Application of Fuzzy Rule-Based Model in Predicting Flank Wear of TiAlN Coatings in PVD Magnetron Sputtering Process

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Abstract

In this paper, a new approach in predicting the flank wear of Titanium Aluminum Nitrite (TiAlN) coated tool using fuzzy logic is implemented. Excellent properties of Titanium Aluminum Nitride (TiAlN) such as its hardness, roughness and resistance to wear make the material is generally used to coat the cutting tool in machining processes. A statistical design of experiment called Response Surface Methodology was used to collect the optimized for fuzzy rules development. The fuzzy rule-based model using Gaussian membership function was proposed to predict the flank wear with respect to changes in input process parameters including the substrate sputtering power, bias voltage and temperature. The proposed fuzzy logic model results were compared against the experimental result to gain the percentage error, mean square error (*M*SE), co-efficient determination (R^2) and model prediction accuracy (A). The average percentage error, *MSE*, R^2 and model prediction accuracy obtained were 20.72%, 0.057, 0.973 and 79.84% respectively. The high prediction performance and good agreement between the experimental values and the proposed fuzzy ruled-based model results shown that the fuzzy logic could be a good alternative approach in predicting TiAlN coatings flank wear.

Keywords: Fuzzy rule-based, flank wear, TiAlN coatings, PVD magnetron sputtering.

1. INTRODUCTION

Physical Vapor Deposition (PVD) magnetron sputtering is a well-known technology in hard coatings industry. In the PVD coating process, the sputtered particle from harder material embedded on the cutting tool in presence of reactive gas in order to enhance the surface performances of coated tool. The hard coatings such as Titanium Nitride (TiN) coating and Titanium Aluminum Nitride (TiAlN) coating are usually used in metal cutting industry due to its coatings performances such as toughness [1].

In high speed machining, the temperature on the cutting tip could exceed to 800°C. This condition are causing tool wear and reducing cutting tool performance. Thus, the cutting tool with high resistance wear is very important to deal with the crucial condition. The cutting tool with high resistance wear promises better tool life and reduces the machining cost directly. The performance could be achieved by applying the thin film coating on the cutting tool. The main objective of applying the thin film coating is to enhance the surface properties while maintaining its bulks properties. The coated tool has been proved forty times better in tool wear resistance compared to the uncoated tool [2].

In coatings processes, the coating properties are directly and indirectly influenced by process parameters. The process parameters such as the sputtering power, substrate bias voltage, substrate temperature, gas pressure and turntable speed should be controlled wisely to gain the optimum coating performances [3]. The non-linear conditions are causing complexity to the coating process and the application to the new materials need trial and error experiments in order to obtain the suitable combination of parameters and desired result. This issue raising up the cost of coating process and causing difficulties to extend the coating technology in other industrial applications.

Modeling is an efficient approach to address the cost and complexity issues in coating process. It can be used to predict the coating performances value and to find the optimum combination of input parameters and output result. Many approaches in design of experiment and intelligent based techniques has been applied for modeling purpose such as Taguchi, full factorial, Response Surface Method (RSM), neural network [4], and fuzzy logic [5]. The design of experiment approaches are usually used to collect optimum and minimum experimental data [6]. However, some limitations of the approaches need to be discussed. The Taguchi approach is difficult to detect the interaction effect of nonlinear process [7] and the full factorial is only suitable for optimization purposes [8]. The neural network needs large number of training data to be robust [9]. The fuzzy logic uses the actual data or expert suggestion to construct the rules. In this study, the application of fuzzy logic to predict the flank wear of TiAlN coatings has been discussed.

2. Experimental Details

2.1 Material and Method

The experiment was run in unbalanced PVD magnetron sputtering system made by VACTEC Korean model VTC PVD 1000 as shown in Fig. 1. The coating chamber was fixed with two vertically mounted TiAl alloys. The titanium alloy was chosen as the target material with respective chemical compositions of the titanium and aluminum were 50% and 50%. The surface of tungsten carbide inserts was cleaned with alcohol bath in an ultrasonic cleaner for 20 minutes. The tungsten carbide inserts were loaded in the rotating substrate holder inside the coating chamber. The Fig. 2 shows the coating chamber with three substrate holders. The rotation speed was set at 5 rpm in order to make the inserts were coated evenly. To produce the electron in the coating chamber for sputtering purpose, the Argon gas was used with controlled pressure. The inserts were coated with the alloy in presence of nitrogen gas.

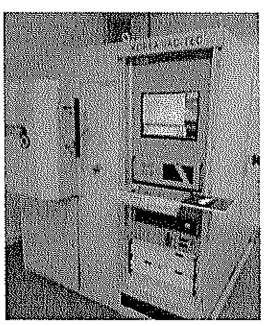


Fig. 1 PVD unbalance magnetron sputtering system VACTEC Korea model PVD VTC 1000

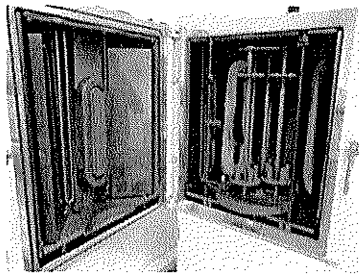


Fig. 2 Substrate holder inside coating chamber

The entire coating process consisted of three stages: (Step 1): substrate ion cleaning, (Step 2): interlayer coating deposition and (Step 3): TiAlN deposition. Firstly, the substrate ion cleaning process was applied in order to remove impurity from the substrate surface for better material adhesion. Secondly, the interlayer coating deposition of TiAl was applied to minimize the coefficient of thermal expansion gradient between the insert and TiAlN coatings. Lastly, the cutting inserts were deposited with titanium aluminum alloy. The process settings of the all stages are shown in Table I. The experimental matrix applied the RSM centre cubic design (CCD) was developed using Design Expert software version 7.03. The influences of sputter power, bias voltage and substrate temperature on the coating flank wear were observed.

Table I: The experiment setting

Step	Process	Details	Setting
Step1	Substrate ion cleaning	Argon pressure Ion source power Substrate bias Duration	5.5×10^{-3} mbar 0.24 kV/ 0.4 A -200V 30 mins
Step 2	Interlayer coating (TiAl)	Ar pressure Duration	4.0×10^{-3} mbar 5 mins (0.2 μm)
Step 3	TiAlN deposition	Ar pressure N_2 pressure Duration	4.0×10^{-3} mbar 0.4×10^{-3} mbar 90 mins

2.2 Flank Wear Measurement

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 lathe machine.

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 the turning process

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

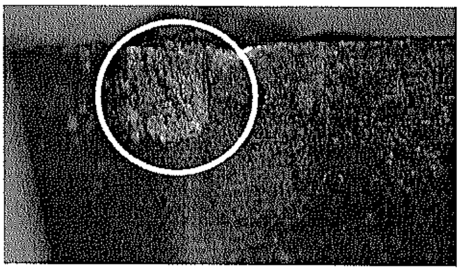


Fig. 3 Flank wear of the coated tool

Table III: Process parameters and experimental result of TiAlN coatings wear

Run	Process parameters			Output
	Sputter Power (kW)	Bias Voltage (Volts)	Substrate Temp. (°C)	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

3. Fuzzy Rule-Based Modeling

Lotfi Zadeh published his high impact paper 'Fuzzy Sets' to open new potential area of mathematical knowledge in 1965. He extended the work on possibility theory into a formal system of mathematical logic and introduced new concept for applying natural language term [10]. Fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degree of membership rather than on crisp membership on classical binary logic [11]. The theory was developed based on fuzzy set theory. It deals with degree of membership and degree of truth to address the multi-valued situation instead just black and white, which varies continuously from zero (not a member) to one (absolutely a member). For example, in flank wear measurement, the exact mathematical meaning (e.g. 2.3 mm) can be assigned to subjective linguistic term (e.g. very wide) via a fuzzy set theory. Conversely, the linguistic term can also be defined with exact mathematical meaning.

A typical steps in developing fuzzy rule-based model includes the following steps:

1. Specify the problem and define linguistic variables.
2. Determine fuzzy sets.
3. Extract and construct fuzzy rules.
4. Encode the fuzzy sets, fuzzy rules and procedures to perform the model.
5. Evaluate and validate the model.

Step 1: Specify the problem and define linguistic variables.

In this study, there are three input variables which are sputtering power, bias voltage and substrate temperature, and a output response which is the flank wear. All the variables and the response are called linguistic variables. The linguistic variables were ranged based on the experimental parameters range. For example, the sputtering power was split in the range of (4-8 kW). Then, every linguistic variable was separated into linguistic values. The input variables using same five linguistic values; Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH). The output variable (flank wear) was separated into nine linguistic values. The linguistic values was ranging from very small (S4) to very wide (W4). The output variable was split in the range of (0-2.3 mm), with any value below this range until 0 was assumed S4 and any value above this range is assumed W4.

Step 2: Determine fuzzy sets.

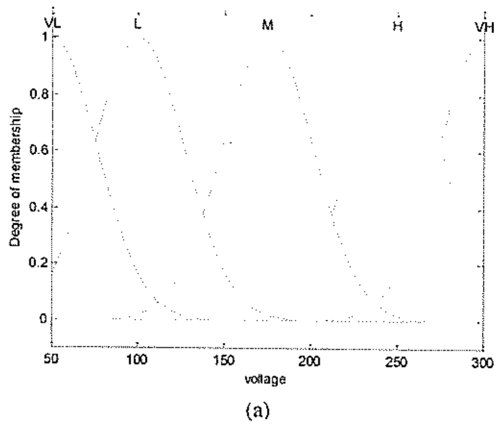
In this model, Gaussian shape was used to describe the fuzzy sets for input variables and output response. The Gaussian membership function (MFs) helps the fuzzy systems theoretical analysis as it is continually and infinitely can be differentiated. Besides that, it assists in achieving smooth and variant fuzzy model surfaces [12]. The Gaussian function depends on two scalar parameters which is σ and c as shown in (1), where x is the variable value, σ is the mean and c is the variance.

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \quad (1)$$

Table IV shows the linguistic variables and ranges for the membership function. The membership functions for voltage and flank wear using Gaussian shape are shown in Fig. 4.

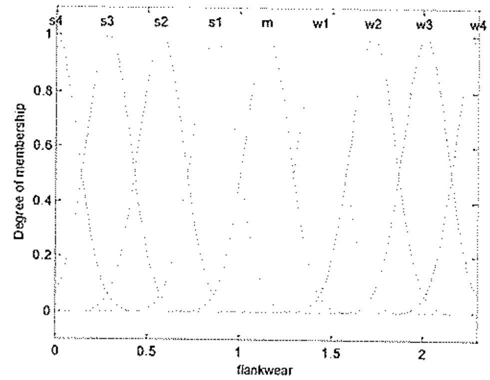
Table IV: Linguistic variables and their ranges for five Gaussian membership functions

Linguistic variables	Linguistic value	Notation	Gaussian
Sputtering power	Very Low	VL	[0.4247, 4]
	Low	L	[0.4247, 4.81]
	Medium	M	[0.4247, 6]
	High	H	[0.4247, 7.19]
	Very High	VH	[0.4247, 8]
Bias voltage	Very Low	VL	[26.54, 50]
	Low	L	[26.54, 100.67]
	Medium	M	[26.54, 175]
	High	H	[26.54, 249.33]
	Very High	VH	[26.54, 300]
Substrate temperature	Very Low	VL	[42.47, 200]
	Low	L	[42.47, 281.08]
	Medium	M	[42.47, 400]
	High	H	[42.47, 518.92]
	Very High	VH	[42.47, 600]
Flank wear	Very Small	S4	[0.1221, 0]
	Small 3	S3	[0.1221, 0.2875]
	Small 2	S2	[0.1221, 0.575]
	Small 1	S1	[0.1221, 0.8625]
	Medium	M	[0.1221, 1.15]
	Wide 1	W1	[0.1221, 1.438]
	Wide 2	W2	[0.1221, 1.725]
	Wide 3	W3	[0.1221, 2.012]
	Very Wide	W4	[0.1221, 2.3]



(a)

Fig. 4 (a). The Gaussian membership functions for VOLTAGE.



(b)

Fig. 4 (b). The Gaussian membership functions for FLANK WEAR.

Step 3: Extract and construct fuzzy rules.

Fuzzy rules construction is a harder stage. This stage includes advises from the expert of the process. A fuzzy rule can be defined as a conditional statement in (2).

$$\text{IF } x \text{ is A, AND } y \text{ is B, THEN } z \text{ is C} \quad (2)$$

where x, y and z are linguistic variables, and A, B and C are linguistic values decided by fuzzy sets on the universe of discourses X, Y and Z, respectively [10]. The x and y are input and z is output of the rule. The z value depends on the combination of x and y by using AND operator. In practice, usually the fuzzy rules are developed based on expert's suggestion to the combination of variables and output response. However, the nonlinear conditions in coating process sometimes may cause the expert suggestion inaccurate. In this work, the fuzzy rules were developed based on the optimum collected experimental data. A set of 15 rules were constructed and the rules could be defined as shown in Table V.

Table V: The constructed rules based on actual data

Rules	IF	AND	AND	THEN
Rule 1:	P is M	V is VL	T is M	wear is S2
Rule 2:	P is L	V is L	T is H	wear is W3
Rule 3:	P is L	V is H	T is L	wear is M
Rule 4:	P is M	V is M	T is M	wear is S1
Rule 5:	P is M	V is M	T is VL	wear is W3
Rule 6:	P is L	V is L	T is L	wear is W4
Rule 7:	P is H	V is H	T is L	wear is S1
Rule 8:	P is L	V is VH	T is VH	wear is W1
Rule 9:	P is H	V is L	T is L	wear is W2
Rule 10:	P is M	V is M	T is VH	wear is M
Rule 11:	P is H	V is H	T is H	wear is M
Rule 12:	P is VH	V is M	T is M	wear is S1
Rule 13:	P is M	V is VH	T is M	wear is W3
Rule 14:	P is H	V is L	T is H	wear is S3
Rule 15:	P is VL	V is M	T is M	wear is S3

Step 4: Encode the fuzzy sets, fuzzy rules and procedures to perform the model.

In this stage, the fuzzy set, fuzzy rules and the procedures were coded into the Matlab program. The following code is example of the program command for the input power variable.

```
a=addvar(a, 'input','power', [4 8]);
a=addmf(a,'input',1,'VL','gaussmf',[0.4247 4]);
a=addmf(a,'input',1,'L','gaussmf',[0.4247 4.81]);
a=addmf(a,'input',1,'M','gaussmf',[0.4247 6]);
a=addmf(a,'input',1,'H','gaussmf',[0.4247 7.19]);
a=addmf(a,'input',1,'VH','gaussmf',[0.4247 8]);
figure;plotmf(a,'input',1);%plot the MF
```

Step 5: Evaluate and validate the model.

Many types of performance measures can be used to evaluate the predicting performance of the rule-based model. Mean squared error (*MSE*) is a way to quantify the difference between predicted and actual value of quantity being predicted. Co-efficient determination (R^2) is measured to see how well the future output response is likely to be predicted by the model. Model prediction accuracy (A) is calculated to determine the accuracy of the model.

4. Result and Discussion

For validation, three testing dataset from separated experiment were used to validate the fuzzy model. The percentage error, *MSE*, R^2 and prediction accuracy for fuzzy rule-based model was determined.

Table VI shows the smallest and the highest percentage error for fuzzy rule-based model were 2.57% and 39.44% respectively. The average of percentage error was 20.72%. The small error value of fuzzy model shows that the predicted flank wear results were very close with actual experimental values.

Table VII shows the *MSE* value of fuzzy rule-based model is 0.057. The table also shows the R^2 of fuzzy model is high with 0.973. Finally, the fuzzy rule-based model shows high model accuracy with 79.84%. The value of accuracy shows that the fuzzy rule-based model has good predicting performance to predict the TiAlN coatings wear.

Fig. 5 shows that the predicted flank wear value of the fuzzy rule-based model has a good agreement with the measured experimental values. This clearly indicates that the fuzzy logic technique is a good alternative for prediction purpose and could be used to predict the TiAlN coatings flank wear within the range of input parameters under consideration.

Table VI: Comparison of actual and the fuzzy rule-based model flank wear value

Parameters (input)			**Flank Wear (output)**		
Power (kW)	Volt (V)	Temp. (°C)	Actual (mm)	Fuzzy (mm)	Error (%)
5	100	280	1.97	1.92	2.57
6.5	150	350	0.97	1.38	39.44
7	145	450	0.73	0.77	20.16
			Average of error (%) =		**20.72**

Table VII: MSE, R2 and prediction accuracy of the fuzzy rule-base model

Performance measures	**Fuzzy rule-based model**
MSE	**0.057**
R^2	**0.973**
Accuracy (%)	**79.84**

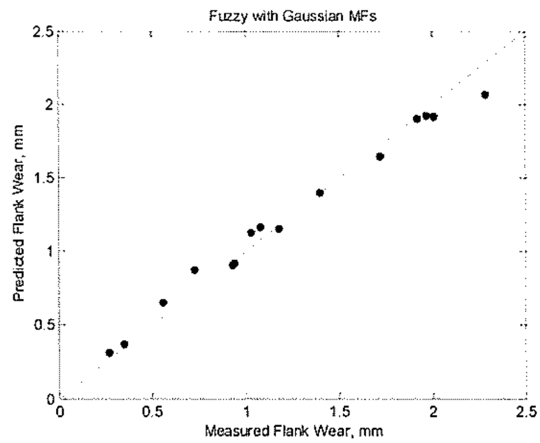


Fig. 5 Predicted and measured flank wear values of TiAlN coating.

5. Conclusion

In this study, prediction the TiAlN coatings flank wear was obtained using fuzzy rule-based model. The fuzzy rules were constructed based on the collected experimental data. The input parameters were the sputtering power, substrate bias voltage and substrate temperature with the TiAlN flank wear as the output response. The Gaussian shapes were selected as membership function for input and output fuzzy set. The centroid area method was selected in defuzzification. This fuzzy rule-based model was validated with three experimental dataset. The results were observed in term of the percentage error, *MSE*, co-efficient determination and model accuracy. The result shown that:

- The smallest and the highest percentage error of fuzzy rule-based were 2.57% and 39.44% respectively.
- The average of percentage error was 20.72%. The small error value indicates that the predicted flank wear results were very close with actual experimental values.

- The *MSE* of fuzzy ruled-based model was 0.057.
- The co-efficient determination of fuzzy ruled-based model was 0.973.
- The model prediction accuracy of fuzzy ruled-based model was 79.84%. This indicates that the model has good predicting performance.
- Thus, fuzzy logic can be a good alternative in predicting the flank wear of TiAlN coatings for PVD magnetron sputtering process
- The optimized collected data using CCD technique can be applied to develop the fuzzy rules even in small numbers of data.

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