Optimizing Abrasive Water Jet Machining Parameters on Cutting Hybrid Metal Matrix Composites Al7075 by Genetic Algorithm

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Abstract

Hybrid Metal Matrix Composites (MMC) Al7075 is a difficult-to-cut material that required non-conventional machining to manufacture automotive, aerospace, and defence components. The composite with minimum Bottom Kerf Width is much desire than minimum Top Kerf Width by the industries. Furthermore, the material cut with less defective work piece can be achieved by Abrasive Water Jet Machining (AWJM), compared to other nonconventional machining. The minimum kerf width lessens the energy used and waste resulted. Moreover, cutting Hybrid MMC Al7075 by AWJM, adding the advantages such as of good quality cutting of composite material, lessen water usage and waste production. These facts formulated that this study aims to search the minimum TKW for three types of Hybrid MMC Al7071 composites machined by AWJM. The data in this study used to model machining parameters as the input and TKW as the output using regression analysis. The model used as fitness function for Genetic Algorithm (GA) to search the minimum TKW. And from this search result, the optimal machining parameters can be determined. Finally, the result of experimental data is compared to the search data. The comparison confirmed that by GA, lesser minimum TKW is obtained, with the lowest value is 6.93% decreased.

Keywords: Abrasive water jet machining, genetic algorithm, top kerf width

1.0 Introduction

Hybrid Metal Matrix Composite AL7075 usage has attracted many manufacturing industries in producing automotive, aerospace, and defence components. The material usage is increasingly replaced conventional material due to the better qualities. The good composite qualities include good dimensional stability at increased fatigue resistance, elevated temperatures, high hardness, high stiffness, better wear and creep resistance (Sambathkumar, Navaneethakrishnan, Ponappa, Sasikumar & Arunkumar , 2016; Bains, Sidhu & Payal, 2016). Hybrid MMC combines a minimum of three materials with atomic bonding among them in the composite (Ahamed, Asokan & Aravindan, 2009). And for Hybrid MMC Al7075, Aluminium Alloy Al7075 material is harder with reinforced materials i.e. TiC and B_4C. The mixed of these materials, developed heterogeneous material that each material property acts independently. The composites can be classified by the percentage composition of TiC and B_4C mixed into the alloy. These features make Hybrid MMC Al7075 is in the difficult-to-cut material type to the manufacturing industries. Furthermore, as the fabrication of the composite is much complex than conventional materials, thus the composite price is much higher in the market. Besides, the mentioned industry components required the material in large size of work piece, this resulted considerable amounts of waste that increased manufacturing cost. Therefore, a nonconventional machining process is required, such as laser, electrical discharge machining (EDM), ultrasonic machining, and Abrasive Water Jet Machining (AWJM).

In this study, AWJM is applied due to the machining is preferred by manufacturing industries for its versatilities and rapid operation, and also produce good quality work piece. However, other nonconventional machining resulted a number of defects, such as recast layer, dross attachment and thermal weakening (Sasikumar, Arulshri, Ponappa & Uthayakumar, 2016). Besides, machining by the laser beam is constrained by the work piece height (Garg, Jain & Bhushan, 2013); EDM machining is only workable on the metallic work piece; ultrasonic machining is a slow, time consuming process and tool wear rate is very high even greater than the metal removal rates expected from the process (Garg, Jain & Bhushan, 2012). Nevertheless, AWJM has no problem these issues (Parikh & Lam, 2009).

AWJM operates by means of a fine and high-velocity slurry jet, resulted from the mixed of abrasive particles to a water jet as an erosion medium and ejected by an orifice (Wantuch, Kudelski & Nieciąg., 2013). Each abrasive material particle acts like a cutting tool point that provide the erosive force (Guptaa, Pandey, Garg, Khanna & Batra, 2014). The erosion medium with ultra-high pressure provides sufficient force for an erosion went to a small orifice to form a water jet (Momber & Kovacevic, 2012). AWJM able to cut with low and specific cutting forces (Srinivasu, Axinte, Shipway & Folkes, 2009), that producing high quality work piece and cut the work piece better than other nonconventional machining. This is due to the machining imposes minimal stresses on the work piece, is less sensitive to material properties, and is a contact less machining process (Vikram & Babu, 2002) that fasten the machining operation. Hence, the machining makes complicated shape of cuts and in a small kerf width (Kminiak & Barcík, 2011) on difficult-to-cut materials possible. Furthermore, AWJM is the environmental friendly technology. The low and specific force by AWJM results the generated waste is less (Selvan & Raju, 2012). This is crucial as AWMJ machines expensive material, and the number of manufacturing industries use is growing because of the machining has a wide range of applications (Krajcarza, Bańkowskia &

Młynarczyka, 2017). Besides, the heat amount generated by AWMJ is negligible (Krajcarz, 2014; Perzel et al., 2017), thus making the process is safe for the material and the worker. AWJM also generates no radiation emission and the noise levels are within human acceptance range from 85 to 95 dB (Palleda, 2007). These features are the list versatility of the machining.

The AWJM is comparatively better than other nonconventional machines in machining Hybrid Metal Matrix Composite Al7075, but less study conducted on this subject. Sasikumar et al. (2016) literature survey finds there are very few papers on the AWJM parameter study and optimization on Hybrid MMC Al7075 MMCs' machining. Hence, the study of these matters support in discovering the material machined by AWJM fullest potential.

In contrary, researches on other material machines by AWJM attracted by many in number of areas. Particularly the study of work piece quality on kerf geometry (Doreswamy et al., 2014; Sasikumar et al., 2016; Guptaa et al. 2014; Karakurt, Aydin & Aydiner, 2014). The kerf is a width of cut made by the operation describes how much material was removed as it cut through the plate. And manufacturing industry requires consistence kerf formation and minimum kerf width (Dubey & Yadava, 2008). For the industries, quality kerf formation features are kerf taper angle, top kerf width, and bottom kerf width and kerf deviation (Sharma, Yadava & Rao, 2010).

In order to have the optimal machining parameters values the maximum or minimum output be determined such as work piece qualities, defective qualities, and amount of waste. For the matter, numerical optimization can be utilized and considered in this study. In numerical optimization, the input is the machining parameters and the output is the work piece qualities. The input-output relation is optimized automatically by an algorithm, to get the desired output. Besides, based on the desired output, the optimal input parameters can be determined. Genetic Algorithm (GA) is selected for the optimization because of GA is the current trend in soft computing that able to search automatically on non-linear input-output relation. GA usage is believed to have more significant result, i.e. Top Kerf Width (TKW), compared to experimental results.

Based on the aforementioned facts, this paper aims to find the optimal machining parameters based on the minimum TKW. This optimization study applied on three types of Hybrid MMC Al7075 composites machined by AJWM. The organization of this paper is as follows. Previous Studies in section 2, discusses this study trend in order to reveal the gap. Methodologies deliberation is covered in section 3 and 4 for Data Acquisition and Regression Analysis, and Genetic Algorithm consecutively. Result and Discussion elaborated in section 5, and ended with Conclusion in section 6.

2.0 Previous studies

Research based on AWJM attracted many researchers in a number of areas. Number of researchers focused on the input or machining parameters of AWJM. For instance, Abrasivo, (2011) studied with the effect on velocity or cutting speed of AWJM. The selection of machining parameters concentrated on abrasive material usage is conducted by Krajcarz & Spadło, (2015) and Cenac et al. (2015). Moreover, the study on related the output parameters include on the heat generated by AWJM operation (Perzel et al., 2017) and on machined work piece qualities such as surface roughness (Selvan & Raju, 2012; Muniappan, Thiagarajan & Somasundaram, 2017), work piece distortion (Hlavac et al., 2012), and depth of cut (Karakurt, Aydin & Aydiner, 2012). Besides, the interest on work piece quality of kerf geometry has attracted many researchers (Deepak Doreswamy et al., 2014; Sasikumar et al., 2016; Guptaa et al., 2014; Karakurt, Aydin & Aydiner, 2014). This trend shows the great potential of kerf geometry, as a subject study and justified the study of this paper.

There are studies on Hybrid MMC Al7075 using other than machining by AJWM. The material used in previous researches can be classified into property qualities (Sambathkumar et al., 2017; Anitha & Balraj, 2017; Nagabhyrava et al., 2017; Sambathkumar et al., 2016); material used in the manufacturing operation (Dhanalakshmi, Mohanasundararaju, & Venkatakrishnan, 2014; Balaji, Sateesh & Hussain, 2015); and machining optimization (Muniappan, Thiagarajan, & Somasundaram, 2017; Rao, Ramanaiah, Rao, Sarcar & Kartheek , 2016; Rao, 2016; Dhanalakshmi, Mohanasundararaju, Venkatakrishnan & Karthik, 2018; Lal, Kumar, Khan & Siddiquee, 2015). GA optimization of machining parameters and applied Hybrid MMC Al7075 material mechanical properties as the output parameters studied by Mahanta et al. (2018); Rao, Geethika & Krishnaveni (2017). And the rest researchers on a similar line of study using statistical based optimization approaches such as Taguchi Method and Grey Relational Analysis. The use of optimization allows estimating the optimal input parameters in search for the best output quality.

Kerf geometry as the output parameters for optimization by GA is so popular because of the algorithm versatility. The studies include the kerf geometry by Wire Electrical Discharged Machining (Altug, Erdem & Ozay, 2015; Varun & Venkaiah, 2015; Shandilya & Tiwari, 2014) and Laser Beam cutting (Shrivastava & Pandey, 2018; Nukman, Hassan & Harizam, 2013; Pandey & Dubey, 2013; Shrivastava, Singh & Shrivastava, 2019; Gautam & Mishra, 2019). In addition, there is study of particular kerf geometry, i.e. kerf taper, kerf deviation, and kerf deviation (Shrivastava & Pandey, 2018). Shrivastava, Singh & Shrivastava (2019) studied on more detail kerf width, i.e. Top Kerf Width and Bottom Kerf Width,that used a Laser Beam to cut Inconel-718 material work piece. These facts are thus GA is exploitable in study on optimizing machining parameters of Hybrid

MMC Al7075 material and considerable the use of TKW as the output parameter in this study.

Sasikumar et al. (2016) studied Hybrid MMC Al7075 material machined by AWJM begin by fabricating the material using two steps stir casting and cut it into 70mm x 50mm x 10mm. Then, the AWJM is used to cut materials with traverse speed 0-15 m/min, along 25mm long slot on 10mm thick material. Afterward, the measurements are done that include the Top Kerf Width using optical microscope. Subsequently, the measurements were analysed by Analysis of Variance (ANOVA). ANOVA result is used to evaluate the input contribution in influencing the output. Successively, a mathematical model is developed by Regression Analysis. And finally the model is examined by a confirmation test and modified to simplify the model. By the studied, this study is different that acts as the sequel, which focusing to gain optimal inputs in order to has the best minimum output, i.e. Top Kerf Width.

3.0 Data acquisition and regression analysis

Data tapped from Sasikumar et al. (2016), with two composition materials which Aluminium Alloy Al7075 is the based material and the reinforced materials are Titanium Carbide (TiC) and Boron Carbide (B_4C). The composite is fabricated by two-step stir casting method – two steps heating on the melting of Al7075 and mixing with the reinforced materials. The casting resulted atomic bonding among Al7075, TiC and B_4C materials. Three types of composites of Hybrid MMC Al7075 are applied in the study. And the difference among the three composites are the value reinforced material composition of Titanium Carbide (TiC) and Boron Carbide (B_4C) at 2.5%, 5%, and 7.5%. The composite hardness increase is believed relatively by the increase of reinforced material percentage mixed into the alloy. The experimental setting to AWJM to cut 25mm long slot on work piece with 10mm thick. The abrasive material of garnet with 80 mesh size and the orifice with a carbide nozzle insert of 0.723 mm in diameter. The abrasive mass flow rate is 5g/s throughout the experiment. Table 1 shows the input and output parameters used and the experimental setting in the study based on the level. The kerf width was measured using optical microscope. This is the initial stage of the whole stages in this paper's methodology shown in Figure 1. Based on the experiment, the minimum TKW is obtained and shown in Table 2. The regression models are also obtained from Sasikumar et al. (2016). And in this study, the regression models used as fitness functions in Genetic Algorithm to obtain the optimal inputs out of the minimum output. Finally, the obtained result from the optimization is evaluated and validated.

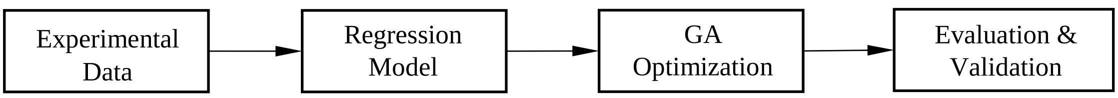

Figure 1: The methodology

Table 1: Parameters use and experimental setting in this study (Modified from: Sasikumar et al., 2016)

Parameter	Symbol	Unit	Level 1	Level 2	Level 3
Input 1: Water jet pressure	x_1	MPa	240	260	280
Input 2: Standoff distance	x_2	mm	1	2	3
Input 3: Jet traverse speed	x_3	mm/minute	30	60	90
Output 1: TKW for Al7075 + (2.5%TiC+2.5%B_4C)	y_1	mm	-	-	-
Output 2: TKW for Al7075 + (5%TiC+5%B_4C)	y_2	mm	-	-	-
Output 3: TKW for Al7075 + (7.5%TiC+7.5%B_4C)	y_3	mm	-	-	-

Table 2: Experimental result (Modified from: Sasikumar et al., 2016)

Material	Al7075 + (2.5%TiC+2.5%B_4C)	Al7075 + (5%TiC+5%B_4C)	Al7075 + (7.5%TiC+7.5%B_4C)
Minimum	0.940	0.890	0.750

$$y_1 = 3.34 - 0.02606x_1 + 0.021991x_3 + 0.038056x_2 + 0.0000667{x_1}^2 - 0.0000819x_1x_3 + 0.0000417x_1x_2 - 0.0000352{x_3}^2 - 0.00333{x_2}^2 \qquad eq.1$$

$$y_2 = 3.59278 - 0.02675x_1 + 0.01238x_3 + 0.039444x_2 + 0.0000667{x_1}^2 - 0.0000681x_1x_3 + 0.0000167{x_3}^2 - 0.00167{x_2}^2 \qquad eq.2$$

$$y_1 = 0.501667 - 0.00286x_1 + 0.014694x_3 + 0.028333x_2 + 0.0000167{x_1}^2 - 0.0000625x_1x_3 - 0.000037{x_3}^2 - 0.00167{x_2}^2 \qquad eq.3$$

Based on regression analysis (Sasikumar et al., 2016), regression coefficients are obtained and used to design mathematical models to estimating the TKW value. The advantages of using the analysis allow the corresponding to a specified amount of the input and outputs; the analysis of confidence is used to determine the value of statistic significant differences and correlation rate, and poor parameters are excluded to a model. Three of mathematical models are used in this paper. Each model represents the type of Hybrid MMC Al7075 - Al7075 + (7.5%TiC+7.5%B_4C); Al7075 + (5%TiC+5%B_4C); Al7075 + (2.5%TiC+2.5%B_4C). These models are stated in following equations (eq.) – eq.1, eq.2, and eq.3. The input parameters are Water Jet Pressure (x_1, MPa), Standoff distance (x_2, mm), and Jet Traverse Speed (x_3, mm/minute). These equations confirmation test with the error rate is less than 5% between the experimental and mathematical models.

4.0 Genetic algorithm

John Holland (Booker et al., 1989; Holland, 1992) was coined the concept and structure of the Genetic Algorithm design. GA is the pictorial of Darwin's theory of the natural genetic evolution system (McCall, 2005).

Because of the effectiveness of the algorithm, GA is among the most popular used evolutionary algorithms for optimization problems (Chen et al., 2017). In this study GA is used as a search technique to obtain the minimum of the objective function. The optimization aims to get the best optimal AWJM machining parameters which lead to minimum TKW of Hybrid MMC Al7071 composite. The fitness function or objective function is directly derived from experimental data in the second step.

Table 3: Standard genetic algorithm

```
Generate initial set of population and pre-set parameters
while stopping criteria is not reached do
        for each chromosome is population do
            Calculate fitness of chromosome
        Select chromosomes for Crossover
        Perform Crossover
        Perform Mutation
        Replace the population with new chromosomes
return Best fit chromosome
```

Table 4: GA pre setting

Parameters	Population size	Mutation rate	Crossover rate
Setting Value	100	1.0	0.8

The step in GA, involve proposing generation of chromosomes at random for the initial population size. The number is open and pre-set, and set together with the crossover and mutation rate as in Table 4 before the algorithm is run. These values are encoded to each individual in the population. The three codes attached also known chromosome is composed in binary (0 or 1) that has number of decision variables. The fitness function evaluates the effectiveness of each chromosome. At the end of the algorithm runs, optimization of continuous parameter presents the best output at optimal input parameters. The standard sequence of GA is shown in Table 3.

The GA changes each parameter value into a bit string in sequence of 1s and 0s to derive the chromosomes (Jafari-Marandi & Smith, 2017). Through the genetic operations, i.e. Selection, Mutation, and Crossover, the chromosomes improve each generation and end at stopping condition – the chromosome change in generation has no improvement. For constructing optimization study, the considered selection of decision variable is Water Jet Pressure (x_1), Standoff Distance (x_2), and Jet Traverse Speed (x_3). Statistically, based Analysis of Variance (ANOVA) with significance level of 0.05 or 95% confidence level, the p-values are satisfied to these variables as significant parameters influencing the TKW. The ANOVA resulted the p-values are less than 0.05 for the three parameters – x_1, x_2, and x_3. The three selected different objective function that represents TKW for three Hybrid MMC Al7075 composites i.e. y_1 for Al7075 + (2.5%TiC+2.5%B_4C); y_2 for Al7075 + (5%TiC+5%B_4C); and y_3 for Al7075

+ (7.5%TiC+7.5%B_4C). These objective functions stated in eq.1, eq.2, and eq.3. affect

The constrains which effected the optimal x_1, x_2, and x_3 selection of this study is taken into account. In the first place, the constraints are within the parameters permit limit that allow the machining to run as follows. The constrains only involve on the upper limit and lower limit of the parameters.

$$240MPa \leq x_1 \leq 280MPa \qquad eq.4$$
$$1mm \leq x_2 \leq 3mm \qquad eq.5$$
$$30mm/minute \leq x_3 \leq 90mm/minute \qquad eq.6$$

Crossover is an operation of splitting each chromosome into two parts, thus the chromosomes to be doubled. Besides, in crossover technique one part of the chromosome is paired and combined with one part of another chromosome (Zain, Haron & Sharif, 2010). The selection of one part of two chromosomes which is the fittest one is known as selective operation. This combination is to form new chromosomes. Therefore, the total number of initial chromosomes and new chromosomes were crossover will return the same. The new chromosomes are expected to inherit good genes out of earlier chromosomes. The repetition run of crossover eventually leading to convergence to an overall good chromosome (Kartci et al., 2019). The attempt is to see the whole spectrum of the GA potential; thus this study applies two types of crossovers. Thus, this represents two strategies which are (i) Multi Objective Optimization; and (ii) Single Optimization runs by sequential for y_1, y_2, and y_3.

Mutation is a process of the flipping the bit in a chromosome. The process alters chromosome randomly to create a better chromosome (Hong et al., 2018). Randomness in mutation that produce that better chromosome, but at very small degree of change in the chromosome. By mutation, the process resulted the search escape from local optima (Hamamoto et al., 2018), thus global optima will be obtained.

To successfully apply GA to a problem, each of the processes has to be tailored so that the fittest chromosome is generated at the operating end. This is due to the new generated chromosomes are evaluated by the pre-set fitness criterion. The evaluation process is repeated until chromosome with the best criteria is obtained (Bouktif et al., 2018). After the process of evolution is done, the fittest chromosome is returned as a global optimal solution to the given problem (Elbaz et al., 2019).

For each individual that resulted from objective functions are evaluated based on following points. For this study, GA result is evaluated based on the issues concerned are as follows:

(1) The GA predicted minimum TKW values are expected to be lower than the minimum TKW value through the experiment. Here, four minimum TKW values are GA generated. Specifically, through GA Multi Optimization and Single Optimization strategies.

(2) The optimal machining of AJWM conditions that lead to the best fitness function which is obtained at the last iteration of the GA is expected to be in the same range of values as those with the machining conditions applied in the experiment.

The model validation is designed in optimization study is in a number of ways. The most common used of test is the experimental validation applied by Gosh et al., (2018), Rosado et al. (2013), Satish Garg, Banwait & Ravneet Kumar (2013), and Roy et al. (2018). Alternatively, the validation also can be conducted by comparing the finding from the optimization approach and the generated values by an objective function (Zain, Haron & Sharif, 2010; Zain, Haron & Sharif, 2010; Kia et al., 2012). By the limitation of this study using data from another study, thus this study applied the second approach – comparing between the objective function and the optimization generated approach.

5.0 Result and discussion

For the issue, by referring to Table 4, the minimum TKW values in mm for the real machining experiment is 0.940 for y_1, 0.890 for y_2, and 0.750 for y_3. Comparatively, Multi Objective optimization by GA, gained lower values for minimum TKW – 0.8963 for y_1, 0.8297 for y_2, and 0.7456 for y_3. Similarly, Single Objective GA optimization, minimum TKW is 0.8910 for y_1, 0.8283 for y_2, and 0.7472 for y_3. These finding shown in Figure 2.

Table 5: The result of experiment and optimization

		unit	Al7075 + (2.5%TiC+ 2.5%B_4C) for y_1	Al7075 + (5%TiC+ 5%B_4C) for y_2	Al7075 + (7.5%TiC+ 7.5%B_4C) for y_3
Experiment Result	**y**	mm	0.940	0.890	0.750
	x_1	MPa	280	280	280
	x_2	mm	1	1	1
	x_3	mm/minute	90	90	90
Multi Objective Optimization	**y**	mm	0.8963	0.8297	0.7456
	x_1	MPa	246.2008	246.2008	246.2008
	x_2	mm	1.0001	1.0001	1.0001
	x_3	mm/minute	88.8998	88.8998	88.8998
Single Objective Optimization	**y**	mm	0.8910	0.8283	0.7472
	x_1	MPa	250.9584	246.8619	249.7683
	x_2	mm	1.0000	1.0000	1.0001
	x_3	mm/minute	89.8422	89.9218	87.5573

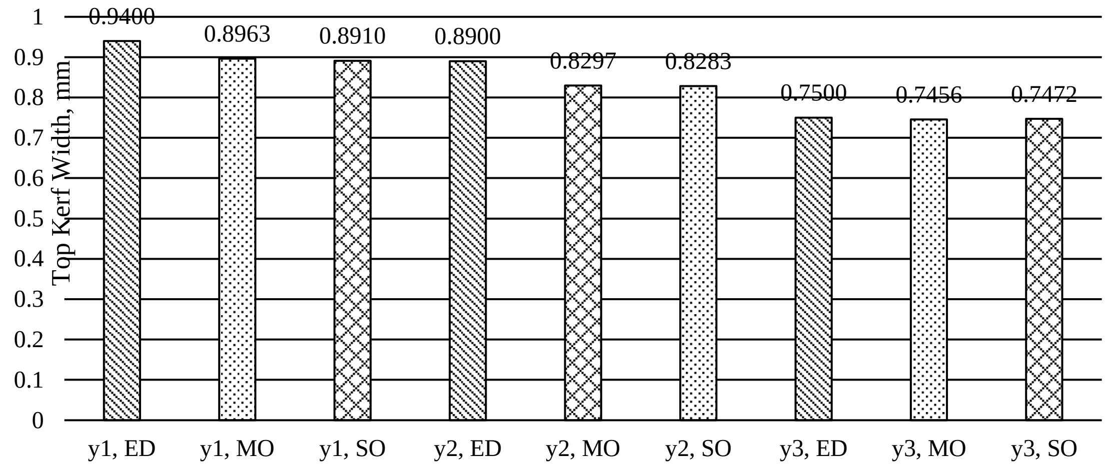

Figure 2: The output y_1, y_2, and y_3 (mm) results of experimental (ED), multi objective GA optimization (MO), and single objective GA optimization (SO)

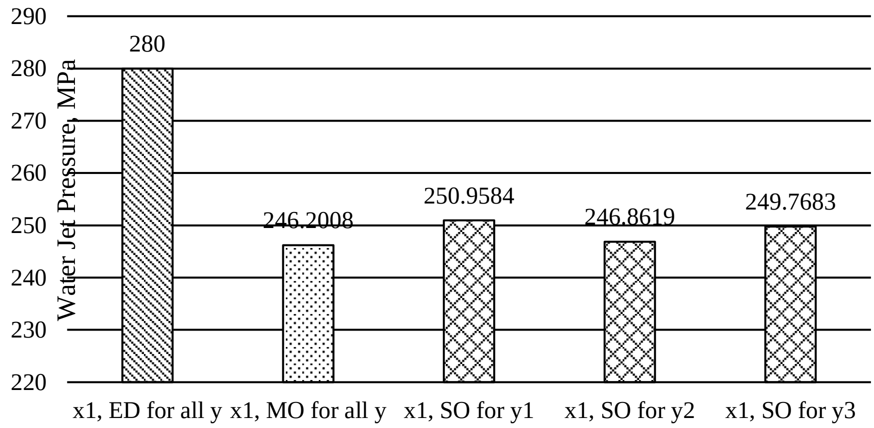

Figure 3: The optimal input water jet pressure (x_1, MPa) results of experimental (ED), multi objective GA optimization (MO), and single objective GA optimization (SO)

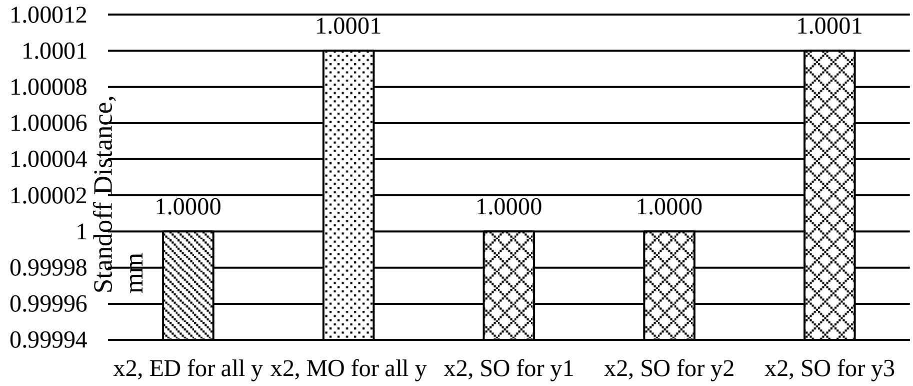

Figure 4: The optimal input standoff distance (x_2, mm) results of experimental (ED), multi objective GA optimization (MO), and single objective GA optimization (SO)

The second issue is on input parameters, is tabled in Table 5 and pictured in Figure 3, Figure 4, and Figure 5. The range of values for the actual setting of cutting conditions that have been applied in the experiment are 240 to 280 MPa for Water Jet Pressure, 1 – 3 mm for Standoff Distance and 30 – 90 mm/minute for the Traverse Speed. Based on Figure 3, the optimal Water Jet Pressure results are estimated by Multi Objective GA technique is 246.2008, and Single Objective are 250.9584 for y_1, 246.8619 for y_2 and 249.7683 for y_3. Besides, in Figure 4, the optimal Standoff Distance results by Multi Objective GA is 1.0001, and Single Objective are 1 for y_1, 1 for y_2 and 1.0001 for y_3. And for Traverse Speed in Figure 5, results by Multi Objective GA is 88.8998, and Single Objective are 89.8422 for y_1, 89.9218 for y_2 and 87.5573 for y_3.

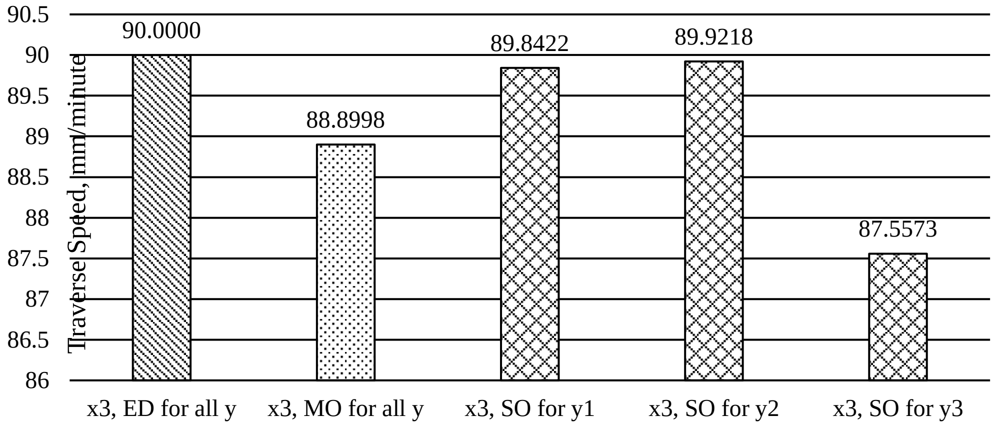

Figure 5: The optimal traverse speed (x_3, mm/minute) results of experimental (ED), multi Objective GA optimization (MO) and single objective GA optimization (SO)

Though, multi-objective optimization studies often contain many solutions or outputs, thus this matter requires Pareto Front analysis. The analysis needed when multiple non dominated outputs generated and selection need to be made. The Pareto Front pictures the outputs distribution by aggregate objective function in varying numerical scalar weights. The picture on graph helps a decision maker to make the decision to pick the best output. However, multi objective optimization with GA in this study resulted single outputs, thus the analysis is not needed.

6.0 Conclusion

These findings are confirmed that GA is effective for estimating better result in searching the minimum TKW point compared to experimental results. Comparatively, the GA search values are lower than the minimum TKW values by experimental, i.e. 0.94 mm for y_1, 0.84 mm for y_2, and 0.75 mm for y_3. The values are decreased by Multi Objective GA at 4.65% for y_1, 6.78% for y_2, and less than 1% for y_3 i.e. 0.59%. And by Single Objective GA the decreased are 5.21% for y_1, 6.93% for y_2, and also less than 1% for y_3 i.e. 0.37%.

This study also discovered the optimal value for each of the machining parameters recommended by the GA which lead to the minimum TKW value. The advantage of the recommended machining parameter value is within allowable value range. The allowable range is the experiment set up and acceptable for the AWJM machine used in this study. By GA search of minimum TKW, the optimal value estimation potential beyond the gain by experimental study can be achieved. The experimental study optimal values are explicitly on the experiment used setting values.

The study's results also show the pattern of the higher the percentage of reinforced material mixed into the Al7075 alloy, the smaller the size of the minimum TKW. Logically, this interprets that the difficulty to cut harder composites which resulted smaller minimum TKW size. Hence, this result rationalized that this study is experimentally and numerically well-grounded.

An issue which can be highlighted is related to the machine parameter values used in this study that resulted the lowest minimum TKW value come from the same source. This is from the observation on both Multi Objective GA and Single Objective GA recommended result values. Based on the observation, the recommended result can be generalized that the optimal machining parameter values are Water Jet Pressure about 246 to 250 MPa, Standoff Distance at 1 mm, and Traverse Speed about 88 to 90 mm/minute.

For future works some improvements could be made to discover wider potential in this scope of study, such as under highly constrained cases for the value of Water Jet Pressure, Standoff Distance, and Traverse Speed. Besides, other output parameters should be considered such as Bottom Kerf Width, Kerf Taper Angle, Surface Roughness, and Work Piece Distortion. And abrasive material characters and AWJM machine orifice size are proposed for the input.

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