Comparative study of surface roughness and cylindricity of aluminium silicon nitride material using MRA GMDH & pattern recognition technique in drilling

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Abstract

Drilling is one of the oldest and the most widely used of all machining processes, comprising about one third of all metal-machining operations. The present work consist of drilling an aluminum silicon nitride composite forged plate using high-speed steel drill bit and was carried by varying the cutting speed and feed. Theoretical analysis in the present work involved monitoring of drilled hole status of composite based on surface roughness and cylindricity using the independent variables machining time, tool tip temperature, vibration, flank wear (both average and maximum), cylindricity and cutting conditions by sophisticated methods of signal analysis like Multiple Regression Analysis (MRA), Group method Data Handling Technique (GMDH) and Pattern Recognition Technique (PRT) like Back Propagation Neural Network (BPNN) was used. Comparisons of the three theoretical methods for estimation of surface roughness and cylindricity with measured one were carried out. The influence of network architecture is used to know the drilled hole status based on surface roughness and cylindricity was studied.

Keywords: MRA, GMDH, PRT, BPNN

1. Introduction

Drilling is one of the oldest and the most widely used of all machining processes, comprising about one third of all metal-machining operations. It is used to create or to enlarge a hole in a work piece by the relative motion of a cutting tool, called a drill or drill bit.
The choice of a drilling method depends on the size, tolerance, and surface finish needed, as well as the production requirements. Several factors influence the quality of drilled holes. The most obvious ones are the cutting conditions (cutting speed and feed rate) and cutting configurations (tool material, diameter, and geometry). Aluminum Matrix Composites (AMC) refers to a class of light weight and high performance aluminum centric material systems. In the present work Aluminum Silicon Nitride (AlSiN) is a Metal Matrix Composite (MMC) have higher thermal conductivity of 170 – 230 W/mK and low material density of 3.3 g/cm3 makes it ideal for weight sensitive applications. Past researchers stated that the machining of Al/SiC materials with different drill bit was difficult due to the presence of reinforced SiC-particulates in the metal matrix composite and it was found that at spindle speed 1300 rpm with 0.025 mm/rev feed rate is recommended for better surface finish using pure carbide drill bit, Alakesh Manna and Kanwaljeet Singh (2011). To predict the effects of thermal distortion of the drill and workpiece on the diameter and cylindricity of dry drilled holes. The model predicts that thermal expansion of the drill is the dominant effect and leads to oversized holes with diameters that increase with depth, Matthew Bono and Jun Ni (2001). The effect of cutting parameters on the hole quality (circularity and hole diameter) and tool wear during the drilling of super alloy Inconel 718 and proposed that cutting speed and feed rate played a great role in the variation of deviation from circularity values. As the feed rate increased, deviation from circularity values also increased, Turgay Kivak et al. (2012). HSS twist drills with different geometry for drilling of carbon/epoxy composites and stated that the delamination develops along the fiber direction and is developed in two phases, the chisel edge action phase and the cutting edge action phase, Sedlacek J and M. Slany (2010). The cutting of metal, high temperatures are generated in the region of the tool cutting edge, and these temperatures have a controlling influence on the rate of tool wear, it was observed that the influence of cutting speed is the most effective parameter that effects tool temperature than other parameters, Ali Fata (2011). The optimum cutting parameters to optimize the surface roughness of the hole and its diameter accuracy in the dry drilling process based on the selected setting parameters. The selected cutting parameters for this study were the cutting speed, feed rate, and the hole depth. The effect of these parameters on the hole diameter accuracy and its surface roughness are measured and analysed. In this study it is revealed that feed rate is prominent factors which affect hole diameter in the dry drilling of aluminum alloy 6061, Ahmad Fauzi and B Ahamed (2010). A vibration monitoring is the most widely used technique because most of the failures in the machine tool could be due to increased vibration level, Jagadish. M.S and H.V. Ravindra. A Multiple Regression model to predict the in-process surface roughness of a machined workpiece in turning operation. The model was developed to use machining parameters, such as feed rate, spindle speed, depth of cut, and vibration as predictors. They have shown that feed rate had the greatest correlation coefficients and other primary variables were much smaller than feed rate, Luke huang and Dr. Joseph C. Chen (2001). The use of algorithms of the Group Method of Data Handling (GMDH) in solving various problems of experimental data processing, Lvakhnenko A.G. and G.A.Lvakhnenko (1995). GMDH is a powerful tool for mathematical modeling that can be used to solve a wide variety of different real-time problems and GMDH was recommended to solve small and medium- sized problems, Dolenko et al. (1996). HSS twist drills with different geometry for drilling of carbon/epoxy composites stated that delamination develops along the fiber direction. It is developed in two phases, the chisel edge action phase and the cutting edge action phase. The feed rate and drill diameter are seen to make the largest contribution to the overall performance, the candle stick drill and saw drill cause a smaller delamination factor than twist drill. The confirmation tests demonstrated a feasible and an effective method for the evaluation of drilling induced delamination factor in drilling of composite material, Tsao C.C. and H. Hocheng (2004). An Artificial Neural Network (ANN) model can be used as a prediction tool flank wear for determining the delamination for any given set of input machining parameters, namely, speed, drill size and feed, Krishnamoorthy, et al. (2011), Panda et al. (2006). Drilling operations on mild steel work piece by high-speed steel (HSS) drill bits over a wide range of cutting conditions. Important process parameters have been used as input for BPNN and drill wear has been used as output of the network. It was concluded that inclusion of chip thickness as input to the neural network not only reduces mean square training error but also it is achieved at a much less number of iteration, Panda et al. (2006).
2. Experimental Work

The experimental work consists of drilling aluminium silicon nitride composite using High-Speed Steel drill bit. The machining was carried out in an automatic drilling machine tool. The experiments were conducted for different cutting speeds and feeds combinations. The cutting speeds considered are 11.309 m/min, 15.39 m/min and 21.36 m/min. Feeds considered are 0.095 mm/rev, 0.190 mm/rev and 0.285 mm/rev. In all the cutting conditions for each hole vibration velocity was measured using Shock Pulse Meter and temperature at tool tip using heat spy was measured during drilling process. And surface roughness, cylindricity and circularity are measured using handysurf meter, digital caliper and tool maker’s microscope respectively. Machining was stopped at regular intervals of time and both average and maximum flank wear was measured using tool makers microscope. Experimental set-up is as shown in the Fig. 1 and location of shock pulse meter sensor probe is shown in Fig. 2. The work material specifications are shown in Table. 1 and tool material specifications are given in Table 2.

![Fig. 1. Experimental set-up](image1)

![Fig. 2. Location of SPM sensor](image2)

Table 1. Composition of work material

| Work material | AlSiN |
|---------------|-------|
| Hardness      | 54.3BHN |
| Al            | Remaining |
| Cu            | 0.479% |
| Mg            | 0.762% |
| Si            | 0.684% |
| Fe            | 0.246% |
| Mn            | 0.028% |
| Ni            | <0.05% |
| Pb            | 0.024% |
| Sn            | 0.011% |
| Ti            | 0.015% |
| Zn            | 0.008% |

Table 2. Drill bit specification

| Tool material | HSS |
|---------------|-----|
| Diameter of the drill bits used | 10mm |
| Chisel edge angle | 120° to 135° |
| Helix angle or rake angle | 30° |
| Point angle | 118° |
| Lip clearance angle | 12° |
3. Result and Discussions

3.1 Multiple Regression Analysis (MRA)

The objective of multiple regression analysis is to construct a model that explains as much as possible, the variability in a dependent variable, using several independent variables. The model fit is usually a linear model, though some times non-linear models such as log-linear models are also constructed. When the model constructed is a linear model, the population regression equation is

\[ Y_i = \alpha + \beta_1 X_{i1} + \ldots + \beta_m X_{im} + e_i \]  

(1)

Where \( Y_i \) is the dependent variable and \( X_{i1}, \ldots, X_{im} \) are the independent variables for \( i \)th data point and \( e_i \) is the error term. Error term is assumed to have zero mean. The co-efficients \( \alpha, \beta_1, \ldots, \beta_m \) are not known and estimates of these values, designated as \( a, b_1, \ldots, b_m \) have to be determined from the sampled data. For this least squares estimation is used, which consists of minimizing.

\[ SS = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (Y_i - a - b_1 X_{i1} - \ldots - b_m X_{im})^2 \]  

(2)

With respect to each of the co-efficients \( a, b_1, \ldots, b_m \). This will give \( k+1 \) equations from which \( a, b_1, \ldots, b_m \) can be obtained. These least squared estimates are the best linear unbiased estimates and hence give the best linear unbiased estimate of the dependent variable.

\[ Y = a + b_1 X_1 + b_2 X_2 + \ldots + b_m X_m \]  

(3)

3.2 Group Method of Data Handling (GMDH)

One of the widely used methods for empirical analysis of data and model building is the multiple regressions. One of the major problems associated with use of regression has been the need to specify functional formulation. It would be preferable in such cases to use the data to determine both the nature of function and parameters of the function. This is the motivation for the development of self-organizing methods in modeling, GMDH is one such method.

Data with the largest variance is put in the training set. The variance for \( i \)th data point is given by

\[ D_i^2 = \sum_{j=1}^{n} (X_{ij} - X_j)^2 / \sigma_j^2 \]  

(4)

Where, \( D_i \) = measure of variance for \( i \)th data point, \( \sigma_j \) = variance for \( j \)th input variable, \( X_j \) = mean for \( j \)th variable

\[ \sigma_j^2 = (1/n) \sum_{i=1}^{n} (X_{ij} - X_j)^2 \]  

(5)

Different models were obtained for 50%, 62.5% and 75% of total data in the training set. The best model was selected from these. Number of variables selected at each layer will be taken as a fixed number or a constantly increasing number (usually given as fractional increase in number of independent variables present in the previous
level). In this work, a fixed number, equal to the number of input variables, was taken. This was done to simplify the computational requirements.

3.3 Pattern Recognition Technique (PRT)

In order to train a neural network to perform a specific task, the weight of each unit is adjusted in such a way that the error between the desired output and the actual output is reduced and Regression Co-efficient (R value) between desired output and the actual output is nearer to one. This process requires that the neural network compute the error derivative of the weight. In other words, it must calculate how the R value and MSE value changes as each weight is increased or decreased slightly. The back-propagation algorithm is the most widely used method for determining the MSE and R value derivative of the weight. During training, the predicted output has been compared with the desired output, and the R value and MSE is calculated. If the R value and MSE value is more than a prescribed limiting value, it is back propagated from output to input, and weight are further modified to obtain the R and MSE value within a prescribed limit. MATLAB was first adopted by researchers and practitioners in control engineering, little's specialty, but quickly spread to many other domains.

Initially, Simple functional relations between the parameters have been plotted to derive a basis for more detailed analysis and arrive at possible information to monitor the drilled hole status based on surface roughness and cylindricity.

3.4 Effect of Speed and Feed on cylindricity and surface roughness

Fig. 3 shows the cylindricity curves for different speeds (11.309 m/min, 15.39 m/min and 21.36 m/min) at a constant feed of 0.190 mm/rev. From the graph it is observed that the deviation of cylindricity values is high at high speeds.

Fig. 4 shows the surface roughness (Ra) curves for different feeds (0.095 mm/rev, 0.190 mm/rev and 0.285 mm/rev) at a constant speed of 15.39 m/min, it’s observed that good surface finish is obtained at high feeds.

![Fig. 3. Cylindricity for different speeds at a constant feed of 0.190 mm/rev](image)

![Fig. 4. Surface roughness for different feeds at a constant cutting speed of 15.39 m/min](image)

3.5 Estimation of Surface Roughness and Cylindricity by Multiple Regression Analysis (MRA)

Fig. 5 shows the multiple regression estimates of surface roughness for various feeds (0.095mm/rev., 0.190mm/rev. and 0.285mm/rev.) at a constant cutting speed 11.309 m/min. From the Fig. 4, it is observed that estimates of surface roughness correlates well with the measured surface roughness values at lower feeds and lower speeds, may be due to the lesser vibration velocity and tool tip temperature build up.

Fig. 6 shows the multiple regression estimates of cylindricity for various cutting speeds (11.309 m/min., 15.39 m/min. and 21.36 m/min.) at a constant feed 0.190 mm/rev. Fig. 4 shows that the deviation of cylindricity increases
along with the speed as well as feed. This is may be due to the lesser vibration velocity at lower cutting speeds and feeds.

3.6 Estimation of Surface Roughness and Cylindricity by Group Method of Data Handling (GMDH)

Fig. 7 shows the comparison of experimental and GMDH estimates of surface roughness from three criteria, for 75% of data in training set at a cutting speed of 11.309 m/min and feed 0.095 mm/rev. From the Fig. 5, it was observed that, the surface roughness obtained by regularity criterion correlates well with the measured surface roughness. Estimates from unbiased and combined criterion gave poor results.

![Fig. 5. Measured and estimated Ra for different feeds at a constant cutting speed of 11.309m/min.](image)

![Fig. 6. Measured and estimated cylindricity for different speeds at a constant feed of 0.190mm/rev.](image)

![Fig. 7. GMDH estimates of surface roughness for 75% of data in training set at speed 11.309m/min. and feed 0.095mm/rev.](image)

![Fig. 8. GMDH estimates of cylindricity for various percentages of data in training set at speed 21.36 m/min. and feed 0.190mm/rev.](image)

3.7 Study of Percentage of Data in the Training Set

Fig. 8 shows the measured and GMDH estimates of cylindricity from regularity criterion, for various percentages of data in the training set, at a cutting speed of 21.36 m/min and feed 0.190 mm/rev. From Fig. 6, it was observed that, with the increase in the percentage of data in the training set, the estimation power of regularity criterion also increases.
3.8 Study of Level of Output Estimation

Fig. 9 shows the measured and GMDH estimates of surface roughness from regularity criterion and 75% of data, for various levels of data in the training set, for cutting speed of 15.39 m/min and feed 0.285 mm/rev. From Fig. 7, it was observed that, with the increase in the level of data in the training set, the standard error (SE) obtained is least and hence level 4 is selected to estimate the surface roughness.

Fig. 10 gives diagrammatic representation of the built up tree structure for estimation of surface roughness by Regularity model at cutting speed of 11.309 m/min. and feed 0.190 mm/rev. The Fig. 8 represents the models built up at Level 4 for 75% of data in the training set. The variables that enter into the final equation and the interactions among the variables can be clearly seen from the figures.

The SE of estimation by regularity criterion and for 75% of data in the training set was only considered for the purpose of comparison. Hence measured parameters viz., machining time, vibration in velocity, flank wear (average and maximum), circularity and tool tip temperature correlate well with cylindricity of the hole.

3.9 Comparative Study of MRA and GMDH

From the Fig. 11 and Fig. 12, it was observed that good estimation is obtained for both multiple regression and GMDH models. Among these, regularity criterion of GMDH gave better estimation than multiple regression analysis. The SE of surface roughness by MRA and GMDH are 0.09156 and 0.0123 respectively. The SE of cylindricity by MRA and GMDH are 0.0027 and 0.0005 respectively.
3.10 Hole Status Based on Surface Roughness (Ra) and Cylindricity by PRT

PRT uses Neural Network to know the status of drilled hole based on surface roughness. Graphs of R value versus number of neurons were plotted for different cutting speed and feed for one thousand epochs and one hidden layer to make further discussion. Fig. 13 shows the variation in R value of the surface roughness for various numbers of neurons during the training set of 50%, 60% and 70% at feed of 0.095 mm/rev and at speed 11.309 m/min. Fig. 14 shows the variation in R value of the cylindricity for various number of neurons during the training set of 50%, 60% and 70% for feed of 0.285 mm/rev and at speed 15.39 m/min. From the Fig. 13 and Fig. 14 it can be depicted that the R value holds good at 60% of training set and 20 neurons and at 60% of training set and at 18 neurons for surface roughness and cylindricity respectively.

Graphs of MSE value versus number of neurons were plotted for different cutting speed and feed for one thousand epochs and one hidden layer to make further discussion. Fig. 15 shows the variation in MSE value of the surface roughness for various numbers of neurons during the training set of 50%, 60% and 70% for feed of 0.190 mm/rev and at speed 11.309 m/min. Fig. 16 shows the variation in MSE value of the cylindricity for various number of neurons during the training set of 50%, 60% and 70% for feed 0.095 mm/rev and at speed 21.36 m/min. From the below Fig. 16 and 17 it is concluded that MSE value holds good for 60% training set and at 20 neurons and for 60% training set and at 18 neurons for surface roughness and cylindricity.
Fig. 17 gives Scatter plot for the surface roughness for speed 11.309 m/min and feed 0.095 at training set 60% for 20 neurons. The overall R value is the combination of all three phases i.e. testing phase, validation phase and training phase. Fig. 18 gives Scatter plot for cylindricity at speed 15.39 m/min and feed 0.285 mm/rev at training 60% for 18 neurons. So from the Fig. 17 and 18 it can be said that there was a better correlation between the input features and output features for the surface roughness and cylindricity respectively. At lower cutting speed and at lower feed it can be concluded that the measured variables correlates well with the surface roughness and for cylindricity it can be concluded that the dependable variables data at medium cutting speed and higher feed correlates well.

4. Conclusion

Based on the experimental and theoretical results, the following conclusions were drawn:

Three different criterion functions of GMDH viz., Regularity, Unbiased and Combined have been tried for surface roughness and cylindricity estimation. The results from the present work show that the regularity criterion function provides good estimation than the other two functions. Different models of GMDH were built by varying the number of data in the training set to 50%, 62.5% and 75% of the total data. It was found that the least error of estimation and best fit was found for 75% of data in the training set.

The optimal level of estimation of GMDH was obtained for regularity criterion at 75% of data training sets at Level-4 for surface roughness and Level-1 for cylindricity with least standard error. In GMDH, measured parameters correlates well with surface finish than cylindricity of the hole. The estimation capability of the GMDH was better at higher cutting conditions than at lower cutting conditions, as the standard errors at higher conditions are very less. This implies that the data handling capability of this estimation method is high.

Comparison of the two theoretical methods for estimation of surface roughness and cylindricity, it was found that regularity criterion function of GMDH had an edge over Multiple Regression Analysis method. The estimation capability of the Multiple Regression Analysis method was better at lower cutting conditions than at higher cutting conditions, due to the lesser value of measured parameters at those conditions. In PRT, BPNN was used to monitor the drilled hole status of composite material based on surface roughness and cylindricity.

Different models of PRT were built by varying the number of data in the training set to 50%, 60% and 70% of the training data. Along with training, validation and testing where divided in equal number of samples to know the drilled hole status. The optimum R value and MSE value for surface roughness was obtained at 60% of training set.
and 20 numbers of neurons and for the cylindricity the optimum R value and MSE value was obtained at 60% of training set and 18 neurons.

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