Research Article

Parametric Optimization of Abrasive Water Jet Cutting on AA 5083 through Multiobjective Teaching-Learning Method

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The industrial sector is seeing an increase in the development of new technologies on a daily basis. Manufacturing advancements have resulted in low-intensity, inadequate outputs from cutting materials. The application of engineering materials requires cutting to produce the desired shapes and sizes. The material's fundamental attributes are altered and utilised to improve machinability. Due to its significant benefits over traditional cutting processes, abrasive water jet cutting (AWJC) is now the most popular nonconventional machining for attaining the best cutting of any material. Because of its highly pressurised water power, the substance can quickly be separated from some properties by the use of a small pin with various kinds of abrasives. Due to the time-consuming process of cutting materials, determining optimal cutting conditions for the multiobjective criteria examined is a tough issue in techniques needing large resources. The operational parameters of the abrasive water jet cutting system must be changed in this article to achieve the lowest possible surface roughness while also attaining the maximum possible material removal rate. The abrasive water jet cutting method was utilised in this investigation to see how effectively the AA5083 aluminium alloy could be sliced. Water pressure, transverse speed, stand-off distance, and abrasive flow rate are some of the major cutting parameters that may be adjusted such that the output values such as material removal rate and surface roughness are at their optimal levels.

1. Introduction

One of the most versatile methods for making precise cuts in various materials is abrasive water jet machining. Precision and efficiency are the primary goals of the cutting method. Sand and gravel may be used as an abrasive at a very high speed through a tiny water jet. As a dynamic approach, AWJ (abrasive water jet) cutting requires careful consideration of several performance-influencing elements. Factors such as water density and flow rate are the most critical to keep in mind when designing a water-based abrasive application. The most significant achievement in terms of growth,

efficiency, and long-term viability has been made. A variety of numerical and statistical model methods, in conjunction with appropriate experiment design, have been used to investigate the effect of water velocity, abrasive materials, and the size and shape of the nozzle on the overall machinability of brittle and ductile materials, as well as the machinability of composite materials [1]. The surface roughness of the AWJ parameters might be predicted using a mathematical model that has been created before. Using regression analysis, researchers were able to predict the results of composite materials based on the experimental data. An abrasive water jet was also used in this investigation, with surface roughness and kerf angle being measured using the design of experiments (DoE). An analysis of cutting quality using Taguchi's predictions reveals that abrasive jet machining's inherent increase in energy is confirmed [2]. A central composite rotatable design was used to study the cutting parameters of flow rate, rotating speed, and water pressure. A variety of groupings of these characteristics were then used to determine the metal removal rate [3]. In abrasive water jet turning, the most critical parameters were found to be the depth of cut and nozzle transverse speed, both of which were statistically significant. On the other hand, the rotational speed is considered a nonsignificant measure [4]. According to the study, increasing water pressure, stand-off distance, and nozzle speed, enhanced output responses lowest kerf profile, surface study, and with increased material removal rate were attained. Conventional machining produces a uniform surface finish on the material. Thus, by determining the surface irregularity of each machined region, the total surface quality of the pat surface may be determined [5, 6].

It is feasible to come up with the best design possible by using evolutionary algorithms since they are rapid and well-organized procedures for testing and assessing experimental architectural approaches. Many engineering applications need the use of optimization in order to decrease the number of variables while simultaneously increasing the desired effect [7, 8]. Precision engineering is vital in complex engineering applications, and it is especially critical in aeronautical applications. Optimization and performance algorithms for machines include approaches for building and comparing machining settings in order to get the best possible machining performance. The most efficient method of maximising efficiency is to lower the many undesired values while optimising the ideal influence on the most desirable variables. In order to produce a high-quality product or a product that is competitive, the optimization strategy must be applied. When it comes to machine tool parameters, parametric optimization is a methodical and efficient approach to setting up and equating them in order to get the best possible outcomes [9, 10].

Author [11] used an artificial bee colony to optimise technique parameters such as water velocity and traversal intensity for surface irregularity, and then compared the results using regression equations, and genetic algorithms to determine the most effective approach. With the use of the Taguchi technique and evolutionary optimization. Consideration was given to the optimization of machining parameters such as mass flow rate, transversal speed, and stand-off distance. For the most part, conventionally machined materials have a homogeneous surface finish. Using grey relation analysis to normalise performance evaluation of varied answers is extensively used, and it has been developed to cope with the complicated aspects of specific work systems [12]. It was possible for the researchers to learn more about the machinability of aluminium alloys by optimising the experimental settings and adjusting the influence of parameter variables such as transverse speed, stand-off distance, and abrasive feed, on the abrasive water jet cutting process on aluminium alloys. The influence of cutting rate, hardness, and surface study on a multiobjective optimization scenario was investigated utilising the Assignment of Weights for normalisation technique in a simulated environment [13]. To minimise surface roughness while simultaneously increasing material removal rate, multiobjective optimization of the abrasive water jet cutting AA5083 was performed in this study. In order to address the optimization of AA5083, full factorial design and multiobjective teaching learning-based optimization (MOTLBO) algorithms are used. The design of experiments is being used to improve the base metal cutting process to optimise variables such as water pressure, abrasive feed, stand-off distance, and nozzle speed, and the results are compared.

2. Materials and Methods

Lightweight aluminium alloys, such as those used in aircraft, are extensively used in a wide variety of applications across the world, notably in the aerospace industry. The principal use for this alloy is in high-strength structural applications. It possesses a high degree of ductility, as well as exceptional toughness and fatigue resistance, making it a great choice for structural applications. When combined with other properties, 5083 alloy has a very high strength-to-weight ratio and is very successful in high-temperature applications and aviation sectors. When compared to other families of aluminium alloys, the 5083 alloy is one of the strongest aluminium alloys currently available on the market. The composition of the AA5083 alloy is shown in Table 1.

It was decided that the block with the parameters of 500 mm in length, 50 mm across its surface area, and 50 mm above its surface area would be the size to be considered for testing using an abrasive water jet cutting machine while performing this experimental investigation. The abrasive water jet cutting measures X-Y actions in millimetres, with the X axis measuring 300 millimetres and the Y axis being 1500 millimetres. A gravity-fed abrasive hopper was included with the equipment. Abrasive flow rate and water pressure are some of the input factors under AWJC that together reduce the output responses. These include nozzle jet angle, water pressure, stand-off distance, and abrasive flow rate. This approach presents difficulties in cutting operations because of the many factors that are involved in it. Three levels of machinability are determined using the full factorial technique for four parameters: water pressure, traverse speed, stand-off distance, and abrasive feed. The factors and levels of machinability are given in Table 2 for

TABLE 1: Composition of AA5083.

Elements	Si	Fe	Cu	Mn	Mg	Zn	Cr	Al
Weight (%)	0.4	0.4	0.1	0.52	4.42	0.25	0.195	Bal.

TABLE 2: Abrasive water jet cutting factors and levels for DoE.

Sl.No	Factors	Units	Levels		
			1	2	3
1	Water pressure	MPa	275	310	345
2	Traverse speed	mm/min	32	40	48
3	Stand-off distance	mm	2	4	6
4	Abrasive feed	g/min	200	300	400

each parameter. In the abrasive water jet cutting operations, sixteen experimental cutting operations are carried out with defined factors, and material removal rate and surface roughness are measured and analysed, respectively.

3. Teaching-Learning-Based Algorithm

Variables such as the size of the population, the number of generations, the number of groups, and so on are taken into account by all population-based evolutionary heuristic algorithms. A further benefit of using evolutionary algorithms is that they make use of features unique only to their algorithms. When it comes to genetic algorithms, unique operators like mutation and crossover are used, whereas inertia weights and cognitive parameters are used in particle swarm optimization. Scout, observer, and employee: Bees are utilised in the bee colony algorithm. The amount of effort needed is further reduced by altering the regularly used parameters in addition to the algorithm-specific variables. Thus, they [14] came up with a unique approach to teaching-learning-based optimization without any specific algorithms operators. Consequently, the term "teaching-learning-based algorithm" refers to an algorithm based on a teaching and learning process.

There are no algorithm-specific variables to deal with in teaching-learning-based optimization, making it simpler to use and implement than other population-based optimization approaches. The convergence rate is improved because TLBO employs the best solution from each generation to alter the current solution. For better results, TLBO employs the influencing parameter's mean value. "Teacher phase" and "learner phase" are two distinct parts of teaching-learning-based optimization. Developed by it, the teaching-learning-based optimization was designed to solve difficulties related to a controlled mechanical application. In a classroom setting, when students first receive information from an instructor and then engage with one another, this phenomenon is set off [14].

In this case, when the algorithm is applied to a class of students, the students serve as the algorithm's population, which is represented by the term "population." Students' findings are used as design variables in the optimization problem, and the results are used as a measure of the suitability of a suggested solution to the situation at hand.

This algorithm is comprised of two stages: the teacher phase and the learner phase [13, 14]. When students are in the instructor phase, the instructor works with them to help them advance their knowledge. For the duration of this teacher term, each student is allocated to a certain teacher. Moving the other outputs closer to the instructor's position and taking the mean value of the parameters into account both helped to enhance them significantly. The student phase entails gathering information on the students and having them engage with one another. In this exercise, two students are picked at random and their replies are compared, with the students' progressing towards better answers as a consequence of the comparison. As opposed to succeeding meta-heuristic algorithms, the teaching-learning-based optimization algorithm's use of governing parameters rather than algorithm-based parameters is the most important benefit of the method [15–17]. This analysis is multiobjective because it contains many goals with opposing objectives, such as maximising material removal rate and minimising surface roughness. To solve a multiobjective optimization problem using the Assignment of Weights technique is required.

3.1. Teacher's Phase. An excellent teacher helps his or her students to improve their knowledge to the highest possible degree. Although this is not possible in real time, an excellent teacher may move the pupils who perform above the mean of the class to a certain extent, dependent on the competence of the whole class. It is estimated as the mean value of the influencing values. The best instructor will be determined during the teacher selection process. The most effective instructor is chosen based on the highest possible COF score. The instructor is now more likely to use his or her expertise to benefit the whole student group. The following equation may be used to improve the performance of each individual learner (1)[14]:

$$Xt_n = Xt_o + \text{random}\left(X_{bt} - (tf * m)\right). \tag{1}$$

Choosing the best or best representation for the following stages and iterations will always lead to the convergence of the target. For a better portrayal of the instructors' phase, MOTLBO's first representation is used as a reference point. It is possible to compute and compare the

shortest distance. During the teacher's phase, the best string is represented and tallied as the result. When a teacher phase ends, all of its valid goal values are transferred over to the learner phase. As a result, the learner and instructor phases are interdependent.

3.2. Learner's Phase. Students (learners) are required to increase their knowledge by engaging with one another throughout the second stage of the MOTLBO algorithm. For the purpose of expanding their knowledge, students are allowed to communicate with one another at random. If another student has greater knowledge than the student who is being taught, the student might pick up new concepts. Each student has the ability to engage with another randomly chosen string in the first stage of this phase, for which randomly selected students are picked for the interaction. When making a pick, it is not possible to choose the same student more than once, nor can any student engage with the same group of students more than once. Only when the superior student interacts with the student can the student's knowledge be strengthened. A relationship between the following (2) and (3) has been established. The COF values of the two pupils will be compared in this section of the paper. The student's COF value exceeds the COF value of the selected student if the student's COF value is greater which is shown in the following equations:

$$X1_{ns} = X_{1s} + \text{rand}\,(X_{1s} - X_{ss}), \tag{2}$$

$$X1_{ns} = X_{1s} + \text{rand}\,(X_{ss} - X_{1s}). \tag{3}$$

In the next iteration, the output of the learner phase will be utilised as the input for the teacher phase. When the requisite number of generations or iterations has been reached, the whole process of going through the instructors' phase and the learners' phase will be repeated.

4. Results and Discussion

4.1. Multiobjective Teaching-Learning-Based Optimization (MOTLBO) Results. It is decided that the number of students in this optimization for MOTLBO will be 20 and that the number of iterations will be 100 in this optimization. The COF generation, after 30 iterations, has reached convergent behaviour and has produced optimal parametric values.

Table 3 summarises the optimal input parameters, MRR, and SR findings for the AA5083 after the necessary generations have been completed. The MOTLBO results of 275 MPa water pressure, a transverse speed of 48 mm/min, a stand-off distance of 2 mm, and an abrasive feed rate of 400 g/min are determined to be the ideal cutting parameters. It is possible to acquire MRR and SR as 6.4584016 g/min and 4.712 Ra for the output response parameters.

4.2. Full Factorial Design. It is possible to evaluate both the main effects and interactions in research using a full factorial design (FFD), which is an easy and methodical methodology. The growing importance put on an element or the rising

number of variables leads to a large rise in the number of test points, even if the design is constructive in nature when the number of variables and levels have been decreased, a factorial design is adequate for the research [18].

It is an absolutely critical parameter in every machining process since it determines how efficient the operation is going to be. Among the parameters studied, the abrasive feed rate was shown to be the most important. With an increase in abrasive feed rate, it was discovered that the MRR improved as in Figure 1. Due to an increase in feed rate, it takes less time to finish the products. The feed rate determines the amount of time it will take to perform the procedure completely. In conjunction with increased water pressure, the kinetic energy of the abrasive particles grows as well. In addition to having higher kinetic energy, abrasive particles have a better cutting ability as a consequence of their increased size, which enables more material to be removed in a given period of time. With increasing stand-off distance, it was discovered that the MRR rises. A divergent jet and low kinetic energy of abrasive particles, caused by the greater distance between the jet and the workpiece, may be attributed to this phenomenon. When the abrasive feed rate and transverse speed interact with one another, the metal removal rate first increases and then decreases with each other when the parameter level is raised to higher settings. With increasing stand-off distance and decreasing removal of material, the metal removal rate is somewhat lower. However, when transverse speed is adjusted, it rises with the decreasing removal of material. If we look at both the stand-off distance and the nozzle transverse speed, the value cuts with a surge in the rate of material removal for both of the input variables.

An increase in stand-off distance and abrasive feed rate results in a rise in surface roughness as shown in Figure 2. Depending on the pace at which the material is fed, cutting time might vary. Abrasive feed rates rise and new particles enter the cutting region, which means the abrasive particle has less time to cut the material. Abrasive particles have less time to cut the material with increasing abrasive feed rates, even if they have more or less cutting energy. This causes the surface to become more abrasive. The abrasive particles travel a greater distance as the stand-off distance rises. Increasing the spacing between the abrasive particles may result in a reduction in cutting capacity, resulting in a loss of sharpness in the material. So when abrasive particles move farther, their cutting effectiveness decreases because of intercollision between particles, as well as distance travelled. The surface finish is influenced by the pressure of the jets. The water surface becomes smoother as the pressure rises. Brittle abrasives break down into smaller ones when water pressure increases. The smoothness of the surface is due to a decrease in the size of the abrasives. Water pressure also causes particles to have more velocity, which results in a smoother machined surface. The bonding strength of any material can only be broken by a significant number of strikes per unit area under a specified amount of pressure. Surface roughness decreases as the rate at which the abrasive is applied rises. This is due to the fact that a higher abrasive flow rate enables a larger number of impacts and cutting edges to be

TABLE 3: Abrasive water jet cutting optimized results of AA5083 by MOTLBO.

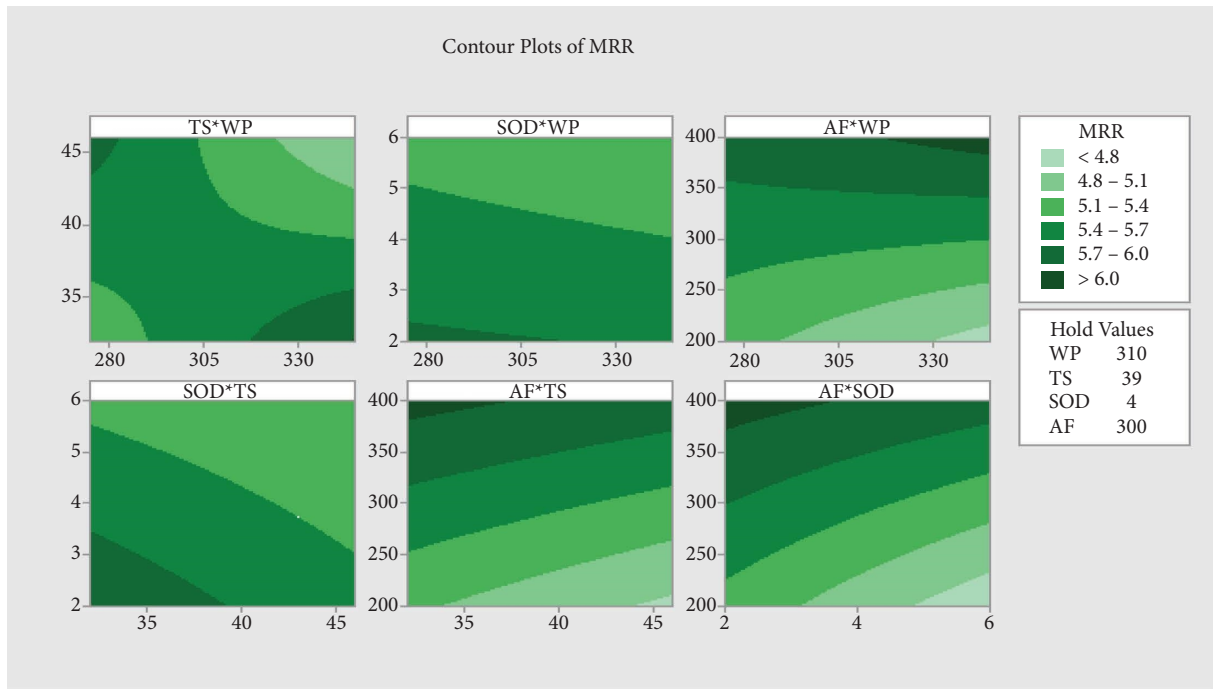| Water pressure (MPa)	Transverse speed (mm/min)	Stand-off distance (mm)	Abrasive feed (g/min)	MRR (g/min)	Surface roughness (Ra)
275	48	2	400	6.458	4.712

FIGURE 1: Contour interactions for metal removal rate.
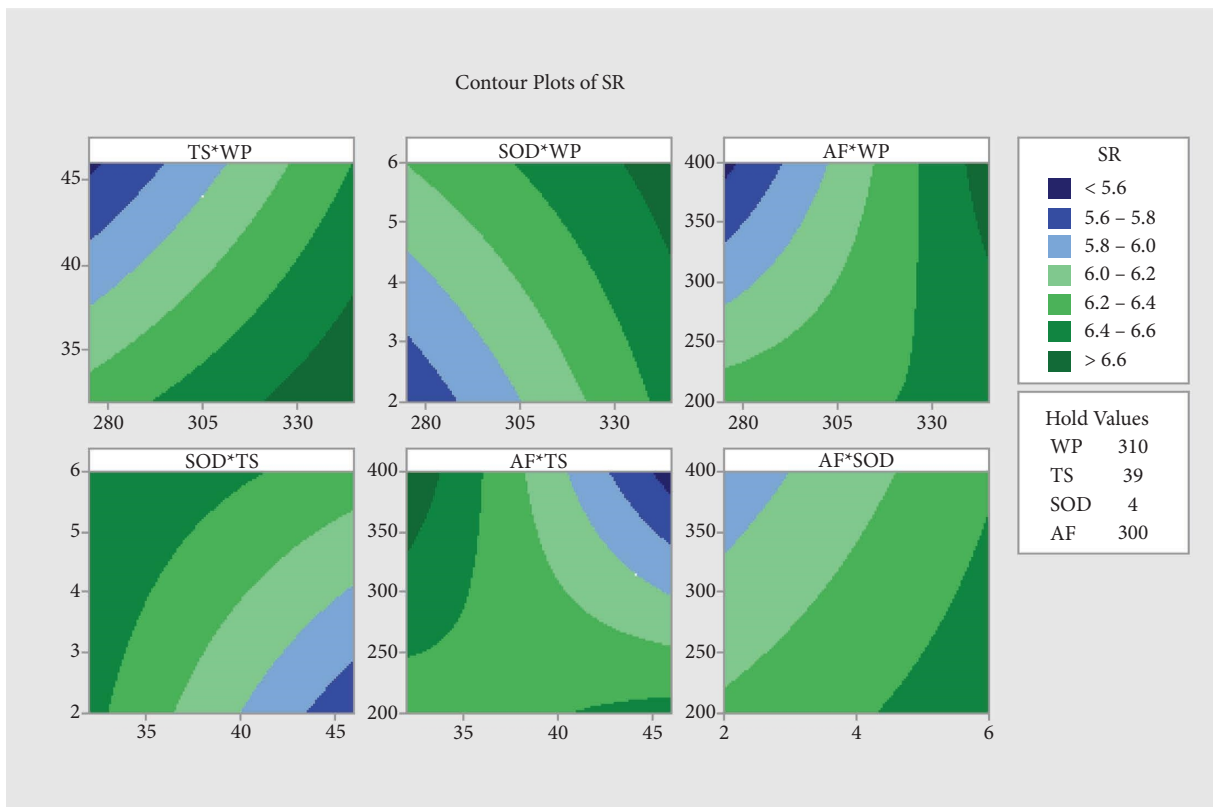
FIGURE 2: Contour interactions for surface roughness.

TABLE 4: Response optimization results of AA5083.

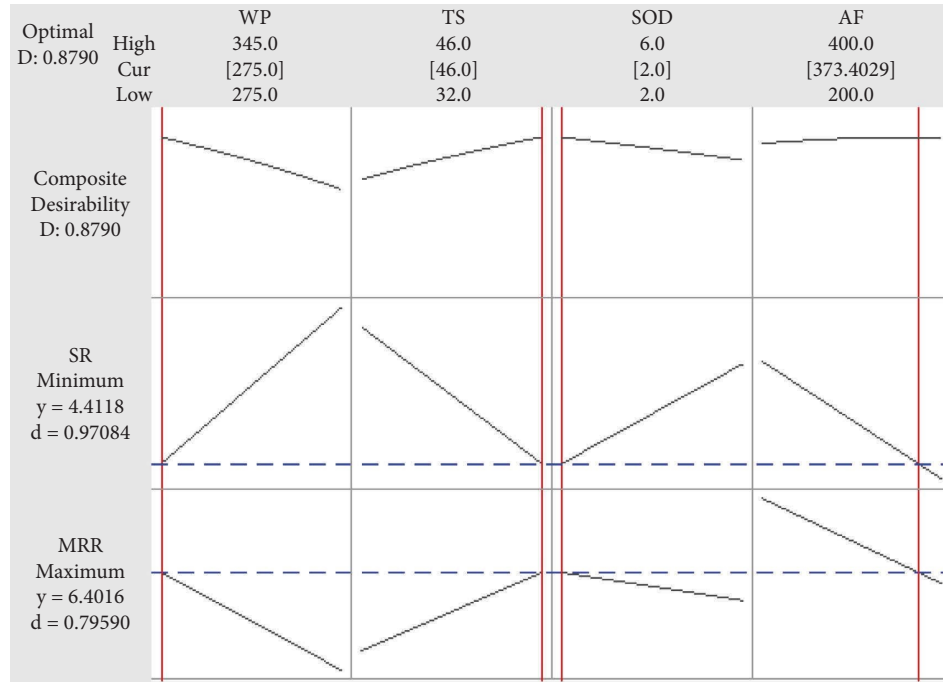| Solution	WP	TS	SOD	AF	SR Fit	MRR Fit	Composite Desirability
1	275	48	2	400	4.41179	6.40164	0.879028

FIGURE 3: Response optimization plot of AA5083.

produced per unit area of a workpiece. Abrasive particle hitting and overall kinetic energy are affected by the rate at which the abrasive particles are fed. The more abrasive is fed into the jet, the more cutting power it will have. Abrasives, on the other hand, clash with one another and lose their kinetic energy when the flow rate is increased. The surface becomes rougher as one moves away from the nozzle entry.

4.3. Response Optimization of Metal Removal Rate (MRR) and Surface Roughness (SR). Response optimization is a systematic approach that is used to determine the optimal mixture of input variable settings that work together to optimise the quality of a single answer or a group of responses. An optimal solution for the variable input combinations is provided by the response optimizer function in statistical analysis software, which also produces optimization graphic plots [19].

Table 4 summarises the optimal input parameters, metal removal rate, and SR findings for the AA5083 after the necessary optimization has been completed. Figure 3 depicts the response optimization plot. 275 MPa water pressure, a transverse speed of 48 mm/min, a stand-off distance of 2 mm, and an abrasive feed rate of 400 g/min are determined to be the ideal cutting parameters. It is possible to acquire metal removal rate and SR as 6.4016 g/min and 4.4118 Ra for

the matching output response parameters. Abrasive feed rate and nozzle transverse speed should be increased in order to get the best results while cutting these materials. Abrasive feed rate and traverse speed play a significant role in cutting parameter reduction and optimization for assessing outputs such as surface roughness and material removal rate, which are two of the most important metrics.

5. Conclusion

To satisfy the demands for greater accuracy and efficiency in production, abrasive water jet cutting is one of the unconventional cutting methods that have been successfully used in numerous industries. This work is based on the abrasive water jet cutting process with the design of experiments for minimising the surface roughness and improving material removal rate to a greater extent and the subsequent studies are exposed.

(i) Designs for testing AA5083 abrasive water jet cutting regression equations for metal removal rate and surface roughness were used.

Abrasive feed and traverse speed were found to be the most important abrasive water jet cut input parameters based on the findings also they play a significant role in cutting parameter reduction and

(i) optimization for assessing the output optimized parameter.

(ii) 275 MPa water pressure, a stand-off distance of 2 mm, a transverse speed of 48 mm/min, and an abrasive feed rate of 400 g/min are determined to be the ideal cutting parameters.

(iii) It is possible to acquire metal removal rate and surface roughness as 6.4016 g/min and 4.4118 for the matching output response parameters. Abrasive feed rate and nozzle transverse speed should be increased in order to get the best results while cutting these materials play a significant role in cutting parameter reduction and optimization for assessing the outputs.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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