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Application of Artificial Neuron Network in Roughness Prediction: A Case Study in Turning of Stainless Steel

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Abstract

Artificial neural networks (ANNs) offer a practical and efficient way to choose the best machining parameters for the turning process to reduce surface roughness, the resulting cutting forces, and maximize tool life. Surface roughness is a significant aspect in the evaluation of cutting performance and plays a significant role in the manufacturing process. The goal of this project is to create a model based on an ANNs that can replicate hard turning of EN-19 steel with only a small amount of cutting fluid. In terms of cutting parameters, this model is meant to forecast the surface roughness. Following training with a set of training data for a specified number of cycles, various network topologies are assessed using input/output data sets specifically designated for this purpose. The root means the square error is determined for the selected architectures. Utilizing linear regression, the regression equation is established. By applying ANN to this equation, we can forecast the surface roughness of test data.

Keywords: Neuron network, artificial intelligence, linear regression, prediction of surface roughness

INTRODUCTION

Human intervention in routine, repetitive, and data-specific industrial operations is drastically decreased by the industry's growing tendency toward automation. artificial neural network (ANN) is a mathematical model or computational model, an information processing paradigm i.e., inspired by the way biological nervous system, such as the brain information system. ANN is configured for solving artificial intelligence problems without creating a model of a real biological system. In the machining process known as turning, a cutting tool—typically a non-rotary tool bit—moves more or less linearly while the workpiece rotates, describing a helical toolpath. In order to achieve accurate diameters and depths, turning is the process of rotating the workpiece (a piece of a material that is relatively rigid, such as wood, metal, plastic, or stone) while a cutting tool is moved along one, two, or three axes of motion.

The process of turning is used to create rotational, usually axisymmetric, pieces with a variety of features such holes, grooves, threads, tapers, different diameter steps, and even curved surfaces. The turning processes, which might be straight turning, taper turning, profiling, or external grooving, among others, are frequently carried out on a lathe, which is regarded as the oldest machine tool.

Turning is frequently used as an additional process to add or enhance characteristics to components that were made using another technique.

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LITERATURE SURVEY

Literature survey on prediction of surface roughness using ANN are as follows.

Mishra et al. [1] stated that Some of the machining variables that have a major impact on the surface roughness in the turning process such as spindle speed, feed rate, and depth of cut were considered as inputs and surface roughness as output. The results show that the neural network model is accurate and dependable for resolving the cutting parameter optimization. The projected surface roughness values generated from ANN were compared with experimental data.

According to Deshpande et al. [2], the models created by the ANN were able to predict surface roughness with an accuracy of more than 98 percent. Additionally, the outcomes of the regression-based prediction models that the authors had previously presented were compared to the predictions made by the artificial neural network. Surface roughness was being predicted by the updated regression models with greater than 90% accuracy. The updated regression model's prediction results were compared to those produced by artificial neural networks based on correlation coefficient values. The study came to the conclusion that artificial neural network models outperformed regression methods in estimating surface roughness, and that these predictions might be used to regulate a process in real time to achieve the required surface roughness.

By using an ANN technique, Chandrasekaran and Devarasiddappa et al. [3] developed a surface roughness prediction model for cylindrical grinding of LM25/SiC/4p metal matrix composites (MMC). The study demonstrated that surface roughness rises as feed increases while decreasing as wheel velocity increases. A minimal surface polish could also be achieved by using fast wheel and workpiece velocities, moderate feed rates, and shallow cuts. Using the response surface method's central composite surface design, Xiao et al. [4] performed the turning test on stainless steel (RSM).

The findings indicate a strong relationship between feed rate and surface roughness. Cutting speed had the least impact, and cutting depth came in second.

In order to realize the efficient and inexpensive cutting of challenging-to-process materials while maintaining processing quality, the cutting parameters were improved, and tool life was studied.

Paul et al. [5] experimentally investigated, and optimized the effect of cutting speed, feed, and depth of cut on the surface finish, tool wear, and cutting force in a continuous dry turning of hardened alloy steel, AISI 4340 having hardness: 48 (48–52) HRC using the Taguchi design of experiments. It was observed that tool wear feed has a significant influence and depth of cut is the least influential of all. Optimal conditions are obtained at cutting speed (140 m/min), feed (0.125 mm/rev), and depth of cut (0.8 mm).

METHODOLOGY

In the Figure 1, all the methodology explained.

Methodology Explanation

- We started by doing research on how artificial intelligence is used in mechanical engineering.
- Then, the material selection for the project was selected.
- We take the reading of the workpiece by changing the different parameters such as speed, feed, and depth of cut and measure the roughness value of every cut on the roughness testing machine.
- Divide whole readings into training data and testing data for validation purposes.
- Next, use MATLAB software to apply an artificial neural network model to estimate surface roughness.
- Calculate the error of every iteration and check which one gives minimum surface roughness.
- Changing the quantity of neurons and hidden layers could accomplish this.

- Then get the best artificial neural network architecture.
- Predict the future surface roughness by giving inputs parameters [6–10].

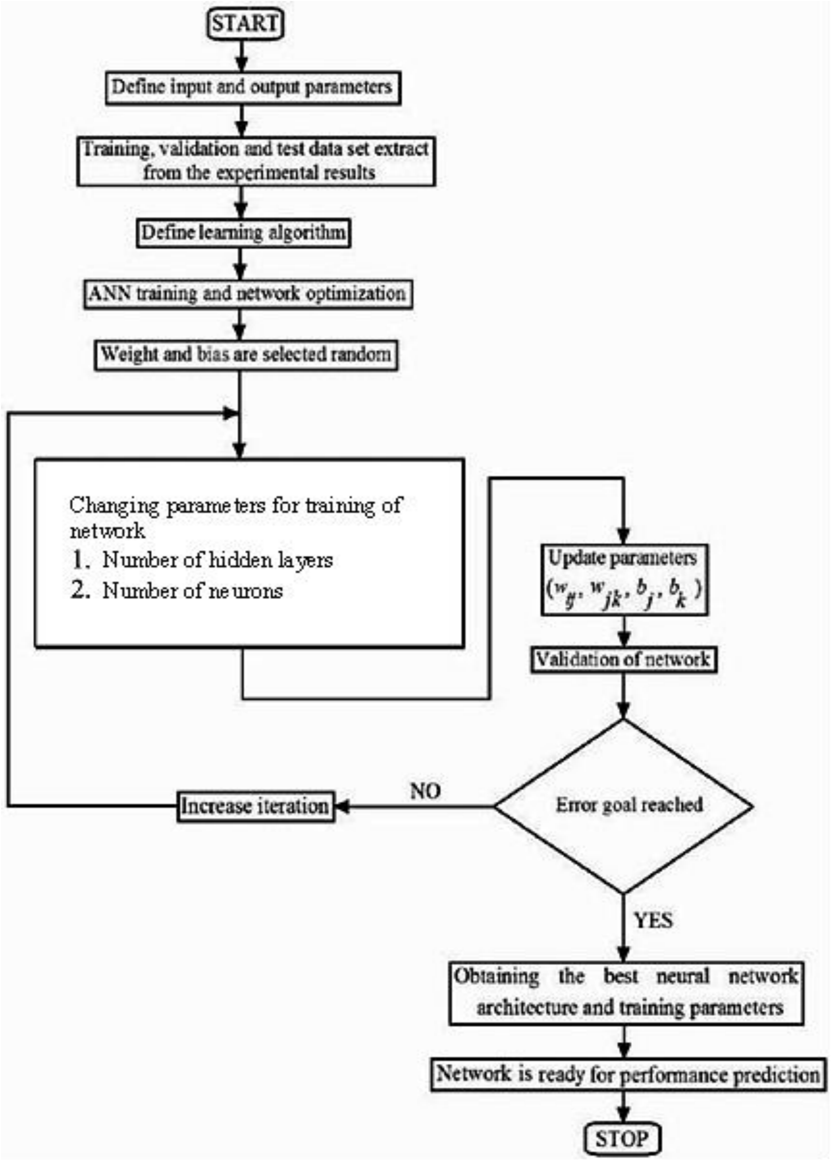

Figure 1. Flowchart for methodology.

EXPERIMENTATION

Experimental Setup and Experimentation

- A rod of EN-19 stainless steel having a size diameter 30 mm × 500 mm long is chosen as a workpiece.
- As was mentioned in the literature review, the turning operation involves a vast number of variables, all of which have an impact on the cutting outcomes. Therefore, only those parameters have been selected that show a considerable influence on the objectives of the study, i.e., speed, feed, depth of cut.
- After the experimental setup, 16 cuts have been taken on the material EN-19 stainless steel by varying the process parameters to get different values of surface roughness. To get more efficient work of turning on the lathe machine the EN-19 stainless steel was cut into two halves.

The ANN prediction the readings obtained from the experimentation is shown in the Tables 1–2.

Table 1. Experimentation readings.

Input		Output	
Speed (rpm)	*Feed (mm)*	*Depth of cut (mm)*	*Surface Roughness*
240	25	24	2.7
240	25	23	2.61
240	25	22	3.16
240	25	21	3.91
240	26	24	2.81
240	27	23	3.91
240	28	22	4.18
240	29	21	3.82
400	25	24	3.09
400	25	23	5.46
400	25	22	4.18
400	25	21	3.49
240	26	24	3.89
240	27	22	4.75
240	28	20	3.94
240	30	18	4.08

Table 2. ANN prediction.

Input			Output	
Speed	*Feed*	*Depth of cut*	*Actual Surface Roughness*	*Predicted Surface Roughness*
240	26	24	2.81	3.40
240	27	23	3.91	3.94
240	28	22	4.18	3.92
240	29	21	3.82	3.79

PREDICTION BY ARTIFICIAL INTELLIGENCE

For our project report, we used two techniques for the prediction of surface roughness:

i. Artificial neural network (ANN)
ii. Prediction by linear regression

Structure of Neural Network

We chose the 3-2-1 neural network, out of ANN architectures such as 3-1-1, 3-2-1, and 3-3-1. It has three input layers, two hidden layers, and one output layer, or depth of cut. Figure 2 shows the network diagram (Table 3).

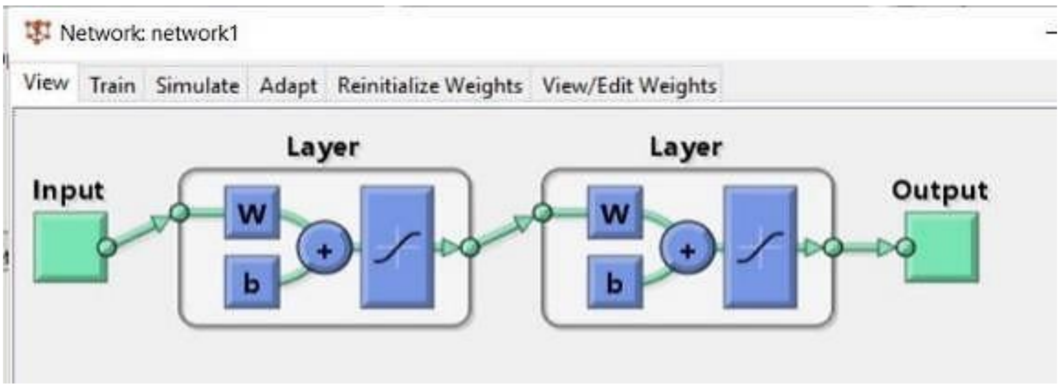

Figure 2. Network diagram.

ANN Plots

- Following neural network training, many charts that display the neural network's performance, fitting, regression, and error are produced.
- The training, validation, and testing regression plots for the target data are shown in Figure 1. The training, validation, and test data's regression coefficient is displayed in this plot. The fourth of the regression plot's four plots, which is shown below, displays all data points and provides the overall regression coefficient, which is R = 0.92259.
- We can calculate a regression coefficient (R) from the plots, and we must train the data until the R is at its best. The regression coefficient r for the test is determined to be 1 in our situation as shown in Figure 3.

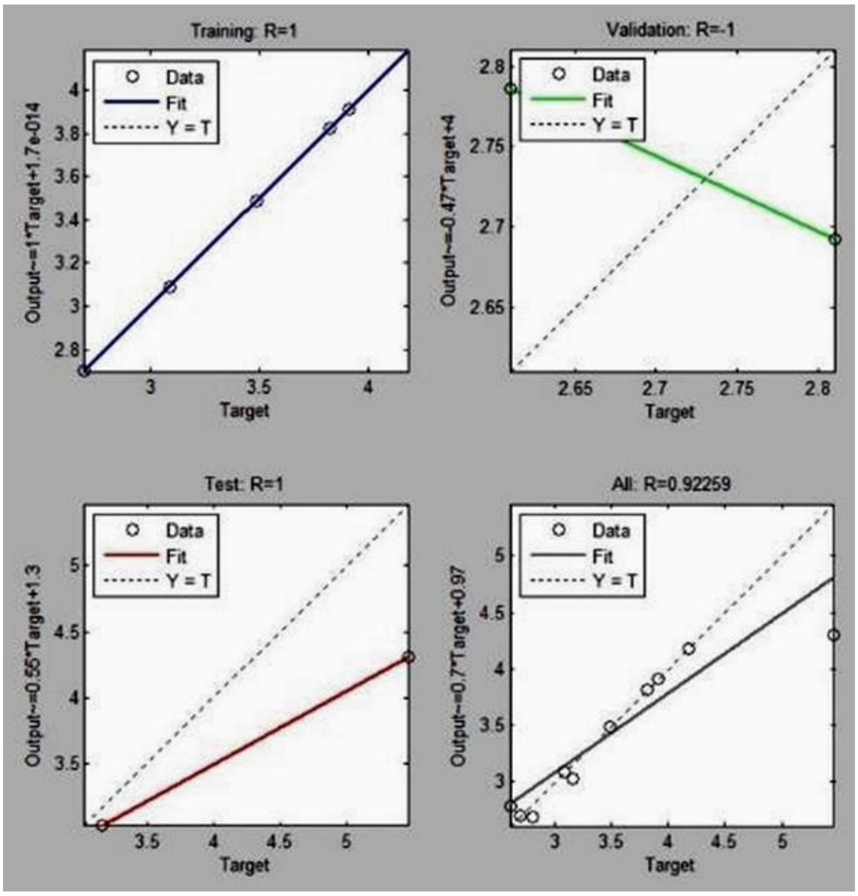

Figure 3. Regression coefficient.

Table 3. Observation table.

Input			Output	
Speed	***Feed***	***Depth of cut***	***Actual Surface Roughness***	***Predicted Surface Roughness***
240	26	24	3.89	3.41
240	27	22	4.75	3.69
240	28	20	3.94	3.98
240	30	18	4.08	4.46

RESULTS AND CONCLUSION

Results

On account of experimental efforts, ANN and linear regression models have been built up to predict surface roughness. It has been discovered that using a linear regression model to forecast the turning operation's output parameters results in the least amount of error when compared to an ANN model. The precision of the linear regression model predicted was admirable.

- This work predicted the surface roughness by linear regression and ANN model with an average error of 0.28 and 0.40, respectively.
- The higher accuracy of surface roughness was found at 3.92 at the setting of speed = 240 rpm, feed 28 mm and depth of cut = 20 mm.
- 3-2-1 provided the least amount of prediction error out of the three ANN architectures (3-1-1, 3-2-1, and 3-3-1).

CONCLUSION

We have described the architecture of an artificial neural network with a 3-2-1 neural network. By applying weights to the input parameters on MATLAB software, after many iterations, we get the ANN model of minimum surface roughness error. In turning operations, surface roughness can be accurately predicted using linear regression.

- Out of three input parameters and speed affect the surface roughness majorly. By increasing speed surface roughness, value also increase. Whereas with change in feed and depth of cut, there is minimal variation in surface roughness value.
- Comparing the values of average error obtained by the linear regression model and ANN model, the Linear regression model predicts minimum error as compared to the ANN model.

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