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Investigation of Response Parameters in C.N.C Surface Grinded (En31) Steel

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Abstract: Surface finish is a vital aspect of manufacturing, and grinding is commonly used to achieve the desired surface quality. This study focuses on using a surface grinding machine to obtain high surface finish and metal removal rate on automotive engine parts and other components. EN31 steel, a versatile alloy used in various industries, is chosen as the material. Three input parameters, namely the number of passes, feed rate, and depth of cut, are considered to optimize surface roughness and metal removal rate. The Taguchi Method, MINITAB software, MATLAB, and ANN techniques are employed to analyze the experimental data and determine the most influential parameters. These findings can be applied in different manufacturing settings to select optimal performance parameters for achieving desired surface quality and metal removal rate.

***Index Terms* - Taguchi,EN31,Alloy, Steel.**

I. INTRODUCTION

Surface Grinding is a metal removal process used to achieve precise finishing on hardened materials with high surface finish quality, close geometric tolerances, and dimensional accuracy. Multi-cutting edge grinding tools are employed to control the metal removal rate and improve surface finish. The friction generated between the grinding wheel and the object's surface causes material to be removed. Steel, a composition of iron and carbon, is widely utilized in various applications. In this experimental investigation, EN31 steel is chosen for its low surface roughness and high metal removal rate. EN31 alloy steel is known for its hardness, compressive strength, and abrasion resistance, making it suitable for automotive components like ball bearings, shafts, gears, and more.

Dr. Taguchi introduced the Taguchi Method, which utilizes Orthogonal Arrays for experiments to optimize control parameters. MINITAB is statistical analysis software commonly used for quality control and data analysis. Artificial Neural Network (ANN) is a computational model inspired by biological neural networks, employed for nonlinear statistical data analysis and as a functional approximation tool. ANN consists of interconnected layers, with input neurons in the first layer, transmitting data to the output neurons in the third layer through the second layer.

Grinding is a process of removing material from the surface of an object using a rotating abrasive wheel. It provides better surface finish and geometric accuracy compared to other tools. Grinding is particularly suitable for hard objects and utilizes abrasive particles with high hardness and heat resistance. The process allows for high cutting speeds and requires minimal pressure, making it compatible with magnetic chucks for work piece holding. [1]

Abrasives are essential components in the manufacturing of grinding wheels. These abrasive particles are bonded together using suitable bonds and applied to disc wheels. Abrasives are hard materials used to cut or wear away other materials. There are two types of abrasives: natural and artificial. Artificial abrasives offer better control over quality and composition, resulting in improved efficiency compared to natural abrasives. Commonly used abrasives include Silicon Carbide (SiC), Aluminium Oxide (Al_2O_3), Boron Carbide, and Boron Nitride. Silicon Carbide is available in different colors, with bluish green being suitable for grinding tip tools. Alundum and Borolon are special forms of white Al_2O_3 that resemble white crystals. Boron Nitride grinding wheels are used for grinding challenging-to-machine steels due to their high grinding ratios and long life. When using Boron Nitride wheels, the grinding process operates at low temperatures, resulting in better surface finish and quality. The hardness of the abrasive particles is a crucial factor in removing material from the object's surface. Soft materials are unable to effectively remove material during the grinding process.

When a grinding wheel is used extensively, the abrasive particles' cutting edges become dull, resulting in a condition known as glazing. Loaded wheel occurs when grinding chips get trapped between the grit. This typically happens when grinding soft and ductile materials. To restore the grinding wheel's effectiveness, a process called dressing is performed using small steel or abrasive disks made of materials like silicon carbide or boron carbide. Alternatively, a dressing wheel with silicon carbide grains in a hard vitrified bond can be utilized. A diamond dressing tool, attached to a small steel bar, is often employed for dressing, with the grinding wheel rotating at a lower speed and a small depth of cut given to the dressing tool.[2]

II. Objectives

The objective of this research work is follows as:

- Assortment of optimal performance parameters for machining of EN31 steel.
- Achieving finest surface quality and dimensional accuracy.
- Calculation of surface grinding response under optimum surroundings by using ANN.
- Lower surface roughness and higher metal removal rate, are two significant performance parameters accomplished in this investigational work.

III. Scope of the Work

EN31 steel is widely utilized in various industries such as automotive, molding, and tooling due to its desirable properties. For this experimental work, EN31 steel was selected as the workpiece material. The aim was to determine the optimal machining parameters on a surface grinding machine. By conducting the investigation, the study sought to establish the most effective parameters for achieving the desired surface finish and metal removal rate. EN31 steel's versatility and widespread usage in different applications make it an ideal candidate for this study.

IV. Literature Review

The literature survey conducted for this research included various research papers on surface grinding processes for machining dissimilar materials such as mild steel, tool steel, and die steel. These papers highlighted the recent advancements in surface grinding techniques, including the utilization of different abrasive wheel materials like diamond, grain size, and wheel grade. Additionally, different methodologies such as ANN, Taguchi, MINITAB, MATLAB, GRA, etc., were explored. Among these methodologies, it was observed that the use of artificial neural networks (ANN) was relatively limited. Therefore, for this research work, ANN was chosen to control the performance parameters of surface grinding. Considering the widespread use of EN31 material for various purposes, it was selected as the workpiece material for machining on the surface grinding machine. The input parameters (number of passes, feed rate, depth of cut) and performance parameters (lower surface roughness, higher metal removal rate) were determined based on a comprehensive review of research papers.

In a study by A. Saravanakumar et al. [3], the surface grinding performance parameters were analyzed for carbon steel (AISI 1042) using an EKR46K grinding wheel. The parameters investigated were grinding wheel speed, table speed, and depth of cut, with the aim of achieving high surface finish and material removal rate (MRR). Design of Experiments (DOE) was utilized to determine the optimal parameter values under different machining conditions. The initial selected values were a wheel speed of 1850 rpm, feed rate of 3 m/min, and a depth of cut of 0.04 mm. The analysis revealed that the depth of cut had the most significant influence on surface roughness (Ra) among the three controllable parameters, while wheel speed and table speed had a minor effect. The parameters were further optimized using the Taguchi Method with an L18 OA (orthogonal array) design of experiments.

In a study by Zhao Tao et al. [4], surface grinding parameters were investigated on a titanium alloy using a five-axis CNC grinding machine. The impact of cutting velocity, feed rate, grinding depth, and abrasive size on surface roughness, residual stress, hardness, and material removal rate (MRR) was measured. Wei Liu et al. [5] conducted experiments on Silicon Nitride Ceramic (Si_3N_4) using a diamond grinding wheel, studying the effects of grain size, wheel speed, and grinding depth on grinding force and surface roughness. Amandeep Singh Padda et al. [6] focused on stainless steel, examining the influence of depth of cut, wheel speed, and wheel grain size on tangential force, material removal rate, and surface roughness.

In a study by B. Dasthagiri et al. [7], EN8 steel was tested using a CNC grinding machine with input parameters of wheel speed, table speed, and depth of cut. An empirical model was developed using RSM to determine the optimal machining parameters for minimizing surface roughness (Ra) and maximizing metal removal rate (MRR). ANOVA was used to assess the adequacy of the model. T.V. Mahajan et al. [8] conducted experiments on AISI D2 steel using a special purpose grinding machine to find the optimum process parameters. Taguchi L9 OA method was employed to achieve maximum MRR and minimum Ra. Pawan Kumar et al. [9] performed experiments on EN24 steel using surface grinding parameters to optimize surface quality and MRR using RSM. Mustafa Kemal Kulekci et al. [10] investigated surface grinding process parameters on AISI 1040 steel plates to achieve optimal surface roughness using Taguchi Method L9 OA, signal-to-noise ratio, and ANOVA.

In a study by Balwinder Singh et al. [11], the effect of grinding wheel speed, workpiece speed, and nozzle angle on surface roughness was examined using Mild Steel as the workpiece material. The experiments were conducted on a surface grinding machine, and a perthometer roughness tester was used to measure surface roughness. It was found that all the input parameters significantly influenced the surface roughness, and the minimum roughness value of 0.77µm was achieved in this investigation. Halil Demir et al. [12] investigated the effect of grain size on surface roughness and grinding forces in AISI 1050 steel. The experiments were performed on a surface grinder, and it was observed that increasing the grinding wheel grain size led to higher surface roughness and grinding forces. Higher depths of cut also resulted in increased grinding forces and the formation of burrs and cracks on the ground surface. P. Puerto et al. [13] analyzed finishing operations on hard material (F5229 steel) and found that aggressive grinding conditions produced coarser grinding wheel topographies, resulting in higher initial roughness. They also noted that radial wear had a significant impact on wheel peripheral topography, with new grains continuously emerging on the wheel surface under aggressive conditions, leading to increased wheel wear compared to soft grinding conditions.

Dinesh Kumar Patel et al. [14] investigated surface roughness in surface and cylindrical grinding of EN8 steel. They analyzed input parameters such as grinding wheel speed, depth of cut, and wheel material for surface grinding, and work speed and different grinding wheel for cylindrical grinding. Experiments were conducted on a surface grinding machine. They used the Taguchi Method, ANOVA, and S/N ratio for analysis. The study concluded that wheel material and grade had the most significant impact on both surface and cylindrical grinding processes.

Do Due Trung et al. [15] focused on the relationship between surface roughness in surface grinding and cutting parameters. They proposed an equation for calculating surface roughness based on wheel velocity, work velocity, and depth of cut. The study indicated that higher workpiece velocity and volume fraction led to increased surface roughness.

Arvind V. Lal et al. [16] conducted experiments on a surface grinding machine using parameters such as grinding wheel type, workpiece hardness, and depth of cut. They found that material hardness had the most significant influence on surface roughness.

Avnish S. Jejurkar et al. [17] performed experiments on AISI 321 stainless steel using a surface grinding machine. They determined the optimum grinding parameters for achieving good surface finish and fine tolerances.

Jayanti Das et al. [18] investigated manual grinding operations and emphasized the role of worker skill in achieving desired surface roughness. They highlighted the importance of optimizing grinding parameters and the geometry of the grinding wheel.

4.1Research Gap

Several experiments have been conducted on surface grinding operations, focusing on different materials (A. Saravanakumar et al., 2017; Zhao Tao et al., 2017; Wei Liu et al., 2016; Amandeep S. P et al., 2015; B. Dasthagiri et al., 2015; T.V. Mahajan et al., 2015; M. M Rahman et al., 2015; Binu Thomas et al., 2014; Pawan Kumar et al., 2013; Mustafa Kemal Kulekci et al., 2012). Most of these experiments aimed to minimize surface roughness and maximize metal removal rate, considering input parameters such as grinding wheel speed, table speed, depth of cut, feed rate, and number of passes (Mr. Rupesh J. Karande et al., 2017; Mukesh Kumar et al., 2015; M. Arvind et al., 2014; Lijhon P. George et al., 2013; Suresh P. Thakor et al., 2014; Kirankumar Ramakantra Jagtap et al., 2011; Halil Demir et al., 2010). However, there is limited research on EN31 steel alloy, which is widely used in various industries. Hence, this study aims to determine the optimal process parameters (number of passes, feed rate, and depth of cut) for achieving the desired MRR and Ra values in surface grinding of EN31 alloy through various approaches.

V. RESEARCH METHODOLOGY

The material used in this experimental work is EN31 steel, chosen for its desirable properties such as low surface roughness and high metal removal rate. A rectangular block of EN31 tool steel measuring 100mm×20mm×16mm is used for the machining process on a surface grinding machine. EN31 steel is a high carbon alloy steel known for its hardness, compressive strength, and abrasion resistance, making it suitable for applications in automotive industries and the production of shear blades, molding dies, bolts, punches, and cutting tools. The micro hardness of EN31 steel is measured at 371 HV using a Micro Hardness Tester [19], and it exhibits excellent resistance to wear in components subjected to abrasion, wear, or high loading [20].

5.1 Chemical Composition of Material

TABLE 5.1
EN31 STEELCHEMICAL COMPOSITIONS

Chemical Composition	**Percentage (%)**
Fe %	88.42
C %	8.80
Cr %	1.86
Na %	0.45
Si %	0.32
Al %	0.14
O %	0.01

5.2 Design of Experiments (DOE)

In the methodology of Design of Experiments (DOE), control factors are systematically identified and experiments are conducted based on this understanding. The control factors, response factors, and various noise factors are considered in the manufacturing process. The main objectives of DOE include understanding the effects of control factors, reducing the influence of noise factors, improving product and process quality, minimizing manufacturing losses, reducing costs and material waste, and mitigating the risk of failure. Response parameters, also known as dependent variables, are used to measure process performance.

TABLE 5.2
CONTROL FACTOR LEVELS

Control factor	**Units**	**Levels**			
		(i)	**(ii)**	**(iii)**	**(iv)**
No of Passes	Nil	1	2	3	4
Feed Rate	mm/min	30	60	90	120
Depth of Cut	mm	0.02	0.04	0.06	0.08

In this experimental work, four levels of control factors were implemented. Design of Experiments (DOE) is a powerful method that involves planning and designing experiments to collect suitable data, which can be analyzed using statistical techniques. DOE helps establish the relationship between process parameters and performance parameters by systematically planning and conducting experiments. It finds extensive applications in science and engineering for process optimization, development, management, and validation tests. The key aspect of DOE is the selection of appropriate input and output parameters, which greatly influence the performance. Various DOE techniques are available, and the choice depends on the specific problem, number of experiments, and parameters involved [21].

5.3 Taguchi Approach

The Taguchi Method, developed by Dr. Taguchi of Nippon Telephones and Telegraph Company in Japan, is a powerful approach based on orthogonal array experiments. It offers a systematic way to conduct experiments with optimal settings of control parameters, allowing for improved quality of manufacturing components and process parameters. Originally applied to enhance the quality of manufactured goods, the Taguchi Method has expanded its applications to various fields, including biotechnology. By carefully selecting and categorizing process parameters as control and noise factors, this method successfully achieves the desired results. It utilizes orthogonal arrays to conduct a set of experiments and analyze the data to predict the quality of components. The Taguchi Method finds frequent application in manufacturing, particularly in automotive industries, as well as in plastic, semiconductor, and metal fabrication processes. It is an effective approach for investigating experimental observations, optimizing procedures, reducing costs, and improving overall design quality through the collaboration of governing variables.

5.4 Signal-to-Ratio S/N

The signal-to-noise ratio is a logarithmic function used to optimize process or product design by minimizing variability. It represents the reduction of process unpredictability against unwanted changes. Taguchi utilizes the signal-to-noise ratio to analyze performance and optimize process parameters, providing optimum results. There are three categories of signal-to-noise ratio: Nominal is better, Smaller is better, and Larger is better. The selection of the appropriate type depends on the nature of the problem. In this work, the Smaller is better signal-to-noise ratio is chosen for surface roughness, while the Larger is better signal-to-noise ratio is selected for MRR.

5.5 Orthogonal Array

Taguchi implemented the use of an orthogonal array (OA), which is an experimental matrix designed by Li. The OA allows for a set of experiments to be conducted efficiently, where process parameters can be easily modified. It enables the analysis of control factors and their combinations. The orthogonality of the array ensures that all combinations of factor levels occur equally, simplifying the determination of the effects of input factors on response variables and noise factors. In this work, the L16 Orthogonal array is utilized to study the effects of control factors and their levels.

The properties of orthogonal array are:

No. of experiments = 16

No. of Levels= 4 (A, B, C, D)

No. of factors= 3 (1,2,3,).

TABLE 5.3

L_{16} ORTHOGONAL ARRAY FOR DESIGN OF EXPERIMENTS

No. of exp.	**No of passes (N)**	**Feed rate (f) mm/min**	**Depth of cut (d) mm**
1	A	A	A
2	A	B	B
3	A	C	C
4	A	D	D
5	B	A	B
6	B	B	A
7	B	C	D
8	B	D	C
9	C	A	C
10	C	B	D
11	C	C	A
12	C	D	B
13	D	A	D
14	D	B	C
15	D	C	B
16	D	D	A

VI. OBSERVATION

For the experimental observations, EN31 steel was used as previously mentioned. A total of 16 rectangular bars of EN31 steel were selected as workpieces. Initially, the bars had varying dimensions with thickness ranging from 15 mm to 20 mm, length from 100 mm to 110 mm, and width from 20 mm to 25 mm, as shown in the figure. Subsequently, a rough grinding process was performed on each specimen using a surface grinding machine. After the grinding operation, the workpieces were transformed to a thickness of 15 mm, width of 20 mm, and length of 100 mm. The specimens were then prepared for the experiments, with numbers 1 to 16 assigned to each specimen for conducting the experiments using the L16 orthogonal array provided by MINITAB.

Fig. 6.1 Specimen at initial condition

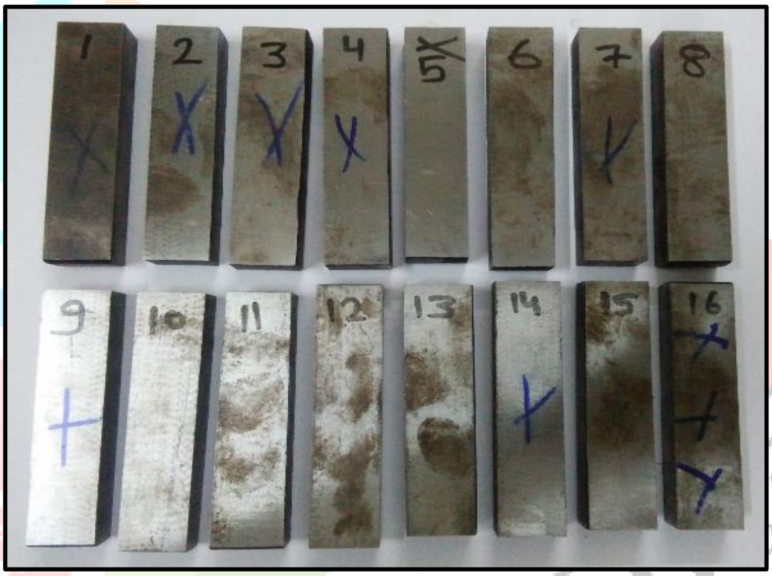

Fig. 6.2 Numbers on specimen

6.1 Design of experiment

The MINITAB-17 software was utilized to implement the design of experiments. The following steps were undertaken in the Taguchi Method for the current experimental study:
Step 1: The Taguchi strategy was formulated using the MINITAB software.
Step 2: Four levels were assigned to each control factor (N, f, d) to enhance the understanding of the surface grinding process.
Step 3: The most appropriate experimental design, the L16 orthogonal array, was selected in the MINITAB software after determining the control factors and their levels.
Step 4: The designated levels for the factors were established.
Step 5: Ultimately, a total of 16 optimal experimental arrangements were generated for conducting the experiments.
Table 6.1 presents the levels of the control factors, while table 6.2 exhibits the combinations of parameters

TABLE 6.1
CONTROL FACTOR LEVELS

Control factors	Units	Levels			
		(i)	**(ii)**	**(iii)**	**(iv)**
No of Passes (N)	Nil	1	2	3	4
Feed Rate (f)	mm/min	30	60	90	120
Depth of Cut (d)	mm	0.02	0.04	0.06	0.08

TABLE 6.2
COMBINATION OF INPUT PARAMETERS

No. of exp.	**No of passes (N)**	**Feed rate (f) mm/min**	**Depth of cut (d) mm**
1.	1	30	0.02
2.	1	60	0.04
3.	1	90	0.06
4.	1	120	0.08
5.	2	30	0.04
6.	2	60	0.02
7.	2	90	0.08
8.	2	120	0.06
9.	3	30	0.06
10.	3	60	0.08
11.	3	90	0.02
12.	3	120	0.04
13.	4	30	0.08
14.	4	60	0.06
15.	4	90	0.04
16.	4	120	0.02

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6.2 Conduction of experiment

A series of 16 experiments were conducted on a surface grinding machine using the optimal combinations of control variables obtained from the Taguchi L16 orthogonal array. Sixteen workpieces were obtained for the experiments, and the values of the control parameters were adjusted based on the Taguchi design. The grinding operation was carried out by mounting the specimens onto the magnetic chuck of the surface grinding machine.

TABLE 6.3
CONSTANT PARAMETERS DURING CUTTING SURFACE GRINDING OPERATION

Fixed parameters	**Description**
Grinding wheel speed	2800 rpm
Grinding wheel type	Aluminium oxide of Grade 80
Voltage of machine	450

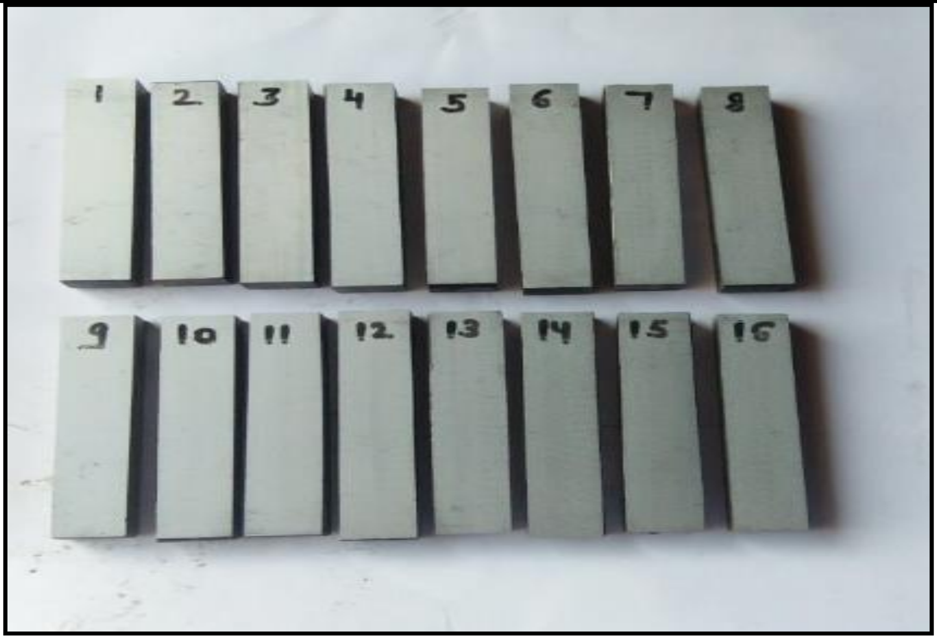

Fig. 6.3 Workpiece after grinding process

6.3 Measurement of surface roughness

The surface roughness of the workpieces was measured using a portable surface roughness tester (SURTONIC S128). Three measurements were taken for each workpiece to ensure accuracy, and the mean value was calculated. The weight of the specimens was measured before and after the grinding process using a weighing machine, and the time for each experiment was measured using a stopwatch to determine the Material Removal Rate.

6.4 Experimental results

All 16 experiments were successfully performed on the surface grinding machine according to the Taguchi design, resulting in the best process quality and optimal conditions. The measurements of surface roughness and Metal Removal Rate (MRR) for all 16 workpieces were recorded and presented in Table. The highest MRR value of 0.10169 grm/sec was achieved with 1 pass, 0.08 mm depth of cut, and a feed rate of 120 mm/min. Conversely, the minimum surface roughness (Ra) of 0.25000 µm was obtained with 1 pass, 0.04 mm depth of cut, and a feed rate of 60 mm/min.

The main effects plots illustrate the relationship between the machining parameters and the response variables. The plots indicate that the feed rate and number of passes have the most significant impact on MRR and surface roughness.

S/N ratio analysis was also conducted, revealing that the feed rate had the highest effect on MRR, followed by the number of passes and depth of cut. Based on their effects on MRR, the feed rate ranked first, the number of passes ranked second, and the depth of cut ranked third.

Similarly, for surface roughness (Ra), the number of passes had the most pronounced effect, followed by the feed rate and depth of cut. According to their effects on Ra, the number of passes ranked first, the feed rate ranked second, and the depth of cut ranked third.

The data obtained from the experimental work was used as input for an Artificial Neural Network (ANN). This data was divided into two sets: the input data set and the output data set for training the ANN. The trained neural network was then utilized to predict the surface grinding response parameters.

VII. RESULTS AND DISCUSSION

7.1 ANN predicted result

TABLE 7.1

Variable	Minimum	Maximum	Mean	Std. Deviation	Jarque-Bera test	Sig
KSE-100 Index	-0.11	0.14	0.020	0.047	5.558	0.062
Inflation	-0.01	0.02	0.007	0.008	1.345	0.510
Exchange rate	-0.07	0.04	0.003	0.013	1.517	0.467
Oil Prices	-0.24	0.11	0.041	0.060	2.474	0.290
Interest rate	-0.13	0.05	0.047	0.029	1.745	0.418

TABLE 7.2 COMPARISON OF ACTUAL AND ANN PREDICTED DATA

No. of Exp.	No. of Passes (N)	Feed Rate (f) mm/min	Depth of cut (d) mm	Experimental MRR (grm/sec)	ANN Predicted MRR (grm/sec)	Experimental Ra (μm)	ANN Predicted Ra (μm)
1	1	30	0.02	0.00532	0.010479	0.37666	0.26039
2	1	60	0.04	0.01527	0.015274	0.25	0.25007
3	1	90	0.06	0.02857	0.020619	0.30666	0.29385
4	1	120	0.08	0.10169	0.10155	0.35666	0.35666
5	2	30	0.04	0.00552	0.0046278	0.27333	0.29174
6	2	60	0.02	0.01327	0.01327	0.39333	0.39332
7	2	90	0.08	0.01818	0.018183	0.40333	0.40333
8	2	120	0.06	0.02655	0.026544	0.55	0.55001
9	3	30	0.06	0.00369	0.0038066	0.44666	0.44662
10	3	60	0.08	0.00554	0.0099557	0.53666	0.25704
11	3	90	0.02	0.00565	0.0056501	0.52666	0.52659
12	3	120	0.04	0.01266	0.012661	0.46333	0.46332
13	4	30	0.08	0.0042	0.0041751	0.51666	0.51669
14	4	60	0.06	0.00621	0.0062065	0.43	0.43
15	4	90	0.04	0.00826	0.0082606	0.63333	0.63329
16	4	120	0.02	0.006	0.006	0.69	0.68992

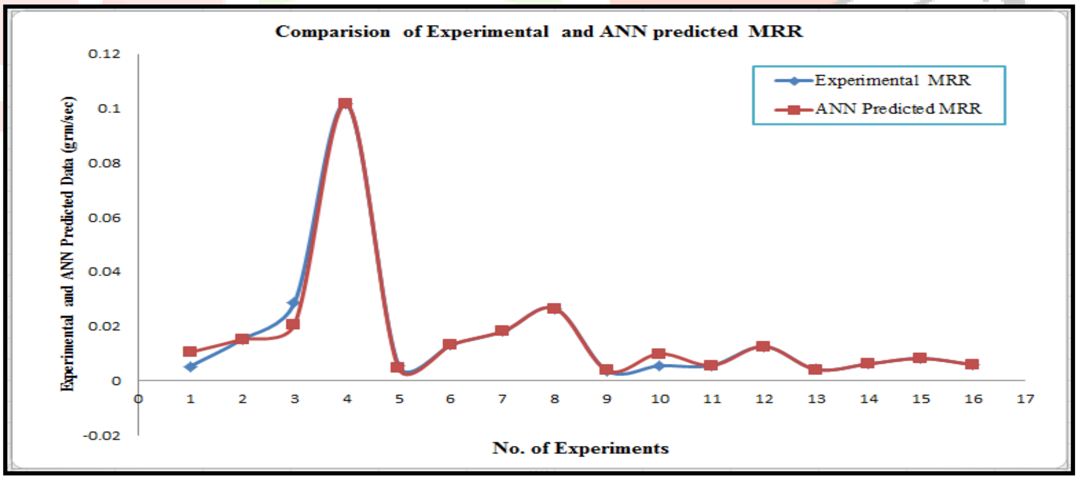

Fig. 7.1 Difference between experimental and predicted MRR

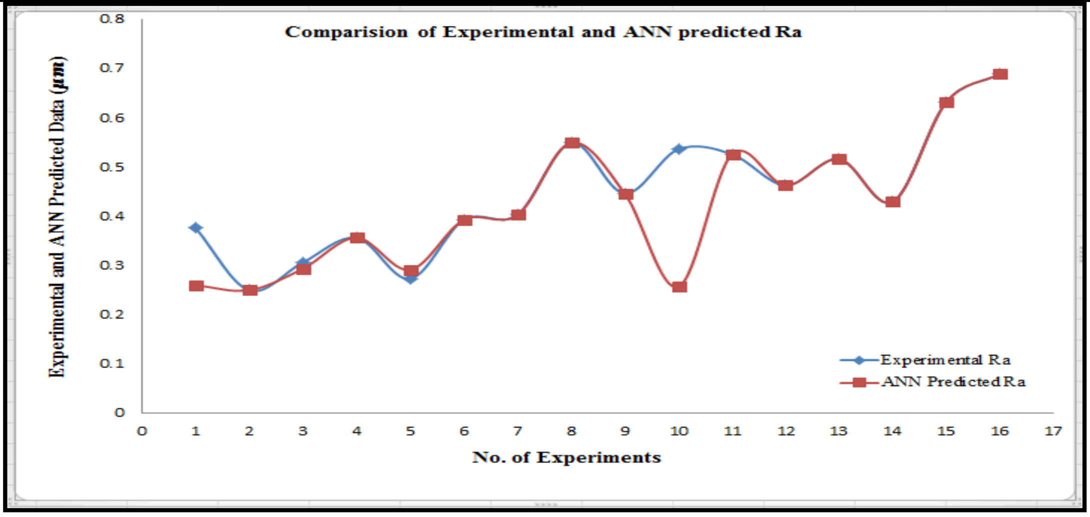

Fig. 7.2 Difference between experimental and predicted Ra

In this research study, EN31 steel alloy was utilized to investigate the effects of depth of cut, number of passes, and feed rate on material removal rate and surface roughness in the surface grinding process. Table 7.1 presents the predicted values of the experimental results obtained using an Artificial Neural Network (ANN) and the differences between the actual data and the ANN predicted data. The table demonstrates that the ANN predicted values closely match the experimental data, with more than 90% similarity, indicating the validity of the current work. This comparison is also depicted in figures 7.1 and 7.2.

Figure 7.1 illustrates the variance between the experimental data and the ANN predicted data. Out of the sixteen experimental values, only three (corresponding to experiment numbers 1, 3, and 10) differ from the predicted values, while the remaining thirteen values match the predicted values. Similarly, in figure 7.2, three experimental values (experiment numbers 1, 5, and 10) differ from the ANN predicted values, while the rest of the investigational values align with the predicted values.

In the experiments conducted on EN31 alloy steel in the surface grinding process, it was determined that the desired surface quality could be achieved, with optimal values of 0.25 μm for surface roughness (Ra) and 0.10169 grm/sec for material removal rate (MRR) being obtained.

7.2 Conclusion

The present work utilizes an ANN developed model to measure the surface roughness and material removal rate of EN31 alloy steel in the surface grinding process, leading to the following conclusions: Both Taguchi DOE in MINITAB and ANN in MATLAB are effectively applied for predicting surface roughness (Ra) and material removal rate (MRR). The primary factors influencing surface roughness and MRR are the number of passes, feed rate, and depth of cut. The dominant parameters for surface roughness are the number of passes and feed rate, while depth of cut has a lesser effect. Increasing the number of passes and feed rate results in higher surface roughness, while MRR increases with increased depth of cut and feed rate. Optimization of EN31 steel parameters yields good surface finish at one pass, a feed rate of 60 mm/min, and a depth of cut of 0.04 mm. Implementing these findings in industries can enhance the lifespan of grinding wheels.

7.2 Future Scope

The analysis of process parameters, understanding of surface grinding process, the potential of artificial neural networks, and future work opportunities can be summarized as follows:

- The application of artificial neural techniques is not limited to surface grinding alone; it can also be extended to cylindrical grinding and other related processes.
- In this experimental work, three parameters were considered, but further expansion can be achieved by incorporating additional parameters such as wheel grade and workpiece speed.
- By exploring different materials or steel alloys, the surface grinding process can be extended to a wider range of applications.
- To gain a comprehensive understanding of surface grinding processes, other parameters like grinding wheel type, power consumption, wheel speed, workpiece hardness, and coolant flow rate can be investigated.
- The study of surface roughness can be expanded to include specimens of varying dimensions, such as different lengths, widths, and thicknesses, without the need for modifications in the machining setup.
- Different ranges of process parameters can be explored on CNC surface grinding machines without requiring adjustments to the parameters or machine setup.

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