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Prediction of surface roughness for CNC turning of AISI 1030 steel : A machine learning approach

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Abstract : In this study, we developed machine learning predictive models for surface roughness of AISI 1030 steel during the CNC turning process. AISI 1030 steel has wide applications for machinery parts, clips, clutches, springs, washer, etc. The surface roughness of 1030 steel plays an important role in wear, corrosion, and fatigue properties during application. Rough surfaces deteriorate wear properties of machining parts and also form nucleation sites for cracks or corrosion. The predictive surface roughness model was developed using experimental data. The surface roughness was taken as a function of feed rate, depth of cut, and radius of the cutting tool during the CNC process. Three different machine learning approaches namely multi-linear regression (MLR), Gaussian process regression (GPR) and support vector method (SVM) were applied. GPR and SVM approaches were applied with PUK and RBF kernel functions. The kernel functions were optimized using correlation parameters, correlation coefficient (CC) and root mean square error (RMSE) values. The developed predictive model matches well with the experimental values.

***Keywords**: AISI 1030 steel, CNC turning, Surface roughness, Machine learning, Gaussian process, Support vector, Kernel functions.*

1. INTRODUCTION

In the age of advanced technology, machining like turning, milling, drilling, etc. has great importance. AISI 1030 Steel has been widely used in the industry like automotive, agriculture, construction, etc. for making the parts such as machinery parts, tools, clips, clutches, springs, washer, etc. due to better wear resistance property. The durability of AISI 1030 steel in various applications depends on the surface roughness of the product. Surface roughness plays an important role in wear, lubrication, corrosion, and fatigue properties of a material [1]. Surface roughness impacts on heat transfer, sealing, and hydrodynamic properties [1]. Rough surfaces have higher friction coefficients than smooth surfaces and in result higher rate of wear. Rough surfaces have irregularities that form nucleation sites for cracks or corrosion sites. These irregularities depend on machining operation and machining parameters. Nowadays, CNC turning is an important machining operation in the manufacturing industry. Turning is a metal removal machining operation in which the rotation of the work piece involves while the cutting tool moves in a linear motion. The schematic of the turning operation is shown in Figure 1.

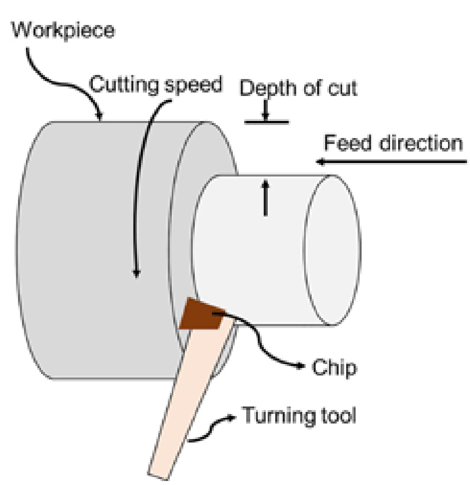

Figure1. Machining of turning operation

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During turning operation, the material is getting removed and surface roughness varies with different turning parameters. The surface roughness depends on turning process parameters such as tool geometry and cutting conditions. Tool geometry parameters are edge geometry, nose radius, and rake angle, etc. and the cutting conditions parameters are feed rate, depth of cut, and spindle speed etc.[2]. Few parameters such as feed rate, tool nose radius, and depth of cut are varied during the operations to achieve better surface roughness.

Krishnan et al. [1] did an experimental study to achieve optimal surface roughness using the CNC machine on IS2062 E250 steel. The study revealed that an increase in feed rate hampers the quality of surface roughness. Bikram et al. [3] investigated the surface roughness and cutting force on stainless steel material and their results confirmed that the surface roughness is highly affected by the feed rate of tool and spindle speed. The roughness of the machined surface is inversely proportional to the feed rate [4]. The investigation on surface roughness of a Teflon material (transmission shaft material) revealed that surface roughness is lower with CNC lathe in comparison to conventional lathe [5].

Further, few researchers performed a computational approach to predict the surface roughness [6-9]. Asilturk et al. [6] studied the effect of depth of cut, cutting speed, and feed rate in turning operation on the surface roughness using AISI 1040 steel. They developed multiple regression and ANN models with experimental data set. The developed ANN model showed better prediction. Neseli et al. [7] studied the effect of the tool geometry parameter on the surface roughness of AISI 1040 steel and they found that the surface roughness varied significantly with nose radius. Asilturk et al. [8] predicted surface roughness of AISI 304 austenitic steel using response surface methodology (RSM) with 1% error. Aghdeeb et al. [9] studied the effect of cutting parameters on surface roughness on Al alloy using the regression model and the simulated annealing method. In this work, we used machine learning techniques to study the relationship between surface roughness and CNC turning process parameters.

In the present work, we developed a predictive model for the surface roughness of AISI 1030 steel during CNC turning using three different machine learning approaches such as multi-linear regression (MLR), Gaussian process regression (GPR), and support vector regression (SVR). The surface roughness is found to be a function of a depth of cut, noise radius, and feed rate. The predicted surface roughness value is validated with the experimental data.

2. MATERIALS & DATA

The data for the simulation work has been taken from the literature [10]. The chemical and mechanical properties of the AISI 1030 test piece are shown in table 1 [10].

Table 1. Chemical composition (in wt.%) and mechanical properties of the AISI 1030material

C	Mn	Si	P	S
0.365	0.799	0.247	0.0166	0.0422
Hardness (HB)	**Tensile Strength (MPa)**	**Yield Strength (MPa)**	**Break off extension (%)**	
126	463.7	341.3	31.2	

3. MODELS

3.1 Multi-linear regression (MLR)

Linear regression is a statistical method that is used to solve the regression problem. This is the basic model of machine learning. It develops the relationship between a dependent variable and an independent variable by using linear equation mx+c, where x is an independent variable, y is a dependent variable, m is intercept and c is the coefficient. MLR is an extended version of linear regression. Unlike linear regression, this method develops the relationship between a dependent variable and two or more independent variables. In MLR, the dependent variable (y) is a linear combination of multiple independent variables $x_1, x_2, ..., x_n$. So, the mathematical representation of MLR is

$$y = b_0 + b_1x_1 + b_2x_2 + ... + b_nx_n$$

Where, b_0 is intercept, b_1 b_2...b_n are coefficient of variables.

In the machine learning approach, this linear equation is used to find the best fit line which gives the minimum difference between predicted output and actual output.

3.2 Gaussian Process Regression (GPR)

Gaussian process regression algorithm is a powerful algorithm in machine learning. This algorithm uses prior knowledge to predict the output of the given data. The objective of GPR is to find the function that fits the data using functions. GPR assigns a probability to each function and then take the mean of the probability distribution to find the best probable characterization of the data. Further, predict the output by using a probabilistic approach [11]. Figure 2 shows a schematic of the GPR process.

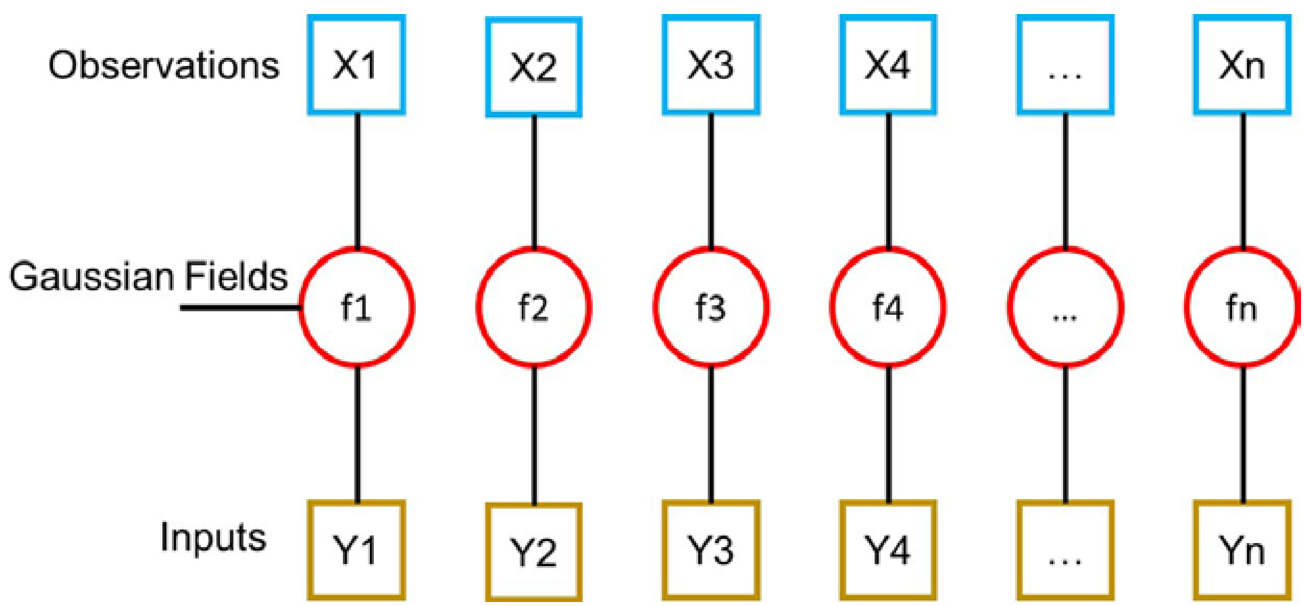

Figure2. Graphical model of Gaussian process

3.3 Support Vector Regression (SVR)

SVM is a supervised machine learning algorithm. This algorithm is used to solve both regression and classification problems. In the present work, we have used SVM – regression to develop the predictive SVR model. The algorithm of SVR is dependent on the support vectors. Data points that are closer to the boundary lines are called support vector which helps to find the best fit hyper plane [12]. Like MLR, SVR does not minimize the error between the predicted output and actual output. The objective of SVR is to find the best line or best hyper plane which lies within a predefined or threshold error value. Figure 3 shows a schematic of the SVR method.

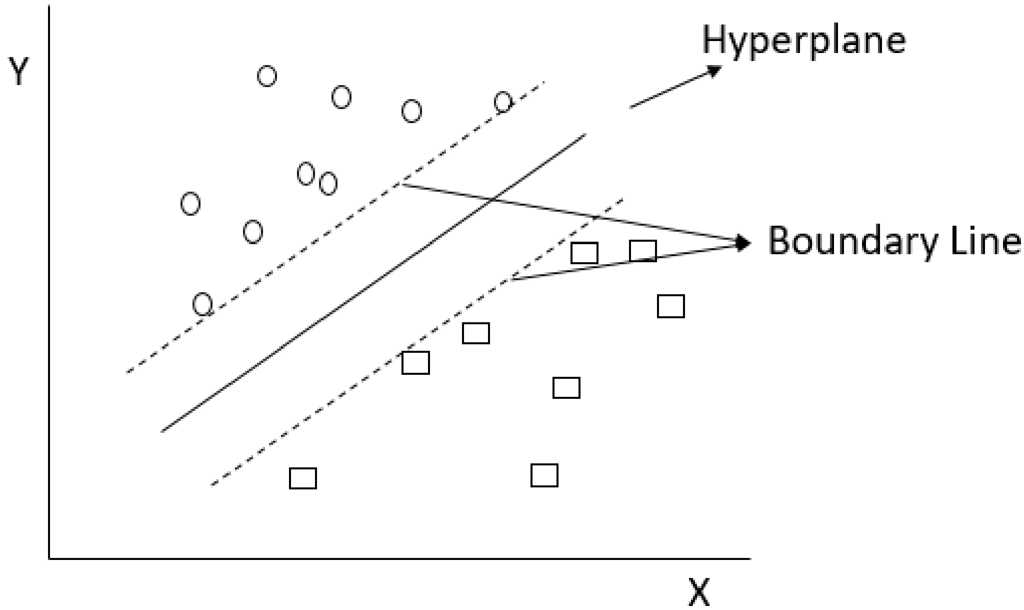

Figure3. Graphical representation of support vector regression

4. RESULT AND DISCUSSION

In our simulation investigation, the machine learning software WEKA version 3.8.4 is used. The machining parameters including depth of cut, feed rate, and insert nose radius were used as independent inputs and surface roughness was taken as a dependent output to develop the MLR, SVR, and GPR predictive model. The number of experiential data is seventy five, which were divided for training the models and testing the models. For training the model, 75% of data was used, and the remaining 25 % of data was used for testing the model.

In MLR, the multi-linear relation between the target (here, surface roughness) and inputs (here, depth of cut, feed rate and insert nose) was developed. However, in CNC turning process, surface roughness follows a non-linear relationship with the depth of cut, feed rate, and insert nose radius. The following relationship may be defined for surface roughness R_a:

$$R_a(\mu m) = t_i d^a f^b r^c$$

Where, t_i is proportionality constant; d is the depth of cut in mm; f is feed rate in mm/min; r is insert radius in mm.

The above equation is non-linear and to convert it in linear we take logs on both sides. After taking logs on both sides, we get the linear form as

$$\log R_a = \log t_i + a \log d + b \log f + c \log^r$$

In MLR, log R_a was taken as target and log d, log f and log r as input values. The MLR machine learning approaches determined the value of constant t_i and coefficients a, b and c. The developed equation for the surface roughness as

$$R_a = 2.6 \times 10^{-4} \frac{d^{0.1649} f^{1.7701}}{r^{1.1826}}$$

Where R_a is in μm, d is in *mm*; f is in *mm/min*; r is in *mm.*

The above relation indicates that surface roughness is increasing with an increase in depth of cut and feed rate but decreasing with the radius of the nose.

In both SVR and GPR approaches, we used two different kernels namely Pearson VII universal kernel (PUK) and radial based function (RBF) to predict the surface roughness of the AISI steel during turning operation. The performance of the model was measured using performance parameters correlation coefficient (CC) and root mean square error (RMSE). CC and RSME parameters are widely used to show the variation between output and input values. The models were tuned with varying kernel function parameters such as noise, γ, and C. The kernel functions were optimized to achieve better performance parameters CC and RMSE. Figure 4 shows the CC value with varying γ at various noise values of 1.0, 0.5, and 0.1 for RBF based GPR model GPR_RBF). The CC value for training and testing models are shown in Figure 4 (a) and Figure 4 (b), respectively. The training and testing models show a similar trend. The CC value is higher for the testing model. With lowering the noise value at 0.1, the CC value increased and reached a maximum at γ = 1.5. Similarly, the CC value varying γ at various C values of 1.0, 0.5, and 0.1 for RBF based SVR model (SVR_RBF) is shown in Figure 5. The training and testing models for SVR_RBF show a similar trend as shown in Figure 5 (a) and Figure 5 (b). Here, the CC value increased with C values from 0.1 to 1 and reached maximum at γ = 2.7. The PUK based GPR model (GPR_PUK) and PUK based SVR model (SVR_PUK) were also tuned with varying kernel function parameters. These optimized values of kernel parameters chose a better hyper plane to fit the data and provide a better value of the performance parameters. The optimal values of user-defined kernel parameters for GPR and SVR approaches are shown in table 2.The values of performance parameters CC and RMSE for GPR_PUK, GPR_RBF, SVR_PUK, SVR_RBF, and MLR models are listed in table 3.

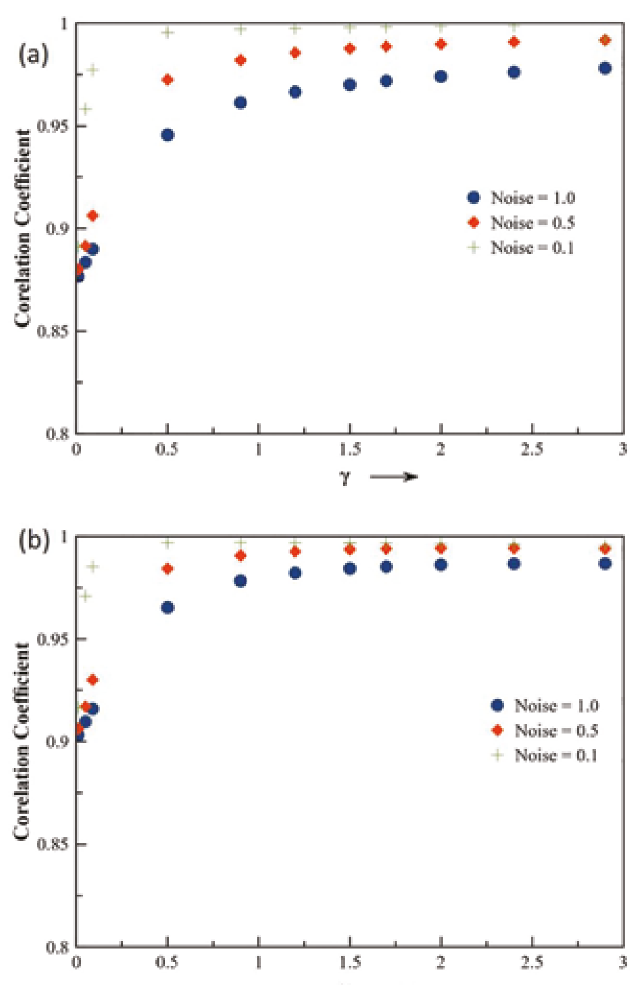

Figure4 CC values of RBF based GPR model for (a) training and (b)testing

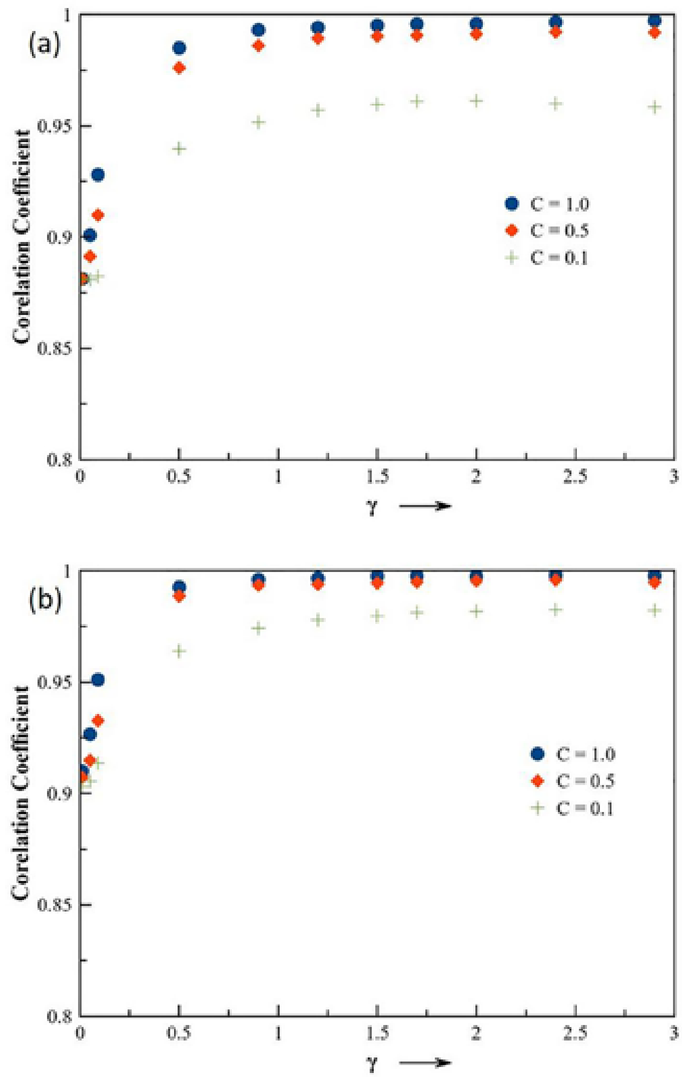

Figure 5.CC values of RBF based SVR model for (a) training and (b)testing

Table 2. User-defined parameter for GPR and SVM using RBF and PUK kernel function

Kernels	GPR	SVR
PUK	Gaussian noise = 0.3, σ = 1, ω = 1	C = 1, σ = 0.7, ω = 1.2
RBF	Gaussian noise = 0.1, γ =1.5	C = 1, γ = 2.7

Table 3. Performance characteristics for surface roughness

Machine learning approach	Training data set			Testing data set	
	CC	RMSE		CC	RMSE
GPR_PUK	0.9981	0.2151		0.9938	0.4032
GPR_RBF	0.998	0.1957		0.9969	0.3062
SVR_PUK	0.9991	0.1432		0.995	0.3580
SVR_RBF	0.997	0.2400		0.9979	0.2557
MLR	0.9806	0.0608		0.9916	0.0459

Figure 6 shows the predicted vs experimental surface roughness for the training models. It shows the comparison of GPR_PUK, GPR_RBF, SVR_PUK, SVR_RBF, and MLR models. The graph confirms the closeness of experimental and predicted values for all the models. MLR model indicates little deviation at higher surface roughness values. This deviation is confirmed by the comparative low CC value of MLR to GPR and SVR models. Similarly, the predicted vs experimental surface roughness for the testing models is shown in Figure 7. In the GPR_RBF model, a small deviation is observed at higher values of surface roughness. The PUK kernel-based models show better CC value than RBF based models. The SVR_PUK model predicts the best result for a nonlinear relationship between the dependent parameter (surface roughness) and independent parameter (depth of cut, feed rate, and nose radius).

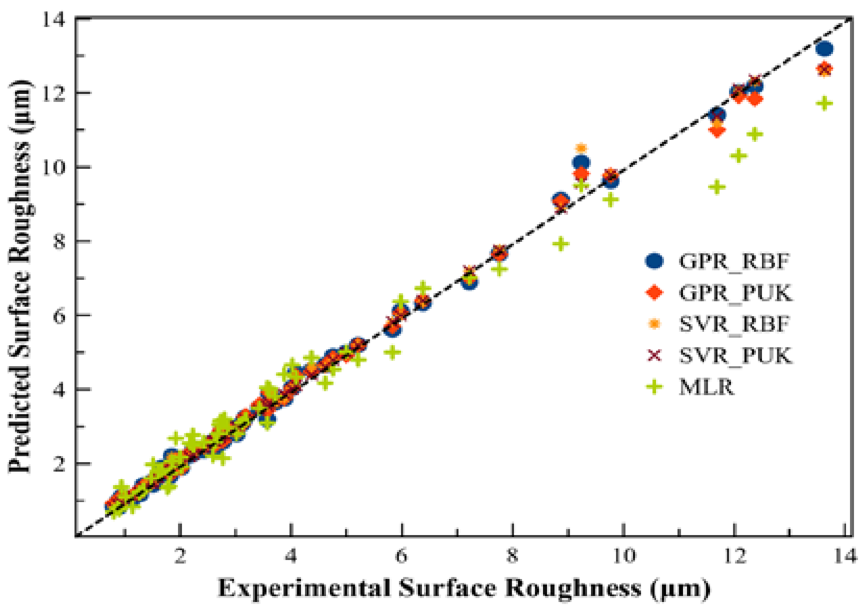

Figure6. Graph of predicted vs. experimental data of training set

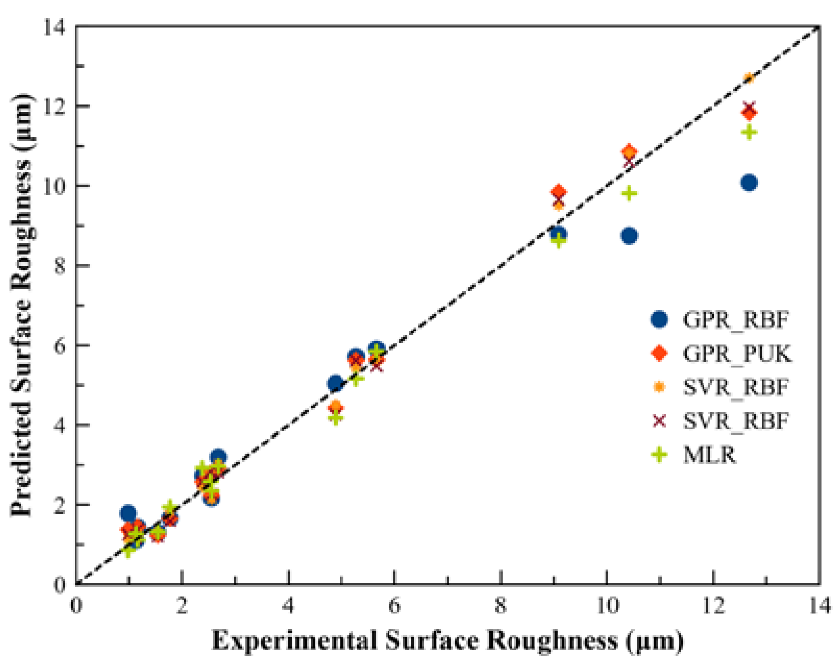

Figure7. Graph of predicted vs. experimental data of testing set

5. CONCLUSION

In the present study, we developed machine learning models to predict the surface roughness of AISI 1030 steel during CNC turning. Three machine learning approaches MLR, GPR, and SVR were applied. In GPR and SVR approaches, two kernel functions PUK and RBF were used and kernel function parameters C, noise, and γ were optimized for better values of performance parameters CC and RMSE. MLR model developed a nonlinear equation to determine the surface roughness in terms of noise radius, depth of cut, and feed rate. Among all the models, the PUK and RBF based SVR model exhibited the best CC performance parameter.

6. REFERENCES

1. B.R. Krishnan and M. Ramesh,"Optimization of machining process parameters in CNC turning process of IS2062 E250 Steel using coated carbide cutting tool", Materials Today : Proceedings, Vol.21, 346-350, 2020.
2. X.A. Vasanth, P.S. Paul and A.S. Varadarajan, "A neural network model to predict surface roughness during turning of hardened SS410 steel", International Journal of System Assurance Engineering and Management, vol. 11, 704-715, 2020.
3. K. Arun Vikram, T.V. Krishna kanth, A.M.V. Praveen and V.V.K. Lakshmi, "Experimental study of surface roughness and cutting forces on stainless steel grade marerials", IJMET, VOL. 10, 87-96, 2019.
4. Pranav R. Kshirsagar, Somesh R. Pise, Sunil A. Pokalekar, Mahindra Goudadaba and Duradundi Sawant. Badkar, "Optimization of Surface Roughness of EN8 Steel in CNC Turning Operation by Taguchi Concept", IJATES, VOL. 4, 289-300, 2016.
5. Temitayo M. Azeez, Omolayo M. Ikumapayi, Ojo P. Bodunde, Simeon A. Babalola and Motunrayo O. Ogundayomi, "Measurement of Surface Roughness on a Transmission Shaft using CNC and Conventional Lathes Machining", IJSTR,Vol. 8, 1626-1633, 2019.
6. Ilhan Asiltürk and Mehmet Çunkas, "Modeling and predication of Surface Roughness in truing operations using artificial neural network and multiple regression method", Expert System with Applications, Vol 38, 5826-5832, 2011.
7. Suleyman Neseli, Suleyman Yaldiz, Erol Turkes, "Optimization of tool geometry parameters for turning operations based on the response surface methodology", Measurement, Vol. 44, 580-587, 2011.
8. Ilhan Asiltürk and Süleyman Neseli, "Multi response optimization of CNC turning parameters via Taguchi method based response surface analysis", Measurement, Vol. 45, 785-794, 2012.
9. Shukry H. Aghdeab, Laith A. Mohammed and Alaa M. Ubaid, "Optimization of CNC Turning for Aluminium Alloy Using Simulated Annealing Method", Vol. 9, 39-44, 2015.
10. Nalbant, Muammer, Hasan Gokkaya, and İhsan Toktaş. "Comparison of regression and artificial neural network models for surface roughness prediction with the cutting parameters in CNC turning." Modelling and Simulation in Engineering (2007).
11. C.E. Rasmussen, C.K. Williams, Gaussian Processes for Machine Learning the MIT Press, Cambridge, MA. (2006).
12. V. Vapnik, Statistical learning theory Wiley, New York. 1 (1998).