IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 26, 2019, accepted September 17, 2019, date of publication September 30, 2019, date of current version October 16, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2944769

On-Line Surface Roughness Prediction by Using a Probabilistic Approach for End-Milling

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ABSTRACT An effective and efficient methodology is proposed to predict surface roughness by online monitoring of surface quality using accelerometer signals. A probabilistic approach, Monte Carlo Simulation, was researched and developed to create an automated tool for on-line prediction of surface quality. Data from 3-axis vibration (Vx, Vy, Vz) signals were used to predict on-line surface roughness. According to an experimental design with four cutting parameters (Cutting speed (Vc), Feed per teeth (Sz), Dept of cut (Dc), Width of cut (Wc)), three-axis vibration signals were used to combine data into a probabilistic model for development of an on-line surface roughness prediction system. Once the probability model was established by using a data set consisting of 71 experiments, the model was tested for 10 different cutting conditions. The probability model shows that the results have convergence values that are close to each other, by as high as 96.37%.

INDEX TERMS Accelerometers, materials processing, metal products, Monte Carlo methods, probabilistic logic, surface roughness.

I. INTRODUCTION

Surface finish quality is an essential requirement of a machined product in today's competitive manufacturing industry. As a classifier of surface finish quality, surface roughness (Ra) may be used to determine irregularities of the machined surface of a product.

In reality, every product is manufactured with a deviation from its desired ideal geometry. During manufacturing processes, machined part surfaces get damaged more or less depending on the machining procedure that is implemented. This damage is decisive for the subsequent properties of the manufactured part such as sliding, lubricating, contact and straightness. To ensure that functional characteristics can be maintained as an important customer request, the surface quality must be checked and classified. For this reason, surface roughness has been one of the most frequently studied subjects in metal cutting by many researchers as a result of industrial quality requirements.

Surface roughness may be directly measured by using various methods, but the most widely used method by common consent is the stylus procedure which is based on mechanical contact. This standardized method is based on a mechanical pulling movement of a diamond-tipped stylus with a radius of 2 to 5 μm in a straight direction over the surface to be evaluated. The deflections of the stylus recordings are converted into electrical information and then amplified electronically for computation of standardized parameters (Ra, Rq, Rz, etc.). The surface roughness measurement diagram is shown in Fig. 1.

Measurement of surface roughness of machined parts must satisfy the following setup performance requirements:

- The machined surfaces must be cleaned from chips and coolants against any interference in measurement.
- The stylus tip must be set on the machined surfaces at the required position carefully. And then, the measurement process must be performed without any manual contact or vibration.
- The stylus tip must be checked periodically and calibrated, if necessary, to ensure that it is not cracked, chipped, stained or otherwise defective.

Because of these time-consuming and labor-intensive setup requirements listed above, modern industry expectations force researchers to focus on new methods for fast and in-process evaluation of surface quality for development of fully automated manufacturing processes.

The associate editor coordinating the review of this manuscript and approving it for publication was Jenny Mahoney.

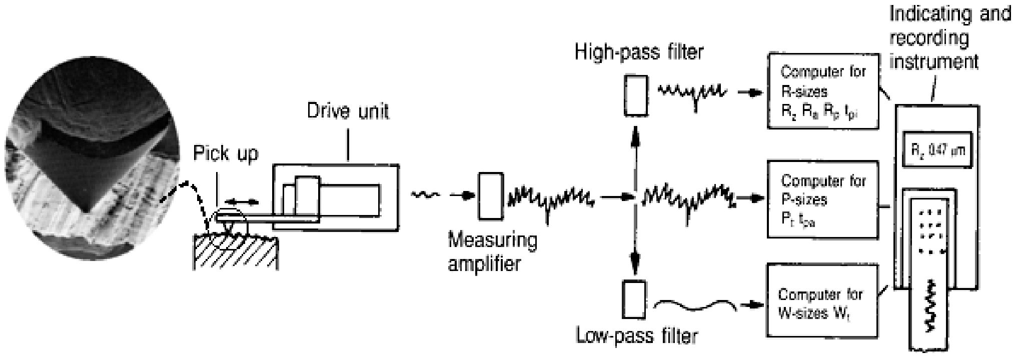


FIGURE 1. A typical mechanism of standardized Stylus tip surface profilometer [1].

An on-line surface roughness prediction system is an approach to indirectly detect surface roughness while machining. Surface roughness is influenced by both controlled factors such as the cutting tool geometry and cutting conditions (depth of cut, cutting speed, feed rate, etc.) and more complex uncontrolled factors such as the microstructure of the work piece, rigidity of the milling process and chatter [2]. On-line surface roughness prediction systems have an advantage of gathering information about uncontrolled process events. In an on-line monitoring system, usage of various highly sensitive sensor equipment needs to be integrated into machining tools. Subsequently, acquired uncontrolled process parameters can be analyzed together with controlled parameters.

Utilization of different sensors has been reported in research on on-line monitoring of surface roughness in end milling such as studies on Dynamometers [3], [4], Accelerometers [5]–[8], Ultrasonic sensors [9] and Optical sensors [10]. Moreover, these studies also include several mathematical models based on statistical regression or artificial intelligence techniques. These models have been constructed to establish the relationship between cutting performance and surface roughness.

In this study, a 3-axis accelerometer sensor was used to develop an on-line surface roughness prediction system. Additionally, a probabilistic model was established and introduced to analyze the relationship between 3-axis vibration signals and off-line surface roughness measurements (Ra). Unfortunately, in reality, uncertainties exist in the manufacturing system and environment that make implementation more sophisticated for a deterministic and reliable decision. That is, the values of the variables that are acting on the system cannot be predicted with certainty. For this reason, a probabilistic approach was implemented on the model after deterministic design results. Thus, by using a probabilistic approach, the probability of the cutting system was quantified.

In this study, an effective and efficient methodology is proposed to predict surface roughness with on-line monitoring of surface quality using accelerometer signals. In this strategy, a data acquisition system with tool vibration signals, surface roughness measured from a particular material and a probabilistic approach — Monte Carlo Simulation — were combined together to create an automated tool for on-line prediction of surface quality. Using this approach, a probabilistic model was generated by utilizing experimental data, which have a poorer correlation with real-time acquired data from 3-axis vibration (Vx, Vy, Vz) signals to predict on-line surface roughness. The details of the methodology are given in the following sections.

TABLE 1. Cutting parameters and ranges for design of 81 experimental runs.

Cutting Speed (Vc-m/min)	Feed per Tooth (Sz- mm/rev)	Depth of Cut (D_c-mm)	Width of Cut (W_c- mm)
150	0.06	0.25	1
175	0.08	0.50	2
200	0.10	0.75	3

II. METHODOLOGY

A. EXPERIMENTAL SETUP

The main aim of this study is to identify an appropriate technique for surface quality monitoring during milling by utilizing sensory signals. An integrated roughness monitoring system was designed and employed to acquire multiple vibration signals at 3 axes, namely, the Vx, Vy and Vz components. The output signals were analyzed in the time domain to identify the key characteristics of the signal that correlate/identify some important milling tool conditions. For this reason, a general full-factorial experimental design (DOE) was implemented for the employed cutting conditions. At least four independent parameters for performing a milling operation had to be determined before machining: Cutting speed (Vc), Feed per tooth (Sz), Depth of Cut (Dc) and Width of Cut (Wc). These parameters were also selected for a full-factorial experimental design on three levels as given in Table 1.

According to the experimental design, 81 down milling cutting experiments were programmed by using the

FIGURE 2. Experimental setup on machine tool.

TABLE 2. Chemical properties of aluminum alloy.

Si%	Fe%	Cu%	Mn%	Mg%	Cr%
0.250	0.382	0.485	0.325	2.720	0.284

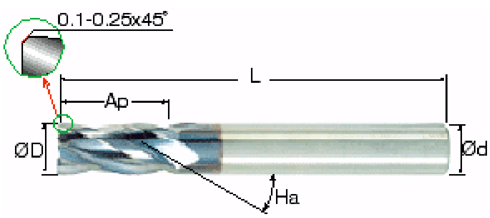


FIGURE 3. ISCAR solid carbide flat-end milling tool (ECC100A22-4C10-IC900) with four flutes.

Pro/Engineer PLM software. The DECKEL-MAHO DMU 60 P Rotary-Table type 5-axis universal machining center was used for machining (Fig. 2).

In the cutting process, an aluminum alloy piece was used which chemical properties analyzed in a spectral analyzer (SPECTRAMAXx©) as given in Table 2.

Tool wear is another important factor which influences surface quality. For this reason, a 10-mm-diameter ISCAR solid carbide flat-end milling tool (ECC100A22-4C10-IC900) with four flutes was used in the experiments for high wear resistance (Fig. 3). The chemical and physical properties of the cutting tools used in the experiments are shown in Table 3. The cutting speeds were chosen according to the

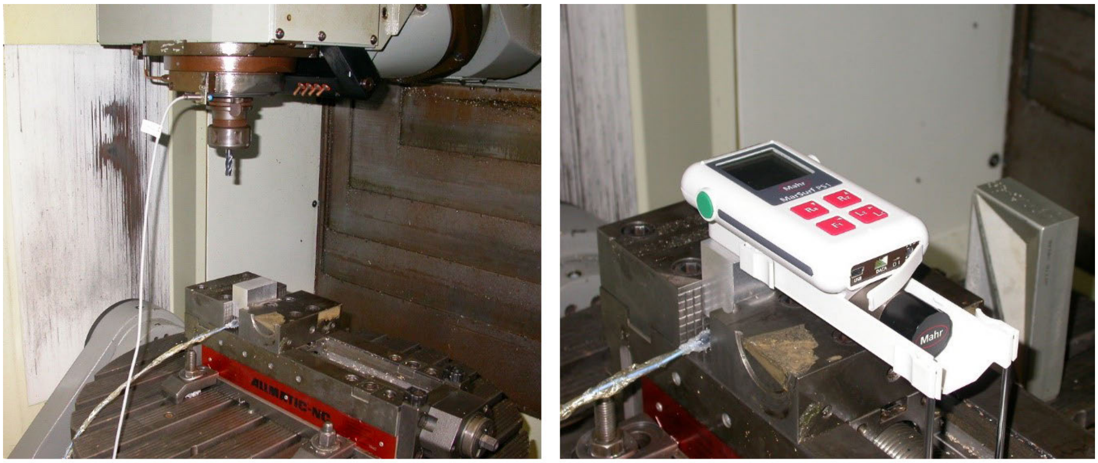
TABLE 3. Chemical and physical properties of cutting tool.

Parameter	Value
D (mm)	10
Flute	4
d (mm)	10
Ap (mm)	22
L (mm)	72
Ha (°)	30
Coating Type	PVD
Coating Layers	Ti Al
Density (g/cm^3)	14.47

manufacturer's values for the ISCAR milling cutters that we used in the tests.

Unfortunately, a sensory system is an extra major requirement for identification of cutting processes for developing an on-line or real-time surface roughness prediction system. In this study, PCB 356A31, a triaxial accelerometer (±500 g) and PCB 480B21, a 3-channel signal conditioner, were used to capture vibration signals. Moreover, a proximity sensor (BDC Electronic, type DCA8/5608KS) placed at the spindle head was used for detection of the rotation of the cutting tool.

After each cutting experiment, the surface roughness of the machined surfaces was measured with an MAHR Surf PS1 surface instrument with a 2-μm stylus radius. The cutting tool was not replaced in each test. The aim here was to exactly simulate the machining process as the tool is not replaced every time a part is machined in the



(a) (b)

FIGURE 4. a. Cutting process and location of the sensors. b. Surface roughness measurement.

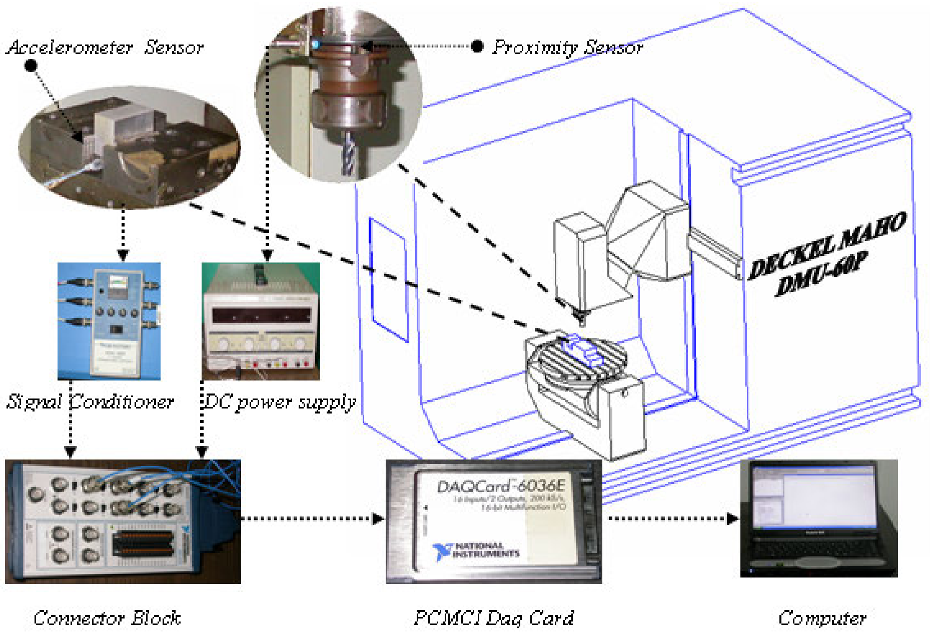


FIGURE 5. Hardware and wiring set-up for the online surface roughness prediction system.

factory environment. The measurements were performed at both directions — vertical and parallel to the cutting direction — and recorded from 3 different locations. The average of the Ra measurements from each set of cutting experiments was used as the main roughness value of the machined surface. Our aim in this study was to measure the surface roughness value as it directly affected the quality of the product. Moreover, for roughness measurements, the cut-off length of the stylus gouge was set to be 6 mm. This process is illustrated in Fig.4 b.

For digitizing and recording the analogue sensor signals, a National Instruments (NI) PCMCI 6036E multifunction data acquisition card was used with an NI BNC 2110 connection block. Signals from sensors were acquired with software developed in the MATLAB Data Acquisition Toolbox V2.9 [11]. The vibrations were measured for each revolution throughout the entire machining process. Fig. 5 shows the hardware and wiring architecture for the online surface roughness prediction (OSRP) system.

The collected signals have to be processed in order to develop an OSRP system. For this reason, a MATLAB program was developed to collect and cooperatively analyze the 3-axis vibration signals generated by the cutting process and the proximity signal for marking the spindle revolution at 10 K samples per second. As given in Fig. 6 with the help of

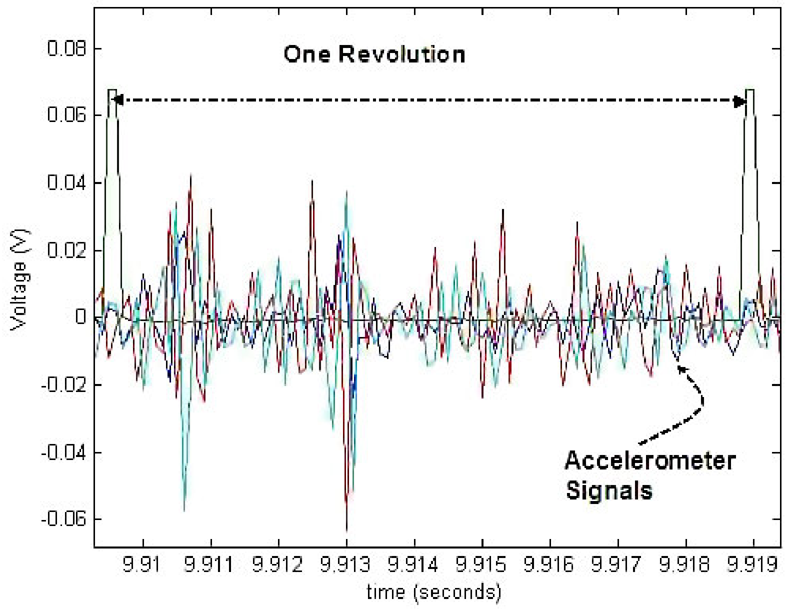


FIGURE 6. Extraction of vibration signals in one revolution of spindle period (Data were logged from cutting conditions of Vc = 200 m/min, Sz = 0.1 mm/rev, equivalent to 6366RPM Spindle Speed and 2547mm/min Feed Rate, 0.75mm Depth of Cut and 2mm Width of Cut).

the proximity signal peaks, the vibration signals were cropped for each revolution.

For statistical feature extraction, the average of absolute vibration data (Vx, Vy, Vz) from the accelerometer signals was calculated for each revolution. The following equation (1) allows three units of average vibration data to be calculated:

$$V_{(x,y,z)} = \frac{1}{n}\sum_{i=1}^{n} |Vibration(i)| \tag{1}$$

where n represents the total number of data units in each revolution (as indicated in Fig. 6), and Vibration(i) represents the vibration data from 1 to n that were recorded as Voltage for a spindle cycle. For comparison and identification, 81 Ra values were collected from all 81 machined surfaces after machining.

Next, the average of all these absolute values from the vibration data was calculated for the probabilistic approach as described in the following sections.

B. PROBABILISTIC METHODS

The probabilistic response of the surface roughness was modeled as follows (2) [12].

$$Z(X) = Z(X1, X2, X3, \ldots, Xn) \tag{2}$$

Z(X) is a random variable describing the response of the system (for example, 3-axis vibration signals with RMS, mean, median, standard deviation, skewness values), and Xi (i = 1, n) are random variables describing the model input variables. In this study, Z corresponded to the experimental data obtained as output signals. For the probabilistic response, Monte Carlo sampling techniques were used. The Monte Carlo method provides approximate solutions to a variety of mathematical problems by performing statistical sampling experiments on a computer.

In a probabilistic analysis, the probability of failure may be quantified by formulating a performance function, which is a function of random variables, by comparing the probabilistic response of the structure.

In serial manufacturing processes, every product differs from others slightly. These differences are a cause of uncertainties in the material, human factor, dimensioning, machine settings, etc. If there are enough samples, each design parameter can be plotted, and the frequency of each design parameter leads to the probability of that design parameter. After that moment, each design parameter is called a random variable. In traditional engineering calculations, the mean value of each random variable is used. However, random variables are not constant, and they change in a range. If the ranges of the results are important for the design, some other values should be used other than the mean value, such as the standard deviation. In standard calculations, the range factors in the results are eliminated by using safety factors. In probabilistic design, the probability distributions of the design parameters are calculated. Probability distribution results show the reliability change of the design. A designer uses the reliability values according to customer desires. This process leads to the maximum safety and quality with the minimum cost.

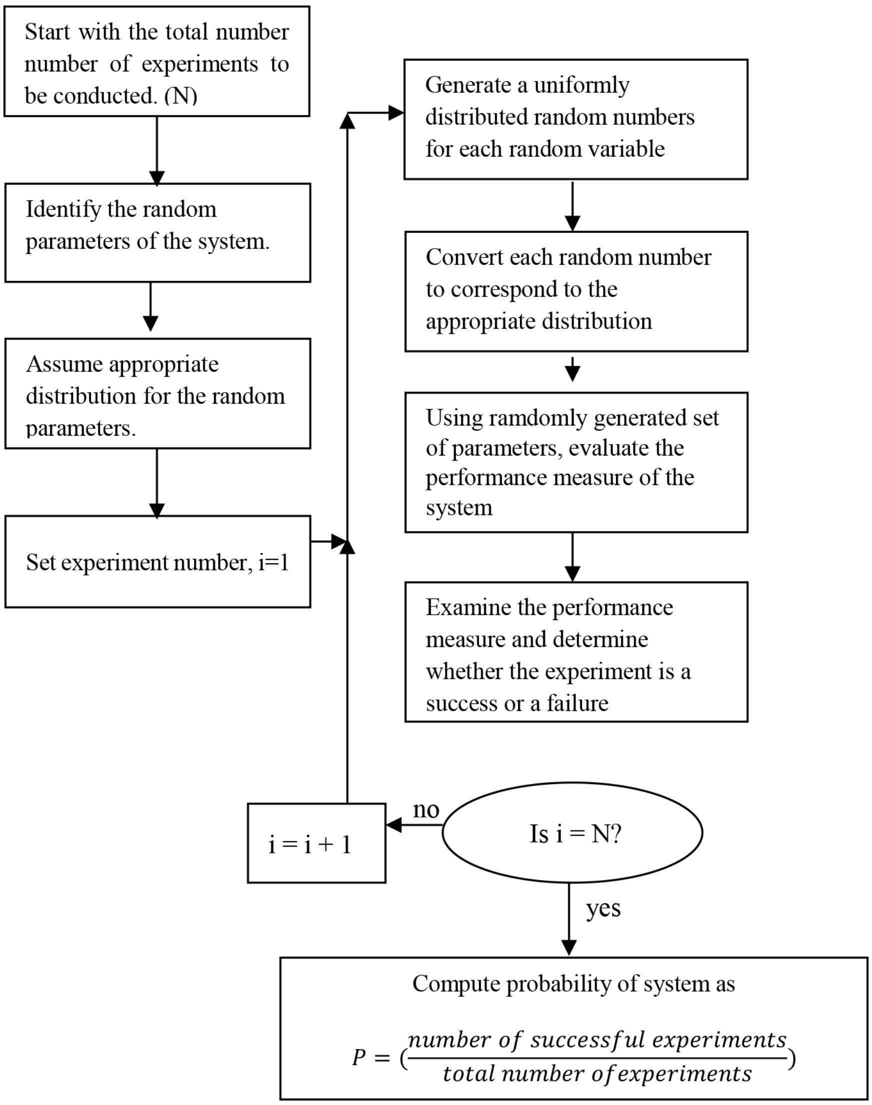


FIGURE 7. Algorithm of Monte Carlo Simulation.

The distributions of design parameters or independent random variables show a type. The most commonly used distribution types are normal, lognormal, uniform, exponential, triangular, beta, gamma and Weibull. The distribution types of the random variables are as shown in Table 4.

TABLE 4. Distribution types of variables.

Random Variable	Distribution Type	Mean Value	Standard Deviation
Vx (V)	Lognormal	0.029325	0.014942
Vy (V)	Lognormal	0.034237	0.017996
Vz (V)	Lognormal	0.028444	0.012936
Ra (μm)	Lognormal	0.878533	0.220400

C. MONTE CARLO SIMULATION

The flow chart of the Monte Carlo Method which is shown in Fig.7 is one of the techniques that edit the values of the parameters at each loop according to their probability of occurrence. In the Monte Carlo Method, uniform distributions of random numbers are generated. These values are transformed into numbers by using one of the parameter's cumulative distribution functions. The number transforming process is achieved based on the chosen parameter's probability density function. To reach a similar distribution type, large numbers of samples are required.

III. RESULTS

In this study, a probabilistic model was generated by utilizing experimental data which have a poorer correlation with real time acquired data from 3-axis vibration (Vx, Vy, Vz) signals to predict surface roughness online. For this reason,

TABLE 5. Cutting conditions and response data for experimental runs.

Run Order	V_c	S_z	D_c	W_c	Vx (V)	Vy (V)	Vz (V)	Ra (µm)	Run Order	V_c	S_z	D_c	W_c	Vx (V)	Vy (V)	Vz (V)	Ra (µm)
1	200	0.08	0.75	2	0.0456082	0.0501528	0.0585928	0.855	42	200	0.08	0.75	3	0.0655720	0.0360321	0.0290529	0.974
2	200	0.06	0.50	1	0.0318121	0.0331106	0.0365190	0.834	43	150	0.08	0.25	1	0.0235345	0.0188276	0.0129845	0.834
3	150	0.06	0.25	1	0.0126599	0.0120107	0.0167176	0.617	44	175	0.08	0.50	2	0.0228853	0.0376552	0.0462575	1.012
4	200	0.10	0.75	1	0.0290529	0.0326237	0.0316498	0.927	45	200	0.08	0.50	3	0.0512890	0.0796927	0.0350583	1.101
5	150	0.06	0.50	1	0.0150945	0.0254822	0.0279168	0.694	46	150	0.10	0.75	3	0.0324614	0.0665458	0.0522628	1.227
6	200	0.10	0.25	3	0.0253199	0.0261314	0.0321368	0.982	47	175	0.10	0.25	1	0.0275922	0.0206130	0.0165553	0.893
7	200	0.08	0.75	1	0.0232099	0.0303514	0.0275922	0.548	48	175	0.06	0.25	2	0.0274299	0.0322991	0.0147699	0.815
8	150	0.10	0.75	2	0.0228853	0.0288906	0.0279168	1.130	49	200	0.10	0.50	1	0.0483674	0.0485298	0.0430113	0.999
9	200	0.06	0.50	3	0.0355452	0.0551843	0.0444721	0.702	50	175	0.06	0.75	3	0.0756350	0.0335975	0.0344091	1.500
10	150	0.10	0.50	2	0.0253199	0.0486921	0.0342467	1.062	51	150	0.08	0.25	3	0.0324614	0.0199637	0.0144453	0.950
11	200	0.08	0.25	1	0.0121730	0.0196391	0.0238591	0.741	52	175	0.10	0.75	2	0.0277545	0.0418752	0.0345714	1.040
12	200	0.08	0.50	1	0.0405767	0.0383044	0.0292152	0.549	53	175	0.10	0.50	2	0.0392783	0.0585928	0.0491790	0.880
13	150	0.06	0.75	1	0.0173668	0.0180161	0.0214245	0.542	54	175	0.10	0.25	2	0.0360321	0.0274299	0.0287283	1.027
14	175	0.06	0.75	1	0.0094138	0.0146076	0.0094138	0.466	55	175	0.10	0.50	3	0.0198014	0.0332729	0.0261314	1.167
15	175	0.08	0.25	2	0.0128222	0.0222360	0.0128222	0.836	56	175	0.08	0.50	1	0.0313252	0.0399275	0.0459328	0.635
16	200	0.10	0.50	3	0.0194768	0.0217491	0.0256445	0.854	57	200	0.08	0.25	2	0.0215868	0.0245083	0.0240214	0.921
17	150	0.06	0.75	2	0.0121730	0.0168799	0.0219114	0.805	58	175	0.10	0.75	1	0.0402521	0.0370060	0.0222360	0.895
18	175	0.06	0.50	1	0.0105499	0.0128222	0.0102253	0.680	59	200	0.06	0.25	3	0.0163930	0.0279168	0.0170422	0.668
19	150	0.06	0.25	3	0.0048692	0.0029215	0.0030838	0.913	60	150	0.10	0.50	1	0.0454459	0.0311629	0.0238591	1.077
20	150	0.08	0.50	2	0.0107123	0.0120107	0.0076284	0.859	61	150	0.06	0.25	2	0.0538859	0.0202884	0.0256445	0.718
21	150	0.06	0.75	3	0.0045446	0.0032461	0.0047069	1.293	62	200	0.08	0.50	2	0.0287283	0.0662212	0.0389536	1.049
22	150	0.10	0.25	2	0.0128222	0.0303514	0.0147699	1.517	63	150	0.08	0.75	3	0.0615143	0.0460951	0.0508020	1.098
23	200	0.06	0.50	2	0.0306760	0.0361944	0.0206130	0.559	64	150	0.06	0.50	3	0.0146076	0.0418752	0.0352206	1.353
24	175	0.10	0.75	3	0.0366813	0.0348960	0.0337598	1.147	65	175	0.08	0.75	2	0.0337598	0.0650850	0.0506397	0.940
25	200	0.10	0.25	2	0.0272676	0.0329483	0.0259691	0.939	66	200	0.10	0.75	2	0.0271052	0.0501528	0.0482051	0.775
26	175	0.08	0.75	3	0.0439852	0.0626504	0.0308383	0.879	67	150	0.08	0.50	1	0.0288906	0.0420375	0.0360321	0.856
27	175	0.08	0.50	3	0.0524251	0.0869965	0.0496659	1.115	68	175	0.10	0.25	3	0.0282414	0.0240214	0.0223983	1.071
28	200	0.06	0.75	2	0.0308383	0.0238591	0.0206130	0.460	69	200	0.06	0.75	3	0.0272676	0.0420375	0.0425244	0.976
29	200	0.10	0.50	2	0.0603782	0.0527497	0.0504774	0.834	70	150	0.10	0.25	3	0.0285660	0.0305137	0.0271052	0.991
30	150	0.08	0.50	3	0.0475559	0.0357075	0.0198014	0.935	71	150	0.08	0.75	1	0.0183407	0.0258068	0.0431736	0.862
31	175	0.06	0.50	3	0.0319745	0.0717396	0.0344091	0.655	72	175	0.06	0.25	1	0.0172045	0.0230476	0.0133092	0.646
32	150	0.08	0.75	2	0.0246706	0.0396029	0.0269429	0.906	73	175	0.08	0.25	3	0.0183407	0.0305137	0.0326237	0.903
33	200	0.10	0.75	3	0.0641112	0.0842373	0.0602158	0.678	74	150	0.10	0.75	1	0.0288906	0.0569697	0.0409013	0.831
34	150	0.10	0.25	1	0.0214245	0.0134715	0.0142830	0.870	75	150	0.10	0.50	3	0.0631374	0.0629751	0.0384667	1.269
35	150	0.08	0.25	2	0.0150945	0.0198014	0.0168799	0.930	76	175	0.06	0.75	2	0.0233722	0.0279168	0.0162307	0.748
36	175	0.06	0.25	3	0.0188276	0.0146076	0.0155815	0.808	77	175	0.08	0.75	1	0.0189899	0.0308383	0.0389536	0.540
37	150	0.06	0.50	2	0.0363567	0.0249953	0.0214245	0.749	78	200	0.06	0.75	1	0.0386290	0.0155815	0.0181784	0.570
38	175	0.06	0.50	2	0.0212622	0.0290529	0.0271052	0.593	79	175	0.08	0.25	1	0.0185030	0.0204507	0.0233722	0.720
39	200	0.06	0.25	1	0.0181784	0.0210999	0.0217491	0.665	80	175	0.10	0.50	1	0.0308383	0.0387913	0.0248329	1.122
40	200	0.10	0.25	1	0.0194768	0.0155815	0.0202884	0.848	81	200	0.06	0.25	2	0.0230476	0.0157438	0.0144453	0.769
41	200	0.08	0.25	3	0.0232099	0.0251576	0.0183407	0.766									

TABLE 6. Verification of the model according to 10 experiments.

Vx	Vy	Vz	Ra	Prediction of Ra	Convergence (%)	Mean Square Percentage Error (%)
0.028728	0.066221	0.038954	1.048	1.008	95.97	4.22
0.061514	0.046095	0.050802	1.098	1.054	95.71	4.51
0.014608	0.041875	0.035221	1.353	1.300	94.59	5.66
0.033760	0.065085	0.050640	0.940	0.911	97.18	2.95
0.027105	0.050153	0.048205	0.750	0.733	95.90	4.30
0.028891	0.042037	0.036032	0.860	0.804	94.87	5.35
0.028241	0.024021	0.022398	1.070	1.057	98.71	1.32
0.027268	0.042037	0.042524	0.977	0.954	97.82	2.13
0.028566	0.030514	0.027105	0.992	0.951	96.03	4.12
0.018341	0.025807	0.043174	0.863	0.832	96.98	3.06

81 experimental runs were programmed and developed by implementing a three-level general fully factorial design. In the cutting experiments, the aluminum alloy material was cut by using 4 cutting conditions (Vc, Sz, Dc Wc). During each machining process of the 81 experiments, 3-axis accelerometer vibration signals (Vx, Vy, Vz) and proximity signals were collected synchronously by using a DAQ system at a 10-K sampling rate. The average of the 3-axis vibration signals was calculated according to a revolution of the spindle for each condition as given in Table 5.

71 experimental data inputs were randomly selected for generating a probabilistic model. So, the remaining

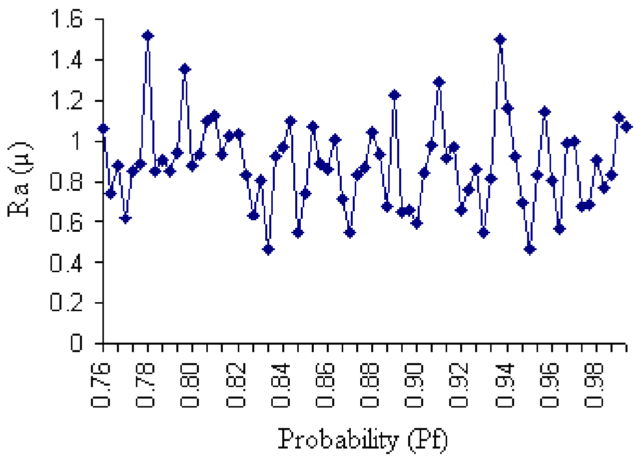


FIGURE 8. Probability distribution of Ra values according to vibration data.

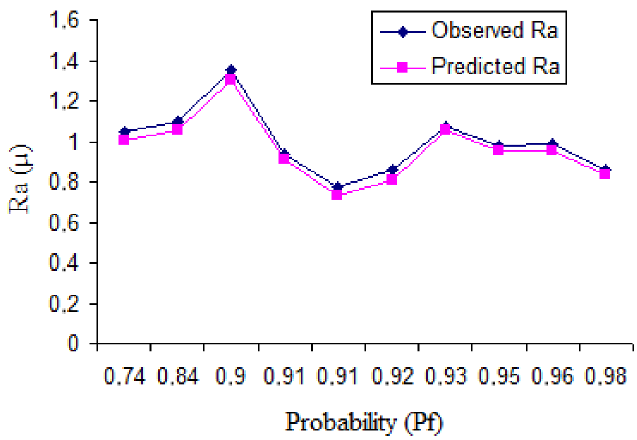


FIGURE 9. Observed and predicted surface roughness values.

10 experimental inputs were reserved for verification of the probabilistic model. These 71 pre-processed average vibration signals and Ra results were imported into a code written in MATLAB. The probability of surface roughness at each condition was predicted by using the output signals. The probability distributions of surface roughness values according to average Vx, Vy and Vz vibration signals are shown in Fig. 8.

To verify the OSRP system, the Vx, Vy and Vz signals of 10 experiments were embedded in the model that was developed. Fig. 9 shows the comparison of the predicted and observed Ra values corresponding to the acquired online Vx, Vy, Vz signals. The figure also shows the probability of the predicted surface roughness (Ra) values.

As shown in Table 6, for the Vx, Vy, Vz values of 10 randomly selected experiments, the predicted surface roughness (Ra) values were converged to observe the surface roughness Ra values at a rate of as high as 96.37% on average.

Additionally, similar to the DIN 4766 standard, a user-defined tolerance limit was assigned between 0.4 and 1 μm to impose the OSRP system code. A warning for the operator

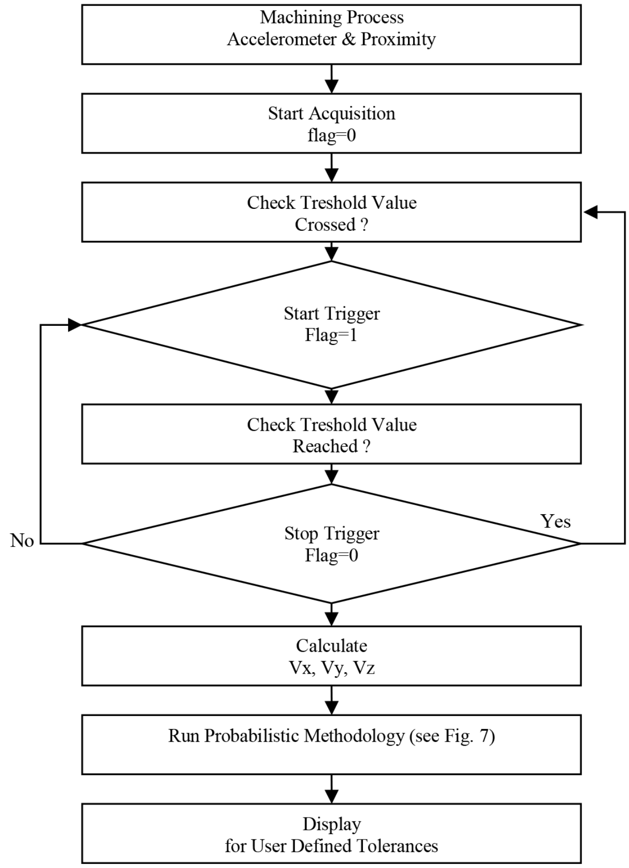


FIGURE 10. Flow chart of OSRP algorithm.

will be generated while exceeding the determined limit (Ra>1 μm) as shown in the flow chart of the OSRP system algorithm (Fig. 10).

IV. CONCLUSION

Off-line direct surface quality inspection techniques need time-consuming and labor-intensive setup requirements that are sometimes unacceptable due to the fact that they slow down the productivity of the manufacturing process. In this study, an on-line surface roughness prediction system was described for end-milling operations.

Many controlled and uncontrolled complex factors in the milling process affect surface roughness. In some circumstances, as presented herein this study, there may be less significant relationships between surface roughness and input parameters such as cutting conditions or sensor signals. In this study, there was quite a number of clusters for the observed data, but also, quite a number of overlaps. For this reason, it was difficult to predict surface roughness by using mathematical methods such as regressions, artificial intelligence (AI) or fuzzy algorithms. Therefore, a probabilistic approach was introduced and used to solve this uncertainty in this study. According to the experimental design with four cutting parameters, three-axis vibration signals were combined into a probabilistic model for development of an on-line surface roughness prediction system. Once the probability model was established by using the data set of 71 experiments, the model was tested for 10 different cutting conditions. The probability model shows that the results that were obtained had convergence values that were close to each other, by as high as 96.37%.

This means that, on-line surface roughness prediction (OSRP) systems may be designed and implemented by using probabilistic models. This will save time to establish the mathematical model for prediction of surface roughness in comparison to other mathematical models such as regression, response surface methodology, neural networks, and so forth.

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