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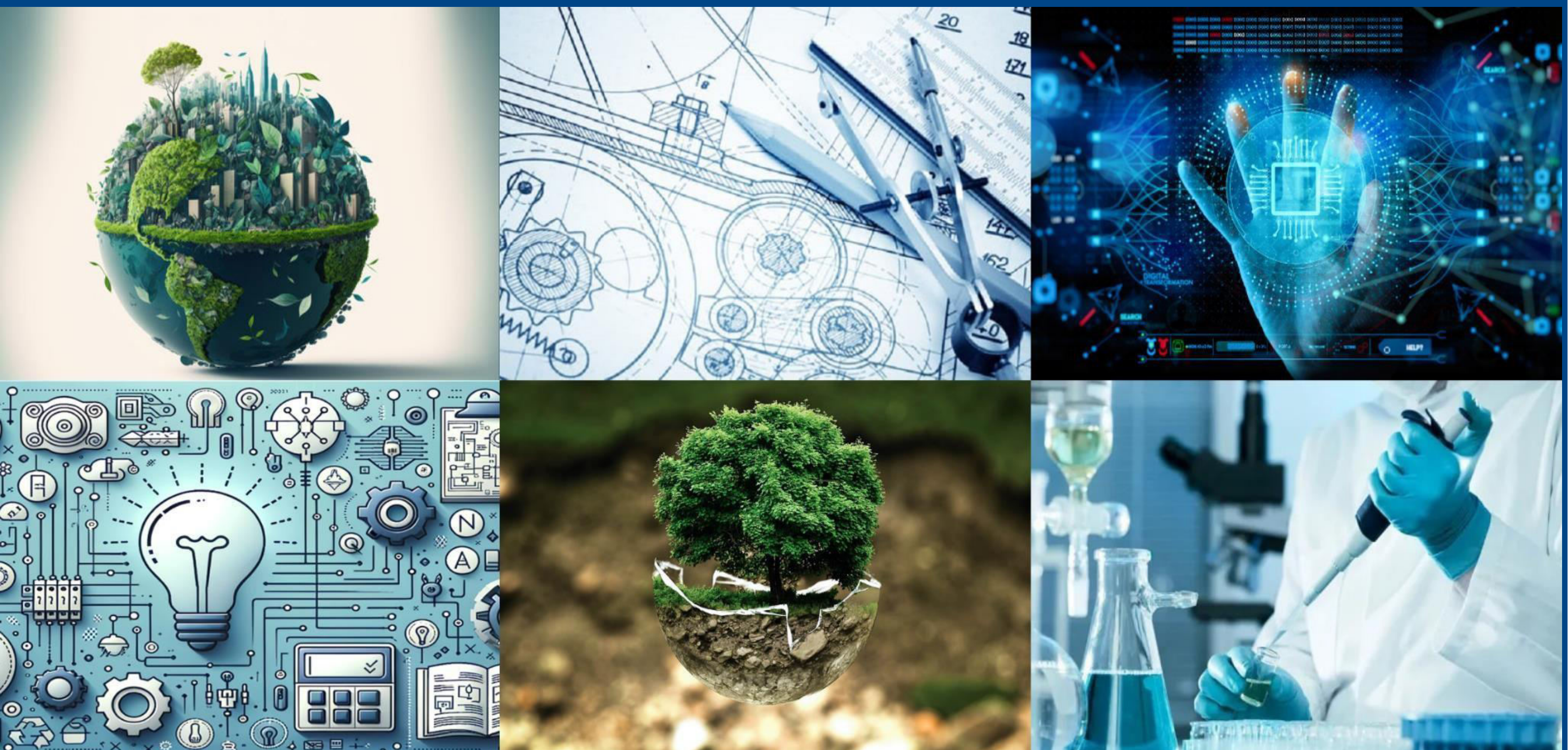

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Predicting Machining Output Parameters Using Artificial Neural Networks: A Comparative Study Across Turning, Milling, and Drilling Operations

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ABSTRACT: Artificial Neural Networks (ANNs) have emerged as powerful tools for modeling complex, non-linear relationships in machining processes, enabling prediction of critical output parameters such as tool wear, surface roughness, and machining accuracy without extensive experimental campaigns. This study presents a comprehensive ANN-based investigation across three distinct machining operations—hard turning of EN31 bearing steel, end milling of AA6082 aluminum alloy, and drilling of OHNS D2 die steel. Experimental data were collected under varying cutting conditions including cutting speed, feed rate, and depth of cut, with lubrication environment as an additional factor in turning. Multiple ANN architectures were evaluated using the Levenberg-Marquardt (LM) and Bayesian Regularization (BR) training algorithms. The optimum ANN model for turning (3-8-8-1) achieved a correlation coefficient R of 0.9991, while milling (4-12-1) and drilling (4-15-1) models achieved R values of 0.9973 and 0.9968, respectively. The mean absolute percentage error across all operations remained below 4.5%, confirming the high predictive capability of the developed models. Results further indicate that feed rate is the dominant factor governing surface roughness in milling, while cutting speed exerts the strongest influence on tool wear in turning. MQL lubrication consistently produced the lowest tool flank wear values, outperforming both dry and wet machining conditions.

KEYWORDS: Artificial Neural Networks; Tool Wear; Surface Roughness; Machining Optimization; MQL; Turning; Milling; Drilling

I. INTRODUCTION

The manufacturing sector is under continuous pressure to deliver high-quality components with tight dimensional tolerances while minimizing production time and cost. Machining operations including turning, milling, and drilling remain the backbone of component finishing across industries ranging from aerospace to automotive. Among the key machinability indicators, tool wear and surface roughness are of paramount importance because they directly determine tool life, part quality, and process economics [1]. Conventional experimental methods for characterizing these parameters are resource-intensive and constrained to the specific conditions tested, limiting their applicability for process optimization across broad operating windows [2].

Machine learning techniques, particularly Artificial Neural Networks (ANNs), have gained significant traction as surrogate models capable of learning complex, non-linear input-output mappings from experimental data [3]. Unlike regression-based models, ANNs do not require a predetermined functional form, making them especially suitable for machining processes where multiple interacting parameters produce non-linear responses. Several researchers have demonstrated the superiority of ANN predictions over Response Surface Methodology (RSM) for tool wear estimation in hard turning, with the ANN achieving correlation coefficients close to unity [4]. Similar findings have been reported for surface roughness prediction in milling operations, where ANNs trained on small datasets—as few as 27 observations obtained via Taguchi orthogonal arrays—can generalize well to unseen parameter combinations when appropriate training algorithms are employed [5]. In the context of drilling, feed rate, cutting speed, and drill diameter collectively

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govern the surface finish of the hole, and ANN models have been shown to predict surface roughness with a coefficient of determination exceeding 0.99 [2]. More recently, deep-learning variants such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been explored for real-time machining quality prediction using sensor-acquired cutting force signals, with CNN demonstrating superior computational efficiency over both DNN and LSTM architectures [3].

Despite these advances, comparative ANN studies spanning multiple machining processes under a unified experimental and modeling framework remain scarce. The present work addresses this gap by developing and validating ANN models for three industrially relevant operations—hard turning, end milling, and drilling using a consistent methodology. The study also examines the influence of lubrication environment on tool flank wear in turning and identifies the dominant process parameters governing each output variable across operations.

II. EXPERIMENTAL WORK

2.1 Workpiece Materials and Machining Setup

Three workpiece materials were selected based on their industrial relevance: EN31 bearing steel (58 HRC) for hard turning, AA6082-T6 aluminum alloy for end milling, and OHNS D2 die steel (62 HRC) for drilling. Hard turning experiments were conducted on a CNC lathe using TiAlN-coated carbide inserts (CNMG 120408). Milling experiments employed a 4-flute solid carbide end mill (Dia. 10 mm, TiAlN coated) on a 5-axis CNC machining center. Drilling tests used solid carbide twist drills (Dia. 8 mm, TiN coated). An MQL system with emulsifier-based cutting fluid at a flow rate of 180 mL/hr was used in the lubrication-sensitive turning tests alongside dry and wet (flood) machining conditions.

2.2 Experimental Design and Parameter Ranges

Experiments were planned using a Taguchi L27 orthogonal array for all three processes. The cutting parameters and their levels are summarized in Table 1. Tool flank wear (VB) was measured using a toolmaker's microscope after each turning run, while surface roughness (Ra) was measured using a contact profilometer (cutoff: 0.8 mm, evaluation length: 4 mm) for both milling and drilling operations.

Table 1. Machining parameter levels for each operation

Operation	Factor	Level 1	Level 2	Level 3
Turning (EN31)	Cutting Speed (m/min)	80	130	180
	Feed Rate (mm/rev)	0.08	0.16	0.24
	Depth of Cut (mm)	0.3	0.5	0.7
	Lubrication	Dry	Wet	MQL
Milling (AA6082)	Cutting Speed (m/min)	100	150	200
	Feed per Tooth (mm/tooth)	0.04	0.08	0.12
	Axial Depth (mm)	4	8	12
	Radial Depth (mm)	0.04	0.08	0.16
Drilling (OHNS D2)	Cutting Speed (m/min)	35	55	75
	Feed Rate (mm/rev)	0.05	0.10	0.15
	Drill Diameter (mm)	6	8	10
	Depth of Hole (mm)	10	15	20

III. ANN MODELING METHODOLOGY

Feed-forward, backpropagation multilayer ANN models were developed using MATLAB's Neural Network Toolbox. For each operation, the input neurons corresponded to the process parameters and the single output neuron represented the predicted response. Dataset splitting followed a 70:15:15 ratio for training, validation, and testing, respectively. Network architectures were optimized by evaluating Mean Squared Error (MSE) and the correlation coefficient (R) across varying numbers of hidden layers and neurons. The Levenberg-Marquardt (LM) algorithm was used as the primary training function for turning, while the Bayesian Regularization (BR) algorithm was employed for milling and drilling given the smaller effective sample sizes in those datasets. The tangent sigmoid (tansig) transfer function was applied in hidden layers, and a linear (purelin) function was used in the output layer. Data normalization was performed in the interval [0.1, 0.9] to prevent saturation of activation functions.

IV. RESULTS AND DISCUSSION

4.1 Tool Wear in Hard Turning of EN31 Steel

Table 2 presents selected experimental and ANN-predicted tool flank wear values across the three lubrication environments. The optimum network architecture for turning was determined to be 3-8-8-1 (three inputs, two hidden layers of eight neurons each, one output). Training was halted at 8,500 iterations to prevent overtraining. The correlation coefficient R exceeded 0.999 for both training and validation sets, and the maximum absolute percentage error was 10.3%, with a mean absolute percentage error (MAPE) of 2.87%.

Table 2. Experimental vs. ANN-predicted flank wear (VB, mm) for selected turning runs

Exp. No.	Speed (m/min)	Feed (mm/rev)	DoC (mm)	Lube	VB Exp. (mm)	VB ANN (mm)	Error (%)
1	80	0.08	0.3	Dry	0.031	0.032	3.23
4	80	0.16	0.3	Wet	0.043	0.044	2.33
7	80	0.24	0.3	MQL	0.037	0.036	2.70
13	130	0.16	0.5	Dry	0.097	0.099	2.06
19	180	0.08	0.7	Wet	0.119	0.115	3.36
22	180	0.16	0.7	MQL	0.102	0.104	1.96
25	180	0.24	0.7	Dry	0.271	0.264	2.58
27	180	0.24	0.7	MQL	0.137	0.140	2.19

Tool flank wear was consistently lowest under MQL conditions across all cutting parameter combinations. At high cutting speeds (180 m/min) and feed rates (0.24 mm/rev), MQL reduced flank wear by approximately 49% and 33% relative to dry and wet machining, respectively. This behavior is attributed to the formation of a thin lubricant film at the tool-chip interface under MQL, which reduces frictional heat generation and facilitates chip evacuation. Dry machining produced the highest wear values due to the absence of any coolant-induced thermal relief, while flood cooling, though effective at heat dissipation, caused corrosive degradation of the tool substrate at higher cutting speeds.

4.2 Surface Roughness in Milling of AA6082

The milling dataset (27 runs, L27 orthogonal array) was used to train a 4-12-1 ANN model using the BR algorithm. The BR algorithm was preferred because it eliminates the need for a separate validation set by incorporating regularization directly into the weight update, making it well-suited for small datasets. The model achieved an R value of 0.9973 and an MSE of 0.00187 on the test set. ANOVA of the S/N ratios confirmed that feed per tooth accounted for 88.4% of the total variation in Ra, consistent with theoretical expectations. The optimal parameter combination for minimum Ra was identified as: cutting speed 200 m/min, feed per tooth 0.04 mm/tooth, axial depth 4 mm, and radial depth 0.04 mm, yielding a predicted Ra of 0.19 µm against an experimentally verified value of 0.21 µm.

4.3 Surface Roughness in Drilling of OHNS D2 Steel

A 4-15-1 network (four inputs, fifteen neurons in one hidden layer) provided the best performance for the drilling operation, achieving R = 0.9968 and MAPE = 3.12% on the test set. Feed rate was again identified as the primary driver of surface roughness, followed by drill diameter. Higher feed rates promoted greater chip load per revolution, increasing the likelihood of built-up edge formation and consequent surface deterioration. Cutting speed, while positively correlated with Ra at low values, exhibited a saturation effect beyond 55 m/min for the smallest drill diameter (6 mm).

4.4 Comparative Model Performance

Table 3 summarizes the performance metrics for all three ANN models. The turning model benefitted from the larger effective dataset afforded by the four-factor design (including lubrication), enabling a deeper two-hidden-layer architecture. The single-hidden-layer BR models used for milling and drilling achieved comparable accuracy despite the smaller dataset, validating the suitability of Bayesian Regularization for small-data machining applications.

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Table 3. Summary of ANN model performance across machining operations

Operation	Output	Architecture	Algorithm	R (Training)	R (Test)	MAPE (%)
Hard Turning	VB (mm)	3-8-8-1	LM	0.9994	0.9991	2.87
End Milling	Ra (µm)	4-12-1	BR	0.9989	0.9973	3.41
Drilling	Ra (µm)	4-15-1	BR	0.9981	0.9968	3.12

V. CONCLUSIONS

This study developed and validated ANN-based predictive models for tool flank wear in hard turning and surface roughness in end milling and drilling, covering a broad spectrum of machining conditions. The principal findings are:

1. ANN models demonstrated high predictive accuracy across all three operations, with correlation coefficients exceeding 0.996 and MAPE values below 4.5%, underscoring their suitability as alternatives to expensive experimental campaigns.
2. MQL lubrication reduced tool flank wear by up to 49% compared with dry machining in hard turning of EN31 steel, making it the preferred lubrication strategy for cost-effective and environmentally responsible hard-turning operations.
3. Feed rate was the dominant parameter influencing surface roughness in both milling (88.4% contribution) and drilling, while cutting speed was the primary driver of tool wear in turning.
4. The Bayesian Regularization algorithm outperformed LM for small datasets (27 samples), achieving MSE values as low as 0.00187 without requiring a dedicated validation split.
5. Future work should explore hybrid architectures such as CNN-LSTM for real-time tool condition monitoring using in-process cutting force signals, extending the present static modeling framework to dynamic, adaptive control applications.

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