Desirability Function Analysis (DFA) in Multiple Responses Optimization of Abrasive Water Jet Cutting Process

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ABSTRACT

This paper introduces optimization of machining parameters for high-pressure abrasive water jet cutting of Hardox 500 steel utilizing desirability function analysis (DFA). The tests were carried out according to the orthogonal matrix (Taguchi) L9. The control parameters of the process such as pressure, abrasive flow rate, and traverse speed was optimized under multi-response conditions namely cutting depth and surface roughness. The optimal set of control parameters was established on the basis of the composite desirability value obtained from desirability function analysis and the significance of these parameters was determined by analysis of variance (ANOVA). The effects show that optimal sets for high cutting depth and small surface roughness is high pressure, middle abrasive flow rate, and small traverse speed. A confirmation test was also leaded to validate the test results. Results of the research have shown that machining efficiency at keeping good level quality of cut surface can be improved this approach.

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1. Introduction

In order to increase the production efficiency, special attention is paid to the optimization of the production technology. The rapid development of the IT field contributed to the fact that the methods of solving optimization tasks (A Radomska-Zalas, et al. 2019), (A Radomska-Zalas, and Perec, 2019), (Gostimirovic et al. 2019) became the subject of research in many research centers.

Desirability function analysis (DFA) assures a real solution to the uncertainty in multiple research data issues. It can be exploited for the complicated manufacturing processes to multi-level optimize by converting the multi response characteristics into a single response function. DFA is an efficient method to examine the relational degree among discrete sequences. Its additional advantage is possibility to analyze of many factors from less available data. It does not engage too tangled mathematical theory and thus can be used by engineers without deep statistical experience.

Research effect of carbon epoxy composite material machining by abrasive water jet was published by Dhanawade and Kumar (Dhanawade and Kumar 2019). Properties of surface morphology, kerf formation and kerf surface features were studied to understand the basic mechanism of cutting. The influence of hydraulic pressure, traverse speed, stand-off distance and abrasive mass flow rate have been tested. The design of experiments using response surface methodology was performed and models to prediction surface roughness and kerf taper was developed. Further, a multi-response optimization was performed on the ground of desirability function to enhance the cut kerf properties.

The machinability research in the turning of hard D3 steel with carbide, ceramic, and coated ceramic tool presented Lakhdar et al. (Lakhdar et al. 2020.) The results of the machining follow control parameters: depth of cut, tool, speed, and the tool feed rate on the output parameters as surface roughness and the cutting force was tested. The modeling of cutting effects was performed using RSM and ANN methods. Additionally, a multi-criteria optimization availing the Desirability Function Analysis was performed. The optimal level of the control factors for the total desirability was finally identified with a maximal error of 2.94%.

The investigation of the welding parameters optimization designed for friction stir welding (FSW) of aluminum-magnesium alloy (AA5052) was introduced by Chanakyan et al. (C. Chanakyan and S. Sivasankar 2020). The experiments were conducted by selecting the different welding process control parameters as tool rotation and traverse speed, and tool pin profiles. The pin profile was made with ceramic tool. Taguchi-based Desirability Function Analysis (DFA) engaged in establishing the optimal process parameters with multi-objective function to maximize the tensile strength and the nugget hardness. The welding parameter of the optimum level was attained by the highest composite desirability value. An effect noticed that the tool pin profiles, and tool rotational speed are the important factors to influence the mixed output responses. On basis of the contour plots and mean effect authors show that the interaction of parameters of welding on the required output response was significant.

Alagarsamy et al. developed a mathematical model (Alagarsamy et al. 2021) and predict the machining performance characteristics of the electric discharge machining (EDM) process using response surface methodology (RSM) coupled with the desirability function approach (DFA). The effect of various factors, such as electrode material, pulse current, pulse ON time, and pulse OFF time were selected as input process parameters with an objective to maximize the material removal rate, minimize the surface roughness, and electrode wear ratio. The machining was conducted on Al-Zn-Mg-Cu (AA7075) alloy composite reinforced with 10% TiO_2 particles produced by stir casting route. Experimental results show that pulse current and pulse ON time are the most significant factors for MRR and SR while electrode materials and pulse current have a notable effect on EWR. Finally, multi-response optimization was performed to predict the EDM parameters by using DFA and the optimum combination of control parameters was identified.

Devarajaiah et al. (Devarajaiah and Muthumari 2018) also were presented the research of cutting by the EDM. In this paper, wire EDM experiments on titanium alloy are conducted using Taguchi L16 array. Desirability function analysis (DFA) was used to simultaneously optimize the responses. The control parameters were optimized using DFA, and results show an improvement in composite desirability factor by 7.88% at the optimum parameter setting.

Panda et al. (Panda et al. 2020) presented the application of Taguchi-based MOORA technique, desirability function analysis, and TOPSIS method for optimizing the surface roughness chromoly steel treated by ECM with the help of hexagonal-shaped brass electrode and brine solution. Multi-objective optimization has been done to investigate the influence of process parameters, i.e., voltage, tool feed rate, and signal on MRR and surface roughness. The optimal factor setting obtained from each optimization technique was compared, and the confirmation test was done to validate the results obtained from electrochemical machining.

Based on the analysis of the literature, it can be concluded that the DFA analysis is an interesting multi-optimization method used in advanced production methods. Therefore, it was decided to use a method for multi-criteria optimization in abrasive waterjet treatment.

2. Materials and methods

2.1. Cut material

Hardox 500 steel was used as the target material. Hardox 500 is a wear-resistant steel grade with a hardness of 470 - 530 HB. It is the most popular of Hardox grade and most often chosen by users. Due to the relatively high hardness, cutting with traditional methods is possible, but they are characterized by low efficiency. Chemical composition presents Table 1.

Table 1. Chemical composition of Hardox 500 steel (SSAB Homepage)

Grade	C max %	Si max %	Mn max %	P max %	S max %	Cr max %	Ni max %	Mo max %	B max %
Sheet	0.27	0.50	1.60	0.025	0.010	1.20	0.25	0.25	0.005
Plate	0.30	0.40	1.30	0.020	0.010	2.20	2.0	0.40	0.005

2.2. Abrasive material

As abrasive material the garnet type J80A from Jinhong Mining, China deposit was used. Abrasive particle distribution presents Fig. 1.

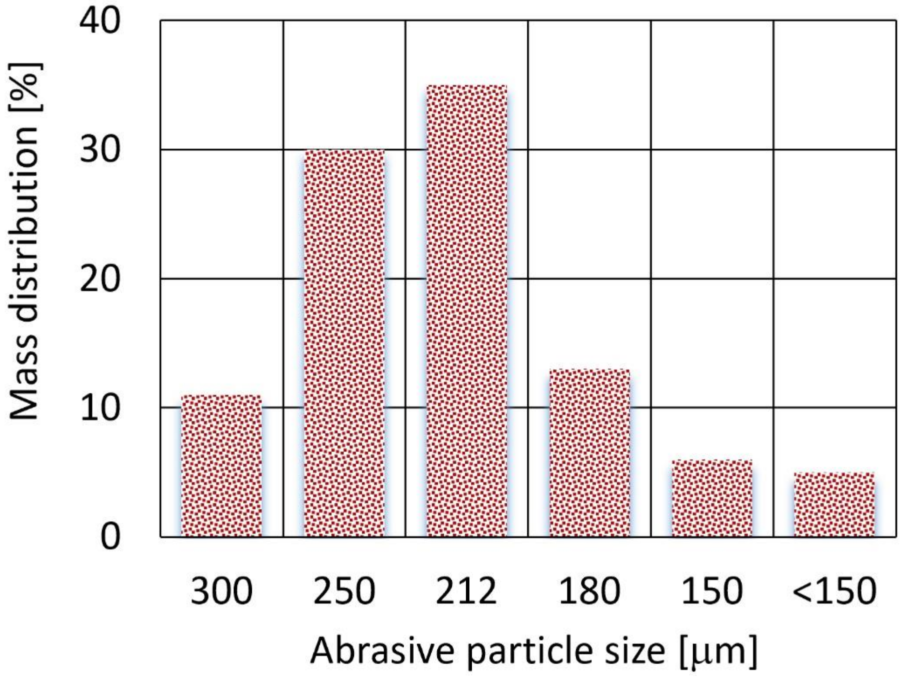

Figure 1. Typical particle distribution of J80A garnet

The shape of grains is near isometric. Particles are characterized by sharp edges and corners. Its color is from light to deep violet with smaller number dark brown to black. Mineral content, chemical composition and physical characteristics presents Table 2.

Table 2. Properties of garnet abrasive material (Jinhong Mining Catalog of Products 2019)

Mineral Content [%]							
Almandine	Ilmenite	Omphacite	Rutile	Quartz	Hornblende	Free Silica	
90-96	1.0	1.5	0.6	<0.1	<0.5	<0.5%	
Chemical Composition [%]							
Fe_2O_3	SiO_2	TiO_2	Al_2O_3	FeO	CaO	MgO	MnO
17	39	0.05	21	8	9.5	5	0.4
Physical Characteristics							
Density [kg/dm^3]	Bulk Gravity [kg/dm^3]	Mohs Hardness	Color	Grain shape	Conductivity	HCl solubility	
3.8-4.1	2.3-2.4	7.5-8.0	Dark red	Sub angular	<25 S/m	<1.0%	

2.3. Desirability function analysis (DFA)

As in other optimization methods based on decision support methods (Aleksandra Radomska-Zalas and Fajdek-Bieda 2021), (Fajdek-Bieda 2021), also in this case, the characteristics of the expected effect were defined.

DFA relies on transform the multi response characteristics into single response function, named composite desirability (D_g). To achieve this effect, the analysis should be carried out in the following steps:

Step 1 Calculation of desirability index

Calculating the individual desirability (d_i) comes for each response on ground the equations, published by Harrington (Harrington 1965) and extended by Derringer and Suich (Derringer and Suich 1980). Aptly to the response characteristics may occur three aspects of the desirability functions.

In the case when the output parameter is favorable and it takes the highest possible values (larger is better), the index d_i is described as follows:

$$d_i = \begin{cases} 0, y_i \le y_{min} \\ \left(\frac{y_i - y_{min}}{y_{max} - y_{min}}\right)^r, y_{min} \le y_i \le y_{max,} r \ge 0 \\ 1, y_i \ge y_{min} \end{cases} \tag{1}$$

Where:
d_i is the individual desirability,
y_i is the expected value,
y_{min} is the lower tolerance limit,
y_{max} is the upper tolerance limit,
r is the weight.

When the y_i exceeds a certain criteria value, which can be viewed as the requirement, the desirability value equals 1. If the y_i is less than a specified criteria value, which is unsuitable, the desirability equals 0.

If the output parameter is favorable when it takes the smallest possible value (smaller the better), the factor d_i is defined as follows:

$$d_i = \begin{cases} 1, y_i \le y_{min} \\ \left(\frac{y_i - y_{max}}{y_{min} - y_{max}}\right)^r, y_{min} \le y_i \le y_{max,} r \ge 0 \\ 0, y_i \ge y_{min} \end{cases} \tag{2}$$

When the y_i is less than a certain criteria value, the desirability value equals 1. If the y_i oversteps the specific value, the desirability value equals 0.

However, in the case when the output parameter is the most favorable (nominal is the best) when it takes the nominal values, the index d_i is described as follows:

$$d_i = \begin{cases} \left(\frac{y_i - y_{min}}{T - y_{min}}\right)^s, y_{min} \le y_i \le T, s \ge 0 \\ \left(\frac{y_i - y_{min}}{T - y_{min}}\right)^t, T \le y_i \le y_{max,} t \ge 0 \\ 0 \end{cases} \tag{3}$$

Where:
T is the individual target value,
s and t are the weight.

In this case the y_i value is required to achieve a particular target T. When the y_i equals T, the desirability value equals 1. If the value of y_i cross a particular range, the desirability value equals 0, and presents the worst case.

The r, s and t weights are defined aptly to the user demand. If the proper response is looked to be near to the target, the weight can assume a larger value. In another case, the weight can accept the minor value.

Step 2 Calculation the composite desirability

The individual desirability factor of all responses is combined to single value using following equation:

$$d_G = \sqrt[w]{\left(d_1^{w1} \times\ d_2^{w2}\ \cdots\ d_i^{wi}\right)} \tag{4}$$

Where:
d_G is the Composite Desirability or overall desirability,
d_i and w_i are the individual desirability and weight of the response y_i,
w is the sum of the individual weights.

Step 3. Determine the optimum level parameters and its combination.

Establishing the optimal level control parameters combination. The high composite desirability value suggests high processing quality.

Step 4. Calculate the predicted optimum conditions.

2.4. Surface roughness

Most popular surface roughness parameter S_a (Balasz, Szatkiewicz, and Krolikowski 2007), (Krolczyk, Kacalak, and Wieczorowski 2021) shows a the mean of the average height difference for the average plane. It gives steady effects because is not substantially affected by scratches, contamination, and measurement noise and the spacing of the varied texture assets. However, for a AWJ surface cut, using this parameter may bring a not very unreliable effect (Perec 2021). This is due to the specific machining marks (Fig. 2).

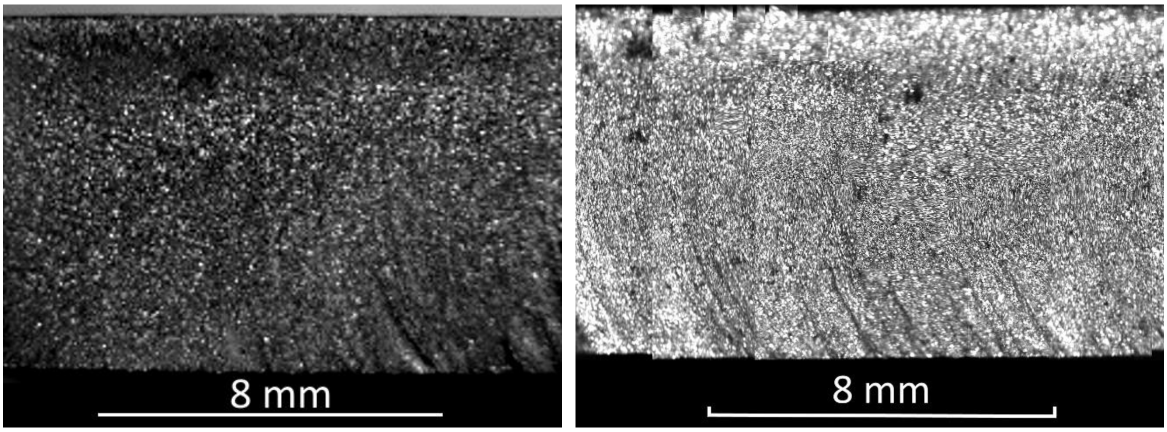

Figure 2. Sample AWJ cut surface: a) optical microscope view, b) SEM view

Therefore, a different surface roughness factor S_z was considered. S_z factor extends the contour (line roughness) factor R_z three-dimensionally (Fig. 3). The maximal height S_z is corresponding to the sum of the maximal peak height S_p and maximal valley depth S_v , as shown in Eq. 5.

$$S_z = \max\left[Z(x,y)\right] + \left|\min\left[Z(x,y)\right]\right| \tag{5}$$

While is often used, this factor is substantially affected by scratches, contamination, and measurement noise due to its use of peak values.

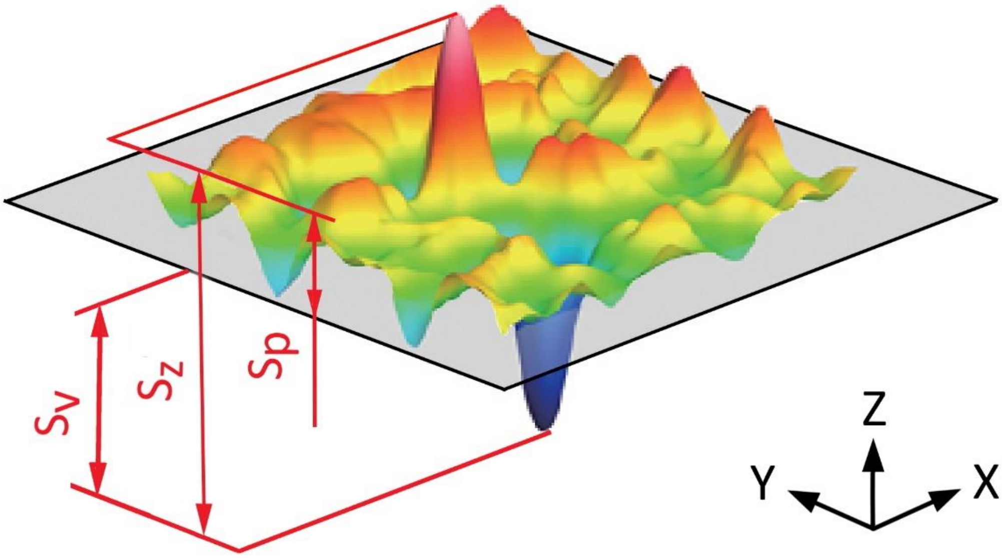

Figure 3. Detail of S_z roughness factor

S_z may find application for sealing systems, surface cosmetic appearance and may be related to the degree of surface wetting by various fluids.

3. Results and discussion

The cutting samples was tested for two output parameters: cutting depth and surface roughness S_Z. The cutting depth was measured on the digital high gauge and the surface roughness with Olympus LEXT™ OLS5100 laser scanning microscope combines unique accuracy and optical implementation with smart tools. The results of the two output parameters were given in the Table 3.

Table 3. Control and output parameters

Test nr.	AFR	Pressure	Traverse speed	Dc	Sz
1	450	400	300	11.05	74.71
2	450	375	200	13.07	90.10
3	450	350	100	19.81	55.26
4	350	400	200	13.75	62.09
5	350	375	100	19.66	63.91
6	350	350	300	8.37	76.18
7	250	400	100	20.30	59.80
8	250	375	300	8.04	61.63
9	250	350	200	10.74	79.145

For the laboratory results, the specific desirability values were obtained using equations (1) for cutting depth and (2) for surface roughness. Finally, on base the individual desirability the composite desirability (d_i) using the equation (4) was calculated. For finding the composite desirability equal weightage is assumed i.e., 0.5 for both the output characteristics. All determined values are given also in the Table 4.

Table 4. Individual and composite desirability values of outputs and its rank

Test nr.	D_c	S_z	$d_{i(Dc)}$	$d_{i(Sz)}$	d_i	Rank
1	11.05	74.71	0.48	0.64	0.55	5
2	13.07	90.10	0.62	0.00	0.00	8
3	**19.81**	55.26	0.95	0.96	0.96	1
4	13.75	62.09	0.66	0.86	0.76	4
5	19.66	63.91	0.94	0.84	0.89	3
6	8.37	76.18	0.16	0.61	0.31	7
7	20.3	59.80	0.97	0.90	0.93	2
8	8.04	61.63	0.00	0.87	0.00	8
9	10.74	79.145	0.46	0.54	0.50	6

In bold is marked set of 1 rank control parameters values

The mean of factor influences at each level on d_i was calculated and given in Table 5 and depicted in Fig. 4. The highest mean d_i is obtained at AFR equal 350 g/s, pressure equal 400 MPa, and traverse speed equal 100 mm/min. Hence, the optimum parameter setting for the simultaneous optimization of cutting depth and surface roughness is obtained at these values of control parameters.

The biggest influence on the on d_i factor was observed for traverse speed is found significant followed by pressure, and AFR. Similar conclusions can be drawn from Fig. 4.

Table 5. Response table Factors Mean composite desirability factor effect

Factors	Mean composite desirability Levels 1	2	3	Factor effects	Rank
AFR	0.4929	**0.6743**	0.5212	0.1814	3
Pressure	0.6083	0.3062	**0.7739**	0.4677	2
Traverse speed	**0.9581**	0.4317	0.2986	0.6595	1
Highest mean factor levels are marked in bold					

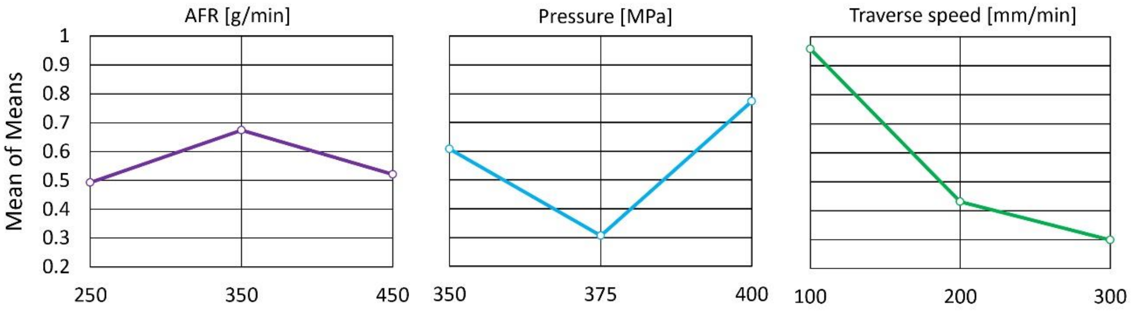

Figure 4. Main effect chart on d_i factor

The next step to improve the effects measures was conducted the additional lab cutting test, at control parameters condition shown in Table 5 and Fig 4. The result of validation and improvement in performance measures are presented in Table 6. Improvement in relation to the initial optimal value observed in cutting depth noted as 6.31% and in surface roughness S_z as 5.18 μm.

Table 6. Improvement in cutting depth and Surface roughness

Test Nr	Description	Control parameters AFR [g/min]	Pressure [MPa]	Traverse speed [mm/min]	Responses Cutting depth D_c [mm]	Surface Roughness S_z [μm]
2	Initial optimum	450	350	100	19.81	55.26
10	Improved optimum	350	400	100	21.06	52.54
		Improvement			6.31%	5.18%

4. Conclusions

Experiments was conducted as per Taguchi L9 orthogonal array with three control process variables, each at three levels. Predictive performance was validated using confirmation test. The primary aim of this research was to obtain the optimal set of control parameters that affect the cutting depth and the surface roughness in the presence of multiple responses. The conducted research confirmed the equity of applying the method in multi-criteria optimization of the Hardox steel cutting process by AWJ and confirmed improvement in performance measures.

On the basis the DFA graph concluded that the best possible combination of the process parameters to optimize the output parameters is: abrasive flow rate = 350 g/min, pressure = 400 MPa, traverse speed = 100 mm/min.

The change in traverse speed causes the biggest changes in effects, next by the abrasive flow rate and the smallest impact was noted for the pressure output.

The proposed methodology of simultaneous optimization can be used also to optimize 4–5 responses, and robustness can be checked. DFA can be carried out with different weights assigned to responses, and results can be compared. Further, a suitable technique can be used for weight optimization. Application of other optimization techniques such as GRA and VIKOR can also be explored.

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