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Optimization of Turning Process Parameters by Genetic Algorithm Approach

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Abstract

In this research, turning parameters were optimized through a genetic algorithm for the purpose to minimize surface roughness and to maximize the material removal rate. High finish quality is guaranteed through minimum surface roughness, and efficient process planning is facilitated through maximum material removal rate optimization. For predicting surface roughness and material removal rate with respect to spindle speed, feed rate, and depth of cut, the empirical models were developed through regression analysis. The high-speed steel cutting tool and aluminium alloy 64430 were employed in experiments on a Craft Master TL-20 lathe machine. The optimal machining conditions were determined using the Genetic Algorithm, which was coded using Python's Distributed Evolutionary Algorithms in Python package. The highest material removal rate of 3463.3918 mm³/min and surface roughness of 0.6574 µm were the optimal results achieved. The validity of the model was established through p-values of 0.1688 for surface roughness and 0.6227 for material removal rate, which were achieved through a paired t-test between experimental and estimated values. This approach provides the industry with the liberty to select parameters for specific application needs.

Keywords: Genetic algorithm, regression modelling, surface roughness, material removal rate, python DEAP

INTRODUCTION

Optimization of turning process parameters is critical to maximizing output and product quality in modern manufacturing. Cutting speed, feed rate, and depth of cut are significant turning input parameters that significantly influence output factors such as MRR and SR. It is usually hard to find a compromise between maintaining a low SR for surface quality and achieving a high MRR for productivity, particularly when turning aluminium alloys. The desirable strength-to-weight ratio, corrosion resistance, and thermal conductivity of these aluminium alloys have earned them widespread usage in the automobile, marine, and aerospace sectors. Their complex machinability, however, often leads to unbalanced cutting behavior and rapid tool wear. Since SR and MRR are contradictory, optimizing one may have an adverse effect, calling for methodical and keen optimization methods. To solve such multi-objective optimization problems in turning processes, scientists have deeply examined advanced computation methods, such as genetic algorithms (GA). For instance, Chowdary *et al*. attained significant improvements in finish through the integration of the Taguchi method with GA to minimize SR in CNC turning of Al-6061 [1]. Though Dhabale and Jatti applied GA for achieving maximum MRR in turning AlMg1SiCu, Doriana and Teti applied GA to optimize tool life and surface integrity [2, 3]. For minimizing SR and cutting forces, few researchers like Usha *et al*. used

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multi-objective GA in minimum quantity lubrication conditions [4]. In order to improve tool wear, MRR, and cutting parameters, studies by Solarte-Pardo *et al*. [5] and Alduroobi *et al*. [6] showed how well GA and ANN operate together. Some hybrid approaches have also been proposed. Kumar *et al*. compared GA with Particle Swarm Optimization (PSO) for AISI 1042 steel, while Malomo *et al*. introduced a Taguchi-ANN-GA model for turning AA6063 that maximizes multiple objectives. Additionally, to maximize machining time, energy consumption, and temperature increase, hybrid models such as GA-Simulated Annealing and GA-Response Surface Methodology have been employed [7–10].

These researches show how hybrid techniques and GAs are being utilized more and more in intelligent machining systems. Even though optimization analyses have long been facilitated by software such as Minitab, MATLAB, and GNU Octave, recent developments have turned Python into an even more powerful platform due to its open-source modules [11, 12]. Predictive modelling and the extremely accurate and versatile use of genetic algorithms are facilitated by packages such as Scikit-learn and DEAP. Although aluminium alloy 64430 is industrially important, not much is known regarding the turning optimization of the alloy. Through empirical models that employ regression analysis to predict SR and MRR and by the application of Python's DEAP framework to optimize cutting parameters to achieve improved machining performance, the present research aims to fill this void [13–15].

MATERIALS AND METHOD

Design of Experiments

The work piece for the present study was prepared from the aluminium alloy 64430, and the test specimens were of 45 mm length and 25 mm diameter. For exactly determining its elemental composition, spectroscopic analysis was conducted. After the operational status of an HMT Craft Master TL-20 lathe machine was observed, experiments in machining were conducted on it. In order to study the effect of cutting speed, feed rate, and depth of cut on surface roughness and material removal rate, a systematic design of experiments was designed with the orthogonal array of (L27). Table 1 gives details about the experimental matrix and levels of parameters. Table 1 shows the independent factors with their values.

Experimental Procedure

The trial machining was planned with an L27 Taguchi orthogonal array (Table 2). 27 samples of the aluminium alloy 64430, 100 mm×25 mm in size, were produced. To ensure consistency, the starting and ending weights and diameters were recorded. A High-Speed Steel (HSS) tool was used throughout in dry cutting conditions. A Mitutoyo gauge was used to measure the surface roughness, and after every turning operation, the Material Removal Rate (MRR) was calculated using formula, MRR (mm^3/min)=$\pi/4\times(di–df)\times f\times d$, where di= initial diameter before experiment (mm), df= final diameter after experiment (mm), f= feed rate (mm/rev), and d= depth of cut (mm).

Regression Analysis of Surface Roughness

To model the effect of machining parameters on surface roughness, SR, a second-order polynomial regression model was created using Python's Scikit-Learn library. Cutting speed v, feed rate f, and depth of cut d were taken as input variables, and SR as the output response. Experimental results from 27 machining trials, based on a Taguchi L27 orthogonal array, were used to train the model.

Table 1. Design of experiments table.

Levels	Cutting speed (rpm)	Feed rate (mm/rev)	Depth of cut (mm)
1	39.26	0.06	0.15
2	78.53	0.15	0.25
3	109.95	0.24	0.35

Table 2. Orthogonal array and observed values table.

Run	Cutting speed (v) (m/s)	Feed rate (f) (m/s)	Depth of cut (d) (m/s)	Surface roughness (µm)	Material removal rate (mm^3/min)
1	39.26	0.06	0.15	0.658	176.184
2	39.26	0.06	0.25	0.778	293.051
3	39.26	0.06	0.35	0.868	409.447
4	39.26	0.15	0.15	0.981	440.461
5	39.26	0.15	0.25	1.158	732.629
6	39.26	0.15	0.35	1.292	1023.619
7	39.26	0.24	0.15	1.203	704.737
8	39.26	0.24	0.25	1.421	1172.206
9	39.26	0.24	0.35	1.591	1637.791
10	78.53	0.06	0.15	0.663	352.368
11	78.53	0.06	0.25	0.783	586.103
12	78.53	0.06	0.35	0.874	818.895
13	78.53	0.15	0.15	0.987	880.922
14	78.53	0.15	0.25	1.166	1465.258
15	78.53	0.15	0.35	1.301	2047.238
16	78.53	0.24	0.15	1.211	1409.475
17	78.53	0.24	0.25	1.432	2344.413
18	78.53	0.24	0.35	1.596	3275.581
19	109.95	0.06	0.15	0.666	493.316
20	109.95	0.06	0.25	0.786	820.544
21	109.95	0.06	0.35	0.877	1146.453
22	109.95	0.15	0.15	0.991	1233.291
23	109.95	0.15	0.25	1.171	2051.361
24	109.95	0.15	0.35	1.305	2866.133
25	109.95	0.24	0.15	1.215	1973.265
26	109.95	0.24	0.25	1.435	3282.178
27	109.95	0.24	0.35	1.621	4585.814

Polynomial feature expansion was used to include linear, quadratic, and interactive effect of the parameters. The developed regression equation is:

$$SR=0.1592-0.0001v+4.3476f+1.7302d+0.0011v^2+0.0008vf+0.0005vd-7.0370f^2+5.0648f\times d-2.0000d^2$$

As given in this equation, f and d significantly contribute positively to surface roughness while v contributes negatively slightly, meaning that higher speed leads to a marginally better finish. The negative quadratic terms for feed and depth of cut imply that smoother shearing contributes towards improving surface polish beyond a specific point. SR is most strongly affected by the interaction term f×d (5.0648) among the others. The R^2 value of 0.9998 of SR's excellent model indicates that it is very good at predicting surface roughness from inputs in machining.

Graphical representations were also generated to visualize the relationship between each input parameter and surface roughness, keeping the other two parameters constant at their mean values (Figure 1). These plots (Cutting Speed vs. SR, Feed Rate vs. SR, and Depth of Cut vs. SR) clearly illustrate the trends and nonlinear effects of individual machining parameters on surface quality, supporting the reliability of the developed model.

Regression Analysis of Material Removal Rate

To study the relation between the machining parameters: cutting speed v, feed rate f, and depth of cut d and the resulting Removal Rate, the linear regression model was created using Python's Scikit-learn module. After 27 experimental observations were used to train the model, the following equation was produced $MRR=-2824.7181+18.6452\times v+9437.7154\times f+5637.1956\times d$.

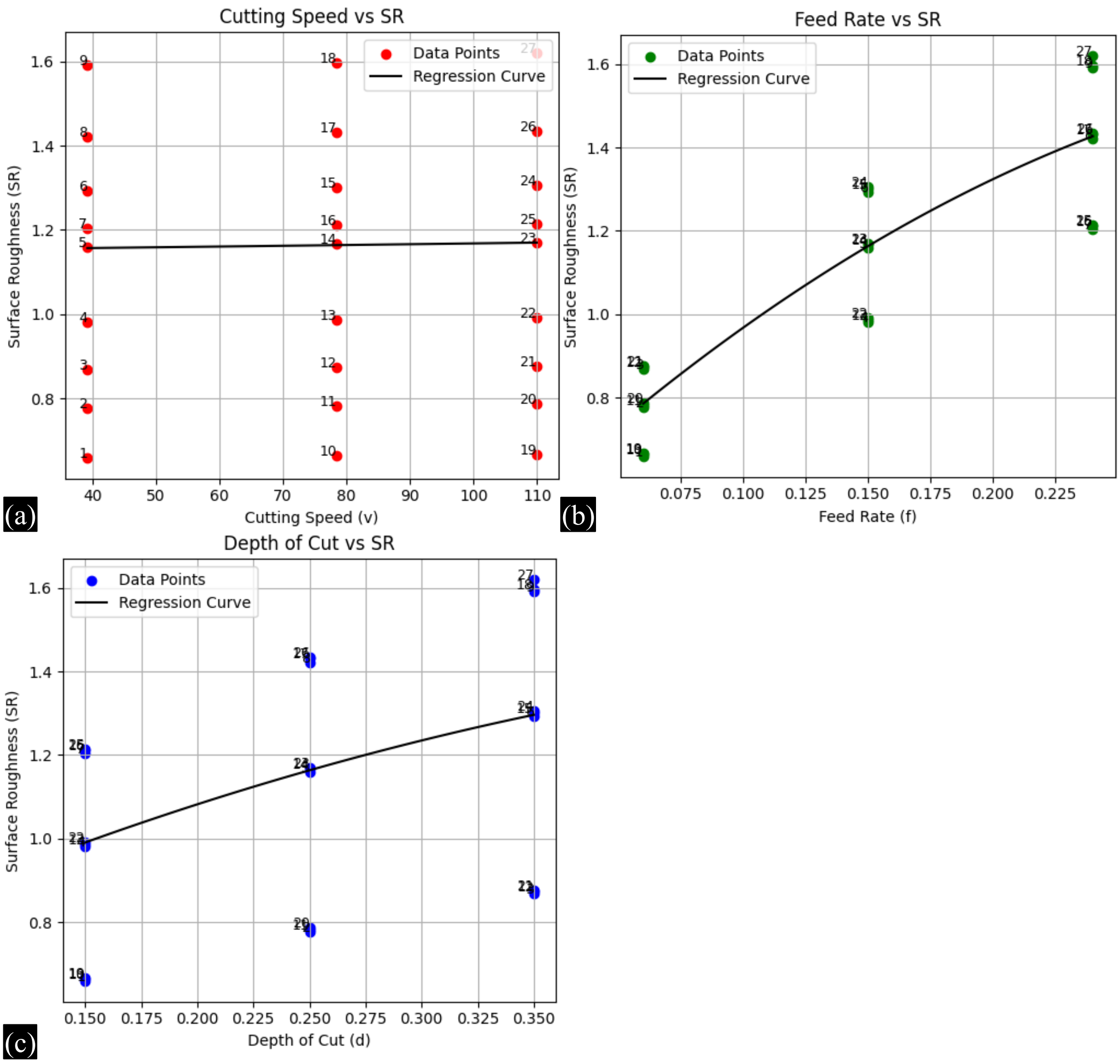

Figure 1. Input vs. output for SR. (a) Cutting speed vs SR; (b) Feed rate vs SR; (c) Depth of Cut vs SR.

In the study range, the intercept, the model offset, has minimal practical significance. Positive coefficients indicate that material removal rate increases with a rise in any one of the input parameters. The feed rate exerts the maximum influence, followed by v and d. Increasing feed and depth cut more material, raising removal rates, consistent with machining philosophy. The model had high predictive accuracy with an R^2 rating of 0.8610.

In order to show patterns, three graphs were plotted: depth of cut vs. MRR, feed rate vs. MRR, and cutting speed vs. MRR. Each one shows that increasing parameters usually means increased MRR. Alignment between actual and expected values is shown by annotated data points, which offer effective MRR optimization by well-informed parameter selection (Figure 2).

Genetic Algorithm Applied on Surface Roughness (SR)

To minimize surface roughness, the Genetic Algorithm (GA) was implemented using the Python programming language, employing the DEAP 1.4 version (Distributed Evolutionary Algorithms in Python) library. The algorithm aimed to minimize SR by identifying optimal combinations of v, f, and d, using a regression-based mathematical model of SR as the fitness function.

Minimize SR

$$=0.1592-0.0001v+4.3476f+1.7302d+0.0011v^2+0.0008v\times f+0.0005v\times d-7.0370f^2+5.0648f\times d-2.0000d^2.$$

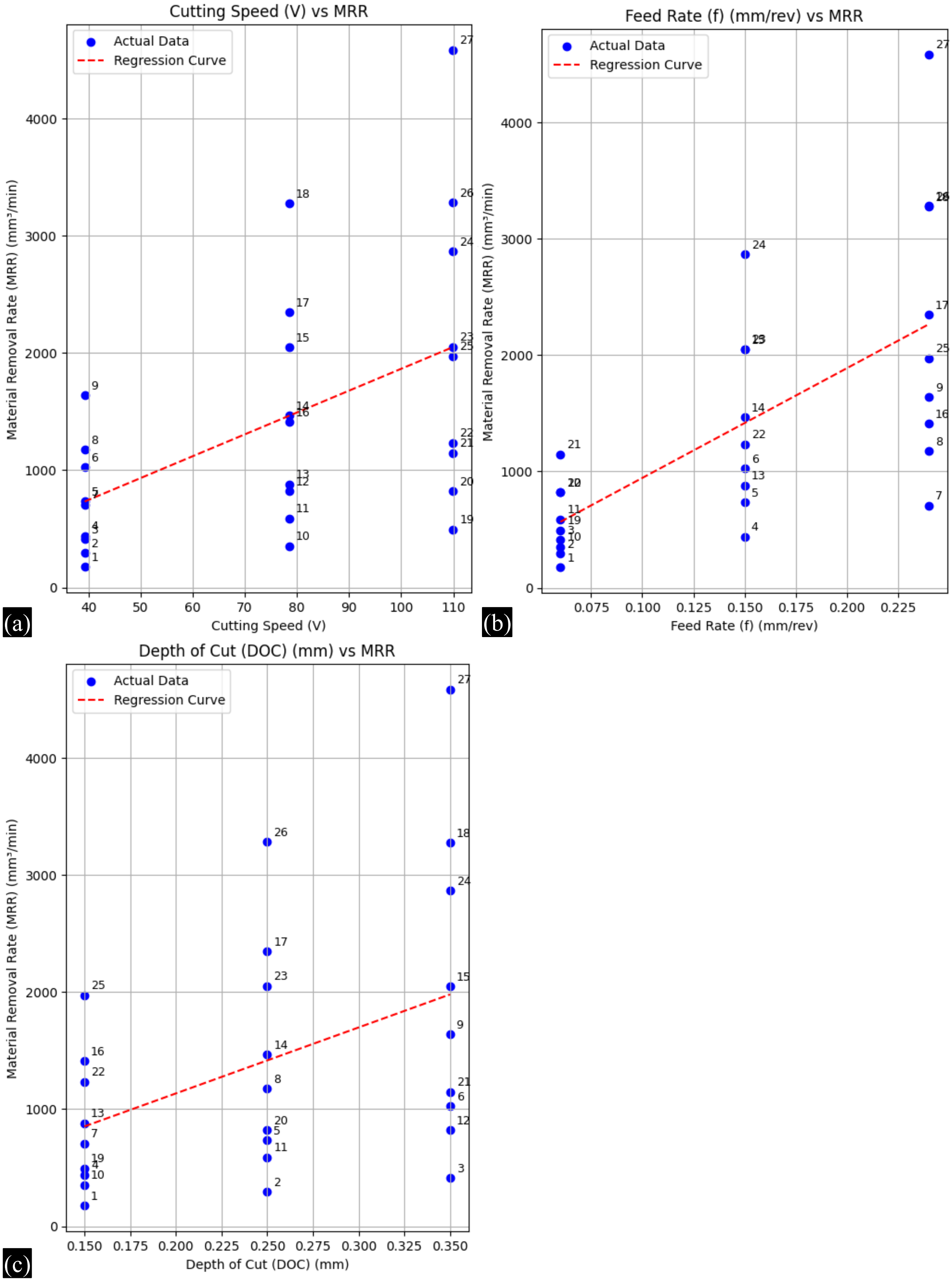

Figure 2. Input vs. output for MRR. (a) Cutting speed vs MRR; (b) Feed rate vs MRR; (c) Depth of cut vs MRR.

This expression was encoded as the fitness function in the GA framework, with the objective of minimizing SR. To ensure the search space remained within practical limits, the decision variables were bounded as follows: $39.26 \leq v \leq 109.95$, $0.06 \leq f \leq 0.24$, and $0.15 \leq d \leq 0.35$. Table 3 shows the genetic algorithm parameters applied to achieve minimum SR value.

Table 3. GA parameters for SR optimization.

Genetic algorithm parameters	Methods and values
Size of population	50
Number of generations	200
Crossover probability	0.7
Mutation probability	0.2
Selection size	3

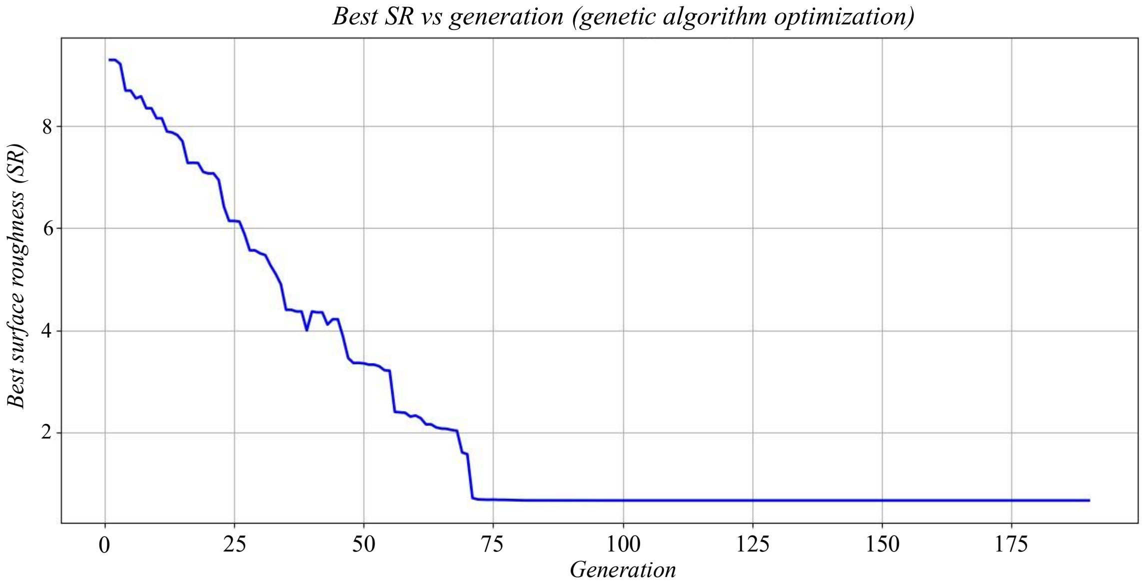

Figure 3. Generation vs. Best SR graph.

More than 200 generations, the Genetic Algorithm lowered surface roughness (SR) from 9.82 to 0.6574 µm. Consistent with machining rules of thumb supporting higher speeds and lower feeds for improved surface finish, the optimum turning parameters were 109.95 m/min cutting speed, 0.0600 mm/rev feed rate, and 0.1500 mm depth of cut (Figure 3).

Genetic Algorithm Applied on Material Removal Rate MRR

To maximize the Material removal rate (MRR) in the turning of aluminium alloy 64430, the Genetic Algorithm (GA) was implemented using the Python programming language, employing the DEAP 1.4 version library.

The algorithm aimed to maximize MRR by identifying optimal combinations of v, f, and d, using a regression-based mathematical model of MRR as the fitness function. Maximize MRR=–2824.7181+18.6452×v+9437.7154×f+5637.1956×d. This expression was encoded as the fitness function in the GA framework, with the objective of maximizing MRR. To ensure the search space remained within practical limits, the decision variables were bounded as follows: $39.26 \leq v \leq 109.95$, $0.06 \leq f \leq 0.24$, $0.15 \leq d \leq 0.35$.

After 200 generations, the Material Removal Rate (MRR) of the Genetic Algorithm was improved from 2939.8165 to 3463.3918 mm³/min at a mutation probability of 0.3. The optimal parameters for effectively optimizing removal rate were: depth of cut 0.3500 mm, feed rate 0.2400 mm/rev, and cutting speed 109.95 m/min (Figure 4).

Confirmation Test

With Python's SciPy library, a statistical validation test was conducted to check the Genetic Algorithm optimization results.

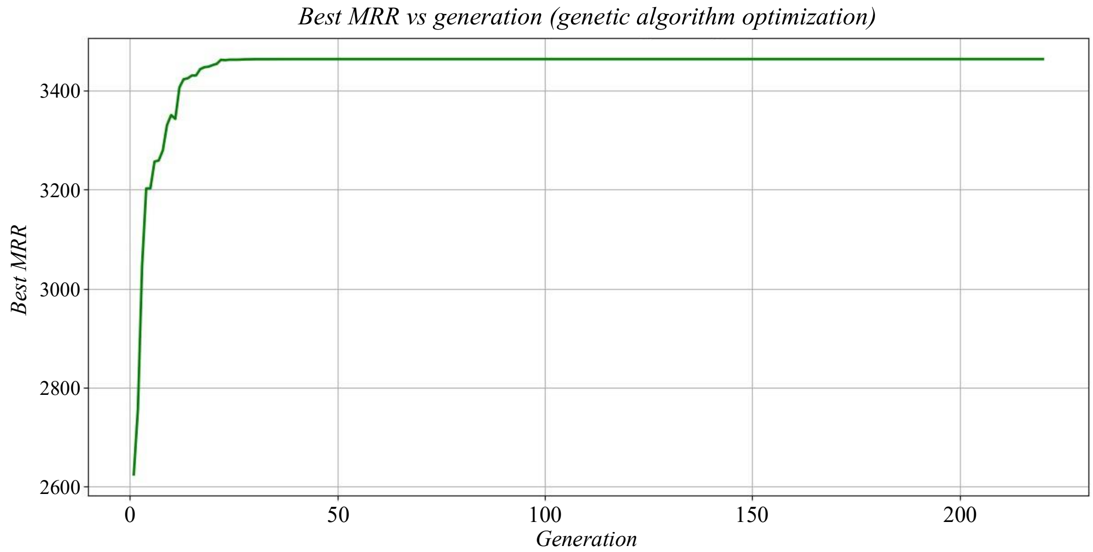

Figure 4. Generation vs. Best MRR graph.

Experimental values of Surface Roughness and Material Removal Rate, from the DOE were compared with GA-predicted values by conducting a Paired T-Test. For obtaining the t-statistic and p-value, the t test_rel function from SciPy.Stats was used. The test results indicated that the SR's t-statistic was 2.1143 and p-value was 0.1688, while that of the MRR was 0.5762 and p-value was 0.6227. Experimental and GA-estimated values do not statistically differ since both p-values are above the 0.05 significance level. This confirms the accuracy and reliability of the GA-based optimization model in predicting machining performance.

RESULTS AND DISCUSSIONS

1. The Genetic Algorithm minimized surface roughness from 9.82 µm to 0.6574 µm using a regression-based fitness function developed in Python. The algorithm was executed with a population size of 50, 200 generations, and a mutation probability of 0.2. This confirms the effectiveness of GA in enhancing surface finish during turning of Aluminum 64430 and minimum SR is achieved when turning operation is kept at highest cutting speed, lowest feed rate, lowest depth of cut
2. The GA maximized material removal rate from 2939.8165 mm^3/min to 3463.3918 mm^3/min using a linear regression model. Optimization was performed with a mutation probability of 0.3 over 200 generations. The optimal parameters obtained were: cutting speed = 109.95 m/min, feed rate = 0.24 mm/rev, and depth of cut = 0.35 mm. It means that at highest cutting speed, feed rate and depth of cut , maximum MRR is achieved.
3. The input factors like feed rate and depth of cut in turning operation and python programming language and its libraries like scikit – learn and DEAP for regression analysis and GA optimization had played very important role in this experimental study.
4. The polynomial regression model for surface roughness achieved an R^2 value of 0.9998, indicating excellent accuracy. The linear regression model for MRR showed an R^2 value of 0.8610. These models provided the objective functions for the Genetic Algorithm optimization.
5. Experiments were conducted on an HMT Craft Master TL-20 lathe using HSS cutting tools. Surface roughness was measured with a Mitutoyo surface tester, and MRR was calculated based on the material volume removed. The Taguchi L27 orthogonal array was used for designing the experiments.
6. A Paired t-Test was performed in Python to validate the optimized results. The p-values obtained were 0.1688 for SR and 0.6227 for MRR, both greater than 0.05. This confirms that there is no significant difference between predicted and experimental values, verifying the accuracy of the models and the optimization process.

7. The integration of Genetic Algorithms with regression modeling in python IDLE is successfully optimized the turning parameters of Aluminum 64430. This GA approach significantly improved surface finish and machining efficiency. The results validate that the research objectives were effectively achieved.

CONCLUSION

This experimental study utilized a Genetic Algorithm (GA) implemented in Python to successfully optimize the machining performance parameters: Surface Roughness (SR) and Material Removal Rate (MRR), in the turning of Aluminium Alloy 64430. As fitness functions for the GA, regression models were initially created for SR and MRR. According to the optimization results, at a cutting speed of 109.95 m/min, feed rate of 0.0600 mm/rev, and depth of cut of 0.1500 mm, the minimum surface roughness of 0.6574 µm was attained. At a cutting speed of 109.95 m/min, feed rate of 0.2400 mm/rev, and depth of cut of 0.3500 mm, the highest material removal rate of 3463.3918 mm^3/min was achieved. These findings demonstrate the efficacy of using Python-coded genetic algorithms, which provide a transparent, adaptable, and affordable substitute for more conventional programs like MATLAB and MINITAB. For contemporary, intelligent manufacturing systems, the method offers a strong and adaptable optimization framework.

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