بسم الله الرحمن الرحيم

Department of Mechanical & Chemical Engineering (MCE)

ISLAMIC UNIVERSITY OF TECHNOLOGY (IUT)

Organisation of Islamic Cooperation

STUDY OF TOOL WEAR & SURFACE ROUGHNESS USING ARTIFICIAL NEURAL NETWORK

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CANDIDATES DECLARATION

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma

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Of course, any errors are ours alone. We seek excuses if there is any mistake found in this report.

ABSTRACT

In any machining operation, tools wear and surface roughness results inaccuracy and inefficiency. So it is always desirable to ensure minimum level of tool wear and surface roughness. Both of them depend on some parameters like feed, spindle speed, depth of cut and operation time. Optimization of these parameters ensures existence of tool wear and surface roughness under the tolerance limit. In this project, our aim is to devise a way of predicting tool wear and surface roughness for a given set of parameters. To do that, we collected experimental results of tool wear and surface roughness for thirty sets of parameters which were selected by Central Composite Rotatable Design (CCRD). Both tool flank and nose wear and surface roughness were measured by taking microscopic images of tool edge and job piece surface after each machining operation and then by using Image Processing Tool of MATLAB. The obtained results were then used for developing Artificial Neural Network (ANN) which was then used for the prediction of tool wear and surface roughness for a given set of parameters. The prediction and actual result were then compared and it was seen that both results coincide with each other

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Chapter 1: Introduction

Turning is a conventional machining process .It is the removal of metal from the outer diameter of a rotating cylindrical work piece. It is used to reduce the diameter of the work piece to a specific dimension and to produce a smooth finish on the metal. Turning is usually done on a conventional lathe machine but now a day, state of the art CNC lathe machines are also used. In a turning operation, the power to turn the work piece at a given rotational speed and to feed the cutting tool at a specified rate and depth of cut is provided by a lathe. The time of operation is very crucial because increase of operation time increases the tool wear and it eventually causes rough surface finish. So there are four parameters in a turning operation. These are

- Spindle Speed,
- Feed
- Depth of cut and
- Operation time

Cutting performance depends on surface roughness, tool flank and noses wear. The cutting parameters mentioned above are the functions of tool wear and surface roughness. So tool wear and surface roughness in a turning operation depends on the selection of spindle speed, feed and depth of cut and operation time. An appropriate selection of these parameters can minimize the tool wear and surface roughness drastically up to a certain extent. So before starting a turning operation, if it can be examined that how much tool wear and surface roughness will be resulted by the set of parameters to be used in that turning operation, we can optimize the parameters to minimize the tool wear and surface roughness. So a system is to be developed to predict the tool wear and surface roughness for a given set of parameters. It can be done in two steps:

1. To conduct a set of experiments using different sets of parameters for each machining operation and then measure the resulted tool wear and surface roughness on each operation.
2. To develop an intelligent system by using these experimental results that is capable of future prediction of tool wear and surface roughness for a given set of parameters.

Numerous advances have been made in developing intelligent systems, some inspired by biological neural networks. Researchers from many scientific disciplines are designing Artificial Neural Networks (ANNs) to solve a variety of problems in pattern recognition, prediction, optimization, associative memory and control.

It has some basic capabilities-

- Massive parallelism,
- Distributed representation and computation,
- Learning ability,
- Generalization ability,
- Adaptively,
- Inherent contextual information processing,
- Fault tolerance, and
- Low energy consumption.

All these properties of ANN are very useful for tool wear and surface roughness study in a turning operation. So it can be selected for the development of the prediction system of tool wear and surface roughness in a turning operation.

1.1 Research Objectives:

This research aims to find a way of predicting tool wear and surface roughness for a given set of parameters by using Artificial Neural Network before starting a turning operation. So the objectives of this research is

1. To conduct a set of experiments using different sets of parameters for each machining operation and then measure the resulted tool wear and surface roughness of that operation.
2. To develop an intelligent system by using these experimental results that is capable of future prediction of tool wear and surface roughness for a given set of parameters

1.2 Organization of the thesis:

To accomplish the objectives, a flow chart was developed to direct all the works sequentially.

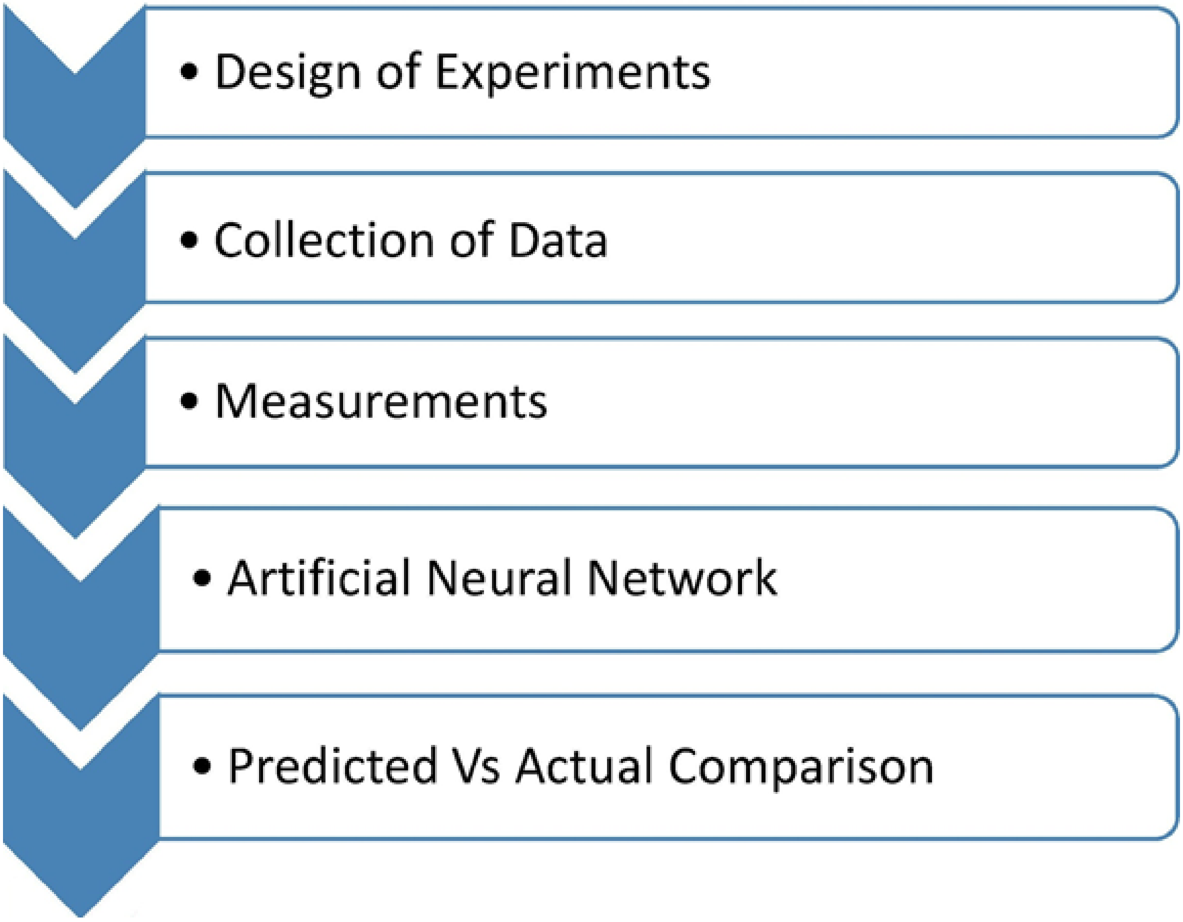


Figure 1: Flow chart of the total project

This thesis comprises of five chapters. Chapter 1 gives a brief overview of the background and concept of this study. Finally, significance of the research and the objectives of this study are summarized. This chapter also outlines the organization of this dissertation.

A comprehensive literature review is given in the Chapter 2, which categorized into four sections. First section summarizes the works done in turning machine in previous days. In the second section, a summary of the works and scopes of Artificial Neural Network is discussed. In the third section, the previous works on turning operation using Artificial Neural Network is discussed. Finally, concluding remarks is given where a brief discussion about the exception of our work than the previous works is mentioned.

Chapter 3 describes the design of experiment. It includes the selection tool and job piece material, type of turning operation (with or without coolant), the use of CCRD of the selection and combination of inputs and the procedure of measuring the tool wear and surface roughness after each operation.

Chapter 4 describes the development and working procedure of Article Neural Network (ANN). It includes how to train ANN, how to test its accuracy acceptability and how to use it for predicting tool wear and surface roughness.

Chapter 5 presents the details design and development of an open loop and a close loop control algorithm for the control of LECD process. It also describes the implementation and the outcome of the control algorithm from the process.

Chapter 6 presents performance analysis of the LECD electrode on austenitic stainless steel (SUS 304) workpiece, a comparative study on four different workpiece materials, a performance comparative study of LECD electrode with circular copper electrode and a process comparative study die sinking EDM of LECD electrode with scanning EDM of a circular copper electrode in fabricating same holes or cavities.

Chapter 2: Literature review

2.1 Existing researches on turning operation

Turning is one the most important machining operation in industries. A significant pool of turning studies has been surveyed in an attempt to achieve better understanding of tool wear, chip formation, surface finish, white layer formation, micro-hardness variation and residual. Stress on the basis of varying tool edge geometry, cooling methods and cutting parameters Most of the works were aimed to find the reasons of tool wear and surface roughness, the parameters related to tool wear and surface roughness and the optimization of these parameters to get minimum tool wear and surface roughness.

Surface roughness generation in a turning operation is examined by using a FFT analyzer. It is found that the roughness profile of a work piece is composed of several periodical components: the cutting tool feed component, the spindle rotational error component, and the chatter vibration error component. To examine the origin of these error components, a series of cutting tests were carried out with different spindle bearing arrangements and with different types of work piece material. (1)

Finite element method (FEM) was used in a work to predict cutting process variables, which are difficult to obtain with experimental methods. In this paper, modeling techniques on continuous chip formation by using the commercial FEM code ABAQUS are discussed. A combination of three chip formation analysis steps including initial chip formation, chip growth and steady-state chip formation is used to simulate the continuous chip formation process. Steady chip shape, cutting force, and heat flux at tool/chip and tool/work interface are obtained. Further, after introducing a heat transfer analysis, temperature distribution in the cutting insert at steady state is obtained. In this way, cutting process variables e.g. contact pressure (normal stress) at tool/chip and tool/work interface, relative sliding velocity and cutting temperature distribution at steady state are predicted. Many researches show that tool wear rate is dependent on these cutting process variables. (2)

A plan of experiments, based on the techniques of Taguchi, was designed and executed on controlled machining with cutting conditions prefixed in work pieces. Afterwards, the roughness was evaluated on work pieces using two different profilometers. The objective was to establish a correlation between cutting velocity, feed and depth of cut with the roughness evaluating parameters R_a and R_t, following the international norms. These correlations were obtained by multiple linear regressions. Finally, confirmation tests were performed to make a comparison between the results predicted from the mentioned correlations and the theoretical results. (3)

No of works are also done on The reason and effect of Residual stress in the hard machined surface. Residual stresses in the hard machined surface and the subsurface are affected by materials, tool geometry and machining parameters. These residual stresses can have significant effect on the service quality and the component life. They can be determined by either empirical or numerical experiments for selected configurations, even if both are expensive procedures. The problem becomes more difficult if the objective is the inverse determination of cutting conditions for a given residual stress profile. This paper presents a predictive model based on the artificial neural network (ANN) approach that can be used both for forward and inverse predictions. The three layer neural network was trained on selected data from chosen numerical experiments on hard machining of 52100 bearing steel, and then validated by comparing with data from numerical investigations (other than those used for training), and empirical data from published literature. Prediction errors ranged between 4 and 10% for the whole data set. Hence, this ANN based regression approach provided a robust framework for forward analysis. (4)

Experiments have been carried out in an attempt to monitor the change of workpiece surface roughness caused by the increase of tool wear, through the variation of the vibration in finish turning, under different cutting conditions. The vibration was measured by two accelerometers attached to the tool and the parameter used to make the correlation with surface roughness was the r.m.s. of the signal. The tool of one experiment was photographed at different stages of the cut in order to explain the wear formation and the behavior of surface roughness as the cutting time elapsed. The material machined was AISI 4340 steel and the tool was coated carbide inserts. The results show that vibration of the tool can be a good way to monitor on-line the growth of surface roughness in finish turning and, therefore, it can be useful for establishing the end of tool life in these operations. Another conclusion is that, when coated tools are used, the behavior of surface roughness as cutting time elapses is very different from that when uncoated tools are used. (5)

The effects of cutting parameters are studied in many times. The process of turning is influenced by many parameters such as the cutting velocity, feed rate, depth of cut, geometry of cutting tool cutting conditions etc. The finished product with desired attributes of size, shape, and surface roughness and cutting forces developed are functions of these input parameters. Properties wear resistance, fatigue strength, coefficient of friction, lubrication, wear rate and corrosion resistance of the machined parts are greatly influenced by surface roughness. Forces developed during cutting affect the tool life hence the cost of production. In many manufacturing processes engineering judgment is still relied upon to optimize the multi-response problem. Therefore multi response optimization is used in this study to optimization problem to finds the appropriate level of input characteristics.(6)
In this project ,the optimal setting of cutting parameters cutting velocity (N) , depth of cut(d) , feed(f) and variation in principal cutting edge angle (Φ) of the tool to have a minimum cutting force and surface roughness(Ra) were evaluated through experiments.

From these works mentioned above, it is clear that the tool wear and surface roughness in turning operation depends on some parameters like feed, depth of cut, Spindle speed, vibration, forces developed during cutting.

2.2 Use of Artificial Neural Network in various fields and its effectiveness

Artificial neural network is a prediction tool. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data are able to deal with non-linear problems and, once trained, can perform prediction and generalization at high speed. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, medicine, power systems, and manufacturing, and optimization, signal processing and social/psychological sciences. They are particularly useful in system modeling such as in implementing complex mappings and system identification. (7)

One thesis was published on IEEE journal in which artificial neural network (ANN) was introduced for electric load forecasting. The ANN is used to learn the relationship among past, current and future temperatures and loads. In order to provide the forecasted load, the ANN interpolates among the load and temperature data in a training data set. The average absolute errors of the 1 h and 24 h ahead forecasts in tests on actual utility data are shown to be 1.40% and 2.06%, respectively. This compares with an average error of 4.22% for 24 h ahead forecasts with a currently used forecasting technique applied to the same data. (8)

Artificial neural network techniques were also applied for modeling and monitoring of machining processes (turning, milling) by sensor integration. Back propagation networks are used for tools classification, tool wear estimation and inverse modeling of the cutting process. Special emphasis is placed on the incorporation of the varying cutting conditions into the learning phase and solutions, which are based upon normal operation, i.e. cutting with sharp tools. Performances of the developed strategies are demonstrated and compared with the practical analysis. (9)

Artificial Neural Network is also used in Image processing works. A Neural network based artificial vision system able to analyze the image of a car given by a camera, locate the registration plate and recognize the registration number of the car was used for license plate recognition of cars. (10)

Not only in engineering field, artificial Neural Network is also being widely used in medical science. Now a day, Artificial Neural Network is extensively used in Clinical decision making, diagnosis, risk and success rate analysis. In these cases, previous data is used for prediction and various decisions making works. (11)

In recent years, Artificial Neural network is widely used in Industries for forecasting, decision making, and machine life calculation, resource and time requirements for various operations, and performance and productivity analysis of the workers. All these things are done taking the help of previous data to train the Neural Network and then use them in further decision making. (12)

From the above, we can come into the conclusion that Artificial Neural Network is a milestone in artificial intelligence. It made the prediction and decision making by Artificial Intelligence more accurate and easier. It can be used in variety of fields and the performance is remarkable.

2.3 Works done on turning operation using Artificial Neural Network

Artificial Neural network is widely used in predicting tool wear, surface roughness and dimensional deviation in turning operation. Most of the prediction was based on some parameters on which tool wear and surface roughness are dependent.

Factors such as cutting force, cutting temperature and vibration signals can be effectively used to predict tool wear. Even though, each of these factors can be used individually to predict tool wear. A regression model and an artificial neural network model were used to predict the tool flank wear. Here cutting force, cutting temperature and displacement of tool vibration signals are effectively used in predicting the tool flank wear .It is found that neural network is superior to the regression model in its ability to predict tool wear. (13)

Surface quality is the most important requirement of part manufacturing because the most important part is meeting the specific requirements of customers. So number of works was done to improve the surface quality by minimizing the surface roughness. It is found out through investigation that the surface roughness depends on three parameters which are cutting speeds of (45, 90, and 135 m/min), feed rate of (0.1, 0.2, and 0.3 mm/rev), and cut depth of (0.05, 0.1, and 0.15 mm). Thus to determine the optimal levels of parameters which gives minimum surface roughness, Neural Network (ANN) was used .The improvement of surface quality was remarkable. (14)

For automatic turning operation, prediction of surface finish and dimensional deviation is an essential prerequisite. In a work on surface finish, it is found that using neural network, surface finish can be predicted within a reasonable degree of accuracy by taking the acceleration of radial vibration of tool holder. It was observed that improves with increasing feed up to some feed where from it starts deteriorating with further increase of feed while turning the steel rod with Tin coated carbide tool, This type of behavior is not observed in turning with HSS tool. Hence, neural network prediction models were developed separately for both cases. Factors like Radial component of cutting force and acceleration of radial vibration were taken to predict dimensional deviation. In the Neural Network, both dry and wet cutting conditions were taken as two different factors. (15)

A number of works were done on the effect of tool wear on surface roughness. Surface roughness increases with the increase of tool wear. So, neural networks were used to predict the surface roughness by using a set of previously collected data of tool wear and surface roughness. Further investigation found that tool wear and surface roughness has the same factors like cutting speed, depth of cut, feed etc.

An investigation on inaccuracy in turning operation found that the main source of inaccuracy in production is machine tool errors. Positional, geometrical, and thermally induced errors of machine tools are responsible for inaccurate turning operation. So, neural network was used to predict the machine tool errors during a turning operation. By predicting, machine tool errors were minimized and accuracy of the turning operation was improved. (16)

So from the above ,it is seen that a number of successful works were performed on turning operation by identifying the parameters responsible for tool wear, surface roughness, inaccurate machining and by using the Artificial Neural Network as a prediction tool.

2.4 Concluding remarks

It was mentioned earlier that that our aim is to predict the tool wear and surface roughness in turning operation using the Artificial Neural Network. A number of works were done on turning machine incorporating Neural Network with it. Most of the works focused on finding the tool wears, surface roughness, inaccurate machining which are caused by parameters like feed, depth of cut, cutting speed, vibration and the geometrical and positional error of machine tool. But in our project of finding out tool wear and surface roughness, we are using four parameters, two of them are widely used which are feed and depth of cut. Other parameters are spindle speed (N) and Time of operation.

We know cutting speed,

$V= \pi DN/60$

D=Diameter, N=Spindle speed

So it is clear that when the diameter is constant, cutting speed (V) is directly proportional to spindle speed (N). In our experiment, the job piece diameters were almost same so we can consider the diameter as constant and in spite of using cutting speed as a parameter, we can use Spindle speed. Our intention to do that is there are various machining operations where diameter of the job pieces remains constant. So for those cases, our project work can be a good resource.

In high speed turning operations, the more the time of operation, the more the tool and job piece will be heated. There are various metallurgical properties like hardness and toughness which are influenced by the heat generated during machining. It has a direct effect on the tool wear and surface roughness. So the time of operation can also be considered as a parameter of tool wear and surface roughness.

Besides, the surface roughness is traditionally measured by Profilometer. But in our project, we first took the microscopic images of the job piece surfaces and then used the Image Processing Tool of MATLAB to find out the surface roughness.

In our project, we measured both the tool flank and nose wear. Previous tool wear predictions focused only on nose wear. Our aim was to find out both kinds of wear so that it can be identified in the future that that which kind of tool wear is more crucial for tool life.

In most of the turning operations, coolant is used to control the temperature of the cutting tool and job piece. As our goal was to analyze the effect of machining time on tool wear and surface roughness, we used dry cut. Unlike the wet cut condition, temperature of the tool and job piece will increase with the time of operation and the effect of the time of machining can be studied.

Chapter 3: Experimental Design

In this project, our aim is to predict the tool wear and surface roughness. It is obvious that the more data we will use, the better prediction we will get. But we have limitation of time and resource. Besides, a huge number of operations will cause inefficiency of the whole project. To get rid of these problems, experimental designing was done. It is widely used in many processes for controlling the effect of parameters. Its usage decreases the number of experiments, using time and material resource.

3.1 Design of experiment

Table 1: Design of experiments

Parameters	Symbols	Levels				
		-2	-1	0	1	2
1. Feed rate (mm/sec)	X1	.12	.24	.33	.43	.56
2. Spindle Speed (RPM)	X2	140	220	360	530	860
3. Depth of Cut (mm)	X3	.1	.2	.3	.4	.5
4. Time of operation (min)	X4	6	8	10	12	14

3.2 Central Composite Rotatable Design (CCRD)

The experimental design techniques commonly used for process analysis and modeling are the full factorial, partial factorial and central composite rotatable designs. A full factorial design requires at least three levels per variable to estimate the coefficients of the quadratic terms in the response model. Thus for the four independent variables 81 experiments plus replications would have to be conducted. A partial factorial design requires fewer experiments than the full factorial. However, the former is particularly useful if certain variables are already known to show no interaction. An effective alternative to the factorial design is the central composite rotatable design (CCRD), originally developed by Box and Wilson and improved upon by Box and Hunter. The CCRD gives almost as much information as a three-level factorial, requires much fewer tests than the full factorial and has been shown to be sufficient to describe the majority of steady-state process responses. The number of tests required for the CCRD includes the standard 2k factorial with its origin at the center, 2k points fixed axially at a distance, say b, from the center to generate the quadratic terms, and replicate tests at the center; where k is the number of variables. The axial points are chosen such that they allow rotatability, which ensures that the variance of the model prediction is constant at all, points equidistant from the design center. Replicates of the test at the center are very important as they provide an independent estimate of the experimental error. For four variables, the recommended number of tests at the center is six.

3.3 Cutting Tool and work piece material:

In all experiments, same cutting tool and work piece material were used. All the experiments were performed in manual lathe machine. The experiments were conducted as a dry cut i.e. in the absence of any coolant.

Tools: Tungsten Carbide inserts (Toshiba T-20, 87.53% tungsten and 12.47 % carbide)

Work piece: Stainless Steel

3.4 Conduction of experiment and measurement of tool wear and surface roughness

By using CCRD, we found out that for four variables, we need to conduct thirty experiments. The CCRD itself also can combine the parameters ta produce thirty sets of parameters. These thirty sets of parameters were used as inputs in the lathe machine. Like for the set number 1- the fee is .24 mm/sec, spindle speed is 220 rpm, depth of cut is 0.2 mm and the operation time is 8 minute. By setting these values of feed, spindle speed and depth of cut, the first turning operation was done in the lathe machine for 8 minutes. Then the images of the cutting tool edge and job piece surface were taken by microscope. The same procedure was repeated for each set of parameters. In this way, thirty set of inputs were used to conduct thirty operations and after each operation, images of tool nose and flank and job piece surface was taken.

After taking all the images, Image processing tool of MATLAB was used to measure the tool wear and surface roughness. Image processing tool develops a graph for the deviation of the tool cutting edge and the job piece surface. Then it takes the average deviation as the tool wear and surface roughness.

These tool wear and surface roughness results are our output. By using this result, the final table was built which was then used for developing the machine learning algorithm.

Table 2: CCRD layout

S.No.	X_1	X_2	X_3	X_4
1	-1	-1	-1	-1
2	1	-1	-1	-1
3	-1	1	-1	-1
4	1	1	-1	-1
5	-1	-1	1	-1
6	1	-1	1	-1
7	-1	1	1	-1
8	1	1	1	-1
9	-1	-1	-1	1
10	1	-1	-1	1
11	-1	1	-1	1
12	1	1	-1	1
13	-1	-1	1	1
14	1	-1	1	1
15	-1	1	1	1
16	1	1	1	1
17	-2	0	0	0
18	2	0	0	0
19	0	-2	0	0
20	0	2	0	0
21	0	0	-2	0
22	0	0	2	0
23	0	0	0	-2
24	0	0	0	2
25	0	0	0	0
26	0	0	0	0
27	0	0	0	0
28	0	0	0	0
29	0	0	0	0
30	0	0	0	0

Table 3: Set of Inputs

Serial No	Inputs			
	Feed (mm)	Spindle Speed (RPM)	Depth of Cut (mm)	Time of Operation (min)
1.	.24	220	.2	8
2.	.43	220	.2	8
3.	.24	530	.2	8
4.	.43	530	.2	8
5.	.24	220	.4	8
6.	.43	220	.4	8
7	.24	530	.4	8
8	.43	530	.4	8
9	.24	220	.2	12
10	.43	220	.2	12
11	.24	530	.2	12
12	.43	530	.2	12
13	.24	220	.4	12
14	.43	220	.4	12
15	.24	530	.4	12
16	.43	530	.4	12
17	.12	360	.3	10
18	.56	360	.3	10
19	.33	140	.3	10
20	.33	160	.3	10
21	.33	360	.1	10
22	.33	360	.5	10
23	.33	360	.3	6
24	.33	360	.3	14
25	.33	360	.3	10
26	.33	360	.3	10
27	.33	360	.3	10
28	.33	360	.3	10
29	.33	360	.3	10
30	.33	360	.3	10

Table 4: Outputs collected for the input

Serial No	Inputs				Outputs		
	Feed (mm)	Spindle Speed (RPM)	Depth of Cut (mm)	Time of Operation (min)	Surface Roughness (µm)	Nose Wear (µm)	Flank Wear (µm)
1.	.24	220	.2	8	1.59663	5.45962	6.02404
2.	.43	220	.2	8	1.21875	5.58173	5.82548
3.	.24	530	.2	8	1.21010	4.56298	5.95481
4.	.43	530	.2	8	0.8.0577	4.48125	4.89712
5.	.24	220	.4	*8*	*1.51538*	6.26923	6.75240
6.	.43	220	.4	8	15.2584	59.6325	69.1235
7	.24	530	.4	8	1.62545	5.66921	6.78326
8	.43	530	.4	8	1.69904	4.92885	7.10721
9	.24	220	.2	12	0.14274	0.685144	0.67750
10	.43	220	.2	12	1.08846	6.25962	7.39808
11	.24	530	.2	12	1.30673	6.53462	6.65817
12	.43	530	.2	12	0.92933	0.79.394	7.7163
13	.24	220	.4	12	1.46106	5.68173	6.86442
14	.43	220	.4	12	1.31394	6.69519	7.02536
15	.24	530	.4	12	1.19135	7.32356	7.11298
16	.43	530	.4	12	1.80865	5.25817	6.12019
17	.12	360	.3	10	1.21253	5.50385	6.60913
18	.56	360	.3	10	1.17500	5.92548	6.70096
19	.33	140	.3	10	1.04423	5.77404	5.87596
20	.33	160	.3	10	1.62452	5.68173	6.40769
21	.33	360	.1	10	1.06731	5.71346	6.45144
22	.33	360	.5	10	1.08606	5.09135	6.43365
23	.33	360	.3	6	1.13606	6.26875	7.35865
24	.33	360	.3	14	1.18077	5.17115	7.25337
25	.33	360	.3	10	1.27067	5.18942	6.79952
26	.33	360	.3	10	1.15577	6.23606	6.44375
27	.33	360	.3	10	1.19712	5.38269	5.87356
28	.33	360	.3	10	1.19823	5.77933	5.92308
29	.33	360	.3	10	1.49760	5.71442	6.56538
30	.33	360	.3	10	1.44904	6.21250	6.59135

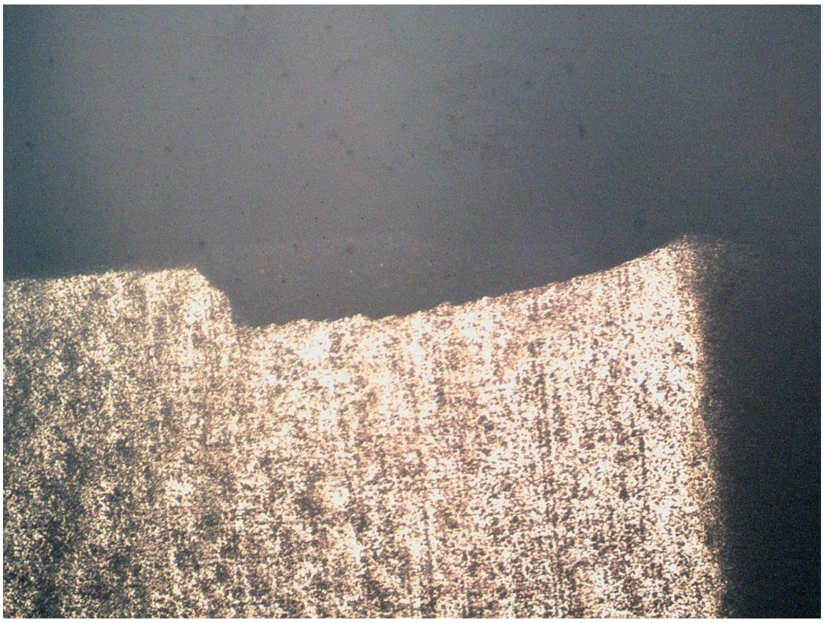


Figure 2: Noses wear for feed-0.24mm/sec, speed-220rpm, depth of cut-0.2mm, Operating time-8min

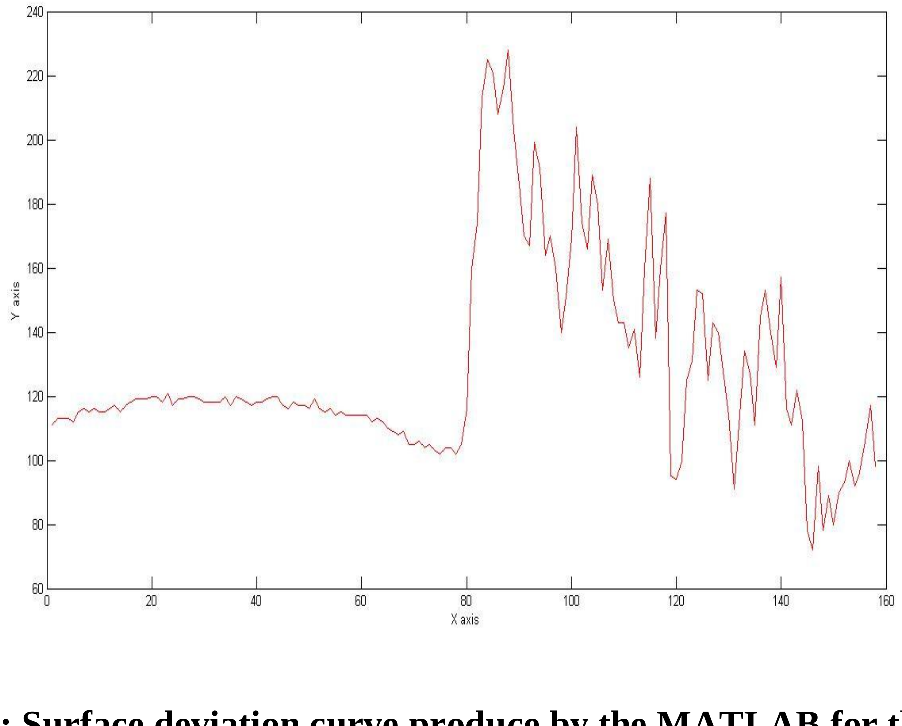


Figure 3: Surface deviation curve produce by the MATLAB for the image shown above

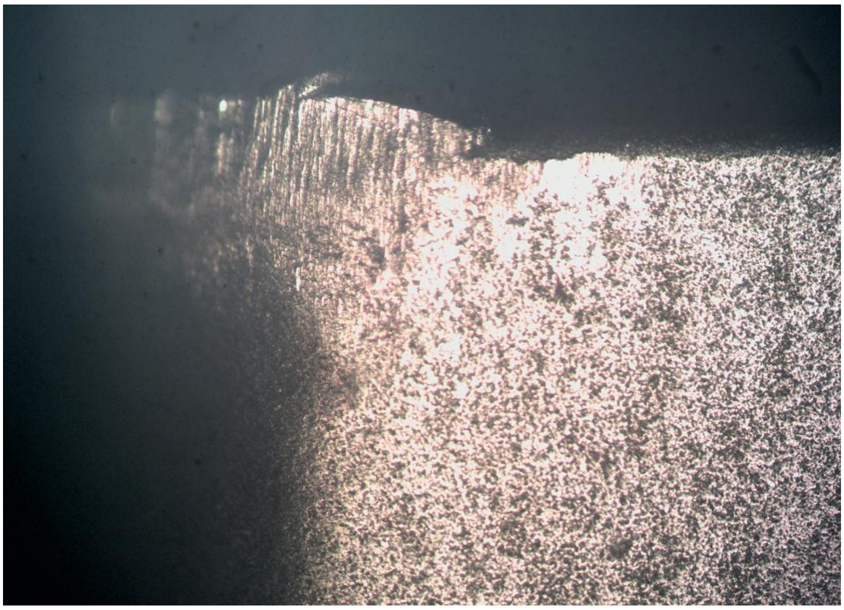


Figure 4: Flank wear for feed-0.43mm/sec, spindle speed-220 rpm, depth of cut-0.2 mm, Operating time-12 min

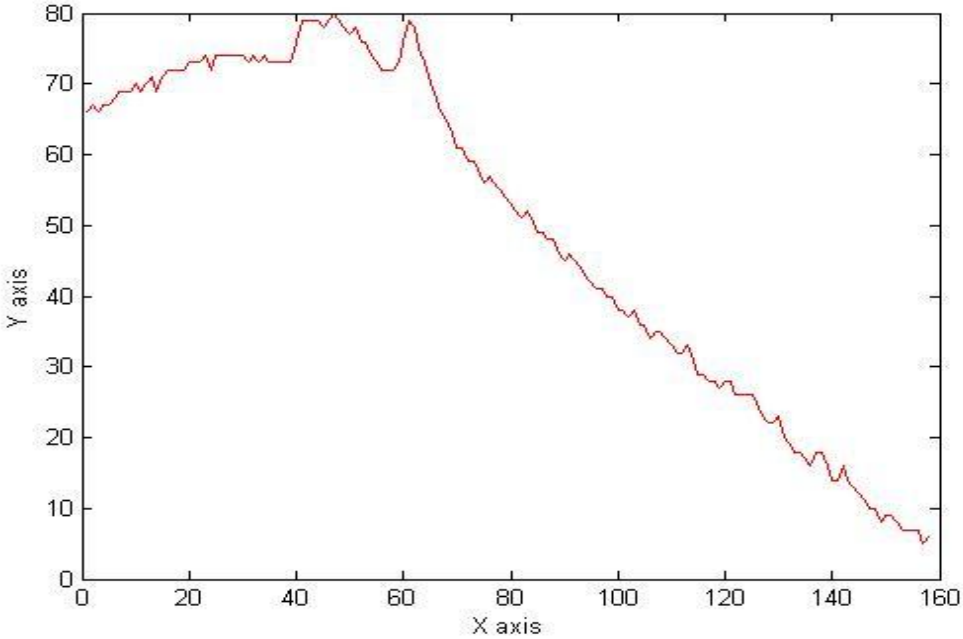


Figure 5: Surface deviation curve produce by the MATLAB for the image shown above

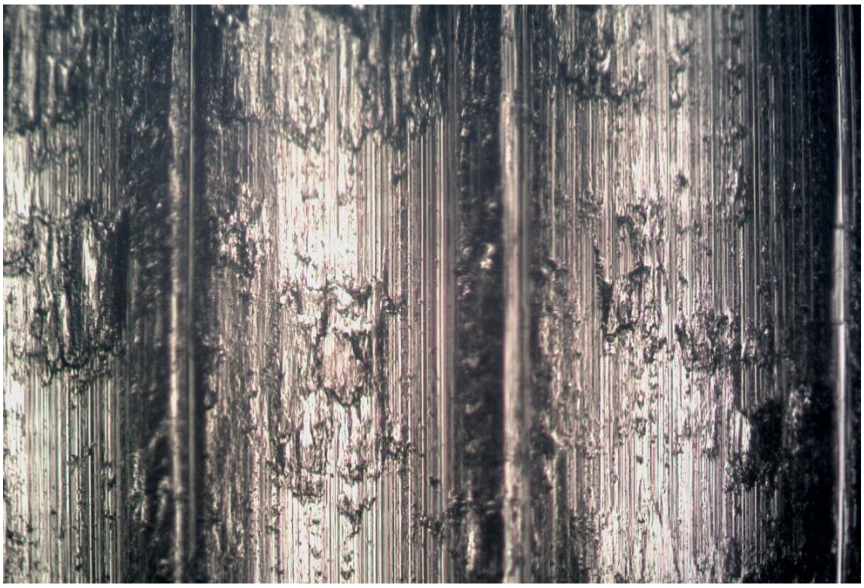


Figure 6: Surface roughness forfeed-0.43mm, spindle speed-220rpm,

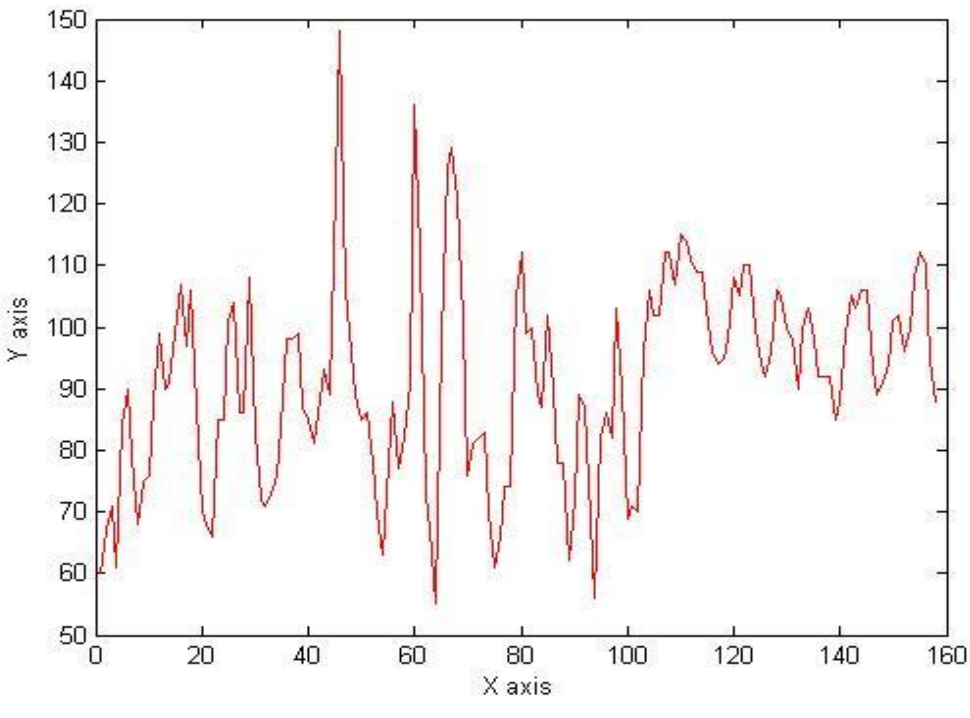


Figure 7: Surface deviation curve produce by the MATLAB for the image shown above

Chapter 4: Artificial neural network

An Artificial Neural Network is a mathematical model inspired by biological neural networks. This consists of an interconnected group of artificial neurons which processes information using a connectionist approach to computation. In most cases a neural network is an adaptive system that changes its structure during a learning phase. Neural networks are used to model complex relationships between Inputs and outputs or to find patterns in data.

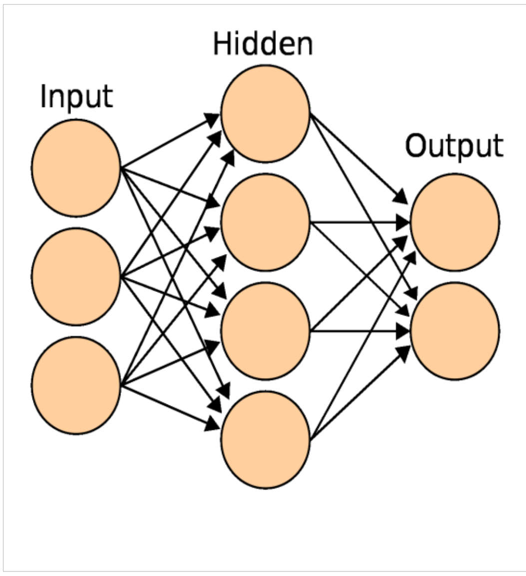


Figure 8: Diagram of Artificial Neural Network

The inspiration of artificial neural network came from central nervous system of human being. It is an artificial network of artificial nodes called neurons, which mimics a biological neural network. There is no single formal definition of what an artificial neural network is. Generally, it involves a network of simple processing elements that exhibit complex global behavior determined by the connections between the processing elements and element parameters. Artificial neural networks are used with algorithms designed to alter the strength of the connections in the network to produce a desired signal.

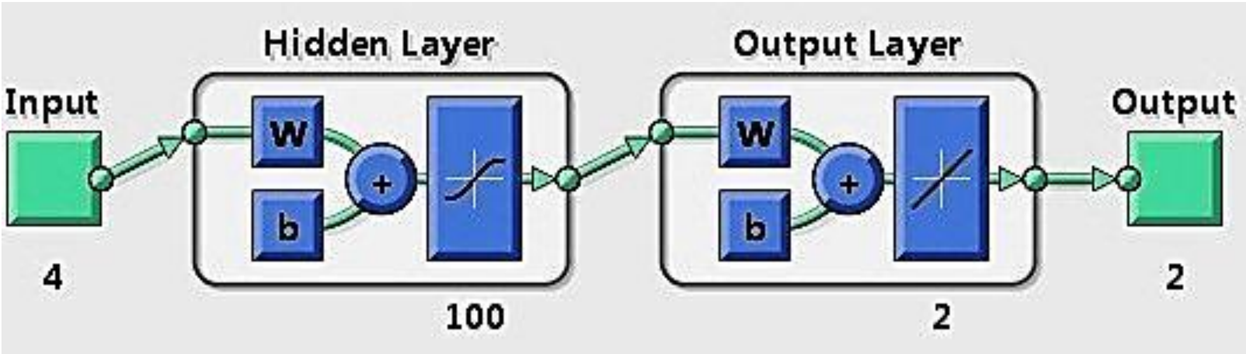


Figure 9: Illustration of Input-hidden-output Layers

4.1: Model of Neural Network:

Neural network models in artificial intelligence are usually referred to as artificial neural networks (ANNs); these are essentially simple mathematical models defining a function $f:X \to Y$ or a distribution over X or Y both sometimes models are also intimately associated with a particular learning algorithm or learning rule. A common use of the phrase ANN model really means the definition of a class of such functions (where members of the class are obtained by varying parameters, connection weights, or specifics of the architecture such as the number of neurons or their connectivity).

4.2: Network function

The word network in the term 'artificial neural network' refers to the inter–connections between the neurons in the different layers of each system. An example system has three layers. The first layer has input neurons, which send data via synapses to the second layer of neurons, and then via more synapses to the third layer of output neurons. More complex systems will have more layers of neurons with some having increased layers of input neurons and output neurons. The synapses store parameters called "weights" that manipulate the data in the calculations.

4.3: ANN is defined by three types of parameters:

1. The interconnection pattern between different layers of neurons.
2. The learning process for updating the weights of interconnection.
3. The activation function that converts Neuron's weighted input to its output activation.

The whole network consists of many simple task doing elements which is called neurons. These neurons are connected by communication links associated with weight. These weights confirm information being used in the net to find a solution for the problem. Neural network which are created can be used to solve problem, find patterns, or even finding solution with given constraints. Each of these neurons has its activation level which is a function of the inputs given to it. Normally, a neuron passes its information by signaling to several neurons. Although it is the fact that one neuron can send only one signal which later will be transmitted to several neurons.

Training an ANN can be done by adjusting the values of the weights/connection. Normally, networks are specified in a manner that input leads to specific target output. In such condition, network is adjusted, based on comparing the output and the target, until the network output matches the target. Typically many such inputs pairs are used, in this supervised learning to train the network.

4.4: Steps involved in developing ANN model:

Steps in the development of ANN model for turning process are:

Step 1: Collection of Data.
Data from the experiment are collected.

Step 2: Separate into training and test data.
Data collected are separated into two sets for training and test on ANN. Total 20 data set are used in training and to test ANN rest 10 data are used. It is given on the table.

Table 5: Data set for Neural Network Training

Serial No	Inputs				Outputs		
	Feed (mm)	Spindle Speed (RPM)	Depth of Cut (mm)	Time of Operation (min)	Surface Roughness (µm)	Nose Wear (µm)	Flank Wear (µm)
1.	.24	220	.2	8	1.59663	5.45962	6.02404
2.	.43	220	.2	8	1.21875	5.58173	5.82548
3.	.24	530	.2	8	1.21010	4.56298	5.95481
4.	.43	530	.2	8	0.8.0577	4.48125	4.89712
5.	.24	220	.4	8	1.51538	6.26923	6.75240
6.	.43	220	.4	8	15.2584	59.6325	69.1235
7	.24	530	.4	8	1.62545	5.66921	6.78326
8	.43	530	.4	8	1.69904	4.92885	7.10721
9	.24	220	.2	12	0.14274	0.685144	0.67750
10	.43	220	.2	12	1.08846	6.25962	7.39808
11	.24	530	.2	12	1.30673	6.53462	6.65817
12	.43	530	.2	12	0.92933	0.79.394	7.7163
13	.24	220	.4	12	1.46106	5.68173	6.86442
14	.43	220	.4	12	1.31394	6.69519	7.02536
15	.24	530	.4	12	1.19135	7.32356	7.11298
16	.43	530	.4	12	1.80865	5.25817	6.12019
17	.12	360	.3	10	1.21253	5.50385	6.60913
18	.56	360	.3	10	1.17500	5.92548	6.70096
19	.33	140	.3	10	1.04423	5.77404	5.87596
20	.33	160	.3	10	1.62452	5.68173	6.40769

Table 6: Data set for Neural Network testing

Serial No	Inputs				Outputs		
	Feed (mm)	Spindle Speed (RPM)	Depth of Cut (mm)	Time of Operation (min)	Surface Roughness (μm)	Nose Wear (μm)	Flank Wear (μm)
1.	.33	360	.1	10	1.06731	5.71346	6.45144
2.	.33	360	.5	10	1.08606	5.09135	6.43365
3.	.33	360	.3	6	1.13606	6.26875	7.35865
4.	.33	360	.3	14	1.18077	5.17115	7.25337
5.	.33	360	.3	10	1.27067	5.18942	6.79952
6.	.33	360	.3	10	1.15577	6.23606	6.44375
7	.33	360	.3	10	1.19712	5.38269	5.87356
8	.33	360	.3	10	1.19823	5.77933	5.92308
9	.33	360	.3	10	1.49760	5.71442	6.56538
10	.33	360	.3	10	1.44904	6.21250	6.59135

Step -3: Define a network structure

Set up a network topology. Here for turning operation problem, the neural network developed is fully connected feed forward multilayer perception. The input and output variables are organized into the input layer and the output layer nodes. The total number of input nodes is 4. Number of output node is three. For obtaining the network structure, the number of hidden layers and number of nodes in each hidden layer are to be defined and also the transfer function of each processing element are defined which is shown in Table 3

Table 7: Details of defined Neural Network

Network:1	No. of Neurons	Transfer function
Input layer	4	Tansig
Hidden layer	100	Tansig
Output layer	3	Pureln

The weight and biases of the network connections are randomly initialized, before start training.

Step 4: Select a Learning Algorithm

Feed forward back propagation learning algorithm is used as the learning mechanism for the defined neural network. This rule changes the connection weights in the way that minimizes the mean squared error of the network.

Step 5: Start training

Present the training pair of input and output to the back-propagation neural network. If the system error is reached before the end of available iterations, the error value is presented and training is stopped. If the network is unable to reach the error value at the end of iterations, then error value is presented for further training. If the network has learned the mapping between input and output, start testing.

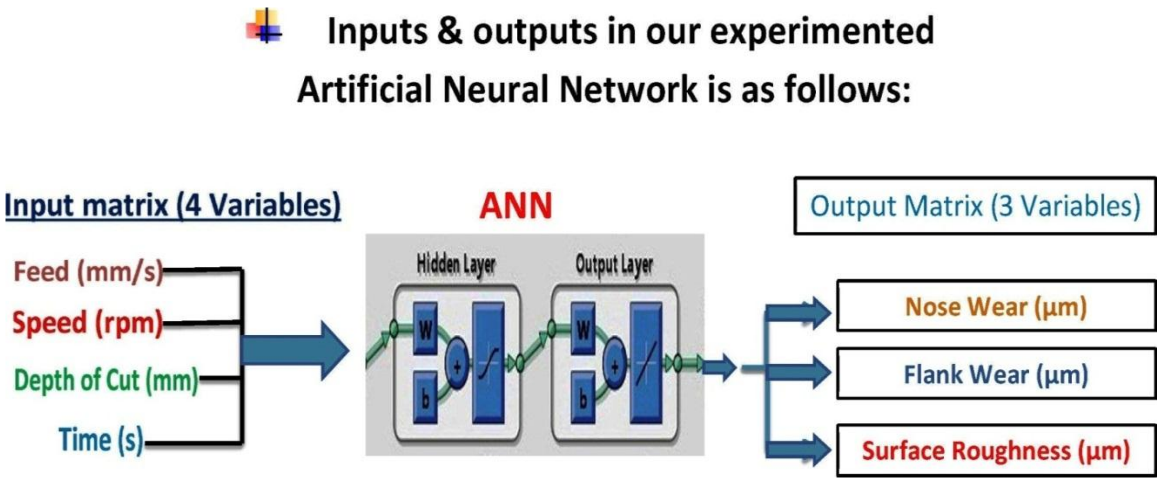


Figure 10: Inputs and output of the Artificial Neural Network

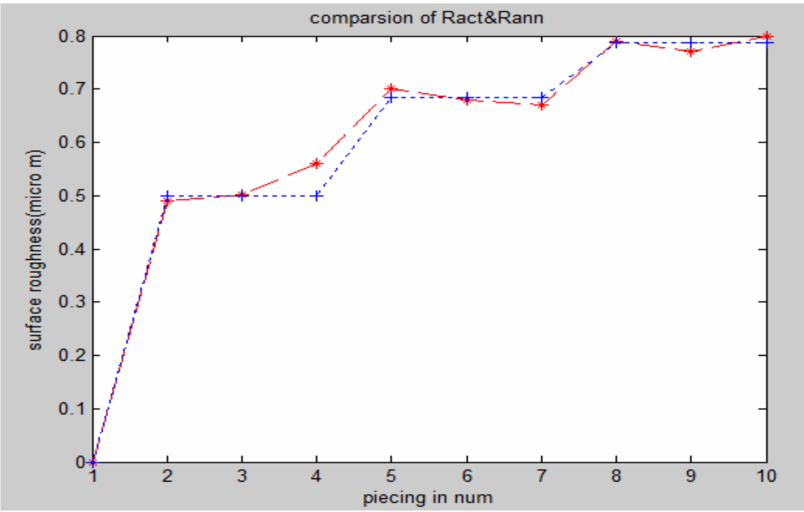


Figure 11: Comparison of Actual roughness versus Roughness predicted through ANN

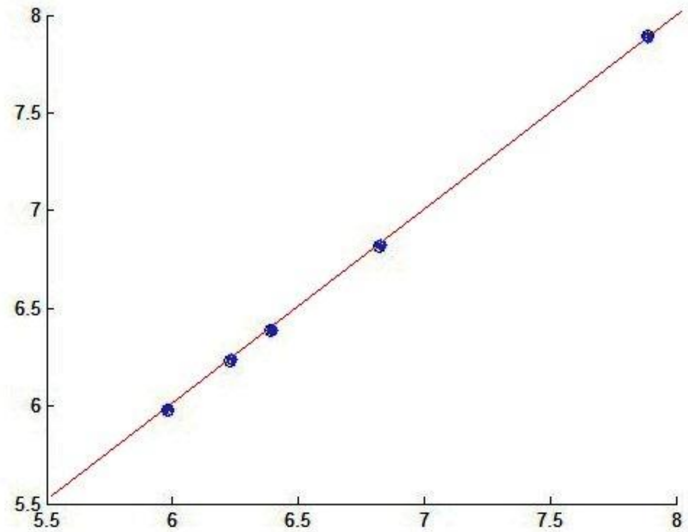


Figure 12: Comparison of actual Nose tool wear versus Nose tool wear predicted by ANN

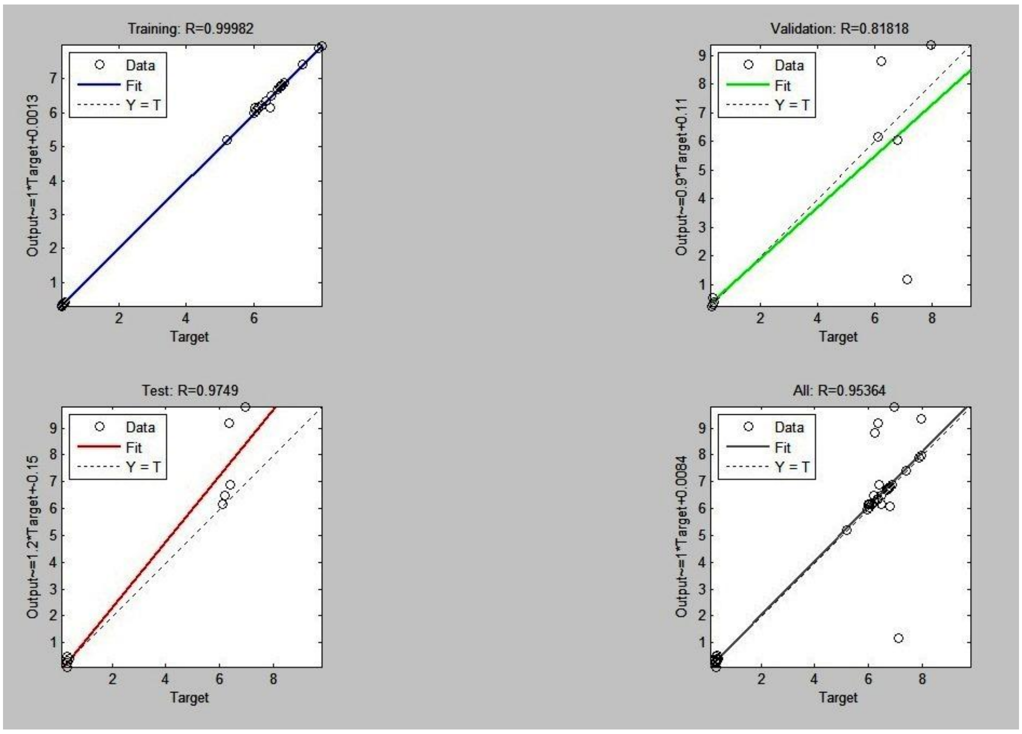


Figure 13: Performance curve for training-testing-validation data set for ANN

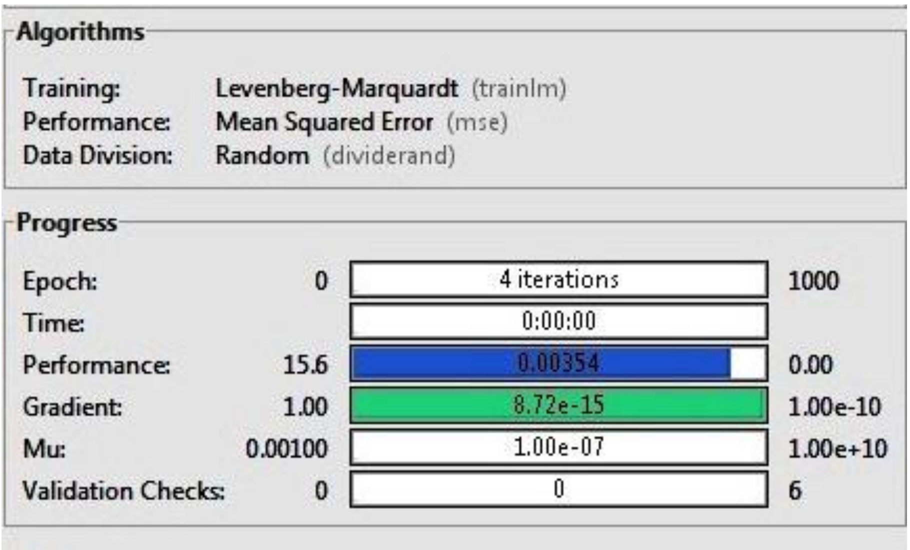


Figure 14: Validation checks trained Artificial Neural Network for selected Epoch

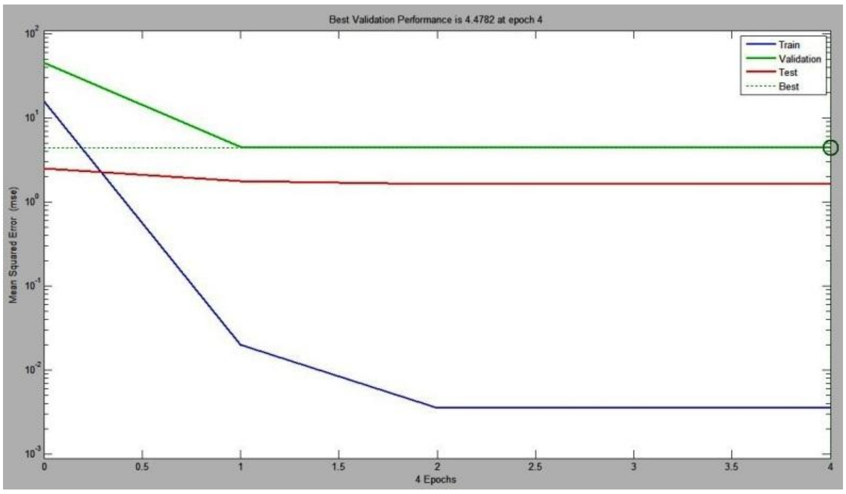


Figure 15: Best validation attained at 4 epochs

4.5: Selection of neural number

It has been seen that that the Artificial Neural Network performance improved with the increase of Neurons. At first 20 neurons were used and it was seen that performance of the neural network is poor. Then 50 neurons were taken and a better performance was observed. After that, 100 neurons were taken and the prediction result was satisfactory. With 500 neurons, the error in prediction became very minimum.

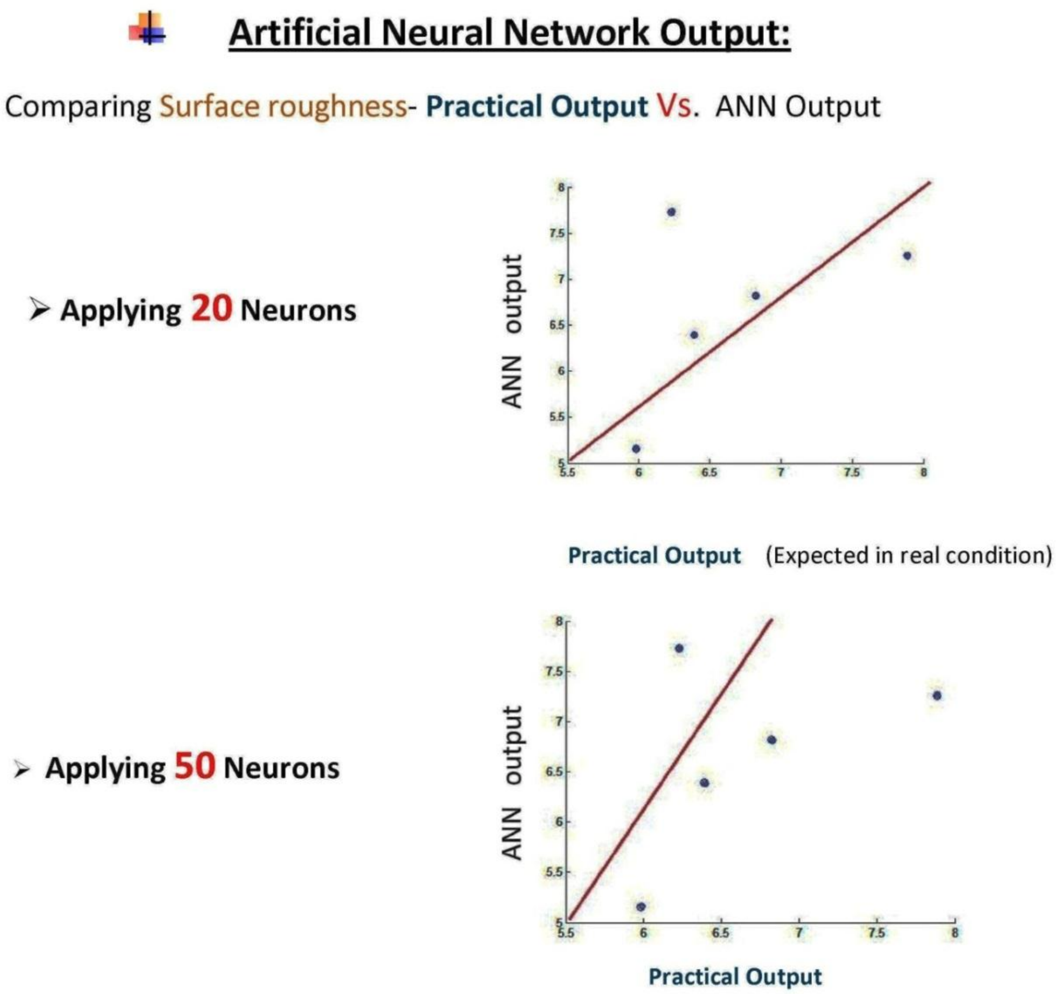
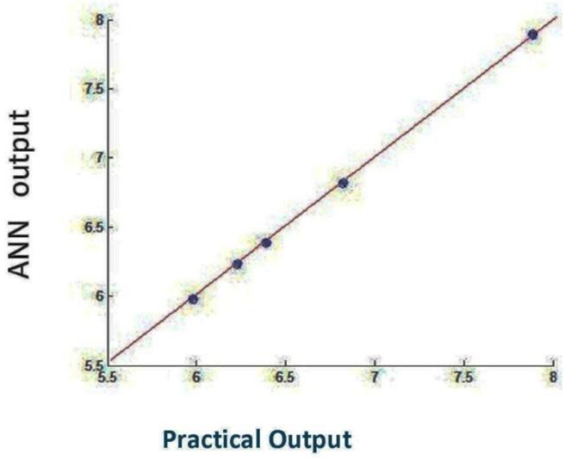


Figure 16: Predicted Vs. Actual output using 20 and 50 neurons respectively

Artificial Neural Network Output:

Comparing **Surface roughness** - **Practical Output Vs.** ANN Output

- **Applying 100 Neurons**



- **Applying 500 Neurons**

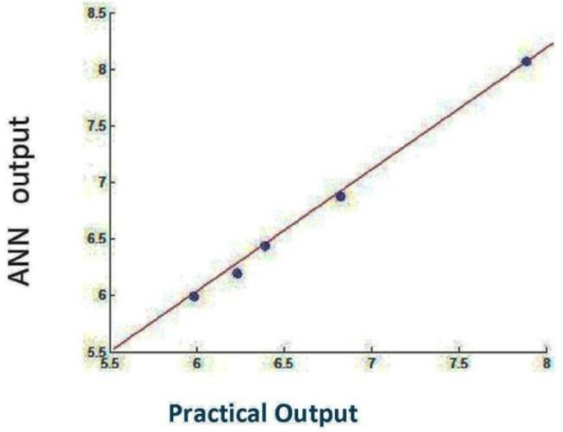


Figure 17: Predicted Vs. Actual output using 100 and 500 neurons respectively

CHAPTER 5: CONCLUSION

In this thesis, practical method has been carried out to optimize the turning machining parameters for dry cut of Stainless Steel based on Artificial Neural Network model. CCRD was used to determine the minimum combination of experimental data range to establish predictive workable Artificial Neural Network.

Artificial Neural Network model was developed by using the ANN tool of MATLAB. Microscopic pictures of tool and job piece surface was taken after each experiment .Then tool wear and surface roughnesses were measured by using Image Processing tool of MATLAB.

It has been tested that the prediction given by the Artificial Neural Network and the actual result of tool wear and surface roughness for a given set of data has similarity. From this, we can conclude that Artificial Neural Network was designed successfully and the objective of our project has been achieved.

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