Integrating Taguchi Method and Support Vector Machine for Enhanced Surface Roughness Modeling and Optimization

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***Abstract*—End milling process is widely used in various industrial applications, including health, aerospace and manufacturing industries. Over the years, machine technology of end milling has grown exponentially to attain the needs of various fields especially in manufacturing industry. The main concern of manufacturing industry is to obtain good quality products. The machined products quality is commonly correlated with the value of surface roughness (Ra), representing vital aspect that can influence overall machining performance. However, finding the optimal value of surface roughness is remain as a challenging task because it involves a lot of considerations on the cutting process especially the selection of suitable machining parameters and also cutting materials and workpiece. Hence, this study presents a support vector machine (SVM) prediction model to obtain the minimum Ra for end milling machining process. The prediction model was developed with three input parameters, namely feed rate, depth of cut and spindle speed, while Ra is the output parameter. The data of end milling is collected from the case studies based on the machining experimental with titanium alloy, workpiece and three types of cutting tools, namely uncoated carbide WC-Co (uncoated), common PVD-TiAlN (TiAlN) and Supernitride coating (SNTR). The prediction result has found that SVM is an effective prediction model by giving a better Ra value compared with experimental and regression results.**

***Keywords*—Support Vector Machine; surface roughness; end milling; Taguchi method**

I. INTRODUCTION

A. Problem Background

In recent years, the machining process becomes important and widely used in manufacturing industries. With the highly competitive industries that have emerged nowadays, manufacturers compete with each other in delivering products of high quality with lower production costs. The effectiveness of the machining process relies on selecting appropriate cutting conditions, which is normally done by the machinists. Machining refers to a process of material removal from a workpiece in a chip form. Machining can be either conventional or non-conventional machining. Non-conventional machining is also considered as modern machining. The popular machining performances evaluated by the significant measure are surface roughness (Ra), tool wear, cutting force, strength, torque, chip shape, etc. Pan et al., [1] found that the machining performance that garnered the most attention from researchers is Ra. Ra is considered as a key factor to determine the surface quality of a product. This is due to the significant role of Ra in the performance of machine parts for wear resistance, ductility, tensile, and fatigue. Ra has a major effect on dimensional accuracy, mechanical parts efficiency and cost of production. Furthermore, Ra also affects the machining process stability diagnosis where a reduction of the surface quality can imply non-homogeneity of the workpiece surface, progressive wear of the tool and cutting tool chatter [2].

Ra is a product's measurement for technological quality and a feature that affects the production cost. Due to the advent development of technology, such as computing capability and data science, the researchers prefer to apply computational approaches to model the machining process [3]. Furthermore, due to the uncertainty and complexity of Ra, it is quite difficult to obtain the Ra value by the analytical equations. Computational approaches, including machine learning (ML) methods have become most interesting area of study, and researchers have shown tremendous interest in developing various models to improve the efficiency of measuring machining performances. ML approaches are capable to solve the optimal solution problem of the machining parameters with either the minimum or maximum machining performance. ML approaches that have been considered by previous studies include Support Vector Machine (SVM) [4]-[5], Artificial Neural Network (ANN) [6] – [7], Bayesian Network [8]-[9], Decision Tree [10], Random Forest [11], etc.

The key problem in the machining process is how to use various cutting conditions and machining parameters to achieve optimum solutions for the machining performances. These optimal solutions must be capable of minimizing the economic aspects of machining operations. Traditionally, during the machining process, the parameter selection for the cutting conditions was usually left to the machinist. However, this approach also relies on the machinist's skills. Furthermore, this traditional way of cutting method requires high production costs due to the fact that the material can only be used once. Machinists’ experience also plays an important role, but often the optimum values for each experiment are difficult to preserve [12]. Hence, there is a need for the development of the computational approaches method in order to solve this problem. The technology growth has brought the ML approaches to be introduced to develop an improved model for the performances of the machining process. Using ML, it is easy to implement machine modelling instead of conventional techniques which are required a more complex physical understanding and knowledge of the machining process. The machining process can be completed in different approaches with the same objectives with the help of ML.

B. Proposed Prediction Model

This study proposed the integration of ML approach with Taguchi Method to prediction machining performance of end milling process. Selected ML approach, which is SVM is applied to estimate a minimum value of Ra in one of the mostly used machining process. SVM is based on the classifier of statistical learning theories [13]. SVM has demonstrated its capability when it delivered a better performance than ANN [14]. SVM has been widely applied in various fields such as health [15]-[16], agriculture [17]-[18], geology [19], and etc. In machining field, SVM has been extensively applied in various studies for the prediction of machining performances in conventional and non-conventional machining.

SVM was proven to give an effective prediction model for several of machining processes. Kumar et al [20] developed prediction models of Ra, cutting force, tangential force and tool wear in the boring process using SVM and response surface methodology (RSM). The machining experiment was carried out using full factorial design with workpiece AISI 4340 steels and multi-layered coated carbide electrode. The result shows that SVM has outperformed RSM for the prediction of machining parameters with the RMSE value of 0.039. Singh et al [21] applied SVM to predict the Ra value for the wired EDM (WEDM) process. The parameters namely servo voltage, pulse on time, pulse off time and peak current were used to develop a model. The experiment was carried out based on 3^k full factorial design. The prediction results show the minimum Ra value can be achieved using SVM approach.

Do Duc et al. [22] predicted the Ra value of 3X13 steel material in CNC hole turning process. The machining experimental was conducted based on DOE with feed rate, cutting speed, tool nose radius and cutting depth as the input parameters. The prediction models of RSM and SVM were developed, and results show that SVM model has outperformed RSM model by giving the mean absolute error (MAE) and mean square error (MSE) of 2.80 % and 0.17 %, respectively. Ramesh and Mani [23] applied SVM to predict the Ra value of abrasive waterjet milling (AWM) process. The experiments were carried out based on the RSM with Box-Behnken method. The input parameters were used to model the Ra are abrasive flow rate, pressure, the step over and the traverse rate. The optimal parameter values are then applied in the ε- SVM model to determine the minimum Ra in the AWM. The prediction result shows significant value of the training data accuracy. The prediction model then improved by tuning its hyperparameters using the fivefold cross validation. The result shows that SVM model has outperformed the quadratic regression model by giving accuracy of 92.4% compared to 70%.

From the review of the previous studies implemented by previous researchers, it can be concluded that SVM is able to give effective prediction results for conventional and modern machining processes. Furthermore, SVM has outperformed other techniques such as RSM and ANN [20], [24]. In the current work, the SVM prediction model is developed to predict the Ra value for end milling processes.

The remainder of this article is organized as follows. Section II discussed the materials and method of the study. It consists of experimental data and the approaches used in this study. Furthermore, the result and discussion were discussed in Section III and finally the conclusion is stated in Section IV.

II. MATERIALS AND METHOD

A. Experimental Data

The data used for the SVM prediction model is based on the actual machining experimental conducted by Mohruni [25]. The experiment was carried out using annealed alpha–beta titanium alloy workpiece and three types of cutting tools; “uncoated carbide WC-Co” (uncoated), “common PVD-TiAlN” (TiAlN) and “Supernitride coating” (SNTR). Cutting speed, feed rate and depth of cut were used as input parameters while Ra was the output parameter. The experiment was conducted based on a 2^3 factorial design. Table I shows the coded value ranges for each of the input parameters. The range values of coded parameters are levels -1, 0, and 1. The experimental data for surface roughness value which is measured using Taylor Hobson Surfronic +3, is given in Table II.

B. Taguchi Method

The experimental data as in Table II were analyzed based on the Taguchi method to obtain the significant parameters for the Ra values. The signal-to-noise (S/N) ratio of the Taguchi method was used as the quality characteristic of the parameters. Instead of standard deviation, the S/N ratio is used as a measurable value given the fact that the standard deviation often decreases as the mean decreases, and increases when the mean increases. This implies that it is impractical to minimize the standard deviation and get the mean target first. According to Salur et al., S/N ratio theory operates in two directions; reduction of variance and mean improvement. In addition, the S/N ratio is correlated with the impact of the factors on the response.

The S/N ratio value is computed based on performance characteristics whether it is larger-the-better, smaller-the-better or nominal-the-better, using Eq. (1) – Eq. (3).

Smaller-the-better:

$$S/N = -\log 10 \left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{1}$$

Larger-the-better:

$$S/N = -\log 10 \left[\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right] \tag{2}$$

Nominal-the-better:

$$S/N = 10 \log \left[\frac{y}{s_y^2}\right] \tag{3}$$

TABLE I. THE RANGE VALUE OF END MILLING PARAMETERS

Variables	Unit	Levels in coded form				
		−1.4142	−1	0	+1	+1.4142
Cutting speed (V)	(m/min)	124.53	130	144.22	160	167.03
Feed rate (F)	(mm/ tooth)	0. 025	0.03	0.046	0.07	0.083
Radial rake angle (°)	γ	6.2	7	9.5	13	14.8

TABLE II. EXPERIMENTAL DATA FOR SURFACE ROUGHNESS

No	Experimental process setting values			Ra (µm) Experimental		
	V (m/min)	F (mm/tooth)	γ (°)	Un-coated	TiAlN coated	SNTR coated
1	130	0.03	7	0.365	0.32	0.284
2	160	0.03	7	0.256	0.266	0.196
3	130	0.07	7	0.498	0.606	0.668
4	160	0.07	7	0.464	0.476	0.624
5	130	0.03	13	0.428	0.26	0.28
6	160	0.03	13	0.252	0.232	0.19
7	130	0.07	13	0.561	0.412	0.612
8	160	0.07	13	0.512	0.392	0.576
9	144.22	0.046	9.5	0.464	0.324	0.329
10	144.22	0.046	9.5	0.444	0.38	0.416
11	144.22	0.046	9.5	0.448	0.46	0.352
12	144.22	0.046	9.5	0.424	0.304	0.4
13	124.53	0.046	9.5	0.328	0.36	0.344
14	124.53	0.046	9.5	0.324	0.308	0.32
15	167.03	0.046	9.5	0.236	0.34	0.272
16	167.03	0.046	9.5	0.24	0.356	0.288
17	144.22	0. 025	9.5	0.252	0.308	0.23
18	144.22	0. 025	9.5	0.262	0.328	0.234
19	144.22	0.083	9.5	0.584	0.656	0.64
20	144.22	0.083	9.5	0.656	0.584	0.696
21	144.22	0.046	6.2	0.304	0.3	0.361
22	144.22	0.046	6.2	0.288	0.316	0.36
23	144.22	0.046	14.8	0.316	0.324	0.368
24	144.22	0.046	14.8	0.348	0.396	0.36

where, n is a sample size and y is a sample value with i=1, 2, 3...n. Surface roughness value targets the minimum value for better performance, hence it applies the “smaller-the-better”. Table III shows the S/N ratio for uncoated, TiAlN and SNTR end milling.

Based on the S/N ratio value in Table III, mean response table was developed for each level for all machining parameters. The ranking was determined for machining parameters at every level by considering the difference between the highest and lowest values. The higher rank shows that the Ra value is more affected by the parameter. Table IV shows the response table for Ra of uncoated end milling.

TABLE III. S/N RATIO FOR UNCOATED, TIALN AND SNTR

No.	Un-coated	S/N Ratio	TiAIN coated	S/N Ratio	SNTR coated	S/N Ratio
1	0.365	8.754	0.32	9.897	0.284	10.934
2	0.256	11.835	0.266	11.502	0.196	14.155
3	0.498	6.055	0.606	4.351	0.668	3.504
4	0.464	6.670	0.476	6.448	0.624	4.096
5	0.428	7.371	0.26	11.701	0.28	11.057
6	0.252	11.972	0.232	12.690	0.19	14.425
7	0.561	5.021	0.412	7.702	0.612	4.265
8	0.512	5.815	0.392	8.134	0.576	4.792
9	0.464	6.670	0.324	9.789	0.329	9.656
10	0.444	7.052	0.38	8.404	0.416	7.618
11	0.448	6.974	0.46	6.745	0.352	9.069
12	0.424	7.453	0.304	10.343	0.4	7.959
13	0.328	9.683	0.36	8.874	0.344	9.269
14	0.324	9.789	0.308	10.229	0.32	9.897
15	0.236	12.542	0.34	9.370	0.272	11.309
16	0.24	12.396	0.356	8.971	0.288	10.812
17	0.252	11.972	0.308	10.229	0.23	12.765
18	0.262	11.634	0.328	9.683	0.234	12.616
19	0.584	4.672	0.656	3.662	0.64	3.876
20	0.656	3.662	0.584	4.672	0.696	3.148
21	0.304	10.342	0.3	10.458	0.361	8.850
22	0.288	10.812	0.316	10.006	0.36	8.874
23	0.316	10.006	0.324	9.789	0.368	8.683
24	0.348	9.168	0.396	8.046	0.36	8.874

TABLE IV. RESPONSE TABLE FOR UNCOATED

Parameters / Level	Cutting speed	Feed rate	Radial rake angle
Level -1	1.1334	1.6638	1.3881
Level -1.4142	0.8113	0.9836	0.8814
Level 0	4.1840	4.7036	4.3541
Level 1	1.5122	0.9817	1.2575
Level 1.4142	1.0391	0.3473	0.7989
Max-Min	3.3727	3.7219	3.4727
Rank	3	1	2

From Table IV, the feed rate is ranked first, followed by radial rake angle and cutting speed. Hence, it can be concluded that, feed rate is the most significant parameter while cutting speed is the least significant parameter for uncoated end milling. The optimal level for surface roughness value of uncoated end milling can be determined based on main effects plot, as shown in Fig. 1.

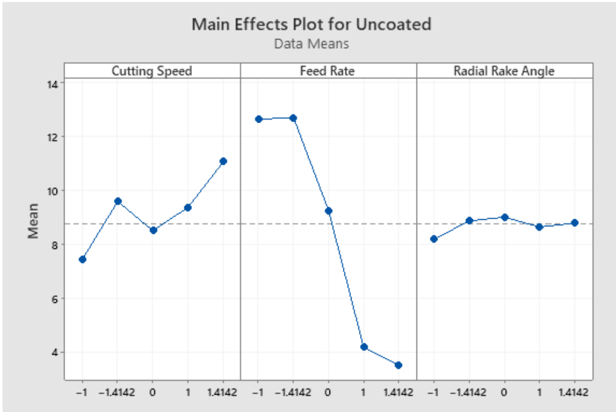

Fig. 1. Main effects plot for uncoated.

Based on the plot, it shows that the optimal solution of Ra for uncoated end milling is where cutting speed at level 1.4142 with 167.03 m/min, feed rate at level -1.4142 with 0.025 mm/tooth and input parameters radial rake angle at level 0 with 9.5°. Table V shows the response table for TiAlN. The table shows that input parameter feed rate is ranked first, trailed by input parameters cutting speed and radial rake angle. Hence, it can be concluded that feed rate is the most significant parameter while radial rake angle is the least significant parameter for TiAlN end milling. The optimal level for surface roughness value of TiAlN end milling can be determined from the main effects plot, as in Fig. 2.

From Fig. 2, the optimal solution can be determined for each of the parameters. The optimal level for TiAlN is where the input parameter cutting speed is at level 1 with 160 m/min, input parameter feed rate at level -1 with 0.03 mm/tooth and input parameter radial rake angle at level -1.4142 with 14.8°. Table VI shows the response table for SNTR and Fig. 3 shows the optimal level for surface roughness value of SNTR.

From Fig. 3, the optimal solution for SNTR can be determined for each of the parameters. The optimal level for SNTR is where the input parameter cutting speed is at level 1.4142 with 167.03 m/min, input parameter feed rate at level -1.4142 with 0.025 mm/tooth and input parameter radial rake angle at level 0 with 9.5°. Based on the response tables for uncoated, TiAlN and SNTR, it can be concluded that feed rate is the most significant parameter for end milling machining process. Feed rate ranked first for all these three coatings. Based on the main effects plots, the optimal level for end milling differs for each of the coating's types.

C. Support Vector Machine (SVM)

SVM was initially proposed by Vapnik [13]. Adapting the concept of Structural Risk Minimization (SRM), SVM is able to obtain rules for decision-making and allow minor errors in setting independent tests so that learning problems can be effectively solved. Basically, SVM prediction model consists of five major steps, which are illustrated in Fig. 4.

The basic SVM regression function theory is presented in Eq. (4) [13].

$$y = f(x) = \rceil . x + b \qquad (4)$$

TABLE V. RESPONSE TABLE FOR TIALN

Parameters / Level	Cutting speed	Feed rate	Radial rake angle
Level -1	1.4021	1.9079	1.3416
Level -1.4142	0.7960	0.8297	0.8527
Level 0	4.2895	4.6728	4.2071
Level 1	1.6156	1.1098	1.6761
Level 1.4142	0.7642	0.3473	0.7899
Max-Min	3.5253	4.3256	3.4172
Rank	2	1	3

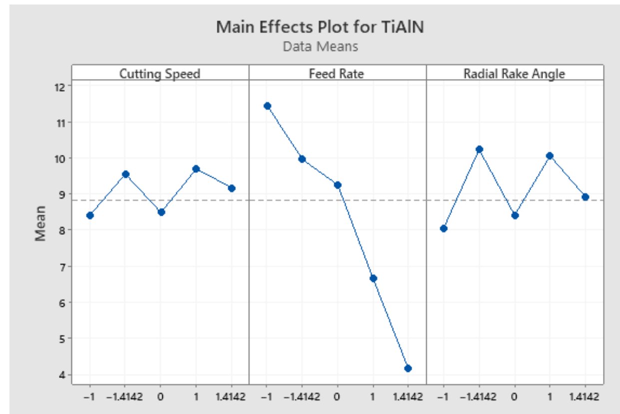

Fig. 2. Main effects plot for TiAlN.

TABLE VI. RESPONSE TABLE FOR SNTR

Parameters / Level	Cutting speed	Feed rate	Radial rake angle
Level -1	1.2400	2.1071	1.3620
Level 1.4142	0.7986	1.0575	0.7385
Level 0	4.2495	4.6196	4.4998
Level 1	1.5612	0.6940	1.4391
Level 1.4142	0.9217	0.2927	0.7315
Max-Min	3.0095	3.9255	3.1377
Rank	3	1	2

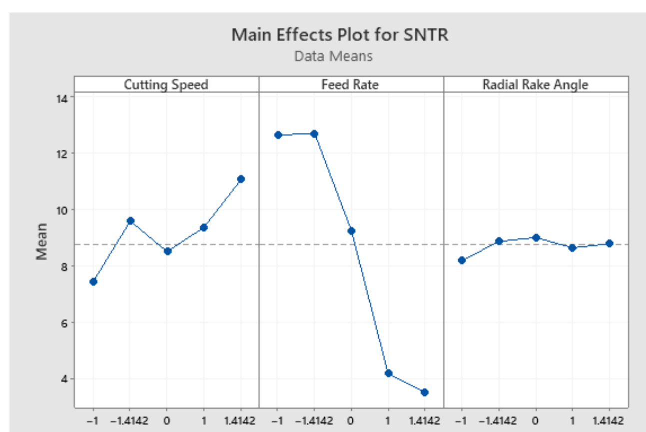

Fig. 3. Main effects Plot for SNTR.

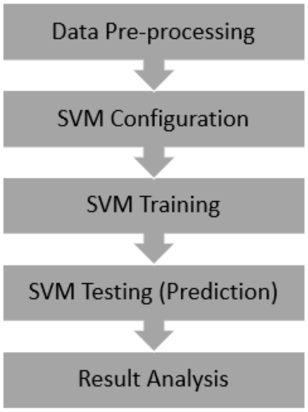

Fig. 4. Steps in SVM.

where, ω is a weight vectors, x is multivariate input, b is a bias, and y is a scalar output. Then, slack variables $\xi_i and\ \xi_i^*$ are introduced to the equation, the SVM model is expressed as:

Minimize

$$\phi(\omega) = \frac{1}{2}||\omega||^2 - C\sum_{i=1}^{n}(\xi_i - \xi_i^*)\cdot C \geq 0$$

$$y - \omega x - b \leq \varepsilon + \xi,$$

Subject to

$$\omega x - b - y \leq \varepsilon + \xi_i^*, \ i = 1,2,\dots,l$$

$$\xi_i, \xi_i^* \geq 0, \qquad (5)$$

where, ε is a loss function, and C is a regularization parameter.

$$y = f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)(x_i \cdot x) + b \qquad (6)$$

SVM model solution is obtained by applying the Lagrange Multiplier method as the following equations:

$$L(\omega, b, \xi, \xi^*) = \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{n}(\xi_i - \xi_i^*) - \sum_{i=1}^{n}\alpha_i(\varepsilon_i + \xi_i - y_i + \omega \cdot x_i + b) - \sum_{i=1}^{n}\alpha * (y_i + \varepsilon_i + \xi_i - \omega \cdot x_i - b) - \sum_{i=1}^{n}(\eta_i\xi_i + \eta_i^*\xi_i^*) \qquad (7)$$

where, $\alpha_i, a_i^*, \eta_i, \eta_i^*$ are the Lagrange Multiplier. Then, the dual problem is:

Maximize

$$Q(\alpha) = \sum_{i=1}^{n} y(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{n}(\alpha_i - a_i^*) - \frac{1}{2}\sum_{i=1}^{n}(a_i - a_i^*)(x_i - x_j) \qquad (8)$$

Subject to

$$\{\sum_{i=1}^{n} y_i(a_i - a_i{}^*) = 0, 0 \leq a_i \leq 0, \ 0 \leq a_i{}^* \leq 0,$$

$$i = 1,2,\dots,n$$

Regression function:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i{}^*)(x_i, x) + b \qquad (9)$$

Nonlinear regression function:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i{}^*)\,K(x_i, x) + b \qquad (10)$$

The solution of K (x_i, x) in the Eq. (9) can be changed into $K(x_i,x) = (\prod(x_i),\rangle(x))$ when using a mapping function. From the equation, *n* is the number of support vectors, K is a kernel function and b is bias. The high-accuracy prediction and good SVM model come with a proper parameter setting. RBF kernel function is used in this paper to predict the Ra of the end milling machining process.

For the SVM data pre-processing, the machining experimental dataset is divided into two datasets: one is for training and the other one is for testing that will be used to get the prediction result. The input data of training and testing data need to be transformed into a sparse format in range [0, 1]. For the SVM configuration, kernel function, Gamma value (for RBF kernel) and regularization parameter C need to be considered. The process of trial and error with different parameter values must be implemented accordingly to get the best prediction model. After completing the training and testing process, the prediction result is analyzed using statistical analysis.

III. Result and Discussion

The SVM prediction models were developed and three models were identified as the best prediction model for all three cutting tools. The models were chosen based on the highest correlation values of developed SVM models. Table VII shows the predicted Ra value of regression based on the result from Zain et al. and SVM.

TABLE VII. RA Values of Predicted Regression and SVM Predictions

No	Predicted *Ra* (µm) Regression			Predicted *Ra* (µm) SVM		
	Uncoated	TiAlN coated	SNTR coated	Uncoated	TiAlN coated	SNTR coated
1	0.306	0.304	0.259	0.2535	0.2633	**0.1372**
2	**0.226**	0.278	0.207	0.2535	0.2633	0.1372
3	0.533	0.519	0.607	0.2752	0.7957	0.8273
4	0.453	0.493	0.554	0.2752	0.7957	0.8273
5	0.334	0.270	0.250	0.1766	0.3022	0.3935
6	0.254	**0.245**	0.197	0.1766	0.3022	0.3935
7	0.561	0.486	0.597	0.7708	0.3430	0.4042
8	0.481	0.460	0.545	0.7708	0.3430	0.4042
9	0.370	0.364	0.369	0.2975	0.3483	0.3798
10	0.370	0.364	0.369	0.2975	0.3483	0.3798
11	0.370	0.364	0.369	0.1272	0.3483	0.3798
12	0.370	0.364	0.369	**0.1272**	0.3483	0.3798
13	0.423	0.381	0.404	0.3720	0.3160	0.4022
14	0.423	0.381	0.404	0.3720	0.3160	0.4022
15	0.310	0.344	0.329	0.3720	0.3099	0.3148
16	0.310	0.344	0.329	0.3720	0.3099	0.3148
17	0.251	0.251	**0.187**	0.3434	0.2500	0.2287
18	0.251	0.251	0.187	0.5212	0.2187	0.1667
19	0.580	0.563	0.691	0.5894	0.7200	0.6874
20	0.580	0.563	0.691	0.4988	0.5709	0.6353
21	0.355	0.382	0.374	0.2269	0.2371	0.2300
22	0.355	0.382	0.374	0.5996	**0.1910**	0.1663
23	0.395	0.334	0.361	0.4728	0.4871	0.6916
24	0.395	0.334	0.361	0.4094	0.4539	0.6385

From Table VII, it shows that, for uncoated, SVM prediction result has outperformed experimental data and regression by giving the Ra value of 0.1275µm, compared with 0.236µm and 0.226µm, respectively. For TiAlN coating, it was found that the SVM prediction result has outperformed experimental data and regression by giving the Ra value of 0.1910µm, compared with 0.232µm and 0.245µm, respectively. For SNTR coating, it was found that the SVM prediction result also has outperformed experimental data and regression by giving the Ra value of 0.1372µm, compared with 0.19µm and 0.187µm, respectively. The graft of prediction result is illustrated in Fig. 5- Fig. 7.

Fig. 5 – Fig. 7 show the graphs of comparison of experimental data, regression and SVM prediction. The prediction results of SVM were then validated based on the statistical analysis using SPSS software to find the accuracy of each model. Table VIII shows input parameters with RMSE values for the best SVM models while Table IX shows the paired sample t-test for each coating types to compare the SVM prediction with experimental data.

It can be seen in Table IX that all pairs are positively correlated with pair of EXP_ SNTR and SVM_SNTR gives the highest correlation value, 0.9682. A good prediction result will give a higher correlation value for each pair. A higher correlation value means that two sets of data are relatively similar to each other. Table X summarizes the result of most minimum Ra values for each coating tool for experimental data, regression and SVM models.

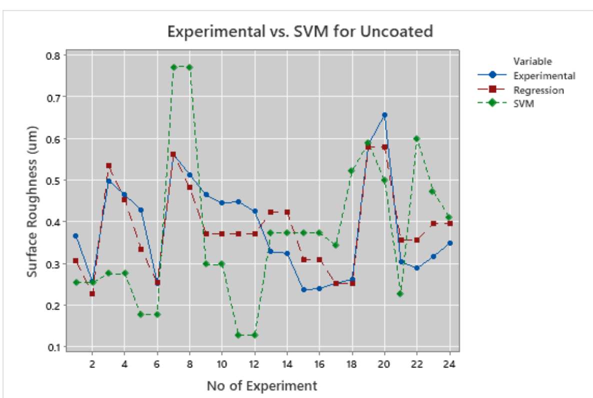

Fig. 5. Experimental vs. SVM for uncoated.

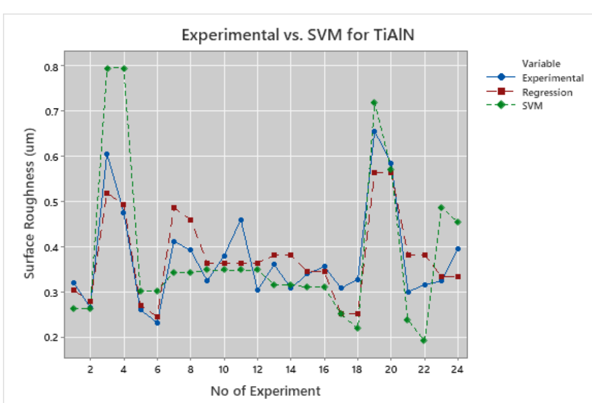

Fig. 6. Experimental vs. SVM for TiAlN.

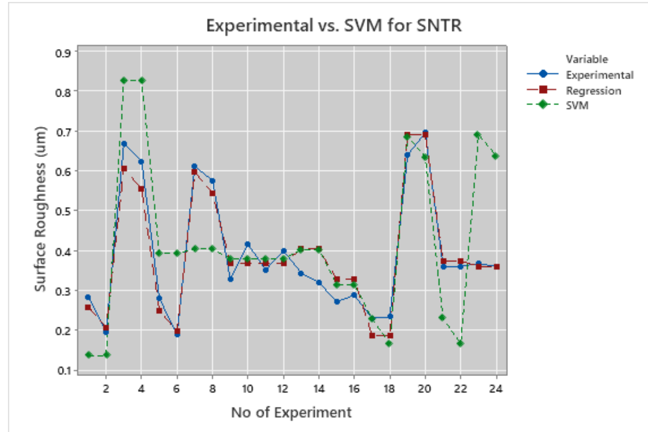

Fig. 7. Experimental vs. SVM for SNTR.

TABLE VIII. INPUT PARAMETERS AND RMSE VALUES FOR THE BEST SVM MODEL

Coating	C	Gamma	No. of support vector	RMSE
Uncoated	100	0.4	78	0.0739
TiAlN	100	0.333	34	0.0650
SNTR	1	0.333	20	0.0634

TABLE IX. PAIRED SAMPLE T-TEST

Paired Sample T-Test						
Pairs	Mean	Standard Deviation	Standard Error Mean	95% Confidence Interval		Correlation
				Lower	Upper	
EXP_UNC and SVM_UNC	0.0128	0.1846	0.0378	-0.0653	0.0904	0.9485
EXP_TIAN and SVM_TIAN	-0.0072	0.1031	0.0210	-0.0508	0.0363	0.9468
EXP_ SNTR and SVM_SNTR	-0.0218	0.1433	0.0292	-0.0823	0.0388	0.9682

TABLE X. MINIMUM RA VALUES IN END MILLING FOR EACH APPROACH

Approach	Uncoated (µm)	TiAlN (µm)	SNTR (µm)
Experimental	0.236	0.232	0.190
Regression	0.226	0.245	0.187
SVM	0.127	0.191	0.133

From Table X, it is shown that SVM model has outperformed experimental and regression model for uncoated, TiAlN and SNTR cutting tools in terms of minimum value of Ra. The minimum Ra has reduced for both regression and SVM about 1.57% and 33.05% respectively. Overall, it could be concluded that SVM is effective to predict the most minimum Ra value of end milling machining process.

IV. CONCLUSIONS

This study utilized the computational approaches method, Taguchi and SVM for modeling and optimization of surface roughness value in one of the traditional machining process, which is end milling. Three types of cutting tools were used to obtain the experimental data that are uncoated carbide WC-Co, common PVD-TiAlN and Supernitride (SNTR) coating. The significant parameters affecting the end milling performance, surface roughness values were obtained using the S/N ratio of the Taguchi method. From the study, it was found that:

1) Input parameter feed rate is the most significant factor affecting surface roughness value for all types of cutting tools.

2) The optimal level for uncoated end milling is where the input parameter cutting speed at level 1.4142 with 167.03 m/min, and input parameter feed rate at level -1.4142 with 0.025 mm/tooth and input parameter radial rake angle at level 0 with 9.5°.

3) The optimal level for TiAlN is where the input parameter cutting speed is at level 1 with 160 m/min, input parameter feed rate at level -1 with 0.03 mm/tooth and input parameter radial rake angle at level -1.4142 with 14.8°.

4) The optimal level for SNTR is where the input parameter cutting speed is at level 1.4142 with 167.03 m/min, the input parameter feed rate at level -1.4142 with 0.025 mm/tooth and the input parameter radial rake angle at level 0 with 9.5°.

5) For the end milling prediction, it has been found that SVM gives better prediction results compared with regression and experimental data for all three types of cutting tools.

6) Within these three cutting tools, uncoated cutting tools give the most minimum Ra which is 0.127µm compared to TiAlN and SNTR, 1.9µm and 1.32µm, respectively. Hence, it can be concluded that the uncoated cutting tool is the best cutting tool amongst the three types of cutting tools that are widely used in traditional machining process, especially end milling.

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