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Determination of Cutting Parameters in End Milling Operation based on the Optical Surface Roughness Measurement

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In this study, a milling system based on the in-line surface roughness measurement during machining process is developed using Artificial Neural Network (ANN) technique. In the proposed system, optimum feed rate and cutting speed are determined by ANN so as to provide the desired surface roughness, which is an important criterion for high quality surface. For this purpose, firstly an algorithm determining the operating principle of the system is developed. According to this algorithm, the optimum cutting parameters are predicted for end milling (finishing) operation by measuring semi-finish machining surface roughness via an optical sensor and then end milling operation is performed with the cutting parameters determined by the system. In the experimental part of this study, surface quality is observed for the milling process before and after the intervention of the system and the results is compared. The experimental results show that the system can be integrated with the modern machining systems in order to obtain the desired surface quality levels.

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NOMENCLATURE

Vc = cutting speed
f = feed rate
d = depth of cut
R_a = surface roughness

1. Introduction

One of the most significant subjects in the area of material removal is surface finishing. Black[1] defines metal cutting as the removal of metal chips from a workpiece in order to obtain a finished product with desired attributes of size, shape, and surface roughness. Surface finishing is a method used very commonly in fields such as molding, automotive, aerospace and defense industries. Controlled surface finishing has become much more important, particularly in sectors requiring precise surface quality, just as aerospace and defense industries.

Contemporarily, for many different purposes, machines are being developed by means of improving processing technology. Widespread mass-production in all areas, competitive environment and large production requirements have made tools, machining time and quality control costs much more important over time. Especially, the increase of CNC machines enabled the production of high precision parts in less time and with lower costs. However, machining vibrations, tool wear and wrong cutting parameters come into prominence as the preventive factors of the desired and efficient usage of this technology. Today, although very complex geometries can be machined much faster with a high dimensional accuracy by the current status of machining technologies, the intended maturity in the surface roughness issue has not been reached yet.

Researchers have paid great attention to the improvement of the surface roughness due to the industrial importance of the subject. In many studies, primarily the correlations between surface roughness and cutting parameters such as cutting speed, feed rate and depth of cut have been analyzed. By means of the experimental works, the specifications

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of surface roughness based on the change in cutting parameters were determined by using different methods.[2-5] In the future works parts of these conducted studies, the possibility of applying these methods on machining process has been mentioned particularly. Rosales et al. proposed an approximation of surface roughness by measuring the cutting forces that occur during machining, apart from cutting parameters.[6] Nouri et al. modeled the cutting forces that occur during machining process and related them to tool wear, instead of surface roughness.[7] Ali et al. have developed an ANN model using tool wear and cutting parameters to determine surface roughness.[8] Chi et al. introduced a methodology based on genetic wavelet network to predict surface roughness with an error less than 3%.[9]

Tsai et al. developed an in-process surface roughness recognition system to predict surface roughness based on vibration and rotation data. In that study, an accelerometer was used as an in-process sensor. Surface roughness was predicted with a back propagation ANN model trained with four input neurons as cutting speed, feed rate, depth of cut and vibration.[10] Kuttolamadom et al. investigated the effects of feed rate on surface roughness for 6061 Aluminum to reduce automotive component manufacture cycle time in machining. They observed that, surface roughness generally increased with an increase of feed rate.[11]

Balij et al. emphasized the influence of cutting parameters such as cutting speed, feed rate and depth of cut on the surface roughness of material St-52 in face milling. In their study, Bayesian neural network model was employed to predict the surface roughness with an error of 6.3%. Also, as a result of experiments the most influential factor was determined as the feed rate.[12] Baek et al. proposed a surface roughness model for face milling operations based on profile, axial and radial runout errors of cutting inserts.[13] Ehmann et al. developed a new method called Surface-Shaping System to represent the surface generation process. The system consisted of two parts: tool kinematics modeling and tool geometry modeling.[14] Moshat et al. studied the parameter optimization of end milling process to provide good surface finish as well as high material removal rate using PCA-based Taguchi method.[15]

Chen et al. studied on the prediction of surface roughness under different cutting conditions such as workpiece material and tool size. For this purpose, a fuzzy-nets approach was developed for the multilevel in-process surface roughness recognition system called FN-M-ISRR. Surface roughness was predicted by extrapolation from recorded vibration data and cutting condition data. It was reported that the proposed fuzzy system predicted the surface roughness with 90% accuracy during milling operation.[16] Lee et al. developed a method for simulating the machined surface by using the acceleration data instead of cutting forces. The algorithm was developed in terms of cutting conditions, cutting tool, workpiece and runout parameters. Then, the surface roughness was predicted by using the measured acceleration and the geometric model of end milling process.[17]

Michalik et al. investigated the surface roughness of thin-walled CK45 material parts during the milling operation. They studied the effects of geometric parameters on the surface roughness using analytical approximation techniques by utilizing the mathematical model of the system.[18] It is claimed that surface roughness is a statement of the surface topography. Surface roughness also has considerable effects on the criterions such as fatigue strength, corrosion resistance and creep life.[19]

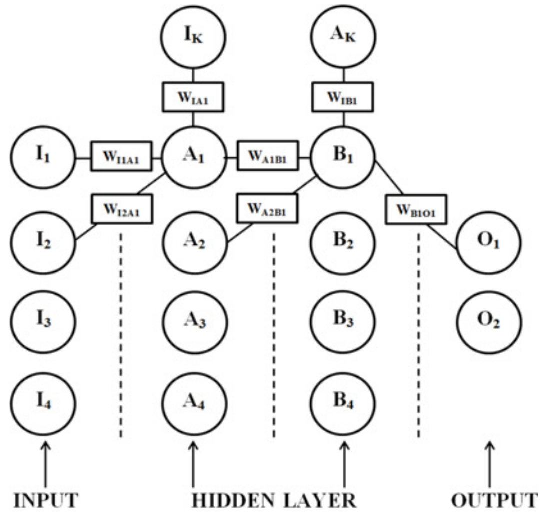

Fig. 1 The detailed ANN model of the developed system

For the prediction of surface roughness or optimization and modeling of cutting parameters, there are also other measurement practices. Generally, contact-type surface roughness measurement systems are the classical methods when the surface roughness measurement is considered. Generally in machining, contact-type stylus profilometers are used to determine the surface roughness. Tomkiewicz used the image processing method for the determination of roughness levels.[20] In that study, he captured the images of the surface during machining and approximated the surface roughness with the ANNs method by converting the images into digital signals. Optical and laser systems seem important in the researches made on non-contact surface roughness measuring systems. Bradley performed some tests by adapting the optical surface roughness sensor to the coordinate-measuring machine.[21] In this study, a machining system, which is able to manufacture components with desired surface quality without an external intervention, is developed. The proposed system is able to machine by using optimum cutting parameters determined by the system trained with the ANN method on the basis of surface roughness value measured with an integrated optical surface roughness sensor. Experimental works were conducted by using a 3-axis CNC machine built as a part of this study and the contribution of the developed system to the desired surface quality of the manufactured parts has been evaluated. The overall machining and quality control time can be reduced with the proposed in-line surface roughness control system.

2. Artificial Neural Networks Model

In this section, artificial neural networks, which constitute the fundamental structure of the milling system is discussed briefly. In the studies presented so far, examinations have been made with the ANN model for the determination of surface roughness on the basis of cutting parameters.[22,23] Within the scope of this study, ANN is used in order to make an approximation of optimum machining parameters using the machining data acquired from experimental measurements. The detailed ANN model of the developed system is presented in Fig. 1.

As seen in Fig. 1, in the basic ANN model, the input cluster is x_1, x_2, …, x_m expressed as X in the vector form. Each input signal is multiplied by the weight ratios w_{k1}, w_{k2}, …, w_{km} and w_{kb}. The sum of the dual multiplications shown in the vector form W_k, is calculated as below.

$$net(X, W_k) = W_k^T X \tag{1}$$

At this point;

$$W_k = [w_{k1} w_{k2} \ldots w_{km} w_{kb}]^T \tag{2}$$

$$X = [x_1 x_2 \ldots x_m b_k]^T \tag{3}$$

After the calculation of the sum of the weighted value, the output of neuron is produced by applying an activation function

$$y_k = f(W_k^T X) \quad \text{and} \quad y_k = f(\Sigma_{i=1}^{m} w_{kj} x_i) \tag{4}$$

Sigmoid function is used as an activation function in the study. Sigmoid function, as opposed to classical artificial neural network functions, can simulate the behavior of nonlinear systems. This function is defined as follows:

$$f(net) = 2/(1 + \exp(-a \cdot net)) - 1 \tag{5}$$

where a denotes the slope of sigmoid function.

Feed-forward neural networks (FNN) used in this study are one of the popular structures among artificial neural networks.[24] These efficient networks are widely used to solve complex problems by modeling complex input-output relationships.[25,26] However, FNNs often end up being over trained. They adopt trials-and-errors to seek possible values of parameters for convergence of the global optimum. The learning process of an FNN cannot guarantee the global optimum, sometimes trapping the network into the local optimum.[24] The back-propagation algorithm is one of the most famous algorithms to train a feed forward network. It has great advantage of simple implementation.[24] The back-propagation algorithm works correctly for networks with more than one input unit in which several independent variables are involved.

In this study, the multilayer feed forward network is used as ANN model. There are one input layer, two hidden layers and one output layer with each neuron fully connected with neurons of adjacent layer. Four input neurons and two output neurons are for the input and output variables. In modeling, the input elements are given as surface roughness, depth of cut, tool diameter and work-piece material. Output elements are composed of cutting speed and feed rate which are indicated in Table 1. Sigmoid function is used for multilayer feed forward network in this study. Backpropagation algorithm is selected as a training algorithm.

In the MATLAB environment, a custom code is developed to apply the formulations instead of neural network toolbox. The details about the developed MATLAB code are as follows: firstly a file with an extension of *.txt including experimental test results is read. Then, data at related columns are assigned to input and output elements to calculate the weight functions and layer elements. Then, all of these data is written

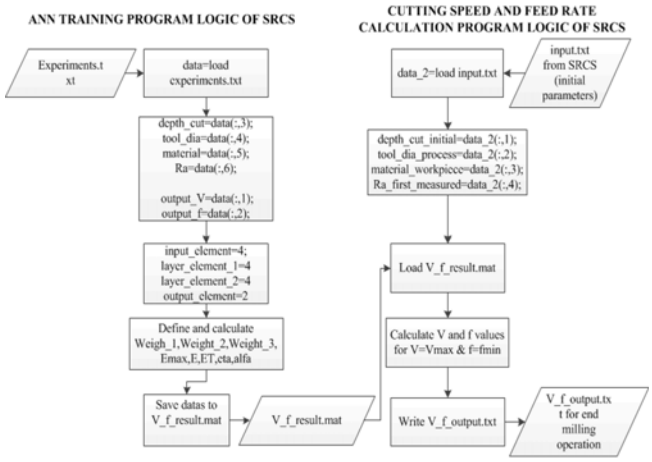

Fig. 2 MATLAB program code logic for ANN

Table 1 Cutting parameters used in ANN model

Inputs of ANN				Outputs of ANN	
R_a(μm)	d(mm)	D(mm)	Material	Vc(m/min)	f(mm/min)

to an output file named as "S_f_result.mat". Later, the output file is used in the main Surface Roughness Control System (SRCS) as an input file. MATLAB program code logic for ANN is shown in Fig. 2.

3. Experimental Setup

The proposed experimental setup is mainly composed of software and hardware of the surface roughness control system (SRCS). The SRCS is composed of a 3-axis CNC milling machine and an optical surface roughness sensor (OSRS). The components of this system are explained in detail in the following sections.

3.1 The software of the SRCS

In order to try the algorithm mentioned above, software for the SRCS has been developed. The user interface and the main control software were developed in Visual Studio environment. The cutting speed and feed rate calculation program based on the ANN method was developed by using MATLAB and was integrated to the main control software. In the SRCS, servo motor motions in the x, y and z axes and all kinds of communications with the machine are performed through the PLC. The SRCS is composed of three sub-categories, which are the manual and automatic operator entry section, optical sensor measurement section and cutting parameters calculation section shown in Fig. 3(a). Initial-cut parameters of the SRCS are defined in the section shown in Fig. 3(b). At this point, the cutting limits in x,y,z, initial feed rate, initial cutting speed and the depth of cut for semi-finish cut can be entered by the user. As seen in Fig. 3(c), the desired value of the R_a, workpiece material, tool diameter and finishing depth of cut determined as the input parameters in the experimental sets are entered into the SRCS.

Home position and manual control sections are placed at the top-left and top-middle side in the panel of the SRCS software as seen in Fig. 3(a). In the position zero section (home position), zero positions for

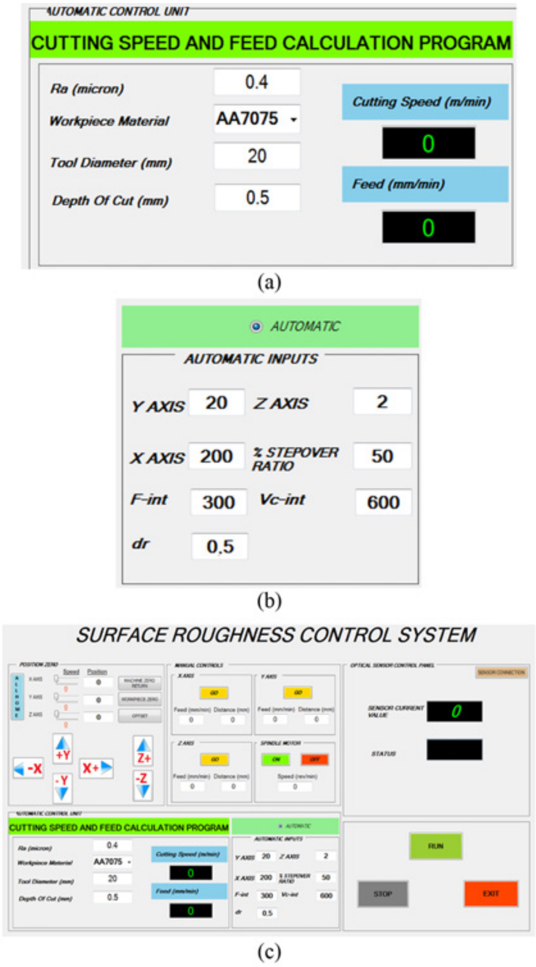

Fig. 3 The user interface of the SRCS (a) main program interface (b) initial parameters entry interface of the SRCS (c) cutting speed and the feed rate calculation program interface of the SRCS

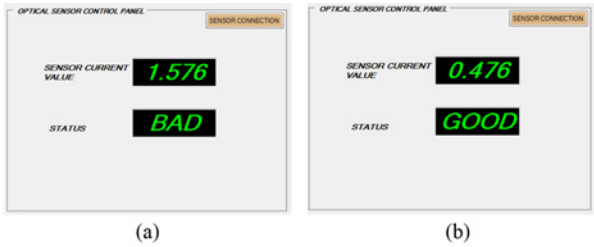

Fig. 4 Status of the surface roughness measured by OSRS (a) undesired result (b) desired result

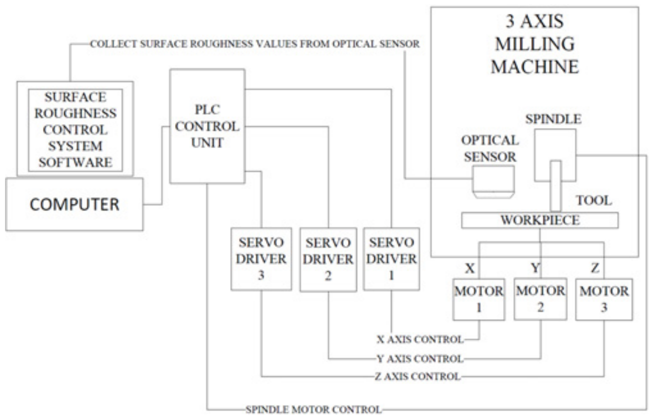

Fig. 5 The line diagram of complete setup

milling machine and workpiece can be defined by the user. In manual control section, x, y and z axis motors and cutting speed can be controlled individually.

The cutting speed and feed rate calculation program may predict more than one cutting speed and feed rate couples. In this case, the process is completed by the selection of the cutting speed corresponding to the maximum feed rate value. The reason for selecting the maximum value of the feed rate is to reduce machining time. Ultimately, the same surface roughness results will be observed from the machined surface independent of the selection. The results of the optical sensor part are shown in Fig. 4. The average roughness value measured with the optical sensor is shown at the top of the screen. The current condition of surface roughness is represented by “status” as shown at bottom of the screen. If the result is below or equal to the reference roughness value, the condition is indicated as “GOOD” and if above, the condition is indicated as “BAD”.

3.2 The hardware of the SRCS

The SRCS is composed of a 3-axis CNC machine and an optical surface roughness sensor. The SRCS was designed and assembled in the scope of this study. 3-axis milling machine, optical surface roughness sensor and control software are shown in a line diagram in order to describe the complete experimental setup (Fig. 5). Here, Optic surface roughness sensor (OSRS) is mounted on the spindle head of 3-axis milling machine. OSRS is connected to System Computer with RS-232 connection to transfer surface roughness data to the software of the SRCS. According to measured roughness data, the software of the SRCS transmits the calculated feed rate and cutting speed data to PLC control unit through RJ45 Ethernet connection in order to control the servo motors and spindle motor.

The frame of the 3-axis CNC machine is constructed by 90×90 and 90×180 heavy-duty aluminum sigma profiles as shown in Fig. 6. In order to provide a 3-axis movement on the SRCS, three servo motors with brakes are used. Movement on 3-axis are provided by delivering the motions coming from the servo motors by means of the anti-backlash couplings to ball screws. HSD brand MT 1090-Y6162Y0019 type of spindle has been chosen for the machining part. The CNC milling machine used in the experiments has been produced and assembled in such a way that it has 4.5 kW head engine power and 18000 rpm maximum rotational speed.

Surface roughness systems are able to make mechanical or optical measurements. However, mechanical measurement systems have not been approved for the SRCS, because these measurement systems have to contact the surface rather slowly and are also expensive. Furthermore, they scratch the surface owing to the mechanical usage of stylus during the measurement. This constitutes a problem in situations requiring precise surface quality. Due to the non-contact measurement capability,

Fig. 6 Developed experimental setup

a Hohner Brand D516 type of optical surface roughness sensor is used to measure the surface roughness of the machined surface. Non-contact roughness measurements are performed continuously by OSRS. Choice of optical sensor has brought many advantages in the SRCS. Rapid data transfer, adaptation to the developed program, easy integration to the CNC milling machine, low cost and suitability for measuring in real time machining may be considered among the most significant advantages.

OSRS is able to measure the surface roughness of the machined metal surfaces between the 0.05 μm and 20 μm. At the end of the machining operation, infrared light beams radiated by a light emitting diode (IR LED) are sent to the surface as shown in Fig. 7. If the surface is perfectly smooth, the light will be reflected at an angle equal to the angle of incidence. In this case, reflection in any other direction will be zero and the ratio between the reflected and scattered beams is infinite. If the surface is absolutely rough, the incident light will scatter at any direction with equal amounts and the ratio between the reflected and scattered beams will be 1. The value of the surface roughness at a point on the surface is determined by comparing the amount of reflected and scattered lights measured by the OSRS. The ratio between the reflected and scattered beams is inversely proportional to the degree of surface roughness.[27]

In this measurement system, the surface roughness (R_a) is not measured directly. Firstly, according to surface profile, reflected and scattered infrared light values are collected by the optical sensor. These reflection and scatter data are related to surface roughness values with the sensor software. R_a is determined on the basis of the reflection/scatter ratio. Before measurement, the sensor is calibrated with the help the workpieces with known surface roughness values. In the calibration process, the workpiece having lower surface roughness is scanned firstly. Therefore, the R_a corresponding to the reflection/scatter ratio acquired by the scanning is entered into the software. Then, the acquired R_a is also entered into the SRCS by the repetition of the same processes for the surface quality of other workpiece having greater R_a. At the end of

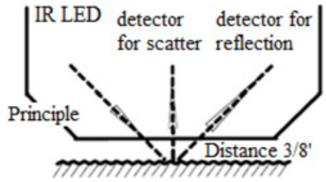

Fig. 7 Measurement principle of OSRS[27]

the calibration procedure, the sensor can measure the correct R_a value corresponding to the reflection/scatter ratio on every point using the calibration parameter F, which is defined as[27]

$$F = (S_S - S_N)/(S_S - S_N) \tag{6}$$

Where S_S denotes the signal coming from the photo detector for reflection and S_N denotes the signal coming from the photo detector for scatter.

3.3 The control structure of the SRCS

The OSRS which constitutes the measurement part of the surface roughness control system (SRCS) and its working principle has been mentioned in the previous section. In this section, information about software of the SRCS and the working principle of the SRCS is presented. The goal of the SRCS is basically to achieve the desired R_a for machined surface of the workpiece by determining optimum cutting parameters and conducting metal removal accordingly by measuring the R_a for the finish cut operation. Before the machining operation, values of the cutting speed and the feed rate for semi-finish cut and the constant depth of cut are entered into software of the SRCS. In addition, values of the desired R_a and the depth of finishing cut are also indicated. The SRCS performs the semi-finish cut according to the parameters defined by the user. The sensor carries out the surface roughness measuring process for the finishing operation. If the surface has the desired surface quality in accordance with the measured R_a, the SRCS performs the cutting operation with the existing parameters and completes the process. If the measured R_a does not match the desired roughness value previous to finishing operation, the SRCS predicts the parameters for the finishing cut according to the necessary R_a. The SRCS carries out the end milling in compliance with the cutting speed and the feed rate determined by the software and completes the process by performing a confirmation measurement. Furthermore, data measured from the experimental set of actual machining parameters is used for the constant training of the SRCS as a new reference set for ANN. Therefore, the developed system can be adapted to any type of CNC milling machines with itself training capability. The algorithm shown in Fig. 8 explains the working principle of the SRCS. The developed SRCS determines the suitable cutting speed and feed rate values in order to obtain the desired surface roughness value at the end of the surface finishing operation with the aid of ANNs.

4. Experimental Results and Discussions

Experimental studies are carried out in order to test the performance

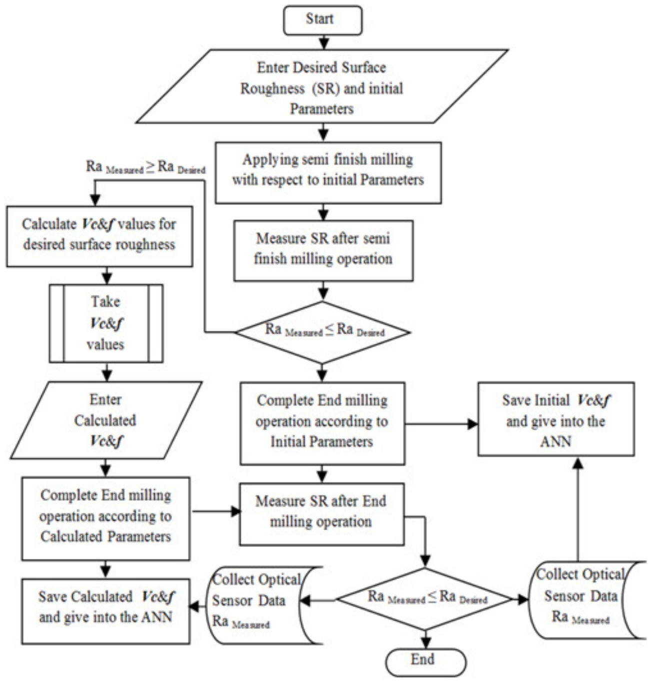

Fig. 8 The proposed algorithm of the SRCS

of the developed Surface Roughness Control System. There are many parameters, which affect the roughness such as cutting speed, feed rate, depth of cut, workpiece material and cutting tool. These fundamental parameters are taken into consideration in the experimental phase. The cutting tool is chosen as Taegutec AES 2200 brand and 2-flute solid carbide end mill for aluminum machining with Ø20 mm diameter. In this study, the cutting angle (approach angle) is 90°. In end mill operations the approach angle is generally 90°. Surya et al. studied the influence of approach angle of face milling cutter on surface roughness. They reported that the surface roughness increases as the approach angle increases.[28] The coolant is not used in the experimental studies so dry machining is performed. In this study, commercially available AA 5083 H111 and AA7075 T6 Aluminum Alloys are used as the workpiece materials. Chemical compositions of these materials are given in Table 2.

Cutting speed is swept from 63 m/min to 628 m/min, and the feed rate is varied between 100 mm/min and 1000 mm/min as presented in Table 3. There are two experimental sets prepared for 0.2 mm and 0.5 mm depths of cut, since the depth of cut is an issue approached as a finishing operation.

Experiments are conducted for 192 different variations on the basis of the test conditions stated above in order to construct the ANN model. The number of sample to test the ANN model is taken as 30. At the end of the experiments, the R_a values have been measured with calibrated Mitutoyo SJ-310 contact-type surface roughness tester and they are used as the input data for the ANN model.

According to the results of the experiments conducted for both ANN training and analyzing the behavior of the SRCS, changes in the R_a value depending on feed rate, cutting speed and depth of cut are presented in Figs. 9~12. Fig. 9 shows the change in the surface roughness depending on the cutting speed under constant feed rates between 100 mm/min and 1000 mm/min at a fixed depth of cut of 0.2 mm. It is observed that

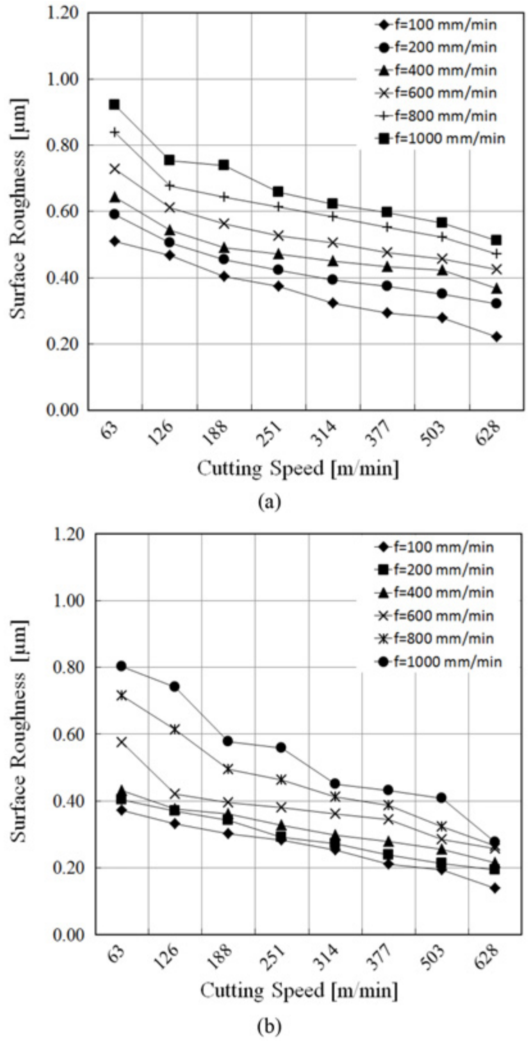

Fig. 9 The change in R_a depending on cutting speed at 100-1000 mm/min feed rates interval for 0.2mm depth of cut (a) for material AA5083 (b) for material AA7075

Table 2 The chemical composition of the AA5083 and AA7075 materials used in the experiments

Material/ Composition	Fe	Si	Mn	Cr	Cu	Mg	Zn	Hardness
AA5083 H111	0.199	0.171	0.513	0.089	0.015	4.599	0.311	27 HRB
AA7075 T6	0.103	0.230	0.029	0.219	1.46	2.75	5.12	87 HRB

Table 3 The experimental sets and cutting parameters used in the experiments

Cutting Speed (m/min)	Feed Rate (mm/min)	Depth of Cut (mm)	Workpiece Material	Cutting Tool	Tool Holder
63	100 200 400 600 800 1000	0.2 0.5	AA5083 AA7075	2 flute end mill cutter with 20 mm Diameter	ER32 Collet
126					
188					
251					
314					
377					
503					
628					

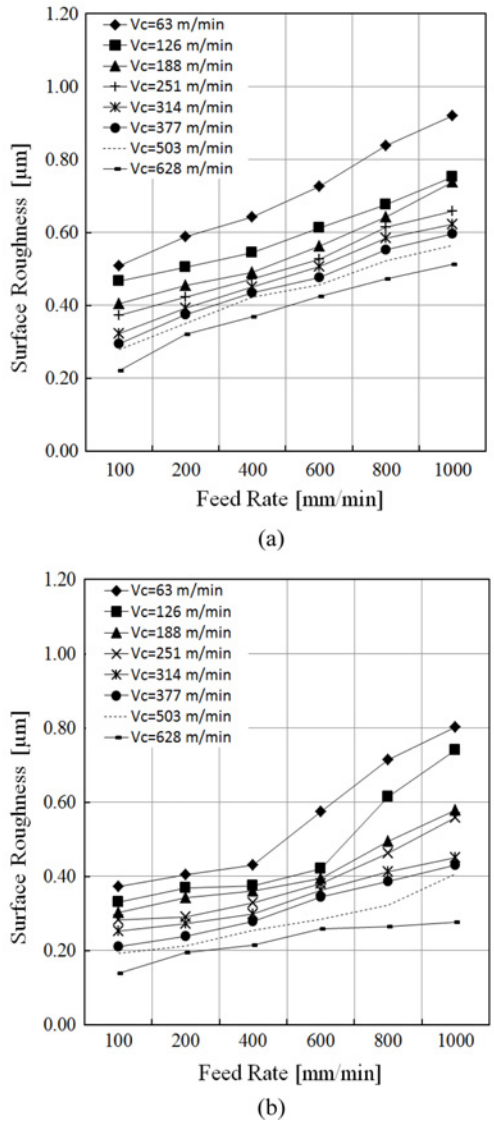

Fig. 10 The change in R_a depending on feed rate at 63-628 m/min cutting speed interval for 0.2mm depth of cut (a) for material AA5083 (b) for material AA7075

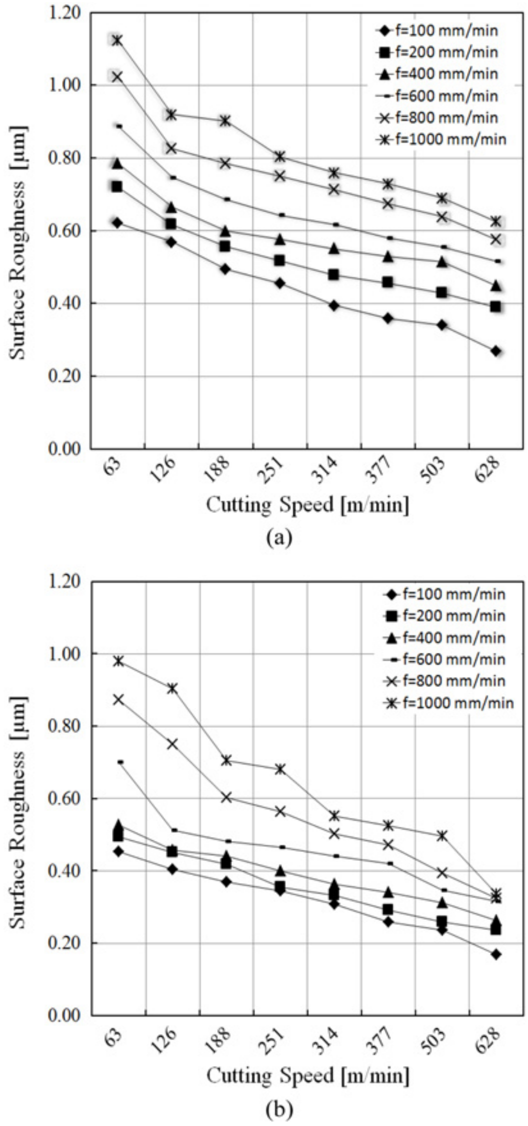

Fig. 11 The change in R_a depending on cutting speed at 100-1000 mm/min feed rates interval for 0.5mm depth of cut (a) for material AA5083 (b) for material AA7075

the surface roughness decreases under the constant feed rate, with an increase in the cutting speed.

Fig. 10 illustrates the relation between the cutting speed and roughness value for various feed rates. The roughness value increases as the feed rate increases for 0.2 mm depth of cut.

Fig. 10 shows the change in the roughness values depending on the cutting speed under constant feed rates between 100 mm/min and 1000 mm/min at a 0.5 mm depth of cut. The R_a value decreases with the increase in the cutting speed in a similar way presented in Fig. 9.

In Fig. 12, the change in R_a with respect to the feed rate under constant cutting speeds between 63-628 m/min at a 0.5 mm depth of cut is given. The R_a increases with the increase in the feed rate approximately in direct proportion in a similar way presented in Fig. 10. The increase in the depth of cut results in increasing surface roughness values. When these results are compared with the findings of similar studies in the literature, it is observed that the changes in R_a with the feed rate, cutting speed and depth of cut show similar behavior. Especially, Palanikumar observed that the R_a value decreases with the increase in cutting speed, and it increases with the increase in feed rate and depth of cut.[29]

The results presented in Figs. 9-12 are used to create the ANN model, which is the main part of the SRCS. Then, the performance of the surface roughness control system is examined experimentally for two different workpiece materials. For this purpose, the initial values of the feed rate and cutting speed are chosen as 1200 mm/min and 251 m/min, respectively. The depth of cut is taken as 0.8 mm for semi-finish operation. The required value of R_a is assigned as 0.6 μm to the SRCS. Moreover, the depth of finishing cut is determined as 0.2 mm. Using these parameters, the surface roughness was measured by OSRS after the semi-finish cut operation as shown in Fig. 13 and the R_a value is determined as 1.576 μm for AA5083 Aluminum alloy.

Since the resulting R_a value was greater than the desired value, the

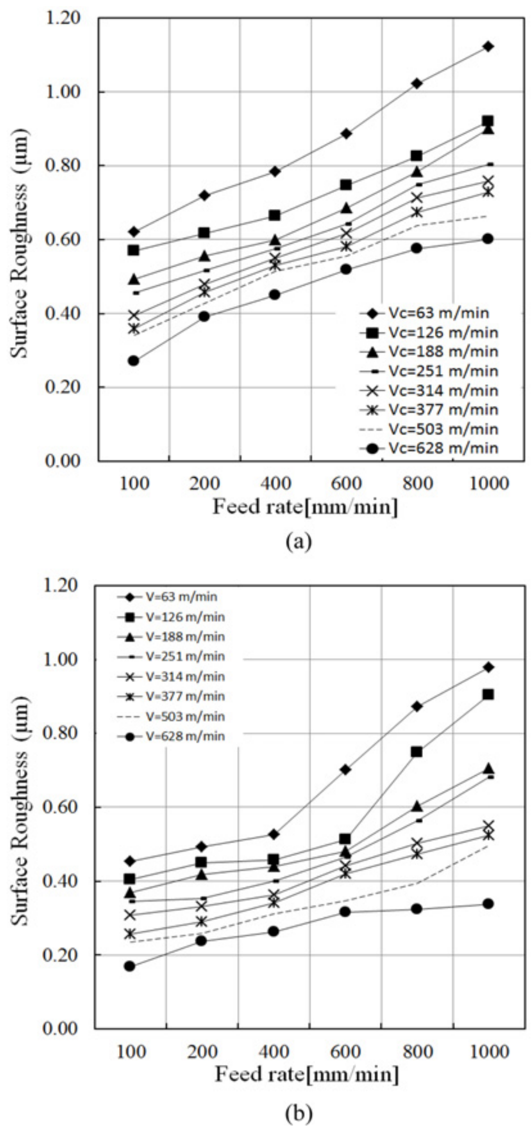

Fig. 12 The change in R_a depending on feed rate at 63-628 m/min cutting speed interval for 0.5mm depth of cut (a) for material AA5083 (b) for material AA7075

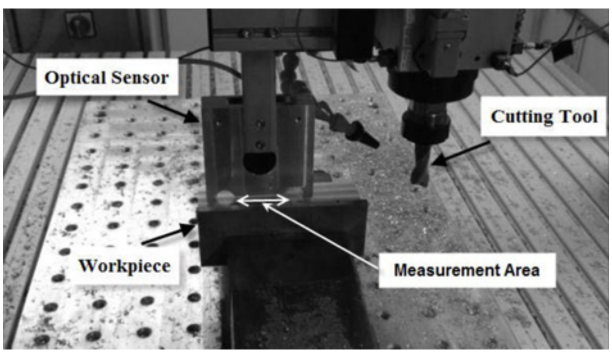

Fig. 13 Spindle and the integrated optical measurement system

SRCS calculated the cutting speed and feed rate to achieve the desired roughness level. The SRCS determined the required optimum cutting

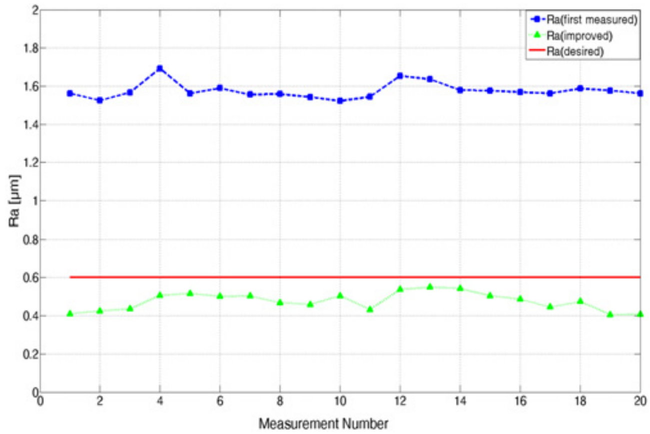

Fig. 14 Surface roughness values before and after the SRCS for AA5083

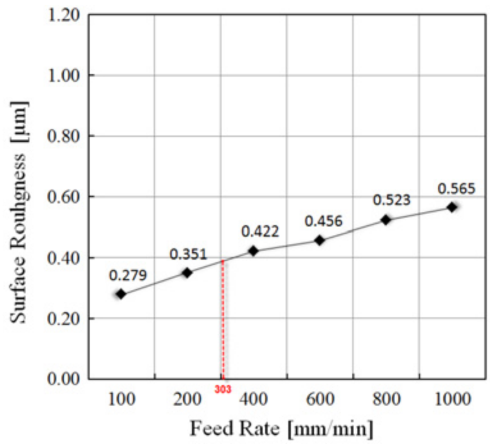

Fig. 15 The change of surface roughness with respect to the feed rate at 503 m/min cutting speed and 0.2 mm depth of cut for AA5083

parameters as Vc=477 m/min and f=303 mm/min for R_a=0.6 μm. Then the system machined the surface of the workpiece automatically with these new cutting parameters and then the roughness measurement was repeated. After the measurement, it was observed that the roughness value was obtained as 0.476 μm and the milling process was finished. Fig. 14 illustrates the roughness values before and after the intervention of the SRCS for AA5083 alloy. The blue curve represents the surface roughness after the semi-finish cut, the red curve represents the desired surface roughness limit and the green curve represents the resulting roughness levels obtained by using the cutting parameters determined by the SRCS.

If a comparison is made between the results of the experimental studies carried out for the training stage of the ANN and the result of the SRCS, it can be seen from Fig. 15 that the R_a value for the feed rate of 303 mm/min at Vc=503 m/min and d=0.2 mm is about 0.4 μm. This roughness value is very close to the roughness value obtained by SRCS and this indicates the efficiency of the developed system.

Fig. 16 shows the microscope images of the machined surface magnified by 25 times before and after the intervention of the SRCS

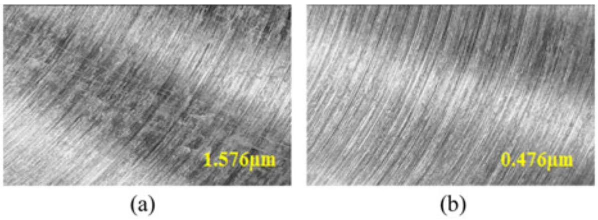

Fig. 16 Machined surface images of AA5083 material (×25) (a) Vc= 251 m/min, f=1200 mm/min, d=0.8 mm (b) Vc=477 m/min, f=303 mm/min and d=0.2 mm

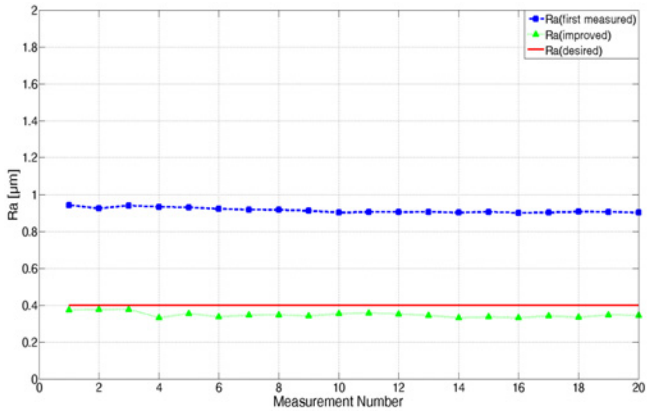

Fig. 17 Surface roughness values before and after the SRCS for AA7075

for the comparison purpose. Carl Zeiss Axioskop 2 Mat was used to get the surface image. As seen from the magnified surface image, which was machined according to the cutting parameters determined by SRCS for the finishing operation, there is a good improvement in the surface roughness.

Similarly, as a result of machining operation with initial parameters Vc=251 m/min, f=1200 mm/min and d=0.5 mm, for AA7075 alloy, R_a is measured as 0.914 μm. This value was also higher than the desired surface roughness of 0.4 μm. The SRCS determined the cutting parameters as Vc=430 m/min and f=758 mm/min, for finishing operation to get desired R_a with constant depth of cut. Using the new cutting parameters determined by SRCS, end milling operation was completed with the resulting surface roughness R_a=0.348 μm. Fig. 17 illustrates the roughness values for AA7075 alloy before and after the intervention of SRCS.

Fig. 18 presents the correlation between the results of the roughness measurements performed by OSRS and a contact type roughness measurement system Mitutoyo SJ-310 for two different materials. The cutting parameters used in the milling operation of different samples for which the R_a values are measured, are given in Table 4. The percentage deviations between the roughness values of optic and contact type measurement systems are 6% and 2% for materials AA 5083 and AA7075, respectively. The reason for these small differences may be noise, ambient light and structural vibration. The results of the comparison presented in Fig. 18 shows that, the OSRS used in this study provides reliable R_a values in comparison with the contact type roughness measurement devices.

The validation error associated with the proposed surface roughness control system is calculated using the R_a values presented in Fig. 18 as

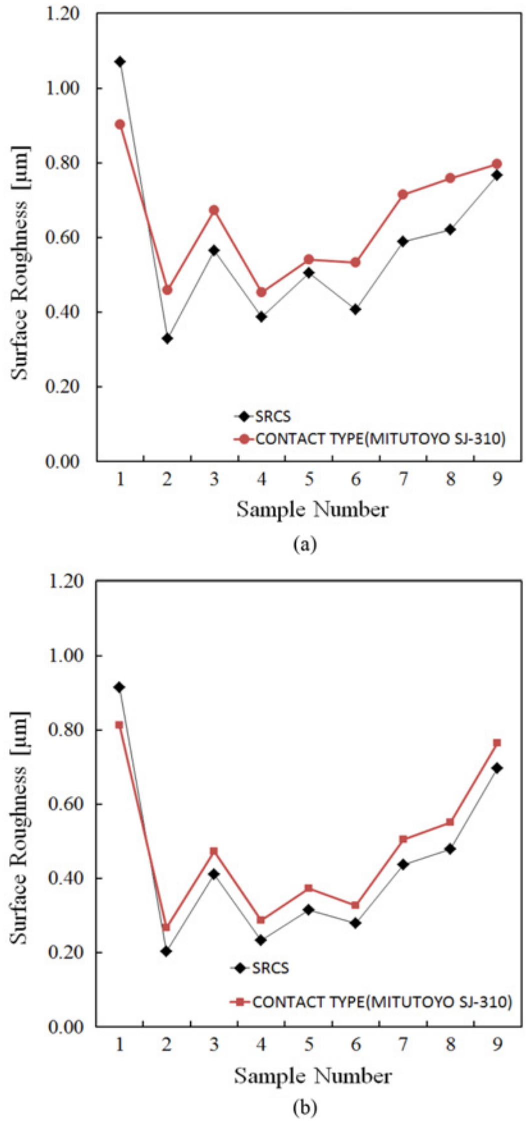

Fig. 18 Comparison of surface roughness levels of OSRS and contact type systems (Mitutoyo SJ-310) (a) for AA5083 (b) for AA7075

Table 4 Cutting parameters used in the comparison of roughness measurement method

Sample Number	Vc (m/min)	f (mm/min)
1	251	1200
2	565	300
3	377	800
4	353	131
5	334	452
6	502	481
7	346	900
8	314	1000
9	440	1500

6.1% for AA5083 and 4.5% for AA7075 materials as the mean differences between optical and contact type R_a measurements.

5. Conclusions

The surface roughness control is achieved on the basis of the optimum cutting speed and the feed rate determined during the finishing operation by means of the SRCS developed in this study. The results of measurements acquired in accordance with the different cutting parameters and the machining surface images show that it is possible to have a more qualified finishing surface by using the proposed SRCS. Also, by virtue of the developed SRCS, the initiative of the operator on the proper selection of the cutting parameters is taken out and the time loss in the total machining process is economized by minimum operator intervention. It is also estimated that the SRCS will reduce the tool wear by determinations of the optimized cutting parameters. With the proposed SRCS, the surface roughness can be continually kept under control during the process and the quality of the surface roughness will be controlled within the production phase. The system with the learning property can be applicable for other types of CNC milling and turning machines.

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REFERENCES

1. Black, J. T., “Flow Stress Model in Metal Cutting,” Journal of Engineering for Industry, Vol. 101, No. 4, pp. 403-415, 1979.
2. Çolak, O., Kurbanoğlu, C., and Kayacan, M. C., “Milling Surface Roughness Prediction using Evolutionary Programming Methods,” Materials & Design, Vol. 28, No. 2, pp. 657-666, 2007.
3. Hayajneh, M. T., Tahat, M. S., and Bluhm, J., “A Study of the Effects of Machining Parameters on the Surface Roughness in the End-Milling Process,” Jordan Journal of Mechanical and Industrial Engineering, Vol. 1, No. 1, pp. 1-5, 2007.
4. Zhang, J. Z., Chen, J. C., and Kirby, E. D., “Surface Roughness Optimization in an End-Milling Operation using the Taguchi Design Method,” Journal of Materials Processing Technology, Vol. 184, No. 1, pp. 233-239, 2007.
5. Agarwal, N., “Surface Roughness Modeling with Machining Parameters (Speed, Feed and Depth of Cut) in CNC Milling,” MIT International Journal of Mechanical Engineering, Vol. 2, No. 1, pp. 55-61, 2012.
6. Rosales, A., Vizán, A., Diez, E., and Alanís, A., “Prediction of Surface Roughness by Registering Cutting Forces in the Face Milling Process,” European Journal of Scientific Research, Vol. 41, No. 2, pp. 228-237, 2011.
7. Nouri, M., Fussell, B. K., Ziniti, B. L., and Linder, E., “Real-Time Tool Wear Monitoring in Milling using a Cutting Condition Independent Method,” International Journal of Machine Tools and Manufacture, Vol. 89, pp. 1-13, 2015.
8. Ali, S. M. and Dhar, N. R., “Modeling of Tool Wear and Surface Roughness under MQL Condition-A Neural Approach,” Canadian Journal on Artificial Intelligence, Machine Learning & Pattern Recognition, Vol. 1, No. 2, pp. 7-25, 2010.
9. Chi, J. and Chen, L. Q., “The Real-Time Prediction of Surface Roughness based on Genetic Wavelet Network,” Advanced Materials Research, Vols. 102-104, pp. 610-614, 2010.
10. Tsai, Y.-H., Chen, J. C., and Lou, S.-J., “An in-Process Surface Recognition System based on Neural Networks in End Milling Cutting Operations,” International Journal of Machine Tools and Manufacture, Vol. 39, No. 4, pp. 583-605, 1999.
11. Kuttolamadom, M., Hamzehlouia, S., and Mears, L., “Effect of Machining Feed on Surface Roughness in Cutting 6061 Aluminum,” SAE International, Vol. 3, No. 1, pp. 108-119, 2010.
12. Bajiæ, D., Lela, B., and Živkoviæ, D., “Modeling of Machined Surface Roughness and Optimization of Cutting Parameters in Face Milling,” Metalurgija, Vol. 47, No. 4, pp. 331-334, 2008.
13. Baek, D. K., Ko, T. J., and Kim, H. S., “Optimization of Feedrate in a Face Milling Operation using a Surface Roughness Model,” International Journal of Machine Tools and Manufacture, Vol. 41, No. 3, pp. 451-462, 2001.
14. Ehmann, K. F. and Hong, M. S., “A Generalized Model of the Surface Generation Process in Metal Cutting,” CIRP Annals-Manufacturing Technology, Vol. 43, No. 1, pp. 483-486, 1994.
15. Moshat, S., Datta, S., Bandyopadhyay, A., and Pal, P., “Optimization of CNC End Milling Process Parameters using PCA-based Taguchi Method,” International Journal of Engineering, Science and Technology, Vol. 2, No. 1, pp. 95-102, 2010.
16. Chen, J. C. and Savage, M., “A Fuzzy-Net-based Multilevel in-Process Surface Roughness Recognition System in Milling Operations,” The International Journal of Advanced Manufacturing Technology, Vol. 17, No. 9, pp. 670-676, 2001.
17. Lee, K. Y., Kang, M. C., Jeong, Y. H., Lee, D. W., and Kim, J. S., “Simulation of Surface Roughness and Profile in High-Speed End Milling,” Journal of Materials Processing Technology, Vol. 113, No. 1, pp. 410-415, 2001.
18. Michalik, P., Zajac, J., Hatala, M., Mital, D., and Fecova, V., “Monitoring Surface Roughness of Thin-Walled Components from Steel C45 Machining Down and Up Milling,” Measurement, Vol. 58, pp. 416-428, 2014.
19. Routara, B. C., Bandyopadhyay, A., and Sahoo, P., “Roughness Modeling and Optimization in CNC End Milling using Response

Surface Method: Effect of Workpiece Material Variation," The International Journal of Advanced Manufacturing Technology, Vol. 40, No. 11-12, pp. 1166-1180, 2009.

20. Zawada-Tomkiewicz, A., "Estimation of Surface Roughness Parameter based on Machined Surface Image," Metrology and Measurement Systems, Vol. 17, No. 3, pp. 493-503, 2010.

21. Bradley, C., "Automated Surface Roughness Measurement," The International Journal of Advanced Manufacturing Technology, Vol. 16, No. 9, pp. 668-674, 2000.

22. Erzurumlu, T. and Oktem, H., "Comparison of Response Surface Model with Neural Network in Determining the Surface Quality of Moulded Parts," Materials & Design, Vol. 28, No. 2, pp. 459-465, 2007.

23. Oktem, H., Erzurumlu, T., and Erzincanli, F., "Prediction of Minimum Surface Roughness in End Milling Mold Parts using Neural Network and Genetic Algorithm," Materials & Design, Vol. 27, No. 9, pp. 735-744, 2006.

24. Che, Z.-G., Chiang, T.-A., and Che, Z.-H., "Feed-Forward Neural Networks Training: A Comparison Between Genetic Algorithm and Back-Propagation Learning Algorithm," International Journal of Innovative Computing, Information and Control, Vol. 7, No. 10, pp. 5839-5850, 2011.

25. Karimi, B., Menhaj, M. B., and Saboori, I., "Multilayer Feed Forward Neural Networks for Controlling Decentralized Large-Scale Non-Affine Nonlinear Systems with Guaranteed Stability," International Journal of Innovative Computing, Information and Control, Vol. 6, No. 11, pp. 4825-4841, 2010.

26. ZareNezhad, B. and Aminian, A., "A Multi-Layer Feed Forward Neural Network Model for Accurate Prediction of Flue Gas Sulfuric Acid Dew Points in Process Industries," Applied Thermal Engineering, Vol. 30, No. 6, pp. 692-696, 2010.

27. Questex Media Group, Inc., "Measuring Surface Roughness with an Optical Sensor," http://archives.sensorsmag.com/articles/0499/0499_58/ (Accessed 18 MAR 2016)

28. Surya, M. S. and Atla, S., "Effect of Approach Angle in Face Milling Using Tungsten Carbide Tool," International Journal of Recent advances in Mechanical Engineering, Vol. 4, No. 2, pp. 15-27, 2015.

29. Palanikumar, K., "Modeling and Analysis for Surface Roughness in Machining Glass Fibre Reinforced Plastics using Response Surface Methodology," Materials & Design, Vol. 28, No. 10, pp. 2611-2618, 2007.