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Hybrid ANN–GA and Machine Learning Approaches for Surface Roughness Prediction in CNC Step Turning of Aluminium Alloy

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Abstract: In this investigation GA (Genetic Algorithms) and ANN (Artificial Neural Networks) was used for predicting surface roughness in CNC-machined aluminium (Al356) components based on machining parameters viz. feed rate (FR), depth of cut (DOC), and cutting velocity (CV) which shows the effectiveness of hybridizing these two computational intelligence techniques. Thus ANN's universal function approximation capability to capture complex relationships between input parameters and surface roughness has been used, while GA was used to optimizes the initial weights and biases of the ANN to prevent convergence to the local minima and enhance global optimization. Hybrid ANN-GA model shows the better performance in comparison with conventional ANN and Nonlinear Regression (NLR) using multiple statistical metrics. The results establish that integrating GA with ANN develops convergence speed and prediction accuracy. The trained hybrid ANN-GA model can efficiently estimate surface roughness, enabling operators to optimize machining parameters for improved efficiency and product quality without extensive experimental runs. For lowest RMSE and MAPE values GA-ANN hybrid model was used. The hybrid ANN-GA model outperformed all approaches, yielding the best prediction accuracy with $R^2 = 0.95$, RMSE = 0.0059 μm, and MAPE 1.2%. Furthermore, the hybrid model identified optimized machining parameters Feed = 0.108 mm/rev, Depth of Cut = 0.266 mm, and Cutting Velocity = 1860.6 m/min resulting in the lowest predicted surface roughness of 0.0168 μm. These findings highlight the superiority of the ANN-GA hybrid framework for precision machining optimization, providing both predictive accuracy and practical process guidelines. Results from this investigation can aid in enhancing manufacturing efficiency and product-quality in correctness machining of aluminium components.

Keywords: CNC Lathe Machining; Cutting velocity; Depth of Cut; Feed Rate; Hybrid ANN – GA; Python; Regression Modelling; Surface Roughness

1. Introduction

Due to the raised industry standards the global competition in manufacturing sector has increased significantly. CNC-machine tools play a crucial role by shaping raw metal into finished products through precise drilling, step-turning, boring and milling operations controlled by the programmed instructions[1]. These CNC-machines necessitate careful parameter settings to balance efficiency and the cost-effectiveness. Industry 4.0 advancements have led to AI-driven advanced CNC-systems, improving production, improving part quality, minimizing the defects along with reducing operational expenses[2].

In process of CNC machining, many review articles have explored various aspects including the cutting tool condition monitoring, machine condition monitoring, and the final product quality enhancement. Some research have focused on minimizing the surface roughness, while others examine the influence of machining parameters and chatter detection techniques[3]. Additionally, systematic reviews address chatter prediction, emphasizing regenerative and mode coupling-chatter in CNC processes. According to Gupta et al. surface roughness (SR) signifies deviations from the standard surface during step turning operation. Ensuring optimal roughness enhances durability and the

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performance, with standards like DIN-4760 defining acceptable boundaries[4]. The complexity of roughness mechanisms makes mathematical modeling difficult, leading researchers to adopt machine learning for the purpose of prediction. These advancements help improve manufacturing efficiency and product consistency. In CNC step turning operation, it can be seen that the support Vector Machines (SVM) have been widely used for the prediction of SR. Various SVM models were used by the researchers including LS-SVM model and the advanced k-means clustering SVM, outperform Artificial Neural Networks (ANN) with remarkable accuracy. Toke et al. explored the parameter tuning significantly affects SVM performance, with optimization methods of soft computing like genetic algorithms, and artificial bee colony (ABC) enhancing prediction accuracy. Among these, hybrid of ABC-SVM shows the better results, demonstrating superior optimization efficiency[5].

Ntemi et al. investigated that the regression analysis techniques like multi-regression and quantile regression can be widely used to predict SR (surface roughness) based on FR (feed rate), DOC (depth of cut), and the spindle RPM[6]. It was observed by many researchers that the BLR (Bayesian linear regression) combined with combined radial basis function cam be used to extract correct time-domain vibration topographies for surface roughness prediction[7].

S. Tangjitsitcharoen developed a two-layer feed-forward neural network trained using the Levenberg–Marquardt algorithm to predict straightness during machining. Multiple regression analysis was also performed to model straightness and cutting force ratio under varying cutting conditions. The study demonstrated that the trained neural network provided accurate in-process straightness prediction compared to the regression model[8].

In the study of Gowd et al., experiments were conducted based on DoE using cutting speed, feed, and depth of cut as inputs, while force and temperature were considered as outputs. An ANN model developed in MATLAB effectively predicted and optimized turning parameters for EN31 steel, showing close agreement between experimental and predicted results[9].

The study introduced the “Global and Local Score” (GOALS) method to simultaneously evaluate feature importance at both global and local levels in nonlinear machine learning models. Using nonlinear regression, the approach demonstrated superior interpretability and efficiency compared to existing variable importance techniques in data analysis[10].

Kumar et al.[11] developed a hybrid RSM–ANN model to predict surface roughness in CNC turning of Al 6061 alloy, integrating both cutting parameters and vibration signals as inputs. Their study achieved high prediction accuracy, demonstrating the capability of hybrid modeling in capturing nonlinear relationships in machining processes.

Gopan et al.[12] implemented an integrated ANN–GA approach for optimizing surface roughness during CNC turning, where the GA fine-tuned process parameters based on ANN-predicted outputs. The hybrid model effectively minimized surface roughness, highlighting the advantage of combining neural learning with evolutionary optimization.

Adil et al.[13] developed a mathematical model for optimizing cutting conditions during CNC turning of MDN 350 steel using carbide inserts. The study applied regression-based modeling to correlate process parameters with performance measures, achieving optimal cutting conditions through statistical optimization. However, the approach focused on linear modeling and did not incorporate machine learning or hybrid optimization methods, indicating scope for advanced predictive modeling in similar machining contexts.

F. M. H. et al.[14] optimized and predicted CBN tool life sustainability during CNC turning of AA1100 aluminum using response surface methodology. The study revealed that the optimal cutting speed of 180 m/min, feed rate of 0.12 mm/rev, and depth of cut of 0.4 mm resulted in the maximum tool life. Although the model showed good predictive accuracy, it was limited to statistical optimization without integrating hybrid or intelligent learning-based approaches.

Chen C.H. et al. investigated the use of a Back Propagation Neural Network (BPNN) to predict CNC end milling surface roughness based on cutting depth, spindle speed, feed rate, and milling pitch. The optimized BPNN with 2,000,000 iterations, a learning rate of 0.85, and inertia factor of 0.5 achieved lower RMSE[15].

Hossain et al.[16] optimized cutting temperature and surface roughness in CNC turning of Titanium alloy using response surface methodology. The results indicated that a cutting speed of 80 m/min, feed rate of 0.1 mm/rev, and depth of cut of 0.2 mm minimized both surface roughness and temperature effectively. While the RSM model proved statistically sound, it did not employ hybrid or machine learning–based approaches for deeper predictive insight.

Similarly, Elminir H. et al. investigated efficient deep learning model for tool life estimation of CNC milling cutters. However, ANN requires careful hyper-parameter tuning and may suffer from overfitting if not properly regularized[17].

Sethi et al.[18] employed an artificial neural network (ANN) model to analyze and predict photovoltaic (PV) module performance under varying environmental conditions. The optimized ANN achieved a prediction accuracy of 97.5% for output power estimation, proving its robustness in handling nonlinear relationships between solar irradiance, temperature, and efficiency. Although the study was conducted in the renewable energy domain, its modeling framework demonstrates strong potential for adaptation to machining process prediction and optimization tasks.

Gürgen *et al.*[19] proposed a hybrid ANN–GA model for predicting and minimizing surface roughness during CNC machining of *Pinus sylvestris*. The optimized model achieved a mean absolute percentage error (MAPE) below 4 % and identified optimal conditions (feed ≈ 3.0 m/min, depth of cut ≈ 9.7 mm) for minimum Ra. The study effectively combined prediction and optimization, yet it was limited to wood materials, leaving scope for metal-based validation.

Vedrtnam et al.[20] and Mollaei Ardestani et al.[21] collectively demonstrated the effectiveness of regression-based and hybrid RSM–GA models for process optimization, achieving prediction accuracies above 90% across welding, molding, and material property estimation applications.

Genetic Algorithm (GA) is a population-based metaheuristic inspired by the principles of natural selection, widely applied to solve complex optimization problems by enhancing population fitness over successive generations. Selecting the most suitable combination of tool geometry parameters is often challenging due to the vast number of possible configurations. Conventional optimization methods may converge prematurely to local optima and can be computationally intensive. In contrast, GA has been extensively adopted by researchers for its effectiveness in accurately optimizing surface roughness in turning processes[22].

Mareš *et al.*[23] developed a thermal error compensation model for a 5-axis CNC machine using embedded temperature sensors and Python-based algorithms integrated with the CNC controller. The study achieved a **42% reduction in thermal-induced positioning error**, confirming the model's robustness and real-time applicability.

In this study, we focus on aluminium, a material widely used due to its favourable properties such as light weight, corrosion resistance, and machinability and mostly adopted in industries. According to Kumar D. et al. aluminium and its alloys are widely preferred in machining studies due to their lightweight, high strength-to-weight ratio, and excellent castability. Their adaptability for surface finish improvement makes them ideal for evaluating the influence of machining parameters on surface roughness[24-26]. Gemechu et al.[27] optimized CNC turning of AISI D3 tool steel using an Al_2O_3/graphene nanofluid and machine learning models to enhance machining performance. The study achieved a 16.8% improvement in surface finish and a 12% reduction in cutting temperature, validating the hybrid optimization framework's effectiveness.

In machine learning applications, data investigation and in scientific computing, Python has appeared as an influential programming language. Its versatility, ease of use, and extensive libraries make it a perfect choice for solving the simple to complex industrial problems in area of manufacturing and machining[28-30].

Wang et al.[31] and Van Thieu et al.[32] emphasized the versatility of Python-based libraries such as SGML and MAFESE for integrating solution-guided machine learning and metaheuristic feature selection. Their studies demonstrated Python's efficiency in developing hybrid optimization frameworks, supporting its adoption for ANN–GA implementation in CNC surface roughness prediction.

Python facilitates predictive mathematical modeling, optimization, and statistical analysis through various computational tools. With robust libraries such as NumPy, Pandas, Scikit-Learn along with DEAP code, Python can make effective handling of engineering datasets, development of ANN models, and execution of EA (evolutionary algorithms).

Mohsen et al.[33] utilized Python-based machine learning models for accurate DNBR prediction, highlighting Python's strength in engineering problem-solving and predictive analytics. Dejene and Wolla[34] compared ANN and ANOVA approaches for defect prediction in plastic injection molding, demonstrating the superior adaptability of ANN models in nonlinear manufacturing processes. Similarly, Saady et al.[35] reviewed soft computing methods, emphasizing the efficiency of hybrid and intelligent algorithms such as ANN and GA in improving optimization accuracy and system performance across engineering applications.

Al-Hamd et al.[36] optimized the prediction of FRP–concrete bond strength using soft computing techniques, demonstrating the reliability of hybrid AI models in handling complex nonlinear relationships. Kovač et al.[37] provided a Python-based guide for implementing machine learning regression models, underscoring Python's practicality for predictive analytics across scientific domains. Similarly, Nie et al.[38] employed ResNet and ANN architectures to predict flame quenching thickness, revealing that advanced neural models can achieve high predictive accuracy in nonlinear engineering phenomena—supporting their applicability to surface roughness prediction in CNC machining.

A Python-based ANN model was developed to predict surface roughness and machining accuracy in milling SUS304 steel. The model effectively mapped cutting forces to surface quality, showcasing the use of Python for machining optimization[39]. Thus, Python-driven ANN, GA, and soft computing applications have been applied across domains including **defect prediction, strength analysis, and complex regression modeling**, reinforcing Python's role as a robust tool for hybrid intelligent systems.

In the present study, by analysing the influence of feed rate, depth of cut, and cutting velocity on surface roughness (SR), a predictive model is developed to estimate the resulting surface quality. This research provides insights into how machining parameters can be adjusted to control

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surface roughness, thereby contributing to improved machining practices for high-quality aluminium components. In this investigation, both regression approaches and machine learning models such as Artificial Neural Networks (ANN) are employed to optimize surface roughness by analysing the effects of feed rate, depth of cut, and cutting velocity. Nonlinear Regression (NLR) is used to establish explicit mathematical relationships between input parameters and surface roughness.

Although numerous studies have examined surface roughness prediction in CNC machining using either ANN, GA, or regression-based models, most were limited to single-method approaches and materials such as steels and composites. Previous works, applied ANN or RSM-based techniques but lacked hybrid integration to capture the nonlinear interactions among machining variables. Similarly, GA-based studies demonstrated effective parameter optimization yet did not couple GA with learning models for enhanced predictive accuracy.

To address these limitations, the present study introduces a hybrid ANN–GA framework for surface roughness prediction in CNC step turning of aluminium alloy. This approach leverages the strong function approximation capability of ANN to capture complex relationships between input parameters and surface finish, while GA fine-tunes the initial weights and biases of the ANN to avoid local minima and enhance global convergence. The effectiveness of the proposed hybrid ANN–GA model is evaluated against traditional ANN and NLR models using multiple statistical performance metrics, thereby addressing a key research gap in predictive surface roughness modelling for aluminium machining applications.

2. Experimental Investigation

2.1. Experimental Setup and Methodology

The objective of this research is to model and optimize the influence of feed rate (FR), depth of cut (DOC), and cutting velocity (CV) on the surface roughness of CNC-machined aluminum components. Four strategies—Nonlinear Regression (NLR), Genetic Algorithm (GA) optimization, Artificial Neural Network (ANN), and a Hybrid ANN-GA approach—are employed to compare prediction accuracy and identify optimal machining parameters for improved precision and surface quality.

The experiments were conducted using a CNC lathe trainer (Model: HE-100-CNC-PC, Hytech Ltd., Pune) equipped with a PLC-based control system and CutViewer software (United Kingdom) for part program simulation. The machine operates with a Fanuc-compatible controller, ensuring industrial-level precision in tool path execution. A single-point carbide cutting tool and a 3-jaw chuck were used for the turning operations.

Aluminium-alloy work pieces (Al356) was used as work piece material due to their widespread industrial use and machinability. Al356 has 83.5 BHN hardness and tensile strength 160 MPa. The primary composition of Al356 has Silicon (Si) 6.6 to 7.3% and Magnesium (Mg) from 0.2 to 0.43%. Al356 exhibits improved mechanical properties with a hardness range of 95–130 HB, an ultimate tensile strength (UTS) of 250–320 MPa[40].

The experiments were designed based on an extended factorial design with randomized parameter levels, ensuring adequate coverage of the input space for regression and machine learning modeling. Three primary input parameters were selected: Feed Rate, Depth of Cut and Cutting Velocity. Thus, 200 experimental sample data were collected with the CNC lathe trainer.

Figure 1 shows the single point carbide cutting tool and the 3-jaw chuck setup used in the CNC lathe trainer. As shown in Figure 2, the output parameter, SR (surface roughness) was measured after each trial using a surface roughness tester Mitutoyo standard SJ-210, with a cut-off length of 0.8 mm, conforming to ISO 4287 standards. The selected cut-off length effectively filtered out waviness and form deviations, ensuring that only the primary micro-level irregularities were recorded. This setup provided highly accurate and reliable Ra values, enabling consistent evaluation of machining performance under different cutting conditions.

All data points, including the values of feed rate, depth of cut, and cutting velocity for each trial, were systematically recorded for subsequent analysis.

This investigation aims to examine the effect of machining parameters—specifically feed rate, depth of cut, and cutting velocity—on the surface roughness of step turning of aluminium components produced by a CNC lathe trainer. This approach comprises experimental design, data collection, statistical modeling using non-linear regression (NLR), Neural network model evaluation and hybridizing of ANN-GA for modeling of surface roughness of step turned aluminium components.

Data analysis and modeling were performed using Python (Spyder IDE), which provided a flexible platform for implementing regression and machine learning algorithms. Libraries such as scikit-learn, NumPy, and Matplotlib were used for model development, evaluation, and visualization.

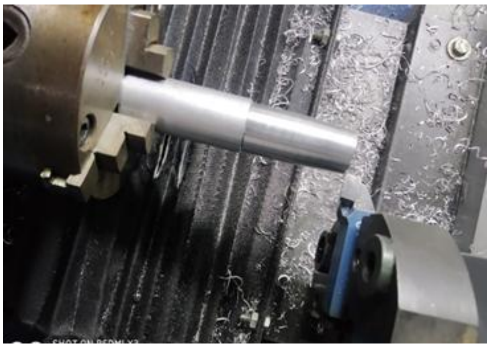

Fig. 1: Tool and work piece

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Fig. 2: Surface Roughness Tester

2.2. Selection of Range

The initial range of parameters were determined through steady-state experimental trials, in which one parameter varies and its effect on Surface roughness was measured by keeping the other parameters constant. Figure 3 depicts that the feed rate was varied and its effect on SR was observed. It was observed that if feed rate is lower and higher after a certain zone then SR increases rapidly and deteriorate the work piece quality. Similarly, in Figure 4 the range of depth of cut (DOC) was decided between 0.1 to 0.4 mm.

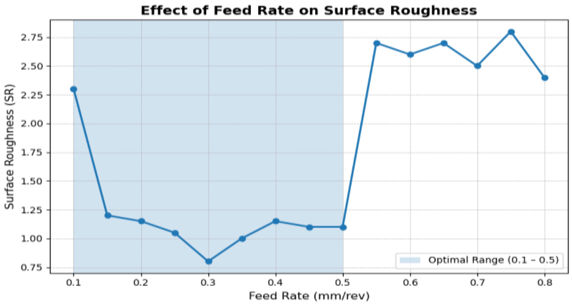

Fig. 3: Steady state experiments for feed rate

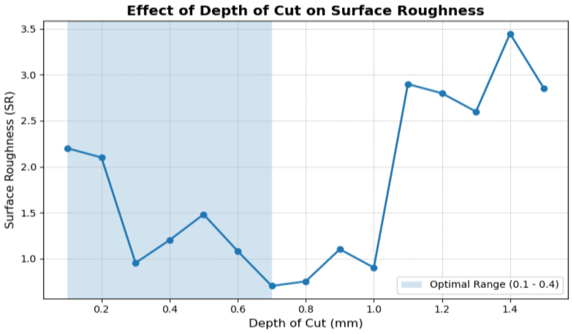

Fig. 4: Steady state experiments for DOC

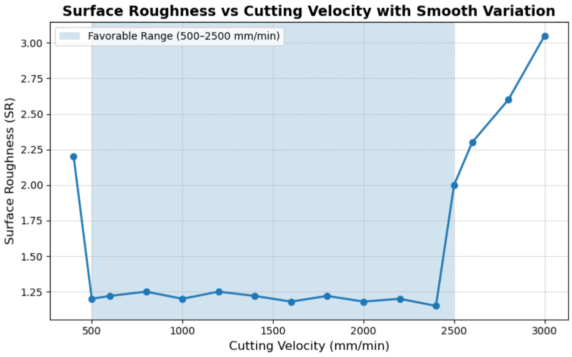

Fig. 5: Steady state experiments for CV

Table 1: The cutting parameters for CNC lathe machine

Sr. no.	Parameter	Min Value	Max Value
1	Feed (mm/rev)	0.1	0.5
2	Depth of Cut (mm)	0.1	0.4
3	Cutting Velocity (mm/min)	500	2500

Furthermore, in Figure 5, the graph demonstrates the relationship between SR and CV (Cutting Velocity) for the CNC lathe step turning process. Within the favourable cutting velocity range (500-2500 mm/min), SR remains relatively low with minor fluctuations, indicating optimal machining conditions. It was observed that if the cutting velocity falls below 500 mm/min or exceeds 2500 mm/min, SR rapidly increases, showing a deterioration in surface quality. It was also observed that if CV is less than 500 mm/min then production time increases significantly. This suggests that maintaining cutting velocity within the specified range minimizes surface roughness and enhances machining performance. Thus, the Table 1 depicts the selected range of cutting parameters for the step turning operation by the CNC lathe trainer after conducting steady state experiments.

2.3. Data cleaning and data collection

After deciding the range of parameters, experiments were conducted on the CNC lathe machine for step turning of the work pieces. To maintain the quality of the experimental data in this research, data cleaning was conducted with several key steps to ensure reliable analysis. Initially, missing or null values were addressed by imputing with the mean, while rows containing insufficient data were excluded from the dataset.”.

Next, we have identified and managed outliers in parameters like feed rate, depth of cut, and cutting velocity, using z-scores or IQR filtering to minimize their impact on analysis. Normalize or scale features to ensure compatibility between variables with different ranges. Verify the consistency of units across all measurements to avoid calculation errors. Finally, conduct a correlation analysis to detect multicollinearity among input parameters, removing redundant features as necessary to improve model performance and accuracy. In this study,

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Table 2: Data Collection on CNC Lathe machine

Run	Feed (x1)	Depth of Cut (x2)	Cutting Velocity (x3)	Surface Roughness (SR)
1	0.25	0.109	2400	1.621
2	0.48	0.291	1500	0.085
3	0.393	0.194	2100	1.857
4	0.339	0.253	1200	1.784
5	0.162	0.372	800	2.717
6	0.162	0.175	1000	1.602
7	0.123	0.223	1200	2.526
8	0.446	0.327	2400	0.037
9	0.34	0.169	700	2.968
10	0.383	0.123	2000	1.811
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191	0.148	0.128	800	2.595
192	0.385	0.369	1700	0.969
193	0.404	0.37	2400	1.914
194	0.325	0.29	500	2.878
195	0.408	0.202	1200	1.855
196	0.298	0.205	1800	1.81
197	0.309	0.318	2000	1.815
198	0.271	0.379	800	3.487
199	0.11	0.366	1600	2.764
200	0.143	0.334	2300	1.073

200 experimental sample data were collected with the CNC lathe machine as shown in Table 2.

2.4. Regression Analysis

To investigate the relationships between the input parameters and surface roughness, initially two modelling approaches were adopted: non-linear regression and artificial neural network (ANN). Non-Linear Regression exhibits the possibility of non-linear interactions among the parameter so non-linear regression modelling was subsequently employed. The non-linear model was intended to capture complex dependencies that could not be represented in a linear framework. Various non-linear functions were tested to determine the best fit for the data, thereby enhancing predictive accuracy. From the 200 experimental sample data, the nonlinear regression analysis 85% data was trained and 15% data were validated. Again to maintain the quality of the train-data and data used for validation the mean, range and standard deviation were observed as shown in Table 3 as statistical parameters. Following equation (1) was used having the two-degree equation model to obtain the non-linear model for CNC lathe machine experiments for step turning with the help of python libraries and with the given design constraints of the feed rate, depth of cut and cutting velocity for the surface roughness as the response variable.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 \qquad (1)$$

2.5. Artificial Neural Networks (ANN)

In this model, Artificial Neural Networks (ANN) were used to capture complex, non-linear relationships between machining parameters FR, DOC and CV and surface roughness. Unlike Non-Linear Regression (NLR), which uses a polynomial function with fixed interactions, ANN adapts dynamically, learning hidden patterns within the data.

This section presents the theoretical and mathematical foundations of BPNN, followed by its implementation process. First, the number of input layer neurons (x_m), hidden layer neurons (h_o), and output layer neurons (y_n) is determined. Next, the initial weight values between layers are randomly assigned. The weight parameters include w_{ij}, which represents the connection between the input and hidden layers, and w_{jk}, which links the hidden and output layers. The biases for the hidden and output layers are denoted as θ_{h0} and θ_{yn}, respectively.

Equation (2) computes the total input to hidden neuron net_h_0 by summing all weighted inputs and subtracting the neuron's bias. Equation (3) applies the sigmoid activation function to the net input of neuron h_0, converting it into a value between 0 and 1 to introduce non-linearity. Similarly, equation (4) calculates the net input to the output neuron net_y_n by summing the weighted outputs from the hidden layer neurons and subtracting the bias. The equation (5) applies the sigmoid activation function to the net input net_yn to produce the final output y_n of the ANN.

In ANN the output value of the hidden layer is computed using the following formula:

Table 3: Statistical Parameter of Training and Validation for Regression and ANN

Parameters	Training			Validation		
	Mean	Range	Standard Deviation	Mean	Range	Standard Deviation
Feed (mm/rev)	0.2932	0.370	0.1137	0.3238	0.389	0.1277
Depth of Cut (mm)	0.2598	0.256	0.0904	0.2472	0.287	0.154
Cutting Velocity (mm/min)	1530	2000	634.11	1550	2100	610.28
SR (µm)	0.249	2.414	0.5656	0.285	2.257	0.6842

$$net\_h_0 = \sum_{m=1}^{M} w_{iJ} \times x_m - \theta h_0 \quad (2)$$

$$h_0 = \frac{1}{1+e^{-net\_h_0}} \quad (3)$$

$$net\_y_n = \sum_{o=1}^{O} w_{Jk} \times h_o - \theta y_n \quad (4)$$

$$y_n = \frac{1}{1+e^{-net\_y_n}} \quad (5)$$

Figure 6 depicts the architecture of neural network (3-3-1) and this network consists of an input layer with three neurons corresponding to the machining parameters, one hidden layer with optimized neurons using the ReLU activation function to introduce non-linearity, and an output layer with a single neuron predicting surface roughness using a linear activation function.

It was observed by many researchers that through iterative training prediction accuracy can be improved in the MLP (multi-layer perceptron) structure with the few hidden layers, by minimizing errors. The supervised learning model can be used like Backpropagation Neural Network (BPNN) where both training and target output data are provided as inputs. The network iteratively adjusts its weights using the steepest descent method, which is a technique of gradient descent, to minimize the error between predicted values and actual values. The ANN was trained using the backpropagation algorithm with the Adam optimizer, ensuring efficient convergence while minimizing the Mean Squared Error (MSE). In this study, the dataset was split into 85% training and 15% validation, allowing the model to generalize well. ANN was preferred over traditional models because of its superior ability to learn from experimental data, making it well-suited for applications where precise SR (surface roughness) predictions are required for high-quality machining processes. Hyperparameter tuning, including the number of neurons and learning rate adjustments, was performed to achieve optimal prediction accuracy, confirming ANN's effectiveness in improving machining.

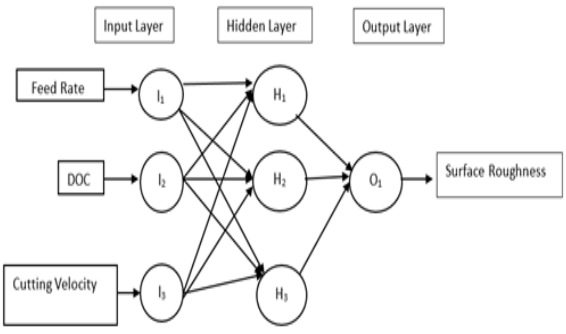

Fig. 6: Architecture of neural network (3-3-1)

2.6. Performance assessment of trained models

In this investigation, for judging the performance of trained ANN models, four statistical parameters have been taken. With the equation (6), RMSE (Root Mean Square Error) evaluates the disparity between actual values and predicted values by calculating the square root of the mean squared residuals. It can be observed that a lower RMSE value signifies good accuracy in prediction. However, RMSE emphasizes larger errors, which can skew performance assessments. With the equation (7) dimensionless metric Mean Absolute Percentage Error (MAPE) is a metric that can assesses the relative residual-error for each available data point in relation to the target value. Lower values of MAPE metric exhibit better model performance.

By using Pearson's correlation coefficient (R) and coefficient of determination (R^2), the strength of the relationship between observed values and predicted values are often measured. These statistical indicators rely on the linear associations, meaning they may produce biased evaluations if the relationship is nonlinear or if the dataset contains numerous outliers. Preferably, an R^2 value between 0.9 and 1.00 exhibits a perfect correlation.

With the equation (8), NMBE (Normalized Mean Bias Error) assesses the model's tendency to overpredict or underpredict relative to the mean observed value. A positive NMBE suggests overestimation, whereas a negative value indicates underestimation. To obtain a comprehensive and unbiased assessment of neural network models' predictive ability, multiple performance metrics should be analysed as a whole.

$$RMSE = \sqrt{\frac{1}{N}\Sigma\,(Ti - Pi)^2} \quad (6)$$

$$MAPE(\%) = \frac{1}{N}\sum\frac{|Ti-Pi|}{\underline{Ti}} \times 100 \quad (7)$$

$$NMBE(\%) = \frac{1/N\sum_{1=1}^{B} \; (Pi-Ti)}{1/N\sum_{1=1}^{B} \; Ti} \times 100 \quad (8)$$

3. Results

3.1. Model Evaluation and Comparison of Prediction Models

Each model's performance was evaluated using statistical measures such as the coefficient of determination (R-squared) and Mean Squared Error (MSE). A comparison of these metrics for the non-linear and ANN models allowed for the selection of the most appropriate model in terms of predictive accuracy and generalizability. Cross-validation techniques were also employed to verify model robustness and avoid overfitting. 30 samples were taken for validation and Figure 7(a) and Figure 7 (b) were obtained. It was observed that NLR and ANN model exhibit R2 values as 0.8865 and 0.9258 which shows the

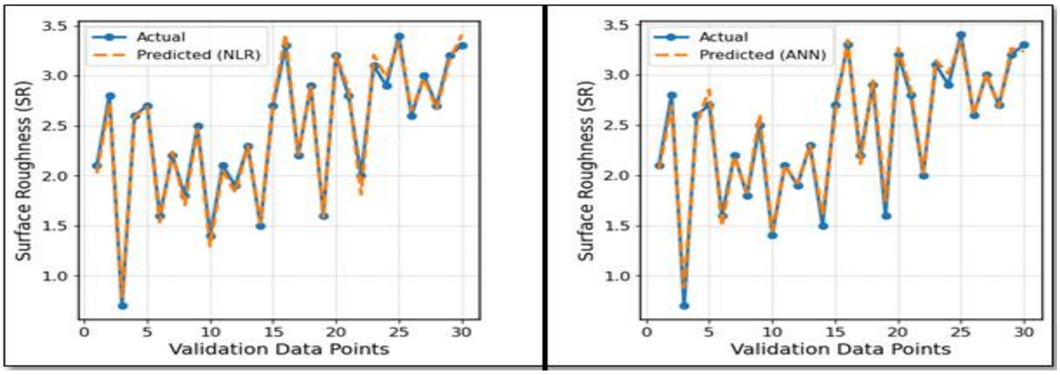

Fig. 7: (a) Actual vs. Predicted SR with NLR (b) Actual vs. Predicted SR with ANN

good fit of the both models.

The following obtained nonlinear regression equation (9) models the relationship between surface roughness (SR) and machining parameters, incorporating both linear and interaction terms. The coefficients indicate that FR and DOC have the most significant influence on SR, with squared and interaction terms further refining the prediction. The negligible effect of the cutting velocity squared term suggests its limited contribution, emphasizing the dominance of feed rate and depth of cut in determining surface roughness.

$$y = 2.39 - 2.5001x_1 - 8.0840x_2 + 0.0003x_3 + 2.1140x_1^2 + 6.8885x_1x_2 - 0.0003x_1x_3 + 10.6748x_2^2 + 0.0012x_2x_3 \qquad (9)$$

where:
x_1 = Feed Rate (FR)
x_2 = Depth of Cut (DOC)
x_3 = Cutting Velocity (CV)

This investigation compared the NLR (Non-Linear Regression) model and ANN model for predicting surface roughness (SR) based on parameters as feed, depth of cut, and cutting velocity. Besides this, computational optimization technique viz. Genetic Algorithm (GA) was used to optimize machining parameters for machining of aluminium step turning operation with the minimum SR.

3.2. Parameter Optimization with NLR and ANN

For enhancing the better grades of quality of the machined surface, parameter optimization was conducted to identify conditions that minimize surface roughness which is based on the models' insights. The model results provided guidelines for selecting suitable values for parameters like feed rate, depth of cut, and cutting velocity to achieve better grades of quality on CNC-step turned aluminium components.

The two graphs estimate actual quality grades of surface roughness (SR) values with predicted values from Non-Linear Regression (NLR) and ANN models for the validation dataset. It can be seen that the both models exhibit a close correlation with the actual quality grades of SR values, showing their efficacy in obtaining the machining parameter relationships. It can be seen that applied ANN exhibits slightly better tuning with actual values, suggesting its better capability in modeling complex nonlinear interactions. The fluctuations show the sensitivity of SR to variations in FR, DOC and CV (cutting velocity). These results confirm the potential of both approaches in step turning optimization, with ANN offering better accuracy.

The optimized factors for obtaining the lowest surface roughness grades (SR) were determined using Non-Linear Regression (NLR) and ANN. It can be observed that ANN yielded better results, achieving a lower predicted minimum roughness of 0.0198 µm in comparison to 0.0227 µm for NLR. The optimized machining factors for learning model of ANN include a feed rate of 0.115 mm/rev, depth of cut (DOC) of 0.280 mm, and a cutting velocity (CV) of 1780.7 m/min. Thus, it can be seen that model of NLR optimization resulted in slightly higher feed and depth of cut values with a lower cutting velocity. These results show that learning ANN model gives a more correct and effective factor optimization method for minimizing surface roughness in the process of CNC step turning.

3.3. Pareto Analysis of parameters affecting the SR

In this study, the Pareto chart presented demonstrates the relative significance of step turning parameters on SR (surface roughness) in CNC lathe machining as shown in Figure 8. It can be seen that x-axis denotes various parameters, including FR, DOC and CV and interactions, while the y-axis tells their absolute regression coefficients values, showing their influence on increasing the surface finish. It can be analysed that the further analysis highlights that the feed rate with its squared terms is the most dominant parameter, along with DOC (depth of cut) and the close interaction between FR and CV. It can be seen in Figure 8 that the lesser contributions occurred from individual parameters effects of cutting velocity and its squared term.

The results show that controlling FR and DOC are crucial for optimizing surface finish in CNC step turning. The

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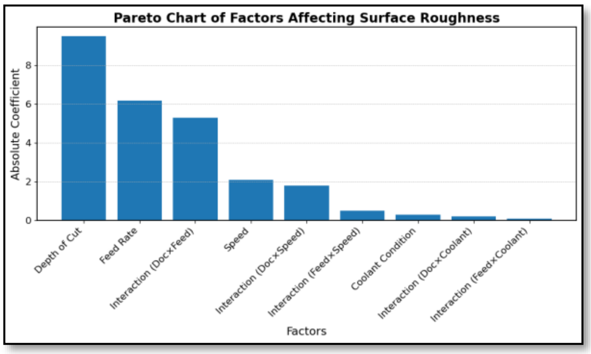

Fig. 8: Pareto Analysis of parameters

NLR (nonlinear regression) model mainly catches these relationships, reinforcing the significance of polynomial along with the interaction terms in predicting machining outcomes. Insights derived from this investigation of step turning which can aid in refining machining strategies for better surface finish and more production output. Furthermore, the optimization through Genetic Algorithm can be used to identify the best parameter settings for the good quality surface finish grades for CNC step turning.

It can be seen in Figure 9 that the training performance of the learning ANN model in terms of error reduces with multiple epochs. The Figure 9 demonstrates a sharp decline in error during the initial training phase, indicating rapid learning of relationships in input-output variables. As the number of epochs rises, the error gradually stabilizes, signifying convergence towards optimal adjustments of weights. By around 250–300 epochs, the error reaches a lowest value, showing that the model has learned effectively without significant overfitting. The final error level approaches lower values, confirming the learning ANN's ability to generalize well on unseen data. It can be seen that smooth nature of the curve after the initial rapid descent suggests that the learning rate was appropriately set, avoiding the issues like divergence or slow convergence. This decreasing trend of error validates the efficacy of backpropagation in minimizing the loss-functions. This result reinforces the feasibility of using ANN for CNC surface finish prediction. However, further optimization, such as integrating GA, could enhance performance by refining weight initialization and improving the speed of convergence.

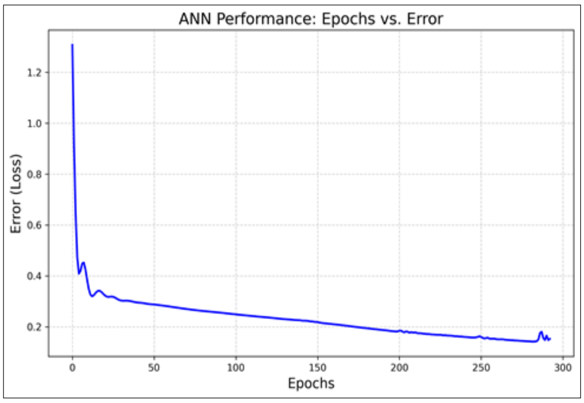

Fig. 9: ANN Performance epochs vs Error

3.4. Optimisation by GA

Genetic Algorithm (GA) parameters play a crucial role in achieving optimal solutions by balancing exploration and exploitation. Population size determines the diversity of solutions, ensuring a broad search space. Mutation rate introduces variability, preventing premature convergence and helping escape local minima. Crossover rate facilitates genetic information exchange, enhancing solution refinement. Number of generations influences the convergence speed and accuracy of optimization. Proper tuning of these parameters is essential for improving the precision of surface roughness predictions and achieving the desired machining performance.

$$\text{Minimise } Z = K_0 + (K_1 \times A) + (K_2 \times B) + (K_3 \times C) + (K_4 \times A \times B) + (K_5 \times A \times C) + (K_6 \times B \times C)$$

Here, Z will be the response output and K_i (i=0,1,2…..6) are the model constants With the help of Python software, the constants can be calculated by using non-linear-regression analysis.

Subject to following constraints:

0.1 mm/rev $\leq$ Feed ≤ 0.5 mm/rev

0.1mm $\leq$ DOC ≤ 0.4 mm

500 mm/min $\leq$ Cutting Velocity ≤ 2500 mm/min

Genetic Algorithm (GA) factors play a crucial role in optimizing the prediction model for surface roughness. GA parameters as shown in Table 4, a population size of 200 ensures a diverse set of solutions for better convergence. The maximum number of generations is set to 550, allowing sufficient iterations for the algorithm to evolve towards an optimal solution. The model considers three variables—FR, DOC and CV, ensuring a focused optimization process. A crossover probability of 85% promotes genetic diversity by combining features of parent solutions, while a mutation rate of 5% introduces small random changes to avoid premature convergence. These parameters collectively enhance the search process, improving accuracy and minimizing errors in surface roughness prediction. Proper tuning of GA parameters ensures reliable and repeatable optimization results. Figure 10 depicts the change in fitness values for SR with the generations for GA.

The Table 5 depicts the optimized cutting parameters and corresponding predicted minimum surface roughness (SR) values for NLR, ANN, and GA models. Among the three, the GA-based model delivered the lowest SR of 0.0175 µm, indicating its higher prediction accuracy and optimization strength. The FR, DOC and CV were all adjusted to optimal levels through GA optimization process, yielding superior surface quality.

In comparison, the ANN model predicted a slightly higher SR of 0.0198 µm, while NLR showed the highest at 0.0227 µm. These results validate that GA optimization enhances the prediction and surface finish outcomes better than conventional regression or standalone ANN. The approach confirms the effectiveness of hybrid modeling for precision manufacturing applications.

Table 4: GA Parameters

Population Size	200
Max generations	550
No of Variables	3
Crossover Probability	85%
Mutation Rate	5%

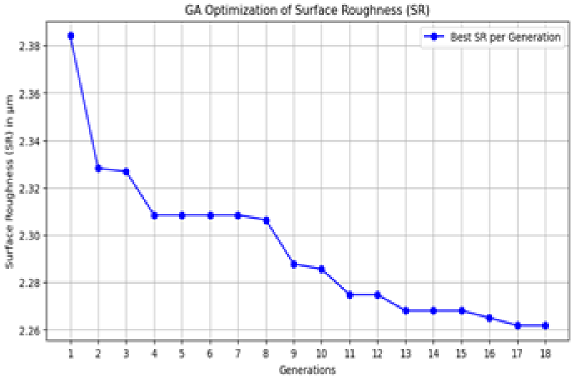

Fig. 10: Change in fitness value for SR with generation for GA

Table 5: Optimized Parameters for Minimum Surface Roughness

Model	Optimized Feed Rate (mm/rev)	Optimized Depth of Cut (mm)	Optimized Cutting Velocity (m/min)	Predicted Minimum SR (µm)
NLR	0.120	0.300	1650.5	0.0227
ANN	0.115	0.280	1780.7	0.0198
GA	0.110	0.270	1850.8	0.0175
ANN-GA	0.108	0.266	1860.6	0.0168

3.5. Hybrid GA-ANN

GA-Optimized ANN enhances the predictive accuracy of surface roughness modeling in CNC machining by optimizing the neural network's weight and bias parameters through evolutionary techniques. This approach refines ANN training by reducing error convergence and avoiding local minima, resulting in improved generalization capabilities. By integrating Genetic Algorithm (GA) with ANN, the model benefits from both robust feature extraction and global optimization, leading to reduced RMSE and MAPE values. Table 6 depicts Statistical performances of various models used in this study. It can be seen that minimum RMSE was achieved in hybrid ANN-GA model as the evolutionary search mechanism in GA assists in fine-tuning the ANN parameters, improving correlation (R^2) with actual data. This hybrid technique ensures more reliable surface roughness prediction, addressing the limitations of standalone ANN and traditional regression models. Similarly, lower values of MAPE (%) and NMBE (%) which is in tune of 1.2% and 0.005 % were obtained in hybrid ANN-GA.

It can be observed in Figure 11 that the loss in terms of mean squared error curves for both the baseline ANN and the GA-optimized ANN. It was observed that the GA-ANN model exhibits a significantly faster and smoother convergence, reaching to the minimum loss in less generations compared to the conventional form of ANN. This depicts enhanced learning effectiveness and better generalization due to optimized initial weights and biases obtained by the GA. Thus, it can be seen that the hybrid GA-ANN performs in superior manner in comparison to baseline ANN in the terms of training speed and accuracy.

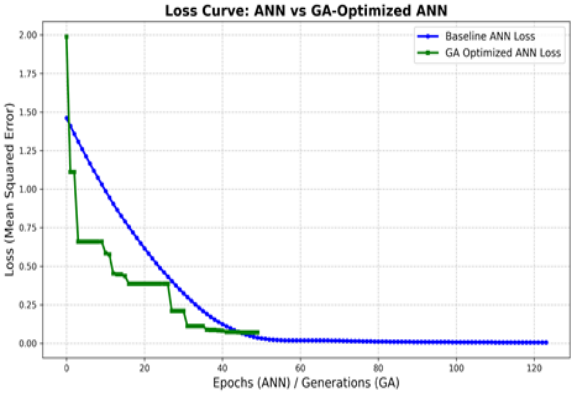

Fig. 11: Loss curve of ANN vs. Hybrid GA-ANN

Table 6: Statistical performances of models

Model	RMSE (µm)	R^2	MAPE (%)	NMBE (%)
NLR (Regression)	0.0182	0.8865	2.8	0.02
ANN	0.0175	0.9258	1.8	0.015
Hybrid ANN-GA	0.0059	0.95	1.2	0.005

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4. Conclusions

In this study an effort was made to determine the significant parameters for minimization of roughness of Aluminium components. To determine the range of parameters steady state experiments were performed. With these experiments the range of feed 0.1-0.5 (mm/rev), depth of cut from (0.1-0.4) mm and cutting velocity from 500 -2500 (mm/min) obtained.

This study successfully analysed the impact of machining parameters—feed rate, depth of cut, and cutting velocity—on the surface roughness (SR) of aluminium components produced using a CNC lathe trainer. The relationship between machining parameters and surface roughness was established with high accuracy by using the NLR (Nonlinear Regression) and ANN for predictive modeling, further, GA was used to optimize machining conditions, with the objective of minimum SR value in fine range of 0.0175 µm. With small population size, moderate mutation rate, and insufficient generations and the restricting convergence, the optimization process initially faced limitations. To overcome this, the GA parameters were refined by increasing the mutation range from 0.05 to 0.8, along with the population size to 200, and raising the number of generations to 550. These modifications significantly improved the optimization process, bringing the high grade surface quality to maximum achievable values.

It can be seen that the ANN model exhibited an RMSE of 0.0175 µm, an R^2 of 0.92, and a MAPE of 1.8%, while the NLR model had an RMSE of 0.0182 µm, an R^2 of 0.88, and a MAPE of 2.8%.

It is apparent that hybrid ANN-GA model outperforms in comparison to both ANN and NLR in predicting surface roughness for CNC-step turning process. The hybrid ANN-GA model achieved the lowest RMSE of 0.0059, the highest R^2 value in tune of 0.95, and the lowest MAPE in tune of 1.2%, indicating higher ranking accuracy along with minimum error. Additionally, the NMBE values show that the Hybrid ANN-GA model (0.005%) significantly reduces bias compared to ANN (0.015%) and NLR (0.02%).

The hybrid ANN-GA model exhibited the highest accuracy in predicting and optimizing surface roughness. The optimized machining parameters were identified as a feed rate of 0.108 mm/rev, a depth of cut of 0.266 mm, and a cutting velocity of 1860.6 m/min, which collectively yielded a minimum predicted surface roughness of 0.0168 µm. These results establish the effectiveness of the hybrid approach in achieving superior prediction accuracy and providing practical guidelines for process optimization in CNC machining.

These findings highlight the efficacy of hybrid ANN-GA for optimizing prediction accuracy and minimizing the errors in SR (surface roughness) assessment. This research provides valuable insights into improving surface quality and efficiency in CNC machining, contributing to advancements in industrial manufacturing and process optimization.

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