Application of Levenberg- Marquardt Based Back Propagation Neurointelligence Algorithm in Studying the Cutting Parameters Effect on Thrust Force & Hole Diameteral Accuracy in Drilling of Aluminum Alloys

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Research Article

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ABSTRACT

In this paper, the effect of the cutting speed, feed rate and the point angle, mechanical properties of aluminium alloys on diametric error and thrust force were investigated and estimated by assistance of a neural network using Levenberg- Marquardt Based Back Propagation Algorithm. Three types of commercial aluminium alloys were selected as the work piece materials for experiments. The neural network analysis were employed to analyze the effect of drilling parameters and predict the response of diametral error and the thrust force toward the drilling parameters changes. The results of network sensitivity and relative importance analysis indicated that feed rate and cutting speed minimize significantly both the diametral error and the thrust force.

INTRODUCTION

Drilling is one of the most important material removal processes that have been widely used in the aerospace, aircraft and automotive industries. Although modern metal-cutting methods, including electron-beam machining, ultrasonic machining, electrolytic machining and abrasive jet machining, have improved in the manufacturing industry, conventional drilling still remains one of the most common machining processes. Aluminum alloys are used in many industrial areas to make different products and it is significant for the world economy. Structural components made from aluminum alloys are vital in the aerospace industry and very important in other areas of transportation and building in which durability, strength and light weight are expected. In several studies diametral error and thrust force were investigated through examined the effect of the machining parameters on the thrust force and diameter deviations for different point angle drill bits. The results show that, low cutting speeds, small constant feed rate are appropriate for the dry machining of AL-6061. Presented an application of Taguchi and response surface methodologies for minimizing the diametral error and thrust force in drilling Al-7075. The optimization results showed that the combination of low cutting speed, low feed rate and high point angle is necessary to minimize both diametral error and the thrust force. Investigated the role of different coatings, point angle and cutting parameters on the hole quality in the drilling of AL-6061 alloy and concluded that the cutting parameters have different effects on hole quality. They have obtained effective results using a low cutting speed and feed rate. By using several materials that were drilled by several cutting conditions, velocity and feed rates indicated that diametral errors were highly dependent on the material properties, the drill geometry and the cutting condition. Used simulation tools and analysis of variance to identify the influence of process parameter on the hole diameter and concluded that feed rate, chisel-edge-to-drill diameter ratio, yield strength and point angle are significant for the hole diameter. Carried out an experimental investigation of the role of various shapes of drills and materials (HSS Tool, Al-6061, Al-6351 and Al-7075) on the hole diameter in drilling. Their experimental results showed that the hole diameter from ductile materials is larger than from brittle materials. Investigated the influence of the cutting parameters and the mechanical properties of a work piece on the hole diameter accuracy in a dry drilling process. His experimental results showed that the machining parameters and the mechanical properties of a work piece affect the hole diameter [1].

MATERIALS AND METHODS

In this paper, a neural network analysis of the experimental data of the cutting parameters and the mechanical properties of three different aluminum alloys on the diametral error and the thrust force of the drilled hole in the dry drilling of is investigated and predicted with the Levenberg- Marquardt Based Back Propagation Algorithm. Training an artificial neural network is an optimization task, since it is desired to find optimal weight sets for a neural network during training process. Traditional training algorithms such as back propagation have some drawbacks such as getting stuck in local minima and slow speed of convergence. This study utilizes combination of the best features of two algorithms; i.e. Levenberg Marquardt Back Propagation (LMBP) for improving the convergence speed of used Neural Network (ANN) training. The algorithm was trained on several experimental datasets. The experimental results showed that the proposed algorithm has better performance than other similar hybrid variants used in several studies. The used Alyuda NeuroIntelligence is a neural networks software application designed to assist neural network, data mining, pattern recognition, and predictive modeling experts in solving real-world problems. Its features only proven neural network modeling algorithms and neural net techniques; software is fast and easy-to-use [2]. It supports all stages of neural net design and application. The software was used in this work [3].

Experimental methods

Diametral error and the thrust forces of the drilled hole were determined by cutting condition. The drilling experiments were conducted in dry cutting conditions on a drilling machine [4]. In this study, three Aluminum alloys from commercial products were chosen as the work materials with the specimen of Aluminum carrying plates for high loads with large work piece plates for self-assembly for product support or for adaptation to specific customer requirements. The plates were fabricated commercially in Egyptian factories for trading purposes shown in Figure 1. The main plate dimensions are 400 mm × 400 mm × 12.7 mm. The mechanical properties of the three aluminum alloys are presented in Table 1. Conventional, HSS. Twist drills with diameter of 24 mm with different point angles 90° and 118° are used for drilling experiment to drill 40 hole for every plate performed in accordance with the plate dimensions [5-8]. The drilling experiments were planned using to be a neural network inputs and outputs. Seven experimental parameters were the cutting speed; feed rate, point angle, material hardness, material tensile strength, yield strength and elongation percent were selected to be the network inputs. Two experimental parameters were Diametral Error (mm) and Thrust forces (Nm) were selected to be the network outputs for the present investigation. The considered experimental parameters are listed in Table 3.

Figure 1. Aluminum test plate.

Proposed neural network model

Artificial Neural Network ability to learn complex non-linear and multivariable relationships between process parameters makes them very useful in many applications. An ANN consists of a number of neurons, which are divided into the three basic layers: input, hidden, and output. The neurons between the layers are linked, having synaptic weights. One of the basic advantages of ANN is its ability to learn from the process. When the architecture of the network is defined, then, through a learning process, weights are calculated to present the desired output. The present research used the optimum neural network piece of Alyuda NeuroIntelligence software available for the development of a multilayer feed forward neural network.

Table 1. Mechanical properties of testing plate materials

Material	Tensile Strength	Yield Strength	Elongation	Hardness
	(MPa)	(MPa)	(%)	(HRB)
Plate 1	310	276	17	95
Plate 2	250	150	20	95
Plate 3	228	103	16	60

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Table 2. Plate with holes detailed dimensions

Width of workpiece plate	Length of workpiece plate	Dimension	Dimension	Dimension	Dimension	Dimension
bWT	lWT	a1	a2	a3	a4	a5
(mm)	(mm)	(mm)	(mm)	(mm)	(mm)	(mm)
32,5	40,0	99,0	101,5	239,0	379,0	519,0

Table3. Experimental parameters as neural network inputs & outputs.

Neural network inputs							Neural network outputs	
Speed Rpm	Feed mm/rev	Point angle	Tensile Strength Mpa	Yield Strength Mpa	Hardness HRB	Elongation %	Diametral mm	Thrust Nm
90	0.15	90	310	276	95	17	0.23	696
90	0.2	90	310	276	95	17	0.02	853
90	0.3	118	310	276	95	17	0.02	1177
90	0.36	118	310	276	95	17	0.01	1608
200	0.15	90	310	276	95	17	0.03	696
200	0.2	90	310	276	95	17	0.13	775
200	0.3	118	310	276	95	17	0.03	1157
200	0.36	118	310	276	95	17	0.06	1236
250	0.15	118	310	276	95	17	0.04	520
250	0.2	118	310	276	95	17	0.06	716
250	0.3	90	310	276	95	17	0.01	686
250	0.36	90	310	276	95	17	0.17	1059
400	0.15	118	310	276	95	17	0.18	559
400	0.2	118	310	276	95	17	0.01	696
400	0.3	90	310	276	95	17	0.03	1000
400	0.36	90	310	276	95	17	0.05	853
90	0.15	90	250	150	95	20	0	657
90	0.2	90	250	150	95	20	0.03	892
90	0.3	118	250	150	95	20	0.34	951
90	0.36	118	250	150	95	20	0.22	1030
200	0.15	90	250	150	95	20	0.09	627
200	0.2	90	250	150	95	20	0.03	785
200	0.3	118	250	150	95	20	0.37	873
200	0.36	118	250	150	95	20	0.09	1030
250	0.15	118	250	150	95	20	0	657
250	0.2	118	250	150	95	20	0.1	686
250	0.3	90	250	150	95	20	0.09	1108
250	0.36	90	250	150	95	20	0.1	1206
400	0.15	118	250	150	95	20	0.07	627
400	0.2	118	250	150	95	20	0.1	853
400	0.3	90	250	150	95	20	0.01	1255
400	0.36	90	250	150	95	20	0.1	1255

90	0.15	90	228	103	60	16	0.15	755
90	0.2	90	228	103	60	16	0.09	853
90	0.3	118	228	103	60	16	0.13	1570
90	0.36	118	228	103	60	16	0.21	1618
200	0.15	90	228	103	60	16	0.25	676
200	0.2	90	228	103	60	16	0.32	902
200	0.3	118	228	103	60	16	0.42	1667
200	0.36	118	228	103	60	16	0.26	1716
250	0.15	118	228	103	60	16	0.06	1030
250	0.2	118	228	103	60	16	0.02	1275
250	0.3	90	228	103	60	16	0.1	1128
250	0.36	90	228	103	60	16	0.13	1137
400	0.15	118	228	103	60	16	0	1226
400	0.2	118	228	103	60	16	0	1363
400	0.3	90	228	103	60	16	0.08	706
400	0.36	90	228	103	60	16	0.09	1530

An elementary neuron with 7 inputs. Each input is weighted with an appropriate value (w). The sum of the weighted inputs and the bias forms the input to the transfer function (f). Neurons can use any differentiable transfer function (f) to generate their output. The standard network that is used for function fitting is a two-layer feed forward network, with a tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. All of the original (48) experimental data were randomly divided into three data sets including training, validation and testing. The back-propagation training algorithms and levenberg–marquardt (lm) were used for anns training. The training set used 70% of the data to build the network, 15% to measure network generalization and 15 % as a testing set of the neural network.

Five-layer network architectures were used as an optimum network to predict the thrust force and diametral error. In consequence of trials, the best network architecture for the prediction of thrust force and diametral error was the 7-10-10-2 topology. The comparison of predicted results from ANN model with experimental measurements shows that there is a very good correlation between them. It is obvious that a neural network is an excellent tool for predicted values of thrust force Fz and diametral error de according to experimentally measured ones. Errors are differences between the outputs and targets and represent a measure of model accuracy. The values for the entire dataset (training, validation and testing) represent high correlation.

Experiments included comparative evaluations for a single statement in the dataset “Dogs are sitting by the door” using mel-cepstral and wavelet transformations both on continuous and discrete scales. We used a 25 ms speech window with mel-cepstral and 32 ms window with wavelet features, due to specific decomposition structure. The mother wavelet chosen for continuous transform in signal decomposition was the Morlet wavelet. The mother wavelet chosen for discrete transform [3,4] with 28 filter length. The stride is set to 10 ms for all extraction methods to ensure a fair comparison. The Decision Tree Ensemble also termed the Random Forest method was used. A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is the same as the original input sample size and the samples are drawn with replacement. Quality of split is measured by “gini” denoting Gini Impurity [5,6]. Max depth of the tree is set at 500. Maximum features to be used for prediction are sqrt (n features). The minimum number of samples required to be at a leaf node is set at 3. A split point at any depth will only be considered if it leaves at least 3 training samples in each of the left and right branches. The minimum number of samples required to split an internal node is set at 5. 400 estimators are used which denotes the number of trees in the forest. Model is kept similar to the three feature extraction methods to test the performance.

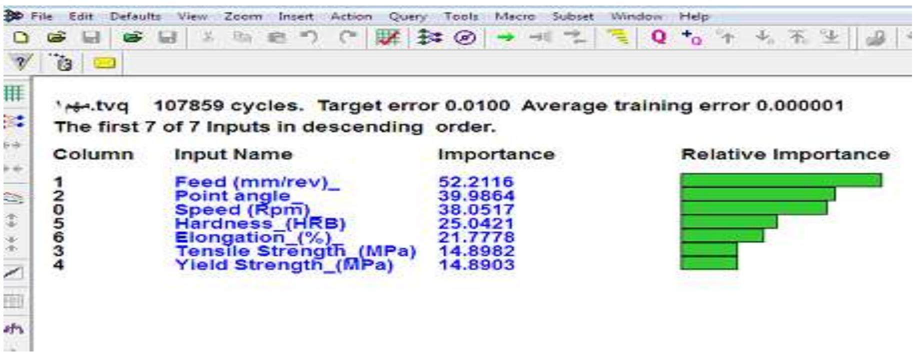
RESULTS AND DISCUSSION

The response graphs for the diametral error and thrust force are shown in Figure 2, relative importance is determined for every machining parameter. Though the term importance often has numerous connotations, sometimes referring to statistical significance while at other times referring to practical significance, our use of the term relative importance refers to the contribution a variable makes to the prediction of a criterion variable by itself and in combination with other predictor variables.

This definition considers only the relative contribution of a variable to total predictable variance and makes no assumptions about either the statistical significance or practical significance associated with a particular predictor. Information regarding a variable’s contribution to predictable variance is helpful when considering the practical utility of a variable, but aspects of the particular situation must also be considered to fully gauge practical importance.

Relative importance weights are a useful supplement because they provide information not readily available from the indices typically produced from a multiple regression analysis.

Figure 2. Effect weights of machining parameters on diametric error and thrust force.



It is observed from Figure 2 that the parameters importance which has different effects for both diametral error and thrust force. The feed rate is the dominant parameter on the diametral error followed by the point angle for all three aluminium alloys [7]. Although a lower Diametral error is always preferred. In the present investigation, when cutting speed 90 rpm, feed rate 0.15 mm/r and point angle 90 are used, the diametral error is minimized. The Diametral error increases as the feed rate, the cutting speed and the point angle increase [8]. Cutting speed is the dominant parameter on thrust force, followed by the hardness HRB. The feed rate has a lower effect on thrust force. In the present investigation, when applied by cutting speed 90 rpm, feed rate 0.15 mm/r and point angle 90, the surface roughness is minimized [9]. The thrust force of the drilled surface increases with increase of feed rate, cutting speed and point angle. The results of the of the network analysis for the sensitivity of diametral error and thrust force are presented in Figure 3. Sensitivity analysis’ aims to describe how much model output values are affected by changes in model input values. It is the investigation of the importance of impreci-sion or uncertainty in model inputs in a decision-making or modeling process. The exact character of a sensitivity analysis depends upon

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the particular context and the questions of concern. Sensitivity studies can provide a general assessment of model precision when used to assess system performance for alternative scenarios, as well as detailed information addressing the relative significance of errors in various parameters shown in Figure 4.

Figure 3. Sensitivity of diametral error to the cutting conditions.

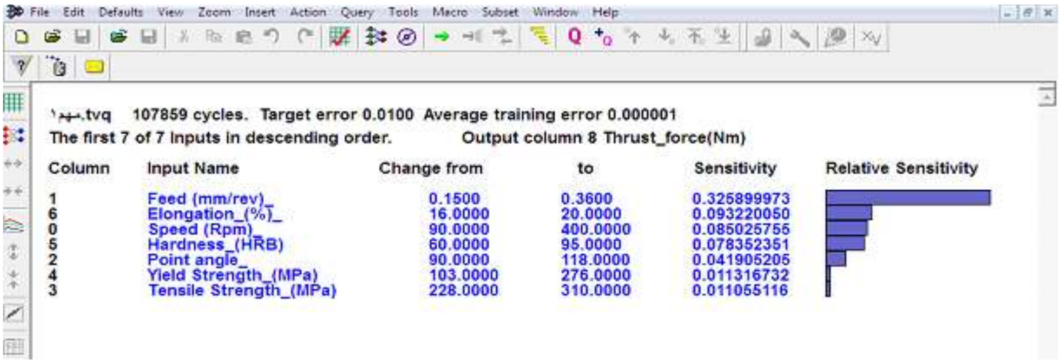
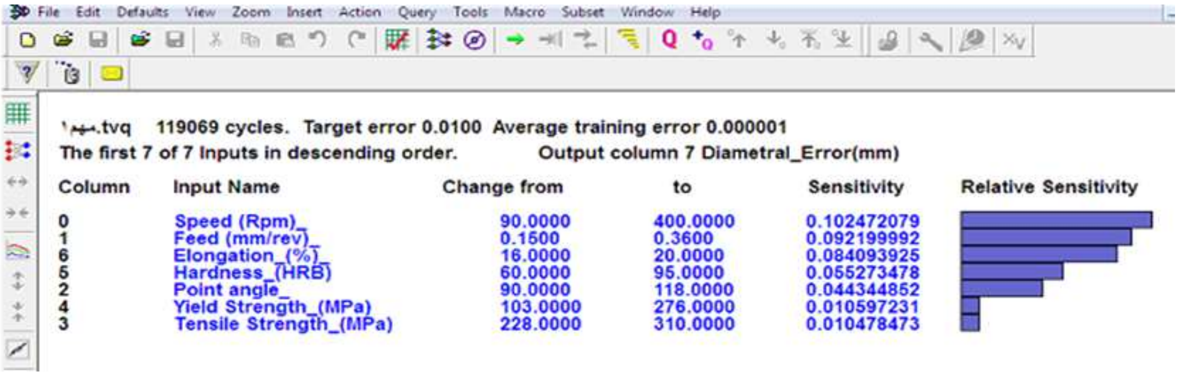


Figure 4. Sensitivity of thrust force to the cutting conditions.



Changes in particular model input values can affect model output values in different ways. It is generally true that only a relatively few input variables dominate or substantially influence the values of a particular output variable or performance indicator at a particular location and time. If the range of uncertainty of only some of the output data is of interest, then undoubtedly only those input data that significantly affect the values of those output data need be included in the sensitivity analysis [10]. From the sensitivity analysis, for all three aluminum alloys the cutting speed changes are a highly significant factor and plays a major role in affecting the diametral error. The effect of the point angle makes low impact on the responses.

For the three types of aluminum. The properties of the work piece material have a significant influence on the diametral error. The burr formation process is heavily dependent on the yield strength, ultimate strength and ductility. Also considering the ductility of materials represented as elongations for the alloys. The higher value of elongation represents better ductility of the material. The elongation percentage of work pieces used in the experiments affects the diametral error and thrust force. As a result, much more Diametral error occurs in ductile materials. This tendency was also mentioned by various other researchers [11].

The final burr geometry determined by the amount of plastic deformation is determined by the ductility of the material represented as elongations. Higher thrust force values can be explained by the highly ductile nature of the alloy, which increases the tendency to form a built-up edge (BUE). Relatively higher work piece ductility increases

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the BUE formation tendency. The presence of the BUE in the drilling process causes an increase in the tool wear and a rougher surface finish.

CONCLUSION

A series of experiment were conducted on three types of aluminum. An attempt has been made to predict the effects of the drilling parameters on diametral error and thrust force. The predicted values of diametral error and thrust force using proposed ANN model was found to be in close agreement with the experimental data. Feed rate was the most influential controllable factor among input parameters which affect the hole diameter.

The cutting speed was the second factor at hole diameter accuracy. The point angle has the lowest effect on the hole diameter. The Best parametric combination of the three control factors is minimization of both the diametral error and thrust force; cutting (90 rpm), feed rate (0.15 mm/rev) and point angle (90). The thrust force obtained. The diametral error and thrust force is minimized which contributes the reduction of the overall manufacturing cost by reducing the number of experiments. The properties of the work piece material have a significant influence on the diametral error. Also considering the ductility of materials represented as elongations for the alloys. The higher value of elongation represents better ductility of the material. The elongation percentage of work pieces used in the experiments affects the diametral error and thrust force.

The amount of diametral error as the final burr geometry determined by the amount of plastic deformation is determined by the ductility of the material represented as elongations. Higher thrust force values can be explained by the highly ductile nature of the alloy, which increases the tendency to form a built-up edge (BUE). Relatively higher work piece ductility increases the BUE.

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