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Original scientific paper

Multi-Response Optimization in MQLC Machining Process of Steel St50-2 Using Grey-Fuzzy Technique

Mario DRAGIČEVIĆ*, Edin BEGOVIĆ, Sabahudin EKINOVIĆ, Ivan PEKO

Abstract: In this paper MQLC turning process of steel St 50-2 is presented. Experimentations were performed using Taguchi L_9 orthogonal array by varying two process parameters such as oil and water quantity while other parameters such as cutting speed, feed rate and depth of cut were kept constant. Process responses that were analyzed in this paper are surface roughness *Ra* and resultant cutting force *Frez*. In order to quantify significance of each process parameter on analyzed response ANOVA was conducted. Fuzzy logic modelling technique was used to describe the effects of process parameters and to create response surface plots. Finally, in order to find out process parameters values that lead simultaneously to optimal surface roughness and resultant cutting force, multi-objective optimization of process responses was conducted by using grey relational analysis (GRA) combined with fuzzy logic technique.

Keywords: grey relational analysis; fuzzy logic; MQLC system; multi-response optimization; steel

1 INTRODUCTION

The green manufacturing (GM) introduces a lot of changes in the manufacturing industry. The GM helps limit negative impacts on the planet and humans, and encourages other manufacturers to follow the same way of production - safe, healthy and sustainable. The GM implies strategy of balancing between economical, ecological and sociological segment of production [1]. Nowadays, cooling, flushing and lubrication in all machining processes in industry are mostly based on traditional-conventional flood cooling. In that view of manufacturing the GM strategy means changes in the type and quantity of cooling, flushing and lubrication, the treatment of waste after machining, and the control of emissions of carbon dioxide. The solution in terms of switching to GM is hidden in preference of alternative types of cooling, flushing and lubricating techniques [2].

The minimum quantity lubrication and cooling (MQLC) system is an effective tool to minimize all sustainability requirements during machining process. The MQLC system refers to a small quantity (50 ml/h) of lubricant which is alternative for the conventional flood cooling system which dispenses more than 200 l/h of lubricant which causes negative effects on humans and nature [3]. The challenge for science/technology field is how to fulfil all technical and economical requirements by MQLC systems with the focus based on all goals of machining process.

Many authors pointed out various studies and conclusions with the aim of improving the sustainability of machining processes [4, 5-7]. The options of fulfilling previously listed demands are based on applying different methods for planning and optimization of the manufacturing process. In that concept different techniques are available like Taguchi method (TM), artificial neural networks (ANN), grey relational analysis (GRA), genetic algorithm (GA), fuzzy logic (FL), adaptive neuro-fuzzy technique (ANFIS) etc. Different alternative techniques in combination with those methods represent a challenge for scientists and researchers because of all technical, economical and environmental requirements. Kumar et al. [8] pointed out that MQL performed 177.77% larger tool life compared to dry and 50.75% to spray impingement cooling (SIC) during turning of Ti-6Al-4V ELI alloy. Authors confirmed that MQL optimal condition (ap = 0.2 mm, f = 0.12 mm/rev, v = 79 m/min) is recommended to utilize for turning of Ti-6Al-4V ELI alloy for industrial applications. Ekinović et al. [9] presented an investigation of selecting the most important MQL parameters during machinability of austenitic stainless steel during turning. 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. Kumar et al. [10] investigated the effects of machining parameters using fuzzy model to predict the tool wear, surface roughness, cutting forces, tool temperature and chip formation during turning Custom 450 stainless steel material with cutting tools coated TiCN, TiAlN and uncoated cemented carbide. The study showed that the TiCN coated tool obtained improved performance, when related to TiAlN coated and uncoated cemented carbide cutting tools. Jagatheesan et al. [11] analyzed the effect of MQL system on the cutting temperature, cutting force and surface roughness during turning of AISI 4320 alloy steel. Experiments were carried out with limited variation of cutting parameters like cutting speed, depth of cut and feed. The authors confirmed that MQL could be suitable to replace conventional cooling and dry machining. Saleem and Mehmood [12] investigated the influence of different machining parameters and two different types of MQL oil sunflower and castor oil during turning Inconel 718 alloy. The MQL performance was compared with dry machining. Three levels of cutting speed (30, 50, 70 m/min.), feed rate (0.168, 0.281, 0.393 mm/rev.) and air pressure (2, 3.5, 5 bar) were analyzed. The depth of cut (1 mm) and spray distances between nozzle and cutting zone (50 mm) were defined. The output values were expressed through tool wear, surface roughness and machined surface integrity. The authors pointed out that in terms of Eco-friendly machining, the MQL system can be considered as an alternative to dry machining, considering all positive effects obtained through the analysis of experimental data. In this paper the influence of different MQLC parameters on the surface roughness and resultant cutting force during turning of St 50-2 steel was investigated. The grey relational analysis in combination with fuzzy logic technique was used to find out the optimal process responses values.

2 EXPERIMENTAL SETUP

Experiments were performed on a conventional PA-501A Potisje lathe in the Laboratory for metal cutting - LORAM at the University of Zenica. In turning operations, the ISO CNMG 120408-WG coated carbide insert TiAlN + TiN was used. The workpiece parts were prepared in the dimension of Ø70 × 450 mm. The workpieces samples were previously prepared with the aim that each workpiece had an equal number of segments (experimental points) of 15 mm in length at a diameter of Ø70 mm, Fig. 1.

Figure 1 Workpieces for experimental research

The turning experiments were conducted at constant machining parameters: cutting speed of 162 m/min, depth of cut of 1 mm and feed rate of 0.107 mm/rev under MQLC conditions, Tab. 1. These constant parameters were optimal solutions in conducted pre-experimentations and multi-response optimization procedure of surface roughness, cutting forces and material removal rate.

Table 1 Input factors of MQLC techniques and their levels of variation

Machining Conditions	Inputs	Units	Variation levels		
			1	2	3
MQLC	Oil Flow (*A*)	ml/h	2.78	5.56	8.34
	Water Flow (*B*)	ml/h	600	1200	1800
	Constant machining parameters: V = 162 m/min, a = 1 mm, f = 0.107 mm/rev				

Table 2 L_9 orthogonal array and outputs results

Exper. No.	Inputs		Outputs	
	A	*B*	*A*	*B*
1.	1	1	379.84	0.88
2.	1	2	398.01	0.79
3.	1	3	397.51	0.80
4.	2	1	422.10	0.73
5.	2	2	419.85	0.75
6.	2	3	409.11	0.76
7.	3	1	439.42	0.73
8.	3	2	447.70	0.71
9.	3	3	440.54	0.75

The cutting forces were measured by Kistler 5070 dynamometer connected with DynoWare software. Measurements of the surface roughness parameter *Ra* were performed on a Perthometer M1 type (Mahr) profilometer, at three different locations. The measured resultant forces *Frez* and average surface roughness *Ra* values during the experiments in MQLC machining environment according to Taguchi L_9 orthogonal array are given in Tab. 2.

Experimental setup and MQLC system are presented in Fig. 2.

Figure 2 Experimental setup and MQLC system

The system used for aerosol formation in the MQLC technique is JOOM (Jet Oil on Water Mist-OoW) manufactured by Daido Metal-Japan. The type of MQLC system is J-T2X-012-2K-T which forms an aerosol in the form of water droplets coated with an oil film. The MQLC system has delivered aerosol at a pressure of 2 bar and with one nozzle at a distance of 50 mm between the nozzle outlet and the cutting zone.

3 METHODOLOGY

3.1 Fuzzy Logic

Fuzzy logic technique is one of the artificial intelligence techniques that is very useful to describe complex processes with imprecise and vague information between inputs and outputs. This technique converts unprecise linguistic terms into numerical values by using different fuzzy membership functions [13-15]. Each fuzzy logic system has four components: the fuzzification module, the fuzzy inference module, the defuzzification module and the knowledge base. Fuzzification module converts various inputs into linguistic variables by using membership functions. The membership function defines how the values of the input and output are mapped to a membership value between 0 and 1. Membership functions can be defined as triangular, trapezoidal, Gaussian etc. The fuzzy inference module uses the knowledge base of fuzzy IF-THEN rules and membership functions to perform fuzzy reasoning and generate the fuzzy (linguistic) output values. The defuzzification module converts the aggregated fuzzy outputs into the non-fuzzy values [16-18]. In this paper fuzzy logic technique was used to describe influence of input process parameters on responses *Frez* and *Ra*, and in combination with grey relational analysis in multi-objective optimization process to model grey relational grade.

3.2 ANOVA

ANOVA method was used to define the statistical significance of each process input factor and to define its contribution on process responses *Frez* and *Ra*.

3.3 Grey Relational Analysis

Grey relational analysis (GRA) is used to perform multi-objective optimization and to determine process parameters levels that lead to optimal multiple process responses *Frez* and *Ra*. Raw data cannot be used in GRA so in the first step the measured output values of *Frez* and *Ra* 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. (1) is used, whereas, if the response is of "lower-the-better" characteristic, Eq. (2) is used.

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{1}$$

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

$i = 1, 2, \ldots, m$ and $k=1, 2, \ldots, n$.

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. (3).

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(k) + \zeta\Delta_{\max}} \tag{3}$$

where $\Delta_{0i}(k)$ is a 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. (4).

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \tag{4}$$

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 [17].

4 RESULTS

4.1 Fuzzy Logic Models of Process Responses

In this paper, in order to define fuzzy logic model of analyzed process responses and perform fuzzy reasoning the Mamdani fuzzy inference system was used. Process parameters: oil flow and water flow are taken as inputs in fuzzy logic system, while resultant force *Frez* and surface roughness *Ra* are considered as outputs (Fig. 3).

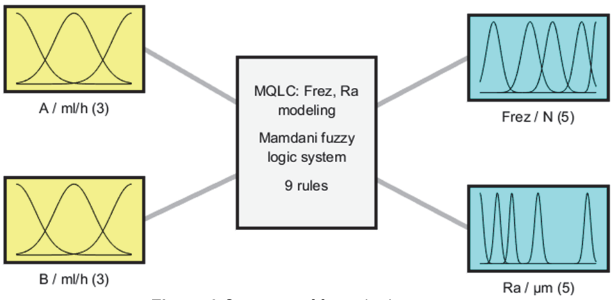


Figure 3 Structure of fuzzy logic system

For each process parameter three Gaussian membership functions were used: low (L), medium (M) and high (*H*) (Figs. 4 and 5). For *Frez* and *Ra* responses five Gaussian membership functions were used: very low (*VL*), low (*L*), medium (*M*), high (*H*), very high (*VH*) (Figs. 6 and 7). In this paper, in order to define fuzzy logic model of analyzed process responses and perform fuzzy reasoning the Mamdani fuzzy inference system was used. In order to define relationship between process parameters and responses a set of 9 IF-THEN fuzzy rules was created. These rules can be seen in Tab. 2. Fuzzy inference system was defined by the following settings: and method: min, or method: max, implication: min, aggregation: max, defuzzification method: centroid.

Table 2 Fuzzy IF-THEN rules between process parameters and responses

1. If (*A* is *L*) and (*B* is *L*) then (*Frez* is *VL*)(*Ra* is *VH*)
2. If (*A* is *L*) and (*B* is *M*) then (*Frez* is *L*)(*Ra* is *H*)
3. If (*A* is *L*) and (*B* is *H*) then (*Frez* is *L*)(*Ra* is *H*)
4. If (*A* is *M*) and (*B* is *L*) then (*Frez* is *M*)(*Ra* is *L*)
5. If (*A* is *M*) and (*B* is *M*) then (*Frez* is *M*)(*Ra* is *M*)
6. If (*A* is *M*) and (*B* is *H*) then (*Frez* is *L*)(*Ra* is *M*)
7. If (*A* is *H*) and (*B* is *L*) then (*Frez* is *H*)(*Ra* is *L*)
8. If (*A* is *H*) and (*B* is *M*) then (*Frez* is *VH*)(*Ra* is *VL*)
9. If (*A* is *H*) and (*B* is *H*) then (*Frez* is *H*)(*Ra* is *M*)

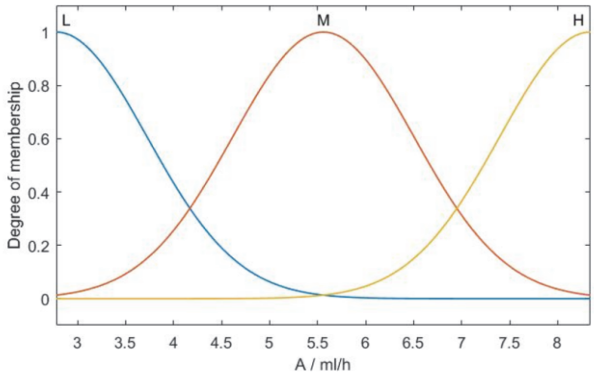


Figure 4 Membership functions for oil flow

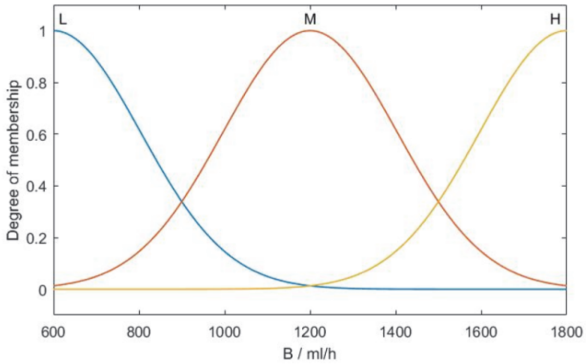


Figure 5 Membership functions for water flow

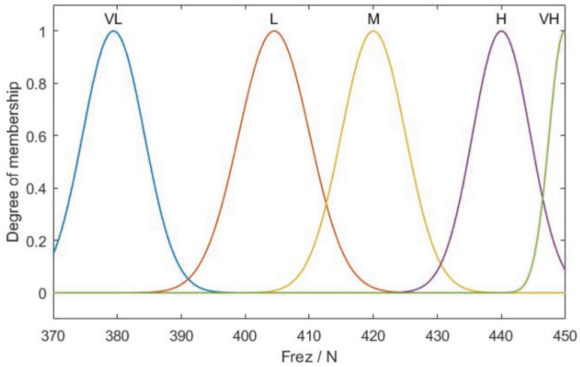


Figure 6 Membership functions for resultant force

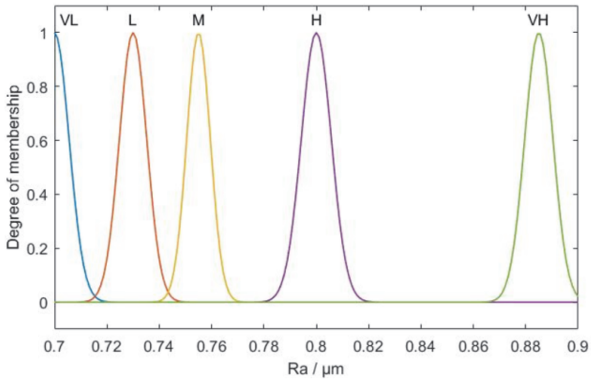
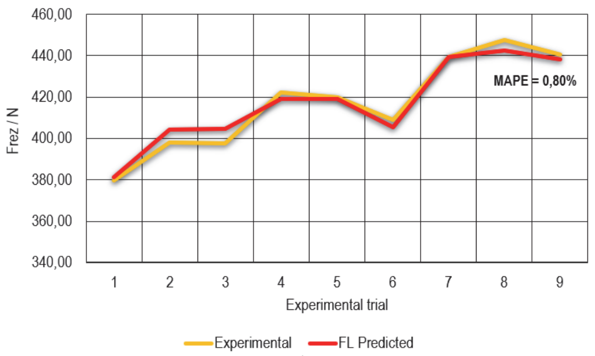
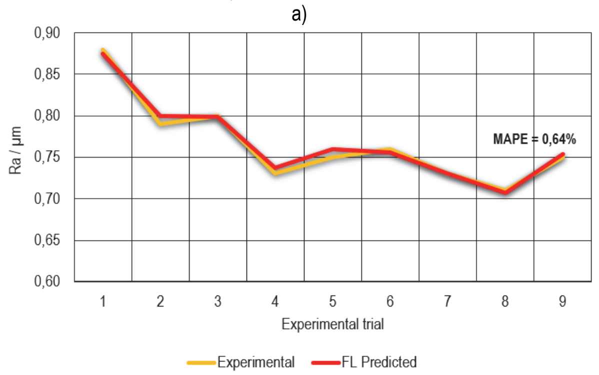


Figure 7 Membership functions for surface roughness



a)



b)

Figure 8 Comparison of experimental and fuzzy logic predicted responses for resultant cutting force and surface roughness

Defuzzification module from the Matlab R2015 toolbox converts fuzzy values of resultant force and surface roughness responses into non-fuzzy values. In order to check the accuracy of developed fuzzy logic model comparison between original experimental data and fuzzy logic predicted data was performed. Mean absolute percentage error (MAPE) was used as comparison measure. MAPE of 0.80% and 0.64% proved high prediction accuracy of developed fuzzy logic models. These comparison results are shown in Fig. 8a and 8b.

After fuzzy logic model for each response was generated it can be further used to create 3D surface plots to analyse the effects of process parameters on the resultant force and surface roughness outputs. These plots are shown in Fig. 9. and Fig. 10.

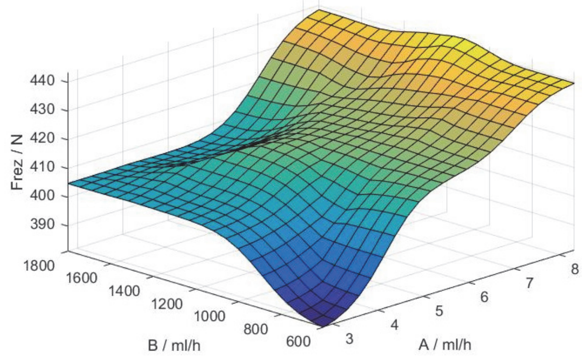


Figure 9 Effect of process parameters on the resultant cutting force

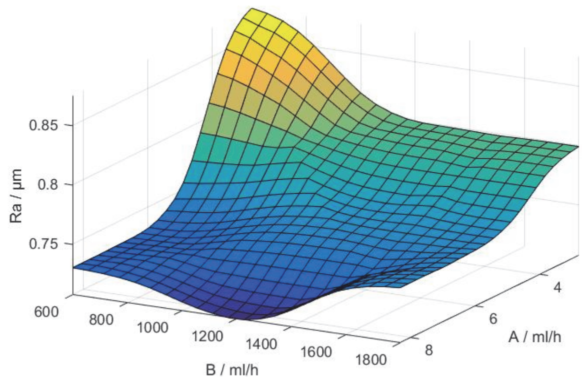


Figure 10 Effect of process parameters on the surface roughness

4.2 ANOVA for Process Responses

In order to determine the significance of each process parameter on the resultant cutting force and surface roughness responses ANOVA was conducted. ANOVA results for each process response is shown in Tabs. 3 and 4.

Table 3 ANOVA results for resultant cutting force

Source	*DF*	Adj *SS*	Adj *MS*	*F*-Value	*P*-Value	Contribution / %
A	2	3865.9	1932.96	31.62	0.004	91.67%
B	2	106.4	53.21	0.87	0.485	2.52%
Error	4	244.5	61.13			
Total	8	4216.9				

Table 4 ANOVA results for surface roughness

Source	*DF*	Adj *SS*	Adj *MS*	*F*-Value	*P*-Value	Contribution / %
A	2	0.014867	0.007433	6.28	0.058	70.79%
B	2	0.001400	0.000700	0.59	0.596	6.66%
Error	4	0.004733	0.001183			
Total	8	0.021000				

4.3 GRA Multi-Response Optimization

In order to perform simultaneously optimization of both analysed process responses grey relational analysis was used. Firstly, process responses data were normalized to a range between 0 and 1 by using Eq. (2) because the goal is to reach minimal resultant cutting force as well as surface roughness. After normalization grey relational coefficients (GRC) for each response were calculated by using Eq. (3). Finally, the grey relational grade (GRG) was determined according to Eq. (4). Based on the calculated GRG the ranking was derived to identify process parameters levels that lead to optimal resultant cutting force and surface roughness responses. These results are shown in Tab. 5.

Table 5 Normalized data, GRC and GRG values

Exp. No.	Normalized data		Grey relational coefficient		Grey relational grade	Rank
	Frez	*Ra*	*Frez*	*Ra*		
1	1.000	0.000	1.000	0.333	0.667	1
2	0.732	0.529	0.651	0.515	0.583	6
3	0.740	0.471	0.658	0.486	0.572	7
4	0.377	0.882	0.445	0.810	0.627	3
5	0.410	0.765	0.459	0.680	0.569	8
6	0.569	0.706	0.537	0.630	0.583	5
7	0.122	0.882	0.363	0.810	0.586	4
8	0.000	1.000	0.333	1.000	0.667	1
9	0.106	0.765	0.359	0.680	0.519	9

4.4 Grey-Fuzzy Reasoning

In this paper in order to model relationships between grey relational coefficients (GRC) of process responses and grey relational grade (GRG) Mamdani fuzzy inference system was used. Inputs in this fuzzy logic system are grey relational coefficients of resultant cutting force and surface roughness, output is calculated grey relational grade. Each input in fuzzy logic system has three Gaussian membership functions: low (*L*), medium (*M*), high (*H*). On the other side for grey relational grade output five Gaussian membership functions were used: very low (*VL*), low (*L*), medium (*M*), high (*H*), very high (*VH*), Fig. 11a and 11b.

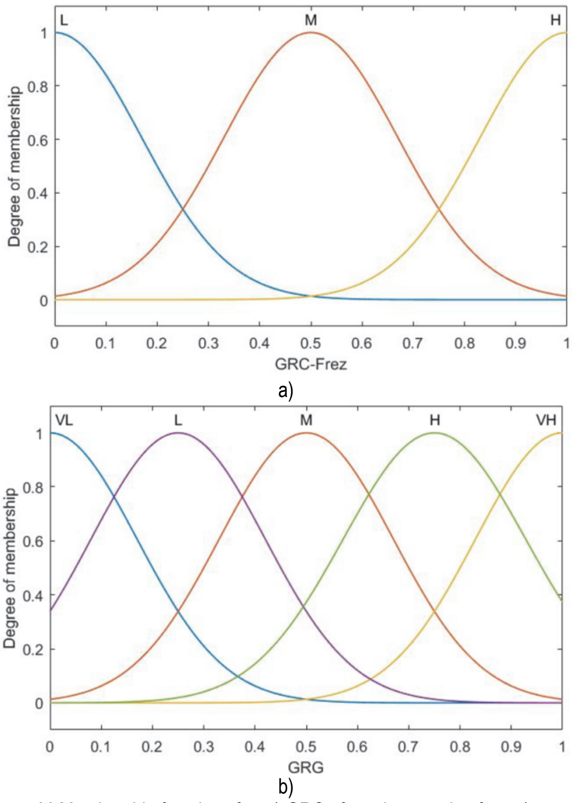


Figure 11 Membership functions for: a) GRC of resultant cutting force (same for GRC for surface roughness); b) GRG

Grey-fuzzy reasoning was conducted using a set of nine fuzzy IF-THEN rules that define relationship between inputs (GRC of resultant cutting force / surface roughness) and output (GRG). Graphical visualization of defined fuzzy IF-THEN rules is shown in Fig. 12. Grey-fuzzy reasoning system was defined by following: and method: min, or method: max, implication: min, aggregation: max, defuzzification method: centroid.

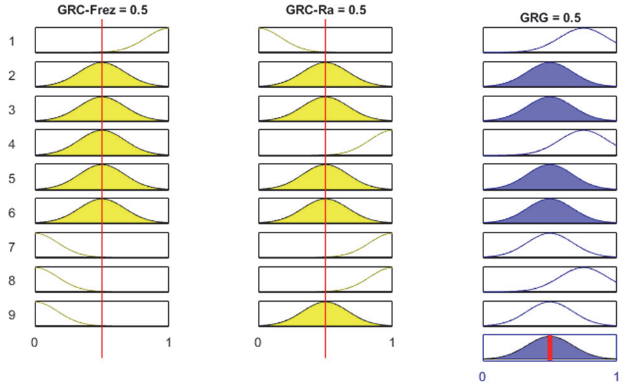


Figure 12 Graphical visualization of grey-fuzzy IF-THEN rules

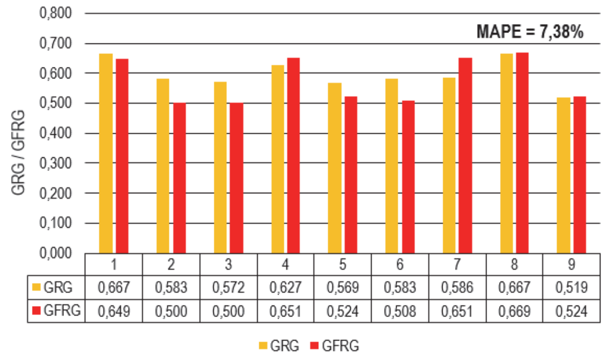


Figure 13 Comparison results between GRG and GFRG

In MATLAB R2015b fuzzy logic toolbox defuzzification was performed to convert output fuzzy values into numerical values. These final numerical values represent grey fuzzy-reasoning grade (GFRG). To check the prediction accuracy of developed grey-fuzzy logic model comparison between GRG and GFRG values was performed. As prediction accuracy measure mean absolute percentage error (MAPE) was used. Comparison results are shown in Fig. 13. MAPE of 7.38% proves good prediction accuracy of developed grey-fuzzy logic model.

In order to define significance of input process parameters on the grey fuzzy reasoning grade (GFRG) ANOVA was conducted (Tab. 6).

Table 6 ANOVA results for grey fuzzy reasoning grade (GFRG)

Source	*DF*	Adj *SS*	Adj *MS*	*F*-Value	*P*-Value	Contribution / %
A	2	0.007270	0.003635	1.49	0.329	15.55
B	2	0.029673	0.014837	6.06	0.062	63.49
Error	4	0.009790	0.002447			
Total	8	0.046733				

Also, main and interaction effects plots of input parameters were generated to define precisely optimal process conditions that lead to the highest GFRG. The highest GFRG represents the best process responses values. Main and interaction effects plots are shown in Fig. 14a and 14b.

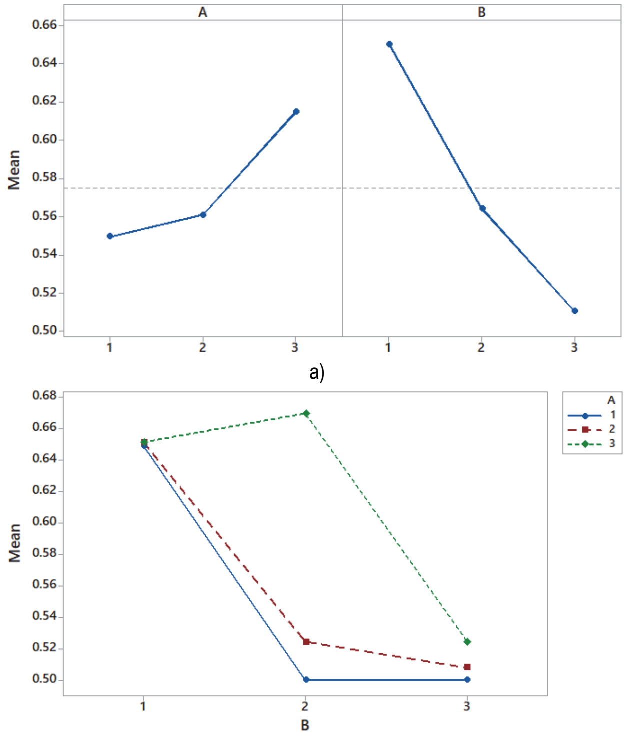


Figure 14 a) Main effects plot for GFRG; b) Interaction plot for GFRG

To define relationship between process parameters, oil flow and water flow and GFRG fuzzy logic modelling was performed. Input process parameters were defined according to previously defined membership functions (Figs. 4 and 5). GFRG was defined by using five Gaussian membership functions: very low (*VL*), low (*L*), medium (*M*), high (*H*), very high (*VH*), same as it was previously defined for grey relational grade (Fig. 15). Nine fuzzy IF-THEN rules were created to define relationship between process parameters and GFRG.

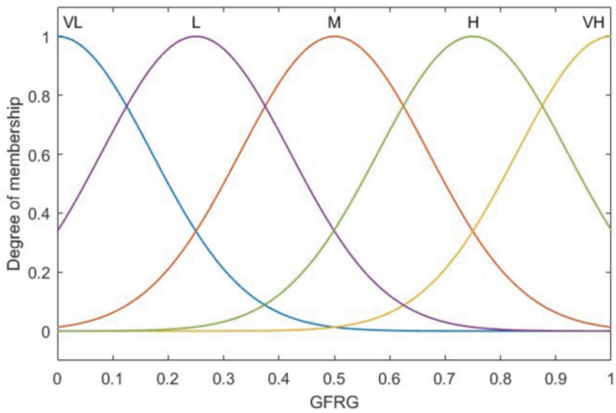


Figure 15 Membership functions for: GFRG

A set of fuzzy IF-THEN rules is shown in Tab. 7. Fuzzy logic system was defined following the same settings that were already mentioned in this paper. Based on the developed fuzzy logic model that define relations between process parameters and GFRG 3D surface plot can be created (Fig. 16). This plot presents influence of oil flow and water flow on the GRFG. This plot together with main and interaction effects plots serves as a good assistance to definition of optimal process conditions in MQLC machining process.

Table 7 Fuzzy IF-THEN rules between process parameters and GFRG

1. If (*A* is *L*) and (*B* is *L*) then (GFRG is *H*)
2. If (*A* is *L*) and (*B* is *M*) then (GFRG is *M*)
3. If (*A* is *L*) and (*B* is *H*) then (GFRG is *M*)
4. If (*A* is *M*) and (*B* is *L*) then (GFRG is *H*)
5. If (*A* is *M*) and (*B* is *M*) then (GFRG is *M*)
6. If (*A* is *M*) and (*B* is *H*) then (GFRG is *M*)
7. If (*A* is *H*) and (*B* is *L*) then (GFRG is *H*)
8. If (*A* is *H*) and (*B* is *M*) then (GFRG is *H*)
9. If (*A* is *H*) and (*B* is *H*) then (GFRG is *M*)

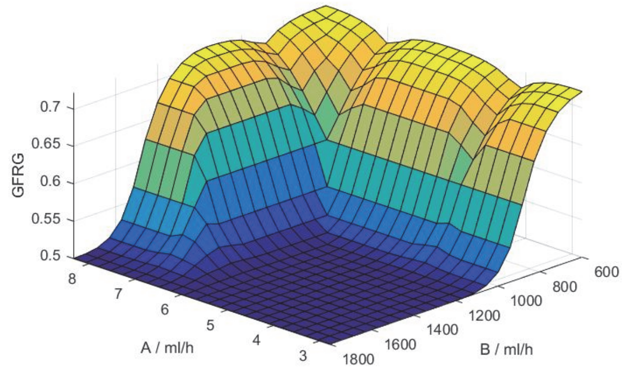


Figure 16 Effect of process parameters on the GFRG

5 DISCUSSION

From results analysis it is visible that both process parameters differently affect cutting force and surface roughness responses. From Fig. 9 it can be derived that the increase of the oil flow and water flow results with the increase of the resultant cutting force. ANOVA presented that oil flow parameter with 91.67% of contribution is more significant on the resultant cutting force than the water flow with 2.52% of contribution. From Fig. 10 it is visible that decrease of the oil flow results with the rougher surface. Increase of the water flow on the lower oil flow values (2.78 ml/h, 5.56 ml/h) results with the lower surface roughness. The optimal surface roughness values can be performed at the highest value of the oil flow (8.34 ml/h) and at the lower and middle value of the water flow (600 ml/h, 1200 ml/h). From ANOVA results for surface roughness it can be observed that the oil flow with 70.79% of contribution is more significant than the water flow with 6.66% of contribution. In order to perform multi-response optimization grey relational analysis combined with fuzzy logic technique was applied. Grey relational analysis showed that the first and eight experimental run gives the highest grey relational grade. The highest grey relational grade means the best compromise solution of both process responses: resultant cutting force and surface roughness. In this case it can be achieved by using process parameters settings *A*1*B*1 and *A*3*B*2. In order to more precisely define multi-response optimization results and to describe the influence of input process parameters on the GRG grey fuzzy reasoning analysis was performed. ANOVA results for GFRG showed that water flow is more significant, with 63.49% of contribution, on the multi-response optimization measure such as GFRG. Main effects and interaction plots of GFRG showed that firstly defined multi-response optimization results obtained in GRA can be modified. As it is visible from Fig. 14, various input process parameters settings lead to the high values of the GFRG. This is also confirmed from Figs. 13 and 16. There is no noticeable difference in GFRG values in the first

(*A*1*B*1), fourth (*A*2*B*1), seventh (*A*3*B*1) and eight (*A*3*B*2) experimental run. The goal of the multi-response optimization procedure is to define compromise solution for the all analysed process responses. According to that it can be derived that the optimal solution would be parameters setting: *A*2*B*1. In order to verify that confirmation experiment with optimal process parameters setting (*A*2*B*1) was conducted. Tab. 8 shows good matching between confirmation experiment results, fuzzy logic predicted and process responses values obtained in original experimentations.

Table 8 Confirmation experiment results

Optimal parameters setting:	*A*2*B*1			
Process responses:	Experiment	Fuzzy logic predicted	Confirmation experiment	Error / %
Frez / N	422.10	419.194	420.23	0.246
Ra / µm	0.73	0.737	0.74	0.405

In Fig. 17 surface roughness measurement from confirmation experiment is presented. These results once more confirmed prediction accuracy of developed fuzzy logic models for process responses as well as optimal setting of process parameters oil flow and water flow.

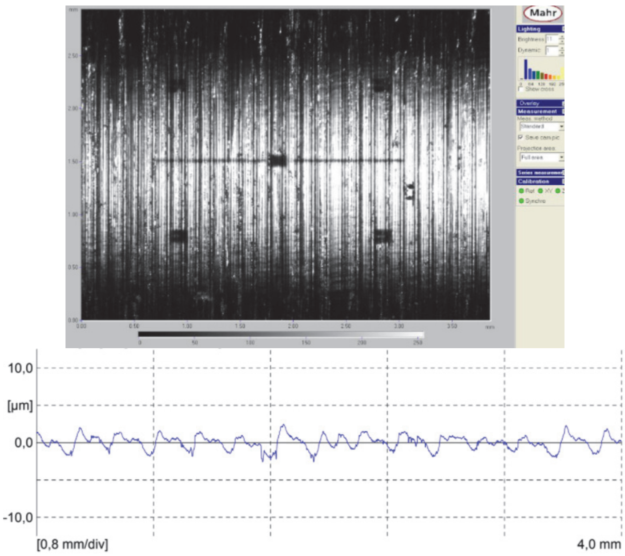


Figure 17 Surface roughness result from confirmation experiment

6 CONCLUSION

In this paper main accent was put on MQLC machining system in turning process of steel St50-2. Experimental research was done in order to examine the influence of main process parameters such as oil and water flow on the cutting force *Frez* and surface roughness *Ra* responses. Experimentations were made according to Taguchi L_9 orthogonal array. From experimental results and further analysis the following conclusions can be derived:

- Fuzzy logic represents a good technique to describe the influence of input process parameters on the analysed responses such as resultant cutting force and surface roughness.
- ANOVA results showed that the oil flow is the most significant parameter for both process responses.
- Increase of the oil flow and water flow results with the increase of the resultant cutting force.
- Decrease of the oil flow results with the higher surface roughness while the increase of the water flow on the lower oil flow values (2.78 ml/h, 5.56 ml/h) results with the lower surface roughness.
- Grey relational analysis combined with fuzzy logic approach represents a novel and effective approach to solve multi-response optimization problem.
- According to grey-fuzzy reasoning analysis a set of multi-response optimization results and related process parameters settings can be defined (*A*1*B*1/*A*2*B*1/*A*3*B*1/*A*3*B*2).
- The most appropriate compromise optimal solution can be achieved with parameters setting: *A*2*B*1. This solution is verified with confirmation experiment.

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Contact information:

Mario DRAGIČEVIĆ, MSc
(Corresponding author)
E-mail: mariodragicevic@hotmail.com

Edin BEGOVIĆ, PhD, Assistant Professor
University of Zenica, Faculty of Mechanical Engineering,
Fakultetska 1, Zenica 72000, Bosnia and Hercegovina
E-mail: edin.begovic@unze.ba

Sabahudin EKINOVIĆ, PhD, Full Professor
University of Zenica, Faculty of Mechanical Engineering,
Fakultetska 1, Zenica 72000, Bosnia and Hercegovina
E-mail: sabahudin.ekinovic@unze.ba

Ivan PEKO, PhD, Assistant Professor
University of Split, Faculty of Science,
Ruđera Boškovića 33, 21000 Split
E-mail: ipeko@pmfst.hr