Estimation of Surface Roughness in Turning by Considering the Cutting Tool Vibration, Cutting Force and Tool Wear

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Abstract: Surface quality along with the low production cost, play significant role in today's manufacturing market. Quality of a product can be described by various parameters. One of the most important parameters affecting the product quality is surface roughness of the machined parts. Good surface finish not only assures quality, but also reduces the product cost. Before starting any machining process, surface finish is predictable using cutting parameters and estimation methods. Establishing a surface prediction system on a machine tool, avoids the need for secondary operation and leads to overall cost reduction. On the other hand, creating a surface estimation system in a machining plant, plays an important role in computer integrated manufacturing systems (CIMS). In this study, the effect of cutting parameters, cutting tool vibration, tool wear and cutting forces on surface roughness are analyzed by conducting experiments using different machining parameters, vibration and dynamometers sensors to register the amount of tool vibration amplitude and cutting force during the machining process. For this, a number of 63 tests are conducted using of different cutting parameters. To predict the surface quality for different parameters and sensor variables, an ANN model is designed and verified using the test results. The results confirm the model accuracy in which the R^2 value of the tests was obtained as 0.99 comparing with each other.

Keywords: Artificial neural networks, Cutting forces, Surface roughness, Vibration

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1 INTRODUCTION

Machining operations usually face challenges to achieve high quality in terms of parts dimensional accuracy, high surface quality, economy of machining in terms of cost saving. Among these challenges, surface roughness has a great influence on product quality, and the part functional properties such as lubricant retentively, void volume, load bearing area, and frictional properties. On the other hand, a high-quality machined surface significantly improves fatigue strength, corrosion resistance, and creep life [1].

Surface roughness is a commonly encountered problem in machined parts. It is defined as the small irregularities of surface texture, which results from the operations of the machining process. Surface roughness is consisting of a multitude of apparently random peaks and valleys [2]. Surface roughness in contacting surfaces, influences the frictional properties of those surfaces during the forming processes [3]. Based on the results of studies over the years, it is well known that the final state of surface roughness is influenced by machining parameters and variables such as spindle speed, feed, and depth of cut, tool flank wear, and vibration level [4, 5].

The relative motion between the cutting tool and work piece will affect the quality of the machining and the surface finish. In turning, the presence of tool vibration is a major factor which leads to poor surface finish [6], [7]. Some researchers have indicated that the vibration amplitude during a machining process causes a worse surface quality in machine parts [8]

Also, the surfaces produced on the workpiece are greatly influenced by the cutting parameters and the cutting force [9, 10]. Researchers in their study have indicated that there are a relationship between the machining parameters such as cutting speed, feed rate and depth of cut and the surface roughness of the machined part [11], [12].

Therefore, the models of surface roughness proposed in previous studies have been made by setting different values of the cutting parameters to show a strong relationship dependency between the independent inputs and the desired output (surface roughness) [5]. Nowadays, researchers are trying to develop a robust and accurate model, which can describe correlations between the cutting parameters and the surface roughness of the machined products. Tool wear is another factor that surface quality is directly influenced by this incident. Tool wear causes a poor surface on the machined parts which in turn increases the production cost. Previous researches have indicated the influence of the tool wear on the surface roughness [13], [14].

Prediction of the surface roughness by using the influencing parameters and variables have been studied by several researchers to enhance the quality of the parts in an affordable manner. There are many prediction tools to achieve accurate results such as artificial neural network, analytical models (ANN), fuzzy logic and etc. [15], [16].

Rahman et al [17], developed a neural-network-based method for on-line fault diagnosis which monitors the level of chatter vibration in a turning operation. The experimental results demonstrated that the model has a high prediction success rate. Lin et al.[18], used a network to create a prediction model for surface roughness and cutting force and claimed that this approach is more reliable than that by regression analysis. Surjya K. Pal et al [19], have applied the back propagation neural network approach to estimate the surface roughness in turning with a HSS tool and compared the predicted and the measured values.

Dimla [17], studied the application of perceptron type of neural networks to tool state classification during turning process. Salgado et al[20], used least-squares support vector machine to predict the surface roughness values given the cutting conditions and the features extracted from the vibration amplitude signals. Daniel Kirby et al [1], used the mean of the vibration signals in the prediction of surface roughness in turning process.

Zhang and Chen [21], developed a process surface roughness adaptive control system in machining of AA6061 alloy. They conducted experiments in all parameters of spindle speed, feed rate and depth of cut factor levels by the use of full factorial experimental design method. The surface roughness was estimated with 91.5% accuracy with the system that can recognize cutting force signals collected during machining and the feed rate was modified in terms of desired surface roughness. Surface roughness estimation modal was presented based on response surface method to investigate the machining parameters such as feed rate, tool geometry and machining time, affecting the roughness of surface produced in dry turning operation [22].

In this study, the effect of cutting parameters, tool vibration amplitude, tool wear and cutting force variation on surface roughness of machined parts is investigated during a turning process. By conducting the experiments using of cutting parameters combinations, cutting force values, vibration amplitudes and tool wear rates were measured and analyzed based on a Taghuchi method.

Artificial neural network (ANN) method was then applied for constructing the estimation model of surface roughness using cutting parameters and measured variables. The obtained results from the ANN method are compared with the measured values of surface roughness to find the reliability and accuracy of the developed method.

2 EXPERIMENTS

In this paper, the effects of cutting parameters and some measured variables on the surface roughness are investigated using some designed experiment. Johnford *TC-35* CNC machine tool was used to perform the experiments. A Sandvik- Coromant insert (TNMG 1604-QM H13) was selected as the cutting tool and a TIZIT Simple (CTANR 2525M16) marked tool was considered as tool holder. The material used for machining was SAE 1050 with $\emptyset 100 \times 1000$ mm of dimension. Chemical Properties of the workpiece are given in Table 1. The cutting parameters used for machining operation were given in Table. 2.

A Dino Capture microscope was used to measure the flank wear. Cutting forces were measured using a Kistler 9272 4-component dynamometer. A TV300 type vibration sensor was used for measuring the vibration signal amplitudes. To evaluate the vibration conditions, the displacement, acceleration and velocity variables can be measured by the sensor. The sensor measures the root mean square (RMS) of the variables. Average surface roughness (Ra) was measured using “Mahr-Perthometer M1”, a surface roughness measuring machine (Fig. 1).

Fig. 1 Mahr-Perthometer M1 surface roughness tester

Table 1 The chemical properties of the workpiece

workpiece	SAE1050 (AISI 1050)							
Chemical compositions (%)	C	Si	Mn	Cr	P	S	Mo	N
	0.49	0.19	0.65	0.03	0.01	0.005	0.01	0.08

Table 2 The cutting parameters

Cutting speed (m/min)	Feed rate (mm/rev)	Cutting depth (mm)	Tool flank wear intervals (mm)
115	0.2	0.7	Initial (0), 0.05, 0.1, 0.15, 0.2, 0.25, 0.3
140	0.25	1.2	
165	0.3	1.7	

The measurements were repeated three times in 10 mm sample length. The range for tool wear was selected between 0-0.3 for a new and worn tool respectively based on ISO3685 standard. For conducting the experiments for investigation of the surface roughness, a total of 63 experiments were designed using Taghuchi L9 array and by taking in to account the wear ranges as: 0, 0.05 0.1, 0.15, 0.2, 0.25, 0.3 mm. Using cutting parameters and Taghuchi method, the researchers created an experimental array for conducting the tests. The cutting force (F_c) and average vibration amplitudes were measured for any of the tests using the sensors.

3 ARTIFICIAL NEURAL NETWORK

Artificial Neural network or parallel distributed processing is an alternative to sequential processing of knowledge as known from symbolic programming [23]. In analogy to the human brain, artificial neural networks consist of single units (neurons) that are interconnected by the so-called synapses. The typical network has 1 input layer, 1 or more hidden layers, and 1 output layer. Each layer has some units corresponding to neurons. The units in neighboring layers are fully interconnected with links corresponding to synapses. The number of hidden layers or number of neurons in hidden layers is defined based on the experience of the model designer which in turn depends on the data set, accuracy of the model and etc.

A small number of hidden layers should be used when the training sample size is moderate or the number of input and output neurons is small. In general, small number of hidden layers and neurons cause inaccurate results where as large number of hidden layers and neurons results in over fitting. Although, there are some methods for determining the number of layers and neurons, they are not useful in many cases [24]. The strengths of the connections between 2 units are called “weights”. In each hidden layer and output layer, the processing unit sums its input from the previous layer and then applies the activation function to compute its output to the next layer according to the following equations [25].

$$v = \sum_{i=0}^{n} w_{ij} x_i \text{ or } \quad v = \sum_{i=0}^{n} w_{ij} x_i + b \quad , \tag{1}$$

where wij is the weight from node i in the input layer to node j in the hidden layer, x_i is the ith input element; and n is the number of nodes in the input layer. After obtaining the results, a nonlinear activation function is used to regulate the output of a node, shown as follows:

$$y = F(v) \tag{2}$$

where F(v) is the output of the jth node in the hidden layer. Subsequently, output from the hidden layer is used as input to the output node. Finally, the overall response from the network is obtained via the output node in the output layer [26]. Sum of squared errors for the nth iteration is defined as:

$$\sum_{i=1}^{k} E_i = \frac{1}{2}\sum_{i=1}^{k}(h_i - y_i)^2 \tag{3}$$

Where $(h_i - y_i)^2$ represents the squared of error values at the output neuron and shows the difference between desired response (h) and computed response (y). The weights are updated based on the errors in such a way that the error signal is minimized to the required threshold. There are some algorithms for updating the weights. In this study the back propagation method has been used to change the weights during the training. This method starts renewing the weights from outputs to inputs. These weights are updated automatically based on the algorithm.

4 SURFACE ROUGHNESS MODELING

After designing and conducting the experiments, the cutting parameters, vibration amplitude, cutting forces and tool flank wear were used as input and the surface roughness as output to train the ANN model. Pythia program was used to train the model. Various number of neurons and layers were tried in this paper to avoid the over fitting problem and the best ANN structure was selected as the surface roughness predictive model. The developed ANN model was designed in three layers and ten neurons. Fig. 2 shows the general structure of the ANN model. As it is seen in Fig. 2, there are six inputs and one output, six neurons in first layer, three neurons in second layer and one neuron in third layer of the model. "logistic" function was used as activation function for estimating the values of any neurons. The function is defined as:

$$F(x) = \frac{1}{(1 + e^{-k(x-x_0)})} \tag{4}$$

In which, k is the steepness of the curve, e is the natural logarithm, x_0 is the x-value of Sigmund's midpoint. A diagram of logistic function for special conditions of the parameters is given in Fig. 3. Since the results of the used logistic activation function is limited between -1 and +1, all of the data are normalized between -1 and +1. Normalization Formula can be written as:

$$\acute{x} = \frac{x - x_{average}}{x_{max} - x_{average}} \tag{5}$$

Where, x is the value of data, $x_{average}$ is the data average, x_{max} is the maximum value and $\acute{x}$ is the normalized value of the data. Table. 3, shows the data and their normalized values. After training process, the estimated values must be denormalized to reach the real values.

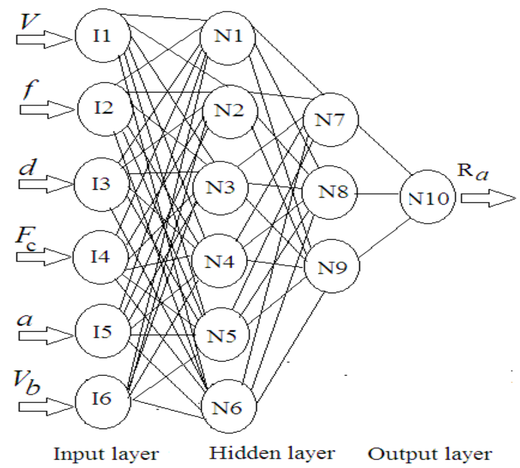

Fig. 2 The designed ANN model

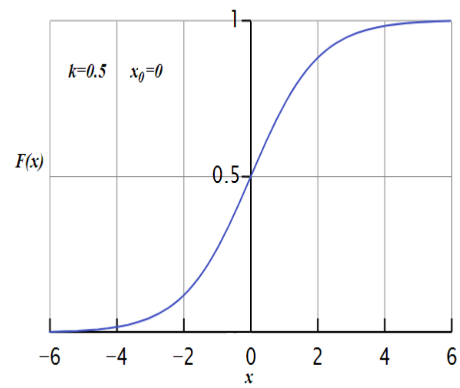

Fig. 3 Logistic activation function diagram for k=0.5 and $x_0 = 0$

5 RESULT AND DISCUSSION

As was mentioned earlier, a multilayer feed-forward back-propagation network was used to design the ANN estimation model of surface roughness. In ANN model, the cutting parameters, Vibration amplitude, cutting force and tool flank wear, were considered as inputs and the measured surface roughness values as target data. Three layers and 10 neurons were selected for designing the model. The network architecture consisted of 6 inputs including: cutting speed (v), cutting depth (d), feed rate (f), cutting force (F_c), vibration amplitude (a), tool wear (V_b). In the experiments, based on Taghuchi design, 63 experiments were prepared in three levels of any cutting parameters and seven levels of tool flank wear including; initial (0), 0.05, 0.1, 0.15, 0.2, 0.25, 0.3 mm for training the network.

The model was trained using Pythia software and the weights were created for the reproduction phase. The weights are given in Table.5 with w_{ni} in which, n is the number of the neurons and i is the number of the weights. Therefore, there are 36 weights in first layer, 18 weights in second layer and three weights in third layer. After creating the weights, they were used to estimate the values of surface roughness for all inputs. By comparing the measured and estimated results, the error was obtained which shows that the model demonstrates an acceptable accuracy. The error and squared error distribution for all of the experiments are given in Fig. 4. As is seen in the figure, maximum error of the prediction model is about 1.05 mm and %95 of prediction errors is less than 0.4 mm.

Table 3 Normalized values of the data

N	V	f	d	V_b	F_c	a	R_a	N	V	f	d	V_b	F_c	a	R_a
1	-1	-1	-1	-1	-0.54	-0.68	-0.266	33	0	-1	0	0.33	-0.16	-0.03	-0.232
2	-1	-1	-1	-0.6	-0.522	-0.450	-0.255	34	0	-1	0	0.66	-0.14	0.16	0.035
3	-1	-1	-1	-0.3	-0.496	-0.221	-0.224	35	0	-1	0	1	-0.11	0.35	0.223
4	-1	-1	-1	0	-0.466	-0.05	-0.222	36	1	1	0	-1	-0.07	-0.50	0.206
5	-1	-1	-1	0.33	-0.436	0.121	-0.229	37	1	1	0	-0.6	-0.02	-0.30	0.211
6	-1	-1	-1	0.66	-0.420	0.226	-0.211	38	1	1	0	-0.3	0.015	-0.10	0.223
7	-1	-1	-1	1	-0.404	0.331	-0.182	39	1	1	0	0	0.04	0.07	0.355
8	0	1	-1	-1	-0.399	-0.603	-0.260	40	1	1	0	0.33	0.08	0.25	0.735
9	0	1	-1	-0.6	-0.375	-0.431	-0.092	41	1	1	0	0.66	0.10	0.45	0.826
10	0	1	-1	-0.3	-0.350	-0.26	0.171	42	1	1	0	1	0.12	0.65	1.000
11	0	1	-1	0	-0.335	-0.078	0.183	43	-1	1	1	-1	0.68	-0.48	0.184
12	0	1	-1	0.33	-0.320	0.102	0.188	44	-1	1	1	-0.6	0.72	-0.34	0.197
13	0	1	-1	0.66	-0.308	0.293	0.201	45	-1	1	1	-0.3	0.77	-0.20	0.201
14	0	1	-1	1	-0.296	0.484	0.243	46	-1	1	1	0	0.82	0.16	0.206
15	1	0	-1	-1	-0.621	-0.584	-0.066	47	-1	1	1	0.33	0.87	0.54	0.217
16	1	0	-1	-0.6	-0.599	-0.412	-0.083	48	-1	1	1	0.66	0.93	0.77	0.244
17	1	0	-1	-0.3	-0.578	-0.240	-0.084	49	-1	1	1	1	0.99	1	0.411
18	1	0	-1	0	-0.558	-0.040	-0.069	50	0	0	1	-1	0.37	-0.45	-0.122
19	1	0	-1	0.33	-0.538	0.16	-0.058	51	0	0	1	-0.6	0.41	-0.33	-0.108
20	1	0	-1	0.66	-0.496	0.33	-0.062	52	0	0	1	-0.3	0.46	-0.22	-0.10
21	1	0	-1	1	-0.455	0.50	0.024	53	0	0	1	0	0.48	-0.05	-0.100
22	-1	0	0	-1	-0.012	-0.60	-0.308	54	0	0	1	0.33	0.50	0.10	-0.077
23	-1	0	0	-0.6	0.017	-0.46	-0.250	55	0	0	1	0.66	0.51	0.36	-0.035
24	-1	0	0	-0.3	0.047	-0.31	-0.210	56	0	0	1	1	0.53	0.61	-0.031
25	-1	0	0	0	0.100	-0.01	-0.158	57	1	-1	1	-1	0.00	-0.54	-0.269
26	-1	0	0	0.33	0.153	0.29	-0.127	58	1	-1	1	-0.6	0.05	-0.33	-0.249
27	-1	0	0	0.66	0.154	0.49	-0.116	59	1	-1	1	-0.3	0.10	-0.12	-0.223
28	-1	0	0	1	0.156	0.69	0.035	60	1	-1	1	0	0.16	0.09	-0.192
29	0	-1	0	-1	-0.337	-0.60	-0.285	61	1	-1	1	0.33	0.21	0.31	-0.096
30	0	-1	0	-0.6	-0.301	-0.48	-0.282	62	1	-1	1	0.66	0.24	0.51	-0.080
31	0	-1	0	-0.3	-0.2	-0.37	-0.265	63	1	-1	1	1	0.26	0.71	0.016
32	0	-1	0	0	-0.2	-0.20	-0.250								

5 RESULT AND DISCUSSION

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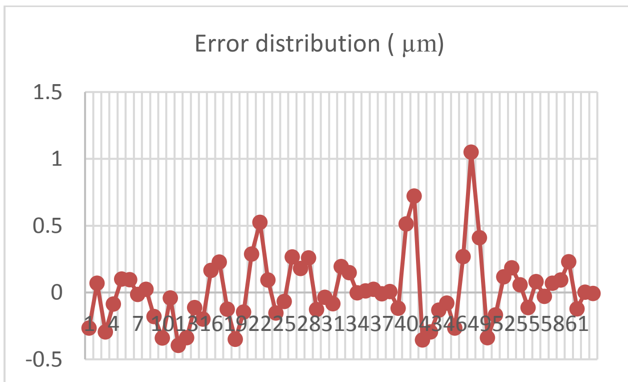
After creating the weights, they were used to estimate the values of surface roughness for all inputs. By comparing the measured and estimated results, the error was obtained which shows that the model demonstrates an acceptable accuracy. The error and squared error distribution for all of the experiments are given in Fig. 4. As is seen in the figure, maximum error of the prediction model is about 1.05 mm and %95 of prediction errors is less than 0.4 mm.



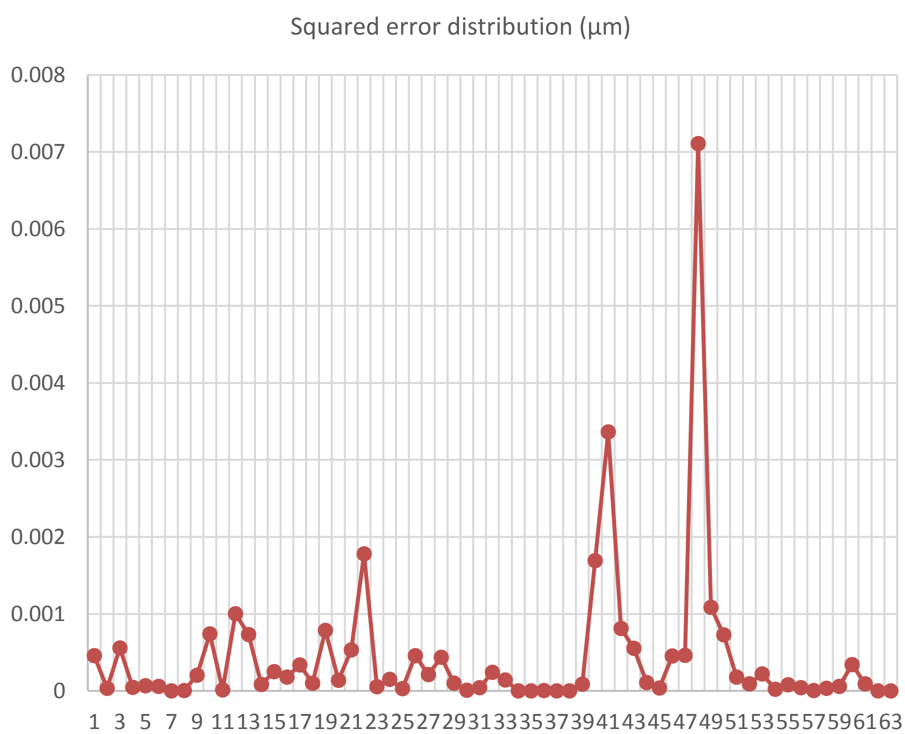


Fig. 4 Distribution of the errors and squared errors for ANN online prediction model

Table 5 The extracted weights during the turning process

w_{ni}		i					
		1	2	3	4	5	6
n	1	-1.7019	2.2509	-0.9022	0.0331	-0.4703	-1.8402
	2	-0.1812	1.2487	-4.2766	-1.0991	1.2560	1.6495
	3	-1.2157	-0.2710	1.5596	0.0851	-2.3222	0.2645
	4	1.5781	-0.6841	-4.5908	2.5701	-1.5665	1.4549
	5	1.0482	0.2834	-2.5396	-0.3683	2.9914	0.4775
	6	3.0859	1.1881	-3.0642	-2.2793	-0.4294	-0.2724
	7	0.3238	-1.2591	-5.3529	0.9693	0.5697	-0.2473
	8	-0.5058	-2.9374	1.0225	3.4570	-4.4526	3.6076
	9	0.0451	2.0405	4.6332	-1.4547	-2.2689	0.2035
	10	1.4271	-0.7333	-3.4743	-	-	-

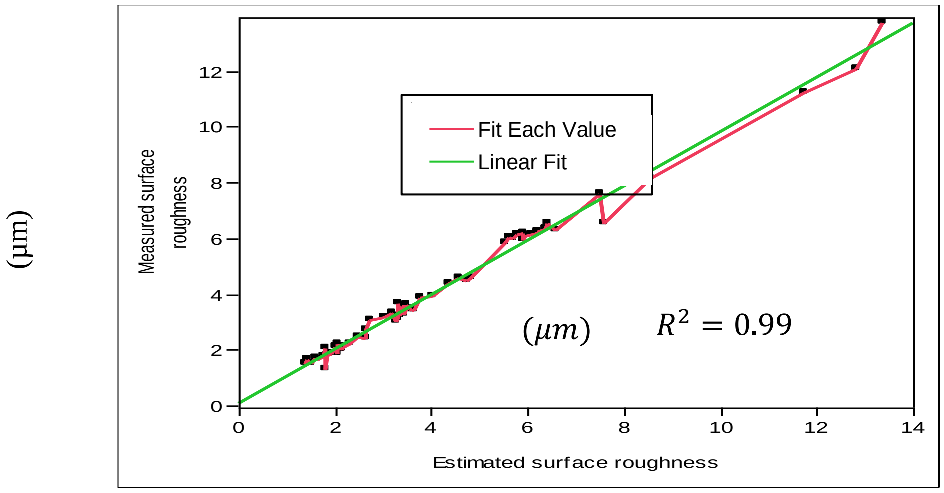


Fig. 5 Comparison of estimated and measured results

The real values of the conducted experiments and the predicted values of the surface roughness are then given in Table 6. In this table, the measured values of surface roughness is shown with R_a and the estimated values of the R_a using of the model is given with $R_{a(m)}$. Also N shows the number of experiments. Fitting graphic of the model for all of the used experiments in training is seen in Fig.5. Based on the ANN simulation model, the predicted and measured results are accurately following each other. The R^2 value is 0.99 which confirms the model reliability.

6 CONCLUSION

In this research, an ANN model was designed for prediction of surface roughness based on the cutting parameters and other effective variables. As it is illustrated in Fig. 5, the prediction errors are remained under 0.007 µm which is an acceptable error for surface roughness estimations. The comparison of obtained results by ANN model for training data and the measured values show a R^2 value of 0.99. This means that the measured and estimated values confirm each other with a high estimation accuracy. The results revealed that ANN is a strong and reliable method for predicting the surface roughness in machined parts. Moreover, it was found that for designing a reliable model for predicting the surface roughness, other variables such as cutting tool vibration, tool wear and cutting force must be considered except for the cutting parameters. In other words, although there are many researches on surface roughness estimation based on cutting parameters, to reach to an accurate result, considering some other variables such as tool vibration is inevitable. Because the level of vibration and cutting tool wear are directly affecting the surface quality of any machined part. By applying this model before any machining process, it is possible to predict the surface roughness and to select the required cutting parameters which in turn causes avoiding any scraped part. Also, another application of the designed ANN model can be considered in creating an adaptive control system to keep the surface roughness in a constant value.

Table 6 The predicted values of surface roughness for all of the conducted experiments.

N	V	f	d	V_b	F_c	a	R_a	$R_{a(m)}$	N	V	f	d	V_b	F_c	a	R_a	$R_{a(m)}$
1	115	0.2	0.7	0	399	1.87	1.68	1.41	33	140	0.2	1.2	0.2	638	2.21	2.00	2.15
2	115	0.2	0.7	0.05	415	1.99	1.79	1.86	34	140	0.2	1.2	0.25	655	2.31	4.56	4.56
3	115	0.2	0.7	0.1	432	2.11	2.08	1.79	35	140	0.2	1.2	0.3	671	2.41	6.34	6.36
4	115	0.2	0.7	0.15	450	2.2	2.10	2.01	36	165	0.3	1.2	0	697	1.96	6.18	6.21
5	115	0.2	0.7	0.2	469	2.29	2.03	2.13	37	165	0.3	1.2	0.05	725	2.06	6.23	6.22
6	115	0.2	0.7	0.25	479	2.34	2.21	2.30	38	165	0.3	1.2	0.1	753	2.17	6.34	6.35
7	115	0.2	0.7	0.3	489	2.4	2.48	2.46	39	165	0.3	1.2	0.15	774	2.26	7.60	7.49
8	140	0.3	0.7	0	492	1.91	1.74	1.76	40	165	0.3	1.2	0.2	794	2.36	11.2	11.7
9	140	0.3	0.7	0.05	508	2	3.34	3.16	41	165	0.3	1.2	0.25	808	2.46	12.0	12.8
10	140	0.3	0.7	0.1	523	2.09	5.85	5.51	42	165	0.3	1.2	0.3	822	2.57	13.7	13.3
11	140	0.3	0.7	0.15	533	2.18	5.96	5.92	43	115	0.3	1.7	0	1171	1.97	5.98	5.68
12	140	0.3	0.7	0.2	542	2.28	6.02	5.62	44	115	0.3	1.7	0.05	1201	2.04	6.10	5.96
13	140	0.3	0.7	0.25	550	2.38	6.13	5.79	45	115	0.3	1.7	0.1	1231	2.12	6.14	6.06
14	140	0.3	0.7	0.3	557	2.48	6.54	6.42	46	115	0.3	1.7	0.15	1261	2.31	6.18	5.92
15	165	0.25	0.7	0	353	1.92	3.59	3.39	47	115	0.3	1.7	0.2	1291	2.51	6.29	6.56
16	165	0.25	0.7	0.05	367	2.01	3.43	3.59	48	115	0.3	1.7	0.25	1331	2.63	6.55	7.60
17	165	0.25	0.7	0.1	380	2.1	3.41	3.64	49	115	0.3	1.7	0.3	1371	2.75	8.13	8.54
18	165	0.25	0.7	0.15	393	2.20	3.56	3.43	50	140	0.25	1.7	0	979	1.99	3.05	2.71
19	165	0.25	0.7	0.2	405	2.31	3.66	3.31	51	140	0.25	1.7	0.05	1006	2.05	3.19	3.02
20	165	0.25	0.7	0.25	431	2.4	3.63	3.48	52	140	0.25	1.7	0.1	1033	2.11	3.23	3.35
21	165	0.25	0.7	0.3	457	2.49	4.45	4.74	53	140	0.25	1.7	0.15	1045	2.19	3.26	3.44
22	115	0.25	1.2	0	735	1.91	1.28	1.81	54	140	0.25	1.7	0.2	1057	2.28	3.48	3.54
23	115	0.25	1.2	0.05	754	1.98	1.83	1.92	55	140	0.25	1.7	0.25	1070	2.41	3.88	3.77
24	115	0.25	1.2	0.1	773	2.06	2.21	2.06	56	140	0.25	1.7	0.3	1082	2.55	3.92	4.00
25	115	0.25	1.2	0.15	806	2.22	2.71	2.64	57	165	0.2	1.7	0	747	1.94	1.65	1.62
26	115	0.25	1.2	0.2	839	2.38	3.00	3.27	58	165	0.2	1.7	0.05	779	2.05	1.84	1.91
27	115	0.25	1.2	0.25	840	2.48	3.11	3.29	59	165	0.2	1.7	0.1	811	2.16	2.1	2.19
28	115	0.25	1.2	0.3	841	2.59	4.56	4.82	60	165	0.2	1.7	0.15	846	2.27	2.39	2.62
29	140	0.2	1.2	0	531	1.91	1.50	1.38	61	165	0.2	1.7	0.2	881	2.39	3.30	3.18
30	140	0.2	1.2	0.05	554	1.97	1.53	1.49	62	165	0.2	1.7	0.25	896	2.49	3.45	3.45
31	140	0.2	1.2	0.1	577	2.03	1.69	1.61	63	165	0.2	1.7	0.3	911	2.6	4.37	4.37
32	140	0.2	1.2	0.15	608	2.12	1.84	2.03									

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