A THESIS REPORT

ON

ANALYSIS OF TOOL WEAR IN DRILLING USING ARTIFICIAL NEURAL NETWORK

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

MASTER OF TECHNOLOGY

IN

PRODUCTION AND INDUSTRIAL ENGINEERING

SUBMITTED BY

ANSHUL GUPTA

2K13/PIE/02

UNDER THE SUPERVISION OF

Dr. RANGANATH M.S.

ASSOCIATE PROFESSOR

DEPARTMENT OF MECHANICAL

& PRODUTION AND INDUTRIAL ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY, DELHI (INDIA)

JULY 2015

DECLARATION

I hereby declare that the work presented in this report, titled **"ANALYSIS OF TOOL WEAR IN DRILLING USING ARTIFICIAL NEURAL NETWORK"**, in partial fulfilment for the award of the degree of M.Tech in production and industrial engineering, submitted in the Department of mechanical engineering, Delhi Technological University, Delhi, is original and to the best of my knowledge and belief, it has not been submitted in part or full for the award of any other degree or diploma of any other university or institute, except where due acknowledgement has been made in the text.

Anshul Gupta
Roll No. 2K13/PIE/02
M.Tech. production and industrial engineering

Date:

CERTIFICATE

This is to certify that the research work embodied in this dissertation entitled **"ANALYSIS OF TOOL WEAR IN DRILLING USING ARTIFICIAL NEURAL NETWORK"** submitted by Anshul Gupta , Roll no. 2K13/PIE/02 student of Master of Technology in production and industrial engineering under Department of Mechanical Engineering, Delhi Technological University, Delhi is a bonafide record of the candidate's own work carried out by him under my guidance. This work is original and has not been submitted in part or full for award of any other degree or diploma to any university or institute.

(Dr. RANGNATH.M.S)
Associate Professor
Department of Mechanical Engineering
Delhi Technological University, Delhi,
India

Date:

ACKNOWLEDGEMENT

I express my deepest gratitude to my guide Dr. Ranganath M.S., Assistant Professor Department of Mechanical Engineering, Delhi Technological University, whose encouragement, guidance and support from the initial to the final level enabled me to develop an understanding of the subject. His suggestions and ways of summarizing the things made me go for independent studying and trying my best to get the maximum in my topic, this made my circle of knowledge very vast. I am highly thankful to him for guiding me in this project.

I am also grateful to Dr. R.S. Mishra, professor HOD, Mechanical Engineering Department, DTU for his immense support.

Finally, I take this opportunity to extend my deep appreciation to my family, for their endless support during the crucial times of the completion of my project.

Anshul Gupta
Roll No. 2K13/PIE/02
M.Tech. Production And Industrial Engineering

ABSTRACT

Tool wear in drilling is an important parameter with respect to surface quality of hole and failure of material. Operation performed with worn out tool may increase manufacturing cost. In this work, an attempt has been made to measure manually with the help of stereoscopic microscope and this result has been compared with a statiscal model in which tool wear is assumed as the function of thrust force , machining time, speed and feed. And also compared with ANN model in which input neurons are drill diameter, torque, thrust force, machining time, feed and speed etc and output is tool wear. Comparison between these three result has also been made. It is found that ANN gives best result and can be used for online tool monitoring. Experiments performed from 1 to 40th hole while drilling operations have performed on material EN-31.Monitoring of tool wear is a high robustness process and can be used in complex production system and in flexible manufacturing system.

Keyword : Tool Wear, Torque, Thrust force, ANN, Back propagation ,feed etc.

LIST OF ABBREVIATION USED

d	Drill diameter(mm)
V	Speed (mm/min)
f	Feed rate (mm/rev)
T	Machinig time(min)
F_c	Thrus Force(N)
ANN	Artificial Neural Network
TW	Tool wear
VMM	Vision measuring machine
M	Number of neurons in input layer
N	Number of neurons in hidden layer
K	Number of neurons in output layer
a_i	Normalized out value value from Input layer
b_i	Output of i^{th} neuron on hidden layer
c_i	Actual output of i^{th} neuron from output layer
I_{bi}	Input of i^{th} neuron on hidden layer
I_{ci}	Output received from outer layer
w_{ab}	Corresponding weight from input layer to hidden layer
w_{bc}	Corresponding weight from input layer to output layer
α	Learning rate
β	Smoothing constant
X_i	Training input

LIST OF TABLES

LIST OF FIGURES

TABLE OF CONTENTS

Chapter 4

Chapter 5

CHAPTER 1

1.INTRODUCTION

Manufacturing industries are very much focussing to minimise the operation cost and improving the better quality of product. Drilling is a versatile operation for making a hole in sheet. Drilling operation contributes near about 30 to 40 % of all cutting operations performed in assembly, mounting fasteners and studs. so tools wear as an important parameter in deciding the quality and reducing the operation cost. Monitoring and prediction of drill wear are an important issue since wear on drill effects the tool life of the drill and hole quality. Therefore, monitoring and prediction of drill wear are an important field of research. So, monitoring and prediction of tool wear in metal cutting operation are a new approach towards the improvement of the quality of a product as well as reduction of the overall cost of the product. Direct visual inspection of cutting edge is not feasible and hence indirect methods using sensory feed back during machining have been is use to assess the wear of the drill. For improving the performance of decision-making in tool condition monitoring, different type of intelligent systems has been put forwarded by many authors.

Monitoring of machining process is a classic and yet unsolved problem in manufacturing engineering. Cutting tool users cannot afford to ignore the constant changes and advancement being made in the field of tool material technology. The best tool is one that has been clearly chosen to get the job done quickly, efficiently and economically. Drilling is one of the most common and fundamental machining processes.Worn drills produce poor quality holes and in extreme cases a broken drill can destroy an almost finished part. A drill begins to wear as soon as it is placed into operation. As it wears, cutting forces will increases, the temperature of the drill rises and this accelerates the physical and chemical processes associated with drill wear and there fore drill wears faster. Different types of drill wear, such as flank wear, crater wear and chisel edge wear and margin wear, can be observed on drill because of the geometry of the drill and the cutting conditions vary along the cutting lips from the margin to the chisel edge. Cutting force can be represented by thrust and torque in drilling operations. Thrust and torque depend upon drill wear, drill size, feed rate and spindle speed. Research results shows that tool breakage, tool wear and work piece deflection are strongly related to cutting force.

1.1 OBJECTIVE OF THIS WORK AND ITS IMPORTANCE

Tool wear has been one of the most important parameters in the process of drilling as it decides the product cost and manufacturing cost. The use of the tool after worn out condition will lead to increase the manufacturing cost due to the wastage of work piece material as well as a tool. Depends a lot on the finish produced by the drilling process. Worn out tool also causes rough surface finish So it is necessary to replace or regrind tool at the right time during metal cutting operation. In this work, tool wear is calculated manually by stereoscopic microscope after every fifth hole and this is also being compared with a model in which tool wear is proposed to be a function of thrust force, speed, torque, machining time. Tool wear is also compared with results obtained by Artificial neural network (ANN) which gives more accurate results in terms of minimum error.

1.2 ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks are powerful tools for the identification of systems typically encountered in the structural dynamics field. Artificial neural networks have been originally developed to simulate the function of the human brain or neural system. Artificial neural networks are massive parallel-interconnected networks that consist of basic computing elements called neurons interconnected via unidirectional signal channels called connection that imitates the human brain. Each processing element has a single output connection that branches into as many collateral connections as desired. Each neuron carries the same signal —the processing output signal. It has the capability to organize its structural constituents, known as neurons, to perform certain computations many times faster than the fastest digital computer in existence today through a process of learning. Neural networks are physical cellular systems, which can acquire, store and utilize experimental knowledge. In the present paper, the most widely used technique, the feed forward back propagation neural network, is adapted for the prediction of tool wear in the end-milling operation. The feed forward back propagation network consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationship between the inputs and outputs are determined and represented by synaptic weights) and an output layer (which emits the outputs of the problem).

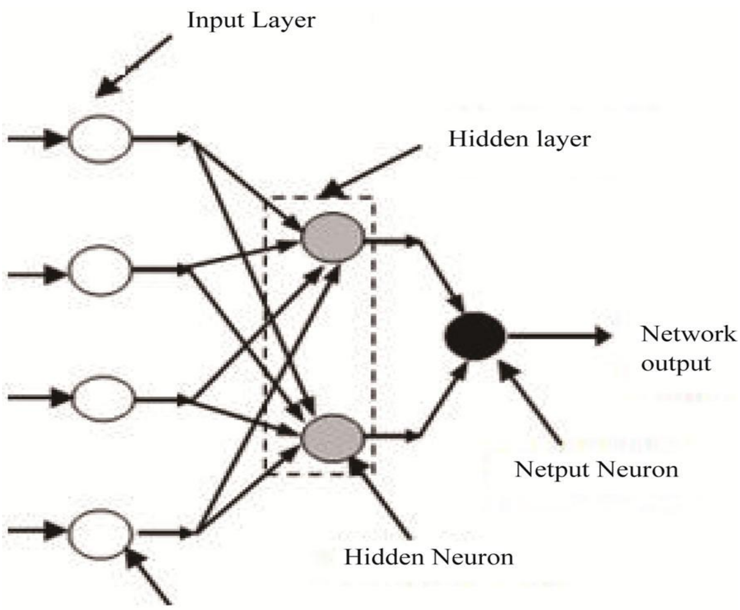


Fig.1.1 A TYPICAL ANN STRUCTURE

Training of an ANN plays a significant role in designing the direct ANN-based prediction. The accuracy of the prediction depends on how it is trained. The training of the neural network using a feed-forward back propagation algorithm has been carried out. The network performs two phases of data flow. First the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow of data, it produces an output. Then the error signals resulting from the difference between the computed and the actual are back propagated from the output layer to the previous layers for them to update their weights. The number of neurons in the hidden layer is intentionally chosen to start with one neuron and hidden neurons are added to the hidden layer incrementally. The addition of hidden neurons continues until there is no further improvement in network performance. The accuracy of the network was evaluated by mean sum of squared error (MSE) between the measured and the predicted values for the training. The feedback from that processing is called the "average error" or "performance". Once the average error is below the required goal, the neural network stops training and is, therefore, ready to be verified.

1.3 TOOL WEAR

Tool wear is an inherent occurrence in every conventional machining process. The tool wear rate is dependent on the tool material itself, the tool shape and geometry, work piece material etc.

- ## TYPE OF DRILL WEAR

Fig.1.2 represents the nomenclature and geometry of a conventional twist drill. Five types of drill wear were artificially induced on the drill point, as shown in Fig1.2, and these are:

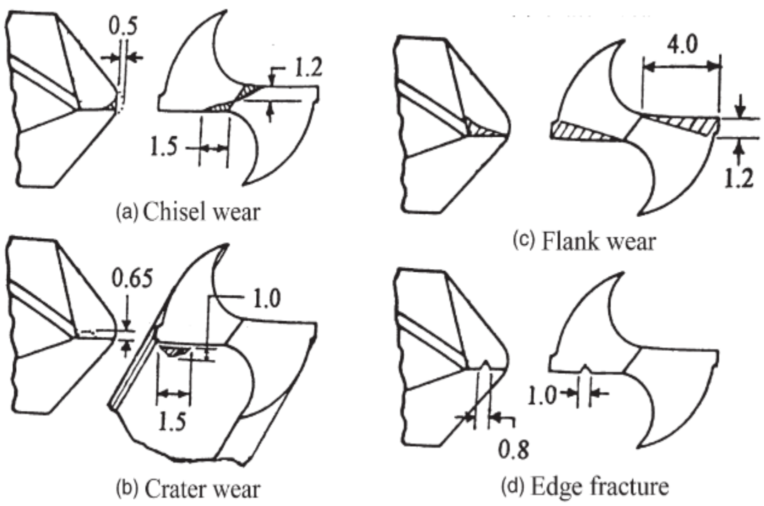


Fig.1.2.TYPES OF DRILL WEAR

- **Chisel wear**:- It normally occurs due to the very high shear and compressive stresses in the flow zone of the tool-work piece interface acting at high temperatures, which causes erosion of the chisel edge.
- **Crater wear:-**It occurs on the rake face of one cutting edge. Crater wear is due to high temperature conditions along the rake surface.

- **Flank wear:-** It occurs on on the two flank or clearance faces of the lips. Flank wear can results in,
  - Poor surface finish
  - Hole tolerance out of range
  - Power increase.

❖ **Cause**

1.Cutting speed too high

2. Percentage of oil in cutting fluid flow too low

3.Insufficient cutting fluid flow

4.Total indicator run-out too large (if wear on margin)

❖ **Action**

1. Decrease cutting speed
2. Increase percentage of oil in cutting fluid (check with oil distributor to be sure to not exceed recommended percentages of oil)
3. Increase cutting fluid flow
4. Check radial run-out (if wear on margin)

➢ **Fracture or breakage** :- It occurs on one lip of the cutting edge. Breakage can result in

- Tool break down
- Destroyed work piece

❖ **Cause:**

1.Insufficient stability

2.Intermittent cutting

3.Insufficient cutting fluid

4.Too high feed or too high/low cutting speed

5.Grade too brittle (P-insert)

6. Insert worn out

❖ **Action:**

1. Improve stability (shorten tool overhang, better work-piece fixturing etc.)
2. Reduce feed, choose tougher geometry (-GR or –GT)
3. Increase cutting fluid
4. Adjust cutting data
5. Choose a tougher grade
6. Determine safe tool life on peripheral insert

➢ Wear on both outside corners of the drill point. This is due to high friction (rubbing) and impact forces between the drill and the machined hole walls.

1.4.THRUST AND TORQUE

Drilling is the most important conventional machining process affiliated to the chipboard processing. In any industry or firm there is high requirement of holes to be produced in the object so as to hold the object or specimen to measure the forces and torque in the body. Very important part which affects this force is the geometry of tool and controls the outcomes. Chip drilling is a drilling process which asks for a very unique set of factors to be set so as to bring the feasible areas in consideration. In this drilling process the parameters or the variables are given importance as they can control the outcome effectively. Any good drilling model is aimed to have precise feed rates, speeds of spindles, and geometries. The analysis of drilling process is known to have complex geometries in it. The complex and intricate geometries of the tool are reason for the varying torque and thrust in the process.

Drill bits are the parts which are used to cut the material and they have a wide variety in their compositions but the shape of such bit tools is mostly cylindrical as the hole to be produced is the basic aim and this can be produced by cylindrical tool only. These bits are made in combination to the static part of the machine which causes the bit to be rotated and produce the desired effect. The bits have two edges.

Exceptionally, specially-shaped bits can cut holes of non-circular cross-section.

Variety of materials is taken in consideration to make the drill bits, which rely upon the shape the feed the speed at which the hole is to be produced.

1.3.1. Steels: Bits made out of the high carbon steels are much better than the low carbon steels they have better properties and ability to drill the other materials with ease.

a) High speed steel (HSS) is a tool steel, it is hard and much effective against high temperature and better than steel of high carbon.

b) Cobalt steel alloys are nothing but alloys formed of HSS and cobalt as its main components they are able to sustain their properties at a high temperature and can drill stainless steels.

Others :

(a) Tungsten carbide and other carbides are substances which are extremely hard to and can drill any material. These materials are used to produce holes where the holes are to be produced in hard materials and the life of the tools is also has to be high

(b) Polycrystalline diamond (PCD): it is the hardest of all materials that are known to the people. It consist of a layer of particles of diamond which provide the body with strength for high cutting power due to diamond whereas, the tungsten provides the resistance to abrasion. It is known that PCD is never operated upon the ferrous materials due to the chemical reaction that takes place in the carbon and iron and formation of an interstitial compound.

Coatings

(a) Titanium nitride (TiN) is a highly hard material which is ceramic in nature and used to coat the HSS bit.

(b) Titanium aluminum nitride (TiAlN) is another type of layer which enhances properties.

(c) Titanium carbon nitride (TiCN).

(d) Diamond powder is an abrasive material and used for cutting hard materials.in this process a huge quantity of heat is generated due to friction and water is provided along with it to stop the damage to the work piece.

(e) Zirconium nitride is another drill bit with high hardness and strength.

1.5 EN-31 (Bearing material)

EN-31 also known as bearing metal, is high quality alloy of steel having good ductility ans shock absorbing capacity with resistance to wear. Hardness of this material is higher than low carbon steel because it consists of nickel (Ni) and chromium (Cr) which leads to increase hardness of material.

EN with a capital 'N' designates Europäische Norm which converts to European Standard. En with a lowercase 'n' implies Emergency Number and was used as a representation for various steel grades in BS 970 until a uniform system was set up after the world war 2.

Effect of alloying of different element in steel is as follows :-

- Manganese – It improves strength,hardness and abration resistance and machiability. It deoxidizes the molten steel and decreases ductility and weldability. It reduces hot shortness , More predominant effect is to increase hardenability.

- Phosphorus – It increases strength and hardness and decreases ductility and notch impact toughness of steel.

- Sulfur - It increases machiability and flowability of molten metal and decreases ductility and notch impact toughness Weldability decreases. It is Found in the form of sulfide inclusions.

- Silicon – It is one of the principal deoxidizers used in steel making. silicon is generally detrimental to surface quality in low carbon steel. It increases hardness also.

- Copper – It is detrimental to hot-working steels; it improves corrosion resistance to atmosphere if added less than .2%.

- Nickel – Nickel is ferritic stabilizer; increases the *hardenability* and impact strength of steels.

- Molybdenum – It improves hardenability; enhances the creep resistance of low-alloy steels,wear resistance toughness, elevated temperature strength . it minimises embrittlement.
- Carbon :- Carbon improves strength of iron and increases hardness, haedenability wear resistance.It reduces ductility, impact strength andweldability.

Chemical composition and some properties is given in table below

TABLE 1.1 CHEMICAL COMPOSITION OF EN 31

Element	Chemical composition (% weight)
Carbon (c)	1.08 %
Nickel (Ni)	0.33%
Chromium (cr)	1.46%
Phosphorous (P)	0.022%
Silicon (Si)	0.25 %
Manganese (Mn)	0.53 %
Molybdenum (Mo)	0.06 %
Sulphur (S)	0.015 %

TABLE 1.2 PROPERTIES OF TOOL WEAR

Properties	Value
Tensile Strength	750 N/mm^2
Yield strength	450 N/mm^2
Reduction of area	45 %
Elongation	30%
Modulus of elasticity	215 000 N/mm^2
Density	7.8 Kg/m^3
Hardness	63 HRC

- ***Forging process :-***

Heat slowly and start forging in 1000-1050°C. Sufficient time at the forging temperature is given to the steel to thoroughly soak through. Re-heating is done as necessary and not forged below 850°C. After forging EN31 steel, cooling slowly preferably in a furnace is done.

- ***Annealing:-***

EN31 is mostly supplied in the annealed and machine able condition. Re-annealing will only be required if the steel is again to be forged or hardened. To anneal, the EN31 steel is heated slowly to 800-810°C, soaked well and allowed to cool in the furnace.

- ***Stress relieving:-***

When parts are to be machined heavily, stress relieving will be complimentary prior to hardening. Heating is done to EN31 carefully up to 700°C, soaked well and allowed to cool in air.

- ***Hardening:-***

Heating at low pace to the hardening temperature around 800-820°C. Maintained until heat is absorbed through. Plenty of time is given to this process of soaking and then quenched in oil.

- ***Tempering:-***

Tempering is done, according to the purpose for which the tool is required, generally in the range of 150°C and 300°C. Heat is soaked well at the selected temperature and absorbs for minimum one hour per 25mm of thickness. Cooling is done slowly in air.

Table 1.3 : TEMPERING PROPERTIES OF EN-31

Temperature °C	150	200	250	300
HARDNESS	63-62	62-61	61-59	57-56

- ***Heat treatment :-***

Heat treatment temperatures, including rate of cooling, heating and absorbing time will vary due to the factors like the shape and size of each EN31 component. Other variations in the process during the heat treatment includes the type of furnace, quenching medium and work piece transport facilities.

Application:-

Major applications for EN31 steels include gauges, taps, swaging dies, balls, ejector pins and roller bearings. It is a good quality steel demanded for wear resisting machine parts and for press tools which do not require a more complex quality.

Ex: Ball and Roller Bearings, Spinning tools, Beading Rolls, Punches and Dies. By its character this type of steel has high resisting nature against wear and can be used for components which are subjected to severe abrasion, wear or high surface loading.

CHAPTER 2

Literature Review

In this we studied certain research papers collected by us and making these papers as our source of light, we proceeded in the direction of measurement of torque and thrust.

Papers that were studied:-

C. Tsao and H. Hoeing [1], presented the prediction and evaluation of thrust force and surface roughness in drilling of composite material using candle stick drill. The approach was based on Taguchi method and the artificial neural network. The experimental results indicated that the feed rate and the drill diameter were the most significant factors affecting the thrust force, while the feed rate and spindle speed contributed most to the surface roughness. In this study, the objective was to establish a correlation between the feed rate, spindle speed and drill diameter with the induced thrust force and surface roughness in drilling composite laminate. correlations were obtained by multi-variable regression analysis and radial basis function network (RBFN) and compared with the experimental results. The results indicated that the RBFN is more effective than multi-variable regression analysis. It used Kistler 9257 piezoelectric dynamometer to measure the forces.

Erkki Jantunen [9] proposed that It is very logical to monitor forces in a cutting process in order to follow the development of cutting tool wear. It is generally known that cutting forces increase as tool wear increases. This is due to the increase of friction between tool and workpiece. In drilling it is possible to monitor torque, drift forces (lateral forces affecting the workpiece) and the feed (thrust, z-axis) force. The idea behind monitoring torque and feed force is very clear, i.e. it isexpected that these forces change as the tool gradually wears. The thrust force has been used as the only measured signal in . The simultaneous monitoring of thrust force and torque is rather common and special electronics have been developed for this purpose. Drill wear as such differs to some extent from the wear of other cutting tools. Due to production tolerances a drill is slightly asymmetric, therefore it only wears at one lip until the height of both lips is equal. The second lip, which is now sharper, starts cutting. This alternating process continues until neither lip has no more clearance at the margin. In the end the drill sticks rotational speed of the spindle is very good (for feed force $R2$=0.94 and for torque R2=0.97). It is concluded that tool wear can be properly estimated knowing the thrust force and other cutting parameters, especially for larger tool wear. Based on tests with different workpiece material hardness, formulas for torque and thrust force have been developed as a function of Brinell hardness of work material, diameter of the drill, feed per revolution, average flank wear and radius at the cutting edge. It is concluded that the variation in drill life is significantly influenced by the workpiece hardness. It is speculated that it could be so that the presence of a few random workpieces with a high hardness may influence the drill life much more than a large number of workpieces with a low hardness. Hence, in an industrial operation, drills may fail very early or after a long time, depending on the occurrence of a few work pieces with a high hardness. This could explain the large variation in drill life observed in industrial conditions. The workpiece hardness also influences the amplitudes of thrust forces and torque occurring in a drilling operation. If the variation in thrust force, on account of changes in flank wear, is to be significant, the variation in workpiece hardness has to be held within 5% of the mean hardness value in order to be able to base the diagnosis of flank wear on the amplitude of thrust force or torque. This is very difficult to achieve in industrial castings. Hence, torque or thrust measurements for monitoring drill wear should be attempted only after a very close tolerance has been obtained in the work piece hardness.

Erkki Jantunen [10] proposed a summary of the monitoring methods, signal analysis and diagnostic techniques for tool wear and failure monitoring in drilling that have been tested and reported in the literature. The paper covers only indirect monitoring methods such as force, vibration and current measurements, i.e. direct monitoring methods based on dimensional measurement etc. are not included. Signal analysis techniques cover all the methods that have been used with indirect measurements including e.g. statistical parameters and Fast Fourier and Wavelet Transform. Only a limited number of automatic diagnostic tools have been developed for diagnosis of the condition of the tool in drilling. All of these rather diverse approaches that have been available are covered in this study In the reported material there are both success stories and also those that have not been so successful. Only in a few of the papers have attempts been made to compare the chosen approach with other methods. Many of the papers only present one approach and unfortunately quite often the test material of the study is limited especially in what comes to the cutting process parameter variation, i.e. variation of cutting speed, feed rate, drill diameter and material and also work piece material. A summary of the monitoring methods, signal analysis and diagnostic techniques for tool wear and failure monitoring in drilling has been given. In this context only indirect monitoring methods such as force, vibration and current measurements have been covered, i.e. direct monitoring methods based on dimensional measurement etc. are not included. In signal analysis statistical parameters calculated from the time domain signal are widely used. Fast Fourier and Wavelet Transform are more sophisticated means of signal analysis that have also been used for tool wear and breakage detection by a number of research groups. Only a limited number of automatic diagnostic tools have been developed for diagnosis of the condition of the tool in drilling. All of these rather diverse approaches that have been available in the literature are covered in this study. In the reported material there are both success stories and attempts that have not been so successful. Only in a few of the papers have attempts been made to compare the chosen approach with other methods, i.e. many of the papers only present one approach and unfortunately quite often the test material the study is based on is limited, especially when it comes to the cutting process parameter variation, i.e. variation of cutting speed, feed rate, drill diameter and material and also work piece material.

Issam Abu-Mahfouz[13], presented that In automated flexible manufacturing systems the detection of tool wear during the cutting process is one of the most important considerations. This study presents a comparison between several architectures of the multi-layer feed-forward neural network with a back propagation training algorithm for tool condition monitoring (TCM) of twist drill wear. The algorithm utilizes vibration signature analysis as the main and only source of information from the machining process. The objective of the proposed study is to produce a TCM system that will lead to a more efficient and economical drilling tool usage. Five different drill wear conditions were artificially introduced to the neural network for prediction and classification. The experimental procedure for acquiring vibration data and extracting features in both the time and frequency domains to train and test the neural network models is detailed. It was found that the frequency domain features, such as the averaged harmonic wavelet coefficients and the maximum entropy spectrum peaks, are more efficient in training the neural network than the time domain statistical moments. The results demonstrate the effectiveness and robustness of using the vibration signals in a supervised neural network for drill wear detection and classification.

Li Xiaoli [16] presented on-line tool breakage detection of small diameter drills by monitoring the AC servo motor current. The continuous wavelet transform was used to decompose the spindle AC servo motor current signal and the discrete wavelet transform was used to decompose the feed AC servo motor current signal in time–frequency domain. The tool breakage features were extracted from the decomposed signals. Experimental results show that the proposed monitoring system possessed an excellent on-line capability; in addition, it had a low sensitivity to change of the cutting conditions and high success rate for the detection of the breakage of small diameter drills. In this paper the AC servo motor current was indirectly measured and the WT was used to detect the tool breakage is the drilling process for small diameter drill. The experimental results conducted show that DWT can clearly detect the small diameter drill tool breakage. The developed current sensoring system has been applied to the on-line detection of tool breakage in drilling process. The experimental set-up can be attached to commercial MCs without changes of the machine.

Li Xiaoli and S.K. Tso [17] presented a simple method for on-line wear state monitoring and tool replacement decision-making using spindle motor and feed motor current signals in drilling. In the paper, the effects of tool wear as well as cutting parameters on the cutting current signals was analyzed. The models on the relationship between the current signals and the cutting parameters was established under different tool wear states with a partial experimental design and regression analysis. Finally, a fuzzy classification method was used to classify the tool wear states so as to facilitate defective tool replacement at the proper time. The validity and reliability of the method was verified by experimental results. The effects of tool wear and cutting parameters on the spindle motor and feed motor current was analyzed. The models regarding the relationship between the current signals and the cutting parameters for different tool wear states i.e, wear 0.2, 0.5, 0.8 mm. was established through experimental study and regression analysis.The membership function concept has been successfully used to calculate the grade of membership for given wear states and applied to the monitoring of the drill wear state whose classification is fuzzy.The grade of membership associated with the relevant flank wear states is always very close to unity based on the established models.

K.Subramanian [14] established the thrust and torque as a function of workpiece material hardness, average flank wear, drill diameter, feed rate and radius at the cutting edge. It was found that tool life is strongly affected by work piece material hardness. It was also shown that cutting force increases as drill wear increases.

Muataz Hazzaf et al [18] , proposed that High speed milling has many advantages such as higher removal rate and high productivity. However, higher cutting speed increase the flank wear rate and thus reducing the cutting tool life. Therefore estimating and predicting the flank wear length in early stages reduces the risk of unaccepted tooling cost. This research presents a neural network model for predicting and simulating the flank wear in the CNC end milling process. A set of sparse experimental data for finish end milling on AISI H13 at hardness of 48 HRC have been conducted to measure the flank wear length. Then the measured data have been used to train the developed neural network model. Artificial neural network (ANN) was applied to predict the flank wear length. The neural network contains twenty hidden layer with feed forward back propagation hierarchical. The neural network has been designed with MATLAB Neural Network Toolbox. The results show a high correlation between the predicted and the observed flank wear which indicates the validity of the models.

S.C. Lin and C.J. Ting [25] ,carried out experiment for drill monitoring using artificial neural network by using drill diameter , torque . thrust force , feed as an input parameter. It was found that the ANN is more superior to conventional method of tool wear monitoring.

S.C. Lin and C.J. Ting [26], Utilization of force signals to achieve on-line drill wear monitoring has presented in this paper. A series of experiments were conducted to study the effects of tool wear as well as other cutting parameters on the cutting force signals and to establish the relationship between force signals and tool wear as well as other cutting parameters when drilling copper alloy. The relationship between cutting force signals and cutting parameters as well as tool wear is then established. The relationship can then be used for on-line drill flank wear monitoring. Feasibility studies show that the use of force signal for on-line drill flank wear monitoring is feasible.

S.S. Panda , D. Chakraborty, and S.K. Pal [28], presented two different types of artificial neural network (ANN) architectures viz. back propagation neural network (BPNN) and radial basis function network (RBFN) have been used in an attempt to predict flank wear in drills. Flank wear in drill depends upon speed, feed rate, drill diameter and hence these parameters along with other derived parameters such as thrust force, torque and vibration have been used to predict flank wear using ANN. Effect of using increasing number of sensors in the efficacy of predicting drill wear by using ANN has been studied. It has been observed that inclusion of vibration signal along with thrust force and torque leads to better prediction of drill wear. The results obtained from the two different ANN architectures have been compared and some useful conclusions have been made.

T.I Liu and S.M.wu [32], Back propagation neural networks BPNs were used for online detection of drill wear. The neural network consisted of three layers input hidden and output The input vector comprised drill size feed rate spindle speed and eight features obtained by processing the thrust and torque signals The output was the drill wear state which was either usable or failure. Drilling experiments with various drill sizes feed rates and spindle speeds were carried out The learning process was performed efectively by utilising backpropagation with smoothing and an activation function slope The online detection of drill wear states using BPNs achieved 100 % reliability even when the drill size feed rate and spindle speed were changed In other words the developed online drill wear detection systems have very high robustness and hence can be used in very complex production environments such as flexible manufacturing systems.

X. Li, S. Dong, P.K. Venuvinod [39] proposed that average wear of a K10 carbide drill bit for drilling on a high silicon aluminium work piece was predicted by using a multilayer back propagation wavelet neural network. BPWNN algorithm was applied to predict Mean value of the cutting torque, thrust force and depth of drill , spindle speed and feed-rate are inputs to the network, and drill wear was the output. Drilling experiments was performed over a wide range of cutting conditions. It effects parameters like drill wear, cutting conditions (spindle speed, drilling depth and feed-rate) on the thrust force and cutting torque. All these parameters was investigated in this paper. Performance of BPWNN has proved to be satisfactory by experimental result.

CHAPTER 3

EXPERIMENTAL SETUP

3.1. Work Piece : work piece is made of EN-31 which has cylindrical shape (Length 70 mm & Diameter 40 mm).

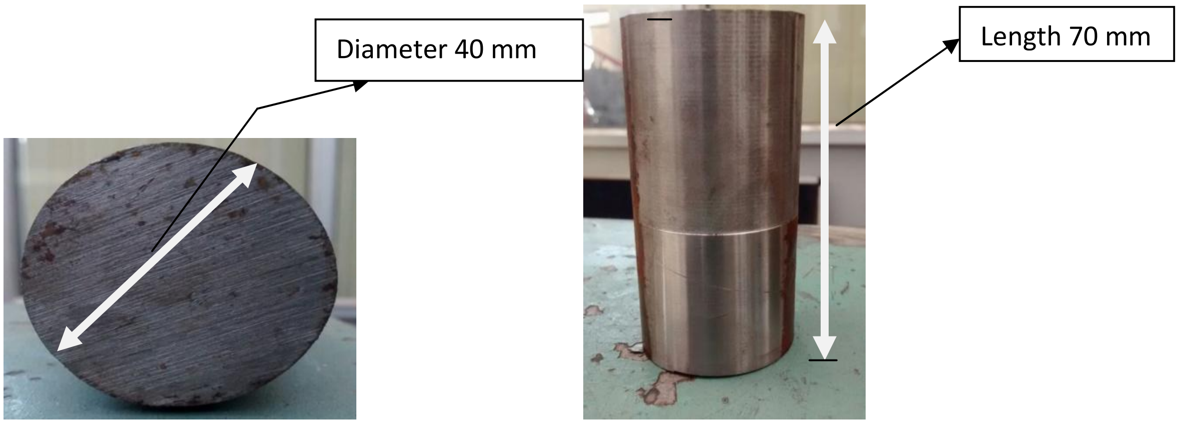


Fig.3.1. Work piece specimen of EN 31

3.2. Drill bit (Tool) :-

Tool made of HSS (High speed steel) has been used to make a hole in work piece. Point angle of tool is 135° and diameter of tool is 10mm.

Fig.3.2. Twist drill of HSS

3.3.Drilling machine :-

The radial drilling machine is primarily intended for drilling medium to large and heavy work piece. The radial drilling machine consists of a heavy, vertical, round column mounted on a large base and drilling head. The drill head consists of a mechanism for rotating and feeding the drill is mounted on a radial arm and can be moved horizontally on the guide-ways and clamped at any desired position. The column supports a radial arm which can be raised and lowered to accommodate work pieces of different heights. The arm may be swung around to any position over the work bed. These three movements in a radial drilling machine when combined together permit the drill to be located at any desired point on a large work piece for drilling the hole I have used radial drilling machine for experiment which has following specification:

Table 3.1 : MACHINE SPECIFICATION (Radial Drilling machine)

Radial drilling machine	Type –RM-62 (Model)
Drilling capacity	50 mm in steel
Drilling rough bores	90 mm in steel
Boring with supported boring bar	1200 mm in steel
Trepanning	200 mm in steel
Tapping whitworth	$1_{3/4}$ inches
Tapic metric fine threads	56 mm
12 spindle speeds	40-1700 rpm
6 spindle feeds	0.12 mm/rev to 1.2 mm/rev
Spindle diameter	81.8
Drilling pressure	1650 kg
Drill power	4.8/6 h.p
Arm elevating motor power	2 H.P
CAPACITIES	Dimension (mm)
Max drilling radius	1500
Min. drilling radius	530
Max drill transverse	970
Diameter of column sleeve	350
Max distance column to spindle	1325
Min distance column to spindle	355
Max distance base plate to spindle	1450
Min distance base plate to spindle	385
Working surface of base plate length	1490

Width	910
Base plate overall length	2190
Overall width	925
Swing of arm	1860
Overall height of machine	2760
Approx. net weight	3160
Length	2810
Width	1280
Height	2983

Fig.3.3. A TYPICAL RADIAL DRILLING MACHINE IN METAL CUTTING LAB, DTU NEW DELHI

3.4 Drilling dynamometer

A dynamometer is a device used to find the torque and thrust in the machine either in drilling or any other machining process. Dynamometer is nothing but a simple electrical machine which is used to measure the value of the force and torque exactly in the process. A dynamometer is first balanced with respect to a known force and then the pointer is moved with respect to the new force coming into action at that point or in that process. It is nothing but a device for the dynamic calculation of the power produced in the engine while in the common available machine it is used for the prediction of torque.

The term **dynamometer** refers to an instrument used to measure force, torque and power. It can also be used to refer to a testing machine capable of applying force of a given precision. A dynamometer is composed of a **transducer** comprising a metallic test specimen which receives the force to be measured and deforms elastically by the application of this force. In modern transducers such deformation (strain) is communicated to a miniature electric circuit attached to the test specimen, resulting in a modification of the electric resistance. This resistance variation is measured by the Wheatstone bridge method, whereby two legs of the electric circuit are supplied with an analog voltage, continuous or intermittent, and an analogue voltage variable according to the force applied to the dynamometer is collected between the two other legs in the circuit.

There are various kinds of dynamometers which are available in the market they are referred according to the source of power they work upon:-

1. Break dynamometer.
2. Break current dynamometer
3. Eddy current dynamometer
4. Hydraulic dynamometer.

Break dynamometers are the oldest in business and are mechanical machines most commonly called as the shoe which when gets in contact of hub rubs against it and produces the desired measurement. Power for the hub to move provided by the engine. Hydraulic dynamometers may be defined as the machines which use hydraulic power to muster up the power to run the components. The load given to the engine is changing depending upon the valve which opens and closes with the change in pressure. Eddy current dynamometers are devices in which the engine is provided or passed through the current and causes the disk to have an effect of lens law and this causes a force on the machine to move and stick to the hub and thereby measure the thrust or torque.

Changing the amount of current in the machine changes the load settings of the machine in which it is placed. If the dynamometer is made in connection to the engine rod then it is coined as engine dynamometer.

If the dynamometer is made in contact to the driving wheels of the vehicle or then is named as chassis dynamometer.

A digital type dynamometer is used to measure thrust and torque.Reading provided by drill tool dynamometer was in MKS unit system.

For giving consistent reliable and accurate measurement, the following requirements should be considered during design and construction of any tool force dynamometers :-

- **Sensitivity** :- The dynamometer should be reasonably sensitive for measuring precision measurement.

- **Rigidity** :- The dynamometer should be quite rigid to withstand the forces without causing deflection which may affect the machining condition

- **Cross sensitivity** :- The dynamometer should be free from cross sensitivity such that one measuring quantity does not affect measurement of the other measuring quantities.

- It should be Stable against humidity and temperature.

- It should give Quick time response.

- It should have high frequency response such that the readings are not affected by vibration within a reasonably high range of frequency.

- Consistency, i.e. the dynamometer should work desirably over a long period.

Fig.3.4.DYNAMOMETER SETUP USED IN THE PROCESS AT METAL CUTTING LAB, DTU

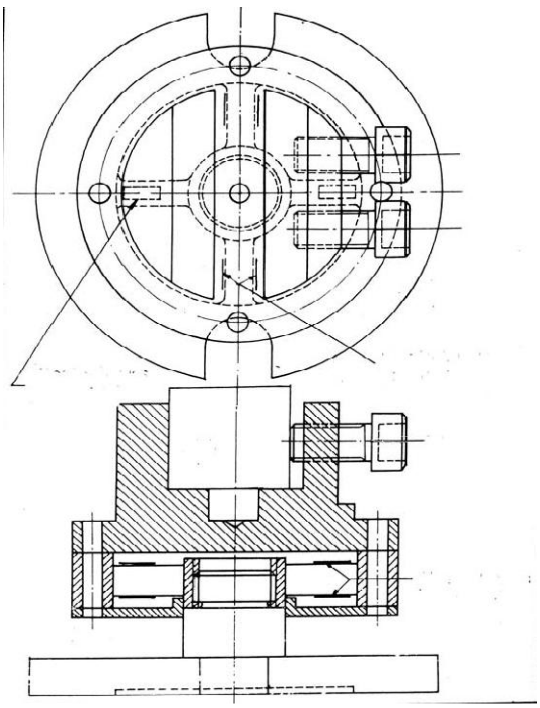


Fig.3.5. SCHEMATIC VIEW OF CONSTRUCTION OF A STRAIN GAUGE TYPE DRILLLING DYNAMOMETER

3.5 STEREOSCOPIC MICROSCOPE

The **stereo** or **stereoscopic** or **dissectingimicroscop**e is an optical microscope variant designed for low magnification observation of a sample, typically using light reflected from the surface of an object rather than transmitted through it. The instrument uses two separate optical paths with two objectives and eyepieces to provide slightly different viewing angles to the left and right eyes. This arrangement produces a three-dimensional visualization of the sample being examined. Stereomicroscopy overlaps macrophotography for recording and examining solid samples with complex surface topography, where a three-dimensional view is needed for analyzing the detail.

The stereo microscope is often used to study the surfaces of solid specimens or to carry out close work such as dissection, microsurgery,watch-making, circuit board manufacture or inspection, and fracture surfaces as in fractography and forensic engineering. They are thus widely used in manufacturing industry for manufacture, inspection and quality control. Stereo microscopes are essential tools in entomology.

The stereo microscope should not be confused with a compound microscope equipped with double eyepieces and a binoviewer. In such a microscope, both eyes see the same image, with the two eyepieces serving to provide greater viewing comfort. However, the image in such a microscope is no different from that obtained with a single monocular eyepiece.

Fig.3.6. STEREOSCOPIC MICRO SCOPE IN METROLOGY LAB,DTU

3.7. VISION MEASURING MACHINE

A vision measuring machine (VMM) is a device for measuring the physical geometrical characteristics of an object. This machine may be manually controlled by an operator or it may be computer controlled. Measurements are defined by a probe attached to the third moving axis of this machine. Probes may be mechanical, optical, laser, or white light, amongst others. A machine which takes readings in six degrees of freedom and displays these readings in mathematical form is known as a VMM.

The typical 3D "bridge" VMM is composed of three axes, X, Y and Z. These axes are orthogonal to each other in a typical three-dimensional coordinate system. Each axis has a scale system that indicates the location of that axis. The machine reads the input from the touch probe, as directed by the operator or programmer. The machine then uses the X,Y,Z coordinates of each of these points to determine size and position with micrometer precision typically.

A vision measuring machine (VMM) is also a device used in manufacturing and assembly processes to test a part or assembly against the design intent. By precisely recording the X, Y, and Z coordinates of the target, points are generated which can then be analyzed via regression algorithms for the construction of features. These points are collected by using a probe that is positioned manually by an operator or automatically via Direct Computer Control (DCC). DCC VMMs can be programmed to repeatedly measure identical parts, thus a VMM is a specialized form of industrial robot.

Fig.3.7. A VISION MESURING MACHINE IN METAL CUTTING LAB , DTU

Fig.3.8. PICTURE OF UNUSED TOOL TAKEN FROM VMM FOR READING A

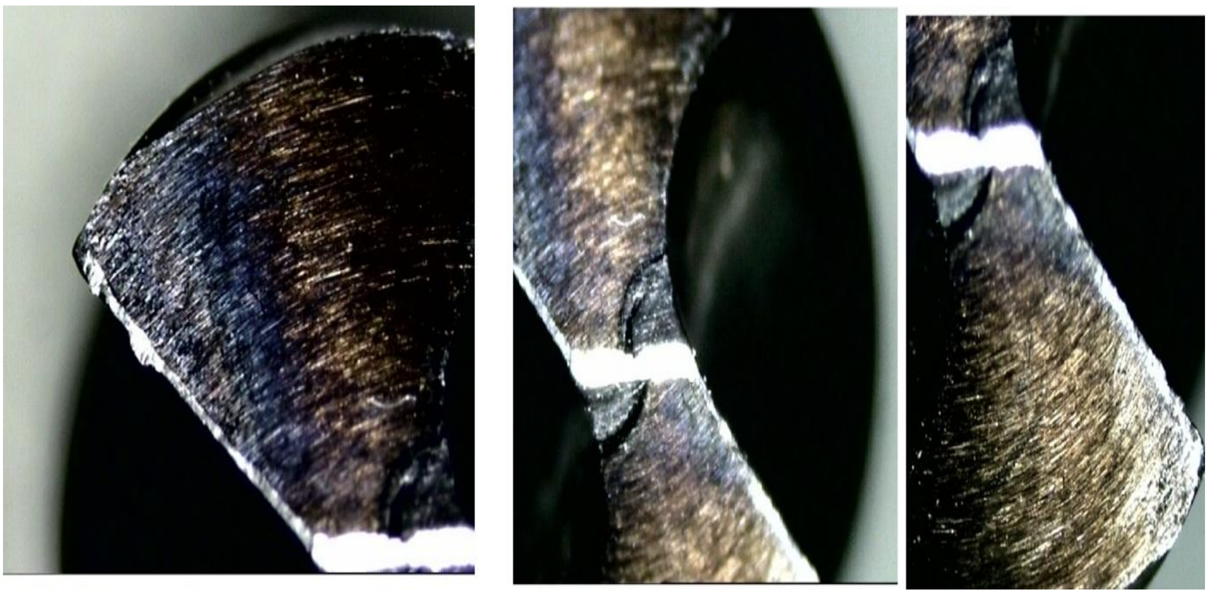


Fig.3.9. TOOL IMAGE OF USED TOOL TAKEN FROM VMM AFTER 40th HOLE FOR READING A

CHAPTER 4

4.1 DATA ANALYSIS

A dynamometer (digital type) is used to measure thrust force (i.e. Cutting force) and torque. The twist drill of 10 mm diameter and made of HSS (high speed steel) has been used. The work piece material is EN-31 (known as bearing metal) and drill depth is to be kept constant 20 mm. The work piece was of cylindrical shape, having diameter 40 mm and length 70 mm. The number of holes were carried out 1 to 40.

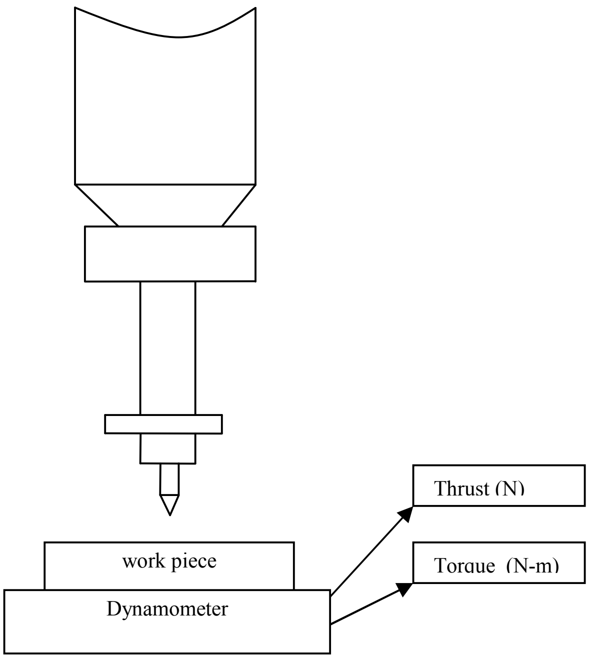


Fig.4.1. A Experimental setup diagram

Two test is being conducted using various combination of speed (13.71 m/min or 440 Rpm & 18.22 m/min or 580 Rpm) and feed (0.12 mm/rev and 0.2 mm/rev) . Tool geometry, work piece hardness, tool geometry, rigidity of machine and temperature are the main parameters that influences the tool wear. These parameter are assumed as constant in the different set of tests.

The maximum flank wear occurs at the outet corner and there is decrease in wear towards the chisel edge corner. High-temperature conditions at the outer corner of drill will leads to accelerate this kind of wear. This flank is determined as the average of four measurements taking two readings on each of the cutting edges. Wear measurements is carried out by using stereoscopic microscope with incident illumination. Wear land was observed under 100x magnification and wear land width was measured by means of a measuring eyepiece. The microscope has a resolution of 20 m under 80× magnifications. Some pictures of twist drill before and after use was taken by VMM (vision measuring macine) are shown in Fig.3.7 & 3.8. The experimental data are as shown in Table 4.1 & Table 4.2.

Two Sets of reading are obtained which are as follows :

READNG SET A – Diameter 10 mm, feed .12 mm/rev, speed 13.71mm/min or 440 RPM

READING SET B - Diameter 10 mm, feed .12 mm/rev, speed 18.22mm/min or 580 RPM

Table 4.1 TOOL WEAR MEASURED FROM MICROSCOPE FOR READING SET A

(diameter 10 mm, feed .12 mm/rev, speed 13.71 mm/min or 440 RPM)

No. Of holes	Machine time (min)	Force (N)	Torque (N-m)	Tool wear (mm)
1	0.415	1814.5	5.886	0.001
5	2.076	1932.57	6.867	0.1
10	4.151	2040.48	7.848	0.18
15	6.226	2089.53	8.004	0.25
20	8.301	2118.96	8.25	0.33
25	10.376	2226.27	8.63	0.45
30	12.541	2374.02	9.123	0.52
35	14.941	2481.93	9.613	0.56
40	16.601	2658.51	10.3	0.61

Table 4.2 TOOL WEAR MEASURED FROM MICROSCOPE FOR READING SET B

(diameter 10 mm, feed .2 mm/rev, speed 18.22 mm/min or 580 RPM)

No. Of hoes	Machining time (min)	Thrust (N)	Torque (N-m)	Tool wear (mm)
1	0.189	3021.48	10.305	0.001
5	0.946	3090.81	10.791	0.09
10	1.891	3149.01	11.772	0.17
15	2.836	3207.87	12.753	0.29
20	3.781	3305.97	12.753	0.38
25	4.726	3374.64	13.734	0.47
30	5.671	3443.31	14.715	0.54
35	6.616	3531.6	15.696	0.62
40	7.561	3688.56	16.677	0.68

4.1.1 Statistical analysis

Tool wear is assumed to be proportional to the variables, such as cutting speed, feed, machining time and cutting force [14] in eq.4.1. The functional relationship between the response parameters, such as cutting speed, feed, time and thrust force for the cutting operation and the integrated independent variables which are given by:

$$T_w = k\, v^a f^b F^c T^d \qquad \text{......................} \ (4.1)$$

where T_w is the tool wear in mm, v the cutting speed in m/min, f the feed in mm/rev, F_c the cutting force in N and T is the machining time in min.

The form of equation (4.1) is non-linear, The software used for statistical analysis was Micro soft EXCEL. The equations obtained for tool wear by statistical analysis are as follows:

$TW = 0.987\times F^{0.8123}\times T^{0.854}\times v^{-1.065}\times f^{2.5}$ .... (4.4)

(Diameter 10 mm, feed 0.12 mm/rev speed 13.81 mm/min or 440 Rpm)

$TW = 0.816\times F^{0.7642}\times T^{07765.}\times v^{-0.98}\times f^{3.2}$ .... (4.5)

(Diameter 10 mm, feed 0.2 mm/rev speed 18.22 mm/min or 580 Rpm)

The modified regression equations were obtained for calculating the estimated values of tool wear are as shown below:

$TW == 0.0069\times F^{0.29}\times T^{0.7999}$... (4.6)

(Diameter 10 mm, feed 0.12 mm/rev speed 13.81 mm/min or 440 Rpm)

Table 4.3 ESTIMATED TOOL WEAR OBTAINED FROM STATISCAL ANALYSIS FOR READING SET A (Diameter 10 mm, feed .12 mm/rev, speed 13.71 mm/min or 440 RPM)

No. Of holes	Machining time	Force (N)	Torque (N-m)	Tool wear (mm)	Estimated Tool wear
5	2.076	1932.57	6.867	0.1	0.108329
10	4.151	2040.48	7.848	0.18	0.191557
15	6.226	2089.53	8.004	0.25	0.266758
20	8.301	2118.96	8.25	0.33	0.337134
25	10.376	2226.27	8.63	0.45	0.408823
30	12.541	2374.02	9.123	0.52	0.484687
35	14.941	2481.93	9.613	0.56	0.564794
40	16.601	2658.51	10.3	0.61	0.626824

The graph is given below shows the variation of actual tool wear with the estimated tool wear calculated from modified regression equation for reading set A.

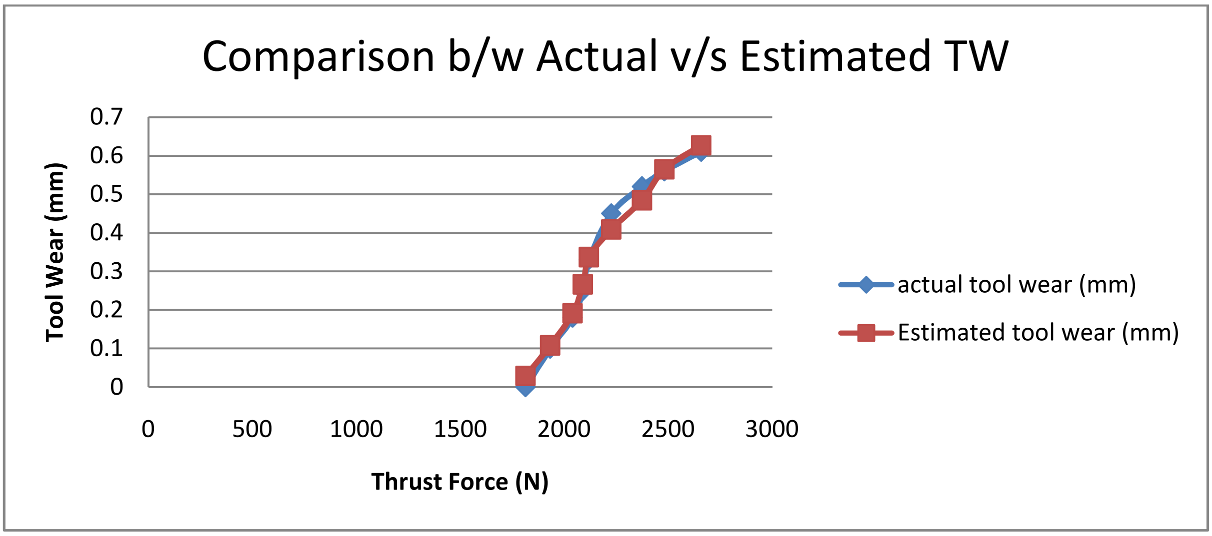


Fig.4.2 COMPARISION BETWEEN ACTUAL TOOL WEAR & ESTIMATED TOOL WEAR FOR READING SET A

Modified Regression equation for reading set B is given in eq. 4.7.

TW== $0.00911\times F^{0.29}\times T^{0.98}$ ....(4.7)

(Diameter 10 mm, feed 0.2 mm/rev speed 18.22 mm/min or 580 Rpm)

Table 4.4 ESTIMATED TOOL WEAR OBTAINED FROM STATISCAL ANALYSIS FOR READING SET B

(diameter 10 mm, feed .12 mm/rev, speed 18.22 mm/min or 580 RPM)

No. Of hoes	Machining time (min)	Thrust (N)	Torque (N-m)	Tool wear (mm)	Estimated tool wear (mm)
5	0.946	3090.81	10.791	0.09	0.088718
10	1.891	3149.01	11.772	0.17	0.175852
15	2.836	3207.87	12.753	0.29	0.263011
20	3.781	3305.97	12.753	0.35	0.351698
25	4.726	3374.64	13.734	0.42	0.440259
30	5.671	3443.31	14.715	0.59	0.529454
35	6.616	3531.6	15.696	0.56	0.620317
40	7.561	3688.56	16.677	0.66	0.716002

The graph is given below shows the variation of actual tool wear with the estimated tool wear calculated from modified regression equation for reading set B.

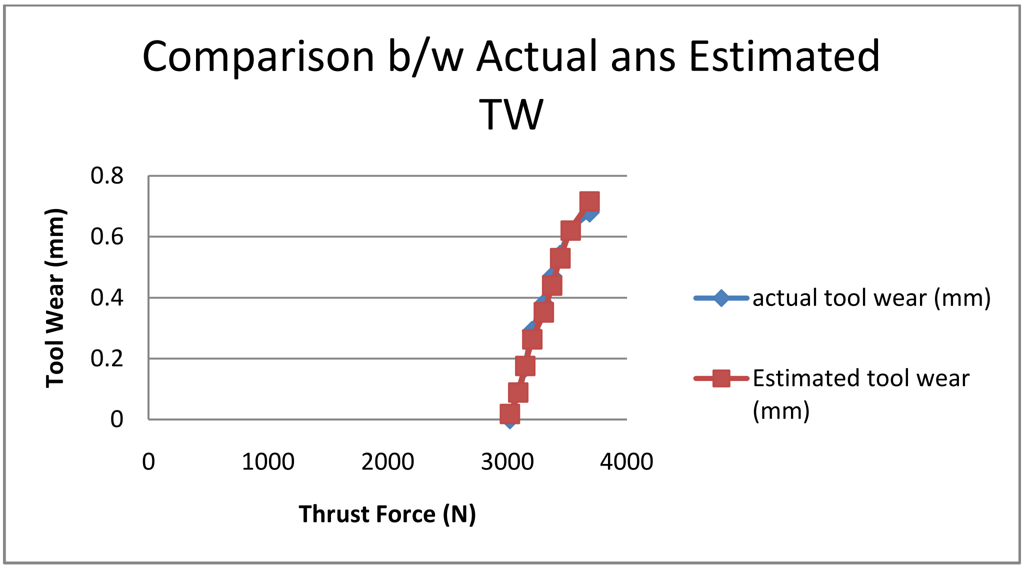


Fig.4.3 COMPARISION BETWEEN ACTUAL TOOL WEAR & ESTIMATED TOOL WEAR FOR READING SET B

4.1.2 ARTIFICIAL NEURAL NETWORK ANALYSIS

These networks are designed to stimulate the information processing of the human brain. These networks have been successfully applied to industrial problems in the areas of pattern classification and automatic control. An ANN that uses back propagation algorithms for modelling tool wear has been developed using machining process parameters as inputs and tool wear as output. Back propagation neural networks are typical feed forward networks, as shown in Fig.4.4.

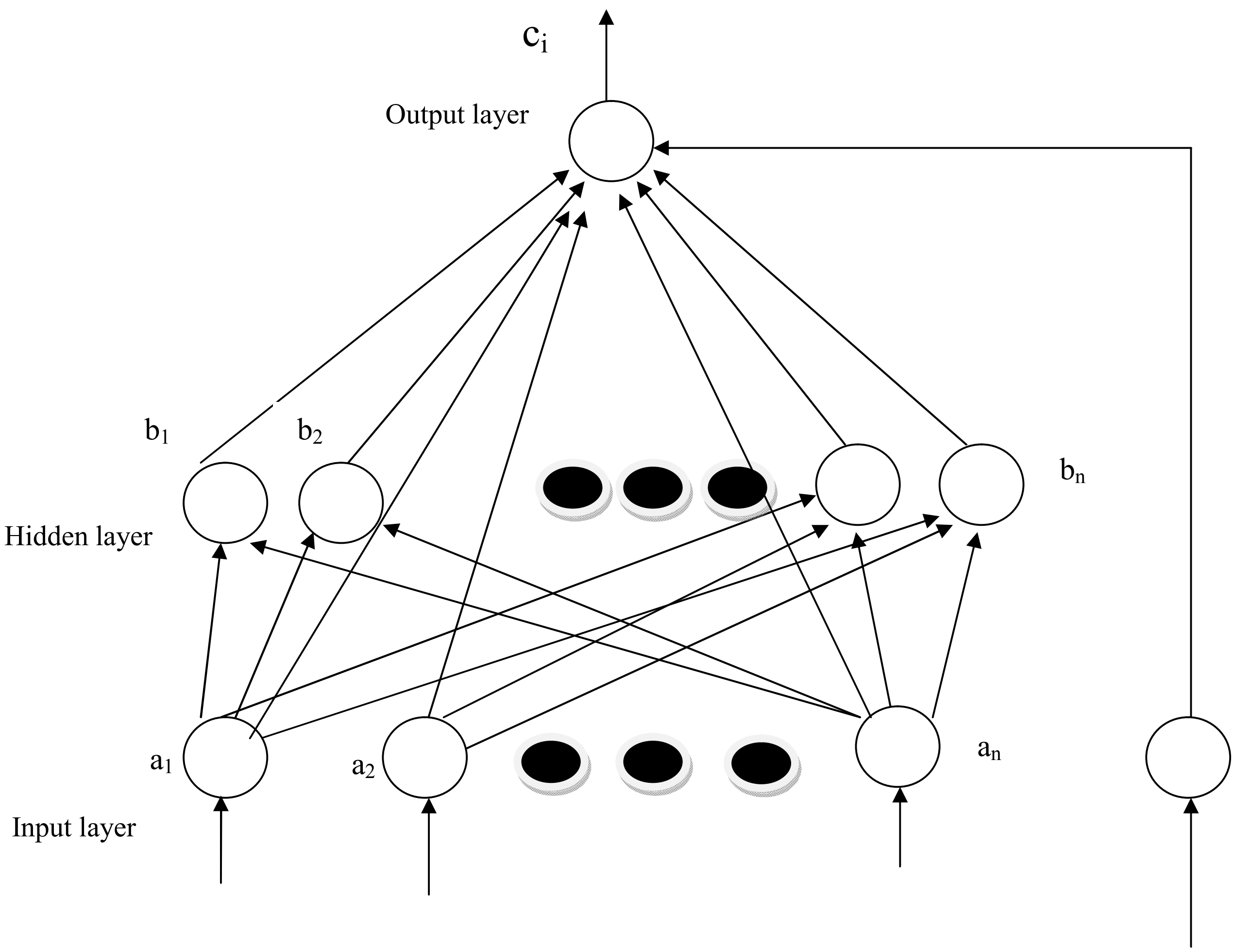


Fig.4.4 A TYPICAL FEED FORWARD NETWORK FOR ANN

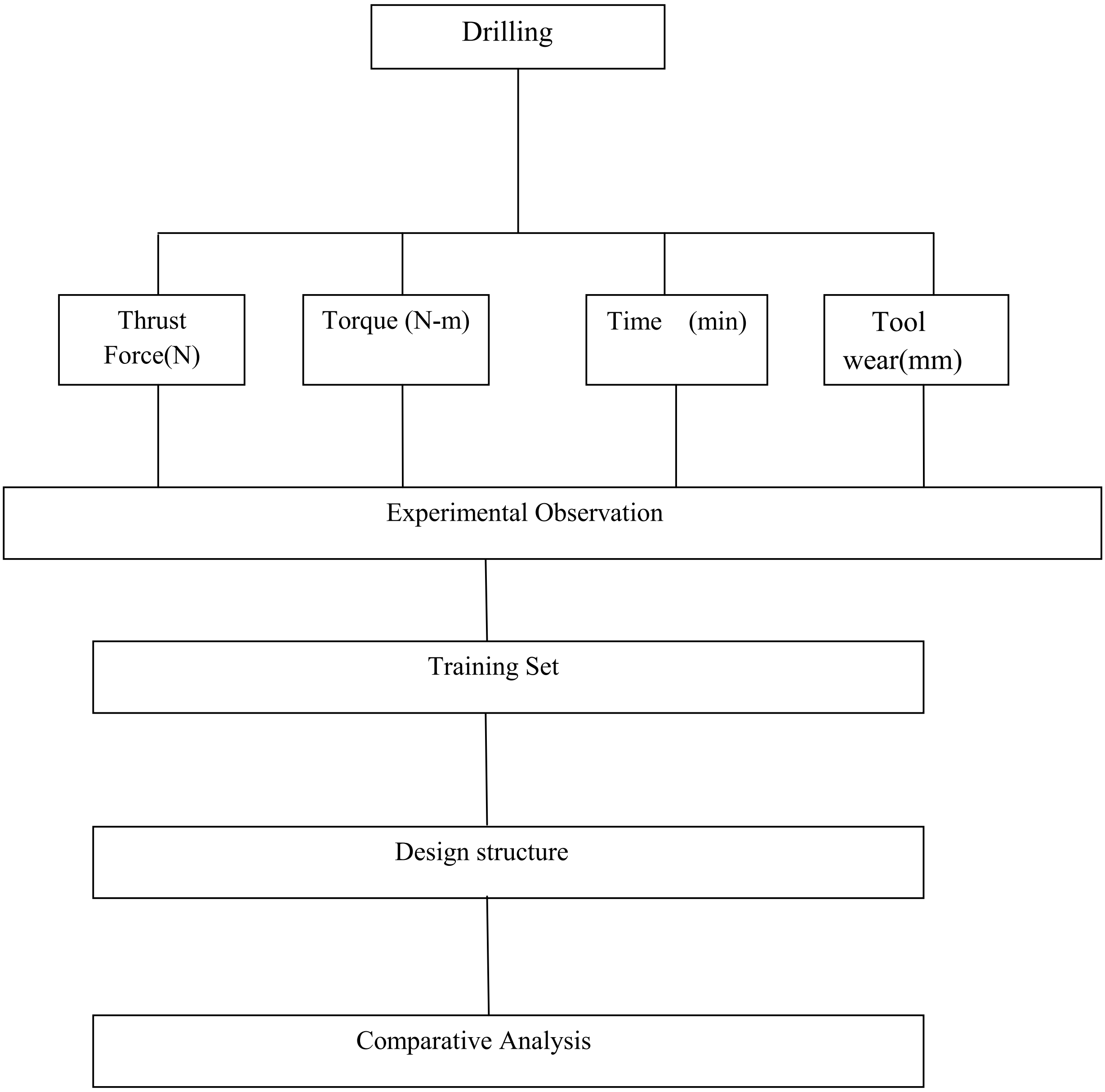


Fig.4.5. PROCESS PARAMETER IN ANN

By Making connections between the input layer and the output layer improves the learning efficiency. The first step of analysis in ANN is to normalize all the raw or input data data to values between 0.1 and 0.9. Two data sets obtained from table 4.1 and table 4.2 has been used for the training of neural network, the learning rate is used 0.08, and no smoothing factor has used. Initially weights are assigned randomly from 0.1 to 0.8; the learning process was stopped after 2000 iterations. The number of neurons in the hidden layer are selected from 10,15 and 20.

The first step of the calculation is to normalize all the raw input data to values between 0.1 and 0.9 as shown in the following equation.

$$a_i = \frac{0.8}{d_{\max} - d_{\min}}(d_i - d_{\min}) + 0.1$$

where d_{max} and d_{min} are the maximum and minimum input data, respectively, and d_i is the i^{th} input data.

The input of the each i^{th} neuron on the hidden layer I_{bi} is calculated by :

$$I_{bi} = \sum_{i=1}^{m} w_{ab} a_i$$

where m is the number of neurons in the input layer and w_{ab} is the numerical weight value of the connection between the two neurons. a_i is the i_{th} normalized output value from the input layer.

The output of the ith neuron on the hidden layer b_i is calculated by applying an activation function to the summed input to that neuron. The output of the each ith neuron on the hidden layer then becomes,

$$b_i = f(b_i) = \frac{1}{1 + e^{-s(I_{bi})}}$$

where s is the slope of the sigmoid function.

The values received by the output layer I_c are the outputs of the hidden and input layers.

$$I_{ci} = \sum_{i=1}^{m} w_{ac} \ a_i + \sum_{i=1}^{n} w_{bc} b_i$$

where m, the number of neurons in the input and n,the number of neurons in hidden layers. W_{ac} and w_{bc} are the weights between the input and output layer and between the hidden layer and output layer respectively. The actual output for the output layer is calculated by applying the same sigmoid function as in the hidden layer,

$$c_i = f(I_{ci})$$

The error between the actual and desired output in the output layer is calculated by

$$\delta_{ci} = f^{'}(I_{ci})(X_i - c_i)$$

where X_i is the i^{th} training input to the neuron and f is the derivative of the sigmoid function.

Calculation of the error (δ_{bi}) For each neuron on the hidden layer is,

$$\delta_{bi} = f(I_{bi}) \sum_{i=1}^{K} \delta_{ci} w_{bc}$$

where K is the number of neurons in the output layer. MATLAB 2013 and neural tool box has been used to analyze the ANN application in the drilling problem of tool wear. The different test data is used for training the neural network structures. In order to find that which neural set will be the best neural network structure of ANN, a simple criteria can be used. Criteria is that the on increasing the no. of neurons on hidden layer optimises the result which gives minimum mean square error from actual tool wear.

For calculating updated new weight following step is to be done,

$$\Delta w_{bc}{}^{new} = (1 - \beta)\alpha\delta_{ci} b_i + \beta \Delta w_{bc}{}^{old}$$

Similarly for w_{ab} and w_{ac} equation can be written.

α is learning rate. By increasing the learning rate number of iteration is required minimum and improves efficiency and β is smoothing constant.

TABLE 4.5 TOOL WEAR OBTAINED FROM ANN ANALYSIS FOR READING SET A
(Diameter 10 mm, feed 0.12mm/rev, speed 13.71 mm/min or 440 RPM)

No .of holes	MT (min)	Force (N)	Torque (N-m)	TOOL WEAR (mm)	6×10×1 TOOL WEAR (mm)	6×15×1 TOOL WEAR (mm)	6×20×1 TOOL WEAR (mm)
5	2.076	1932.57	6.867	0.1	0.1392	0.1324	0.1221
10	4.111	2040.48	7.848	0.18	0.1987	0.1888	0.1849
15	6.226	2089.53	8.004	0.25	0.2590	0.2523	0.2517
20	8.301	2118.96	8.25	0.33	0.3351	0.3319	0.3304
25	10.376	2226.27	8.63	0.45	0.4518	0.4504	0.4502
30	12.541	2374.02	9.123	0.52	0.5207	0.5204	0.5203
35	14.941	2481.93	9.613	0.56	0.5620	0.5609	0.5603
40	16.601	2658.51	10.3	0.61	0.6172	0.6113	0.6105

TABLE 4.6. TOOL WEAR OBTAINED FROM ANN ANALYSIS FOR READING SET B
(Diameter 10 mm, feed 0.2mm/rev, speed 18.22 mm/min or 580 RPM)

No .of holes	MT (min)	Force (N)	Torque (N-m)	Tool Wear (mm)	6×10×1 Tool Wear (mm)	6×15×1 Tool Wear (mm)	6×20×1 Tool Wear (mm)
5	0.946	3090.81	10.791	0.09	0.1350	0.1233	0.1153
10	1.891	3149.01	11.772	0.17	0.1903	0.1820	0.1753
15	2.836	3207.87	12.753	0.29	0.2954	0.2917	0.2905
20	3.781	3305.97	12.753	0.35	0.3850	0.3805	0.3813
25	4.726	3374.64	13.734	0.42	0.4209	0.4210	0.4202
30	5.671	3443.31	14.715	0.56	0.5615	0.5510	0.5503
35	6.616	3531.6	15.696	0.59	0.5913	0.5911	0.5910
40	7.561	3688.56	16.677	0.66	0.6614	0.6614	0.6608

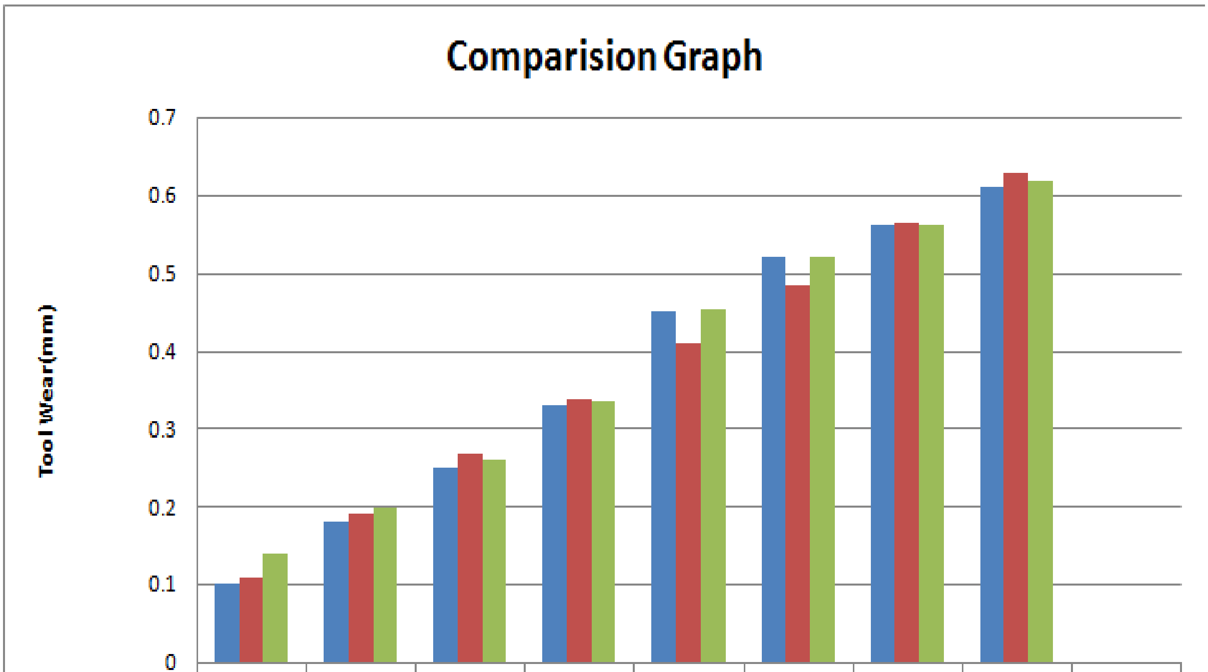
CHAPTER 5

RESULTS COMPARISION AND CONCLUSION

5.1 COMPARISION OF RESULTS

A comparison graph is plotted is shown in Fig.4.6 . it compares actual value with estimated Value calculated from statistical analysis and also compare with ANN structure (6x10x1) for reading set A.

(diameter 10 mm, speed 13.71 mm/min or 440 RPM, feed .12 mm/rev)

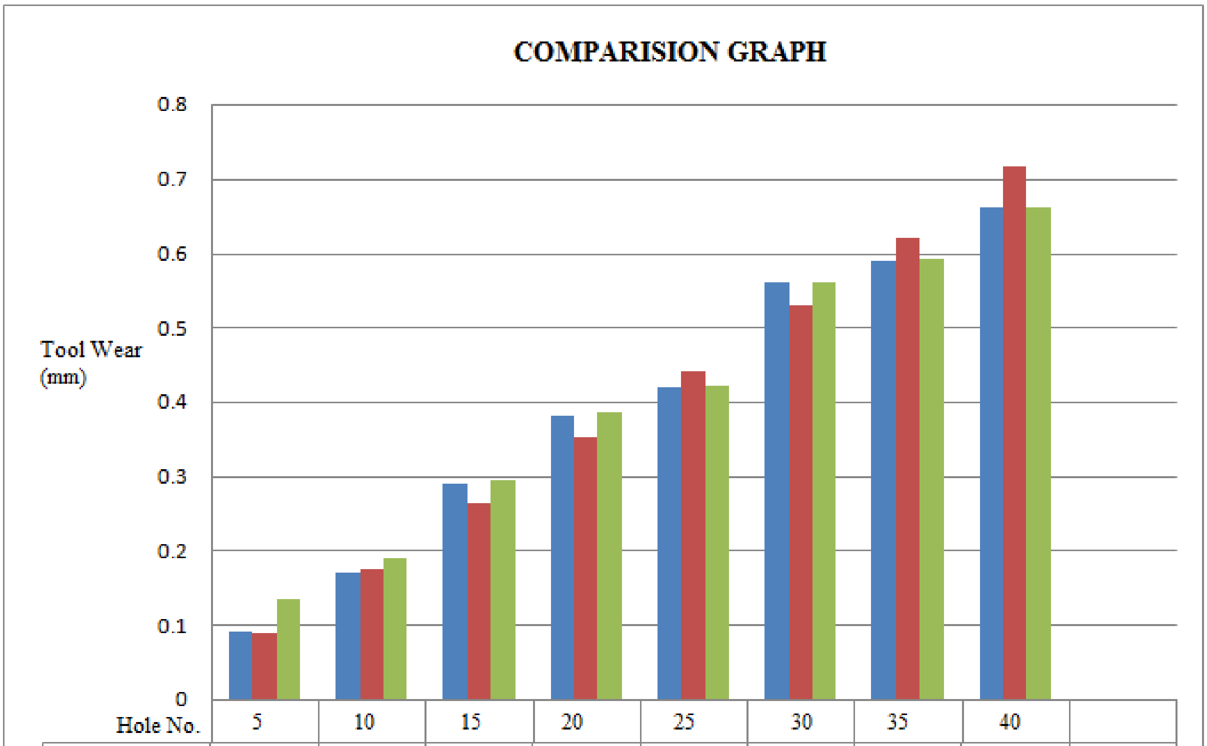


Hole No.	5	10	15	20	25	30	35	40
Actual TW	0.1	0.18	0.25	0.33	0.45	0.52	0.56	0.61
Estimated TW	0.1083289	0.1915569	0.2667577	0.3371344	0.4088227	0.4846870	0.5647943	0.6268239
ANN(6x10x1)	0.1392	0.1987	0.259	0.3351	0.4518	0.5207	0.562	0.6172

Fig.4.6. TOOL WEAR COMPARISION FOR READING SET A

A comparison graph is plotted is shown in Fig.4.7 . it compares actual value with estimated Value calculated from statistical analysis and also compare with ANN structure (6x10x1) for reading set B.

(diameter 10 mm, speed 18.22 mm/min or 440 RPM, feed 0.2 mm/rev)



Hole No.	5	10	15	20	25	30	35	40
Actual TW	0.09	0.17	0.29	0.38	0.42	0.56	0.59	0.66
Estimated TW	0.088718	0.175851	0.263010	0.351697	0.440258	0.529453	0.620317	0.716002
ANN(6x10x1)	0.135	0.1903	0.2954	0.385	0.4209	0.5615	0.5913	0.6614

Fig.4.7. TOOL WEAR COMPARISION FOR READING SET B

Graphs are plotted between tool wear and different parameter like thrust force and torque for both of the reading sets A and B. Fig. 4.8 and Fig.4.9 demonstrates that torque and thrust force increase as tool wear increases.

Graphs for variation of tool wear with respect to thrust force and toque in Fig. 4.8 and Fig.4.9 respectively.

(Diameter 10mm , feed .12 mm/rev, speed 13.72 mm/min or 440 rpm)

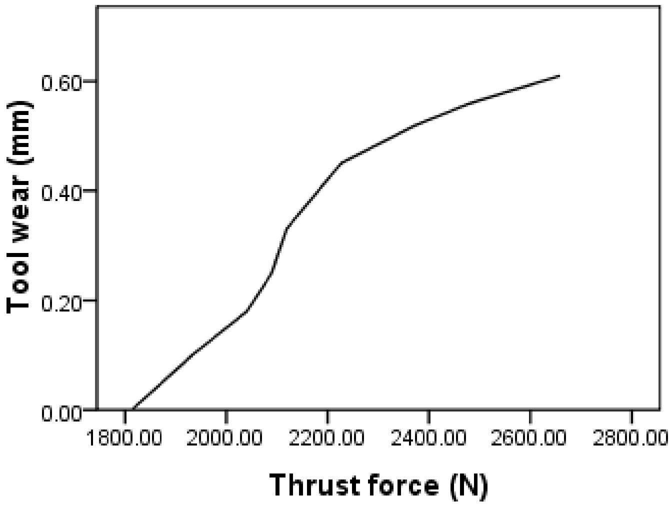


Fig.4.8. GRAPH BETWEEN TOOL WEAR AND THRUST FORCE FOR READING SET A

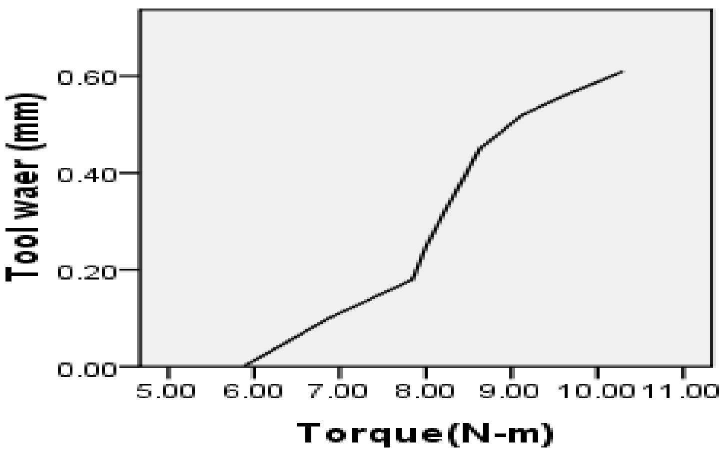


Fig.4.9. GRAPH BETWEEN TOOL WEAR AND TORQUE FOR READING SET A

Graphs for variation of tool wear with respect to thrust force and torque (Diameter 10mm , feed .2 mm/rev, speed 18.22 mm/min or 580 rpm) is shown in below graph in Fig.4.10 and Fig.4.11.

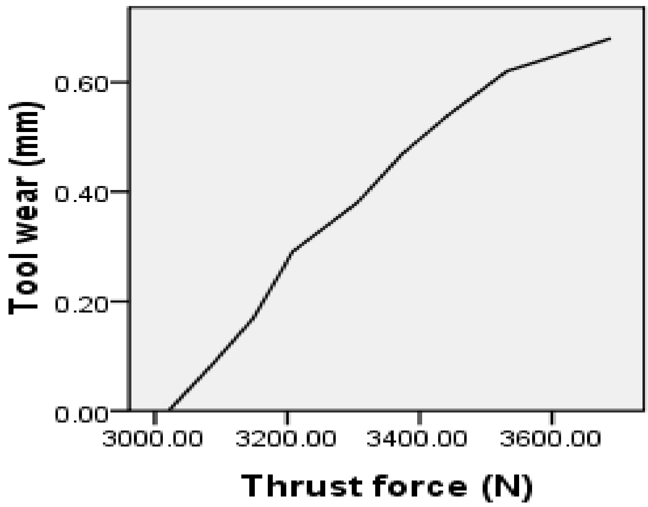


Fig.4.10.GRAPH BETWEEN TOOL WEAR AND THRUST FORCE FOR READING SET B

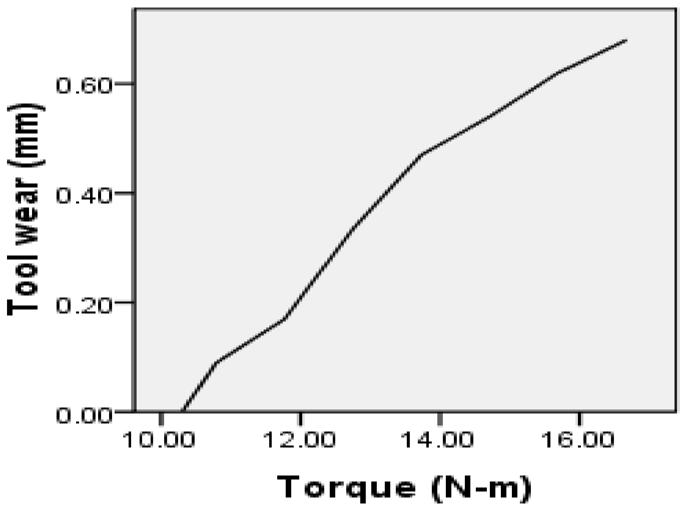


Fig.4.11. GRAPH BETWEEN TOOL WEAR AND TORQUE FOR READING SET B

5.2 CONCLUSION

Based on the observation Tables 4.2 and 4.3, following observations is made regarding statistical analysis. The focus of the work is on 10 mm drill diameter. It is assumed that tool wear depends on the cutting speed, feed, machining time and thrust force. The regression equations obtained is statistically justified in statistical sense and the modified regression equations is used for estimating the values of tool wear. A back propagation algorithm is used for the prediction of tool wear. It is assumed that tool wear depends on drill diameter, cutting speed, feed, machining time, thrust force and torque. Following observations were made regarding neural networks:

- Drill diameter, feed, cutting speed, time, force and torque is given as inputs and flank is estimated using different structures of ANN (Tables 4.5 and 4.6). These input can be used to train the neural network for getting the estimated values of tool wear. The work has demonstrated that tool wear depends on these variables.
- In both set of reading i.e. A and B , 6x20x1 gives best result because of minimum error from actual value. Here it is cleared that on increasing the number of neurons on hidden layer gives more accurate results.
- The comparative analysis has been done between the actual values of tool wear and the estimated values obtained by statistical analysis and neural network analysis.

- As per the Fig.4.6 and Fig.4.7, the estimated values obtained by neural network structures, are comparing well with the actual values obtained during experimentation for all the combinations of cutting speed and feed.

- Experimental results show that this method can be effectively employed in practice as the algorithm is easy and reliable. Neural network has shown the capability of generalization and has the ability for its application in tool wear analysis.

REFERENCES

1. C. Tsao and H. Hocheng, Evaluation of thrust force and surface roughness in drilling composite material using Taguchi analysis and neural network, Journal of Materials Processing Technology, Vol. 203, No. 1-3, 2008, pp. 342-348.

2. Abbu-Mahfouz, (2003). Drilling wear detection and classification using vibration signals and artificial neural network, International Journal of Machine Tools & Manufacture. 43(2003) 707–720.

3. B. Byrne, D.A. Dornfeld et al., Tool condition monitoring (TCM)—the status of research and industrial application, Annals of the CIRP 44 (2) (1995) 541–567.

4. D.A. Dornfeld, Neural network sensor fusion for tool condition monitoring, Annals of the CFRP 39 (1) (1990) 101–1051.

5. D.E. Dimla Jr, P.M. Lister, N.J. Leighton, Neural network solutions to the tool condition monitoring problem in metal cutting—a critical review of methods, International Journal of Machine Tools and Manufacture 37 (9) (1997) 1219–1241.

6. D. Iliescu, D. Gehin, F. Girot, M.E. Gutierrez, Modeling and tool wear in drilling of CFRP, International Journal of Machine Tools and Manufacture 50 (2010) 204-213.

7. E. Govekar, J. Gradisek, I. Grabe, (2000). Analysis of acoustic emission signals and monitoring of machining processes, Ultrasonic .38 (2000). 598–603.

8. E. Govekar, I. Grabec, Self-organizing neural network application to drill wear classification,ASME Journal of Engineering for Industry 116 (1994) 233–238.

9. E. Jantunen, (2002). A summary of methods applied to tool condition monitoring in drilling, International Journal of Machine Tools & Manufacture. 42 (2002) 997–1010.

10. E. Jantunen, H. Jokinen, Automated On-line Diagnosis of Cutting Tool Condition (Second version), International Journal of Flexible Automation and Integrated Manufacturing 4 (3-4) (1996) 273–287.

11. G.S. Hong, M. Rahaman, Q. Zhou, (1996). Using neural network for tool condition monitoring based on wavelet decomposition, International Journal of Machine Tools & Manufacture. 36 (5) (1996) 551–566.

12. I.N. Tansel, C. Mekdeci, O. Rodriguez, B. Uragun, Monitoring drill conditions with wavelet based encoding and neural network, International Journal of Machine Tools & Manufacture 33 (4) (1993) 559–575

13. Issam Abu-Mahfouz, Drilling wear detection and classification using vibration signals and artificial neural network, International Journal of Machine Tools and Manufacture 43 (2003) 707-720.

14. K. Subramanian, N.H. Cook, Sensing of drill wear and prediction of drill life , Journal of Engineering for Industry, Transactions of the ASME 101 (1977) 295–301

15. L. Dan, J. Mathew, Tool wear and failure monitoring techniques for turning a review, Int. J. Mach. Tools Manufacture. 30 (4) (1990) 579–598

16. L. Xiaoli, (1999). On-line detection of the breakage of small diameter drills using current signature wavelet transform, International Journal of Machine Tools & Manufacture. 39 (1999) 157–164.

17. L. Xiaoli, S.K. Tso, (1999). Drill wear monitoring based on current signals, Wear 231 (1999) 172–178.

18. Muataz Hazza F. Al Hazza1, Erry Y.T. Adesta, & Muhammad Riza, Flank wears Simulation by using back propagation neural network when cutting hardened H-13 steel in CNC End Milling.

19. P.G. Li, S.M. Wu, Monitoring drilling wear states by a fuzzy pattern recognition technique, Journal of Engineering for Industry, Transactions of the ASME 110 (2) (1988) 297–300.

20. P. Bhattacharyya, D. Sengupta, S. Mukhopadhyay, (2007). Cutting force-based real-time estimation of tool wear in face milling using a combination of signal processing techniques, Mechanical Systems and Signal Processing 21 (2007) 2665–2683.

21. Q. Zhang, A. Benveniste, (1992). IEEE Trans. Neural Network.3 (1992) 889. R. Mauri, S Matti, (1995). Tool wear and failure in the drilling of stainless steel, Journal of Materials Processing Technology. 52 (1995) 35–43.

22. R.P. Lippmann, An introduction to computing with neural nets, IEEE ASSP Magazine 4(2) (1987) 4–22.

23. Ranganath M S, Vipin, R S Mishra, Application of ANN for Prediction of Surface Roughness in Turning Process: A Review, International Journal of Advance Research and Innovation, 3, 2013, 229-233.

24. S. Braun, E. Lenz, Machine Tool Wear Monitoring, Mechanical Signature Analysis, Theory and Applications, pp. 321–342, Academic Press Ltd, 1986.

25. S.C. Lin, C.J. Ting, Drill wear monitoring using neural networks, International Journal of Machine Tools and Manufacture 36 (4) (1996) 465–475.

26. S.C. Lin, C.J. Ting, Tool wear monitoring in drilling using force signals,wear 180 (1995) 53-60.

27. S. Li, W.S. Lau, Y.Z. Zhang, (1992). In-process drill wear and breakage monitoring for a machining center based on cutting force parameters, International Journal of Machine Tools and Manufacture. 32 (1992) 855–867.

28. S.S. Panda, A.K. Singh, D. Chakraborty, S.K. Pal, (2006). Drill wear monitoring using back propagation neural network, Journal of Materials Processing Technology 172 (2006) 283–290.

29. S.S. Panda, D. Chakraborty, S.K. Pal, (2008). Flank wear prediction in drilling using back propagation neural network and radial basis function network, Applied Soft Computing 8 (2008) 858–871.

30. Szu H, Telfer B, Kadambe S, (1992). Neural network adaptive wavelets for signal representation and classification. Opt Eng 1992; 36(9): 1907–1916.

31. T.I. Liu, S.M. Wu, On-line detection of drill wear, ASME Journal of Engineering for Industry 112 (1990) 299–302.

32. T.I. Liu, K.S. Anantharaman, Intelligent classification and measurement of drill wear, ASME Journal of Engineering for Industry 116 (1994) 392–397.

33. T.I. El-Wardany, D. Gao, M.A. Elbestawi, Tool condition monitoring in drilling using vibration signature analysis, International Journal of Machine Tools and Manufacture 36 (6) (1996) 687– 711.

34. T.I. Liu, W.Y. Chen, Intelligent detection of drill wear, Mechanical Systems and Signal Processing 12 (6) (1998) 863–873.

35. T.I. Liu, K.S. Anantharaman, Intelligent classification and measurement of drill wear, Journal of Engineerin M. Routio, M. Sa¨yna¨tjoki, Tool wear and failure in the drilling of stainless steel, Journal of Materials Processing Technology 52(1) (1995) 35–43.

36. T.I. Liu, E.J. Ko, On-line recognition of drill wear via artificial neural networks, monitoring and control for manufacturing processes, PED, ASME 44 (1990) 101–110.

37. T. Nagao, Y. Hatamura, M. Mitsuishi, In-process prediction and prevention of the breakage of small diameter drills-based on theoetical analysis, Annals of the CIRP 43 (1) (1994) 85–88.

38. X. Li, S. Dong, P.K. Venuvinod, Hybrid learning for tool wear monitoring, International Journal of Advanced Manufacturing Technology 16 (2000) 303–307.

39. Young Jun Choi, Min Soo Park, Chong Nam Chu, (2008). Prediction of drill failure using features extraction in time and frequency domains of feed motor current, International Journal of Machine Tools & Manufacture.48 (2008) 29-39.

40. Z. Wang, D. Dornfeld, In process tool wear monitoring using neural networks, in Proceedings of the 1992 Japan–USA Symposium on Flexible Automation, 1992, pp. 263-270.

MATLAB FILE FOR READING SET A

```
clc;
clear all;
close all;

slope_sigmoid=0.5;
alpha=0.08;
beta=1;
gama=0.3;
y_length=20;

iteration_count=2000;

xdiameter=[ 10    10    10    10    10    10    10    10    10];
xspeed=[ 13.7100   13.7100   13.7100   13.7100   13.7100   13.7100
13.7100   13.7100   13.7100];
xfeed=[ 0.1200    0.1200    0.1200    0.1200    0.1200    0.1200    0.1200
0.1200    0.1200];
xtime= [ 0.4150    2.0760    4.1510    6.2260    8.3010   10.3760   12.5410
14.9410   16.6010];
xforce=[1814.5 1932.57 2040.48 2089.53 2118.96 2226.27 2374.02 2481.93
2658.51];
xtorque=[5.886 6.867 7.848 8.004 8.25 8.63 9.123 9.613 10.3];
x_toolwear=[0 0.1 0.18 0.25 0.33 0.45 0.52 0.56 0.61];


x_total_input=[xdiameter; xspeed; xfeed; xtime; xforce; xtorque];

x_total_input_max=max(max(x_total_input));
x_total_input_min=min(min(x_total_input));

x_total_input_normalized=0.8*(x_total_input-
x_total_input_min)./(x_total_input_max-x_total_input_min)+0.1;

x_total_input=x_total_input_normalized;

x_total_input=x_total_input(:,2);
x_toolwear=x_toolwear(:,2);

[x_input_type x_measurement] =size(x_total_input);

weight_xy= rand(y_length, x_input_type);
weight_yz= rand(1, y_length);
weight_zx= rand(1, x_input_type);

for lp=1:iteration_count

i_y=weight_xy*x_total_input;
yi_slope=1./(1+exp(-slope_sigmoid*i_y));

i_z = weight_yz*yi_slope+ weight_zx*x_total_input;
zi_slope=1./(1+exp(-slope_sigmoid*i_z));

% differentiator_zi=cat(2,i_z,sum(i_z)/length(i_z))-
cat(2,sum(i_z)/length(i_z),i_z);
% differentiator_yi=cat(2,i_y,(sum(i_y')/length(i_y))')-
cat(2,(sum(i_y')/length(i_y))',i_y);
```

```
differentiator_zi=zi_slope.*(1-zi_slope);
differentiator_yi=yi_slope.*(1-yi_slope);

delta_zi= differentiator_zi.*(x_toolwear-zi_slope);

delta_zi_times=[];
for u=1:y_length
    delta_zi_times=cat(1,delta_zi,delta_zi_times);
end

weight_yz_times=[];

for v=1:x_measurement
    weight_yz_times=cat(1,weight_yz,weight_yz_times);
end

delta_yi= differentiator_yi.*delta_zi_times.*weight_yz_times';


weight_xy_new=gama*alpha*delta_yi*x_total_input'+beta*weight_xy;
weight_zx_new=gama*alpha*delta_zi*x_total_input'+beta*weight_zx;
weight_yz_new=gama*alpha*delta_zi*yi_slope'+beta*weight_yz;

weight_xy=weight_xy_new;
weight_yz=weight_yz_new;
weight_zx=weight_zx_new;


end

[x_toolwear; zi_slope; [x_toolwear-zi_slope]^2]'
```