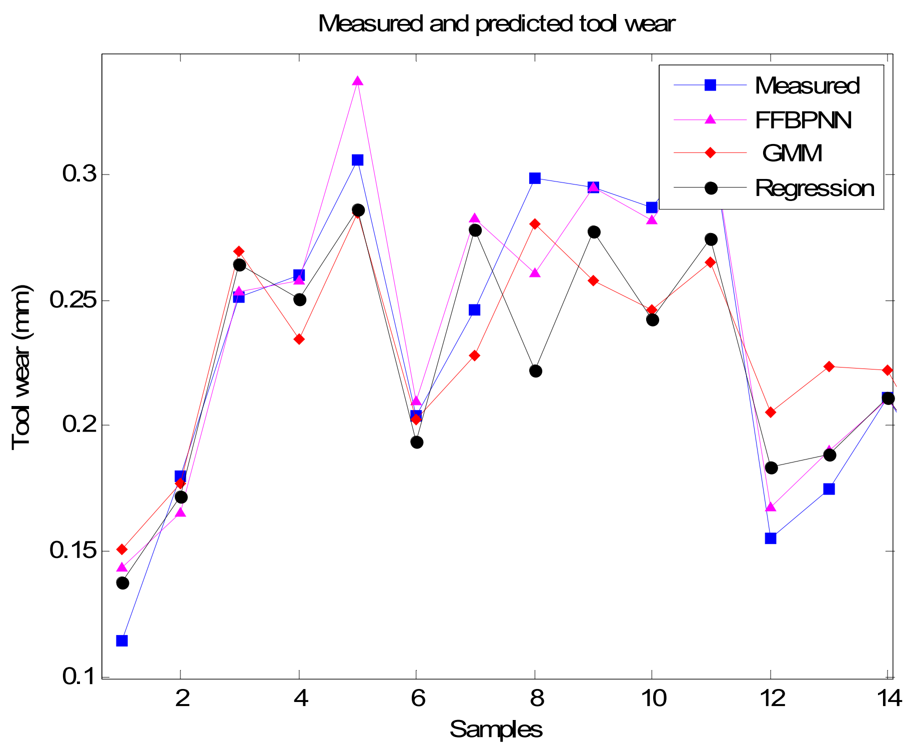

Figure 5.33: Measured and predicted tool wear using data set 2

In Data set 3, the maximum standard deviation of force and vibration values in the Y and Z direction were added to the data set. Therefore the dataset included cutting time, cutting speed, feed rate, depth of cut, coolant, the maximum values of force and vibration in the X, Y and Z direction and standard deviation of force and vibration in the X, Y and Z direction. There were total of seventeen variables in this set. Figure 5.34 shows a sample of the measured and predicted tool wear using this data set.

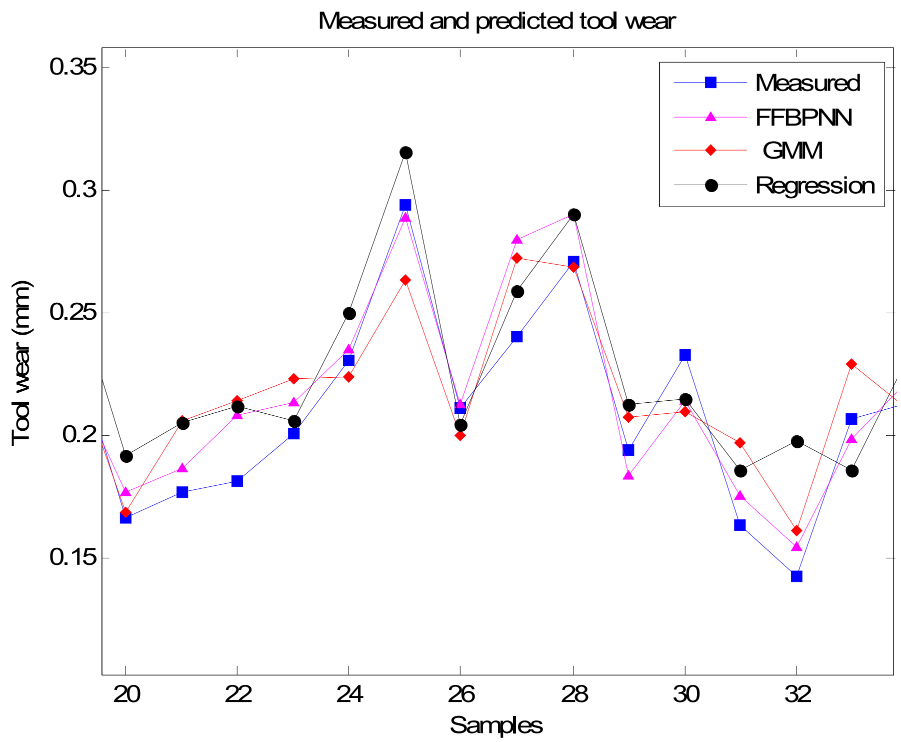

Figure 5.34: Measured and predicted tool wear using data set 3

Data set 4 had all thirty five variables. These included the cutting parameters and all the statistical features extracted from the force and vibration signal (maximum, standard deviation, variance, skewness and kurtosis for the signals at the three axis X, Y, and Z). Figure 5.35 shows a sample of the measured and predicted tool wear using this data set.

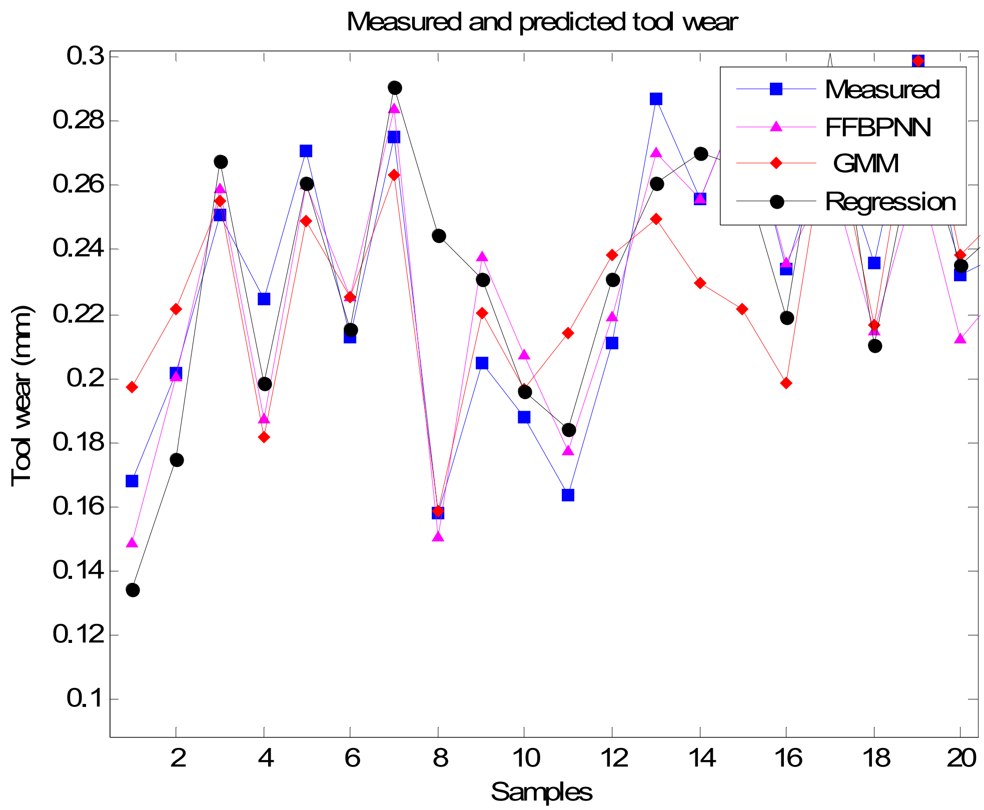

Figure 5.35: Measured and predicted tool wear using data set 4

Data set 5 included the fourteen significant variables indicated by the stepwise regression. These variables were cutting time, cutting speed, feed rate, coolant, forces values (X-maximum, Z-standard deviation, X-variance, Y-skewness and Y-kurtosis), and vibration values (X-maximum, Y-standard deviation, X-skewness, Y-skewness and Z-skewness). Figure 5.36 shows a sample of the measured and predicted tool wear using this data set.

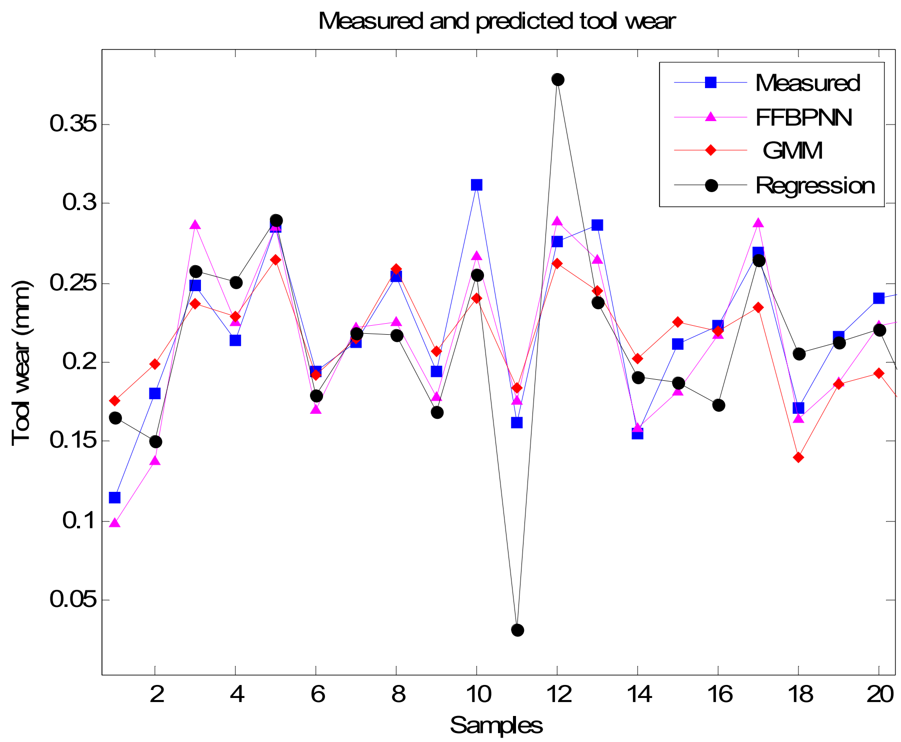

Figure 5.36: Measured and predicted tool wear using data set 5

5.11 Comparison of modeling methods as predictors of tool wear

The performance of the different tool prediction models was compared based on five different criteria: sum of squares error (SSE), the coefficient of determination (R^2), root mean squared error (RMSE), percentage relative error (%RE), and the mean absolute error (MAE). These criteria are discussed in section 4.5. Tables 5.2- 5.6 list the results of the three models for the five specified data subsets of different variable combinations.

Table 5.2: Comparison of the models performance in the Data Set 1

	SSE	R^2	RMSE	%RE	MAE
FFBPNN	0.03793	0.78913	0.02171	9.12439	0.01609
Regression	0.04934	0.72506	0.02471	10.35724	0.01900
GMR	0.06334	0.66912	0.02824	11.82676	0.02224

Table 5.3: Comparison of the models performance in the Data Set 2

	SSE	R^2	RMSE	%RE	MAE
FFBPNN	0.04863	0.72930	0.02444	10.25848	0.01807
Regression	0.06611	0.65272	0.02800	11.78239	0.01975
GMR	0.06374	0.65101	0.02828	11.93360	0.02188

Table 5.4: Comparison of the models performance in the Data Set 3

	SSE	R^2	RMSE	%RE	MAE
FFBPNN	0.06700	0.62805	0.02793	11.69275	0.02014
Regression	0.41915	-1.37957	0.06425	26.82602	0.03415
GMR	0.09161	0.49689	0.03364	14.21671	0.02440

Table 5.5: Comparison of the models performance in the Data Set 4

	SSE	R^2	RMSE	%RE	MAE
FFBPNN	0.08522	0.51432	0.03153	13.22406	0.02212
Regression	30.88359	-166.76326	0.52919	223.10398	0.16781
GMR	0.35600	-1.01080	0.06648	27.99556	0.03801

Table 5.6: Comparison of the models performance in the Data Set 5

	SSE	R^2	RMSE	%RE	MAE
FFBPNN	0.04608	0.74816	0.02392	9.99185	0.01772
Regression	0.31786	-0.68022	0.05518	23.12839	0.02676
GMR	0.07580	0.59432	0.03090	12.97346	0.02425

The performance criteria show that the Neural Network is better in predicting tool wear than the regression model and GMR in all the data subsets tested. The SSE, RMSE, %RE, and MAE values of the FFBPNN model are the lowest for all the data subsets. Also its coefficient of determination R^2 is the highest among the three tested models based on the same training and testing data.

FFBPNN showed a better performance when data set 1 was used. This included the cutting parameters and the maximum values of force and vibration in the X-direction. This shows that these variables are the most informative variables toward the tool wear.

Among the different data subsets, data set 4 showed very high prediction errors and low R^2 compared to other data sets. Data set 4 included all the variables as inputs to the prediction model which indicates that many variables may not carry relevant relative information toward tool wear.

The GMR and regression model performance varied depending on the input data sets. The regression model performed better when using data sets 1 and 2 which included the least number of variables. Moreover the results of the regression model with data set 4 indicated the largest prediction error and lowest R^2 compared to other data sets and prediction models. GMR model performance was better than the regression model when data sets 3, 4, and 5 were used. The regression model develops a linear relationship between the tool wear and the process variables.

Although the variables were transformed using power transformation techniques, still the model has a larger error than the Neural Network and GMR models. Other transformation techniques could be implemented to investigate the possibility of improving the prediction of tool wear using the regression analysis.

The modeling based on Neural Network has proven to be more accurate than the other techniques; this may be attributed to the ability of Neural Networks to model a non-linear process such as tool wear [27].

The Neural Network with the least prediction error was when the machining parameters and the maximum values of force and vibration in the X direction were used as inputs to the network. The predictive accuracy of the Neural Network was 90.88% which is 2.70% and 1.23% higher than the predictive accuracy of the GMR and regression models respectively.

In addition using the significant input variables indicated by the stepwise regression resulted in an accuracy of 90.01% for the Neural Network model. This is 2.98% and 13.14% higher than the prediction accuracy of the GMR and regression models respectively.

Using all the machining parameters and all the features extracted from the force and vibration signal resulted in the lowest prediction accuracy for all three models. The prediction accuracies were 86.78%, 123.10%, and 72.00% for the Neural Network, Regression, and GMR models respectively.

6 Conclusions and future work

6.1 Conclusions

In the present study, the importance of tool wear monitoring while machining Titanium alloys is discussed and prediction models of tool wear are presented.

This work presented an experimentation approach to study the tool wear in turning operations of titanium alloys as a difficult to cut material. Since tool wear is very critical to the process, different modeling approaches to predict tool wear are presented to help improve the efficiency of the machining process.

The experimental work consisted of controlled machining tests with force and vibration measurements, as well as tool wear and surface roughness. Experimental tests were carried out using fresh inserts and a test matrix was created to cover combinations of machining parameters namely cutting speed, feed rate, depth-of-cut and coolant strategy. The measurements were used to analyze the relation between the cutting conditions and the measured cutting force, vibration and tool wear. It was observed that the tool wear rate was more rapid at higher cutting speed and feed rates especially when cutting under dry conditions, which is due to the high temperature that increases the tool wear.

The collected signals were processed to acquire the features to be used as input to the model of predicting the tool wear using PCA and stepwise regression techniques. Features that demonstrated an effective trend towards the tool wear were used as inputs to the prediction model with the cutting conditions.

The implemented modeling methods included feed-forward back-propagation Neural Network, regression analysis and Gaussian Mixture Regression. Based on the prediction results presented in previous sections, it can be concluded that tool wear can be predicted using these models and that the Neural Network based method is the most accurate among these methods. Modeling with Neural Networks provided a better prediction because of its capability to model more complex non-linear process such as tool wear.

Neural network modeling yielded the least prediction error when the machining parameters and the maximum values of force and vibration in the X direction were used as inputs to the network. The prediction accuracy of the Neural Network was 90.88% which was 2.70% and 1.23% higher than the prediction accuracy of the GMR and regression models respectively.

In addition using the significant input variables indicated by the stepwise regression resulted in an accuracy of 90.01% for the Neural Network model. This was 2.98% and 13.136% higher than the prediction accuracy of the GMR and regression models respectively

Using all the machining parameters and all the features extracted from the force and vibration signal resulted in the lowest prediction accuracy for all the three models. The prediction accuracies were 86.78%, 123.10%, and 72.00% for the Neural Network, Regression, and GMR models respectively.

6.2 Future Work

The primary purpose of this study was to produce a reliable estimate of tool life in metal cutting process of Titanium alloys. The mechanism of material removal, cutting performance, and tool failure characteristics were analyzed during the turning process of titanium alloys.

As a result of this study, a detailed database summarizing the results of cutting tests was created. It includes the different cutting parameters used (cutting speed, feed rate, depth-of-cut and coolant strategy), measured cutting force, vibration, tool wear and surface roughness. In addition, a sample of the chips produced in each cutting test was collected. The study can be extended as follows:

1. Include the measurements of temperature and lathe machine power consumption that may help optimize the turning process of titanium alloys.
2. Develop a model to predict the surface roughness and the cutting forces using Neural Network and GMR.
3. Study the chip characteristics and establish a relationship with tool wear.

7 References

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Appendix: Stepwise Regression Results

```
b = stepwisefit(p,t);
Initial columns included:  none
Step 1, added column 1, p=0
Step 2, added column 6, p=0
Step 3, added column 4, p=2.04134e-005
Step 4, added column 3, p=0.000187989
Step 5, added column 5, p=0.00114043
Step 6, added column 30, p=0.00681707
Step 7, added column 31, p=0.000684678
Step 8, added column 11, p=0.00403615
Step 9, added column 32, p=0.018959
Step 10, added column 25, p=0.0257861
Step 11, added column 21, p=0.00577326
Step 12, added column 19, p=0.0218164
Step 13, added column 16, p=0.000552005
Step 14, added column 12, p=0.0181981
Final columns included:  1 3 4 5 6 11 12 16 19 21 25 30 31 32
    'Coeff'           'Std.Err.'       'Status'    'P'
    [      0.0015]    [8.4928e-005]    'In'        [1.9789e-048]
    [           0]    [6.5253e+012]    'Out'       [          1]
    [      0.2807]    [     0.0749]    'In'        [2.1294e-004]
    [ 7.4510e-004]    [1.0428e-004]    'In'        [6.7765e-012]
    [-1.9966e-005]    [5.9364e-006]    'In'        [8.6953e-004]
    [ 7.6214e-005]    [1.8019e-005]    'In'        [3.1062e-005]
    [-4.5341e-005]    [8.3883e-005]    'Out'       [     0.5892]
    [ 1.0721e-004]    [6.4401e-005]    'Out'       [     0.0970]
    [-5.9170e-005]    [3.0763e-004]    'Out'       [     0.8476]
    [-3.4390e-004]    [5.3621e-004]    'Out'       [     0.5218]
    [-4.9401e-004]    [1.3016e-004]    'In'        [1.7815e-004]
    [ 6.8176e-007]    [2.8712e-007]    'In'        [     0.0182]
    [-5.6700e-006]    [6.5841e-006]    'Out'       [     0.3898]
    [-1.6864e-006]    [4.4700e-006]    'Out'       [     0.7062]
    [ 1.6175e-004]    [     0.0028]    'Out'       [     0.9542]
    [      0.0162]    [     0.0044]    'In'        [2.7148e-004]
    [ 7.5044e-004]    [     0.0015]    'Out'       [     0.6191]
    [ 2.5974e-004]    [2.6790e-004]    'Out'       [     0.3330]
    [      0.0025]    [5.5947e-004]    'In'        [1.4988e-005]
    [-3.9012e-005]    [1.3997e-004]    'Out'       [     0.7806]
    [      0.0047]    [     0.0015]    'In'        [     0.0023]
    [      0.0028]    [     0.0019]    'Out'       [     0.1535]
    [-3.4761e-004]    [     0.0040]    'Out'       [     0.9314]
    [     -0.0030]    [     0.0038]    'Out'       [     0.4383]
    [     -0.0172]    [     0.0073]    'In'        [     0.0195]
    [      0.0194]    [     0.0359]    'Out'       [     0.5894]
    [-2.8294e-004]    [3.6804e-004]    'Out'       [     0.4426]
    [      0.0072]    [     0.0090]    'Out'       [     0.4241]
    [      0.0323]    [     0.1105]    'Out'       [     0.7704]
    [      0.0705]    [     0.0163]    'In'        [2.0174e-005]
    [     -0.0208]    [     0.0062]    'In'        [8.4482e-004]
    [      0.0088]    [     0.0028]    'In'        [     0.0018]
    [-1.1619e-004]    [3.8228e-004]    'Out'       [     0.7614]
    [-5.2060e-005]    [5.7314e-005]    'Out'       [     0.3644]
    [-1.0867e-005]    [3.2799e-005]    'Out'       [     0.7406]
```

VITA

Azza Al Hassani received the B.Sc. degree in Mechanical Engineering with honor from United Arab Emirates University, Al Ain, UAE in 2005. After her graduation, she joined the Mechanical Engineering Department at UAE University where she worked as Scientific Assistant. From 2006 to 2011 she was employed as a Mechanical Engineer at the Engineering and Commissioning departments of Abu Dhabi Transmission and Dispatch Company (TRANSCO), Al Ain. In 2011, she received a Master degree of Management Sciences (MMSC) from the University of Waterloo, Ontario, Canada under a program developed by Abu Dhabi Water and Electricity Authority (ADWEA).

In July, 2011, she joined Emirates Nuclear Energy Corporation (ENEC), Abu Dhabi, UAE as a Senior Mechanical Engineer in the Chief Program Office. Currently she holds the position of Head of Reactor System at ENEC.

Azza is a member of the American Society of Mechanical Engineers (ASME) and Society of Engineers-UAE.