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Mathematical Modelling and Optimization of Tool Geometry to Machine Hard Metals Using PCBN Inserts

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Abstract. Hard metals are highly preferred in critical applications to withstand severe stresses and deformations. But they pose difficulties while machining in the form of rapid tool-wear and poor dimensional accuracy of the work-pieces. In conventional practice, hard metals are annealed to facilitate machining and hardness is restored back after machining. This is followed by grinding operation to finish the components. Hence, each component undergoes two stages of heat treatment and grinding operation additionally, which increases production time and cost apart from higher process rejections. This study and experimental work are carried out to facilitate direct machining of hard metals without the need of heat treatment and grinding operations. As any machining operation is highly influenced by the tool geometry, in the current experiments, the tool geometry is varied and corresponding machining forces are measured. Using experimental data, mathematical model is formulated with Artificial Neural Networks to relate the machining force with tool-geometry. Optimum tool geometry for minimum of the machining force is identified using Genetic Algorithm and the same is validated experimentally. The result shows that the machining forces are least at the optimum tool geometry to facilitate direct machining of hard metals.

Keywords: Hard metals · Tool Geometry · Machining Force · Mathematical Modelling · Artificial Neural Networks · Optimization · Genetic Algorithm · Experimental Validation

1 Introduction

Hard metals are extensively used in critical applications in view of their superior functional characteristics. But they show poor machinability and pose hurdles in the form of rapid tool wear, excessive tool consumption, poor surface finish, thermal distortions and dimensional in-accuracy [1]. An alternate solution for this problem is softening the raw material before machining and restoring back its original hardness after machining. Here, heat treatment is required in two stages. Next to it, grinding operation is performed to finish the work-piece and to eliminate thermal deformations that are caused in the heat treatment [2]. In view of repeated heat treatments that are followed by grinding

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operation, machining of hard metal is risky, time taking and it is a costly affair [3]. Hence, there is a necessity of direct machining of hard metals without the need of heat treatments and grinding.

Cutting tool geometry has significant influence on machining performance [4]. Careful selection of tool geometry enables machining of hard metal with minimum of cutting force. Among the tool geometrical parameters, the most influential parameters are rake angle, cutting angle and nose radius [5]. Tools with negative rake angle are stronger but require larger force to penetrate into work-metal. Tool with positive rake angle easily penetrates into the work material at the cost of its strength [6]. Hence, rake angle should be selected to strike a balance between cutting force and mechanical strength of the tool. Proper cutting angle gradually approaches the cutting zone to cause less impact on the tool. Hence, cutting angle should be carefully selected [7]. Nose radius is incorporated on the cutting tool to avoid breakage of tool tip. But larger nose radius results in cutting tool vibration due the chatter of the tool. Appropriate nose radius reduces the stress concentration on the tool and improves the surface finish [8].

Cutting force is a performance indicator that indicates the ease of machining. It is understood that lesser the cutting force, easier is the machining of components [9]. In order to select proper tool geometry, experiments are conducted using tool inserts of variable tool geometry. Cutting forces are measured at corresponding tool geometry. Tool geometrical parameters are available in a broad range and more number of tools are required for experimental study. Hence, the experimental cost and time goes beyond the reach. For this reason, mathematical modelling is adopted to choose optimum cutting tool geometry.

Mathematical model generates an output in the form of an equation that relates tool geometry with machining force. This equation is used for predicting the machining force at a given combination of the tool geometrical parameters. This equation is also used as objective function for optimization of tool geometry for minimum of machining force. Experimental validation is carried out to verify the optimum results. The experimental cutting force is compared with analytical cutting force and if their deviation is found to be within the limits, then the genuineness of the results is confirmed and optimum tool geometry is finalized [10]. This method would be followed with any other tool and work material combinations. Any mathematical model and optimization technique would be considered alternatively based upon the accuracy of results and fitness of the model.

Researchers and analysts prefer Artificial Neural Networks (ANN) because of the ability of handling linear as well as non-linear data for variety of systems without implicit assumptions as for the case of conventional mathematical modelling methods [11]. The fitness of the mathematical model using ANN is found to be better when compared to other techniques [12]. The most widely used technique for optimization of machining conditions is Genetic Algorithm (GA). The accuracy of results is found to be better when compared to other optimization techniques. The execution time and number of iterations for GA is less [13, 14]. Hence in the present case, ANN and GA are used for mathematical modelling and optimization respectively.

Table 1 Tool geometrical parameters considered in the experiments

Level	1	2	3
Tool geometry			
Point Angle γ (degree)	60	75	90
Nose Radius R (mm)	0.4	0.8	1.2
Rake Angle α (degree)	−3	−6	−9

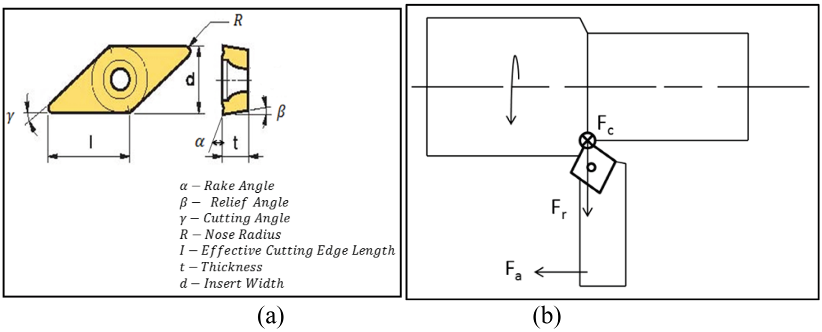


Fig. 1. (a) Cutting tool geometry; (b) Cutting force components

2 Experimentation

Hard metal specimens of MDN 350 of size ϕ 90 X 500 mm are chosen in the current study. The machining experiments are performed in the form of turning operation using PCBN inserts on Kirloskar Lathe machine equipped with 3-axis digital dynamometer at constant cutting parameters. The tool geometrical elements viz. Point angle (γ), nose radius (R) and rake angle (α), which are described in Fig. 1(a)are altered as shown in Table 1.

The cutting forces generated during cutting process are measured using Lathe Tool dynamometer. In the dynamometer, forces in the three directions viz. Radial direction (F_r), tangential direction (F_c) and axial direction (F_a) are observed as shown in the Fig.1 (b). The resultant of the three components of forces is calculated by eq.1

$$F_{Res} = \sqrt{F_r^2 + F_c^2 + F_a^2} \quad (1)$$

The variation of resultant machining force with nose radius, rake angle and cutting angle are shown in the Figs. 2, 3 and 4 respectively.

3 Mathematical Modelling Using ANN

Artificial Neural Networks technique is implemented in Matlab R2016 software with one input layer, one hidden layers and an output layer as shown in the Fig. 5(a). Three neurons are allocated to the input layer as there are 3 input variables. The number of

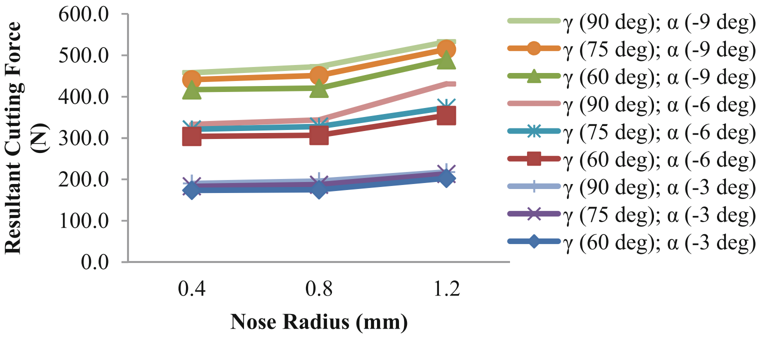


Fig. 2. Variation of machining force with nose radius

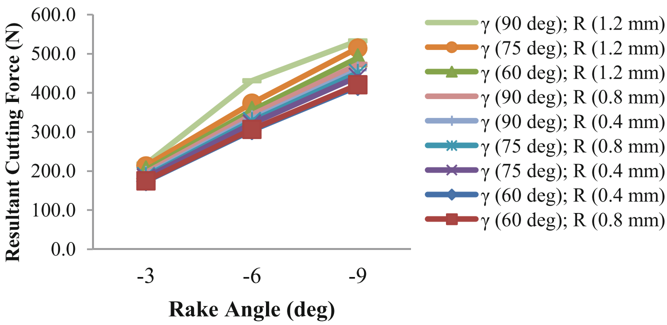


Fig. 3. Variation of machining force with rake angle

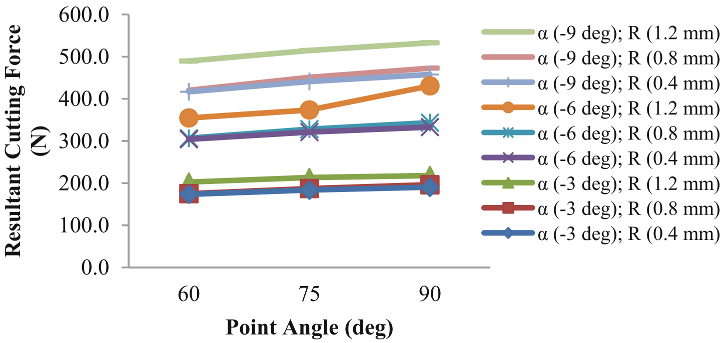


Fig. 4. Variation of machining force with point angle

neurons in the hidden layer is chosen as 6, which is twice the number of input variables. The performance of the network is better when the number of hidden layer neurons is twice the input layer neurons [14]. Since there is one output, the number of neurons in the output layer is '1'. The values of input and output variables are normalized between 0.1 and 0.9 and imported in the Neural Network architecture. The 70% of the data is used for training, 15% for testing and 15% for validation. The Neural Network is trained in

NN tool of Matlab software using Levenberg- Marquardt back-propagation algorithm. The mean square error (MSE) between actual output (experimental F_{Res}) and desired output (F_{Res} predicted by the neural network) is evaluated by the software and MSE plot is generated. The training is stopped when the values of MSE for training, testing and validation are converged as shown in the Fig. 5(b).

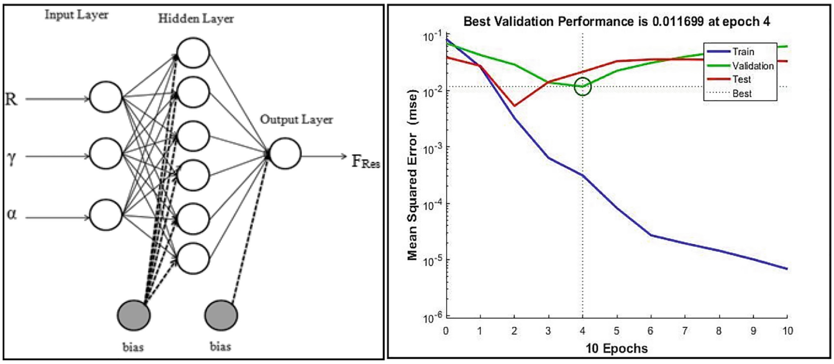
Similarly, the coefficient of determination 'R' relating the actual and the desired outputs is calculated for training, testing, validation and for overall data and regression plots are generated in the software as shown in Fig. 6.

Once the results of MSE plot and regression plots are satisfied after number of iterations, the values of weights connecting input, hidden and output neurons are finalized. The equation of machining force in terms of tool geometrical parameters is expressed by Eq. (2). Here, f_1, f_2, f_3, f_4, f_5 and f_6 are transfer functions relating hidden layer with the output layers, which are given by Eqs. (3) to (8).

$$F_{Res} = 3.0315 + 0.00215f_2 + 3.022f_3 + 2.812f_4 - 1.325f_5 + 3.946f_6 - 4.485 \quad (2)$$

$$f_1 = \frac{1}{1 + exp(-(-0.03855R + 4.6501\gamma + 2.2067\alpha - 5.5897))} \quad (3)$$

$$f_2 = \frac{1}{1 + exp(-(-2.4662R - 2.3543\gamma - 3.8338\alpha + 3.1924))} \quad (4)$$



(a) (b)

Fig. 5. (a) Architecture of ANN; (b) Mean square error plot for training, validation and testing

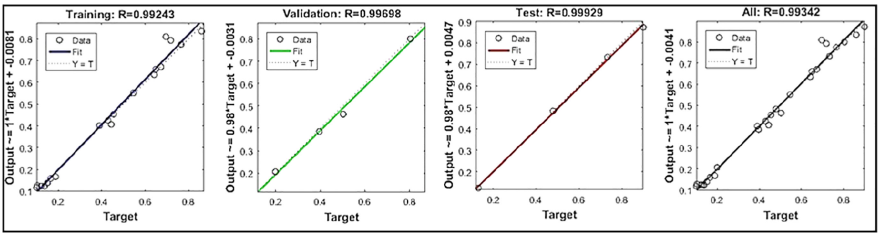


Fig. 6. Regression plots for training, validation, testing and complete data

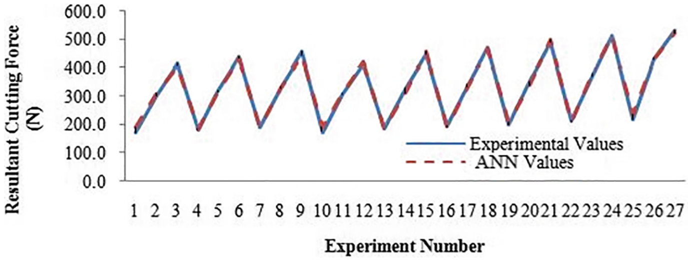


Fig. 7. Comparison of analytical values of resultant cutting force with that of experimental values

$$f_3 = \frac{1}{1 + exp(-(-0.2413R + 5.2901\gamma - 1.3042\alpha + 1.209))} \tag{5}$$

$$f_4 = \frac{1}{1 + exp(-(0.033814R + 0.27746\gamma + 4.8446\alpha + 1.7639))} \tag{6}$$

$$f_5 = \frac{1}{1 + exp(-(-0.07284R - 3.196\gamma - 3.4142\alpha + 3.8709))} \tag{7}$$

$$f_6 = \frac{1}{1 + exp(-(0.00015R + 2.9372\gamma - 4.9244\alpha - 5.0289))} \tag{8}$$

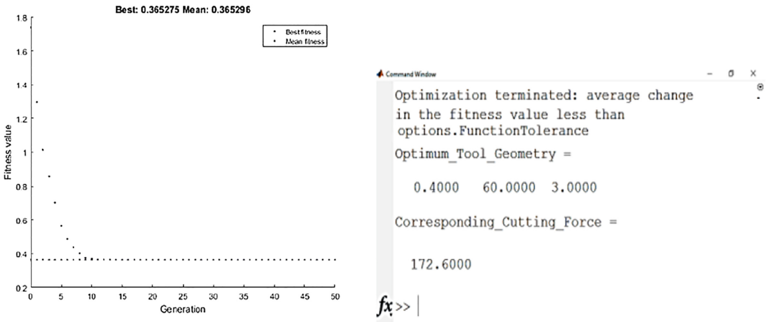
The values of resultant machining force are calculated using the mathematical model and de-normalized to get the real values. The comparison is made between the calculated and experimental values as explained in Fig. 7. This unveils the condition of predicted and experimental resultant force values. In the present work, they are in good agreement in all the experiments. Thus, the selected mathematical model is confirmed to be fit and reliable.

4 Optimization Using Genetic Algorithm

A fitness or objective function file is created in Matlab R2016 using Eqs. (2) to (8). Another file with Genetic Algorithm code is created, wherein the constraints of the input variables are defined and the fitness function is imported. The program is executed and the optimum results are obtained when the best and mean fitness values are converged as shown in the Fig. 8(a). The output of the program is seen in the command window of Matlab R2016 as shown in the Fig. 8(b), which gives the optimum combination of tool geometrical parameters as Nose Radius = 0.4 mm; Cutting Angle = 60°; Rake Angle = 3° and its corresponding machining force as 172.6 N.

5 Experimental Validation

Experimental validation is conducted in order to verify the results predicted by analytical method and ensure suitability of the approach.MDN 350 specimen is machined with PCBN tool insert with optimum tool geometry. The resultant cutting force is evaluated



(a) (b)

Fig. 8. (a) Convergence of best and mean values of fitness function; (b) Optimum tool geometry and corresponding cutting force in machining MDN 350 specimens using PCBN tool inserts

Table 2. Results of experimental validation

Optimum Tool Geometry	Experimental Resultant Cutting force (N)	Analytical Resultant Cutting force (N)	Deviation (%)
$\alpha = 3^{o}$ $\gamma = 60^{o}$ R = 0.4 mm	173.60	172.60	0.57

from the measured cutting force components compared with anticipated values as shown in Table 2. The deviation is found to be less than 1 %. As per the precision machining standards practiced in manufacturing industry, deviations within 10 % are fairly good [10]. Hence, this confirms the suitability and reliability of the analytical approach i.e. mathematical modelling using ANN and optimization using GA, adopted in the current work for tool geometry optimization.

6 Conclusion

The highlights of the current experimental investigation and outcomes of mathematical modeling and optimization are enlisted as follows.

- Tool geometrical parameters viz. Nose radius, rake angle and point angle have significant influence on machining of hard metals. For a variation of 0.4 mm in nose radius, the machining force is decreased by 16%.The variation of rake angle by 3° resulted in reduction of machining force by 75%. The machining force is minimized by 7% for a variation of point angle by 15°.
- ANN is found to be more reliable in mathematical modelling of machining data. The coefficient of determination is observed to be 99% and mean square error is found to be least of the order of 10^{-2}.

- GA is observed to be very accurate in optimization of tool geometry. The experimental and GA results are closer and their deviation is found to be within 1%.
- With a randomly selected tool geometry for PCBN insert, the machining force was observed to be in the range of 304 N -533 N. Using optimum tool geometry of rake angle = –3°; point angle = 60° and nose radius = 0.4 mm, the machining force is minimized to 173 N. Based upon this study, an average improvement of **58.66%** is achieved in the machining of hard metals with PCBN tool inserts.

The present work shows a significant contribution in machining of hard metals. It facilitates direct machining of hard metals, thus eliminating the need of additional heat treatment and grinding operation. Thereby, machining cost and time would be substantially minimized and process rejections would be avoided.

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