Research Article

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Application of Genetic Algorithm Technique for Machining Parameters Optimization in Drilling of Stainless Steel

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Abstract: This work is aimed at developing relations between the pertinent variables that affect drilling process of stainless steel using artificial neural network. The experiments were conducted on vertical CNC machining centre. The parameters used were spindle speed and feed rate. The effect of machining parameters on entry burr height, exit burr height and surface roughness was experimentally evaluated for different spindle speeds and feed rates. A model was established between the drilling parameters and experimentally obtained data using ANN. The predicted values and measured values are fairly close, which indicates that the developed model can be effectively used to predict the burr height and surface roughness in drilling of stainless steel. Genetic algorithm (GA) technique was used in this work to identify the optimized drilling parameters. Confirmation test was conducted with the optimized parameters and it was found that confirmation test results were similar to that of GA-predicted output values.

Keywords: Drilling, Machining parameters, Artificial neural network, Genetic algorithm

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1 Introduction

Drilling is a key technology in several applications of strategic or societal importance, including exploration for and extraction of oil, gas, geothermal and mineral resources in

- environmental monitoring and remediation
- underground excavation and infrastructure development
- scientific study of the Earth's subsurface
- manufacturing sector

Optimization of machining parameters in drilling operations will help in lowering the costs and improve quality. From the studies presented in [1], it is understood that spindle speed and feed rate are the two important drilling parameters that play a crucial role in controlling the quality of the drilled hole. In drilling operation, surface roughness and burr height are the two important quality parameters that are given utmost importance in most research works. Surface roughness plays an important role in product quality and manufacturing process planning. Surface roughness has been an important design feature and quality measure in many situations, such as parts subject to fatigue loads, precision fits, fastener holes and aesthetic requirements. Furthermore, in addition to tolerances, surface roughness imposes a critical constraint for cutting parameter selection in manufacturing process planning [2]. Burr formation affects work piece accuracy and quality in several ways: dimensional distortion on part edge; challenges to assembly and handling that are caused by burrs in sensitive locations on the work piece; and damage done to the work subsurface from the deformation associated with burr formation [3]. The exit burrs during drilling are the projected materials, which affect the quality of the finished parts. Special tools are necessary to remove burrs formed inside a cavity, and it was estimated that the deburring cost is as high as 30% of the cost of the final product [4]. Thus, it is necessary to control the burr formation at the production stage by selecting the appropriate drilling process parameters. All these factors necessitate an accurate model to predict the effects on stainless steel for a specified combination of drilling process parameters. Owing to the development of multi-response optimization and advanced modelling techniques such as artificial neural network (ANN), it has now become possible to accurately predict the impact of multiple variables. Neural network has the ability to learn from the pattern acquainted before. Once the network has been trained, with sufficient number of sample data sets, it can make predictions, on the basis of its previous learning, about the output related to new input data set of similar pattern [5]. Because of its multidisciplinary nature, ANN is becoming popular among researchers, planners, designers and so on as an effective tool for the accomplishment of their work. Therefore, ANN is being successfully used in many industrial areas as well as in research works. ANN model has superiority in solving problems in which many complex parameters influence the process and results, when process and results are not fully understood and where historical or experimental data are available.

Huang and Chen [6] successfully developed an ANN model to predict surface roughness from a given set of experimental data. Singh *et al.* [7] proposed a model to formulate tool wear using ANN. The selection of optimal machining parameters plays an important part in computer-aided manufacturing. The direct search method is one of the most popular mathematical optimization methods. It computes the first derivative of an objective function and sets it to zero, where the function becomes a maximum or minimum. The second derivative of the objective function is then used to determine the maxima or minima. Clearly, therefore, the objective function in classical and direct optimization must be continuous and twice differentiable. However, this requirement is generally not met in real-world problems [8]. This has led to the evolution of many optimization software. Oktem *et al.* [9] and Suresh *et al.* [10] in their works used ANN together with genetic algorithm (GA) to minimize the surface roughness. GAs have been used with increasing interest in a large variety of applications. They search the solution space simulating the evolution of survival of the fittest according to Darwin's theory. The GAs use a structured exchange of data to explore all regions of the domain and lead some operators to exploit potential areas. Besides genetic operator's basic concepts such as chromosome representation, generation of initial population, stopping criteria and fitness function are important in GAs [11]. Deepan Bharathi Kannan *et al.* [12] in their work successfully used ANN modelling and GA optimization technique for identifying optimized parameters in laser welding of nickel titanium shape memory alloys. Deepan Bharathi Kannan *et al.* [13, 14] also successfully used ANN modelling and GA optimization technique for predicting the optimized parameters in drilling of copper and brass materials.

From the above literatures, it is understood that ANN modelling and GA optimization techniques are more suitable for identifying optimized parameters in all manufacturing processes and there are very few works related to optimization of machining parameters in drilling of stainless steel. Hence, in this work, an attempt is made to use ANN and GA for optimizing machining parameters in drilling of stainless steel plates.

2 Materials and methods

CNC milling machines (also called machining centres) are computer-controlled vertical mills with the ability to move the spindle vertically along the Z-axis. This extra degree of freedom permits their use in die sinking, engraving applications and 2.5D surfaces such as relief sculptures. When combined with the use of conical tools or a ball nose cutter, it also significantly improves milling precision without impacting speed, providing a cost-efficient alternative to most flat-surface hand-engraving work. In this work, CNC machine was used for carrying out drilling operation. The specification of the CNC machine used in this work is given below:

- Name of the maker: Leadwell
- Speed: 12 to 6000 rpm
- Dimension: 550 in X-axis/350 in Y-axis/300 in Z-axis

The experiments were conducted based on Box–Behnken design. Stainless steel plate composition is shown in Table 1.

Table 1: Chemical Composition of Stainless Steel Work Piece

Name of the Elements	Percentage
Carbon	0.1040
Chromium	15.1400
Manganese	10.66
Nickel	0.1610
Phosphorous	0.0262
Sulphur	0.0314
Silicon	0.4530

Table 2: Experimental Observations Obtained by Drilling Using CNC Machine

Hole No.	Spindle Speed (rpm)	Feed (mm/rev)	Entry Burr Height (mm)	Exit Burr Height (mm)	Surface Roughness (μm)
1	350	0.076	0.086667	0.746667	3.7
2	350	0.076	0.11	1.053333	2.36
3	350	0.076	0.053333	1	1.99
4	350	0.076	0.05	1.393333	1.71
5	350	0.076	0.073333	1.01	2.17
6	350	0.038	0.033333	0.193333	1.91
7	350	0.038	0.03	0.25	3
8	350	0.203	0.106667	0.716667	2.88
9	350	0.203	0.146667	0.54	2.07
10	540	0.203	0.366667	0.356667	3.01
11	540	0.038	0.023333	0.426667	1.9
12	540	0.076	0.083333	0.573333	1.89
13	540	0.076	0.056667	0.503333	3.43
14	270	0.076	0.106667	0.146667	3.05
15	270	0.076	0.133333	0.546667	1.79
16	270	0.038	0.12	0.256667	1.61
17	270	0.203	0.18	0.586667	1.93

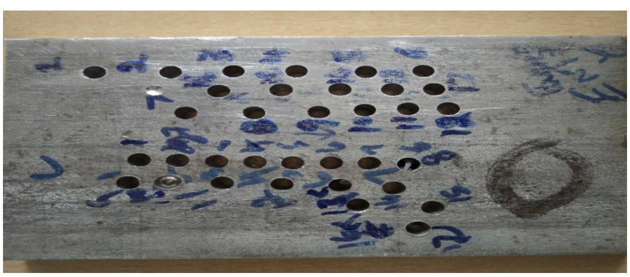

Figure 1: Drilled stainless steel plate.

The factors considered for this work were drill spindle speed and feed rate. The ranges for spindle speeds are 270, 350 and 540 rpm. Feed rate ranges are 0.038, 0.076 and 0.023.

The experimental run with input and output parameters is shown in Table 2.

The drilled stainless steel plate is shown in Figure 1.

3 Results and discussion

3.1 ANN

An artificial neural network is a mathematical or computational model which is inspired by the biological neurons' functional aspects. The basic unit of ANN is the neuron. In this work, neural power professional version 2.5 software was used for carrying out the modelling and optimization. In this work, 14 input and output values (80% of the data) are used for training the neural network and remaining 3 output values (20% of the data) were used for testing the neural network. Legvenberg–Marquardt back propagation learning algorithms with eight neurons in the hidden layer were used in this work [13]. Hyperbolic tanh function was used for both hidden and output networks. Hyperbolic tanh is given by Equation 2.

$$F(x) = \frac{1 - \exp(-ax)}{1 + \exp(-ax)} \tag{1}$$

Root mean square value (RMSE) is generally used for identifying the accuracy of the prediction. The formula for RMSE is

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P - E)^2} \tag{2}$$

where E is the experimental value,
P the predicted value and
n the number of testing data.

Entry burr height, exit burr height and surface roughness values were predicted through ANN and its values along with experimental values are presented in Tables 3 and 4.

From the table, it can be seen that the average difference between experimental values and ANN-predicted

Table 3: Difference between Measured Values and ANN Values for Burr Thickness

Entry Burr Height			Exit Burr Height		
Experimental Value	ANN-Predicted Value	Difference	Experimental Value	ANN-Predicted Value	Difference
0.086667	0.074667	0.012	0.74667	1.0407	0.294
0.11	0.074667	0.035333	1.0533	1.0407	0.012666
0.053333	0.074667	0.021334	1	1.0407	0.040667
0.05	0.074667	0.024667	1.3933	1.0407	0.35267
0.073333	0.074667	0.0013336	1.01	1.0407	0.030667
0.033333	0.031667	0.0016665	0.19333	0.22167	0.028333
0.03	0.031667	0.0016665	0.25	0.22167	0.028334
0.10667	0.12667	0.02	0.71667	0.62833	0.088334
0.14667	0.12667	0.02	0.54	0.62833	0.088333
0.36667	0.36667	4.79E−12	0.35667	0.35667	6.44E−12
0.023333	0.023333	1.95E−11	0.42667	0.42667	1.69E−11
0.083333	0.07	0.013333	0.57333	0.53833	0.035
0.056667	0.07	0.013333	0.50333	0.53833	0.035
0.10667	0.10667	6.70E−13	0.14667	0.14667	1.04E−11

Table 4: Difference between Measured Value and ANN Value for Surface Roughness

Surface Roughness		
Experimental Value	ANN-Predicted Value	Difference
3.7	2.386	1.314
2.36	2.386	0.026
1.99	2.386	0.396
1.71	2.386	0.676
2.17	2.386	0.216
1.91	2.455	0.545
3	2.455	0.545
2.88	2.475	0.405
2.07	2.475	0.405
3.01	3.01	9.63E−13
1.9	1.9	8.73E−12
1.89	2.66	0.77
3.43	2.66	0.77
3.05	3.05	2.92E−13

values for entry burr height, exit burr height and surface roughness are 0.011762, 0.073857 and 0.43343, respectively.

The ANN neural structure containing input, hidden and output layers is shown in Figure 2.

Testing of the ANN modelling was done with remaining 3 experimental values (20%) and its values are shown in Table 5.

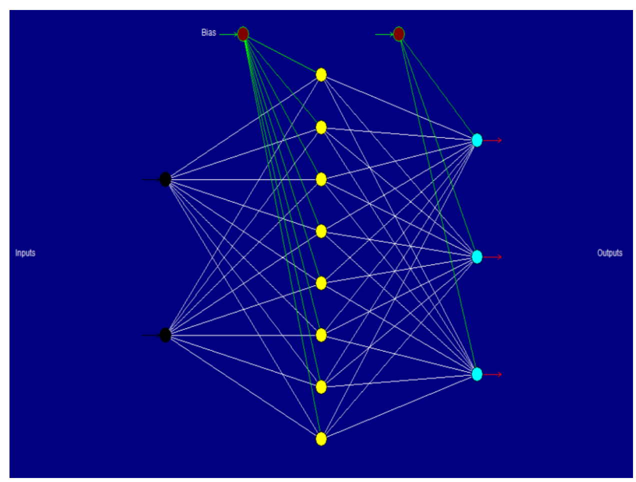

Figure 2: ANN structure.

3.2 Genetic Algorithm

A relation is created between input parameters and multi-objective function with the help of ANN modelling. This relation is fed into the GA optimization technique to identify the optimized parameters. GA is a simple optimization technique which works based on evolution concepts. The major steps involved in GA are as follows:

(i) Randomly initialize population.
(ii) Evaluate objective function.
(iii) Find fitness function.
(iv) Apply genetic operators such as reproduction, crossover and mutation until stopping criteria.

Table 5: ANN Testing Data Values

Experiment No.	Entry Burr Height (mm)		Exit Burr Height (mm)		Surface Roughness (μm)	
	Experimental Values	ANN-Tested Values	Experimental Values	ANN-Tested Values	Experimental Values	ANN-Tested Values
15	0.133333	0.106667	0.546667	0.146667	1.79	3.05
16	0.12	0.11452797	0.256667	0.08095119	1.61	3.3454286
17	0.18	0.045074922	0.586667	0.74545195	1.93	2.412888

Table 6: Optimized Parameters

Experiment	Speed (rpm)	Feed (mm/rev)	Entry Burr Height (mm)	Exit Burr Height (mm)	Surface Roughness (μm)
Optimal solution	539.8754	0.038038841	0.02	0.42	1.90
Feasible solution	540	0.03	0.026	0.48	2.01

The parameters used in GA are taken from the previous work and are as follows [13]:

Population size: 100
Crossover rate: 0.9
Mutation rate: 0.01
Selection type: Roulette method
Crossover type: single point crossover

From the GA optimization technique, the optimized parameters are obtained and their corresponding output values are shown in Table 6.

4 Conclusions

- Spindle speed and feed values mainly control the quality and production rate in drilling operation.
- ANN modelling technique can be effectively used for modelling machining parameters in drilling operations.
- GA optimization technique can be effectively used for optimizing machining parameters in drilling operations.
- In drilling of stainless steel using CNC vertical milling machine, GA optimization prediction is very good and the optimized parameters are speed 540 rpm and feed 0.03 mm/rev.

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