ANN MODEL TO PREDICT BURR HEIGHT AND THICKNESS

A Thesis by

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I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Industrial and Manufacturing Engineering.

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ABSTRACT

The drilling of metals produces undesirable projections at the surface of the hole called burrs, which are very costly to remove from the work piece. Any effort involved in simplifying the drilling process that decreases the burr size significantly helps in reducing deburring cost. This study focuses on the burrs formed in drilling of AL6061-T6 at the exit side of the work piece as they are usually larger and have complicated shape and size. Two models are developed using backpropagation neural networks to predict burr height and thickness separately as a function of point angle, chisel edge angle and lip clearance angle. The results of this research show that the height and thickness of the burr can be controlled by proper selection of drill bit that consists of suitable geometric parameters. The optimal geometric parameters that yield minimum burr height and thickness are also suggested. Thus, the model assists in identifying suitable drill bit that yields minimum burr height and thickness and as a result helps in reducing deburring cost.

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CHAPTER 1

INTRODUCTION

Drilling is one of the widely used machining processes making up approximately 25% of all the machining processes performed in the production of goods [1]. The drilling of a through hole consists of three phases. In the first phase drill enters into the work piece. In the second phase a steady state torque and thrust is attained as drill bit advances to the other end of the work piece. In the third phase the drill point breaks through the underside of the work piece. The drilling of holes produces undesired projection of material that result from plastic deformation, known as burrs [6]. A burr is defined as “an undesirable projection of material formed as the result of the plastic flow from a cutting or shearing operation” [2]. The magnitude of the burr is defined by its height and thickness. The burrs can be classified as entrance and exit burr. The exit burr is usually larger than the entrance burr and is of prime importance owing to the difficulty of removing it from the work piece. The presence of burr hinders productivity, automation of machining process as well as quality [3]. Therefore the burr must be removed to allow for ease of assembly. The cost of deburring amplifies as complexity of parts and precision requirement of hole increases. For high precision components such as aircraft engines the deburring cost is 30% of the manufacturing cost. Whereas, for automobile components, it is 14% of the manufacturing expenses [4, 5]. Sofranos [6] pointed out deburring costs for various manufactured items as indicated in the Table 1.

Table 1

Typical Drilling Deburring Expenditures for a Selected Group of Facilities [6]

Item (Dia in inches)	**Hole Range**	**Approximate Annual Deburring Cost**
Valves, Housing, pistons	1/16 to 1/18	$ 140,000
Combination valve	1/16 to 1/8	$ 30,000
Special valves	various	$ 8,000
Complex brackets	1/16 to 3/8	$ 8,000

Deburring is usually performed by hand using abrasive and finishing tools and hence consumes significant time and may turn out to be a bottleneck in the production. Moreover, as it is the last operation performed on the produced part it may damage the edges of the part or the appearance resulting in considerable loss. For manual deburring, studies have shown that as burr thickness increases, the time required to deburr the part also increases exponentially [7]. The high cost of deburring, decreased hole and surface quality, and monotonous manual deburring work has lead to focus attention on automation of deburring process [8]. But due to the contour of burr the automation of deburring process is difficult. Any effort to automate the deburring process requires proper understanding of the burr formation mechanism and dependable model of burr formation. Understanding burr formation in machining process allows one to gain knowledge on the parameters that affect burr height and thickness and may lead to the development of burr minimization and prevention strategies [9]. The process of burr formation in drilling is a complicated phenomenon affected by many parameters such as drill geometry, material property and process conditions. Selecting tools and process parameters according to the work piece material and hole quality requirement is critical for the minimization and prevention of burr formation. Then the cost associated with deburring can be greatly reduced. One of the best strategies is to eliminate or prevent the burr from occurring in the first place as this would reduce deburring cost. Besides, in cases where the burrs cannot be completely eliminated, deburring operation can be simplified due to reduced burr size and shape [4].

Several experimental studies have been carried out to investigate effects of process parameters like speed, feed and tool geometry on drilling burr formation, and also a number of drilling burr formation mechanisms have been proposed. The burr formation can be modeled using experimental, analytical formulation and simulation. An analytical model was proposed by Sofronas [6] that minimizes burr height and thickness based on drill geometry and other process parameters. Sangkee Min [14] developed a drilling burr expert system to predict and control drilling burrs in drilling of stainless steel. Park [26] developed a simulation based two dimensional finite element model in drilling of stainless steel 304L to determine the burr formation mechanism in orthogonal cutting. Dornfeld, Guo [18] proposed a three dimensional finite element model to predict and identify different stages in the formation of burr in drilling of 304-stainless steel. Sokolowski [31] used neural networks and fuzzy logic to predict formation of burr in face milling. Hambli [32] proposed a neural network model to predict burr height formation in blanking process.

As drilling burr formation is a very complicated phenomenon affected by many parameters such as drill geometry, material property and process conditions. Therefore it is imperative to develop a reliable model that predicts the burr size to reduce deburring cost as burrs cannot be completely eliminated. “However, no generally accepted analytical model is available in drilling up to now” [25]. The thesis differs from other studies carried out on burr formation as it attempts to develop a prediction model, which determines whether a drill bit consisting of important geometric parameters yields a minimum burr or not. The important geometric parameters are determined based on the literature review of previous studies carried out on burr formation. An artificial neural network (ANN) model is developed that predicts burr height and thickness. ANN is selected because of its capability to learn and simplify from examples and adjust to changing conditions. In addition they can be applied in manufacturing area as they are an effective tool to model non linear systems.

1.1 Objective

Prediction control of the burr is necessary to make the drilling process more efficient by minimizing the deburring operations as burr removal signifies additional operation and deburring cost. Therefore it is imperative to optimize the parameters that affect the quality of the drilled holes by reducing burr height and thickness through the proper use of drill bits. Selecting tools and process parameters according to the work piece material and hole quality requirement is critical for the minimization or prevention of burr formation. Then, the cost associated with deburring method can be greatly reduced. The importance of cost reduction, quality enhancement, and reduction of monotonous deburring work necessitate development of an effective model that would predict the burr formation. Therefore, the objective of this study is to develop a prediction model, which identifies whether a drill bit with certain geometric parameters would yield minimum burr or not. In this thesis an ANN model will be developed that predicts burr height and thickness based on the geometric parameters of the drill bit. The model would provide an opportunity to perform “what if “analysis. New inputs can be fed in to the model within the range of the existing input parameters to determine their effect on burr height and thickness. The optimal input parameters that yield minimum burr can be selected to perform the drilling experiment and thus deburring time and cost can be minimized.

Consequently, this model reduces deburring cost, and enhances quality of the drilled holes due to reduced burr height and thickness.

CHAPTER 2

BURRS IN DRILLING

This chapter give a brief introduction to the type of drill bit used in this research and is followed by background on burrs in drilling and review of literature from previous research. In background, introduction to burr, different types of burr, burr formation mechanism, burr measurement techniques are introduced.

2.1 Introduction to Drill Bit Geometry

Various types of tools are used in drilling to produce holes. Out of them twist drill bits are the most commonly available and widely used drilling tools. As in this research twist drills will be used to perform drilling operation, only the geometry associated with this type of drill will be discussed. Generally twist bits are made from either high speed steel (HSS), or carbon steel. The typical geometry of a twist drill is as shown in Figure 1. “The HSS drill bits are suitable for drilling most types of material, when drilling metal the HSS stands up to the high temperatures. Whereas, the carbon steel bits are specially ground for drilling wood and should not be used for drilling metals, they tend to be more brittle, less flexible than HSS bits” [10]. The twist drills are available with variety of coatings including titanium, black oxide and cobalt.

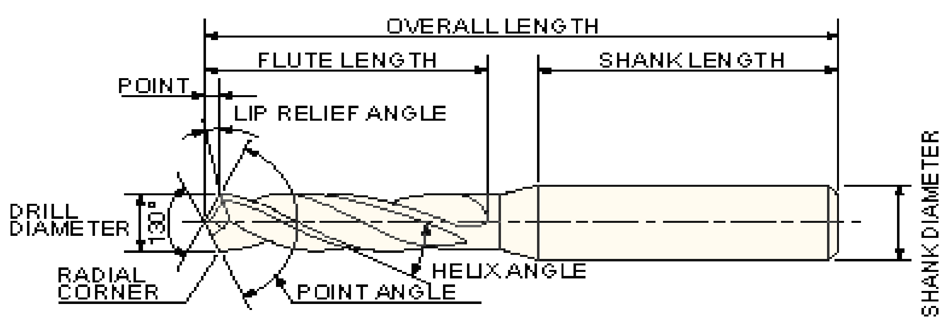


Figure 1. Geometry of Twist Drill [11]

Some of the important geometrical parameters associated with twist drill bit used in this thesis are as follows [12]:

Chisel Edge: The edge at the end of the web that connects the cutting lips.

Chisel Edge Angle: The included angle between the chisel edge and cutting lip, as viewed from the end of a drill.

Lip Relief Angle: The axial relief angle at the outer corner of the lip; measured by projection to a plane tangent to the periphery at the outer corner of the lip.

Helix Angle: The angle formed by the leading edge of the land with a plane containing the axis of a drill.

Point Angle: The included angle between the cutting lips projected upon a plane parallel to the drill axis and parallel to the two cutting lips.

Flutes: Helical or straight grooves cut or formed in the body of a drill to provide cutting lips, permit removal of chips, and allow cutting fluid to reach the cutting lips.

Relative Lip Height: The difference in indicator reading between the cutting lips of a drill. It is measured at a right angle to the cutting lip at a specific distance from the axis of the tool.

Web: The central portion of the body that joins the lands. The extreme end of the web forms the chisel edge on a two flute drill.

Secondary cutting edge: The cutting edge formed by the intersection of the face of the notch with relieved surface of the point, resulting in partial removal of the chisel edge [5].

Web Thickness after Notching: "The thickness of the remaining web at the point after notching [5].

2.2 Background on Burrs

The machining process produces burrs as a result of plastic deformation [13]. It is a by-product of manufacturing, and greatly influences the cost of the finished part. Burrs can be defined as any material that protrudes further beyond the adjoining surfaces and are intolerable protrusions only when shape or size of a part is hindered from performing its function. The projection is regarded as a burr only if it is the result of plastic flow caused by a cutting tool. A burr is not considered a burr if the part serves its function and meets the requirement of the user [13]. Burr is formed both at the entrance and at the exit of the workpiece. The exit burr is important as it is larger in size and is most difficult to remove causing deburring problems. Therefore, lot of studies have focused their attention on exit burr [14]. The magnitude of burr can be defined by its height (h) and thickness (w) as shown in the Figure 2.

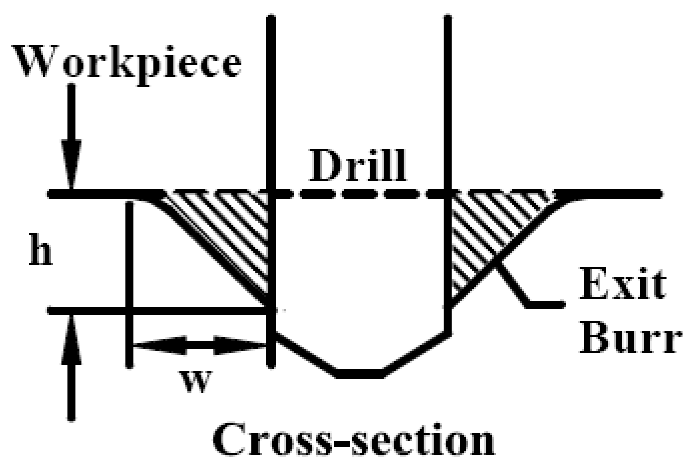


Figure 2. Burr Height and Thickness

2.2.1 Burr Classification

Kim. J [15] identified four types of burr in drilling of Ti-6Al-4V as shown in the Figure 3. The Type I is a uniform burr, this type has a consistent height and thickness around the outside edge of the hole and is effortless to deburr after drilling. Type II looks alike to Type I, but has a leaned-back shape. Type III burr has a severe rolled-back shape, whereas, Type IV is also similar to type III but has a comparatively small height and broadened exit.

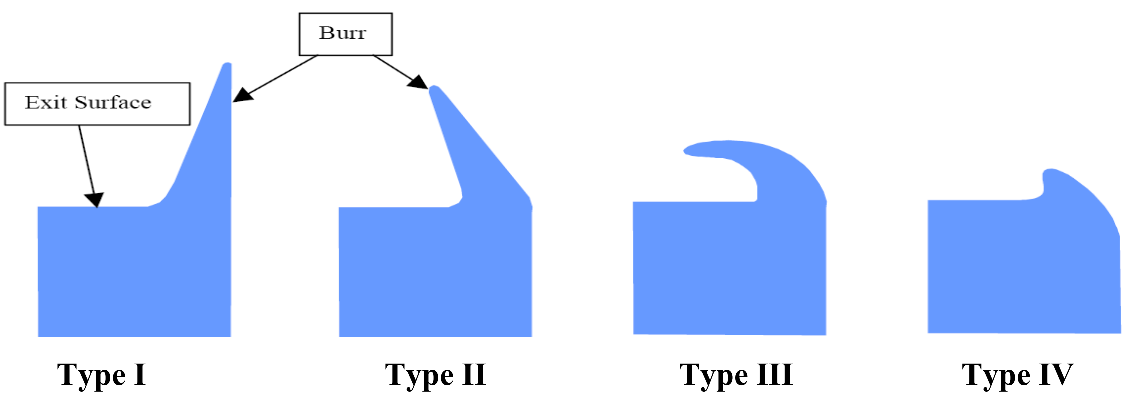


Figure 3. Types of Drilling Burr on Titanium [15]

In conventional drilling, the feed and speed helps to establish the shape and the sizes of the exit burrs. Three main types of burr have been recognized as uniform burrs, crown burrs, and transient burrs as shown in Figure 4 formed in the drilling of stainless steel. A uniform burr is usually formed at low feed rates and speeds and is generally small having a uniform cap along the hole perimeter, whereas, a crown burr is generally formed at higher feeds and speeds and is characterized by large flake . A transient burr is a blend of uniform and crown burr[16].

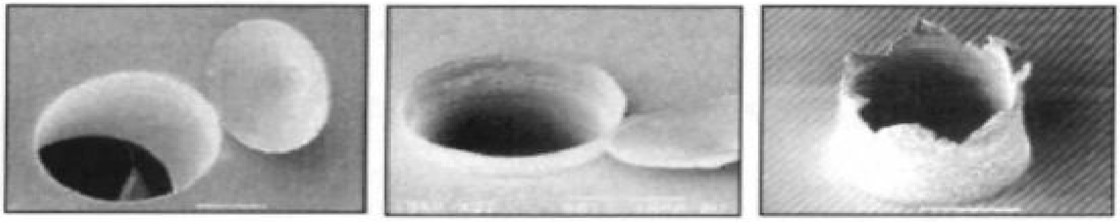


Figure 4. Uniform, Transient and Crown Burr [16]

Tazakawa [17] also identified three types of burrs in drilling i.e. Roll-over burrs, Poison burrs and Tear burrs. He stated that the above mentioned burrs appear relatively in drilling of all materials. The roll-over burrs were usually formed in the drilling of aluminum and were generally characterized by large size, whereas the poison burrs were smaller in size and were usually formed in the drilling of brass. Finally the tear burrs had a size that lie between roll-over and poison burr.

2.2.2 Burr Formation Mechanism

The burr formation mechanism was divided into five categories by Dornfeld and Park [14] using finite element analysis as shown in the Figure 5. The stages are steady state, burr initiation; development, initial fracture and burr formation respectively. The process is in steady state when the tip of the drill is completely embedded in the work piece. In the burr initiation stage a bulge is formed due to the plastic deformation as the drill tends to move towards the exit of the work piece. Whereas in the development stage the bulge formed in the previous stage enlarge and grows due to the plastic deformation of the material in all directions. Further in the initial fracture stage the growing bulge stops increasing as the material has expanded to its maximum point. Therefore an initial fracture is initiated due to lack of ductility at the edge of the drill. Finally in the last stage, bulge tear and the projected material turn into a burr. [9, 18]. "In the uniform burr, the initial fracture occurs at the edge of the drill and it leads the formation of cap. Whereas in the crown burr, the initial fracture occurs at the center of the drill and the rest of material deforms plastically and forms a crown burr” [19].

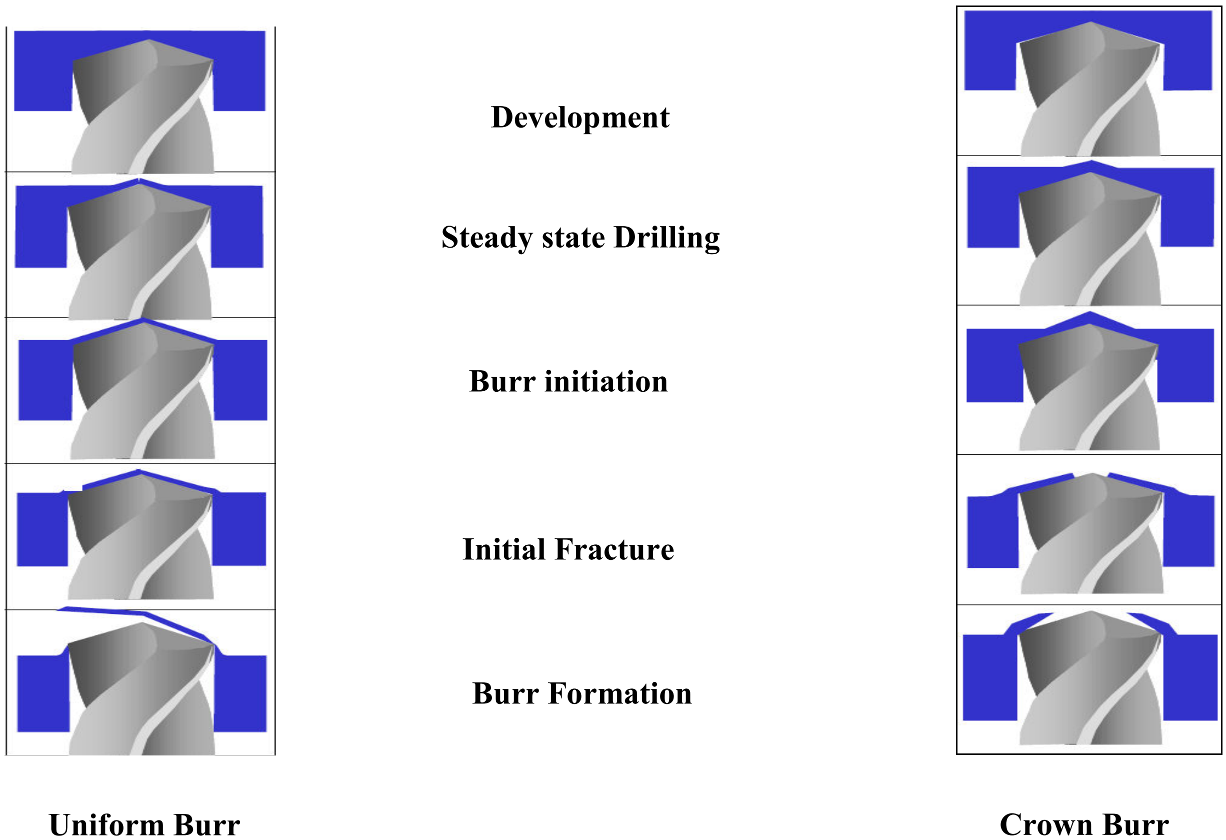


Figure 5. Stages in Burr Formation [19]

2.2.3 Burr Measurement

One of the main challenges in burr research is burr measurement owing to their complex and irregular shape and size. It is usually very difficult to measure burr accurately. Therefore, burr values are collected from the edge surface of a work piece for burr height and thickness by dividing the surface into several parts. “In each of these parts, the distance of the highest peak to the deepest valley is measured”. Then, the average of these values is taken. This gives a good picture of the achieved edge quality in the direction of the burr height and burr thickness [27].

There are several methods available to measure the geometry of the burr specifically the burr height and thickness. These methods can be divided into contact and non contact method. Generally, in a contact method a stylus and height gage is used to measure the burr geometry. Whereas, the non- contact method is subdivided into optical microscope, optimal CMM, laser and white light method and the image processing technique [28]. In the optical microscope method the focal point distance between the plane of the work piece exit surface and the top surface of the burr represents the burr height. The cross-wire will be set to zero at the base of the burr and is moved to the highest peak of the burr and the reading is noted. As many points across the hole periphery can be measured depending upon the accuracy required and average value of the measurements represents the burr height. The measurements done by this method are not very accurate due to the orientation and size of the burr but this limitation is easily overcome by other measurement techniques that use light source as a primary medium for burr measurement [17].

In laser measurement the laser beam spot size and the emit reflection of the edge of the burr and requires proper laser sensor to determine the size and shape of burr. Generally the laser beam spot size is 30 μm. The emitted light from the laser is recorded on Charged Couple device (CCD) through lens. As the height of the burr changes, the corresponding reflection angle also changes and therefore the peak point of light intensity of beam on CCD also changes. The CCD then calculates the change and corresponding burr height is obtained [40].

A new method that was recently used in measurement of height and thickness of the burr is the image processing technique. In this technique a charged couple device is mounted above the work piece. Based on the resolution of the lens the visibility of the image can be varied. A snapshot of the work piece was taken and the image is used to measure the profile of the burr along the circumference of the hole. The height was measured along different positions along the circumference of the hole and average of these values was taken that represents burr height. The measurement accuracy of the proposed system was 50µm. it was noted that a higher resolution camera would assist in increasing the accuracy the technique [41].

2.3 Literature Review

A relatively large amount of research has been conducted to understand the phenomenon of burr formation in drilling operations. The burr formation model can be developed using experimental, analytical formulation and simulation. A lot of experimental studies have been carried out to understand the effect of tool geometry, material, speed, feed, and tool orientation on burr formation [17]. Further work up till now has been done on the classification and documentation of the drilling burr formation process by Gillespie Takazawa, Stein and others, but is primarily limited to experimental studies [18].

An analytical model was proposed by Sofronas [6] that minimizes burr height and thickness based on drill geometry and drilling conditions. This model exhibited instability in identifying several key parameters and has too many assumptions. Nevertheless, it was the first attempt in the direction of the development of an analytical model for drilling burr formation and has verified the complexity of the problem. Lee modified the model developed by Sofronas's to "solve for the burr initiation force aimed at minimizing burr size based on various feed control schemes". However Lee's model, failed to put any new information into the burr formation process [18].

Sofronas [6] summarized several factors that contribute to the formation of burr based on the literature review on drilling and burr formation as shown in the Figure 6. According to his survey drill geometry, material of the work piece, machine rigidity, drilling condition and cutting fluids influence the formation of the burr.

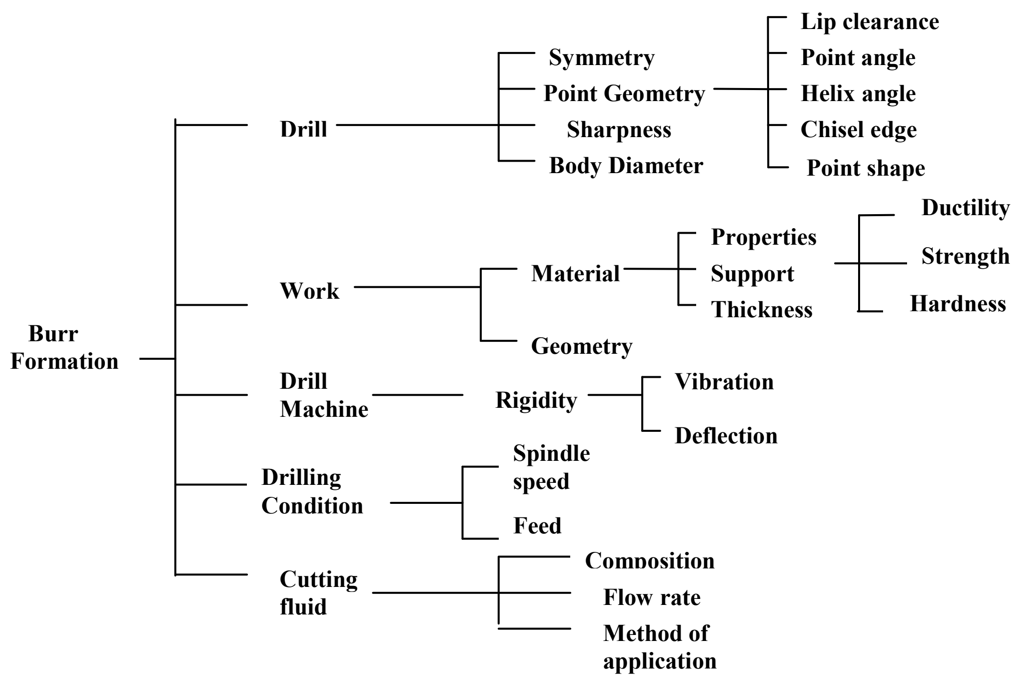


Figure 6. Factors which may contribute to Drilling Burr Formation [6]

Hasegawa et.al [20] conducted an experiment on aluminum and investigated the effect of cutting speed, feed and drill geometry on burr formation. According to their study smaller burrs were formed at higher speed. But there was no effect of speed on burr thickness till 50m/min. Additionally, smaller burrs were formed at lower feeds and size of the burr increased with the increase in feed. Further, they also analyzed the effect of drill shapes like lip clearance angle, point angle, and helix angle on burr. It was suggested that lip clearance angle of more than 10^o does not affect the burr thickness. Whereas, angles smaller than 10^o resulted in increase of burr thickness. Furthermore, higher values of helix angle in the range of 40^o resulted in low burr thickness. But the thickness of the burr increased with the point angle in the range of 100^o and then decreased with the point angle ranging from 180^{o} to 200^{o}. In general, optimal point angle for aluminum should be between 118 and 140$^{o.}$ But in this study 180^{o} was optimal.

Pande and Relekar [21] studied the influence of drill diameter, feed, length to diameter ratio, and material hardness on burr height and thickness. It was determined that a drill bit diameter in the range of 8- 10mm resulted in the low values of burr height. Also at lower feeds smaller chips were formed but size increased with the higher feed. Additionally, L/D ratio of 0.45 to 0.75 resulted in smaller burrs. The hardness of the material in the range of 130-140 BHN resulted in minimum values of exit burrs. Stein [22] studied the formation of burr in precision drilling of stainless steel. According to his study, feed rate, speed, and tool wear influence the formation of burr. The summary of the survey conducted by him of various literatures available in burr formation is as shown in the Figure 7.

1. Material: 1018 steel, 303Se stainless steel, 6061-T6 AL, 17-4PH Stainless steel, other aluminum alloys
2. Feed: ranged between 0.005 ipr –0.0015 ipr
3. Drill diameter: ranged between 0.125” -0.25”
4. Burr height: ranged between 0.003” -0.010”
5. Burr thickness: ranged between 0.001”- 0.002”
6. Drill geometry: point angle, helix angle, radial lip drills
7. Low feed rates 0.0005 ipr reduce burr size
8. High cutting speed reduces or do not influence burr size
9. Reduction in tool wear reduces burr size
10. Reaming after drilling is generally not effective in reducing burr size
11. Sulfo-Chlorinated mineral oil cutting fluid reduces burr size

Figure 7. Burr formation summary from the experimental work [22]

Lim et.al [23] analyzed the formation of burr with a new concept drill. The new concept drill vary from conventional drill bit in that chisel edge is almost reduced or removed by thinning and the point angle is increased from 123^o to $139^{o.}$ Also the web is increased from 2.33 to 3.0. These characteristics of the drill bit helped to reduce burr thickness due to the improved hole accuracy resulting from improved stiffness and decreased cutting resistance.

Kim et.al [24] proposed the use of adhesive for the prevention of exit burrs in micro drilling of metal. In his research, a copy paper smeared with cyanoacrylate was coated uniformly at the exit surface of the workpiece. When a copy paper smeared with cyanoacrylate adhesive was used as a backup the stress around the hole was marginally over yield strength but there was 40% stress acting on the backup layer which sustained the deformation of aluminum and prevented the exit burr. The cyanoacrylate was found valuable in preventing exit burr in low hardness metals, such as aluminum and copper. However, for harder material, such as 304-stainless steel the cyanoacrylate adhesive could not prevent the formation of exit burr.

Sofranos [6] developed a theoretical model that was used to analyze exit burr. The developed model used drill geometries and cutting conditions like drill feed, point Angle, helix angle, lip clearance angle to reduce the burr height and thickness. According to his study he proposed that an increase in the helix angle from 25^o to 36^o yielded in 88% reduction of burr height and 47% reduction of burr thickness. In addition, when feed was reduced from 0.008 to 0.002 in/rev, there was a reduction in burr height and thickness by 83% and 61% respectively. Furthermore, there was a reduction of 26% and 11% in burr height and thickness when point angles were decreased from 112^o to 98^o. The lip clearance angle also showed minimum values of burr height and thickness when the angle was increased from 7^o to12^o.

Lee and kiha [25] proposed various solutions for burr minimization in metals. Based on their experimental study an internet based milling burr expert system was developed. This system predicted burr by considering all influential parameters that affect burr formation in milling. Further a drilling based burr expert system was also proposed that consists of database of drill geometry, work piece, and cutting parameters. The burr type was predicted using Bayesian statistics. Experimental results of milling AlSi7Mg showed that tool geometry like rake and lead angle has a significant effect on burr formation and optimal speed and feed were 1600 rpm and 0.08mm/rev respectively.

Min [14] developed a drilling burr expert system "is a networked consulting service for the design of drilling process with respect to burr minimization through the internet". It consisted of drilling burr control chart and the drilling burr database system. The drilling burr control chart helped in predicting burr and provided a framework for selecting the cutting parameters like speed and feed. The drilling experiment was performed on AISI 4118 stainless steel with split point twist drills. The information regarding drill geometry, work piece, cutting parameters, and burr information was entered into the drilling burr database system. The drilling experiment reveled that speed had no effect on burr formation when feed was relatively under 0.04mm/rev. But speed had a considerable effect on burr formation with higher feed. Further Bayesian statistics was used to predict burr size due to statistical nature of experimental data. The proposed Drilling Burr Expert System provides systematic information on burr minimization with respect to drilling process.

Park [26] developed a two dimensional finite element model in drilling of stainless steel 304L to determine the burr formation mechanism in orthogonal cutting. This burr formation mechanism was divided into four stages initiation, development, initial fracture and final development of burr. Dornfeld, Guo [18] proposed a three dimensional finite element model that considers the “dynamic effects of mass and inertia, strain hardening, strain rate, automatic mesh contact with friction capability, material ductile failure and temperature mechanical coupling”. The burr formation process was also classified into four stages initiation, development, pivoting point, and final burr formation.

From the literature review it is clear that burrs are inevitable in the machining process and primarily depend upon drill geometry, work piece material, speed and feed. “Although some analytical models have been developed till now there is no generally accepted model for drilling” [25]. The studies on burr have determined some important geometric parameters that affect burr size and have suggested the optimal values of these geometric parameters that result in minimum burr. But these values are not consistent and have differed from one research to another. However, even if accurate values of these geometric parameters are proposed then also it would be impossible to manufacture such a drill bit to that degree of accuracy. In case, even if manufactured it would be highly expensive and whatever cost was intended to save on deburring operations will be now be spent on manufacturing the drill bit to highest accuracy in terms of geometry. The best method would be to develop a model, which identifies whether a drill bit that has certain geometric parameters would yield minimum burr or not. Then the model would assist in choosing the right drill bit that reduces burr to a certain extent and minimizes deburring cost. This requires a model that could predict burr size to a highest degree of accuracy. In this thesis an Artificial Neural Network (ANN) model will be developed that predicts burr size and provides an opportunity to perform “what if “analysis by changing the values of existing parameters to determine their effect on burr size and therefore saves significant amount of time and cost as experiment can be avoided. So far ANN has been used in predicting burr in milling and blanking operation. This thesis attempts to incorporate ANN in prediction of burr in drilling operation.

The next section provides an introduction to neural networks, which is used as tool to predict burr size in this research. The introduction presents a brief overview to the basics of neural network and its applications. The basic architecture of feed forward neural network model is also presented. Literature review of past research associated with use of neural networks in drilling is also discussed.

Chapter 3

NEURAL NETWORKS

3.1 Introduction to Neural Networks

An Artificial Neural Network (ANN) is “an information processing paradigm, such as the brain, process information. The key element of this paradigm is the structure of the information processing system. It is composed of a large number of highly interconnected processing elements called neurons working in unison to solve specific problems” [29]. ANNs can be used to identify patterns and trends from complex or vague data that are very complicated to recognize by human being or other computer techniques. The ANN has to be trained using a learning process. The trained network can then be used to gain insight into new situation and to answer “what if” questions. Because of their immense ability to identify patterns or trends in data they have been greatly used in many applications including forecasting, industrial process control, customer research, data validation, and risk management etc[29].

There are various types of neural network available like feed forward neural network with single and multi perceptron, Adaline, radial basis function and Kohenen self organizing map. Among them the feed forward networks are the most simple and are used in prediction by training input data to obtain the desired output. The basic architecture of feed forward networks with multi layer perceptron is as shown in Figure 8. The first layer is called the input layer, and the last layer is the output layer. The intermediate layer is called hidden layer and it can be more than one. The information is fed forward from the input layer to output layer through the hidden layers in a simple feed forward neural network model. Whereas, in the backpropagation neural networks the output value is compared to the desired value and the difference is back propagated through the network. The backpropagation algorithm adjusts the weights of the neural network such that the output of the network matches the desired output. This cycle is repeated until the desired value is obtained with minimum root mean square error and is basically called training the neural network [30]. "This iterative process is called backpropogation as the error is propagated backwards through the layers of the neural network" [43].

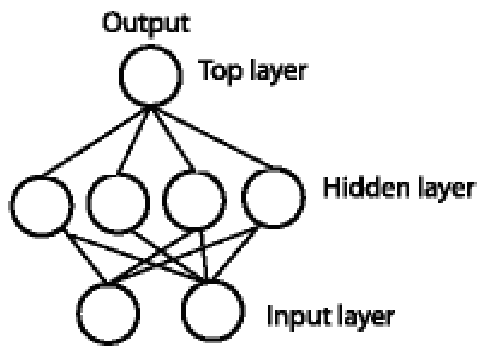


Figure 8: Feed Forward Neural Network [30]

3.1.1 Literature Review

A lot of research has been conducted using neural networks in the field of machining. But very few studies have used neural networks to predict the burr height. The review of past studies carried out in drilling using neural networks is described below:

Sokolowski [31] proposed a neural network model to predict the burr height by considering the effect of cutting velocity, feed, depth of cut, work piece material and exit angle on burr formation. A feed forward backpropagation neural network was used with a structure of 5-10-3. The output was classified into three types of burr namely small medium and large based on the height of the burr. The developed model successfully predicted the burr height in face milling. It was also evident that neural network could act as a universal tool to model burr formation and also would be very important from practical application standpoint because of their relative use of small data sets. Hambli [32] developed a neural network model to predict burr height in blanking process. The input to the feed forward neural network model was tool-die clearance and punch–die clearance and wear state of the tool and the corresponding output was burr height. The model showed good agreement with the experimental results with an error of less than 0.1% for any point. Sudhakaran [13] proposed a neural network model to identify the effect of drill geometry specifically lip height and point angle on burr height in drilling of aluminum 2024-T3. Feed, lip height and point angle were inputs to the model with output being burr height. The best architecture was 4-6-4 and showed good consensus with the experimental result. It was noted that burr height increases with the increase in lip height irrespective of any point angle.

Karri [33] predicted thrust and torque in drilling operations using neural networks. Eight inputs were considered and the result showed an average percentage deviation of less than 2% at the testing stage. Both thrust and torque were predicted to targeted accuracy with the help of neural networks, which was very difficult to achieve using conventional mechanics of cutting approach for prediction of thrust and torque. Sanjay and Jyothi [34] proposed a backpropagation neural network model to predict surface roughness in drilling. Drill diameter, feed, speed and machine time were used as input to ANN model. Further neural network model was more consistent for different combinations of speed and feed compared to mathematical model developed to predict surface roughness. Singh et.al [35] developed a neural network model to predict flank wear. Various process parameters like speed, feed, thrust force, torque force, and drill diameter were considered as inputs and corresponding maximum flank wear was measured. The network parameters such as momentum coefficient, number of hidden layers and learning coefficient were determined on trail and error. The best network architecture was considered to be 5-4-1 depending upon the mean square error. Out of 49 data values 34 were used for training the network and 15 were used for testing. The output showed good agreement with the experimental results. Therefore neural network was considered as an important tool for prediction of drill wear.

Dini [36] developed a neural networks model to predict delamination in drilling of glass fiber reinforced plastic (GFRP). The delamination was measured at both entry and exit side of the tool. Peel–up and push-out damage were measured at entry and exit side respectively as a function of feed rate, tool size and cutting forces. Two types of neural network model were developed to analyze and predict the delamination. Using the first network delamination was categorized into 4 groups namely no damage, low, medium and high damage, while the second network was used to predict the damage. The developed model showed very good agreement with the experimental results. Mahfouz [37] proposed a neural network model to monitor tool wear. Vibrations and acoustic emissions were measured for 0.5 diameter HSS twist drills. Based on the experimental results wear was classified into four types of categories. The wears were classified as chisel wear, rake crater, edge fracture, and corner wear. This information was fed into the neural network. The network correctly identified the chisel and corner wear up to 80% accuracy and edge and crater wear to around 70% accuracy.

Chao and Hwang [38], proposed a neural network model for the prediction of cutting tool life. Experiments were conducted to collect tool life data on lathe for turning operation. Each experiment is performed until a flank wear reaches a maximum of 0.7mm.the tool life is obtained by summing up the total cutting time. The results of this experiment were used in the development of a neural network model. The results were then compared against backward stepwise regression model and the artificial neural network model made the most accurate prediction. Karri et.al [39], proposed a three layer neural network model to determine the internal surface roughness in drilling. Three types of neural network model were developed and the one which had lowest RMS error was selected for prediction. The input to the model was frequency, speed, thrust, feed, tool type, diameter and torque. The experiments were tested for 15 different conditions and out of which 12 exhibited an error of less than ± 0.7μm showing considerable prediction capability.

Chapter 4

METHODOLOGY

From the literature it is evident that there is no generally accepted model for burr prediction. The objective of this research is therefore to develop a model to predict burr height and thickness depending upon the geometric parameters of the drill bit using neural networks. A reliable neural network model requires values of burr height and burr thickness. Therefore drilling experiment was conducted on Aluminum 6061-T6 and values of burr height and burr thickness were obtained. These experimental values were then used to develop the neural network model. The section 4.1 describes the experimental parameters used to conduct the experiment. The section 4.2 and 4.3 explains the procedure used to perform the drilling experiment and the type of burrs observed during the drilling of AL6061-T6.

4.1 Experimental Parameters

The input parameters of the drill bit affecting burr height and thickness is selected based on the review of previous studies conducted on burr minimization From the literature it can be concluded that point angle, helix angle, lip relief angle and chisel edge angle, are important parameters that affect burr height and thickness. For this project the effect of chisel edge, point angle and lip relief angle will be used as input parameters as they have a considerable effect on burr formation. The input parameters of the 36 drill bits are shown in Appendix A. The values of all geometric parameters associated with the 36 drill bits are listed in Appendix B. The cutting parameters like speed and feed are determined based on the material handbook and are as shown in Table 2 along with other parameters used for the drilling experiment.

Table 2

Experimental Parameters

Material:	AL 6061- T6
Material Thickness	0.5 inch
Speed	5000 rpm
Feed	37.5 ipm
Drill Bit	HSS with black oxide coating
Drill Diameter	0.25 inch
Inputs	Chisel edge angle, Lip relief angle, Point angle
Outputs	Burr height, Burr Thickness

4.2 Experimental Procedure

The drilling experiment was carried out on the CNC Fadal machine and Aluminum 6061-T6 material was used. The CNC machine is programmed to perform drilling experiment at the required speed and feed. The 36 HSS twist drill bits with different input parameters is used to perform the drilling experiment and the responses of these variables on burr height and thickness are measured. Five holes are drilled using each drill bit and corresponding burr height and thickness was measured. For the measurement of burr height, optical microscope combined with x-cap image processing software was used; where as burr thickness was measured using a universal profile projector. In order to measure the burr height and thickness the circumference of the hole was divided into 5 parts. From each part the distance from the highest peak to lowest valley was measured. Then the average of these 5 values for each hole was taken. Similarly the same process was followed for remaining four holes. Then the average of these 5 averages was taken to give accurate representation of burr height and thickness. The experimental setup for the measurement of burr height using image processing technique is as shown in Figure 9

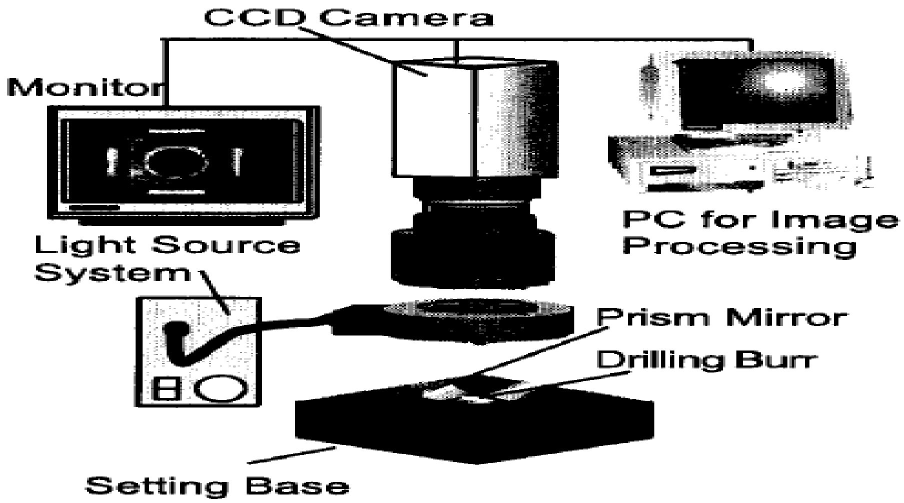


Figure 9. Image Processing Measurement System [41]

The work piece was placed on the setting base. The burr on the exit side of the work piece was viewed from the CCD camera. The 0.75x resolution lens is used depending upon hole diameter and visibility of the image. A light system source was used to get uniform illumination on the focused profile of the burr. Once the view of the burr height is clearly visible the snapshot was taken through the camera and is saved in the computer. The recorded image was accessed through the X-CAP image processing software and measurements of the burr height are recorded along 5 different locations around the circumference of the hole. The measurements were made in such a way that both maximum and minimum height of the burr was recorded along with the other values. Then the average of this values were taken, which represents the burr height.

To measure the burr thickness, burr was mounted on setting base in such a way that the edge of the burr is clearly visible on the screen of the profilometer. A uniform light source was used to get good reflection of the burr edge on the screen of the profilometer. The thickness of the burr was measured along four different locations by keeping the cross-wire at one edge of the work piece and setting the x-axis at zero. The cross wire was moved to the other end of the work piece and the reading was noted. Similar, to the measurement of burr height both maximum and minimum values were also noted and the average of these values was taken that represents burr thickness.

The burr height and thickness values obtained from the drilling experiment for 36 drill bits are as shown in the Appendix C and Appendix D respectively. The distribution of average burr height and burr thickness for 36 drill bits is as shown in Figures 10 and 11.

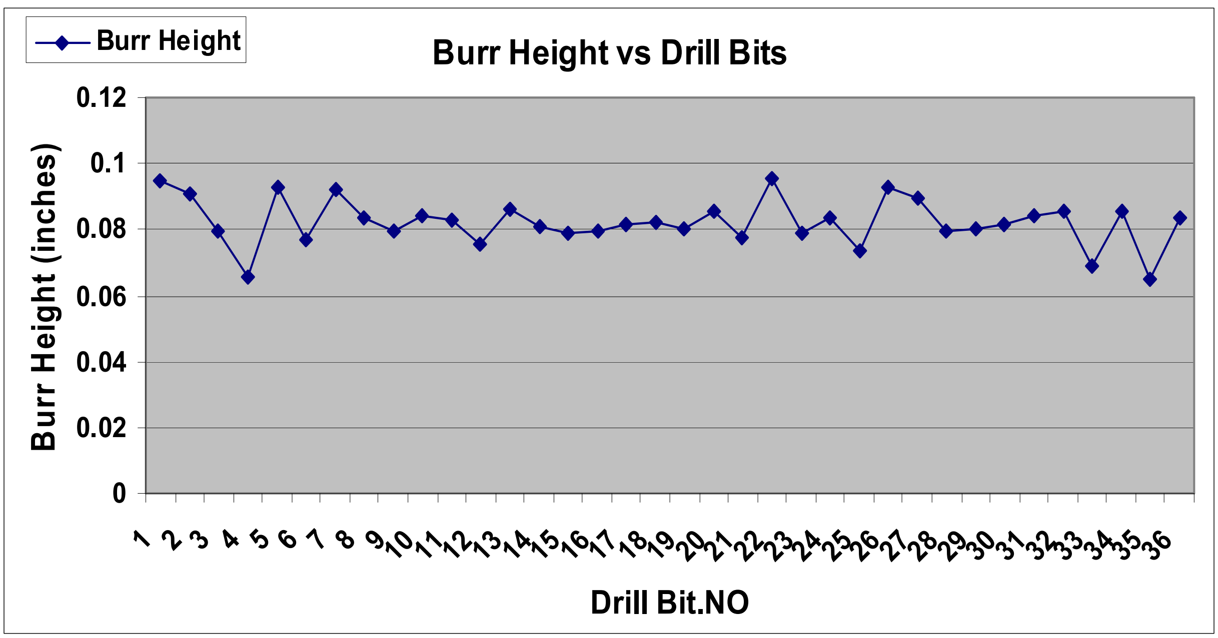


Figure 10. Distribution of Burr Height for 36 Drill Bits

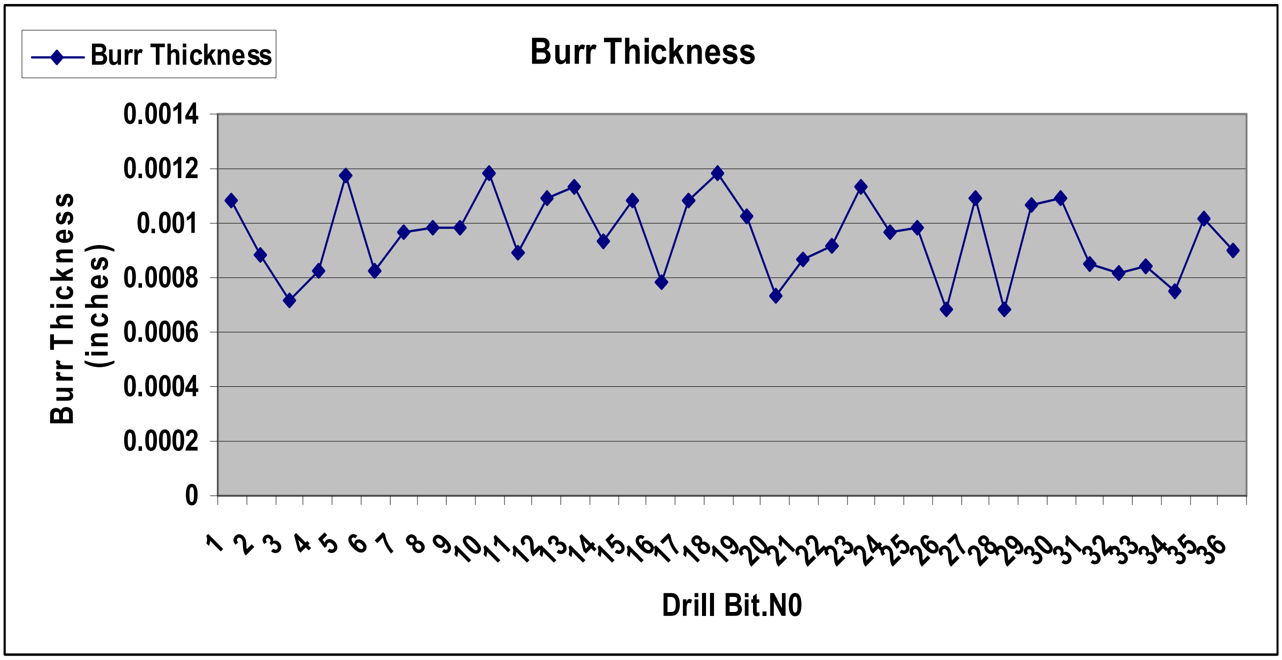
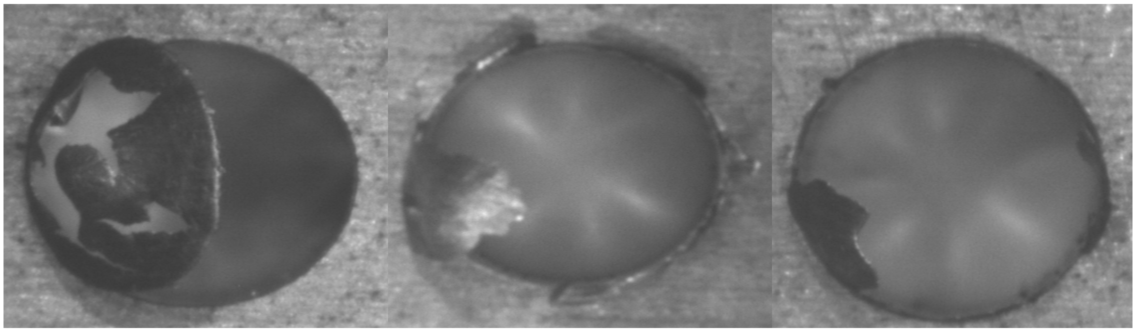


Figure11. Distribution of Burr Thickness for 36 Drill Bits

The burrs from the drilling experiment varied in shape from one drill bit to another. But generally had a shape similar to the burrs observed in previous studies on burr formation. The next section discusses the type of burrs observed in drilling of AL 6061-T6.

4.3 Burrs Observed during Drilling Experiment

The previous experimental studies conducted on burr formation suggest that uniform burrs are generally formed under low speed and feed and crown burrs under high speed and feed. In this research, the feed and speed were kept constant and the values recommended from the handbook for drilling of aluminum 6061-T6 is used. These values for speed and feed are comparatively higher than the values suggested from experimental studies carried out on burr formation for obtaining minimum burr. But the burrs produced from the drilling experiment shows that uniform burrs are also formed under high speed and feed. The burrs observed in this study generally fall in all the three categories as shown in the Figure 12.



Uniform Burr Crown Burr Transient Burr

Figure 12. Burrs Observed in Drilling of AL-6061-T6

The presence of uniform burrs under high speed and feed confirmed that even at high speed and feed the size and shape of the burr can be controlled by altering the geometric parameters of the drill bit. The geometric parameters can be selected by developing a model that would assist in determining the optimal parameters that result in reduced burr height and thickness.

The next chapter discusses the development of the neural network model that would assist in predicting burr height and thickness. Based on the model results, optimum input parameters that yield minimum burr height and thickness are suggested.

Chapter 5

MODELING AND ANALYSIS

The chapter discusses the development of neural network model using the values of burr height and thickness obtained from the drilling of AL6061-T6 followed by the model results and validation. The statistical analysis of the input parameters on burr height and thickness is also presented. The chapter concludes by specifying the range of input parameters for burr height and thickness that yield minimum burr height.

5.1 Model Development

To develop a prediction model Neuralware ProII plus software is used. The 36 data values obtained from the experiment are divided into training and test sets. Out of the 36 data set 23 data are used for training and 13 for testing. The training and test data for burr height are shown in Tables 3 and 4. While training and test data for burr thickness is shown in Tables 5 and 6. The data is divided in such a way that the maximum and minimum values of the test set is within the maximum and minimum value of training set. This is done to ensure that model predicts well within the maximum and minimum values of training set. Two separate models are developed for the prediction of burr height and thickness. The input parameters are same for both the models with output being burr height and burr thickness respectively for two different models. The model is developed using lip relief angle, point angle, and chisel edge angle as the main input parameters. The development of both the burr height and burr thickness model is discussed in the following sections.

Table 3

Training Set Data Values for Burr Height

No.	Lip Relief Angle	Point Angle	Chisel Edge Angle	Burr Height (inches)
1	15	138	116	0.092328
2	16	128	112	0.080928
3	15	129	122	0.0925
4	15	129	109	0.085689
5	14	132	120	0.094966
6	15	130	116	0.08321
7	12	128	109	0.084388
8	15	129	120	0.08554
9	16	129	118	0.068634
10	15	128	120	0.082758
11	15	128	113	0.075384
12	14	127	116	0.090812
13	15	129	113	0.079173
14	15	130	123	0.064667
15	14	128	114	0.095386
16	15	131	118	0.084347
17	14	130	117	0.085521
18	14	128	114	0.07357
19	16	130	125	0.092683
20	15	128	117	0.082424
21	16	131	118	0.079878
22	14	130	120	0.08055
23	15	128	104	0.081384
MAX	**16**	**138**	**125**	**0.095386**
MIN	**12**	**127**	**104**	**0.064667**

Table 4

Test Set Data Values or Burr Height

No.	Lip Relief Angle	Point Angle	Chisel Edge Angle	Burr Height (inches)
1	12	128	115	0.083467
2	14	128	113	0.07872
3	15	127	114	0.081534
4	16	128	114	0.076924
5	16	129	115	0.079727
6	15	128	109	0.086298
7	14	128	114	0.08357
8	15	130	121	0.077331
9	15	128	117	0.08943
10	14	128	115	0.0655
11	15	128	118	0.079748
12	14	130	115	0.079775
13	15	131	119	0.0801264
MAX	**16**	**131**	**121**	**0.08943**
MIN	**12**	**127**	**109**	**0.0655**

5.1.1 Burr Height Model

A backpropagation neural network model with three inputs and one output (burr height) is selected. The 23 inputs as shown in Table 3 is fed into the model and trained for different weights until a suitable mapping between the experimental and neural network data is obtained. The weights are changed by trial and error depending upon the deviation of the model output value from the desired experimental value. The process of comparing neural network output with the actual experimental data and adjusting weights is called backpropagation iteration. The backpropagation algorithm will adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. In this thesis after conducting several trails a good mapping is obtained for the experimental and neural network values for the architecture as shown in Appendix E.

Table 5

Training Set Data Values for Burr Thickness

No.	Lip Relief Angle	Point Angle	Chisel Edge Angle	Burr Thickness (inches)
1	15	138	116	0.0009667
2	15	128	104	0.0010867
3	15	129	122	0.0006800
4	15	131	118	0.0008467
5	15	129	109	0.0007467
6	15	128	117	0.0010933
7	15	130	116	0.0009667
8	15	129	120	0.0007333
9	15	129	113	0.0010800
10	15	128	120	0.0008933
11	15	128	113	0.0010900
12	12	128	109	0.0011870
13	14	127	116	0.0008820
14	14	132	120	0.0010800
15	15	130	123	0.0010170
16	14	128	114	0.0009200
17	14	130	120	0.0010667
18	14	130	117	0.0008133
19	14	128	114	0.0009867
20	16	130	125	0.0011733
21	16	128	112	0.0009340
22	16	131	118	0.0009867
23	16	129	118	0.0008400
MAX	**16**	**138**	**125**	**0.001187**
MIN	**12**	**127**	**104**	**0.00068**

Table 6

Test Set Data Values for Burr Thickness

No.	Lip Relief Angle	Point Angle	Chisel Edge Angle	Burr Thickness(inches)
1	14	128	114	0.0008970
2	14	130	115	0.0007200
3	16	128	114	0.0008230
4	12	128	115	0.0009800
5	15	128	109	0.0011340
6	15	131	119	0.0010270
7	15	130	121	0.0008667
8	15	128	117	0.0011800
9	15	127	114	0.0010933
10	14	128	115	0.0008254
11	15	128	118	0.0006800
12	14	128	113	0.0011330
13	16	129	115	0.0007800
MAX	**16**	**131**	**121**	**0.00118**
MIN	**12**	**127**	**109**	**0.00068**

The best network architecture was found to be 3-1-1 which represents 3 inputs, 1 hidden layer with six neurons and 1 output. The transfer function is TanH, and learning algorithm Delta – Rule was used with an initial learning rate = 0.85 and the momentum (smoothing factor) = 0.7. The learning rule helps in modifying the weights on the inputs according to the algorithm and the transfer function helps in transferring the output of the network. The architecture shown in Appendix-E was trained for 500,000 iterations. The Figure 13 shows the comparison of the experimental values with the neural network predicted values for the 23 training set.

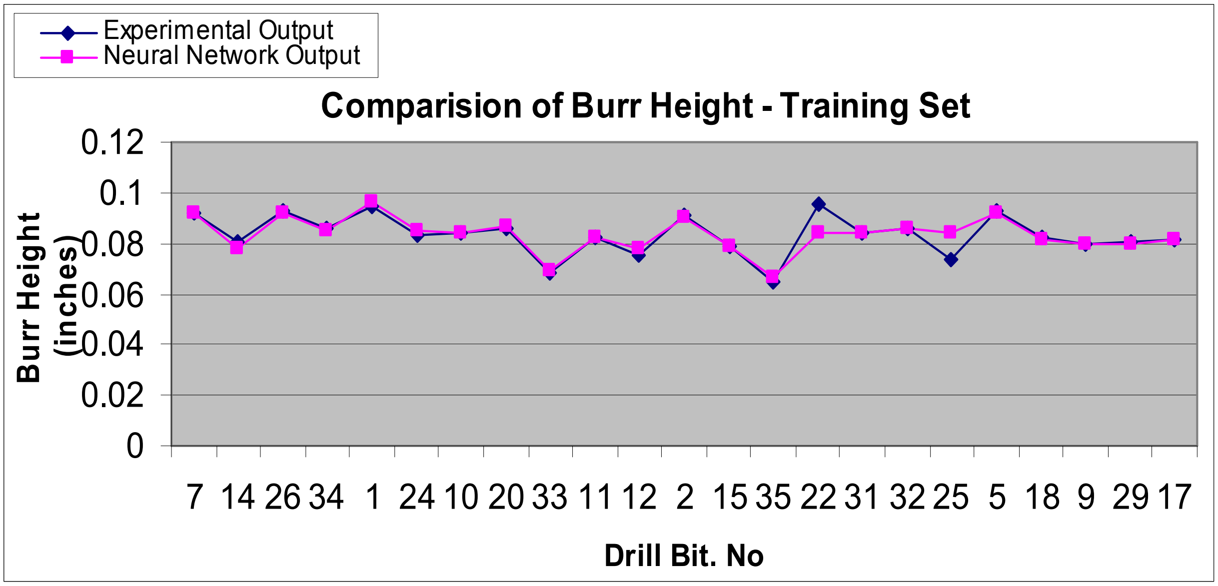


Figure 13. Comparison of Burr Height for Training Data Set

The network architecture used for the training the model was used for testing the model. The input parameters are same as used in the training the model. But 13 new values from the drilling experiment are presented to test the model. Figure 14 shows the plot between the experimental value and the neural network predicted value for the test data set.

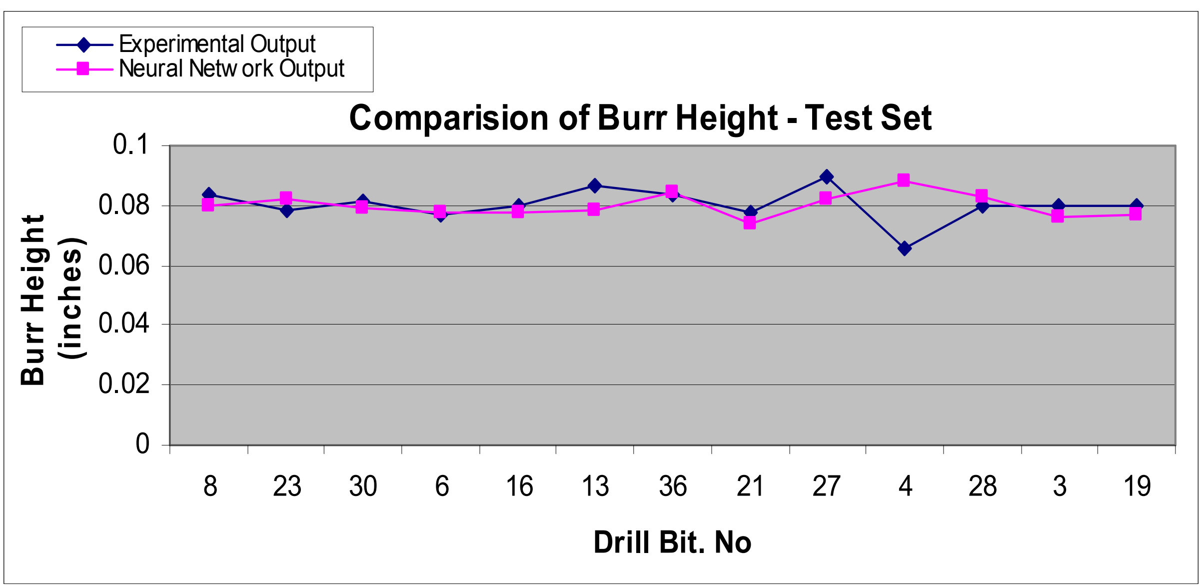


Figure 14. Comparison of Burr Height for Test Data Set

5.1.2 Burr Thickness Model

The procedure used to develop burr height model was used to develop the burr thickness model and the best architecture was found to be 3-1-1 with three inputs, 1hidden layer with six neurons, and 1 output as shown in Appendix F. The transfer function was TanH, and learning algorithm Ext DBD was used with an initial learning rate = 0.9 and the momentum (smoothing factor) = 0.8. The model was trained for 500,000 iterations.

Figures 15 and 16 show a comparison of experimental value and the neural network predicted value for both the training and test data set.

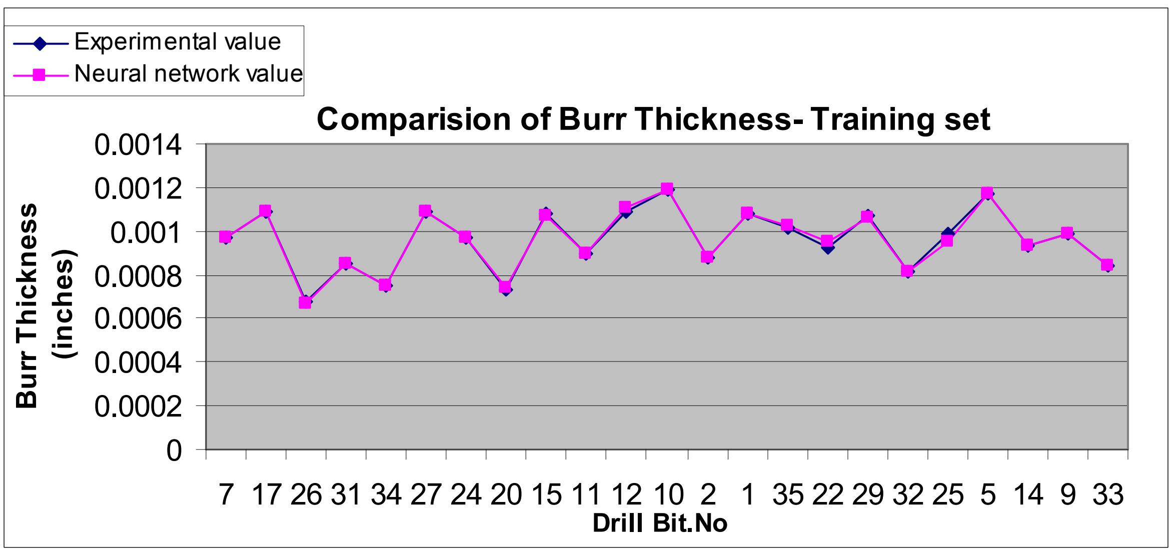


Figure 15. Comparison of Burr Thickness for Training Data Set

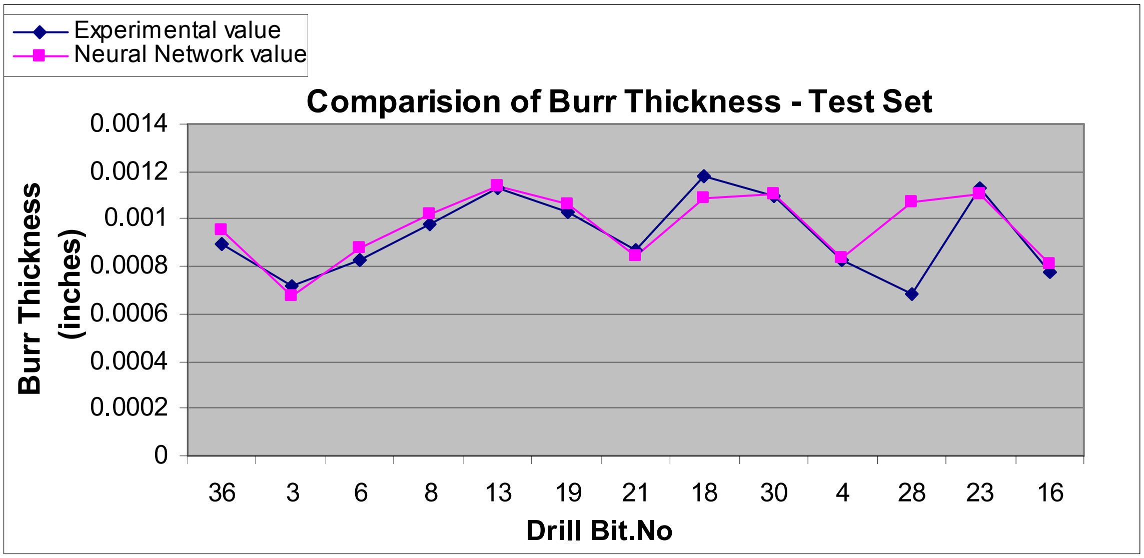


Figure 16. Comparison of Burr Thickness for Test Data Set

The experimental result and the neural network result obtained from the model for burr height along with their input parameters is listed in the Appendix G and Appendix H for both the training and test data set. Whereas, the experimental and neural network result for training and test set of burr thickness is listed in Appendix I and J.

The root mean square errors (RMSE) for burr height and burr thickness model are 0.007349 and 0.0001149, respectively. Though, the value of root mean square error indicates that the developed model represents the experimental data to a good accuracy. The performance of the model can be further enhanced by reducing the RMS error significantly by using all 36 data set for training the model. Because the model developed by current approach of splitting the data into training and testing data set may yield different results when used in real world [42]. Also as the data is split into two sub samples randomness may be introduced into the system resulting in higher error than when all available data set is used. An approach that considers all the available data values in construction of the model has been proved to give reduced error in most of the cases compared to the traditional model built using data splitting method. In this research an error estimation method called bootstrap that uses all the available data is used in an attempt to reduce the error. The bootstrap method has been proved to provide comparatively low error than the traditional model [42]. The following section discusses the bootstrap method, procedure used to develop the model, and results obtained this method.

5.2 Bootstrap

Bootstrap technique was introduced by Efron as a method for estimation of error. This method utilizes the entire sample of n observations. It is a resampling technique in which bootstrap data sets are generated by resampling the original data set consisting of n observations with replacement [42].

Efron "developed the bootstrap method of estimation and showed that it gives the nonparametric maximum likelihood estimate of the excess error of a prediction rule [Efron]; i.e. the bootstrap methods corrects for the bias of the apparent error. Bootstrap data sets are created by resampling $\hat{F}$ with replacement and are generated as follows. Let $\hat{F}$ be the empirical distribution function for T_n with mass 1/n on t_1, t_2, ……...,t_n; and let T_n^* be a random sample of size n taken *iid* with replacement from $\hat{F}$, where ti* is a single random observation, $t_i=(x_i,y_i)$. Thus if an observation is selected twice, probability mass 2/n is assigned to that observation. True error is estimated through independent bootstrap training sets T^{*1}, T^{*2}, ..., T^{*B}; where B is the total number of bootstrap samples, each generated as described above. For each T^{*b}, a prediction model is constructed, $\hat{f}\left[T^{*b},x_i\right]$. The first term of the bootstrap estimate of Err is the resubstitution error of the final model. The second term is the difference, summed over all bootstrap validation models, of the average error over the original sample and the average error over the bootstrap sample. In other words, this second term subtracts off the mean apparent error from the mean error over the original sample, using the same bootstrap model. This is repeated B times" [42].

$$\hat{\mathrm{E}}\mathrm{rr}_{\mathrm{BOOT}} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left| \mathrm{y}_{\mathrm{i}} - \hat{\mathrm{f}}[\mathrm{T}_{n}, \mathrm{x}_{\mathrm{i}}] \right| + \frac{1}{B}\sum_{b=1}^{B}\left(\frac{1}{n}\sum_{i=1}^{n}\left| y_i - \hat{f}[T^{*b}, x_i^*] \right| - \frac{1}{n}\sum_{i=1}^{n}\left| y_i^* - \hat{f}[T^{*b}, x_i^*] \right| \right)$$

In this research based on the 36 sample observations of burr height and thickness obtained from the experiment, 20 bootstrap datasets with each consisting of 36 sample observations are generated for burr height and burr thickness. The 20 bootstrap data sets are trained using the same architecture used for developing burr height and burr thickness model (refer Appendix E and F) and are tested with sample observations of original data set that is not present in the bootstrap data set. For example if first bootstrap data set consisting of 36 sample observations has 2 sample observations exactly similar to the original sample observations. Then these two sample observations are eliminated from the original data set and the first bootstrap data set is tested with the remaining 34 sample observations of the original data set. Once all the 20 bootstrap data sets are tested the RMS error is obtained and averaged to get a single value. The obtained RMS value is compared with the RMS value obtained from model developed using data splitting. As bootstrap data set uses all the data it generally performs well than the traditional method and the new application model is built using all 36 data values.

5.2.1 Bootstrap Results

The RMS value of 20 bootstrap data sets and the original model is as shown in the Table 7. From the Table, it can be observed that the bootstrap method has a lesser RMS value than the model built using data splitting.

Table 7

Generalization Model Error

	RMS Training +Test set (n=36)	RMS Test set (n=13)	Bootstrap
BURR HEIGHT	0.005187	0.007349	0.007117
BURR THICKNESS	0.00006964	0.0001149	0.0001099

As the bootstrap data set has a lesser value of RMS error compared to data split model all the 36 data sets are used for training the model. The RMS value of the model built using all the 36 data values along with RMS value of data split model is shown in Table 8. The model built using all 36 data outperforms the model built with data splitting as there is a significant decrease in the RMS error. Hence the data split model would be ignored and our prediction model will be based on all 36 data samples obtained from the drilling experiment. This model will be referred as application model. The architecture of the model is similar to the burr height and burr thickness architecture shown in Figure 13 and 16.

Table 8

Application Model Error

	RMS Training set (n=23)	RMS Training set (n=36)
BURR HEIGHT	0.0034035	0.0031956
BURR THICKNESS	0.00001125	0.00002939

The plot of the 36 experimental and neural network predicted data is shown in Figure 17 and 18 for both burr height and thickness. The 36 experimental and neural networks predicted data values are listed in Table 9 and 10 respectively for both burr height and thickness.

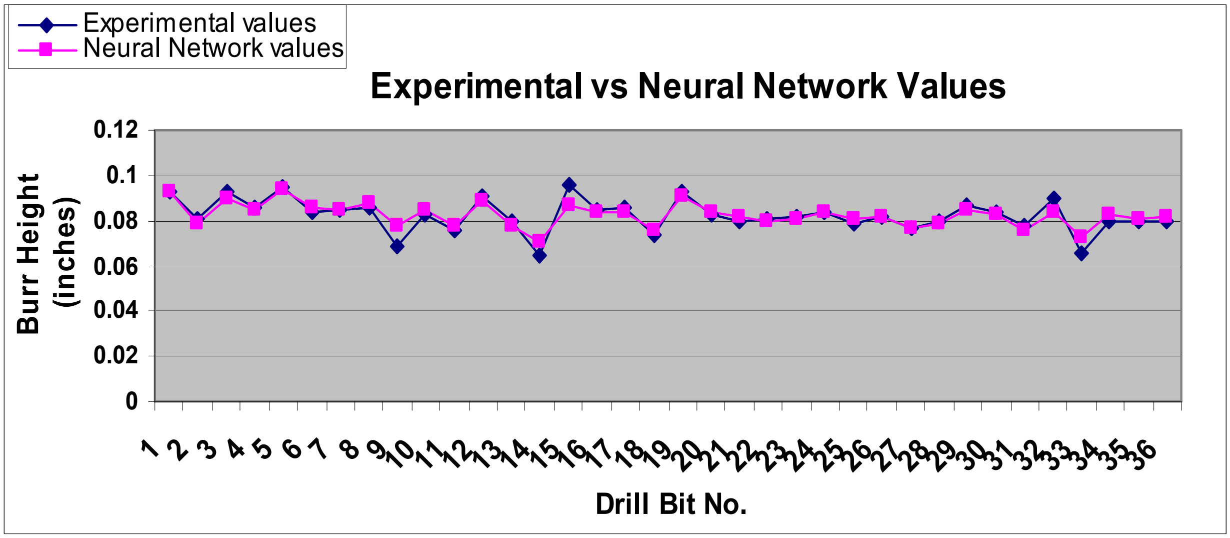


Figure 17. Comparison of Experimental and Neural Network values for Burr Height

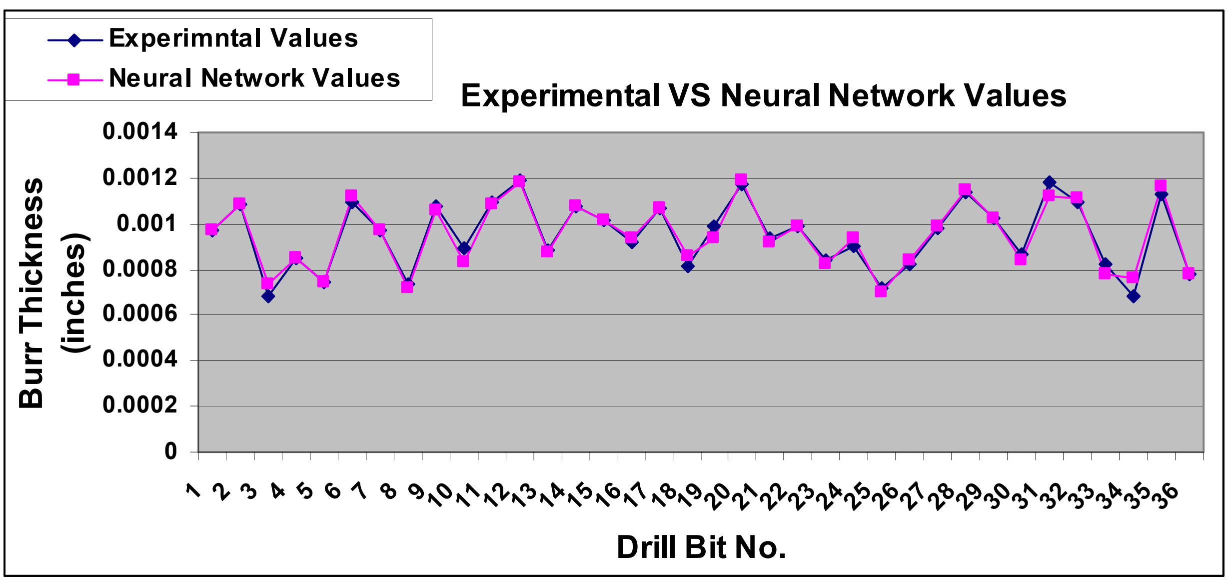


Figure 18. Comparison of Experimental and Neural Network values for Burr Thickness

Table 9

Comparison of Experimental and Neural Network Value
For Burr Height (inches)

Drill Bit No	Experimental Value	Neural Network Value
1	0.092328	0.092674
2	0.080928	0.078269
3	0.0925	0.089833
4	0.085689	0.084414
5	0.094966	0.093716
6	0.08321	0.085946
7	0.084388	0.085092
8	0.08554	0.087417
9	0.068634	0.077683
10	0.082758	0.084234
11	0.075384	0.078143
12	0.090812	0.088778
13	0.079173	0.077585
14	0.064667	0.070145
15	0.095386	0.086512
16	0.084347	0.083517
17	0.085521	0.083353
18	0.07357	0.075512
19	0.092683	0.090748
20	0.082424	0.083552
21	0.079878	0.081286
22	0.08055	0.080057
23	0.081384	0.081089
24	0.083467	0.084199
25	0.07872	0.08103
26	0.081534	0.082161
27	0.076924	0.07647
28	0.079727	0.078685
29	0.086298	0.084769
30	0.08357	0.082512
31	0.077331	0.075878
32	0.08943	0.083552
33	0.0655	0.073077
34	0.079748	0.082401
35	0.079775	0.080841
36	0.080126	0.081464

Table 10

Comparison of Experimental and Neural Network Value
For Burr Thickness (inches)

Drill Bit No	Experimental value	Neural Network value
1	0.000967	0.000967
2	0.001087	0.001088
3	0.00068	0.000738
4	0.000847	0.000848
5	0.000747	0.000747
6	0.001093	0.001124
7	0.000967	0.000974
8	0.000733	0.00072
9	0.00108	0.001059
10	0.000893	0.000828
11	0.00109	0.001085
12	0.001187	0.001183
13	0.000882	0.000877
14	0.00108	0.00108
15	0.001017	0.001017
16	0.00092	0.000935
17	0.001067	0.001064
18	0.000813	0.000855
19	0.000987	0.000935
20	0.001173	0.001192
21	0.000934	0.000923
22	0.000987	0.000989
23	0.00084	0.000822
24	0.000897	0.000935
25	0.00072	0.000696
26	0.000823	0.000844
27	0.00098	0.000989
28	0.001134	0.001142
29	0.001027	0.001024
30	0.000867	0.00084
31	0.00118	0.001124
32	0.001093	0.001109
33	0.000825	0.000782
34	0.00068	0.000763
35	0.001133	0.001162
36	0.00078	0.000782

5.3 Model Validation

The model is validated by determining the hypothesis test. The following section will display the results obtained by using hypothesis testing for both burr height and burr thickness model. The model is validated by taking the difference of experimental values and the neural network predicted values at 95% confidence interval.

5.3.1 Hypothesis test for Burr Height Model - Difference of Means

The procedure used to validate the model is as follows:

- Parameter of interest: Difference between the means of burr height (μ)
- Null hypothesis (H_0) = (μ_1-μ_2) = D_0
- Alternative hypothesis (H_1) = (μ_1-μ_2) $\neq D_0$
- Significance level (α) = 0.05
- Test statistic : Two sample z- test statistic , since n >30

$$Z = \frac{\bar{d} - D_0}{S_d / \sqrt{n}}$$

Where, $\bar{d}$ and S_d represent the mean and standard deviation of the sample of differences.

Here D_0 = 0, since we want to hypothehesize that there is no difference between the population means and also $\alpha/2$ = 0.025 and n = 36, $\bar{d}$ = -0.000214556 and S_d = 0.00323362

Z = - 0.398109085

- Rejection Region: Reject H_0 if interval does not include zero
- From the z – distribution table $Z\alpha/2(0.475)$ = 1.96
- Since $|Z| < Z\alpha/2$, we fail to reject the null hypothesis

Therefore, it can be concluded that mean of the neural network model and the experimental model for the burr height are equal.

5.3.2 Hypothesis test for Burr Thickness Model - Difference of Means

The procedure used to validate the model is as follows:

- Parameter of interest: Difference between the means of experimental burr thickness (μ_1) and neural network predicted burr thickness ($\mu 2$)
- Null hypothesis (H_0) = (μ_1-μ_2) = D_0
- Alternative hypothesis (H_1) = (μ_1-μ_2) $\neq D_0$
- Significance level (α) = 0.05
- Test statistic : Two sample z- test statistic , since n >30

$$Z = \frac{\bar{d} - D_0}{S_d / \sqrt{n}}$$

Where $\bar{d}$ and S_d represent the mean and standard deviation of the sample of differences. Here $D_0 = 0$, since we want to hypothehesize that there is no difference between the population means and also $\alpha/2 = 0.025$ and n = 36, $\bar{d}$ = -0.00000089 and S_d = 0.0000298.

$Z = -0.178976228$

- Rejection Region: Reject H_0 if interval does not include zero
- From the z – distribution table Z $\alpha/2$ (0.475) = 1.96
- Since $|Z| < Z\alpha/2$, we fail to reject the null hypothesis

Therefore, it can be concluded that mean of the neural network model and the experimental model for the burr thickness are equal.

From the results obtained from the RMSE method and hypothesis test it can be concluded that the developed neural network backpropogation model for both burr height and burr thickness predicts the experimental data with good accuracy. The model can identify drill bit that yields minimum burr height and thickness and help in selection of drill bit that reduces deburring cost by substituting a new input variable that is in between the maximum and minimum values of training data set for both burr height and burr thickness. The next section discusses the significance of input parameters selected based on previous study to determine their effect on burr height and thickness

5.4 Statistical Analysis of Input Parameters

In order to validate the affect of input parameters on burr height and thickness the analysis of variance (ANOVA) was conducted. The analysis is performed using the software Design Expert V.6. For the analysis three input factors lip relief angle, point angle, and chisel edge angle are used to study the influence on two response factors burr height and thickness. The lip relief angle is varied at two levels from 12-14 and from 15-16 because of the limited range of the lip relief angle. But the point angle and chisel edge angle is varied at three levels. The three levels at which the point angle is varied are 127-130, 131-134, and 135- 138. While the levels for chisel edge angle are 104-110, 111-118, and 119-125. The analysis is conducted at significance level of 0.05 (α=0.05) or at confidence level of 95 %. The design matrix used for ANOVA analysis is shown in Appendix K. The result of the analysis for burr height and burr thickness is shown in Table 11 and Table 12 respectively.

Table 11

ANOVA output for Burr Height

Source	Sum of Squares	Degrees of Freedom	Mean Square	F value	P<=value	
Model	4.127E-003	17	2.428E-004	11.42	<0.0001	Significant
A-(Lip Relief Angle)	8.503E-006	1	8.5036E-006	0.40	0.5291	
B- (Point Angle)	2.203E-003	2	1.102E-003	51.82	<0.0001	
C- (Chisel Edge Angle)	2.027E-004	2	1.014E-004	4.77	0.0114	
AB	2.050 E-004	2	1.025E-004	4.82	0.0108	
AC	2.698 E-004	2	1.349E-004	6.35	0.0029	
BC	4.973E-004	4	1.243E-004	5.85	0.0004	
ABC	7.402E-004	4	1.851E-004	8.71	<0.0001	

Table 12

ANOVA output for Burr Thickness

Source	Sum of Squares	Degrees of Freedom	Mean Square	F value	P<=value	
Model	2.224E-006	9	2.472 E-007	7.44	< 0.0001	Significant
A-(Lip Relief Angle)	3.036E-007	1	3.036E-007	9.13	0.0034	
B- (Point Angle)	3.149 E-008	2	1.575E-008	0.47	0.6244	
C-(Chisel Edge Angle)	6.482E-007	2	3.241E-007	9.75	0.0002	
BC	1.241E-006	4	3.103E-007	9.34	<0.0001	

From the Table 11, it can be observed that the P-value for the model as well for the input factor ABC is less than the selected significance level of 0.05, which indicates that the developed model and the input factors are significant. Similarly from Table 12, it can be concluded that P-value for the model and input factor BC has significant impact on burr thickness. The developed ANOVA model is adequate and reliable as the errors (residuals) are normally and independently distributed along the straight line as shown in Figure 19 and 20 for both burr height and burr thickness. Further the plots of residuals indicate that there are no outliers present for both burr height and burr thickness as shown in Figure 21 and 22. The plots shown in the Appendix L and M does not follow a particular structure, which indicates that the residuals are spread in a random manner and there is no particular pattern present in these plots.

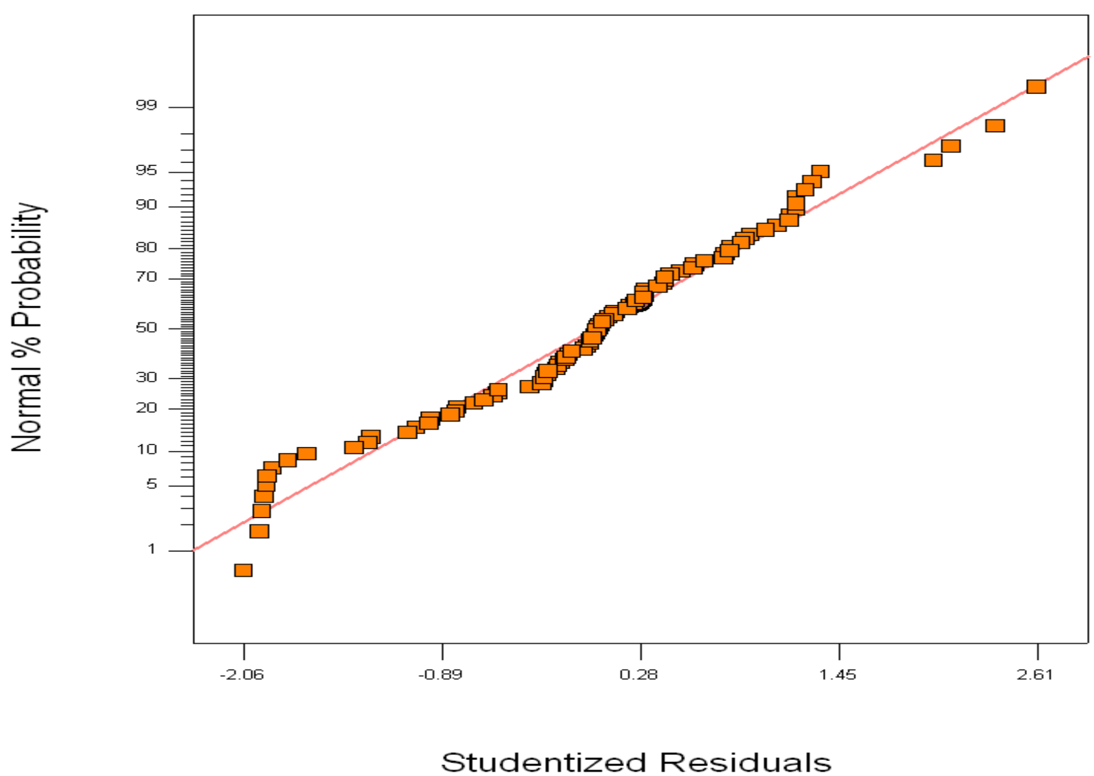


Figure 19. Normal probability Plot of Residuals for Burr Height

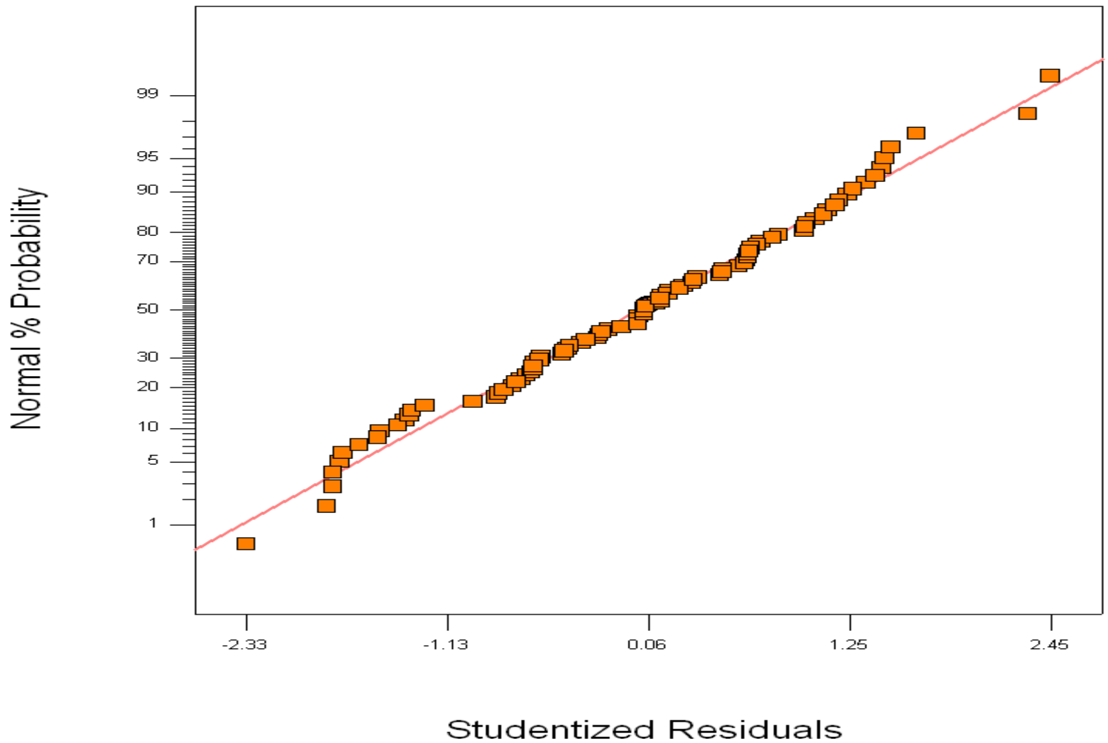


Figure 20. Normal Probability Plot of Residuals for Burr Thickness

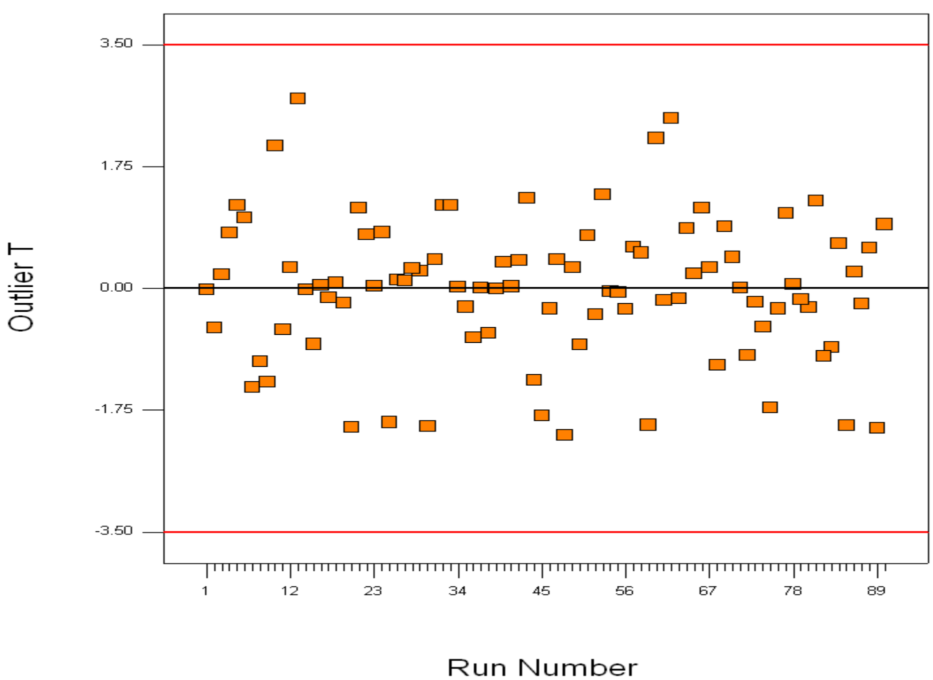


Figure 21. Outlier plot of the residuals for Burr Height

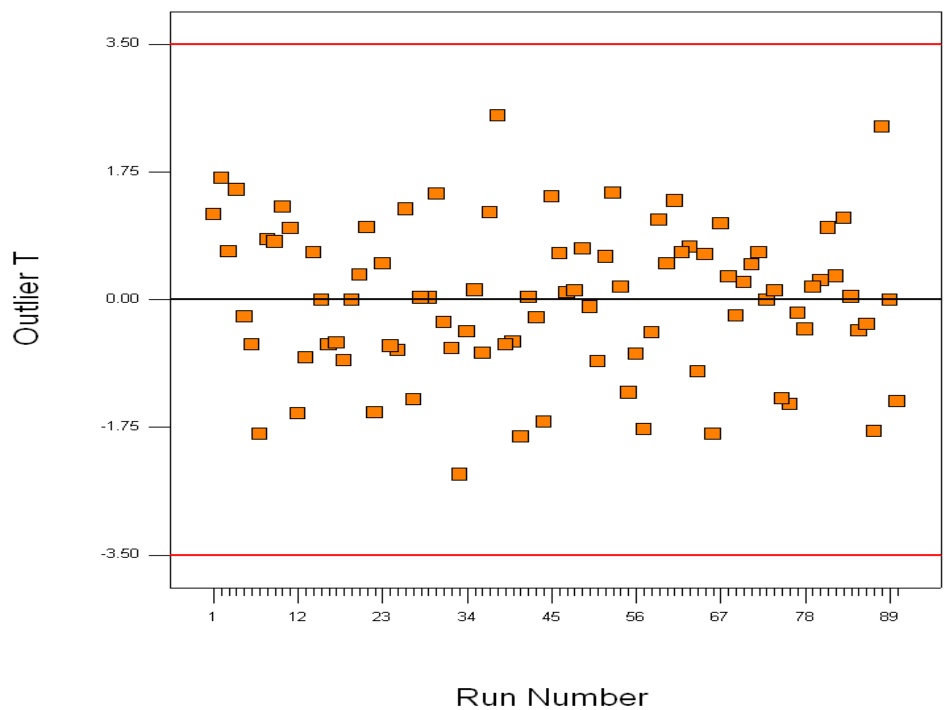


Figure 22. Outlier plot of the residuals for Burr Thickness

The values of bur height and thickness were also analyzed to see any trend in the existing data for different input angles. The graphs shown in Appendix N, O, and P show the effect of chisel edge angle, point angle and lip relief angle on burr height and burr thickness respectively. From the graph shown in Appendix N, we can see that burr height increases with an increase in chisel edge angle, whereas burr thickness decreases with an increase in chisel edge angle. For point angle, we can see an increase in burr height as point angle increases. Also when lip relief angle and chisel edge angle are increased to 16 and 125 a minimum value of height is obtained for a point angle of 132 but again values higher than 132 show an increase in burr height. A minimum value of burr thickness is obtained for a point angle in the range of 129-132 but as lip relief angle and chisel edge angle are increased to 16 and 125 the burr thickness decreases for angles greater than 132 and for values from 127-129. The maximum value of thickness is obtained in the range of 130-132. The lip relief angle of 16 yields minimum burr height and thickness, when point angle is the range of 132 and 138 and chisel edge angle is in the range of 114 and 125.

5.5 Input Parameters for Burr Height and Thickness

The model developed using all 36 data values is used for predicting the optimal range for burr height and burr thickness input parameters. The three input parameters lip relief angle, point angle, and chisel edge angle range from 12-16^0, 127-138^0, and from 104-125^0. A total of 1320 combinations were possible between these 3 input parameters. These data values were fed into the model and the corresponding burr height and burr thickness values were obtained. The values which yield lowest values of burr height and thickness were selected as they determine the optimal input parameters. The minimum value of burr height was obtained for the input parameters as shown in the Table 13. From the table it can be observed that a lip relief angle of 13, point angle of 127-128, and chisel edge angle varying from 108-115 yields optimum value of burr height. Although a lip relief angle, point angle, and chisel edge angle of 13, 127, and112 yields minimum value there is not too much of variation in burr height from 127-128^0, 108-1150. The values of different input parameters that yield minimum burr height are shown in Appendix Q.

Table 13

Recommended Input Parameters for Burr Height

Lip Relief Angle	Point Angle	Chisel Edge Angle	Burr Height
13	127	110-114	0.0654656

Similarly, the minimum value of burr thickness 0.000617 was obtained for 64 different combinations of input parameters. The range that yields minimum value of burr thickness is shown in Table 14. The values of 64 input parameters that yield minimum burr thickness is shown in Appendix R. Hence it can be concluded that any drill bit that varies in the range mentioned above for the three input parameters would yield a minimum value of burr thickness.

Table 14

Recommended Input Parameters for Burr Thickness

Lip Relief Angle	Point Angle	Chisel Edge Angle	Burr Thickness
12-16	130-132	105-115	0.000617

Hence any drill bit that has a value specified in the Table 13 and 14 would yield a minimum value of burr height or burr thickness provided other geometric parameters of the drill bit has a value with in the range specified in Table 15.

Table 15

Range of Other Geometrical Parameters

	Lip Height	chisel (web) after notching	Secondary Cutting Edge	2ndary cutting edge angle	Notch Rake angle
Max	0.0016	0.06	0	140	7
Min	0.0001	0.004	-0.0027	130	4

CHAPTER 6

CONCLUSION AND FUTURE WORK

The study concentrated on predicting exit burr as they are usually very large in size and are difficult to remove from the work piece material. Since burr removal is the last operation performed on the hole it consumes significant time and diminish the edge quality of the hole. The process of removing burr is called deburring and is expensive and time consuming because of the complex shape and size of the burr. The deburring of parts is costly and time consuming as special purpose tools are needed and time to deburr amplifies with the increase in height and thickness of the burr. From the literature review and from the experimental results it is evident that the burr is affected by many variables such as drill geometry, speed and feed. The study attempts to develop a model that is intended to predict burr size both burr height and thickness based on geometric parameters of the drill bit. The burr height and thickness are predicted as a function of chisel edge angle, point angle, and lip relief angle that have a significant impact on burr size. Hence the objective of this study was to develop a prediction model, which identifies whether a drill bit with certain geometric parameters would yield minimum burr or not. A neural network model is selected to develop a prediction model because of their capability to learn and simplify from examples and adjust to changing conditions. In addition they can be applied in manufacturing area as they are an effective tool to model a non linear system.

The experiment was conducted on Al6061-T6 and the average burr height and thickness was recorded. These values were used to develop the prediction model using neural networks. The burrs observed from the experimental results fall into three categories namely uniform burr, crown burr and transient burr. The burr height and thickness were predicted separately. The best architecture was 3-1-1 with three inputs, one hidden layer with six nodes, and one output for both burr height and thickness model. The performance of the model is enhanced by considering all available data in order to reduce the root mean square error using bootstrap technique. The RMS errors for burr height and burr thickness are 0.0031956 and 0.00002939 respectively. The model is validated using hypothesis by taking the difference of experimental values average and neural network predicted average. The result indicated that there is no significant difference between the two models and at 95% confidence interval means are equal. Both the model shows a good agreement with the experimental data. The validated model is now used to study the effect of input parameters on burr height and thickness. Since the experimental data is very limited in range, the missing data are predicted using neural network model with in the maximum and minimum value of input parameters. The burr height and thickness is predicted for a 1320 possible combinations with in the range of input parameters and used for statistical analysis. The analysis proves that the selected input parameters have a significant effect on burr height and thickness.

From the 1320 combinations range of input parameters are suggested that yield minimum burr height and thickness. For burr height the recommended range of lip relief angle, point angle and chisel edge angle are 13, 127, 110-114 respectively. Whereas for burr thickness the recommended range are 12-16, 130-132, and 105-115 for lip relief angle, point angle and chisel edge angle. The above recommendation would hold good only when the other geometrical parameters are within the range specified in Table 15. Since both burr height and thickness are vital in reducing cost it is necessary that the user chooses his parameter of interest depending upon the type of application and importance. Thus developed model can predict burr height and thickness based on the geometric parameters of the drill bit and is used to recommend range of geometric parameters that yield minimum burr height and thickness.

Future work

The result of this study suggests a possible direction for further research in reduction of exit burr in drilling operation. The following are recommended:

1. The present study focused on developing a prediction model using the three input parameters. The study could be extended to analyze the effect of other geometric parameters on burr height and thickness.

2. The prediction model could also be developed based on different combinations of speed and feed.

3. The lip relief angle, point angle, and chisel edge angle vary from 12-16, 127-138, and 104-125. Because of the limited range, parameters within this range that yield minimum burr height and thickness was suggested. The range of the input parameters can be extended to identify other possible combination that would yield minimum burr height and thickness.

4. The study was conducted on Al-6061-T6 material; future research can be conducted on stainless steel and on other aluminum alloys to prove the effect of material on burr height and thickness.

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APPENDICES

Appendix A

Input Parameters

Drill #	Lip Relief	Point Angle	Chisel Edge
1	14	132	120
2	14	127	116
3	14	130	115
4	14	128	115
5	16	130	125
6	16	128	114
7	15	138	116
8	12	128	115
9	16	131	118
10	12	128	109
11	15	128	120
12	15	128	113
13	15	128	109
14	16	128	112
15	15	129	113
16	16	129	115
17	15	128	104
18	15	128	117
19	15	131	119
20	15	129	120
21	15	130	121
22	14	128	114
23	14	128	113
24	15	130	116
25	14	128	114
26	15	129	122
27	15	128	117
28	15	128	118
29	14	130	120
30	15	127	114
31	15	131	118
32	14	130	117
33	16	129	118
34	15	129	109
35	15	130	123
36	14	128	114
Max	**16**	**138**	**125**
Min	**12**	**127**	**104**

Appendix B

Geometric Parameters associated with 36 Twist Drill Bits

Drill Bit #	Lip Relief	Lip Height	chisel (web) after notching	Point Angle	secondary Cutting Edge	Chisel edge angle	secondary cutting edge angle	Notch Rake angle
1	14	0.0013	0.007	132	-0.0009	120	133	6
2	14	0.0009	0.006	127	0	116	130	6
3	14	0.0016	0.004	130	-0.0015	115	134	7
4	14	0.0001	0.005	128	0	115	134	6
5	16	0.0002	0.008	130	-0.0012	125	130	4
6	16	0.0016	0.006	128	-0.001	114	140	6
7	15	0.0013	0.006	138	0	116	135	5
8	12	0.0007	0.007	128	0	115	133	5
9	16	0.0015	0.007	131	-0.001	118	135	6
10	12	0.0015	0.006	128	-0.0017	109	134	5
11	15	0.0007	0.006	128	-0.0017	120	133	5
12	15	0.0008	0.006	128	-0.0006	113	134	7
13	15	0.0002	0.007	128	-0.0015	109	132	6
14	16	0.0012	0.006	128	-0.002	112	130	4
15	15	0.0003	0.006	129	-0.002	113	137	6
16	16	0.0006	0.006	129	-0.0006	115	133	5
17	15	0.0011	0.007	128	0	104	138	6
18	15	0.001	0.006	128	0	117	133	6
19	15	0.0003	0.008	131	0	119	135	5
20	15	0.0002	0.006	129	-0.0018	120	133	6
21	15	0.0007	0.006	130	0	121	133	7
22	14	0.0013	0.06	128	0	114	132	6
23	14	0.0008	0.007	128	0	113	138	6
24	15	0.0013	0.004	130	-0.0019	116	131	5
25	14	0.0006	0.006	128	-0.0015	114	133	7
26	15	0.0012	0.007	129	-0.0008	122	133	6
27	15	0.0014	0.006	128	-0.0027	117	134	5
28	15	0.0001	0.006	128	-0.0012	118	135	6
29	14	0.001	0.007	130	-0.002	120	133	6
30	15	0.0004	0.006	127	-0.0025	114	132	7
31	15	0.0009	0.006	131	-0.0007	118	138	6
32	14	0.0008	0.006	130	-0.0019	117	130	5
33	16	0.0006	0.008	129	-0.0018	118	137	6
34	15	0.0014	0.005	129	-0.001	109	137	6
35	15	0.0008	0.006	130	-0.0005	123	134	6
36	14	0.001	0.006	128	-0.0005	114	132	6

Appendix C

Burr Height Values for the 36 Drill Bits

Drill Bit #	Lip Relief	Lip Height	chisel (web) after notching	Point Angle	secondary Cutting Edge	Chisel edge angle	secondary cutting edge angle	Notch Rake angle	Burr Height
1	14	0.0013	0.007	132	-0.0009	120	133	6	0.0949655
2	14	0.0009	0.006	127	0	116	130	6	0.0908125
3	14	0.0016	0.004	130	-0.0015	115	134	7	0.0797748
4	14	0.0001	0.005	128	0	115	134	6	0.0655
5	16	0.0002	0.008	130	-0.0012	125	130	4	0.0926827
6	16	0.0016	0.006	128	-0.001	114	140	6	0.0769236
7	15	0.0013	0.006	138	0	116	135	5	0.092328
8	12	0.0007	0.007	128	0	115	133	5	0.0834665
9	16	0.0015	0.007	131	-0.001	118	135	6	0.0798775
10	12	0.0015	0.006	128	-0.0017	109	134	5	0.0843884
11	15	0.0007	0.006	128	-0.0017	120	133	5	0.0827576
12	15	0.0008	0.006	128	-0.0006	113	134	7	0.075384
13	15	0.0002	0.007	128	-0.0015	109	132	6	0.0862975
14	16	0.0012	0.006	128	-0.002	112	130	4	0.080928
15	15	0.0003	0.006	129	-0.002	113	137	6	0.0791726
16	16	0.0006	0.006	129	-0.0006	115	133	5	0.079727
17	15	0.0011	0.007	128	0	104	138	6	0.081384
18	15	0.001	0.006	128	0	117	133	6	0.0824236
19	15	0.0003	0.008	131	0	119	135	5	0.0801264
20	15	0.0002	0.006	129	-0.0018	120	133	6	0.08554
21	15	0.0007	0.006	130	0	121	133	7	0.0773308
22	14	0.0013	0.06	128	0	114	132	6	0.095386
23	14	0.0008	0.007	128	0	113	138	6	0.078072
24	15	0.0013	0.004	130	-0.0019	116	131	5	0.0832105
25	14	0.0006	0.006	128	-0.0015	114	133	7	0.07357
26	15	0.0012	0.007	129	-0.0008	122	133	6	0.0924995
27	15	0.0014	0.006	128	-0.0027	117	134	5	0.08943
28	15	0.0001	0.006	128	-0.0012	118	135	6	0.0797485
29	14	0.001	0.007	130	-0.002	120	133	6	0.08055
30	15	0.0004	0.006	127	-0.0025	114	132	7	0.081534
31	15	0.0009	0.006	131	-0.0007	118	138	6	0.0843465
32	14	0.0008	0.006	130	-0.0019	117	130	5	0.0855215
33	16	0.0006	0.008	129	-0.0018	118	137	6	0.068634
34	15	0.0014	0.005	129	-0.001	109	137	6	0.085689
35	15	0.0008	0.006	130	-0.0005	123	134	6	0.0646665
36	14	0.001	0.006	128	-0.0005	114	132	6	0.08357

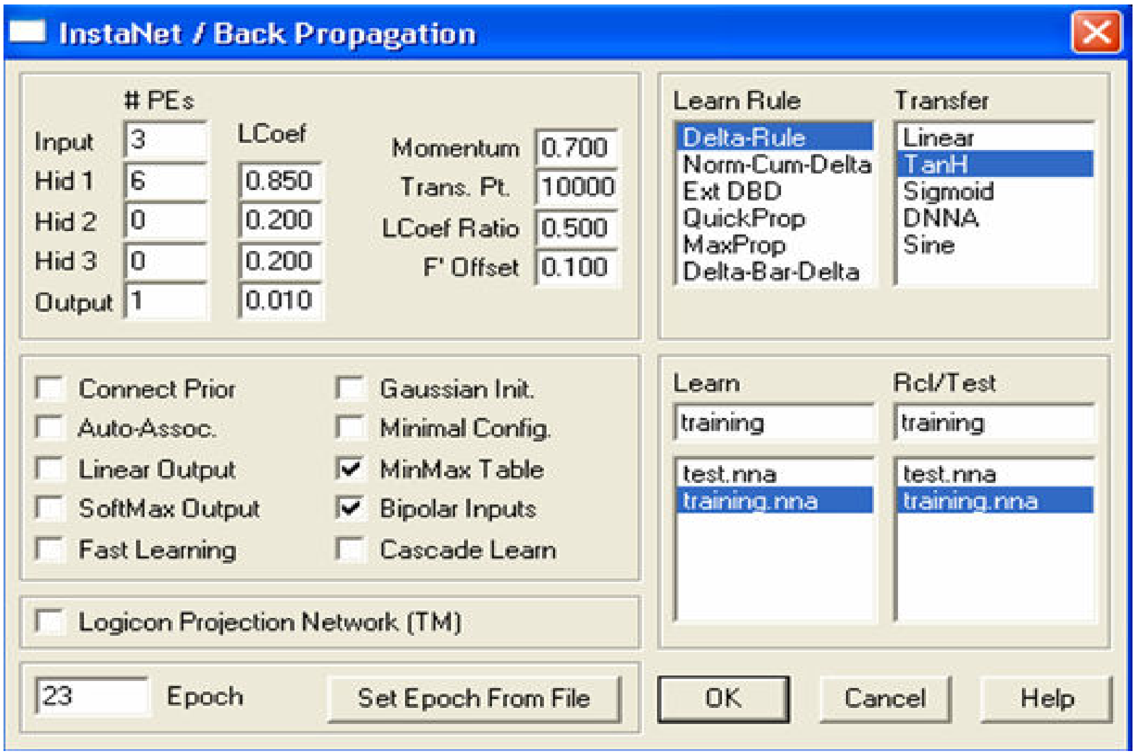
Appendix D

Burr Thickness Values for 36 Drill Bits

Drill Bit #	Lip Relief	Lip Height	Chisel (web) after notching	Point Angle	secondary Cutting Edge	Chisel edge angle	secondary cutting edge angle	Notch Rake angle	Burr Thickness
1	14	0.0013	0.007	132	-0.0009	120	133	6	0.00108
2	14	0.0009	0.006	127	0	116	130	6	0.000882
3	14	0.0016	0.004	130	-0.0015	115	134	7	0.00072
4	14	0.0001	0.005	128	0	115	134	6	0.000825
5	16	0.0002	0.008	130	-0.0012	125	130	4	0.001173
6	16	0.0016	0.006	128	-0.001	114	140	6	0.000823
7	15	0.0013	0.006	138	0	116	135	5	0.000967
8	12	0.0007	0.007	128	0	115	133	5	0.00098
9	16	0.0015	0.007	131	-0.001	118	135	6	0.000987
10	12	0.0015	0.006	128	-0.0017	109	134	5	0.001187
11	15	0.0007	0.006	128	-0.0017	120	133	5	0.000893
12	15	0.0008	0.006	128	-0.0006	113	134	7	0.001093
13	15	0.0002	0.007	128	-0.0015	109	132	6	0.001133
14	16	0.0012	0.006	128	-0.002	112	130	4	0.000933
15	15	0.0003	0.006	129	-0.002	113	137	6	0.00108
16	16	0.0006	0.006	129	-0.0006	115	133	5	0.00078
17	15	0.0011	0.007	128	0	104	138	6	0.001087
18	15	0.001	0.006	128	0	117	133	6	0.00118
19	15	0.0003	0.008	131	0	119	135	5	0.001027
20	15	0.0002	0.006	129	-0.0018	120	133	6	0.000733
21	15	0.0007	0.006	130	0	121	133	7	0.000867
22	14	0.0013	0.06	128	0	114	132	6	0.00092
23	14	0.0008	0.007	128	0	113	138	6	0.001133
24	15	0.0013	0.004	130	-0.0019	116	131	5	0.000967
25	14	0.0006	0.006	128	-0.0015	114	133	7	0.000897
26	15	0.0012	0.007	129	-0.0008	122	133	6	0.00068
27	15	0.0014	0.006	128	-0.0027	117	134	5	0.001093
28	15	0.0001	0.006	128	-0.0012	118	135	6	0.00068
29	14	0.001	0.007	130	-0.002	120	133	6	0.001067
30	15	0.0004	0.006	127	-0.0025	114	132	7	0.001093
31	15	0.0009	0.006	131	-0.0007	118	138	6	0.000847
32	14	0.0008	0.006	130	-0.0019	117	130	5	0.000813
33	16	0.0006	0.008	129	-0.0018	118	137	6	0.00084
34	15	0.0014	0.005	129	-0.001	109	137	6	0.000747
35	15	0.0008	0.006	130	-0.0005	123	134	6	0.001017
36	14	0.001	0.006	128	-0.0005	114	132	6	0.000897

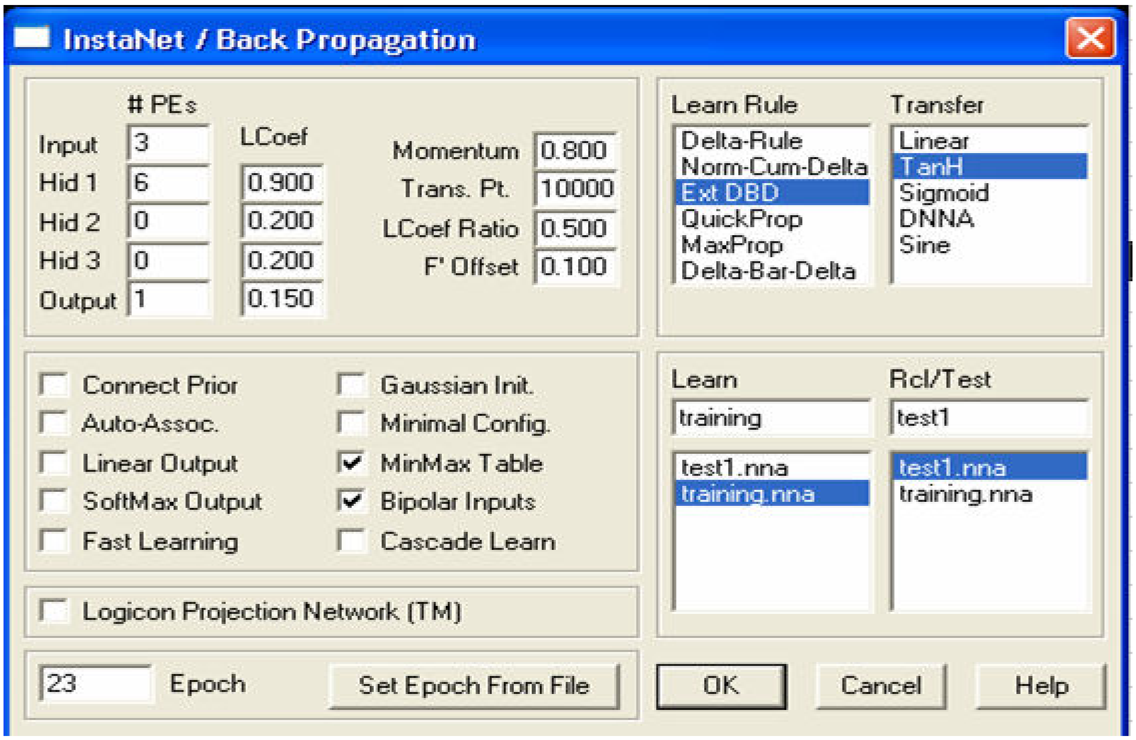
Appendix E

Burr Height Model Network Architecture



Appendix F

Burr Thickness Model Network Architecture



Appendix G

Experimental and Neural Network Burr height values for 23 Input Parameters of Training Set

Drill Bit #	Lip Relief Angle	Point Angle	Chisel Edge Angle	Experimental Value	Neural Network Value
7	15	138	116	0.092328	0.091926
14	16	128	112	0.080928	0.077969
26	15	129	122	0.0925	0.092213
34	15	129	109	0.085689	0.085112
1	14	132	120	0.094966	0.096078
24	15	130	116	0.08321	0.08455
10	12	128	109	0.084388	0.083939
20	15	129	120	0.08554	0.086686
33	16	129	118	0.068634	0.069245
11	15	128	120	0.082758	0.082288
12	15	128	113	0.075384	0.078229
2	14	127	116	0.090812	0.09057
15	15	129	113	0.079173	0.079186
35	15	130	123	0.064667	0.066434
22	14	128	114	0.095386	0.084443
31	15	131	118	0.084347	0.084222
32	14	130	117	0.085521	0.085859
25	14	128	114	0.07357	0.084443
5	16	130	125	0.092683	0.091726
18	15	128	117	0.082424	0.081752
9	16	131	118	0.079878	0.07937
29	14	130	120	0.08055	0.079663
17	15	128	104	0.081384	0.081798

Appendix H

Experimental and Neural Network Burr height values for 13 Input Parameters of Test Set

Drill Bit #	Lip Relief Angle	Point Angle	Chisel Edge Angle	Experimental Value	Neural Network Value
8	12	128	115	0.083467	0.080207
23	14	128	113	0.07872	0.081932
30	15	127	114	0.081534	0.078908
6	16	128	114	0.076924	0.077869
16	16	129	115	0.079727	0.077621
13	15	128	109	0.086298	0.078259
36	14	128	114	0.08357	0.084443
21	15	130	121	0.077331	0.074096
27	15	128	117	0.08943	0.081752
4	14	128	115	0.0655	0.087793
28	15	128	118	0.079748	0.082857
3	14	130	115	0.079775	0.075842
19	15	131	119	0.080126	0.076666

Appendix I

Experimental and Neural Network Burr Thickness values for 23 Input Parameters of Training Set

Drill Bit #	Lip Relief Angle	Point Angle	Chisel Edge Angle	Experimental value	Neural Network value
7	15	138	116	0.000967	0.000966
17	15	128	104	0.001087	0.001087
26	15	129	122	0.00068	0.000666
31	15	131	118	0.000847	0.000847
34	15	129	109	0.000747	0.000751
27	15	128	117	0.001093	0.001092
24	15	130	116	0.000967	0.000969
20	15	129	120	0.000733	0.000743
15	15	129	113	0.00108	0.001072
11	15	128	120	0.000893	0.000897
12	15	128	113	0.00109	0.001103
10	12	128	109	0.001187	0.001187
2	14	127	116	0.000882	0.000882
1	14	132	120	0.00108	0.00108
35	15	130	123	0.001017	0.001024
22	14	128	114	0.00092	0.000954
29	14	130	120	0.001067	0.001063
32	14	130	117	0.000813	0.000817
25	14	128	114	0.000987	0.000954
5	16	130	125	0.001173	0.001169
14	16	128	112	0.000934	0.000933
9	16	131	118	0.000987	0.000989
33	16	129	118	0.00084	0.00084

Appendix J

Experimental and Neural Network Burr Thickness values for 13 Input Parameters of Test Set

Drill Bit #	Lip Relief Angle	Point Angle	Chisel Edge Angle	Experimental Value	Neural Network Value
36	14	128	114	0.000897	0.000952
3	14	130	115	0.00072	0.000676
6	16	128	114	0.000823	0.000877
8	12	128	115	0.00098	0.001017
13	15	128	109	0.001134	0.001139
19	15	131	119	0.001027	0.001059
21	15	130	121	0.000867	0.000844
18	15	128	117	0.00118	0.001092
30	15	127	114	0.001093	0.001108
4	14	128	115	0.000825	0.000835
28	15	128	118	0.00068	0.001069
23	14	128	113	0.001133	0.001106
16	16	129	115	0.00078	0.000807

Appendix K

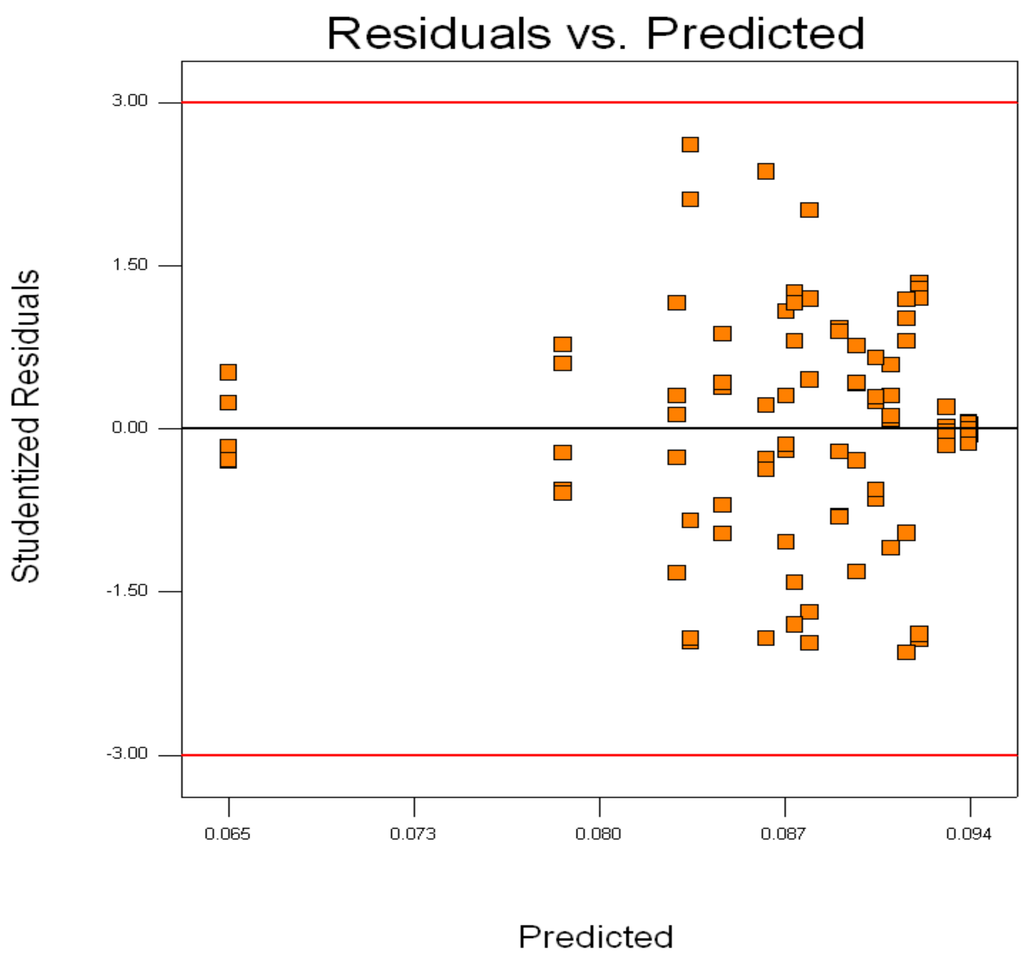
ANOVA Design Matrix

No	Lip Releif Angle	Point Angle	Chisel Edge Angle	Burr Height	Burr Thickness
1	12-14	127-130	104-110	0.082989	0.001213
2	12-14	127-130	104-110	0.088537	0.00125
3	12-14	127-130	104-110	0.086481	0.00107
4	12-14	127-130	104-110	0.086691	0.001195
5	12-14	127-130	104-110	0.091766	0.001039
6	15-16	127-130	104-110	0.077666	0.000649
7	15-16	127-130	104-110	0.076235	0.001237
8	15-16	127-130	104-110	0.081035	0.000652
9	15-16	127-130	104-110	0.081769	0.00069
10	15-16	127-130	104-110	0.076126	0.001123
11	12-14	131-134	104-110	0.088868	0.001221
12	12-14	131-134	104-110	0.091772	0.001117
13	12-14	131-134	104-110	0.091809	0.001129
14	12-14	131-134	104-110	0.093232	0.000966
15	12-14	131-134	104-110	0.084665	0.000826
16	15-16	131-134	104-110	0.084512	0.001243
17	15-16	131-134	104-110	0.098035	0.001246
18	15-16	131-134	104-110	0.097837	0.000953
19	15-16	131-134	104-110	0.08472	0.000875
20	15-16	131-134	104-110	0.097448	0.000955
21	12-14	135-138	104-110	0.093192	0.001012
22	12-14	135-138	104-110	0.093069	0.001212
23	12-14	135-138	104-110	0.086077	0.001249
24	12-14	135-138	104-110	0.086031	0.001233
25	12-14	135-138	104-110	0.088518	0.001249
26	15-16	135-138	104-110	0.078559	0.001061
27	15-16	135-138	104-110	0.085374	0.00118
28	15-16	135-138	104-110	0.08496	0.001236
29	15-16	135-138	104-110	0.0874	0.001242
30	15-16	135-138	104-110	0.096277	0.001245
31	12-14	127-130	111-118	0.064778	0.001243
32	12-14	127-130	111-118	0.064225	0.000883
33	12-14	127-130	111-118	0.067598	0.000933
34	12-14	127-130	111-118	0.064268	0.000766
35	12-14	127-130	111-118	0.066459	0.000953
36	15-16	127-130	111-118	0.081929	0.000918
37	15-16	127-130	111-118	0.084285	0.000629
38	15-16	127-130	111-118	0.083567	0.001108
39	15-16	127-130	111-118	0.087814	0.001066
40	15-16	127-130	111-118	0.077542	0.001032
41	12-14	131-134	111-118	0.091747	0.000708
42	12-14	131-134	111-118	0.086871	0.000905
43	12-14	131-134	111-118	0.092631	0.000971
44	12-14	131-134	111-118	0.091876	0.000617
45	12-14	131-134	111-118	0.093805	0.001247
46	15-16	131-134	111-118	0.083517	0.000756
47	15-16	131-134	111-118	0.096946	0.00062

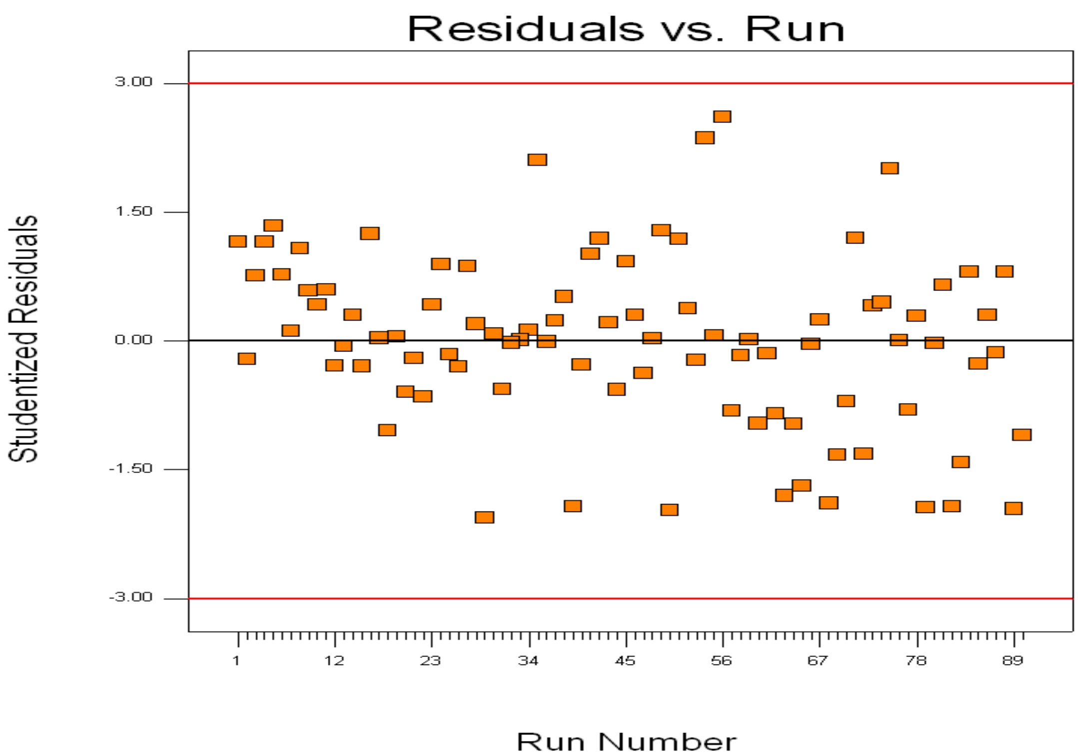
48	15-16	131-134	111-118	0.096218	0.000628
49	15-16	131-134	111-118	0.09536	0.000625
50	15-16	131-134	111-118	0.088065	0.000846
51	12-14	135-138	111-118	0.094399	0.001249
52	12-14	135-138	111-118	0.093423	0.001165
53	12-14	135-138	111-118	0.092919	0.001164
54	12-14	135-138	111-118	0.093636	0.001217
55	12-14	135-138	111-118	0.093495	0.001247
56	15-16	135-138	111-118	0.093154	0.000618
57	15-16	135-138	111-118	0.081267	0.000787
58	15-16	135-138	111-118	0.0965	0.001237
59	15-16	135-138	111-118	0.080112	0.001017
60	15-16	135-138	111-118	0.090088	0.00106
61	12-14	127-130	119-125	0.094339	0.000917
62	12-14	127-130	119-125	0.075498	0.001114
63	12-14	127-130	119-125	0.092247	0.00114
64	12-14	127-130	119-125	0.08008	0.001247
65	12-14	127-130	119-125	0.075621	0.001243
66	15-16	127-130	119-125	0.0819	0.000813
67	15-16	127-130	119-125	0.08637	0.000839
68	15-16	127-130	119-125	0.08655	0.000884
69	15-16	127-130	119-125	0.080814	0.000994
70	15-16	127-130	119-125	0.088397	0.000769
71	12-14	131-134	119-125	0.09464	0.00113
72	12-14	131-134	119-125	0.094508	0.001249
73	12-14	131-134	119-125	0.094256	0.000827
74	12-14	131-134	119-125	0.094607	0.000727
75	12-14	131-134	119-125	0.094412	0.001245
76	15-16	131-134	119-125	0.081822	0.000617
77	15-16	131-134	119-125	0.08021	0.00117
78	15-16	131-134	119-125	0.090956	0.001186
79	15-16	131-134	119-125	0.092795	0.001098
80	15-16	131-134	119-125	0.092396	0.000617
81	12-14	135-138	119-125	0.094715	0.000658
82	12-14	135-138	119-125	0.094527	0.000652
83	12-14	135-138	119-125	0.094667	0.000621
84	12-14	135-138	119-125	0.093916	0.000627
85	12-14	135-138	119-125	0.094422	0.000621
86	15-16	135-138	119-125	0.091855	0.000617
87	15-16	135-138	119-125	0.092044	0.000617
88	15-16	135-138	119-125	0.093514	0.000619
89	15-16	135-138	119-125	0.088163	0.001032
90	15-16	135-138	119-125	0.088516	0.000634

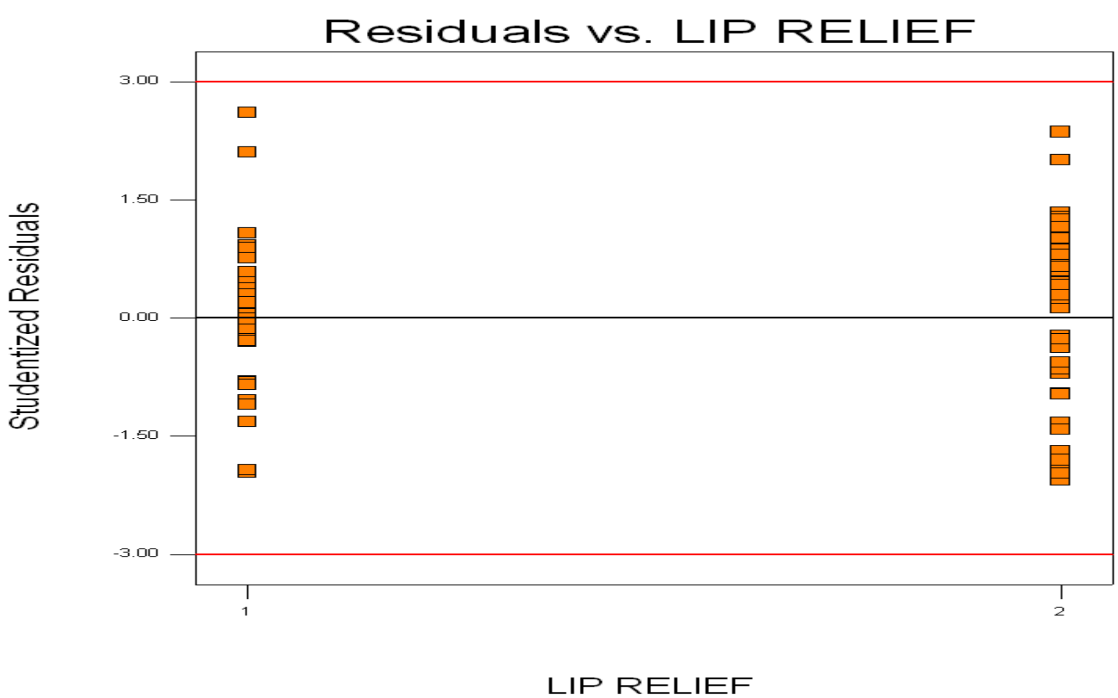
Appendix L

Model Adequacy Graphs for Burr Height

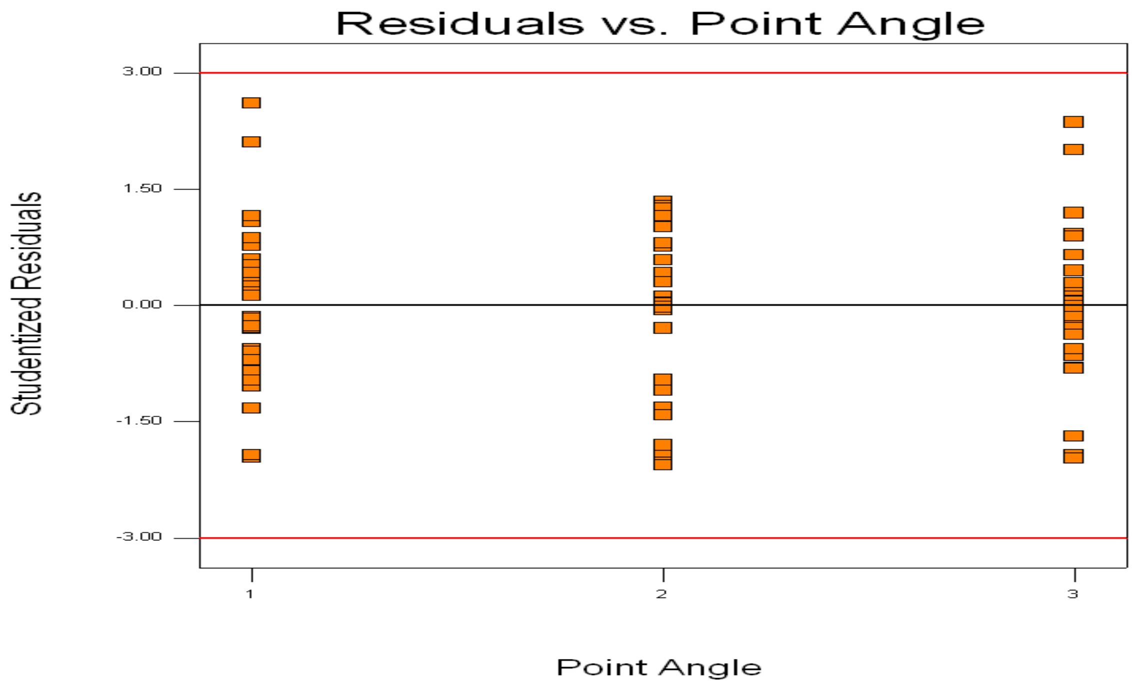


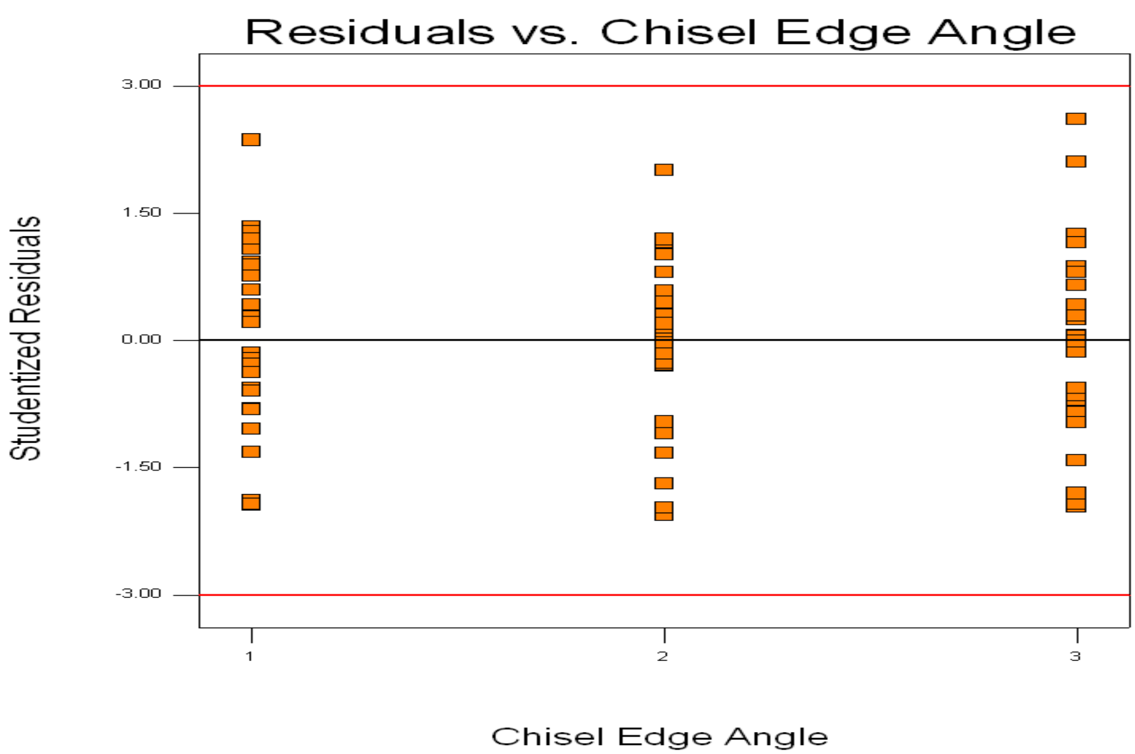
Appendix L (Continued)



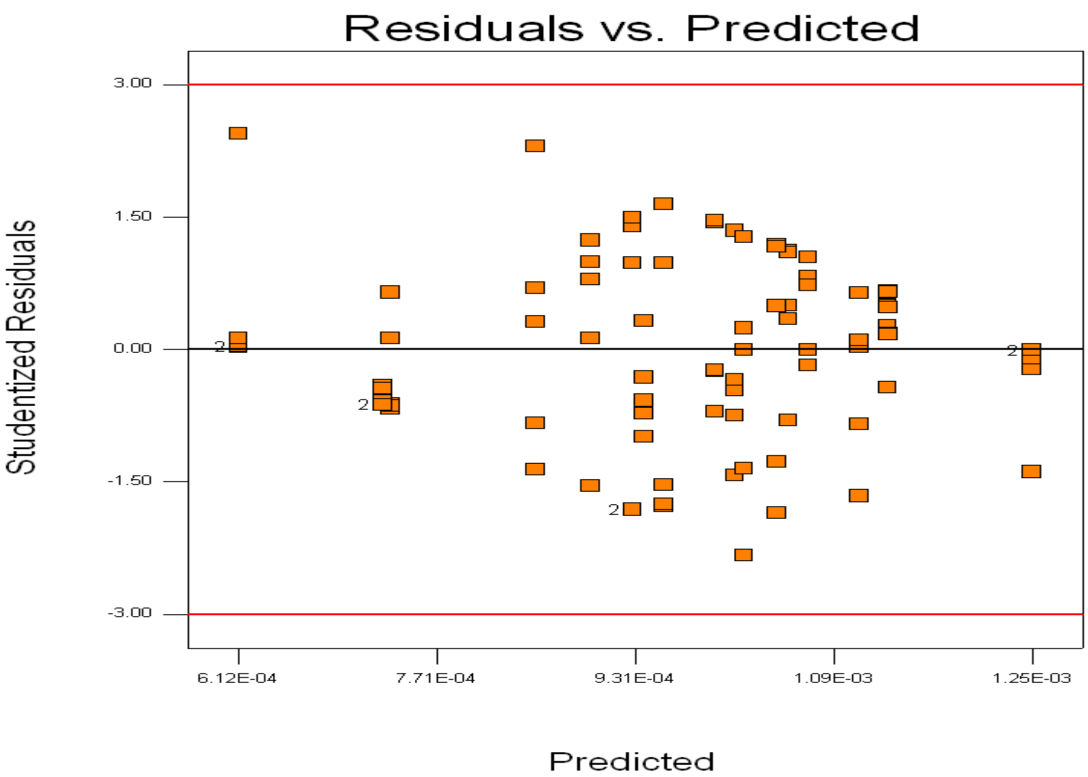


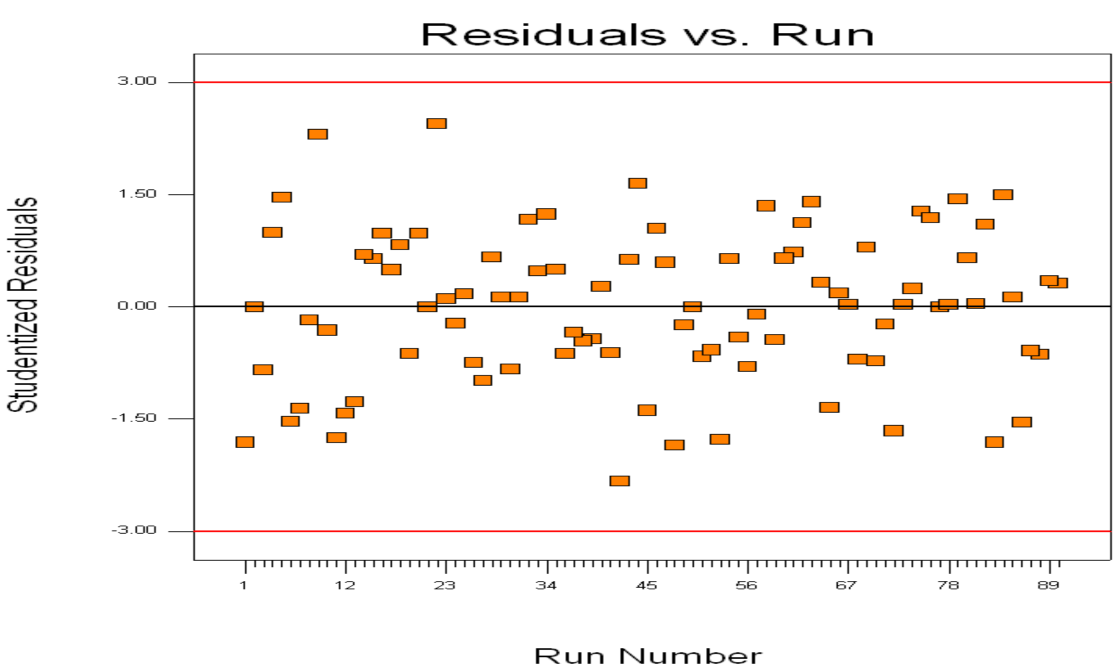
Appendix L (Continued)





Appendix M
Model Adequacy Graphs for Burr Thickness





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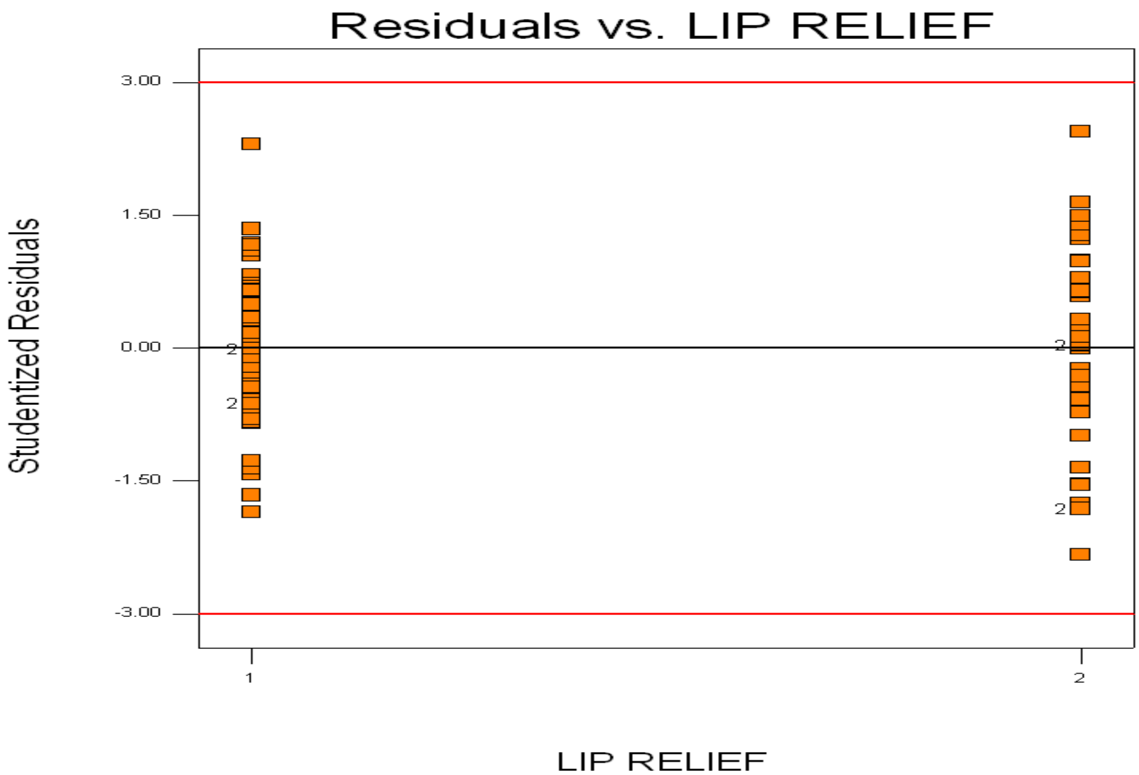

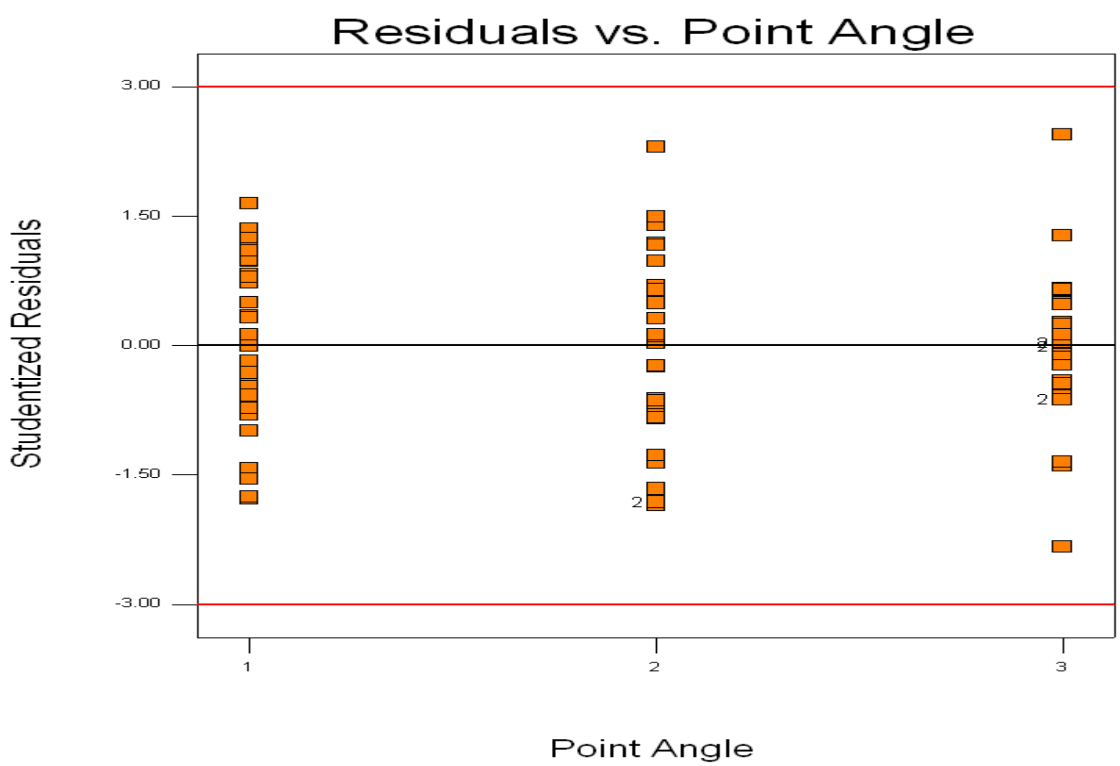

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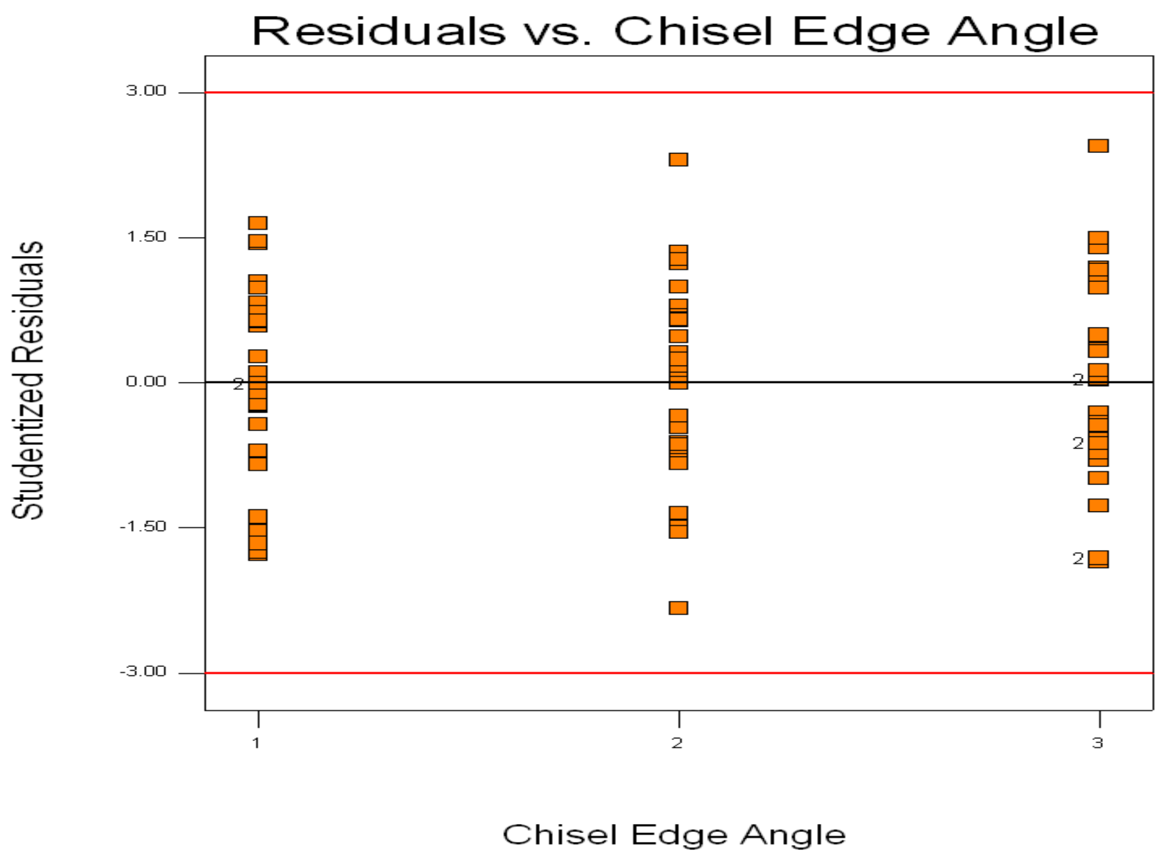
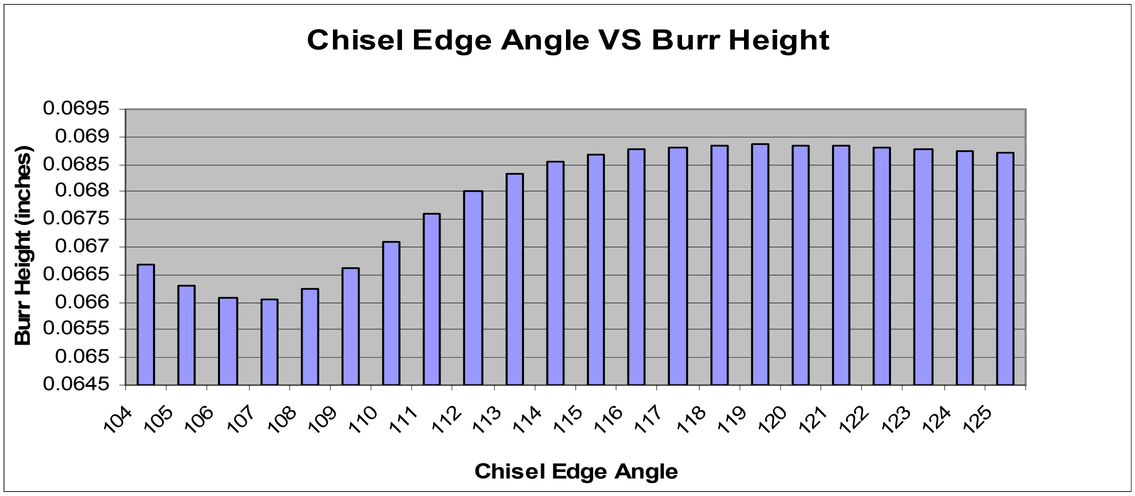
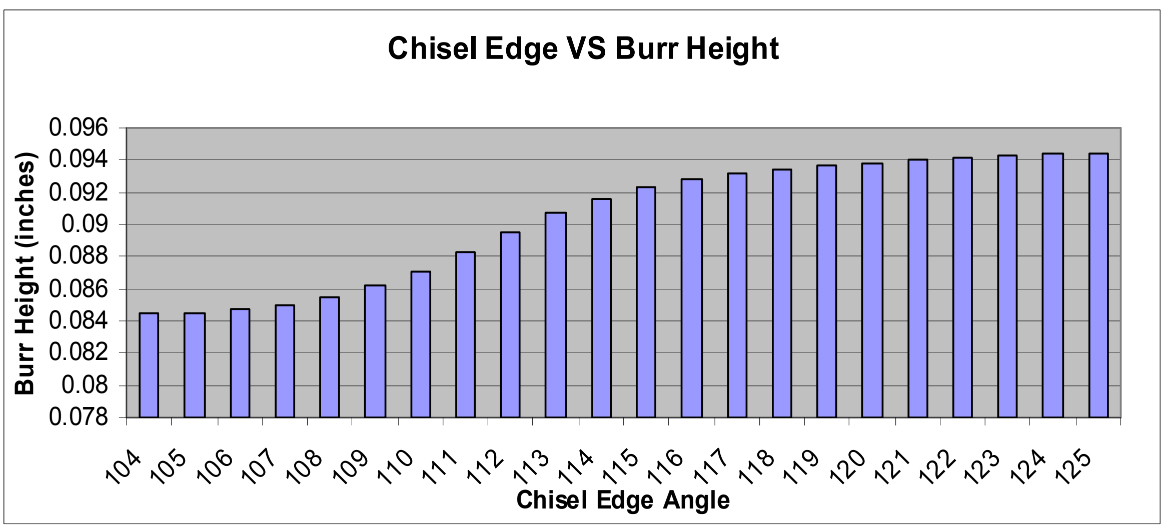


Appendix N

Effect of Chisel Edge angle on Burr Height and Burr Thickness

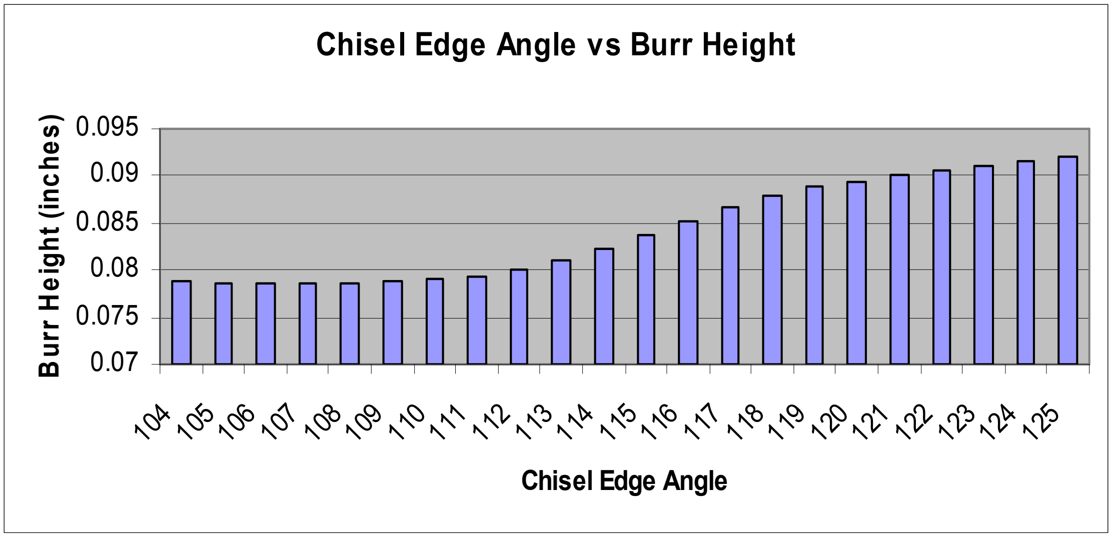


When Lip Relief Angle = 12 and Point Angle =127

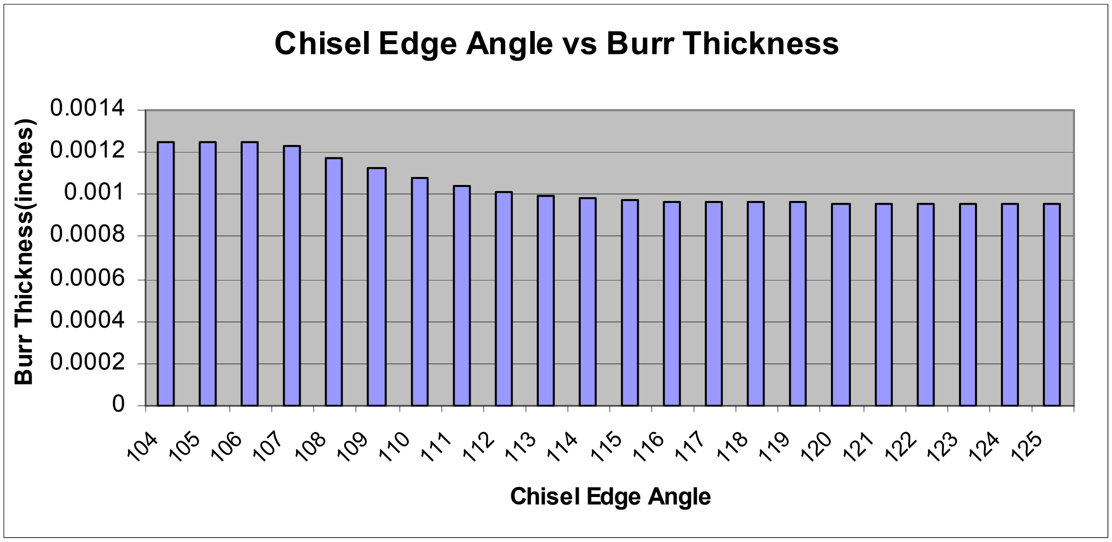


When Lip Relief Angle = 14 and Point Angle =132

Appendix N (continued)

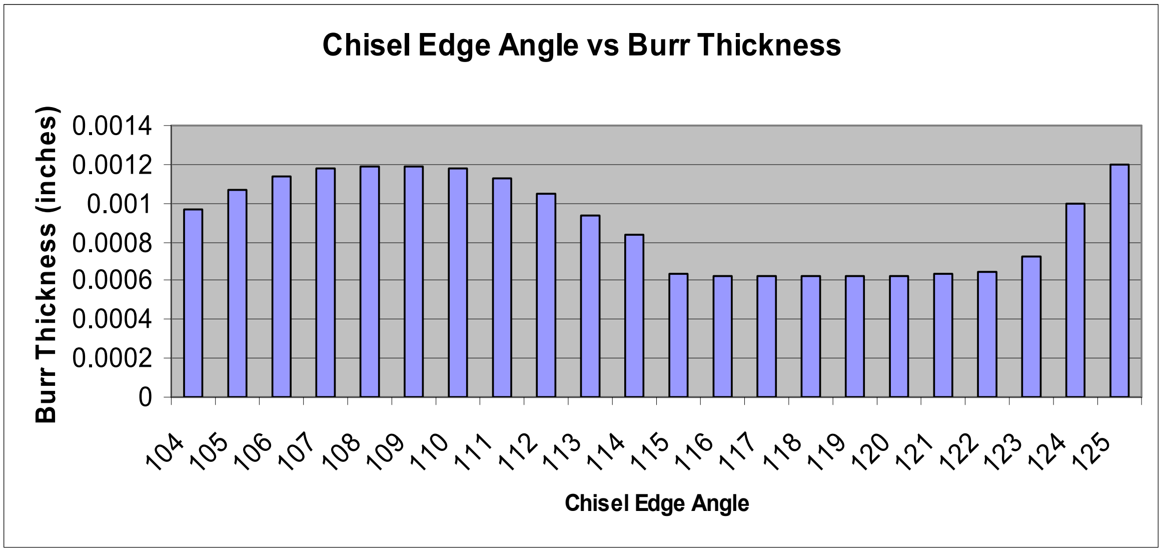


When Lip Relief Angle = 16 and Point Angle =138

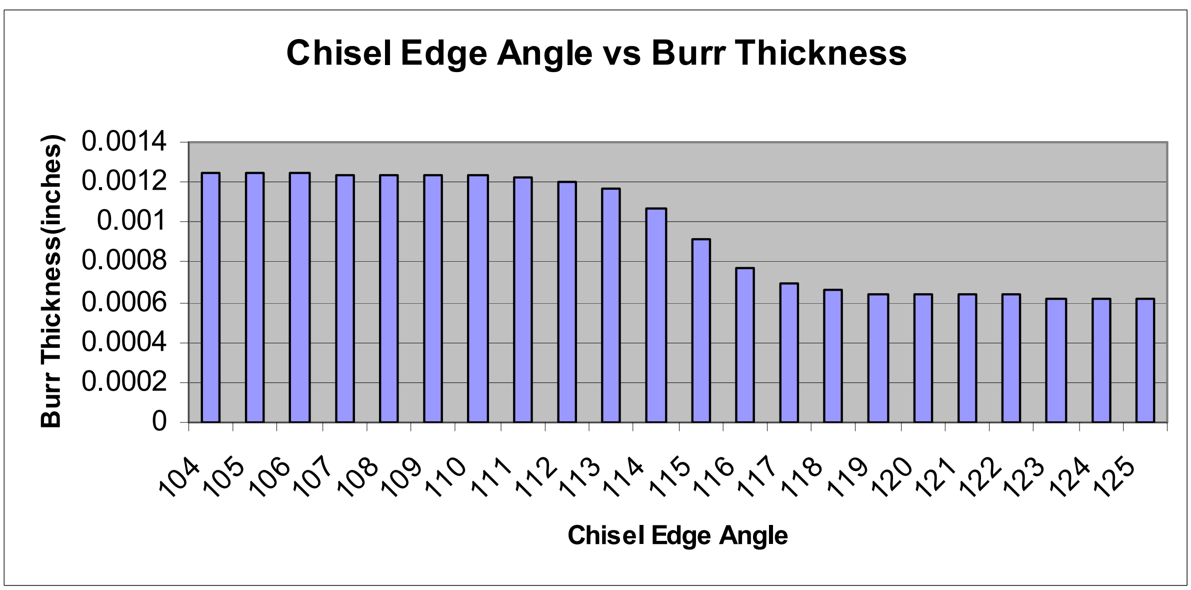


When Lip Relief Angle = 12 and Point Angle =127

Appendix N (continued)



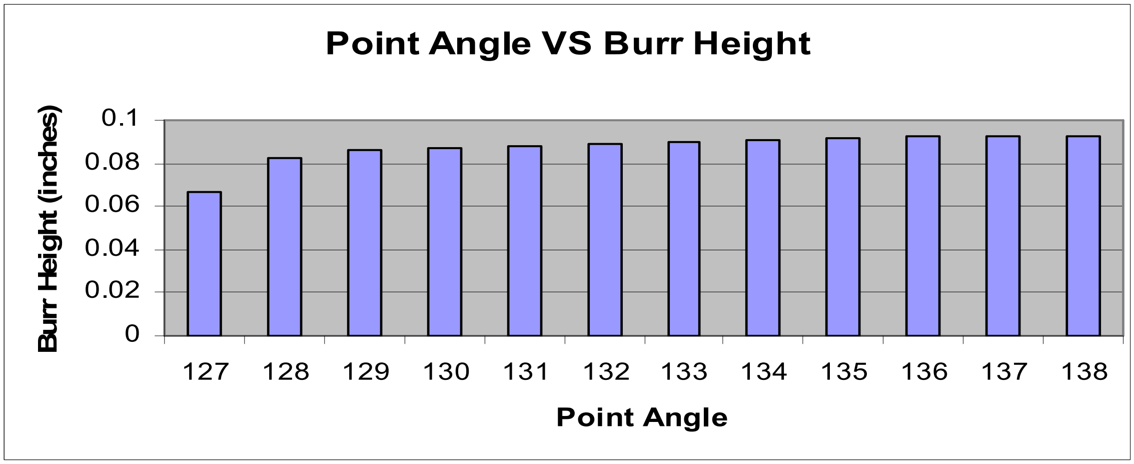
When Lip Relief Angle = 14 and Point Angle =132



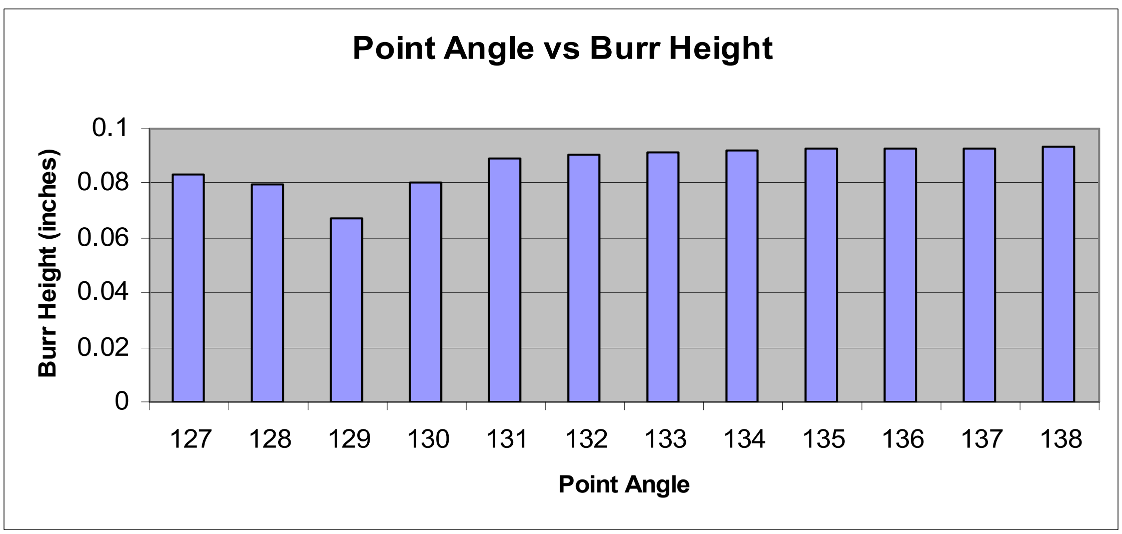
When Lip Relief Angle = 16 and Point Angle =138

Appendix O

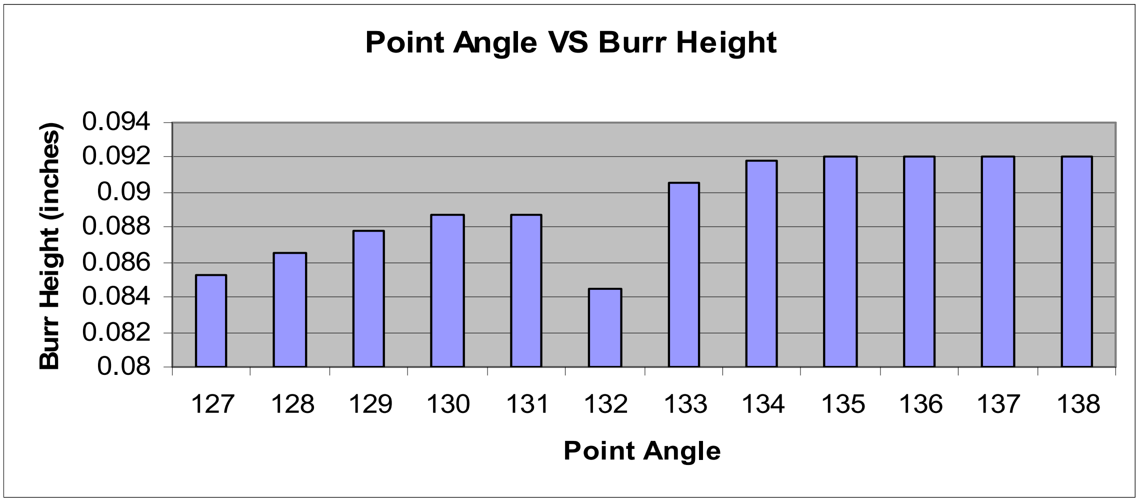
Effect of Point Angle on Burr Height and Burr Thickness



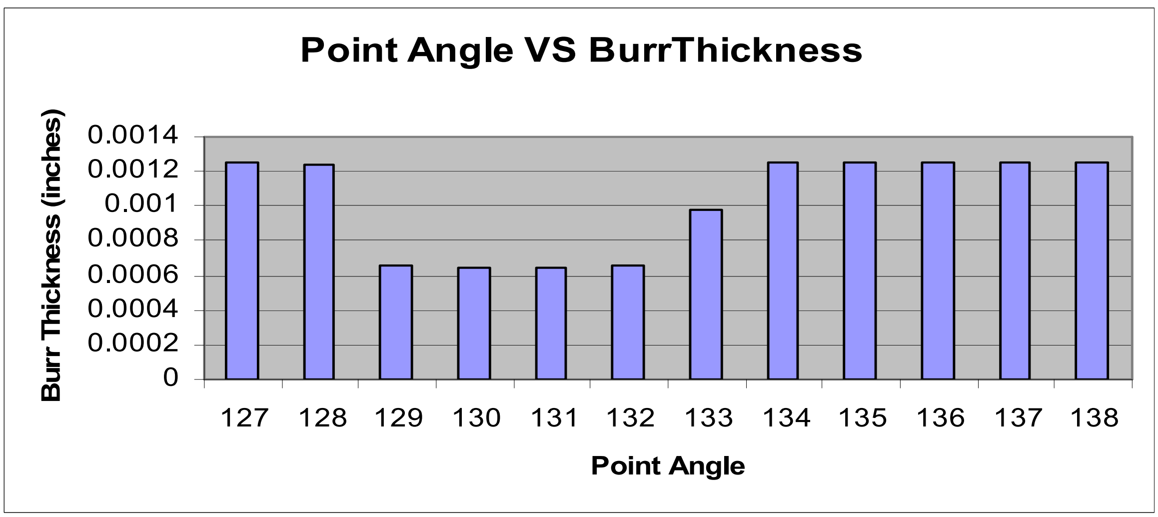
When Lip Relief Angle =12 and Chisel Edge Angle = 104



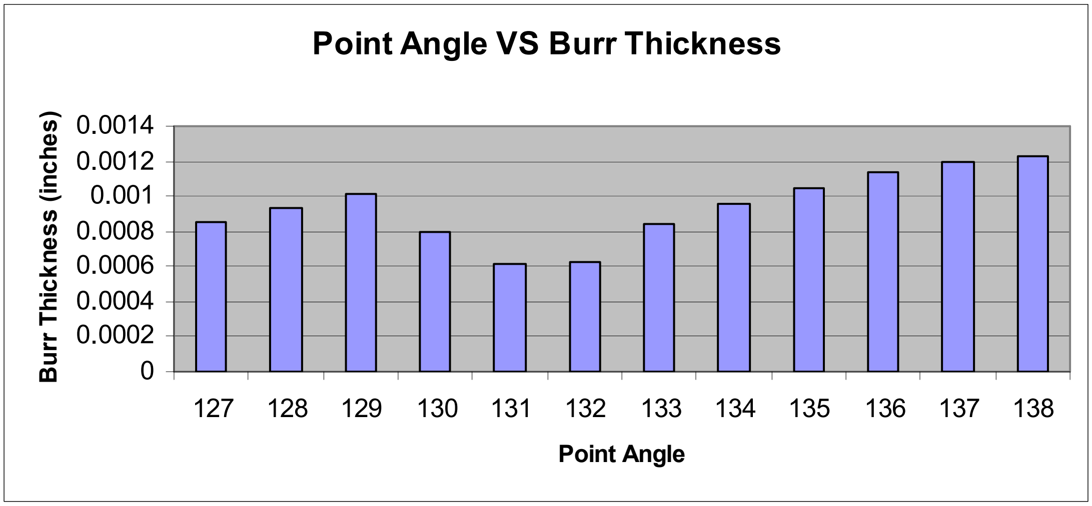
When Lip Relief Angle =12 and Chisel Edge Angle = 114



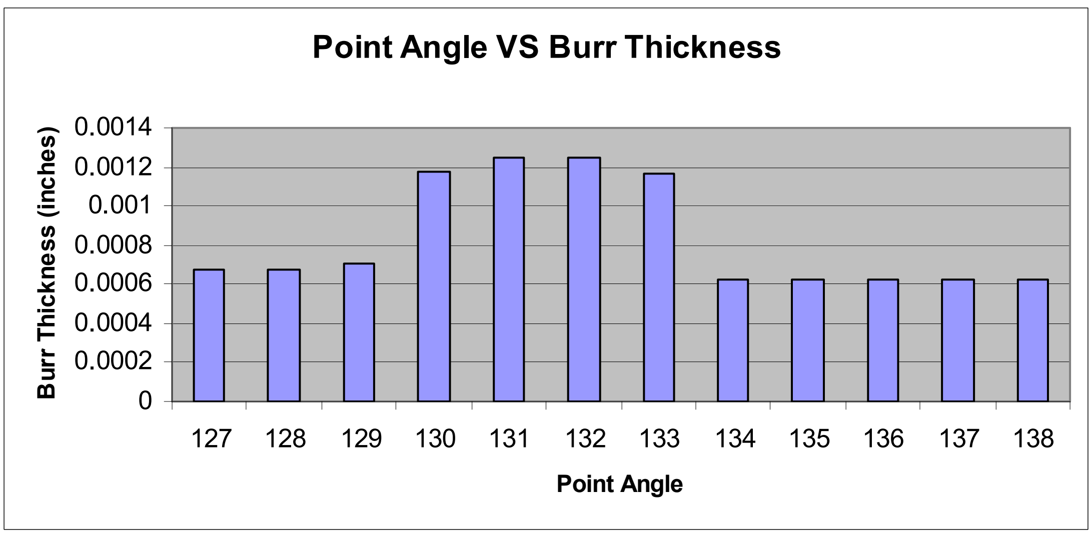
When Lip Relief Angle =16 and Chisel Edge Angle = 125



When Lip Relief Angle =12 and Chisel Edge Angle = 104



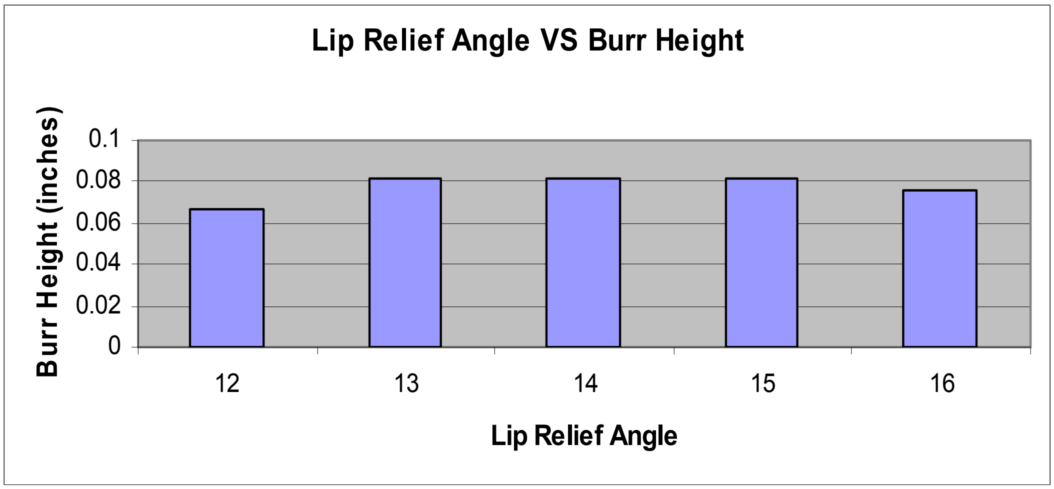
When Lip Relief Angle =14 and Chisel Edge Angle = 114



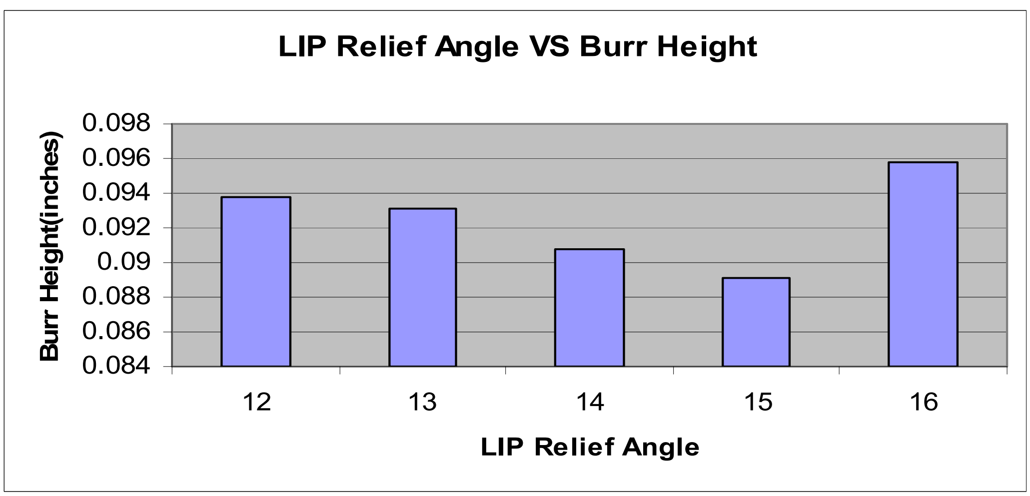
When Lip Relief Angle =16 and Chisel Edge Angle = 125

Appendix P

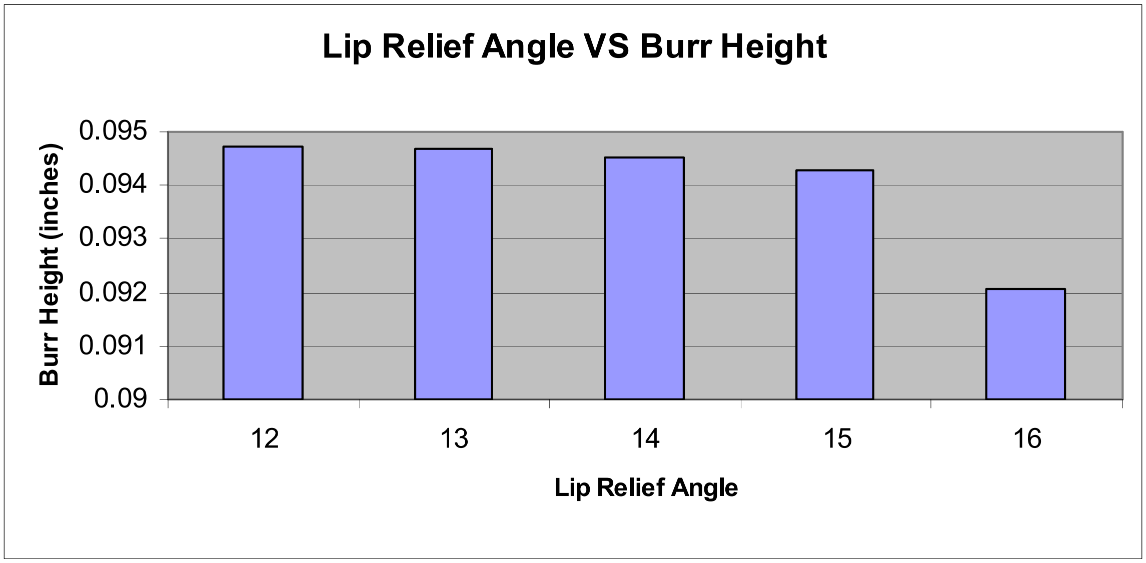
Effect of Lip Relief Angle on Burr Height and Burr Thickness



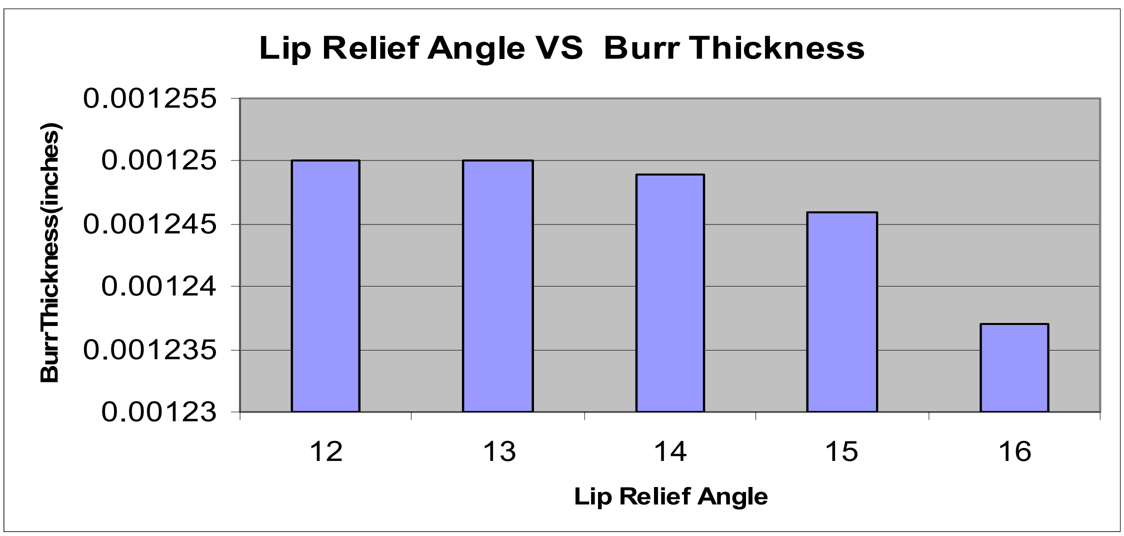
When Point Angle =127 and Chisel Edge Angle = 104



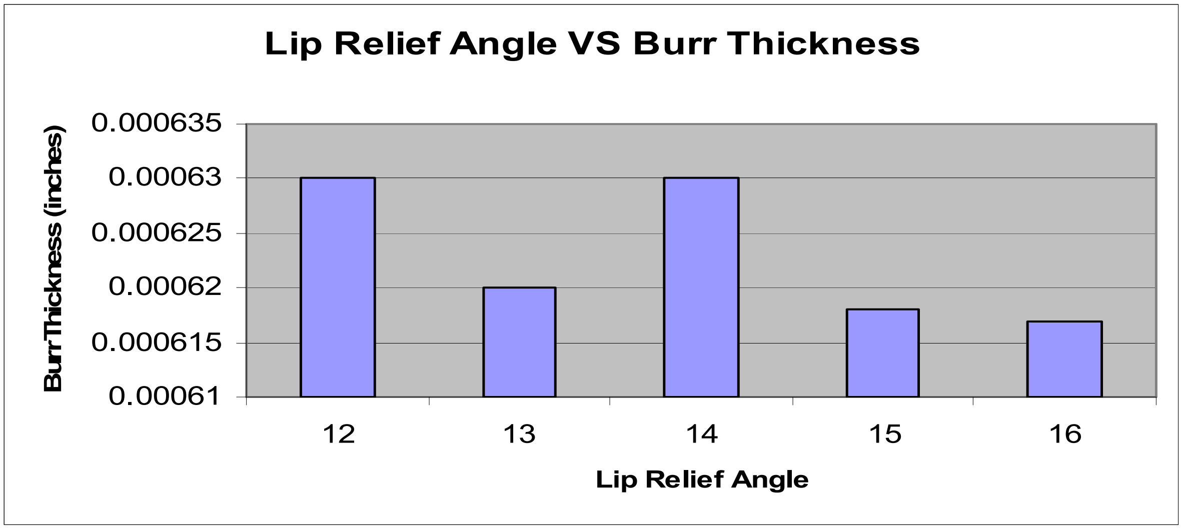
When Point Angle =132 and Chisel Edge Angle = 114



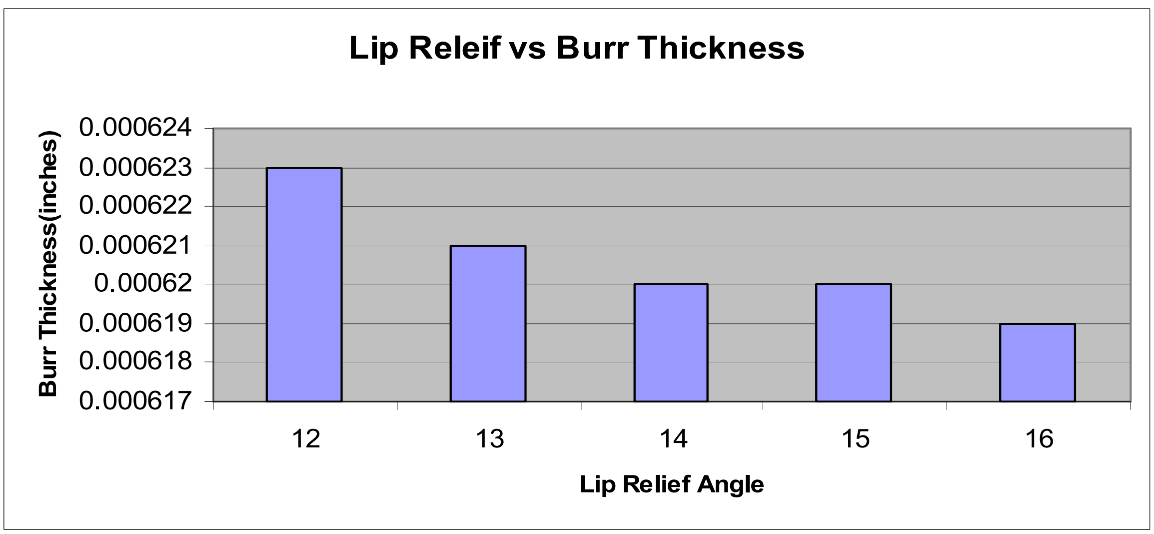
When Point Angle =138 and Chisel Edge Angle = 125



When Point Angle =127 and Chisel Edge Angle = 104



When Point Angle =132 and Chisel Edge Angle = 114



When Point Angle =138 and Chisel Edge Angle = 125

Appendix Q

Recommended Input Parameters for Burr Height

Lip Relief Angle	Point Angle	Chisel Edge Angle	Burr Thickness
13	127	110	0.06479
13	127	111	0.064268
13	**127**	**112**	**0.064225**
13	127	113	0.064495
13	127	114	0.064975

Appendix R

Recommended Input Parameters for Burr Thickness

Lip Relief Angle	Point Angle	Chisel Edge Angle
12	131	108
12	131	109
12	131	110
12	131	111
12	131	112
12	131	113
12	131	114
12	130	108
12	130	109
13	131	111
13	131	112
13	131	113
13	131	114
14	130	109
14	131	109
14	131	110
14	131	111
14	131	112
14	131	113
14	131	114
14	131	115
15	130	107
15	130	108
15	130	109
15	130	110
15	130	111
15	131	108
15	131	109
15	131	110
15	131	111
15	131	112
15	131	113
15	131	114
15	131	115
15	132	111
15	132	112
15	132	113
16	130	105
16	130	106
16	130	107
16	130	108
16	130	109
16	130	110
16	130	111
16	130	112
16	131	105
16	131	106

16	131	107
16	131	108
16	131	109
16	131	110
16	131	111
16	131	112
16	131	113
16	131	114
16	131	115
16	132	107
16	132	108
16	132	109
16	132	110
16	132	111
16	132	112
16	132	113
16	132	114