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A Generic Framework for Modeling and Optimization of White Layer Thickness in WEDM during Machining Al7075/SiC$_P$ Metal Matrix Composites

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Abstract: This work proposes an efficient strategy for modeling and optimization of white layer thickness of wire electrical discharge machined SiC particulate reinforced Al7075 metal matrix composites. A generic and systematic framework is implemented to facilitate the modeling and determination of optimal process performance characteristics through investigation of interactions of the variety of process control factors. To machine the advanced materials like metal matrix composites, the available details may not be adequate and it drives to derive them by a series of experimentations. White layer thickness, among the numerous performance characteristics of the WEDM process, has its importance while representing the machined surface quality of the component. The white layer makes the machined surface rough, hard and contains lot of micro-cracks. Therefore, the employed modeling and optimization methodology improves the performance of the process by suggesting appropriate process environment conditions which can reduce the whit layer thickness and facilitates the process engineers to make the components with the designed surface quality. Based on Taguchi's robust orthogonal design of experiments, the white layer thickness is measured and formulated using response surface methodology. Consequently, powerful artificial intelligence called genetic algorithms (GA) is implemented to determine the best combination of the control variable settings. The derived optimal process variables are conformed to the experimental results. These results reveal the compliance of the proposed model representing the thickness of the white layer thickness during the process. Also, the resulted optimal parameters are capable of machining the Al7075/SiCP MMCs more efficiently and with better surface quality.

Keywords: Al7075SiC$_P$ MMC; White layer thickness; WEDM, Modeling; Optimization.

1 INTRODUCTION

Wire-electrical discharge machining (WEDM) has proven as an effective non-traditional machining process for producing complex contours over the components made of difficult-to-cut materials. In the present aerospace and automobile industries the metal matrix composites (MMC) as advanced materials found potential application for the specialized components. While machining MMCs, Lau et al. [1,2] made several comparative studies between EDM wire-cut and laser cutting processes and stated as the former produces better surface quality, edge accuracy and little heat-affected zone while the latter resulting the poor cut edge profile and larger heat-affected zone.

However, WEDM has a slower machining rate for all the tested composite materials. Yue et al. [3] made an experimental study on WEDM of Al_2O_3 particulate reinforced aluminium composites to investigate the surface morphologies of the machined components under various machining conditions. This investigation found a considerable variation in the machined surface topographies rather than the surface roughness. Guo et al. [4] investigated the effect of various process Control parameters on the WEDM performance measures for machining Al_2O_3 particulate reinforced MMCs.

WEDM is a thermo-electric metal removal process in which material is eroded by the application of a series of electric sparks between the work piece and the wire electrode in the presence a continuously supplied dielectric fluid. During machining the metal gets melted and flushed away from the cutting zone by dielectric fluid. Due to the high current and voltages lead to form numerous and wide debris and are not completely washed from the cutting zone. The residuals of the debris recast over the machined surfaces and forms a layer called recast layer or white layer. The white layer makes the machined surface rough, hard and contains lot of micro-cracks.

According to Ramasawmy et al. [5] the white layer contains several globules, pock marks, micro-cracks etc, and their density depends mainly on the machining conditions. In WEDM process, the factors like surface roughness, white layer thickness and the surface cracks are the considerable factors while improving the surface

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Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

quality of the machined components. The surface quality of the component increases the properties of fatigue strength, wear and corrosion resistance of the machined component [6].

Usually, the manufacturers of the WEDM machines provide the database of electrode materials and the operational details and process control variables for most regularly used materials only. The information provided by the manufactures of WEDM is not adequate for machining such advanced materials. Hence, the database of feasible control variables of WEDM for machining MMCs could widen their applications in industries. In this consequence, one of the most significant machined surface characteristics of WEDM process is white layer thickness. Pulse-on time is the main significant factor for the white layer [7]. From the literature survey, it has been observed that no extensive work has been done to analyze the white layer thickness of the work material Al/SiC_P MMCs during WEDM. Therefore, an extensive experimental work is needed to completely understand the individual and interactive effects of various WEDM control parameters. This investigation aimed to provide the empirical model to predict the white layer thickness (WLT) in terms of the most significant WEDM control parameters for Al7075/SiC_P MMC using response surface methodology (RSM) and to find the optimal control variables which machine the composite with minimum possible kerf using genetic algorithms (GA). ANOVA is conducted to analyze the individual and the interactive significance of the chosen control factors on the white layer thickness.

2 EXPERIMENTAL PROCEDURES

Initially, the design of experiments is employed to minimize the total number of experimental runs. From the literature survey, pulse-on time, pulse-off time and wire tension are selected as the process machining variables along with the particulate size and the volume fraction of SiC_P. Using the robust Taguchi's L_{27} orthogonal array consists of 27 experiments [12] are conducted to measure the white layer thickness. Then the machining experiments are conducted on a five-axis CNC-Wire Electrical Discharge Machine, Model Number CT 520A, made by Joemars Machinery and Electric Industrial Co.Ltd., Taiwan. SiC_P reinforced Al7075 metal matrix composites are used as work pieces for machining. These MMCs are produced by stir casting rout. The MMCs are produced with different particulate sizes as 25, 50 and 75µm reinforced each at distinct volume fractions as 5, 10 and 15%. The details of work specimens, the electrode and the other machining conditions are listed in Table 1. The levels of process variables are selected based on the literature and the pilot experiment as listed Table 2. The design of experimental matrix presented in Table 3. For each experiment, the thickness of the white layer is measured by using Computerized Optical Microscope, model GX51 inverted microscope made by OLYMPUS CORPORATION with the magnification range of 20µm.

These measurements of the white was considered at three different locations along the machined length in the perpendicular direction and the averages of them is considered as the final white layer thickness and are listed in Table 3. Fig. 1 shows the experimental setup used to measure the response white layer thickness and the Fig. 2 represents the white layer thickness width of the machined components.

3 PROPOSED FRAMEWORK FOR MODELING AND OPTIMIZATION

A systematic framework is adopted to develop the model and to determine the optimal machining conditions which minimizes the white layer thickness. Figure 3 presents the structure of the adopted framework. The procedure of the response surface methodology includes [8]:

1. Develop and simulate the design of experiments in the region where the path of the search has no substantial improvement in the response.
2. Compute the regression coefficients for the model:

$$\begin{aligned} Y = {} & b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 \\ & + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{44}x_4^2 + b_{55}x_5^2 \\ & + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{14}x_1x_4 + b_{15}x_1x_5 \\ & + b_{23}x_2x_3 + b_{24}x_2x_4 + b_{25}x_2x_5 + b_{34}x_3x_4 \\ & + b_{35}x_3x_5 + b_{45}x_4x_5 \end{aligned} \tag{1}$$

3. Using the developed model, estimate the nature of the stationary point of the response surface as the stationary point is one where the gradient vanishes.

This systematic procedure of RSM facilitates experimenter to study the process in detailed about necessary replications, optimum region of the response and choice of experimental designs.

Genetic algorithm (GA) is an effective evolutionary technique, which guides the direction search based on the nature of the objective function in the search space. The GA has been used in the area of machining MMCs by a verity of the machining process [9]. Basically GA works on three generic operators called selection, crossover and mutation. In the selection operation, the good strings in the mating pool are selected and carried to the crossover operation. The crossover operator hopefully creates the better new strings by recombination of the best strings together. Finally, the mutation operator alters the substring locally to hopefully create a better string. Hence one generation of the GA simulation is completed. The procedure repeated for all the generations.

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

Table 1: Machining conditions

S. No.	Description
1	Work piece (anode) : Al7075/SiCp
2	Tool (cathode) : Brass wire of diameter 250 μm
3	Work piece height: 6 mm
4	Cutting length: 75 mm.
5	Angle of Cut: Vertical
6	Location of work piece : centre to the table
7	Servo reference voltage : 35V
8	Average voltage gap maintained: 40V
9	Die-electric temperature: 25°C
10	Die-electric fluid: Distilled water

Table 2: Control factors and their levels

S.No.	Variable	Notation	Levels		
			1	2	3
1	Particulate size (μm)	X_1	25	50	75
2	Volume of SiC (%)	X_2	5	10	15
3	Pulse-on Time (μs)	X_3	5	7	9
4	Pulse-off Time (μs)	X_4	25	35	45
5	Wire Tension (gms)	X_5	1	5	9

Figure 1: Experimental setup for WLT measurement

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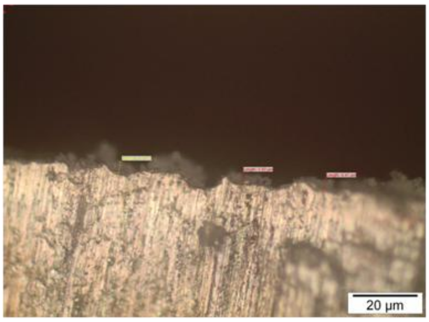

Figure 2: Schematic representation of WLT measurement

Table 3: Design of experimental matrix: Taguchi's L_{27} orthogonal array

S.No.	Coded control factor					WLT (µm)
	X_1	X_2	X_3	X_4	X_5	
1	1	1	1	1	1	3.580
2	1	1	2	2	2	3.585
3	1	1	3	3	3	3.589
4	1	2	1	2	2	3.573
5	1	2	2	3	3	3.553
6	1	2	3	1	1	3.605
7	1	3	1	3	3	3.535
8	1	3	2	1	1	3.577
9	1	3	3	2	2	3.595
10	2	1	1	2	3	3.562
11	2	1	2	3	1	3.551
12	2	1	3	1	2	3.620
13	2	2	1	3	1	3.533
14	2	2	2	1	2	3.579
15	2	2	3	2	3	3.598
16	2	3	1	1	2	3.556
17	2	3	2	2	3	3.56
18	2	3	3	3	1	3.564
19	3	1	1	3	2	3.535
20	3	1	2	1	3	3.585
21	3	1	3	2	1	3.599
22	3	2	1	1	3	3.561
23	3	2	2	2	1	3.563
24	3	2	3	3	2	3.568
25	3	3	1	2	1	3.544
26	3	3	2	3	2	3.534
27	3	3	3	1	3	3.594

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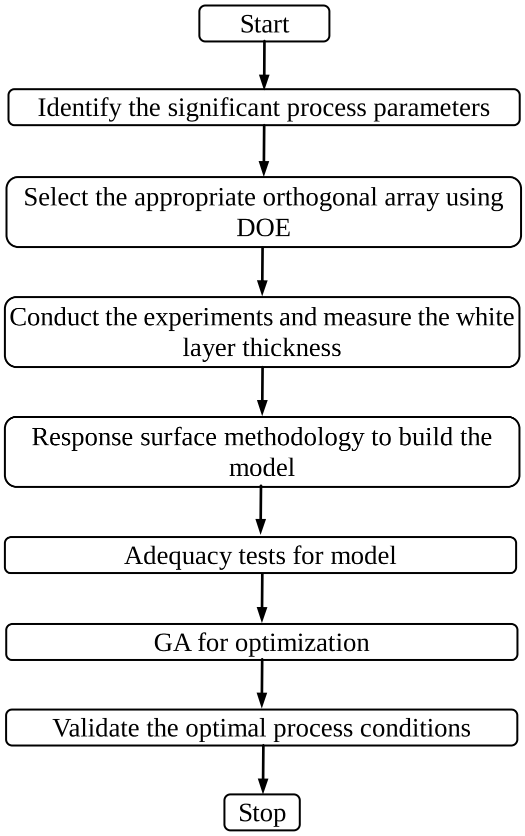

Figure 3: Proposed framework for modeling and optimization

4 MODELING OF WHITE LAYER THICKNESS

Using the measured values of the WLT the mathematical model is developed based on response surface methodology. This model relates the considered WLT with various control variable settings during machining Al7075/SiC_P. WEDM is such a complex process that interaction effects of the control variables are more significant on machining performances. Therefore the second order polynomial models are fitted for the output responses in terms of the coded variables. The postulated model can be represented in terms of regression coefficients as:

$$\begin{aligned}\mathrm{WLT} = {} & 3.57 - 0.0064x_1 - 0.0082x_2 + 0.021x_3 - 0.017x_4 + 0.0007x_5 \\ & + 0.0019x_1^2 - 0.0003x_2^2 + 0.0076x_3^2 - 0.0061x_4^2 - 0.0002x_5^2 \\ & + 0.0002x_1x_2 - 0.0004x_1x_3 + 0.0004x_1x_4 + 0.0003x_1x_5 - 0.0014x_2x_3 \\ & + 0.0015x_2x_4 - 0.0004x_2x_5 - 0.0015x_3x_4 + 0.0002x_3x_5 - 0.0004x_4x_5\end{aligned} \quad (2)$$

In the above equation x_1, x_2, x_3, x_4 and x_5 represent the logarithmic transformations for the control factors, particulate size, volume of particulate, pulse-on time, pulse-off time and wire tension respectively and they are given below:

$$x_1 = \frac{\ln(X_1) - \ln(50)}{\ln(75) - \ln(50)};\ x_2 = \frac{\ln(X_2) - \ln(10)}{\ln(15) - \ln(10)};\ x_3 = \frac{\ln(X_3) - \ln(7)}{\ln(9) - \ln(7)};\ x_4 = \frac{\ln(X_4) - \ln(35)}{\ln(45) - \ln(35)};\ x_5 = \frac{\ln(X_5) - \ln(5)}{\ln(9) - \ln(5)} \quad (3)$$

The above transformations are obtained by the following formula.

$$x = \frac{\ln(X_n) - \ln(X_{n0})}{\ln(X_{n1}) - \ln(X_{n0})} \quad (4)$$

where x is the coded value of any factor corresponding to its natural value X_n; X_{n1} is the natural value of the factor of the + level, and X_{n0} is the natural value of the factor corresponding to the base level or zero level.

5 ANALYSIS OF VARIANCE

The developed quadratic response model is confirmed for its adequacy by conducting the following statistical tests. Firstly, analysis of variance (ANOVA) is carried out for the quadratic response surface model and the statistics is given in the Tables 4. The value of "Prob. > F" (the overall significance of the regression model) in the Table 4 confirms that the developed model is significant to 95% accuracy while representing the experimental values [10].

In the second, the multiple regression coefficient (R^2) is computed to check whether the fitted models actually describe the experimental data. The statistics of R^2 are defined as the ratio of variability explained by the model to the total variability in the actual experimental data and is used as a measure of goodness of fit [10]. If R^2

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

approaches to unity, the better the model fits the experimental data. In other words, it is the proportion of variation in the dependent variable (response) that can be explained by the predictors (factor) in the model. From Table 4, R^2 for WLT is found to be 0.9962. This shows that the second-order model can explain the variation in WLT up to the extent of 99.62%.

From Table 4, adjusted R^2 for WLT is found to be 0.9860. It can be observed that the values of R^2 and adjusted R^2 are much closer to each other. This proves that the developed model represents the process adequately. Thus, the developed mathematical model is checked for their adequacy using a normal probability plot of residuals. The diagnostic plots are drawn to check whether the data is normally distributed and for any assumption is violated. In a normal probability plot, if all the data points fall near the line, an assumption of normality is reasonable. Otherwise, the points will curve away from the line, and an assumption of normality is not justified [10].

The normal probability plot of the residuals for the output response, WLT is shown in Fig. 4 and it can be observed that the residuals are located on a straight line, which means that the errors are distributed normally.

6 INFLUENCE OF CONTROL VARIABLES

From the Table 4, it can be observed that the main effects of particulate size (X_1), the percentage of the reinforcement (X_2), pulse-on time (X_3), pulse-off time (X_4) and wire tension (X_5) are significant on WLT. Also, the interactive effects of particulate size and Pulse-on time (X_1X_3), particulate size and pulse-off time (X_1X_4), volume fraction and pulse-on time (X_2X_3), volume fraction and pulse-on time (X_2X_4), pulse-on time and pulse-on time (X_3X_4) are significant.

From the Figs. 5 and 6, the decreased trend of WLT can be observed in the increased size and volume of particulate. The reason for this is the presence of large or higher amount ceramic particulate in the path of the cut the released heat is utilized to melt the matrix (as ceramic cannot be melted) which is covered around particulate only. Therefore, lesser the matrix material is melted and would decrease the amount debris to recast over the surface. However, formation of the white layer is greatly affected by the pulse-on time and pulse-off time as shown in Figs. 7 and 8 respectively. The wire tension has almost insignificant for this from the Fig.9.

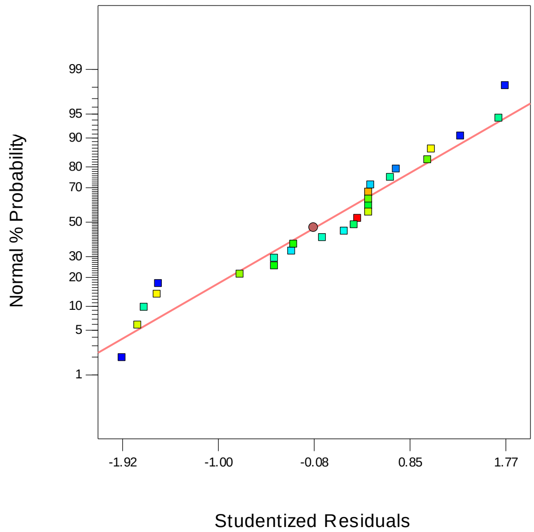

Figure 4: Normal probability plot of residuals for WLT

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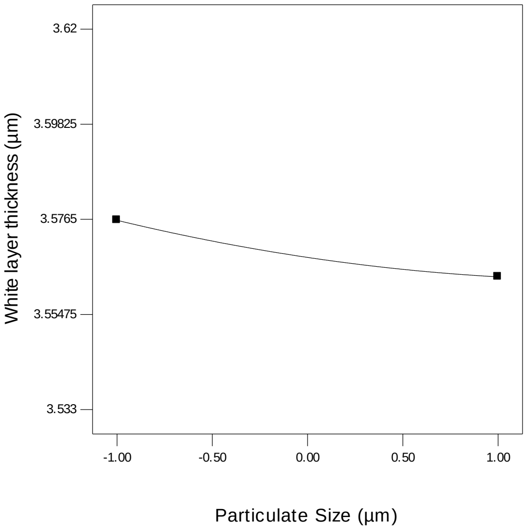

Figure 5: Effect of particulate size on WLT

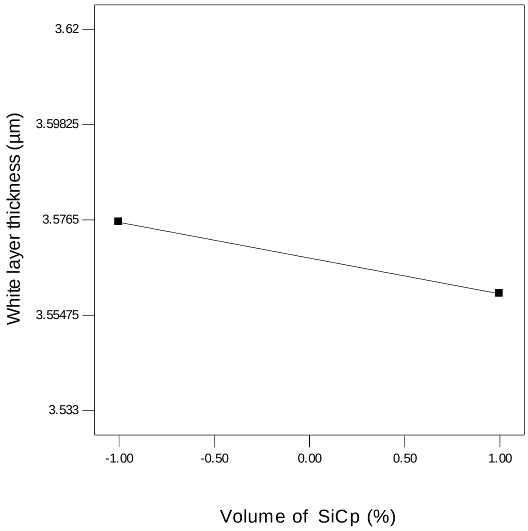

Figure 6: Effect of volume fraction of SiCP on WLT

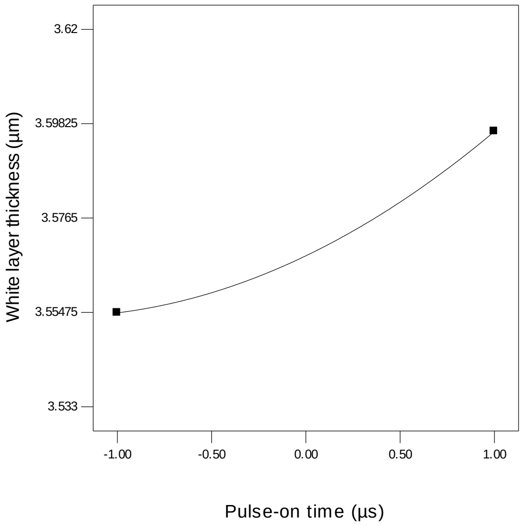

Figure 7: Effect of pulse-on time on WLT

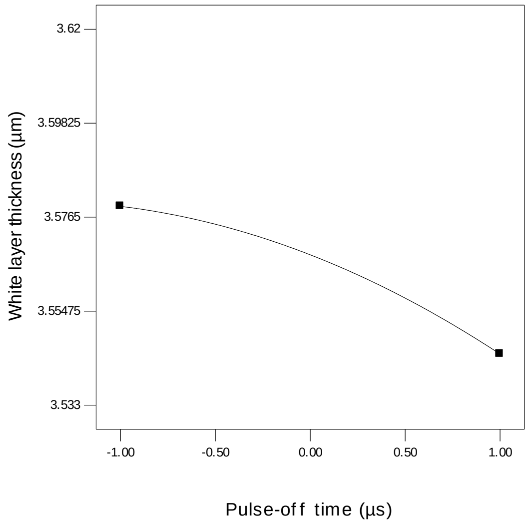

Figure 8: Effect of pulse-off time on WLT

Figs. 10 and 11 exhibits that WLT is significantly influenced by when the particulate size combined with pulse-on time and pulse-off time. At particular particulate size recast layer is increasing for the increasing pulse-on time and is decreasing for the increased pulse-off time. The same effect can be observed with volume factions also as presented in the Figs. 12 and 13. For the combination of pulse-on time and pulse-off time which is also significant for the WLT and among these, the pulse-on time shown a dominating nature for the increased WLT as shown in Fig. 14.

7 FORMULATION OF OPTIMIZATION PROBLEM

In order to optimize the measured response, the problem is formulated as a single objective optimization problem of minimization of WLT subjected to the boundaries of the variables varied in the machining experiments. The problem is formulated as follows:

To find: X_1, X_2, X_3, X_4 and X_5 (5)

Minimize:

$$\begin{aligned}\mathrm{WLT} = {} & 3.57 - 0.0064x_1 - 0.0082x_2 + 0.021x_3 - 0.017x_4 + 0.0007x_5 \\ & + 0.0019x_1^2 - 0.0003x_2^2 + 0.0076x_3^2 - 0.0061x_4^2 - 0.0002x_5^2 \\ & + 0.0002x_1x_2 - 0.0004x_1x_3 + 0.0004x_1x_4 + 0.0003x_1x_5 - 0.0014x_2x_3 \\ & + 0.0015x_2x_4 - 0.0004x_2x_5 - 0.0015x_3x_4 + 0.0002x_3x_5 - 0.0004x_4x_5\end{aligned} \tag{6}$$

Subjected to,

$25\ \mu m \le X_1 \le 75\ \mu m$ (7)

$5\ \% \le X_2 \le 10\ \%$ (8)

$5\ \mu s \le X_3 \le 9\ \mu s$ (9)

$25\ \mu s \le X_4 \le 45\ \mu s$ (10)

$1\ g \le X_5 \le 9\ g$ (11)

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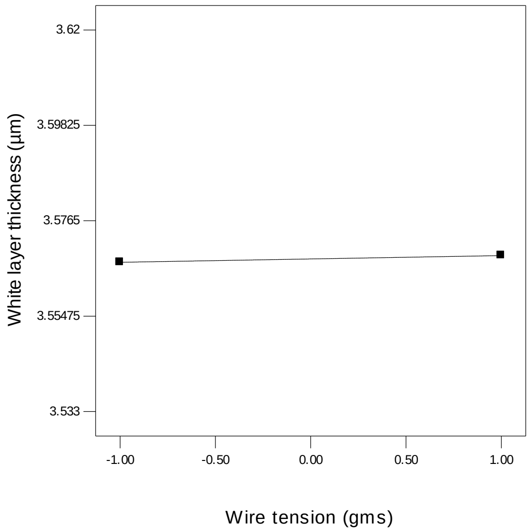

Figure 9: Effect of wire tension on WLT

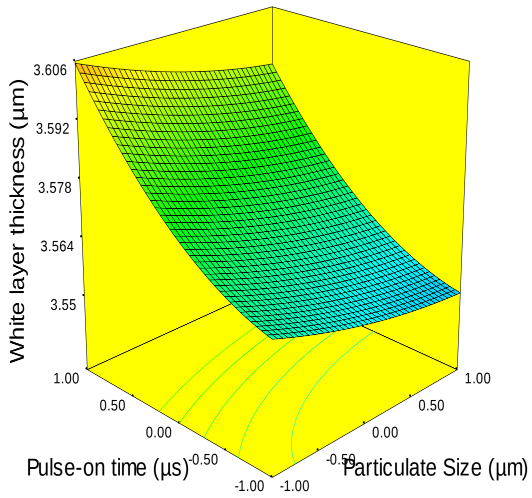

Figure 10: Interactive effect of particulate size and pulse-on time on WLT

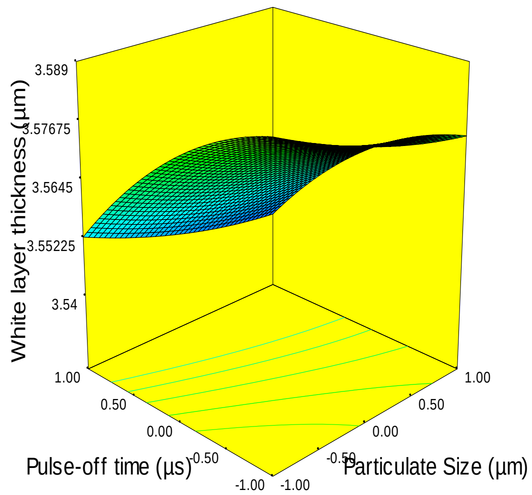

Figure 11: Interactive effect of particulate size and pulse-off time on WLT

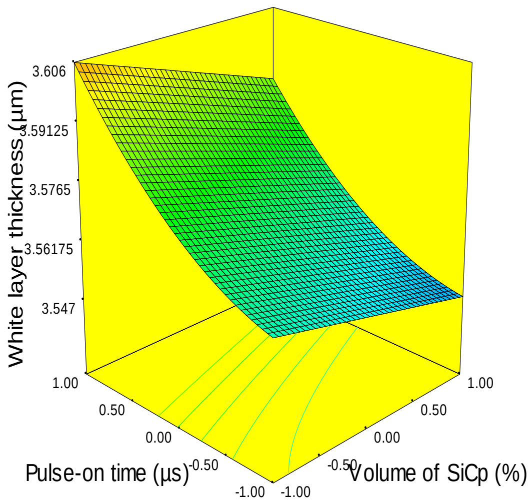

Figure 12: Interactive effect of volume of SiC_P and pulse-on time on WLT

8 OPTIMIZATION USING GA

Applying genetic algorithms is an idyllic approach for the complex multi-variable optimization problems [11]. GA as non-traditional optimization methods are being successfully implemented for a variety of the manufacturing applications [12]. Krishna et al. [13] used GA coupled with ANN to develop a hybrid model and optimization of surface roughness in electric discharge machining. Devim et al. [14] determined the optimum cutting conditions for cutting forces and tool wear in turning of particulate reinforced MMCs using GA. Thiagarajan et al. [15] developed a GA procedure to optimize the grinding parameters for maximum material removal by imposing constraints on roughness. Palanisamy et al. [16] implemented GA to find the optimum machining parameters for end-milling operations. They highlighted the accuracy and effectiveness of the GA based on the good agreement between the GA results and the experimentally validated results of this investigation. The methodology of the GA begins with the generation of a set of strings (or chromosomes) randomly called a population.

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

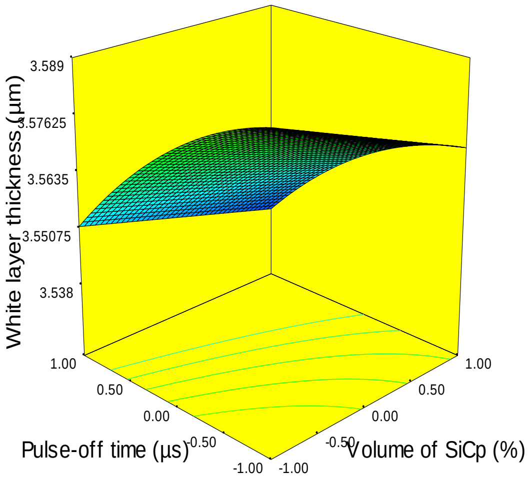

Figure 13: Interactive effect of volume of SiC_P and pulse-off time on WLT

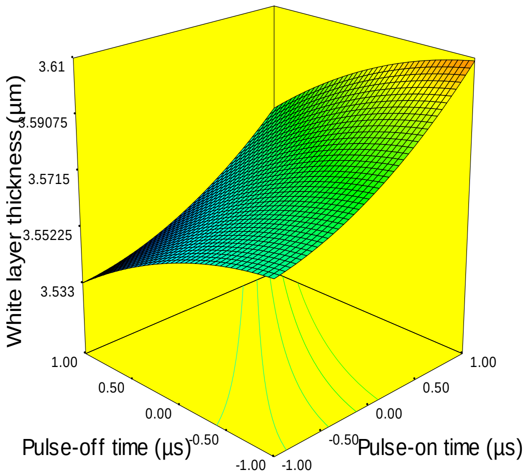

Figure 14: Interactive effect of pulse-on time and pulse-off time on WLT

Table 4: ANOVA [Partial sum of squares] for WLT

Source	Sum of squares	d. f.	Mean square	F-value	Prob. > F
Model	0.014568	20	0.000728	2730.237	<0.0001
X_1	0.000257	1	0.000257	961.5545	<0.0001
X_2	0.001201	1	0.001201	4499.785	<0.0001
X_3	0.005407	1	0.005407	20266.08	<0.0001
X_4	0.001459	1	0.001459	5467.023	<0.0001
X_5	2.59E-06	1	2.59E-06	9.695536	0.0207
X_1X_2	5.12E-07	1	5.12E-07	1.918246	0.2153
X_1X_3	5.99E-07	1	5.99E-07	2.244738	0.1847
X_1X_4	2.59E-07	1	2.59E-07	0.972227	0.3622
X_1X_5	1.41E-07	1	1.41E-07	0.529487	0.4942
X_2X_3	1.31E-05	1	1.31E-05	48.99719	0.0004
X_2X_4	2.1E-05	1	2.1E-05	78.82854	0.0001
X_2X_5	9.23E-07	1	9.23E-07	3.457906	0.1123
X_3X_4	1.62E-05	1	1.62E-05	60.56948	0.0002
X_3X_5	2.5E-07	1	2.5E-07	0.937201	0.3704
X_4X_5	3.73E-07	1	3.73E-07	1.399513	0.2816
X_1^2	1.43E-05	1	1.43E-05	53.56228	0.0003
X_2^2	6.64E-07	1	6.64E-07	2.488343	0.1658
X_3^2	0.000355	1	0.000355	1331.717	<0.0001
X_4^2	9.62E-05	1	9.62E-05	360.5644	<0.0001
X_5^2	9.92E-09	1	9.92E-09	0.037174	0.8535
Residual	5.492E-005	7	7.846E-006		
Pure Error	2.341E-005	5	4.682E-006		
Cor Total	0.015	26			
Std. dev.	2.801E-003			R2	0.9962
Mean	3.57			Adj. R2	0.9860
< - refers to significant terms					

Traditionally, a binary coding system is adopted to represent the chromosomes in terms of either zeros or ones. After, the fitness value (objective function value) is computed for each member of the population. The three fundamental GA operators called reproduction; crossover and mutation are operated on the population to create a new population also called child population. The child population is further evaluated and tested for

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

determination with reference to the parent population. In the simulation of GA, an iteration of these three operators is named as a generation [17].

In this investigation, GA is implemented in the formulated objective function to find the global minimum value of WLT. The implementation of GA is clearly explained in the Tables 5, 6 and 7 for minimizing the WLT as objective. An iteration of the algorithm, the sample calculations are presented here. The bit lengths of 5, 4, 4, 3 and 3 are chosen for X_1, X_2, X_3, X_4 and X_5 respectively. The initial population with 27 chromosomes is randomly generated as a first step of the algorithm and is shown in Table 5. The decoded decimal values of WLT of the generated chromosome strings of individual input variables are listed in Table 5. For example, from Table 5, the first string (10100 0110 0101 001 101) is decoded to values equal to X_1=59; X_2=9; X_3=6; X_4=28; X_5=7 using linear mapping rule as presented in the eq.11.

$$x_i = X_i^L + \frac{X_i^U - X_i^L}{2^{l_i} - 1} \times decoded\ value \qquad (12)$$

Then the objective function WLT value is computed which is obtained as 3.527. The fitness function value at this point using the transformation rule F (x (1)) = 1.0 /(1.0+3.527) is obtained as 0.221. This fitness function value is used in the reproduction operation of the GA. Similarly, other strings in the population are evaluated and fitness values are calculated. Table 5 shows the objective function value and the fitness value for all the 27 strings in the initial population. In the next step, good strings in the population are to be selected to form the mating pool. In this work, roulette-wheel selection procedure is used to select the best strings. As a part of this procedure, the average fitness of the population is calculated by adding the fitness values of all strings and dividing the sum of the population size and the average fitness of the population $(\bar{F})$ is obtained as 0.2199.

Now, random numbers between zero and one are generated in order to form the mating pool. From Table 6, random number generated for the first string is 0.544 fifteenth strings from the population gets a copy in the mating pool, because that string occupies with the probability of 0.544 as shown in the column of cumulative probability in Table 6. In a similar manner, the other strings are selected according to the random numbers generated in Table 6 and the complete mating pool is formed. The mating pool is displayed in Table 7. By adopting the reproduction operator, the inferior points have been automatically eliminated from further consideration.

As a next step in the generation, the strings in the mating pool are used for the crossover operation. In the crossover operation, two strings are selected at random and crossed at a random site. Since the mating pool contains strings at random, pairs of strings are picked-up from the top of the list as shown in Table 7. Thus strings 8 and 14 participate in the first crossover operation. In this work, two-point crossover [18] is adopted with the probability, pc=0.85 to check whether a crossover is desired or not. To perform crossover, a random number is generated with crossover probability (pc) of 0.85. If the random number is less than pc then the crossover operation is performed, otherwise the strings are directly placed in an intermediate population for subsequent genetic operation. When crossover is required to be performed then crossover sites are to be decided at random by creating random numbers between (0, l-1), where l represents the total length of the string. For example, when a crossover is required to be performed between the strings 8 and 14, two crossover sites are to be selected randomly based on two point crossover operation. Here, the random sites are happened to be 5, 16. Thus the portions between sites 5 and 16 of the strings 8 and 14 are swapped to create the new offspring as shown in Table 7. However, with the random sites, the children strings produced may or may not have a combination of good strings of parent strings, depending on whether or not the crossing sites fall in the appropriate locations. If good strings are not created by crossover, they will not survive too long because reproduction will select against those chromosomes in subsequent generations. In order to preserve some of the best chromosomes that are already present in the mating pool, all the chromosomes are not used in crossover operation. When a crossover probability of p_c is used, the expected number of strings that will be subjected to crossover is only $100p_c$ and the remaining percent of the population remains as they are in the current population. The calculations of intermediate population are shown in the Table 7. The crossover is mainly responsible for the creation of new strings.

The third operator, mutation, is then applied to the intermediate population. Mutation is basically intended for local search around the current solution. Bit-wise mutation is performed with a probability, p_m=0.10. A random number is generated with p_m; if the random number is less than p_m then the bit is altered from 1 to 0 or 0 to 1 depending on the bit value otherwise no action is taken. Mutation is implemented with the probability, p_m=0.10 as shown in Table 7. The procedure is repeated for all the strings in the intermediate population. This completes one iteration of the GA. The above procedure is continued until the maximum number of generations is completed. For better convergence, the algorithm is run for 500 generations.

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

Table 5: Initial population with fitness values in GA (Minimization of WLT)

S. No.	Chromosomes					X_1	X_2	X_3	X_4	X_5	WLT	Fitness value
1	10100	0110	0101	001	101	57	9	6	28	7	3.5271	0.221
2	11101	1011	0110	100	001	72	12	7	36	2	3.5908	0.218
3	11001	1011	1001	100	001	65	12	7	36	2	3.5794	0.218
4	10011	1100	1011	011	011	56	13	8	34	4	3.5523	0.220
5	11001	1100	1100	011	001	65	13	8	34	2	3.5649	0.219
6	10101	1101	0011	111	101	59	14	6	45	7	3.5785	0.218
7	11000	0100	1111	101	100	64	8	9	39	6	3.5940	0.218
8	10101	0010	1100	110	001	59	6	8	42	2	3.5893	0.218
9	10011	0000	1101	010	111	56	5	8	31	9	3.5654	0.219
10	10111	1101	0011	011	000	62	14	6	34	1	3.5599	0.219
11	10011	1111	0011	010	101	56	15	6	31	7	3.5382	0.220
12	10101	1010	1010	000	111	59	12	8	25	9	3.5309	0.221
13	11000	1100	0011	111	001	64	13	6	45	2	3.6223	0.216
14	00011	0011	0110	001	010	30	7	7	28	3	3.4583	0.224
15	11011	0101	0011	101	011	69	8	6	39	4	3.5845	0.218
16	10011	1111	1101	000	111	56	15	8	25	9	3.5341	0.221
17	11001	0011	1100	101	010	65	7	8	39	3	3.5899	0.218
18	01111	1111	1000	001	101	49	15	7	28	7	3.5217	0.221
19	10011	0101	0101	010	010	56	8	6	31	3	3.5234	0.221
20	00100	0010	0010	110	001	31	6	6	42	2	3.5196	0.221
21	10001	1101	0110	001	110	52	14	7	28	8	3.5272	0.221
22	11010	1001	0010	000	010	67	11	6	25	3	3.5000	0.222
23	10001	1101	0011	110	011	52	14	6	42	4	3.5736	0.219
24	01010	0101	1110	100	001	41	8	9	36	2	3.5255	0.221
25	11101	0110	1111	000	001	72	9	9	25	2	3.5034	0.222
26	11111	0111	0001	000	111	75	10	5	25	9	3.5326	0.221
27	11001	0110	0101	000	001	65	9	6	25	2	3.4802	0.223

Table 6: Selection in GA (Minimization of WLT)

S. No.	Expected Count	Probability	Cumulative Probability	Random number	Selected String number
1	1.004	0.0372	0.037	0.544	15
2	0.990	0.0367	0.074	0.291	8
3	0.993	0.0368	0.111	0.504	14
4	0.999	0.0370	0.148	0.816	22
5	0.996	0.0369	0.185	0.200	6
6	0.993	0.0368	0.221	0.514	14
7	0.990	0.0367	0.258	0.631	17
8	0.991	0.0367	0.295	0.063	2
9	0.996	0.0369	0.332	0.493	13

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

10	0.997	0.0369	0.368	0.814	22
11	1.002	0.0371	0.406	0.918	25
12	1.003	0.0372	0.443	0.678	21
13	0.984	0.0364	0.479	0.984	26
14	1.020	0.0378	0.517	0.365	10
15	0.992	0.0367	0.554	0.420	12
16	1.003	0.0371	0.591	0.355	10
17	0.991	0.0367	0.627	0.336	9
18	1.006	0.0372	0.665	0.155	4
19	1.005	0.0372	0.702	0.406	11
20	1.006	0.0373	0.739	0.900	24
21	1.004	0.0372	0.776	0.926	25
22	1.010	0.0374	0.814	0.779	21
23	0.994	0.0368	0.851	0.450	12
24	1.005	0.0372	0.888	0.463	12
25	1.010	0.0374	0.925	0.462	13
26	1.003	0.0372	0.962	0.407	11
27	1.015	0.0376	1.000	0.950	25

Table 7: Crossover and Mutation in GA (Minimization of WLT)

Selection	Mating pool	Cross over?	Cross-over site	Offspring	Mutation sites	Mutated chromosome
15	11011 0101 0011 101 011	No	--	11011 0101 0011 101 011	--	11010 1001 0010 000 010
8	10101 0010 1100 110 001	YES	5,16	10101 0011 0110 001 001	3	11100 1110 0011 111 001
14	00011 0011 0110 001 010	YES	5,16	00011 0010 1100 110 010	--	10011 0000 1101 010 111
22	11010 1001 0010 000 010	No	--	11010 1001 0010 000 010	--	10001 1101 0011 110 011
6	10101 1101 0011 111 101	No	--	10101 1101 0011 111 101	--	10011 1100 0011 111 011
14	00011 0011 0110 001 010	No	--	00011 0011 0110 001 010	--	10101 1101 1011 011 101
17	11001 0011 1100 101 010	YES	9,16	11001 0011 0110 100 010	8,12	00111 1101 0010 001 101
2	11101 1011 0110 100 001	YES	9,16	11101 1011 1100 101 001	--	10111 1101 0011 011 000
13	11000 1100 0011 111 001	NO	--	11000 1100 0011 111 001	--	10011 1111 1101 000 111
22	11010 1001 0010 000 010	NO	--	11010 1001 0010 000 010	--	10101 1010 1010 000 111
25	11101 0110 1111 000 001	NO	--	11101 0110 1111 000 001	--	11001 0011 1100 101 010
21	10001 1101 0110 001 110	NO	--	10001 1101 0110 001 110	--	10110 1111 0011 011 000
26	11111 0111 0001 000 111	YES	13,16	11111 0111 0001 011 111	--	10011 1101 1101 000 111
10	10111 1101 0011 011 000	YES	13,16	10111 1101 0011 000 000	--	10011 1100 1011 011 011
12	10101 1010 1010 000 111	NO	--	10101 1010 1010 000 111	--	11101 1000 1100 011 001
10	10111 1101 0011 011 000	NO	--	10111 1101 0011 011 000	--	11011 0101 0011 101 011
9	10011 0000 1101 010 111	NO	--	10011 0000 1101 010 111	6,9	11000 0101 0011 111 001
4	10011 1100 1011 011 011	NO	--	10011 1100 1011 011 011	--	01111 1111 1000 001 101
11	10011 1111 0011 010 101	NO	--	10011 1111 0011 010 101	--	11011 0101 0011 101 011
24	01010 0101 1110 100 001	NO	--	01010 0101 1110 100 001	--	10011 1100 0101 011 011
25	11101 0110 1111 000 001	NO	--	11101 0110 1111 000 001	--	11001 0100 1011 010 001
21	10001 1101 0110 001 110	YES	5,13	10001 1010 0110 001 110	--	10100 0110 0101 001 101
12	10101 1010 1010 000 111	YES	5,13	10101 1101 1010 000 111	14,18	00100 0010 0010 010 011

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

12	10101 1010 1010 000 111	NO	--	10101 1010 1010 000 111	--	11111 0111 0001 000 111
13	11000 1100 0011 111 001	NO	--	11000 1100 0011 111 001	--	10100 0110 0101 001 101
11	10011 1111 0011 010 101	NO	--	10011 1111 0011 010 101	--	11101 1011 0110 100 001
25	11101 0110 1111 000 001	NO	--	11101 0110 1111 000 001	--	10011 1111 1101 000 111

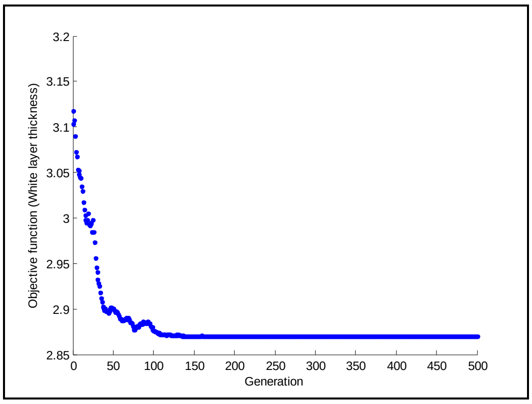

Figure 15: Convergence graph for minimization of WLT

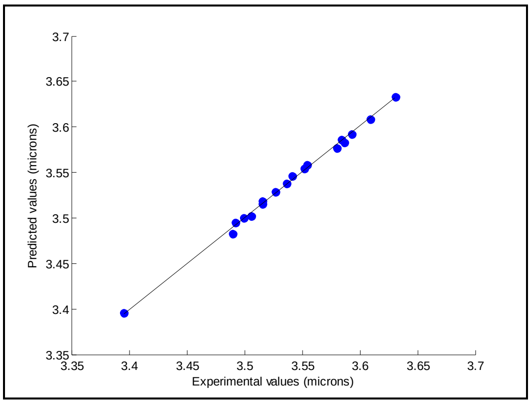

Figure 16: Predicted values vs. experimental values for WLT

9 RESULTS AND DISCUSSION

In order to find the optimal set of machining parameters which results the global minimum value for WLT, the MATLAB GA toolbox is used to simulate the algorithm. One of the major advantages with GA is that it the users need not supply any supporting information excluding the objective function values and constraints. In addition, no assumptions are to be made while applying the algorithm and it works with a population of points instead of a single point, thus the expected solution may be a global solution. GA narrows down the search space as the search progresses.

In the present problem, GA is run for 500 generations and the algorithm is converging to the objective function value of 2.87. The fitness value convergence graph is displayed in Fig. 15 and the optimal values of the control factors are listed in Table 8. The following results are resolved from the simulation results from the proposed methodology: From the experimental observations Table 3 the least WLT value measured is 3.533 µm for the 13th experiment, However, after optimization using GA, it is observed from Table 8 that WLT is decreased to 2.87 µm it means around 18.76% of the WLT can be minimized by adopting the machining control variables listed in Table 8.

10 CONFIRMATION EXPERIMENTS

The next step to the optimization is the experimental validation of the obtained results of the proposed method. Therefore, the conformation experiments are conducted to validate the predicated response surface model of the WLT. The values of the control variables are selected within the upper and lower limit values used for experimentations in the design matrix and to drive the models. The same experimental setup is used to conduct the validation tests in the manufacturing facility. Total eighteen confirmation experiments are performed with distinct parameter settings and the measured WLT values are listed in Table 9. A comparative study between the predicted and experimental results is carried out and furnished in Table 9.

Fig. 16 shows the one-to-one plots drawn between the predicted values and the experimental values. It is observed from the figures that the proposed methodology ensures the reasonable predictions and it can be concluded that the developed mathematical models have good agreements with the experimental test lines. Slight variations between the results might be due to the random factors like probable material defects and minute tool deflection from its mean position because of electrodynamics forces on the wire.

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

Table 8: Optimum machining conditions for WLT

Control factors and Responses	Optimum value
Particulate size (µm)	75
%volume of SiC_p	14.182
Pulse-on time (µs)	6.472
Pulse-off time (µs)	44.642
Wire tension (gm)	6.896
WLT (µm)	2.87

Table 9: Validation of results for WLT

Exp. No.	Machining conditions					WLT (µm)		
	Size of SiC_P (µs)	Volume of SiC_P (%)	Pulse-on time (µs)	Pulse-off time (µs)	Wire tension (gm)	Predicted	Experiment	Deviation (%)
1	25	7	5	29	1	3.3945	3.3955	0.0295
2	50	10	8	26	6	3.5151	3.5181	0.0853
3	75	13	9	42	3	3.6306	3.6326	0.0551
4	50	8	6	30	6	3.5261	3.5281	0.0567
5	75	11	7	40	3	3.6084	3.6089	0.0139
6	25	13	8	38	7	3.5360	3.5380	0.0566
7	75	15	9	35	9	3.5923	3.5916	0.0195
8	25	3	7	37	5	3.5049	3.5019	0.0856
9	50	6	7	39	3	3.5509	3.5539	0.0845
10	25	5	6	27	6	3.4889	3.4828	0.1748
11	75	9	7	41	9	3.5862	3.5832	0.0837
12	50	12	9	42	7	3.5798	3.5768	0.0838
13	25	10	5	32	4	3.4985	3.4995	0.0286
14	50	14	6	37	3	3.5536	3.5586	0.1407
15	75	15	5	35	5	3.5833	3.5863	0.0837
16	25	8	8	38	8	3.5407	3.5457	0.1412
17	75	9	7	25	4	3.5153	3.5153	0.0000
18	50	6	6	30	2	3.4913	3.4943	0.0859

11 CONCLUSIONS

1. With the aim of quality surface production in WEDM for machining Al7075/SiC_P MMCs, white layer thickness is considered as objective function to optimize the process parameters in this investigation.
2. Base on Taguchi's design of experiments the experimental runs were conducted on stir cast composite work pieces.
3. The measured results were carried to develop a model using response surface methodology and the model is tested for its adequecy based on several statistical tests.
4. ANOVA is conducted to analyze the individual and interaction effects of the process parameters on the white layer.
5. Consequently, GA is used to determine the optimal parameters which reduced the WLT to 2.87 µm.
6. Hence, with the GA-based optimization system developed to machine Al7075/SiCP using WEDM would improve the machining efficiency by 18.76% using optimal cutting parameters.
7. Also the proposed methodology could help to automate the machining system at the computer aided process planning (CAPP) stages to produce high quality components of Al7075/SiCP MMCs with better surface quality in WEDM.

Int. J. of Mechanical Computational and Manufacturing Research, Vol. 2. No.1, (2013) 13–27, ISSN: 2301-4148

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