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RESEARCH ARTICLE - MECHANICAL ENGINEERING

An ANN-Based Method to Predict Surface Roughness in Turning Operations

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Abstract In recent years, there has been a growing interest for the prediction of machining characteristics (such as surface roughness and tool wear) during machining. Several machining parameters such as cutting speed and cutting depth are known to affect the surface characteristics. Various methods are used to investigate the relative contribution of these parameters on the surface characteristics. Therefore, selecting a set of parameters according to the relative contributions is important in the prediction of the surface characteristics effectively. In this paper, a new alternative parameter selection method based on artificial neural networks is suggested. Within this scope, forward and stepwise selection methods are proposed. A statistical hypothesis test is used as an elimination criterion. The suggested methods are used to predict the surface roughness in turning operations effectively. Successful results were obtained in the prediction of surface roughness by using these methods.

Keywords ANN · Prediction · Surface roughness · Hypothesis test

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Nomenclature

K	Tool stiffness coefficient (N/m)
CD	Cutting depth (mm)
OL	Tool overhang length (mm)
S	Tool damping ratio (%)
SRA	Side rake angle (°)
ECA	End cutting angle (°)
NR	The number of revolutions per minute (rpm)
WD	Workpiece diameter (mm)
BRA	Back rake angle (°)
IH	Insert hardness (HV)
SCA	Side clearance angle (°)
AA	Approach angle (°)
WH	Workpiece hardness (HV)

1 Introduction

The main aspect of manufacturing is to shape metals as machining and non-machining forms. In machining methods, machines are operated for a long time, the process parameters such as cutting speed and feed rate can be adjusted easily, and the high quality of surface is obtained at desired level; therefore, the machining methods outperform the other manufacturing methods. It is very important to choose the appropriate production parameters in machining. If the production parameters are not chosen properly, excessive cutting tool wear is observed and the surface quality deteriorates. After acceptable dimensions and tolerances are found, obtaining a satisfactory quality of surface becomes important. The surface quality is affected by workpieces, cutting tools, machines and machining conditions. Surface quality directly affects mechanical life of components. Therefore, the prediction of surface roughness is needed for high-quality machining. The chatter vibration adversely affects surface roughness. It is the one which is formed with a self-excited mechanism between the workpiece and the tool. A wavy surface is observed on the workpiece due to both previous cycle and the structural vibration in turning operations. While the system is vibrated at chatter frequency which is very close to the structural mode, the maximum chip thickness may increase exponentially depending on the phase shift between two consecutive waves. The growth of variable chip thickness increases the cutting forces by amplifying the vibration and leads to the wavy surface on the workpiece [1].

The problems due to machining are divided into groups as quality of product, tool life, productivity and chatter vibration. Different optimization methods are used for the machining in the literature. Genetic algorithm and the sequential quadratic programming are used in most of the machining problems. Abuelnaga and El-Dardiry [2] summarized the different optimization methods used in the machining (genetic algorithm, sequential quadratic programming, etc.). Aggarwal and Singh [3] summarized the optimization problems in accordance with the traditional and the latest technology in turning processes. Mukherjee and Ray [4] summarized the advantages and disadvantages of machining optimization problems. Kurdi [5,6] performed a multi-purpose optimization for milling operations by using sequential quadratic programming and they also used a Pareto diagram. Krishna [7] calculated the optimum conditions of operation for grinding using a differential evolution algorithm. Saikumar and Shunmugon [8] calculated the optimum cutting speed, feed rate and cutting depth for milling by using a differential evolution algorithm. The aim of their study is to obtain the desired surface roughness.

In machining literature, the optimization techniques are divided into three parts as traditional methods, statistical methods and heuristic methods. Geometric programming [9], dynamic programming [10] and sequential quadratic programming [11] for the traditional methods, design of experiments [12–18] for the statistical techniques, and hill climbing algorithm [19], artificial neural networks (ANN) [20], simulated annealing [21], genetic algorithm [22], differential evolution algorithm [7], particle swarm algorithm [23–25] for the heuristic methods have been used in the literature.

Several methods are used to predict surface roughness such as artificial neural networks, Taguchi and regression models [26–28]. Significant amount of study is performed regarding ANN modelling to predict surface roughness. Mostly, cutting speed, feed rate and depth of cut are taken into consideration. In some studies, the hardness of the material is also taken into account [29]. Kumar and Chauhan [30] studied surface roughness of Al 7075/10/SiCp and Al 7075 hybrid composites in turning operations. They observed that response surface methodology (RSM) is superior to ANN in surface roughness prediction. Sahoo et al. [31] performed experiments to machine AISI 1040 steel under dry cutting conditions. RSM and ANN were used to predict surface roughness. They claimed that ANN is more appropriate than RSM. The percentage error is between -2.63 and 2.47% for RSM, whereas the maximum error ranges between -1.27 and 0.02. Furthermore, compared to nonlinear regression, ANN produced successful results in different studies [32,33].

When the optimization studies conducted within the manufacturing process in the literature are examined, the method of analysis of variance is used in the calculation of variables' relative contribution. Analysis of variance is generally used when the number of variables is low compared to data mining methods. As the number of variables increases, calculations are getting more complex. Therefore, some variables (low contributed variables) should be removed from the model and more effective variables should be added to the model to increase prediction accuracy. Only regression variable elimination methods are used in the literature but when the number of variables increases, these elimination methods do not produce successful results and the accuracy decreases. There is no good way for the elimination of low contributed variables from the model when the number of variables is high. In this study, a new variable selection method is proposed to address this issue. Therefore, a simpler model will be obtained by selecting proper variables in the data analysis.

In this study, the surface roughness is predicted considering the variables affecting the surface roughness in turning process. It is determined that 13 factors affect the surface roughness. By means of the weights obtained in the ANN, the relative contribution (weights) of each variable is determined. According to the relative weights, the variables are added into the model starting from the highest one. The variable selection steps are determined by using the paired t test.

In the second part of the study, the used methods are presented. In the third part, the details of empirical study are given. In the fourth part, the empirical and numerical results are shown, respectively. In the last part, the results and suggestions are presented. This study will enable the operators and engineers to machine more effectively while obtaining the desired surface roughness in machining operations.

2 Methodology

2.1 Artificial Neural Networks (ANN)

An artificial neural network is a network which automatically develops the knowledge generation and formation in the way of learning. It is the structure which is developed

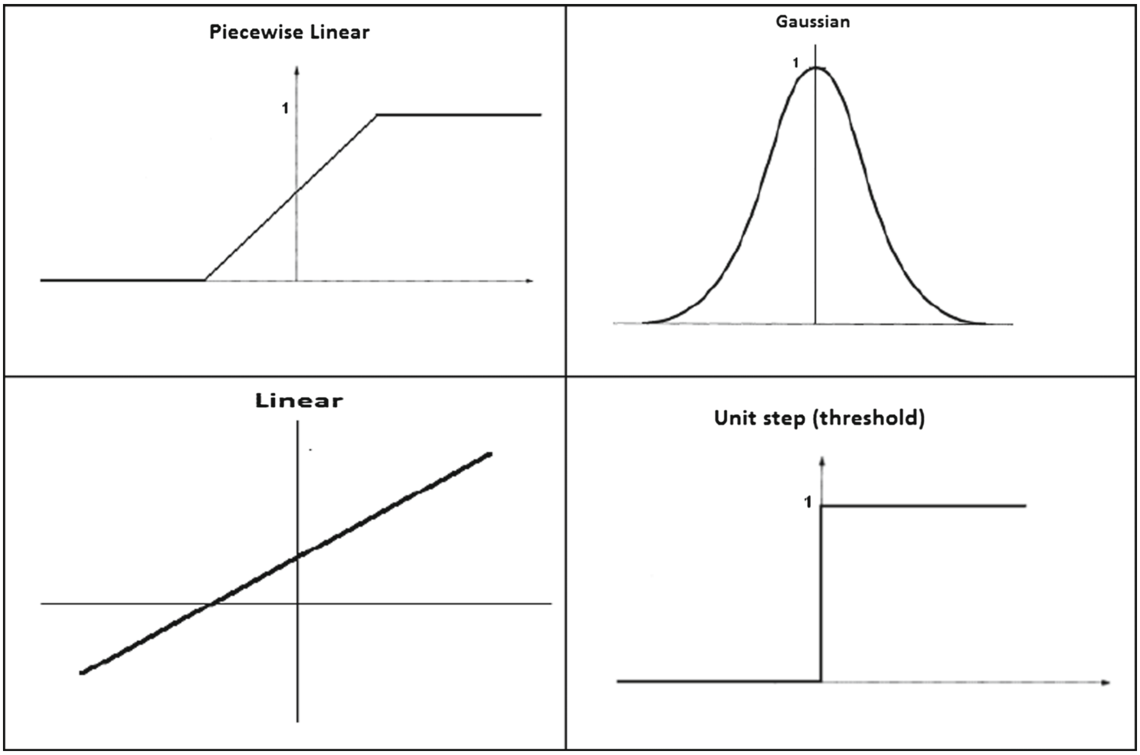

Fig. 1 Different activation functions

for hard or impossible events to be programmed. Nowadays, artificial neural networks which resolve many problems are developed with the hierarchical and parallel connections of neural cells.

Artificial neural cells are connected to each other and ordered as layers. They ensure the collection, storage and generalization of information in the learning process. Artificial neural cells which resemble the principles of neural cells are defined as the process elements. Each process element has five properties: inputs, weights, the sum function, the activation function and outputs [34]. Process elements are connected to each other by means of networks. Process elements and connections form the artificial neural networks. Weight values associated with the connections are calculated in learning process.

Set of input nodes	:	$X = X_1, \ldots, X_n$
Set of connection weights	:	$W = W_1, \ldots, W_n$

where n denotes the number of inputs.

The sum function is presented in Eq. (1)

$$u = \sum\nolimits_{i=1}^{n} w_i x_i + b \tag{1}$$

where b is the bias.

The activation function can have different functions. The sigmoid function is presented as an example in Eq. 2

$$y = \frac{1}{1 + e^{-u}} \tag{2}$$

where y takes values between 0 and 1 and shows the output value.

The other most frequently used activation functions are given in Fig. 1.

The error for network, E, is given in Eq. 3

$$E = \frac{1}{2} \sum_{J} \left(y_j - d_j\right)^2 \tag{3}$$

y_j is the activity level of the jth unit and d_j is the desired output of the jth unit. Neural networks have different architectures such as feedforward, feedback, network layers and perceptrons. An example for a simple feedforward network is given in Fig. 2. Feedforward ANN permits signal from input to output (only one way). There is no loop in this network. It is especially used in pattern recognition. The learning process is given in Fig. 3. Incoming neural activations are multiplied by the set of connection weights as inputs. In the middle of Fig. 3, the sum function is given. Output activations are multiplied by connection weights as outputs.

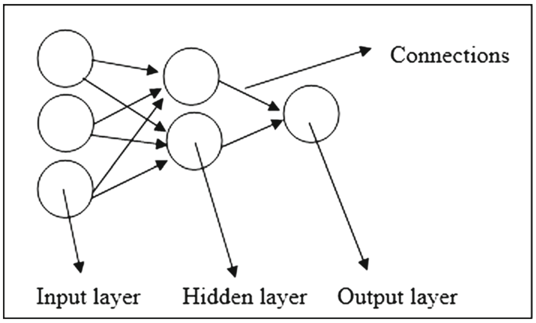

Fig. 2 Feedforward networks

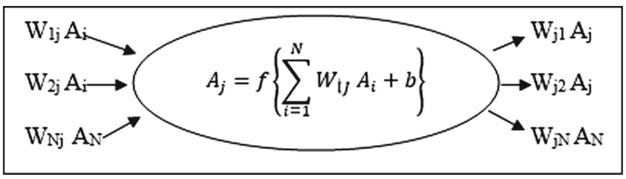

Fig. 3 Cycle of learning process. W_{ij}: connection weights; A_i: incoming neural activations; A_j: output activations

2.1.1 Running of ANN

The operation of artificial neural networks consists of data collection, training, testing and running stages [34].

1. *Data collection stage* In this stage, sample data are collected. Pre-processing should be conducted for the data in specified conditions. The pre-processing makes data representing the same thing similar and data representing the different things different.
2. *Training stage* In this stage, the connections in the network are formed to find the right connections between output and input data. To this end, specific error rate and replication number are determined. If artificial neural network is trained too much with the same data, it will recognize only this data set. This condition is known as overtraining. Many different sample data should be used to prevent overtraining. Moreover, a part of the data should be kept for testing. Whether or not overtraining occurs will be seen by checking the testing results. The training algorithms used in the artificial neural networks can be summarized as follows:

   Quick This method creates a proper structure for the network by using the features of specific rules and data. In this method, parameters are: hidden layer number, alpha and eta values and the hidden units in the layers.
   Dynamic It forms the first structure of network and improves its topology by adding and removing hidden units.
   Multiple In this algorithm, more than one artificial neural networks with different topologies are developed in the beginning. The parallel method is used for the training of the networks. The model which has the lowest value of square root of sum of squares is chosen at the end of training. In this method, parameters are: network parameters, alpha and eta values, the cycle number repeated without any improvements in the network and the pyramid structure of the network.
   Prune The training starts with a broad network structure. The weakest units are removed from the input and hidden layers in the training process. This method generally works slowly but produces much better results than the other methods. Parameters of this method are: the number of hidden layers, the number of hidden units, alpha and eta values, the cycle number repeated without any improvements in the network, the number of pruning operation of input layer made without any improvement, the number of pruning operation of hidden layer made without any improvement, the number of input layer to be removed in the pruning of only one input layer, the number of hidden layer units to be removed in the pruning of only one hidden layer and the pruning cycle of a hidden layer/input layer unit without any improvement.
   Radial Basis Function Network (RBFN) It adapts a curve according to the value of target variable in the multi-dimensional space. It classifies the data according to the output data by using a method similar to the k-average clustering analysis. The training of the model requires less time. More data are required to obtain better results. In this method, parameters are: alpha value, the cycle number made without any improvement on the network, the width of hidden layer (the number of cluster to be used), the number of coincident clusters and the number of regions.
   Exhaustive Prune It starts with a broad network structure and removes the weak units in the hidden layers from the network. The training parameters are chosen by being sure that the whole space of possible models is searched. This method is the slowest one but produces the best results. The more the data increases in size, the more the training takes time.

3. *Testing stage* In this stage, some data are kept for testing. If the testing stage produces accurate results, it is understood that the connections are appropriate. If the testing stage is inaccurate, the training stage is started again and it is repeated until the right connections are obtained.
4. *Prediction stage with new data* In this stage, new (unused) data are entered and results are provided. The artificial

neural network benefits from the past results like humans and makes predictions about the future.

2.2 Hypothesis Tests

Hypothesis tests are divided into two as parametric and nonparametric hypothesis tests depending on the scale on the measurement of evaluated variables. In the parametric hypothesis tests, the determined parameter is equal to its known value, lower and higher than it and different from it. There are two hypotheses in relation with the parameters. These are "null hypothesis" (H_0)" and "alternative hypothesis" (H_a) [35].

2.2.1 The Steps of Hypothesis Test

Two opposing hypotheses are stated as H_0 and H_a. It is revealed that the parameter in the null hypothesis (θ) is not different from its revealed value (θ_0) and there are differences between parameters in the alternative hypothesis [35].

$$\begin{aligned} &H_0 : \theta = \theta_0 \\ &H_a : \theta \neq \theta_0 \quad \text{or} \quad H_a : \theta > \theta_0 \quad \text{or} \quad H_a : \theta < \theta_0 \end{aligned}$$

2.2.2 t Test

t Test is the most widely used method in the hypothesis tests. The average of two value groups is taken and this average is compared whether the difference between them is statistically significant or not. In this context, there are three types of *t* tests. These tests are one-sample *t* test, independent *t* test and paired samples *t* test [35].

The aim of this test is to check whether or not obtained results change under different conditions. The following hypothesis is stated in order to test the difference between averages under two different conditions or settings [35]. The test statistic is calculated by using the following equation (Eq. 4).

$$t = \frac{\text{Sample statistic} - \text{H}_0 \text{ hypothesis value}}{\text{Standart error}} = \frac{\bar{d} - 0}{\frac{S_d}{\sqrt{n}}} \tag{4}$$

H_0: $\mu_d = 0$ (The difference between average values is equal to zero), H_a: $\mu_d \neq 0$ ($\mu_d < 0$ or $\mu_d > 0$) (The difference between average values is not equal to zero), S_d: the error of test statistic. n: Sample size. $\bar{d}$: The average of the differences between two samples.

2.3 Experimental Design

Experimental design is used for decreasing the number of experiments and designing the experiments properly. It is firstly developed by the British statistician R.A. Fisher et al. in 1920. The methods used in the statistical experimental design are divided into three as full factorial, fractional factorial and Taguchi method [36].

2.3.1 Taguchi Experimental Design

Taguchi design is an optimization method which is based on parameter, system and tolerance design. The orthogonal arrays are used to show different experimental designs. Different factors are tested in the minimum number with the orthogonal array and the simultaneous change is conducted between factors. Generally, L4, L8 and L16 arrays are used for 2 factor levels and the L9 and L27 arrays are used for three factor levels [36].

3 Experimental Study

The experimental study is conducted in the laboratory and a manual turning lathe is used in the machining experiments. The number of revolutions is set to 355, 500, 710 rpm and AISI-4140, AISI-1040, Al-2024 and Al-7075 bars are used as material. The cutting tools' cross section is 625 mm^2. The length of the cutting tools is 150 mm. The length of each

Table 1 Dimensions of workpieces

Workpiece material	Diameter (mm)	Length (mm)
Al-2024	40	300
Al-7075	60	300
AISI-1040	60	300
AISI-4140	40	300

Table 2 Tool overhang length

Workpiece material	Tool overhang length (mm)
Al-2024	80, 90, 100, 110
Al-7075	90
AISI-1040	80, 90
AISI-4140	80, 90

Table 3 Tool geometry

Tool angles	Value range (°)
Approach angle	93–100
End clearance angle	5
Back rake angle	−5 to 0
End cutting angle	35–45
Side clearance angle	−7 to 0
Side rake angle	−7 to 0

Table 4 AISI 4140 material composition

Element	Fe	Cr	Mn	C	Si	Mo	S	P
AISI 4140								
%	96.875–97.77	0.8–1.1	0.75–1	0.38–0.43	0.15–0.3	0.15–0.25	0.04	0.035

Table 5 AISI 1040 material composition

Element	Fe	Mn	C	S	P
AISI 1040					
%	98.9–99	0.6–0.9	0.37–0.44	≤0.05	≤0.04

Table 6 Al-7075 alloy composition

Element	Al	Zn	Mg	Cu	Cr
Al-7075					
%	90	5.6	2.5	1.6	0.23

Table 7 Al-2024 alloy composition

Element	Al	Cu	Mg	Mn
Al-2024				
%	93.5	4.4	1.5	0.6

Fig. 4 Hammer test

Table 8 Independent variables

Tool stiffness ratio (K)
Cutting depth (CD)
Tool overhang length (OL)
Tool damping ratio (S)
Side rake angle (SRA)
End cutting angle (ECA)
The number of revolution (NR)
Workpiece diameter (WD)
Back rake angle (BRA)
Insert hardness (IH)
Side clearance angle (SCA)
Approach angle (AA)
Workpiece hardness (WH)

workpiece is 300 mm. The tool overhang lengths are chosen as 80, 90, 100 and 110 mm. The feed rate of cutting tool is set to 0.06 mm/rev. The insert materials are K-MTCVD-coated cobalt-reinforced carbide, Tinalox Sn gold-coated carbide and Wc/Co carbide PVD-TiAlN Al2 plus coatings. The radius of the insert is 0.8 mm. End clearance angle is 5°. The dimensions of workpieces used in the experiments, the tool overhang lengths and the cutting tool angles are given in Tables 1, 2 and 3, respectively.

The composition of materials is given in Tables 4, 5, 6 and 7 [37].

In the studies, the structural constants such as stiffness coefficient (K) and structural damping ratio (S) of the cutting system are needed to measure the rigidity and damping behaviour of the system. The accelerometer is connected in the feed direction and the hammer tests are conducted manually by using an impact hammer (see Fig. 4). The data obtained during the hammer tests are performed by using CUT PRO 8.0 software and the structural constants are calculated. The stable cutting depths are determined by increasing the cutting depths at the same rpm value. The chatter sound is recorded by using a microphone and is processed in LABVIEW 7.1 software.

The 13 variables affecting the surface roughness are listed in Table 8.

Surface roughness values are measured at stable cutting depths. MITUTUYO surface roughness device is used during the measurement. The experimental set-up for surface roughness is given in Fig. 5.

4 Results and Discussion

In this section, experimental and numerical results are given.

4.1 Experimental Results

The values of surface roughness are measured from the machined surface at predetermined stable cutting depths. Experiments are repeated three times at the same cutting conditions. The average surface roughness values (µm) and stable cutting depths (mm) are shown in Tables 9 and 10 in

Fig. 5 Experimental set-up for surface roughness measurement

Table 9 Average surface roughness and stable cutting depths for Al-2024

Tool overhang length (mm)	The number of revolutions (rpm)		
	355	500	710
80	13.7/14.7	12.18/14.1	11.05/13.5
90	8.48/13.2	8.41/12.5	8.02/12
100	4.78/10	3.35/9.5	2.34/9
110	4.12/7.9	3.01/7.4	2.13/7

accordance with the different tool overhang length and the number of revolutions. It is observed that as the number of revolutions increases and the stable cutting depth decreases at the same tool overhang length, average surface roughness decreases.

4.2 Numerical Results

The numerical study is carried out by using SPSS Clementine and MINITAB. An ANN model is developed by using the independent variables given in Table 8 and the dependent variable is surface roughness. By means of 13 independent variables for the model in Table 8, the surface roughness is predicted. Firstly, L18 Taguchi experimental design is conducted for optimizing the ANN parameters. The training parameters and levels used in the artificial neural networks are presented in Table 11. Six different algorithms are considered in the training stage. 60, 70 and 80% are chosen as the ratios of training. The data used in the training and testing are obtained by dividing the data in three different ways. Three levels are used for the division of data within this scope. The estimated average accuracy is determined in accordance with L18 experimental design as shown in Table 12. Three different experimental runs were performed at each setting of the experiment because the connection weights change in every run.

Table 11 Training parameters used in ANN

Training algorithms	Training ratio (%)	Data division
1—Quick	1–60	1
2—Dynamic	2–70	2
3—Multiple	3–80	3
4—Prune		
5—RBFN		
6—Exhaustive Prune		

Signal-to-noise (S/N) ratios are given for estimated average accuracy in Fig. 6. According to these ratios, the second level of training algorithms (Dynamic), the third level of training ratio (80%) and the second level of data division were chosen to maximize estimated average accuracy.

By using these optimized ANN parameters, the relative weights are calculated for 13 independent variables. The relative weights are the connection weights obtained from the artificial neural network. In the calculation of weights, each run is replicated independently 30 times and the average values are considered since the connection weights change at every run. In Table 13, the relative weights of the independent variables are given. It is observed that the stable cutting depths, the tool overhang length and stiffness ratio affect the surface roughness more than the other variables.

Table 10 Average surface roughness and stable cutting depths for aluminium alloy and steels

Tool overhang length (mm)	Material	The number of revolutions (rpm)		
				710
80	AISI 1040			3.8/4
80	AISI 4140			2.61/3
		355	500	710
90	Al-7075	5.59/9	4.87/8.5	4.1/8
90	AISI 1040	3.64/5.1	3.6/4.4	3.44/3.8
90	AISI 4140	2.08/3.7	2.07/3.2	1.97/2.6

Table 12 L18 experimental design for ANN parameters (Response: estimated average accuracy)

Training algorithm	Training ratio	Data division	Estimated average accuracy
1	1	1	97.48
1	2	2	96.10
1	3	3	98.33
2	1	1	97.72
2	2	2	97.94
2	3	3	97.95
3	1	2	97.29
3	2	3	96.30
3	3	1	98.01
4	1	3	95.77
4	2	1	96.52
4	3	2	97.84
5	1	2	97.34
5	2	3	92.96
5	3	1	93.44
6	1	3	95.16
6	2	1	96.04
6	3	2	97.90

4.2.1 *Forward Selection Method*

The forward selection method is based on the addition of independent variables to the model with paired t test starting from the variable whose relative weight is the highest. The steps of the method are given as follows:

1. Determine model parameters (the number of runs and p value)

Table 13 Relative weights according to independent variables

Variables	Relative weights
Cutting depth (CD)	0.418
Tool overhang length (OL)	0.301
Stiffness ratio (K)	0.152
Tool damping ratio (S)	0.142
Side rake angle (SRA)	0.123
The number of revolution (NR)	0.109
Workpiece diameter (WD)	0.071
Insert hardness (IH)	0.061
Back rake angle (BRA)	0.059
Workpiece hardness (WH)	0.054
Side clearance angle (SCA)	0.04
Approach angle (AA)	0.039
End cutting angle (ECA)	0.038

2. The variable whose relative weight is the highest is selected among the independent variables.
3. This variable is added into the model.
4. The model is run (a predetermined number of times).
5. A paired t test is performed to compare the results before and after the variable addition.
6. Whether or not the variable is added is determined according to the criterion of the paired t test (the p value or equivalently paired t test statistic).
7. Steps 1–6 are repeated until all variables are considered in the model and the method stops.

In this analysis, p value and the number of run are selected as 0.3 and 10, respectively. The variable CD (Cutting Depth)

Fig. 6 S/N ratios for mean estimated average accuracy

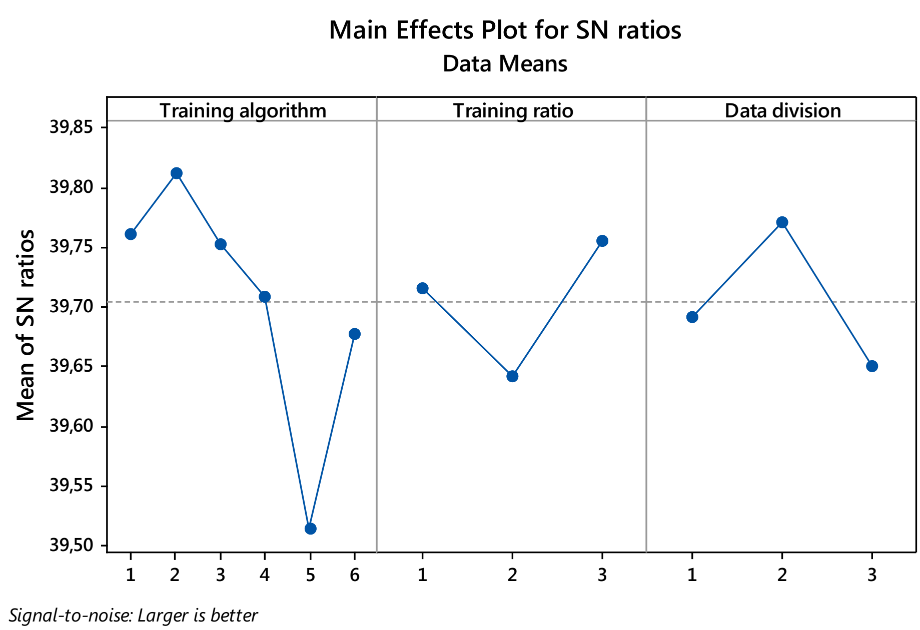

Table 14 Stages of forward selection method

Stages	Comparison	t value	p value	Result
1	(CD + OL) versus CD	4.105	0.003	OL is added
2	(CD + OL + K) versus (CD + OL)	−1.214	0.256	–
3	(CD + OL + S) versus (CD + OL)	−0.927	0.378	–
4	(CD + OL + SRA) versus (CD + OL)	−0.239	0.817	–
5	(CD + OL + NR) versus (CD + OL)	2.606	0.028	NR is added
6	(CD + OL + NR + WD) versus (CD + OL + NR)	2.196	0.056	WD is added
7	(CD + OL + NR + WD + IH) versus (CD + OL + NR + WD)	−0.358	0.728	–
8	(CD + OL + NR + WD + BRA) versus (CD + OL + NR + WD)	−0.337	0.744	–
9	(CD + OL + NR + WD + WH) versus (CD + OL + NR + WD)	0.479	0.643	–
10	(CD + OL + NR + WD + SCA) versus (CD + OL + NR + WD)	1.261	0.239	SCA is added
11	(CD + OL + NR + WD + SCA + AA) versus (CD + OL + NR + WD + SCA)	0.425	0.681	–
12	(CD + OL + NR + WD + SCA + ECA) versus (CD + OL + NR + WD + SCA)	0.784	0.453	–

which has the highest relative contribution in the model is added into the model in the first stage. Since there is no developed model in which the cutting depth can be compared in the first stage, this variable is automatically added. The model is run 10 times and the average value is taken. After the CD (cutting depth) variable is entered into the model, the other independent variables are, respectively, added to the model as to their relative weights. In the next stage, tool overhang length (OL) is added. The model is run 10 times and the average value is taken. After 10 runs, the models before and after (OL) is added are compared. The test statistics t is obtained as 4.105 and equivalently the p value is obtained as 0.003. Because p value <0.3, the variable (OL) enters into the model. The results of the model are given in Table 14. It is efficient to predict the surface roughness if the model consists of the cutting depths (CD), tool overhang length (OL), the number of revolutions (NR), workpiece diameter (WD) and side cutting angle (SCA).

4.2.2 Stepwise Selection Method

The stepwise selection method is based on both the addition and extraction of independent variables with paired t test. The steps of the method are given as follows:

1. Determine model parameters (the number of runs and p value)
2. The variable whose relative weight is the highest is selected among the independent variables.
3. This variable is entered into the model.
4. The model is run a predetermined number of times.
5. A paired t test is performed to compare the results before and after the variable addition.
6. Whether or not the variable is added is determined according to the result of the paired t test (the p value or equivalently paired t test statistic).
7. After runs, the variable which has the lowest relative contribution is removed from the model.
8. Whether or not the variable is removed is determined according to the results of the paired t test (the p value or equivalently paired t test statistic).
9. Steps 1–8 are repeated until all variables are considered and the method stops.

In this analysis, p value and the number of run are selected as 0.3 and 10, respectively. The variable CD (Cutting Depth) which has the highest relative contribution to the model enters into the model in the first stage. Since there is no developed model in which the cutting depth can be compared to in the first stage, this variable is automatically added. The model is run 10 times. After the cutting depth is entered into the model, the other independent variables are, respectively, entered into or removed from the model as to their relative weights. In the next stage, tool overhang length (OL) is added (forward stage/stage 1). The model is run 10 times. After 10 runs, the models before and after OL is added are compared. The t test statistic value is obtained as 5.487 and the p value is obtained as 0.00. Since $p < 0.3$, the variable (OL) enters into the model. The model is checked for removal of variables (backward stage/stage 2). When 10 runs are completed, the tool overhang length (OL) variable has the lowest relative contribution. Because tool overhang length (OL) is a significant variable in forward stage, it is not removed. Except the 10th stage (backward), the other backward stages are not given in Table 15 because the same results are obtained. In the 10th stage, side rake angle (SRA) is removed because $p = 0.378 > 0.3$. The results of the model are given in Table 15. It is efficient to predict the surface roughness if

Table 15 Stages of stepwise selection method

Stages	Comparison	t value	p value	Result
1	(CD + OL) versus (CD)	5.487	0.000	OL is added
3	(CD + OL + K) versus (CD + OL)	0.865	0.409	–
5	(CD + OL + S) versus (CD + OL)	0.746	0.475	–
7	(CD + OL + SRA) versus (CD + OL)	3.214	0.011	SRA is added
9	(CD + OL + SRA + NR) versus (CD + OL + SRA)	2.012	0.075	NR is added
10 (Backwad stage)	(CD + OL + NR + SRA) versus (CD + OL + NR)	−0.927	0.378	SRA is removed
11	(CD + OL + NR + WD) versus (CD + OL + NR)	−0.234	0.82	–
13	(CD + OL + NR + IH) versus (CD + OL + NR)	0.249	0.809	–
15	(CD + OL + NR + BRA) versus (CD + OL + NR)	−0.477	0.644	–
17	(CD + OL + NR + WH) versus (CD + OL + NR)	−0.972	0.356	–
19	(CD + OL + NR + SCA) versus (CD + OL + NR)	0.082	0.937	–
21	(CD + OL + NR + AA) versus (CD + OL + NR)	−0.675	0.516	–
23	(CD + OL + NR + ECA) versus (CD + OL + NR)	−0.208	0.84	–

Table 16 Results of three models in terms of average estimated accuracy

Replication	All variables (13 independent variables)-1	Forward selection method (5 independent variables)-2	Stepwise selection method (3 independent variables)-3
1	0.98169	0.9868	0.9675
2	0.98282	0.9858	0.9715
3	0.98221	0.9714	0.9743
4	0.98338	0.9828	0.9749
5	0.98283	0.9714	0.9729
6	0.97824	0.9702	0.9714
7	0.94639	0.9825	0.9624
8	0.97868	0.9846	0.9732
9	0.97766	0.9862	0.9626
10	0.98601	0.9673	0.9679
Mean	0.977991	0.9789	0.96986

Table 17 Comparison of the models by paired t test

	Paired differences					t	df	Sig. (two-tailed)
	Mean	SD	SEM	95% CI of the difference				
				Lower	Upper			
Pair (1–2)	−.000909	.01527	.0048318	−.0118393	.0100213	−.188	9	.855
Pair (1–3)	.008131	.00936	.0029615	.0014315	.0148305	2.746	9	.023
Pair (2–3)	.00904	.01014	.00321	.00179	.01629	2.819	9	.020

the model consists of the cutting depths (CD), tool overhang length (OL) and the number of revolutions (NR).

In Table 16, the results of three developed models are presented. The results are compared by using paired t test in Table 17. It is observed that there is no significant difference between the models at 1% significance level and the model which includes all the variables. Also, there is no significant difference between the first and second model at 5% significance level. However, forward selection method outperforms the stepwise selection method at 5% significance level.

5 Conclusion

In this study, a new variable selection method based on ANN is proposed. Within this scope, forward and stepwise selection methods are proposed. For the variable addition/elimination criterion, p significance value is considered. The proposed methods are used in an experimental study (the prediction of surface roughness). While it is observed that the variables affecting the surface roughness are the cutting depths, tool overhang length, the number of revolutions, workpiece diameter and side cutting angle in the forward selection method, the cutting depths, tool overhang length and the number of revolutions affected surface roughness significantly in the stepwise selection method. The successful results are produced in the selection of variables affecting surface roughness and in the prediction of surface roughness in turning. The selection of variables does not change the prediction accuracy of the model at 1% significance level. Also, there is no significant difference between the first and second model at 5% significance level. This study will enable the operators and engineers to work more efficiently. A sensitivity analysis may be conducted in accordance with different p values in the future studies. Moreover, the results may be compared for the different prediction problems in manufacturing such as tool wear prediction, cutting force prediction in the future works.

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