

# ANN Approach for Modelling Parameters in Drilling Operation

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## Abstract

Drilling is one of the most widely used machining operations in industries. The general problems that occur in drilling are poor surface roughness and ovality. In this article efforts are made to reduce the above said problems while drilling 6mm hole in brass plate with the help of Artificial Neural Network (ANN) modelling technique and Genetic Algorithm (GA) optimization technique. It was found that proper parameters selection plays a vital role in reducing the surface roughness and ovality errors. Brass plates are widely used in manufacturing of couplings, while manufacturing it, there is need to make holes of diameter 6mm. Thus the results found in this work will be helpful for coupling manufacturing industries to improve the quality of drilled holes.

**Keywords:** ANN, Brass, Drilling, GA, Ovality, Surface Roughness

## 1. Introduction

Brass alloys have been extensively used in automotive, electronic, energy, construction and marine applications by virtue of their corrosion resistance in non-acidic environments, good mechanical properties and fabric ability, high thermal and electrical conductivity and low cost. Brass plate with drilled holes is used in building lock. The general machining parameters considered in drilling operations are spindle speed and feed rate. Optimization must be done to increase the material removal as well as to improve the whole quality. Authors in their work<sup>1</sup> stated that the effort to reduce operating costs and improve the quality of manufactured parts leads to the introduction of on-line monitoring of machining operations, which significantly contributes to improving the quality of manufactured parts as well as reducing the total cost of production. In spite of that monitoring the hole making process is still unresolved problem in industrial practice.

Surface roughness, often shortened to roughness, is a measure of the texture of a surface. It is quantified by the vertical deviations of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small the surface is smooth<sup>2</sup>. The surface roughness and hardness of brass components are improved with the aid of a burnishing process, under different forces and number of tool passes. In addition, they observed that such processes can also improve the wear resistance of the brass components and studied the effect of burnishing force and velocity on the wear characteristics of the same alloy<sup>3</sup>. Learning procedures for predicting surface roughness with neural networks was proposed. Tool wear is an important factor which affects the surface roughness of drilled holes. Tool wear is the gradual failure of cutting tools due to regular operation. Tool wear can be caused when the spindle speed is low or feed rate is high<sup>4</sup>. A model was developed to predict drill wear using an artificial neural network and they successfully controlled

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the tool wear by optimizing various parameters such as feed rate, spindle speed, thrust force and torque. The chip flow angle largely affects the surface finish. Chip flow angle is the angle through which the chip flows over the work piece<sup>5</sup>. Developed a model to predict chip flow angle in orthogonal turning of mild steel by neural network approach and they concluded that decreasing feed or tool nose radius decreases the chip flow angle<sup>6</sup>. The surface roughness height  $R_a$  and  $R_t$  of turned surfaces are found by varying tool insert, work piece material, tool nose radius, rake angle, depth of cut, spindle speed, feed rate and they concluded that ANN can be used for predicting surface roughness. Vertical and horizontal diameter of the drilled hole varies slightly which in turn leads to problem in assembly. Ovality is the degree of deviation from perfect circularity of the cross section of the core or cladding of the fiber<sup>7</sup>. A model was developed to predict the magnitude of the error due to eccentricity of a hole in the biaxial residual stress field and they found that the results of ANN shows good agreement with FEA. Genetic algorithm is a search algorithm, which relies on analogies to natural processes, based on the principles of evolution and hereditary. Such systems maintain a population of potential solutions they have some selection processes based on fitness of individuals, and some recombination operators. One type of evolutionary search is Genetic Algorithm (GA). GAs are a random evolutionary search algorithm that mimics the principle of natural genetics. One way of searching in a large space is to pick solutions at random. This is an aimless unless the samples picked are used to guide further research. This is the basic principle of GA, which maintains a whole family of solutions in parallel.

To optimize drilling sequence a model developed by genetic algorithm and they used genetic algorithm for Total Sales man Problem (TSP) to reduce the total time and distance of tool travel for drilling sequence.<sup>8</sup> Nowadays glass materials are used for so many purposes but machining of glass materials costs much hence the machining parameters should be optimized to reduce the costs of drilling of glass materials. The authors have<sup>9</sup> successfully implemented ANN for modelling machining parameters in drilling operations and compared the results of genetic algorithm and particle swarm optimization. The results indicated that the model can be effectively used for predicting the machining conditions yielding the minimum cost of operation. ANN was successfully implemented in modelling flow parameters of heat exchangers.<sup>10</sup>

## 2. Experimental Setup

The experiments were conducted based on design of experiments concept. The factors considered for this work were spindle speed and feed rate. The experiments were carried out in CNC milling machine. To conduct the experiment, the work material brass was cut in to plates of thickness 10mm. The work piece was held in a rigid fixture attached to the dynamometer, which is mounted on the machining table. The high speed steel tool was held in collet chuck and separate tools were used for each individual hole. The selected machining parameters for various spindle speed and various feed rate are tabulated in Table 1. The spindle speeds used are 4540, 2270, 1860 and the feed rates used are 0.038, 0.076, and 0.203. The experiments were conducted based on box behnken method.

## 3. Results and Discussion

The experimental values were fed to neural power software. 80% of the data were taken for training and 20% of data were taken for validation and testing. The ovality and surface roughness values were predicted based on backpropagation algorithm. Table 2. and Table 3. shows that the difference

**Table 1.** Experimental Run values

| Hole no | Spindle speed (rpm) | Feed (mm/rev) | Surface roughness ( $\mu\text{m}$ ) | Ovality (mm) |
|---------|---------------------|---------------|-------------------------------------|--------------|
| 1       | 4540                | 0.203         | 1.01                                | 0.42         |
| 2       | 4540                | 0.038         | 1.32                                | 0.11         |
| 3       | 4540                | 0.076         | 2.08                                | 0.39         |
| 4       | 4540                | 0.076         | 1.12                                | 0.45         |
| 5       | 2270                | 0.076         | 2.46                                | 0.38         |
| 6       | 2270                | 0.076         | 1.6                                 | 0.32         |
| 7       | 2270                | 0.076         | 1.25                                | 0.15         |
| 8       | 2270                | 0.076         | 3.16                                | 0.05         |
| 9       | 2270                | 0.076         | 1.78                                | 0.39         |
| 10      | 2270                | 0.038         | 0.78                                | 0.31         |
| 11      | 2270                | 0.038         | 1.12                                | 0.03         |
| 12      | 2270                | 0.203         | 1.72                                | 0.01         |
| 13      | 2270                | 0.203         | 2.05                                | 0.35         |
| 14      | 1860                | 0.203         | 3.39                                | 0.3          |
| 15      | 1860                | 0.038         | 2.24                                | 0.04         |
| 16      | 1860                | 0.076         | 1.58                                | 0.05         |
| 17      | 1860                | 0.076         | 3.72                                | 0.04         |

**Table 2.** Difference between observed and calculated values using ANN

| Ovality  |            |            |
|----------|------------|------------|
| OBSERVED | CALCULATED | DIFFERENCE |
| 0.42     | 0.45       | 0.03       |
| 0.11     | 0.19       | 0.08       |
| 0.39     | 0.42       | 0.03       |
| 0.45     | 0.42       | 0.03       |
| 0.38     | 0.258      | 0.122      |
| 0.32     | 0.258      | 0.062      |
| 0.15     | 0.258      | 0.108      |
| 0.05     | 0.258      | 0.208      |
| 0.39     | 0.258      | 0.132      |
| 0.31     | 0.17       | 0.14       |
| 0.03     | 0.17       | 0.14       |
| 0.01     | 0.18       | 0.17       |
| 0.35     | 0.18       | 0.17       |
| 0.3      | 0.3        | 3.14       |

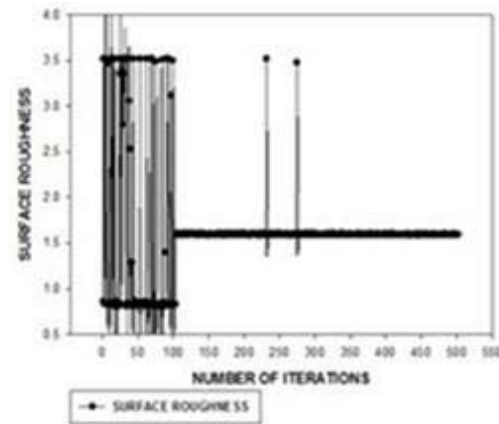
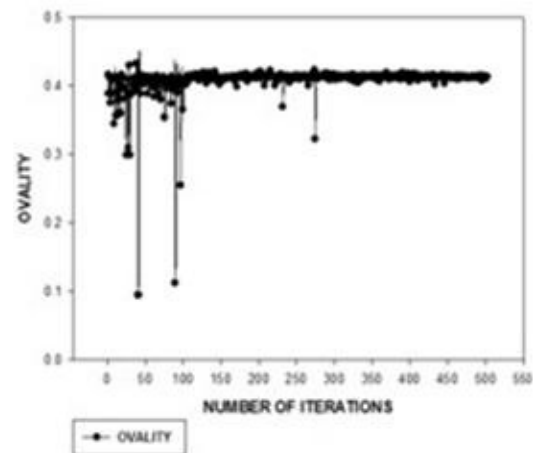
**Table 3.** Difference between observed and calculated values using ANN

| Surface roughness |            |            |
|-------------------|------------|------------|
| OBSERVED          | CALCULATED | DIFFERENCE |
| 1.01              | 0.97       | 0.04       |
| 1.32              | 1.12       | 0.20       |
| 2.08              | 1.6        | 0.48       |
| 1.12              | 1.6        | 0.48       |
| 2.46              | 2.05       | 0.41       |
| 1.6               | 2.05       | 0.45       |
| 1.25              | 2.05       | 0.8        |
| 3.16              | 2.05       | 1.11       |
| 1.78              | 2.05       | 0.27       |
| 0.78              | 0.95       | 0.17       |
| 1.12              | 0.95       | 0.17       |
| 1.72              | 1.885      | 0.165      |
| 2.05              | 1.885      | 0.165      |
| 3.39              | 3.39       | 1.11       |

between observed and calculated ovality, surface roughness values. The optimal machining parameters were obtained using GA and the values are shown in Table 4. and Figure 1. was obtained by using GA and it shows the variations of surface roughness with respect to number of iterations. The variations of ovality with respect to number of iterations are shown in Figure 2.

**Table 4.** optimized values obtained from GA

| MACHINING PARAMETERS                | OPTIMIZED VALUE | ITERATION NUMBER | SPEED (rpm) | FEED (mm/rev) |
|-------------------------------------|-----------------|------------------|-------------|---------------|
| OVALITY (mm)                        | 0.0939          | 41               | 4072.4520   | 0.1993        |
| SURFACE ROUGHNESS ( $\mu\text{m}$ ) | 0.8068          | 24               | 3783.1590   | 0.1936        |

**Figure 1.** Variations of surface roughness.**Figure 2.** Variations ovality against number of iterations.

## 4. Conclusions

- Spindle speed and feed value mainly affects the quality and production rate in drilling operation.
- ANN modelling technique can be effectively used for modelling machining parameters in drilling operations.
- Genetic Algorithm can be effectively used for optimizing machining parameters in drilling operations.

- For drilling 6 mm hole in brass in using CNC vertical milling machine the best spindle speed and feed for surface ovality are 4072.4520(rpm) and 0.1993(mm/rev).
- For drilling 6 mm hole in brass in using CNC vertical milling machine the best spindle speed and feed for surface Roughness are 3783.1590(rpm) and 0.1936(mm/rev)

## 5. References

1. Munia Raj A, Manoharan N. Experimental investigation and analysis of torque in drilling Al-15%SiC-4% graphite metal matrix composites using response surface methodology. *Indian Journal of Science and Technology*. 2014 Oct; 7(S6):87-94.
2. Al-Dhifi SZS. Improvement in the wear resistance of brass components by the ball burnishing process. *Journal of Materials Processing Technology*. 1999; 96(1-3):73-80.
3. Asilturk I. Predicting surface roughness of hardened AISI 1040 based on cutting parameters using neural network and multiple regression. *International Journal of Advanced Manuf. Technol*. 2012; 63(1-4):249-57.
4. Singh AK, Panda SS, Pal SK, Chakraborty D. Predicting drill wear using an artificial neural network. *International Journal of Advanced Manufacturing Technology*. 2006; 28(5-6):456-62.
5. Kiyak M, Altan M, Altan E. Prediction of chip flow angle in orthogonal turning of mild steel by neural network approach. *International Journal of Advanced Manufacturing Technology*. 2007; 33(3-4):251-9.
6. Zhong ZW, Khoo LP, Han ST. Prediction of surface roughness of turned surfaces using neural networks. *International Journal of Advanced Manufacturing Technology*. 2006; 28(7-8):688-93.
7. Kim C, Yang W-H. Prediction of error due to eccentricity of hole in hole drilling method using neural network. *KSME International Journal*. 2002; 16N(11):1359-66.
8. Kumar A, Pachauri P. Optimization drilling sequence by genetic algorithm. *International Journal of Scientific and Research Publications*. 2012 Sep; 2(9):1-7.
9. Kannan DB, Kannan RG. Application of artificial neural network modelling for machining parameter optimization in drilling operation. *International Conference on Advance Manufacturing and Materials Engineering*. 2014; 5:2242-9.
10. Shekar M, Krishna MP, Venkatesan M. Artificial neural network based prediction of pressure drop in heat exchangers. *Indian Journal of Science and Technology*. 2015 May; 8(S9):87-92.