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SURFACE ROUGHNESS PREDICTION IN CNC END MILLING MACHINING USING ARTIFICIAL NEURAL NETWORKS

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Abstract. *Surface finish is an important factor when evaluating the quality of products in modern industry. Surface roughness is the most used index for determining the surface finish in the machining process. This paper presents an artificial neural network (ANN) method to predict surface roughness (R_a) and to analyze the effects of spindle speed (n), feedrate (f), and depth of cut (d) on average surface roughness (R_a) in computer numerical control (CNC) end milling operations. The results indicate that the ANN model can successfully predict surface roughness.*
Keywords: Surface roughness, Artificial neural network, CNC machine

1. **Introduction.** Computer numerical control (CNC) machines are widely used and play an important role in modern factories. CNC machines have been widely implemented to not only increase productivity but also improve the accuracy of product. Surface finish is an important factor in the evaluation of the quality of products [1] in modern industry. However, it is difficult for CNC machines to achieve an excellent surface finish, as defects still occur in production because of tool conditions and chatter. Surface roughness is the most used index to determine surface finish in the machining process. Various simple surface roughness amplitude parameters include roughness average, root mean square (RMS) roughness, and maximum peak to valley roughness. The average roughness (R_a) is used in this study. Figure 1 shows the standard terminology and symbols used to describe surface roughness [2] and R_a is defined by the following equation:

$$R_a = \frac{1}{L}\int_0^L |Y(x)|dx, \tag{1}$$

where R_a is the arithmetic average deviation from the mean line (center line), L is the sampling length, and Y is the ordinate of the profile curve.

The formation of surface roughness is complicated and process dependent, making it difficult to calculate its value through analytical formulae. In recent years, researchers have developed some prediction strategies to improve surface roughness. Karayel [3] proposed a neural network approach for the prediction and control of surface roughness in a CNC lathe. Brezocnik and Kovacic [4] proposed a genetic algorithm approach to predict surface roughness. Wen et al. [5] proposed free pattern search (FPS) to construct the surface roughness prediction model explicitly. FPS takes advantage of the expression tree in gene expression programming (GEP) to encode a solution and to express a non-determinative tree using a fixed length individual. Zain et al. [6] presented an ANN model for predicting a surface roughness performance measure in end milling machining. It was found that the 3–1–1 network structure gave the best ANN model [6].

In this study, the ANN method is used to predict surface roughness (R_a). Because the ANN method has the advantage of learning ability, it can capture nonlinear and complex

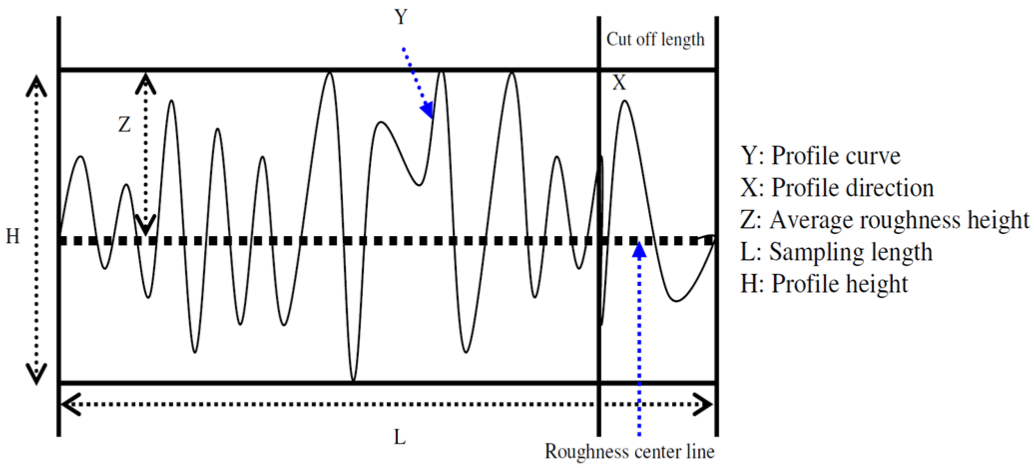

FIGURE 1. Surface roughness definition

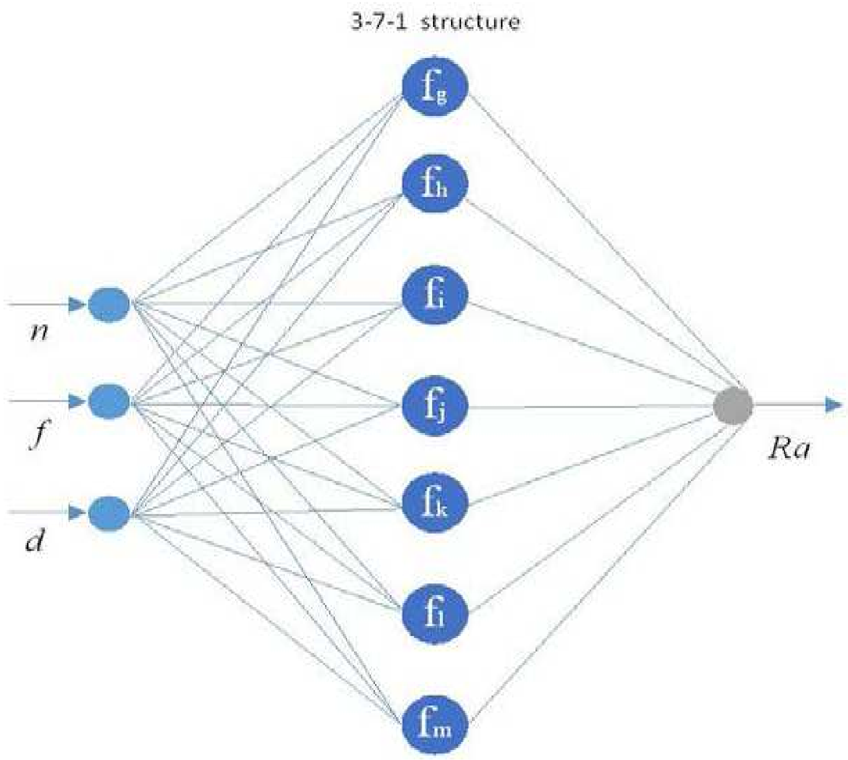

FIGURE 2. ANN structure

input-output relationships. Hence, it is suitable for use in predicting surface roughness in CNC machines.

The remainder of the paper is organized as follows. Section 2 derives the ANN, and Section 3 describes the experimental setup. Section 4 describes the prediction values of surface roughness that are obtained in the study, and Section 5 presents the conclusions.

2. **Artificial Neural Network (ANN).** ANN methods are popular and can be applied to many industrial situations. They are suitable for modeling various manufacturing functions due to their ability to learn complex nonlinear and multivariable relationships between process parameters. In this study, ANNs are used as an alternative way to estimate the surface quality in machining.

ANNs consist of a number of elementary units called neurons. A neuron is a simple processor, which takes one or more inputs and produces an output. Each input into the neuron has an associated weight that determines the "intensity" of the input. Figure 2 shows the ANN structure comprising three layers: the input layer, hidden layer, and output layer. The network structure has three nodes in the input layer, seven nodes in the first hidden layer, and one node in the output layer. The three nodes of the input layer represent the three decision values of the case study, which are spindle speed n, feedrate f, and depth of cut d. The single node of the output layer represents the predicted surface roughness value of the case study.

Many techniques are used for training a neural network. In this study, classic backpropagation algorithms were employed to model surface roughness. Backpropagation is essentially a gradient descent algorithm that takes account of the error function of the network, which is a sum of squares, with the weights as its variables. To minimize this function, the derivative of the error function is calculated, making it possible to determine a local, or preferably global, minimum. This is realized by taking small steps, iteratively, along the direction of the negative of the derivative. In this way, the convergence of the training algorithm is ensured.

3. **Experimental Setup.** Figure 3 shows the CNC end milling machine, including the CNC controller and XYZ table. A number of cutting experiments were carried out to obtain experimental data in dry cutting conditions. The milling experiments were conducted on Al 6061-T6 according to the design of the experiment. The surface roughness R_a was measured by Mitutoyo SJ-301. During the milling operation, the most important machining parameters are the spindle speed (n), feedrate (f), and depth of cut (d). In this study, tool wear is not considered to affect the result of the cutting process because a new tool is used, the total machining length is short, and the material being utilized is soft. In this study, the ranges of the model variables are 1500 $\sim$ 3500rpm for n, 5 $\sim$ 25mm/min for f, and 0.05 $\sim$ 0.7mm for d.

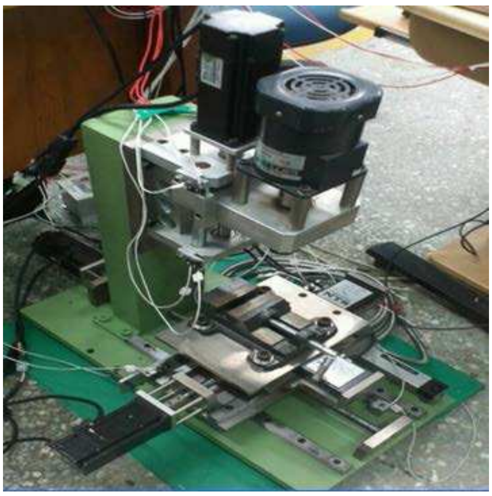

FIGURE 3. The CNC end milling machine

4. **Prediction of Surface Roughness.** MATLAB version was used to create, train, and test the ANNs. The RMS defines the numerical value of the difference between the actual and predicted values of surface roughness as well as the percentage by which it is possible to quickly and easily assess the quality and performance of ANNs. Table 1 shows the comparison of the measured values of roughness R_a and predicted values used for R_a ANNs. Figure 4 shows one measurement example with n = 2000rpm, d = 0.1mm, and f = 15mm/min. From Table 1, it can be concluded that the correlation between the predicted and experimental data is very close. The average percentage of the total RMS error in the training set was 1.2%; thus, the percentage error is within

TABLE 1. Measurement values and prediction values of surface roughness (R_a)

Text	f (mm/min)	N (rpm)	d (mm)	R_a (μm) measurement	R_a (μm) prediction	Error (%)
1	25	1500	0.7	3.65	3.6499	0.003%
2	25	2000	0.5	3.05	3.055	0.272%
3	25	2500	0.3	2.90	2.893	0.241%
4	25	3000	0.1	2.75	2.738	0.556%
5	25	3500	0.05	2.63	2.6135	0.503%
6	20	1500	0.5	2.54	2.5476	0.169%
7	20	2000	0.3	2.40	2.4056	0.233%
8	20	2500	0.1	2.29	2.2702	1.007%
9	20	3000	0.05	2.11	2.1808	3.355%
10	20	3500	0.7	2.01	2.0116	0.080%
11	15	1500	0.3	1.94	1.9659	1.335%
12	15	2000	0.1	1.88	1.8501	1.763%
13	15	2500	0.05	1.81	1.7856	1.348%
14	15	3000	0.7	1.76	1.7629	0.023%
15	15	3500	0.5	1.67	1.67	0.000%
16	10	1500	0.1	1.16	1.1559	0.636%
17	10	2000	0.05	1.10	1.1055	0.802%
18	10	2500	0.7	1.04	1.0287	0.772%
19	10	3000	0.5	0.93	0.95463	2.648%
20	10	3500	0.3	0.91	0.89068	1.767%
21	5	1500	0.05	0.64	0.65035	1.617%
22	5	2000	0.7	0.77	0.75487	1.965%
23	5	2500	0.5	0.71	0.67998	4.228%
24	5	3000	0.3	0.59	0.6087	3.750%
25	5	3500	0.1	0.53	0.54088	2.053%

FIGURE 4. Surface roughness measurement example (20X)

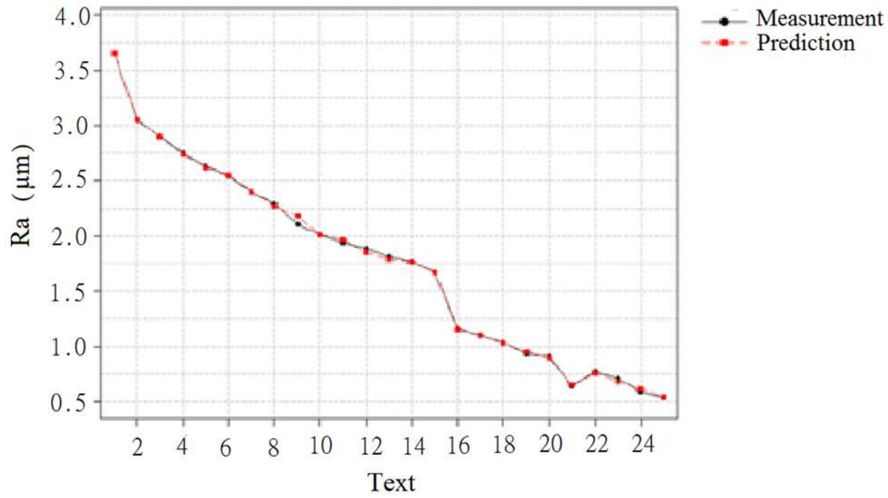

FIGURE 5. R_a comparison of experimental values and predicted values

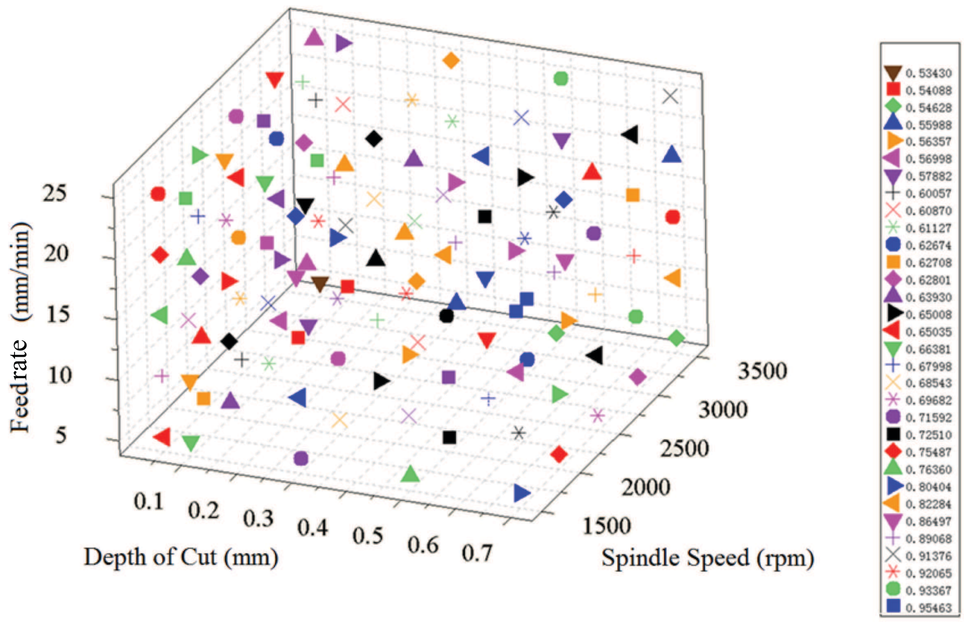

FIGURE 6. Interaction effects of spindle speed, feedrate, and depth of cut on R_a

the permissible values. Figure 5 illustrates a comparison of the experimental values with the ANN predicted values for surface roughness. From Figure 5, it can be clearly seen that the predicted values in the training set almost follow the same trend as that of the corresponding experimental values. Furthermore, to determine their interaction effects to the end milling machining, the contour plots were generated considering each three-parameter combination, including spindle speed, feedrate, and depth of cut, as shown in Figure 6. This figure is important for choosing suitable process parameters to achieve the desired surface quality. The maximal R_a occurs when the $n = 1500$rpm, $f = 25$mm/min, and $d = 0.7$mm. This indicates that when d is greater, the cutting force is greater. Thus, the maximal R_a occurs when d and f are at their maximum.

5. **Conclusions.** In this paper, an ANN model is developed to predict the surface roughness (R_a) in the CNC end milling operation. The ANN structure has three nodes in the input layer, seven nodes in the first hidden layer, and one node in the output layer. The three nodes for the input layer are spindle speed n, feedrate f, and depth of cut d. The single node of the output layer represents the predicted surface roughness. The maximal

prediction error is about 3.3% using the ANN structure. This result indicates that the model is capable of predicting the surface roughness accurately. In the future, Grey or Fuzzy theory could also be applied in the prediction of surface roughness for CNC end milling machines.

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