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ANN-NSGA-II DUAL APPROACH FOR MODELLING AND OPTIMIZATION OF PROCESS PARAMETERS FOR PERFORMANCE IMPROVEMENT IN VERTICAL TURRET MILLING MACHINING

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Abstract
Machining parameters optimization is most important factor to get enhanced productivity, quality and sustainability in manufacturing processes. Conventional single-objective approaches of optimization often fail to address the complex multi objective nature problems. In this study, multi objective optimization framework is implemented that includes Grey Relational Analysis (GRA), multiple linear regression, artificial neural networks (ANN), and Non-dominated Sorting Genetic Algorithm II (NSGA-II). These methods were used to optimize vertical turret milling machine performance. The output parameters such as material removal rate (MRR) and surface roughness (Ra) were considered as key responses parameters. The methodology begins with GRA for initial multi-objective parameter screening using a full factorial design with 81 experimental runs on EN24 steel. The regression analysis and ANN modeling were used to capture both linear and nonlinear relationships between input parameters such as spindle speed, feed rate, and depth of cut and output responses are material removal rate and surface roughness. NSGA-II method implemented to optimization for global parameter selection. The results demonstrate that GRA successfully identified optimal parameters with verification experiments showing surface roughness while the ANN model achieved high prediction accuracy for MRR (>90% in most cases) and variable performance for Ra, and NSGA-II provided Pareto-optimal solutions balancing multiple objectives with validation experiments confirming less than 5% error from predicted values.

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1.0 INTRODUCTION
Due to globalization, the adoption of advanced and efficient manufacturing technologies is recognized as a critical parameter of productivity, innovation, and sustainability. As per United Nations Sustainable Development Goals (SDGs 9) framework that promotes resilient infrastructure, inclusive and sustainable industrialization, and innovation. The advanced manufacturing processes which are found in vertical turret milling machines are essential for economic growth and technological advancement [1], [2].

Many reports are now focused on the use of technology to get sustainable manufacturing advantages. A vertical turret milling machine is a highly widely used in different manufacturing and metalworking companies. From this machine, various milling operations such as cutting, drilling, and boring with precision and efficiency. Due to its distinguishing feature such as vertical spindle orientation and the movable ram and turret, it is positioned at multiple angles and elongated over the worktable. This type of milling machine use the combination of flexibility and power. This makes it ideal for both production work and custom fabrication [3]. It mostly used in tooling, fixture, die making, and maintenance departments due to its ability to handle complex shapes and detailed parts. Use of this machine for various difficult to cut material are reported in the literature in detailed manners. EN24 alloy steel is one of the high carbon alloy steel usually used for different applications such as swords, automotive Drive shafts, Aerospace landing gears Oil and gas drilling bits.

Different optimization such as Taguchi method, Grey Relational Analysis (GRA) and Design of Experiments (DOE) are used for different machining processes [4]. The combination of Taguchi and GRA was used to optimize turning operations considering multiple performance characteristics like surface roughness and tool wear, demonstrating effective multi-objective optimization by Zeng et al. [5]. In this study, they are used the Taguchi method with an L9 orthogonal array to optimize cylindrical grinding parameters (Depth of cut (DOC), feed rate, and work speed) for EN24 steel. They conducted experiments before and after heat treatment and evaluated the material removal rate (MRR). It is observed that DOC had the highest impact on MRR before heat treatment. However, feed rate is dominated parameter after treatment. The optimize parameters such as DOC 0.025 mm, WS 270 rpm, FR 0.02 mm shows significant importance to improved MRR. In another study on cylindrical grinding [6] shows that input process parameters such as feed rate and depth of cut significantly affect the MRR. In comparative investigations conducted by Rahman et al [7] [8] with Computer Numerical Control (CNC) turning and drilling on different steel grades, shows the material specific responses and the importance of environmentally friendly practices in modern manufacturing are most important parameters [9].

Rasoulnia et al. [10] conducted the experiment and used the combination of Taguchi and ANOVA to analyze cutting forces. Results show that use of hybrid statistical tools improve reliability in process control. Researchers also used a Taguchi based Grey Relational Grade method to optimize multiple machining responses simultaneously for MRR and surface finish. Zhang et al. [11] experimented the turning machining on EN8 steel using a conventional lathe. They observed that surface roughness and MRR are highly responsive to spindle speed and DOC. Sodhi et al. [12] applied the optimization method to the boring process parameters for steel.

They used Taguchi analysis to enhance productivity and dimensional accuracy. Nemah et al. [13] focused on CNC turning operations and adopted statistical modeling to evaluate the effects of key input parameters on machining efficiency. Venkatesan et al. [13] analyzed dry machining of Inconel 625 with coated carbide tools. They highlighted how cutting speed and feed rate critically influence surface integrity and tool wear. Researcher also implemented Taguchi methodology to improve surface roughness in lathe facing operations. They are emphasizing the importance of feed rate and nose radius. Singh et al [14] was performed the optimization for turning aluminum 7075 alloy. In this study they confirm that the effectiveness of statistical tools in lightweight material machining. An environmentally conscious approach of optimization was applied on lead brass alloy by Toulfatzis et al [15]. Latar on a hybrid optimization method applied in the various machining process. Amir et al. [16] used Taguchi and fuzzy logic was applied to a multi-hole drilling operation, successfully managing multiple input and output variables. The influence of machining parameters on surface roughness in CNC turning was further explored in [17] where they reinforced the practicality of Taguchi methods in precision manufacturing. Now a days, the advancements in optimization method related smart manufacturing technologies have opened new research area for improving the performance and reliability in the traditional machining systems. One of the developments is integration ANN methods for the optimizations with vertical turret milling machines. Surface roughness prediction models using ANN have been successfully developed to analyze the effects of cutting conditions during turning of free machining steel. These models commonly use process parameters such as feed rate, cutting speed and depth of cut. These experiments planned to use orthogonal arrays and training performed through back-propagation algorithms. Results typically show that cutting speed and feed rate significantly influence surface roughness reduction. However, the depth of cut has a lesser effect with 3D surface plots.

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Often it is used to illustrate the interaction effects of these cutting conditions [18]. In ANN the complexity is too high due to overfitting. This may leads to decreased prediction accuracy on new or unseen data. The ANN models require careful tuning of hyper-parameters and sufficient high-quality training data. As there is poor training or noisy data can adversely impact model performance and generalization [19]. Combining ANN with NSGA-II can help overcome these limitations. The ANN is good at modeling complex and non-linear relationships. This feature helps to predict outcomes from various input parameters. When ANN is paired with NSGA-II, which is good at balancing multiple objectives and exploring large solution spaces. This combination improves the accuracy and efficiency of the optimization process.

It is evident from the literature that in the numerous studies, the optimization of machining parameters was done using different techniques such as GRA, regression modeling, ANN or metaheuristic algorithms like NSGA-II. There is a noticeable gap found in combining these frameworks for multi-objective process optimization. Therefore, this study works on the structured systematic approach. Initially started with GRA for parameter screening, after that by regression and then ANN modeling for both linear and nonlinear predictions. Later on, NSGA-II was employed to achieve globally optimal solutions that consider the competing demands of multiple output objectives in vertical turret milling machine operations (figure 1).

2.0 EXPERIMENTAL PROCEDURE

The experimental study was carried out on a vertical turret milling machine (Figure 2a and 1b). The machining process parameters selected as key input factors were cutting speed, feed rate, depth of cut. Each of these parameters was assigned three levels, following the design suggested by the grey relational analysis on 81 orthogonal array to ensure systematic and efficient experimentation across various parameter combinations. The investigated parameters included Spindle speed (rpm), Feed rate (mm/min), Depth of cut (mm) (table 1). These input parameters are the fundamental variables which that has more impact on machining performance of vertical turret milling. Spindle speed (200-600 rpm) shows the cutting velocity

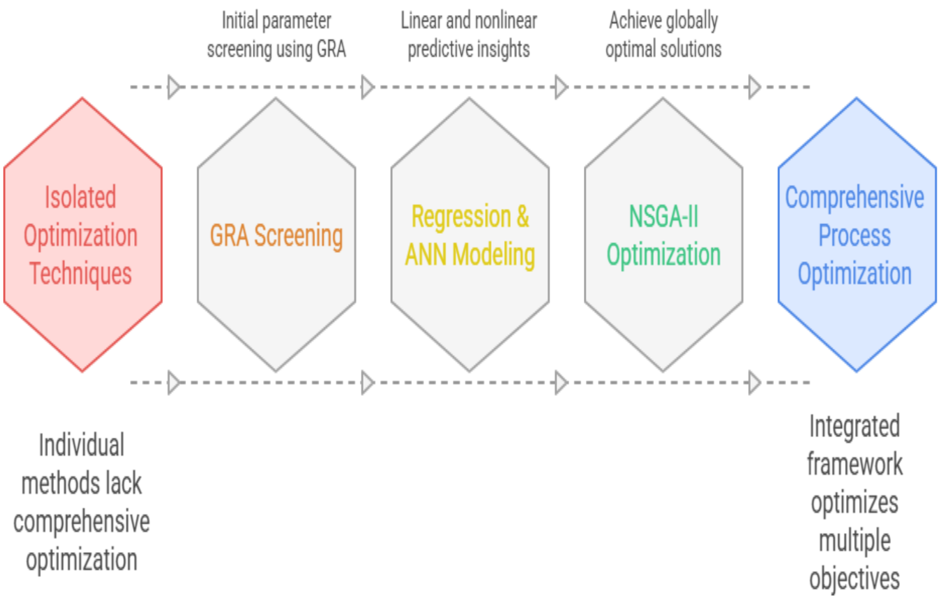

Figure 1: Integrated framework to achieve the comprehensive multi-objective process improvement

It affects tool life, surface roughness and thermal generation during machining. At higher speeds, it generally improving surface quality but potentially reducing tool durability. Feed rate (88-118 mm/min) on EN24 steel confirms that feed rate contributes up to 85.51% in the variation in surface roughness [20] [21]. Depth of cut (0.1-0.5 mm) is also affects the MMR and cutting forces. Deeper cuts of materials increasing the productivity but potentially compromising on the surface roughness and tool stability. These parameter ranges were specifically selected based on literature present for EN24 steel machining. In Theses literature have similar studies have demonstrated for optimal performance within these operations [22]. The response variables are surface roughness, material removal rate also affect

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significantly on the performance. The experiments were accounted for by conducting a full set of 81 experiments for each vibration level, resulting in a total of 81 experimental runs to capture process variability effectively. A full factorial design $3^3 = 27$ parameter combinations × 3 replicates 81 total runs was executed. The GRA analysis in Table 3 presents normalized GRG values averaged across replicates for the 27 unique parameter sets, while raw individual run data (81 experiments) fed the regression and ANN models. Material removal rate and surface roughness were measured after each milling operation using data acquisition and surface profilometry setup. During the measurement, accurate amount of material removed and the resulting surface quality were determined. These quantified values were utilized as response variables for subsequent predictive modeling and optimization with all milling experiments conducted under industrially relevant conditions to ensure practical applicability of the results.

Table 1: Input parameter with levels

Input Parameter	Typical Levels / Range		
Spindle Speed (rpm)	600	340	220
Feed Rate (mm/min)	88	102	118
Depth of Cut (mm)	0.1	0.3	0.5

Table 2: Chemical composition of EN24 steel in wt%

Materials	Chemical composition in wt%							
	C	Si	Mn	P	S	Cr	Mo	Ni
EN 24 alloy steel	0.43%	0.4%	0.9%	0.05	0.05	1.20%	0.25%	2.0%

In this study, carbide tool is used because it has high cutting speed capability, wear resistance, heat resistance, long tool life and high cutting speed capability. In this study EN24 as a workpiece because it has high wear resistance, dimensional stability, it provides high tool life, and suitable for precision machining. Table 2 shows Chemical composition of EN24 steel in wt%.


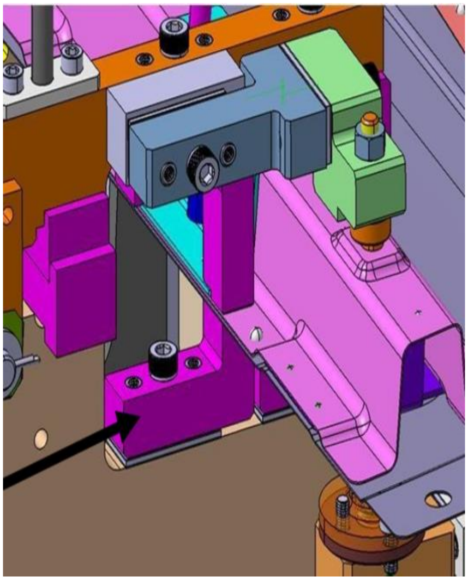

Figure 2: Experimental set up (machine) and schematic of the resting block

3.0 RESULT AND DISCUSSION:

In this section, the results are deliberately discussed with the initial support of an empirical modelling such as multiple variable regression, grey relation analysis ANN and NSGAII. Besides, the influences of process parameters on selected response have been discussed with the models. Later, the intelligent optimization has been performed with the subjected algorithm.

3.1 Grey Relational Analysis

Initially the Gray relation analysis were carried out. Grey Relational Analysis (GRA) is an effective technique that enables simultaneous optimization of multiple output parameters, such as surface roughness and material removal rate (MRR), which traditional methods like Taguchi or DOE struggle to handle directly. This approach also allows for straightforward ranking of experimental trials based

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on their GRG values, making it highly versatile and powerful for solving real-world multi-objective machining optimization problems. In GRA process optimization multiple experimental runs were taken to determine the optimal machining parameters. This is based on performance of both Ra and MRR. The GRA acts as a multi-objective function which allow the experiments to be systematically ranked. The trial with the highest GRG was designated as rank 1. This signifying that the most favourable operational settings. Through this method the optimal parameters were identified as spindle speed at 600 rpm, feed rate at 102 mm/min and depth of cut at 0.5 mm. These parameters comparative investigations representing the configuration with most effective trade-off between minimizing surface roughness and maximizing material removal.The verification of the optimization process was done by performing machining using the optimal settings. The output readings were taken for Ra and MRR. The surface roughness of the first workpiece treated with the optimum parameter setting was 1. 397 m and the material removal rate was 1020 mm^3/min. The repeated test with second workpiece using the same input values obtained from the optimization gives almost the same results. The surface roughness having a 1. 7% difference whereas the MRR remained the same. This shows close agreement in the repeated experiments proves that the GRA, based optimization is good and that selected parameter set is practically effective in achieving the desired performance of precision machining on the other hand (table 3).

Initially, the multi-objective optimization such as Grey Relational Analysis (GRA) is used. In the next phase of this study focuses on predictive analysis and optimization models to further enhance the machining parameters. Regression analysis is first employed to establish empirical relationships between input parameters and output responses. This provides analytical equations which characterize the process behaviour. After that the ANN model is developed to capture complex nonlinear possibilities. This improves the prediction accuracy for key responses like surface roughness and material removal rate. After generating the predictive models, the NSGA-II optimization technique is then applied. This utilizing the outputs of regression and ANN models to identify a global set of input parameters. This offers the best trade-offs among multiple objectives. This integrated approach links the findings of GRA with advanced modelling and optimization techniques This provides a robust framework for data-driven decision-making in machining parameter selection.

3.2 Multiple Linear Regression

Before applying the artificial neural network (ANN) model, multiple linear regression analysis was performed on the Grey Relational Analysis (GRA) data. For the material removal rate (MRR), the regression model showed a high coefficient of determination R squared value of 0.97. This indicate that the linear regression model could explain 97% of the variance. The linear regression model could explain 97% of the variance in the MRR data, thus fitting the data very well. However, for surface roughness (Ra), the regression model yielded a much lower R squared value of 0.57, suggesting that the linear model was unable to capture the variation in Ra effectively. This comparatively poor fit for surface roughness signalled the presence of nonlinear relationships and complexities in the data that linear regression could not adequately model. Consequently, ANN modelling was employed to better capture these nonlinear interactions and improve prediction accuracy, especially for surface roughness, leveraging its ability to model complex and nonlinear patterns in machining process data.

3.3 ANN Model Evaluation

Artificial Neural Networks (ANNs) is a computer framework that replicates the neural architecture of the human brain, allows to acquire knowledge and represent difficult patterns from the data. Artificial Neural Networks have interconnected layers of nodes (or neurons), with each neuron process incoming data and transmitting the results to following layers. These networks generally have an input layer, one or more hidden layers, and an output layer. The secret layers are where the network achieves the ability to relate the input variables with the output variable activation functions. This work involved the development of an ANN model in Python, by employing tools such as Tensor Flow and Keras for its implementation. This model was developed to forecast machining output parameters, including MRR and surface roughness predicated on different input variables such as The input variables, including Spindle speed (rpm), Feed rate (mm/min), Depth of cut (mm), The tuning parameters of this models were selected to enhance the predictive performance relating these machining parameters. The artificial neural network architecture had two hidden layers. The first hidden layer had 16 neurons using the ReLU (Rectified Linear Unit) activation function, which helps the model to handle complex patterns without an issue like vanishing gradients. The second

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hidden layer had 16 neurons. The terminal output layer used a linear activation function (ReLU), that can be suitable for predicting continuous values, such as surface roughness. The model was trained with a learning rate of 0.001, which allowed the weight to updates and prevents overshooting of ideal values during the training. The model undergoes training for 100 epochs, means that the dataset was passed through the training network 100 times to improve the accuracy. A batch size of 10 was used, so the model updates its weights frequently during training, so it can help to learn faster. The data was shuffled several times during training to prevent the order based-bias, and a random stage of 40 was set to guarantee the results could be repeated. The whole training only took 55 secs to complete, that shows the model is faster. Subsequent to training, the ANN model underwent evaluation on test data to assess its prediction efficacy. The meticulously adjusted hyper parameters encompassing the selection of neurons, learning rate and activation functions. This facilitated the model's precise representation of the intricate correlations between the input machining parameters and the output results. The model architecture, with two hidden layers, facilitated the effective learning of non-linear interactions in the machining process, rendering it a potent instrument for forecasting surface roughness and optimizing the procedure. Table 4 shown below is the Hyperparameters set for the ANN model implementation.

Table 5 shows the comparative experimental values with ANN for critical machining parameters. Each experimental run actual measured values are directly used for ANN-based predictions. This table provides the additional metrics including mean squared error (MSE), absolute percentage error (APE) and accuracy for both MRR and Ra. From the table 31 experimental run shows the actual MRR is 612 mm^3/min while the ANN predicts 593.39 mm^3/min. This corresponding to an APE of 3.04% and an accuracy of 96.96%. It is signifying strong predictive agreement between the input and output parameters. However, in some trials such as run 1, it exhibits much higher errors of APE 99.87% for MRR, 6.87% accuracy. This shows specific points where the model’s prediction diverges significantly from experimental outcomes. Across most experimental runs such as MRR in runs such as 19, 5, and 13, the ANN model demonstrates reliable alignment. It repeatedly achieves high accuracy typically over 90% and low APE values. However, the prediction of Ra presents more variability, with APEs ranging widely and accuracy sometimes dropping below 80%. Run 1 with an APE of 98.57% and 16.57% accuracy shows that the model is less robust in predict surface roughness compared to MRR. In several runs, such as run 11 for Ra, the ANN achieves excellent agreement as APE 0.09%, Accuracy 99.91%. It reinforces its potential for high-fidelity prediction when training data sufficiently reflects the tested process window. These findings indicate that while the ANN is highly effective for MRR prediction across varied experimental conditions. Its performance for Ra is inconsistent that suggest that further model refinement or expanded training data may be necessary to achieve consistently high performance for surface roughness prediction. The figure 3 shows a comparative graph between the measured material removal rates (MRR) for each experimental run and the values predicted by ANN model. The blue line indicates that the actual experimental data, while the orange line shows the predictions from the ANN. For most experimental runs, the prediction by the ANN closely follows the trend of the actual MRR data Its shows that the model captures the general behaviour well. In experimental runs, the actual MRR sharply increases or decreases. The ANN prediction also goes up or down in a very similar way. There are some experimental runs around 30 and 70. The ANN predictions are slightly higher or lower than the actual values. It shows that the ANN sometimes limits the exact value but remains close overall. This small difference between prediction and reality is common in complex manufacturing processes due to noise and variations. It may be due to unseen patterns in experimental settings. Overall the ANN model demonstrates strong predictive ability for MRR with most predicted values being very close to the measured ones. It confirms effectiveness and reliability as a tool for estimating machining outcomes. The attached figure 4 displays the comparison between the experimentally measured surface.

Roughness (Ra) and the values predicted by the artificial neural network (ANN) across each experimental run. The blue line represents the actual Ra values which reveals substantial variability and some sharp changes. This changes especially around runs 30 to 40 (Figure 4). In contrast the orange line for the ANN predictions tends to follow general upward or downward trends seen in the real data. It the often smooths out the extreme variations observed in the experiments.

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Table 3: Gray relational analysis table

Job No.	Spindle Speed	Feed Rate (mm/min)	Depth of Cut (mm)		MRR (µm))))			Ra	Normalized Ra	Normalized MR	Ra Deviation	MRR Deviati	Ra GRC	MRR GRC	Grade	Rank
1	600	88	0.1	17	1.458	0.961	0	0.039		1		0.926		0.33	0.63	8
2	600	102	0.3	61	1.2	0.434	1	0.406		0		0.555		1	0.77	3
3	600	118	0.5	11	3.822	0.599	0.599	0.307		0.306		0.649		0.64	0.64	2
4	600	88	0.3	52	2.326	0.528	0.306	0.172		0.649		0.649		0.64	5	11
5	**600**	**102**	**0.5**	**10**	**1.422**	**0.608**	**0.841**	**0.039**		**1**		**0.94**		**0.41**	**0.84**	**1**
6	600	118	0.1	23	3.247	0.06	0.313	0.313		0.94		0.615		0.48	10	16
7	600	88	0.5	88	1.853	0.701	0.701	0.1		0.299		0.834		0.48	4	4
8	600	102	0.1	20	2.991	0.636	0.53	0.106		0.106		0.752		0.48	9	13
9	600	118	0.3	70	1.891	0.894	0.47	0.47		1		0.853		0.40	7	7
10	340	88	0.1	17	4.106	0.556	0	0.444		1		0.333		0.33	19	19
11	340	102	0.3	61	7.745	0.434	1	0.732		0		0.469		1	0.40	25
12	340	118	0.5	11	5.99	0.268	0.268	0.732		0		0.702		26	4.64	6
13	340	88	0.3	52	7.393	0.378	0.306	0.946		0.649		0.346		0.48	7.44	22
14	340	102	0.5	10	4.671	0.841	1	0.594		0.594		0.435		0.84	4.92	9
15	340	118	0.1	23	4.64	0.701	0.56	0.56		0.435		0.435		12	5.33	23
16	340	88	0.5	88	7.442	0.701	0.533	0.989		0.626		0.396		13	4.38	15
17	340	102	0.1	20	4.927	0.098	0.972	0.316		0.333		0.333		22	6.19	24
18	340	118	0.3	70	5.332	0.53	0.279	0.47		0.515		0.396		18	5.81	17
19	220	88	0.1	17	4.381	0.238	0.764	0.763		0.564		0.333		23	5.98	22
20	220	102	0.3	61	6.19	0.503	1	0.75		0		0.307		21	5.10	18
21	220	118	0.5	11	5.814	0.503	1	0.75		0		0.333		14	5.41	5
22	220	88	0.3	52	5.989	0.263	0.306	0.714		0.649		0.438		20	5.47	21
23	220	102	0.5	10	5.107	0.306	0.841	0.16		0.588		0.438		6	4.35	10
24	220	118	0.1	23	5.418	0.08	0.455	0.16		0.68		0.398		17	0.76	26
25	220	88	0.5	88	5.472	0.872	0.481	0.481		0.601		0.398		15	0.06	12
26	220	102	0.1	20	4.35	0.08	0.579	0.579		0.47		0.515		16	0.05	20
27	220	118	0.3	70	4.991	0.078	0.579	0.579		0.47		0.515		9	2.25	14

Table 4: Hyperparameters set for the ANN model implementation.

Hyperparameter	**Value**
Learning Rate	0.001
Layer 1 (Neurons and Activation)	16 Neurons, ReLU
Layer 2 (Neurons and Activation)	16 Neurons, ReLU
Epochs	100
Batch Size	10
Execution Time (ANN Training)	40sec
Execution Time (Total)	55sec
Shuffle	True
Random State	45
Activation Function (Output Layer)	Linear

ANN model generally makes moderate predictions in runs where measured surface roughness sharply increases or decreases. A good example is spot around experimental run 30, where actual Ra shows a huge spike, but an ANN prediction only partially captures the spike height. ANN model is better at following the broad pattern of surface roughness changes, but it has difficulties in predicting sudden or extreme changes. This is also a finding of similar studies where complicated behaviours are present. This means that while the ANN model works better in estimating Ra. One more to get a higher accuracy could be to train model with more data or slightly change the network architecture so that it better represents the outliers and rapid process changes.

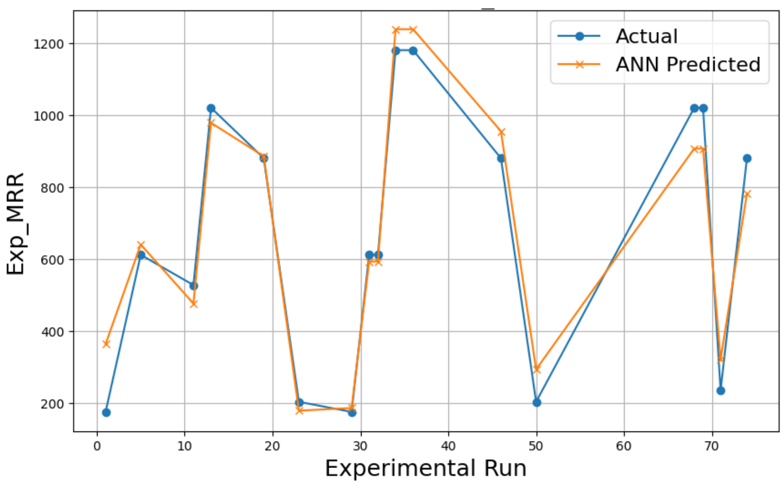

Figure 3: Actual vs ANN MRR

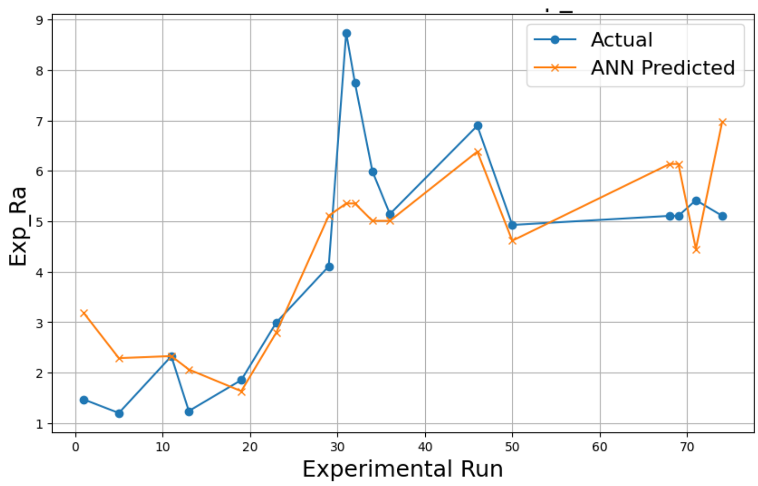

Figure 4: Actual vs ANN for surface roughness

Table 5: Comparison of experimental values with ANN for critical machining parameters

Experimental Run	Spindle_speed	Feed_rate	Depth_cut	Actual Exp_MRR	ANN Predicted Exp_MRR	MSE Exp_MRR	APE Exp_MRR	Accuracy Exp_MRR	Actual Exp_Ra	ANN Predicted Exp_Ra	MSE Exp_Ra	APE Exp_Ra	Accuracy Exp_Ra
31	340	102	0.3	612	593.39	346.37	3.04	96.96	8.74	5.35	11.45	38.73	61.27
1	600	88	0.1	176	364.09	35377.28	99.87	6.87	1.47	3.18	2.93	16.57	16.57
23	600	102	0.1	204	179.44	603.19	12.04	87.96	2.99	2.79	0.04	6.61	93.39
32	340	102	0.3	612	593.39	346.37	3.04	96.96	7.75	5.35	5.72	30.88	69.12
19	600	88	0.5	880	885.53	30.53	0.63	99.37	1.85	1.63	0.05	11.87	88.13
29	340	88	0.1	176	186.84	117.53	6.16	93.84	4.11	5.11	1.01	24.42	75.58
11	**600**	**88**	**0.3**	**528**	**476.92**	**2608.69**	**9.67**	**90.33**	**2.33**	**2.33**	**0.00**	**0.09**	**99.91**
71	220	118	0.1	236	321.69	7342.30	36.31	63.69	5.42	4.45	0.93	17.83	82.17
5	600	102	0.3	612	640.41	807.04	4.64	95.36	1.20	2.29	1.18	90.59	9.41
13	600	102	0.5	1020	978.25	1742.99	4.09	95.91	1.24	2.06	0.68	66.47	33.53
50	340	102	0.1	204	293.95	8091.86	44.10	55.90	4.93	4.61	0.10	6.34	93.66
34	340	118	0.5	1180	1238.15	3381.58	4.93	95.07	5.99	5.01	0.96	16.39	83.61
68	220	102	0.5	1020	907.00	12769.17	11.08	88.92	5.11	6.14	1.06	20.14	79.86
36	340	118	0.5	1180	1238.15	3381.58	4.93	95.07	5.14	5.01	0.02	2.62	97.38
69	220	102	0.5	1020	907.00	12769.17	11.08	88.92	5.11	6.14	1.06	20.14	79.86
46	340	88	0.5	880	954.98	5622.02	8.52	91.48	6.89	6.38	0.26	7.43	92.57
74	220	88	0.5	880	781.91	9622.26	11.15	88.85	5.11	6.97	3.45	36.36	63.64

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3.4 NSGA-II Algorithm Analysis

The NSGA-II is a widely utilized multi-objective optimization technique intended to address issues with many conflicting purposes. In contrast to conventional optimization techniques that seek a singular solution, NSGA-II can identify a collection of optimal answers, referred to as the Pareto-optimal front, where no individual solution is superior to others across all objectives. This enables users to select from a range of trade-off solutions based on their objectives. The fundamental characteristics of NSGA-II encompass rapid non-dominated sorting, crowding distance computation, and elitism. Rapid non-dominated sorting categorizes individuals into several fronts according to their dominance, with the initial front including the non-dominated solutions. Crowding distance promotes variation among solutions by assessing the proximity of individuals parameters. Also, it ensure ensures the preservation of optimal solutions across generations. Figure 5 shows the Flow diagram for the NSGA II. The NSGA-II algorithm was applied for this study in Python. Libraries like DEAP or PyGMO that offer effective tools for evolutionary algorithms were used. The regression-derived values for served as the objectives in the NSGA-II algorithm. The purpose was to concurrently optimize several competing goals and identify a set of trade-off solutions. The NSGA-II algorithm facilitated the exploration of the solution space, optimizing the trade-offs among various machining process parameters. Through the evolution of the population throughout multiple generations, the algorithm successfully identified a collection of Pareto-optimal solutions that provided optimal trade-offs between competing objectives such as MRR and Surface roughness. The hyperparameters are essential in influencing the behaviour and performance of the NSGA-II algorithm. In this implementation, two critical hyperparameters were established, Generations and Population Size, as shown in Table 6. NSGA-II algorithm hyperparameters, like generations (40) and population size (40), were similarly selected through controlled experiments ensuring effective Pareto front convergence and diversity. Using the NSGA-II algorithm, Global optimal values for the outputs are determined along with their respective input values which are shown in Table 7 given below, Graph shows the Pareto-optimal solutions (yellow points) and the Global Optimal Solution (red cross) which offers a lucid representation of the optimal trade-offs among the objectives.

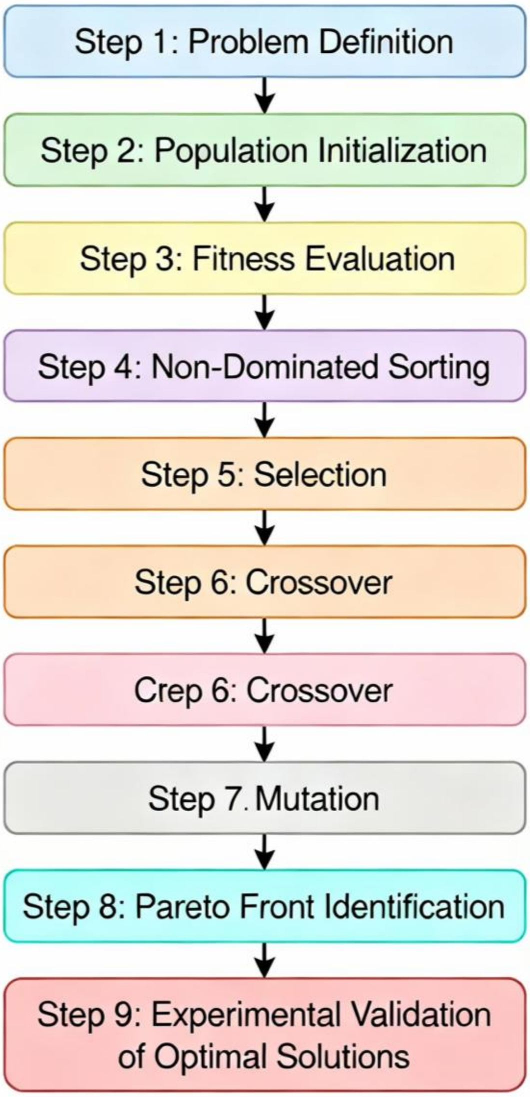

Figure 5: Flow diagram for the NSGA II

Table 6: Hyperparameters used for the development of the algorithm.

Hyperparameter	Value
Generations	40
Population Size	40

Table 7: Global optimal values for the outputs

Optimal Spindle Speed	Optimal Feed Rate	Optimal Depth of cut	Optimal MMR	Optimal Surface roughness
600	117	0.1	306.52	1.95

The Pareto front (Figure 6) diagram illustrates the optimal trade-off solutions between material removal rate and surface roughness. These results obtained from NSGA-II optimization. The curve demonstrates the inverse relationship between both variable. The material removal rate increases from approximately 140 to 300 mm³/min. The surface roughness decreases from about 2.29 to 1.96 µm. This trade-off reflects the fundamental conflict in machining operations.

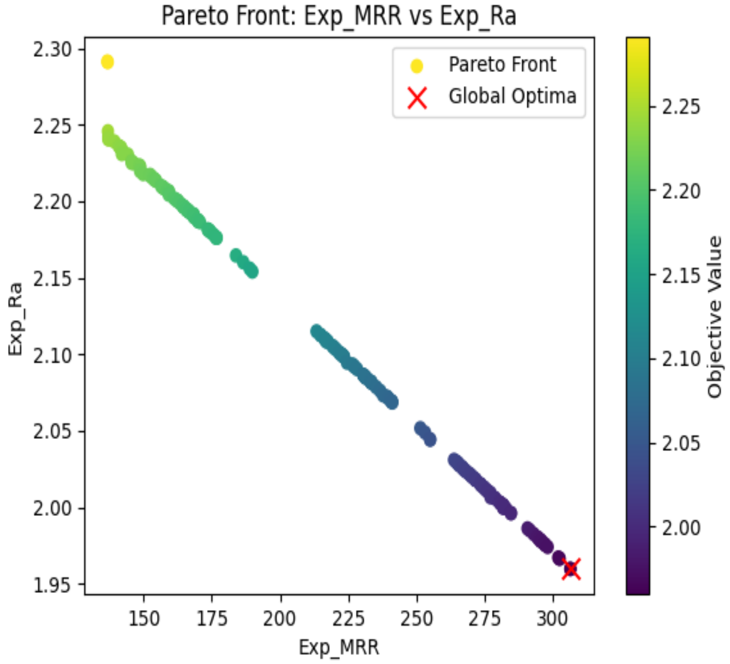

Figure 6: Pareto front experiment MRR vs experiment Ra

The higher productivity typically results in better surface quality but achieving both simultaneously requires careful parameter selection. The well distributed Pareto front with its smooth and slightly concave shape indicates the excellent convergence of the NSGA-II algorithm. This provides the decision makers with comprehensive options across the entire feasible solution space. The red 'X' shows the best overall choice from selected from the Pareto front. It is placed at the curve spot at approximately 300 mm³/min for the MRR and surface roughness of 1.96 µm. This point shows a good balance between productivity and quality objectives. It shows the point of maximum material removal but also maintaining good surface finish standards. The colour starts from yellow to purple shows the objective values. The uniform distribution of solutions proves that the NSGA-II method does the important showcase of keeping a variety while covering the optimal solutions. This Pareto analysis helps the manufacturers to make smart decisions by take care about productivity and surface quality.

CONCLUSION

In this study, the analysis of machining parameters is done, by employing GRA, Multiple linear regression, ANN and NSGA-II methods, to predict and improve key results such as MRR and surface roughness. The research was done in several steps, each one is helping to make the machining process better in the terms of quality and performance. Using GRA, the study found the best machining parameters that can balance between surface roughness and MMR. T

he parameter combination of speed 600 rpm, a feed rate of 102 mm/min, and depth of cut 0.5 mm. Tests showed that these settings work well and are reliable for effective high-precision machining tasks. The ANN model did a great job by predicting material removal rate during the machining, it matched the actual result close in most the tests. This shows it is useful tool for estimating machining performance. Overall, the ANN model is strong potential for predicting machining results.

The NSGA-II optimization method clearly shows that the trade-off between material removal rate and surface roughness. Overall, the study shows that both ANN and NSGA-II methods are effective tools for predicting key machining results

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