The International Journal Of Engineering And Science (IJES)
|| Volume || 3 || Issue || 7 || Pages || PP-58-71 || 2014 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

"Surface Roughness Analysis And Compare Prediction And Experimental Value For Cylindrical Stainless Steel Pipe (Ss 316l) In CNC Lathe Turning Process Using ANN Method For Re-Optimization And Cutting Fluid"

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ABSTRACT

Surface quality of the machined parts is one of the most important product quality indicators and most frequent customer requirements. Metal cutting processes are important due to increased consumer demands for quality metal cutting related products more precise tolerances and better product surface roughness that has driven the metal cutting industry to continuously improve quality control of metal cutting processes. The average surface roughness (R_a) represents a measure of the surface quality, and it is mostly influenced by the following cutting parameters: the cutting speed, feed rate, and depth of cut. This paper presents optimum surface roughness by using CNC Lathe for 316L stainless steel pipe with Artificial Neural Networks Optimization (ANNO). The approach is based on Multiple Regression Analysis (MRA) Method and Artificial Neural Networks (ANN). The main objectives is to find the optimized parameters and the most dominant variables cutting speed, feed rate, axial depth and radial depth. The ANN model indicates that the feed rate is the most significant factor affecting surface roughness. The mathematical model developed by using multiple regression method shows the accuracy of surface roughness Prediction. The result from this research is useful to be implemented in both time-consuming and laborious works in industry to reduce time and cost in surface roughness prediction.

KEYWORDS: *316L SS Pipe Specimen, CNC Lathe, Turning, surface roughness, Artificial Neural Network (ANN) and Re-Optimization.*

Date of Submission: 16 July 2014 Date of Publication: 30 July 2014

I. INTRODUCTION

The challenge of modern machining industries is mainly focused on the achievement of high quality in term of work piece dimensional accuracy, surface finish, high production rate, less wear on the cutting tools, economy of machining in terms of cost saving and increase of the performance of the product with reduced environmental impact. End milling is a very commonly used machining process in industry. The ability to control the process for better quality of the final product is paramount importance. The mechanism behind the formation of surface roughness in CNC Lathe turning process is very dynamic, complicated, and process dependent. Several factors will influence the final surface roughness in a CNC Lathe operations such as controllable factors (spindle speed, feed rate and depth of cut) and uncontrollable factors (tool geometry and material properties of both tool and workpiece). Some of the machine operator using 'trial and error' method to set-up Lathe machine cutting conditions. This method is not effective and efficient and the achievement of a desirable

value is a repetitive and empirical process that can be very time consuming. Thus, a mathematical model using statistical method provides a better solution. Multiple regression analysis is suitable to find the best combination of independent variables which is spindle speed, feed rate, and the depth of cut in order to achieve desired surface roughness. Unfortunately, multiple regression model is obtained from a statistical analysis which is have to collect large sample of data. Realizing that matter, Artificial Neural Network (ANN) is state of the art artificial intelligent method that has possibility to enhance the prediction of surface roughness. This paper will present the application of ANN to predict surface roughness for CNC Lathe process. The accuracy of ANN to predict surface roughness will be compared with mathematical model that built using multiple regression analysis.

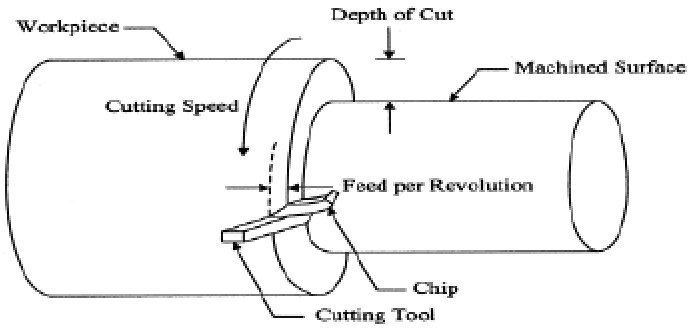

Figure 1 : Diagram for turning process of SS 316L Pipe specimen

Machining Parameters affects the surface roughness

Surface roughness is an important measure of product quality since it greatly influences the performance of mechanical parts as well as production cost. Surface roughness has an impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life, etc. It also affects other functional attributes of parts like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity, etc. Sometimes, various catastrophic failures causing high costs have been attributed to the surface finish of the components in question. As a result, there have been a great many research developments in modeling surface roughness and optimization of the controlling parameters to obtain a surface finish of desired level since only proper selection of cutting parameters can produce a better surface finish. But such studies are far from complete since it is very difficult to consider all the parameters that control the surface roughness for a particular manufacturing process. Figure shows the fishbone diagram with the parameters that affect surface roughness . In the manufacturing industries, various machining processes are adopted for removing the material from the work piece for a better product. Out of these, end milling process is one of the most vital and common metal cutting operations used for machining parts because of its ability to remove materials faster with a reasonably good surface quality. In recent times, computer numerically controlled (CNC) machine tools have been implemented to realize full automation in milling since they provide greater improvements in productivity, increase the quality of the machined parts and require less operator input.

Cutting tool properties	Tool materials
	Tool Shape
	Tool Signature(Rake angle, Nose radius)
	Runout error
	Tool overhang
	Cutting edge geometry
Machining parameter	Cutting Speed
	Feed Rate
	Depth of Cut
	Tool Angle
	Cutting Fluid
Work-piece properties	Work-piece Material
	Work-piece Length, Diameter etc.
	Work-piece Hardness
	Mechanical Properties
Cutting condition	Cutting Force
	Friction
	Cutting Velocity
	Types of Chip Formation
	Vibration

Figure 2 : Fishbone Diagram showing parameters affecting surface roughness

II. LITERATURE REVIEW

[01] Lee and Ren, (1996) Surface finish plays an important role in affecting friction, wear, and lubrication of contacting bodies.

[02] Previously, Oktem et al. (2005) proposed the genetic programming approach to predict surface roughness based on cutting parameters (spindle speed, feed rate and depth of cute) and on vibrations between cutting tool and work piece. From this research, they conclude that the models that involve three cutting parameters and also vibrating, give the most accurate predictions of surface roughness by using genetic programming.

[03] Chang et al.(2007) were stablished a method to predict surface roughness in-process. In their research, roughness of machined surface was assumed to be generated by the relative motion between tool and work piece and the geometric factors of a tool. The relative motion caused by the machining process could be measured in process using a cylindrical capacitive is placement sensor (CCDS). The CCDS was installed at the quill of a spindle and the sensing was not disturbed by the cutting. A simple linear regression model was developed to predict surface roughness using the measured signals of relative motion. Surface roughness was predicted from the displacement signal of spindle motion. The linear regression model was proposed and its effectiveness was verified from cutting tests.

[04].Tasdemir et al. (2008) applied ANN to predict surface roughness a turning process. This method was found to be quite effective and utilizes fewer training and testing data.

[05] Hazim et.al (2009) developed a surface roughness model in end milling by using Swarm Intelligence. From the studies, data was collected from CNC cutting experiments using Design of Experiments approach. The inputs to the model consist of Feed, Speed and Depth of cut while the output from the model is surface roughness. The model is validated through a comparison of the experimental values with their predicted counterparts.

[06].Benardos & Vosniakos presented various methodologies and practices that were employed to predict surface roughness. The approaches listed in their review paper were classified into those based on machining theory, experimental investigation, designed experiments, and artificial intelligence.

[07].Choudhury *et al.* discussed the development of surface roughness prediction models for turning EN 24T steel (290 BHN) using a response surface methodology. A factorial design technique was used to study the effects of the main cutting parameters such as cutting speed, feed, and depth of cut on surface roughness. The tests were carried out using uncoated carbide inserts without any cutting fluid.

[08] V. Pallavi, Anoop kumar and T. Mohandas (2012). Optimization of turning parameters for surface roughness using taguchi method. International Journal of Mechanical Engineering. Vol. 5 : Issue 2.

[09] Surinder kumar, Meenu and P.S. Satsangi (2012). A genetic algorithmic approach for optimization of surface roughness prediction model in turning using UD-GFRP composite. Indian Journal of Engineering and Materials Sciences. Vol. 19, 386-396.

[10]. Kushnaw *et al.* observed that the main factor affecting the inclination angle is the diameter of the periphery, and machined diameters depend on change in depth of cut and the cutting condition.

[11]. Akkus *et al.* found that the feed rate is the most significant factor that contributes to the surface roughness using ANOVA and regression.

[12]. Grzesik & Wanat the results show that by keeping equivalent feed rates (0.1 mm/rev for conventional, and 0.2 mm/rev for wiper inserts), the obtained surfaces have similar roughness parameters and comparable values of skewness and kurtosis. With wiper inserts and a high feed rate it is possible to obtain machined surfaces with <0.8 µm of Ra compared with conventional inserts that present high values of surface roughness .

III. THEORITICAL BACK GROUND

A. Multiple Regression Analysis

After the surface roughness is obtained for all experiments,a table needs to be filled in order to obtain several values for the analysis. In order to obtain regression coefficient estimates β0, β1, β2, and β3, it is necessary to solve the given simultaneous system of linear equations.

$$n\beta_0 + \beta_1 \Sigma X_{1i} + \beta_2 \Sigma X_{2i} + \beta_3 \Sigma X_{3i} = \Sigma Y_i \quad (1)$$

$$\beta_0 \Sigma X_{1i} + \beta_1 \Sigma X_{1i}^2 + \beta_2 \Sigma X_{1i}X_{2i} + \beta_3 \Sigma X_{1i}X_{3i} = \Sigma X_{1i}Y_i \quad (2)$$

$$\beta_0 \Sigma X_{2i} + \beta_1 \Sigma X_{1i}X_{2i} + \beta_2 \Sigma X_{2i}^2 + \beta_3 \Sigma X_{2i}X_{3i} = \Sigma X_{2i}Y_i \quad (3)$$

$$\beta_0 \Sigma X_{3i} + \beta_1 \Sigma X_{1i}X_{3i} + \beta_2 \Sigma X_{2i}X_{3i} + \beta_3 \Sigma X_{3i}^2 = \Sigma X_{3i}Y_i \quad (4)$$

The simultaneous system of linear equations above can be simplified into matrix form. The values of regression coefficients estimated can be obtained easier then.

$$\begin{bmatrix} n & \Sigma X_{1i} & \Sigma X_{2i} & \Sigma X_{3i} \\ \Sigma X_{1i} & \Sigma X_{1i}^2 & \Sigma X_{1i}X_{2i} & \Sigma X_{1i}X_{3i} \\ \Sigma X_{2i} & \Sigma X_{1i}X_{2i} & \Sigma X_{2i}^2 & \Sigma X_{2i}X_{3i} \\ \Sigma X_{3i} & \Sigma X_{1i}X_{3i} & \Sigma X_{2i}X_{3i} & \Sigma X_{3i}^2 \end{bmatrix} \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{Bmatrix} = \begin{Bmatrix} \Sigma Y_i \\ \Sigma X_{1i}Y_i \\ \Sigma X_{2i}Y_i \\ \Sigma X_{3i}Y_i \end{Bmatrix}$$

After the simultaneous system of linear equations above is solved the regression coefficient estimates will be substitute to the following regression model for surface roughness.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} \quad (5)$$

Where;
Yi = Surface Roughness (µm)
X1i = Cutting Speed (M/min.)
X2i = Feed Rate (mm/min)
X3i = Depth of Cut (mm)
When the mathematical model is obtained, the value of predicted surface roughness for each experiments can be calculated.

B. ARTIFICIAL NEURAL NETWORKS

ANN is a computational approach that quite different from conventional digital computation. The digital computers operate sequentially and do something arithmetic computations extremely vary fast. On other side the biological neurons in the human brain are slow devices and are capable of performing a tremendous amount of computation works which necessary to do in everyday complex tasks. Commonsense reasoning and dealing with fuzzy logic situations. The underlining reason is that unlike a conventional computer, but the brain contains a huge number of neurons, information processing elements of the biological nervous system is acting in parallel. ANNs are parallel distributed information processing structure consisting of processing elements interconnected via unidirectional signal channels called connection weights. Although modeled after biological neurons, ANNs are much simplified. Some of the major attributes of ANNs are:
a) They can learn from examples and generalize well on unseen data.
b) They are able to deal with situation where input data are erroneous, incomplete, or fuzzy.

C.BIOLOGICAL NEURAL NETWORKS

The fundamental unit of biological neural network is called a neuran or a nerve cell shows in the following figure:

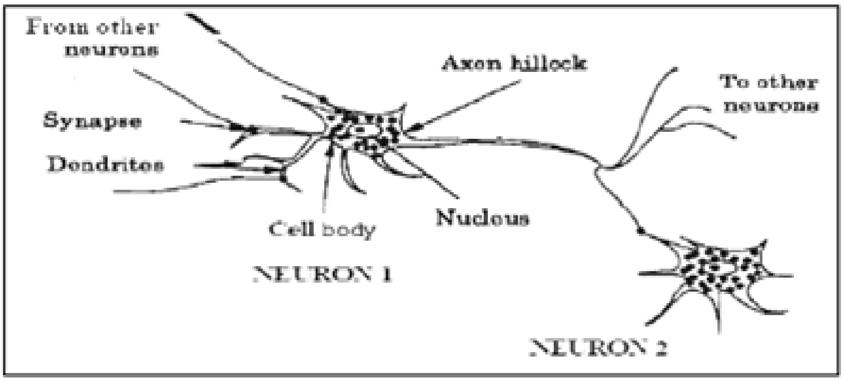

Figure 3: Diagram for Biological Neuron Networks

It consist of a cell body where the cell nucleus is located. Tree like nerve fibers called dendrites are associated with cell body. These dendrites receive signals from other neurons. Extending from the cell body is a single long fibre called the axon, which eventually branches.

D. Mathematical Artificial Neural Network (ANN)

Artificial Neural Network is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data. Some networks are supervised, in that a human determines what the network should learn from the data.

For this study, the network is given a set of inputs and corresponding desired outputs, and the network tries to learn the input-output relationship by adapting its free parameters.

The activation function *f(x)* used here is the sigmoid function which is given by:

$$f(x) = \frac{1}{1 + \exp(-x)}$$

Between the input and hidden layer:

$$x = \sum_{j=1}^{m} \omega_{kj} u_j + \theta_k \qquad k = 1 \text{to } i$$

and between hidden layer and output layer:

$$x = \sum_{j=1}^{m} \omega_{kj} u_j + \theta_k \qquad k = 1 \text{to } i$$

Where;
m = number of input nodes
n = number of hidden nodes
i = number of output nodes
u = input node values
v = hidden node values
ω = synaptic weight
θ = threshold

In back-propagation neural network, the learning algorithm has two phases. First, a training input pattern is presented to the network input layer. The network then propagates the input pattern from layer to layer until the output pattern is generated by the output layer. If this pattern is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated.As with any other neural network, a back-propagation one is determined by the connections between the neuron (the network's architecture), the activation function used by the neurons, and the learning algorithm (or the learning law) that specifies the procedures for adjusting weights.

Typically, a back-propagation network is multilayer network that has three or four layers. The layers are fullyconnected, that is, every neuron in each layer is connected to every other neuron in the adjacent forward layer. Figure 3.2 shows the neural network computational model. The neural network computational model coding is built using MATLAB 2008 software.

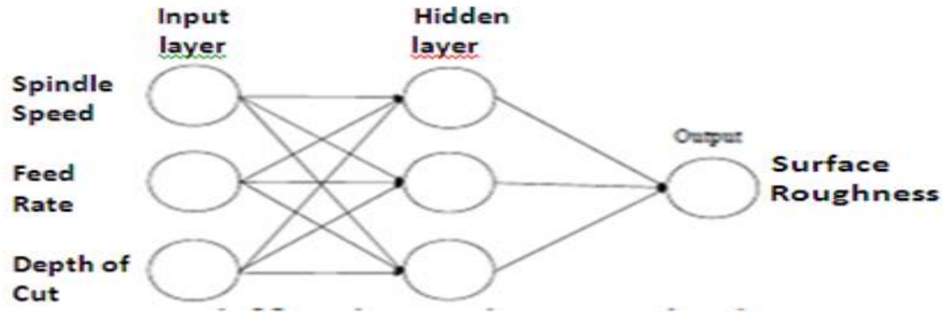

Figure 4 : Neural network computational model

IV. EXPERIMENTAL METHODOLOGY FOR SS 316L PIPE

The specimens of 316LStainless Steel pipe used for experimentation of the following Table shows nominal and actual composition of 316L SS used for the study. It was subjected to turning operation which was carried out on Lathe Machine. As 316 LSS is a hard material, carbide tool was selected .Carbide leaves a better finish on the part and allows faster machining. Carbide tools can also withstand higher temperatures than standard high speed steel tools. Cylindrical specimen of 12 cm diameter was safely turned in the four jaw chuck by supporting the free end of the work. If work piece is quite long it needed to face and centre drill the free end supported by the tailstock.

Without such support, the force of the tool on the work piece would cause it to bend away from the tool, producing a strangely shaped result.

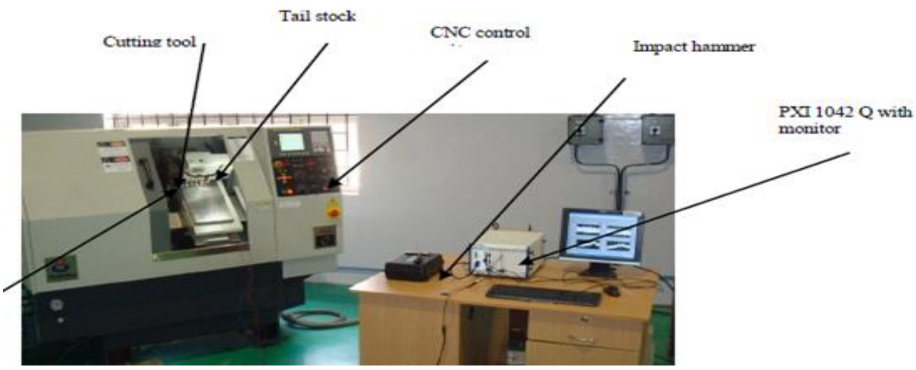

Figure 5: Experimental set up for 316LSS specimen in **CNC-Galaxy- MINDAS-O** Turning Operation

INSERT NOMENCLATURE

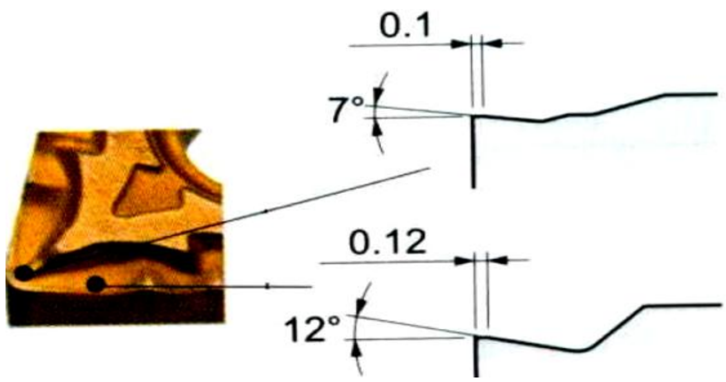

Figure 06 : Nomenclature for insert(PCLNL2020K12) rake angle, nose radius and inclination angle

Work piece inserted in the 4-jaw chuck and tightened in the jaws until they just started to grip the work piece. The work piece was then rotated to ensure that it is seated evenly and to dislodge any chips or grit on the surface that might keep it from seating evenly. Work piece was kept as parallel as possible with the center line of the lathe. The selected tool was tightly clamped in the tool holder. The angle of the tool holder was properly adjusted so that the tool remained approximately perpendicular to the side of the work piece. The turning was carried out on different sections of the work piece. For each section, all the three parameters, viz. cutting speed, depth of cut and feed rate, were varied as shown in Table 2. The surface roughness of each specimen was tested on the surface roughness tester (Mitutoyo Roughness tester SJ-400) also. The average values of Ra were obtained from three readings for each specimen.

Table 1: Chemical composition of pipe SS 316L work specimen

Designation/ Wt. %	Cr	Ni	C	Mn	Si	P	S	Mo
Nominal Value 316 L	16-18	10-14	0.03	2.0	1.0	0.045	0.03	2.0-3.0
Actual Value 316 L	17.34	10.69	0.024	1.748	0.471	0.034	0.018	2.08

Table 2: Mechanical Properties for Work piece

S.No.	Mechanical properties	Values(Min.)
1	Tensile Strength	485 MPa
2	Yield Srength	170 MPa
3	Elongation (%)	4%
4	Hardness Brinell (HB)	217
5	Hardness Rockwell (B)	95
6	Expansion (µm/m/°C) at 0-315 °C	16.2
7	Density	8000 Kg/m^3
8	Elastic modulus	193 GPa

EXPERIMENTAL WORK DESIGN

To achieve the objectives, multiple regression analysis is used for statistical method and Artificial Neural Network is used as artificial intelligent method. The experiment is performs by using a CNC Lathe. The work piece tested is 316LSS of dimension 1000 mm length and 120mm diameter and pipe thickness 5mm. The Lathe and cutting tool is choose as the turning operation.

For this research, Full Factorial Design Experiment is applied. Full Factorial Experiment is the experiment where all the possible combinations levels of factors are realized. The table 3 below is the Full Factorial Experiment's table for this research. The parameters considered are Spindle Speed, Feed Rate, and Depth of Cut. Thus, the numbers of experiment need to be executed are $N = 27$ experiments.

Fig.7a: Rough Surface Roughness on SS 316L Pipe before optimization

Fig.7b : Smooth Surface Roughness on SS 316L Pipe after optimization

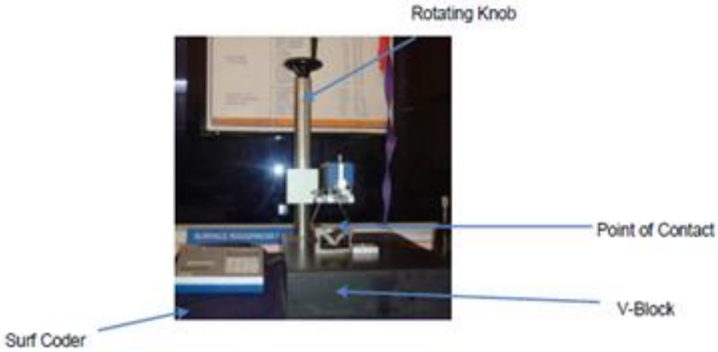

Figure 8 : Surface Roughness Tester

SURFACE TEXURE FOR 316L STAINLESS STEEL PIPE

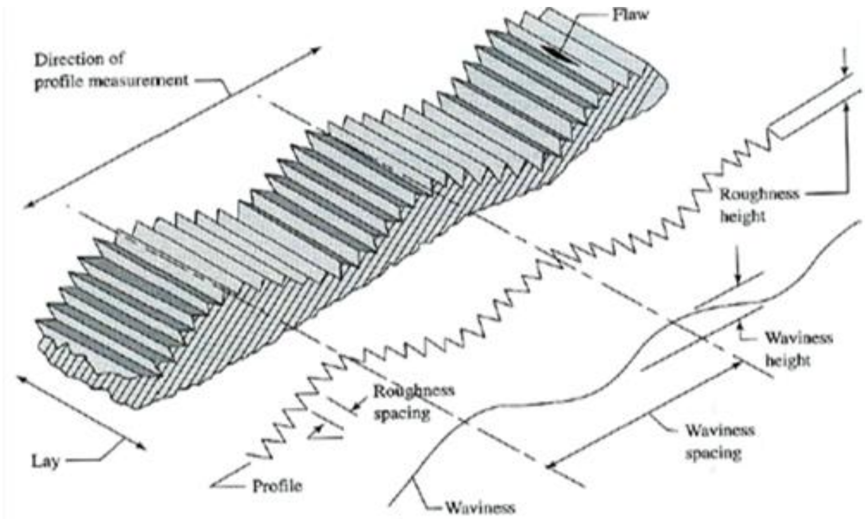

Figure 9 : surface texture of 316L stainless steel pipe

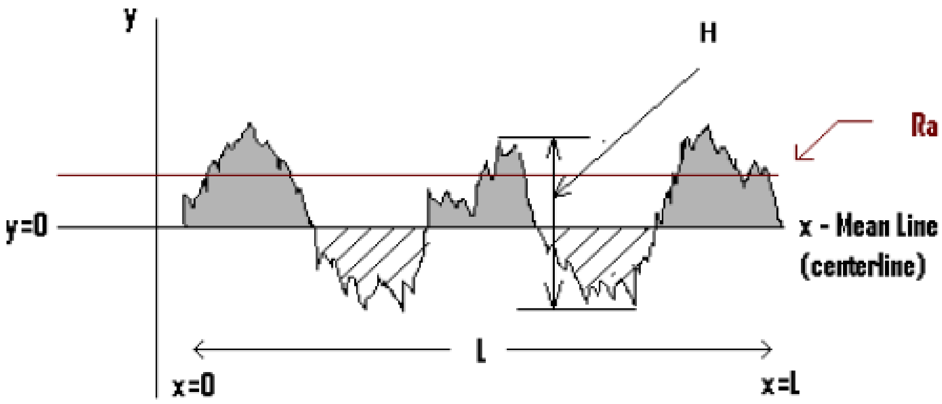

Figure 10 : Surface roughness profile for stainless steel pipe 316L

Where
Ra = deviation of the arithmetic average from the centre line,
L = total length of the sampling profile,
H= the height of the profile above and below the centre line,
The integral is generally approximated by using trapezoidal rule when average surface roughness is estimated from digital data;

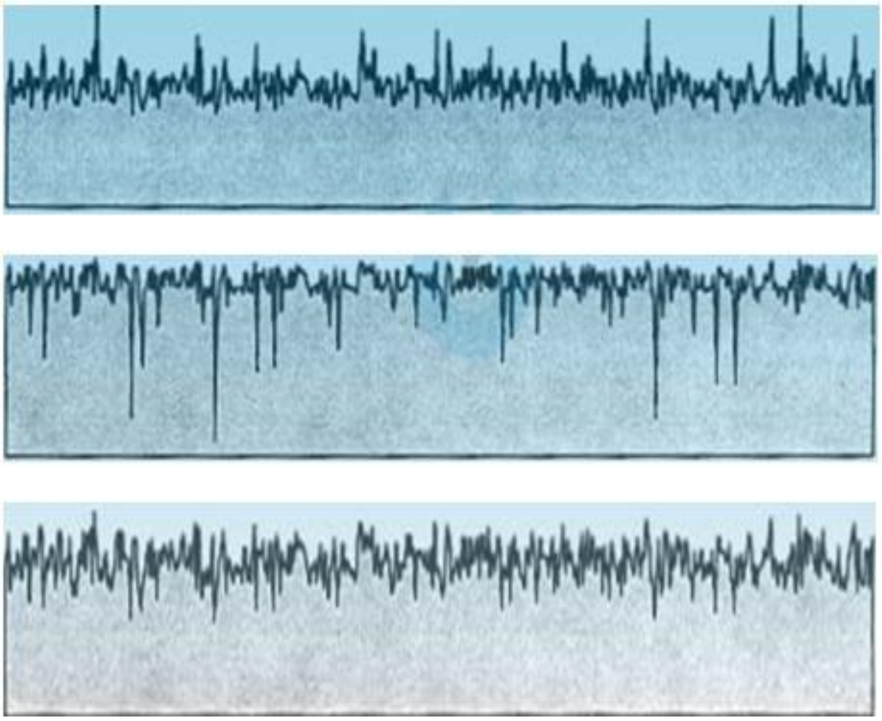

Figure 11 **:** Various surface roughness shapes having the same Ra value

Table 3: Surface Roughness Obtained From The Experiments

No. of Expts.	Cutting Speed (M./Min.)	Feed Rate (Rev./Min.)	Axial Depth of Cut (mm)	Radial Depth of Cut (mm)	Surface Roughness (µm)
01	110	0.10	0.10	0.12	1.173
02	110	0.10	0.15	0.17	1.681
03	110	0.10	0.20	0.22	1.275
04	110	0.15	0.10	0.12	2.265
05	110	0.15	0.15	0.17	2.443
06	110	0.15	0.20	0.22	2.367
07	110	0.20	0.10	0.12	3.840
08	110	0.20	0.15	0.17	3.586
09	110	0.20	0.20	0.22	3.307
10	150	0.10	0.10	0.12	1.276
11	150	0.10	0.15	0.17	1.301
12	150	0.10	0.20	0.22	1.603
13	150	0.15	0.10	0.12	2.392
14	150	0.15	0.15	0.17	2.138
15	150	0.15	0.20	0.22	2.137
16	150	0.20	0.10	0.12	3.637
17	150	0.20	0.15	0.17	2.469
18	150	0.20	0.20	0.22	2.773
19	190	0.10	0.10	0.12	0.640
20	190	0.10	0.15	0.17	1.224
21	190	0.10	0.20	0.22	1.301
22	190	0.15	0.10	0.12	2.392
23	190	0.15	0.15	0.17	1.808
24	190	0.15	0.20	0.22	2.215
25	190	0.20	0.10	0.12	2.723
26	190	0.20	0.15	0.17	2.316
27	190	0.20	0.20	0.22	2.469

Then, the regression coefficient can be substituted into the general equation for multiple regression which shown as equation 3.5 in previous chapter. The mathematical model obtains to predict surface roughness is;

$\hat{Y}= 2.1066 - 0.0011X1 + 0.0040X2 - 0.00971X3$ (9)

Where;

$\hat{Y}$= Surface Roughness (µm)

X1 = Cutting Speed (M/min.)
X2 = Feed Rate (mm/min)
X3 = Depth of Cut (mm)

ANN Model

Besides using multiple regression in surface roughness prediction, artificial neural network a branch of artificial intelligent has been implemented as an alternative approach. The predicted surface roughness has been perform using artificial neural network in MATLAB. Table in following shows the predicted surface roughness using this method. The input data for three independent variables spindle speed, feed rate, and depth of cut while actual surface roughness acted as target. The network propagates the input pattern from layer to layer until the output is generated. Then the result output will be compared with the target which is actual surface roughness in this study. smallest error is achieved. The error is calculated and propagated back through network. Then, the weight will be changed and the same process repeated until the

The plot of predicted surface roughness (output) against the actual surface roughness (target) in Figure 12 below shown that both are correlated. This is because the predicted surface roughness is approaching towards the actual surface roughness with the coefficient of determination, *R* is 0.98508.

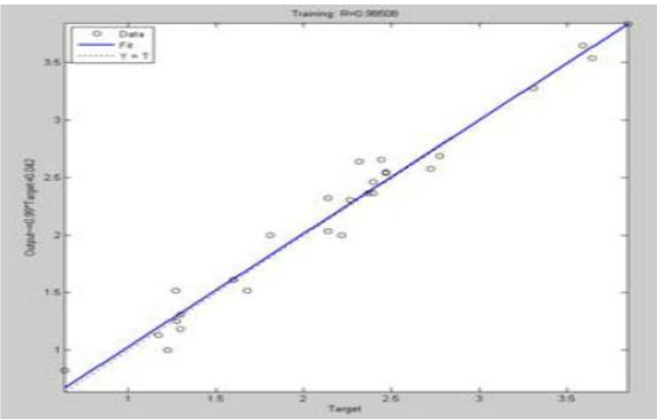

Figure : 12 Predicted surface roughness against the actual surface roughness

Durmus karayel presented a neural network approach for the prediction and control of surface roughness in a computer numerically controlled (CNC) lathe. Experiments have been performed on the CNC lathe to obtain the data used for the training and testing of neural network. The parameters used in the experiment were reduced to three cutting parameters which consisted of depth of cut, cutting speed and feed rate. Each of the other parameters such as tool nose radius, tool overhang, approach angle, work piece length, work piece diameter and material of pipe. A feed forward multilayered neural network was developed.
The adaptive learning rate was used. Therefore, the learning rate was not selected before training and it was adjusted during training to minimize training time.

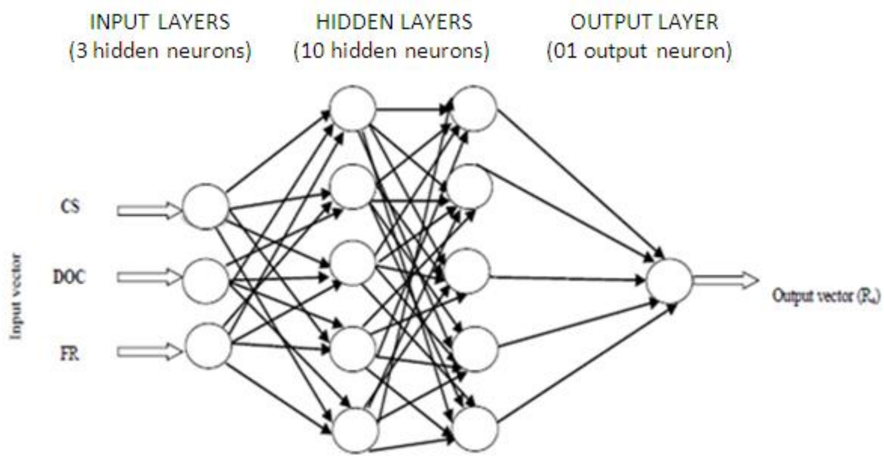

Figure 13 : Feed Forward Neural Network for predicting surface roughness value

Table 4: The optimum values of neural network parameters

Sl.No	Parameter	Values
1	Number of Input layer	1
2	Number of Input layer unit	3
3	Number of hidden layer	1
4	Number of hidden layer unit	5
5	Number of Output layer	1
6	Number of Output layer unit	1
7	Number of epochs	1000

Table 5 shows comparison between actual and predicted surface roughness using multiple regression analysis (MRA) and artificial neural network (ANN). To measure the accuracy for both prediction models, average error for both models is calculated as follows.

$$\phi_i = \left| \frac{Ra_i - \hat{Ra}_i}{Ra_i} \right| \times 100\%$$

Where

$Ø_i$ = Percentage error for each experiment

Ra_i = Experiment surface roughness

$\hat{Ra}_i$ =Predicted surface roughness

Table 5: Comparison between Actual and Predicted Surface Roughness

No. of Expnts.	Actual Surface Roughness (μm)	Predicted Surface Roughness (μm)	
		Multi-Regression Analysis (MRA)	Artificial Neural Network(ANN)
01	1.173	1.590	1.130
02	1.681	1.540	1.518
03	1.275	1.491	1.517
04	2.265	2.502	2.306
05	2.443	2.452	2.653
06	2.367	2.403	2.363
07	3.840	3.334	3.832
08	3.586	3.284	3.645
09	3.307	3.307	3.275
10	1.276	1.315	1.253
11	1.301	1.266	1.307
12	1.603	1.216	1.610
13	2.392	2.227	2.462
14	2.138	2.178	2.322
15	2.137	2.128	2.036
16	3.637	3.059	3.535
17	2.469	3.010	2.543
18	2.773	2.960	2.688
19	0.640	1.040	0.824
20	1.224	0.991	1.000
21	1.301	0.941	1.184
22	2.392	1.952	2.362
23	1.808	1.903	1.998
24	2.215	1.853	1.996
25	2.723	2.784	2.575
26	2.316	2.734	2.639
27	2.469	2.685	2.540

From the average percentage error calculated, the effectiveness of each method can be determined and can be compared.

GRAPH PLOT FOR COMPARISON OF EXPERIMENTAL, MULTIPLE REGRESSION AND NEURAL NETWORK SURFACE ROUGHNESS VALUES.

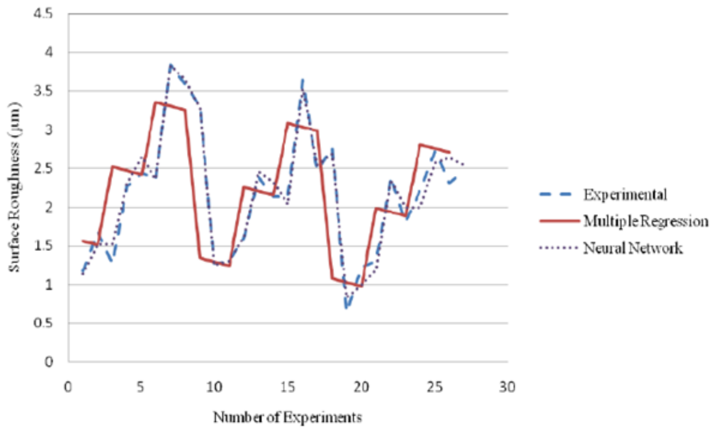

Figure 14 : Plot of predicted by multiple regression and neural network with experimental surface Roughness

V. CONCLUSION AND DISCUSSIONS

In this paper, a review of the ANN technique to develop the prediction model for surface roughness has been discussed. Examples of studies are given with their relative abilities and limitations in the relation to modeling of machining process focusing on the prediction of a surface roughness measured by using ANN approaches. ANN can produce an accurate relationship between cutting parameters and surface roughness. It can be used for modeling surface roughness, so that it can be predicted close to real value before machining stage. ANN model shows higher accuracy than the traditional statical approaches.

In this research study, The experiments were conducted on CNC Lathe using the carbide tool insert (CCGT-09T30FL),machining variables such as surface finish measured value and vibration in CNC Lathe machining processes. On the basis of this investigation, the following conclusions can be drawn.

[01]. It was found that good surface finish is obtained during the cylindrical SS 316L pipe turning process with optimum turning conditions.

[02]. Cutting Speed, Feed Rate and Depth of Cut plays an important role in the cylindrical turning parameters.

[03]. The optimum parameters of cylindrical turning process to overcome the problem of poor surface finishing in the stainless steel pipe.

[04]. Close tolerance can be achieved.

[05]. Increase in cutting parameters affects the vibration of the turning machine, grinding wheel, more metal removal and excessive heat on the work piece. The above causes will results in poor surface finish.

[06]. ANN is the fast fourier transform (FFT) function and its graphic display were integrated in to the software program developed by Mat lab view, data were visualized in real time.

[07]. The method presented effectively measure surface finish and vibration of bearing. The goal of this research is successfully met.

[08]. ANN has been used to learn the collected. Neural network configuration was trained. The results of neural network model shown close matching between the model output and directly measured vibration. This method seems to have prediction potentials for non-experimental pattern additionally ANN methodology.

[09]. Optimization method will reduce the physical testing cost, lead time of prototype manufacturing cost and it will reduce the defects of surface roughness of stainless steel pipes of the company.

[10]. For this problem, the average percentage error in MRA model is 13.12%, while in ANN model, the average percentage error is 6.32%.

[11]. The result from this research is useful to be implemented in both time-consuming and laborious works in industry to reduce time and cost in surface roughness prediction.

[12]. The optimized surface Roughness further it can be used for other optimizing processing methods.

This study is valuable for the Researchers to develop their basic knowledge about fundamental methodology and procedures are conducted.

ACKNOWLEDGEMENTS

First of all I would like to express my deepest gratitude and sincere thanks to **M.S. Tyagi (Sr. Manager, P & A) and all supporting employees of Salasar Stainless steel Pvt. Ltd., Jindal nagar, Ghaziabad (UP) – INDIA,** they allow to me and provide their valuable time and keep interest in my research work in their industry. His intellectual advice has helping me in every step of my research work. I express my sincere thanks to our beloved **Chairman (Dr. B.S. Goel) and Director (Dr. Sandeep Kumar Singh) of Aryan Institute of Technology, Jindal Nagar, Ghaziabad (UP)-INDIA** for valuable suggestions and Motivation to this Efforts for research works.

The aim of this research work was to investigate the effects of the cutting parameters (the cutting speed, the feed rate and the depth of cut) on minimize the average surface roughness, during the turning of the stainless steel pipe (SS 316L) using cutting carbide tool insert (CCGT-09T30FL) and cutting fluid . The turning is safe for the environment (atmosphere, water) and health of machine as well as cheaper. Therefore, it is also useful to analyze the effect of cutting conditions on the surface quality in turning of pipes during the first phase of this work, surface roughness was measured using the surface profilometer which gives a relatively good indication of the measured roughness. The relationships among the inputs and corresponding outputs are established from the measured data as well as the trends of surface roughness changing with cutting regimes changes.

The designing and the optimization of the experimentally obtained data were performed using the regression analysis and feed forwards ANNs model. In general, the results of this research are in good agreement with the experimentally obtained data.

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