*Advanced Production and Industrial Engineering*
*R.M. Singari and P.K. Kankar (Eds.)*

*doi:10.3233/ATDE220811*

# Optimization of Surface Roughness: Effect of Machining Parameters on EN23

KRITI BARNWAL[a], DEEPIKA MISHRA[b] and RAVI SHANKAR PRASAD[b]
[a] *Kisaan Steels Pvt Ltd, Ghaziabad and Research Scholar M Tech, BITs Pilani*
[b] *Department of Mechanical Engineering, JK Lakshmipat University Jaipur*

**Abstract.** EN23 is one of the most commonly used materials to fabricate forging die in Indian industries. The dies are manufactured through machining process and the parameters of the machining process have considerable impact on the roughness value of the material's surface. While forging, it was found that die life varies with the change in the machining parametric value and this took my interest to investigate the area. Speed in rpm, feed in mm/rev, and depth of cut in mm were chosen as the process parameters for the investigation of the machining. Design of experiment was used to know the number of specimens required for proper investigation. Specimens were prepared using a L9 orthogonal array and a full factorial design. The optimal machining parameters were obtained using the Taguchi method. The optimal surface roughness value acquired using the L9 orthogonal array is fairly similar to the value obtained using the full factorial technique, according to a comparison of the results. Additionally, a mathematical tool called ANFIS was used to simulate the optimization process and anticipate the surface roughness values.

**Keywords.** DoE, ANFIS, Machining Parameters, Process Optimization.

## 1. Introduction

Manufacturing through turning, is one of the most commonly used fabricating process to shape metallic materials. While shaping material the quality of the product can be identified mostly due to its dimensional accuracy as well as its surface roughness. In traditional methods, dimensional accuracies were achieved usually due to machine capabilities and operators' skills. With extensive use of CNC machine this limitation has been taken care in modern industries. The surface roughness depends on the machining parametric values and analysis of the process needs a well-defined method. There are various machining parameters that toggles the surface roughness of the machined products and found that the life of the die gets affected significantly. So different machining parametric values were opted to machine materials to get a desired surface roughness value. Surface roughness of high and medium carbon steels is least affected by other factors, such as cutting fluid and cutting tool, etc. [1]. The same can be modelled in ANFIS, which can also be used to find the surface roughness before performing machining.

In order to perform analysis, there is a need to design the experiment to incorporate the variation in the input parameters to obtain the output parametric values. In the current study, the experiment was designed using a full factorial as well as a L9 orthogonal array. A method is necessary to optimise the process since it is highly challenging to determine the ideal combination of input parametric values for which a desired output parametric value can be attained. Taguchi supports to reduce the number of experiment for determining the optimum cutting parameters [2]. Taguchi approach obtaining the optimized cutting parameter gives very close results to full factorial [3].

The orthogonal experiment design and Taguchi approach was used to reduce the variation in the input parameters and enhance the product quality economically [4]. Further research revealed that the effects of speed, feed and depth of cut on the rate of machining are all highly significant [5].

The improvement in the surface finish and force of cutting was obtained through grey-relational analysis (GRA). The experiment was planned using the Taguchi L27 array, and ANOVA was performed to know the significance of the input factors. It was discovered that the interaction between the input parameters did not significantly affect the output parameters, with feed rate, cutting depth, cutting speed, and chrome ratio being the most important input parameters that significantly affected the machining output parameters. [6].

High strength and temperature resistance (HSTR) material's electric discharge machining process's characteristics were optimized using the Taguchi method. The experiment was planned using a L9 orthogonal array, and trials were carried out as a result. Using MINITAB software, the trial data were further examined to get the optimized input parameter values for a better machining rate and good surface finish [7]. Investigations were done into how the surface roughness of pockets affected the machining parameters (speed, feed, Depth of cut, and tool path). The experiment's design made use of the Taguchi L27 orthogonal array. On a vertical milling machine with three axes, trails were done. The MINITAB programme was used to calculate the Taguchi function (Smaller is Better), and it was discovered that tool path has little to no impact on surface roughness. Additionally, it was discovered that optimum levels of the input parameter produce up to 95% accurate results [8].

Additionally, the procedure can be modelled to forecast the outcomes of the optimization process for machining a component. An approach is the adaptive neuro-fuzzy inference system (ANFIS). In a machining operation, the surface roughness value and tool profile were estimated using ANFIS. RSM was used to model the system, and the composite desirability approach was then used to further optimize it (CDA). It was discovered that the result generated by RSM is more distant from the experimental value than the result anticipated using ANFIS. The parameters influencing the surface finish, temperature, and force of cutting were identified using the ANOVA. Feed rate affects surface roughness, while cutting speed affects cutting force, temperature, and feed rate [9]. The roughness of surface and temperature while turning AISI304 stainless steel were predicted using ANFIS based PSO (partial swarm optimization). Fuzzification layer, product layer, normalized layer, rule layer, and output layer are the five layers that make up ANFIS. The ANFIS training technique makes use of the Gaussian membership function. It was discovered that employing ANFIS-based PSO to forecast results is a very effective and potent tool for industrial companies [10]. In order to estimate the brass surface roughness value using the ANFIS model, the milling parametric values of speed, feed, and depth of cut were examined. It was discovered that these values were in good agreement with the measured values, with an average error of 2.75 percent [11]. Using ANFIS, a model was created to obtain the roughness, tool wear ratio, and metal cutting rate of the micro-machining process. Speed, feed, depth of cut, and average grey level were utilized to determine all three outputs with respect to the model's four input parameters. It was discovered that the mathematical tool may be used to get the experimental results [12]. For a cryogenically treated stainless steel insert with other inserts, a relationship between input parameters (feed, DoC, speed) and output parameters (roughness of surface and force of cutting) was established using the ANFIS tool. It was discovered that the predicted results are very close to the experimental data [13]. Studying the impact of various turning factors on the material removing rate and surface roughness of stainless steel 202 revealed that the ANFIS model accurately predicts the output value to within 98 percent of the actual value. [14].

## 2. Work Methodology

In this study, EN23 was selected for investigation since it is preferred, to manufacture gears, bolts, nuts, spindles, etc. It was difficult to find the circular bar in the market therefore 200mm square cross section was purchased. The 200mm square cross section was further converted into 17mm square bar with the extensive use of band saw machine. Further it was converted into circular cross section of 15.5 mm diameter using conventional lathe machine. Further specimens were machined using CNC machine as per the DoE. To verify the material, a tensile test and spectro analysis were performed. Speed, feed and depth of cut were the three parameters chosen for analysis. The L9 array was used to design trials with three levels for each parameter.

As illustrated in figure 1, machined surfaces were examined using a surface roughness testing device (SJ-210 Model), and the parameters are listed in Table 1. To determine the chemical composition of the substance EN23, spectro analysis was performed (as Ti-0.02, Cr-0.02, Si-0.45, Fe-0.22, Cu-0.02, Mn-0.03, Mg-0.5, Zn-0.02, and Al).

**Figure 1.** Digital surface roughness tester-sj-210 model (Mitutoyo).

**Table 1.** Selected Machining Parameters

| Symbol | Parameters | Unit | Levels | | |
|---|---|---|---|---|---|
| | | | 1 | 2 | 3 |
| X1 | Speed | Rpm | 1300 | 1500 | 1700 |
| X2 | Feed | mm/rev | 0.02 | 0.06 | 0.1 |
| X3 | Depth of Cut | Mm | 0.3 | 0.6 | 0.9 |

Experiment was designed to know the minimum number of specimen that were required for analysis of optimization process. Since it is difficult to improve the machine capability, the quality of product can be improved by selecting proper process parametric values [4]. The selection of input parametric values controls the output parametric results by the selection of significant level of controlling factors [15]. The full factorial as well as orthogonal array were used for designing of experiments. The selected input process parameters, levels, and relationship between parameters are required for the design of experiment [16]. Speed, feed, and depth of cut—three levels of each—were considered as the three input parameters for the current experiment.

It has been discovered that practically all potential combinations of the elements and their levels are taken into account in full factorial analysis. In order to consider variation in the surface roughness three readings were taken on each specimen and recorded. The three readings were averaged and used as output results for further analysis. These were contrasted with those of the fractional factorial experiment, which was carried out using the Taguchi method.

**Table 2.** S/N ratios (smaller is better)

| Level | A | B | C |
|---|---|---|---|
| 1 | -35.89 | -32.27 | -34.98 |
| 2 | -32.53 | -34.95 | -31.71 |
| 3 | -35.13 | -36.32 | -36.86 |
| Delta | 3.36 | 4.05 | 5.16 |
| Rank | 3 | 2 | 1 |

**Table 3.** Optimum Value of Factor and their Level

| Parameters | Optimal value | Values |
|---|---|---|
| Speed (v, rpm) | 2 | 1500 |
| Feed (f, mm/rev) | 1 | 0.02 |
| Depth of Cut (t, mm) | 2 | 0.6 |

The S/N ratio was calculated using a smaller-is-better type of control function, and the procedure was optimized for an objective function (Surface Roughness).

Tables 2 and 3 make it clear that the best surface roughness value from the Taguchi analysis was reached at a cutting speed of 1500 rpm, a cut depth of 0.6 mm, and a feed rate of 0.02 mm/rev, which is extremely near to the full factorial result. The comparison demonstrates that the Taguchi approach produces excellent outcomes. Figure 2 shows the response of SN Ratios.

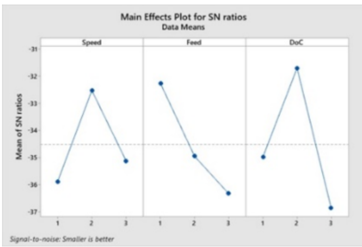
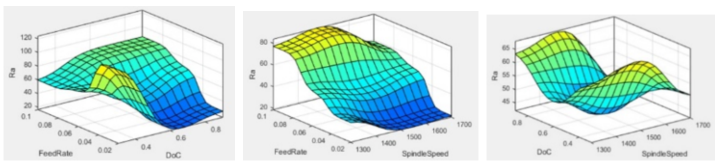



**Figure 2.** Response of SN Ratios.

## 3. Adaptive Neuro-Fuzzy Interference System

In the current work, a tool for investigation is named the adaptive neuro-fuzzy inference system (ANFIS) [17]. ANFIS combines a fuzzy inference system with a neural network and forms a hybrid mathematical tool. The neural network gives the system a sense of flexibility, whereas the fuzzy logic manages its unpredictability. The hybrid system generates a fuzzy rule from the given input and develop a model to predict the output values.

ANFIS was employed in the current study to simulate the machining parameters and forecast surface roughness. The input file for creating the fuzzy interference system (FIS) is the experimental data gathered using the full-factorial technique. This FIS system includes a hybrid optimization method that generated the FIS using 50 epochs with a tolerance of 0.00001. Trapezoidal input and linear output were the two types of membership functions. ANFIS is developed using the FIS output, and experimental data (full-factorial random sample) is used to further test and validate the model. To observe the characteristics with modification in the input parametric values, the ANFIS model was created, model structure was obtained, and a surface plot was generated. There were 27 fuzzy rules, and training was finished at epoch 2 with a training error of 0.0000657. Testing was done when training was finished. The 30% of experimental data that was utilized served the intended objective. An average testing error of 0.0000590 was discovered. Figure 3a depicts the plot of surface roughness against feed rate and DoC. Figure 3b depicts the relationship between feed rate and spindle speed and surface roughness. Figure 3c displays the plot of surface roughness against DoC and spindle speed.




a b c

**Figure 3.** Variation of Ra using ANFIS Model with variation in (a) Feed & DoC, (b) Feed & Speed and (c) DoC & Speed.

## 4. Result and Discussion

The experiments were conducted using full factorial data and surface roughness (in microinch) were measured. The surface roughness value varies from 124.02 to 16.40 microinch. The process was optimized using taguchi method to minimize the number of samples required to test. It was found that the optimized surface roughness value was 18.95 and very close to the roughness value obtained through full factorial.

ANFIS tool was used to validate the data obtained from full factorial and L9 orthogonal array. It was found that the roughness value predicted using ANFIS model is 16.40 (for 1300 rpm, 0.02 mm/rev, 0.9 mm) and 19 (for 1500 rpm, 0.02 mm/rev, 0.6 mm) respectively for full factorial and Taguchi method.

## 5. Conclusion

It was found that the reduced number of specimens are required to perform the Taguchi analysis. The obtained surface roughness value using Taguchi analysis is very close to the minimum surface roughness value obtained using full factorial method. The surface roughness value obtained through Taguchi analysis differs by 2.55 approximately (within 15%) from that obtained using full factorial method. The roughness value predicted using ANFIS tool is quite close to that obtained through Taguchi analysis and lie within 0.26%. Therefore, the Taguchi method can be used to obtain the optimized parametric roughness value and ANFIS tool can be used to predict the roughness values very close to the optimized results.

## References

[1] M. Kumar Verma and A. Srivastava, "Investigation about machining issues in turning process of EN-31 steel," *Mater. Today Proc.*, vol. 50, pp. 2361–2364, 2022, doi: 10.1016/j.matpr.2021.10.238.

[2] I. Asiltürk and H. Akkuş, "Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method," *Meas. J. Int. Meas. Confed.*, vol. 44, no. 9, pp. 1697–1704, 2011, doi: 10.1016/j.measurement.2011.07.003.

[3] S. Gurugubelli, R. B. R. Chekuri, and R. V. Penmetsa, "Experimental investigation and optimization of turning process of EN8 steel using Taguchi L9 orthogonal array," *Mater. Today Proc.*, no. xxxx, pp. 1–5, 2022, doi: 10.1016/j.matpr.2022.01.474.

[4] P. J. Ross, *Taguchi Techniques for Quality Engineering, 2nd Edition*. McGraw-Hill, 2017.

[5] M. Mia, P. R. Dey, M. S. Hossain, T. Arafat, S. Ullah, and S. M. T. Zobaer, "Taguchi S/N based optimization of machining parameters for surface roughness, tool wear and material removal rate in hard turning under MQL cutting condition," *Measurement*, 2018, doi: 10.1016/j.measurement.2018.02.016.

[6] A. Kalyon, M. Günay, and D. Özyürek, "Application of grey relational analysis based on Taguchi method for optimizing machining parameters in hard turning of high chrome cast iron," *Adv. Manuf.*, vol. 6, no. 4, pp. 419–429, 2018, doi: 10.1007/s40436-018-0231-z.

[7] N. Nagaraju, R. Surya Prakash, G. Venkata Ajay Kumar, and N. G. Ujwala, "Optimization of Electrical Discharge Machining Process parameters for 17-7 PH Stainless Steel by using Taguchi Technique," *Mater. Today Proc.*, vol. 24, pp. 1541–1551, 2020, doi: 10.1016/j.matpr.2020.04.474.

[8] A. M. Pinar, "Optimization of Process Parameters with Minimum Surface Roughness in the Pocket Machining of AA5083 Aluminum Alloy via Taguchi Method," *Arab. J. Sci. Eng.*, vol. 38, no. 3, pp. 705–714, 2013, doi: 10.1007/s13369-012-0372-5.

[9] M. K. Gupta *et al.*, "Modeling and performance evaluation of Al2O3, MoS2 and graphite nanoparticle-assisted MQL in turning titanium alloy: an intelligent approach," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 42, no. 4, pp. 1–21, 2020, doi: 10.1007/s40430-020-2256-z.

[10] M. Aydin, C. Karakuzu, M. Uçar, A. Cengiz, and M. A. Çavuşlu, "Prediction of surface roughness and cutting zone temperature in dry turning processes of AISI304 stainless steel using ANFIS with PSO learning," *Int. J. Adv. Manuf. Technol.*, vol. 67, no. 1–4, pp. 957–967, 2013, doi: 10.1007/s00170-012-4540-2.

[11] I. Maher, M. E. H. Eltaib, A. A. D. Sarhan, and R. M. El-Zahry, "Investigation of the effect of machining parameters on the surface quality of machined brass (60/40) in CNC end milling - ANFIS modeling," *Int. J. Adv. Manuf. Technol.*, vol. 74, no. 1–4, pp. 531–537, 2014, doi: 10.1007/s00170-014-6016-z.

[12] S. Palani, U. Natarajan, and M. Chellamalai, "On-line prediction of micro-turning multi-response variables by machine vision system using adaptive neuro-fuzzy inference system (ANFIS)," *Mach. Vis. Appl.*, vol. 24, no. 1, pp. 19–32, 2013, doi: 10.1007/s00138-011-0378-0.

[13] N. Manikandan, K. Balasubramanian, D. Palanisamy, P. M. Gopal, D. Arulkirubakaran, and J. S. Binoj, "Machinability Analysis and ANFIS modelling on Advanced Machining of Hybrid Metal Matrix Composites for Aerospace Applications," *Mater. Manuf. Process.*, vol. 34, no. 16, pp. 1866–1881, 2019, doi: 10.1080/10426914.2019.1689264.

[14] I. Shivakoti, G. Kibria, P. M. Pradhan, B. B. Pradhan, and A. Sharma, "ANFIS based prediction and parametric analysis during turning operation of stainless steel 202," *Mater. Manuf. Process.*, vol. 34, no. 1, pp. 112–121, 2019, doi: 10.1080/10426914.2018.1512134.

[15] M. S. Phadke, *Quality Engineering Using Robust Design 1st*, 1st ed. Prentice Hall PTR Upper Saddle River, NJ, USA ©1995.

[16] D. Vijayan and V. Seshagiri Rao, "Parametric optimization of friction stir welding process of age hardenable aluminum alloys−ANFIS modeling," *J. Cent. South Univ.*, vol. 23, no. 8, pp. 1847–1857, 2016, doi: 10.1007/s11771-016-3239-1.

[17] E. M. Jyh-Shingh Roger Jang, Chuen Tsai-Sun, *Neuro Fuzzy and Soft Computing- A Computational Approach to Learning and Machine Intelligence*. Prentice-Hall of India Private Limited, New Delhi, 1997.