STUDY OF CUTTING FORCES AND PREDICTION OF SURFACE QUALITY ANALYSIS USING NEURAL NETWORK MODEL, SUPPORT VECTOR REGRESSION MODEL BY VARIOUS TEXTURED TOOL CONDITION FOR Ti-6Al-4V ALLOY

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ABSTRACT: To evaluate the performance of the textured tool on surface quality with three different types of the textured pattern using Wire-Cut Electrical Discharge Machining (W-EDM) on tungsten carbide cutting tools with two different groove depth dimensions 100 µm & 200µm respectively and the tools are coated with both TiN and TiAlN using Physical Vapour Deposition (PVD) technique. Surface roughness is predicted using the Support Vector Regression, multilayer Artificial Neural Network model (ANN) model. ANN training is carried out with a pure line transfer function and backpropagation algorithm. Easy off machining and good surface finish are achieved through TiAlN coated tool with linear texture along the perpendicular to chip flow direction than the tools considered for experimental and predicted conditions.

KEYWORDS: Surface roughness, coated tool, friction, ANN, SVR.

1. INTRODUCTION:
Modified tools surface on the rake face and flank face of cutting tool has a higher impact on the minimizing the friction between the contact surfaces. Also, it the lubrication between the interfaces. Turning of titanium alloy material undergoes various difficulties are stress induction during the formation of chip, larger friction coefficient between the tool-chip interface, larger temperature rise [1, 2]. The cutting tool wear behaviors were analyzed with various coated wear-resistant films of TiN, TiAlN, and ZrC etc. and their combinations improve the tool wear characteristics during machining of Hard-to-cut materials [3-9]. Modified tool (textured) surface has been introduced to improve the load capacity, coefficient of friction and wear resistance and there are attributed physical mechanisms such as wear debris entrapment through the hydrodynamic effect [10-18]. Machining impact with textured tools on surface roughness was examined with a coated tool for AISI 1030 steel with various experimental results. The experimental studies were analyzed on Artificial Neural Networks (ANN) for the different set of parameters and the results are compared by statistical error analyzing method [19,20]. Similar kinds of investigations were made by various authors [21, 22 and 23]. In the present study, three different types of micro surface texture at two depths 100µm and 200 µm on top surface (rake face) tool are reproduced by Wire-EDM (W-EDM) and coated with two TiN&TiAlN. Machining tests are conducted on Titanium Grade 5 (Ti-6Al-4V) alloy. Two different models are used for the comparison of surface roughness such as Artificial Neural Network (ANN), Support Vector...
Regression (SVR) or Support Vector Machine (SVM) for analyzing any of the combinations cutting parameters.

2. EXPERIMENTAL METHOD

Titanium alloy (Ti6Al4V) work material with 25 mm diameter and the 150 mm length rod is selected and the chemical element proportion is provided in Table 1. The Electrical Discharge Machining (EDM) is used for producing the linear textures and cross textures on the cutting tool as shown in figure 1. The texture groove dimensions are 250 μm width and 100 μm, 200 μm by W-EDM process. Titanium experiments are performed by CNC turning (LEADWELL-Fig.2) turning center with CNMA120408 (uncoated, coated carbide) inserts for executing the machining operation. The PCLNL 1616 H12 type tool holder with a rake angle of -6° was used for the turning purpose. The physical and mechanical properties of tungsten carbide tool as shown in Table 2. The coatings of TiN and TiAlN are processed using Physical Vapour Deposition (PVD). The machining parameters are chosen as 60, 90, 120 m/min with a constant depth of cut of 0.5mm and feed rate of 0.1 mm/rev and using molybdenum disulfide (MoS2) mixed with gear oil. The Kistler 9257B piezo-electric type 3-component dynamometer was used for the measurement of forces for the different types of tools. The surface roughness measurement was measured using the Mitutoyo SJ411 surface roughness tester.

Figure 1: 3D confocal topography images for a) NT, b) CR.T, c) PR.T, and d) PE.T [23].
**Figure 2:** CNC Machine setup

| Composition (wt. %) | WC + 6%Co |
|--------------------|-----------|
| Density (g/cm³)    | 14.5      |
| Hardness (GPa)     | 16.0      |
| Toughness (MPa.m¹/₂) | 14.8    |
| Thermal Conductivity (W/(m.K)) | 75.4 |
| Flexural Strength (MPa) | 2000 |

**Table 1:** Chemical Composition of Ti-6Al-4V

| Element   | Composition (wt. %) |
|-----------|---------------------|
| Aluminium | 5–6.75%             |
| Vanadium  | 3.5–4.5%            |
| Carbon    | <0.1%               |
| Iron      | <0.3%               |
| Oxygen    | <0.2%               |
| Nitrogen  | <0.05%              |
| Hydrogen  | <0.015%             |
| Titanium  | Balance             |

**Table 2:** Chemical composition and properties of WC/Co material
3. RESULT AND DISCUSSIONS

3.1 EFFECT OF TEXTURES ON CUTTING FORCES

Figure 3: Cutting forces for various textured tools (100µm) (a) Uncoated, (b) TiN (c) TiAlN

Figure 4: Cutting forces for various textured tools (200µm) (e) Uncoated, (f) TiN (g) TiAlN

Figure 3 and Figure 4 shows the impact of fabricated cutting tools with conventional tool (without groove) on cutting forces for the considered groove depths and tools at 60, 90 and 120 m/min with turning of Ti-6Al-4V alloy. From figure 3, the larger force of 160 N was observed for the conventional (non-textured) tool and the lesser force of 130 N was noticed with TiAlN coated conventional (non-textured) tool at minimum considered cutting speed (60m/min). However, at 120m/min similar behavior was noticed and the least force was observed as 109N than the other types of conventional (non-textured) tools considered for a groove depth of 100 µm. Similarly, the reduction in cutting forces was noticed with considered textured tools. The 6-12 % reduction of cutting forces were found in textured tools with conventional (non-textured) tools for all the considered conditions. Moreover, the least force was observed with TiAlN coated perpendicular textured tool for all the considered cutting conditions. The evidence for the diminishing effect in cutting forces due to the formation of a thin film which reduces the shear strength of the material work-piece top surface and presence MoS2. Also, it induces the capillary action and acts as a transporting medium between the contact surfaces. Similar profound was observed for the grooved depth of 200 µm.

3.2. EFFECT OF TEXTURE ON SURFACE ROUGHNESS

The functional performance and quality of the machining are assessed by the surface finish produced by the machined work-piece. The surface finish was considered based on the degree of damage on the peak and valley height on the machined surface. The measured surface finish was represented in figure 7. The Rₐ value was considered for the mean value of 30 measured points, at different positions of the workpiece by using the surface roughness apparatus. The surface roughness was found to be less for the TiAlN perpendicular textured tool with an average equal to 0.208µm. The predictions were analyzed using ANN and SVR. The various errors are Mean Absolute Deviation (MAD), Mean Square Error (MSE) and Mean
Absolute Percentage Error (MAPE). The factors for the machining experimentation were shown in section 2.

3.3. PREDICTION OF SURFACE ROUGHNESS THROUGH ANN AND SVR

3.3.1. NEURAL NETWORK

Neural network models is a simple mathematical model that is used to predict surface roughness through MATLAB software with the help of the Back Propagation Neural Network (BPNN) algorithm. Figure 5 shows the developed neural network model.

3.3.2. DESIGNING THE MODEL

The experiments were conducted according to the four different input parameters coating, groove depth, texture, and speed. The different levels of each parameter are shown in below table 3.

| Factors     | 1  | 2  | 3  | 4  |
|-------------|----|----|----|----|
| Groove Size | 100| 200| -  | -  |
| Speed       | 60 | 90 | 120| -  |
| Coating     | NC | TiN| TiAlN| - |
| Texture     | NT | PET| PAT| CRT|

Table 3: Experimental level and Parameters

3.3.3. CHOICE OF THE NUMBER OF HIDDEN NEURONS

The selection of the optimal number of hidden neurons (N) is the necessary challenging tasks in ANN modeling. Simon Haykin [21] has stated that N should lie somewhere between 2 and infinity. Similarly, Hecht Nelisen [22] utilize the Kolmogorov's theorem to calculate the number of hidden neurons N=2(n+1) where n is the number of input neurons. In general, this value must be defined based on the requirement of the problem. The choice of the high value of neurons (N) can be reduced the error which causes the complexity of the problem. Thus an optimal N value must be considered which gives a tolerable error associated with ANN.

3.3.4. CHOICE OF PARAMETERS

The main important parameters to be considered are the learning rate and the momentum factor. The learning rate is very small, the computations become slow, thereby takes much time to complete. The learning rate is larger the model becomes unstable (oscillatory). In order to control the learning rate without disturbing the stability of the model the momentum factor. The values of the learning rate and momentum factor should lie between 0 & 1.

Figure 5: Neural Network model
3.3.5. EVALUATION OF THE MODEL

The evaluation of the model is done using measured values of the least square error with the training data which is fed into the model. The training is stopped, when the least square value of error has been obtained without vary much deviation of least square error value for any number of iterations. The final model was developed based on regression value and accuracy of the regression plot for any given set of input parameters. The Mean Square Error (MSE) is used to validate the performance of ANN data.

3.3.6. ANN MODEL RESULT

The ANN model is developed and trained, a set of test data was given as input to the developed model. The output from the model is obtained and tabulated shown in Table 4. The average sum of mean square error by this method is found to be equal to 0.276.

| Experimental Output | ANN Output | Error | Mean Absolute Deviation | Mean Square Error | MAPE |
|---------------------|------------|-------|-------------------------|------------------|------|
| 0.309               | 0.633      | -0.324| 0.324                   | 0.105            | 1.049|
| 0.394               | 1.535      | -1.141| 1.141                   | 1.302            | 2.896|
| 1.582               | 1.200      | -0.382| 0.382                   | 0.146            | 0.241|
| 0.361               | 0.654      | -0.293| 0.293                   | 0.086            | 0.812|
| 0.627               | 0.953      | -0.326| 0.326                   | 0.106            | 0.520|
| 0.663               | 0.720      | -0.057| 0.057                   | 0.003            | 0.086|
| 1.535               | 0.744      | 0.791 | 0.791                   | 0.626            | 0.515|
| 1.200               | 1.440      | -0.240| 0.240                   | 0.058            | 0.200|
| 0.554               | 1.100      | -0.546| 0.546                   | 0.298            | 0.986|
| 0.753               | 0.933      | -0.180| 0.180                   | 0.032            | 0.239|
| MEAN                |            |       |                         | 0.276            | 0.754|

Table 4: ANN Outputs

3.3.7. SUPPORT VECTOR REGRESSION MODEL (SVR)

The SVR model used to find out the real number values for the large combination of possibilities. In this operation, the tolerance $\varepsilon$ is considered based on the trial and error method to the SVR for the machining operation. However, the main motive is to minimizing the error and increase the margin by compensated error.

3.3.8 SVR MODEL PERFORMANCE AND RESULTS

Based on the SVR model formation, the set of developed and trained data's was given as input to the developed model. The output from this model is obtained through the SVR and it is tabulated in Table 5. The average sum of mean square error for this method is found to be 0.044.
Table 5: SVR Outputs

The performance of the SVR model can be predicted by the performance plots against the test data fed into the model. This plot is shown in figure 6, where the test output is plotted against the number of inputs.

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Table 5: SVR Outputs

| Experimental Output | SVR Output | Error  | Mean Absolute Deviation | Mean Square Error | MAPE  |
|---------------------|------------|--------|-------------------------|------------------|-------|
| 0.309               | 0.043      | 0.266  | 0.266                   | 0.071            | 0.861 |
| 0.394               | 0.193      | 0.201  | 0.201                   | 0.040            | 0.510 |
| 1.582               | 1.579      | 0.003  | 0.003                   | 0.000            | 0.002 |
| 0.361               | 0.374      | -0.013 | 0.013                   | 0.000            | 0.036 |
| 0.627               | 0.648      | -0.021 | 0.021                   | 0.000            | 0.033 |
| 0.663               | 0.875      | -0.212 | 0.212                   | 0.045            | 0.320 |
| 1.535               | 1.489      | 0.046  | 0.046                   | 0.002            | 0.030 |
| 1.200               | 1.145      | 0.055  | 0.055                   | 0.003            | 0.046 |
| 0.554               | 0.232      | 0.322  | 0.322                   | 0.104            | 0.581 |
| 0.753               | 1.174      | -0.421 | 0.421                   | 0.177            | 0.559 |
| MEAN                |            | 0.156  | 0.044                   | 0.298            |       |
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**Figure 6:** Performance plot of SVR

**Figure 7:** Comparison of ANN, SVR and Experimental Results
4. COMPARISON OF RESULTS

The test data is given as input into the two models considered for the evaluation of predicted outputs from the two models. From the comparison plot, the output of the two models compared with the actual experimental output. It was found that the SVR plot is giving a much accurate prediction compared to the ANN plot as shown in figure.7. and the comparison between the error values is shown in Table 6. Based on the comparison plot, the SVR model is better in predicting the output as compared to ANN for MSE, MAD, and MAPE errors.

| COMPARISON | MAD  | MSE  | MAPE |
|------------|------|------|------|
| ANN        | 0.428| 0.276| 0.754|
| SVR        | 0.156| 0.044| 0.298|

Table 6: Comparison of Error

5. CONCLUSIONS:

The effect of the different combinations of texture, coating and groove depth for the evaluation of surface roughness and cutting force for the turning of titanium alloy was investigated. Conclusions are shown below:

- The perpendicular textured tool with TiAlN coating enhances machinability aspects for the groove depth of 100 μm.
- It reduces the cutting force by 6-12% with non-textured tool due to combined effect coating and reduction in tool-formation of chip interface friction.
- The SVR and ANN models were developed to predicted surface roughness values for the considered input conditions. Based on the predicted surface roughness value, the SVR model performed better than the ANN model for considered input conditions.
- The comparative study shows the different types of errors for the SVR model and ANN models. The SVR give better result than ANN models which ensures the degree of accuracy is high in the SVR model than the ANN model.

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