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Modelling and Prediction of Surface Roughness in CNC Turning Operation using Support Vector Machine

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Abstract

Surface roughness is one of the most significant technical requirements for machined product. Nowadays, machining process in manufacturing sector has been replaced with computers to control machines tool which is known as Computer Numerical Control (CNC) machining where a numbers of process parameters were set in order to control the output.Turning process is one of the most important processes in machining production where a turning machine is used to create rotational parts by cutting away unwanted material. In this study, a Support Vector Machine (SVM) was applied to model and predict the surface roughness of carbon steel AISI 1045 in CNC turning operation. Performance of three different type of SVM models namely Least Square SVM (LS- SVM), SVM- KM and Spider was compared. In the development of predictive models, turning parameters of feed rate, depth of cut and cutting speed were considered as input variables to the model. The prediction results showed that Spider SVM able to predict better as compared to the other two models where the best kernel function is radial basis kernel (RBF).

Keywords: CNC Turning Operation; Support Vector Machine; Modelling and prediction

Introduction

Machining is a process where selective part of a metal is removed from a work piece in order to produce the required shape of a metal product. For conventional machining operations, the processes include milling, drilling, grinding, and turning. Meanwhile for modern machining operation, it covered wire electrical discharge machining (WEDM), electrical discharge machining (EDM), abrasive water jet (AWJ), and electrochemical machining (ECM).

Turning process is one of the most important processes in machining production where a turning machine is used to create rotational parts by cutting away unwanted material. It will produced rotational, typically axi- symmetric part, that has features such as grooves, holes, threads, tapers, various diameter steps, and contoured surfaces. Turning is also a common method for metal cutting because of its ability to remove materials faster with a reasonable good surface quality [1]

In machining process, the quality of the finished surface is one of the most crucial requirements for product specification. A reasonably good surface finish is desired to improve the tribological properties, fatigue strength, corrosion resistance and aesthetic appeal of the product [2]. Besides that, a surface finished of a product will also determine the functional behavior of the part.

The estimation of surface roughness by dynamic simulation of the system is very difficult because determination of the machine tool parameters is not easy and parameters including damping and stiffness change in the course of time [3]. Generally, the desired cutting parameters are selected based on experience or use by the hand book. However, this approach can be time consuming and it did not guarantee the desired surface finished. This can also lead to cost increasing for the machining industry. Therefore, the modeling of cutting parameters is essential for increasing productivity and thus reducing process cost [1].

With increase demands in productivity, modern manufacturing plants are charged with the responsibility of obtaining the desired surface quality with minimum number of operations or processes [4]. Different modeling methodologies have already been applied for solving the problems of prediction in surface profiles and roughness like design of experiment (DOE), regression analysis (RA) as well as artificial intelligent (AI).

Artificial intelligent offer a wide scope of application in mapping actual situation especially in the area of manufacturing where the inter relationships are very complex and thus help to build intelligent support system in manufacturing area. Therefore, this study is carried out to model and predict the surface roughness in CNC turning operation using SVM architecture. SVM is very effective in mapping multi- dimensional parametric problems wherein standard analytical approaches become very complicated to handle [4]. The process parameters which are cutting speed, feed rate and depth of cut were used to evaluate the effect on the surface roughness of AISI 1045 during CNC turning operation[6],[8], and [13].

Literature Review

Surface roughness of machined product has become a quality index of the product and also a technical requirement for mechanical product. It is very important to achieve the desired quality surface to ensure the functionality of the product as being specified. However, to ensure the quality of finished surface of machined product is not easy since surface roughness is influenced by several process parameters such as work piece geometry, machining parameters, tool properties and also cutting phenomena.

The estimation of surface roughness by dynamic simulation of the system is very difficult because determination of the machine tool parameters is not easy and parameters including damping and stiffness change in the course of time [3]. Over the years, various methodologies and strategies had been adopted by researchers in order to predict surface roughness. According to Bernados and Vasniakos[5] there were a few approach of determined the surface roughness that had been done by researchers which are machining theory based, experimental investigation, design experiment and artificial intelligent (AI).

Experimental study did by Durmus [3] use artificial neural network (ANN) to predict and control surface roughness in CNC lathe. The cutting parameters were trained with feed forward multi layered neural network using scaled conjugate gradient algorithm (SCGA), which is a type of back propagation. The same approached was also done by Asilturk and Cunkas [6] where the surface roughness during turning process of AISI 1040 steel was predicted based on ANN and multiple regression. It shown that the advantage of ANN as compared to multiple regression are simplicity, speed, and capacity of learning.

CNC Turning Operation. CNC turning is the removal of metal from the outer diameter of a rotating cylindrical work piece. Turning is used to reduce the diameter of the work piece, usually to a specified dimension, and to produce a smooth finish on the metal. Performance evaluation of CNC turning is based on the performance characteristics like surface roughness, material removal rate, tool wear, tool life, cutting force and power consumption [7].

According to Poornima and Sukumar [8], the cutting tool geometry also plays a very important role in turning process where the rake angle and the nose radius of the turning inserts directly affect the cutting forces, power and surface finish. Meanwhile, Car et. al [9] performed optimization of machining parameters in turning process using Genetic Algorithm (GA). This was done by finding optimal cutting parameters that can provide greater efficiency and productivity of the machine tool. The aims were to yield minimum machining time with the minimum production cost. Based on the result, it was able to satisfy cutting parameters goal function.

Furthermore, studies from others [3], [6], [8], and [13] had also shown that the greatest influence on the surface roughness is exhibited by the feed rate, followed by depth of cut and cutting speed.

Support Vector Machine. Support vector machine (SVM) is a supervised learning model with learning algorithm which analyzed data and recognized patterns that is used for classification and regression analysis. The samples are classified using a subset of training samples called support vectors where the idea behind SVM classifier is that it creates a feature space using attributes in the training data. It then tries to identify a decision boundary or a hyper-plane that separates the feature space into two halves where each half contains only the training data points belonging to a category [10]. In the case of classification, an optimal hyperplane is found that separates the data into two classes. Whereas in the case of regression a hyperplane is to be constructed that lies close to as many points as possible [11].

There are two types of SVM that is linear SVM which separates the data point using a linear decision boundary and, non- linear SVM which separates data point using non- linear decision boundary. For linear SVM, it wills works well for datasets that can easily be separate by hyper plane into two parts with the equation is

$$(w, x)+b= 0 \tag{1}$$

where w and x are vectors and the direction of w is perpendicular to the linear decision boundary [10]. The optimal regression function is given by the minimum of

$$\emptyset(w,\xi) = \frac{1}{2}\|w^2\| + C\sum_i(\xi_i^- + \xi_i^+) \tag{2}$$

where$C$ is a pre-specified value, $\xi_i^-$and$\xi_i^+$are slack variables representing upper and lower constraints on the outputs of the system.

However for complex datasets, non-linear SVM classifier needs to be used. It will transform the datasets into a high dimensional space where the data can be separated using linear decision boundary. The kernel approach is used to address the curse of dimensionality. The function is given by

$$f(x) = \sum(\bar{\alpha}_i - \bar{\alpha}_i^*)\, K\,(x_i, x) + \bar{b} \tag{3}$$

where

$$(\bar{w}, x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x_i, x_j) \tag{4}$$

$$\bar{b} = -\frac{1}{2}\sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\big(K(x_i, x_r) + K(x_i, x_s)\big) \tag{5}$$

The bias term, b being accommodates within the kernel function and the function becomes

$$f(x) = \sum_{i=1}^{l}(\bar{\alpha}_i - \bar{\alpha}_i^*)\; K\,(x_i, x) \tag{6}$$

There are several choices of kernel function available which are known as follow:

i) Linear kernel

$$K(x_i, x_j) = x_i^T, x_j \tag{7}$$

ii) Polynomial kernel

$$K(x_i, x_j) = (x_i^T, x_j + t)^d, \quad t \geq 0 \tag{8}$$

with$t$ the intercept and d the degree of the polynomial.

iii) Radial Basis Function (RBF) kernel

$$K(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}} \tag{9}$$

withσ^2 the variance of the Gaussian kernel.

SVM is very effective in mapping multi- dimensional parametric problems wherein standard analytical approaches become very complicated to handle [4]. This approach has demonstrated many potential applications such as in manufacturing [12], [13], image processing [14], bio-medical [15] and also bio-plantation [16]. Caydas and Ekici [13] investigated surface roughness of AISI 304 austenitic stainless steel in CNC turning from the three developed models of SVM which is least- square SVM (LS-SVM), Spider SVM and SVM-KM. Model of feed forward neural network based on back propagation also being built to compare the result with the SVMs. The prediction results showed that all the SVMs performed better than neural network.

Materials and Methodology

In this study, three different type of SVM models such as SVM-KM, least square SVM (LS- SVM) and Spider SVM were applied to estimate the surface roughness of carbon steel AISI 1045 as a function of cutting speed, feed rate and depth of cut during CNC turning operation. Different types of SVM kernels also been analyzed in determining the best kernel and parameters suited for regression of given data.

Data Collection. The data set used in this study was obtained from [17], where it consists of 15 experimental measurement data of surface roughness. All of the data was used for the training purpose of the SVM model as shown in Table 1.

The workpiece that has been used in the experiment was carbon steel AISI 1045 where the chemical and physical properties are shown in Table 2 and Table 3.

Training the SVM. In order to estimate the surface roughness, the SVM model was trained with 15 experimental data as shown previously in Table 1. In this model, three parameters were selected as the inputs (x_i) including cutting speed, feed rate and depth of cut. Meanwhile the output (y_i) was surface roughness.

The SVM model was developed using MATLAB R2009a software with three different SVM toolboxes. The performance of these three different toolboxes namely least- square SVM (LS- SVM) [18], SVM- KM [19] clustering by k- mean and spider SVM [20] were evaluated. For each type of SVM model developed, few different kernel functions were applied in order to analyze the best kernel and parameter that will give the best result. The SVM tuning parameters sigma (σ), gamma (γ) and C were manually adjusted to get the best SVM output.

Table 1. Training data.

Exp. No.	Feed Rate, (mm/rev)	Cutting speed (m/s)	Depth of cut, (mm)	Surface Roughness (m)
1	100	0.1	0.8	0.59
2	300	0.1	0.8	0.77
3	100	0.3	0.8	3.42
4	300	0.3	0.8	3.20
5	100	0.2	0.1	1.82
6	300	0.2	0.1	1.47
7	100	0.2	1.5	1.62
8	300	0.2	1.5	1.46
9	200	0.1	0.1	0.42
10	200	0.3	0.1	3.54
11	200	0.1	1.5	0.76
12	200	0.3	1.5	3.35
13	200	0.2	0.8	1.27
14	200	0.2	0.8	1.37
15	200	0.2	0.8	1.58

Table 2. Chemical properties AISI 1045.

Element	Content (%)
Carbon, C	0.43- 0.50
Manganese, Mn	0.60- 0.90
Sulfur, S	0.05 (max)
Phosphorus, P	0.04max)

Table 3. Physical properties AISI 1045

Properties	Metric
Tensile strength	585 MPa
Yield strength	450 MPa
Modulus of elasticity	200 GPa
Shear modulus	80 GPa
Elongation at break	12%

For the LS-SVM model, three different kernel functions were applied to train the SVM which were linear kernel, polynomial kernel and Gaussian radial basis function (RBF). For the linear kernel, the value of γ was varied from 10 to 20000 in order to find the best value of tuning parameter for the model. Meanwhile for the polynomial kernel, the degree value had been set to default which is 3 and the software will automatically tune it to find the best performance. Gaussian RBF which was applied most often in the literature had ranges of parameters being set $\gamma \in$ [10,20, 100…20000] and $\sigma^2 \in$ [1, 10, 20…300] respectively. Compared with the other two kernels, RBF kernel can reduce the computational complexity of the training process and improve the model performance. The training part for this model was performed by MATLAB invoking the function 'trainlssvm (model)'.

On the other hand, the SVM- KM model was trained with RBF kernel functions where the tuning parameters were varied in ranges of $C \epsilon$ [10, 50, 100…350] and $\sigma \epsilon$ [0.001, 0.025, 0.05…1] respectively. The regression function used for this model was ‘svmreg’. For the Spider SVM, the same process need to be done where the tuning parameters need to be varies in order to determine the best possible output of the SVM model. The optimizer for this model was set to ‘andre’ which is one of the parameters set for the ‘svr’ function in MATLAB. The variation of tuning parameters was set in ranges of$\sigma\epsilon$ [0.25, 0.50, 0.75…30] and $C \epsilon$ [10, 50, 100…5000]. Both of SVM-KM and Spider SVM were experimented with RBF kernel function only.

Verifying Test Data. After running for train data, the SVM model was being verified with test data set in order to ensure the accuracy of the system. The test data used for this verification was a separate different set of data as shown in Table 4 below.

Table 4. Test data

Exp. No.	Feed Rate, (mm/rev)	Cutting speed (m/s)	Depth of cut, (mm)	Surface Roughness (m)
1	100	0.3	0.1	2.79
2	200	0.1	0.1	0.64
3	300	0.2	0.8	1.58

Obtaining and Analyzing Result. The result of this model was evaluated based on the different value between the actual readings of surface roughness and the predicted value from the model. The error of the readings was presented in term of mean absolute percentage error (MAPE) and root mean square error (RMSE). The calculation was performed using Equation 10 and 11.

$$MAPE = \frac{1}{n}\sum_{m=1}^{n}\left|\frac{x_m - y_m}{x_m}\right| \times 100 \qquad (10)$$

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}(x_m - y_m)^2}{n}} \qquad (11)$$

Results and Discussion

Three types of SVM (LS-SVM, SVM-KM and Spider SVM) were applied to analyze the performance of each model with different kernel functions and parameters. Each of the SVM model was trained with the training data and the resulted output was recorded. The steps were followed by the test data in order to verify the model’s capability in predicting the best result.

LS-SVM. There are two tunable parameters that need to be adjusted to get the best result.For RBF kernel, different combination ofγandσ^2have been tried to get the optimal parameter pairs. It was found that the selection of γ at 2000 andσ^2at 100 is the most satisfied value to achieve the best performance of the SVM model. The resulted MAPE and RMSE for training data at the selected parameters were 1.649% and 0.0588 as shown in Fig. 1 and Fig. 2.

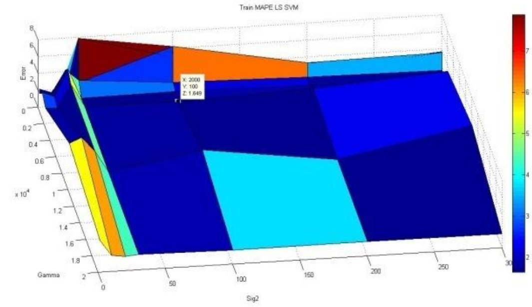

Fig.1 Train MAPE for LS-SVM.

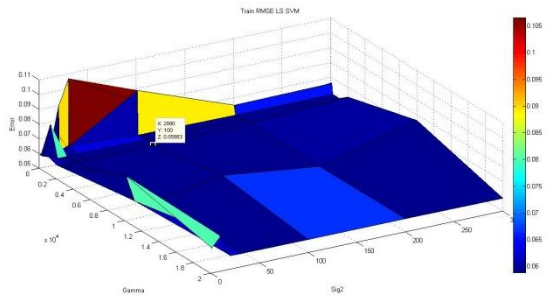

Fig.2 Train RMSE for LS-SVM.

Validation for the LS –SVM model was performed using test data to ensure the accuracy of the developed model. Fig. 3 shows the result of MAPE that is 19.70% at γ is 2000 and σ^2 at 100.

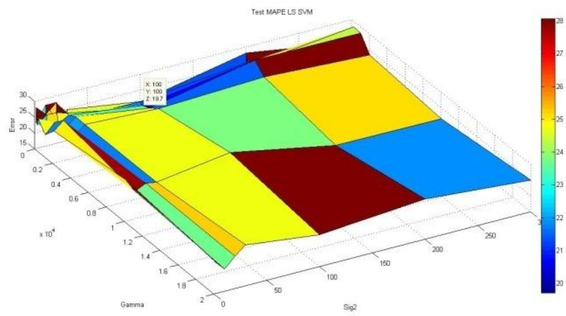

Fig.3 Test MAPE for LS-SVM

Meanwhile in Fig. 4 is the result of RMSE at the same tuning parameters that is 0.3181. Both errors resulted higher compared to training result. However, it is still in acceptable range and tolerable.

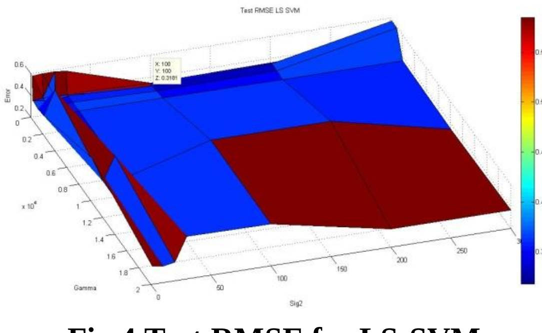

Fig.4 Test RMSE for LS-SVM

For the polynomial kernel, the tuning parameter was set by default at 3 degree and it was automatically tuned for the best performance. The model give the same result throughout variation of parameters which is for train MAPE 8.262% and train RMSE is 0.138. The model validation with test data gave result of MAPE is 24.66% and RMSE is 0.354. The values of these errors are also constant throughout variation of tuning parameters.

Meanwhile for linear kernel, parameter that needs to be varies in order to find the optimum value is onlyγ. From the training data, it showed that the model produced error at almost the same value which is in average the MAPE is 18.519% and RMSE is 0.284. The model was validated with test data where the result gave average MAPE is 19.121% and RMSE 0.284.

SVM-KM. For SVM- KM, the kernel function used was RBF. There were two tuning parameter that have been varied to get the optimal value for the best estimation result. It was found that at point C= 50 and σ (sig) = 0.25, the lowest error for train MAPE was obtained which is 8.603%. From Fig. 5, it shows that the error was increasing for value of σ greater than 0.25.

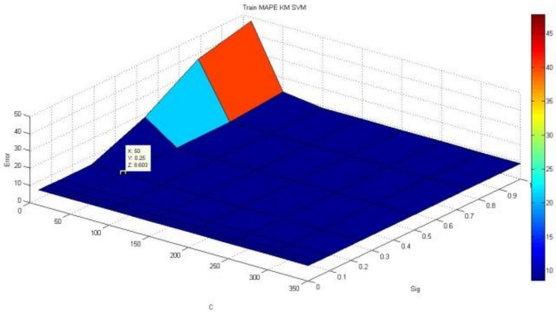

Fig.5 Train MAPE for SVM-KM

For the result of RMSE, the lowest error occurred at point where C= 50 and σ = 0.25 too which is 0.108. This is shown in Fig. 6.

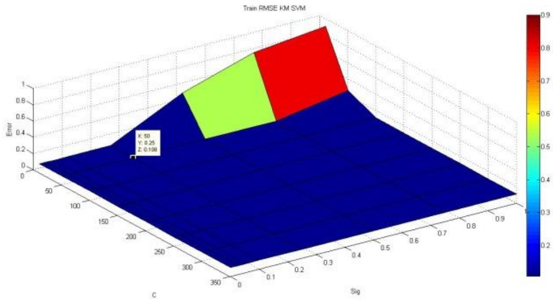

Fig.6 Train RMSE for SVM-KM

The validation of this model, the test MAPE is slightly higher as compared to the train MAPE that is 14.34%. The value of parameters selected at this result are C= 50 and σ = 1.0. Meanwhile for the test RMSE, the value is 0.2135 where it was obtained from the same parameters value. This is shown in Fig. 7 and Fig. 8.

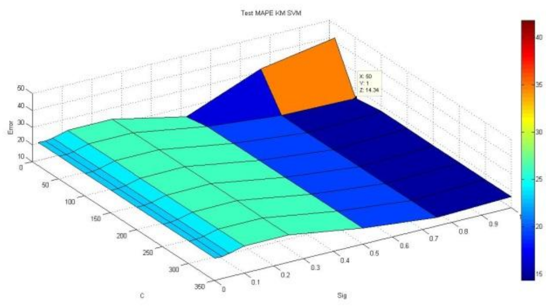

Fig.7 Test MAPE for SVM-KM

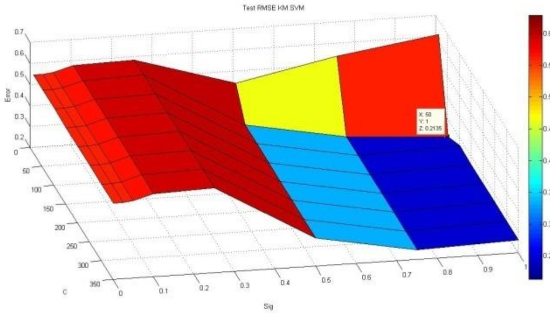

Fig.8 Test RMSE for SVM-KM

Spider SVM. The RBF kernel function was also being used to model Spider SVM where the tuning parameters were C and σ. The lowest error for train MAPE is 1.521% at point C= 1000 and σ = 1. Meanwhile for train RMSE, the best result obtained was 0.06071 with the same value of tuning parameter. The result is shown in Fig. 9 and Fig. 10.

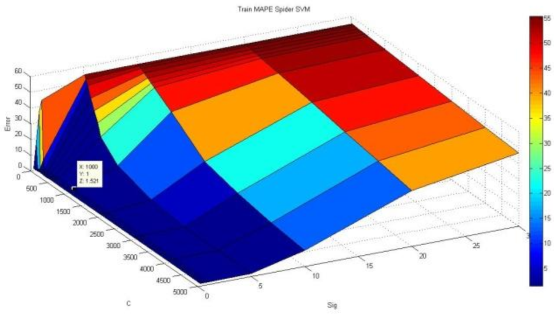

Fig.9 Train MAPE for Spider SVM

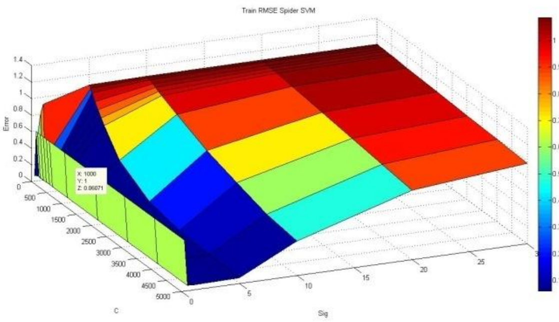

Fig.10 Train RMSE for Spider SVM

From the validation of test data, best MAPE was obtained at C= 10 and σ = 0.5 where the error is 12.25%. It shows a slight increase from the result of train MAPE. This is shown in Fig. 11.

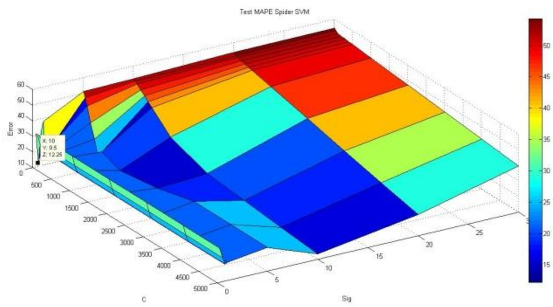

Fig.11 Test MAPE for Spider SVM

In the meantime, the optimum value for tuning parameters for test RMSE are C= 5000 and σ = 10 where the error is 0.1361 as shown in Fig. 12.

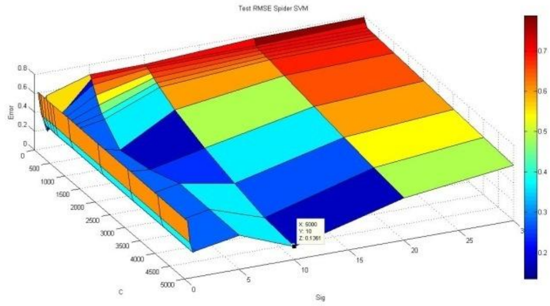

Fig.12 Test RMSE for Spider SVM

Based on three different models used in this study, the resulted errors were summarizes in Table 5. From the results, it shows that Spider SVM give the best performance with the lowest error as compared to the other two types of SVM (LS- SVM and SVM- KM). Other than that, RBF kernel function was proved to give better result as compared to polynomial and linear kernel.

Table 5. Training and test errors for all SVM models

Model	Train MAPE	Train RMSE	Test MAPE	Test RMSE
LS- SVM : RBF kernel	1.649	0.059	19.700	0.318
LS- SVM : Polynomial kernel	8.262	0.138	24.660	0.354
LS- SVM : Linear kernel	18.519	0.284	19.121	0.284
SVM-KM	8.603	0.108	14.340	0.214
Spider	1.521	0.061	12.250	0.136

Conclusion

In this study, three different SVM models were applied to predict the surface roughness during CNC turning. It can be concluded that Spider SVM produced the most outstanding result as compared to LS-SVM and SVM-KM. It was also found that RBF kernel function made a better kernel function because it predicts better than linear and polynomial kernel.For future work, this developed model can be extended for the optimization purpose where the best input parameters can be applied to get the best surface roughness.

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