Modelling of End Milling of AA6061-TiCp Metal Matrix Composite

S Vijay Kumar1*, Muralimohan Cheepu2*, D Venkateswarlu3, P Asohan1, V Senthil Kumar1

1Department of Production Engineering, National Institute of Technology Tiruchirappalli 620015, Tamil Nadu, India
2Department of Mechatronics Engineering, Kyungsung University, Busan 48434, Republic of Korea
3Department of Mechanical Engineering, Marri Laxman Reddy Institute of Technology and Management, Telangana 500043, India

*Corresponding author E-mail: muralicheepu@gmail.com

Abstract: The metal-matrix composites (MMCs) are used in various applications hence lot of research has been carried out on MMCs. To increase the properties of Al-based MMCs many ceramic reinforcements have been identified, among which TiC is played vital role because of its properties like high hardness, stiffness and wear resistance. In the present work, a neural network and statistical modelling approach is going to use for the prediction of surface roughness (Ra) and cutting forces in computerised numerical control milling machine. Experiments conducted on a CNC milling machine based on the full factorial design and resulted data used to train and checking the network performance. The sample prepared from in-situ technique and heat treated to get uniform properties. The ANN model has shown satisfactory performance comparatively.

1. Introduction
Milling and end milling are the most important machining processes in these days. Milling operations are widely used in automotive, aerospace and transportation sector since complex geometric shapes can be produced, ability to fast removal of material accuracy and excellent surface finish [1]. In past decades, modern industries are attracted to use of CNC milling machine which is very useful for its flexibility, accuracy and versatility that allows manufacture of products in short time, and low cost with high quality and good surface finish. All the products in manufacturing industries greater attention taking place for surface roughness as surface finish effects the mechanical properties, and fatigue behaviour, lubrication and electrical conductivity [2]. Without using expensive machinery and facilities with the process of reactive slag the composites of Al–TiC created with the ingredients of TiO2, cryolite, and commercial graphite. Specimens at different percentages of TiC in aluminum matrix composites were prepared and microstructures characterization is evaluated [3]. Jerome et al. [4], have been prepared the composites of Al–TiC (5, 10 and 15 wt.%) with molten metal and a reactive mixture of K2TiF6 and graphite powder. The property of high temperature sliding wear resistance of the composites with the addition of ceramic particulate was investigated. The Al-TiC MMCs were prepared by in situ process later subjected to shaping operation. The resulted outputs such as chip formation and cutting force were observed and investigated [5]. To find the machinability of materials Al/SiC PMMC and Al alloy both materials are compared for surface integrity such as surface roughness, residual stress, microstructure and micro hardness etc. [6]. Cutting forces were predicted by BP neural network model which later used to optimize.
ball-end milling operation. The network is compared with an analytical model and accuracy of analytical model is also compared [7]. The capability of ANN as a modeling technique for modeling of processes has been tried to verify in previous studies. Feed forward back propagation is selected as the algorithm with traingdx, learngdx, MSE, logsig as the training, learning, and performance and transfer functions, respectively. Three nodes in the input layer and one node in the output layer, different number of node in hidden layer eight networks have been formed [8]. Sivasankaran et al [9], to study the variations in composite behavior with respect of workability and plastic deformations, developed an ANN model to find the effects of process parameters on the former’s and analysis done. Machining processes are also used for fabrication materials to remove the weld flash after friction welding using either milling or turning operations. The friction welds after welding generates the weld flash, and to keep the inter layers, the specimens need to make very precision grooves all are done by using milling process [10-19].The feed forward back propagation artificial neural networks were used by few researchers to study the influence of cutting parameters on thrust force and cutting torque in drilling operation. Feed forward back propagation algorithm with multi-layer perception model was created by using cutting feed, cutting speed, and fraction of reinforcement particles by volume as nodes in input layer and thrust force, cutting force as node in output layer [20]. In milling process the influences of dynamic radii, cutting feedrate, and radial and axial depths of cut on milling forces is studied [21]. When the depths of cut an immersion are constant few studies [22] at different feed rates in tangential, radial, and axial directions per tooth determined the average cutting forces. Pure aluminum and aluminum alloys have been reinforced by in situ with ceramic particles such as, TiC,Al2O3, B4C,TiB2,and SiC. TiC particles reinforces aluminum metal(composite which was produced by in situ) by insitu very effectively since TiC particles which are generated in In-Situ casting are free from thermodynamic deformities, interface of the matrix and particle is clean, no absorbed gases, oxide films hence much stronger and stable [23]. Al6061–TiC are new generation of aluminum alloy based particulate reinforced metal-matrix composites (MMCs) which are particularly used in aerospace and automobile industries[24-29]. From previous literature less research work available in the field of machining of composite materials Al6061–TiC. In order to bridge the research gap this study is carried out. The objective of this study is to formulate both ANN and Regression model of end milling process of Al6061–TiCp composites.

2. Experimental Procedure

The present work involves of modeling of Al 6061/TiC (particulate reinforcement) metal matrix composites for end milling process using both ANN and statistical model. The various steps involved in this work are composite preparation, heat treatment, resign of experiments, machining and modeling. Al–TiCp composites have been synthesized in-situ in molten metal by reacting K2TiF6 and graphite. The commercial aluminium 6061 alloy was selected as a matrix material. The mixture of 186.4g of K2TiF6 and 15.9g of graphite powders used to get 10wt% of TiC. The melt temperature was kept at 900˚C and allowed to soak at 1 hr. The mixture was mixed in molten metal and stirred for 30 minutes in order to disperse the newly formed TiC particles throughout the molten metal uniformly. After stirring the slag which is floating was removed and the molten metal was poured in mild steel die. The chemical reaction given by

\[ 3K2TiF6 + 22Al + 6KCF4 \rightarrow 3Al3Ti + K3AlF6 + 3AlCl + 9KAlF4 + \text{heat} \]

Aluminum is soft and ductile at its pure state. Most commercial uses require greater strength. The strength can be achieved by the annexed of other elements which produce different alloys, which alone or in accompanied gives strength to the metal. The work piece was casted first solution hardened and subjected aging of three cycles. For solution hardening the sample is heated to 540˚C and allowed it to soak for 2 hours and quenched in water. Later the first cycle of aging was done at 200˚C soaked it for 2 hours and allowed for furnace cooling. Similarly remaining two cycles were done at 225 and 250˚C.

The inputs taken for the end milling process are depth of cut, speed and feed & output parameters are cutting force and surface. Each input parameter has three stages namely low, medium and high level. According to full factorial design the total numbers of experiments are 27. Because of each input factor has importance role to play on cutting force and surface roughness and the number of input parameters are less and have low levels hence full factorial design is most suitable. The main advantage of full
factorial design is each and every combination is being tested so the model obtained is robust model. The various levels of parameters are given in Table 1.

Table 1 various levels of parameters for modeling

| Parameter     | Low | Medium | High |
|---------------|-----|--------|------|
| DOC (mm)      | 1   | 2      | 3    |
| Speed (RPM)   | 400 | 800    | 1250 |
| Feed (mm/min) | 40  | 80     | 125  |

Table 2 The experimental results used in the present study for modeling

| DOC(mm) | Speed(RPM) | Feed (mm/min) | Ra(μm)  | Fy(N)  |
|---------|-------------|---------------|---------|--------|
| 1       | 400         | 40            | 0.6460  | 39.24  |
| 1       | 400         | 80            | 0.6833  | 68.67  |
| 1       | 400         | 125           | 0.8433  | 98.1   |
| 1       | 800         | 40            | 0.5866  | 29.43  |
| 1       | 800         | 80            | 0.6466  | 58.86  |
| 1       | 800         | 125           | 0.7533  | 127.53 |
| 1       | 1250        | 40            | 0.8466  | 29.43  |
| 1       | 1250        | 80            | 0.8533  | 49.05  |
| 1       | 1250        | 125           | 0.8433  | 58.86  |
| 2       | 400         | 40            | 0.6933  | 117.72 |
| 2       | 400         | 80            | 0.8400  | 117.72 |
| 2       | 400         | 125           | 0.8433  | 127.53 |
| 2       | 800         | 40            | 0.8600  | 58.86  |
| 2       | 800         | 80            | 0.9800  | 78.48  |
| 2       | 800         | 125           | 0.8433  | 107.91 |
| 2       | 1250        | 40            | 1.1100  | 39.24  |
| 2       | 1250        | 80            | 0.7933  | 49.05  |
| 2       | 1250        | 125           | 0.9866  | 58.86  |
| 3       | 400         | 40            | 1.0166  | 98.1   |
| 3       | 400         | 80            | 0.9066  | 137.34 |
| 3       | 400         | 125           | 1.0566  | 137.34 |
| 3       | 800         | 40            | 0.9066  | 88.29  |
| 3       | 800         | 80            | 0.9300  | 68.67  |
| 3       | 800         | 125           | 0.8500  | 98.1   |
| 3       | 1250        | 40            | 0.9466  | 68.67  |
| 3       | 1250        | 80            | 1.1200  | 78.48  |
| 3       | 1250        | 125           | 0.9533  | 117.72 |

Figure 1 Photograph of the machined specimens at DOC (a) 1 mm, (b) 2 mm and (c) 3 mm.
Milling is perhaps the most versatile operation and most of shapes can be generated by milling operation. End milling is a vertical type of milling in which the axis of rotation is vertical axis of work piece. End milling cutters are used to make slots, grooves, irregular shaped surfaces. The experiments are conducted according to full factorial design on a Denford vertical type CNC milling machine with 8 mm HSS end mill cutter, the experimental conditions are given in Table 2. Though for this composite the carbide tool is suggested, keeping this point mind the milling was done by using HSS tool for machining. Throughout the experiment the diameter of the tool kept constant and three tools were used to get reliable results by avoiding tool wear, built-up edge by replacing the tool in fixed intervals, and the machining specimens are illustrated in figure 1.

2.1 Modeling
In order to achieve an accurate model a number of networks created, trained and tested for entire data set with hidden layers with varying hidden layer neurons. The log-sigmoid transfer function used widely used to process the inputs in the hidden layers:

\[ y = \frac{1}{1+e^{-x}} \]

The transfer function for calculating output layer by calculating a the output hidden layer from its inputs as

\[ f(x) = \left( \frac{e^x - e^{-x}}{e^x + e^{-x}} \right) = 1 \text{ range (-1,1)} \]

By the back propagation algorithm weights are updated vigorously. Levenberg–Marquardt algorithm trains the network. These training algorithms have high precision in such function approximation. The network efficacy cane be judged by average error (MSE) and the MSE is:

\[ E_p = \sum_{P=1}^{P} \sum_{k=1}^{k} (d_{p,k}-o_{p,k})^2 \]

Where dpk and opk are in the calculated output for kth responses, respectively.

The k denotes the total number of neurons in the output of layer and denotes the total number epochs. It is assumed that within 100 epochs the model get convergence. Initially three nodes in input layer, two nodes in the hidden layer and two nodes in output layer has been taken and trained. Likewise the node’s numbers in hidden layer increased up to 32 neurons similarly for two hidden layers also done. The normalization was done by dividing each column with the local maximum value. Each network checked with different combinations of transfer functions, however attention has paid on Iodsigmoid and pure line transfer functions due to their fast convergence. The training conditions are shown in figure 2.
Figure 2 Training conditions for modelling (a) input parameters, (b) Epochs vs. MSE graph for 3-30-3 network

3. Results and Discussions

3.1 Results of 3-30-3 network

The surface roughness and cutting forces, the output function can be set as

$$Ra \text{ or } F_y = f (\text{Speed, Feed, DOC})$$

The model by regression analysis is as follows:

$$Ra = a_0 + a_1(\text{Speed}) + a_2(\text{Feed}) + a_3(\text{DOC})$$

$$\text{Cutting force} = b_0 + b_1(\text{Speed}) + b_2(\text{Feed}) + b_3(\text{DOC})$$

Where $a_0$, $b_0$ are the average of responses; $a_1$, $a_2$, $a_3$... $b_1$, $b_2$, $b_3$... are constants depend on main factors. The main factors can be obtained by:

$$a_i \text{ or } b_i = \sum((X_i Y_i)/n)$$

where ‘i’ varies from 1 to n, in which $X_i$ is respective value of a factor and ‘$Y_i$’ the respective desired value found from the experimental and ‘n’ denotes the total number of observations. From the analysis of variance results the regression equations are shown below;

The regression equation is

$$Ra (\text{mic. m}) = 0.506 + 0.116 \text{ DOC (mm)} + 0.000082 \text{ Speed (rpm)} + 0.00102 \text{ Feed (mm/min)}$$

The regression equation is

$$F_y (N) = 36.9 + 19.3 \text{ DOC (mm)} - 0.0435 \text{ Speed (rpm)} + 0.441 \text{ Feed (mm/min)}$$

From Table 3 it is clear that as the feed increases for the same depth of cut and same speed the surface roughness and cutting force increases. Figure 3 gives the convergence of the network 3-30-3. The experimental and regression predicted analysis values for the cutting force, depth of cut and speed and feed are predicted with ANN model and estimated the percentage error. The overall trend of the percentage error was gradually increasing with the speed and feed rate. Table 3 shows ANN results for the depth of cut.
Table 3 Results of 3-30-3 network

| DOC (mm) | Speed (rpm) | Feed (mm/min) | Experimental results | ANN results | Percentage errors |
|----------|-------------|---------------|----------------------|-------------|-------------------|
| 1        | 400         | 40            | Ra(μm) 0.646        | Ra(μm) 0.6055 | Fy(N) 39.24       | 6.26 -3.99        |
| 1        | 400         | 80            | Ra(μm) 0.6833       | Ra(μm) 0.6833 | Fy(N) 68.67       | -7.4E-08 1.94E-11 |
| 1        | 400         | 125           | Ra(μm) 0.8433       | Ra(μm) 0.8433 | Fy(N) 98.1        | 3.68E-08 4E-08    |
| 1        | 800         | 40            | Ra(μm) 0.5866       | Ra(μm) 0.5866 | Fy(N) 29.43       | 2.62E-08 1.33E-07 |
| 1        | 800         | 80            | Ra(μm) 0.6466       | Ra(μm) 0.7021 | Fy(N) 58.86       | -8.58 4.94        |
| 1        | 800         | 125           | Ra(μm) 0.7533       | Ra(μm) 0.7533 | Fy(N) 127.53      | -0.000063 -4.6E-08 |
| 1        | 1250        | 40            | Ra(μm) 0.8466       | Ra(μm) 0.8466 | Fy(N) 98.1        | 6.07E-08 1.33E-07 |
| 1        | 1250        | 80            | Ra(μm) 0.8533       | Ra(μm) 0.8533 | Fy(N) 49.05       | 3.42E-08 4E-08    |
| 1        | 1250        | 125           | Ra(μm) 0.8433       | Ra(μm) 0.8433 | Fy(N) 127.53      | 2.75 5.61         |
| 2        | 400         | 40            | Ra(μm) 0.6933       | Ra(μm) 0.6933 | Fy(N) 117.72      | -4.5E-08 1.66E-08 |
| 2        | 400         | 80            | Ra(μm) 0.84         | Ra(μm) 0.84  | Fy(N) 117.72      | 7.04E-10 1.67E-08 |
| 2        | 400         | 125           | Ra(μm) 0.8433       | Ra(μm) 0.8433 | Fy(N) 127.53      | -5.24514 -1.98    |
| 2        | 800         | 40            | Ra(μm) 0.86         | Ra(μm) 0.86  | Fy(N) 58.86       | 4.63E-08 -0.000001 |
| 2        | 800         | 80            | Ra(μm) 0.98         | Ra(μm) 0.9312 | Fy(N) 78.48      | 4.97 -2.43        |
| 2        | 800         | 125           | Ra(μm) 0.8433       | Ra(μm) 0.8433 | Fy(N) 107.91     | 1.14E-08 -3.6E-08 |
| 2        | 1250        | 40            | Ra(μm) 0.98         | Ra(μm) 0.9866 | Fy(N) 39.24      | 41.87 0.94       |
| 2        | 1250        | 80            | Ra(μm) 0.7933       | Ra(μm) 0.7933 | Fy(N) 49.05      | 4.82E-08 4E-08    |
| 2        | 1250        | 125           | Ra(μm) 0.9866       | Ra(μm) 0.9866 | Fy(N) 58.86      | 5.14 3.99        |
| 3        | 400         | 40            | Ra(μm) 1.0166       | Ra(μm) 1.0166 | Fy(N) 98.1       | 98.1 -2.8E-08 4E-08 |
| 3        | 400         | 80            | Ra(μm) 0.9066       | Ra(μm) 0.9465 | Fy(N) 137.34     | 140.14 -4 -2.039 |
| 3        | 400         | 125           | Ra(μm) 1.0566       | Ra(μm) 1.0566 | Fy(N) 137.34     | -2.8E-08 -1.6E-11 |
| 3        | 800         | 40            | Ra(μm) 0.9066       | Ra(μm) 0.9066 | Fy(N) 88.29      | 88.29 1.06E-08 -2.2E-08 |
| 3        | 800         | 80            | Ra(μm) 0.93         | Ra(μm) 0.9299 | Fy(N) 68.67      | 68.67 5.42E-08 4.72E-11 |
| 3        | 800         | 125           | Ra(μm) 0.85         | Ra(μm) 0.8937 | Fy(N) 98.1      | 94.17 -5.14 3.99  |
| 3        | 1250        | 40            | Ra(μm) 0.9466       | Ra(μm) 0.9103 | Fy(N) 68.67      | 71.7 3.83 -4.41  |
| 3        | 1250        | 80            | Ra(μm) 0.9533       | Ra(μm) 0.9533 | Fy(N) 78.48      | 78.48 3.84E-08 7.5E-08  |
| 3        | 1250        | 125           | Ra(μm) 0.9533       | Ra(μm) 0.9533 | Fy(N) 117.72     | 117.72 6.13E-08 1.67E-08  |
From the ANN model and experimental results, over all the values taken for present study, surface roughness and depth of cut both need to be diminished. Figure 4 shows connection between the experimental and predicted data for a correlation factor of force $F_y$. It is observed that the linearity of the graphs indicates the predicted values are almost equal to the experimental values and satisfied the modeling predictions. In the surface roughness plot in figure 4(b), the experimental data and predicted data variation are expressed compared to the cutting force. The graph linearity is slightly different from the cutting force graph and the graph has more inclination which means the larger variation of difference in predicted values. This is because of tool flute has higher impact than DOC.
Figure 5 the results of the ANN prediction and regression model prediction of (a) Cutting force and (b) surface roughness

The cutting force plot in figure 5 (a), shows that the parameters which are all used have significant, the predicted values, experimental and regression model values are accurate and followed the similar trend with the minor variations in the values. It is observed that the with increasing data set values from data sets 1 to data sets 6, the cutting force values are gradually decreased. It is fact that the ANN prediction values always shows higher accuracy than the regression model. The experimental results always falls in between the ANN prediction and Regression prediction values. The modeling values suggests that the ANN prediction and regression model values can be taken as average of them for the final reliable parameters, as per the correlation studies. In figure 5(b) shows the surface roughness plots of experimental, regression model and ANN prediction values. It indicates in the surface roughness plot, the major contributor for surface roughness is tool flute. In general minimum surface roughness can be achieved by a milling tool with very less depth of cut and higher count of flutes. Figure 5(a) shows the cutting force plots. The major factor contributes for reduction of cutting force is speed. From the results (table 2) it is clear that with the increase in cutting speed cut resulted in reduction in the cutting force value. For the given speed cutting force increases with the increase in depth of cut and feed and there by surface roughness increases. This is due to higher speeds reduce the point of contact time hence reduces cutting force whereas the increased depth of cut and feed increases time of point of contact hence cutting forces increases. Also the reaction force offered by the metal while milling process is going on also contributes to the cutting force. From the table 3 and figures 4, the achievable optimal value of surface roughness is at the optimum toll flutes, and depth of cut 1 mm, cutting speed 800 rpm and 40 mm/min feed rate. From the experimental results the cutting forces are minimum at the same cutting parameters where surface roughness is minimum which indicates that the point of contact time is lesser than surface roughness also lesser for the given parameters. Figure 5(b) shows the surface roughness plots are almost all are similar of ANN prediction, experimental conditions and regression model prediction values. The obtained readings are suggested that the techniques used in the present study is normal and obtained the robust values. The machining of milling parameters optimization is not easy to achieve in reality due to the production targets materials change, the selection of machining parameters done based on industrial applications. Any DOE techniques or Minitab software gives the design parameters for the output functions (surface roughness and cutting force) by considering target values, minimum and maximum values, later optimized values of cutting force and surface roughness are obtained using regression model and 3-30-3 network. Surface roughness and DOC verifications are carried out for the models. The prediction values from regression analysis are lower compared to the ANN prediction and experimental values for cutting force. Whereas the regression analysis values are the highest values predicted for surface roughness.
4. Conclusions
The composite Al 6061/TiC (particulate) was prepared by In-Situ casting method and heat treated. Then the composite was machined to obtain slots on its surface by end milling based on full factorial design. The required output parameters cutting force in Y-axis direction and the surface Roughness was measured. The obtained data set was used for both ANN model and Regression model. The predicted values are compared with the experimental value. Based upon modelling results the following conclusions are drawn.

- In ANN modeling the combination of log-sigmoid, log-sigmoid and tan-sigmoid, tan-sigmoid transfer functions resulting poor convergence and huge errors.
- The combination of log-sigmoid, tan-sigmoid transfer functions resulting poor convergence and large number of iterations.
- The log-sigmoid, purelin and tan-sigmoid, purelin transfer functions combinations are given speed convergence and satisfactory results.
- Among the ANN and Regression models ANN has shown satisfactory performance comparatively.

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