Susai Mary J
Research Scholar
Department of Electronics and Instrumentation Engineering
B S Abdur Rahman Crescent Institute of Science and Technology, Chennai
India

Sai Balaji M A
Associate Professor
Department of Mechanical Engineering
B S Abdur Rahman Crescent Institute of Science and Technology, Chennai
India

Dinakaran D
Professor
Centre for Automation and Robotics
Hindustan Institute of Technology and Science, Chennai
India

Prediction and Geometric Adaptive Control of Surface Roughness in Drilling Process

Surface roughness is an essential factor to evaluate the quality of component that decides the wear and fatigue properties and influences the quality of assembly. This research article focuses on real time control of surface finish in drilling using geometric adaptive control strategy. The dynamometer sensor and accelerometer are used to capture the force and vibration signals during drilling. A cubic SVM model is employed to model the surface roughness using the force, vibration and machining parameters. The accuracy of the prediction model is found to be 94 %, and the model is successfully used to control the roughness in drilling. The adaptive scheme uses a Neural Network (NN) controller to adjust the drilling parameters for ensuring the set roughness tolerance. The performance of the controller shows the potentiality of the presented methodology for the practical application in industries.

Keywords : *Adaptive control, CNC drilling, Roughness, Space Vector Machine (SVM).*

1. INTRODUCTION

Drilling is a primary and indispensible machining process and accounts for 40% of the metal cutting operations and has a large number of applications in the manufacturing and aerospace industries [1]. The surface roughness of the drilled holes is an essential factor to be monitored and controlled for better assembly of parts. The functional attributes of the products such as friction, wear, lubrication, coating, fatigue are greatly affected by the surface roughness of the component.

The surface roughness is an important output variable in machining which is to be measured and controlled in real time. Surface roughness measurement in real time through direct methods such as stylus profilometers, scanning electron microscope and optical methods are used less due to the difficulty in online implementation [2]. Therefore, indirect methods of measurement of surface roughness through other auxiliary variables such as force, vibration, acoustic emission, ultrasound, current, power, torque etc., can be achieved which serves as an indication of surface roughness [3,4,5].

A review of various advanced monitoring techniques in machining for monitoring of tool wear and surface roughness was presented by Teti et al [6]. Many empirical models have been developed by various researchers for prediction of internal surface roughness of the drilled holes. But, they are not efficient due to other influential factors such as tool geometry, tool and workpiece material etc [7]. Hence, in recent years neural networks and fuzzy logics are used in modeling of surface roughness due to its ability to model nonlinear dynamic systems. An indirect method of roughness prediction using force and torque measurements was proposed by Sanjay et al [2] and a comparative study was made between ANFIS and neural network modeling.

Visshy Karri et al [3] have presented a comparison study for prediction of surface roughness of drilled holes using back propagation, radial basis function and optimization layer by layer neural networks. Marek Vrabel et al had used a feed forward back propagation neural network for modeling and prediction of surface roughness in drilling Udimet 720. A back propagation neural network was used by Sanjay et al for estimating the surface roughness and the results were compared to the mathematical analysis using inverse co-efficient matrix method [4].

Cruz et al had estimated the hole diameter and surface roughness of holes using a multi sensory approach with hall effect, acoustic emission, accelerometer and dynamometer sensors by a back propagation feed forward neural network algorithm [8].

Support Vector Machine (SVM) model for predicting roughness in machining process was proposed by a few researchers [9]. Roughness model of aluminium components during milling was developed using Least Square SVM which gives an accuracy of 92% [10]. SVM prediction model for surface roughness of AISI 304 austenitic stainless steel was developed and three different SVM models were compared. Spider SVM prediction model was found to be suitable for turning process [11]. A surface roughness prediction and classification using SVM was proposed by Issam et al [12] and a comparison was made with k-nearest neighbour, decision tree and random forest classifiers and the effectiveness of SVM was proved.

Received: August 2018, Accepted: October 2018
Correspondence to: J. Susai Mary,
B S Abdur Rahman Crescent Institute of Science and Technology, Chennai-44, India
E-mail: susaimaryj@gmail.com
doi: 10.5937/fmet1903424S

A comparative study on LS-SVM, ANOVA and neural networks for roughness prediction of AISI 4340 steel and AISID2 steel were carried out [13]. The results showed that LS-SVM outperformed in terms of high accuracy. The experimental results showed the SVM is an effective tool for modelling of surface roughness of machined components. Based on the conclusions in the previous studies the present research uses a cubic SVM for the prediction of surface roughness in drilling of EN24 steel.

In conventional drilling machines, cutting para– meters such as feed, speed and depth of cut are selected prior to machining based on machining handbooks or programmer's experience. These parameters signifi– cantly affect the production time, cause early failure of tool and also affect product quality. Hence, the cutting parameters must be varied based on the changes in the output state of the process to maintain the workpiece quality and improve tool life. To satisfy these criteria an adaptive control strategy for real time adjustment of the machining parameters to maximize productivity and surface finish is essential.

Geometric adaptive control is specifically used in finishing operations to obtain a desired surface quality or part dimension irrespective of tool wear or tool deflection. A geometric adaptive control strategy in drilling can be used for maintaining the surface quality of the drilled holes at prescribed limit by varying the machining parameters; speed and feed based on auxiliary measurements such as force, vibration, current, acoustic emission and ultrasound that can be used for the prediction and control of surface roughness.

A geometric adaptive control system of drilling process for real time control of surface roughness was proposed by Maral Vrabel [14] using neural networks for both predictive and adaptive controllers. An adaptive control system for achieving improved surface finish in high speed machining was presented by Giriraj et al for cutting speed correction to obtain consistent part quality by reducing the cutting force [15]. An in-process adaptive control to maintain the surface quality of the machined part in end milling was proposed by Potsang et al [16]. A neural network was applied as a decision making algorithm to predict the roughness and maintain it within the specification by adjusting the feed rate while maintaining the spindle speed constant based on force measurements.

Lieh-Dai Yang et al [17] presented a fuzzy net based in-process surface roughness method to adaptively control the feed rate in end milling operations. The fuzzy nets consist of two subsystems; one for surface roughness prediction and the other for feed rate control. If the desired surface roughness is not achieved then a new value of feed rate is proposed to the system by the fuzzy controller. An adaptive control for in-process control of surface roughness using multiple regressions was proposed by Julie et al. The multiple regression based in-process surface roughness evaluation and adaptive control resulted in 100% success and implemented to control the surface roughness during milling operations [18]. The influence of cutting parameters in drilling nanocomposite laminates was presented by Zarif et al. The optimum drilling conditions were determined by the Taguchi's signal to noise ratio analysis [19]. Susai mary et al has presented an adaptive control method using multi-objective optimization techniques for control of tool wear and surface roughness [20,21].

This paper presents a method for geometric adaptive control of surface roughness by adjusting the speed and feed rate based on auxiliary measurements of vibration and force signals. The vibration and force signals are analyzed in time domain to get the root mean square (RMS) of the signals which is a dominant measure for the prediction of surface roughness. The RMS of vibration, RMS of force, speed and feed serves as input to the cubic SVM roughness model. Based on the predicted roughness value both the machining parameters; speed and feed are adjusted in online to maintain the surface roughness of the drilled holes within the required specification thereby maintaining the surface finish and product quality.

2. EXPERIMENTAL SETUP AND DETAILS

Drilling experiments were conducted on a 3 HP milling machine (Model: LV-45, Make: LMW). Experiments were conducted based on a L25 orthogonal array with speed varying from 800 rpm to 1450 rpm and feed from 75 mm/min to 140 mm/min. Through holes were drilled on a EN24 circular workpiece with 6mm twist drill bits. An accelerometer (KISTLER 8636C50) and tool dynamometer (RDMT-303) were used to measure the vibration and force signals during drilling. A schematic diagram and photograph of the experimental setup is given in figure 1 and 2.

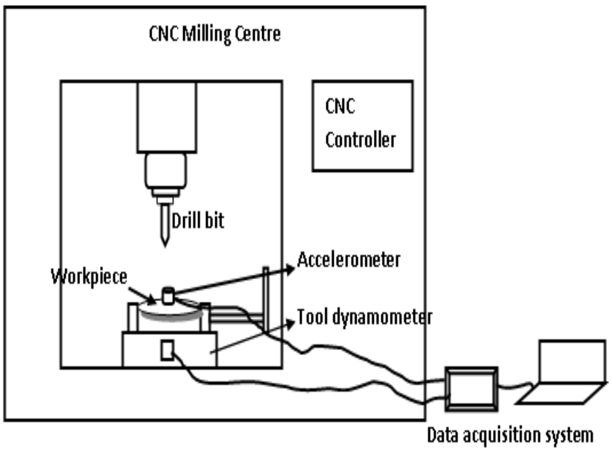

Figure 1. Schematic diagram of experimental setup

During each drilling operation the force and vibration signals were recorded using LabVIEW software at a rate of 5k samples per second. A stylus profilometer (Taylor Hobson) was used to measure the surface roughness of the drilled holes. An additional ten experiments were conducted separately for validation purposes within the recommended cutting ranges.

A time domain analysis of the vibration and force signals acquired during drilling operations was carried out with LabVIEW software. The Root Mean Square (RMS) of the vibration and force signals serve as a good indication for surface roughness and hence used in the modeling of surface roughness [22, 23].

Figure 2. Photograph of Experimental setup

The variations of RMS of vibration and RMS of for–ce with surface roughness are given in figure 3 and 4.

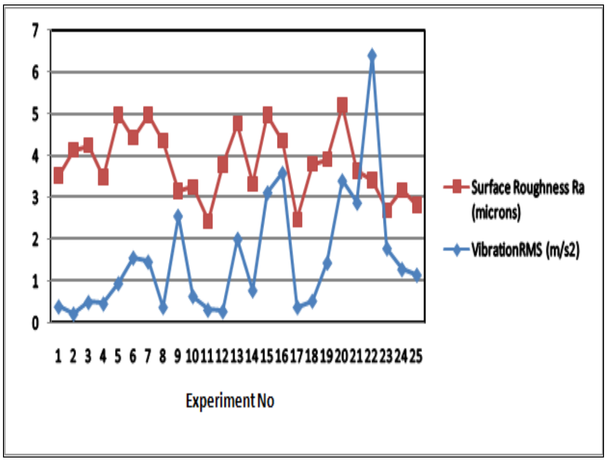

Figure 3. RMS of vibration and Surface roughness for different experiments

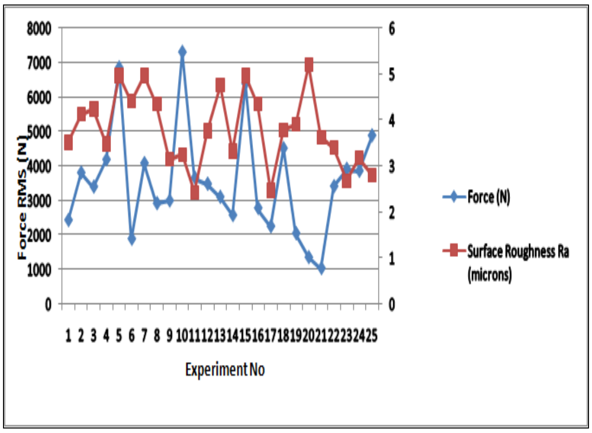

Figure 4. RMS of force and Surface roughness measured for different experiments

3. RESULTS AND DISCUSSION

The presented geometric adaptive control system for surface roughness prediction and control involves the modeling of surface roughness; validation of the model; developing a adaptive control strategy using neural networks and validation of the control system. Each intent is discussed in detail and the results are presented.

2.1 Cubic SVM modeling of Surface roughness

Support Vector Machines are a most popular machine learning algorithms used for classification and modeling. For prediction of surface roughness in turning and milling SVM [9,11], LS-SVM [10,13] and spider SVM [12] were used by various researchers. A cubic SVM for prediction of surface roughness of the drilled holes is presented in this paper. It uses a 5-fold cross validation for accurate prediction of surface roughness. The inputs to the model includes the machining parameters; speed, feed, the RMS of vibration signals and RMS of force signals as shown in figure 5.

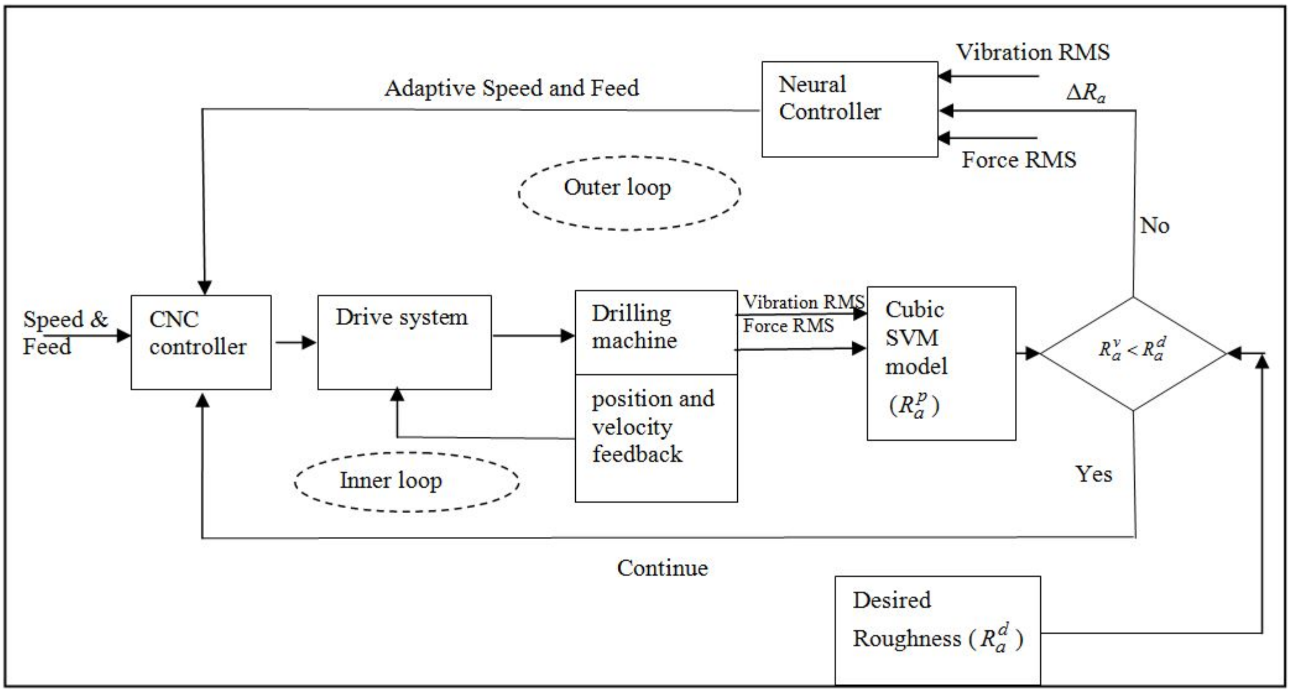

Figure 7. Geometric adaptive control for surface roughness control

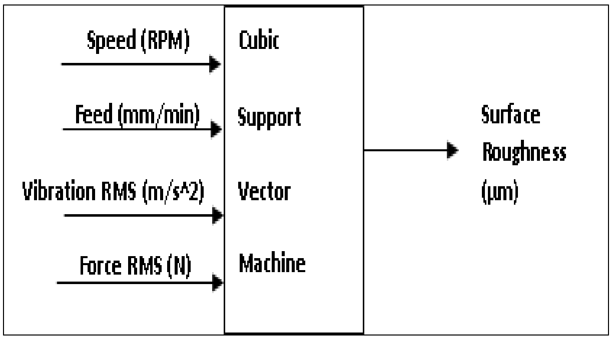

Figure 5. Cubic SVM model for surface roughness prediction

The model is trained with an accuracy of 98 % and validation of the model with a new data set results in an accuracy of 94 % given in figure 6.

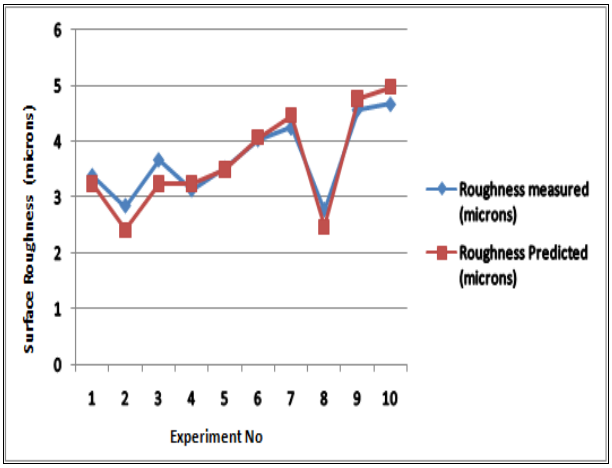

Figure 6. Validation output of the cubic SVM model

2.2 Geometric adaptive control of surface roughness by neural networks

The purpose of the presented adaptive control scheme given in figure 7 is to adjust the CNC drilling process parameters; speed and feed based on the deviation in the desired surface roughness value (R_a^d) as required. In this work the desired roughness value of the drilled holes is taken as 3 µm. When the roughness value predicted (R_a^p) by the cubic SVM model exceeds 3 µm, an error signal ΔR_a is generated [16]. Depending on the error data, the adaptation algorithm for change in feed rate and spindle speed of the CNC drilling machine is given by:

$$\Delta F = \left(1 - \frac{F_a - F_d}{F_a}\right) \quad (1)$$

and $$\Delta S = \left(1 - \frac{S_a - S_d}{S_a}\right) \quad (2)$$

where ΔF, ΔS are the percentage change in feed and speed respectively. F_a is the actual feed and F_d is the desired feed. S_a is the actual speed and S_d is the desired speed. The desired speed and feed rates are those which give the minimum roughness value taken from the experimental results.
The adapted feed and speed rates will be

$$F_{new} = F_{old} * \Delta F \quad (3)$$

$$S_{new} = S_{old} * \Delta F \quad (4)$$

A neural controller is designed to implement these changes in speed and feed to minimize the surface roughness of the workpiece in the next machining cycle. The inputs to the neural controller are the error (ΔR_a), RMS of vibration signals and RMS of force signal. A feed forward back propagation network with a Leven–berg-Marqardt algorithm is used for training the cont–roller. The output from the controller is the percentage change in feed rate and spindle speed as shown in figure 8.

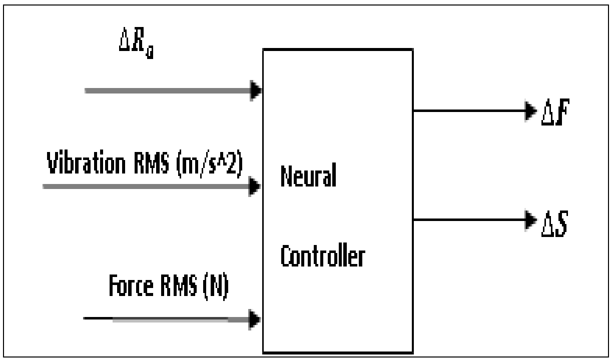

Figure 8. Neural network controller for control the feed and speed rate

The results of the presented adaptive control scheme were validated for six different experimental conditions with GAC given in table 1.It was found that the surface roughness of the drilled holes were minimum with adaptive control than the experiments conducted without GAC. The variations in speed, feed and surface roughness are given in figures 9,10 and 11.

Table 1. Validation data

Exp No	Speed (RPM)	Feed (mm/min)	Surface Roughness (without GAC)	% Change in Speed (ΔS)	% Change in Feed (ΔF)	New Speed (RPM)	New Feed (mm/min)	Surface Roughness (with GAC)
1	800	75	3.510	1.085	0.8065	868	60	1.0095
2	950	90	4.962	1.424	0.7228	1352	65	1.7170
3	1100	120	3.323	1.078	0.7665	1185	92	1.5370
4	1300	140	5.193	0.731	0.6452	952	90	2.9357
5	800	140	4.417	1.484	0.7903	1187	110	2.2147
6	1100	140	4.962	1.360	0.5326	1496	75	2.9664

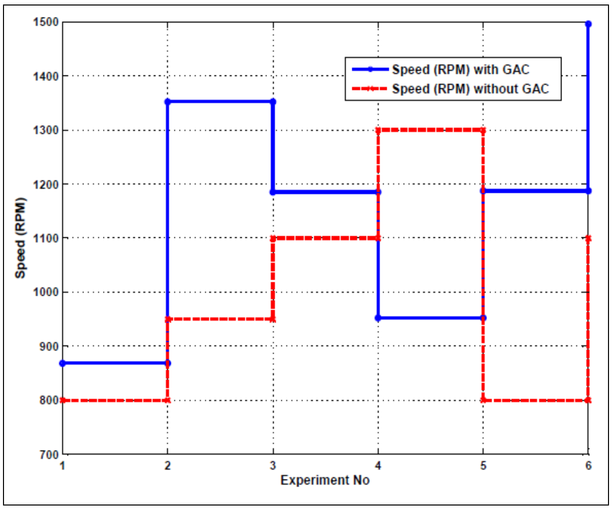

Figure 9. Spindle speed with and without GAC

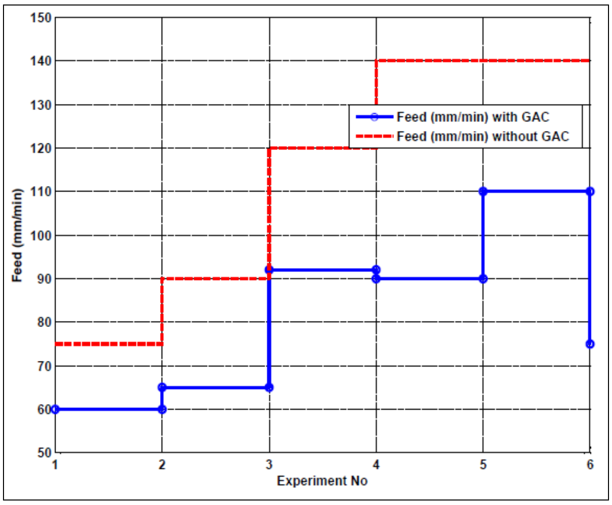

Figure 10. Feed rate with and without GAC

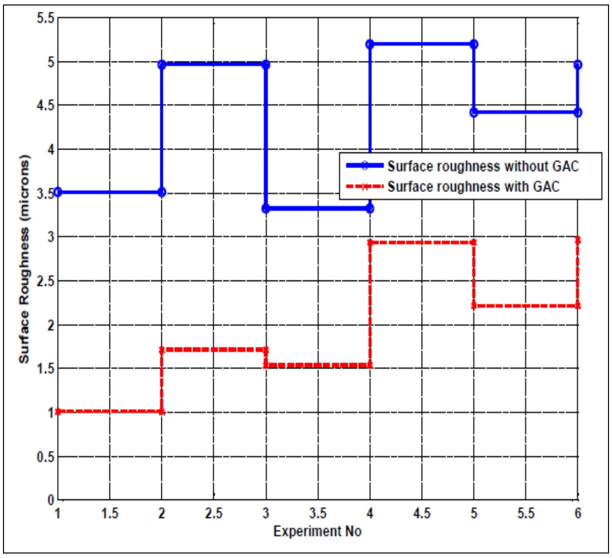

Figure 11. Surface roughness of drilled holes with and without GAC

4. CONCLUSION

A geometric adaptive control strategy for online control of surface roughness is presented. A cubic SVM model for the prediction of surface roughness using vibration and force signals is developed. The model is capable to predict the roughness of the drilled holes with an accuracy of 94 %. A neural network controller is used for implementing the adaptive control scheme for changing the feed and speed values to maintain the roughness within the prescribed limits. Results show that the GAC is able to control the surface roughness in real time and improves the quality of the workpiece. The limitation of the work is that the tool wear variations are negligible and are not considered for roughness model. The research can be further extended by considering the state of tool wear for prediction and control of surface roughness.

REFERENCES

[1] HMT, Production Technology, Tata McGraw-Hill Publishing Co. Ltd., 1980

[2] Sanjay, Prithvi: Hybrid intelligence systems and artificial neural network (ANN) approach for modeling of surface roughness in drilling", Cogent Engineering, vol.1(1), 2014.

[3] Vishy Karri, Tossapol Kiatcharoenpol, Prediction of internal surface roughness in drilling using three feedforward neural networks - a comparsion, Proceedings of the 9th International Conference on Neural Information Processing (ICONIP'OZ) , vol. 4,2003.

[4] C. Sanjay,C. Jyothi, A study of surface roughness in drilling using mathematical analysis and neural networks, International Journal of Advanced Manufacturing Technology, vol.29, pp. 846–852, 2006.

[5] D.Dinakaran, S.Sampathkumar, K.Madhivanan, An experimental investigation of surface roughness monitoring in surface grinding through ultrasonic technique, Mechatronics and Intelligent Manufacturing, vol.1, pp.107-118, 2012.

[6] R. Teti , K. Jemielniak, G. O'Donnell, D. Dornfeld, Advanced monitoring of machining operations, CIRP Annals - Manufacturing Technology, Vol.59, pp.717-739, 2010.

[7] Galloway D. F., Some Experiments on the Influence of Various Factors on Drill Performance, Transactions.A.S.M.E, Vol. 19, pp. 191, 1957.

[8] Carlos Eduardo Dorigatti Cruz, Paulo Roberto de Aguiar, Monitoring in precision metal drilling process using multi-sensors and neural network, International Journal of Advanced Manufacturing Technology, vol.66, pp.151–158, 2013.

[9] Ashanira Mat Deris, Azlan Mohd Zain, Roselina Sallehuddin, Overview of Support Vector Machine in Modeling Machining Performances, Procedia Engineering, vol.24, pp. 308-312, 2011.

[10] Zhuoda Jiang, Intelligent Prediction of Surface Roughness of Milling Aluminium Alloy Based on Least Square Support Vector Machine, IEEE Chinese control and decision conference, 2010.

[11] Ulas Çaydas, Sami Ekici, Support vector machines models for surface roughness prediction in CNC

turning of AISI 304 austenitic stainless steel, Journal of Intelligent Manufacturing, vol 23, pp. 639–650, 2012.

[12] I. Abu-Mahfouz, O. El Ariss, A. H. M. Esfakur Rahman, A. Banerjee, Surface roughness prediction as a classification problem using support vector machine, International Journal of Advanced Manufacturing Technology, vol.92(1-4), pp.803-815, 2017.

[13] N.Zhang, D. Shetty, An effective LS-SVM based approach for surface roughness prediction in machined surfaces, Neurocomputing, Vol.198, pp. 35-39, 2016.

[14] Marek Vrabel, Ildiko Mankova, Jozef Beno, Monitoring and control of manufacturing process to assist the surface workpiece quality when drilling, Procedia CIRP (41), pp.735-739, 2016.

[15] Giriraj B, Gandhinathan R, Prabhu raja V, Vijayaraghavan T, Adaptive control in high speed machining for improved surface finish, Indian Journal of Engineering and material sciences, Vol 15, pp.311-316, 2008.

[16] Potsang B Huang, Wei-Jung Shiang, Yuan-Tsan Jou, Chuhsien Chang, Chengghieh Ma,'An, In-Process Adaptive Control Of Surface Roughness In End Milling Operations, Proceedings of the Ninth International Conference on Machine Learning and Cybernetics, Qingdao, 11-14 July 2010.

[17] L.D. Yang, J.C. Chen, H.M. Chow, C.T. Lin, Fuzzy-nets-based in-process surface roughness adaptive control system in end-milling operations, International Journal of Advanced Manufacturing Technology,vol.28, pp. 236–248, 2006.

[18] Julie Z. Zhang . Joseph C. Chen, The development of an in-process surface roughness adaptive control system in end milling operations, International Journal of Advanced Manufacturing Technology, vol.31, pp. 877–887, 2007.

[19] Zarif Karimi N, Heidary H, Yousefi J, Sadeghi S, Minak G, Experimental Investigation on Delamination in Nanocomposite Drilling, FME Transactions , Vol.46, pp.62-69, 2018.

[20] Susai Mary J, Sabura Бanu U, Dinakaran D, Nakandhrakumar R S, Adaptive optimization using Grey relational analysis and PID control of CNC drilling process, IEEE International Conference on Robotics Automation Control and Embedded sytems 18-20 February, Hindustan Univeristy , RACE- 2015.

[21] Susai mary J, Sabura banu U, Dinakaran D, Nakandhrakumar R S, Adaptive control by multi-objective optimization with fuzzy inference system and neural predictive controller, INSIGHT- Non-Destructive Testing and Condition Monitoring, vol.59(1), pp. 38-44 , 2017.

[22] Md.Sayem Hossain Bhuiyan, Imtiaz Ahmed Choudhury, Investigation of tool wear and surface finish by analyzing vibration signals in turning Assab-705 steel, Machining Science and Technology: An International Journal, vol.19-2, pp.236-261, 2015.

[23] Erkki Jantunen, A summary of methods applied to tool condition monitoring, International journal of machine tools and manufacturing, vol.42-9, pp. 997-1010, 2002.

ПРЕДИКЦИЈА И ГЕОМЕТРИЈСКА АДАПТИВНА КОНТРОЛА ХРАПАВОСТИ ПОВРШИНЕ КОД ОБРАДЕ БУШЕЊЕМ

С. Мери Ј., С. Балаји М. А., Динакаран Д.

Храпавост површине је примарни фактор у евалуацији квалитета компоненте која одређује својства хабања и замора и квалитет склопа. Ово истраживање се бави контролом квалитета завршне обраде у реалном времену код обраде бушењем, применом стратегије геометријске адаптивне контроле. Мерење силе и сигнала вибрација за време бушења обављено је динамометром са сензором и акцелерометром. Запремински СВМ модел је употребљен за моделирање храпавости површине коришћењем силе, вибрација и параметара обраде. Утврђено је да тачност модела за предикцију износи 94% и модел је успешно коришћен за контролу храпавости приликом обраде бушењем. Адаптивна шема користи контролер на бази неуронских мрежа за подешавање параметара бушења да би се обезбедила постављена толеранција храпавости. Перформансе контролера показују све могућности приказане методологије за практичну примену у индустрији.