FACTA UNIVERSITATIS
Series: **Mechanical Engineering** Vol. 18, N° 1, 2020, pp. 13 - 29
https://doi.org/10.22190/FUME191024009J

Original scientific paper

EXPERIMENTAL ANALYSIS AND OPTIMIZATION OF THE CONTROLLABLE PARAMETERS IN TURNING OF EN AW-2011 ALLOY; DRY MACHINING AND ALTERNATIVE COOLING TECHNIQUES

Sonja Jozić, Ivana Dumanić, Dražen Bajić

Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture,
University of Split, Split, Croatia

Abstract. *The latest trends in machining research show that great efforts are being made to understand the impact of different cooling and lubrication techniques as well as cutting parameters on machining performances. This paper presents the investigation results of different cutting parameters and different cutting environments such as dry machining, minimum quantity lubrication (MQL) and minimum quantity lubrication with compressed cold air (MQL+CCA) on average surface roughness, cutting force and material removal rate. The experiments were designed based on three input parameters and three different cutting environments when turning of EN AW-2011 alloy. Taguchi-based grey relational analysis was used to identify the optimal process parameters by which minimum values of surface roughness, minimum value of cutting force and maximum value of material removal rate will be achieved. The results showed that minimum quantity lubrication in the stream of compressed cold air, in comparison to dry and minimum quantity lubrication machining, gives the best machining performances. Therefore, the use of MQL + CCA method, which reduces the amount of lubricant may represent in the described extent of turning operations an alternative to turning processes most often carried out by wet method that causes considerable costs for purchasing, maintaining and using cutting fluids.*

Key Words: *Turning, Dry Machining, Minimum Quantity of Lubrication, Compressed Cold Air Cooling, Taguchi Design, Grey Relational Analysis*

Received October 24, 2019 / Accepted December 19, 2019
Corresponding author: Sonja Jozić
University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, R. Boškovica 32, 21 000 Split, Croatia
E-mail: sjozic@fesb.hr

1. INTRODUCTION

Nowadays, modern mechanical industries are constantly trying to design products and processes that can run faster, last longer and operate more precisely. Contemporary high-performance machines that undergo higher loads and increase moving speed of the moving parts are requiring that bearings, seals, shafts, machine guides, gears and other mechanical elements have to be dimensionally and geometrically accurate or the surface texture of the manufactured parts must be precise [1]. Therefore, the objective of machining operations is to produce mechanical elements with specified quality as productive as possible. To achieve the highest possible efficiencies in machining processes, understanding the relationships between process responses and the process controlling factors must be attained. The machining processes generate heat that is distributed into tool, workpiece, chips and environment. The most efficient way to reduce the temperature during machining is to apply a cutting fluid. Therefore, the cooling process becomes an integral part of every machining process. The most popular method of cooling the cutting zone is a conventional one, by flooding. The main disadvantage of this cooling method is a high flow rate of refrigerants and the fact that only a small part reaches the contact area between the cutting edges and the material being machined.

As a result of the economic (high cost of cutting fluids) and ecological (negative effects on humans and the environment) pressures, the industry seeks for newer methods to minimize the consumption of harmful lubricants, [2]. In recent years, several technologies have been developed in order to increase the overall effectiveness of the process like flood cooling, cryogenic cooling, solid coolants/lubricants, high pressure coolants (HPC), minimum quantity lubrication (MQL)/near dry machining (NDM), internal tool cooling and cooling with compressed air/gases [3]. The concept of dry machining, which has been suggested by many contemporary researchers, has many advantages such as: the absence of adverse effects on humans and the environment, the reduction of variable machining costs due to the lack of cutting fluid, easier recycling of a chip that is not contaminated with the cutting fluids and the possibility of applying high cutting speeds and reducing the cutting forces and thus the longer tool life [4]. The loss of its positive effects, namely lubrication, cooling and chip flushing, is imposed by the elimination of the coolant. Also, during the dry machining, the mechanical and thermal loads of the cutting tool are increased [5].

Minimum quantity lubrication is a cooling technique during which a very small amount of lubricant agent is applied during the machining process. MQL results in a significant reduction in the cutting temperatures along with favorable work-chip and work-tool interactions. This leads to a reduction in the surface roughness as well as cutting forces. Dhar et al. [6] investigated the MQL technique when turning AISI-1040 steel and their results of the study indicated that the MQL machining system is more efficient than a conventional flood coolant system. Priarone et al. [7] performed milling experiments of titanium aluminides with different types of cooling conditions; dry, wet and MQL. They have shown that MQL gave the best results in terms of surface roughness even when compared to wet machining [7, 8]. Sharma et al. [9] concluded that MQL leads to decreasing of the cutting temperature which results in improving the tool life as well as the surface roughness. Maruda et. al [10] and Maruda et al. [11] concluded that the use of the MQL cooling technique reduces the machined surface roughness parameters and cutting force values when turning the carbon steel compared with compressed air cooling and dry machining. The MQL research in the literature has shown so far that this technique has proved its efficiency, e. g.: allowing reduction in lubricant use from 50 % to 90 % [12] and lower energy consumption, better performances and environment protection [13].

The extension of the MQL system is a system where minimal quantity of lubricant is combined with compressed cold air (MQL + CCA). In such systems, the lubricant is used to reduce friction while compressed cold air enhances the cooling and flushing action [14]. Pervaiz et al. [14] and Pervaiz et al. [15] explored the machinability of Ti6Al4V using a vegetable oil-based MQL system mixed with sub-zero temperature air. It was observed that the vegetable oil-based cooling strategy had promising potential to replace conventional flood cooling methods. Yuan et al. [16] reported that MQL with compressed cold air significantly reduced cutting force, tool wear and surface roughness when machining titanium alloy (Ti6Al4V). Singh and Sharma [17] concluded that using a Ranque-Hilsch vortex tube in addition to the MQL cooling process during turning of commercially pure titanium led to an improvement reducing surface roughness values and cutting forces when compared to MQL process.

Multiple characteristic optimization methods have been the focus of the recent research directed at improving product quality and reducing the costs of the machining process. Among various optimization methods are grey relational analysis (GRA), technique for order preferences by similarity to ideal solution (TOPSIS), genetic algorithms (GA), desirability analysis (DA), metaheuristic algorithms and other methods that allow multiple performance characteristics to be optimized simultaneously. Diyaley and Chakraborty [18] used six most popular metaheuristic algorithms to determine optimal values of the cutting parameters during roughing and finishing milling operations in order to minimize total production time and total production cost. Gopal and Prakash [19] used GRA and TOPSIS to optimize milling parameters in order to minimize cutting force, surface roughness and temperature during end milling process, and both methods gave the similar optimal cutting parameters. Fratila and Caizar [20] conducted an experimental investigation on milling of AlMg3 alloy under conventional flood lubrication, minimal quantity lubrication and dry milling. By using the Taguchi optimization methodology, they found optimal cutting parameters for minimal cutting power and surface roughness. Yan and Li [21] used a multi-objective optimization method based on weighted grey relational analysis and response surface methodology (RSM) to optimize the cutting parameters in milling process. They tried to evaluate trade-offs between sustainability, production rate and cutting quality. Lin [22] used the Taguchi method together with GRA to deal with optimization of the turning operations, for the machining of S45C steel, with the multiple performance characteristics (tool life, cutting force, surface roughness). S. Tripathy and D.K. Tripathy [23] performed multi-response optimization of the cutting parameters using grey relational analysis together with the TOPSIS method. To obtain favorable process output values such as radial thrust force, cutting power and coefficient of friction when dry turning of Ti-6Al-4V. Li et al. [24] combined the Taguchi-based grey relational analysis and the kernel principal component analysis (KPCA) to optimize machining parameters such as type of inserts, feed rate and depth of cut.

Mia et al. [25] optimized cutting forces, surface roughness, cutting temperature, and chip reduction coefficient when turning of Ti-6Al-4V in dry and high-pressure coolant condition using GRA combined with the Taguchi method. In their next paper [26] they experimentally investigated surface roughness, cutting force, and feed force when turning the same workpiece material under cryogenic (liquid nitrogen) condition. They performed multi-response optimization according to the models of responses by response surface methodology (RSM) and artificial neural network. Aman et al. [27] utilized the Taguchi method and the response surface method (RSM) to find out the influence of depth of cut, cutting speed, cutting environment, cutting tool geometry and feed rate on power consumption.

It can be observed that whereas different studies have found MQL and MQL+CCA as an improvement and benefits over dry machining, wet machining and flood lubrication, fuller understanding of MQL and MQL+CCA process is still required. Also, few research projects have been performed for which the cutting environments (dry, MQL and MQL+CCA) were variables. It is evident from the review of available literature that no studies have been found on the use of MQL in turning of the aluminum alloy EN AW-2011. This alloy is often called a free machining alloy and it is well suited to the use in automatic lathes. Boswell et al. [28] provided an overview of the effectiveness of MQL during conventional machining; turning, milling, grinding, drilling for different workpiece materials such as steel, aluminum alloys (A7175, A6061, A1050) and difficult-to-cut materials (Ti-48Al-2Cr-2Nb intermetallic alloy, Ti-6Al-4V titanium alloy, nickel-based alloys and iron-based alloys).

As noted earlier, the objective of this study is to research the effects of cutting environments (dry machining, MQL, MQL + CCA) on surface roughness, cutting force component in the Z direction and on the material removal rate in the longitudinal turning at varying cutting parameters (cutting speed, feed rate, depth of cut). Cutting force components in X and Y direction were not taken into consideration because of the negligible small values of Fx and Fy in comparison to Fz. In this study, the use of the Taguchi method to design the tests and grey relational analysis to find an optimum cutting environment from the machining response, such as cutting force, surface roughness and material removal rate was reported. Confirmation test was established after optimizing machining parameters.

2. EXPERIMENTAL WORK

The aim of the experimental study was to evaluate the influence of cutting parameters and cutting environments on the surface roughness, cutting force and the rate of material removal. The experiments were carried out on the universal lathe machine with a spindle motor of 11 kW power and the spindle speeds in the range from 11.2 rpm to 2240 rpm. Turning inserts, the VCGT 160404-AS produced by ISCAR were mounted on the tool holder SVJCR 2020K-16.

The workpiece material was EN AW-2011, aluminum alloy. The chemical composition of the material in mass fraction was Al (91.4%), Cu (4%), Fe (0.7%), Pb (0.6%), Bi (0.6%), Si (0.4%) and Zn (0.3%). Physical and mechanical properties of the alloy are presented in Table 1.

The workpieces were shafts with dimensions of 300 mm length and 75 mm in diameter with machined slots to perform experiments and measurements much easier, Fig. 1. The workpiece was clamped into the chuck, while the other side was supported by a tailstock to prevent vibration during machining.

The surface roughness was measured using the Mitutoyo Surfest SJ 301 profilometer. Sampling length and the cut-off length for the measurements of surface roughness were selected to be 5.6 mm and mm 0.8, respectively. Every measurement was repeated at three different locations and the average value was considered.

The system for measuring the cutting force consists of dynamometer Kistler 9257A mounted between the cutting tool and the tool support as well as multi-channel charge amplifier Kistler 5007A. The charge amplifier serves to amplify and convert the electrical charge delivered from the dynamometer into corresponding voltage and then forwards the signals to the A/D interface board (BMC USB-AD16f). The NextView 4 software was used for analyzing the cutting forces. All the measuring instruments were calibrated before the measurements were carried out. Measurements and analysis equipment are shown in Fig. 2.

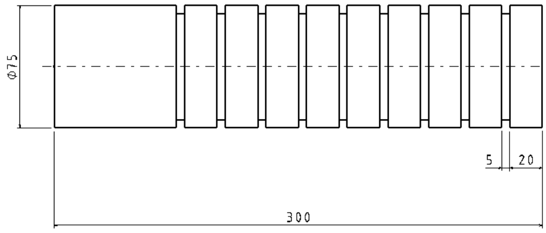

Fig. 1 Dimension of the workpiece

Table 1 Physical and mechanical properties of used material in experimental part

Alloy EN AW-2011	
Density g/cm³	2.82
Coefficient of thermal expansion (20-100 °) 10-6/K	23.4
Modulus of elasticity MPa	72500
Tensile strength (Rm) MPa	320
Yield strength (Rp0,2) MPa	270
Elongation A50 (%)	8
Brinell hardness	90

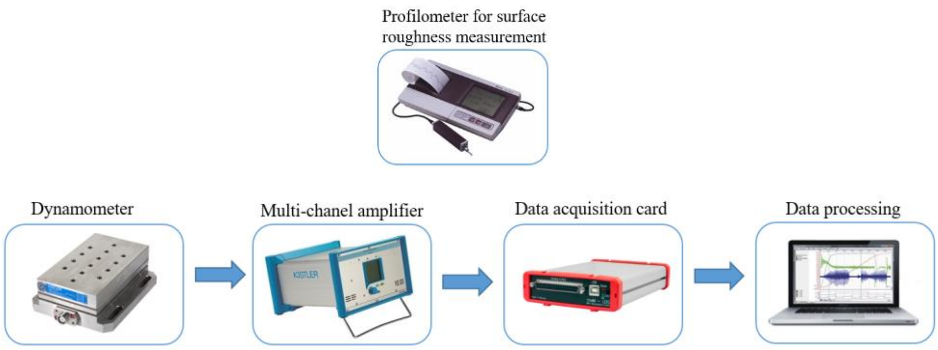

Fig. 2 Measurement and analysis equipment

Minimum quantity lubrication (MQL) is an intermediate solution for switching from the conventional use of cutting fluids to dry machining. As such it belongs to semi dry methods of cooling and lubrication. MQL technique shows the great potential and advantages over conventional cutting fluids systems, especially if the economic and environmental aspect of application of chosen techniques of cooling and lubrication in machining is taken into consideration.

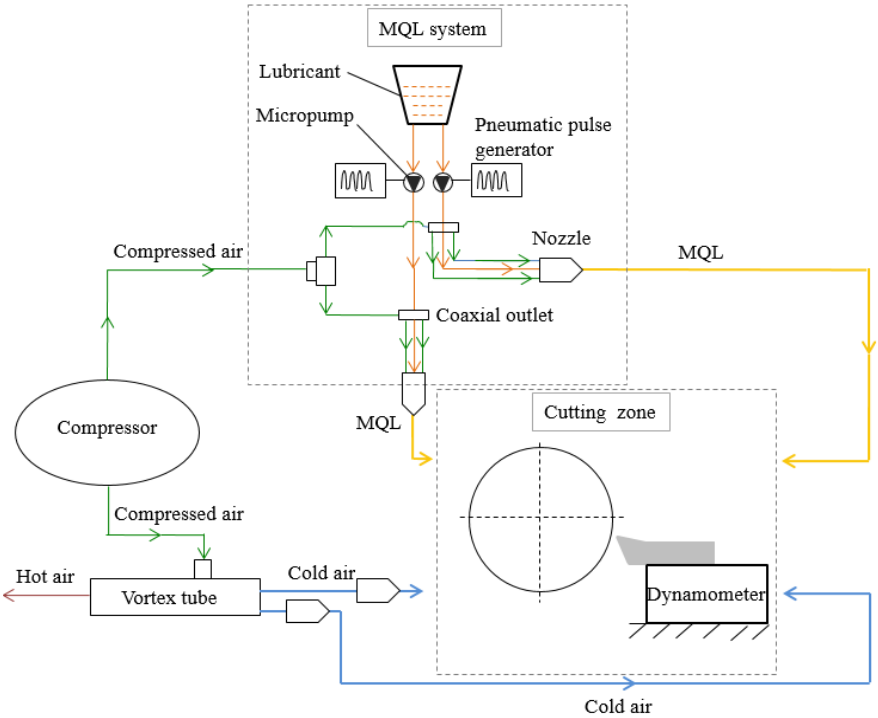

Fig. 3 Schematic view of the experimental set up

The minimum quantity lubrication system Vectolub was applied in this work for the turning process. In this system, every micropump, whose working frequency is set by a pneumatic pulse generator, delivers the lubricant through the coaxial line into a bifluid projection nozzle. The compressed air is provided by an external compressor and delivered into the MQL. The air and the lubricant are parallel conducted in a coaxial line. In the nozzle, the lubricant is broken down and transported into microdroplets by the air. Thus, a homogeneous lubricant film at the friction point is formed.

In this study, Cold Air Guns which use a vortex tube were used to improve the performance of the MQL process as shown in Fig. 3. A high-pressure air stream enters the vortex tube tangentially and after passing through the chamber, the compressed inlet air accelerates at a high rate of speed. The hot gas stream leaves the tube through the control valve, while the cold gas stream passes through the cold end, near the entrance nozzle.

2.1. Controllable parameters and process responses

Cutting speed v_c, feed rate f, the depth of cut a_p and cutting environments were considered as controllable variables. The values of machining parameters were selected from the manufacturer's handbook recommended for the tested material together with the machine tool capabilities. All factors had three levels as shown in Table 2. Cutting environment as the fourth controllable variable were dry, MQL and MQL with compressed cold air (MQL + CCA).

Table 2 Machining parameters and their levels

Machining parameters	Level 1	Level 2	Level 3
Cutting speed, v_c [m/min]	200	300	400
Feed rate, f [mm/rev]	0.05	0.15	0.25
Depth of cut, a_p [mm]	1	1.75	2.5
Cutting environment, CE	Dry	MQL	MQL+CCA

The process responses that have been considered are surface roughness, cutting force and material removal rate. In this study, surface roughness average (*Ra*) is the surface parameter used to evaluate surface roughness. The required surface roughness cannot be achieved as easily as physical dimensions due to the influence of many factors. The most important of them are: workpiece and tool material, tool geometry, tool wear, machining parameters, dynamic behavior of machining system, application of cooling and lubrication agents. Cutting forces are important physical variables that provide relevant information about machining processes such as machinability, tool conditions, power consumption, etc. Cutting parameters, type of cooling methods, and cutting tool geometry are the most important parameters that affect cutting forces. The material removal rate (MRR) indicates the amount of material removed from the workpiece per unit of time. The higher the values of the cutting parameters, the greater value of the material removal rate is provided, and thus the less cycle time.

2.2. Design of experiments and experimental results

The influence of the controllable factors on the process performances was examined using the Taguchi approach. The Taguchi method generally requires a small number of experiments and L9 orthogonal array was chosen to investigate the influence of machining parameters (v_c, f, a_p), on cutting output variables (*Fz*, *Ra*, *MRR*). The influence of cutting environment on mentioned response variables was examined by performing three sets of experiments: dry turning, MQL turning and MQL+CCA turning. Therefore, it is carried out a total of 27 experiments. Highly efficient production can be achieved by increasing the volume of the removed material per time unit. In this study, the material removal rate in the turning process is calculated using the equation:

$$MRR = v_c a_p f \tag{1}$$

The design of experiments together with experimental results is given in Table 3.

Table 3 Design of experiments based on L9 orthogonal array and experimental results

	Cutting speed [m/min]	Feed rate [mm/rev]	Depth of cut [mm]	Cutting condition	Ra [μm]	Fz [N]	MRR [mm3/s]
				Dry	0.53	46.55	
1	200	0.05	1	MQL	0.41	42.30	166.67
				MQL+CCA	0.47	39.88	
				Dry	1.43	176.18	
2	200	0.15	1.75	MQL	1.28	160.35	875
				MQL+CCA	1.34	144.94	
				Dry	4.91	427.06	
3	200	0.25	2.5	MQL	4.68	343.38	2083.33
				MQL+CCA	4.77	337.39	
				Dry	0.35	82.94	
4	300	0.05	1.75	MQL	0.22	73.71	437.50
				MQL+CCA	0.26	69.94	
				Dry	1.45	267.77	
5	300	0.15	2.5	MQL	1.31	230.26	1875
				MQL+CCA	1.36	231.73	
				Dry	4.58	223.77	
6	300	0.25	1	MQL	4.42	164.66	1250
				MQL+CCA	4.44	179.26	
				Dry	0.48	114.17	
7	400	0.05	2.5	MQL	0.42	107.94	833.33
				MQL+CCA	0.46	97.19	
				Dry	1.49	117.64	
8	400	0.15	1	MQL	1.42	109.82	1000
				MQL+CCA	1.42	100.04	
				Dry	4.61	270.74	
9	400	0.25	1.75	MQL	4.39	272.21	2916.67
				MQL+CCA	4.44	229.13	

3. Results and Discussion

The different machining aspects of EN AW-2011 studied by using dry, MQL, MQL + CCA cutting environments are presented below.

3.1. Surface roughness and material removal rate

The three machining parameters, namely, the cutting speed, the feed rate and the depth of cut are found to influence surface roughness but as mentioned in the introduction the feed rate is the parameter that has the highest influence on surface roughness. Fig. 4 represents the value of surface roughness with the increasing of feed rate at varied cutting environments for cutting speed of 200 m/min. From Fig. 4 it can be observed that the surface roughness increases with the increase in the feed rate for all cutting environments. This is because at large feed rates the distance between peaks and valleys of the feed marks generated by the tool grooves is much more important.

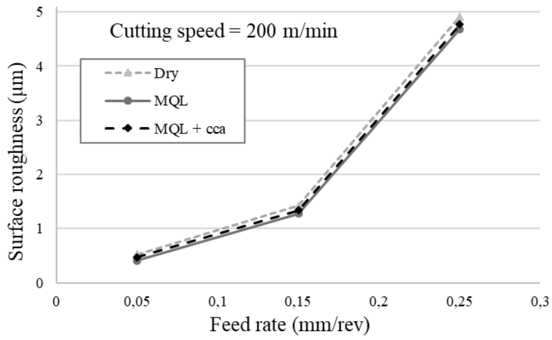

Fig. 4 Influence of feed rate to surface roughness

Experimental runs with the results are given in Table 3 where it can be clearly seen that MQL resulted in lower surface roughness values when compared to MQL + CCA and dry cutting process for all the combinations of parameters. This is because in MQL process, the formation of defects (built up edge, debris, adhesion of micro particles, etc.) is reduced due to better lubrication in comparison with MQL + CCA where compressed cold air carries off a small amount of lubricant from the cutting zone.

3.2. Cutting forces

Fig. 5 shows cutting force *Fz* under different cutting environment. The cutting force has minimal value during the 1st trial by using MQL + CCA environment. The cutting force increases with the increase of the depth of cut and the feed rate due to an increase of the cutting action area. Also, the increase of these two parameters causes the material removal to become difficult due to increasing shear force. MQL + CCA resulted in lower cutting forces values when compared to MQL and dry cutting process.

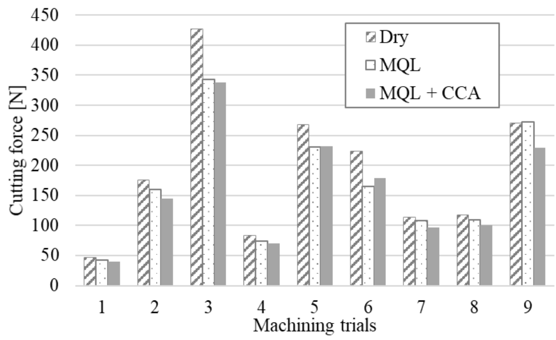

Fig. 5 Effect of cutting parameters on cutting force under different cutting environments

The reduced temperature at the cutting zone accomplished by compressed cold air and lubricate effect of MQL leads to avoiding the adhesion and welding of chips, reduction in friction produced and hence a reduction in the cutting force. The maximum value of cutting force (third trial) at the same parameters came out to be 27 % lower for MQL + CCA compared to dry processing, which is a quite significant reduction.

4. Optimization Methodology - Grey Relation Analysis

The Taguchi's method uses a signal-to-noise ratio (S/N) as the core criterion for analysis of experimental data. The purpose of the S/N ratio is to identify a control factor that reduces process variability by reducing the impact uncontrollable factors i.e. factors of noise. A positive effect on an output variable denotes the term "signal" while the term "noise" refers to an undesirable effect on an output variable. Therefore, estimating the deviation of the output variable from the desired value is equal to the S/N ratio. The high value of S/N ratio indicates the optimal level of control factors and it is determined by using three types of quality characteristic: "higher the better", "smaller the better" and "nominal the best."

For machining in general the small values of surface roughness *Ra* and cutting force *Fc* are desirable as well as a large value of the material removal rate. The following equations are used to calculate the S/N ratio, for smaller the better characteristic, equation (2), and higher the better characteristic, equation (3):

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

$$S/N = -10 \cdot \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^{-2}\right) \tag{3}$$

where: i – experiment number, y_i – measured value of output variable, n –replicates number.

Based on the calculation of S/N ratio and the mean effect plot analyses, three sets of optimal input parameters, within the offered levels, will be obtained, one set per cutting environment (dry, MQL, MQL+CCA) and furthermore, each set has optimal input parameters for every output variable. This will allow the determination of optimal parameters for each process response separately.

The following is explained determining of optimum parameters when dry turning, for minimum surface roughness. The S/N ratio analysis was used to generate the response table for the S/N ratio of surface roughness, *Ra*, (Table 4). Delta value is the difference between the highest and lowest average value of each input variable and ranks are assigned according to the delta value. The factor with the largest delta has the greatest influence on Ra. Main effects plot for S/N rations for surface roughness, based on the data in Table 4, is shown in Fig. 6.

Table 4 Response table of S/N ratio - *Ra* for dry turning

Level	v_c	f	a_p
1	-3.80	7.00	-3.72
2	-2.44	-3.27	-2.42
3	-3.45	-13.44	-3.56
Delta	1.36	20.44	1.30
Rank	2	1	3

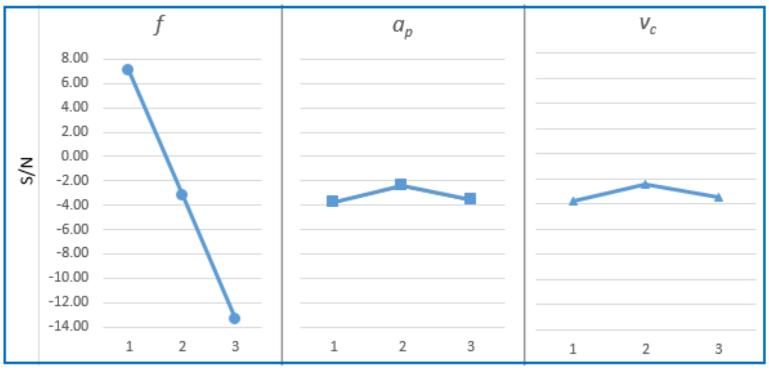

Fig. 6 Main effect plots of S/N ratio - *Ra* for dry turning

The trend of the plot indicates that *Ra* is greatly influenced by variations in feed rate, (rank 1). From the known theory and also from the experimental result (Table 3) it can be seen that surface roughness increases as feed rate increase. Minimum surface roughness is achieved with levels of the control parameters for which the S/N ratio has a maximum value, A2 (cutting speed of 300 m/min), B1 (feed of 0,05 mm/rev) C2 (depth of cut of 1,75 mm).

Ultimately, it is more effective and beneficial if it is possible to identify only one set of optimal parameters for all cutting environments and for all the responses. The grey relational analysis, GRA, was adopted in the study to find optimal controllable variables for multi-objective function. Furthermore, the statistical analysis of variance was performed to find the influence of the controllable process factors on the multi-objective function.

The first step of the grey relation analysis, GRA is the grey relation generation performed in order to make experimental data comparable. During this step, the cutting force, surface roughness and *MRR* are normalized between zero and one.

Depending on characteristics of a data sequence, various methodologies of carrying out grey generation are available. In this study, a linear data pre-processing method for the cutting force and surface roughness is the lower-the-better and is expressed as:

$$x_{ij} = \frac{\max y_{ij} - y_{ij}}{\max y_{ij} - \min y_{ij}} \tag{4}$$

where x_{ij} is the value after the grey relation generation, min y_{ij} is the smallest value of original data y_{ij} for the $j\mathrm{t_h}$ response of the experiment i, and max y_{ij} is the largest value of y_{ij} for the jth response.

The normalized value of the original sequence for material removal rate which is larger-the-better performance characteristic can be expressed as:

$$x_{ij} = \frac{y_{ij} - \min y_{ij}}{\max y_{ij} - \min y_{ij}} \tag{5}$$

Table 5 shows the normalized values of surface roughness *Ra*, cutting force *Fz* and material removal rate *MRR*.

Table 5 Normalized experimental results

	Cutting environment	Ra [μm]	Fz [N]	MRR [mm3/s]
1	Dry	0.9346	0.9828	0
	MQL	0.9602	0.9938	
	MQL+CCA	0.9474	0.3999	
2	Dry	0.7435	0.6480	0.2576
	MQL	0.7746	0.6889	
	MQL+CCA	0.7616	0.7287	
3	Dry	0	0	0.6970
	MQL	0.0491	0.2161	
	MQL+CCA	0.0299	0.2316	
4	Dry	0.9735	0.8888	0.0985
	MQL	1	0.9126	
	MQL+CCA	0.9929	0.9224	
5	Dry	0.7378	0.4114	0.6212
	MQL	0.7692	0.5083	
	MQL+CCA	0.7579	0.5045	
6	Dry	0.0708	0.5251	0.3939
	MQL	0.1038	0.6778	
	MQL+CCA	0.1002	0.8520	
7	Dry	0.9453	0.8081	0.2424
	MQL	0.9581	0.8242	
	MQL+CCA	0.9496	0.8520	
8	Dry	0.7288	0.7992	0.3030
	MQL	0.7450	0.8194	
	MQL+CCA	0.747	0.8450	
9	Dry	0.0633	0.4038	1
	MQL	0.1108	0.3999	
	MQL+CCA	0.1011	0.5112	

The second step of the GRA is the determination of referent sequence x_{0j} for j_{th} response. The performance of experiment i is considered as the referent for response j if normalized value x_{ij} is equal to 1 or nearer to 1 than the value for any other experiment.

In the next step, the grey relation coefficient is used for determining relation degree between x_{ij} and x_{0j}. The larger the grey relation coefficient, the closer x_{ij} and x_{0j}. Grey relation coefficient ξ_{ij} can be calculated as:

$$\xi_{ij} = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{\text{ij}} + \zeta\Delta_{\max}} \tag{6}$$

where ζ is the index of distinguishability called distinguishing coefficient $\zeta \in (0,1]$. In this work, the value of coefficient ζ is assumed as 0.5.

$$\Delta_{ij} = \ | x_{0j} - x_{ij} | \tag{7}$$

$$\Delta_{\min} = \min\{\Delta_{ij}, i = 1, 2, ..., m; \ j = 1, 2, ..., n\} \tag{8}$$

$$\Delta_{\max} = \max\{\Delta_{ij}, i = 1, 2, ..., m; \ j = 1, 2, ..., n\} \tag{9}$$

The last step is the determination of the grey relation grade which enables multiple optimizations and is calculated using equation:

$$y_i = \frac{1}{n}\sum_{j=1}^{n} \xi_{ij} \tag{10}$$

where n is a number of experiment.

The larger value of grey relation grade, the closer the corresponding controllable parameter combination to optimal. Therefore, the experiment with the highest grey relation grade would be the best choice. Table 6 shows the grey relation coefficients and grade for each experiment. The highest grey relational grade is the order to 1. The nearest optimum controllable parameters combination is in the experiment 1 with MQL cutting environment (A1B1C1D2).

The optimal levels, levels with the highest grey relation grade of the process parameters are MQL + CCA cutting environment, high cutting speed (400 m/min), low feed rate (0.05 mm/rev) and intermediate depth of cut (1.75 mm). These optimal levels are shown in bold in Table 7. Optimal combination of parameters is A3B1C2D3.

Table 6 Grey relational coefficients and grey relational grade

	Cutting environment	Ra [µm]	Fz [N]	MRR [mm3/s]	Grade	Grey order
	Dry	0.8844	0.9667		0.7281	5
1	MQL	0.9263	0.9876	0.3333	0.7491	1
	MQL+CCA	0.9049	1		0.7461	2
	Dry	0.6609	0.5868		0.5501	21
2	MQL	0.6893	0.6164	0.4024	0.5694	19
	MQL+CCA	0.6771	0.6482		0.5759	18
	Dry	0.3333	0.3333		0.4298	27
3	MQL	0.3446	0.3894	0.6226	0.4522	25
	MQL+CCA	0.3401	0.3942		0.4523	24
	Dry	0.9496	0.8181		0.7081	6
4	MQL	1	0.8513	0.3568	0.7360	4
	MQL+CCA	0.9860	0.8656		0.7361	3
	Dry	0.6560	0.4593		0.5614	20
5	MQL	0.6842	0.5042	0.5690	0.5858	16
	MQL+CCA	0.6738	0.5023		0.5817	17
	Dry	0.3498	0.5129		0.4383	26
6	MQL	0.3581	0.6081	0.4521	0.4727	22
	MQL+CCA	0.3572	0.5814		0.4636	23
	Dry	0.9014	0.7227		0.6739	9
7	MQL	0.9227	0.7400	0.3976	0.6867	8
	MQL+CCA	0.9084	0.7716		0.6925	7
	Dry	0.6484	0.7134		0.5932	15
8	MQL	0.6622	0.7346	0.4177	0.6049	12
	MQL+CCA	0.6640	0.7629		0.6149	11
	Dry	0.3480	0.4561		0.6014	14
9	MQL	0.3599	0.4545	1	0.6048	13
	MQL+CCA	0.3574	0.5057		0.6210	10

Table 7 Means for grey relational grades

Parameter	Level 1	Level 2	Level 3	Rank (max-min)
v_c [m/min]	0.5837	0.5871	**0.6326**	3 (0.0489)
f [mm/rev]	**0.7174**	0.5819	0.5040	1 (0.2134)
a_p [mm]	0.6012	**0.6337**	0.5685	2 (0.0652)
C**E**	0.5871	0.6068	**0.6093**	4 (0.0222)

5. Analysis of Variance for Grey Relation Grade

The percentage contribution by the sum of squares each of the process parameters to the total sum of squared deviations was used to evaluate the importance of the controllable parameter on the performance characteristic. The sum of squared deviations SS for the considered factor can be defined as:

$$SS = \frac{k}{m}\sum_{t=1}^{k} y_t^2 - \frac{y^2}{m} \tag{11}$$

where k is the number of levels, m is the total number of experiments, y_t is the total sum of the grey relation grade at t_{th} level and y is the total sum of the grey relation grade. The total sum of the squared deviations SST can be defined as:

$$SS_T = \sum_{i=1}^{m}\sum_{j=1}^{n} y_{ij}^2 - \frac{y^2}{m} \tag{12}$$

where y_{ij} are individual observations.

Finally, percentage contribution P can be calculated as:

$$P = \frac{SS}{SS_T} \tag{13}$$

It can be observed from Table 8 that the feed rate had the greatest influence on the grey relation grade. For multiple performance characteristics, the cutting environment did not have an impact on the experiments. The cutting environment might have an effect on some performance characteristics individually.

Table 8 Percentage contribution of input parameters on response variables

	SS	Percentage contribution
v_c	0.0134	5%
f	0.2099	78%
a_p	0.0191	7%
C**E**	0.0027	1%
SS_T	0.2706	

6. CONFIRMATION TEST

Once the optimal level of controllable parameters is selected, the final step is to predict and verify improvement of the performance characteristic using the optimal level of the controllable parameters. Based on the previous discussion, the most significant parameters with optimal level are cutting speed at level 3, feed rate at level 1 and depth of cut at level 3. The estimated grey relation grade can be calculated as:

$$\hat{y} = y_t + \sum_{i=1}^{p} (y_i - y_t) \tag{14}$$

where y_t is the total mean of the grey relation grade, p is the number of the controllable parameter that significantly affects the multiple performance characteristic and y_i is the mean of the grey relation grade at the optimal level. Table 7 shows the estimated grey relational grade for optimal controllable parameters calculated using Eq. (12).

Also, Table 8 presents the results of the confirmation experiment. In this study, a confirmation experiment was conducted by utilizing the levels of the optimal parameters combination of the turning process, A3B1C2D3. As shown in Table 9, the surface roughness was improved from 0.41 µm to 0.3 µm, the cutting force was slightly reduced from 42.30 N to 36.28 N and the material removal rate increased from 166.67 mm3/s to 583.33 mm3/s. Also, a good agreement between the actual and predicted grey relational grade was obtained and multiple characteristics in turning operations are improved.

Table 9 Results of the confirmation experiment

	Initial controllable parameters	Optimal controllable parameters	
		Prediction	Experiment
Setting level	A1B1C1D2	A3B1C2D3	A3B1C2D3
Ra [µm]	0.41		0.3
Fz [N]	42.30		36.28
MRR [mm3/s]	166.67		583.33
GRG	0.7491	0.7814	0.7737
Improvement in GRG			0.0246

7. CONCLUSION

This paper presents a comprehensive experimental evaluation of an alternative cooling method when turning EN AW-2011. The use of the Taguchi method and the grey relational analysis to optimize the turning operations with the multiple performance characteristics has been reported. Optimum values of cutting parameters and optimum machining condition were found out to minimize two response variables: the surface roughness and cutting force and also to maximize the material removal rate. The conclusions are summarized as follows:

i. Using MQL and MQL+CCA lead to improvement in surface roughness and cutting force when compared to dry turning.
ii. The maximum percentage reduction in cutting force during MQL+CCA turning is
iii. 27 % and 19 % in comparison to dry and MQL turning, respectively.

iv. Using the optimal levels of the controllable parameters (A3B1C2D3) in the machining process, it is possible to decrease surface roughness and cutting force as well as to maximize the material removal rate.

v. Feed rate is the dominant factor affecting the main cutting force, surface roughness and material removal rate.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

1. Kant, G., Sangwan, K.S., 2015, *Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm*, Procedia CIRP 31, pp. 453-458.
2. Adler, D.P., Hii, W.W-S., Michalek, D.J., Sutherland, J.W., 2006, *Examining the role of cutting fluids in machining and efforts to address associated environmental/health concerns*, Machining Science and Technology, 10(1), pp. 23-58.
3. Hong, S.Y., Broomer, M., 2000, *Economical and ecological cryogenic machining of AISI 304 austenitic stainless steel*, Clean Products and Processes, 2, pp. 157–166.
4. Goindi, G., Sarkar, P., 2017, Dry Machining: *A Step towards Sustainable Machining - Challenges and Future Directions*, Journal of Cleaner Production 165, DOI: 10.1016/j.jclepro.2017.07.235
5. Lawal, S.A., Choudhury, I.A., Nukman, Y., 2012, *A Critical Assessment of Lubrication Techniques in Machining Processes: A Case for Minimum Quantity Lubrication Using Vegetable Oil-Based Lubricant*, Journal of Cleaner Production, doi: 10.1016/j.jclepro.2012.10.016.
6. Dhar, N.R., Islam, M.W., Islam, S., Mithu, M.A.H., 2006, *The influence of minimum quantity of lubrication (MQL) on cutting temperature, chip and dimensional accuracy in turning AISI-1040 steel*, Journal of Materials Processing Technology 171(1), pp. 93-99.
7. Priarone, P.C., Rizzuti, S., Rotella, G., Settineri, L., 2012, *Tool wear and surface quality in milling of a gamma-TiAl intermetallic*, The International Journal of Advanced Manufacturing Technology, 61, pp. 25-33.
8. Jianxin, D., Tongkun, C., Lili, L., 2005, *Self-lubricating behaviours of Al2O3/TiB2 ceramic tools in dry high-speed machining of hardened steel*, Journal of the European Ceramic Society 25, pp. 1073–1079.
9. Sharma, V.S., Dogra, M., Suri, N.M., 2009, *Cooling techniques for improved productivity in turning*, International Journal of Machine Tools and Manufacture, 49(6), pp. 435-453.
10. Maruda, R.W., Legutko, S., Krolczyk, G.M., 2014, *Effect of minimum quantity cooling lubrication (MQCL) on chip morphology and surface roughness in turning low carbon steels*, Applied Mechanics and Materials, 657, pp.38-42.
11. Maruda, R.W., Legutko, S., Krolczyk, G.M., Raos, P., 2015, *Influence of cooling conditions on the machining process under MQCL and MQL conditions*, Tehnički vjesnik, 22(4), pp. 965-970.
12. Dixit, U.S., Sarma, D.K., Davim, J.P., 2012, *Environmentally friendly machining*. Springer Science & Business Media, LLC, New York.
13. Nouioua, M., Yallese, M.A., Khettabi, R., Chabbi, A., Mabrouki, T., Girardin, F., 2017, *Optimization of Machining Process During Turning of X210Cr12 Steel Under MQL Cooling as a Key Factor in Clean Production.* International Conference Design and Modeling of Mechanical Systems, DOI: 10.1007/978-3-319-66697-6_83.
14. Pervaiz, S., Deiab, I., Rashid, A., Nicolescu, M., 2017, *Minimal quantity cooling lubrication in turning of Ti6Al4V: influence on surface roughness, cutting force and tool wear.* Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 231(9), pp. 1542-1558.
15. Pervaiz, S., Rashid, A., Deiab, I., Nicolescu, C.M., 2016, *An experimental investigation on effect of minimum quantity cooling lubrication (MQCL) in machining titanium alloy (Ti6Al4V)*, The International Journal of Advanced Manufacturing Technology, 87(5-8), pp. 1371-1386.
16. Yuan. S.M., Yan, L.T., Liu, W.D., Liu, Q., 2011, *Effects of compressed cold air temperature on cryogenic machining of Ti–6Al–4V alloy*, Journal of Materials Processing Technology, 211(3), pp. 356-362.

17. Singh, G., Sharma, V.S., 2017, *Analysing machining parameters for commercially pure titanium (Grade 2), cooled using minimum quantity lubrication assisted by a Ranque-Hilsch vortex tube*, International Journal of Advanced Manufacturing Technology, 88, pp. 2921–2928.
18. Diyaley, S., Chakraborty, S., 2019, *Optimization of multi-pass face milling parameters using metaheuristic algorithms,* Facta Universitatis-Series Mechanical Engineering, 17(3), pp. 365 – 383.
19. Gopal, P.M., Prakash, K.S., 2018, *Minimization of cutting force, temperature and surface roughness through GRA, TOPSIS and Taguchi techniques in end milling of Mg hybrid MMC*, Measurement, 116, pp. 178–192.
20. Fratila, D., Caizar, C., 2011, *Application of Taguchi method to selection of optimal lubrication and cutting conditions in face milling of AlMg3*, Journal of Cleaner Production, 19(6-7), pp. 640-645.
21. Yan, J., Li, L., 2013, *Multi-objective optimization of milling parameters–the trade-offs between energy, production rate and cutting quality*, Journal of Cleaner Production, 52, pp. 462-471.
22. Lin, C.L., 2004, *Use of the Taguchi method and grey relational analysis to optimize turning operations with multiple performance characteristics,* Materials and manufacturing processes, 19(2), pp. 209-220.
23. Tripathy, S., Tripathy, D.K., 2017, *Multi-response optimization of machining process parameters for powder mixed electro-discharge machining of H-11 die steel using grey relational analysis and topsis.* Machining science and technology, 21(3), pp. 362-384.
24. Li, N., Chen, Y-J., Kong, D.D., 2019, *Multi-response optimization of Ti-6Al-4V turning operations using Taguchi-based grey relational analysis coupled with kernel principal component analysis*, Advanced Manufacturing, 7, pp. 142-154.
25. Mia, M., Khan, M.A., Dhar, N.R., 2017, *Study of surface roughness and cutting forces using ANN, RSM, and ANOVA in turning of Ti-6Al-4V under cryogenic jets applied at flank and rake faces of coated WC tool,* International Journal of Advanced Manufacturing Technology, 93(1–4), pp. 975–991.
26. Mia, M., Khan, M.A., Rahman, S.S., Dhar, N.R., 2017, *Mono-objective and multi-objective optimization of performance parameters in high pressure coolant assisted turning of Ti-6Al-4V,* International Journal of Advanced Manufacturing Technology, 90(1–4), pp. 109–118.
27. Aman, A., Hari, S., Pradeep, K., Manmohan, S., 2008, *Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi's technique—A comparative analysis,* Journal of Materials Processing Technology, Volume 200(1) – May 8, 2008
28. Boswell, B., Islam, M.N., Davies, I.J., Ginting, Y.R., Ong, A.K., 2017, *A review identifying the effectiveness of minimum quantity lubrication (MQL) during conventional machining,* International Journal of Advanced Manufacturing Technology, 92, pp. 321–340.