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ORIGINAL ARTICLE

Investigation of the performance of the MQL, dry, and wet turning by response surface methodology (RSM) and artificial neural network (ANN)

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Abstract In this approach, response surface methodology (RSM) and artificial neural network (ANN) techniques were used in order to search for optimal prediction of uncontrollable machining factors that leads to better machining performance. The experiment has been established using 3 levels and 4 factors Box-Behnken design (BBD) for tangential force and surface roughness measurements according to combinations of cutting speed, feed rate, and cutting depth using multilayer-coated tungsten carbide insert with various nose radius in turning of X210Cr12 steel under dry, wet, and MQL machining. Consequently, it could be possible to investigate the efficiency of MQL technique for an environment-friendly ecological machining. Then, a comparative between ANN and RSM models has been established to determine the best approach according to model accuracy and capability for predicting surface roughness and cutting force. The ANN method provides more accurate results and proved its effectiveness as soon as its correlation coefficients, mean prediction errors (MPEs), and root mean square errors are rather small compared to those obtained by the RSM method.

Keywords MQL · ANN · RSM · Optimization · Green process

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Nomenclature

MQL	Minimum quantity lubrication
BBD	Box-Behnken design
Vc	Cutting speed (m/min)
Ap	Depth of cut (mm)
F	Feed rate (mm/rev)
R	Tool nose radius (mm)
Ra	Arithmetic mean roughness (μm)
Fz	Tangential force (N)
ANN	Artificial neural network
RSM	Response surface methodology
ANOVA	Analysis of variance
DF	Degrees of freedom
MS	Mean squares
SS	Sum of squares
R^2	Determination coefficient
P	Probability of significance
F	Variance ratio
CVD	Chemical vapor deposition
AISI	American Iron and Steel Institute
MPE	Mean predicted error
RSME	Root mean square

1 Introduction

Improving machining processes should take into account different considerations such as economic, ecological, and physical aspects. The MQL process is considered as economically and environmentally friendly. Furthermore, reducing the lubricant can improve machining performances and reduce the machining costs. The liquid used in MQL should be biodegradable and also environmentally friendly.

The lubrication during the conventional manufacturing processes represents up to 20% of machining costs [1, 2]. The complete elimination of the lubricant could be useful in the first time but if the tool wear and part quality are considered, it will be difficult. In this case, the minimum quantity of lubricant could be used to uphold a sensible tool life and part quality. It has been found that the thermal deformation and the surface error are seriously affected by the machining lubricant [3].

The dry machining is gaining more and more ground in the industrial world to meet the ecological and environmental aspect, and it offers the opportunity to make important savings. However, the temperature in the rake face is higher than conventional coolant process and must be controlled as far as possible [4]. Furthermore, the high cutting temperature generates residual stress, dimensional deformation, and a premature failure of the cutting tools. The solution of using the lubricant is not always preferred because in some cases, it improves the chip formation and generates additional costs for degreasing before recycling operations [5]. The use of cutting fluids also causes many problems for the human health. Various diseases related to the use of these cutting fluids are cutaneous and respiratory, related to handling oils [6, 7]. Therefore, it is highly recommended to eliminate or reduce the use of these fluids. This trend has created a need in the industry for a human and environmental comprehensive preventive approach while ensuring a better quality of the manufactured product.

In this way, several research studies have been established using the MQL technique in order to minimize the lubricant consumption. An experimental study carried out by Rahim et al. [8] qualify the minimum quantity lubrication “MQL” as a sustainable cooling technique using a synthetic lubricant. The effectiveness of this technique has been justified according to the variation of the temperature and the cutting speed in chip formation during the machining of AISI 1045 steel by an uncoated carbide tool. A reduction of the cutting temperature was observed, along with much reduced cutting forces and improved chip formation under MQL than those of dry machining. The influence of the cooling condition on the tool flank wear (VB) and on the surface roughness (Ra) during the turning of the AISI-4340 steel has been studied experimentally by Dhar et al. [9]. The authors found a significant reduction in the rate of the tool wear and the surface roughness under MQL along with a decrease of the temperature in the cutting zone. It has been also proved by Varadarajan et al. [10] that the MQL technology should be a good alternative in terms of the cutting force, the surface roughness, and the tool chip contact length. Hadad and Sadeghi [11] have studied the effects of the machining parameters on turning performance such as machining forces, surface roughness, and temperature. The results indicate that the surface finishes were improved due to the reduction of wear and damage when using the MQL process.

MQL research literature, so far, indicates that the MQL technique has proved its efficiency, allowing for reduction in lubricant use (50 to 90%) [12], energy consumption, better performance, and environment protection.

In order to respond to the requirements of its applications in manufacturing processes, it is very important to forecast the surface roughness and cutting force. Consequently, it is necessary to search the best modeling approach of these output parameters. To obtain this objective, several approaches can be used as well as surface response methodology (RSM) and artificial neural network (ANN). RSM is considered a quick and useful procedure for the investigation and optimization of complex processes as well as for modeling machining output parameters. Asiltürk et al. [13] found that response surface methodology represents a good tool for predicting surface roughness in machining of Co28Cr6Mo. Elbah et al. [14] investigated the performance of mixed ceramic tool when turning AISI 4140 steel using RSM modeling; their results indicate that the developed mathematical models could adequately describe the performance indicators within the limits of the factors that are being investigated. RSM was employed by Kasim et al. [15] in their experiment to determine the cause-and-effect relationship between the control variables and the studied response; their results indicate that RSM modeling can give accurate results. Chabbi et al. [16] established a predictive modeling and multi-response optimization of technological parameters in turning of polyoxymethylene polymer (POM C) using RSM; their results of the confirmation tests show that the developed models are effectively able to predict the output responses.

The ANN has come up as one of the most efficient methods for empirical modeling, especially for non-linear systems, as well as for modeling of output parameters in machining areas. Das et al. [17] justified the use of artificial neural network to develop relationship between cutting process parameters and surface roughness when machining of Al-4.5Cu-1.5TiC metal matrix composites, by its capability to detect non-linear relationships. Moreover, Palavar et al. [18] concluded that the prediction of aging effects on the wear behavior of Inconel 706 super alloy using ANN can provide effective results and that the method can be effectively used to determine weight loss values in the determined parameters with a high coefficient of determination value. In addition, the ANN approach can save time in experimental processes and reduce costs as it provides quicker results. Kant and Sangwan. [19] develops a predictive and optimization model by coupling the two artificial intelligence approaches, "artificial neural network and genetic algorithm," as an alternative to conventional approaches in predicting the optimal value of machining parameters leading to minimum surface roughness; their predicted results by the proposed model indicate a good agreement between predicted and experimental values. They concluded that the proposed approach is capable of determining the optimum machining parameters.

Several researches discuss the accuracy and capability of surface response methodology and artificial neural network approaches in the status of comparative study. Venkata and Murthy [20] developed statistical models to investigate the effect of cutting parameters on surface roughness and root mean square of workpiece vibration in boring of stainless steel, and their results indicate that ANNs were found to be better than the RSM model in the prediction of cutting parameters. Ranganathan et al. [21] concluded that the ANN and RSM models are robust and accurate to estimate the surface roughness of the workpiece when hot turning of this steel. Besides, Bingöl et al. [22] agreed root mean square error (RMSE), coefficient of determination (R^2), and absolute average deviation (AAD) as criteria of comparison between RSM and ANN for the evaluation of heavy metal biosorption process. A batch sorption process was performed using *Nigella sativa* seeds (black cumin), a novel and natural biosorbent, to remove lead ions from aqueous solution with the process variables: pH, biosorbent mass, and temperature. They concluded that the ANN model was found to have a higher predictive capability than the RSM model. On the other hand, other researchers found that RSM is better than the ANN approach in several investigations and studies. Truly, after predicting the tensile strength of friction stir-welded AA7039 aluminum alloy joints, Lakshminarayanan and Balasubramanian [23], concluded that RSM has a main advantage compared with ANN, and this advantage consists of its ability to quantify the factor contributions from the coefficients in the regression model, identifying the insignificant main factors and interaction factors or insignificant terms in the model. Moreover, in their comparison between ANN and RSM approaches for modeling surface roughness when turning of Al7075/10/SiCp and Al 7075 hybrid composites, Kumarand Chauhan [24] concluded that the ANN prediction model produced a greater parentage error than did the RSM prediction model with (R^2) values of 0.99571 and 0.9972, respectively.

The current study investigates the dry, wet, and MQL turning using a comparative assessment between modeling by the RSM and the ANN using 3 levels and 4 factors Box-Behnken design (BBD). The developed models were used to predict the surface roughness and the tangential cutting force according to the studied cutting parameters (cutting speed, cutting depth, feed rate, and the tool nose radius) for different cases of lubrication mode. A comparative between ANN and RSM models has been established to determine the best approach according to model accuracy and capability for predicting surface roughness and cutting force when turning of X210Cr12 steel using multilayer-coated tungsten carbide insert (GC-4215) with various nose radii (r). Similarly, it could be possible to investigate the efficiency of MQL technique for an environment-friendly ecological machining.

2 Design of experiment

2.1 Tools

The experimental conditions and cutting parameters are set according to different aspects such as the material to be machined, the machine tool, cutting tool, and lubrication mode, and the tests are carried out using a conventional lathe "TOS TRENCIN" model SN-40.

The workpiece material is the X210Cr12 steel. The mechanical properties of the latter are defined in the Table 1; the diameter (*d*) and length (*l*) of the part machined are respectively 80 and 330 mm.

As regards the cutting tool, the multilayer-coated tungsten carbide insert was chosen. The coating grade is GC4215 (ISO P15-CVD-coated carbide) selected with different nose radius. The ISO tool holder reference is PSBNR 2525 K12. The tool geometry is characterized by the following angles: $\chi r = +45°$, $\lambda = -6°$, $\gamma = -6°$, and $\alpha = +6°$.

The tool holder has been connected on four components of piezoelectric dynamometer (Kistler 9257B), linked to a multichannel charge amplifier (type 5011B), data acquisition hardware, and graphical programming environment (DynoWare 2825A1–1) for data analysis and visualization. Regarding the surface roughness of the machined workpiece, the measurements have been taken directly after each test using a roughness meter (Mitutoyo Surftest SJ-201) which consists of a diamond tip (probe), with a radius of 5 μm moving in a linear manner on the machined surface. The schematic diagram of the experimental setup and the MQL system are shown in Fig. 1.

2.2 Procedure

In order to study the lubricating performances and its effect on the studied outputs, the cooling condition has been taken as an

Table 1 Chemical composition of X210Cr12 steel

Element	C	Si	Cr	Mn	Ni	W	V	P	S	Cu
Content %	2.10	0.30	11.50	0.40	0.31	1	1	0.03	0.03	0.25

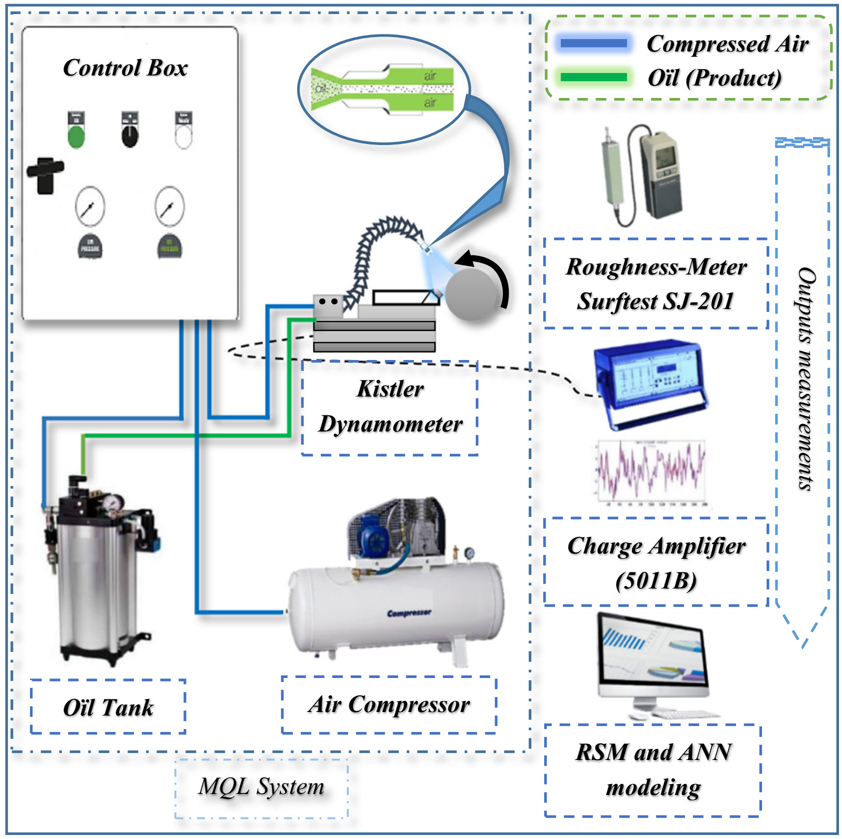


Fig. 1 Experimental setup for outputs measurement and data analysis

output, and the tests have been designed using 3 levels and 4 factors of Box-Behnken design as the cutting speed (Vc; 150, 250, and 350 m/min), the feed rate (f; 0.08, 0.12, and 0.16 mm/rev), the nose radius variation (r; 0.8, 1.2, and 1.6 mm) and the depth of wear (ap; 0.2, 0.4, and 0.6 mm). For the cooling condition, the 27 turning tests have been performed under traditional lubrication mode, dry machining, and with the MQL technique using a synthetic oil with a flow rate of 120 ml/h and an air pressure of pulverization of 6 bar. The different parameters defined are shown in Table 2.

The combination of the parameters of the BBD with the measured values of surface roughness and cutting force are represented in Table 3. The roughness values represent the mean of three measured values for each test, and the studied cutting force (Fz) was measured by a force sensor during the cutting process. The consideration and the study of uncontrollable factors allow us to extract optimal scheme for better productivity regarding the high part quality, low machining cost, and low energy consumption. The studied outputs of the orthogonal plan are selected in order to analyze and study the influence of the different cutting parameters on the material's machinability (X210Cr12 steel) and for prediction using the response surface methodology (RSM) and the artificial neural network (ANN). The RSM and ANN approaches are compared in terms of the predicted data and their coefficient of determination (R^2), model predicted error (MPE), and root mean square error (RSME). The given terms are calculated through the following formulas:

$$R^2 = \frac{\sum_{i=1}^{n}\left(y_{i,pr} - y_{i,ex}\right)}{\left(y_{i,pr} - y_{\text{average}}\right)^2} \tag{1}$$

$$\text{MPE}(\%) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\left(y_{i,ex} - y_{i,pr}\right)}{y_{i,ex}}\right| \tag{2}$$

$$\text{RSME} = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{i,ex} - y_{i,pr}\right)^2}{n}} \tag{3}$$

where n is the number of experiments, $y_{i,ex}$ is the experimental value of the ith experiment, $y_{i,pr}$ is the predicted value of the

Table 2 Factors and levels used in the experimental plan

Level	Vc (m/min)	f (mm/rev)	r (mm)	ap (mm)
1	150	0.08	0.8	0.2
2	250	0.12	1.2	0.4
3	350	0.16	1.6	0.6

Table 3 The experimental results

	Vc (m/min)	f (mm/rev)	r (mm)	ap (mm)	DRY		WET		MQL	
					Fz (*N*)	Ra (µm)	Fz (*N*)	Ra (µm)	Fz (*N*)	Ra (µm)
1	250	0.08	0.8	0.4	129.61	0.67	126.11	0.58	125.09	0.38
2	350	0.12	1.2	0.2	116.16	0.67	114.63	0.64	107.54	0.63
3	250	0.08	1.2	0.2	91.54	0.65	84.29	0.49	83.06	0.59
4	250	0.16	1.2	0.6	294.49	0.92	280.45	0.85	280.67	0.82
5	150	0.16	1.2	0.4	231.61	1.01	220.13	0.91	206.62	0.9
6	150	0.08	1.2	0.4	156.1	0.68	137.24	0.5	125.68	0.41
7	150	0.12	0.8	0.4	174.07	0.95	171.22	0.91	163.47	0.6
8	250	0.12	1.6	0.6	265.82	0.64	244.45	0.62	236.8	0.58
9	350	0.16	1.2	0.4	203.25	1.1	198.2	0.88	199.65	0.79
10	350	0.08	1.2	0.4	133.11	0.6	131.89	0.54	118.14	0.45
11	150	0.12	1.2	0.6	261.04	0.65	259.45	0.62	246.79	0.6
12	350	0.12	1.6	0.4	194.26	0.85	189.9	0.71	183.23	0.64
13	250	0.12	1.2	0.4	177.19	0.89	169.07	0.88	166.49	0.88
14	250	0.12	1.6	0.2	103.8	0.67	102.32	0.64	94.01	0.62
15	350	0.12	1.2	0.6	246.04	0.96	232.75	0.83	232.09	0.72
16	150	0.12	1.6	0.4	211.73	0.68	198.03	0.66	194.2	0.58
17	250	0.12	1.2	0.4	169.94	0.99	167.11	0.97	161.61	0.95
18	250	0.12	0.8	0.2	93.45	0.81	91.61	0.76	90.74	0.66
19	250	0.08	1.6	0.4	143.9	0.87	143.49	0.41	138.1	0.53
20	250	0.12	0.8	0.6	230.24	0.81	228.19	0.81	227.89	0.56
21	250	0.12	1.2	0.4	173.63	1.01	168.4	0.98	159.78	0.95
22	350	0.12	0.8	0.4	171.36	0.7	160.44	0.67	160.71	0.45
23	250	0.08	1.2	0.6	204.99	0.9	204.04	0.57	175.29	0.54
24	250	0.16	1.2	0.2	132.02	1.32	125.88	1.08	106.08	0.97
25	250	0.16	0.8	0.4	205.59	1.34	198.61	1.06	188.93	0.87
26	250	0.16	1.6	0.4	235.42	0.92	216.43	0.83	220.86	0.76
27	150	0.12	1.2	0.2	133.52	1.05	120.32	0.97	117.21	0.87

*i*th experiment calculated by the model, and $y_{average}$ is the average value of the experimentally determined values.

2.3 Modeling methods

2.3.1 Response surface methodology approach

RSM consists of a mathematical group and statistical techniques used in the development of an adequate functional relationship between a response of interest; RSM is a process that includes the following steps:

1. Define the independent input variables and the desired output responses
2. Adopt an experimental design
3. Perform a regression analysis with the mathematical model RSM
4. ANOVA analysis for independent input variables to find the parameters that significantly affect the response
5. Determine the status of the mathematical model of RSM and decide if this model is in need of screening variables or not
6. Optimize and conduct a confirmation experiment to verify the predicted performance characteristics. The relation between the cutting conditions and the technology machining factors is given as

$$\mathrm{Y} = \mathrm{F}\,(\mathrm{ap}, \mathrm{Vc}, \mathrm{f}, \mathrm{r}) \tag{4}$$

The second-order model response surface can be fitted into the following Eq. (5):

$$\begin{aligned} y_{cc} = {} & \beta_0 + \beta_1.x_1 + \beta_2.x_2 + \beta_3.x_3 + \beta_4.x_4 + \beta_5.x_1.x_2 \\ & + \beta_6.x_1.x_3 + \beta_7.x_1.x_4 + \beta_8.x_2.x_3 + \beta_9.x_2.x_4 \\ & + \beta_{10}.x_3.x_4 + \beta_{11}.x_1^2 + \beta_{12}.x_2^2 + \beta_{13}.x_3^2 + \beta_{14}.x_4^2 \end{aligned} \tag{5}$$

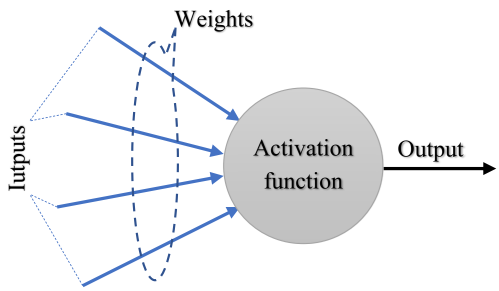


Fig. 2 An artificial neuron

where 'y' is the corresponding response (Ra, Fz); 'cc' represents the corresponding cooling condition; and x_1, x_2, x_3, x_4 represent the turning parameters. The term β is the regression coefficient. From Eq. (5) the relationship is defined between the studied output and the turning parameters as given below:

$$y = \beta_0 + \beta_1.Vc + \beta_2.f + \beta_3.r + \beta_4.ap + \beta_5.Vc.f + \beta_6.Vc.r + \beta_7.Vc.ap + \beta_8.f.r + \beta_9.f.ap + \beta_{10}.r.ap + \beta_{11}.Vc^2 + \beta_{12}.f^2 + \beta_{13}.r^2 + \beta_{14}.ap^2 \quad (6)$$

2.3.2 Artificial neural networks

An ANN is a data processing and modeling technique that arose in pursuit of mathematical modeling of the learning process which was inspired by the human brain. ANN is especially useful for classification and function approximation problems usually when rules such as those that might be used in an expert system cannot easily be applied [21]. Neural computing requires a number of neurons, to be connected together into a neural network. Neurons are arranged in layers. Each neuron within the network is usually a simple processing unit which takes one or more inputs and produces an output. At each neuron, every input has an associated weight which modifies the strength of each input as indicated in Fig. 2. The neuron simply adds together all the inputs and calculates an output to be passed on [25]. ANNs combine artificial neurons in order to process information.

In the present study, the artificial neural networks were built using MATLAB software with the neural network toolbox. Several ANN models were designed and tested to explore the optimal architecture, the most suitable activation function, and the best training algorithm. The main criteria used were MPE, the RSME, and the R^2 values of all the network models (training, validation, and test).

3 Results and discussion

3.1 Cooling effect on machining factors

During machining, the obtained tangential force and surface roughness leads to an important improvement under MQL cooling. Under certain combination of the cutting parameters, dry machining results a worst surface quality during turning. Figure 3 illustrates a comparative graphic for Ra and Fz under different cooling conditions of the experimental measures. It can be also observed that the MQL mode provides better surface quality and minimize cutting force; this technique affects not only product quality but also respects the ecological aspect and preserves the environment by reducing the uses of lubricating oils which implies less machining cost, because some turning operation requires lubrication.

Figure 4 presents a normal probability plot. This representation is basically a plot of the ordered observations from a sample of data against the corresponding percentage points from the standard normal distribution for the studied factors Ra and Fz under such cooling condition; this plot indicates if the data follow a normal distribution, in which case the points will follow a straight line, since some scattering is expected even with the normal data. As shown in Fig. 4, it can be assumed that the data is normally distributed.

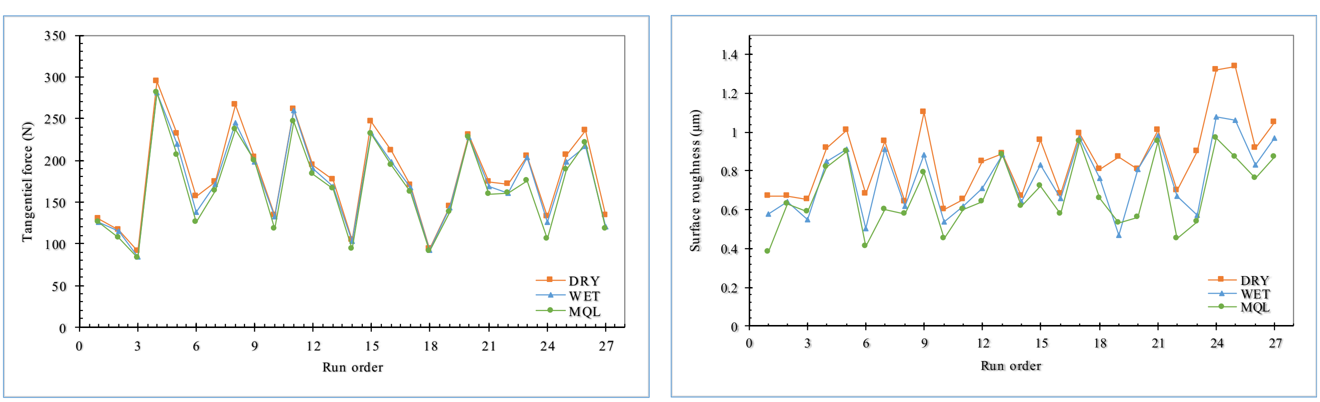


Fig. 3 Comparison of dry, wet, and MQL experimental results

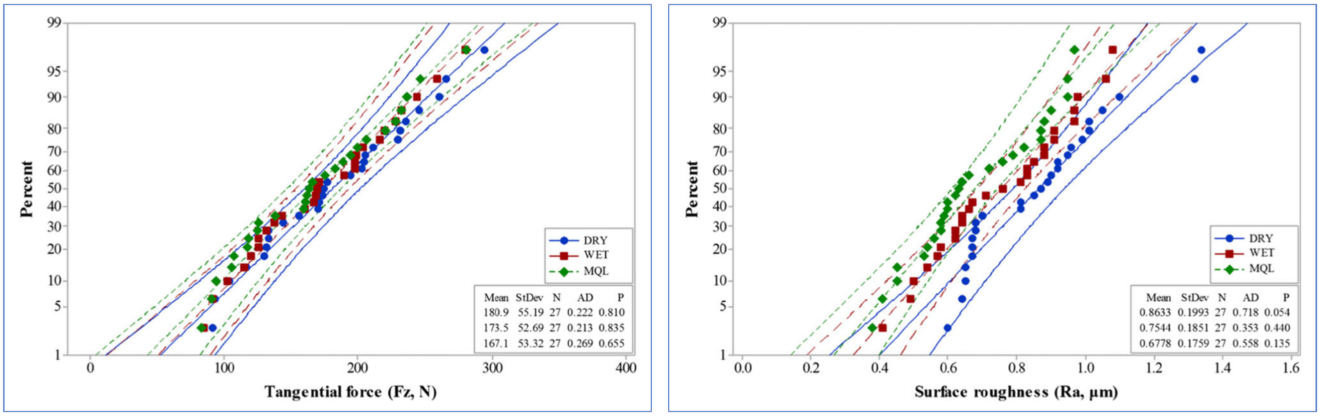


Fig. 4 Normal probability plots of Ra and Fz

3.2 RSM modeling

3.2.1 Cutting force modeling

ANOVA is a statistical technique used to identify the significance of the factor(s) or interaction factors on a particular response predicated on the experimental data. It regresses the total variability of the response into individual contributions of each of the factors and the error. It determines the ratio between the regression mean square and the mean square error and is termed as F-ratio or variance ratio. F-ratio is utilized to

Table 4 ANOVA analysis for dry machining results

Source	SS	DF	MS	F-Value	*P*-value	Cont. %	Remark
A. Tangential force model							
Model	78,361.79	14	5597.27	79.94	< 0.0001		Significant
Vc	899.43	1	899.43	12.85	0.0038	1.14	–
f	16,363.68	1	16,363.68	233.70	< 0.0001	20.66	–
r	1890.28	1	1890.28	27.00	0.0002	2.39	–
ap	57,703.36	1	57,703.36	824.11	< 0.0001	72.86	–
Vc × f	7.21	1	7.21	0.10	0.7538	0.01	Not significant
Vc × r	54.46	1	54.46	0.78	0.3951	0.07	–
Vc × ap	1.39	1	1.39	0.02	0.8902	0.01	–
f × r	60.37	1	60.37	0.86	0.3714	0.08	–
f × ap	600.74	1	600.74	8.58	0.0126	0.76	Significant
r × ap	159.14	1	159.14	2.27	0.1575	0.20	Not significant
Vc^2	581.44	1	581.44	8.30	0.0138	0.73	Significant
f^2	13.89	1	13.89	0.20	0.6640	0.02	Not significant
r^2	9.24	1	9.24	0.13	0.7227	0.01	–
ap^2	49.57	1	49.57	0.71	0.4166	0.06	–
Residual	840.23	12	70.02			1.06	
Cor. total	79,202.02	26					
B. Surface roughness model							
Model	0.96	14	0.07	12.85	< 0.0001		Significant
Vc	1.63E-03	1	1.63E-03	0.30	0.592	0.15	Not significant
f	0.42	1	0.42	77.68	< 0.0001	40.46	Significant
r	0.04	1	0.04	6.54	0.025	3.40	–
ap	7.01E-03	1	7.01E-03	1.30	0.276	0.67	Not significant
Vc × f	7.23E-03	1	7.23E-03	1.34	0.269	0.69	–
Vc × r	0.04	1	0.04	8.19	0.014	4.26	Significant
Vc × ap	0.12	1	0.12	22.11	0.001	11.52	–
f × r	0.10	1	0.10	17.85	0.001	9.30	–
f × ap	0.11	1	0.11	19.62	0.001	10.22	–
r × ap	2.25E-04	1	2.25E-04	0.04	0.841	0.02	Not significant
Vc^2	0.05	1	0.05	8.94	0.011	4.65	Significant
f^2	8.53E-03	1	8.53E-03	1.59	0.232	0.82	Not significant
r^2	0.05	1	0.05	8.71	0.012	4.53	Significant
ap^2	0.03	1	3.10E-02	5.76	0.034	3.00	–
Residual	0.064	12	5.38E-03			6.25	
Cor. total	1.033	26					

Table 5 ANOVA analysis for wet machining results

Source	SS	DF	MS	F-Value	*P*-value	Cont. %	Remark
(a) Tangential force model							
Model	71,530.75	14	5109.34	95.95	< 0.0001		Significant
Vc	514.57	1	514.57	9.66	0.0090	0.71	–
f	14,189.31	1	14,189.31	266.47	< 0.0001	19.66	–
r	1169.00	1	1169.00	21.95	0.0005	1.62	–
ap	54,712.81	1	54,712.81	1027.48	< 0.0001	75.81	–
Vc × f	68.72	1	68.72	1.29	0.2781	0.10	Not significant
Vc × r	1.76	1	1.76	0.03	0.8589	0.00	–
Vc × ap	110.36	1	110.36	2.07	0.1756	0.15	–
f × r	0.05	1	0.05	0.00	0.9764	0.00	–
f × ap	303.11	1	303.11	5.69	0.0344	0.42	Significant
r × ap	7.70	1	7.70	0.14	0.7104	0.01	Not significant
Vc^2	386.13	1	386.13	7.25	0.0196	0.54	Significant
f^2	0.03	1	0.03	0.00	0.9805	0.00	Not significant
r^2	1.82	1	1.82	0.03	0.8565	0.00	–
ap^2	41.26	1	41.26	0.77	0.3960	0.06	–
Residual	639.00	12	53.25			0.89	
Cor. total	72,169.74	26					
(b) Surface roughness model							
Model	0.86	14	0.06	23.67	< 0.0001		Significant
Vc	0.01	1	7.50E-03	2.89	0.1148	0.74	Not significant
f	0.53	1	0.53	203.97	0.000	52.40	Significant
r	0.07	1	0.07	27.19	0.0002	6.98	–
ap	0.01	1	6.53E-03	2.52	0.1385	0.65	Not significant
Vc × f	0.00	1	1.22E-03	0.47	0.5051	0.12	–
Vc × r	0.02	1	2.10E-02	8.10	0.0147	2.08	Significant
Vc × ap	0.07	1	0.07	28.10	0.0002	7.22	–
f × r	9.00E-04	1	9.00E-04	0.35	0.5668	0.09	Not significant
f × ap	0.02	1	0.02	9.26	0.0102	2.38	Significant
r × ap	0.00	1	1.22E-03	0.47	0.5051	0.12	Not significant
Vc^2	0.05	1	0.05	19.54	0.0008	5.02	Significant
f^2	0.07	1	0.07	27.19	0.0002	6.98	–
r^2	0.08	1	0.08	29.60	0.0001	7.60	–
ap^2	0.05	1	4.56E-02	17.59	0.0012	4.52	–
Residual	0.03	12	2.59E-03			3.08	
Cor. total	1.01	26					

quantify the significance of each of the parameters. In general, when the F value increases, the consequentiality of the concrete parameter also increases. The ANOVA analysis has been performed using design expert 9.0 software.

From Table 4a, the ANOVA analysis results show that the depth of cut is the most affecting parameter on tangential force with a contribution of 72.86%. It is worth to note that when we increase the cutting depth (ap), the workpiece to be machined exerts a resistance to the penetration on the tool in the two tangential and axial directions which contributes in the increase in the tangential force (Fz). The feed rate (f) is also an important significant parameter that affects the tangential force with a contribution of 20.66%, followed by the tool nose radius (r) and the cutting speed (Vc) with a contribution of 2.39 and 1.14%, respectively. The results found are in good agreement with the previous researcher's works [26–28].

The collected observations of the first analysis correspondent to dry machining can be integrally granted to wet and MQL results; from Tables 5a and 6a, it can be observed that the cutting depth has the strongest influence on tangential force with a contribution of 75.81% in wet turning and 72.30% under MQL cooling technique, followed by feed rate with a contribution of 19.66 and 21.57%

Table 6 ANOVA analysis for MQL machining results

Source	SS	DF	MS	F-Value	*P*-value	Cont. %	Remark
(a) Tangential force model							
Model	73,044.32	14	5217.45	70.87	< 0.0001		Significant
Vc	230.65	1	230.65	3.13	0.1021	0.31	–
f	15,946.88	1	15,946.88	216.62	< 0.0001	21.57	–
r	1015.13	1	1015.13	13.79	0.0030	1.37	–
ap	53,452.07	1	53,452.07	726.10	< 0.0001	72.30	–
Vc × f	0.08	1	0.08	0.00	0.9740	0.00	Not significant
Vc × r	16.85	1	16.85	0.23	0.6409	0.02	–
Vc × ap	6.33	1	6.33	0.09	0.7744	0.01	–
f × r	89.49	1	89.49	1.22	0.2918	0.12	–
f × ap	1695.79	1	1695.79	23.04	0.0004	2.29	Significant
r × ap	7.95	1	7.95	0.11	0.7481	0.01	Not significant
Vc^2	339.98	1	339.98	4.62	0.0500	0.46	Significant
f^2	45.19	1	45.19	0.61	0.4485	0.06	Not significant
r^2	88.42	1	88.42	1.20	0.2946	0.12	–
ap^2	3.76	1	3.76	0.05	0.8251	0.01	–
Residual	883.39	12	73.62			1.19	
Cor. total	73,927.71	26					
(b) Surface roughness model							
Model	0.782	14	0.06	30.42	< 0.0001		Significant
Vc	0.007	1	6.53E-03	3.56	0.084	0.66	Not significant
f	0.407	1	0.41	221.58	< 0.0001	41.04	Significant
r	0.003	1	0.00	1.64	0.225	0.30	Not significant
ap	0.023	1	2.25E-02	12.27	0.004	2.27	Significant
Vc × f	0.006	1	5.63E-03	3.06	0.106	0.57	Not significant
Vc × r	0.011	1	0.01	6.00	0.031	1.11	Significant
Vc × ap	0.032	1	0.03	17.64	0.001	3.27	–
f × r	0.017	1	0.02	9.20	0.010	1.70	–
f × ap	0.003	1	0.00	1.36	0.266	0.25	Not significant
r × ap	0.001	1	9.00E-04	0.49	0.497	0.09	–
Vc^2	0.128	1	0.13	69.76	< 0.0001	12.92	Significant
f^2	0.063	1	6.31E-02	34.34	0.0001	6.36	–
r^2	0.227	1	0.23	123.52	< 0.0001	22.88	–
ap^2	0.043	1	4.32E-02	23.52	0.0004	4.36	–
Residual	0.022	12	1.84E-03			2.22	
Cor. total	0.992	26					

and the nose radius (r) by a contribution of 1.62 and 1.37% (for each cooling technique wet and MQL, respectively). At large nose radius, the contact surface is more important than with low nose radius; in this case, the resulting tangential force will be more important and the cutting power (Pc) required for the machining process increases.

The obtained mathematical quadratic models according to Eq. (6) are shown in the Eqs. 7, 8, and 9 with an R^2 of 98.94, 99.11, and 98.81%, respectively, for tangential force under dry, wet, and MQL cooling conditions:

$$Fz_{Dry} = 123.47-0.46\times Vc-139.09\times f-25.97 \times r-0.06\times ap-0.33\times Vc\times f-0.09\times Vc\times r + 0.02\times Vc\times ap+242.81\times f\times r + 1531.87\times f\times ap+78.84\times r\times ap+1.04 \times 10^{-3}\times Vc^2+1008.59\times f^2+8.22\times r^2 + 76.21\times ap^2 \tag{7}$$

$$Fz_{Wet} = -3.82-0.28\times Vc+663.41\times f+4.01\times r + 196.26\times ap-1.03\times Vc\times f+0.01\times Vc \times r-0.26\times Vc\times ap+6.87\times f\times r + 1088.12\times f\times ap+17.34\times r\times ap+8.50 \times 10^{-4}\times Vc^2+49.21\times f^2+3.64\times r^2 + 69.53\times ap^2 \tag{8}$$

$$Fz_{Mql} = 120.81-0.36\times Vc-45.17\times f-67.77\times r + 2.63\times ap+0.03\times Vc\times f-0.05\times Vc \times r-0.06\times Vc\times ap+295.62\times f\times r + 2573.75\times f\times ap+17.62\times r\times ap+7.98 \times 10^{-4}\times Vc^2-1819.27\times f^2+25.44\times r^2 + 20.97\times ap^2 \tag{9}$$

Three-dimensional (3D) response surface plots, predicated on the quadratic model, were drawn to study the

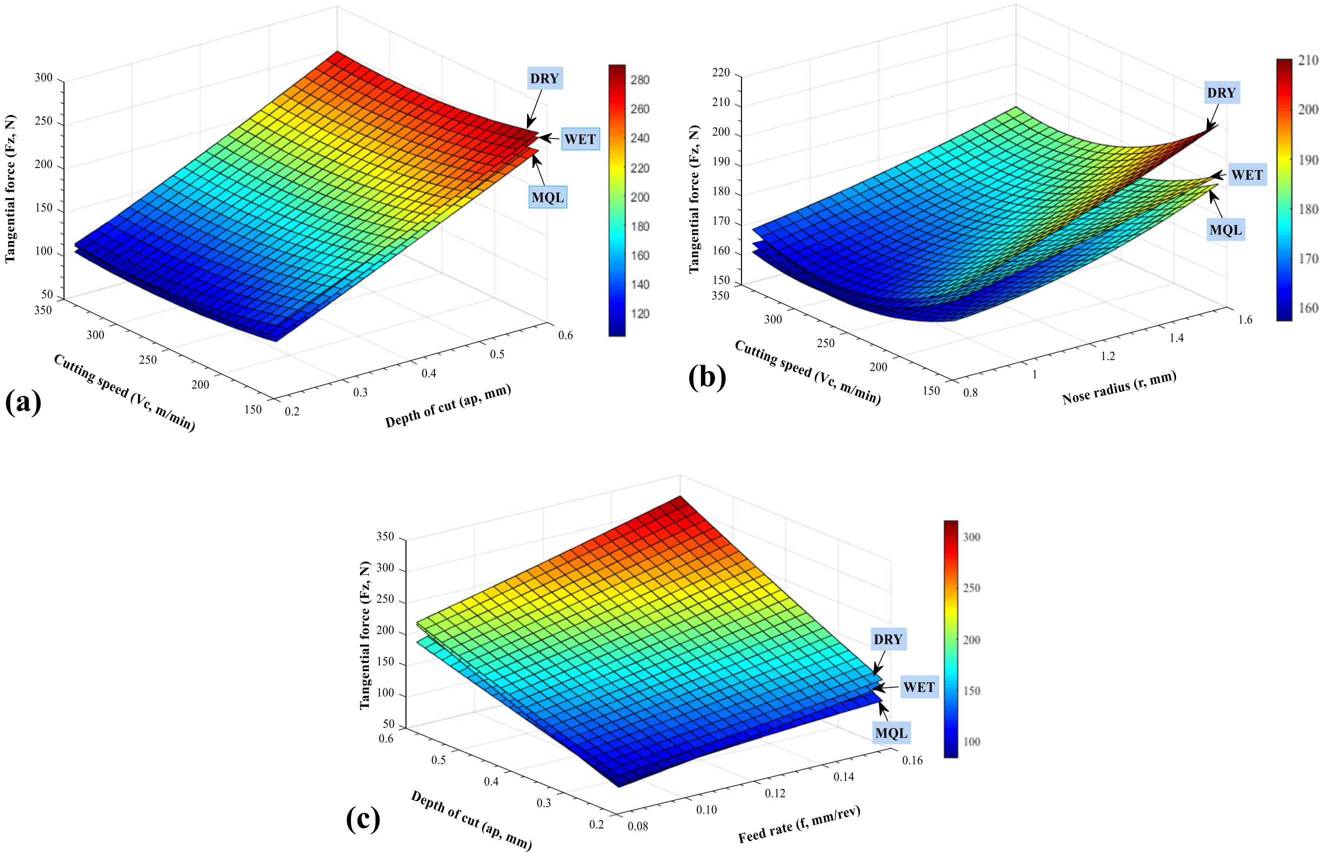


Fig. 5 Effect of cutting factors on cutting force for dry, wet, and MQL turning

effect of the input machining parameters on tangential force and surface roughness. These plots can supplementary provide further assessment of the relationship between the process parameters and replication. 3D surface plots are drawn as two of the factors was maintained constant at their middle level, while the other two are varied.

Table 7 Multi-objective optimization of response parameters

Condition	Goal	Lower limit	Upper limit
Vc (m/min)	Is in range	150	350
f (mm/rev)	Is in range	0.08	0.16
r (mm)	Is in range	0.8	1.6
ap mm)	Is in range	0.2	0.6
(a) Dry machining			
Fz (*N*)	Minimize	91.54	294.49
Ra (µm)	Minimize	0.6	1.34
(b) Wet machining			
Fz (*N*)	Minimize	84.29	280.45
Ra (µm)	Minimize	0.41	1.08
(c) MQL machining			
Fz (*N*)	Minimize	83.06	280.67
Ra (µm)	Minimize	0.38	0.97

Figure 5 represents the 3D surface plots that illustrate the cutting force evolution according to cutting speed and depth of cut, cutting speed and nose radius, and depth of cut and feed rate. It can be observed that the lubrication can improve the machinability of this kind of steel; in addition, MQL cooling provides low cutting force because it reduces the contact friction. Figure 5a shows that the tangential force increases with the increase of depth of cut and feed rate, and from all the results, it can concluded that the depth of cut exhibits maximum influence on the cutting force components. Figure 5a–c confirms that the tangential force increases while the tool nose radius and the feed rate increase; this can be explained by increasing chip cross-section with increasing feed rate, depth of cut, and nose radius that increases the friction in the cutting area.

3.2.2 Surface roughness modeling

The surface roughness is considered as one of the most critical constraints for the selection of cutting parameters in the planning of the machining process. From Tables 4b,

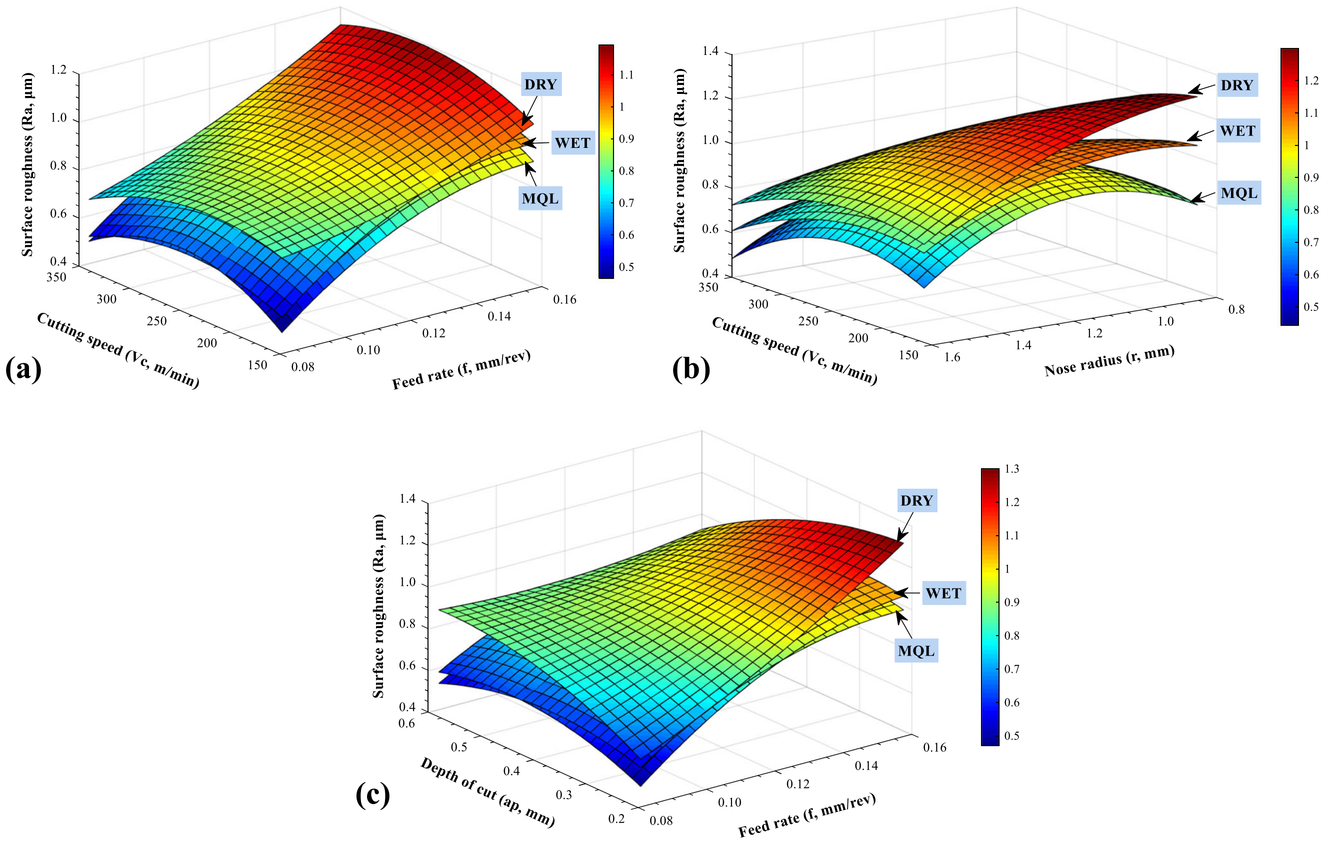


Fig. 6 Effect of cutting factors on surface roughness for dry, wet, and MQL turning

5b, and 6b, it can be known that the feed rate (f) is the most affecting parameter on surface roughness with a contribution of 40.46, 52.40, and 41.04% in dry, wet, and MQL machining, respectively. During the turning process, the generated surface is a helical furrow resulting from the tool nose shape and helicoids movement tool–workpiece generated by the machine tool. In this case, the use of large feed rate results in a worst surface roughness, because at large feeds, the distance between peaks and valleys is much more important. On the other hand, the use of large nose radius can improve significantly the surface quality by crushing of asperities. The ANOVA analysis shows that the nose radius is a significant parameter on surface roughness with a contribution of 3.40 and 6.98% in dry and wet turning. Similar results were found by Meddour et al. [26] and Bouzid et al. [29].

The obtained quadratic models are shown in Eqs. 10, 11, and 12 and their determination coefficients (R^2) are of 93.75, 96.51, and 97.26%, respectively, for surface roughness under the different cooling conditions:

$$\begin{aligned} Ra_{Dry} = & -1.18 - 3.24 \times 10^{-3} \times Vc + 15.76 \times f + 1.81 \\ & \times r + 1.79 \times ap + 0.01 \times Vc \times f + 2.62 \\ & \times 10^{-3} \times Vc \times r + 8.62 \times 10^{-3} \times Vc \\ & \times ap - 9.68 \times f \times r - 20.31 \times f \times ap - 0.09375 \\ & \times r \times ap - 9.5 \times 10^{-6} \times Vc^2 + 25 \times f^2 - 0.58 \\ & \times r^2 - 1.90625 \times ap^2 \end{aligned} \tag{10}$$

Table 8 Obtained optimization values of RSM

Cooling condition	Vc (m/min)	f (mm/rev)	r (mm)	ap (mm)	Fz (N)	Ra (µm)	Desirability
DRY	273.073	0.081	1.390	0.204	85.315	0.595	1
WET	296.703	0.081	1.249	0.204	83.861	0.401	1
MQL	247.083	0.084	0.827	0.203	81.155	0.375	1

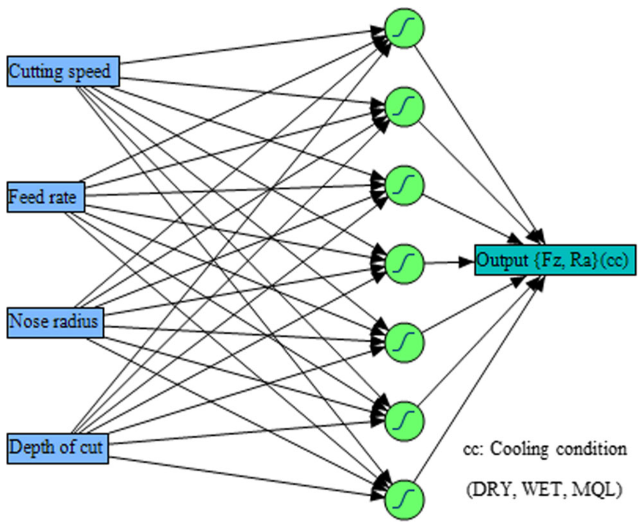


Fig. 7 Optimal architecture 4-7-1 for output modeling

$$Ra_{Wet} = -2.05 + 2.75 \times 10^{-4} \times Vc + 28.59 \times f + 1.35 \times r + 1.47 \times ap - 4.37 \times 10^{-3} \times Vc \times f + 1.81 \times 10^{-3} \times Vc \times r + 6.75 \times 10^{-3} \times Vc \times ap - 0.93 \times f \times r - 9.68 \times f \times ap - 0.21 \times r \times ap - 9.75 \times 10^{-6} \times Vc^2 - 71.875 \times f^2 - 0.75 \times r^2 - 2.31 \times ap^2 \quad (11)$$

$$Ra_{Mql} = -3.77 + 5.26 \times 10^{-3} \times Vc + 29.38 \times f + 3.21 \times r + 0.60 \times ap - 9.37 \times 10^{-3} \times Vc \times f + 1.31 \times 10^{-3} \times Vc \times r + 4.5 \times 10^{-3} \times Vc \times ap - 4.06 \times f \times r - 3.12 \times f \times ap + 0.18 \times r \times ap - 1.55 \times 10^{-5} \times Vc^2 - 67.96 \times f^2 - 1.28 \times r^2 - 2.25 \times ap^2 \quad (12)$$

Figure 6 shows the evolution of the surface roughness according to cutting speed and feed rate, cutting speed and nose radius, and depth of cut and feed rate. As indicated in Fig. 6a, c the feed rate affects largely the surface quality; Fig. 6c illustrates the qualitative effect of large tool nose radius, in which the roughness has undergone an important improvement and a better surface quality obtained at a high level of cutting speed, and these observations justify the use of high speeds, low feeds, and cutting inserts with large nose radius (r = 0.8 to 1.6 mm) in the finishing process where a low roughness is desired. Furthermore, the MQL cooling contribute in the improvement of the surface quality.

3.2.3 Optimization process

The desirability function approach of the RSM has been employed for multi-objective optimization of the studied

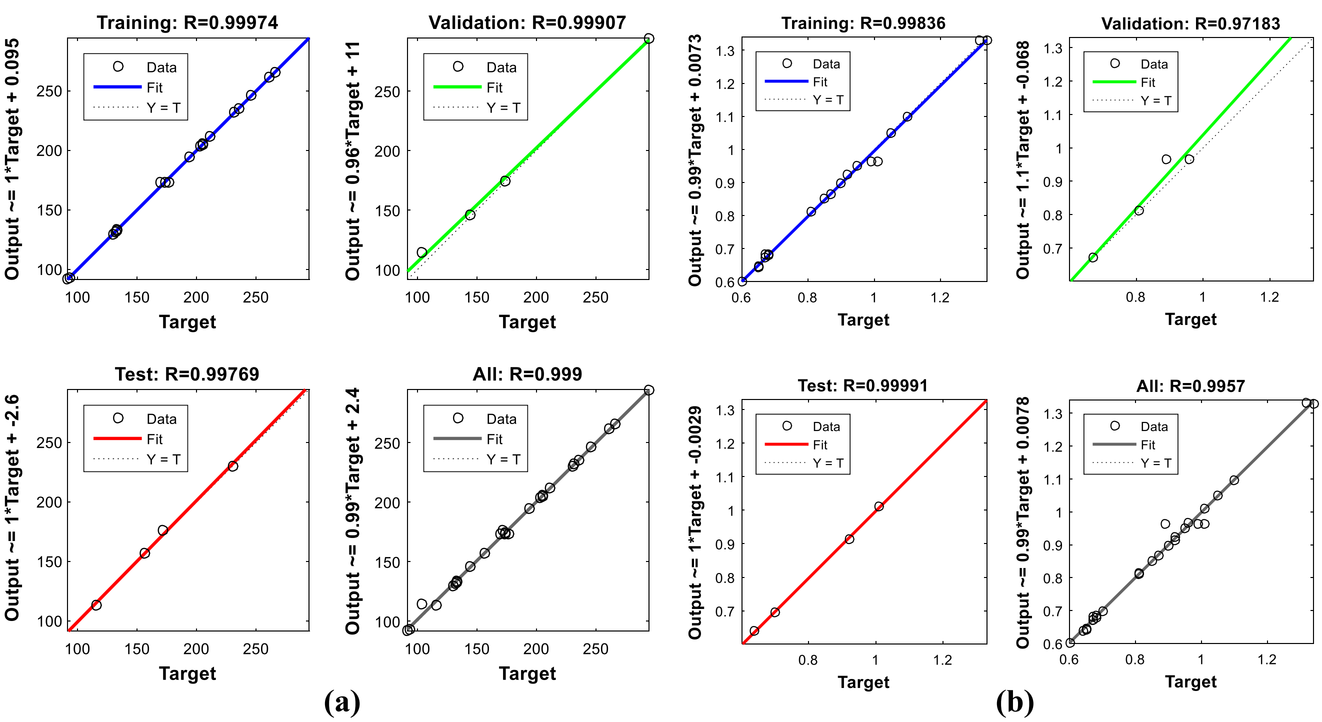


Fig. 8 Correlation between the predicted and the experimental data using the training, validation, and test datasets for **a** tangential force and **b** surface roughness in dry condition

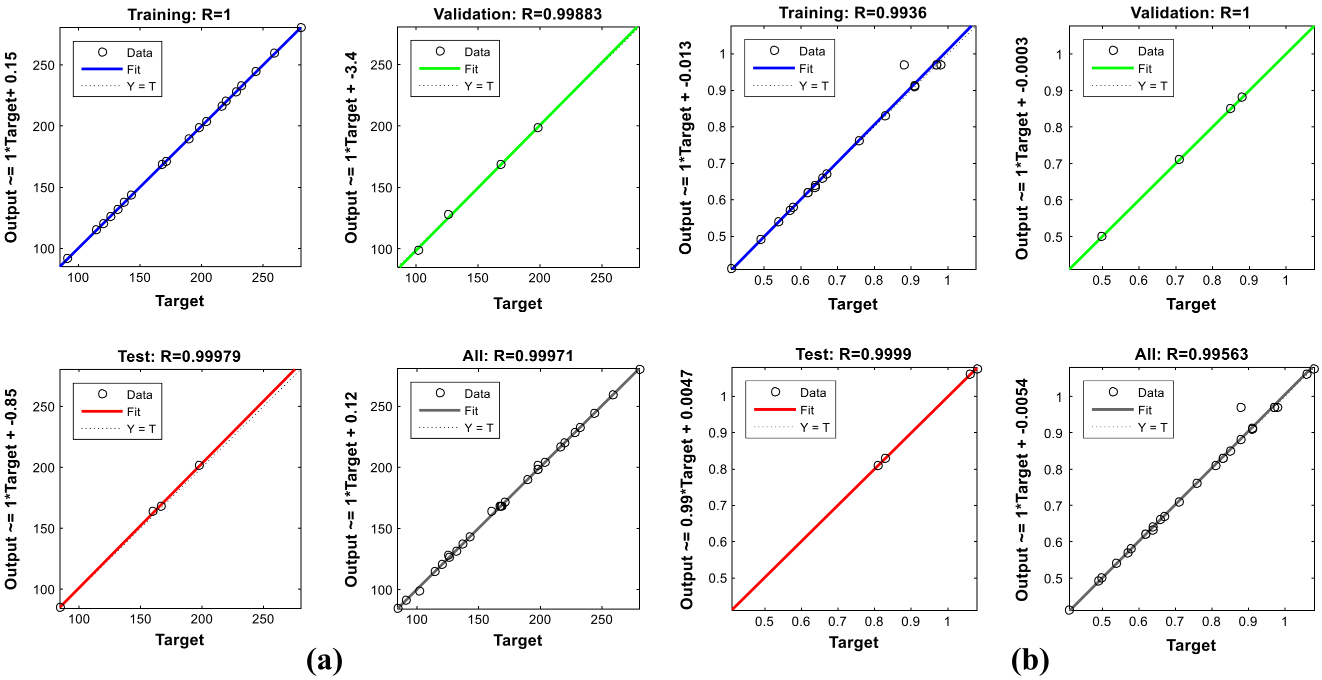


Fig. 9 Correlation between the predicted and the experimental data using the training, validation, and test datasets for **a** tangential force and **b** surface roughness in wet condition

outputs. This approach searches for a combination of factor levels that simultaneously provide the minimum surface roughness with the minimum cutting force for each cooling condition. The aim here is focused on finding the optimum cutting parameters in order to obtain the desired tangential force and surface roughness (Fz and Ra). The optimization was performed using Design Expert 9.0 software. The application of

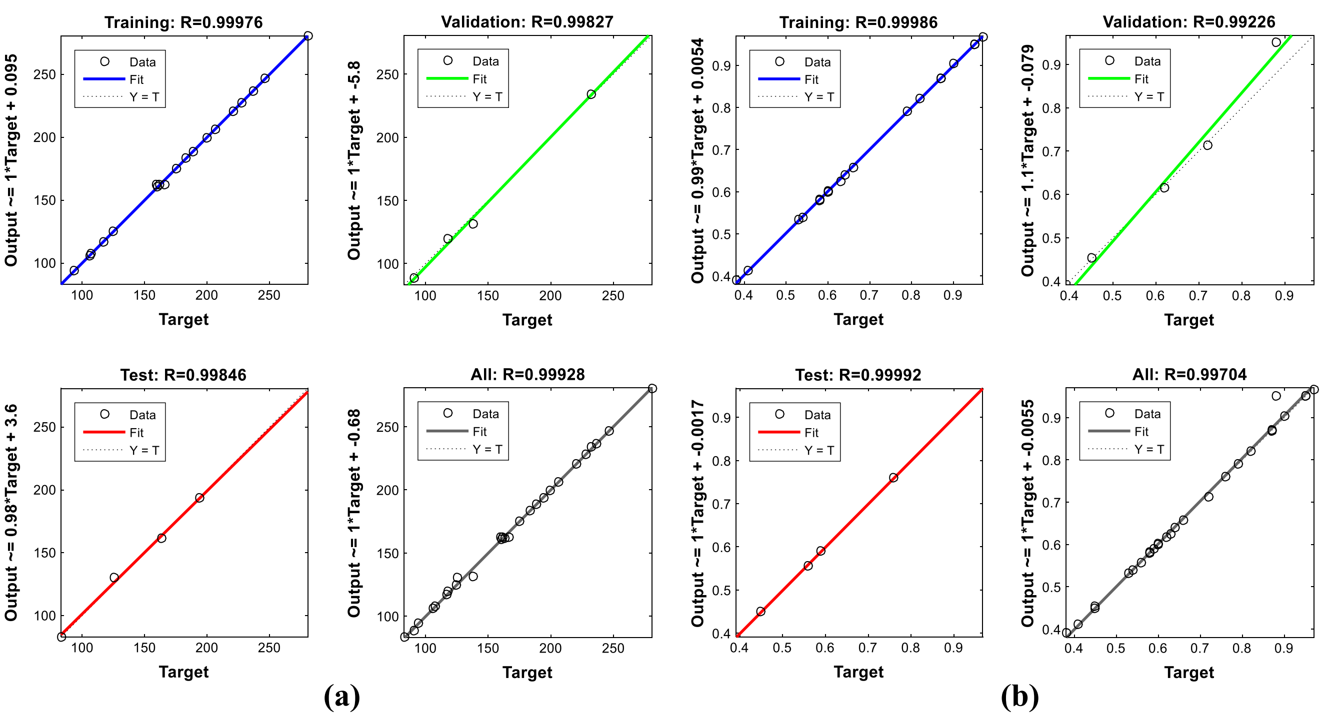


Fig. 10 Correlation between the predicted and the experimental data using the training, validation, and test data sets for **a** tangential force and **b** surface roughness in MQL condition

Table 9 Comparison of prediction results for RSM and ANN under dry machining

Number	Predicted tangential force (Fz)		Absolute prediction error (%)		Predicted surface roughness (Ra)		Absolute prediction error (%)	
	RSM	ANN	RSM	ANN	RSM	ANN	RSM	ANN
1	130.92	129.61	1.01	0.00	0.62	0.68	7.15	1.76
2	108.49	113.34	6.61	2.42	0.63	0.67	5.66	0.03
3	84.23	91.54	7.98	0.00	0.60	0.65	7.37	0.61
4	296.78	294.49	0.78	0.00	0.93	0.91	0.77	0.59
5	232.57	231.61	0.41	0.00	1.06	1.01	5.36	0.00
6	156.03	156.79	0.05	0.44	0.78	0.68	14.09	0.23
7	177.76	174.38	2.12	0.18	0.95	0.95	0.48	0.14
8	266.15	265.82	0.13	0.00	0.71	0.64	10.55	0.19
9	212.57	203.25	4.59	0.00	1.13	1.10	2.35	0.25
10	141.40	133.11	6.23	0.00	0.67	0.60	11.25	0.17
11	264.49	261.04	1.32	0.00	0.61	0.64	6.60	1.19
12	185.55	194.26	4.48	0.00	0.81	0.85	4.26	0.19
13	173.59	173.59	2.03	2.03	0.96	0.96	8.24	8.41
14	114.85	114.07	10.65	9.89	0.77	0.67	15.05	0.41
15	248.35	246.04	0.94	0.00	0.93	0.97	3.26	0.63
16	210.24	211.73	0.70	0.00	0.63	0.68	7.78	0.53
17	173.59	173.59	2.15	2.15	0.96	0.96	2.69	2.54
18	102.36	93.45	9.54	0.00	0.86	0.81	6.69	0.09
19	148.26	145.92	3.03	1.40	0.82	0.87	5.32	0.48
20	228.44	229.86	0.78	0.17	0.83	0.81	2.57	0.38
21	173.59	173.59	0.02	0.02	0.96	0.96	4.62	4.47
22	167.83	176.68	2.06	3.10	0.71	0.70	1.73	0.48
23	198.41	204.99	3.21	0.00	0.88	0.90	2.36	0.26
24	133.58	132.02	1.18	0.00	1.30	1.33	1.48	0.76
25	197.01	205.59	4.17	0.00	1.31	1.33	2.58	0.79
26	229.88	235.42	2.35	0.00	0.89	0.92	3.58	0.53
27	126.98	133.52	4.90	0.00	1.00	1.05	4.72	0.12

desirability function leads to better solution than most other techniques for multi-response optimization. The optimization conditions are presented in Table 7. The gradient algorithm was used to calculate the desirability function between 0 and 1. Acceptance of optimization is estimated with desirability function [21]. If the desirability value closes to 0 the response should be completely unaccepted, and if its value closes or equal to 1, the response would be accepted.

In this investigation, the optimal combinations of cutting parameters are presented in Table 8; the optimum settings were found as 273.073 m/min of cutting speed, 0.081 mm/rev of feed rate, 1.390 mm of nose radius, and 0.204 mm of cutting depth for dry machining optimization; Vc = 296.703 m/min, f = 0.081 mm/rev, r = 1.249 mm, and ap = 0.204 mm for WET machining; and Vc = 247.083 m/min, f = 0.084 mm/rev, r = 0.827 mm, and ap = 0.203 mm for MQL machining. Desirability values were found to be 1 for surface roughness and tangential in the different cooling conditions.

3.3 ANN modeling

The back-propagation algorithm was used as learning algorithm. The Levenberg-Marquadt (TRAINLM) was selected as training algorithm. LM algorithms are fast and consume less memory [30]. The hyperbolic tangent sigmoid transfer function (TANSIG) has been used as activation function. The optimal network was found to be a feed forward neural network by a single hidden layer consisting seven neurons. The structure of the selected artificial neural network (4-7-1) has been drawn in Fig. 7. The obtained networks are used for predicting the studied factors. The total number of the created networks is six that have the same architecture (4-7-1). Three of them are used for prediction of surface roughness under

Table 10 Comparison of prediction results for RSM and ANN under Wet machining

Number	Predicted tangential force (Fz)		Absolute prediction error (%)		Predicted surface roughness (Ra)		Absolute prediction error (%)	
	RSM	ANN	RSM	ANN	RSM	ANN	RSM	ANN
1	124.71	126.21	1.11	0.08	0.56	0.58	3.45	0.01
2	110.66	114.78	3.46	0.13	0.62	0.64	3.65	0.01
3	77.85	85.12	7.64	0.99	0.47	0.49	3.74	0.37
4	281.67	280.45	0.43	0.00	0.84	0.85	0.59	0.15
5	221.86	220.09	0.79	0.02	0.98	0.91	8.06	0.01
6	144.80	137.39	5.51	0.11	0.53	0.50	5.67	0.00
7	174.63	171.24	1.99	0.01	0.90	0.91	1.10	0.00
8	250.34	244.36	2.41	0.04	0.61	0.62	1.08	0.61
9	200.47	198.36	1.15	0.08	0.90	0.88	2.08	0.28
10	139.99	131.83	6.14	0.04	0.51	0.54	4.94	0.00
11	258.81	259.42	0.25	0.01	0.62	0.62	0.00	0.01
12	181.27	189.86	4.54	0.02	0.70	0.71	1.88	0.00
13	168.19	168.41	0.52	0.39	0.94	0.97	7.20	10.25
14	112.52	98.89	9.97	3.36	0.69	0.64	8.59	0.70
15	235.21	232.62	1.06	0.05	0.84	0.83	1.20	0.00
16	193.04	201.37	2.52	1.69	0.60	0.66	8.84	0.00
17	168.19	168.41	0.65	0.78	0.94	0.97	2.75	0.02
18	95.55	91.63	4.30	0.02	0.81	0.76	7.02	0.00
19	144.23	143.49	0.52	0.00	0.44	0.41	6.50	0.09
20	227.82	228.14	0.16	0.02	0.80	0.81	1.03	0.00
21	168.19	168.41	0.12	0.01	0.94	0.97	3.74	1.00
22	160.21	164.06	0.15	2.26	0.70	0.67	5.22	0.00
23	195.49	204.07	4.19	0.01	0.58	0.57	1.75	0.01
24	129.21	127.92	2.65	1.62	1.05	1.08	3.09	0.36
25	193.26	198.56	2.69	0.03	1.01	1.06	4.72	0.13
26	213.22	216.37	1.48	0.03	0.83	0.83	0.40	0.00
27	113.26	120.34	5.87	0.02	0.94	0.97	3.44	0.00

the three cooling conditions, and the rest are used for predicting the tangential force. Training the neural network is an important operation for accurate results; less training makes the ANNs inefficient and may provide inaccurate prediction.

For the tangential force, the determination coefficients (R^2) of the developed predictive models are 99.80, 99.94, and 99.78%, respectively, for dry, wet, and MQL machining. Concerning that of surface roughness, their R^2 are 99.14, 99.12, and 99.40%, respectively, for the dry, wet, and MQL prediction models.

Each network will be trained starting from different initial weights and biases, and with a different division of the first dataset into training, validation, and test sets. It is good to note that the test sets are a good measure of generalization for each respective network, but not for all the networks, because data that is a test set for one network will likely be used for training or validation by other neural networks. This is why the original dataset was divided into two parts, to ensure that a completely independent test set is preserved. The performance capability of each network was examined based on the correlation coefficient between the network predictions and the experimental values using the training, validation, and test dataset. The performances of the prediction models of cutting force and surface roughness using the training validation and test dataset are shown in Figs. 8, 9, and 10.

3.4 Comparative results of ANN and RSM models

The trend in modeling using RSM has a low-order nonlinear behavior with a regular experimental domain and relatively small factor region, due to its limitation in building a model to fit the data over an irregular experimental region. Moreover, the main advantage of RSM is

Table 11 Comparison of prediction results for RSM and ANN under MQL machining

Number	Predicted tangential force (Fz)		Absolute prediction error (%)		Predicted surface roughness (Ra)		Absolute prediction error (%)	
	RSM	ANN	RSM	ANN	RSM	ANN	RSM	ANN
1	122.87	125.09	1.78	0.00	0.35	0.39	8.77	2.89
2	101.58	107.54	5.54	0.00	0.61	0.62	2.91	0.96
3	77.95	83.07	6.15	0.02	0.56	0.59	4.73	0.04
4	284.34	280.65	1.31	0.01	0.84	0.82	2.90	0.13
5	208.40	206.62	0.86	0.00	0.91	0.90	0.88	0.36
6	135.77	130.20	8.03	3.59	0.46	0.41	13.31	0.63
7	167.82	161.54	2.66	1.18	0.63	0.60	4.24	0.35
8	244.89	236.80	3.41	0.00	0.62	0.58	6.54	0.01
9	199.91	199.64	0.13	0.00	0.79	0.79	0.47	0.05
10	126.72	119.57	7.26	1.21	0.49	0.45	9.54	0.00
11	243.83	246.79	1.20	0.00	0.57	0.60	4.72	0.18
12	177.44	183.23	3.16	0.00	0.61	0.64	4.62	0.06
13	162.63	162.63	2.32	2.32	0.93	0.95	5.30	7.96
14	108.58	94.01	15.50	0.00	0.67	0.62	8.80	0.62
15	232.55	234.36	0.20	0.98	0.70	0.71	2.08	0.92
16	190.32	193.48	2.00	0.37	0.55	0.58	4.81	0.20
17	162.63	162.63	0.63	0.63	0.93	0.95	2.46	0.00
18	93.01	88.21	2.50	2.79	0.67	0.66	1.96	0.33
19	131.80	131.28	4.56	4.94	0.51	0.53	4.09	0.50
20	223.67	227.88	1.85	0.00	0.56	0.56	0.67	0.59
21	162.63	162.63	1.78	1.78	0.93	0.95	2.46	0.00
22	163.15	160.71	1.52	0.00	0.47	0.45	5.28	0.82
23	170.25	175.28	2.87	0.00	0.53	0.54	2.70	0.28
24	109.68	106.08	3.39	0.00	0.98	0.97	1.07	0.31
25	186.31	188.92	1.38	0.00	0.84	0.87	2.87	0.03
26	214.17	220.86	3.03	0.00	0.75	0.76	1.75	0.02
27	107.84	117.20	8.00	0.01	0.84	0.87	3.64	0.09

its ability to exhibit factor(s) contributions from the coefficients in the regression model. This ability is powerful for identifying the insignificant main factors and interaction factors or insignificant quadratic terms in the model which can reduce the complexity of the problem. On the other hand, this technique requires good definition of ranges for each factor to ensure that the response(s) under consideration changes in a regular manner within this range.

From another side, it is noted that ANNs perform better than the other techniques, especially RSM when highly nonlinear behavior is considered. Also, this technique can build an efficient model using a small number of experiments; however, the technique accuracy would be better when a larger

Table 12 Comparison between RSM and ANN

	Cooling condition	RSM Predicted data		ANN Predicted data	
		R^2	MPE	R^2	MPE
Cutting force	DRY	0.9894	3.09	0.9980	0.81
	WET	0.9911	2.68	0.9994	0.44
	MQL	0.9881	3.45	0.9984	0.74
Surface roughness	DRY	0.9375	5.50	0.9914	0.97
	WET	0.9651	3.77	0.9912	0.55
	MQL	0.9726	4.21	0.9940	0.68

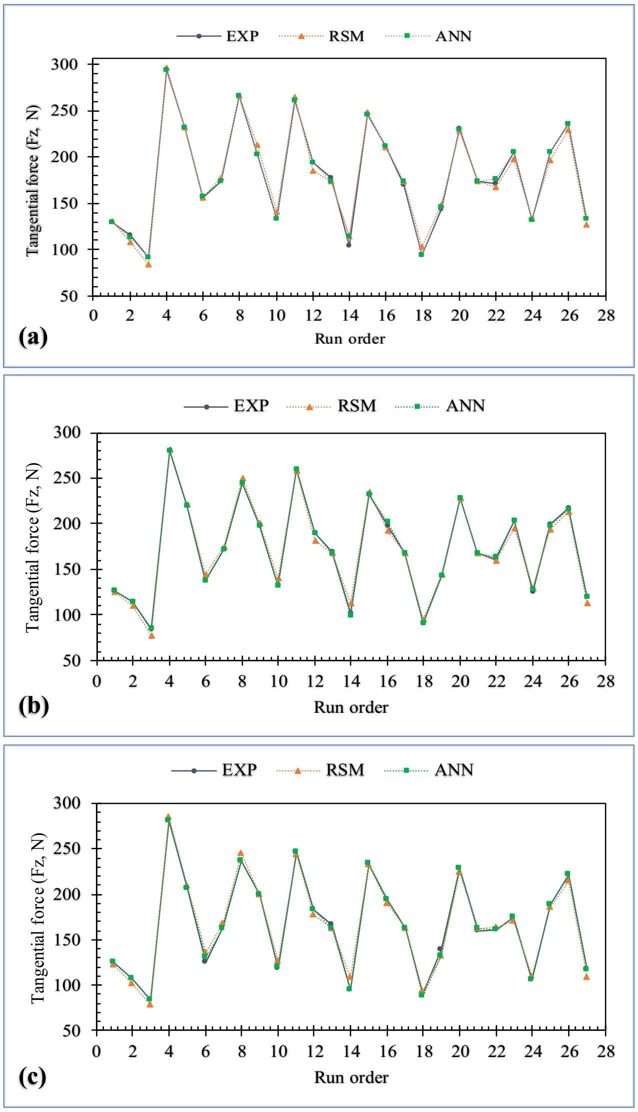


Fig. 11 Experimental data versus the predicted RSM and ANN data for tangential force under **a** dry, **b** wet, and **c** MQ

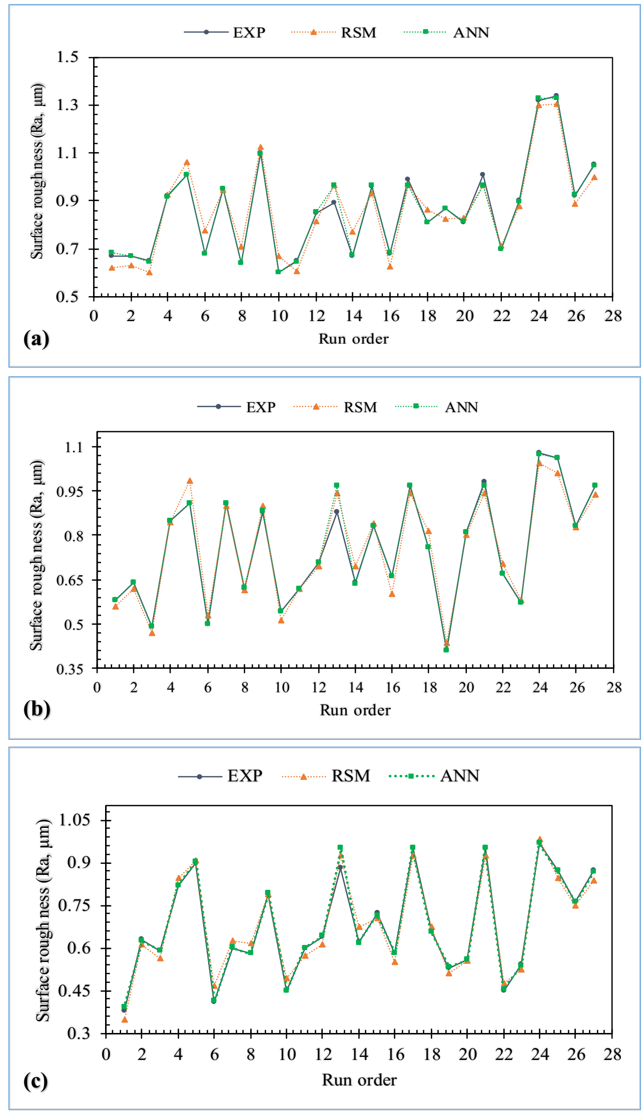


Fig. 12 Experimental data versus the predicted RSM and ANN data for surface roughness under **a** dry, **b** wet, and **c** MQL

number of experiments are used for modeling. On the other hand, the ANN model itself provides little information about the design factors and their contribution to the response in further analysis has not been done. Generation of ANN model requires a large number of iterative calculations whereas it is only a single-step calculation for a response surface model.

In this study, the predictive models developed by RSM and ANN were compared on the basis of their prediction accuracy using their coefficient of determination (R^2), mean predicted error (MPE), and root mean square error (RSME). Tables 9, 10, and 11 show the RSM and the ANN prediction comparison for tangential force and surface roughness.

Despite the fact that the R^2 of RSM models are initially good, from the prediction results, in some cases, the RSM models have over-fitted the data and have not generalize well. According to the case of the tangential force modeling results presented in Table 9, the obtained APE values by RSM are 6.61, 7.98, 6.23, and 9.64 for tests numbered 2, 3, 10, and 18, respectively. These deductions are to be favorably retained in ANN modeling with APE values of 2.41 for test 2 and just 0.00 for tests 3, 10, and 18, as it was presented in Table 9. However, the ANN provides good results with very low errors (APE). The ANN models proved their effectiveness as soon as their determination coefficients and mean prediction errors (MPE) presented in Table 12 are rather small compared to those obtained by the RSM models.

Figures 11 and 12 illustrate the performance of RSM and ANN predictive models for Fz and Ra. The most

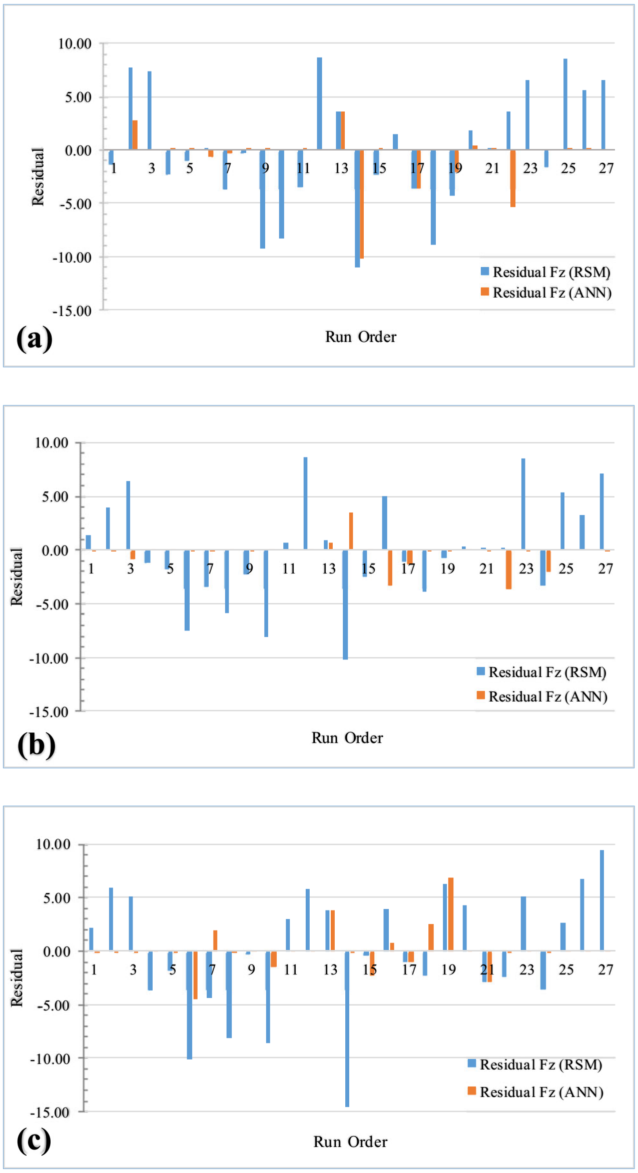


Fig. 13 Comparison between RSM and ANN models residuals for Fz under **a** dry, **b** wet, **c** MQL

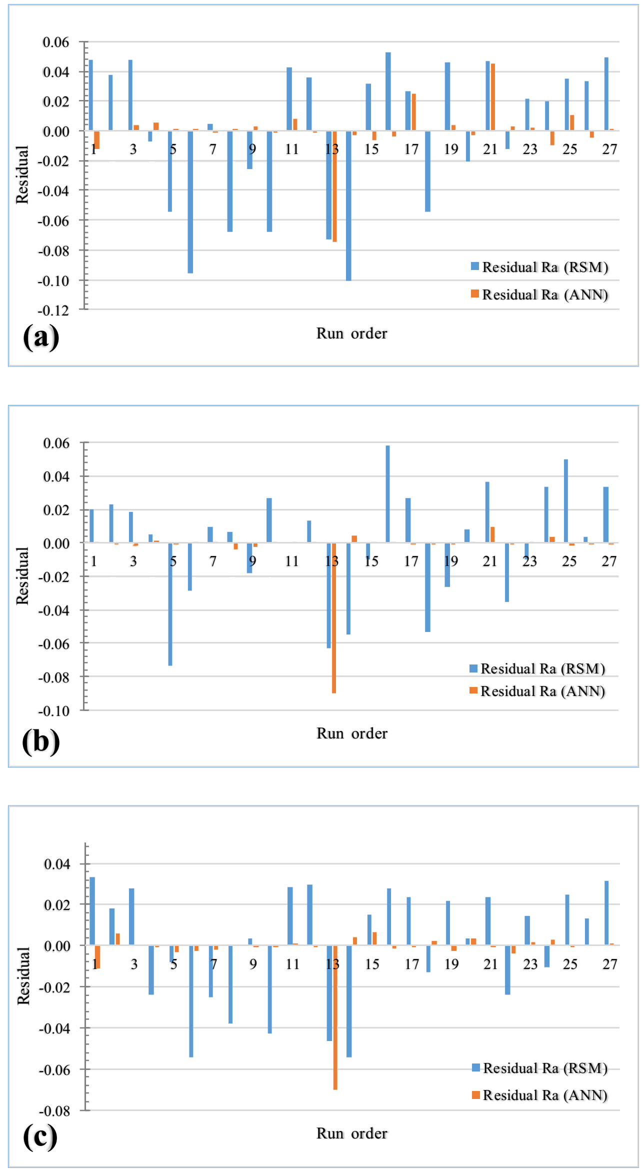


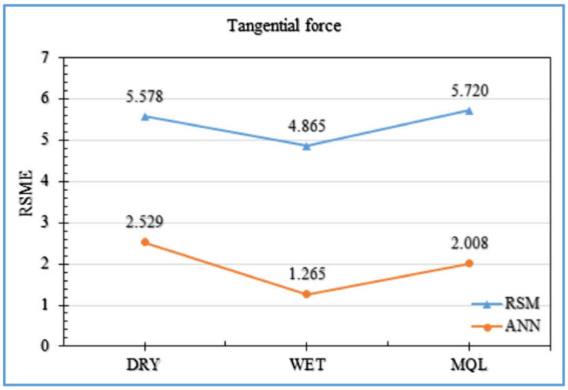
Fig. 14 Comparison between RSM and ANN models residuals for Ra under **a** dry, **b** wet, and **c** MQL

approximate points here are those with a lower failure rate; the deviations of the predicted and experimental data are smaller for ANN models as compared to RSM models. The developed ANN models provide more accurate results than those predicted by RSM where the data have been over-fitted especially in roughness models.

Certainly, the obtained R^2 for the surface roughness RSM models are 0.9375, 0.9651 and 0.9726 and their values for ANN models are 0.9914, 0.9912, and 0.9940. This can also clarify the capability of ANN models, as shown in Figs. 13 and 14, which illustrates the lower residuals in Fz and Ra (at the different cooling conditions) for ANN models as compared to RSM models. Furthermore, the RSME values in Fig. 15 confirm that the prediction capability of ANN models was found to be better than RSM models for the tested material and process. Otherwise, in different conditions, the two methods can be complementary in order to improve better predictive modeling and optimization.

4 Conclusion

This study investigates the MQL efficiency and compares the performance of both the response surface methodology (RSM) and the artificial neural network (ANN) according to their prediction and generalization capabilities using experimental results based on the Box-Behnken design for surface roughness and cutting force under dry, wet, and MQL turning. It has been found that



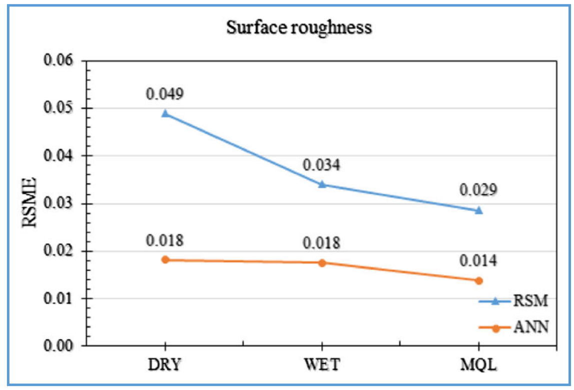


Fig. 15 Comparison of RSME values of RSM and ANN models for tangential force and surface roughness

1. The tangential cutting force is largely affected by the cutting depth surface, and the feed rate is the main affecting parameter on surface roughness.
2. The use of cutting inserts having large nose radius improves the surface quality and provides a low surface roughness that allows achieving the needed precision.
3. The response surface methodology is a good modeling tool that helps in identifying the insignificant main factors and interaction factors or insignificant quadratic terms in the model which reduce the complexity of the problem.
4. The comparative study indicated that the ANN models were found to be better for prediction accuracy of surface roughness and cutting force within the range they trained than the RSM models in terms of better correlation and lower error.
5. The minimum quantity lubrication can achieve the required machining factors for eliminating the problems of flood cooling. MQL machining can be qualified as a green machining process when the optimization is considered.

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