Evaluation of: MOSSA, MOALO, MOVO and MOGWO Algorithms in Green Machining for High Production Performance in Turning of X210Cr12 Steel

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Abstract

The current study investigates the Wet and MQL machining, when turning of X210Cr12 steel, using a multilayer-coated carbide insert (GC-4215) with various nose radius, the consideration of the tool geometry with different cooling modes allow as to assess the comportment of the machined steel against the cutting combinations. The response surface methodology (RSM) has been used for regression analysis and to evaluate the contribution of the cutting parameters on surface roughness, tangential force and cutting power using ANOVA analysis. The developed models have been used to predict the studied output factors according to the selected cutting parameters for wet and MQL machining. A comparative between the cooling techniques have been established to determine the most effective technique in terms of part quality, lubricant consumption and power consumption. Finally, four new optimization technics have been used for the process optimization using the MQL models for an environment-friendly machining.

Key words: MQL, RSM, optimization, green process.

Nomenclature

MQL	Minimum Quantity Lubrication	*ANOVA*	Analysis of variance
BBD	Box-Behenken design	*DF*	Degrees of Freedom
Vc	Cutting speed (m/min)	*MS*	Mean Squares
ap	Depth of cut (mm)	*SS*	Sum of Squares
f	Feed rate (mm/rev)	R^2	Determination coefficient
r	Tool nose radius (mm)	*P*	Probability of significance
Ra	Arithmetic mean roughness (µm)	*F*	Variance ratio
Fz	Tangential force (N)	*CVD*	Chemical vapor deposition
ANN	Artificial neural network	*AISI*	American Iron and Steel Institute
RSM	Response Surface Methodology	*MPE*	Mean predicted error
		RSME	Rout mean square

1 Introduction

Turning operations are one of the most significant manufacturing processes in metal-cutting operations. In industry, manufacturing processes are planned and improved in order to obtain either maximum quality or minimum cost. 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.

In the conventional manufacturing processes, the use of lubricant 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 general, the flank wear (VB) is the most used factor to assess cutting tool life. Its progress regarding the machining time passes through three phases: initial wear phase, wear stabilization, and accelerated wear. The life time of a cutting tool is influenced by a range of incontrollable factors. At high speeds, the contact surface of the tool-workpiece generates latter a quantity of heat which alters the cutting edges by complex physicochemical phenomena [3, 4]. The tool life is characterized by the time taken to reach the limit value of the wear criterion considered in specific cutting conditions.

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 [5].

Dry machining is more advanced in the manufacturing industry, by respecting the ecological and environmental aspect, it offers the advantage to make important savings, However, the temperature generated in the rake-face is higher than classic lubrication and required to be controlled as far as possible [6]. Moreover, high cutting temperature causes residual stresses and dimensional deformation in the cutting zone. The solution of lubricant exploitation is not at all times ideal because in some situations it causes additional costs for degreasing before reprocessing operations [7]. The use of cutting liquids as well causes several human health problems. Many diseases such as cutaneous and respiratory are related to handling oils [8, 9]. Consequently, it is extremely recommended to remove or decrease the use cutting fluids. This tendency has created a necessity

in the industry for a human and environmental preventive approach while ensuring the same production performance.

In this way, several research studies have been established using the MQL technique in order to minimize the lubricants consumption. An investigation carried out by Rahim et al. [10] qualify the minimal quantity of lubricant as a sustainable cooling system when using synthetic lubricants. The efficiency of MQL has been evaluated according to the temperature behavior and chip formation during turning of AISI 1045 steel using an uncoated carbide insert. The results show a reduced temperature and cutting forces and improved chip formation under MQL compared to dry machining.

The impact of the application cooling on flank-wear and surface roughness during turning of the AISI-4340 steel has been studied by Dhar et al. [11]. They found a significant decrease in the tool-wear rate and better surface roughness under MQL with a diminution of temperature in the cutting area. Also, it has been demonstrated by Varadarajan et al. [12] that the MQL should be a good alternative in relations to the cutting forces, surface roughness and tool-chip contact length. Hadad and Sadeghi [13] have evaluated the effects of turning parameters on cutting forces, surface roughness and temperature. Their results indicate that the surface finishes were better due to the decrease of tool-wear when applying the Minimal Quantity Lubrication.

Tunc et al. [14] studied the effect of MQL on surface integrity in robotic milling of austenitic stainless steel. The experiments showed that the surface roughness is not affected by the MQL setting. However, the surface residual stresses can be decreased by well controlled MQL flow rate.

MQL research literature indicate that the lubricant quantity has been reduced under MQL technique (50% to 90%) [15, 16, 17], providing more energy consumption, better performance, and environment protection.

In order to respond to the requirements of its applications in manufacturing process, it is very important to forecasting 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). Response surface methodology (RSM) is considered as a quick and useful procedure for the investigation and optimization of complex processes as well as modeling machining output parameters. Asiltürk et

al. [18] found that response surface methodology represents a good tool for predicting surface roughness in machining of Co28Cr6Mo. The response surface methodology (RSM) was employed by Kasim et al. [19] in their experiment to determine the cause and the effect of the relationship between the control variables and the studied response, their results indicate that RSM modeling can give accurate results. Chabbi et al. [20] 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 de output responses.

The current study investigates the wet and MQL machining, when turning of X210Cr12 steel, using a multilayer-coated carbide insert (GC-4215) with various nose radius (r), the consideration of the tool geometry with different lubrication modes allow as to evaluate the behavior of the machined steel against these stets combination. The response surface methodology (RSM) was used for mathematical modeling and to evaluate the contribution of the cutting parameters including tool nose radius on surface roughness, tangential force and cutting power using ANOVA analysis. The developed models were used to predict the studied output factors according to the selected cutting parameters for wet and MQL machining. A comparative between the cooling techniques have been established to determine the most effective technique in terms of part quality, lubricant consumption and power consumption. Finally, four new optimization technics have been used for the process optimization using the MQL models for an environment-friendly 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 (mm) and 330 (mm).

Table 1 Chemical composition of work piece material

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

As regards the cutting tool is 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 microns moving in a linear manner on the machined surface. The schematic diagram of the experimental set up and the MQL system are shown in Fig. 1.

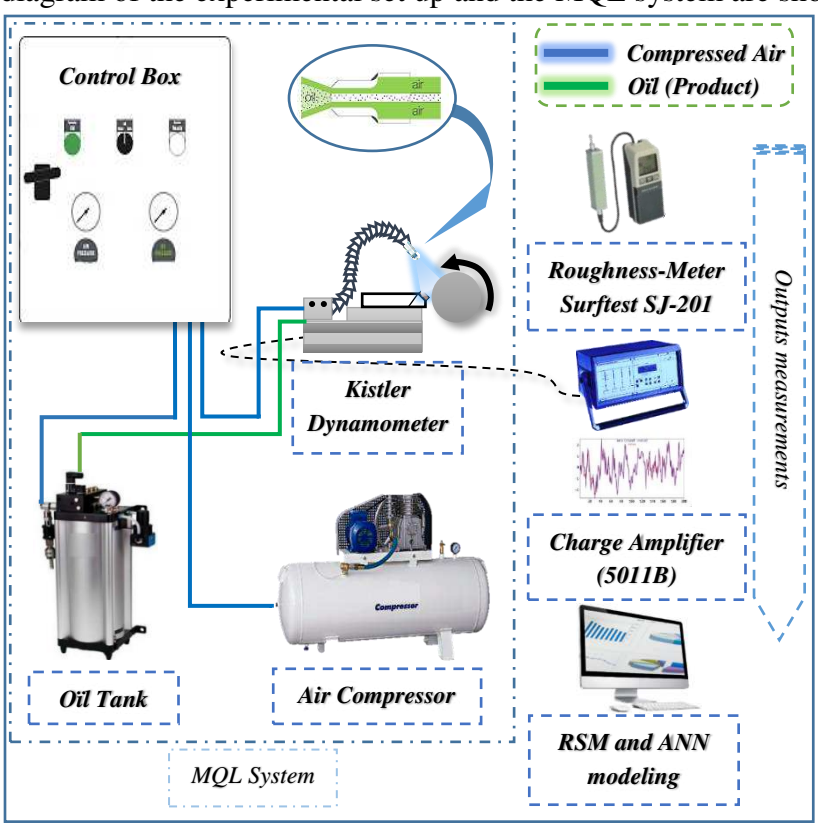


Fig. 1. Experimental set up for outputs measurement and data analysis.

2.2 Procedure

In order to study lubricating performances and its effect on the studied outputs, the cooling condition has been taken as an output, and the tests have been designed using 3 levels and 4 factors Box-Behenken 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 1.6mm) and the depth of were (ap; 0.2, 0.4 and 0.6 mm). For the cooling condition, the 27 turning tests have been performed under traditional lubrication mode and MQL technique using a synthetic oil with a flow rate of 120ml/h and an air pressure of pulverization of 6 bar. The different parameters defined were shown in table 2.

Table 2 Machining process parameters.

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

The combination of the parameters of the BBD with the measured values of surface roughness, the cutting force and the calculated cutting power 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's sensor during the cutting process. The cutting power required in the turning process can be calculated by the eq. 1:

$$Pc = \frac{Fz \times Vc}{60} \tag{01}$$

Where Pc is cutting power (W), Fz is the tangential force (N) and Vc is cutting speed (m/min). The consideration and the study of uncontrollable factors allow us to extract optimal scheme for better productivity regarding to 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). The RSM developed models are evaluated in terms of their prediction accuracy, coefficients of determination (R^2) and their mean predicted errors (MPE). The given terms are calculated through the following formulas:

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

$$MPE(\%) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\left(y_{i,ex} - y_{i,pr}\right)}{y_{i,ex}}\right| \quad (3)$$

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 ith experiment which calculated by the model.

Table 3 The experimental results.

Cutting Parameters				Response Factors					
				WET			MQL		
Vc (m/min)	f (mm/rev)	r (mm)	ap (mm)	Ra (µm)	Fz (N)	Pc (W)	Ra (µm)	Fz (N)	Pc (W)
250	0.08	0.8	0.4	0.58	126.11	525.46	0.38	125.09	521.21
350	0.12	1.2	0.2	0.64	114.63	668.68	0.63	107.54	627.32
250	0.08	1.2	0.2	0.49	84.29	351.21	0.59	83.06	346.08
250	0.16	1.2	0.6	0.85	280.45	1168.54	0.82	280.67	1169.46
150	0.16	1.2	0.4	0.91	220.13	550.33	0.9	206.62	516.55
150	0.08	1.2	0.4	0.5	137.24	343.10	0.41	125.68	314.20
150	0.12	0.8	0.4	0.91	171.22	428.05	0.6	163.47	408.68
250	0.12	1.6	0.6	0.62	244.45	1018.54	0.58	236.8	986.67
350	0.16	1.2	0.4	0.88	198.2	1156.17	0.79	199.65	1164.63
350	0.08	1.2	0.4	0.54	131.89	769.36	0.45	118.14	689.15
150	0.12	1.2	0.6	0.62	259.45	648.63	0.6	246.79	616.98
350	0.12	1.6	0.4	0.71	189.9	1107.75	0.64	183.23	1068.84
250	0.12	1.2	0.4	0.88	169.07	704.46	0.88	166.49	693.71
250	0.12	1.6	0.2	0.64	102.32	426.33	0.62	94.01	391.71
350	0.12	1.2	0.6	0.83	232.75	1357.71	0.72	232.09	1353.86
150	0.12	1.6	0.4	0.66	198.03	495.08	0.58	194.2	485.50
250	0.12	1.2	0.4	0.97	167.11	696.29	0.95	161.61	673.38
250	0.12	0.8	0.2	0.76	91.61	381.71	0.66	90.74	378.08
250	0.08	1.6	0.4	0.41	143.49	597.88	0.53	138.1	575.42
250	0.12	0.8	0.6	0.81	228.19	950.79	0.56	227.89	949.54
250	0.12	1.2	0.4	0.98	168.4	701.67	0.95	159.78	665.75
350	0.12	0.8	0.4	0.67	160.44	935.90	0.45	160.71	937.48

250	0.08	1.2	0.6	0.57	204.04	850.17	0.54	175.29	730.38
250	0.16	1.2	0.2	1.08	125.88	524.50	0.97	106.08	442.00
250	0.16	0.8	0.4	1.06	198.61	827.54	0.87	188.93	787.21
250	0.16	1.6	0.4	0.83	216.43	901.79	0.76	220.86	920.25
150	0.12	1.2	0.2	0.97	120.32	300.80	0.87	117.21	293.03

2.3 Response surface methodology approach

Response surface methodology (RSM) consists of a group of mathematical and statistical techniques used in the development of an adequate functional relationship between a response of interest [21], response surface methodology (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 in need of screening variables or not, and finally;
6. optimize and conduct a confirmation experiment to verify the predicted performance characteristics.

The relation between the studied outputs (Ra, Fz and Pc) and cutting parameters (Vc, ap, f and r) is characterized by a digital model developed through response surface methodology (RSM), used for prediction of incontrollable response factor(s) in machining processes according to the entered cutting parameters.

The relation between the cutting conditions and the technology machining factors is given as:

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

The second order model response surface can be fitted into the following Eq. (11):

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

Where ‘y’ is the corresponding response (Ra, Fz and Pc), ‘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:

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

2.4 Integrated RSM- MOSSA, MOALO, MOVO, MOGWO approach

Optimization algorithms are the branch of intelligent techniques used to search for optimal machining settings. In the current study, several algorithms named MOSSA, MOALO, MOVO, and MOGWO have been integrated with the response surface methodology to find the minimum of surface roughness and cutting force in a multi-objective optimization approach, according to following constraints: cutting speed [150 to 350(m/min)], feed rate [0.08 to 0.16(mm/rev)], nose radius [0.8 to 1.6(mm)] and cutting depth [0.2 to 0.6(mm)]. The optimization process has been carried out using MATLAB Software.

3 Results and discussion

3.1 ANOVA Analysis

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 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.

Tables 4, 5 and 6 illustrate the ANOVA results for surface roughness (Ra), cutting force (Fz), and cutting power (Pc) respectively, for a 95% confidence level. In these tables, the values of DoF, the sum of squared deviations (SS), and mean square (MS) of each model terms are listed. The main purpose is to analyze the influence of the cutting parameters (Vc, f, r, ap) on the total variance of

the results. When “P” values in the models are less than 0.05, indicating that the models are adequate and that the terms have a significant effect on the responses, which are desirable.

Table 4 ANOVA analysis for surface roughness in wet and MQL machining.

Source	SS	DF	MS	F-Value	P-value	Remark
Wet machining						
Model	0.86	14	0.06	23.67	< 0.0001	Significant
Vc	0.01	1	7.50E-03	2.89	0.1148	Not significant
f	0.53	1	0.53	203.97	0.000	Significant
r	0.07	1	0.07	27.19	0.0002	Significant
ap	0.01	1	6.53E-03	2.52	0.1385	Not significant
Vc×f	0.00	1	1.22E-03	0.47	0.5051	Not significant
Vc×r	0.02	1	2.10E-02	8.10	0.0147	Significant
Vc×ap	0.07	1	0.07	28.10	0.0002	Significant
f×r	9.00E-04	1	9.00E-04	0.35	0.5668	Not significant
f×ap	0.02	1	0.02	9.26	0.0102	Significant
r×ap	0.00	1	1.22E-03	0.47	0.5051	Not significant
Vc^2	0.05	1	0.05	19.54	0.0008	Significant
f^2	0.07	1	0.07	27.19	0.0002	Significant
r^2	0.08	1	0.08	29.60	0.0001	Significant
ap^2	0.05	1	4.56E-02	17.59	0.0012	Significant
Residual	0.03	12	2.59E-03			
Cor Total	1.01	26				
MQL machining						
Model	0.782	14	0.06	30.42	< 0.0001	Significant
Vc	0.007	1	6.53E-03	3.56	0.084	Not significant
f	0.407	1	0.41	221.58	< 0.0001	Significant
r	0.003	1	0.00	1.64	0.225	Not significant
ap	0.023	1	2.25E-02	12.27	0.004	Significant
Vc×f	0.006	1	5.63E-03	3.06	0.106	Not significant
Vc×r	0.011	1	0.01	6.00	0.031	Significant
Vc×ap	0.032	1	0.03	17.64	0.001	Significant
f×r	0.017	1	0.02	9.20	0.010	Significant
f×ap	0.003	1	0.00	1.36	0.266	Not significant
r×ap	0.001	1	9.00E-04	0.49	0.497	Not significant
Vc^2	0.128	1	0.13	69.76	< 0.0001	Significant
f^2	0.063	1	6.31E-02	34.34	0.0001	Significant
r^2	0.227	1	0.23	123.52	< 0.0001	Significant
ap^2	0.043	1	4.32E-02	23.52	0.0004	Significant
Residual	0.022	12	1.84E-03			
Cor Total	0.992	26				

Table 5 ANOVA analysis for tangential force in wet and MQL machining.

Source	SS	DF	MS	F-Value	P-value	Remark
Wet machining						
Model	71530.75	14	5109.34	95.95	< 0.0001	Significant
Vc	514.57	1	514.57	9.66	0.0090	Significant
f	14189.31	1	14189.31	266.47	< 0.0001	Significant
r	1169.00	1	1169.00	21.95	0.0005	Significant
ap	54712.81	1	54712.81	1027.48	< 0.0001	Significant
Vc×f	68.72	1	68.72	1.29	0.2781	Not significant
Vc×r	1.76	1	1.76	0.03	0.8589	Not significant
Vc×ap	110.36	1	110.36	2.07	0.1756	Not significant
f×r	0.05	1	0.05	0.00	0.9764	Not significant
f×ap	303.11	1	303.11	5.69	0.0344	Significant
r×ap	7.70	1	7.70	0.14	0.7104	Not significant
Vc^2	386.13	1	386.13	7.25	0.0196	Significant
f^2	0.03	1	0.03	0.00	0.9805	Not significant
r^2	1.82	1	1.82	0.03	0.8565	Not significant
ap^2	41.26	1	41.26	0.77	0.3960	Not significant
Residual	639.00	12	53.25			
Cor. Total	72169.74	26				
MQL machining						
Model	73044.32	14	5217.45	70.87	< 0.0001	Significant
Vc	230.65	1	230.65	3.13	0.1021	Significant
f	15946.88	1	15946.88	216.62	< 0.0001	Significant
r	1015.13	1	1015.13	13.79	0.0030	Significant
ap	53452.07	1	53452.07	726.10	< 0.0001	Significant
Vc×f	0.08	1	0.08	0.00	0.9740	Not significant
Vc×r	16.85	1	16.85	0.23	0.6409	Not significant
Vc×ap	6.33	1	6.33	0.09	0.7744	Not significant
f×r	89.49	1	89.49	1.22	0.2918	Not significant
f×ap	1695.79	1	1695.79	23.04	0.0004	Significant
r×ap	7.95	1	7.95	0.11	0.7481	Not significant
Vc^2	339.98	1	339.98	4.62	0.0500	Significant
f^2	45.19	1	45.19	0.61	0.4485	Not significant
r^2	88.42	1	88.42	1.20	0.2946	Not significant
ap^2	3.76	1	3.76	0.05	0.8251	Not significant
Residual	883.39	12	73.62			
Cor. Total	73927.71	26				

Table 6 ANOVA analysis for cutting power in wet and MQL machining.

Source	SS	DF	MS	F-Value	P-value	Remark
Wet machining						
Model	2107692	14	150549.4	143.41	< 0.0001	Significant
Vc	869184	1	869184	828.00	< 0.0001	Significant
f	238487.4	1	238487.4	227.18	< 0.0001	Significant
r	20660.08	1	20660.08	19.68	0.000812	Significant
ap	930273.6	1	930273.6	886.20	< 0.0001	Significant
Vc×f	8062.543	1	8062.543	7.689	0.016918	Significant
Vc×r	2747.07	1	2747.07	2.617	0.131696	Not significant
Vc×ap	29105.78	1	29105.78	27.727	0.000199	Significant
f×r	0.840	1	0.840	0.0008	0.977894	Not significant
f×ap	5262.293	1	5262.293	5.0129	0.04488	Significant
r×ap	133.691	1	133.691	0.127	0.727384	Not significant
Vc^2	3211.595	1	3211.595	3.059	0.105775	Not significant
f^2	0.055	1	0.055	5.26E-05	0.994333	Not significant
r^2	83.198	1	83.198	0.079	0.783102	Not significant
ap^2	565.546	1	565.546	0.538	0.477047	Not significant
Residual	12596.76	12	1049.73			
Cor. Total	2120288	26				
MQL machining						
Model	2172268	14	155162	121.864	< 0.0001	Significant
Vc	856718.9	1	856718.9	672.867	< 0.0001	Significant
f	277144.1	1	277144.1	217.669	< 0.0001	Significant
r	16590.58	1	16590.58	13.030	0.00358	Significant
ap	923330.5	1	923330.5	725.184	< 0.0001	Significant
Vc×f	18649.32	1	18649.32	14.647	0.002	Significant
Vc×r	743.698	1	743.698	0.584	0.459	Not significant
Vc×ap	40520.01	1	40520.01	31.824	0.0001	Significant
f×r	1553.674	1	1553.674	1.220	0.291	Not significant
f×ap	29440.84	1	29440.84	23.122	0.0004	Significant
r×ap	138.062	1	138.062	0.108	0.747	Not significant
Vc^2	3594.364	1	3594.364	2.823	0.118	Not significant
f^2	705.077	1	705.077	0.553	0.471	Not significant
r^2	1681.911	1	1681.911	1.320	0.272	Not significant
ap^2	22.91725	1	22.917	0.017	0.895	Not significant
Residual	15278.83	12	1273.236			
Cor. Total	2187547	26				

3.1.1 Cutting parameters versus surface roughness

The surface roughness is considered as one of the most critical constraints for the selection of the cutting parameters in the planning of the machining process. The table 4 present the significant parameters and the figure 2 illustrate the contribution of this parameters on Ra, it can be observed that the feed rate (f) is the most affecting parameter on surface roughness with a contribution of 52% and 41% in wet and MQL machining respectively, followed by the quadratic term (r^2) which corresponds to nose radius with a contribution of 8% and 23% (for 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 a worst surface roughness, because at large feeds the distance between peaks and valleys is more important.

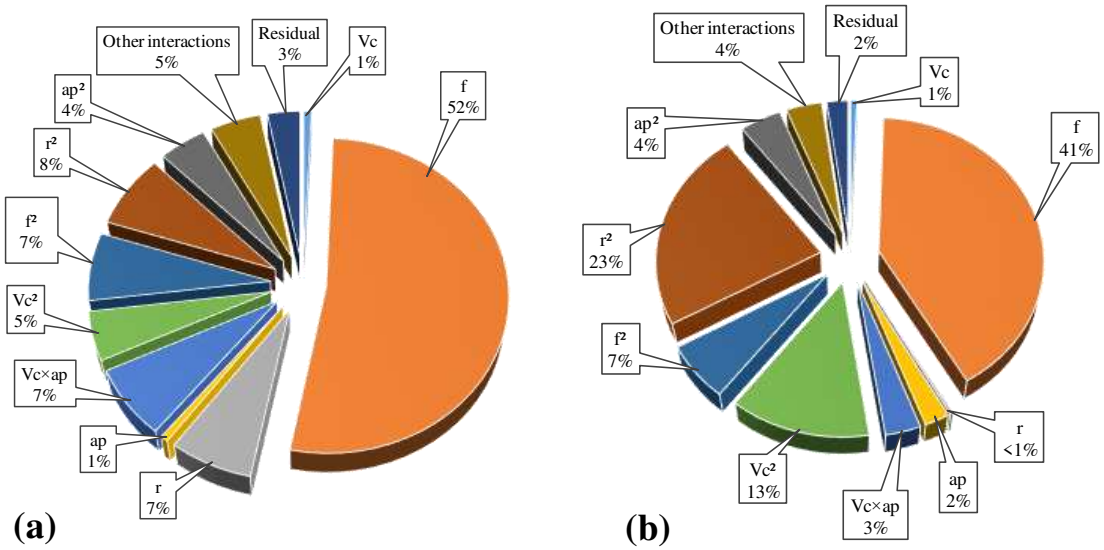


Fig. 2. Terms contribution (%) on Ra: a) Wet turning, b) MQL turning

Three-Dimensional (3D) response surface plots, predicated on the quadratic model were drawn to study the effect of the input machining parameter on tangential force and surface roughness. These plots can supplementarily 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 other two are varied.

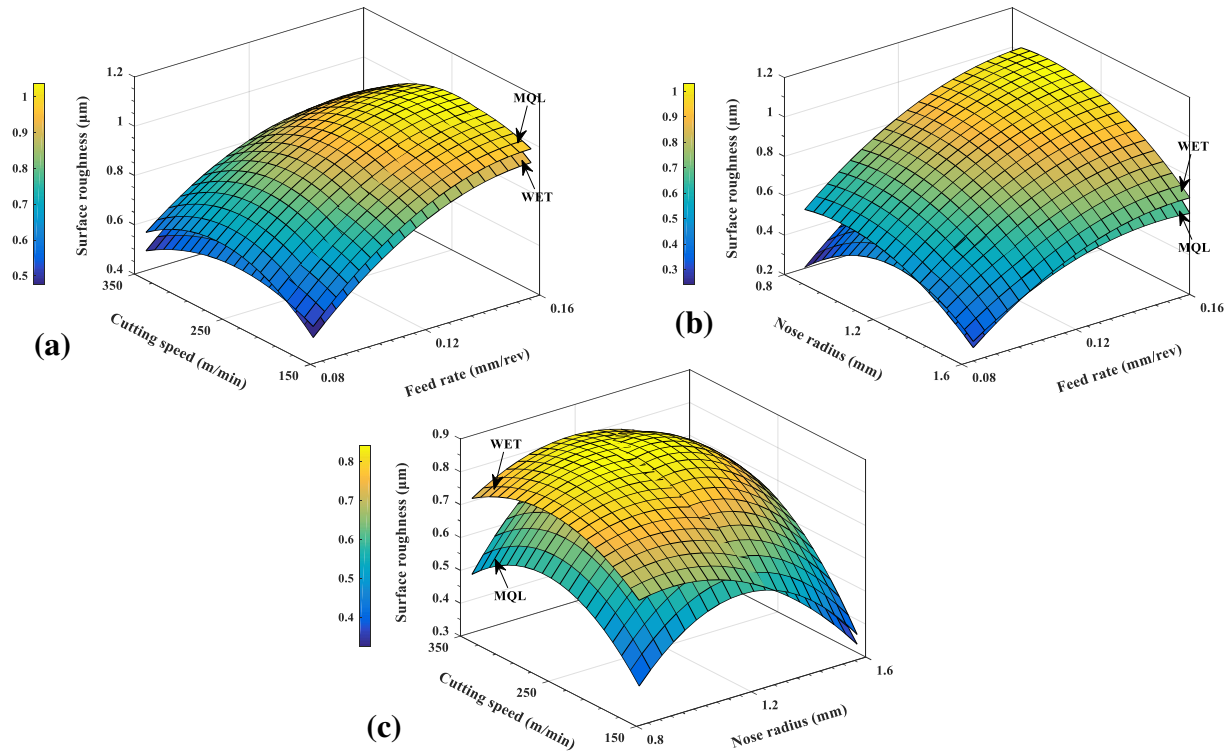


Fig. 3. Effect of cutting factors on surface roughness for wet and MQL turning

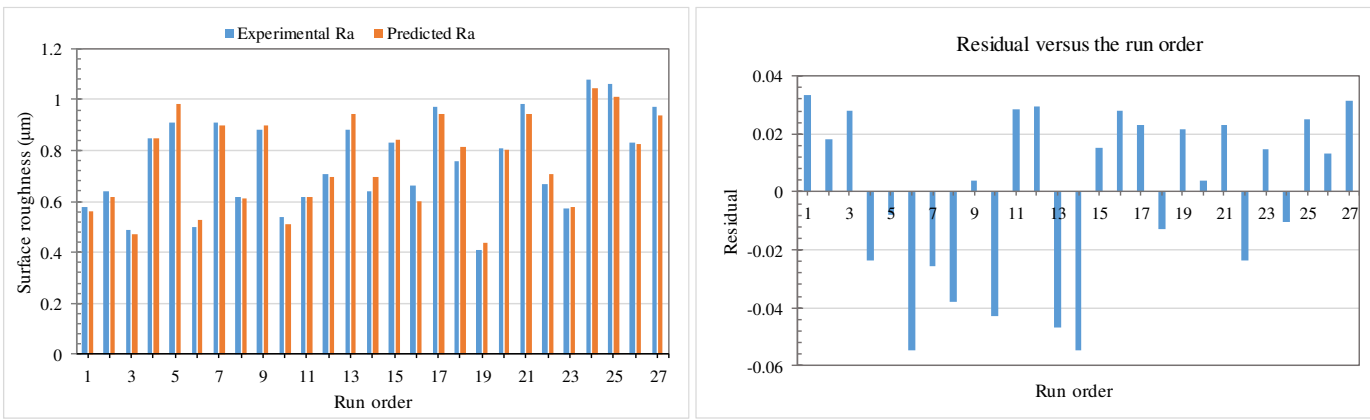
The figure 3 shows the evolution of the surface roughness according to cutting speed and feed rate, nose radius and feed rate, and cutting speed and nose radius. As indicated in fig. 3(a, b), the feed rate affect largely the surface quality, the surface roughness (Ra) rapidly increases with increasing feed rate and this is function of the generated surface of helical furrow. The fig. 3c illustrates the qualitative effect of large tool nose radius, with which the roughness has undergone an important improvement, the use of large nose radius can improve significantly the surface quality by crushing of asperities, also, a better surface quality obtained at high level of cutting speed, despite that the cutting speed has a week effect on Ra. These observations justify the use of high speeds, low feeds and cutting inserts with a large nose radius (r = 1.2 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.

The obtained quadratic models are shown in equations 7 and 8 with an R^2 of 96.51% and 97.26% respectively for surface roughness under wet and MQL cooling conditions.

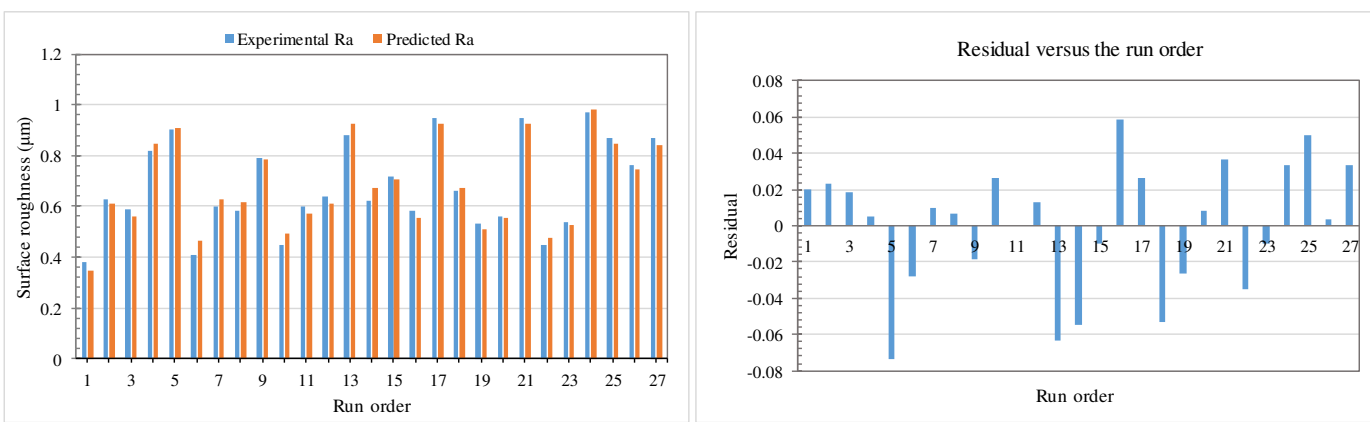
$$Ra_{Wet} = -2.05 + 2.75 \times 10^{-4} \times Vc + 28.59 \times f + 1.35 \times r + 1.47 \times ap - 4.37 \times 10^{-3} \times Vc \times f + 1.81 \times 10^{-3} \times Vc \times r + 6.75 \times 10^{-3} \times Vc \times ap - 0.93 \times f \times r - 9.68 \times f \times ap - 0.21 \times r \times ap - 9.75 \times 10^{-6} \times Vc^2 - 71.875 \times f^2 - 0.75 \times r^2 - 2.31 \times ap^2 \quad (7)$$

$$Ra_{Mql} = -3.77 + 5.26 \times 10^{-3} \times Vc + 29.38 \times f + 3.21 \times r + 0.60 \times ap - 9.37 \times 10^{-3} \times Vc \times f + 1.31 \times 10^{-3} \times Vc \times r + 4.5 \times 10^{-3} \times Vc \times ap - 4.06 \times f \times r - 3.12 \times f \times ap + 0.18 \times r \times ap - 1.55 \times 10^{-5} \times Vc^2 - 67.96 \times f^2 - 1.28 \times r^2 - 2.25 \times ap^2 \quad (8)$$

The performances of these RSM-models for prediction of surface roughness can be deducted from the figure 4. This figure represents a comparative between the experimental data and the prediction data of the RSM models along with their residuals for surface roughness, it can be clearly observed that the predicted values are very close to the experimental one in both wet and MQL machining, the model accuracy is needed in order to control the part quality.



(a)



(b)

Fig. 4. Performance of prediction-models and its residuals for Ra: a) WET turning, b) MQL turning.

3.1.2 Cutting parameters versus tangential force

The cutting force depends on the material to be machined, the tool geometry and the cutting conditions. In turn, the cutting force affects energy consumption, vibration, workpiece tolerances and tool life. Changing the cutting depth, feed rate and speed has variable effects depending on the load applied to the tool. When cutting, the doubling of the cutting depth doubles the cutting force. The cutting forces also increase with the feed rate, but to a lesser extent. Increasing the feed rate does not increase the cutting forces to the same extent as the increase in feed depth, because increasing the feed rate causes the thickness of the chip to increase.

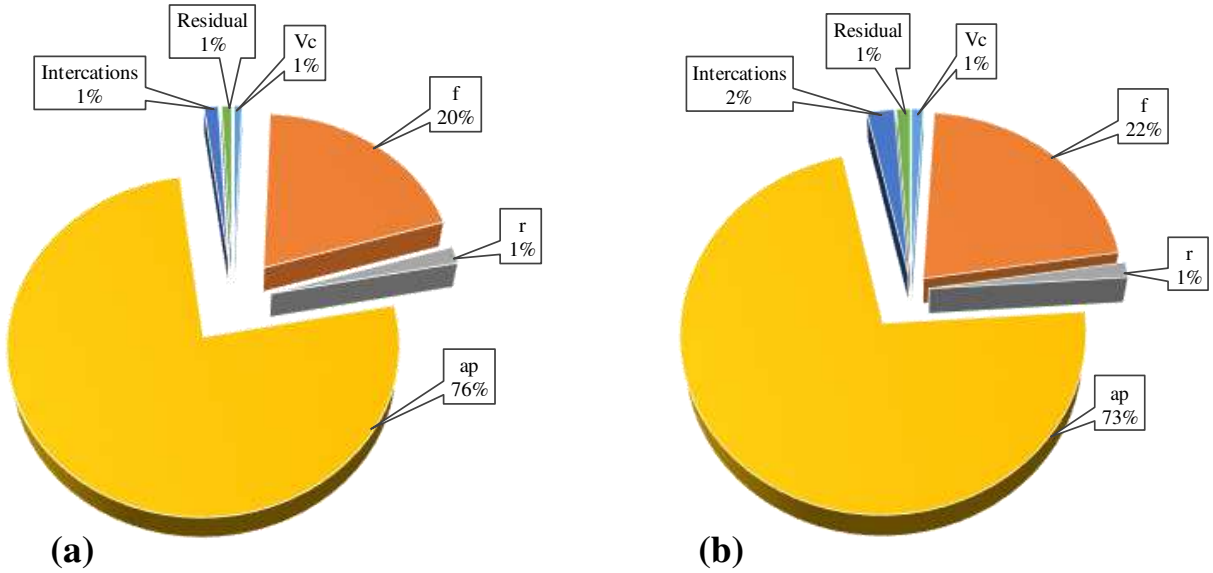


Fig. 5. Terms contribution (%) on Fz: a) Wet turning, b) MQL turning

From the figure 5, it can be observed that the cutting depth has the strongest influence on tangential force with a contribution of 76% in wet turning and 73% under MQL cooling technique, followed by feed rate (f) with a contribution of 20% and 22% and the nose radius (r) by a contribution of 1% (for each cooling technique Wet and MQL respectively). The significant terms presented in table 5 are those with large "F" values, despite the fact that the contribution of (Vc) is very low, but from its 'P' value, the cutting speed (Vc) is a significant parameter. The effect of the terms (Vc and r) and the other interactions become negligible due to large effect of cutting depth. 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). Also, at large nose radius, the contact surface is larger 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 increase. The results found are a good agreement with the previous researcher's works [15, 16 ,17].

Fig. 6 represent the 3D surface plots that illustrates the cutting force evolution according to cutting speed and depth of cut, cutting speed and nose radius, 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. Fig. 6a shows that the tangential force increases with the increase of depth of cut and feed rate, from all results it can concluded that the depth of cut exhibits maximum influence on cutting force components. The Fig. (6b-c) confirm 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.

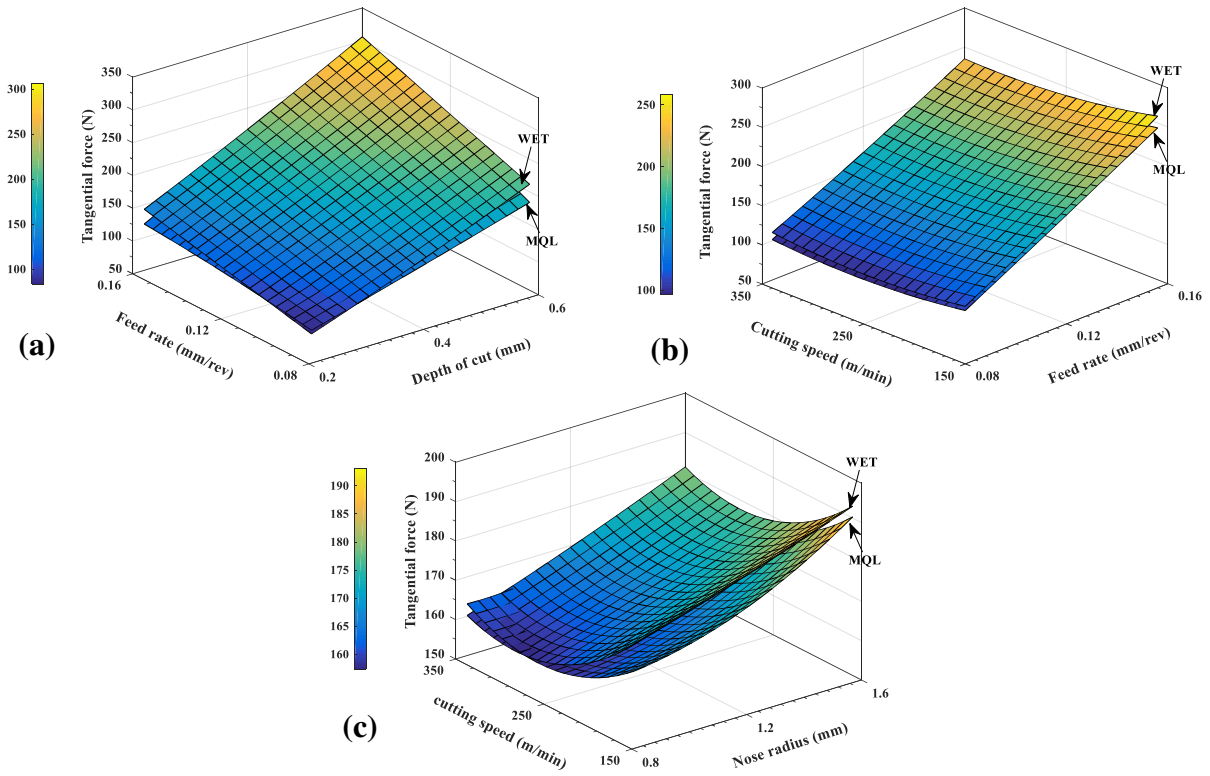


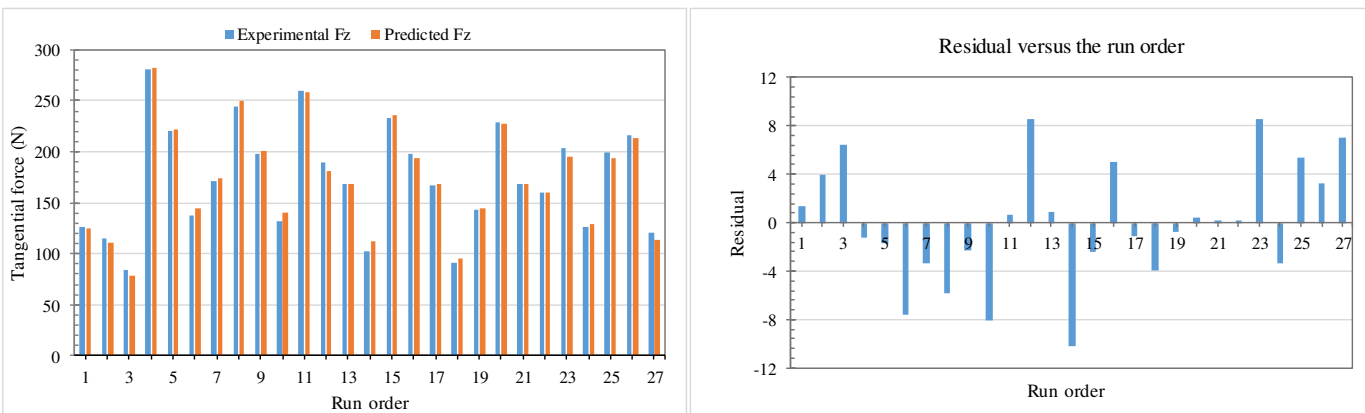
Fig. 6. Effect of cutting factors on tangential force for wet and MQL turning

The obtained mathematical quadratic models according to Eq. (6) are shown in the equations 9 and 10 with an R^2 of 99.11%, and 98.81% respectively for tangential force under dry, wet, and MQL cooling conditions.

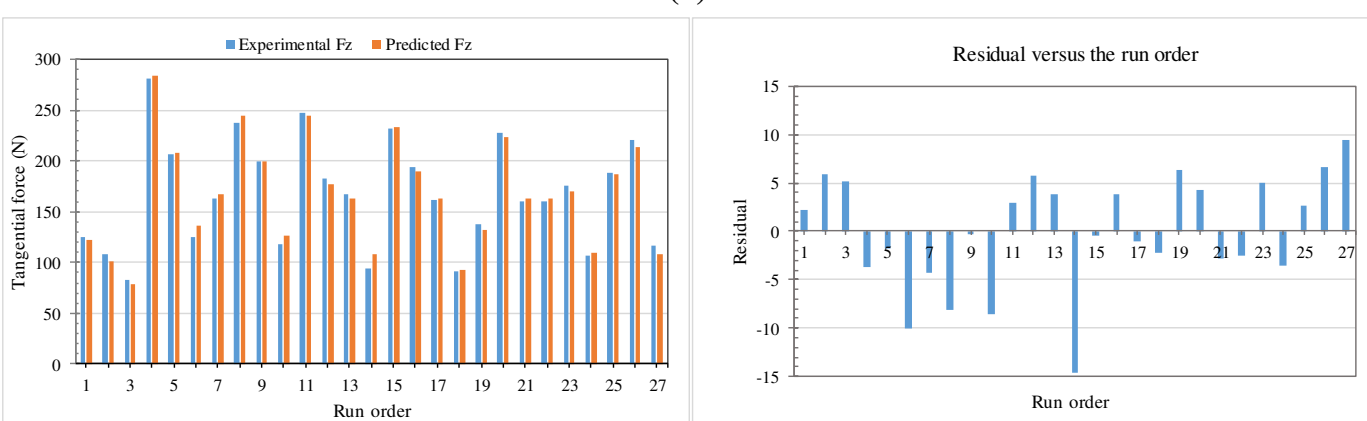
$$Fz_{Wet} = -3.82 - 0.28 \times Vc + 663.41 \times f + 4.01 \times r + 196.26 \times ap - 1.03 \times Vc \times f + 0.01 \times Vc \times r - 0.26 \times Vc \times ap + 6.87 \times f \times r + 1088.12 \times f \times ap + 17.34 \times r \times ap + 8.50 \times 10^{-4} \times Vc^2 + 49.21 \times f^2 + 3.64 \times r^2 + 69.53 \times ap^2 \quad (9)$$

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

The performances of Fz prediction models can be deducted from **7**. From the comparative between the experimental data and the RSM prediction data shows that the predicted data are very close to



(a)



(b)

Fig. 7. Performance of prediction-models and its residuals for Fz: a) WET turning, b) MQL turning.

experimental one. Residual plots confirm the prediction capability of the Fz models for both wet and MQL machining, and prove that the RSM present a good tool for predicting Fz on the tested material and process.

3.1.3 Cutting parameters versus cutting power

Concerning the cutting power, the developed model is presented in table 6. The most significant factor was the depth of cut followed by cutting speed and feed rate. The figure 8 shows the

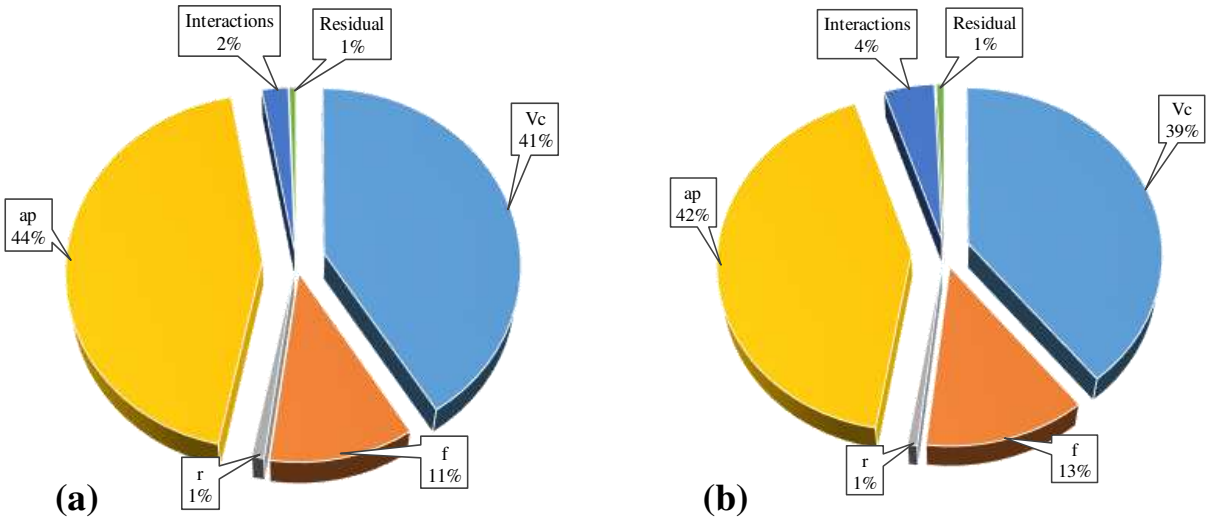


Fig. 8. Terms contribution (%) on Pc: a) Wet turning, b) MQL turning

contribution of the cutting setting on Pc, the depth of cut (ap) affect largely the cutting power with a contribution of 44 and 42%, followed by (Vc) with a cont. of 41 and 39% and feed rate (f, cont. 11 and 13%) respectively for wet and MQL turning. When we increase the depth of cut, the volume of material to be removed will be much larger, thus provoking a resistance between the workpiece and the cutting tool generating cutting forces which increases the consumption of the energy and consequently the cutting power required for machining process will be more important. Similar results were reported by Aouici et al. [26] when turning AISI D3. Moreover, Davim and Figueira [27] when turning AISI D2 steel using traditional and wiper cutting tools found that the cutting speed, depth of cut and feed rate have the major statistical significance regarding cutting power.

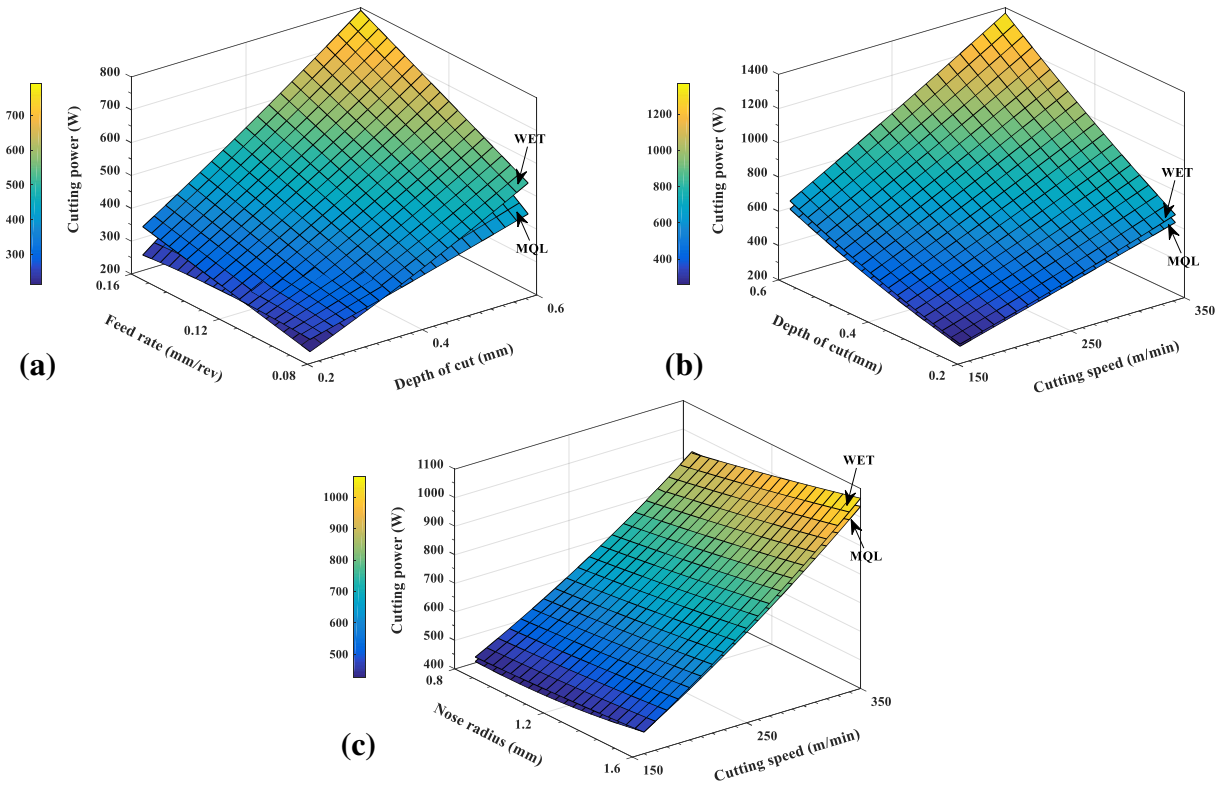


Fig. 9. Effect of cutting factors on cutting power for wet and MQL turning

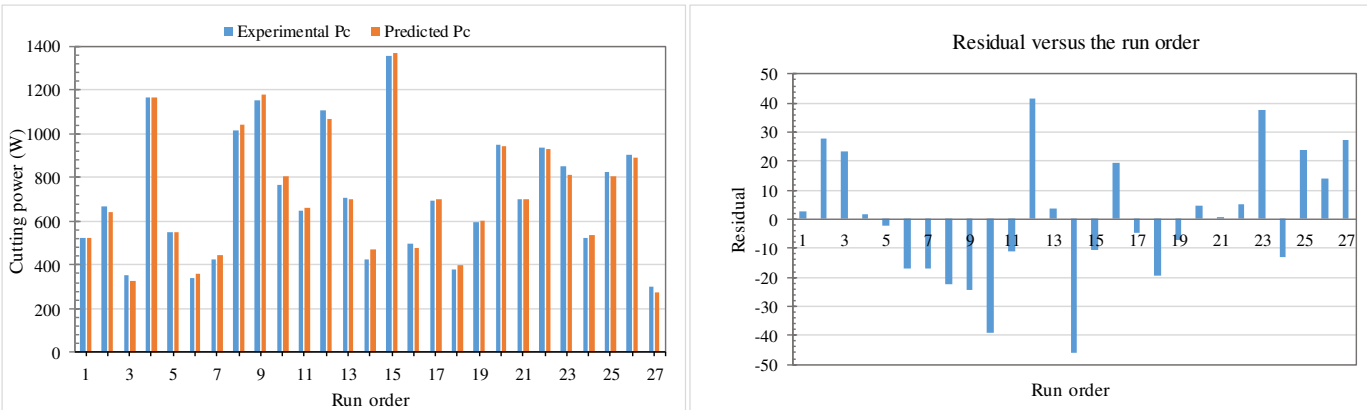
The figure 9 shows that the cutting speed and the depth of cut were the factors that affect the cutting power. The cutting power rises with the increase of ap. It is obviously noted that if the cutting speed is increased, the power required for the machining process will increase. On the other hand, the variation in cutting depth generates a resistant mechanical-load, because the surface contact between tool-workpiece increased along with the increase of the depth, and the consumption of the energy increase in proportion to the increase of the cutting forces.

The obtained mathematical quadratic models according to Eq. (6) are shown in the equations (7, 8 and 9) with an R^2 of 99.41% and 99.30% respectively for cutting power under wet, and MQL cooling conditions.

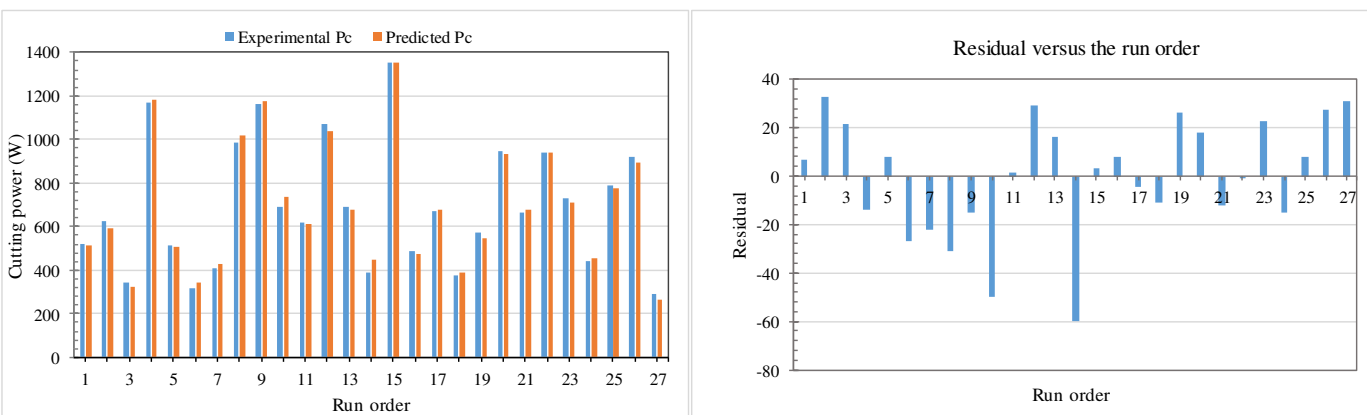
$$Pc_{Wet} = 370.95 - 2.37 \times Vc - 1144.79 \times f - 151.64 \times r - 510.86 \times ap + 11.22 \times Vc \times f + 0.65516 \times Vc \times r + 4.26 \times Vc \times ap + 28.64 \times f \times r + 4533.85 \times f \times ap + 72.26 \times r \times ap + 2.45 \times 10^{-3} \times Vc^2 + 63.58 \times f^2 + 24.68 \times r^2 + 257.44 \times ap^2 \quad (8)$$

$$Pc_{MQL} = 959.26 - 3.09 \times Vc - 4511.31 \times f - 435.826 \times r - 1287.61 \times ap + 17.07 \times Vc \times f + 0.34 \times Vc \times r + 5.032 \times Vc \times ap + 1231.77 \times f \times r + 10723.95 \times f \times ap + 73.43 \times r \times ap + 2.59E - 003 \times Vc^2 - 7186.198 \times f^2 + 110.99 \times r^2 + 51.82 \times ap^2 \quad (8)$$

The capability of these models for predicting cutting power is illustrated in the figure.10. As has been found in Ra and Fz results, the RSM regression models provide accurate results in predicting of cutting power with low errors.



(a)



(b)

Fig. 10. Performance of prediction-models and its residuals for Pc: a) WET turning, b) MQL turning.

4 Multi-objective optimization procedure

In this section, four recent multi-objective metaheuristics algorithms have been used to define the optimal machining parameters for the MQL machining finding the minimum of tangential force (Fz_{MQL}) and surface roughness (Ra_{MQL}). The used algorithms for this approach are Multi-Objective Salp Swarm Algorithm (MOSSA) [25], Multi-Objective Ant Lion Optimizer (MOALO)

[22], Multi-Objective Verse Optimizer (MOVO) [24], and Multi-Objective Grey Wolf Optimizer (MOGWO) [23]. The population size (*np*) and the maximum number of iterations (Max_it) are set as: $np = 100$, $Max_{it} = 500$.

In order to study the convergence behavior of the investigated algorithms, the history of the obtained best Pareto fronts values is plotted (as given in Fig. 11). It can be seen from the figure that all the investigated algorithms are able to converge to the best pareto front. The compromise for both objectives is given in the zoom part of the figure 11.

Table 7 represents 10 best solutions which gives the same importance (compromise) for the surface roughness and tangential force in case of MQL turning. Moreover, the best solution to achieve low force is $X = \{265.25, 0.080, 1.04873, 0.200\}$ corresponding to $Fz_{MQL} = 77.7031$ N. In the other hand, the values of $X = \{261.75, 0.080, 0.6818, 0.200\}$ provide the best surface finish "Ra_{MQL}" with value of 0.1103 µm.

Table 7. Optimal Solutions

N	Fz_{MQL}(N)	Ra_{MQL} (µm)	Vc (m/min)	f (mm/rev)	r (mm)	ap (mm)
1	79.00576454	0.303650957	265.2600502	0.0800000	0.832064045	0.200000
2	79.04957604	0.301973358	277.4466886	0.0800000	0.851193371	0.200000
3	79.05892295	0.299046042	264.1914266	0.0800000	0.826447035	0.200000
4	79.07810194	0.298639838	276.8849237	0.0800000	0.847144437	0.200000
5	79.14869366	0.288637772	268.8537448	0.0800000	0.824585169	0.200000
6	79.22522623	0.283316008	263.6868656	0.0800000	0.812263012	0.200000
7	79.32499241	0.276633736	260.4783905	0.0800000	0.802247926	0.200000
8	79.33385863	0.276258662	260.0469215	0.0800000	0.801364429	0.200000
9	79.35007273	0.269589793	270.5976148	0.0800000	0.811228561	0.200000
10	79.47541325	0.258025202	268.4081861	0.0800000	0.798294671	0.200000

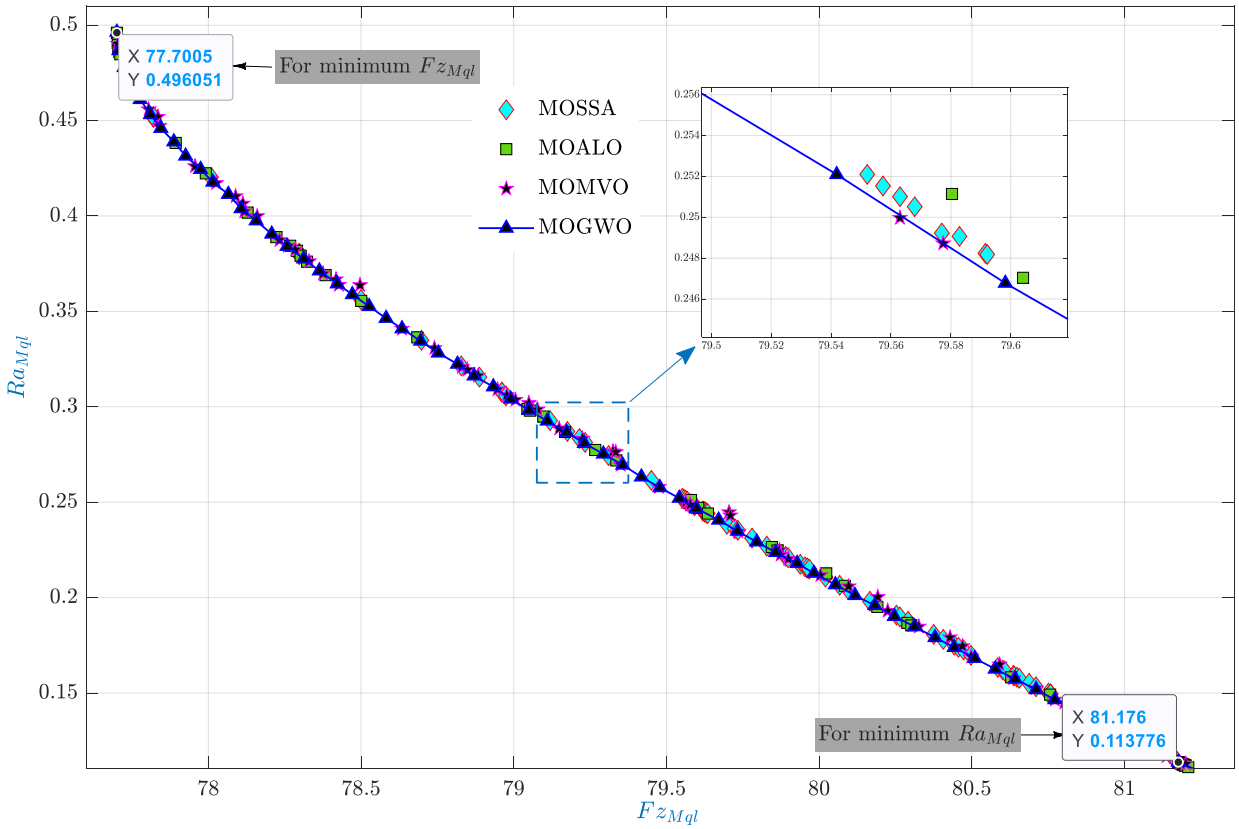


Fig 11. The best Pareto fronts achieved by the approaches for the machining problem

5 Conclusion

This study investigates the MQL efficiency as compared to Wet machining in order to reduce lubrication consumption in machining operation, and also investigates the contribution of optimization algorithms in the industrial field for an intelligent manufacturing approach.

As found in previous researches that the tangential cutting force is largely affected by the cutting depth surface, and the feed rate is the main affecting parameter on surface roughness. Also, the use of cutting inserts having large nose radius improves the surface quality and provides a low surface roughness that allows to achieve the needed precision.

The response surface methodology is a good modeling tool that helps identifying the insignificant main factors and interaction factors or insignificant quadratic terms in the model which reduce the complexity of the problem.

The Minimum Quantity Lubrication can achieve the required machining factors eliminating the problems of flood cooling. MQL machining can be qualified as a green machining process when the optimization is considered.

The tested optimization algorithms are found to be helpful for better productivity in the industrial field.

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Code availability: Not applicable

Authors' contributions: (optional)

Additional declarations for articles in life science journals that report the results of studies involving humans and/or animals: Not applicable

Ethics approval: I certify that the paper follows the ethical rules of good scientific practice mentioned in the "Ethical Responsibilities of Authors" of the journal.

Consent to participate (include appropriate statements): Not applicable

Consent for publication (include appropriate statements)

Mourad NOUIOUA hereby declare that I participated in the study and in the development of the manuscript and authorize the full the publishing of manuscript data.

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