COMPARISON OF ADAPTIVE NEURO FUZZY INFERENCE SYSTEM AND RESPONSE SURFACE METHOD IN PREDICTION OF HARD TURNING OUTPUT RESPONSES

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ABSTRACT: Hard turning has been used to replace cylindrical grinding to obtain high quality surface finish of complex parts with hardness above 45 HRC. Surface roughness is characterized among the most critical attributes in hard turning and it is important to the manufacturer to have accurate understanding of the machining process prior to its optimization process. The aim of this paper is to compare the capability of adaptive neuro-fuzzy inference system (ANFIS) model with response surface method (RSM) in developing the correlation of machining parameter and output responses. The input for both models are cutting speed (v), feedrate (f), and depth of cut (d), whereas the output responses are flank wear (V_b) and surface roughness (R_a, R_q and R_z). The results indicate that the accuracy of predicted values of ANFIS model overwhelmed the predicted value of RSM model with up to 42% higher. At this level of accuracy, ANFIS model shows its applicability to be an objective function in evolutionary algorithm.

KEYWORDS: *Hard Turning; RSM; ANFIS*

1.0 INTRODUCTION

Manufacturing high quality products and at the same time reducing the cost and time consumption is an ultimate target of manufacturers to compete in the industry. One of the areas that has been focused to achieve these criteria is the metal cutting process where hard turning has been used to replace cylindrical grinding to obtain high-quality surface finish of cylindrical steel product with hardness above 45 HRC. This is due to its advantage which is flexibility in producing complex shape with a level of surface finish achieved by cylindrical grinding (range: 51 nm to 3.2 μm). Surface finish is characterized as the level of smoothness of a surface after it has been machined. The surface finish results from a combination of surface roughness, waviness, and flaws remaining on the workpiece, where surface roughness is regard as among the highly important attributes in hard turning since it may become the factor that affect the resistance to corrosion, fatigue limit, rate of wear and tribological properties of machined workpieces [1].

In turning processes, the most investigated process parameters are cutting speed, feedrate, and depth of cut. This is due to the fact that these parameters are highly changeable during the hard turning process, and highly influence the time consumption of that process. On the other hand, the commonly studied output responses in lathe machining operation are surface roughness and flank wear. As shown in Figure 1(a), the average roughness (R_a) calculated as the average distance of the profile from the centerline. The root-mean-square roughness (R_q) is taken as the root-mean square of the profile distance from the centerline, and the peak-to-valley distance (R_z) is the largest distance between the lowest and highest points of the profile for a given length of evaluation. Figure 1(b) shows the flank wear monitoring by measuring the average wear land size (V_b). These parameters may be optimized for achieving the optimum production time at the optimum machining cost. Recently, the optimization of those parameter have been done through evolutionary algorithm (EA) such as particle swarm optimization (PSO) [2]. Usually, the algorithm utilizes response surface method (RSM) model as its objective function. However, prior to optimization, performance of the model should be developed accurately.

RSM has been widely used as the objective function of EA to represent behavior of machining performance due to its feasibility and it’s still being utilized in machining statistical research [3–7]. Mir and Wani [8] perform a comparison between the performance of mixed ceramic, CBN and coated carbide inserts when machining AISI D2 cold work steel using combination of cutting speed, cutting time (feedrate), and tool hardness as input parameters. Particularly the effect of cutting parameters on surface roughness and tool wear of the inserts was highlighted by applying RSM methodology. It was reported that cutting speed and cutting time had the most effect on surface roughness, followed by tool hardness, and the correlation coefficient (R^2) is 96.23 %. Benlahmidi et al. [9] reported experimental results on the cubic boron nitride (CBN7020) wear behavior when machining hardened hot work steel (AISI H11). In the experiment, surface roughness is examined as a function of cutting conditions and the R^2 is 74.05 %. Singh et al. [10] compare the performance of single nanoparticle-enriched cutting fluid and hybrid nanofluid in turning operation and produce regression models with correlation coefficient are 90.75 % and 89.63 %.

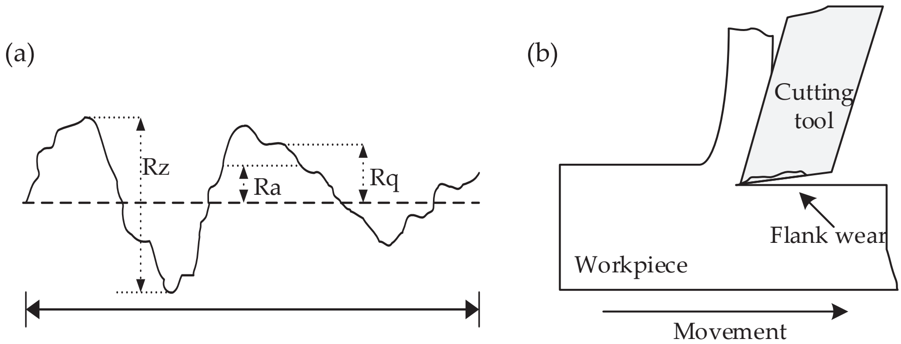

Figure 1: Machining output response: (a) surface roughness and (b) flank wear

Although RSM has been accepted as an objective function for EA until recently [11-12], its accuracy to correlate the input parameter and output responses is still can be improve to ensure the optimization process is completed accurately. In the field of EA, there are researchers that utilized artificial intelligence (AI) approach as the objective function which is artificial neural network (ANN) [13-14]. This is because conventional mathematical tools are quantitative in nature and they are not well suited for uncertain or highly nonlinear problems. AI tools such as ANN is excellent in pattern recognition but still it is still lack of human reasoning capabilities, which can be further improved. In the present work, an adaptive neuro-fuzzy inference system (ANFIS) model is utilized to predict accurate relation between machining parameter and its output responses. ANFIS is chosen based on its capability to combine the learning capability of ANN and the human reasoning of fuzzy logic. The accuracy of the present work was compared with the RSM model to show accuracy improvement of ANFIS model.

2.0 METHODOLOGY

2.1 Assessment of secondary data

The experimental assessment is based on the work of Das et al. [1]. The material of machined workpiece was AISI 4140 high strength steel. The composition of the material includes C 0.386 %, Si 0.377 %, Mn 0.67 %, P 0.032 %, S 0.029 %, Cr 1.04 %, Mo 0.091 %, Ni 0.0143 % and Fe 97.232 %. Prior to machining, heat treatment was applied to the workpiece at 920˚C for 30 minutes and undergone oil quenching. In addition, tempering was done at 400˚C for 2 hours to obtain a workpiece with 52 HRC of hardness. The cutting tool of the process was coated Al2O3 + TiCN mixed ceramic insert. Das et al. [1] performed the hard turning experiments in dry cutting environment. Surface roughness tester was used to measure surface roughness responses for each machining condition on individual test. The final value for the response was taken from an average value after the measurement of surface roughness was performed at multiple locations of machined work surface. The values of each experimental hard turning parameters and responses are depicted in Figure 2 and Figure 3.

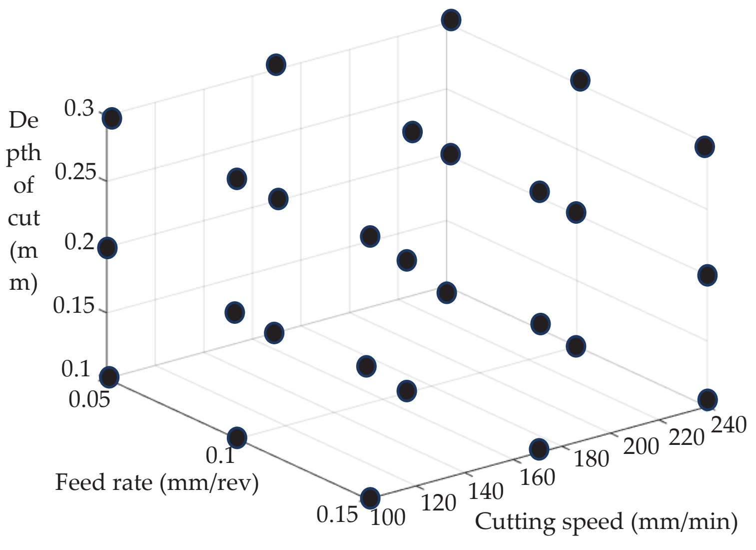

Figure 2: Cutting parameters by Das et al. [1]

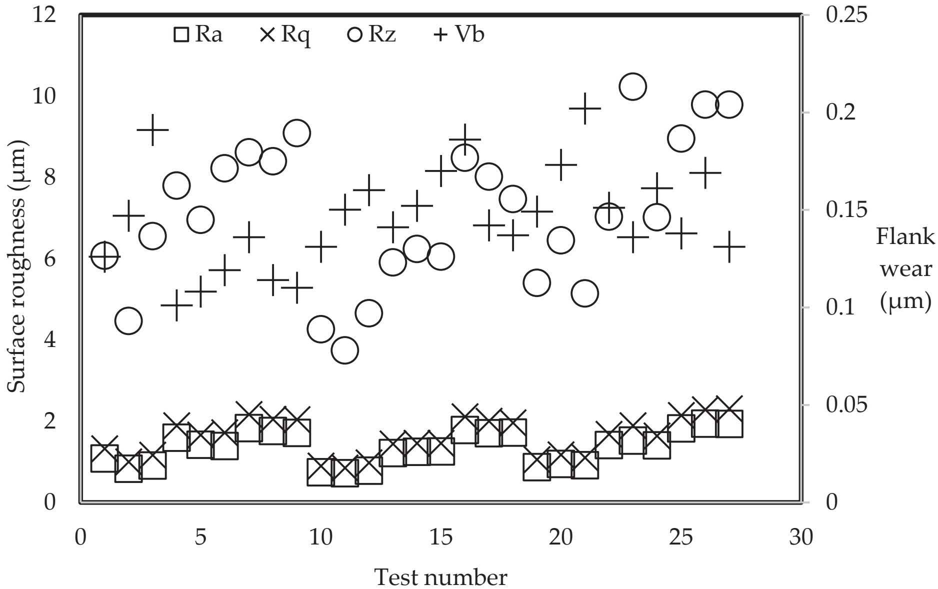

Figure 3: Output responses from experiment by Das et al. [1]

2.2 Architecture of ANFIS

The ANFIS model is a hybrid method where a fuzzy inference system (FIS) and neural networks are combined. The combination exploits the reasoning capability of FIS and self- learning capability of neural network. A first-order Sugeno fuzzy model was used in the structure of the neuro-fuzzy system. Figure 4 shows the architecture of the ANFIS in this study which consists of 27 fuzzy rules with three Generalized bell membership functions were assigned to each input variable. The inputs of the model are the cutting speed (*v*), federate (*f*), and depth of cut (*d*). The output of the models is flank wear (V_b) or surface roughness (R_a, R_q and R_z).

3.0 RESULTS AND DISCUSSION

By utilizing the secondary data in Figure 3, the quadratic (second-order) polynomial model are developed for surface roughness and flank wear. The response variables are flank wear (V_b) and surface roughness (R_a, R_q, R_z), whereas the inputs are cutting parameters (*v*, *f*, *d*). Using RSM, surface roughness model and flank wear model are presented in Equations (1)-(4), respectively.

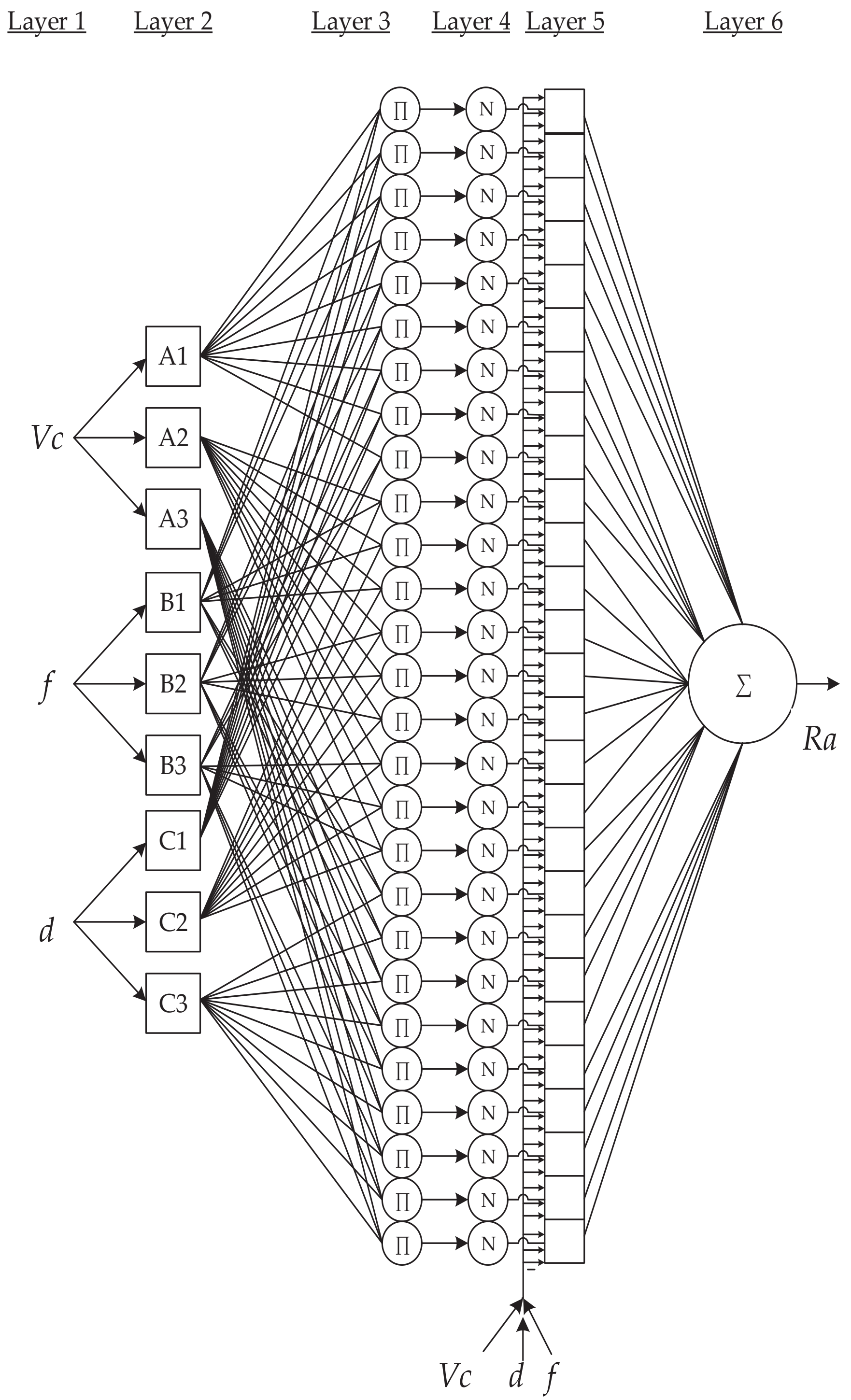

Figure 4: ANFIS network architecture

$$R_a = 1.60104 - 0.013926 \times v + 11.44093 \times f - 1.92894 \times d + 0.011072 \times v \times f + 0.00757172 \times v \times d + 0.11708 \times f \times d + 0.0000337985 \times v^2 - 20.08834 \times f^2 + 1.07791 \times d^2 \quad (1)$$

$$R_q = 2.06994 - 0.018192 \times v + 12.82785 \times f - 2.12393 \times d + 0.01509 \times v \times f + 0.00764454 \times v \times d - 1.04765 \times f \times d + 0.000045217 \times v^2 - 22.90798 \times f^2 + 1.85634 \times d^2 \quad (2)$$

$$R_z = 9.90102 - 0.10376 \times v + 49.4459 \times f + 6.83969 \times d + 0.063661 \times v \times f - 0.00826475 \times v \times d - 2.95399 \times f \times d + 0.000300133 \times v^2 - 120.60532 \times f^2 - 10.63466 \times d^2 \quad (3)$$

$$V_b = 2.06994 - 0.018192 \times v + 12.82785 \times f - 2.12393 \times d + 0.01509 \times v \times f + 0.00764454 \times v \times d - 1.04765 \times f \times d + 0.000045217 \times v^2 - 22.90798 \times f^2 + 1.85634 \times d^2 \quad (4)$$

As shown previously in Figure 4, there are 27 fuzzy rules in the ANFIS model architecture. Each input variable is assigned with three generalized bell membership functions. An example of membership function diagrams of the inputs of flank wear prediction process after learning can be found in Figure 5. The inputs of the model are the cutting speed, feedrate, and depth of cut. The output of the model is R_a, R_q, R_z or V_b. In order to generate a relation between a given set of input and output data, the least squares and back-propagation gradient descent methods are combined and the combination has been used to train the generalized bell membership function parameters. For each epoch of the hybrid learning process, signals travelled in a forward and a backward route. Initially, signals travel forward up to layer 4, and consequent parameters will be optimized by the least squares method, where at the same time, the premise parameters remain fixed. Next, the error signal is transferred backward, and the premise parameters will be updated by the back-propagation gradient descent method.

Figure 6 illustrates the prediction capability of the ANFIS and RSM, on the basis of correlation coefficient (R^2) on flank wear. The x-axis is the experimental value of flank wear and y - axis is the predicted value by ANFIS model and RSM model. The solid line represents fit and the R^2 value obtained from Equation (5) and the rest between 0 and 1. The R^2 value approaching 1 shows a perfect correlation between predicted and experimental value. Figure 6(a) shows that the R^2 value is 0.9999 for ANFIS model, and R^2 value is 0.707 obtained by RSM model which is illustrated in Figure 6(b). By comparing the R^2 value for every response in Figure 7, it can be seen that every ANFIS model predict the experimental values better than the RSM model. The performance different between both models are significant for R_z and V_b compared with R_a and R_q.

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(E_i - \bar{E}\right)\left(P_i - \bar{P}\right)}{\sqrt{\sum_{i=1}^{n} \left(E_i - \bar{E}\right)^2 \sum_{i=1}^{n} \left(P_i - \bar{P}\right)^2}} \right)^2 \tag{5}$$

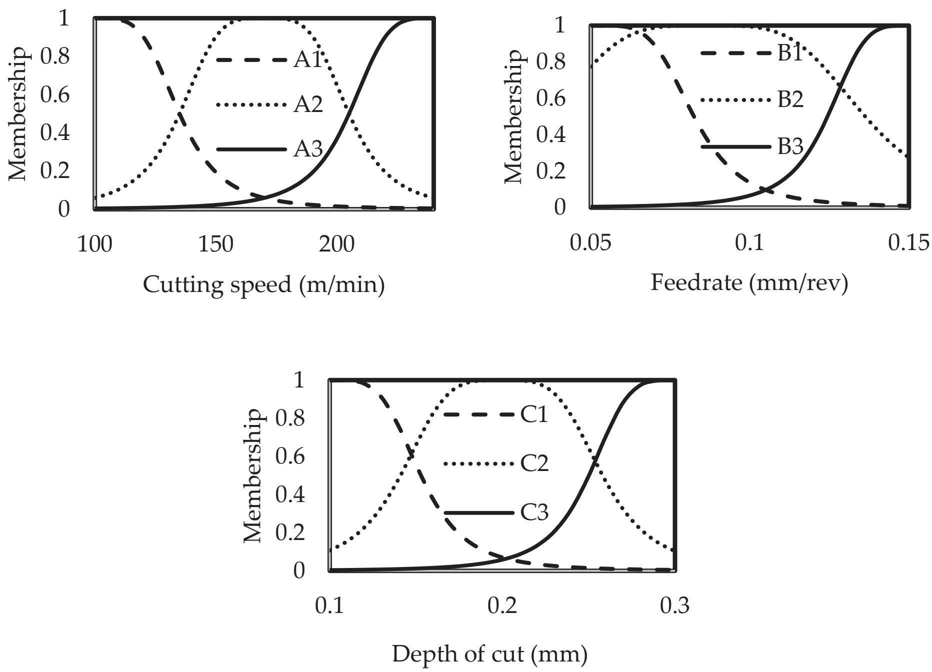

Figure 5: ANFIS membership functions for flank wear V_b

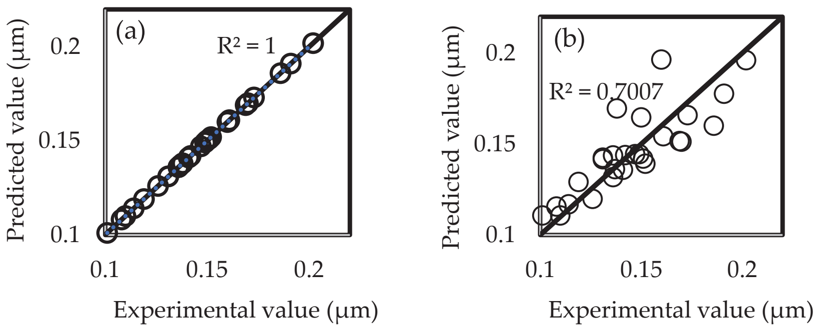

Figure 6: Comparison between experimental and predicted values for flank wear via (a) ANFIS and (b) RSM

The relative errors of ANFIS model and RSM compared with the experimental values presented graphically as scatters in Figure 8. The relative errors obtained from the RSM model was found to vary from - 6.25% to 13.15% for surface roughness (R_a), and from – 13.93% to 22.81% for flank wear (V_b), whereas the relative errors for ANFIS model were approaching zero. Therefore, the data was fitted better in the ANFIS model compared to the RSM model.

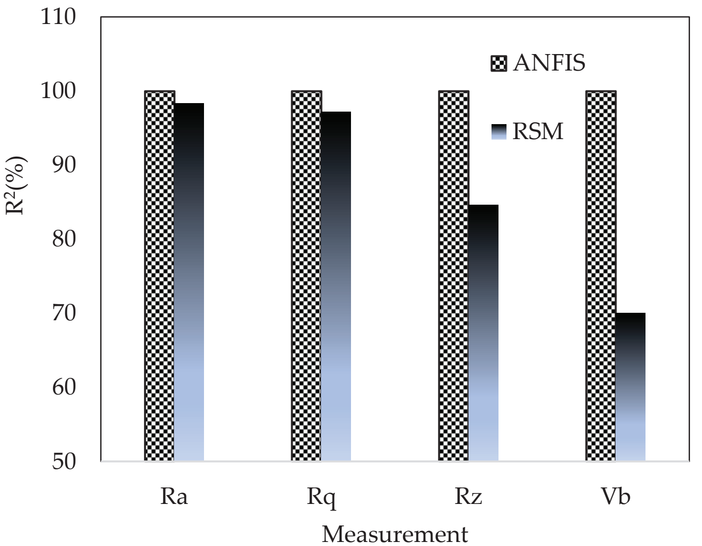

Figure 7: Correlation coefficient of output responses

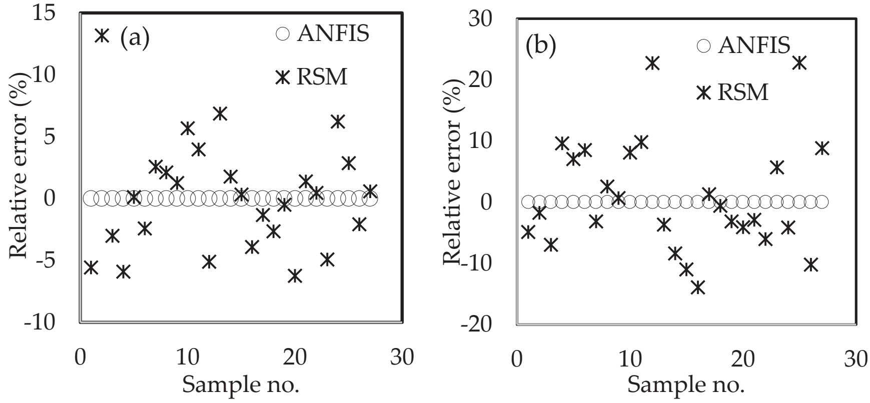

Figure 8: Comparison of relative error of predicted value by ANFIS and RSM with experimental value of (a) R_a and (b) V_b

4.0 CONCLUSION

The capability of ANFIS model to predict the output responses of hard turning has been compared with RSM model. It is shown that ANFIS model is capable to represent output responses of hard turning at up to 42 % higher compared to the RSM model. With an appropriate network architecture, the application has the capability to achieve equivalence to the available experimental data. Therefore, the current work has a high potential to be accurately integrated with the evolutionary algorithm to the output responses of hard turning of AISI 4140 steel using PVD-TiN coated Al2O3 + TiCN mixed ceramic inserts under dry environment.

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