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Neural Network Process Modelling for Turning of Aluminium (6061) Using Cemented Carbide Inserts

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ABSTRACT

This paper deals with study using soft computing techniques, namely Artificial Neural Networks ANN, in predicting the surface roughness in turning process. Some of machining variables that have a major impact on the surface roughness in turning process such as spindle speed, feed rate and depth of cut were considered as inputs and surface roughness as output. Surface roughness, is the most specified customer requirements in a machining process. For efficient use of machine tools, optimum cutting parameters (speed, feed and depth of cut) are required. Therefore it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness. The turning process parameter optimization is highly constrained and nonlinear. In present work, machining process was carried out on Aluminium (6061) material and surface roughness was measured using Surface Roughness Tester. To predict the surface roughness, neural network model was designed through Multilayer Pereceptron network for the data obtained. The predicted surface roughness values computed from ANN, are compared with experimental data and the results obtained, conclude that neural network model is reliable and accurate for solving the cutting parameter optimization.

Keywords: *Aluminium (6061); Neural Network; Multilayer Perceptron; Surface Roughness; Turning*.

1.0 Introduction

Surface roughness is mainly a result of process parameters such as tool geometry (i.e. nose radius, edge geometry, rake angle, etc) and cutting conditions (feed rate, cutting speed, depth of cut, etc). The important cutting parameters discussed here are cutting speed, feed and depth of cut. It is found in most of the cases surface roughness decreases with increase in cutting speed and decrease in feed and depth of cut. Hence to improve the efficiency of process and quality of the product it is necessary to control the process parameters. Surface roughness is the parameters with main focus, as it dictates the aesthetics and sometimes ergonomical characteristics of the product. Statistical Design of Experiments may be used to reduce the total number of trials in order to save the time and resources without compromising the accuracy of prediction. These readings may be used to train and validate the Neural Network. ANN is found to be very useful with simulations tasks which have complex and explicit relation between control factors and result of process.

2.0 Artificial Neural Networks

Neural Networks are information processing systems and can be used in several areas of engineering applications and eliminate limitations of the classical approaches by extracting the desired information using the input data.

The advantage of the usage of neural networks for prediction is that they are able to learn from examples only and that after their learning is finished, they are able to catch hidden and strongly non linear dependencies, even when there is significant noise in the training set .Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems.

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As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the weights between

Fig 1: Neural Network Architecture

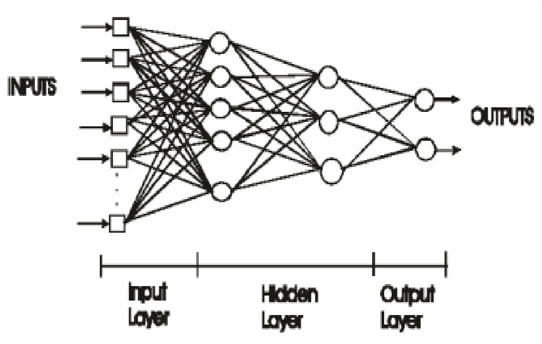
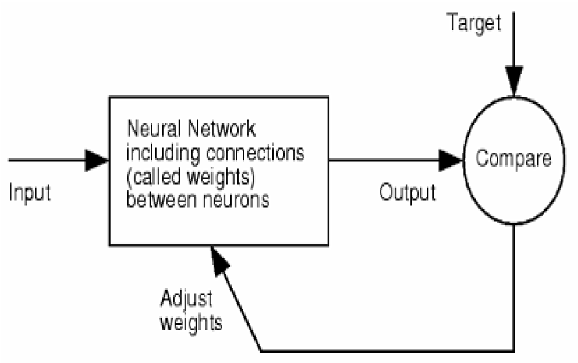


Fig 2: Feedback Control System in NN



elements. We can train a neural network to perform a particular function by adjusting the values of the weights elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target.

2.1. Types of neural networks

When used without qualification, the terms "Neural Network" (NN) and "Artificial Neural Network" (ANN) usually refer to a Multilayer Perceptron Network. However, there are many other types of neural networks including Probabilistic Neural Networks, General Regression Neural Networks, Radial Basis Function Networks, Cascade Correlation, Functional Link Networks, Kohonen networks, Gram-Charlier networks, Learning Vector Quantization, Hebb networks, Adaline networks, Heteroassociative networks, Recurrent Networks and Hybrid Networks.

DTREG implements the most widely used types of neural networks: Multilayer Perceptron Networks (also known as multilayer feed-forward network), Cascade Correlation Neural Networks, Probabilistic Neural Networks (PNN) and General Regression Neural Networks (GRNN).

3.0 The Multilayer Perceptron Neural Network Model

The following diagram illustrates a perceptron network with three layers:

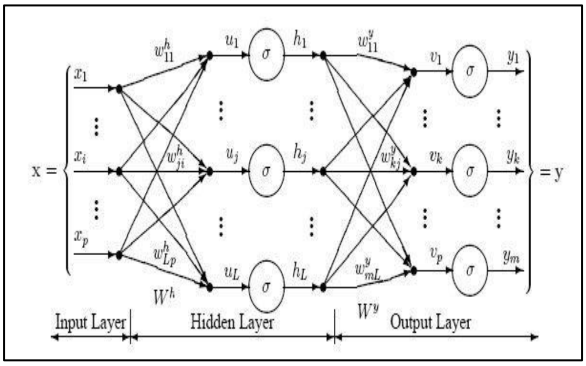
This network has an **input layer** (on the left) with three neurons, one **hidden layer** (in the middle) with three neurons and an **output layer** (on the right) with three neurons.

There is one neuron in the input layer for each predictor variable. In the case of categorical variables, *N*-1 neurons are used to represent the *N* categories of the variable.

- **Input Layer**: A vector of predictor variable values (x1...xp) is presented to the input layer.
- The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron.
- **Hidden Layer**: Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (wji), and the resulting weighted values are added together producing a combined value uj. The weighted sum (uj) is fed into a transfer function, σ, which outputs a value hj. The outputs from the hidden layer are distributed to the output layer.
- **Output Layer**: Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (wkj), and the

resulting weighted values are added together producing a combined value vj. The weighted sum (vj) is fed into a transfer function, σ, which outputs a value yk. The y values are the outputs of the network.

Fig 3: A Perceptron Network with Three Layers

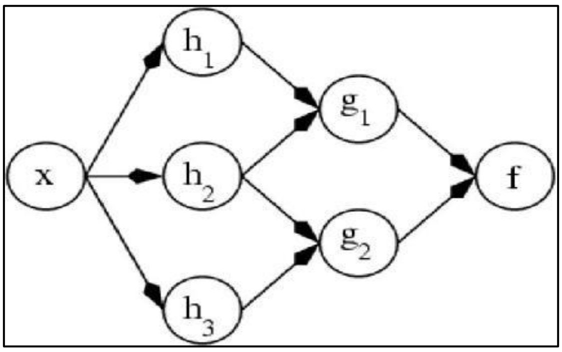


If a regression analysis is being performed with a continuous target variable, then there is a single neuron in the output layer, and it generates a single y value. For classification problems with categorical target variables, there are N neurons in the output layer producing N values, one for each of the N categories of the target variable.

3.1 Multilayer perceptron architecture

The network diagram shown above is a full-connected, three layer, feed-forward, perceptron neural network.

Fig 4: Multilayer Perceptron Architecture



"Fully connected" means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer. "Feed forward" means that the values only move from input to hidden to output layers; no values are fed back to earlier layers (a Recurrent Network allows values to be fed backward).

All neural networks have an input layer and an output layer, but the number of hidden layers may vary. Here is a diagram of a perceptron network with two hidden layers and four total layers:

When there is more than one hidden layer, the output from one hidden layer is fed into the next hidden layer and separate weights are applied to the sum going into each layer.

3.2 Training multilayer perceptron networks

The goal of the training process is to find the set of weight values that will cause the output from the neural network to match the actual target values as closely as possible.

There are several issues involved in designing and training a multilayer perceptron network:

- Selecting how many hidden layers to use in the network.
- Deciding how many neurons to use in each hidden layer.
- Finding a globally optimal solution that avoids local minima.
- Converging to an optimal solution in a reasonable period of time.
- Validating the neural network to test for overfitting.

4.0 Experiment Set Up

Experiment set up includes, CNC Lathe, Surface Roughness Measuring instrument, Cutting Tool Material, and Work piece material.

CNC Lathe consists of the machine unit with a three jaw independent chuck, a computer numerically controlled tool slide, which cud move accordingly to two axis horizontal and vertical X and Z axis. X axis represents the vertical movement which gives the depth of cut where as Z axis represents the location of the cutting tool.

Surface Roughness Measuring instrument Surtronic 3+ is a portable, self-contained instrument for the measurement of surface texture and is suitable for use in both the workshop and laboratory. Parameters available for surface texture evaluation are: Ra, Rq, Rz (DIN), Ry and Sm.

The Cutting Tool Material was a 30 mm square tool with 60 mm length having the same tool angles as for a normal turning tool. The tool used was cemented carbide insert type. The geometry of tool is : Rake angle 60 (+ve), 50 (+ve) clearance angle, 600 (+ve) major cutting edge angle, 600 (+ve) included angle and 00 cutting edge inclination angle.

Work piece material,The 6061 Aluminum we have chosen for turning is actually a Heat Treatable Alloy manufactured in the form of bars by HINDALCO.

This standard structural alloy, one of the most versatile of the heat-treatable alloys, is popular for medium to high strength requirements and has good toughness characteristics.

Applications range from transportation components to machinery and equipment applications to recreation products and consumer durables.

Alloy 6061 has excellent corrosion resistance to atmospheric conditions and good corrosion resistance to sea water. This alloy also offers good finishing characteristics and responds well to anodizing. Alloy 6061 is easily welded and joined by various commercial methods.

5.0 Results

Table 1:. Chemical Composition of Aluminum Alloy

Element	Weight%
Cu	0.15-0.4
Mg	0.7-1.2
Si	0.4-0.8
Fe	0.7 max
Mn	0.2-0.8
Other	0.4

Table 2: Case Processing Summary

		N	Percent
Sample	Training	21	77.8%
	Testing	6	22.2%
Valid		27	100.0%
Excluded		0	
Total		27	

Table 3: Network Information

Input Layer	Factors	1	s
		2	f
		3	d
	Number of Units[a]		9
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		1
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Ra
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Table 4: Model Summary

Training	Sum of Squares Error	1.481
	Relative Error	.148
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	6.613
	Relative Error	.775

Dependent Variable: Ra

a. Error computations are based on the testing

Fig 5: Layers Activation Function

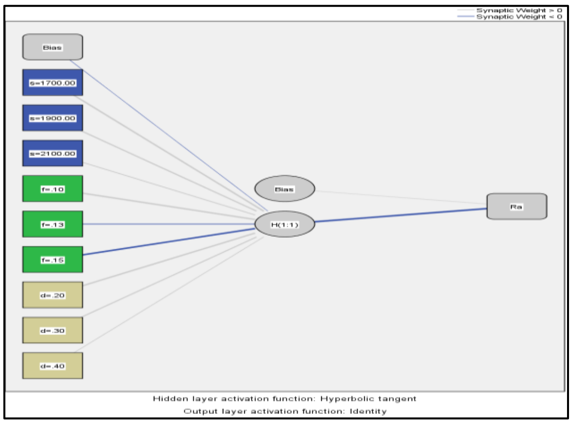


Fig 6: Ra verses Predicted Values

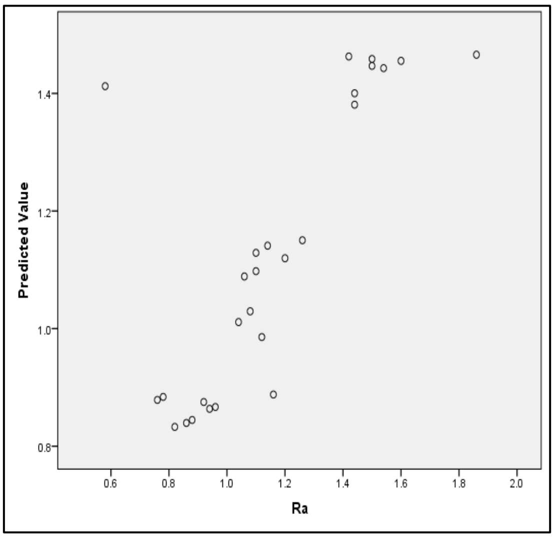


Fig 7: Residual Verses Predicted Values

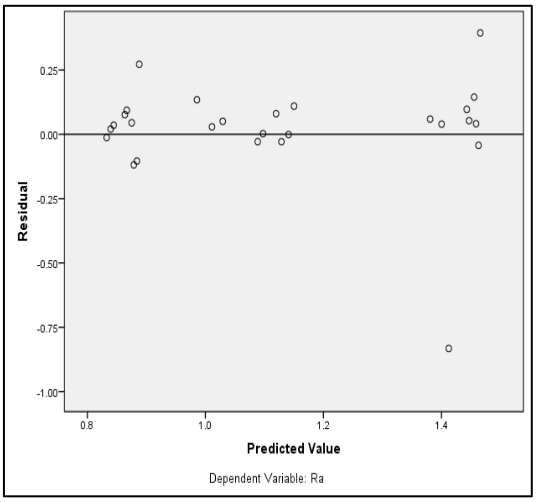


Table 5: Descriptive Statistics

	Mean	Std. Deviation	N
Ra	1.1504	.30404	27
s	1900.0000	166.41006	27
f	.1267	.02094	27
d	.3000	.08321	27

Table 6: Neural Networks Multilayer Perceptron Predicted Values

S	f	d	Ra	MLP_PredictedValue
1700	0.1	0.2	0.82	0.83
1700	0.1	0.3	0.94	0.86
1700	0.1	0.4	0.96	0.87
1700	0.13	0.2	1.12	0.99
1700	0.13	0.3	1.06	1.09
1700	0.13	0.4	1.1	1.1
1700	0.15	0.2	1.44	1.38
1700	0.15	0.3	1.54	1.44
1700	0.15	0.4	1.5	1.45
1900	0.1	0.2	0.86	0.84
1900	0.1	0.3	0.92	0.88
1900	0.1	0.4	0.76	0.88
1900	0.13	0.2	1.04	1.01
1900	0.13	0.3	1.2	1.12
1900	0.13	0.4	1.1	1.13
1900	0.15	0.2	1.44	1.4
1900	0.15	0.3	1.6	1.46
1900	0.15	0.4	1.5	1.46
2100	0.1	0.2	0.88	0.84
2100	0.1	0.3	0.78	0.88
2100	0.1	0.4	1.16	0.89
2100	0.13	0.2	1.08	1.03
2100	0.13	0.3	1.14	1.14
2100	0.13	0.4	1.26	1.15
2100	0.15	0.2	0.58	1.41
2100	0.15	0.3	1.42	1.46
2100	0.15	0.4	1.86	1.47

Table 7: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.451	3	.484	11.687	.000[b]
	Residual	.952	23	.041		
	Total	2.403	26			

a. Dependent Variable: Ra

b. Predictors: (Constant), d, f, s

6.0 Conclusion

In this study, surface finishing has been investigated in turning of aluminium 6061 using cemented carbide inserts. Neural network models are developed for predicting surface roughness. The following conclusions are drawn from the study:

- Neural network based predictions of surface roughness are carried out and compared with a non-training experimental data. These results show that neural network models are suitable to predict surface roughness patterns for a range of cutting conditions and can be utilized in intelligent process planning for turning with carbide insert tools.
- The cutting parameters considered for study are Cutting Speed, Feed and Depth of cut. The results obtained have shown that surface roughness value increases as the feed and depth of cut increases and as the spindle speed increases the surface roughness value decreases.
- The experimental studies suggest that ANN is a powerful tool and can be used for more accurate prediction of surface roughness.

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