
DETERMINATION OF THE EFFECT OF MACHINING PARAMETERS ON THE SURFACE FINISH OF MEDIUM CARBON STEEL DURING TURNING OPERATION ON LATHE MACHINE USING AN ARTIFICIAL NEURAL NETWORK

Ihom A. P., Sam A. B., Offiong A. A., and Odeh E. U.

Department of Mechanical Engineering, University of Uyo, PMB 1017, Uyo, Nigeria

Corresponding Email: ihomaondona@uniuyo.edu.ng

Phone Number: +2348035813571

ORCID ID: <https://orcid.org/0000-0002-6293-869x>

DOI: <https://doi.org/10.5281/zenodo.16967598>

ABSTRACT: The effect of machining parameters on the surface finish of medium carbon steel during turning operation on the lathe machine was thoroughly investigated using an artificial neural network (ANN). This study utilized data from a previous study on the effect of machining parameters on the surface roughness of medium carbon steel using a lathe machine. In this analysis, the neural network toolbox of MATLAB 2015 was used to predict the surface roughness of steel. In the MATLAB software, the dataset was partitioned into three sets: the training (70%), test (15%), and validation (15%) sets. The training data are used to adjust the weight of the neurons, the validation data are used to ensure the generalization of the network during the training stage, and the testing data are used to examine the network after being finalized. The stopping criteria are usually determined by pre-set error indices (such as mean square error, MSE) or when the number of epochs reaches 1000 (default setting). However, the number of epochs was set at 1000 for this study. The result revealed that the predicted model of the 3-10-1 architecture network fits the actual values for both training, testing, and validation sets well, as can be seen in their correlation coefficients (R^2) of 0.9992, 0.9897, and 0.9765 for the training, testing, and validation data, respectively. Notably, a large sensitivity to a parameter shows that the system's performance can drastically change with a small variation in the parameter and vice versa. Following this analogy, the process input variable, namely, the feed rate, has the highest impact on the surface roughness of steel, followed by the cutting speed and then the cut depth. Finally, the effect of machining parameters on the surface finish of medium carbon steel during turning operation on the lathe machine was successfully determined using ANN.

Keywords: ANN; Surface finish; Feed rate; Machining parameters; Relative importance; Lathe machine.

1. INTRODUCTION

An artificial neural network (ANN) is an artificial intelligence technique derived from neural networks found in the nervous system of humans. ANN is a set of interconnected simulated neurons comprising several input signals with synaptic weights. An ANN model simply sums the products of inputs and their corresponding connection weights (w) and then passes it through a transfer or activation function to obtain the output of that layer and feed

it as an input to the next layer. A bias term is added to the summation function to raise or lower the input received by the activation function. The activation function performs the non-linear transformation of the input, making it capable of learning and performing more complex tasks. The general relationship between input and output in an ANN model can be expressed as shown in Equation 1 (Fazeli *et al.*, 2013):

$$y_k = f_o \left[\sum_j w_{kj} \cdot f_h \left(\sum_i w_{ji} x_i + b_j \right) + b_k \right] \quad \text{..... Equation 1}$$

where x is an input vector; w_{ji} denotes the connection weight from the i th neuron in the input layer to the j th neuron in the hidden layer; b_j represents the threshold value or bias of the j th hidden neuron; w_{kj} stands for the connection weight from the j th neuron in the hidden layer to the k th neuron in the output layer; b_k refers to the bias of the k th output neuron and f_h and f_o are the activation functions for the hidden and output neuron respectively.

ANN is one of the main tools used in ML. As the “neural” part of their name suggests, they are brain-inspired systems that are intended to replicate the way humans learn. Artificial neural networks have been around since the 1940s but have garnered significant impact in the last several decades (Luke, 2018). They are also referred to as “perceptrons,” which consist of input and output layers as well as (in most cases) a hidden layer consisting of units that transform the input into something that the output layer can use. They are excellent tools for finding patterns that are far too complex or numerous for a human programmer to extract and teach the machine to recognize (Luke, 2018). Figure 1.1 shows a schematic representation of the 2-8-1 model of the ANN.

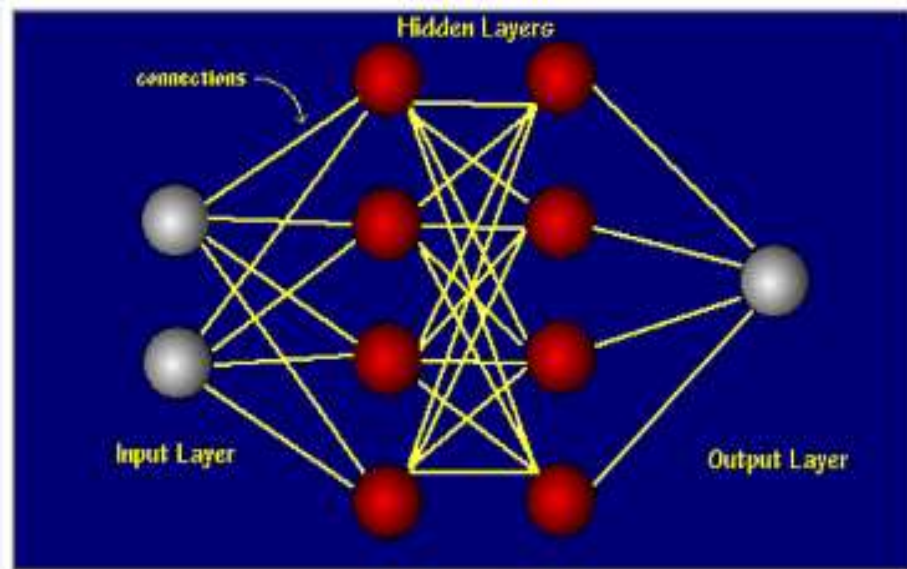


Figure 1.1: Model of the artificial neural network

(Source: Sam *et al.*, 2024)

In information technology (IT), a neural network is a system of hardware and software patterned after the operation of neurons in the human brain. Girish and Kuldeep (2015) submitted that artificial neural networks are inspired by the biological nervous system (the brain), which consists of many highly interconnected elements called neurons. The brain stores and processes information by adjusting the neuronal linking patterns. In a similar

manner, the “neurons” in ANNs are connected together to form a network that mimics a biological nervous system. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between neurons such that a particular set of inputs leads to a specific output target (Girish and Kuldeep, 2015).

Neural networks are generally designed to recognize patterns in a given set of data. These networks are trained to respond (or adapt) to different input patterns at different levels, thereby extracting certain desired features at each level. The specific tasks include classification, clustering, and prediction. Therefore, neural networks can be used to predict the surface finish quality from multiple input data of factors affecting machining operations.

The lathe is a machine tool used principally for shaping pieces of metal (and sometimes wood or other materials) by causing the workpiece to be held and rotated by the lathe, while a tool bit is advanced into the work thereby initiating the cutting action.

The basic lathe that was designed to cut cylindrical metal stock has been further developed to produce screw threads, tapered work, drilled holes, knurled surfaces, and crankshafts. Modern lathes offer various rotating speeds and a means to manually and automatically move the cutting tool into the workpiece. Turning operations are specifically performed on the lathe and involve a single-point tool removing material from a rotating work piece to generate a cylindrical shape. Figure 1.2 shows a pictorial representation of the straight turning operation. Figure 1.3 shows the engine lathe (Emco Maximat Super II).

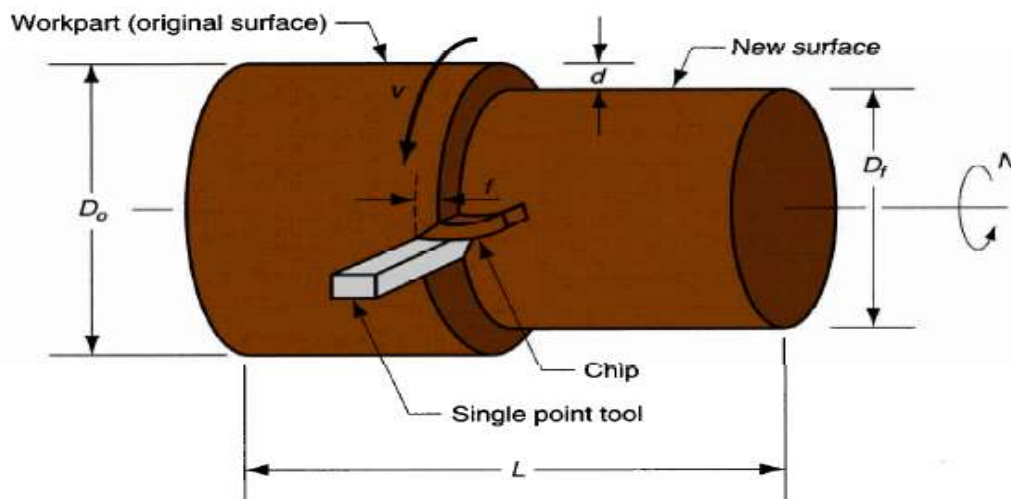


Figure 1.2: Turning operation

Source: Groover (2002)



Figure 1.3: Engine lathe (EMCO Maximat Super II)

Source: Sam (2024)

Variations of turning performed on the lathe include: facing, contour turning, chamfering, cut-off, and threading (Groover, 2002).

Several researchers and studies have unanimously agreed that the cutting speed, feed rate, and cut depth are the basic parameters affecting the turning operation of plain carbon steel (Groover, 2002; Jain 2009; Sam, 2024). These parameters may be varied to obtain optimum values for different grades of steel. However, other factors affecting the machining condition include workpiece material, cutting fluid, tool material, shape, and surface finish.

- i. **Cutting Speed (v):** The cutting speed of a tool is the speed at which the metal is removed from the work material by the tool. In a lathe, it is the work piece speed in m/min.

$$V = DN/1000 \text{ (m/min)}$$

Where D and N are the diameter of the workpiece (mm) and the cutting speed (rpm), respectively.

- ii. **Feed Rate (f):** The feed of the cutting tool in lathe work is the distance, the tool advances for each work-piece revolution in mm.

- iii. **Depth of cut (d):** The depth of cut is the perpendicular distance (mm) measured from the machined surface to the uncut surface of the workpiece.

A measure of how easily a material (or metal) can be cut is called “machinability.” “Machinability” is not an exact term. It is neither an absolute material nor a mechanical property; hence,, it could mean different things to different people (DeVries, 1992).

Several parameters describe certain defined characteristics of the roughness of a surface. The common roughness parameters usually considered in studies are Ra, Rq, Rz, and Rt. Individual variables describe the characteristics of a surface based on certain conditions.

The roughness average (Ra) is the arithmetic average of the absolute values of the profile heights over the evaluation length. This can also be referred to as the center line average value (CLA), which can be defined as the arithmetical mean deviation from the mean line of a profile.

RMS Roughness is the root mean square average of the profile heights over the evaluation length. Rq is the square root of the arithmetic mean of the squares of the ordinates from the mean length.

The average maximum profile height, Rz, is the average of the successive values of Rti calculated over the evaluation length. It also refers to the average difference between the five highest peaks and the five deepest valleys within the sampling length, which is measured from a line parallel to the mean line and does not cross the profile. This parameter is the same as Rz (DIN) when the evaluation length has five sampling lengths.

The maximum height of the profile, Rt, is the vertical distance between the highest and lowest points of the profile within the evaluation length.

These parameters vary depending on the description of surface roughness and the area of application. However, the most well-known parameter is Ra, which is commonly used in specifications by design engineers and the only parameter often taught to students (Sam *et al.*, 2024).

The objective of this research work is to determine the effect of machining parameters on the surface finish of medium carbon steel produced during the turning operation on a lathe machine using an ANN.

2. MATERIALS AND METHOD

The main material used in this work was steel samples. The steel samples were analyzed at the Defense Industry Corporation of Nigeria, Kaduna, Republic of Nigeria. The results obtained from this analysis indicated that the selected workpiece contained 0.3% carbon, indicating that it was in the medium carbon steel category. Other materials and tools used in this research work include data from previous work on the effect of machining parameters on the surface roughness of medium carbon steel using lathe machine (Sam, *et al.*, 2024), Microsoft Excel, and Design Expert (version 13.0.5.0) Minitab software package for design of experiments. Table 1 shows the data obtained from previous studies.

Table 2.1: Selected cutting parameters with respective surface roughness values.

Cutting speed (rpm)	Feed rate (mm/rev)	Depth of the cut (mm)	Mean Roughness (μm)	Surface Value
55	0.15	0.25	1.62	
55	0.21	0.35	2.20	
200	0.15	0.75	0.52	
200	0.21	0.35	3.79	
300	0.15	0.25	1.43	
300	0.21	0.75	0.95	

2.2 Method

The data in Table 2.1 were further expanded using the “Rand function” in Microsoft Excel. This function generated 500 data points from the original data. These data points were used to perform the analyses in the ANN.

2.2.1 Artificial neural network (ANN)

In this analysis, the neural network toolbox of MATLAB 2015 was used to predict the surface roughness of steel. Table 2.2 presents the settings chosen for the ANN model. In the MATLAB software, the dataset was partitioned into three sets: the training (70%), test (15%), and validation (15%) sets. The training data are used to adjust the weight of the neurons, the validation data are used to ensure the generalization of the network during the training stage, and the testing data are used to examine the network after being finalized. The stopping criteria are usually determined by pre-set error indices (such as mean square error, MSE) or when the number of epochs reaches 1000 (default setting). However, the number of epochs was set at 1000 for this study.

Table 2.2: Parameter settings for the ANN model

Parameters	Values
Training dataset	350 (70% of the dataset)
Testing the dataset	75 (15% of the dataset)
Validation dataset	75 (15% of the dataset)
Number of hidden layers (%)	1
Number of neurons in the hidden layer	1–20
Activation function (hidden layer)	Tansig
Activation function (output layer)	Purelin
Number of Epochs	1000
Learning rate	0.70
Architecture selection	Trial and error
Target goal MSE	10^{-5}
Minimum performance gradient	10^{-5}

This section discusses the performance of the network architectures in terms of training, testing, and validation efficacy. With prediction capability being the primary objective of a trained ANN, the performance of a particular ANN during testing with test data should be considered as the best ANN architecture. The number of neurons in the hidden layer influences the ANN model's generalization ability. Therefore, to determine the optimal architecture for the networks, a trial-and-error approach was used to select the optimum number of neurons in the hidden layer. In this direction, a series of topologies were examined, in which the number of neurons varied from 1 to 20. The mean square error (MSE) was used as the error function. The decision on the optimum topology was based on the minimum error of testing. Each topology was repeated 25 times to avoid random correlation due to random weight initialization. After repeated trials, a network with five hidden neurons in the hidden layer produced the best performance for the ANN model with a validation MSE value of 0.07. Figure 2.1 shows the optimal architecture of the ANN network.

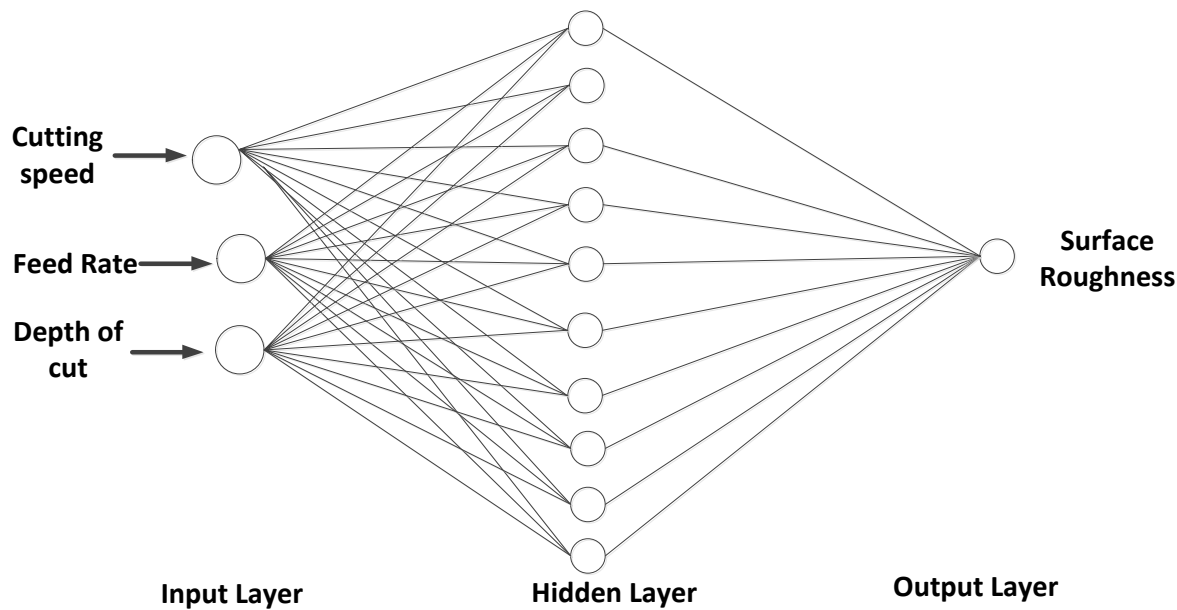


Figure 2.1: Optimal neural network architecture

The training process for this ANN model was truncated at 18 epochs for a 3-10-1 network architecture with a validation MSE of 0.07 (Figure 2.2). Therefore, the 3-10-1 architecture is considered the best neural network for the present problem because of its superior prediction capability.

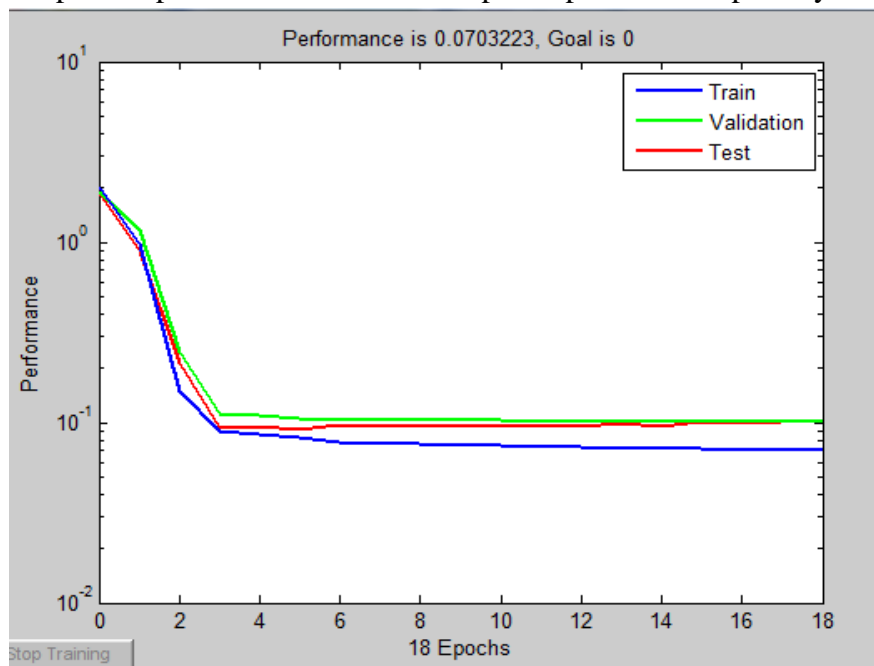


Figure 2.2: Performance of neural network validation

3. RESULTS AND DISCUSSION

3.1 Results on the artificial neural network

3.1.1 Performance of the ANN model

The predicted model of the 3-10-1 architecture network fits well to the actual values for training, testing, and validation sets, as shown in their correlation coefficients (R^2) of 0.9992, 0.9897, and 0.9765 for training, testing, and validation data, respectively. These data are shown in Table 3.1.

Table 3.1: ANN model performance using three error metrics

	Samples	R^2	MSE	RMSE
Training	350	0.9992	0.0727	0.2696
Validation	75	0.9897	0.0702	0.2649
Testing	75	0.9765	0.09545	0.3089

The model generated by applying the LM algorithm is given in Equation 3.1

$$\rho_f = \sum_{j=1}^{10} \{ \text{purelin}[LW_{j,1}(\sum_{i=1}^3 \sum_{j=1}^{10} \text{tansig}(X_i * IW_{i,j} + b_1))] + b_2 \} \dots \text{Equation 3.1}$$

Equation 3.1 in MATLAB represents the trained ANN model correlating the three input parameters and the final downhole mud density. Here, ‘*purelin*’ and ‘*tansig*’ are MATLAB activation functions that calculate the output of the layer from its network input. Purelin gives a linear relationship between the input and output, with the algorithm being $\text{purelin}(n) = n$. In contrast, *transit* is a hyperbolic tangent sigmoid transfer function that is mathematically equivalent to ‘*tanh*’. Tansig is faster than tanh in MATLAB simulations; thus, it is used in neural networks. The transit relation is given by Eq. 3.2.

$$\text{Tansig} = \frac{2}{(1 + \exp(-2 \text{network})) - 1} \dots \text{Equation 3.2}$$

LW and IW are the weights of the connections from the input layer to the hidden layer and from the hidden layer to the input layer, respectively. The values in Table 3.2 are used to predict the mean surface roughness using equation 3.1. However, the value of x_i in Equation 3.1 represents the individual data points for each input variable. Here, x represents the input variables, namely, cutting speed, feed rate, and depth of cut; N is the number of neurons (in this case is 10); j is the number of input variables, which in our case are three; b_1 is the bias of the hidden layer, and b_2 is the bias of the output layer. Table 3.2 lists the weights of the developed empirical correlation’s biases (Equation 3.1) that can be used to predict the steel surface roughness.

Table 4.2: Weights and biases of the ANN model in Equation 3.1

j=1	j=2	j=3	b_1	w_2	b_2
-3.02863674	-1.636437021	2.646439835	-1.118235062	0.046831421	-0.4699
-5.191115166	3.708114772	-1.578231103	4.762424188	-0.484710305	
-1.419177055	6.53629716	-0.453379246	0.842343953	0.468247954	
2.063118723	6.647224278	2.633763064	-8.728126835	-0.153482475	
0.992522795	-3.478719212	-0.778281229	-0.674892988	0.731828231	
1.118054605	3.419086563	-0.972844653	-5.627495455	2.201766854	
1.83216248	-1.454781175	-2.197071105	-1.981536035	-1.869291855	
3.396942642	-2.616009925	-4.80666587	-4.016707679	1.263706672	

7.40234124	6.829960651	-1.360393685	7.894672918	0.256841568
-1.045877708	3.708730273	-4.036595503	6.605382793	2.446736086

For example, the surface roughness is predicted using cutting speed, feed rate, and cut depth. The value of W_1 will be taken at $j = 1$ for cutting speed, $j = 2$ for feed rate, and $j = 3$ for cut depth. For example, the term $\sum_{j=1}^j w_{1,j}x_j$ for steel surface roughness in Table 3.3 can be calculated as follows; $\sum_{j=1}^j w_{1,j}x_j = w_{1,1}x_1 + w_{1,2}x_2 + w_{1,3}x_3$; where the values of $w_{1,1}$, $w_{1,2}$, and $w_{1,3}$ are -3.0286, -1.6364, 2.6464 respectively. This will be repeated for the 10 rows of the matrix, and the corresponding values for each row can be obtained from the tables.

3.1.2 Relative importance of independent variables in the Ann model

Sensitivity analysis aims to vary the input variables of the model and assess the associated changes in the model output. This method is particularly useful for identifying weak points of the model (Lawson and Marion, 2008). Therefore, the sensitivity analysis has provided ways of explaining the degree of contribution of each input variable to the network. The contribution of each input variable to the prediction of the dependent variable is referred to as its relative importance. Many methods exist in the literature for calculating the relative importance of input variables. Examples include: Garson's algorithm, connection weights algorithm, use of partial derivatives, and Lek's profile method. The connection weights algorithm was chosen for this study. The choice is predicated on the fact that Olden *et al.* (2004) compared different techniques for assessing input variable contributions in ANNs. Their study showed that the method of connection weights was the least biased among the others. This position was corroborated by Watts and Worner (2008). The connection weights algorithm proposed by Olden and Jackson (2002) calculates the sum of the products of the final weights of the connections from input neurons to hidden neurons with the connections from hidden neurons to output neurons for all input neurons. The connection weights from input neurons to hidden neurons are presented in columns 2–4 of Table 3.3, whereas the connection weights from the hidden to output neurons are presented in column 5 of Table 3.3. The relative importance of a given input variable can be defined as shown in Equation 3.3.

$$RI_x = \sum_{y=1}^m w_{xy}w_{yz} \quad \text{.....} \quad \text{Equation 3.3}$$

Where RI_x is the relative importance of the input variable x . $\sum_{y=1}^m w_{xy}w_{yz}$ is the sum of the product of the final weights of the connection from the input neuron to the hidden neurons with the connection from the hidden neurons to the output neuron, y is the total number of hidden neurons, and z is the output neurons.

Table 3.3: The final connection weights

	Cutting Speed(rpm)	Feed Rate(mm/rev)	Depth of the cut (mm)	Mean Surface Roughness (μm)
HIDDEN LAYER	INPUT 1	INPUT 2	INPUT 3	OUTPUT
1	-3.02863674	-1.636437021	2.646439835	0.046831421
2	-5.191115166	3.708114772	-1.578231103	-0.484710305
3	-1.419177055	6.53629716	-0.453379246	0.468247954

4	2.063118723	6.647224278	2.633763064	-0.153482475
5	0.992522795	-3.478719212	-0.778281229	0.731828231
6	1.118054605	3.419086563	-0.972844653	2.201766854
7	1.83216248	-1.454781175	-2.197071105	-1.869291855
8	3.396942642	-2.616009925	-4.80666587	1.263706672
9	7.40234124	6.829960651	-1.360393685	0.256841568
10	-1.045877708	3.708730273	-4.036595503	2.446736086

Table 3.4 presents the sum of the products of the connection weights and rank of the input variables.

Table 3.4: Connection weight products, relative importance, and input rank

HIDDEN LAYER	INPUT 1	INPUT 2	INPUT 3
1	0.414228422	0.223816451	0.361955127
2	0.495455449	0.353913487	0.150631064
3	0.168771767	0.777311341	0.053916892
4	0.181867016	0.585962811	0.232170173
5	0.189069131	0.662673362	0.148257507
6	0.202914244	0.620525474	0.176560283
7	0.334091457	0.26527667	0.400631873
8	0.313961408	0.241783935	0.444254656
9	0.474731338	0.438023087	0.087245575
10	0.118968661	0.421868323	0.459163016
SUM	2.894058893	4.591154941	2.514786165

	INPUT 1	INPUT 2	INPUT 3
RELATIVE IMPORTANCE (%)	28.94058893	45.91154941	25.14786165

3.1.3 Effect of machining parameters on the surface roughness of medium carbon steel using an ANN

Figure 3.1 shows the relative importance of the various input parameters. Notably, a large sensitivity to a parameter shows that the system's performance can drastically change with a small variation in the parameter and vice versa. Following this analogy, the process input variable, namely, the feed rate, has the highest impact on the surface roughness of steel, followed by the cutting speed and then the cut depth. These findings are in sync and resonate with the literature. For instance, Rafai and Islam (2009) investigated the effects of cutting speed, feed rate, and cut depth on dimensional accuracy and surface finish in dry turning of AISI 4340 (30 HRC) steel. The authors reported that the extent of the influence of feed rate on surface roughness was much higher than the influence of cutting speed and cut depth. Furthermore, the influence of the three main turning parameters on the machinability of homogenized Al–Cu/TiB₂ MMC was investigated by Senthil *et al.* (2013). A significant drop in the surface roughness was noted from 50 to 100 m min⁻¹ cutting speed. Thereafter, the roughness remained constant. The surface roughness value increased rapidly with increasing feed. Surface roughness was only slightly impacted by the increase in the depth of cut.

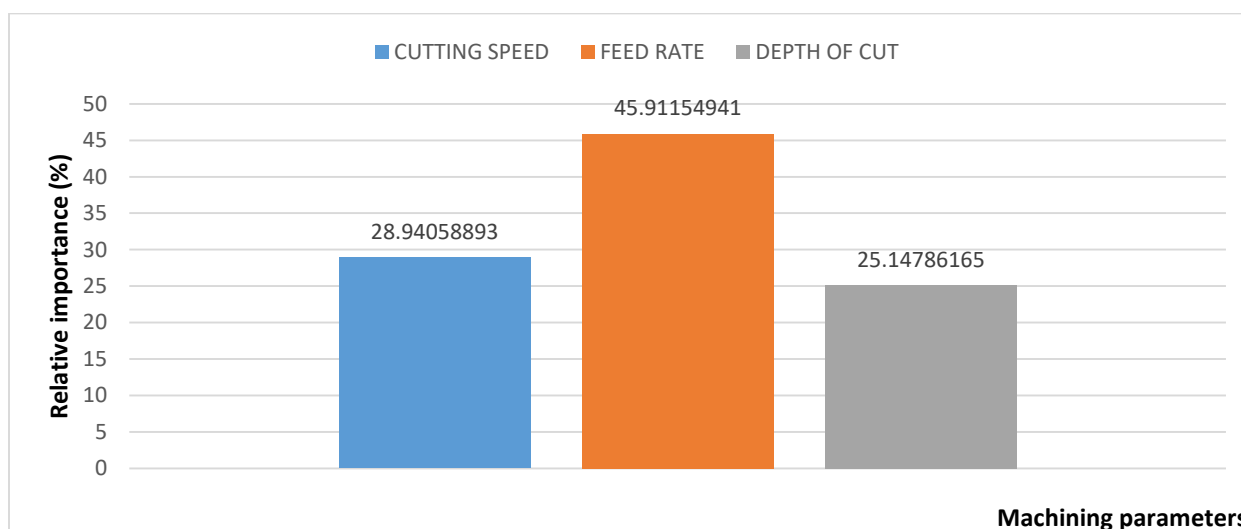


Figure 3.1: Relative importance of input variables on SR prediction

4. CONCLUSION

This study has considered the ‘Determination of the Effect of Machining Parameters on the Surface Finish of Medium Carbon Steel during Turning Operation on the Lathe Machine using Artificial Neural Network (ANN)’ and has drawn the following conclusions:

1. The predicted model of the 3-10-1 architecture network fits well to the actual values for both training, testing, and validation sets, as shown in their correlation coefficients (R^2) of 0.9992, 0.9897, and 0.9765 for the training, testing, and validation data, respectively.
2. Notably, a large sensitivity to a parameter shows that the system’s performance can drastically change with a small variation in the parameter and vice versa. Following this analogy, the process input variable, namely, the feed rate, has the highest impact on the surface roughness of steel, followed by the cutting speed and then the cut depth.
3. Finally, the effect of machining parameters on the surface finish of medium carbon steel during turning operation on the lathe machine was successfully determined using ANN.

Author Contribution

This is to publicly declare that the four authors of this publication (names listed above) were involved in the conceptualization of this research topic. Prof. A.P. Ihom, the first author was saddled with the responsibility of data curation and assisted by the other three authors with formal analysis. No outside funding was received for this project. The major financial contributor to this project was the third author. The four authors were jointly involved in the research project; playing various roles as supervisors, investigators and resource providers to enable the project go through the various stages of conceptualization, data curation, formal analysis, funding, investigation, methodology, project administration, resource provision, software provision, supervision, validation, writing original draft and final report, and final paper for publication. This was adopted by all the four members of the research team.

Funding

The members of this research team wish to publicly declare that this project was self-funded by team members.

Data Availability

The data used for this work is available in the University of Uyo, Uyo-Nigeria library, in the M.Eng.degree report submitted to the University. It is also available in journal publication made from the work. The references included in our journal publication are duly referenced. Every second party data used in the publication is duly referenced and credit given to source.

Conflict of Interests

The authors wish to publicly declare that there is no conflict of interest in this publication all the four authors have agreed to submit their work for journal publication.

Financial Interests

We wish to publicly declare that this is a self-sponsored research work contributed to by the research team members.

Non-Financial Interests

This work is free of all encumbrances, whether financial or non-financial interests

REFERENCES

- Devries, J. (1992). Effects of cutting tool parameters on vibration. *ICMMR* 2016, 7, 7006: 1-4.
- Fazeli P., João F., Messias S., Anderson P. and Pedro B. (2013). Artificial Neural Networks for Surface Roughness Modeling of Machining Processes *International Journal of Advanced Manufacturing Technology* 49: 879-902.
- Girish, K., & Kuldip, S. (2015). Predictive Modeling and Optimization of Machining Parameters to Minimize Surface Roughness Using AN Coupled with Genetic Algorithm *Procedia CIRP* 31: 453-458.
- Groover, T. N. T. (2002). Effect of Cutting Speed and Cut Depth on the Surface Roughness of Mild Steel in Turning Operation Unpublished BSc. Thesis, Universiti Malaysia Pahang,
- Jain, R. K. (2009) *Production Technology*, 16th Edition, Delhi: Khanna Publishers, pp.1108-1168.
- Lawson and Marion (2008). Investigation of Surface Roughness Cutting Parameters for a Non-Ferrous material using an artificial neural network in CNC turning. *Journal of Mechanical Engineering Engineering Research*, 3(1): 1-14.
- Luke, D. (2018). What is an artificial neural network? <https://www.digitaltrends.com/cool-tech/what-is-an-artificial--neural-network/> (accessed on May 11, 2018)
- Olden, T., & Jackson, P. Z. (2002). Optimization of cutting parameters in turning operation of mild steel. *International Review of Applied Engineering Research*. 4 (3): 251-256.

- Olden M. Dubsky J. , Sadílková Z., and Poruba Z. (2004) Cutting forces during turning with variable depth of cut. <http://dx.doi.org/10.1016/J.Pisc.2015.11.055>, (Accessed on July 9, 2018).
- Rafai, M. and Islam, H. (2009). Investigation of Cutting Force and Vibration Signals in Turning: Mathematical Modeling Using Response Surface Methodology *Journal of Mechanical Engineering and Automation* 5(3): 64-68.
- Sam, A. B. (2024) *Effect of machining parameters on the surface roughness of medium carbon steel using lathe machine. M. Eng.* Department of Mechanical and Aerospace Engineering, University of Uyo-Nigeria
- Sam, A. B., Ihom, A. P., Markson, I. E., & Odeh, E. U. (2024). Effect of Machining Parameters on the The Surface Roughness of Medium Carbon Steel Using a Lathe *European Journal Of Theoretical and Applied Sciences*, vol. 2, no. 4, 1-5. DOI: 10.59324/ejtas.2024.2 (4).xx
- Senthil, K. T., Mahadevan, G., & Vikraman, T. R. (2014). Evaluation of Surface Finish on Machining of Mild Steel Using High Speed Steel Tool in Lathe with Normal Coolant (or) Nano Material Added Coolant. *IOSR Journal of Mechanical and Civil Engineering*. 11: 1-9.
- Watts K, Worner G. (2008) Optimal Cutting Parameters for Turning Operations with Costs of Quality and Tool Wear Compensation. Proceedings of the 2012 International Conference on Industrial Engineering and Operations Management, Istanbul, Turkey. 924-932