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Application of ANFIS in predicting TiAlN coatings flank wear

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***Abstract*— In this paper, a new approach in predicting the flank wear of Titanium Aluminum Nitrite (TiAlN) coatings using Adaptive Network Based Fuzzy Inference System (ANFIS) is implemented. TiAlN coated cutting tool is widely used in machining due to its excellent resistance to wear. The TiAlN coatings were formed using Physical Vapor Deposition (PVD) magnetron sputtering process. The substrate sputtering power, bias voltage and temperature were selected as the input parameters and the flank wear as an output of the process. A statistical design of experiment called Response Surface Methodology (RSM) was used in collecting optimized data. The ANFIS model was trained using the limited experimental data. The triangular, trapezoidal, bell and Gaussian shapes of membership functions were used for inputs as well as output. The results of ANFIS model were validated with the testing data and compared with fuzzy rule-based and RSM flank wear models in terms of the root mean square error (*RMSE*), co-efficient determination (R^2) and model accuracy (*A*). The result indicated that the ANFIS model using three bell shapes membership function obtained better result compared to the fuzzy and RSM flank wear models. The result also indicated that the ANFIS model could predict the output response in high prediction accuracy even using limited training data.**

Keywords- ANFIS technique; flank wear; TiAlN coatings; PVD magnetron sputtering

I. INTRODUCTION

In high-speed machining process, the cutting tool is consistently dealing with high localized stress at the tool tip and high temperature which exceeds 800°C. In this process too, the cutting tool slides off the chip along the rake face and the newly cut workpiece surface [1]. These conditions are causing tool wear, reducing the cutting tool performances and quality of parts and deteriorating the tool life. The tool wear problem also could be influenced by workpiece material, cutting interface, cutting tool performance and geometry, and machine condition. In addition, tool wear condition has a direct effect on the economics of cutting operations, final product quality and process reliability [2]

Meanwhile, the cutting tool with high resistance wear promises better tool life and directly reduces machining cost. This performance could be enhanced by applying the thin film coating on the cutting tool. The main purpose of the thin film coating application is to improve the tool surface properties while maintaining its bulks properties. The performance of the coated tool has been proven in wear mechanism [3], hardness and adhesion [4] and tool life [5]. It is also has been ascertained that the coated tool is forty times better in tool wear performance compared to the uncoated tools [6]. This finding promises prolonging of tool life and enables the implementation of minimum liquid lubrication to reduce cost of coolant that makes up 16 to 20% of manufacturing cost [7]. This finding too contributes in minimizing environmental impacts produced by discarding of cutting fluid [8].

Physical Vapor Deposition (PVD) coating process plays essential roles in order to make the cutting tool perform better. It has been selected as a main coating process in hard coating purposes. However, two main challenging issues that need to be encountered in the coating process are cost and customization. The challenge to ensure reasonable cost in the process of coating and efficient process of treatment should be well-addressed as it directly affects the cutting tool market value [9]. Besides the equipment maintenance, other reasons that lead to high machining costs are the material usage and labor and the number of trial-and-error experiment. The new application of coating to the other process such as drilling and milling also are causing other trial and error experiments so that it could suit the parameters with the material used. Therefore, many researchers have developed models to address the coating process issues. Model development reduces resources wastage such as materials, equipment utilization, human resources and working time related to the trial and error experiments run.

The coating process model is very useful to predict the coating performances while looking for the optimized value. However, limited number of experimental data due to experimental cost issue is a major constraint in modeling

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work. Various techniques such as design of experiment [10], neural network [11], fuzzy logic [12] and Adaptive Network Based Fuzzy Inference System (ANFIS) have been applied. The design of experiment approaches like Taguchi, full factorial and Response Surface Methodology (RSM) are widely used to collect optimum and minimum experimental data [13].

The ANFIS model is trained by using actual experimental data. Then, the rules can be modified by expert. The ANFIS has been proven to be well-suited for modeling nonlinear industrial processes such as end-milling [14, 15], welding [16], water jet machining [17] and wire electrical discharge machine (WEDM) [18] . In view of the nonlinear conditions of a the magnetron sputtering coating process, the ANFIS model is employed for predicting the flank wear value of TiAlN coatings. So far, there is no study has been carried out on application of ANFIS technique for predicting the flank wear of TiAlN coatings. The main purpose of this study is to investigate the application of ANFIS model for predicting the flank wear of TiAlN coatings by using limited number of experimental data. Part II explains how the experimental data was collected. Part III describes how the ANFIS modeling was done. Part IV indicates and discuss the result of the study.

II. EXPERIMENTAL DETAILS

A. *Material and Method*

In this study, the experiment was run in unbalanced PVD magnetron sputtering system made by VACTEC Korea model VTC PVD 1000. Fig. 1 shows the PVD magnetron sputtering system. The coating chamber has two vertically mounted TiAl alloys which were selected as coating material. The chemical compositions of the TiAl alloy were titanium and aluminum with even percentage. The cutting tool inserts were hold in substrate holders with adjustable planetary rotation.

Figure 1. PVD unbalanced magnetron sputtering system VACTEC Korea model VTC PVD 1000.

Before the coating process, the surface of tungsten carbide cutting tool insert was cleaned with alcohol bath in an ultrasonic cleaner. After a 20- minute-bathing, the substrates were dried and then loaded in the rotating substrate holder. The rotation speed was set at 5 rpm. Then, an inert gas, Argon was pumped into the chamber with controlled gas pressure. Argon was used to produce electron. The nitrogen gas was also pumped in as a reactive gas. The substrate was coated with the alloy in the presence of nitrogen gases.

The coating process consisted of substrate ion cleaning, deposition of interlayer coating of TiAl and deposition of TiAlN coating. In order to produce better adhesion, the impurity on the substrate surface was removed through the substrate ion cleaning process. The coefficient of thermal expansion gradient between the insert and TiAlN coatings was minimized through the interlayer coating deposition of TiAl. Then, the coating process was done in the presence of nitrogen gas to produce TiAlN. The detail process settings of the three stages are shown in Table I. A design of experiment technique called Response Surface Modeling (RSM) centre cubic design using Design Expert software version 7.03 was used to develop the experimental matrix. After the experiment, the influences of sputter power, bias voltage and substrate temperature on the coating flank wear were analyzed.

TABLE I. THE EXPERIMENT SETTING

Process	**Substrate ion cleaning**	**Interlayer coating deposition**	**TiAlN deposition**
Argon pressure (mbar):	5.5 x 10^{-3}	4.0 x 10^{-3}	4.0x 10^{-3}
N_2 pressure (mbar):	-	-	0.4 x 10^{-3}
Ion source power (kV/A):	0.24 / 0.4	0.24 / 0.4	0.24 / 0.4
Substrate bias (V):	-200	-200	-50-300
Duration (mins):	30	5 (0.2 μm)	90

B. *Flank Wear Measurement*

Figure 2. GATE-Precision milling machine and lathes model G-410-TCV

The flank wear of coated cutting tool for single point turning was determined based on the ISO 3685:1993(E) standard. The wear of twenty tungsten carbide cutting tool inserts coated with TiAlN were measured. The coated tools were focused to dry turning of steel using GATE-Precision milling and lathe machine model G-410-TCV, as shown in Fig. 2. The details of turning process are shown in Table II. The flank wear was measured using Axiomat 2 microscope with Axiovison software. Fig. 3 shows a example of flank wear from the experiment. Table III shows the flank wear values of the machined coated cutting tools.

TABLE II. DETAILS OF TURNING PROCESS

Item	Details
Process	Dry turning
Workpiece material	D2 X115Cr VMo121 steel
Machine type	MAMOC lathe model SM200
Feed rate, (mm/rev)	0.26
Depth of cut, (mm)	1.6
Cutting speed, (m/min)	200
Fixed cutting length (m)	18

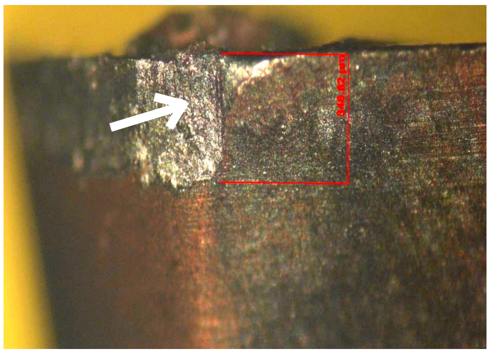

Figure 3. Flank wear on the coated tool (white arrow)

TABLE III. PROCESS PARAMETERS AND EXPERIMENTAL RESULT OF TIALN COATINGS FLANK WEAR

Run	Process variables			Result
	Sputter Power (kW)	Bias Voltage (Volts)	Substrate Temp. (°C)	Flank Wear (mm)
1	6.00	50.00	400.00	2.29
2	4.81	100.67	518.92	1.08
3	4.81	249.33	281.08	0.73
4	6.00	175.00	400.00	1.40
5	6.00	175.00	200.00	0.94
6	4.81	100.67	281.08	2.01
7	7.19	249.33	281.08	1.92
8	6.00	175.00	400.00	0.57
9	6.00	175.00	400.00	1.26
10	4.81	249.33	518.92	1.97
11	7.19	100.67	281.08	1.18
12	6.00	175.00	600.00	1.72
13	7.19	249.33	518.92	0.35
14	6.00	175.00	400.00	0.86
15	8.00	175.00	400.00	0.27
16	6.00	300.00	400.00	1.03
17	7.19	100.67	518.92	0.93
18	4.00	175.00	400.00	0.56
19	6.00	175.00	400.00	0.85
20	6.00	175.00	400.00	0.83

III. ANFIS MODELING

Adaptive Network Based Fuzzy Inference System (ANFIS) was presented by Jang in 1993 [19]. In this system, a hybrid learning procedure is used to construct an input-output mapping based on the human knowledge and training data pairs. The fuzzy inference system is employed in the framework of adaptive networks. ANFIS is normally contains a five-layer feed forward neural network excluding inputs to construct the inference system. Each layer consists of several nodes described by nodes function. The nodes in previous layer feed input to nodes in next layer.

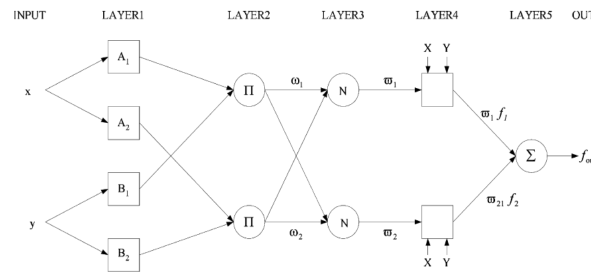

Figure 4. The ANFIS structure with five layers and nodes [20]

The Fig. 4 illustrates the structure of ANFIS with five layers. To illustrate the procedures of an ANFIS, it is assumed that the system has two inputs (x_1, x_2) and one output (y). The ANFIS rules based contains fuzzy if-then rules of Sugeno type. The rules can be stated as:

Rule 1: If *x* is *A1* and *y* is *B1* then *z* is *f1(x,y)*
Rule 2: If *x* is *A2* and *y* is *B2* then *z* is *f2(x,y)*

where *x* and *y* are the inputs of ANFIS, *A* and *B* are the fuzzy sets $f_i\,(x, y)$ is a first order polynomial and represents the outputs of the first order Sugeno fuzzy inference system.

TABLE IV. PARAMETERS SETTING FOR ANFIS MODEL

ANFIS Setting	Details
Input Variables	Power, Voltage, Temperature
Output Response	Flank Wear
Input MFs Type	Triangular, Trapezoidal, Bell, and Gaussian
No. of MFs	2,3 and 5
Output MFs Type	Constant and linear
Optimization Method	Hybrid of the least-squares and the back propagation gradient descent method.
Epochs	100

In this study, three variables were selected for inputs of the ANFIS model to predict an output response. In order to find the best combination, three parameters in the ANFIS model were adjusted which were the type of input membership function (MFs), number of MFs and the type of output MFs. The model were developed using different shape of input membership function (MFs) type which were triangular, trapezoidal, bell and Gaussian shapes, with number of the MFs were two, three and five. In purpose of training the model, a hybrid of the least-squares method and the back propagation gradient descent method was used to emulate a given training data set. The constant and linear of output MFs type were employed to produce the flank wear value. The details of model setting is shown in Table IV. The details of ANFIS model is shown in Table V.

TABLE V. DETAILS OF ANFIS MODEL

ANFIS Info
Number of nodes: 78
Number of linear parameters: 108
Number of nonlinear parameters: 27
Total number of parameters: 135
Number of training data pairs: 20
Number of checking data pairs: 3
Number of fuzzy rules: 27

IV. RESULT AND DISCUSSION

After the training process, the initial membership functions for input variables were derived by training. Fig. 5 (a)-(c) show the initial of MFs, while Fig. 5 (d)-(f) show the final MFs of the constant output.

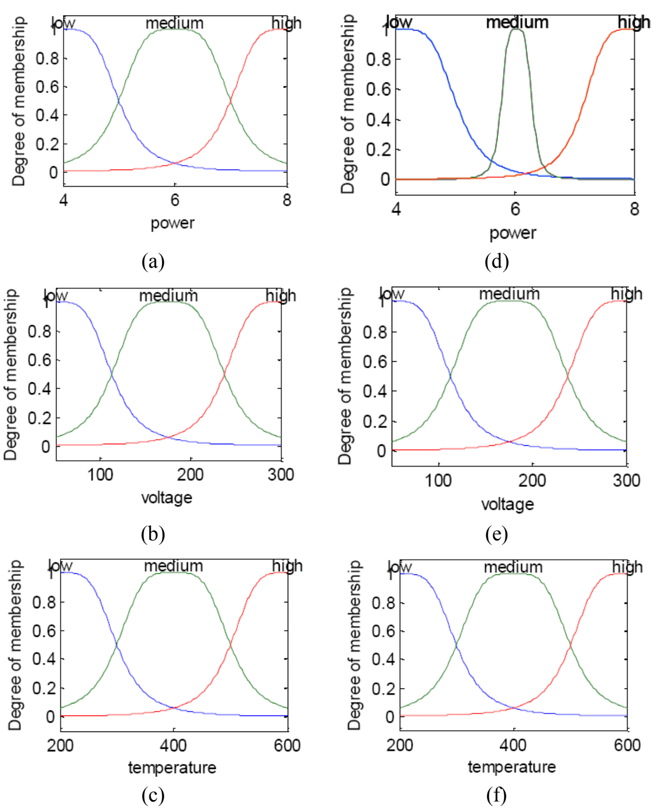

Figure 5. The MFs for the input variables before (a-c) and after (d-f) training

From the figures, a major change obviously can be seen on the shape of POWER membership function after the training process. Otherwise, the membership functions of the VOLTAGE and TEMPERATURE indicated only a slight changes. Fig. 6 shows the convergence of the ANFIS training. Meanwhile, the *RMSE* became steady after 2 epochs. The limited number of data cause the converging process is very fast and steady in that epoch.

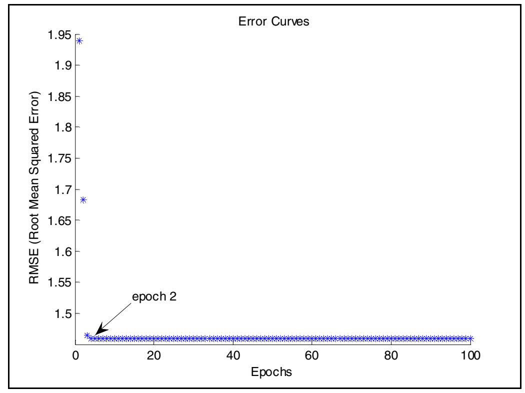

Figure 6. Convergence of ANFIS training

To verify the performance of the proposed ANFIS model, the following measures were used. The root mean squared error (*RMSE*) in (1) was used to quantify the difference between predicted and actual values. Meanwhile, the co-efficient determination (R^2) in (2) was calculated in order to see how well the future output response is likely to be predicted by the model. Lastly, the prediction accuracy (A) in (3) was computed to determine the accuracy of the models.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left|v_a - v_p\right|\right)^2} \quad (1)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(v_a - v_p)^2}{\sum_{i=1}^{n}(v_p)^2}\right) \quad (2)$$

$$A = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{\left|v_a - v_p\right|}{v_a}\right) \times 100\% \quad (3)$$

where n is number of testing data, v_a is experimental value and v_p is predicted value.

Three testing dataset from separated experiment were used to verify the proposed model. The testing dataset is shown in Table VI. Meanwhile, Table VII shows the wear values for the ANFIS models with different type of output (linear or constant), different shape of input membership function (triangular, trapezoidal, Gaussian and bell) and different number of membership function (2, 3 and 5).

TABLE VI. VALIDATING DATA

Testing	Power (kW)	Volt (V)	Temp. (°C)	Actual Result
wear 1	5	100	280	1.97
wear 2	6.5	150	350	0.97
wear 3	7	145	450	0.73

TABLE VII. RESULT FOR ANFIS MODEL WITH DIFFERENT TYPE AND NUMBER OF MFS

MFs		Linear			Constant		
		wear 1	wear 2	wear 3	wear 1	wear 2	wear 3
TriMF	2	2.030	0.929	0.854	1.980	1.390	1.230
	3	1.970	1.190	0.827	1.610	1.060	0.642
	5	2.300	0.366	0.317	1.970	0.295	0.285
TrapMF	2	2.060	1.270	0.587	1.910	1.240	0.754
	3	1.850	0.839	0.659	1.520	0.962	0.516
	5	2.000	0.251	0.186	2.010	0.254	0.209
BellMF	2	2.033	1.193	0.863	2.100	1.350	1.130
	3	1.923	0.940	0.728	2.030	0.312	0.263
	5	2.040	0.484	0.360	2.000	0.345	0.197
GaussMF	2	2.011	1.072	1.003	1.850	1.330	1.170
	3	1.960	1.015	0.740	2.030	0.930	0.360
	5	2.040	0.484	0.360	1.990	0.410	0.268

Table VIII shows the *RMSE*, R^2 and prediction accuracy of the ANFIS models. The result shows that most of the models with linear output indicate less *RMSE*, and higher in R^2 and *A* compared to the model with constant output.

TABLE VIII. *RMSE*, R^2 AND MODEL ACCURACY FOR THE ANFIS MODELS

MFs		Linear			Constant		
		RMSE	R^2	*A*(%)	*RMSE*	R^2	*A*(%)
TriMF	2	0.083	0.996	91.91	0.377	0.942	62.57
	3	0.139	0.990	88.01	0.220	0.965	86.80
	5	0.463	0.883	54.80	0.467	0.839	56.48
TrapMF	2	0.199	0.981	81.64	0.160	0.987	88.61
	3	0.110	0.992	90.22	0.288	0.929	82.34
	5	0.521	0.801	49.95	0.512	0.811	50.93
BellMF	2	0.154	0.989	85.21	0.327	0.957	66.48
	3	0.033	0.999	98.09	0.467	0.847	55.05
	5	0.355	0.916	65.22	0.475	0.838	53.68
GaussMF	2	0.170	0.986	83.35	0.335	0.949	65.51
	3	0.032	0.999	97.20	0.218	0.972	80.72
	5	0.344	0.924	65.95	0.419	0.874	53.68

Meanwhile, the model that used 3 bell MFs in the input variables indicates the highest prediction accuracy with 98.09%. On the other hand, the model with 3 Gaussian MFs shows the smallest *RMSE* with 0.032. However, both models show the same R^2 with 0.999. The smooth shapes of the Gaussian and bell MFs helps in variant of fuzzy surface.

Besides that, Table IX shows the comparison of 3 bell MFs of ANFIS model with fuzzy and RSM flank wear model [21] in terms of *RMSE*, R^2 and prediction accuracy. The comparison used same types and number of input variables. From the table, the ANFIS model indicates better performances compared to the other models to predict the flank wear.

TABLE IX. COMPARISON OF ANFIS WITH FUZZY AND RSM FLANK WEAR MODELS IN TERMS OF *RMSE*, R^2 AND MODEL ACCURACY

Performance measures	ANFIS BellMFs 3-3-3	Fuzzy TriMFs 5-7	RSM model [21]
RMSE	0.033	0.2394	0.0714
R^2	0.999	0.972	0.997
A (%)	98.09	83.42	93.28

Besides that, Fig. 7 shows agreement between actual and predicted wear value of the ANFIS, fuzzy and RSM models. The Fig. 7 shows that the predicted values of ANFIS model has a better agreement with the actual training values compared to the fuzzy and RSM models. Therefore, the ANFIS model is a good alternative to predict the flank wear of TiAlN coatings.

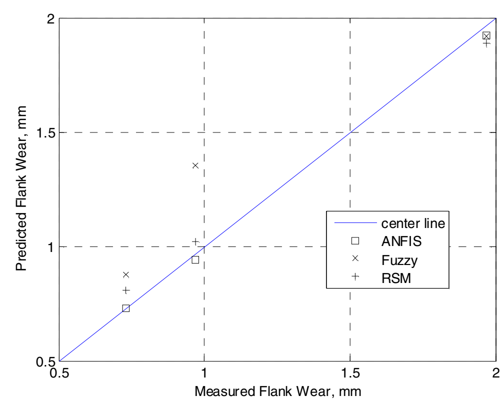

Figure 7. Predicted and measured flank wear value of TiAlN coating using ANFIS, fuzzy and RSM model.

V. CONCLUSION

In this study, the ANFIS model was used in predicting the flank wear of TiAlN coatings. The 20 experimental data were used for the model training purpose and 3 testing dataset were used for validation. The input parameters were the sputtering power, substrate bias voltage and substrate temperature with the flank wear of TiAlN coatings as the output response. The triangular, trapezoidal, bell and Gaussian shapes were selected as input membership function with number of membership function were two, three and five. The *RMSE* became steady after 2 epochs and a major change obviously can be seen on the shape of POWER membership function after the training process. The results in terms of the *RMSE*, co-efficient determination and model prediction accuracy were compared with fuzzy rule-based and RSM flank wear models. The results have shown that:

- The ANFIS model that used linear output showed better performances compared to the constant output.
- The ANFIS model with 3 bell MFs in the input variables indicated the highest prediction accuracy with 98.09%.
- Otherwise, the model with 3 Gaussian MFs showed the smallest *RMSE* with 0.032.
- Both of the models indicated same R^2 with 0.999.
- The ANFIS models with five MFs indicated higher *RMSE* and less R^2 and prediction accuracy compared to the models with two and three MFs. Therefore, the small number of MFs is most suitable to be used in ANFIS modeling structure.
- The 3 bell MFs of ANFIS model showed better performances compared to the fuzzy and RSM flank wear models in terms of *RMSE*, R^2 and prediction accuracy.
- The better agreement between the measured and predicted values of ANFIS model showed that the proposed ANFIS model can be a good option in predicting TiAlN flank wear.
- The result also indicated that the ANFIS model could predict the output response even using limited experimental data for training purpose.

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