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NUMERICAL PREDICTION OF SURFACE ROUGHNESS IN TURNING OPERATION USING TAGUCHI METHOD AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT
Surface Roughness plays an important role in assessment of surfaces quality; however, minimizing of time and cost consumption in production processes is one of the very important target. In this research, selective cutting conditions and specimens are used in turning operations to produce machined surfaces. Mitutoyo SurfTest-SJ201® is used to obtain surface roughness parameter Ra for the resulted machined surfaces. The Taguchi Method with analysis of variance using Minitab 17® is used as numerical technique to predict Ra for non-machined specimens at suggested cutting conditions. An introduced artificial neural network ANN is modeled using MATLAB 2014a®, to predict Ra at the previous suggested cutting conditions. Comparison between results from turning operations and those obtained from both the Taguchi method and ANN prediction is introduced. Moreover, effect of cutting conditions on Ra is introduced throughout the topography of the machined surfaces.

Keywords: Surface roughness – Turning operation -Taguchi Method – ANOVA – Artificial neural network

INTRODUCTION
Surface roughness is one of the most important critical quality indicator for the machined surfaces. It affects the several properties such as wear resistance, fatigue strength, coefficient of friction, lubrication and corrosion resistance of the machined surfaces. Due to the need of minimizing cost and time in assessment of surfaces quality, numerical techniques plays an important role in prediction of surface roughness.
The Taguchi method is an efficient method for designing process that operates consistently and optimally over a variety of conditions. To determine the best design, it requires the use of a strategically designed experiment. The experimental design proposed by Taguchi involves using orthogonal arrays to organize the parameters affecting the process [1]. The optimum parameter combination was obtained [2] using Taguchi method by adopts a set of orthogonal arrays to investigate the effect of parameters on specific quality characteristics. [3] studied optimal cutting parameters for turning operations based on orthogonal array, signal-to-noise (S/N) ratio, and the analysis of variance (ANOVA) using Taguchi method. The effect of depth of cut and feed in variation of feed force were affected more as compare to speed [4]. Empirical model for the prediction of surface roughness was developed by applying the analysis of variance [5]. For optimizing surface roughness, tool wear and material removal rate in precision turning, orthogonal array of Taguchi method were coupled with grey relational analysis considering four parameters, cutting speed, depth of cut, feed rate, tool nose radius [6]. Minimizing the surface roughness in machining mild steel have been planned using Taguchi's experimental design technique [7]. Taguchi technique was used to reduce the number of experiments in optimization of cutting parameters on surface roughness and tool flank wear in hard turning of heat treated and tempered steel.
Recently, there has been a lot of emphasis on using the Artificial Neural Network ANN technique for describing the relationship between the process parameters and the surface roughness parameters. ANN is currently one of the most powerful modeling techniques based on the statistical approach. Especially, ANN did not require any kind of mathematical model. ANN models was developed [9] during turning of free machining steel to presented the effect of feed rate, cutting speed and depth of cut on surface roughness. The ANN model [10] predicted the surface roughness performance measured in the machining process by considering the Artificial Neural Network as the essential technique for measuring surface roughness. Surface roughness, tool wear and the required power depending on cutting

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speed, feed rate and cutting time were calculated [11] using ANN and support vector regression (SVR) methods. The results showed that ANN and SVR models yielded higher accuracy than the RSM model. Neural-network-based methodology with the acceleration of the radial vibration of the tool holder as feedback was used in prediction of surface roughness in turning process the back-propagation algorithm was used for training the network model [12]. Prediction of the surface roughness was studied on development of a back propagation neural network model for prediction of surface roughness in turning operation using speed, feed, depth of cut and the cutting forces as inputs to the neural network model [13]. Artificial neural network ANN has been used [14] to predict the surface roughness values. The results show that ANN model has better accuracy as compared with multiple regression analysis model.

The aim of the present study is to introduce an accurate numerical technique in prediction of surfaces quality that minimize cost and time in machining surfaces operations. Nine specimens are machined by designed cutting conditions. The obtained surface roughness parameters Ra resulted at the designed cutting conditions, are used as input data to both the Taguchi method design and artificial neural network ANN models to predict surface roughness Ra for non-machined 18 specimens. Comparison between predicted surface roughness parameters Ra from both the Taguchi method design and artificial neural network ANN models with those resulted from experiments is introduced. Furthermore, the importance of this study is to confirm the fact that trusted numerical prediction is a fast and inexpensive good study versus expensive and time-consuming experimental work.

EXPERIMENTAL STUDY

Nine specimens AISI 1040 steel are machined for the experimental study by turning operation using a cemented carbide-cutting tool equipped with inserts. The insert type was KPGN 160412 and the shank type was MSKNR/L 2525M16 for approach angle $\chi=35°$. The Chemical composition and mechanical properties of AISI 1040 steel is listed in tables (1) and (2) as:

Table (1) Chemical composition (Wt. %)

C	Fe	Mn	P	S	Others
0.37	98.8	0.7	0.035	0.045	0.05

Table (2) Mechanical properties

Yield tensile strength σ_{yield} (MPa)	450
Ultimate tensile strength $\sigma_{ultimate}$ (MPa)	515
Hardness Vickers (HV)	155
Modulus of Elasticity (GPa)	200

The used cutting conditions are as listed in table (3).

Table (3) Cutting conditions

Cutting speed	v (rev/min)	560	640	960
Feed rate	f (mm/rev)	0.16	0.17	0.20
Depth of cut	d (mm)	0.2	0.3	0.4

The nine specimens are machined using a combination of cutting conditions as listed in table (4).

Table (4) Cutting conditions for nine specimens

Specimen No.	Cutting conditions		
	v rev/min	f mm/rev	d mm
1	560	0.16	0.2
2	560	0.17	0.3
3	560	0.20	0.4
4	640	0.16	0.3
5	640	0.17	0.4
6	640	0.20	0.2
7	960	0.16	0.4
8	960	0.17	0.2
9	960	0.20	0.3

All specimens are measured using *Mitutoyo SurfTest-SJ201* that give the surface profile and roughness parameter of the measured surface as a result.

NUMERICAL TECHNIQUES

To provide a simple, efficient and systematic approach to optimize the design for performance, quality and cost; Taguchi method and Artificial Neural Network ANN are used. In the same manner, instead of using 27 specimens to analyze the effect of cutting conditions on surface roughness parameter R_a, obtained R_a from the nine machined specimens are used in both Taguchi method and artificial neural network ANN to obtain a trusted numerical technique that can predict the roughness parameter R_a for the rest 18 non machined specimen.

Taguchi Method

Taguchi method is widely used as a powerful tool for designing high-quality system during research and development, so that, high quality products can be produced in a minimum time and minimum cost. This method uses a special design of orthogonal array to study the entire parameter space with a minimum number of experiments. In the framework of Taguchi method using orthogonal array *OA*. The *OA* follows a random run order. The run order is a completely random ordering of the experiments, which is followed when running the experiments so that, experimental error is reduced as far as possible. Taguchi recommends analyzing the mean response for each run in the inner array and also suggest to analyze variation using an appropriately selected signal to noise ratio *S/N*. There are three signals to noise ratios of common interest for optimization of static problem as in equations (1), (2) and (3) respectively [15]. The appropriate categories of the *S/N* ratio are chosen

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depending on the nature of the quality characteristic. *S/N* ratio for smaller-the-better criterion is employed when the aim is to make the response as small as possible. The analysis of variance ANOVA is used to investigate which design factors and their interactions affect the response significantly.

Smaller-the-better:

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (1)$$

Larger-the-better:

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \quad (2)$$

Nominal-the-better

$$S/N = 10\log\left(\frac{\bar{y}^2}{s^2}\right) \quad (3)$$

Where y_i is the *i-th* observed value of the response (quality characteristic), n is the number of observations in a trial, $\bar{y}$ is the average of observed values (response) and s is the variance.

The present study aimed to produce minimum surface roughness R_a in a turning operation that, smaller R_a represent better or improved surface roughness. Therefore, a smaller-the-better quality characteristic is implemented and introduced in this study.

Modeling of R_a using Taguchi Method and design of experiment

Taguchi method is a quality tool that helps improve the work efficiently. It is possible to select suitable factors as shown in table (5), which indicates factors and their levels in the cutting experiments, that contains three factors and each factor has three levels.

Table (5) Using levels in Tauchi method

Cutting conditions	Factor level		
	Level 1	Level 2	Level 3
v (rev/min)	560	640	960
f (mm/rev)	0.16	0.17	0.20
d (mm)	0.2	0.3	0.4

The orthogonal array is selected with *L9* (3^3) method which gives the order of experiment as shown in table (6).

Table (6) L9 (3^3) orthogonal array

Trial	Natural factor			Coded factor			Response
	v rev/min	*f* mm/rev	*d* mm	A	B	C	R_a µm
1	560	0.16	0.2	1	1	1	3.46
2	560	0.17	0.3	1	2	2	3.35
3	560	0.20	0.4	1	3	3	4.42
4	640	0.16	0.3	2	1	2	3.38
5	640	0.17	0.4	2	2	3	3.98
6	640	0.20	0.2	2	3	1	3.89
7	960	0.16	0.4	3	1	3	3.26
8	960	0.17	0.2	3	2	1	2.87
9	960	0.20	0.3	3	3	2	2.48

In general, the parameter optimization process of the Taguchi method is based on eight steps of planning, conducting and evaluating results of matrix experiments to determine the best levels of control parameters. Those eight steps are listed as follows:

- Identify the performance characteristics (responses) to optimize and process parameters to control (test).
- Determine the number of levels for each of the tested parameters.
- Select an appropriate orthogonal array, and assign each tested parameters into the array.
- Conduct an experiment randomly based on the arrangement of the orthogonal array.
- Calculate the mean and *S/N* ratio for each combination of the tested parameters.
- Analysis the experimental result using the mean, *S/N* ratio and ANOVA test.
- Find the optimal level for each of the process parameters.
- Conduct the confirmation experiment to verify the optimal process parameters.

Artificial Neural Network ANN

ANN is one of the most powerful techniques, currently being used in various fields of engineering for complex relationships, which are difficult to describe with physical models. The input and output data set of the ANN model is generated to predict surface roughness. The input parameters of the artificial neural network model are cutting speed, feed rate and depth of cut. The output of this ANN model is Surface Roughness R_a.

Modeling of R_a using artificial neural networks ANN

Artificial neural network ANN, branch of artificial intelligent has been implemented as an alternative approach. The predicted surface roughness has been perform using artificial neural network code in *MATLAB 2014a*. Artificial neural network ANN with feed-forward back-propagation algorithm and tan-sigmoid activation function is trained using the experimental results. The network architecture has been presented in figure (1). Neurons are arranged in the form of layers in the feed forward ANN, and output of the cells in a layer are fed to the next layer through weights as input.

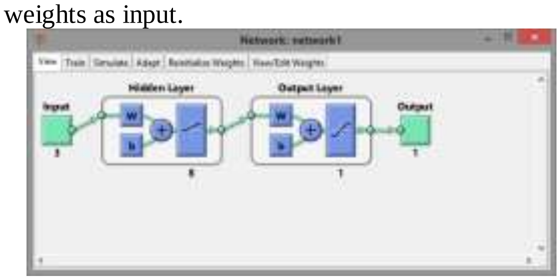

Figure (1) ANN architecture

As, the input and output vectors are supplied to the network, it is a supervised learning scheme. After training the network the results shows that the training data and the predicted training data has come to a very close value as shown in figures (2).

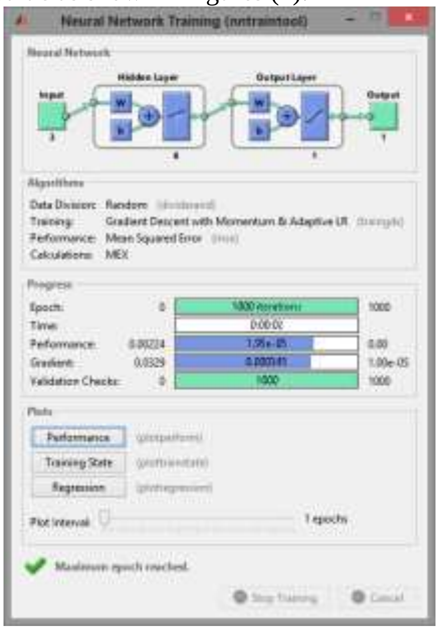

Figure (2) ANN training

Figure (3) shows the result of the training data of the actual data with the predicted data. The test result also shows that good agreement are observed between the actual and predicted data.

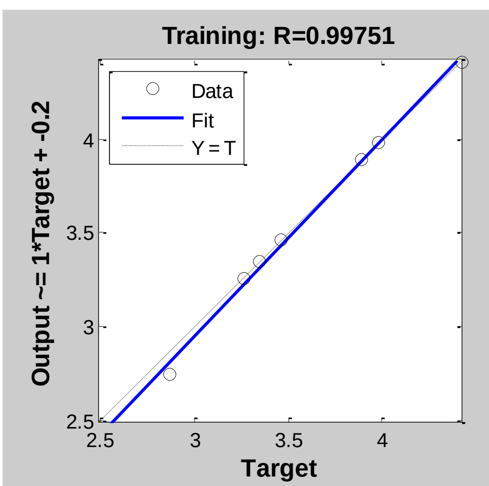

Figure (3) ANN training results

Table (7) illustrates the new combinations of the used Cutting conditions for probable 18 trials, which will be used in prediction R_a in both Taguchi method, and ANN for the rest of non-machined specimens.

Table (7) Cutting conditions for probable 18 trials

Trial	Cutting speed v rev/min	Feed rate f mm/rev	Depth of Cut d mm
1	560	0.16	0.3
2	560	0.16	0.4
3	560	0.17	0.2
4	560	0.17	0.4
5	560	0.2	0.2
6	560	0.2	0.3
7	640	0.16	0.2
8	640	0.16	0.4
9	640	0.17	0.2
10	640	0.17	0.3
11	640	0.2	0.3
12	640	0.2	0.4
13	960	0.16	0.2
14	960	0.16	0.3
15	960	0.17	0.3
16	960	0.17	0.4
17	960	0.2	0.2
18	960	0.2	0.4

RESULTS AND DISCUSSION

The combination for the three cutting conditions: cutting speed, feed rate, and depth of cut have placed as shown in table (8) according to their places in the orthogonal array *L9* shown in table (6). These combinations are considered as input (inner array). Because the signal to noise ratio *S/N* should be as smaller as possible, the quality characteristic "smaller-is-better" is used. *S/N* values are calculated from equation (1), and the results have been arranged in the last column of array. R_a and *S/N* ratio represent the output in outer array. The results were analyzed by using main effects for both R_a values and signal to noise ratio *S/N* and ANOVA analyses.

Table (8)

Trial	Cutting conditions			Coded Factor				*S/N* ratio (dB)
	v rev/min	f mm/rev	d mm	A	B	C	R_a µm	
1	560	0.16	0.2	1	1	1	3.46	-10.7815
2	560	0.17	0.3	1	2	2	3.35	-10.5009
3	560	0.20	0.4	1	3	3	4.42	-12.9084
4	640	0.16	0.3	2	1	2	3.38	-10.5783
5	640	0.17	0.4	2	2	3	3.98	-11.9977
6	640	0.20	0.2	2	3	1	3.89	-11.7990
7	960	0.16	0.4	3	1	3	3.26	-10.2644
8	960	0.17	0.2	3	2	1	2.87	-9.1576
9	960	0.20	0.3	3	3	2	2.48	-7.8890

Main Effects

In terms of the average effects, the average value of surface roughness R_a and *S/N* ratio for each parameter (A, B, an C) at each level (level 1, level 2 and level 3) are obtained and the results are summarized in table

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(9) and table (10) respectively. For example, level 1 in table (9) is the average of R_a for the first three trial 1, 2, and 3 labeled in table (8), therefore, level 1 for cutting speed (A) = (3.46+ 3.35+ 4.42) / 3 = 3.743. Level 1 for feed rate (B)=(R_a at trial no.1 + R_a at trial no.4 + R_a at trial no.7) / 3, this is according to the distribution of trial in table (8), therefore, level 1 for feed rate (B) = (3.46 + 3.38 + 3.26) / 3 = 3.367. For level 1 for depth of cut (C) = (3.46 + 3.89 + 2.87) / 3 = 3.407, and so on for other levels.

Table (9) Main effect for R_a Ratios

Cutting conditions	Level 1	Level 2	Level 3	δ (Max. – Min.)	Rank
v	3.743	3.750	2.870	0.880	1
f	3.367	3.400	3.597	0.230	3
d	3.407	3.070	3.887	0.817	2

Table (10) Main effect for S/N Ratios

Cutting conditions	Level 1	Level 2	Level 3	δ (Max. – Min.)	Rank
v	-11.397	-11.458	-9.104	2.355	1
f	-10.541	-10.552	-10.865	0.324	3
d	-10.579	-9.656	-11.723	2.067	2

Figure (4) shows the main effects for both R_a and *S/N* ratio depending on data in table (9) and table (10). Because of using "smaller-is-better" quality characteristic in this study, the smaller average of R_a that appears in Figure (4) represents the higher quality of the surface. Thus, the combination of parameters and their levels A3-B1-C2 is belongs to cutting speed 960 rev/min, feed rate 0.16 mm/rev and depth of cut 0.3 mm and represents the optimum condition. The difference between the maximum and minimum of three levels for each parameter $\delta_{(\text{Max. – Min.})}$, indicates the effect of the parameter on surface roughness R_a. The Rank of this effect is in descending order of this difference $\delta_{(\text{Max. – Min.})}$, that the cutting speed has the highest effect on the surface roughness followed by depth of cut and then the feed rate.

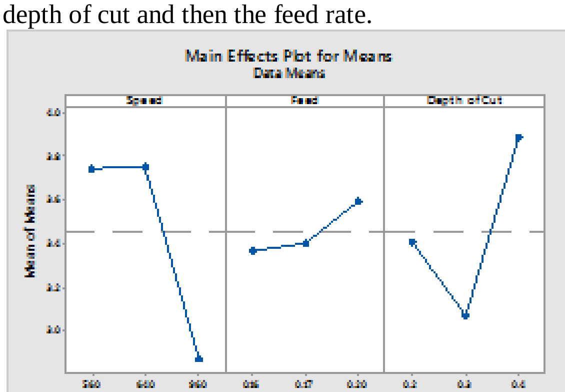

Figure (4-a) Main effects graph for R_a

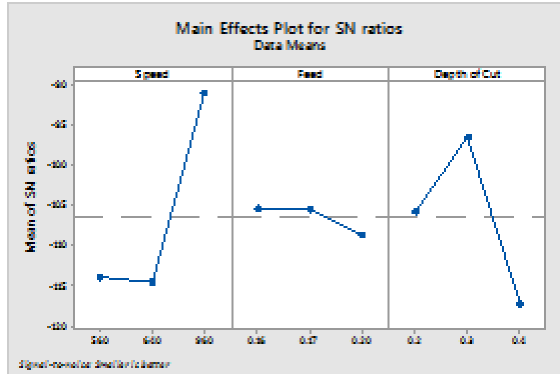

Figure (4-b) Main effects graph for S/N

Analysis of Variance ANOVA for S/N ratio

The statistical analysis is performed using ANOVA. This analysis was prepared using software *MINITAB 17*. The ANOVA results for *S/N* ratio are shown in table (11) and table (12).

Table (11) Analysis of Variance for S/N ratio

Source	Deg. of Freedom	Sum of squares	Mean squares	F	P	%
v	2	10.8073	5.4036	12.96	0.072	59.12%
f	2	0.2034	0.1017	0.24	0.804	1.11%
d	2	6.4356	3.2178	7.72	0.115	35.21%
Er %	2	0.8341	0.4170			4.56%
Total	8	18.2803				100%

The percentage contribution of source to the total variation defines parameter sensitivity. It is clear from table (12) that changing the factor levels of A and C contributes to nearly 92.87% of the total variation. In addition, the percentage contribution of source to the total variation confirms that cutting speed has the maximum contribution to the total variation then depth of cut and finally feed rate

Table (12) Analysis of Variance for Means

Source	Deg. of Freedom	Sum of squares	Mean squares	F	P	%
v	2	1.53716	0.76858	14.91	0.063	56.03%
f	2	0.09269	0.04634	0.90	0.527	3.38%
d	2	1.01069	0.50534	9.80	0.093	36.84%
Er %	2	0.10309	0.05154			3.75%
Total	8	2.74362				100%

The assumed combination of cutting conditions in table (7) are used as an input data to both of introduced Taguchi method and ANN to obtain the required predicted surface roughness R_a. Table (13) shows the obtained predicted surface roughness R_a from Taguchi method and ANN for the nine experimental trials and 18 predicted trials.

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Table (13) Predicted surface roughness R_a from Taguchi method and ANN

Trial	*v* rev/min	*f* mm/rev	*d* mm	Ra Exp. µm	*S/N* dB	Ra (Tag.) µm	Ra (ANN) µm
1	560	0.16	0.2	3.46	-10.7815	3.608	3.4269
2	560	0.17	0.3	3.35	-10.5009	3.304	3.3452
3	560	0.2	0.4	4.42	-12.9084	4.318	4.4065
4	640	0.16	0.3	3.38	-10.5783	3.278	3.3798
5	640	0.17	0.4	3.98	-11.9977	4.128	3.9803
6	640	0.2	0.2	3.89	-11.799	3.844	3.8901
7	960	0.16	0.4	3.26	-10.2644	3.214	3.2597
8	960	0.17	0.2	2.87	-9.15764	2.768	2.8455
9	960	0.2	0.3	2.48	-7.88903	2.628	2.4947
Predicted specimens							
1	560	0.16	0.3			3.271	3.438
2	560	0.16	0.4			4.088	4.076
3	560	0.17	0.2			3.641	3.459
4	560	0.17	0.4			4.121	4.294
5	560	0.2	0.2			3.838	3.801
6	560	0.2	0.3			3.501	4.377
7	640	0.16	0.2			3.614	3.471
8	640	0.16	0.4			4.094	3.857
9	640	0.17	0.2			3.648	3.376
10	640	0.17	0.3			3.311	2.973
11	640	0.2	0.3			3.508	3.789
12	640	0.2	0.4			4.324	4.370
13	960	0.16	0.2			2.734	2.906
14	960	0.16	0.3			2.398	2.647
15	960	0.17	0.3			2.431	2.521
16	960	0.17	0.4			3.248	3.291
17	960	0.2	0.2			2.964	2.494
18	960	0.2	0.4			3.444	3.654

Figure (5) illustrates comparison between obtained surface roughness parameter R_a from experimental data and predicted data from Taguchi and ANN. High good agreement between results from experimental work and those obtained from ANN are significantly observed more than those from Taguchi method. Therefore, Artificial Neural Network techniques are more accurate and precious than Taguchi method.

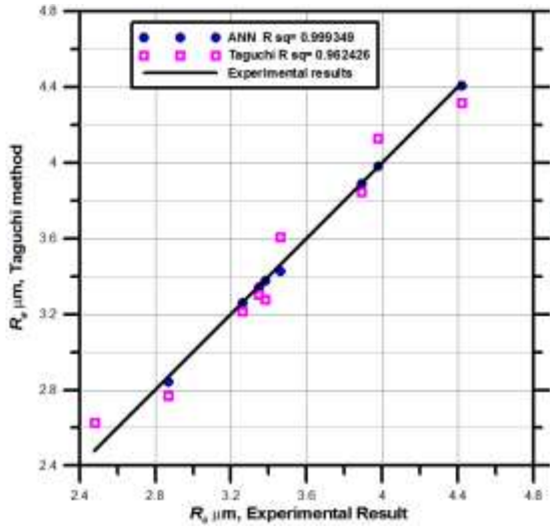

Fig. (5) Comparison between experimental and predicted results

Figure (6) illustrates comparison between predicted surface roughness R_a from Taguchi method and ANN. It is clear that accepted agreement between predicted results from Taguchi method and those predicted by ANN is observed. Nevertheless, Taguchi method can be denoted as an acceptable numerical method.

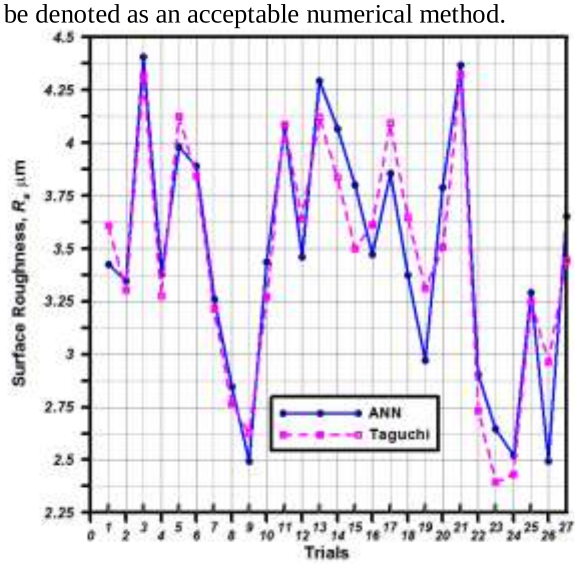

Fig. (6) Comparison between predicted Surface roughness R_a from Taguchi and ANN

Table (14) shows the maximum and minimum absolute difference between results obtained from numerical techniques (Taguchi method and ANN) and experimental results. It is clear that ANN has less difference than Taguchi method.

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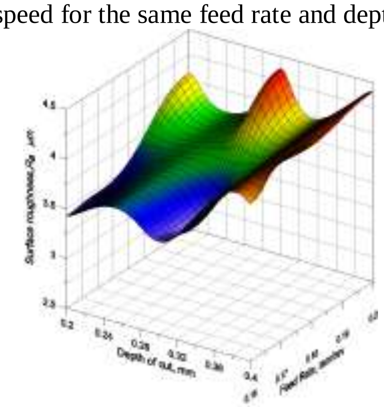
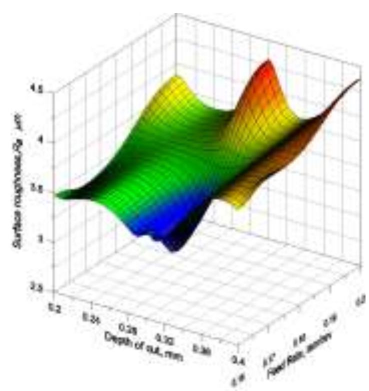
Table (14) difference between results from Taguchi method and ANN with experimental results

	Taguchi method	ANN
Absolute maximum difference %	5.959%	0.957%
Absolute minimum difference %	1.171%	0.003%

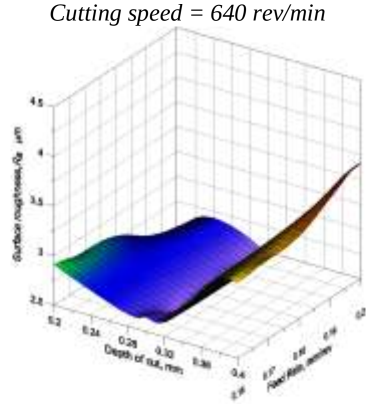
Figure (7) shows the effect of cutting speed on predicted surface roughness R_a from ANN. It is clear that surface roughness R_a decreased with increasing cutting speed for the same feed rate and depth of cut.



Cutting speed = 560 rev/min



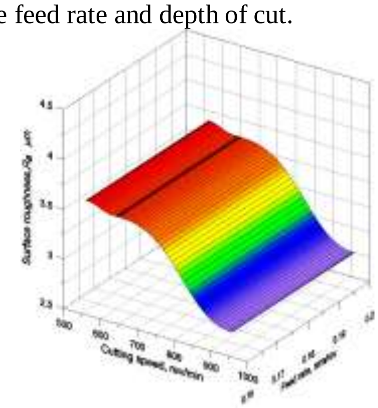
Cutting speed = 640 rev/min



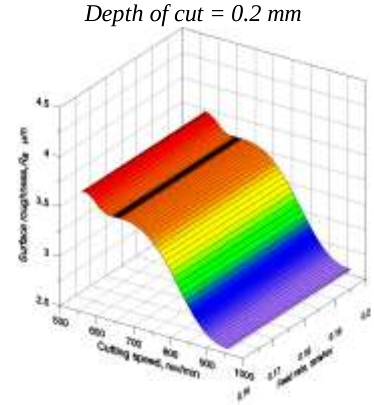
Cutting speed = 960 rev/min

Figure (7) Effect of cutting speed on Surface roughness R_a

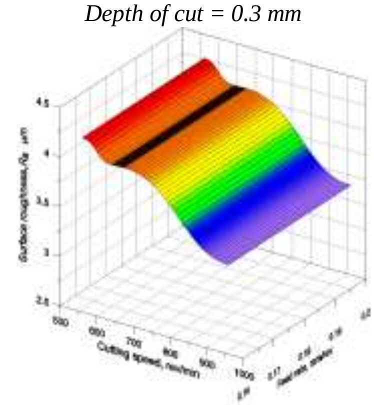
Figure (8) shows the effect of depth of cut on predicted surface roughness R_a from ANN. It is clear that surface roughness R_a increased with increasing depth of cut for the same feed rate and depth of cut.



Depth of cut = 0.2 mm



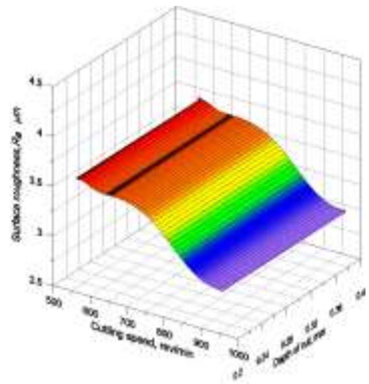
Depth of cut = 0.3 mm



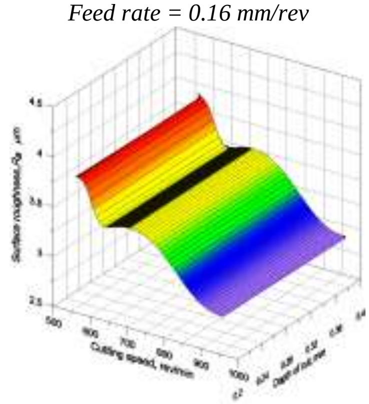
Depth of cut = 0.4 mm

Figure (8) Effect of depth of cut on Surface roughness R_a

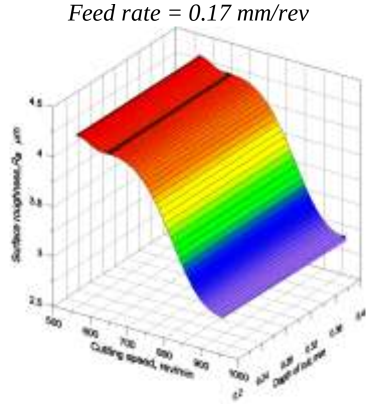
Figure (9) shows the effect of feed rate on predicted surface roughness R_a from ANN. It is clear that surface roughness R_a increased with increasing feed rate for the same feed rate and depth of cut.



Feed rate = 0.16 mm/rev



Feed rate = 0.17 mm/rev



Feed rate = 0.2 mm/rev

Figure (9) Effect of feed rate on Surface roughness R_a

Figures (7), (8) and (9) represents the relation between Cutting conditions and the predicted surface roughness R_a from ANN. It is observed from these figures that, the influence on surface roughness R_a by cutting speed has the higher effect than depth of cut and feed rate. This is compatible with the same observation obtained from Taguchi method.

CONCLUSION

Due to the greatest importance of minimizing time and cost consumption on assessment of machined surfaces in machining surfaces operations. Numerical techniques are extremely needed for this purpose. The main purpose of this research is to provide an effective and accurate numerical technique to predict surface roughness. Two numerical techniques Taguchi method and artificial neural network ANN are modeled to predict surface roughness Ra at 18 combination of three values for cutting speed, feed rate and depth of cut as cutting conditions based on nine experimental results. High good agreement between results from experimental work and those obtained from ANN are significantly observed more than those from Taguchi method. Absolute maximum difference between experimental results and predicted results by ANN is 0.597% while 5.959% is the Absolute maximum difference between experimental results and predicted results by Taguchi method. The percentage contribution of cutting conditions to the total variation of surface roughness Ra in Taguchi method, confirms that cutting speed has the higher contribution to the total variation than depth of cut and feed rate. The relation between cutting conditions and predicted surface roughness Ra from ANN is observed that, the influence on surface roughness Ra by cutting speed has the higher effect than depth of cut and feed rate. The present work resulted that predicted surface roughness using artificial neural network is very accurate and precise more than Taguchi method.

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