PRINT ISSN 1119-8362
Electronic ISSN 2659-1499

Full-text Available Online at
https://www.ajol.info/index.php/jasem
https://www.bioline.org.br/ja

J. Appl. Sci. Environ. Manage.
Vol. 28 (5) 1467-1475 May 2024

Optimization of Material Removal Rate in Computer Numerical Control Lathe Machine in Turning AISI 1040 Steel

***[1]NTUKIDEM, BI; [1]ACHEBO, JI; [1]OZIGAGUN, A; [1]UWOGHIREN, FO; [2]OBAHIAGBON, KO**

Department of Production Engineering,[2]Department of Chemical Engineering, University of Benin, Benin City, PMB 1154, Nigeria.

**Corresponding Author Email: ntukidembenson55@gmail.com*
**ORCID: https://orcid.org/0009-0008-9374-774X*
**Tel: +2348037921915*

Co-Authors Email: joseph.achebo@uniben.edu; andrew.ozigagun@uniben.edu; frank.uwoghiren@uniben.edu; kess.obahiagbon@uniben.edu

ABSTRACT: The Computer Numerical Control (CNC) of a Lathe Machine helps in shaping hard materials like metal and wood, while rotating on two axes and the amount of materials removed per unit time during the production process provides the material removal rate (MRR). Hence, the objective of this paper was to optimize the Material Removal Rate in a Computer Numerical Control Lathe Machine in Turning AISI 1040 Steel while focusing on cutting parameters such as depth of cut, cutting speed, and feed rate. Employing a central composite design with twenty experimental runs, ANOVA analysis revealed cutting speed (F-value: 80.40) as the most influential parameter on MRR. Initially, Artificial Neural Networks (ANN) predicted MRR, yielding optimal parameters: depth of cut (0.25 mm), cutting speed (250 m/min), feed rate (0.20 mm/rev), resulting in MRR of 27.88 mm^3/min. Genetic Algorithm (GA) optimization surpassed ANN, yielding higher MRR (29.07442 mm^3/min) with optimal parameters: depth of cut (0.65 mm), cutting speed (221.09 m/min), and feed rate (0.21 mm/rev). Confirmatory tests validated predictions. This study provides insights into enhancing CNC turning efficiency and productivity.

DOI: https://dx.doi.org/10.4314/jasem.v28i5.18

Cite this Article as: NTUKIDEM, B. I; ACHEBO, J. I; OZIGAGUN, A; UWOGHIREN F. O; OBAHIAGBON, K.O. (2024). Optimization of Material Removal Rate in Computer Numerical Control Lathe Machine in Turning AISI 1040 Steel. *J. Appl. Sci. Environ. Manage.* 28 (5) 1467-1475

Dates: Received: 21 February 2024; Revised: 22 March 2024; Accepted: 20 April 2024 Published: 09 May 2024

Keywords: Material removal rate; Artificial Neural Network; Genetic Algorithm; Optimization

Machining is a subtractive manufacturing process involving precision tools and machinery to remove material from a workpiece, achieving desired dimensions and surface finishes. It employs cutting, grinding, or similar methods to produce precise components, meeting engineering specifications. Turning, a subset of machining, is performed on a lathe machine where a single-point cutting tool, is used to remove material from a rotating workpiece creating cylindrical shapes. During turning, the workpiece rotates on its axis while the cutting tool is traversed linearly along the surface of the rotating workpiece thereby removing material, producing cylindrical shapes with precise dimensions and surface finishes. Achieving optimal performance and desired outcomes in turning hinges greatly upon the manipulation of various factors known as cutting parameters. These are the variables that can be controlled or adjusted during the machining operation to influence the outcome and machining performance. Several cutting parameters exist but for this work, the cutting speed, feed rate and depth of cut have been selected. The cutting speed is the workpiece surface's rotational speed relative to the tool's edge. Feed rate dictates tool movement relative to the workpiece during cutting while the depth of cut determines the tool's depth within the workpiece

**Corresponding Author Email: ntukidembenson55@gmail.com*
**ORCID: https://orcid.org/0009-0008-9374-774X*
**Tel: +2348037921915*

radius during machining operations like turning or boring. A key response is the material removal rate (MRR) defined as the volume of material removed from the workpiece per unit of time during the turning process expressed in mm^3 per minute.

It is often utilized as a criterion to maximize the production rate (Kalpakjian and Schmid, 2013) and also serves as an indicator of production efficiency in machining processes (Abolghasem and Mancilla-Cubides, 2022). A higher material removal rate indicates faster machining, which is often desirable to increase productivity and reduce manufacturing costs. Several factors influence the material removal rate, including the selected cutting parameters as well as the properties of the workpiece material and the cutting tool.

Higher cutting speed and feed rate increase material removal rates, but deeper cuts may also enhance MRR at the expense of tool life and surface finish. Achieving an optimal material removal rate requires balancing the cutting parameters to maximize efficiency without compromising other factors such as surface quality, tool life and energy consumption. Various studies aim to determine optimal material removal rates in turning operations using diverse approaches. Romesh *et al.* (2017) utilized Response Surface Methodology (RSM) to optimize Material Removal Rate (MRR) in CNC Lathe turning of EN8 Steel. Depth of cut proved most influential, contributing 72.64% to MRR, followed by cutting speed (32.84%), while feed rate had minimal impact. RSM analysis identified optimal parameters to be 1200rpm cutting speed, 0.3mm depth of cut, and 0.25mm/rev feed rate, achieving 5476.16mm^3/min MRR.

A study conducted by Edem *et al.* (2020) employed the Taguchi method to optimize cutting parameters. The aim was to achieve minimum surface roughness values and high material removal rates during the turning of AISI 1018 steel and AISI 314 stainless steel alloy. Machining was performed under flood cutting environment using carbide inserts.

Their findings indicated that feed significantly influenced both surface roughness and material removal rate. Optimal results revealed that a cutting speed of 110 m/min, feed of 0.10 mm/rev, and 1.0 mm depth of cut resulted in a higher material removal rate of 10844.62mm^3/min for turning both materials. Kumar *et al.* (2020) optimized CNC turning of EN19 alloy steel, maximizing material removal rate and minimizing surface roughness. Using Response Surface Methodology, they found feed as the dominant factor for material removal rate.

Optimal values were: cutting speed 859.5960 rpm, feed 0.090mm/min, depth of cut 2.0 mm, determined via ANOVA. In investigating the impact of cutting parameters, Ehibor and Aliemeke (2021) explored the influence of cutting speed, depth of cut, and feed on surface roughness and material removal rate during the turning of AISI 1045 carbon steel. Employing the Taguchi technique with an orthogonal array and analysis of variance, they studied cutting characteristics.

Optimal surface roughness was achieved at a cutting speed of 330 rpm, a feed rate of 0.2 mm/rev, and a depth of cut of 0.6 mm. Similarly, maximum material removal rate occurred at a cutting speed of 630 rpm, a feed rate of 0.4 mm/rev, and a depth of cut of 1.0 mm. Martowibowo and Damanik (2021) utilized Genetic Algorithm (GA) to optimize dry turning of AISI 316L steel with tungsten carbide inserts. They conducted 18 experimental runs to analyze the impact of cutting speed, feed rate, depth of cut, and tool nose radius on material removal rate (MRR) and surface roughness (SR). Their findings revealed that MRR was significantly affected by a combination of cutting speed, feed rate, and depth of cut, while SR was influenced by feed rate and depth of cut. Optimal values were determined as 0.64cm^3/min for MRR and 0.458µm for SR, with corresponding parameters including 0.4 mm tool nose radius, 96.9m/min cutting speed, 0.035 mm/rev feed rate, and 0.217mm depth of cut. In an effort to accurately predict machining parameters, Muthuram and Frank (2021) merged optimization methods and predictive models to forecast the ideal parameters for turning Ti-6-Al 4-V Titanium alloy. The goal was to enhance surface roughness while mitigating the impact on material removal rate. Titanium alloy was selected for its high specific strength, resistance to chemical corrosion, and widespread application in aerospace and automotive sectors.

Drawing on experimental data from Ramesh *et al.* (2012), various Artificial Intelligence techniques, including Genetic Algorithm (GA) and Artificial Neural Network (ANN), were employed and compared to identify the most effective prediction method. Results showed that ANN outperformed other models with a mean absolute percentage error of 1.08%. ANN was then combined with GA to determine the optimal combination for minimizing surface roughness while maximizing material removal rate. The study concluded that the highest MRR and lowest surface roughness were achieved at an optimized cutting speed, feed, and depth of cut of 280 m/min, 0.18 mm, and 1 mm, respectively. Abolghasem and Mancilla-Cubides (2022) conducted a study aiming to optimize surface roughness and material removal rate in aluminum turning operations. Cutting speed, feed rate, depth of cut, and cutting tool nose radius were considered as process parameters. Artificial Neural Networks (ANN) and Particle Swarm Optimization (PSO) were employed to predict and search for optimal parameter values to minimize surface roughness (Ra) and maximize material removal rate (MRR). Findings indicate an inverse relationship between surface roughness and MRR, with maximum MRR (38201.6mm^3/min) achieved at a cutting speed of 1995.84 rpm, feed rate of 1 mm/rev, depth of cut of 0.12 mm, and nose radius of 0.3 mm, resulting in a surface roughness of 0.994 µm. A recent study by Al-Tamimi and Sanjay (2023) employed an intelligent machining model featuring four strategies to minimize resultant force, specific cutting energy, and maximize metal removal rate in the dry cutting of Inconel alloy 825 on a CNC lathe. The study analyzed the effects of cutting speed, feed rate, and depth of cut on these responses. Optimized parameters were determined, highlighting the significant influence of cutting speed and feed rate on resultant force, and feed rate and depth of cut on metal removal rate and specific cutting energy. Additionally, a hybrid method (ANFIS-PSO) was developed and validated, achieving successful prediction and optimization of the responses. Implementation of ANFIS-PSO to maximize material removal rate yielded optimal cutting parameters: 101 m/min cutting speed, 0.43 mm/rev feed rate, and 0.54 mm depth of cut. Elsiti and Elmunafi (2023) conducted a multi-response optimization study on turning martensitic stainless steel (AISI 420) using Grey Relational Analysis (GRA). The study aimed to optimize the material removal rate (MRR), tool life, and surface roughness.

Turning operations utilized a coated carbide tool (KC5010), with cutting speed, feed rate, and depth of cut as the considered process parameters. Cutting speed was found to have the most significant impact on the responses. The optimized process parameters were 100 m/min cutting speed, 0.16 mm/rev feed rate, and 0.2 mm depth of cut, resulting in a tool life of 33.7 min, total material removed of 107.8 cm^3, and a surface roughness of 0.38 µm. Abass *et al.* (2023) engaged a Multi-Objective Genetic Algorithm (MOGA) to optimize the material removal rate (MRR) and other turning responses of AISI 1045 steel.

The optimized parameters yielded a feed rate of 0.075 mm/rev, cutting speed of 91.5 m/min, and depth of cut of 0.55 mm, resulting in an MRR of 3774.37mm^3/min. Das *et al.* (2024) employed three Multiple Criteria Decision-Making (MCDM) tools: GRA, VIKOR, and MOORA, to assess the effects of speed, feed, and depth of cut (DOC) on Material Removal Rate (MRR) and Surface Roughness (SR) during the turning process of Cu–Ni alloys with a carbide cutting tool. Findings reveal that turning at a spindle speed of 1500 rpm, feed rate of 0.57 mm/rev, and DOC of 1.2 mm achieves optimal MRR and SR. Utilizing the Grey Relational Grade-based Taguchi methodology, Zhujani *et al.* (2024) optimized surface roughness, tool wear, and material removal rate during the turning of Inconel 718. Cutting speed, feed rate, and depth of cut were chosen as the cutting parameters. ANOVA results highlighted the depth of cut (69.30%) as the most influential factor on multiple performance characteristics, followed by cutting speed (14.52%), nose radius (11.87%), and feed rate (3.79%). The findings indicated that the highest material removal rate of 4550 mm^3/min was achieved with a cutting speed of 100 m/min, a feed rate of 0.091 mm/rev, and a depth of cut of 0.4mm. Abderazek *et al.* (2024) introduced an innovative multi-objective optimization algorithm termed Improved Differential Evolution and Nelder-Mead (IDE-NM). Their study incorporated three lubrication conditions and five key process parameters: cutting speed, feed rate, depth of cut, lubrication mode, and cutting material type. With three objectives in mind, they employed artificial neural network (ANN) modeling to analyze the experimental results. Comparative analysis with four alternative algorithms demonstrated that IDE-NM surpassed them all, demonstrating its capability to provide optimal outcomes. Hence, the objective of this paper was to optimize the Material Removal Rate in a Computer Numerical Control Lathe Machine in Turning an AISI 1040 Steel while focusing on cutting parameters such as depth of cut, cutting speed, and feed rate.

MATERIALS AND METHODS

AISI 1040 steel is a medium carbon steel renowned for its balanced combination of properties, making it a versatile material in various industrial applications. With a carbon content ranging between 0.37% to 0.44%, along with alloying elements such as manganese, phosphorus, and sulfur, it offers a robust level of strength while retaining excellent ductility. This balance of strength and ductility makes it particularly well-suited for applications where components need to withstand mechanical stress while maintaining flexibility and resilience.

It also exhibits notable wear and fatigue resistance, ensuring longevity and durability in components subjected to repetitive stress and strain. In addition to its mechanical properties, AISI 1040 steel is valued for its ease of shaping and forming using machining techniques. Its good machinability allows for efficient manufacturing processes, enabling the production of intricate components.

Consequently, AISI 1040 steel finds extensive usage across diverse sectors such as automotive, machinery, and general engineering, where it is particularly suitable for demanding applications requiring reliable performance. Typical uses include cylinder head studs, carriage and U bolts, concrete reinforcing, shafts, shipping containers and the construction of automotive bodies.

Twenty cylindrical blanks of AISI 1040 steel, each measuring 200 x 50mm, were utilized in the experiments conducted on a Yunnan Machine Tool works CY-K6150B CNC lathe machine, with carbide turning inserts employed for the machining process. The quantity of material removed per unit of time expressed in mm^3 per minute during the turning process is known as the material removal rate. It can be computed using equation (Kalpakjian and Schmid, 2021) (1).

$$MRR = \pi D_{avg} d f N \qquad (1)$$

Where $D_{avg} = \frac{D_o + D_f}{2}$ in mm, D_o is the initial workpiece diameter in mm, D_f is the final workpiece diameter in mm, d is the depth of cut in mm, f is the feed rate in mm/rev and N is the rotational speed of the workpiece. The initial and final diameters of the workpieces were measured using a digital Vernier caliper. The workpiece parameters and cutting parameter ranges are presented in tables 1 and 2 respectively.

Table 1: Workpiece Parameters

Workpiece Material	AISI 1040 medium carbon steel
Length (mm)	200
Diameter (mm)	50
Chemical composition (%)	C (0.37 - 0.44), Fe (98.47 - 99.20, Mn (0.60% - 0.90), P (≤ 0.040), S(0.050), Cr, Ni, Mo, Cu, Si and V (≤ 0.25)
Tensile strength (MPa)	620 MPa
Yield strength(MPa)	415 MPa
Bulk modulus (GPa)	160 GPa
Shear modulus (GPa)	80 GPa
Tensile strength(MPa)	620 MPa
Brinell Hardness	201
Poissons Ratio	0.29
Elongation at Break (%)	25
Reduction of Area (%)	50

Table 2: Cutting parameter ranges

Cutting Parameter	**Range**
Depth of cut (mm)	0.25, 0.50 and 0.75
Cutting speed (m/min)	150, 200 and 250
Feed rate (mm/rev)	0.10, 0.15 and 0.20

Figures 1 and 2 show sample of the workpiece and the CNC lathe machine setup respectively.

Fig 1: Workpiece sample

Fig2: CNC Lathe with workpiece

This study focuses on predicting and optimizing material removal rate (MRR), with turning experiments conducted according to the Central Composite Design Matrix (CCD) outlined in table 3, which also includes the experimental results for material removal rate.

The ANOVA table highlights cutting speed as the primary parameter significantly impacting the material removal rate, with an F-value of 80.40. This is followed by the depth of cut (F-value 11.89) and their interaction effects (AB and AC). Adjusting these parameters appropriately can lead to substantial improvements in MRR during machining operations. The predictive R-squared value of 0.8624 reasonably aligns with the adjusted R-squared value of 0.9163, indicating a good fit of the model. Moreover, the high R-squared value of 0.9560 suggests that 95.60% of the variation in the responses can be accounted for. The outcome of a one-way analysis of variance (ANOVA) presented in table 4, assesses the significance of cutting parameters in maximizing material removal rate.

ANN Modelling: After the completion of experiments and the acquisition of datasets, the subsequent focus lies on the development of the ANN model.

The neural network was trained to predict material removal rate via a feed-forward backpropagation algorithm, with the input layer utilizing the hyperbolic tangent transfer function to compute the layer output from the network input. The output layer employed the linear transfer function, while each hidden layer consisted of 10 neurons. Network performance was monitored using the Mean Square Error of Regression (MSEREG). The network properties for the material removal rate are presented in figure 3.

Table 3: Experimental Data Set

std	run	Depth of Cut (mm)	Cutting Speed (m/min)	Feed Rate (mm/rev)	Experimental MRR (mm^3/min)
1	1	0.25	150.00	0.10	9.32
5	2	0.25	150.00	0.20	11.1
16	3	0.50	200.00	0.15	8.82
7	4	0.25	250.00	0.20	27.47
19	5	0.50	200.00	0.15	14.82
2	6	0.75	150.00	0.10	18.61
11	7	0.50	115.91	0.15	11.42
6	8	0.75	150.00	0.20	8.99
10	9	0.92	200.00	0.15	15.44
12	10	0.50	284.09	0.15	27.66
18	11	0.50	200.00	0.15	10.92
8	12	0.75	250.00	0.20	11.92
15	13	0.50	200.00	0.15	9.82
4	14	0.75	250.00	0.10	16.2
13	15	0.50	200.00	0.07	10.1
3	16	0.25	250.00	0.10	22.85
14	17	0.50	200.00	0.23	9.97
20	18	0.50	200.00	0.15	9.82
17	19	0.50	200.00	0.15	10.3
9	20	0.08	200.00	0.15	19.71

Table 4: ANOVA table for the Material Removal Rate

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	
Model	658.86	9	73.21	24.12	< 0.0001	significant
A-depth of cut	36.10	1	36.10	11.89	0.0062	
B-cutting speed	244.05	1	244.05	80.40	< 0.0001	
C-feed rate	4.53	1	4.53	1.49	0.2500	
AB	107.90	1	107.90	35.54	0.0001	
AC	51.51	1	51.51	16.97	0.0021	
BC	8.36	1	8.36	2.76	0.1279	
A^2	81.58	1	81.58	26.87	0.0004	
B^2	136.22	1	136.22	44.87	< 0.0001	
C^2	1.32	1	1.32	0.44	0.5243	
Residual	30.36	10	3.04			
Lack of Fit	8.11	5	1.62	0.36	0.8540	not significant
Pure Error	22.25	5	4.45			
Cor Total	689.22	19				

R-Squared = 0.9560, Adj R-Squared = 0.9163, Pred R-Squared =0.8624

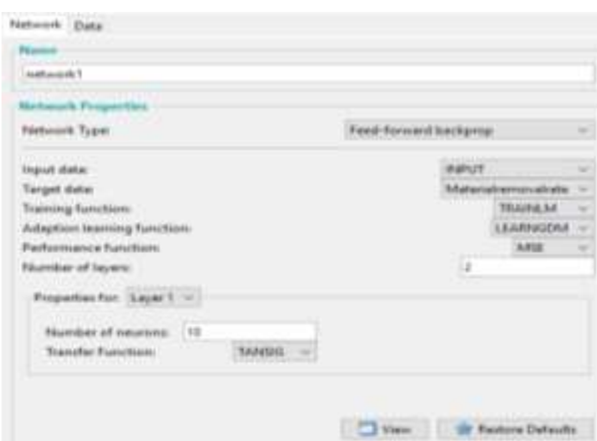

Fig 3: ANN properties for predicting Material removal rate

For this study, the Levenberg-Marquardt training algorithm was utilized, allocating 60% of the data for network training, 25% for validation, and 15% for testing the network's performance. The network training diagram for the material removal rate is presented in figure 4. Figure 5 illustrates the performance trajectory and the gradient plot of the neural network during both training and validation phases. The peak model performance on the validation dataset (1.9448) was observed following the third training epoch, signifying the epoch where the most accurate prediction for the material removal rate was achieved**.** The gradient plot shows that nine (9) epochs were used during the training process for the material removal rate. However, the most accurate prediction occurred at the 3rd epoch, as evidenced by the lowest failure rate observed at this stage. Beyond the 3rd epoch, the validation failure rate increased.

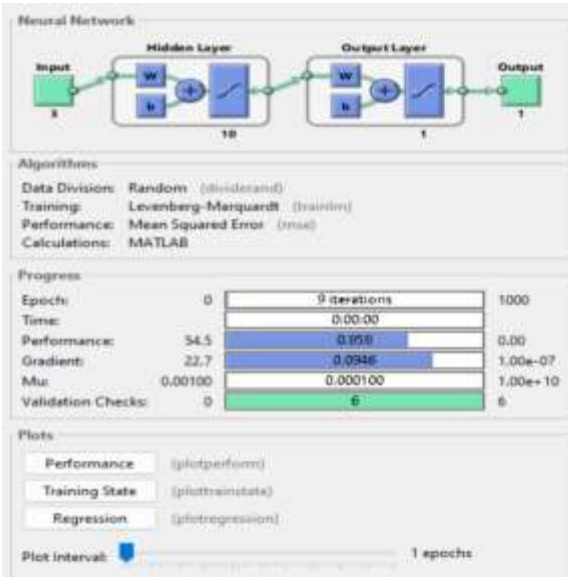

Fig 4: Network training diagram for predicting material removal rate

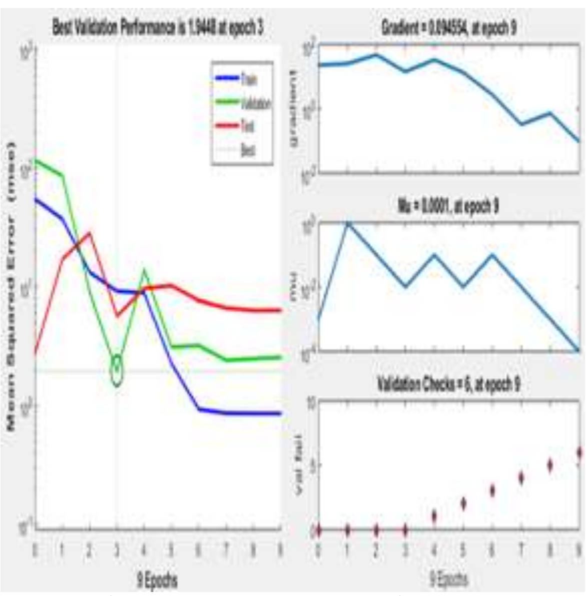

Fig 5: Performance curve and gradient plot for trained network

RESULTS AND DISCUSSION

Figure 6 presents regression plots, illustrating scatter plots that compare the predicted outputs against the actual target outputs for the training, validation, and testing datasets. These plots are evaluated using correlation coefficients (R), which assess the degree of alignment between the neural network's predictions and the actual target values. The correlation coefficients for the training, validation, and test datasets were found to be 0.89169, 0.99196, and 0.85959, respectively. An overall correlation coefficient of 0.91726 was computed across all datasets. This cumulative R value suggests a strong positive correlation between the neural network's predictions and the actual target values, affirming the network's proficiency in predicting material removal rate.

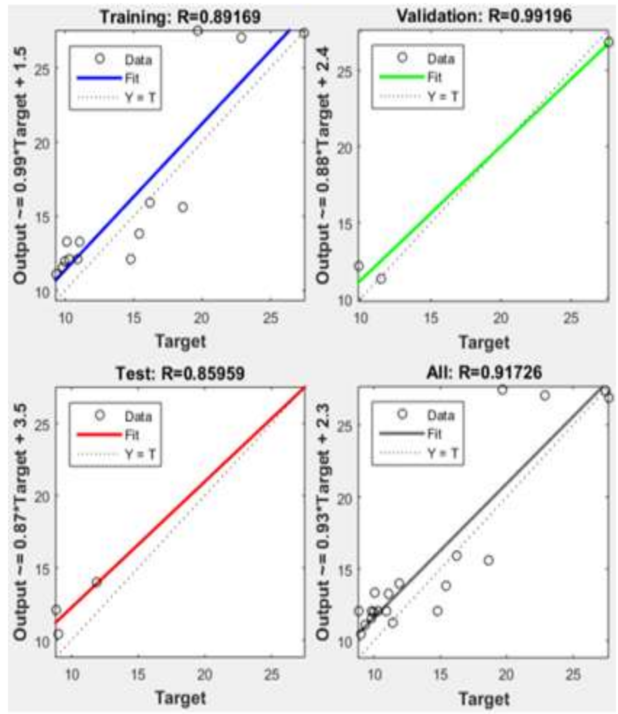

Fig 6: Regression plot of training, validation and testing for material removal rate

The predicted values for the material removal rate using the trained neural network are given in table 5. From the experimental data, the highest MRR recorded is 27.66mm^3/min, achieved under the conditions of a depth of cut of 0.50 mm, cutting speed of 284.09 m/min, and feed rate of 0.15 mm/rev. In contrast, the neural network (ANN) prediction yields a maximum MRR of 27.8838 mm^3/min. This prediction corresponds to a depth of cut of 0.25 mm, cutting speed of 250 m/min, and feed rate of 0.20 mm/rev. Upon comparison, it is observed that the experimental and predicted maximum MRR values are close in magnitude, indicating good agreement between the two sets of results. However, the ANN prediction slightly surpasses the experimental result, suggesting that the neural network model is capable of accurately forecasting material removal rates under specific machining conditions. The experimental outcomes were compared with the predictions generated by the ANN, and the accuracy of the network's predictions is depicted in figure 7.

Table 5: ANN Predicted result for material removal rate

S/N	Depth Of cut (mm)	Cutting speed (m/min)	Feed rate (mm/rev)	Experimental MRR (mm^3/min)	ANN Predicted MRR (mm^3/min)
1	0.25	150	0.10	9.32	10.6464
2	0.25	150	0.20	11.1	13.5828
3	0.50	200	0.15	8.82	11.807
4	0.25	250	0.20	27.47	27.8838
5	0.50	200	0.15	14.82	11.807
6	0.75	150	0.10	18.61	19.216
7	0.50	115.91	0.15	11.42	20.7385
8	0.75	150	0.20	8.99	13.3449
9	0.92	200	0.15	15.44	15.0993
10	0.50	284.09	0.15	27.66	27.1234
11	0.50	200	0.15	10.92	11.807
12	0.75	250	0.15	11.92	14.8329
13	0.50	200	0.20	9.82	11.807
14	0.75	250	0.10	16.2	14.2787
15	0.50	200	0.07	10.1	10.6663
16	0.25	250	0.10	22.85	23.5348
17	0.50	200	0.23	9.97	11.4856
18	0.50	200	0.15	9.82	11.807
19	0.50	200	0.15	10.3	11.807
20	0.08	200	0.15	19.71	18.7691

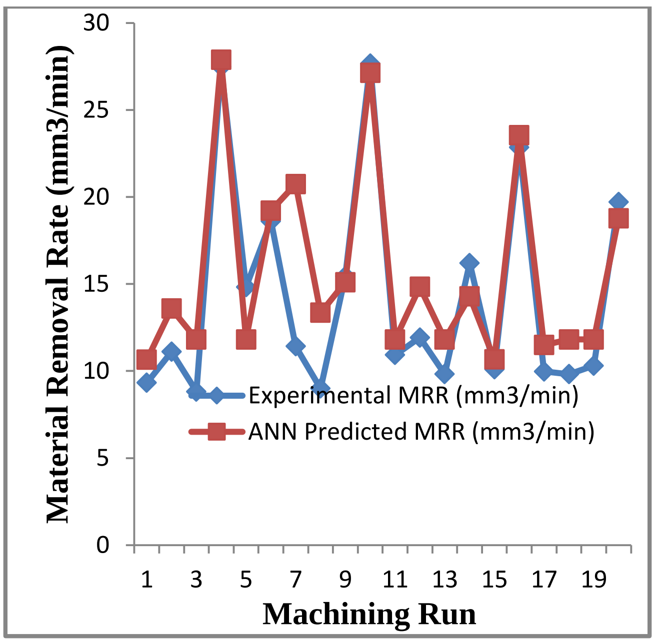

Fig 7: Experimental data versus ANN predictions

Genetic Algorithm (GA) optimization: Genetic algorithm optimization, a search algorithm inspired by natural selection and genetics, was employed for the optimization process. The objective function for maximizing MRR is

$$function\ y = Ntukidem(x)$$
$$\%\ y(1) - -Objective\ 1$$
$$- -\ equation\ for\ the\ Material\ Removal\ Rate\ (MRR)$$
$$—\ Maximize$$
$$\%\ Material\ Removal\ Rate\ (MRR)$$

$$y(1) = 22.196434531576 + \left(44.645605802651 * x(1)\right) - \left(0.32084043953033 * x(2)\right) + \left(47.183327212683 * x(3)\right) - \left(0.2938 * x(1) * x(2)\right) - \left(203 * x(1) * x(3)\right) + \left(0.409 * x(2) * x(3)\right) + (38.058296636373 * x(1)^2) + (0.001227343325342 * x(2)^2) - (130.77775737561 * x(3)^2) \quad (2)$$

Where $x(1)$ = depth of cut, $x(2)$ = cutting speed and $x(3)$ = feed rate with their lower and upper bounds taken as the lowest and highest values on the design matrix.

The GA optimization was facilitated through the MATLAB software package, employing the Optimization Toolbox. Iterative processes were conducted to attain optimality, encompassing the determination of fitness limits, selection of crossover and mutation functions, as well as the management of generations and migration. Using a population size of 50, termination occurred at the 270th generation where optimality was achieved. Table 6 presents the optimal solutions for the cutting parameters and material removal rate (MRR) obtained from the Genetic Algorithm (GA), along with the ANN's optimal results and the outcomes of confirmatory tests conducted using the optimal GA parameters. The confirmatory test results align well with the predictions made by the GA.

Table 6: Optimal Solutions and Confirmatory Test Results

S/N	Parameter	ANN Optimal prediction	GA Optimal Solution	Confirmatory test
1.	Depth of cut (mm)	0.25	0.65	0.65
2.	Cutting speed (m/min)	250	221.09	221.09
3.	Feed rate (mm/rev)	0.20	0.21	0.21
4.	Material removal rate (mm^3/min)	27.8838	29.07442	29.49

The maximum MRR predicted by the ANN is 27.8838mm^3/min corresponding to a depth of cut of 0.25 mm, cutting speed of 250 m/min, and feed rate of 0.20 mm/rev. The GA optimal solution yields a maximum MRR of 29.07442mm^3/min and this optimized result is achieved with a depth of cut of 0.65 mm, cutting speed of 221.09 m/min, and feed rate of 0.21 mm/rev. It is observed that a significant improvement in MRR occurs with the GA optimal solution compared to the ANN solution as the GA optimization process has effectively identified machining parameters that result in higher material removal rates. This suggests that GA has successfully optimized the machining parameters to maximize MRR beyond what the ANN model predicted. Confirmatory tests validated the predictions, highlighting the efficacy of advanced optimization techniques.

Conclusion: This study highlights the cutting speed as the most significant parameter in optimizing material removal rate (MRR) during CNC turning of AISI 1040 steel. While Artificial Neural Networks (ANN) initially predicted MRR satisfactorily, Genetic Algorithm (GA) optimization notably improved MRR beyond ANN's capabilities. Confirmatory tests using the optimal GA parameters affirmed the predictions, underscoring the efficacy of advanced optimization techniques such as GA in enhancing machining performance. These findings contribute to the ongoing efforts in optimizing CNC turning processes, offering insights for improving productivity and cost-effectiveness in machining operations.

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