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RESEARCH

Surface Roughness Prediction in CNC Hole Turning of 3X13 Steel using Support Vector Machine Algorithm

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A B S T R A C T

This paper presents research on a prediction method of surface roughness in the hole turning process of 3X13 steel. The experimental matrix was designed by using the Central Composite Design (CCD) with four input parameters including cutting speed, feed rate, cutting depth, and tool nose radius. Using the response surface method (RSM), a quadratic polynomial model was proposed to predict the surface roughness. Besides, another method that was used to predict surface roughness was the Support Vector Machine (SVM) algorithm. Using SVM, the predicted surface roughness was more accurate than that one when predicting surface roughness using RSM method. Using RSM, the mean absolute error and mean square error between experimental and expect results were 13.37 % and 3.93 %, respectively. While, using SVM, these values were only 2.80 % and 0.17 %, respectively. The SVM can be used to improve the prediction accuracy of surface roughness in hole turning process of 3X13 steel.

1. INTRODUCTION

A lathe is the most common machining method in cutting processes. The workload done by the lathe method estimates about 40 % of the total machining methods [1]. The roughness of the hole surface during machining has a great influence on the workability and longevity of the product, so it is often chosen as an indicator to evaluate the efficiency of the processing. In order to have a basis for adjusting the technological system in machining to ensure the surface roughness as required, many studies have been published to determine the influence of the parameters of the processing process to obtain desired surface roughness.

Kulshreshtha [2] investigated the effect of cutting speed, feed rate and depth of cut on the roughness of the surface when using a tungsten carbide-coated cutting piece to turn EN 36 steel. He found out that all three parameters have a significant effect on the surface roughness. As the cutting speed increases, the surface roughness increases. Meanwhile, if the feed rate increases and the depth of cutting is reduced, the surface roughness decreases.

Ahmed [3] used carbide-coated cutting pieces to test the aluminum alloy turning process. The cutting speed, the feed rate and the depth of cutting are the three parameters that he selected as input

parameters when designing the experimental matrix in this study. The influence of parameters on surface roughness has also been shown: the feed rate has a great influence on the surface roughness, when increasing the feed rate, the roughness of the machining surface increases rapidly. Cutting velocity and depth of cut have a negligible effect on surface roughness.

Nitin Ambhore et al. [4] conducted experiments to investigate the effect of cutting speed, tool amount and cutting depth on surface roughness when turning AISI 52100 steel with a cutting piece marked CNMG120408-MF5. The testing process was conducted by RSM method based on CCD test matrix. This study has shown that the amount of tooling is the parameter that has the most influence on the surface roughness, followed by the degree of influence of the cutting speed. The depth of cutting has a negligible effect on the surface roughness.

Mohruni et al. [5] studied the process of turning AISI D2 steel by CBNC cutting tool. The two parameters of the cutting parameters that they selected were the input parameters to design the experimental process during the experimental process of this study, including the cutting speed and the feed rate. The experiments have been designed by them according to the response surface method (RSM) based on the CCD design. Their research has shown that both cutting speed and feed rate parameters have a significant effect on surface roughness.

Taraman et al. [6] used tungsten carbide cutting pieces to machine the ASE 1018 steel The parameters they selected were the input parameters in the development of the experimental matrix, including the cutting speed, feed rate and cutting depth. Experimental matrix was built by RSM method based on CCD matrix. This study has shown that when the cutting speed increases, the roughness of the surface decreases, as the value of the feed rate and the depth of cutting increase the surface roughness.

Doniavi [7] and colleagues studied AISI 1060 steel turning experiments using cutting pieces covered with K10 bits. Cutting speed, feed rate and cutting depth are the three parameters that they choose in the process of developing the experimental matrix, the test matrix is designed in Box-Behnken format with 20 experiments (L20). Their study determined that the cutting speed and the feed rate have a great influence on the surface roughness, in which the influence of feed rate on the surface roughness is greater than the influence of the cutting speed. As the cutting speed increases, the roughness of the surface is reduced. Cutting depth has a negligible effect on surface roughness.

Dinesh et al. [8] experimented with EN 24 alloy steel turning by cutting pieces covered with cemented bits. They have applied a 2^k (L16) test matrix to develop the test matrix with four input parameters: cutting speed, feed rate, cutting depth and tip radius. The results of their study showed that only the feed rate is a parameter that significantly affects the surface roughness, when the feed rate increases the surface roughness increases, the remaining three parameters have negligible influence to surface roughness.

Singh et al. [9] used the RSM method based on the design of a CCD-type experiment to build the AISI 52100 steel lathe test matrix with ceramic-coated cutting pieces. The cutting speed, feed rate, insert flank angle, and insert nose radius were selected as input parameters during the experiment. The results of their study have determined that the tool salary is the parameter that has the most influence on the surface roughness, followed by the influence of the insert nose radius and cutting speed. The insert flank angle negligible influences on the surface roughness.

Feng et al. [10] used cutting tools coated with Ti (C, N) - Al_2O_3 - TiN mixtures in the process of turning two materials including 8620 steel and aluminum alloy 6061T. The type of experimental plan they used in this study is a 2^{k-1} part design form (where k = 5 is the number of input parameters). Five input parameters are used to develop the test matrix, including the hardness of the workpiece, the feed rate, the angle of the tool, the depth of cutting, and the cutting speed. Their research has identified that all five parameters as well as the interaction between them have a significant effect on surface roughness.

El-Axir et al. [11] applied RSM method and Taguchi technique to test dry aluminum alloy 6061-T6. The parameters they selected during the design of the experimental matrix included the tool overhang, cutting speed, feed rate, and the depth of cut. Their research has shown that

cutting speed and feed rate are two parameters that have a significant effect on surface roughness. Tool overhang and cutting depth have negligible effect on surface roughness.

Tanikić et al. [12] when studying the dry-rolled cold rolled alloy type (Cold Rolled Alloyed) type Č.4732 with a cutting piece covered with tungsten bits that used the cutting velocity, the feed rate and the depth of cutting to be three. Input parameters to build experimental matrix. The experimental matrix was constructed with 27 experiments, each cutting parameter receiving three values. This study has determined that all three parameters have a great influence on the surface roughness. Where the cutting speed is the parameter that has the most influence on the roughness, followed by the influence of the feed rate and the depth of cut. The interaction between parameters has negligible influence on surface roughness.

Shahabi et al. [13] tested the process of turning AISI 304 steel by cutting pieces covered with cemented bits with the symbol CNGP-12-04-04_H13A. The testing process was performed by RSM method based on CCD test matrix. Cutting speed, feed rate, cutting depth and machining time are selected as 4 parameters to build the test matrix. Research results have shown that cutting speed, feed rate and machining time have a significant influence on surface roughness. Cutting depth has a negligible effect on surface roughness.

Through some of the listed studies, it is shown that, in each specific processing condition, the cutting parameters and cutter nose radius have the effect on the surface roughness with a relatively different levels and rules. Therefore, to have a basis for adjusting the parameters of the technological system to machine the part surface with the required surface roughness, it is necessary to conduct the experimental research in each specific condition.

In hole finish turning processes, the lathe method has more advantages than other machining methods (grinding, boring, broaching) because the lathe is highly versatile, easy to place the workpieces with the with complex structures, especially when processing the holes with non-standard sizes [1]. 3X13 steel (GOST standard - Russian Federation) is the type of steel commonly used to manufacture components in the shipbuilding, oil and gas, chemical technology, food processing, and medical industries. Turning is one of the most common machining methods to manufacture these components. However, up to date, there have not been studies that were mentioned to investigate influence of machining parameters on the surface roughness. The selection of the cutting parameters when turning this steel was performed based on the experience of the workers. It takes more time to determine the technical parameters when turning this steel in specific cases. This issue also influences on the economic and engineering effectiveness of turning processes. Therefore, it is necessary to investigate the fluence of machining parameters on the surface roughness in hole turning of 3X13 steel. The research results will be more useful to determine the technical parameters. Otherwise, there is also a need to build a surface roughness model to express the relationship between surface roughness and technical parameters to predict the achievable surface roughness in specific cases. It takes less time to set up the operating machine, testing time, and machining efficiency.

In this paper, the effect of cutting speed, feed rate, cutting depth, and cutter radius on the surface roughness was investigated in hole turning process of 3X13 steel. In addition, the RSM based on a CCD experimental matrix will be applied to develop a surface roughness model. The SVM algorithm was also applied to predict surface roughness. The comparison of the predicted surface roughness using RSM method and SVM algorithm was also performed.

RSM and SVM that were chosen to predict the surface roughness because RSM is a popular method that has been applied by many scientists to predict the surface roughness in machining processes. Besides, SVM was selected to predict the surface roughness because SVM has some advantages in comparing with other common and popular algorithm. Firstly, SVM is memory efficient, which means it takes a relatively lower amount of calculation resources to train the model and presenting the solution by means of a small subset of training points gives enormous computational advantages. Secondly, there are non-linear or complex relationships between features and labels. The option to convert non-linear relationships to higher-dimensional problems can be solved using the support vector regression (SVR).

Table 1. Equivalent symbols of 3X13 steel

Russia	USA	German	Japan	France	UK	EU	Italy	Spain	China	Sweden
GOST	SAE	DIN	JIS	AFNOR	BS	EN	UNI	UNE	GB	SS
3X13	420	1.4028	SUS420J2	410F21	420S45	1.4028	GX30Cr13	F.3403	3Cr13	2304

2. EXPERIMENTAL METHOD

2.1 Material

The experimental material used in this study was 3X13 steel. The Equivalent symbols of this steel, according to some standards were presented in Table 1.

Fig. 1. Test Specimens.

Table 2. Chemical composition of 3X13 steel.

Chemical composition [%]				
C	Si	Mn	Cr	S
0.42	1.00	1.00	13.00	0.005

Before the test, the workpiece was heat-treated to achieve the hardness of 56HRC. The outer diameter, inner diameter, and height of the test specimen are 80 mm, 50 mm and 22 mm, respectively, as shown in Fig. 1. The chemical compositions of the workpiece material were listed in Table 2.

2.2 Experimental machine and cutting tool

The turning CNC machine (Doosan Lynx 220L) was used to perform the experiments as described in Fig. 2. The cutting tool that was used for turning process was a PVD-Coated turning insert (produced by Korloy, Korea) with 5 separate nose radii (0.1 mm, 0.2 mm, 0.3 mm, 0.4 mm and 0.5 mm).

Fig. 2. Experimental machine.

2.3 Measurement system

SJ-301 surface test (Mitutoyo – Japan) was used to measure the surface roughness. For each experiment, the workpiece's surface roughness was measured repeating at least 3 times, and the average surface roughness value was used for analysis and evaluation of experimental results.

2.4 Experimental Design

The Central Composite Design (CCD) approach-based on Response Surface Methodology (RSM) was used to determine the effect of cutting parameters on the surface roughness. According to this experimental design, each independent variable was studied at five different levels coded as -α, −1, 0, +1, and +α, which the number of α is $\alpha = (2k)^{1/4}$, where k is the number of input factors. The value of each input factor at each level depicted in table 3. The CCD included 30 experiments which had 6 experiments as replication of the central points. The number of experiments is $2^k+2k+cp=2^4+2*4+6=30$, where k=4, and cp=6 is number of center points. Experiments incorporating 8 factorial points, axial points. These 30 experiments based on CCD and obtained results are shown in Table 4.

Table 3. Independent variables and coded levels.

Independent Variables	Unit	Symbol	Code	Variation levels				
				-2	-1	0	1	2
Cutting speed	m/min	v	X_1	100	140	180	220	260
Feed rate	mm/rev	f	X_2	0.02	0.04	0.06	0.08	0.1
Depth of cut	mm	t	X_3	0.05	0.1	0.15	0.2	0.25
Tool nose radius	mm	r	X_4	0.1	0.2	0.3	0.4	0.5

Table 4. The cutting conditions and the experimental results.

No.	Code variable				Actual variable				Ra (µm)
	X_1	X_2	X_3	X_4	v (m/min)	f (mm/rev)	t (mm)	r (mm)	
1	-1	-1	1	-1	140	0.04	0.2	0.2	1.12
2	1	1	1	1	220	0.08	0.2	0.4	4.08
3	-1	-1	-1	1	140	0.04	0.1	0.4	2.88
4	1	-1	1	1	220	0.04	0.2	0.4	1.4
5	0	0	0	0	180	0.06	0.15	0.3	2.18
6	0	0	0	0	180	0.06	0.15	0.3	2.34
7	1	-1	-1	-1	220	0.04	0.1	0.2	1.7
8	1	1	-1	-1	220	0.08	0.1	0.2	2.16
9	1	-1	1	-1	220	0.04	0.2	0.2	1.24
10	0	0	0	0	180	0.06	0.15	0.3	2.18
11	1	1	1	-1	220	0.08	0.2	0.2	3.32
12	-1	1	1	1	140	0.08	0.2	0.4	5.22
13	0	0	0	0	180	0.06	0.15	0.3	2.2
14	-1	-1	1	1	140	0.04	0.2	0.4	2.08
15	-1	1	1	-1	140	0.08	0.2	0.2	3.04
16	-1	1	-1	-1	140	0.08	0.1	0.2	2.84
17	1	1	-1	1	220	0.08	0.1	0.4	2.88
18	-1	1	-1	1	140	0.08	0.1	0.4	5.66
19	-1	-1	-1	-1	140	0.04	0.1	0.2	2.16
20	1	-1	-1	1	220	0.04	0.1	0.4	2.22
21	-2	0	0	0	100	0.06	0.15	0.3	2.8
22	0	2	0	0	180	0.1	0.15	0.3	3.94
23	2	0	0	0	260	0.06	0.15	0.3	1.44
24	0	-2	0	0	180	0.02	0.15	0.3	2.09
25	0	0	-2	0	180	0.06	0.05	0.3	1.92
26	0	0	2	0	180	0.06	0.25	0.3	2.32
27	0	0	0	-2	180	0.06	0.15	0.1	2.66
28	0	0	0	2	180	0.06	0.15	0.5	2.84
29	0	0	0	0	180	0.06	0.15	0.3	2.22
30	0	0	0	0	180	0.06	0.15	0.3	2.12

3. RESULTS AND DISCUSSION

The experimental results were listed in Table 4. Minitab 16 software was used to evaluate the analysis of variance (ANOVA) and regression parameters. The results are shown in Fig. 5. ANOVA and regression analysis of surface roughness are conducted, and the results are listed in Table 5.

The results in Table 5 showed that:

Cutting speed, feed rate, tool nose radius significantly influences on the surface roughness. The feed rate has the most influence on the surface roughness, followed by cutting speed; by contrast, the effect of depth of cut on surface roughness is negligible. Surface roughness decreased with increasing of cutting speed. The increasing of feed rate leads to a reduction in surface roughness. The surface roughness grown-up or down with the tool nose radius (the surface roughness fluctuates with

the change in tool nose radius). These statements were described in Fig. 3.

The interaction on surface roughness among cutting parameters: The interaction between feed rate and depth of cut on surface roughness is the most, followed by the relevance between cutting speed and tool nose radius. The remaining factors have an insignificant influence on the surface roughness.

In detail, the influence degree of the interactions on the surface roughness decreased gradually according to the orders of the interaction between feed rate and insert nose radius, the interaction between cutting speed and depth of cut, the interaction between cutting speed and feed rate, the interaction between depth of cut and insert nose radius. These results are described in Fig. 4.

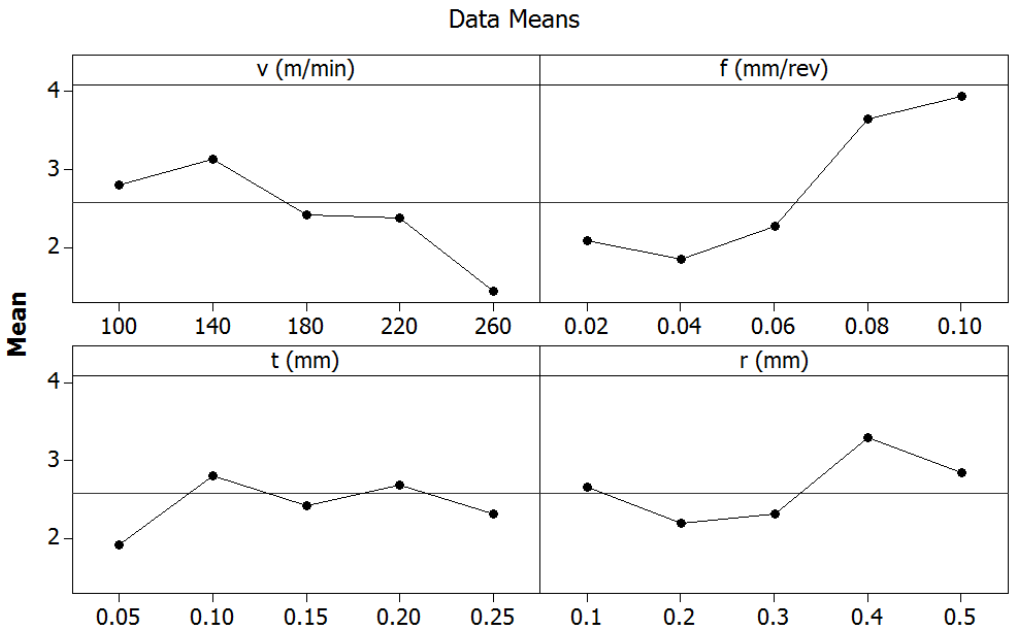

Fig. 3. Effect of cutting parameters on surface roughness.

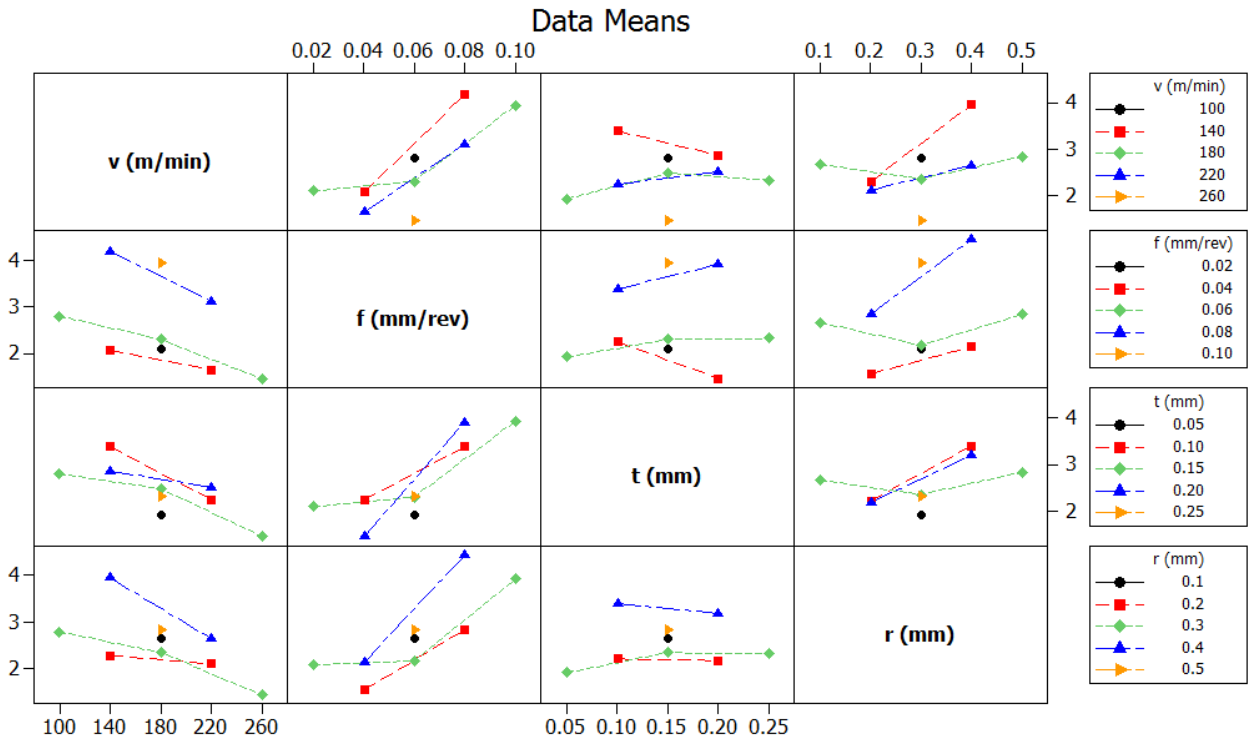

Fig. 4. Interaction/relevance among turning parameters on surface roughness.

Table 5. ANOVA of surface roughness (Ra).

Multiple R		0.9397				R Square		0.8831	
Adjusted R Square		0.7740				Standard Error		0.4948	
ANOVA									
	df	*SS*	*MS*	*F*	*Significance F*				
Regression	14	27.7436	1.9817	8.0930	0.0001				
Residual	15	3.6730	0.2449						
Total	29	31.4166							
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*	
Intercept	2.2067	0.2020	10.9232	0.0000	1.7761	2.6373	1.7761	2.6373	
X_1	-0.3633	0.1010	-3.5971	0.0026	-0.5786	-0.1480	-0.5786	-0.1480	
X_2	0.7542	0.1010	7.4664	0.0000	0.5389	0.9695	0.5389	0.9695	
X_3	-0.0083	0.1010	-0.0825	0.9353	-0.2236	0.2070	-0.2236	0.2070	
X_4	0.3833	0.1010	3.7951	0.0018	0.1680	0.5986	0.1680	0.5986	
X_1^2	0.0198	0.0945	0.2095	0.8369	-0.1816	0.2212	-0.1816	0.2212	
X_2^2	0.2435	0.0945	2.5776	0.0210	0.0422	0.4449	0.0422	0.4449	
X_3^2	0.0198	0.0945	0.2095	0.8369	-0.1816	0.2212	-0.1816	0.2212	
X_4^2	0.1773	0.0945	1.8764	0.0802	-0.0241	0.3787	-0.0241	0.3787	
$X_1 * X_2$	-0.1650	0.1237	-1.3338	0.2022	-0.4287	0.0987	-0.4287	0.0987	
$X_1 * X_3$	0.1975	0.1237	1.5965	0.1312	-0.0662	0.4612	-0.0662	0.4612	
$X_1 * X_4$	-0.2825	0.1237	-2.2836	0.0374	-0.5462	-0.0188	-0.5462	-0.0188	
$X_2 * X_3$	0.3275	0.1237	2.6473	0.0183	0.0638	0.5912	0.0638	0.5912	
$X_2 * X_4$	0.2575	0.1237	2.0815	0.0549	-0.0062	0.5212	-0.0062	0.5212	
$X_3 * X_4$	-0.0450	0.1237	-0.3638	0.7211	-0.3087	0.2187	-0.3087	0.2187	

The results from Fig. 4 show that the interaction between the input parameters has a rather complicated effect on surface roughness. The analysis of the small figure of 16 figures in Fig. 4 explained clearly this statement. For example, in the 4th figure of the first row and fourth column, the formation describes the interaction effect between the cutting speed and insert nose radius on the surface roughness. When the cutting speed changes from 100 m/min to 260 (m/min), the changing of insert nose radius does not influence on the surface roughness. When the cutting speed was 140 m/min, increasing of the insert nose radius causes the surface roughness increase quickly. When the cutting speed was 180 m/min, increasing the insert nose radius from 0.1 mm to 0.3 mm will slow down the surface roughness, but if the insert nose radius increases from 0.3 mm to 0.5 mm, the surface roughness increases. When cutting speed was 220 m/min, the surface roughness would slightly increase if the insert nose radius value increases.

4. PREDICTING OF SURFACE ROUGHNESS BY RSM METHOD AND SVM ALGORITHM

4.1 Prediction of surface roughness using RSM method

The RSM method predicts surface roughness by using Eq (1) to calculate the value of surface roughness corresponding to specific values in the investigated domain of the cutting parameters. Specifically, according to the coding form of cutting parameters, Eq (1) is used to calculate surface roughness corresponding to values of cutting parameters in the range $-2 \le X_1, X_2, X_3, X_4 \le 2$. In this study, using coded values of cutting parameters in Table 4 to calculate surface roughness, the results are presented in Table 6.

The surface roughness was modelled as a quadratic function of the cutting speed, feed rate, depth of cut, and insert nose radius as by Eq. (1) with the determination coefficient R^2 of 0.8831. In this model, the input factors were calculated by coded values.

The value of R^2 shows that this regression model is suitable for the data set in Table 4, which is 88.31 %. In other words, 88.31 % of the change in surface roughness can be explained by the difference in the cutting parameters, while 11.69 % of the difference in surface roughness is not due to the change.

$$R_a = 2.2067 - 0.3633\,X_1 + 0.7542.X_2 - 0.0083.X_3 + 0.3833.X_4 + 0.0198.X_1^2 + 0.2435.X_2^3 + 0.0198.X_3^2 + 0.1773.X_4^2 - 0.1650.X_1.X_2 + 0.1975.X_1.X_3 - 0.2825.X_1.X_4 + 0.3275.X_2.X_3 + 0.2575.X_2.X_4 - 0.0450.X_3.X_4 \quad (1)$$

Table 6. Comparison of prediction and experimental of surface roughness.

Order	Experimental surface Roughness Ra (μm)	Predicted surface roughness Ra (μm)		Absolute error	
		RSM	SVM	RSM	SVM
1	1.12	1.393	1.173	24.38 %	4.73 %
2	4.08	3.901	4.020	4.39 %	1.47 %
3	2.88	3.276	2.917	13.75 %	1.28 %
4	1.4	1.553	1.485	10.93 %	6.07 %
5	2.18	2.207	2.254	1.24 %	3.39 %
6	2.34	2.207	2.254	5.68 %	3.68 %
7	1.7	2.143	1.718	26.06 %	1.06 %
8	2.16	2.151	2.142	0.42 %	0.83 %
9	1.24	1.956	1.222	57.74 %	1.45 %
10	2.18	2.207	2.254	1.24 %	3.39 %
11	3.32	3.275	3.338	1.36 %	0.54 %
12	5.22	5.128	5.259	1.76 %	0.75 %
13	2.2	2.207	2.254	0.32 %	2.45 %
14	2.08	2.119	2.041	1.88 %	1.88 %
15	3.04	3.371	2.987	10.89 %	1.74 %
16	2.84	3.038	3.316	6.97 %	16.76 %
17	2.88	2.958	2.941	2.71 %	2.12 %
18	5.66	4.974	5.623	12.12 %	0.65 %
19	2.16	2.369	2.085	9.68 %	3.47 %
20	2.22	1.919	2.159	13.56 %	2.75 %
21	2.8	3.013	2.801	7.61 %	0.04 %
22	3.94	4.689	3.858	19.01 %	2.08 %
23	1.44	1.559	1.441	8.26 %	0.07 %
24	2.09	1.672	2.032	20.00 %	2.78 %
25	1.92	3.015	1.828	57.03 %	4.79 %
26	2.32	2.982	2.228	28.53 %	3.97 %
27	2.66	2.149	2.687	19.21 %	1.02 %
28	2.84	3.683	2.867	29.68 %	0.95 %
29	2.22	2.207	2.254	0.59 %	1.53 %
30	2.12	2.207	2.254	4.10 %	6.32 %

4.2. Regression of surface roughness using SVM

The goal of a Support Vector Machine (SVM) is to find the optimal hyper plane (Hyper plane may be plane or curve) to classify data into two separate regions so that the distance between the closest point and the hyper plane is at maximum. This is also called the margin. Figure 5 illustrates a hyper plane and a margin.

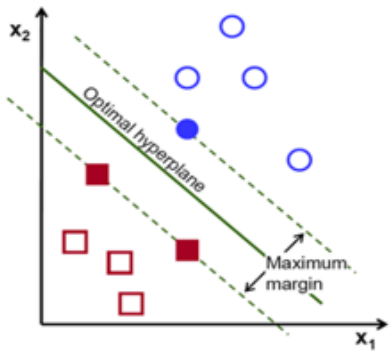

Fig. 5. Illustration of the hyper plane and the margin.

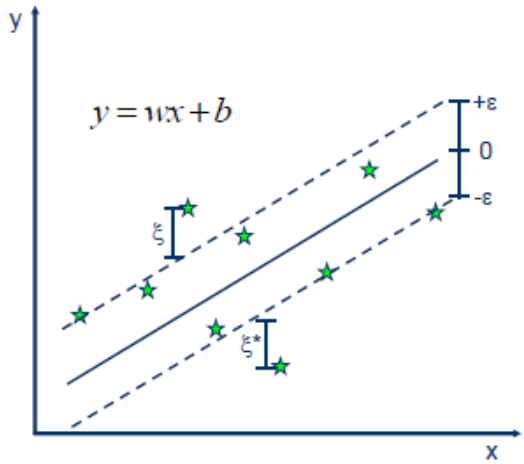

Fig. 6. Linear regression with the epsilon range.

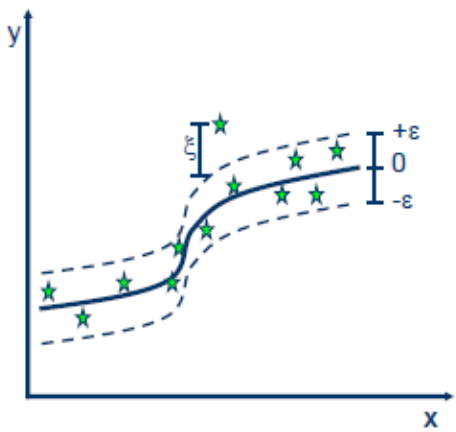

Fig. 7. Nonlinear regression with the epsilon range.

Assume, the equation of a hyper plane is $w.x+b=0$. The goal for the SVM algorithm is to find w and b to maximize the margin. The SVM algorithm not only applies to solving classification problems but also to finding solutions to regression subjects. The SVM algorithm is based on a loss function, which is tolerant of error for points distant from the true value within a small epsilon. This means that this function gives zero error for all the points in training set that lie in the epsilon range. Figures 6 and 7 illustrate linear and nonlinear regression within the epsilon range [14].

For SVR, the input x is mapped into m dimension feature space by a nonlinear mapping function first, and then the linear model is built, which is based on this dimension feature space by Eq (2):

$$f(x,w)=\sum_{i=1}^{m} w_i.g_i(x)+b \tag{2}$$

where: $g_i(x)$ $i=1,2...,m$ is a set of nonlinear mapping functions.

The accuracy of the estimate is evaluated by loss function L(y,f(x,w)). SVR uses a loss function called epsilon – an insensitive loss function which proposed by Vapnik:

$$L=\begin{cases}0 \ if \ |y-f(x,w)|\le\varepsilon \\ |y-f(x,w)| \ otherwise\end{cases} \tag{3}$$

Thus, SVM is performed linear regression in multi dimension feature space using function L and minimizing $\|W\|^2$ for decreasing complexity of the model. This problem can be solved by introducing slug variables ζ_i and ζ_i^* with i = 1, 2, … n to measure the deviation of the training samples which lie outside of the epsilon range. Therefore, SVR is minimized by the function below:

$$\min\frac{1}{2}\|w\|^2+C.\sum_{i=1}^{n}(\zeta_i+\zeta_i^*) \tag{4}$$

with constraints:

$$\begin{Bmatrix} y_i-f(x_i,w)\le\varepsilon+\zeta_i^* \\ f(x_i,w)-y_i\le\varepsilon+\zeta_i \\ \zeta_i\ \zeta_i^*\succ 0\forall i=1,...,n \end{Bmatrix} \tag{5}$$

Applying the duality theorem for minimizing problems, we finally obtain the function f(x):

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*).K.(x_i, x) + b \quad (6)$$

where: nSV is the number of support vector, and $K(x_i, x)$ is the kernel function which can be defined as:

$$K(x_i, x) = \sum_{j=1}^{m} g_j(x_i).g_j(x) \quad (7)$$

We used SVR to build a model for prediction surface roughness with the C = 106 and the ε = 0.0001.

4.3 Comparison performance between the two methods

To compare the precision of RSM and SVM in prediction of surface roughness, the predicted MAE (mean absolute error) and MSE (mean square error) will be calculated and compared.

$$\%MAE = \left(\frac{1}{n}\sum_{i}^{n}\left|\frac{e_i - p_i}{e_i}\right|\right)100\% \quad (8)$$

$$\%MSE = \left(\frac{1}{n}\sum_{i}^{n}|e_i - p_i|\right)100\% \quad (9)$$

Where e is experimental value, ρ is forecast value, η is the number of run (experiment).

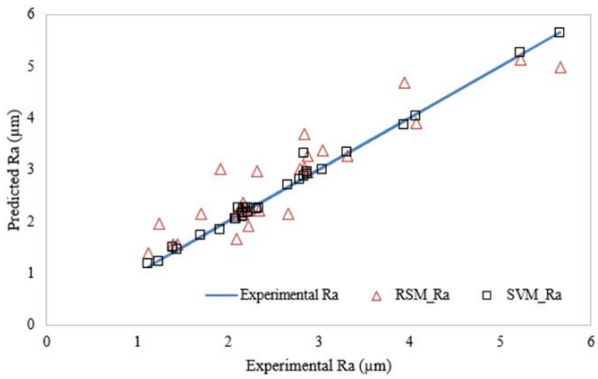

Fig. 8. Comparison of predicted and experimental surface roughness.

Table 7. Comparison of MBE and MSE by using the different predicted method.

Method	% MAE	% MSE
RSM	13.37 %	3.93 %
SVM	2.80 %	0.17 %

The comparison of predicted results and experimental results of surface roughness were listed in Table 6 and described in Fig. 8. In almost cases, it seems that the predicted results of surface roughness by using SVM that were closer to experimental results than by using RSM. The results from Table 7 shows the differences between RSM and SVM algorithm in prediction of surface roughness. From the results, it seems that the difference between predicted and experimental value (MAE) of surface roughness surface using SVM is 2.8 %, which was lower performance compare to the RSM with 13.37 % of MAE. So, from the below results in table 7 it can be concluded that the SVM model is more suitable to predict the surface roughness for hole turning. The mean square error (MSE) of RSM model is 3.93 %, by contrast the figure for SVM is only 0.17 %.

5. CONCLUSION

In this experiment work, 3X13 steel has been turned to investigate the relationship between cutting parameters and surface roughness. The following conclusions of this study are given:

Cutting speed, feed rate, and tool nose radius had significantly influence on the surface roughness. The most effecting parameter is feed rate, followed by tool nose radius, and cutting speed. Depth of cut is least significant effect on the surface roughness.

The interaction of feed rate and depth of cut had the most influence on the surface roughness. Followed by the interaction influence of the workpiece velocity and insert nose radius. The interaction influence of other factors that does not significantly influence on the surface roughness. In detail, the influence degree of the interactions on the surface roughness was very complex rules. When changing the value of the input parameters, the surface roughness sometimes increases, and sometimes decreases.

It is considered as the first study applying SVM to predict the surface roughness of the part in turning process of 3X13 steel. By SVM model, the predicted results of surface roughness were very closed to the experimental results. In comparison of predicted results of SVM and RSM method, the predicted results were also improved so much. In the detail, the MAE decreased from 13.37 % (RSM) to 2.80 % (SVM), and the MSE decreased from 3.93 % (RSM) to 0.17 % (SVM)

This research studied the accuracy of using SVM in predicting surface roughness at turning; it will give a promising research direction in applying SVM to predict evaluation criteria. Other machining methods (milling, grinding) are the directions for the next research.

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