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Modelling the Cutting Process and Cutting Performance in Abrasive Waterjet Machining Using Genetic-Fuzzy Approach

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Abstract

Unconventional machining processes are used only when no other traditional machining process can meet the necessary requirements efficiently and economically. Abrasive Waterjet Machining (AWJM) is one of the most recently developed mechanical type unconventional hybrid manufacturing technologies. It is superior to many other cutting techniques in processing various materials, particularly in processing difficult to cut materials. This technology is being increase used in various industries. Therefore, optimum choice of the process parameters is essential for the economic, efficient, and effective utilization of these processes. Process parameters of AWJM are generally selected either based on the experience, and expertise of the operator or from the propriety machining handbooks. In most of the cases, selected parameters are conservative and far from the optimum. This hinders optimum utilization of the process capabilities. Selecting optimum values of process parameters without optimization requires elaborate experimentation which is costly, time consuming, and tedious. Process parameters optimization of AWJM essential for exploiting their potentials and capabilities to the fullest extent economically. This paper presents a Fuzzy Logic (FL) - based modeling of AWJM process and optimization of its rule base, data base and consequent part utilizing a Genetic Algorithm (GA). A binary coded GA has been used for the said purpose. While modeling with FL, the output parameters, namely Material Removal Rate (MRR) and Surface Finish (Ra) have been predicted for different combinations of process parameters, such as water jet pressure at the nozzle exit diameter of abrasive-water jet nozzle traverse or feed rate of the nozzle mass flow rate of water and mass flow rate of abrasives between nozzle and the work piece.

Keywords: *Abrasive Waterjet Machining, Fuzzy Logic, Machining Parameter, Genetic Algorithm*

1. Introduction

The best of AJM and WJM processes have been combined to create a process known as AWJM. AWJM technology was first commercialized in the late 1980`s as a pioneering breakthrough in the area of non-traditional processing technologies. It is used to cut the target materials with a fine high pressure water abrasive slurry jet. AWJM is superior to many other cutting techniques in processing various materials. Such as no thermal distortion on the work piece, omni-directional cutting capability, high machining versatility to cut virtually any material and small cutting forces. This technology has found extensive applications in industry, particularly in contouring or profile cutting and in processing difficult to cut materials such as ceramics and marbles, and layered composites.

This process relies on erosive action of abrasive laden water jet for applications of cutting, drilling, cleaning, and de-scaling of thick sections of very soft to very hard materials at higher rates. A stream of small abrasive particles is introduced and en trained in the water jet in such a manner that water jet’s moment um is partly transferred to the

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abrasive particles. Role of carrier fluid (water) is primarily to accelerate large quantities of abrasive particles to a high velocity and to produce a highly coherent jet [1]. Import ant process parameters of AWJM can be categorized as hydraulic parameters: water pressure, and water flow rate (or waterjet nozzle diameter); abrasive parameters: type, size, shape, an d flow rate of abrasive particles; cutting parameters: traverse rate, SOD, number of passes, angle of attack, and target material; and mixing parameters: mixing method (forced or suction), abrasive condition (dry or slurry) and mixing chamber dimensions. Variety o f materials that can be machined by AWJM include copper and its alloys, aluminum, lead, steel, tungsten carbide, titanium, ceramics, composites, acrylc, concrete, rocks, graphite, silica glass, etc. Most promising application includes machining of sandwiched honeycomb structural materials frequently used in aerospace industries. Visual examination of the cutting process in AWJM suggests two dominant modes of material removal. First is erosion by cutting wear due to particle impact at shallow angles on the top surface of the kerf. Second is deformation wear due to excessive plastic deformation caused by particle impact at large angles, deeper into the kerf [1 and 2].

2. Literature Survey

Different researchers have carried out process parameters optimization of different types of AMPs from time to time using different optimization models and solution techniques. Table 1 present s the summary of such past studies highlighting the decision variables, objective functions, constraints, variable bounds, remarks, and their limitations. Chakravarthy and Babu [3] used combination of Simple Genetic Algorithms (SGA) and fuzzy logic for optimal selection of three AWJM parameters namely waterjet pressure, jet traverse rate, and abrasive flow rate. SG A was used to generate a set of strings of input parameters. A fuzzy rule base was used to predict depth of cut using these parameters as input. Those parametric combinations, for which predicted depth of cut was equal to the desired depth of cut within a specified error amount, were identified as feasible combination s. The feasible parametric combinations were used for optimization to minimize total cost of production. Kovacevic and Fang [4] have applied fuzzy set theory for selecting (though not the optimum values) four AWJM process parameters namely water jet pressure, jet traverse rate, abrasive flow rate, and inside diameter of AWJM nozzle to achieve the desired depth of cut. Universes of discourse for AWJM process parameters were discretized into 17 levels with 5 linguistic terms and triangular member ship function was used for each parameter. Five fuzzy rules were employed for each of the four AWJM process variables.

Researcher (Year)	Decision Variables	Objective Function (s)	Constraints & Variable Bounds	Remarks & Limitations
Abrasive-Waterjet Machining (AWJM) Chakravarthy & Ramesh Babu (1998)	Three decision variables, each with five levels of variations	Maximize production rate	No constraints and variable bounds used	Essentially single objective optimization
	Water jet pressure (60, 130, 200, 270, 350 MPa)	Minimize Abrasive consumption	-	Fuzzy rule base contained 125 rules which were developed based on 125 experiments on Paradiso Granite
	Jet traverse rate (30, 70, 150, 230, 325mm/min)	Assigning suitable weight ages to each of these objectives they were combined in a single objective as total cost of machining, which is to be minimized	-	GA parameters used: no of variables=3; string length=26; population size= 50; Crossover probability=0.5; Mutation probability=0.2
	Abrasive flow rate (30,50,90,130,170 g/min)	Total cost of machining = $[W_{pr}(C_1+C_2+C_3+C_4+C_5+C_6)+W_{ac}C_1]$x(length of cut/Jet transverse rate), W_{pr} and W_{ac} are weight ages for production rate and abrasive consumption respectively and C_1 = abrasive consumption cost9S/h); C_2 = machine hourly cost (S/h); C_3 = labor cost per Hour (S/h); C_4 = cost of primary nozzle (S/h); C_5 = cost of secondary nozzle (S/h); C_6 = cost of power consumption (S/h)	-	-

3. Experimental Set Up

The experiments were conducted with a commercial abrasive waterjet apparatus illustrated schematically in Figure 1. Details of the machine and process settings are listed in Table 2. In this research work, To establish input-output relationships of AWJM process, five process parameters, namely, water jet pressure at the nozzle exit diameter of abrasive-water jet nozzle traverse or feed rate of the nozzle mass flow rate of water and mass flow rate of abrasives and two responses, such as Material Removal Rate (MRR) and Surface Finish (Ra) of the process have been considered in the present study. Aluminum silicon carbide is used as the work piece for experimentation and interested readers can read reference [5] for more details of the experimental description.

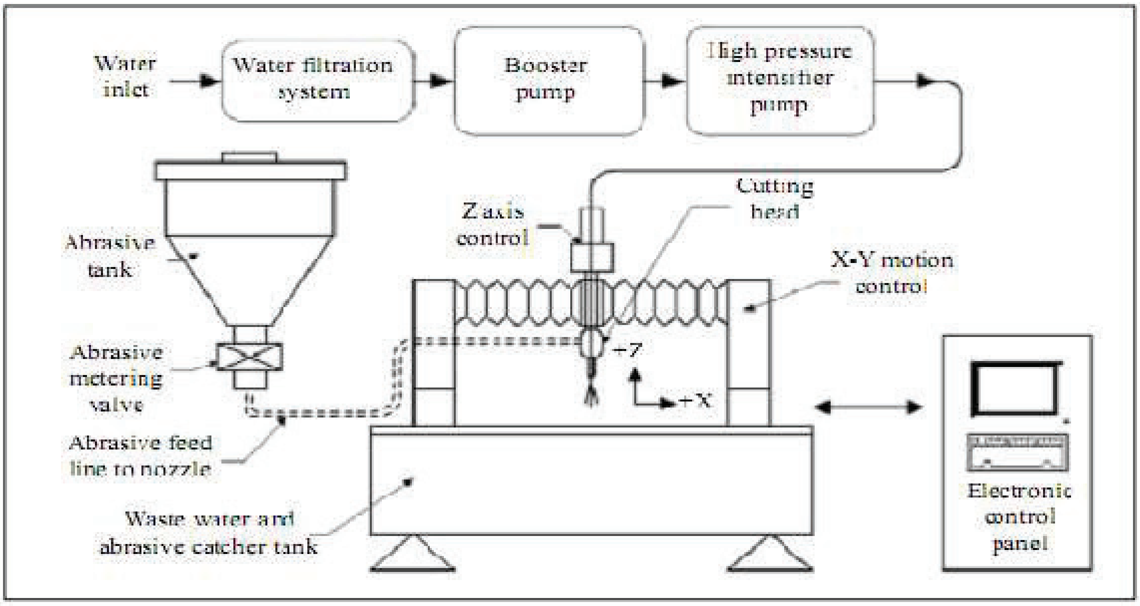


Figure 1: A Schematic Illustration of the Experimental Set-Up

Table 2: Literature Survey and Selection of the Variable Bounds for AWJM process

UCM	Decision Variable	References								Selected Bound Variables (Unit)
		[10]	[110]	[12]	[13]	[14]	[15]	[16]	[17]	
AWJM	Waterjet Pressure at the Nozzle Exit ‘P_w’ (MPa)	Not Mentioned	50-400	Up to 400	137-241	69-350	150-350	150-280	50-400	50-400(MPa)
	Diameter of Abrasive Waterjet Nozzle ‘d_{awn}’(mm)	—	—	—	4.3	—	0.8-1.1	0.8-2.4	—	0.5 -5 (mm)
	Nozzle Feed Rate ‘f_n’ (mm/s)	—	2.5		3 - 10	0.2-25	1.67-13.33	3.33-25	0.33 - 6.67	0.2 - 25(mm/s)
	Mass Flow Rate of Water ‘M_w’ (Kg/s)	—	Up to 0.2 Kg/s	—		Waterjet Diameter 0.127 - 0.635mm	Waterjet Diameter 0.3mm	Waterjet Diameter 0.3mm	—	0.01-0.2 (Kg/s)
	Mass Flow Rate of Abrasives	—	0.0075	0.00167 -0.0833	0.033	0.0005 - 0.025	0.0075 - 0.013	0.0033 - 0.0125	0.00033 - 0.0033	0.0003 - 0.08(Kg/s)

	'M_a' (Kg/s)									

4. Modeling OF AWJM Process

Following optimization model was developed using analysis of Hashish [1] for predicting depth of cut due to cutting and de formation wear and assuming width of cut equal to diameter of the abrasive waterjet. In this model, variation in the velocity of abrasive waterjet (which is true for shallow depth of cut), and its effects on the kerf wall drag have been neglected for both cutting wear and deformation wear zones. Also, threshold velocity concept has not been considered for the depth of cu t due to cutting wear.

Decision Variables: Five, namely Water Jet Pressure at the Nozzle Exit 'P' (MPa); Diameter of Abrasive-Waterjet Nozzle 'd_{awn}' (mm); Traverse or Feed Rate of the Nozzle 'f' (mm/s); Mass flow Rate of Water 'M_w' (kg/s) and Mass Flow Rate of Abrasives 'M_a' (kg/s).

Objective Functions:

Maximize MRR:

Max $d_{awn} f_n (h_c + h_d)$ mm^3/s

Where indentation depth due to cutting wear 'h_c' and indentation depth due to deformation wear 'h_d' is calculated using the formula.

Surface Roughness Constraint:

$1.0 - 18.26/ (R_a)_{max} (\rho_a/\sigma_{fw})^{0.5} r_m v_{a \geq 0.0}$

Where mass flow rate of abrasive particles 'M' (kg/s); mean radius of abrasive particles 'r_m' (mm); and velocity of abrasive particles 'v_a' (mm/s).

Variable Bounds: Based upon the survey of range of values of decision variables presented in the Table 2, following variable bounds were formulated:

$50.0 \leq P_w \leq 400.0$ (MPa); 0 5 $d_{awn} \leq 5.0$ (mm); 0 2 $\leq f_n \leq$ 25 0 (mm/s);
0 02 $\leq M_w \leq$ 0 2 (kg/ s); and $0.0003 \leq M_a \leq 0.08$ (kg/s)

5. Forward Modeling of AWJM Process Using FL-GA

In the present approach, five variables, such as water jet pressure at the nozzle exit 'P' (MPa); diameter of abrasive-waterjet nozzle 'd_{awn}' (mm); traverse or feed rate of the nozzle 'f' (mm/s); mass flow rate of water 'M_w' (kg/s) and mass flow rate of abrasives 'M_a' (kg/s) are considered as inputs to the Mamdani approach of Fuzzy Logic Controller (FLC) [6], and there are two outputs (that is, MRR and Ra) that can be predicted from the controller. It is important to note that, the performance of the FLC purely depends on its Knowledge Base (KB), which consists of both the data base (that is, membership function distribution of the variables) as well as its rule base. For simplicity, triangular membership function distributions have been assumed for both the input and output variables. Moreover, both the input and output variables are considered to have three linguistic terms (L – Low, M – Medium and H - High). Figure 2 shows the membership function distributions of the input and output variables.

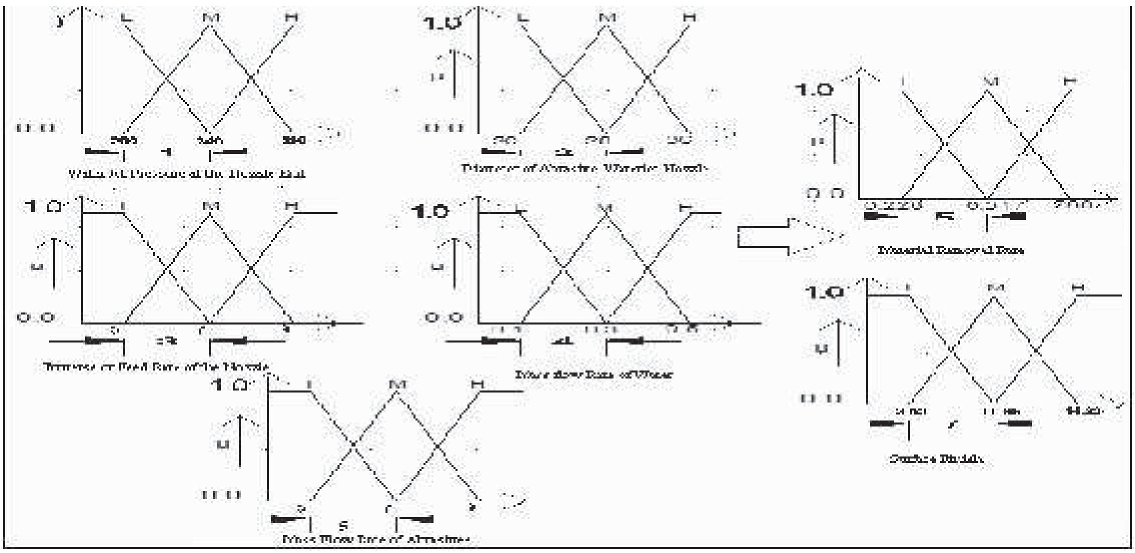


Figure 2: Manually Constructed Membership Function Distribution of the Input-Output Variables

As there are three linguistic terms for each input variable, there is a maximum of 3^5 = 243 rules possible. One such rule of the FLC may look like the following:

IF A is M AND B is L AND C is H AND D is M AND E is H, THEN MRR is L, Ra is M.

However, the KB (That is, data base and rule base) of the manually constructed FLC, which is based on the designer's knowledge and experience of the process, may not be optimal in most of the cases. Thus, an attempt has been made to evolve the optimal FLC, off-line using GA. GA are computerized search and optimization algorithms belonging to the class of EA and work with a set or population of solutions a s opposed to traditional optimization technique and evolve the set of optimum solutions clustered around the global optimum solution using the principles of natural genetics and natural selection [7]. Operation of GA begins with generation of a set of random solutions (known as population). Each solution is evaluated to find its fitness value. Higher fitness value indicates goodness of the solution. The generated population is then operated by the reproduction, crossover, and mutation operators to create the ne w population which is evaluated and tested for the termination criterion. One cycle of three GA operations and the subsequent evaluation constitute a generation in the GA terminology. Reproduction or selection operator selects good solutions from the current generation in proportionate to their fitness value to form a mating pool. Crossover operator creates new and hope fully better solutions by crossing over the solution s selected from the mating pool according to the crossover probability. Mutation operator alters a good solution locally to hope fully create a better solution and helps in maintaining the diversity in the population. This procedure of GA operations is continued until the termination criterion is met or for a specified number of generations. GA are naturally suit able for solving maximization problems. But, minimization problems can be easily transformed into maximization problems using some suitable transformation; therefore GA can also solve minimization problems in an equally effective manner. The schematic diagram showing the operating principle of GA-FLC system is shown in Figure 3.

The `a` values indicate the base widths of right-angle triangles and half-base widths of isosceles triangles. The responsibility of searching a good KB of FLC is given to the GA. The rule base of this FLC contains 243 rules. One bit will be used to represent the presence or absence of each rule (1 is for presence and 0 is for absence). Moreover, there are seven real variables, such as a_1, a_2,……., a_7 (refer to Figure 2), which represent the half base widths of the triangular membership functions of the variables, and 10 bits are used to represent each variable. For this FLC, there are two outputs – MRR and Ra, and each of the output is indicated using three linguistic terms (that is, L, M and H). Each linguistic term is represented by two bits (00 for Low, 01 and 10 for Medium and 11 for High). Thus, there are five bits representing the two outputs for each rule of the FLC. The total number of rules of this FLC is 243 and five bits are used to represent the output of each rule. Hence, the total number of bits required to represent the consequent part of the FLC is coming to be equal to 243× 5 = 1215-bits. Thus, the GA-string will be 70 + 1215 = 1285 bits long, which will look as follows:

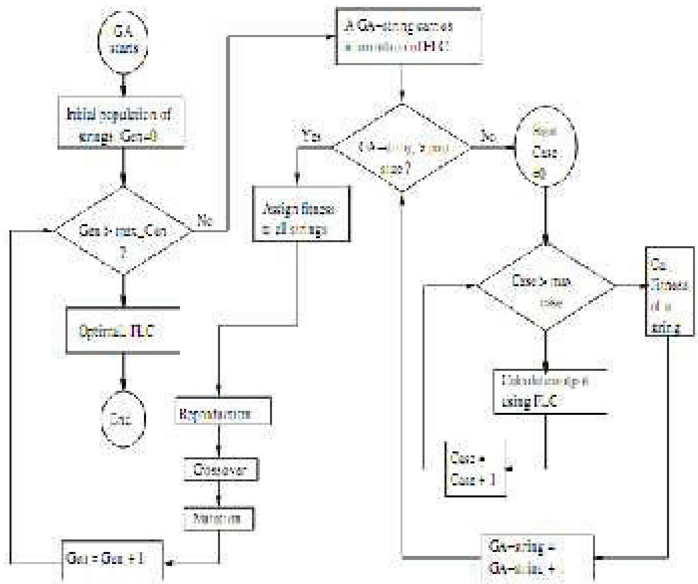
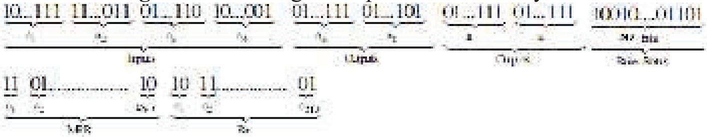


Figure 3: Working Principle of GA-FLC System



Thus, populations of GA-strings represent a number of candidate FLCs knowledge base (whose number equals the population size). As a batch mode of training is adopted in the present work, the whole training data consist of one thousand training set is passed through the FLC, represented by a GA-string. The fitness (f) of a GA-string (that is, average RMS deviation in prediction) is determined using the expression given below:

$$f = \frac{1}{N}\sum_{i=1}^{N}\sqrt{\frac{1}{m}\sum_{j=1}^{m}(T_{oj} - O_{oj})^2}$$

Where T_o is the target output, O_o represents the predicted output, m denotes the number of responses and N is the number of training scenarios. The operations like reproduction, crossover and mutation are then applied to modify the population of solutions. It is important to note that the mating pool is formed with the good strings being selected from the population based on their fitness values using reproduction. In this study, the mating pairs which will participate in crossover are selected with a uniform crossover of fixed probability ($p_c = 0.5$) and exchange properties between the two parents to form the children solutions. The local minima (if any) can be avoided with mutation, which brings a local change to the solution. During optimization, the half base-widths of different triangles representing membership function distributions of the inputs and outputs, A, B, C, D, E, MRR and Ra are considered as the real variables, whose ranges of variation are kept fixed to (15.0, 40.0), (4.0, 8.0), (0.5, 2.0), (0.01, 0.2), (0.05, 0.1), (0.005, 0.097), and (1.0, 2.35), respectively.

6. Result Analysis and Discussion

As the performance of GA depends on its parameters, a thorough study is carried out to determine the optimal parameters. In this study, uniform crossover and bit-wise mutation have been adopted. In order to identify the best parameters of GA, a study has been conducted by varying one parameter at a time. The following GA parameters are found to yield best result:
Crossover Probability, $p_c = 0.00083$
Mutation Probability $p_m = 0.5$
Population Size = 125
Maximum Number of Generations = 180
The optimized membership function distributions obtained for the input and output variables of the FLC are seen to be similar to the Figure 2. However, the optimal values of seven real variables, such as a_1, a_2, a_3, a_1, a_4, a_5, a_6, and a_7 are found to be equal to 33.744, 8.000, 0.688, 0.189, 0.121, 0.97 and 2.265, respectively. Thirty eight one rules are found to be present in the optimal rule base of the FLC. Once the optimal FLC is evolved, it is tested for its effectiveness in prediction of the two responses, namely surface roughness and material removal rate. The percentage deviations in prediction of the two outputs for ten test cases are shown in Figure. 4.

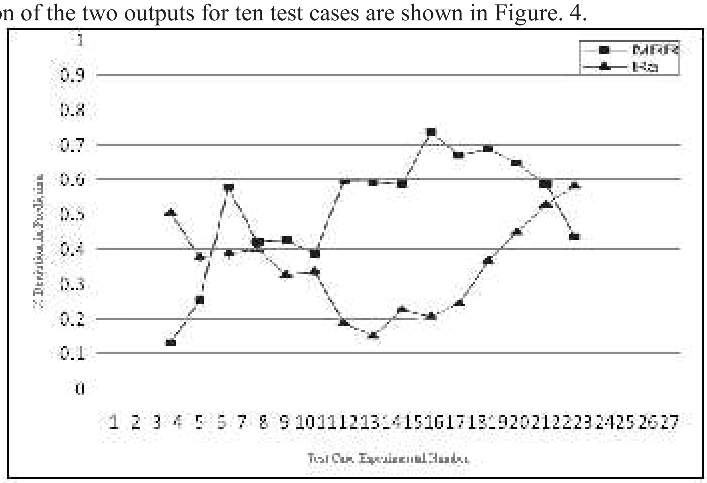


Figure 4: Percent Deviation in Prediction of Ra and MRR Using GA-FLC Approach

It has been observed that the values of percentage deviation are found to lie in the ranges of (0.14, 0.61) and (0.12, 0.75) for the outputs Ra and MRR, respectively. Moreover, the average absolute percentage deviation in prediction of Ra and MRR are found to be equal to 0.6031 and 1.712, respectively. Thus the GA-trained FLC is found to successfully model and predicted the outputs in a near optimal sense with good accuracy for the AWJM process. It is important to note that the approach proposed in [8] uses a statistical approach that was carried out response wise and it may not be able to capture the dynamics of the entire process. In the present paper, a GA tuned FLC has based proposed to model the AWJM process after considering both the responses and obtained reasonable prediction accuracy.

7. Conclusion

In this work, the optimal machining parameters for aluminum silicon carbide material for the multi performance characteristic in AWJM machining were determined by Fuzzy-Genetic approach. The formulated optimization models are multi- variable non-linearly constrained single and multi-objective optimization problems. For AWJM processes, the formulated objective functions and constraints are very complicated and implicit functions of the decision variables. An attempt has been made to carry out the forward modeling of the AWJM process by using an FLC. A batch mode of training is adopted which requires a large amount of data. The training data has been generated artificially (at random) by using the response equations obtained through response surface methodology. The optimal FLC is evolved with the help of a genetic algorithm. The accuracy in prediction of the responses is tested for ten different test cases and found a reasonably good prediction for both the outputs. The optimization results were confirmed graphically with the help of the graphs showing dependence of the objective function and constraint on the decision variables. Only single objective optimization was done to check the suit ability and validity of the material removal models, on the basis of which optimization models were formulated. Hence by properly adjusting the control factors, work efficiency and product quality can be increased.

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