VIŠECILJNA OPTIMIZACIJA PARAMETARA MQLC PROCESA TOKARENJA POMOĆU GREY-FUZZY PRISTUPA

MULTI-OBJECTIVE OPTIMIZATION OF MQLC TURNING PROCESS PARAMETERS USING GREY-FUZZY APPROACH

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REZIME

U ovom radu je istražen utjecaj različitih ulaznih parametara obrade na hrapavost obrađene površine, silu rezanja i proizvodnost tijekom procesa tokarenja korištenjem MQLC (minimalne količine za hlađenje i podmazivanje) sustava. Plan eksperimenata je definiran prema Taguchi metodi. Odabrano je ortogonalno polje L9 (3^4) gdje su četiri ulazna parametra varirana na tri razine. Parametri koji su varirani u eksperimentima su: brzina rezanja (v_c), dubina rezanja (a_p), posmak (f) te vrsta čeličnog materijala obratka. Siva relacijska analiza u kombinaciji s fuzzy logikom je korištena kako bi se pronašle razine ulaznih parametara obrade kojima se postižu optimalne vrijednosti odzivnih veličina procesa.

Original scientific paper

SUMMARY

In this paper the influence of different machining parameters on the surface roughness, cutting force and material removal rate during turning process using MQLC (minimum quantity lubrication and cooling) system was investigated. The experimental plan was defined using Taguchi's method. Orthogonal array L9 (3^4) was selected for four input parameters varied on three levels. Parameters that were varied in experiments are: cutting speed (v_c), depth of cut (a_p), feed rate (f) as well as workpiece steel material. The grey relational analysis in combination with fuzzy logic technique was used to find out the input parameters levels that lead to optimal process responses values.

1. INTRODUCTION

The modern concept of sustainable manufacturing or green manufacturing represents a lot of changes in rules and limitations in the manufacturing industry. Most of them are related to proper use and disposal of waste during the manufacturing processes and balancing between the economic, ecological and sociological aspects of manufacturing. The most commonly used cutting fluids (CFs) in machining processes are still conventional emulsions. In recent years, in manufacturing industry special attention on machining processes and use of conventional CFs was given. A significant component in sustainable stability of machining process represents proper choice of type and quantity of CFs as well as proper choice of appropriate combination of cutting parameters, cutting tool and workpiece materials. During past decades, several technologies have been developed with the aim to increase effectiveness of machining processes and fulfilment of sustainability requirements: cooling with cold compressed air (CCA), cryogenic cooling (CC) with different gasses, high pressure cooling (HPC), minimum quantity lubrication (MQL) and minimum quantity lubrication and cooling (MQLC), near dry machining (NDM). Also, the solution in the way of fulfilling previously listed demands hides in applying various methods and techniques of planning and optimization of the manufacturing systems. Today there are different methods like Taguchi method (TM), artificial neural networks (ANN), grey relational analysis (GRA), genetic algorithm (GA), fuzzy logic (FL), adaptive neuro-fuzzy technique (ANFIS) and etc. Above mentioned alternative techniques and methods represent a challenge for many scientists and researchers because they have to fulfill all technical and economic requirements placed for achieving of ultimate goals of machining process. From above listed cooling, flushing and lubricating techniques, the MQL and MQCL methods are extremely popular to use in the machining processes due to improvement of the machining processes productivity, reduction of purchasing costs and disposal CFs as well as the reduction of the machine/tool system cleaning time and energy consumption compared with conventional cutting fluid systems. Mozammel et al. [1], Senevirathne et al. [2], Gurraj et al. [3] are argued that very important parameters during MQL and MQLC machining are type and ratio of cutting fluids and lubricant, pressure (2-6 bar), flow rate (5-500 ml/h), number (1-2), distance (5-30 mm) and angle (30-60°) of nozzles. Mourad et al. [4] during turning of X210Cr12 steel with multilayer coated cutting tool concluded that MQL technique has a positive effect on reducing friction between cutting tool and workpiece. In their investigation temperature in the cutting zone is reduced and consequently the tool wear is lower about 23.34% compared with conventional and about 40% compared with dry machining. Yunn et al. [5] reported about experiments carried out using the MQL technique during milling of Inconel 718. The authors used different combinations of oil and water ratio in the MQL system (10:90, 40:60, 60:40 and 100:0) and oils with different viscosities. For all experiments the pressure was 5 bar, nozzles were 20 mm away from the cutting zone at an angle of 45°. Oil flow for all combinations of oil and water ratios is 20 ml/h, 60 ml/h and 100 ml/h. The authors pointed out that with lower ratio of oil and water (with lower viscosity oils) during high milling with higher flow can achieve more efficient aerosol penetration into the cutting zone. In this research, the optimum water and oil ratio and the flow rate where the best output performance values are obtained during milling Inconel 718 alloys are 60:40 and 60 ml/hr. Ekinović et al. [6] presented an investigation of the MQL turning process of X5CrNi18-10 stainless steel with the objective of screening and selecting the most important MQL parameters on machinability of austenitic stainless steel. Results indicated that the most important parameters for simultaneous reducing of surface roughness and cutting forces were oil and water flow rate followed by the spray distance. Faga et al. [7] analyzed the effect of varied cutting speed with constant feed and depth of cut on the tool wear, energy consumption, cutting force and surface roughness during turning titanium Ti-6Al-4V alloy under different machining conditions (dry machining, conventional emulsion, MQL technique and MQLC technique). The authors confirmed that during variation of input factors using MQL or MQCL techniques, the relationship between the type of oil, delivered quantity and the delivery method in the cutting zone represents a significant influence on control and efficiency of the mentioned techniques. Shokoohi et al. [8] conducted a research on hardened steel AISI 1045 during turning process by using dry machining, conventional cooling emulsion, and MQCL techniques where CO_2 as a cooling medium is used. Under the conditions of MQCL technique and cooling with conventional emulsion two types of vegetable oils were used. By analysis of variance with regard to the output values like surface roughness, energy consumption and shape of the separated chips, it is evident that the type of vegetable oil has a significant influence from the point of view of its viscosity. Better output values are achieved by oil with lower viscosity. The aerosol (oil particles) penetrates more efficiently into the cutting tool/workpiece zone and the cutting zone is better cooled compared with dry and conventional machining. Zerti et al. [9] carried out multi-objective optimization by grey relational analysis (GRA) technique that is based on Taguchi design analysis in order to simultaneously optimize surface quality and productivity. The tool-material pair used in this study is AISI D3 steel/ mixed ceramic tool. Zerti et al. [10] investigated the influence of the different machining parameters represented by cutting speed (v_c), depth of cut (a_p), and feed rate (f) on the output values expressed through surface roughness, cutting force and power, and material removal rate (*MRR*) during dry hard turning operation of martensitic stainless steel (AISI 420). Authors applied response surface methodology (RSM) and artificial neural network (ANN) approaches for modeling of process responses values. The results indicated that (*Ra*) is strongly influenced by the feed rate (80.71%), while the depth of cut has the highest influence on the cutting force (65.31%), cutting power (37.56%) and material removal rate (36.45%). Furthermore, ANN and RSM models were found to predict well experimental results.

In this paper GRA in combination with fuzzy logic approach is applied to find out the combination of input turning parameters levels that lead to optimal process responses: resultant cutting force, surface roughness and material removal rate during machining of three different steels using MQLC system.

2. EXPERIMENTAL SETUP

The experiments were carried out on a conventional PA-501A Potisje lathe with the ISO designation CNMG 120408-WG quality coated carbide insert of cutting tool. The workpieces materials used for experiments were: St 50-2, C45, 42CrMo4. All experimental tests were carried out by the use of an advanced MQLC system, which generates oil-on-water droplet aerosol with a constant pressure supply of 2 bar. The cutting forces were measured using a Kistler 5070 dynamometer connected with DynoWare software. From their values the resultant cutting force *Fr* is calculated. Measurements of the surface roughness parameter *Ra* were performed on a Perthometer M1 type (Mahr) profilometer, at five different locations. Material removal rate, MRR was calculated as follows:

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

where v_c [m/min] is cutting speed, a_p [mm] is depth of cut, f [mm/rev] feed rate.

Experimental setup is presented in Figure 1.

2.1. Planning experiments with Taguchi method

Planning experiments with Taguchi method includes the use of orthogonal arrays for organizing input parameters and levels on which those parameters should be varied. In this paper, in order to reduce the number of experiments Taguchi L_9 orthogonal array is selected. Input parameters are cutting speed v_c, depth of cut a_p, feed rate f as well as steel workpiece material (St 50-2, C45 and 42CrMo4). The parameters with their levels selected for conducting the experiments are shown in Table 1. The outputs *Fr*, *Ra* and *MRR* are measured for all 9 experiments and are shown in Table 2 respectively.

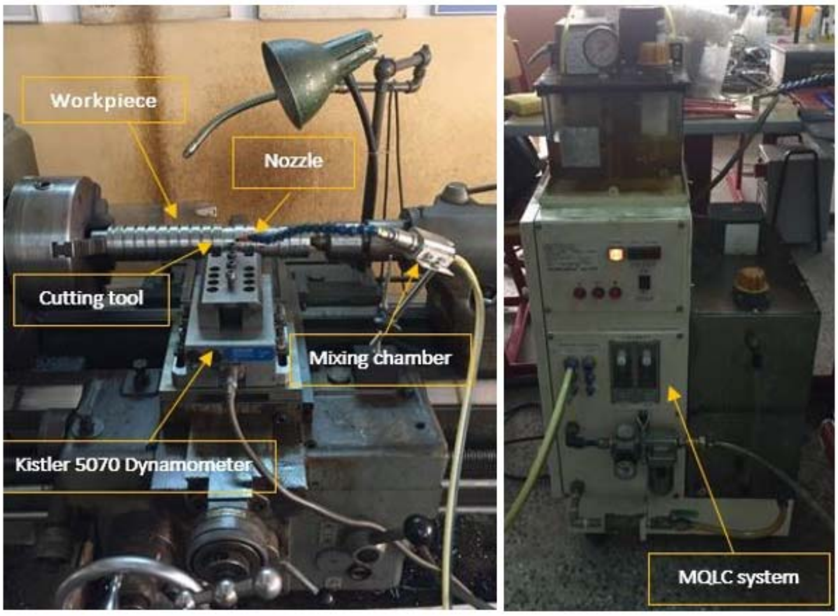


Figure 1. *Experimental setup*

Table 1. Machining parameters and their levels

Parameter /Level	Symbol	Level 1	Level 2	Level 3
Cutting speed v_c [m/min]	A	58	110	162
Depth of cut a_p [mm]	B	1	2	3
Feed rate f [mm/rev]	C	0.107	0.214	0.321
Workpiece material	D	St 50-2	C45	42CrMo4

Table 2. Experimental plan and results

Trial No.	Input parameters				Outputs		
	A	B	C	D	*Fr* [N]	*Ra* [μm]	*MRR* [mm^3/s]
1.	1	1	1	1	512.91	1.55	103.39
2.	1	2	2	2	1676.44	0.9	413.57
3.	1	3	3	3	3067.77	1.4	930.53
4.	2	1	2	3	901.24	0.6	392.18
5.	2	2	3	1	2376.87	1.22	1176.53
6.	2	3	1	2	1086.96	1.15	588.26
7.	3	1	3	2	1140.26	0.88	866.35
8.	3	2	1	3	786.09	0.85	577.57
9.	3	3	2	1	1929.60	1.22	1732.71

3. METHODOLOGY

3.1. Grey relational analysis (GRA)

Grey relational analysis (GRA) is applied for determining the optimum conditions of various input parameters considered to obtain the best quality characteristics considering single and multiple responses [11-15].

Raw data cannot be used in GRA so in the first step the measured output values of *Fr*, *Ra* and *MRR* should be normalized to a range between 0 and 1. Expressions which are used for normalization by GRA are different depending on characteristic of response. If the characteristic of response is of ‘’higher-the-better’’, Eq. [2] is used, whereas, if the response is of ‘’lower-the-better’’ characteristic, Eq. [3] is used.

$$x_i^*(k) = \frac{x_i(k) - min\, x_i(k)}{max\, x_i\,(k) - min\, x_i\,(k)} \tag{2}$$

$$x_i^*(k) = \frac{max\, x_i(k) - x_i(k)}{max\, x_i(k) - min\, x_i(k)} \tag{3}$$

i = 1,2,…,m and k=1,2,…,n.

where, $x_i(k)$ are the observed and $x_i^*(k)$ are the normalized data for the i^{th} experiment and k^{th} response respectively.

After normalization, the grey relational coefficient (*GRC*) is calculated. *GRC* expresses the relationship between ideal and normalized data. *GRC* value can be estimated using Eq. [4].

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}(k) + \zeta\Delta_{max}} \tag{4}$$

where $\Delta_{0i}(k)$ is difference between $x_i^0(k)$ and $x_i^*(k)$ ($x_i^0(k)$ is an ideal sequence). ζ is distinguishing coefficient. It takes value between 0 and 1. Generally, ζ=0.5 is preferred. A higher *GRC* value of experiment indicates that it is closer to the optimal solution with respect to a particular response.

Grey relational grade (*GRG*) can be calculated by averaging the *GRC* values that correspond to individual experiment, Eq. [5].

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i\,(k) \tag{5}$$

where n is number of process responses.
The corresponding experiment with the highest *GRG* presents the best combination of input process parameters values that lead to the optimal process responses.

3.2. Fuzzy logic approach in grey relational analysis

Fuzzy logic theory was developed to deal with decision making problems that are difficult to deal with because of their uncertain and vague information. This theory converts the imprecise linguistic terms to understandable numerical values by considering different fuzzy membership functions [15-17]. The use of ''higher-the-better'' and ''lower-the-better'' performance characteristics in GRA produces some uncertainty within the results. Fuzzy logic can be effectively used in these cases to reduce and control these uncertainties [15]. Also, the grey based fuzzy technique can make significant improvement in the performance characteristics of the process [18-22]. Each fuzzy logic system consists of four components: the fuzzification module, the fuzzy inference module, the defuzzification module and the knowledge base. Fuzzification module uses different membership functions to convert inputs into linguistic variables. The membership function defines how the values of the input and output are mapped to a membership value between 0 and 1. There are various available membership functions such as triangular, trapezoidal, Gaussian etc. The fuzzy inference engine uses the knowledge base of fuzzy IF-THEN rules and performs fuzzy reasoning for generating the fuzzy (linguistic) output values. The defuzzification module converts the aggregated fuzzy values into a crisp non-fuzzy outputs [23].

3.3. ANOVA method

ANOVA method is used to define the significance of each input process parameter and to find out their contribution on the process responses values [14, 15].

4. RESULTS AND DISCUSSION

4.1. Grey relational analysis

The process responses values for all 9 experiments are used to calculate the grey relational coefficients. The data are firstly normalized and brought to a range between 0 and 1 by using Eq. (2) for *MRR* which has ''higher-the-better'' characteristic and Eq. (3) for *Fr* and *Ra* because they have ''lower-the-better'' characteristic. After normalization the grey relational coefficients (*GRC*) for each process response are calculated by using Eq. (4) and the grey relational grade (*GRG)* by using Eq. (5). Based on the obtained *GRG*, ranking is given to identify the best input parameters combination. From ranking, it is observed that fourth experiment has the highest *GRG* of 0.715 This input parameters combination can be considered as the best combination to perform an experiment and to reach better process responses values. All calculated values are shown in Table 3.

4.2. Grey-fuzzy reasoning analysis

In this paper to perform grey-fuzzy reasoning analysis Mamdani fuzzy inference system was used. Grey relational coefficients for *Fr*, *Ra*, *MRR* are inputs to fuzzy logic system, while *GRG* is considered as output (Figure 2). For each input in fuzzy logic system three triangular membership functions were used: low (L), medium (M) and high (H). On the other side five triangular membership functions were used for output: very low (VL), low (L), medium (M), high (H), very high (VH) (Figure 3).

Table 3. Normalized data, grey relational coefficients and grey relational grades

Trial No.	Normalized data			Grey relational coefficient			*GRG*	Ranking
	Fr	*Ra*	*MRR*	*Fr*	*Ra*	*MRR*		
1	1.000	0.000	0.000	1.000	0.333	0.333	0.556	5
2	0.545	0.684	0.190	0.523	0.613	0.382	0.506	7
3	0.000	0.158	0.508	0.333	0.373	0.504	0.403	9
4	0.848	1.000	0.177	0.767	1.000	0.378	0.715	1
5	0.270	0.347	0.659	0.407	0.434	0.594	0.478	8
6	0.775	0.421	0.298	0.690	0.463	0.416	0.523	6
7	0.754	0.705	0.468	0.671	0.629	0.485	0.595	4
8	0.893	0.737	0.291	0.824	0.655	0.414	0.631	3
9	0.445	0.347	1.000	0.474	0.434	1.000	0.636	2

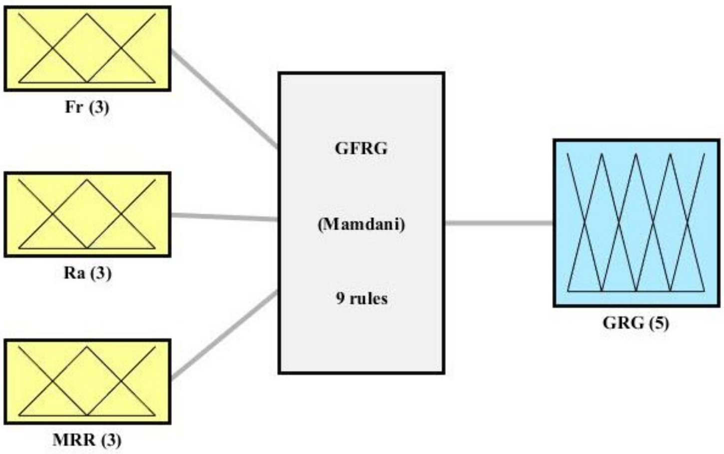
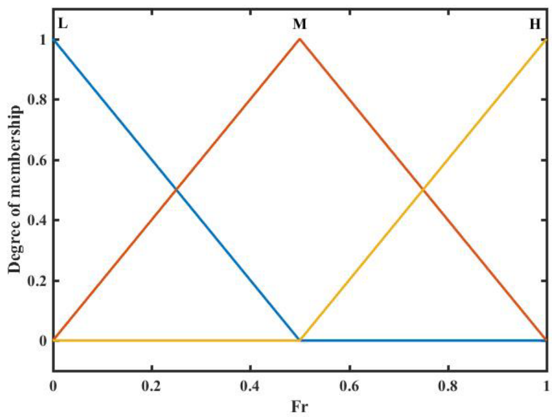


Figure 2. *Structure of three inputs and one output fuzzy logic system*



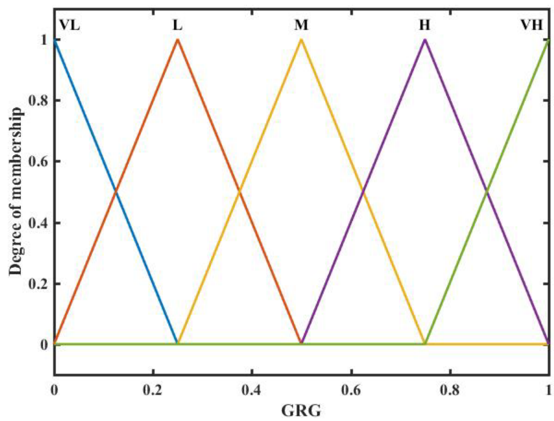


Figure 3. *Membership functions used for: a) Fr input, b) GRG output*

The fuzzy inference system performs fuzzy reasoning using fuzzy IF-THEN rules. Here, a set of nine rules was developed to model the relation between inputs (grey relational coefficients of *Fr*, *Ra* and *MRR*) and output (grey relational grade).

The graphical representation of the developed nine rules can be seen in Figure 4.

Fuzzy inference process was defined by the following: and method: min, or method: max, implication: min, aggregation: max and defuzzification method: centroid.

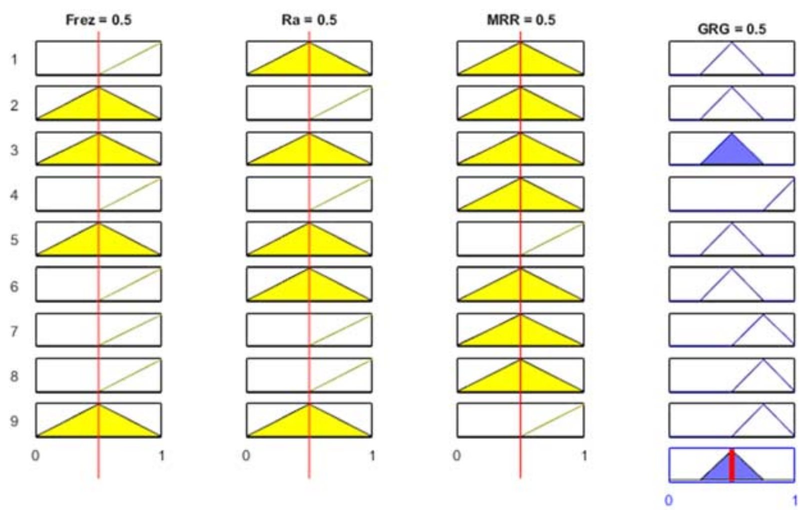
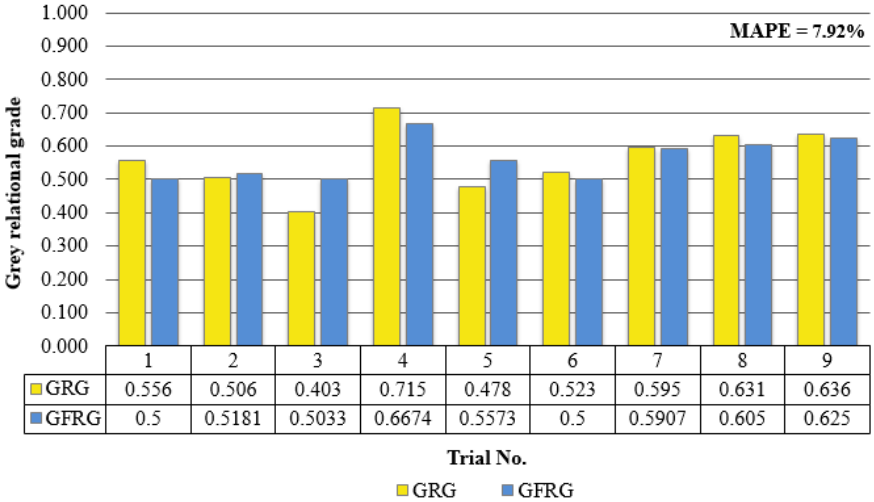


Figure 4. *Graphical representation of fuzzy IF-THEN rules*

Finally, the deffuzifier from the Matlab R2015b toolbox converted fuzzy values into *GFRG* numerical values. In order to assess the prediction accuracy of developed fuzzy logic model, the *GRG* and *GFRG* values were compared. Mean absolute percentage error (MAPE) was used as comparison measure. MAPE of 7.92% proves good prediction accuracy of developed fuzzy logic model. These comparison results, *GRG* and *GFRG* values and MAPE are shown in Figure 5.



	1	2	3	4	5	6	7	8	9
GRG	0.556	0.506	0.403	0.715	0.478	0.523	0.595	0.631	0.636
GFRG	0.5	0.5181	0.5033	0.6674	0.5573	0.5	0.5907	0.605	0.625

Figure 5. *Comparison between grey relational grade (GRG) and grey-fuzzy reasoning grade (GFRG)*

The higher values of *GFGR* determined the best multiple process responses characteristics. Analysis of the means was performed for *GFRG*. Difference between maximal and minimal average of GFRG values defines the rank of input parameters that affects the multiple responses. These values are listed in Table 4. Figure 6 shows main effects of input parameters on *GFRG*. Greater inclination of input parameter line defines a higher influence of that parameter on the multiple responses characteristics.

Table 4. Response table for grey-fuzzy reasoning grade (*GFRG*)

Level / Parameter	Cutting speed v_c [m/min] A	Depth of cut a_p [mm] B	Feed rate f [mm/rev] C	Workpiece material D
Level 1	0.5071	**0.5860**	0.5350	0.5608
Level 2	0.5749	0.5601	**0.6035**	0.5363
Level 3	**0.6069**	0.5428	0.5504	**0.5919**
Max-Min	0.0998	0.0433	0.0685	0.0556
Rank	1	4	2	3

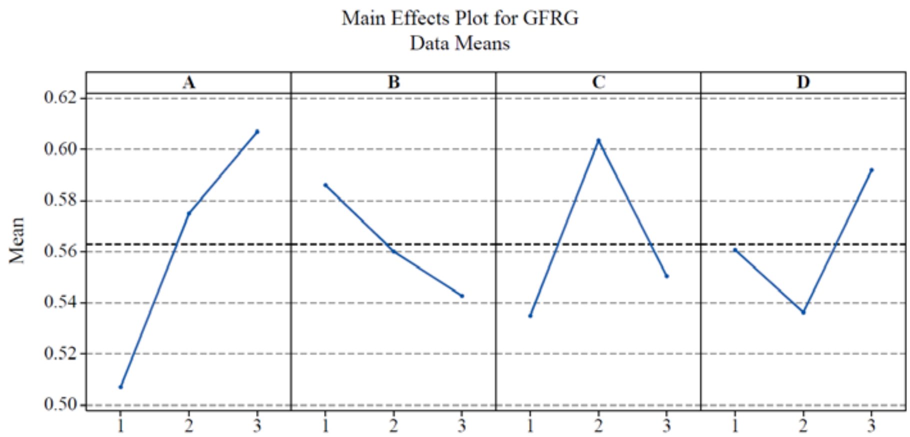


Figure 6. *Main effects plot for grey-fuzzy reasoning grade (GFRG)*

Based on Table 4 and Figure 6 the optimum setting of input process parameters is identified as cutting speed 162 m/min, depth of cut 1 mm, feed rate 0.214 mm/rev and workpiece material 42CrMo4, represented as $A_3B_1C_2D_3$. This is marked in bold font in Table 4. The use of these conditions will at the same time minimize *Fr* and *Ra* and maximize *MRR* throughout turning within the range of studied process parameters.

4.3. Analysis of variance (ANOVA)

To analyse the significance of input parameters on multiple responses characteristics, the obtained *GFRG* was subjected to ANOVA (Table 5). It can be seen from Table 5 that the degrees of freedom for residual error are zero. Normally this happens because the experimentation with 4 parameters at 3 levels, using Taguchi L_9 OA, does not provide enough data. Hence ANOVA pooling should be conducted. ANOVA pooling is a process of revision and re-estimation of ANOVA results in order to ignore an insignificant parameter whose contribution is less [14, 24] In this paper the depth of cut and workpiece material are parameters that have the smallest influence on *GFRG*. Aiming to develop later a functional relationship between *GFRG* and controllable process parameters (v_c, a_p and f), ANOVA pooling was done by exception workpiece material parameter (Table 6). From the pooled ANOVA it is obvious that cutting speed is the most influential parameter that contributes towards *GFRG* by 50.51% . It is followed by feed rate with contribution of 25.13% and depth of cut of 9.22%.

Table 5. Analysis of variance for grey-fuzzy reasoning grade (before pooling)

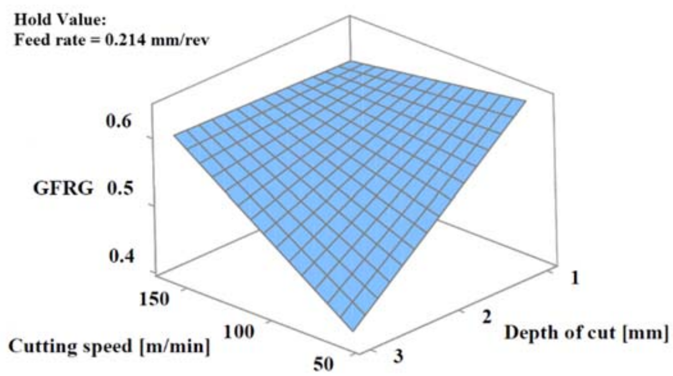
Source	DF	Adj SS	Adj MS	F	P	% Contribution
A	2	0.015570	0.007785	*	*	*
B	2	0.002844	0.001422	*	*	*
C	2	0.007747	0.003873	*	*	*
D	2	0.004665	0.002332	*	*	*
Residual error	0	*	*			
Total	8	0.030825				

Table 6. Analysis of variance for grey-fuzzy reasoning grade (after pooling)

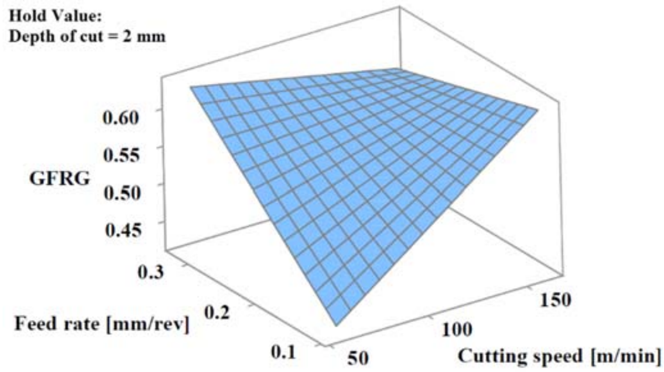
Source	DF	Adj SS	Adj MS	F	P	% Contribution
A	2	0.015570	0.007785	3.34	0.231	50.51
B	2	0.002844	0.001422	0.61	0.621	9.22
C	2	0.007747	0.003873	1.66	0.376	25.13
Residual error	2	0.004665	0.002332			15.13
Total	8	0.030825				100.00

In order to define the relationship between the input process parameters and the obtained *GFRG* the following regression equation was developed (Eq. (6)). Based on the regression model corresponding surface plots were created and presented in Figure 7.

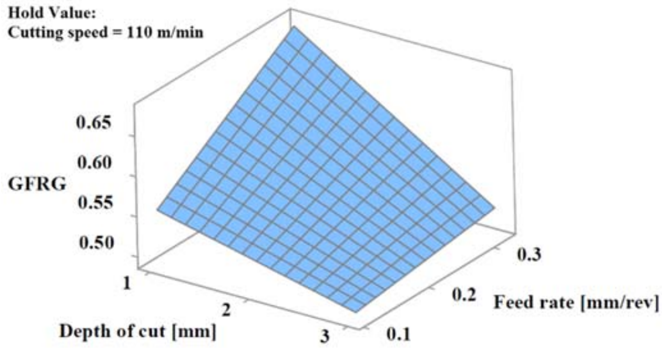
$$GFRG = 0.386 + 0.00103\,A - 0.1279\,B + 2.11\,C + 0.001115\,A{*}B - 0.01188\,A{*}C - 0.231\,B{*}C \quad (R^2=0.81) \tag{6}$$



a)



b)



c)

Figure 7. *Surface plots showing the effects of different process parameters on GFRG values*

4.4. Confirmation test

After the optimal combination of input process parameters was found out, in order to check the improvement in the process responses values a confirmation experiment was performed. Results of that experiment are shown in Table 7 and they are compared with responses values from initial parameters setting. Data form Table 7 reveal that optimal parameters setting lead to *Fr* of 661.14 N, *Ra* of 0.65 μm and *MRR* of 577.57 mm^3/s. Thus the experimental *GFRG* is 0.735, which shows an improvement by 0.235.

Table 7. Comparison table for initial and optimal parameters settings

	Initial parameters setting	Optimal parameters setting	
		Prediction	Experiment
Setting levels	$A_1B_1C_1D_1$	$A_3B_1C_2D_3$	$A_3B_1C_2D_3$
Fr (N)	512.91	-	661.14
Ra (μm)	1.55	-	0.65
MRR (mm^3/s)	103.39	-	577.57
GFRG	0.5	0.6994	0.735
Improvement in GFRG		0.1994	0.235

6. CONCLUSION

In this present paper in order to conduct an optimization of multiple process responses: cutting force, surface roughness and material removal rate an experimentation with four input parameters was conducted. These process parameters are: cutting speed, depth of cut, feed rate and workpiece material. Taguchi L_9 (3^4) orthogonal array was used to accomplish experiments in turning operation using MQLC system.

- From the investigation it was found out that cutting speed of 162 m/min, depth of cut of 1 mm, feed rate of 0.214 mm/rev and workpiece material 42CrMo4 is optimal combination of input parameters levels.

- ANOVA defined cutting speed as the most influential parameter on the process responses.
- Improvemet of the grey-fuzzy reasoning grade from 0.5 to 0.735 confirmed the improvement in the turning process and in process responses: cutting force, surface roughness and material removal rate. This improvement proved the suitability and effectiveness of grey-fuzzy approach in solving such multi-objective optimization problems.

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