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Comparison between Taguchi Method and Response Surface Methodology (RSM) in Modelling CO_2 Laser Machining

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Abstract

The applications of Taguchi method and RSM to modelling the laser parameters when machining industrial PVC foams is presented. The influence of cutting speed, laser power, frequency, duty cycle, and gas pressure on kerf width has been considered in this investigation according to Taguchi method using a standard orthogonal array L_{27} and RSM using a central composite design. Taguchi technique as well as 3D surface plot of RSM revealed that the cutting speed is the most significant factor in minimizing kerf width followed by laser power and etc. A predictive mathematical model was then developed through a regression analysis in both analytical tools to study the response. Though both the techniques predicted near values of average error, the RSM technique seems to be more promising in predicting the response via mathematical modelling over the Taguchi technique.

Keywords: *Laser Cutting; Kerf Width; DOE Method; PVC Foam; Mathematical Model.*

1. Introduction

Industrial PVC foams are widely used as a core material in composite/sandwich for marine applications as they own low density with high moisture resistance values. PVC foams are closed-cell and have good physical properties as compared to other foams of similar density. On the other hand, laser advancements stand advantage to cut thermoset material with high level of precision and flexibility. Laser machining is one of the non-contact advanced processing techniques with narrow kerf in almost all categories of materials such as metals, non-metals, ceramics and composites [1]. In polymer, it is complicated to identify the best parameters for machining the materials due to their poor thermal and physical properties compared to metals or ceramic [2].

The main challenge in laser cutting of materials is to select the most appropriate parameters. Laser power, cutting speed, frequency, duty cycle and gas pressure are the most important parameters for laser cutting depending on materials being cut. Effective parameters should be controlled to obtain a high quality of laser cutting. Determination of the parameters by classical experimental design methods requires a large amount of experimental data, which has been found costly and time consuming [3,4]. To overcome the difficulties, researchers applied DOE methods such as factorial design, Taguchi method and response surface methodology are now widely used in place of OFAT experimental approach. The response surface methodology approach was successfully used to investigate the laser cutting performance of medium density fibreboard [5]. In another investigation, the effect of assist gas pressure on quality of the cut CFRP material, namely pure oxygen, pure nitrogen and 50% oxygen - 50% nitrogen, central composite design (CCD) of RSM was successfully applied as an analytical tool [6]. RSM was also derived ironically to identify the effect of five factors on cut quality, namely kerf width, dross height and slope of the cut [7].

Combining of RSM and Taguchi technique was used to developed mathematical model on surface roughness and power consumption [8]. The Taguchi method was used to find the optimal cutting parameters for laser machining [9]. An integrated approach whereby the combination of ANN technique and Taguchi's algorithm was also used in optimizing the CO_2 laser welding process to obtain the optimal setting [10]. An integrated investigation using Taguchi and principle component analysis in gaining best of kerf width, kerf deviation and kerf taper, where, pulse width and cutting speed was found very much influential to response [11]. Researchers also investigated a selection of cutting parameters towards cut quality on carbon fibre reinforced plastics (CFRP) composite and later optimized up to the desired response with RSM [12]. In a laser drilling investigation, machining parameters on recast layer and micro-crack formation were performed by means of Taguchi method [13]. Taguchi methodology was also

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successfully applied for parameter optimization during micro-engraving of photo-masks. Five factors, each at two levels, were selected and the experiment was designed using L_{16} orthogonal array [14].

2. Experimental Details

The Helius Hybrid 2514 CO_2 laser beam cutting machine was used to conduct this experimental research. The investigated research work was conducted using H80 industrial PVC foam as work materials with the density of 80 kg/m^3 and 20 mm thickness, supplied by marine composites industry, UES International Pte. Ltd. The kerf width 'responses' that were obtained after the experimental runs were observed by optical comparator with embedded digital micrometer with an accuracy of 1 micron, which allows easy access to measure both X-axis and Y-axis directions. The estimated values of kerf width are based on Equation 1:

$$\text{Kerf Width (mm)} = \frac{\text{Upper Kerf Width} + \text{Lower Kerf Width}}{2} \quad (1)$$

Preliminary experiments were critically designed and conducted to identify the design range for each tested process parameters. Thus, from the initial screening results, five parameters were identified significant, namely laser power, cutting speed, frequency, duty cycle, and gas pressure; they were found to be most influencing and correlated to the kerf width. Table 1 summarizes the constant values, whereas Table 2 summarizes the design parameters and their respective levels employed throughout the entire number of experimentations.

Table 1. Parameters setting for constant parameters

S.O.D (mm)	F.D (mm)	Lens (mm)	Nozzle Type	Gas Selection	Material Thickness (mm)
1	0	7.5	Conical	Nitrogen	20

S.O.D: stand-off distance; F.D: Focal Distance

Table 2. Experimental design parameters and levels.

Parameter	Code	Unit	Level 1	Level 2	Level 3
Cutting Speed	A	mm/min	1800	1900	2000
Laser Power	B	W	550	625	700
Frequency	C	Hz	1700	1775	1850
Duty Cycle	D	%	80.0	82.5	85.0
Gas Pressure	E	Bar	1.5	2.0	3.0

3. Analytical Tools

3.1. Taguchi's Experimental Design

The Taguchi method is a unique statistical experimental design approach that greatly improves the engineering productivity [15]. Taguchi suggests the production process to be applied at optimum levels with minimum variation in its functional characteristics. In general, the signal-to-noise (S/N) ratio (η, dB) represents quality characteristics for the observed data in the Taguchi method. S/N ratio is an index to evaluate the quality of manufacturing process. Here, the 'signal' represents the desirable value and the 'noise' represents the undesirable value, where signal to noise ratio expresses the scatter around the desired value. The experimental result should be transformed into the S/N ratios, mainly three types: smaller-the-better, nominal-the-best (Equation 2), and larger-the-better (Equation 3). In this case, lower values of the kerf width is desirable for maintaining high cut quality; hence smaller-the-better S/N ratio was computed based on Equation 4 as shown [16]:

Table 3. Central-composite design (RSM)

Standard	Exp. Run	Factor levels					Response
		A	*B*	*C*	*D*	*E*	Kerf width (mm)
1	26	-1	-1	-1	-1	1	0.264
2	21	1	-1	-1	-1	-1	0.451
3	30	-1	1	-1	-1	-1	0.639
4	15	1	1	-1	-1	1	0.476
5	25	-1	-1	1	-1	-1	0.618
6	12	1	-1	1	-1	1	0.499
7	32	-1	1	1	-1	1	0.644
8	6	1	1	1	-1	-1	0.475
9	29	-1	-1	-1	1	-1	0.457
10	28	1	-1	-1	1	1	0.471
11	24	-1	1	-1	1	1	0.614
12	19	1	1	-1	1	-1	0.822
13	27	-1	-1	1	1	1	0.603
14	10	1	-1	1	1	-1	0.518
15	23	-1	1	1	1	-1	0.778
16	8	1	1	1	1	1	0.528
17	13	-1	0	0	0	0	0.604
18	20	1	0	0	0	0	0.455
19	2	0	-1	0	0	0	0.452
20	5	0	1	0	0	0	0.513
21	11	0	0	-1	0	0	0.546
22	7	0	0	1	0	0	0.557
23	17	0	0	0	-1	0	0.516
24	4	0	0	0	1	0	0.653
25	14	0	0	0	0	-1	0.553
26	31	0	0	0	0	1	0.472
27	3	0	0	0	0	0	0.602
28	22	0	0	0	0	0	0.629
29	9	0	0	0	0	0	0.611
30	1	0	0	0	0	0	0.597
31	18	0	0	0	0	0	0.519
32	16	0	0	0	0	0	0.603

$$S/N = 10 \log\left(\frac{\bar{y}}{s_y^2}\right) \tag{2}$$

$$S/N = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y^2}\right) \tag{3}$$

$$S/N = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right) \tag{4}$$

Where, y_i is the observed data at the i^{th} trial, and n is the number of trials of the same level with the aim of always keeping maximize of the S/N ratio. A parameter level corresponding to the maximum average S/N ratio is called optimum level for that parameter [17]. The predicted value of S/N ratio (η_{opt}) at optimum parameter levels is analysed by Equation 5 as follows [18]:

$$\eta_{opt} = \bar{\eta} + \sum_{i=1}^{k}\left(\eta_{mi} - \bar{\eta}\right) \tag{5}$$

Where, $\bar{\eta}$ is the average S/N ratio of all experimental runs, k is the number of control factors, and η_{mi} is the mean S/N ratio for i^{th} control factor corresponding to optimum parameter level. S/N ratio calculated for optimum level as Equation 6:

$$\eta_0 = \eta_m + (\eta A_3 - \eta_m) + (\eta B_1 - \eta_m) + (\eta C_2 - \eta_m) + (\eta D_1 - \eta_m) + (\eta E_1 - \eta_m) \tag{6}$$

η_o is optimum S/N ratio, η_m is the overall mean of S/N values, ηA_3 is the third level of cutting speed, ηB_1 is the first level of laser power, ηC_2 is the second level of frequency, ηD_1 is the first level of duty cycle and ηE_1 is the first level of gas pressure. According to the formula Equation 6, η_o was found as 9.126 dB. Some verification experiments are conducted at suggested optimum parameter levels to validate the predicted responses. The experiments are performed as per standard L_{27} orthogonal array and the analysed S/N ratio (η values) corresponding to each experimental run is given in Table 4.

3.2. RSM Experimental Design

Response surface methodology (RSM) is an analytical method that is commonly used to statistically justify the significance of the relationship between input variables (independent variables) to output variables (response). Statistical branch revolves around deriving information about the properties of random processes from sets of observed samples [19]. It is most helpful to construct a model which provides a mathematical representation of the given situation for most of the statistical based investigation [20]. In some system, the nature of the relationship between y and x values might be known. Then, a model can be written in the form [21]:

$$y = f\left(x_1, x_2, \ldots\ldots\ldots. x_n\right) + \varepsilon \tag{7}$$

Where ε characterizes noise or error observed in the output y. If we signify the expected output as:

$$E\left(y\right) = \left(x_1, x_2, \ldots\ldots\ldots\ldots x_n\right) = y \tag{8}$$

So the surface represented by:

$$\hat{y} = f\left(x_1, x_2, \ldots\ldots\ldots\ldots x_n\right) \tag{9}$$

In RSM, the experiments are performed using CCD matrix (for first-order response model factorial design matrix can be used, but due to lack-of-fit, first-order-response model is avoided generally) to develop a second order response model as:

$$Y = b_o + b_1 X_1 + b_2 X_2 + \ldots + b_{11} X_1^2 + b_{22} X_2^2 + b_{12} X_1 X_2 + \ldots b_{n-1,n} X_{n-1} X_n, \tag{10}$$

where, Y is response and X_i are different factors. The regression coefficients b_i can be computed by least-square method. Significance of factors and their interactions can be computed using statistical analysis. Using above response model optimum value of responses and optimal setting of parameters can be computed [22].

Table 4. L_{27} orthogonal array (Taguchi)

Standard	Exp. Run	Factor levels					Responses	
		A	B	C	D	E	KW (mm)	η_{KW} (dB)
1	2	1	1	1	1	1	0.430	7.341
2	27	1	1	1	1	2	0.440	7.141
3	12	1	1	1	1	3	0.452	6.897
4	7	1	2	2	2	1	0.487	6.241
5	25	1	2	2	2	2	0.483	6.312
6	22	1	2	2	2	3	0.513	5.791
7	4	1	3	3	3	1	0.587	4.627
8	19	1	3	3	3	2	0.506	5.926
9	20	1	3	3	3	3	0.637	3.924
10	26	2	1	2	3	1	0.395	8.079
11	10	2	1	2	3	2	0.428	7.381
12	14	2	1	2	3	3	0.461	6.726
13	21	2	2	3	1	1	0.381	8.393
14	24	2	2	3	1	2	0.487	6.258
15	1	2	2	3	1	3	0.451	6.926
16	15	2	3	1	2	1	0.456	6.821
17	5	2	3	1	2	2	0.480	6.375
18	9	2	3	1	2	3	0.435	7.240
19	18	3	1	3	2	1	0.352	9.069
20	13	3	1	3	2	2	0.446	7.013
21	17	3	1	3	2	3	0.391	8.168
22	23	3	2	1	3	1	0.430	7.331
23	16	3	2	1	3	2	0.492	6.161
24	6	3	2	1	3	3	0.461	6.726
25	8	3	3	2	1	1	0.423	7.473
26	11	3	3	2	1	2	0.434	7.250
27	3	3	3	2	1	3	0.391	8.168

The observed data from the experimental runs were then fed into a commercially available analytical tool to analyse, optimize and establish a predictive mathematical model to estimate the kerf width. In this case, a half fractional factorial, with 5 factors, 10 axial points at the face, and 6 centre point, were used which gives a total of 32 design point. The design, which is called a face-centred central-composite design, the axial point was then placed at the low and high values. Table 3 shows the complete experimental design matrix, where the runs were randomized to avoid bias in response gain. The extreme right column shows the experimentally observed average reading of kerf width.

3.3. Analysis of Variance

ANOVA is a computational technique to quantitatively estimate the contribution that each parameter makes on the overall observed response. ANOVA is accomplished by separating the total variability of the S/N ratios (SS_{tot}), which is measured by the sum of the squared deviations from the total mean S/N ratio into contributions by each of the parameters and the error:

$$SS_{tot} = SS_T + SS_E \tag{11}$$

The total sum of square deviations from the total mean S/N ratio can be calculated as [23]:

$$SS_T = \sum_{i=1}^{n_t} (\eta_i - \bar{\eta})^2 \tag{12}$$

where, η_t is the total number of experiment trials, η_i is the S/N ratio in i^{th} trial in the OA and $\bar{\eta}$ is the total mean S/N ratio:

$$\bar{\eta} = \frac{1}{n_t}\sum_{i=1}^{n_t} \eta_i \tag{13}$$

The sum of square due to parameter Q can be computed as:

$$SS_Q = \sum_{i=1}^{k} n_{Qk}[\bar{\eta}_{Qk} - \bar{\eta}]_i^2 \tag{14}$$

Subsequently, SS_T can be used to measure the relative influence of the process parameters on the response. The percentage contribution (ρ) of parameter Q can be calculated as:

$$\rho(\%) = \frac{SS_Q}{SS_T} \times 100 \tag{15}$$

The final step in the optimization methodology is the verification of the improvement of the quality characteristic. For that purpose, a confirmation experiment should be carried out implying the (near) optimal levels of the control parameters.

4. Results and Discussion

4.1. Taguchi's Technique

The response analysis, represented by graphs in Figure 1, indicates the change in response when a given factor varies from lower to higher level. Figure 1 represents the main effects plot for the mean value of kerf width against cutting speed, laser power, frequency, duty cycle, and gas pressure. It can be seen that greater laser power and duty cycle give a better kerf width. This phenomenon is witnessed probably due to an increase of the incident laser power absorbed by the work materials. On the other hand, it was experiencing inverse effects for cutting speed over the kerf width. The effect of the cutting speed is correlated by the fact that, as the cutting speed increases, the interaction time between the laser beam and work materials distorts.

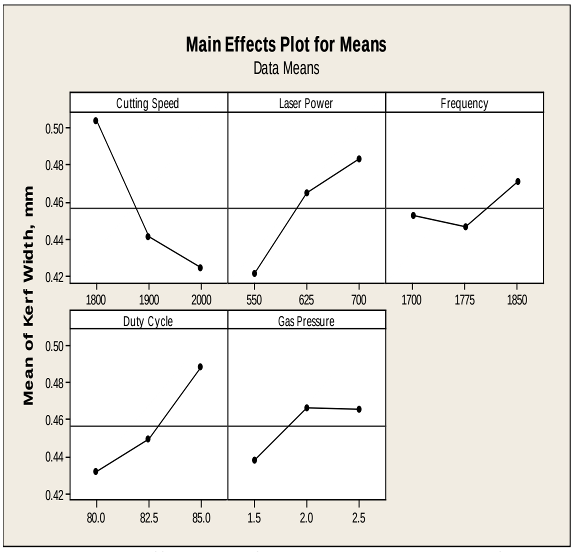


Figure 1. Main effects plot of design parameters over kerf width

The effect of various factors at different levels for responses kerf width is shown in Table 5. The optimum parameter level for minimum value of kerf width is $A_3B_1C_2D_1E_1$. Tabulated in Table 5, the optimal combination of the parameters for the kerf width could be achieved by using a cutting speed of 2000 mm/min, laser power of 550 W, frequency of 1775 Hz, duty cycle of 80 %, and gas pressure of 1.5 Bar. The ANOVA table of the S/N ratio for the kerf width as shown in Table 6 clearly indicates that, the influence of cutting speed has the greatest effect (43.65 % contribution) on the kerf width, followed by the laser power (24.98 % contribution), and duty cycle (20.87 % contribution). However, the other parameters are least significant effect (3.98 % - 6.52 % contribution) compared to earlier.

4.1.1. Regression Analysis

The second-order response surface representing the kerf width can be expressed as a function of cutting parameters such as cutting speed, laser power, frequency, duty cycle and gas pressure. From the observed data for kerf width, the response function has been determined in coded factors units as:

Kerf Width *= 0.46 - 0.026*A + 0.023*B – 0.011*C - 5.556E-005*D + 0.014*E – 0.040*A*B – 0.016*A*C - 5.075E-003*A*E + 0.027*B*C - 0.011*B*E +0.011*C*E + 7.250E-003*D*E* (16)

4.2. RSM Technique

The influence of cutting speed, laser power, frequency, duty cycle and gas pressure was investigated through the modelling stages. The analysis of variance (ANOVA) for kerf width of Industrial PVC foam is shown in Table 7. This analysis was carried out for level of confidence not less than 95 % which is a criteria to be set into RSM.

Table 7 presents the ANOVA for kerf width. The significance of the model is revealed according to the F-value of 5.15 model. There was only a probability of 0.11 % of noise in this "F-Value model". If the values of "Probability > F", and if they are lesser than 5 % (0.05), then the model is said to be sound; thus, A, B, D, AC, AD, BD, and BE are considered as excellent model terms. In case that the values are greater than 0.1 (10 %), the model terms are said to be insignificant and impractical to be considered. The "Lack of Fit F-value" of 2.28 reveals that lack of fit, related to the pure error, is not significant. In this case, since, the intention here is to fit the model, it is good to have an insignificant lack of fit.

The cutting speed and laser power are two parameters affecting the kerf width. According to Figure 2(a), higher cutting speed at lower duty cycle gives a smaller kerf width due to a less interaction time. On the other hand, Figure 2(b) reveals that frequency is inverse proportional to the kerf width. Hence, the greater the cutting speed, the higher the frequency and the smaller kerf width is attainable. It should be noted that the effect of duty cycle slightly decreases the kerf width, while, laser power is inverse to that effect as its correlation is clearly visible in Figure 2(c). Therefore, it can be summarized that combination of lower side laser power and higher side duty cycle produces better kerf width. The lower laser power and gas pressure, it is then more favourable for kerf width, as shown in Figure 2(d). It is clearly evident that kerf width increases with laser power as the laser beam energy mainly depends on laser power. High laser power generates high thermal energy, which produces higher kerf width in return.

Table 5. S/N ratio response

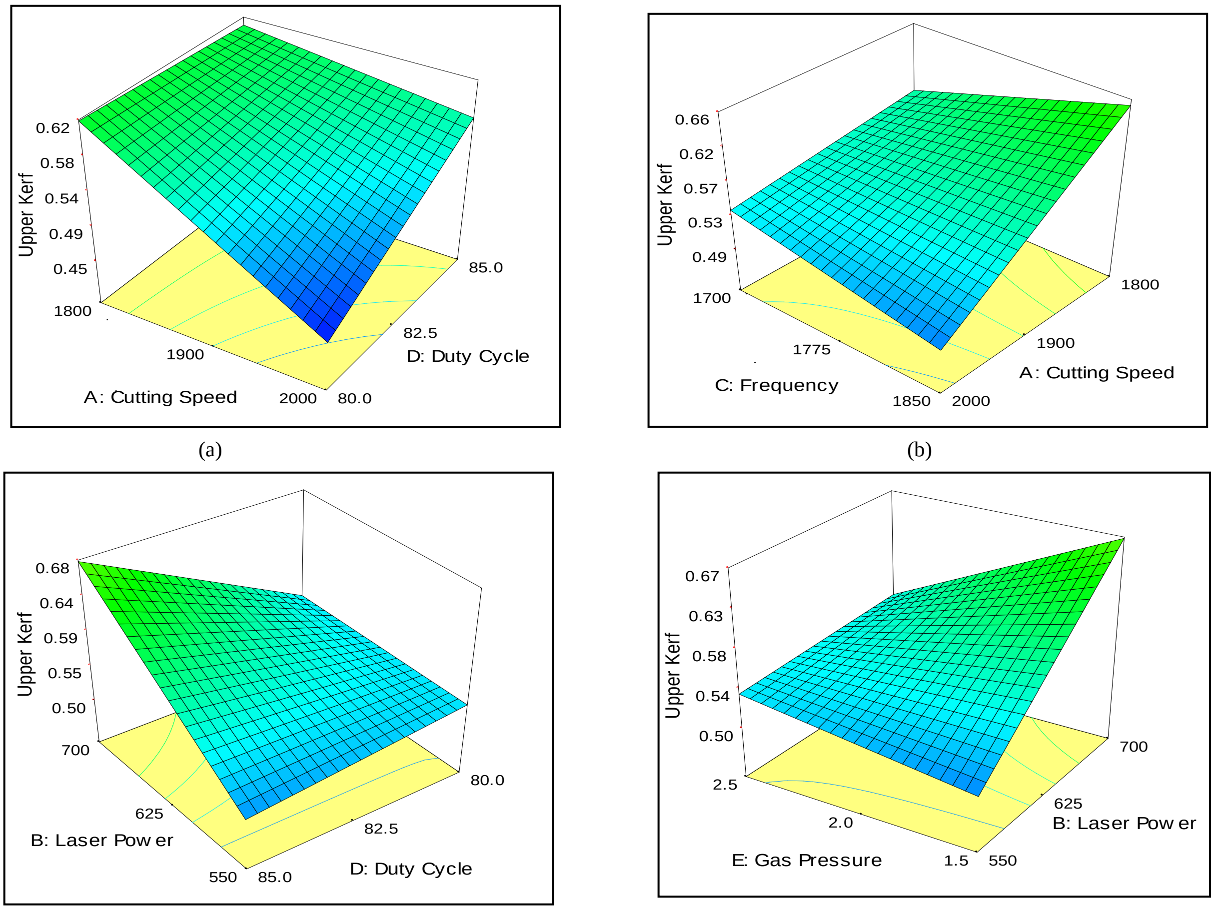
Source	Factors	S/N ratios (dB) Level 1	Level 2	Level 3	Delta	Rank
A	Cutting speed	6.022	7.133	7.484[a]	1.462	1
B	Laser Power	7.535[a]	6.682	6.423	1.112	2
C	Frequency	6.892	7.047[a]	6.700	0.346	5
D	Duty cycle	7.316[a]	7.003	6.320	0.996	3
E	Gas pressure	7.264[a]	6.646	6.730	0.617	4

[a]Optimum parameter level

Table 6. ANOVA for S/N ratio

Source	df	SDG	MS	F-Value	Contribution (%)
A	2	0.0316	0.0158	11.862	43.65
B	2	0.0181	0.0090	6.788	24.98
C	2	0.0029	0.0014	1.082	3.98
D	2	0.0151	0.0075	5.671	20.87
E	2	0.0047	0.0024	1.771	6.52
Total	26	0.072			

df: degrees of freedom; SDG: sum of square; MS: mean square



(c) (d)

Figure 2. 3D surface of kerf width model; (a) effects of cutting speed and duty cycle, (b) effects of cutting speed and frequency, (c) effects of laser power and duty cycle, and (d) effects of laser power and gas pressure.

4.2.1. Mathematical Modelling

The models for the quality of cut were developed to evaluate the relationship of laser cutting parameters to the kerf width. Through these models, experimental results of kerf width by any combination of machining parameters can be estimated. From the factor of interaction (2FI) behaviour of model, the polynomial equation implied several process parameters as Equation 10. The developed mathematical models are listed below in terms of actual factors. Equation 17 is for the prediction of kerf width. Optimization is carried out by finding the desirability value in Table 8, which shows a part of the result generated. The optimum condition is when kerf width equals 0.278 that can be achieved when machining at cutting speed of 1800 m/min, laser power of 550 W, frequency of 1700 Hz, duty cycle of 80 %, and gas pressure of 2.5 Bar. This optimum condition is not similar with the one obtained using Taguchi method. This may be due to a small number of data that caused the misleading of the result. Therefore, it is recommend that the RSM (CCD) be used to obtain an accurate optimization condition.

4.3. Experimental Validation

Experimental validation is the final step in the modelling process to investigate the accuracy and robustness of the established model. Thus, in order to verify the capability of the developed regression model and RSM model, five randomly picked validation experiments were carried out within the range of explored experimental parameters. Table 10 presents the experiments order, the actual values, the predicted values and their deviations (percentage errors) for Taguchi regression model as well as Table 9 for RSM model. It is a common practice for a nonlinear process, if the average error deviation is less than 15 %, then the optimization can be considered valid for the model to be accepted. The final analysis involves comparing the predicted values of the established model with experimentally validated values; it was found that the average error was below 15 %, confirming and concluding the methodology in establishing the model was systematic in performing this scientific research. The Taguchi method revealed the error was 14.61 %, meanwhile the RSM showed 8.93 %.

$$\textbf{Kerf Width} = 7.769 - 0.0028*A - 0.0080*B + 0.0099*C - 0.3360*D + 2.7906*E - 9.17E\text{-}08*A*B - 4.22E\text{-}06*A*C + 1.28E\text{-}04*A*D - 3.54E\text{-}04*A*E - 4.02E\text{-}06*B*C + 2.18E\text{-}04*B*D - 1.01E\text{-}03*B*E + 5.67E\text{-}06*C*D + 1.17E\text{-}04*C*E - 0.0210*D*E \quad (17)$$

Table 7. ANOVA table for kerf width (RSM).

Source	Sum of Square	Degrees of freedom	Mean Square	F Value	P Value
Model	0.21	15	0.014	5.15	0.0011
A	0.044	1	0.044	16.17	0.0010
B	0.035	1	0.035	13.02	0.0024
C	0.0008	1	0.0008	0.30	0.5905
D	0.014	1	0.014	5.19	0.0368
E	0.008	1	0.008	2.99	0.1030
AB	0.000008	1	0.000008	0.003	0.9584
AC	0.016	1	0.016	5.96	0.0267
AD	0.016	1	0.016	6.07	0.0254
AE	0.005	1	0.005	1.86	0.1920
BC	0.008	1	0.008	3.04	0.1006
BD	0.027	1	0.027	9.88	0.0063
BE	0.023	1	0.023	8.51	0.0101
CD	0.00002	1	0.00002	0.007	0.9358
CE	0.003	1	0.003	0.11	0.7405
DE	0.011	1	0.011	4.11	0.0597
Residual	0.043	16	0.003		
Lack of fit	*0.036*	*11*	*0.003*	*2.28*	*0.1872*
Pure Error	*0.007*		*5*	*0.001*	
Cor Total	0.25	31			

Table 8. Optimization using desirability criterion.

No.	*A*	*B*	*C*	*D*	*E*	Kerf Width	Desirability	
1	1800	550	1700	80.0	2.5	0.278	0.976	Selected
2	1800	554	1700	80.0	2.5	0.280	0.971	
3	1800	550	1700	80.8	2.5	0.289	0.956	

Table 9. Experimental validation (RSM)

Exp. No.	Factor levels A	B	C	D	E	Values	Response Kerf width
1	1850	663	1813	81.3	1.8	Actual	0.547 mm
						Predicted	0.609 mm
						Error	10.18 %
2	1950	663	1813	83.8	2.3	Actual	0.533 mm
						Predicted	0.559 mm
						Error	3.09 %
3	1950	588	1813	81.3	2.3	Actual	0.441 mm
						Predicted	0.511 mm
						Error	13.70 %
4	1850	663	1738	83.8	1.8	Actual	0.602 mm
						Predicted	0.643 mm
						Error	6.38 %
5	1850	588	1738	81.3	1.8	Actual	0.487 mm
						Predicted	0.549 mm
						Error	11.29 %
						$\overline{X}$ **Error**	**8.93 %**

Table 10. Experimental validation (Taguchi)

Exp. No.	Factor levels A	B	C	D	E	Values	Response Kerf width
1	1850	663	1813	81.3	1.8	Actual	0.547 mm
						Predicted	0.609 mm
						Error	10.18 %
2	1950	663	1813	83.8	2.3	Actual	0.533 mm
						Predicted	0.559 mm
						Error	3.09 %
3	1950	588	1813	81.3	2.3	Actual	0.441 mm
						Predicted	0.511 mm
						Error	13.70 %
4	1850	663	1738	83.8	1.8	Actual	0.602 mm
						Predicted	0.643 mm
						Error	6.38 %
5	1850	588	1738	81.3	1.8	Actual	0.487 mm
						Predicted	0.549 mm
						Error	11.29 %
						$\overline{X}$ **Error**	**8.93 %**

5. Conclusion

The experiment reveals the high level of interest in comparing Taguchi and RSM to predict response in laser non-linear process. Normally, there is a lack of comparative studies concerning the performance of the optimization techniques; in other words which method would be better for a given optimization problem. Both analytical tools are outstanding at developing mathematical modelling in laser processing. However, RSM is more promising due to its giving very low average error towards modelling and experimental validation. The desirability criterion available in RSM will easily help users to determine the optimum condition. Significance of interactions and square terms of parameters are more clearly predicted in RSM. The RSM shows significance of all possible combinations of interactions and square terms as depicted in Table 5. Taguchi technique is normally used in linear interactions only. This is due to the fact that in Taguchi design, interactions between controls factors are aliased with their main effects. 3D surfaces generated by RSM can help in visualizing the effect of parameters on response in the entire range specified whereas Taguchi technique gives the average value of response at given level of parameters (Figure 1 and 2). Thus RSM is a promising analytical tool to predict the response which suits the range of parameters studies.

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