Assessment of Surface Integrity in Diamond Grinding – Based Hybrid Machining of Tungsten Free Carbide based Hard Metal

Jayant Kumar Jha¹,a, S. K. Jha¹,b

¹Division of Manufacturing Processes and Automation Engineering, Netaji Subhas Institute of Technology, Delhi University, New Delhi, India

Email -  a jayantjha90@gmail.com,  b skjha63@rediffmail.com

Abstract. Hybrid machining process comprises of applying at least two process components all the while or successively in synergistic way to improve the machining performance. One such machining process is diamond grinding in presence of high frequency electric sparks. This process is all about making trade-off between surface finish and process efficiency. This paper attempts to model the surface roughness using artificial neural network with supervised learning in which back propagation algorithm is used for minimizing error and estimation of adaptive weights. Experimental data for machining of TN20 Russian grade cermet is used for development of neural network.

Keywords: Electro-spar Machining, Grinding, Surface Roughness, Artificial Neural Network (ANN)

1. Introduction

Owing to the progress in the field of advance materials or tool materials with high retention of strength and other properties even at raised temperature, high hardness and their superb wear opposition attributes represents a challenge in machining process. Traditional machining is inadequate for machining of these materials. It is difficult to machine complicated shapes like a turbine blades and blind hole cavity with reasonable accuracy with traditional machining processes. Grinding appears to be one of the solutions from the class of conventional material processing techniques but grinding of very hard material still poses a problem due to requirement of high normal forces [1]. As these forces getting larger and larger, more the material gets susceptible for lateral cracks due to this grinding of these material considered to be done at moderate parameter settings. Lowering of these parameter setting causes low material removal rate. Therefore, it is necessary to find such methods in which materials resistivity to deform or materials can be made softer while grinding concurrently. One such method has been developed by combining grinding and electro-sparks process synergistically. This process is named by various names in the available literatures such as Abrasive electro-discharge grinding (AEDG) by Kozak [2]. Similarly, Koshy et al [3] and Lee and Ahn [4] called these process as Electro-discharge diamond grinding (EDDG) and In-process electro-discharge dressing (IEDD) respectively. From understanding point of view these process remains same as material removal occurs due to mechanical action or to be precise abrasive action of the grinding wheel in which
abrasives are embedded into the surface while high frequency electric sparks plays more of supporting role. There are two possibilities by these processes can be conceptualized. In first possibility, workpiece is integral part of the electrical circuitry whereas in second configuration, separate electrode is being used for dressing of the grinding wheel i.e. workpiece is not being part of the electrical circuitry or in another advantage of this process is workpiece need not to be electrically conductive. Another advantage of second configuration is that material removal occurs completely due to abrasive action of grinding i.e. electric sparks take part in material removal negligibly. Disadvantages associated with second configuration is that another electrode is needed for the processing and high amount of grinding normal forces comes into play. In first configuration, lower grinding normal forces led us increase in protrusion height. It has been observed that application of electric spark led us to increase grain protrusion height. This can be achieved up to 60% of grinding grain size where as in case of pure grinding it is significantly lower [3] and [5]. Electric sparks between grinding wheel and workpiece can only be generated when interelectrode gap (IEG) is lower than that of the ionization potential of dielectric medium. Due to ionization of dielectric medium localized temperature in the vicinity of electric sparks create a plasma channel which melts and vaporizes the workpiece material in the form of crater. One thing to note that material removal due to grinding occur only when the protrusion height is greater than interelectrode gap (IEG).

![Diagram](image.png)

**Figure 1.** (a) Workpiece is part of the electric Circuit (b) Separate electrode used for Dressing [6]

1 – Spindle, 2 – Grinding Wheel, 3 - Workpiece, 4 – Separate Dressing Electrode

Rahim et al., [7] compared the pure grinding and electro-discharge grinding with respect to tool quality and performance measure such as surface roughness for the machining of Poly crystalline diamond (PCD). Albeit strikingly comparable surface roughness and tool edge sharpness were found to be similar but residual stress and graphitization differs in both the process. The parameters selected for analysis are open circuit voltage, current, pulse duration, grinding wheel velocity and in feed or
depth of cut. Lata, Rana and Walia, [8] presents the experimental study based on Taguchi orthogonal array on machining of High carbon alloy steel for material removal rate (MRR), Surface roughness (Ra) and Tool wear (TW). Process parameter were under consideration are current, different abrasive tool and cutting time. Yadav, Singh and Kumar, 2011 [9] experimented on High Speed Steel with parameter such as grinding wheel rotational speed (RPM), current, pulse on time and duty cycle to estimate the optimization of Wheel Wear rate (WWR), Material Removal rate (MRR) and Surface roughness (Ra).

2. Experimentation

2.1. Experimental Detail

Experimentation was conducted using universal cutting grinder, Russian trademark 3D642E, was tweaked to work in such a way that grinding wheel was connected to positive pole of the electric circuit whereas conductive workpiece was connected with negative pole schematic for that is shown in figure 2. Custom designed pulse generator was used for source of power supply. Out of two Electrospark diamond grinding configurations mentioned above, we maintained that workpiece is inclusive of the electrical circuitry i.e. grinding and EDM action occur simultaneously. Tap water and small chunk of soda was used as dielectric medium. In this paper, an analysis for surface integrity is considered after machining of Tungsten free hard metal. There is various criterion or aspects for assessing such as residual stresses, hardness, cracks, waviness, surface roughness etc. Out of all these one of most popular surface integrity characteristics for judging the surface integrity is surface roughness. In this literature, surface roughness is considered for analysis of surface integrity due to its importance. Surface roughness measurement was done using SURTRONIC 3 PLUS by Taylor Hobson.

Figure 2. Schematic Diagram of EDDG process [10]
Grinding wheel of flaring cup-shaped was based on bronze alloy having synthetic diamond embedded into the grinding wheel body was used for performing the experimentation. Designation of grinding wheel was $12A2-45^\circ$ AC6, 100/80 M1-01 – 100 which is based on USSR standards. $12A2-45^\circ$ stands for model of the grinding wheel where 12 stands for designation of shape of the wheel core i.e. cup-shaped wheel, A represents designation of the shape of the diamond layer, 2 represents designation of diamond layer location i.e. side of the wheel [11]. For better understanding please see figure 2. AC6 stands for synthetic diamond with strength of 6 N, 100/80 provides the USSR mesh size which gives the grit dimensions is of 90 µm and M1-01 – 100 stands for metal bond and diamond concentration of 100 %. Further, diamond embedded grinding wheel specification and dimensions are provided in Table 1.

![Cup shaped Grinding Wheel](image)

Table 1. Diamond Embedded Grinding Wheel Specification

| S.no | Bonding          | Mesh Number (USSR) | Diameter of Grinding Wheel (mm) | Width (mm) |
|------|------------------|--------------------|---------------------------------|------------|
| 1    | Bronze based alloy | 100/80             | 150                             | 10         |

2.2. Workpiece material

Hard metals or cermet are basically composite material often designated as ceramic and carbide composites due to that they possess excellent mechanical properties such as strength, hardness, and ability to retain its properties at elevated temperature, they are extensively used in cutting tool production. Hard metals or cermet usually classified into two categories, namely cemented carbides (WC based composites) and TiCN based composites, in which either ceramic or refractory material dispersed though metal matrix so that these ceramic fibres imparts refractory type characteristics. Converse is also true in which metal can be reinforced into ceramic matrix to impart metal like characteristics into ceramic materials. This name cermet derives from the fact that these composites are made up of ceramic (cer) and metals (met). TiC-, TiN- or TiCN based hard metals or cermet called as tungsten free carbide. Their properties belong in the range of tungsten carbide to ceramics. In this work, workpiece material was selected from Russian Hard metals or cermet, designated as TN20 i.e. Titanium carbide-based cermet for experimentation. This material is one of common tool material for cutting operations. Dimensions and Properties of the workpiece are as follows in Table 2 and Table 3 respectively:

![Dimension of Workpiece](image)

Table 2. Dimension of Workpiece

|                     | 16.5 mm |
|---------------------|---------|
| Length              |         |
| Height              | 16.5 mm |
| Thickness           | 5.25 mm |
Table 3. Composition and Mechanical Properties of TN20

| Composition (Wt. %) | Properties          |
|---------------------|---------------------|
| TiC                 | Density $(10^3 \text{kg/m}^3)$ | Transverse rupture strength (GPa) | Hardness (HRA) | Elastic Modulus (GPa) |
| 79                  | 5                   | 1.1                  | 91              | 413                   |

3. Neural Network
Prediction using Artificial neural network (ANN) technique seems to be a good strategy due to its capability to predict complex dependency between target variable and feature variable in comparison to linear and exponential regression models. Neural Network consists of several node imitating neuron analogous to biological neuron. Neuron or node connected to each other via adaptive weights parallelly. These weights adapt such that error cost function is minimized with iterations. Another advantage of neural network is that it can handle imprecise data or incomplete data as well. Even after becoming a popular method, artificial neural network application in electro-spark diamond grinding is scarce. Unune and Mali [12] applied artificial neural network (ANN) and response surface methodology (RSM) technique for material removal rate (MRR) and Surface Roughness (Ra) in machining of Inconel 718 with electro-discharge diamond grinding (EDDG). They compared results obtained from neural network and response surface method and found that ANN gives better prediction as comparison to RSM model. Furthermore, Unune, Nirala and Mali [13] developed an artificial neural network (ANN) and Response surface methodology (RSM) for machining of Monel K-500 with abrasive mixed electro-discharge diamond grinding (AMEDDG). In this literature, further control parameter is been optimized using non-dominated sorted genetic algorithm (NASGA). Dubey, Srivastava and Srivastava developed a software for computer aided hybrid neural network genetic algorithm for optimization of process parameters. Furthermore, this developed model is applied on experimental data from literature [14] for machining of High-Speed Steel with Electro-discharge diamond grinding. In this paper, an artificial neural network is trained to predict the surface roughness in electro-spark diamond grinding. For that experiment was conducted and data was prepared on the basis of experiment results. Current, pulse on time, grinding wheel speed and depth is considered as process parameters. Experiments was conducted on three levels in each process parameter is shown in table 4. Neural Networks modelling is done using Jupyter Notebook with python kernel. For data processing and mathematical operations done using Pandas and NumPy libraries whereas plotting was done using Seaborn and Matplotlib libraries. Neural Network modelling can be divided into three segments: Data preparation, training of neural network and prediction of surface roughness using developed model using test data.

Table 4. Process parameters levels

| Parameters                  | Levels |
|-----------------------------|--------|
| Current (A)                 | 4      | 5      | 6      |
| Pulse on Time (µs)          | 7.6    | 11     | 23     |
| Grinding wheel Speed (m/s)  | 15     | 20     | 35     |
| Depth of cut (mm)           | 0.36   | 0.38   | 0.40   |

3.1. Data Processing
Training data and Test data is prepared with respect to experimental data. Total 81 experiments were conducted based on different process parameters setting as of table 4. For the training of neural
network 65 randomized observations was used for training of neural network and 16 observations used to test the neural network i.e. 80% data is used for training the neural network and 20% data is used for testing of the neural network. Further, data is normalized to minimize the error propagation and speedily convergence of gradient descent while training neural network. Normalization equation is given by

\[
y = \frac{x - x_{\text{mean}}}{x_{\text{max}} - x_{\text{min}}}
\]

Where, \(x\) = value of input vector at any instance, \(x_{\text{mean}}\) = mean value of \(x\) vector \(x_{\text{max}}\) = Maximum value in \(x\) vector, \(x_{\text{min}}\) = minimum value in \(x\) vector

### 3.2. Training of Neural Network

In this paper, three layered architecture in which first layer is input layer having four neurons which imitates parameters Current, Pulse on time, grinding wheel speed and depth of cut is considered. To find optimum number of hidden layer neurons, neural network is trained by changing number of hidden layer neurons from 1 to 10 number hidden layer neuron and mean square error is computed in each case, it was found that optimum number of hidden neurons for training of neural network is found to be 5 with mean square error of 5.2%.

Neural Network is trained using backpropagation network for quick learning of adaptive weights. Sigmoid function used as activation function. Sigmoid function is given by

\[
h_w(x) = \frac{1}{1 + e^{-w x}}
\]

Where \(w\) is the weight matrix, \(x\) = input vector from preceding layer, and \(h_w(x)\) = output layer for succeeding layer (can be scaler or vector depends on the number of output neurons). While training the neurons error in cost function is minimized using backpropagation algorithm in which output layer value is compared with experimental value of surface roughness. This error is then backpropagated for adjusting of weights so that error can be minimized iteratively.
The error cost function is

\[ \text{Mean Squared Error (MSE)} = \frac{1}{N} \sum_{i=1}^{N} (h_w(x) - y)^2 \]

Where \( N \) = Number of training data, \( y \) = experimental data or actual data.

After running through 50,000 iterations, mean squared error was found to be 0.052460. In figure 6, a bar plot is plotted with predicted surface roughness and experimental surface roughness for test dataset. It can be found to predicted data conform to experimental data most of the time.

4. Results and Discussion

It has been observed that at higher depth of cut, surface roughness (Ra) increases because at higher depth of cut higher chip thickness will be achieved which is in line with drawn conclusion from [15]. Surface roughness (Ra) increases with higher current density whereas pulse on time is not having significant effect on surface roughness. At higher current, due to increase in spark energy larger crater would be formed at workpiece surface as it can be seen from experimental data that with the increase in pulse on time, surface roughness decreases slightly. This is due to that fact that at higher pulse on time leads to higher exposure of spark energy at workpiece surface. Absolute Maximum error and absolute minimum error while predicting surface roughness is about 9.83% and minimum error was found to be 0.13% respectively.
So, from the above discussion and experimentation, it can be seen that surface roughness is increased due to increase grinding wheel velocity, current and depth of cut whereas increase in pulse on time lead to slight decrease in surface roughness.

5. Conclusion
In this paper, artificial neural network is created for prediction of surface roughness in electro-spark diamond grinding. Artificial neural network can easily learn the pattern hidden inside the experimental data and from that it can predict surface roughness for given parameters. In this paper, predicted surface roughness from the neural network is very close to experimentally measured data as calculated error between them 13% to 0.09%. Furthermore, this model can be made more accurate by finding weights on neuron by using other optimization techniques and heuristic optimization technique such as genetic algorithm (GA), particle swarm optimization etc for future course of action.

Acknowledgments
The authors wish to thank colleagues from the Integrated Technology of Machine Building Named after M. F. Semko (Formerly Material cutting Department) of National Technical University “Kharkov Polytechnic Institute”, Ukraine, erstwhile USSR for their support and cooperation during the course of this work.

References
[1] I. Inasaki, "Grinding of Hard and Brittle Materials," CIRP Annals, vol. 36, no. 2, pp. 463-471, 1987/01/01/ 1987.
[2] J. Kozak, Abrasive electrodischarge grinding (AEDG) of advanced materials. 2002, pp. 83-101.
[3] P. Koshy, V. K. Jain, and G. K. Lal, "Mechanism of material removal in electrical discharge diamond grinding," International Journal of Machine Tools and Manufacture, vol. 36, no. 10, pp. 1173-1185, 1996/10/01/ 1996.
[4] E.-S. Lee and S.-O. Ahn, "Precision surface grinding of Mn–Zn ferrite with in-process electro-discharge dressing (IEDD)," *International Journal of Machine Tools and Manufacture*, vol. 39, no. 10, pp. 1655-1671, 1999/10/01/ 1999.

[5] J. A. Sanchez, N. Ortega, L. N. Lopez de Lacalle, A. Lamikiz, and J. A. Marañon, "Analysis of the electro discharge dressing (EDD) process of large-grit size cBN grinding wheels," *The International Journal of Advanced Manufacturing Technology*, journal article vol. 29, no. 7, pp. 688-694, July 01 2006.

[6] E. Y. Grodzinskii and L. S. Zubotova, "Electrochemical and electrical discharge abrasive machining," *Sov. Eng. Res.*, vol. 2, no. (3), pp. 90-92, 1982.

[7] M. Z. Rahim, G. Li, S. Ding, J. Mo, and M. Brandt, "Electrical discharge grinding versus abrasive grinding in polycrystalline diamond machining—tool quality and performance analysis," *The International Journal of Advanced Manufacturing Technology*, journal article vol. 85, no. 1, pp. 263-277, July 01 2016.

[8] R. Rana, R. S. Walia, and S. Lata, "Development and Investigation of Hybrid Electric Discharge Machining Electrode Process," *Materials Today: Proceedings*, vol. 5, no. 2, Part 1, pp. 3936-3942, 2018/01/01/ 2018.

[9] G. K. Singh, V. Yadava, and R. Kumar, "Experimental study and parameter optimisation of electro-discharge diamond face grinding," *International Journal of Abrasive Technology*, vol. 4, no. 1, pp. 14-40, 2011.

[10] S. K. Jha, "Pobisheniye Rabotasposovnoschi Almaznikh Krugov Pychyom Stabilizatsii Uslovii Vzaimodeistviya Ekh s Obrabativayemym Materialom," Phd Thesis Phd Thesis, Kharkov StatePolytechnical University, Kharkov, Ukraine, 1992.

[11] (2018, 26.08.2018). *Poltava Diamond Tools Catalogue*. Available: [http://poltavadiamond.com.ua/en/site/content/products](http://poltavadiamond.com.ua/en/site/content/products)

[12] D. R. Unune and H. S. Mali, "Artificial neural network–based and response surface methodology–based predictive models for material removal rate and surface roughness during electro-discharge diamond grinding of Inconel 718," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 230, no. 11, pp. 2082-2091, 2016.

[13] D. R. Unune, C. K. Nirala, and H. S. Mali, "ANN-NSGA-II dual approach for modeling and optimization in abrasive mixed electro discharge diamond grinding of Monel K-500," *Engineering Science and Technology, an International Journal*, vol. 21, no. 3, pp. 322-329, 2018/06/01/ 2018.

[14] V. K. Jain and R. G. Mote, "On the temperature and specific energy during electrodischarge diamond grinding (EDDG)," *The International Journal of Advanced Manufacturing Technology*, journal article vol. 26, no. 1, pp. 56-67, July 01 2005.

[15] S. Agarwal and P. Venkateswara Rao, "Modeling and prediction of surface roughness in ceramic grinding," *International Journal of Machine Tools and Manufacture*, vol. 50, no. 12, pp. 1065-1076, 2010/12/01/ 2010.