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An ANN Approach to Determine the Surface Roughness in End Milling Cutter

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A B S T R A C T

Surface finish is an important indication in the manufacturing process, particularly during milling processes. The goal of this project is to predict surface roughness using artificial neural networks. The neural network model efficiently determines the ideal cutting parameter values for various milling settings, resulting in reduced surface roughness. The current study is an experimental inquiry into end milling of M.S material using a carbide tool, examining the effect of various cutting settings on surface roughness. Using an artificial neural network (ANN), the study creates a link between surface roughness and cutting input parameters such spindle speed, feed, and depth of cut. The findings of this study have practical implications for industrial application, providing a way to minimise the time and expenses involved with surface roughness prediction.

Keywords: End milling, Surface roughness, Neural networks, ANN.

1. Introduction

End milling is a critical and widely used metal cutting operation among milling techniques due to its ability to remove material quickly while keeping relatively good surface quality. Its ability to produce varied configurations with milling cutters adds to its importance in machining items. Surface roughness emerges as an important factor in the machining process, significantly influencing machining performance. Many businesses place a premium on maintaining high-quality surface finishes in machined products. Surface roughness is a technological quality parameter for a product, with a significant impact on production costs and overall quality. The parameter represents the geometry of the machined surface, which, when paired with surface texture, has a substantial impact on the part's operating properties. Aside from its aesthetic implications, surface roughness influences a variety of practical properties, including as light reflection, heat transfer, coating characteristics, surface friction, and fatigue resistance. However, understanding the mechanism that causes surface roughness creation is complex, dynamic, and process-dependent, making it difficult to determine using analytical formulas. Existing theoretical models frequently lack accuracy and adaptability to specific processes and cutting circumstances. Given these complications, machine operators commonly rely on artificial neural network (ANN) algorithms to determine optimal milling machine cutting settings, providing the necessary surface roughness. This adaptive technique is useful in negotiating the complex and dynamic nature of surface roughness in end milling operations.

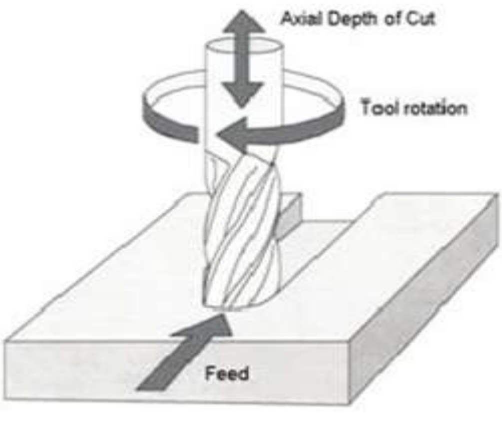

Fig. 1 - Milling Operation

Milling procedures are widely used in a variety of industries, including aerospace and car manufacture. The range of applications extends from simple operations to the creation of final products with sophisticated geometry, forms, and demanding accuracy and surface quality requirements. Milling procedures are more complicated to model than other machining processes. End milling, in particular, is intended to remove material by coordinating the motions of the tool and workpiece. The spindle speed controls the tool's rotational motion, while the feed rate controls the workpiece's linear motion. Figure 1 illustrates the dual-motion technique.

2. Literature Review

During this literature review, papers on the optimisation of milling processes from various project businesses were examined, reinforced by insights from standard textbooks. Proposes optimising CNC end milling process settings for better surface quality and higher material removal rates (MRR) [1]. The emphasis is on surface polish as a quality feature and MRR as a performance metric directly related to productivity [2]. Adaptive Neuro-Fuzzy Inference System (ANFIS) predicts surface roughness in end milling operations using spindle speed, feed rate, and depth of cut as input parameters. ANFIS is modelled using triangular and trapezoidal membership functions, with the triangular membership function resulting in a reduced average prediction error of roughly 4% [3-5]. Advocate using Genetic Programming (GP) to anticipate surface roughness in end milling operations [6-8]. Create an empirical surface roughness model for medium carbon steel end milling, with parameters optimised using Genetic Algorithms (GA) [9]. Propose a two-part technique that uses support vector machines for surface roughness prediction and particle swarm optimisation for parameter optimisation in end milling. The study shows that Particle Swarm Optimisation (PSO) produces consistent near-optimal results with little effort [10]. Use a fuzzy net-based model to forecast surface roughness in end milling operations, taking into account factors such as speed, feed, depth of cut, vibration, tool diameter, tool material, and workpiece material [11–12]. Investigates the effects of cutting speed, particle size, and particle volume percentage on surface roughness while turning 2024Al alloy composites supplemented with Al_2O_3 particles [13-15]. The grey-Taguchi approach is used to optimise milling settings for A6061P-T651 aluminium alloy, which results in better flank wear and decreased surface roughness [16-17]. Determine the best cutting parameters for Inconel 718 by using statistical experimental design, artificial neural networks, and genetic optimisation approaches [18-20]. Create an Artificial Neural Network (ANN) to model and forecast tool life in milling components composed of Aluminium (7075) material. The (ANN) model is very accurate and correlates well with experimental data [21–23]. The full approach consists of three steps: Taguchi experimental design, (ANN) modelling, and experimental validation, with a minor accuracy error of 3.034% [24-25].

3. Experimental Study

Three main machining characteristics are taken into account when developing models based on experimental data to forecast surface roughness of M.S material with a carbide tool: spindle speed, feed rate, and axial depth of cut. The literature emphasises the importance of these characteristics in determining surface roughness. The experimental research consists of 27 trials, with three levels for each of the three factors, adjusting one component at a time in a methodical way (3^3=27). A 12 mm diameter end mill cutter with four flutes and carbide tips is used to machine the M.S. material workpiece. Table I shows the three levels chosen for spindle speed, feed rate, and depth of cut. The machining is carried out on a vertical milling machine, with the M.S. workpiece securely secured on a vice attached to the machine table. Figure 2 illustrates the machining process and the action of the end milling tool. Each experiment entails controlling the spindle speed and feed rate accurately, as well as varying the depth of cut with each pass. Throughout the studies, surface roughness is assessed at four different spots on the workpiece after each pass. This systematic technique enables the gathering of detailed data on the effects of spindle speed, feed rate, and depth of cut on the surface roughness of the M.S material.

Table 1 - Experiment Sets

Factors or Properties	Sets or Levels	Values
Depth of Cut (DOC)	3	0.2,0.3,0.4
Feed Rate(f)	8	0.04,0.05,0.06
Speed (m/mm)	4	110,130,150

The 'real surface roughness' values for certain cutting circumstances are calculated by averaging surface roughness measurements taken at four separate points, roughly at equal intervals throughout the length of the machining. Table 2 displays the experimental data, which provide a detailed picture of surface roughness under various cutting settings.

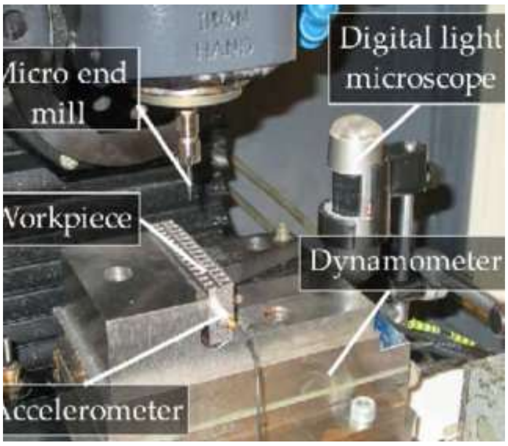

Fig. 2 - Machining Process of Milling

Table 2 - Results of Test Carried out for Various parameters

Trail No	Speed	Feed (f)	Depth of cut (DOC)	Surface Roughness (Ra)
1	110	0.04	0.2	0.21
2	110	0.04	0.3	0.31
3	110	0.04	0.4	0.24
4	110	0.05	0.2	0.26
5	110	0.05	0.3	0.27
6	110	0.05	0.4	0.24
7	110	0.06	0.2	0.32
8	110	0.06	0.3	0.34
9	110	0.06	0.4	0.30
10	130	0.04	0.2	0.19
11	130	0.04	0.3	0.22
12	130	0.04	0.4	0.27
13	130	0.05	0.2	0.26
14	130	0.05	0.3	0.28
15	130	0.05	0.4	0.22
16	130	0.06	0.2	0.30
17	130	0.06	0.3	0.32
18	130	0.06	0.4	0.20
19	150	0.04	0.2	0.20
20	150	0.04	0.3	0.21
21	150	0.04	0.4	0.23
22	150	0.05	0.2	0.24
23	150	0.05	0.3	0.30
24	150	0.05	0.4	0.23
25	150	0.06	0.2	0.24
26	150	0.06	0.3	0.22
27	150	0.06	0.4	0.29

4. ANN Modeling

A neural network is a highly adaptable modelling tool capable of understanding the links between input and output parameters. Using experimental datasets, artificial neural networks (ANNs) may learn and express the intricacies of nonlinear and interacting effects. An ANN's design generally consists of an input layer for data presentation, an output layer for network response generation, and one or more hidden layers in between. The network's features are established by the topology, weight vectors, and activation functions used in the hidden and output layers.

In particular, networks with biases, a sigmoid layer, and a linear output layer may approximate any function within a finite number of discontinuities. This versatility makes artificial neural networks an effective tool for collecting complicated correlations and patterns within data, as seen in Figure 3.

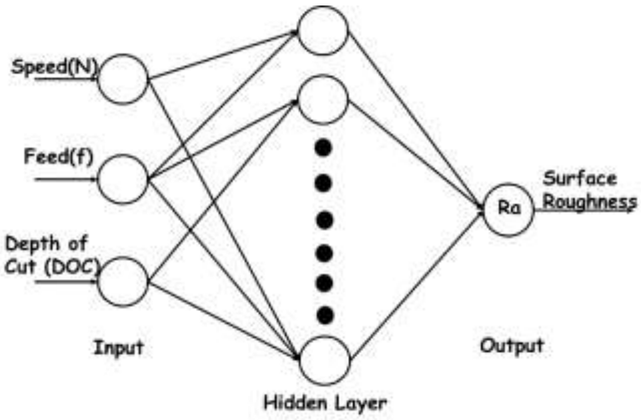

Fig. 3 - ANN Diagram

The knowledge inside the neural network is encoded by connectivity weights, which are modified throughout the learning stage using the backpropagation technique. The objective is to minimise the mean square difference between the network's actual output and the planned output pattern. In this scenario, a neural network is used to develop a surface roughness prediction model for the end milling process. Out of the 27 trials, 24 experimental datasets are used to train the network. Before using a neural network for modelling, it is critical to define the network's design, which includes the number of hidden layers, the number of neurons in each layer, and the transfer function for each layer. Given that three inputs produce one output, the number of neurons in the input and output layers are set to three and one, respectively. The number of neurons in a single hidden layer is optimal. A MATLAB programme was created to optimise the hidden layer neurons and pick an acceptable transfer function. This programme takes an experimental method, comparing the trained neural network to another set of three data points picked at random from the initial 27 experimental datasets. This guarantees that the neural network can generalise and make correct predictions for data outside the training set.

Table 3: ANN and Experimental Result Comparison

Speed of Rotation (RPM)	Feed Rate(f)	Depth of Cut (DOC)	Surface Roughness (Ra)	Assumption of Ra	Error
110	0.04	0.2	0.28	0.297	6.071
130	0.05	0.3	0.24	0.2701	11.14
150	0.06	0.4	0.299	0.3019	0.960

Table 3 shows the verification findings together with the predictions made by the Artificial Neural Network (ANN) model. Surprisingly, the predictions obtained from the ANN model closely match the documented observations. The average prediction error for the dataset is found to be 6.057%, with a maximum prediction error of 11.14%. In every example, the maximum error tolerance was constantly maintained. It's worth noting that the use of Tan Sigmoid transfer functions played an important role in reaching these outcomes. The transfer function selection, as well as the neural network's overall design, contribute to the model's capacity to accurately approximate and anticipate surface roughness throughout the end milling process. The observed low average prediction error demonstrates the created ANN model's dependability and accuracy in predicting surface roughness from unseen data.

5. Conclusion

In this study, an integrated strategy including experimental observations and artificial neural networks is applied with the purpose of forecasting surface roughness in the milling process. The major goal is to understand how the three main factors, spindle speed, feed rate, and depth of cut, influence surface roughness. The results show a strong connection between anticipated values and actual experimental data. This study provides important insights into a fundamental component that influences production rates and costs. The overall purpose is to make it easier to evaluate surface roughness prior to machining a product. This capacity, when seamlessly integrated into the factory floor environment, has the potential to save both time and costs, enabling the manufacture of surfaces with desired quality. This study's key findings include the detection of minimal surface roughness values (0.2 Km) for specified cutting parameters of 110 m/min for cutting speed, 0.04 mm/min for feed rate, and 0.2 mm for depth of cut. Maximum surface roughness values (0.32 Km) were found under various cutting settings, including 110 m/min cutting speed, 0.06 mm/min feed rate, and 0.30 mm depth of cut. The study found a clear association between increased feed rate and surface roughness. The models established in this study provide a useful tool for forecasting surface roughness in the end milling process. Overall, these findings add to the wider purpose of improving efficiency and quality control in manufacturing processes, which aligns with the industry's goals of reaching optimal production outcomes.

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