An integrated study of surface roughness in EDM process using regression analysis and GSO algorithm

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Abstract. The aim of this study is to develop an integrated study of surface roughness (Ra) in the die-sinking electrical discharge machining (EDM) process of Ti-6Al-4V titanium alloy with positive polarity of copper-tungsten (Cu-W) electrode. Regression analysis and glowworm swarm optimization (GSO) algorithm were considered for modelling and optimization process. Pulse on time (A), pulse off time (B), peak current (C) and servo voltage (D) were selected as the machining parameters with various levels. The experiments have been conducted based on the two levels of full factorial design with an added center point design of experiments (DOE). Moreover, mathematical models with linear and 2 factor interaction (2FI) effects of the parameters chosen were developed. The validity test of the fit and the adequacy of the developed mathematical models have been carried out by using analysis of variance (ANOVA) and F-test. The statistical analysis showed that the 2FI model outperformed with the most minimal value of R² compared to the linear model and experimental result.

1. Introduction
Managing quality has been a key determinant in an organizations’ in order to get lower total costs as well. The high quality of finished products includes of high surface finish, less tool wear and high production rate, but in term of economy machining is lower cost [1]. Therefore, the selection of optimum process parameters plays a significant role. The success of the manufacturing process is determined upon by the selection of appropriate process parameters [2]. The purpose of the optimization process is to look for a solution which is as close as possible to the target and as robust as possible [3,4,5]. The first step for process parameter optimization is developing a mathematical model in order to have a better understanding the principles leading the machining process [6]. Basically, a model has to be developed with the aid of mathematical equations and requires input data (control parameters).

In manufacturing industries, machining process is one of the most important and widely being used compared to forming, casting and joining processes [7,8]. Basically, there are two types of machining processes which are traditional (milling, turning, grinding, drilling and others) and modern machining (abrasive water jet, electrical discharge machining, electrochemical machining and others) [9].
Nowadays, electrical discharge machining (EDM) is one of the widely used machining processes due to its capability of machining geometrically complex or hard material component which need precise and high accuracy [10].

Moreover, EDM is an alternative method of serial or batch production of difficult-to-cut parts when it is not possible to create by using conventional machining methods [11]. In this study, die-sinking EDM process has been selected for conducting experiments. Basically, in a die-sinking EDM, material is removed by controlling erosion through a series of electric sparks between the tool (electrode) and the workpiece to have the eroding effect on work-piece in order to form a replica of tool on work piece [12]. In this process an electric spark is used as the cutting tool to cut (erode) the workpiece to produce the finished part to the desired shape [13]. Thousands of electrical discharges per second are generated and discharge produces a crater by melting and vaporization [13, 14]. Some melted material is flushed away by the dielectric fluid [11]. A dielectric fluid not only flushes out the chips, but also confines the electric discharge. Thus a perfect reproduction of the shape of the tool on the workpiece is reproduced [15, 16].

Surface roughness (Ra) will play a critical role in evaluating and measuring the surface quality of the machined product. Ra greatly affects the functional attributes of products which are frictionless, wear resistance, fatigue, lubricant, light reflection, and coating. It is a measure of the technological quality of a product and it is a factor that significantly affects the manufacturing cost as well [17, 18]. Ra was known as a significant outcome in the manufacturing process and it materializes a major part in the manufacturing system. The quality of finished products was determined by how closely the finished product adheres to certain qualifications including the dimensions and surface quality. Ra value is influenced by many factors such as machining parameters, cutting phenomena, workpiece properties and cutting tool properties and its prediction and control is a demand to the researchers [9].

There are many literatures with the relevant investigations on the integrated study of surface roughness. Patel et al. [19] developed surface roughness prediction model for EDM of Al2O3/SiCw/TiC ceramic composite on discharge current, pulse on time, duty cycle and gap voltage. The model was developed based on the response surface methodology. It was observed that the optimization process by using trust-region method gives the optimal value of surface roughness (1.88 μm) at the combination setting of 3A of discharge current, 10μs of pulse on time and 0.88 of duty cycle. It can be concluded that the developed models can predict the surface roughness accurately within 95% confidence interval.

Bhattacharya et al. [20] proposed a study on surface integrity model for the EDM of M2 Die Steel. The mathematical models were developed for surface roughness, recast layer thickness, and surface crack density based on the response surface methodology (RSM) which considered peak current and pulse on duration as the machining parameters. It is observed that the peak current and pulse duration should be kept as low as possible in order to achieve the minimum value of surface roughness.

Mandal et al. [21] presented a study on modelling and optimization of machining nimonic C-263 super alloy using multicut strategy in wire electrical discharge machining (WEDM). The mathematical modelling for cutting rate, surface roughness, spark gap and wire wear ration were developed by using regression analysis, which considered pulse on time (TON), pulse off time (TOFF), servo voltage (SV) and dielectric flow rate (FR) as the machining parameters. It can be observed that all the mathematical models suggested are fairly fitted with the experimental result with a confidence level of 95%. Moreover, the minimum surface roughness value of 1.38 mm can be achieved by optimal setting of controlling parameters (TON 0.95μs, TOFF 200μs, SV 75V, and FR 8L/min). Thus, it can be concluded that the multicut strategy improves the surface roughness of the work piece.

Gopalakannan et al. [22] employed RSM approach for the prediction of material removal rate (MRR), electrode wear rate (EWR) and surface roughness (SR) of Al 7075-B4C MMC. Pulse current, gap voltage, pulse on time and pulse off time were selected as the cutting parameters. It was reported that the proposed mathematical models match the experimental values reasonably well with R² of 0.9838 for MRR, 0.9627 for EWR and 0.9875 for SR.
Anitha et al. [23] presented a multi-objective optimization approach by modelling MRR and SR of EDM process using artificial neural network (ANN) approach. The study considered pulse current, pulse duration, duty cycle and voltage as the input process parameters. The results show an improvement with a better productivity, a reduced material removal time and a product cost at the desired surface finish. The optimized value of the present research is found to be 51.588 mm3/min with a level of surface finish of 0.0955 μm.

Thus, this study carried out an experimental design in order to conduct a comprehensive investigation on the influence of EDM parameters towards the Ra. Furthermore, the study will apply regression analysis and glowworm swarm optimization (GSO) algorithm for modeling and optimization processes.

2. Experimentation
A number of experiments were conducted on a die-sinking electrical discharge machine, model AG40L Sodick. Ti-6Al-4V titanium alloy has been selected as a work piece material while copper-tungsten was considered as an electrode. EDM oil was used as dielectric fluid. The mechanical properties and chemical composition of the Ti-6Al-4V are illustrated as in Table 1. The Ti-6Al-4V titanium alloy was cut to a size of 100mm × 60mm × 5mm for experimental and machined using 8mm diameter of the electrodes. Machining depth was kept constant at 1.5mm for every experimental run. The machining parameters considered in the study are pulse on time (A), pulse off time (B), peak current (C) and servo voltage (D). Meanwhile, the design factors (machining parameters) with their designation, units and respective levels are listed in Table 2. The experimental setup can be seen as in Figure 1.

![Figure 1. Experimental setup using EDM machine](image)

Table 1. Chemical composition and mechanical properties of Ti-6Al-4V.

| Mechanical composition | Mechanical properties | Values |
|------------------------|-----------------------|--------|
| Al 6.37 | Tensile strength (MPa) | 960–1270 |
| V 3.89 | Yield strength (MPa) | 820 |
| Fe 0.16 | Elongation 5D (%) | ≥8 |
| C 0.002 | Reduction in area (%) | ≥25 |
| Mo <0.01 | Density (g/cm3) | 4.42 |
| Mn <0.01 | Modulus of elasticity tension (GPa) | 100–130 |
| Symbol | Name             | Units | Level Low (-1) | Level High (+1) |
|--------|------------------|-------|----------------|-----------------|
| A      | Pulse on time    | µs    | 150            | 230             |
| B      | Pulse off time   | µs    | 60             | 90              |
| C      | Peak current     | A     | 10             | 12              |
| D      | Servo voltage    | Volt  | 30             | 60              |

**Table 2.** Factor and level for EDM parameters of titanium alloy.

The experiment was run according to the full factorial design of experiment methodology with added four center points which resulted in a total number of 20 experimental runs. The arrangement of the experiment’s parameters was noted as coded terms; the low level (-), center point (cp) and high level (+) as presented in Table 3.

**Table 3.** Two level full factorial experiments with four factors and four center points.

| Run | Machining parameters |
|-----|----------------------|
|     | A (µs)   | B (µs)   | C (A)    | SV (V)   |
| 1   | -        | -        | -        | -        |
| 2   | +        | -        | -        | -        |
| 3   | -        | +        | -        | -        |
| 4   | +        | +        | -        | -        |
| 5   | -        | -        | +        | -        |
| 6   | +        | -        | +        | -        |
| 7   | -        | +        | +        | -        |
| 8   | +        | +        | +        | -        |
| 9   | -        | -        | -        | +        |
| 10  | +        | -        | -        | +        |
| 11  | -        | +        | -        | +        |
| 12  | +        | +        | -        | +        |
| 13  | -        | -        | +        | +        |
| 14  | +        | -        | +        | +        |
| 15  | -        | +        | +        | +        |
| 16  | +        | +        | +        | +        |
| 17  | cp       | cp       | cp       | cp       |
| 18  | cp       | cp       | cp       | cp       |
| 19  | cp       | cp       | cp       | cp       |
| 20  | cp       | cp       | cp       | cp       |
2.1. Experimental results
The Ra values of the machined workpiece were measured by using Mitutoyo Formtracer surface roughness tester. Before conducting the measurement, the workpiece was blown using a hair dryer to ensure no debris and dielectric fluid was present. Basically, the measurement of surface roughness needed was repeated for three times. Then, the average value of Ra was taken. The experimental run orders and their results were presented in Table 4.

| Run | Machining parameters | Machining response |
|-----|----------------------|-------------------|
|     | A (µs) | B (µs) | C (A) | SV (V) | Ra (µm) |
| 1   | 150    | 60     | 10    | 30     | 2.6106  |
| 2   | 230    | 60     | 10    | 30     | 3.7860  |
| 3   | 150    | 90     | 10    | 30     | 2.6137  |
| 4   | 230    | 90     | 10    | 30     | 3.5734  |
| 5   | 150    | 60     | 12    | 30     | 3.4860  |
| 6   | 230    | 60     | 12    | 30     | 3.4398  |
| 7   | 150    | 90     | 12    | 30     | 2.5694  |
| 8   | 230    | 90     | 12    | 30     | 2.9312  |
| 9   | 150    | 60     | 10    | 60     | 2.4475  |
| 10  | 230    | 60     | 10    | 60     | 2.3038  |
| 11  | 150    | 90     | 10    | 60     | 2.2949  |
| 12  | 230    | 90     | 10    | 60     | 2.4646  |
| 13  | 150    | 60     | 12    | 60     | 2.5322  |
| 14  | 230    | 60     | 12    | 60     | 2.5121  |
| 15  | 150    | 90     | 12    | 60     | 2.5067  |
| 16  | 230    | 90     | 12    | 60     | 2.5430  |
| 17  | 190    | 75     | 11    | 45     | 2.3455  |
| 18  | 190    | 75     | 11    | 45     | 2.6518  |
| 19  | 190    | 75     | 11    | 45     | 2.5493  |
| 20  | 190    | 75     | 11    | 45     | 2.4989  |

Moreover, the machining layout of work piece and electrodes are shown in Figure 2 and Figure 3, respectively.
Figure 2. Ti-6Al-4L titanium alloy work piece after machining

Figure 3. Copper-tungsten electrodes after machining

3. Modeling
Regression analysis is a conceptually simple method for investigating functional relationships among variables. The relationship is expressed in the form of an equation or a model connecting the response or dependent variable and one or more predictor or independent variables [22]. Regression equations are found out using software of statistical analysis called Design Expert Version 6.0.4. To gain this job, linear and 2 factor interaction (2FI) models, both were exercised to investigate the parametric effect on response. We denote the response variable by $Y$ and the set of predictor variables by $x_1, x_2, ..., x_n$, where $n$ represents the number of independent variables. The relationship between $Y$ and $x_1, x_2, ..., x_n$ can be approximated by the regression model as in (1).

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{14} x_1 x_4 + \beta_{23} x_2 x_3 + \beta_{24} x_2 x_4 + \beta_{34} x_3 x_4$$

(1)

Where $Y$ is the estimated responses (Ra), $x_n$ are the variables for four machining parameters (A, B, C and D) and $\beta_n$ are regression parameters or coefficients. The coefficient $\beta_i$ are the linear terms while the coefficient $\beta_{ij}$ are the interaction terms.

3.1 Regression models of surface roughness
According to the results of machining experiments given in Table 4, regression models for both linear and 2FI models are developed. The equations of the fitted model for Ra according to the four variables ($x_1 = A$, $x_2 = B$, $x_3 = C$ and $x_4 = D$) as in (1) can be written as follows:

$$Ra = 3.2756 + (0.0039x_1) - (0.0068x_2) + (0.0266x_3) - (0.0225x_4)$$
Ra = -5.1249 + 0.0422x_1 + 0.0174x_2 + 0.8116x_3 - 0.0431x_4 + (5.8552E - 05x_1x_2) \\
- 0.0029x_1x_3 - 0.0003x_1x_4 - 0.0051x_2x_3 + 0.0005x_2x_4 + 0.0031x_3x_4 

(3)

3.2 Model adequacy test

The analysis of variance (ANOVA) and F-test were performed to justify the goodness of fit of the developed mathematical models as well as the significance of individual machining parameters. Table 5 shows the pre-ANOVA model summary statistic of Ra. It can be seen that the value of R-squared for the 2FI model is calculated as 0.835, which is much better as it is near to 1 compared to the linear model (0.608). Moreover, it indicates that the presented data fit in the developmental model. Hence, the 2FI model suggested is the most appropriate.

Table 5. Model summary statistics for Ra.

| Model  | R\(^2\) | Adj. R\(^2\) | Pred. R\(^2\) |
|--------|---------|-------------|---------------|
| Linear | 0.608   | 0.504       | 0.169         |
| 2FI    | 0.835   | 0.651       | -0.088        |

\(^a\)suggested

Table 6 and Table 7 shows the summary of the ANOVA results of the proposed models for Ra. The ANOVA table contains the degree of freedom (DF), sum of square (SS), mean of square (MS), F-value and P-value. As seen from Table 6, the developed linear model is significant with the P-value of 0.0049, which indicates that the model is significant at 95% confidence level. The suggested 2FI model also statistically significant for Ra which is 0.0163. Moreover, the MS value of the linear model (0.5975) is larger than the value of MS of residual (0.1026), thus the computed F value is 5.8265 implies that the model is significant. As presented in Table 7, it can be observed that the MS value of the 2FI model is 0.3275, which is also larger that the MS value of the residual (0.0722). Hence, the computed F value implies the model is also significant (4.5397). Table 8 and 9 both show the value of R-squared (R\(^2\)), adjusted R-squared (Adj. R\(^2\)) and predicted R-squared (Pred. R\(^2\)) statistics. R\(^2\) value indicates the adequacy of the suggested model. The highest R\(^2\) value, the better the model fits the experimental data, which is R\(^2\) is always between 0 and 100%. Linear model shows that 60.8% of the variation is attributed to process parameters. 2FI model shows higher values of R\(^2\) compared to the linear model which explains variations in the Ra to the extent of 83.5%. The suggested model with the higher of Adj. R\(^2\) values are the better fit variables of the model. We can see that, 2FI model produced higher values of Adj. R\(^2\) (65.1%) compared to the linear model (50.4%) which explains the addition of interaction variables in the model gets the model better fit. Pred. R\(^2\) determines how well the model predicts responses for new observations. Larger values of Pred. R\(^2\) indicate models of greater predictive ability. For linear model, the Pred. R\(^2\) of 0.169 is not reasonable agreement with the Adj. R\(^2\) of 0.504 because the difference between the adjusted and predicted R\(^2\) is more than 0.2 which was not recommended for model to be adequate. 2FI model also a negative value of predicted R\(^2\) (-0.088) implies that the overall mean is a better predictor of the Ra.

Table 6. ANOVA for linear model of Ra.

| Source  | DF | SS   | MS   | F value | P value |
|---------|----|------|------|---------|---------|
| Regression | 4  | 2.3901 | 0.5975 | 5.8265  | 0.0049  |
| Source     | DF | SS   | MS   | F value | P value |
|------------|----|------|------|---------|---------|
| Regression | 10 | 3.2784 | 0.3278 | 4.5397 | 0.0163 |
| Residual error | 9   | 0.6499 | 0.0722 |         |         |
| Total      | 19 | 3.9283 |      |         |         |

Table 7. ANOVA for 2FI model of Ra.

| Source     | R²  | Adj. R² | Pred. R² |
|------------|-----|---------|----------|
| Regression | 0.608 | 0.504 | 0.169 |

Table 8. ANOVA model adequacy for linear model of Ra.

| Source     | R²  | Adj. R² | Pred. R² |
|------------|-----|---------|----------|
| Regression | 0.835 | 0.651 | -0.088 |

Table 9. ANOVA model adequacy for 2FI model of Ra.

Figure 4 and 5, respectively present the normal probability plot of residuals for both linear and 2FI models of Ra. It can be seen all the residuals are falling on the straight line for both models. It indicates that errors are normally distributed, which satisfy the normality test conditions. Therefore, the model developed is adequate and valid. Figure 6 and 7 show a plot of experimental versus the predicted values of Ra. Since all the predicted values are close to the experimental values, confirming that the models could predict the responses accurately.

Figure 4. Normal probability plot for linear model
3.3 Confirmation test

Confirmation test was purposely performed to verify the adequacy and validation of the models developed within the given range of the machining parameters as presented in Table 2. Three sets of
experiments were selected randomly. In order to estimate the accuracy of the prediction models, percentage error and average percentage error criteria were used as in (4):

$$PE(\%) = \frac{|\text{Predicted value} - \text{Experimental value}|}{\text{Experimental value}} \times 100$$

Where PE is the prediction error in %.

The predicted values and the actual experimental values were compared and their percentage error was calculated. The results of the confirmation test for Ra values are presented in Table 10. Prediction errors of linear model validations are found to be 16.57%, 16.31% and 11.49%. On the other hand, prediction errors of 2FI model are found to be 2.36%, 23.65% and 3.43%. Thus, the average prediction errors for both models are considered as 14.79% for the linear model and 9.81% for the 2FI model. The average percentage error on 2FI model of the Ra seems to be on slight lower rather than the linear model. And even some of the percentage error is in negative value.

**Table 10. Results of the confirmation test.**

| Model | Machining parameters | Experimental value (\(\mu m\)) | Predicted value (\(\mu m\)) | % Error |
|-------|----------------------|-------------------------------|-----------------------------|---------|
|       | ON (\(\mu s\)) | OFF (\(\mu s\)) | IP (A) | SV (V) |       |       |       |
| Linear | 150 | 60 | 10 | 30 | 2.6106 | 3.0432 | 16.57 |
|        | 230 | 60 | 10 | 60 | 2.3038 | 2.6796 | 16.31 |
|        | 190 | 75 | 11 | 45 | 2.4989 | 2.7860 | 11.49 |
|        | Average percentage error (%) | | | | | 14.79 |
| 2FI | 150 | 60 | 10 | 30 | 2.6106 | 2.6722 | 2.36 |
|        | 230 | 60 | 10 | 60 | 2.3038 | 1.7590 | 23.65 |
|        | 190 | 75 | 11 | 45 | 2.4989 | 2.4131 | 3.43 |
|        | Average percentage error (%) | | | | | 9.81 |

4. Optimization

Glowworm swarm optimization (GSO) algorithm is a nature inspired heuristics for optimization problem in swarm intelligence algorithms. Swarm intelligence is a type of artificial intelligence based on the collective behavior of decentralized, self-organized systems [25]. GSO algorithm was proposed by Krishnanand and Ghose in 2005 which is a derivative-free, meta-heuristic algorithm and mimicking the glow behavior of glowworms. The idea of the GSO algorithm comes from the biological behavior of the glowworms that attract mates or prey. The concept was like the brighter the glow, the more is the attraction. Moreover, GSO algorithm shares some general features with a well-known ant colony optimization (ACO) and particle swarm optimization (PSO), but with several significant differences and modifications [26].

The computational flowchart of the basic GSO algorithm can be summarized as in Figure 8 [27]:

\[\text{Figure 8} \quad \text{Computational flowchart of the basic GSO algorithm}\]
4.1 Optimization of surface roughness using GSO

The best selection of machining parameters improves not only on EDM cost, but also the surface integrity to a large extent by minimizing the roughness value of the work piece material. To evaluate the optimum performance of the GSO algorithm, the experimental data and mathematical modelling of two EDM processes are considered. Matlab R2014b was used for parametric optimization of the EDM processes with the following parameters: population size of glowworms \((n)\) and the maximum iteration \((t_{\text{max}})\) are set to 20 and 100, respectively. Other parameter settings include initial luciferin
value $(\ell_0) = 5$, luciferin decay constant $(\rho) = 0.4$, luciferin enhancement constant $(\gamma) = 0.6$, beta $(\beta) = 0.08$, step size $(s) = 0.03$, neighbourhood range $(\ell_\text{m}(i)) = 3$ and parameter used to control the number of neighbour $(nt) = 5$. In the present study, an effective GSO algorithm is developed to optimize the optimal combinations of machining parameters with the better surface roughness. The problem of optimization of machining parameters can be described by minimizing surface roughness as objective function. To formulate the objective function of optimization, both regression models which are given by equation (2) and (3), respectively were tested. Therefore, the objective function is written as follows:

$$
\text{minimize } Ra (A,B,C,D) = 3.2756 + 0.0039A - 0.0068B + 0.0266C - 0.0225D
$$

(5)

$$
\text{minimize } Ra (A,B,C,D) = -5.1249 + 0.0422A + 0.0174B + 0.8116C - 0.0431D + (5.8552E - 05AB)
- 0.0029AC = 0.0003AD - 0.0051BC + 0.0005BD + 0.0031CD
$$

(6)

Where Ra is surface roughness in $\mu m$, A is pulse on time in $\mu s$, B is pulse off time in $\mu s$, C is peak current in A and D is servo voltage in V.

The minimization of the objective function in (5) and (6) are subjected to the boundaries of the cutting condition values. Considering the lowest level is Level 1 and the highest level is Level 2, the limitation range of the optimization constraints are given as follows in (7)-(10):

$$
150\mu s \leq A \leq 230\mu s
$$

(7)

$$
60\mu s \leq B \leq 90\mu s
$$

(8)

$$
10A \leq C \leq 12A
$$

(9)

$$
30V \leq D \leq 60V
$$

(10)

The lowest and highest limitation range of cutting parameter is set as an input of GSO algorithm. The minimum Ra value is obtained at the last iteration $(t\text{max})$ where the glowworms $(n)$ that carry luciferin $(Ra)$ being in the optimum position.

5. Results and discussion

Table 11 summarizes the results of the parametric optimization for consuming both linear and 2FI models of Ra as objective function with experimental results. The objective functions were optimized subject to feasible bound of the control variables as exhibited in (6)-(9). The table includes an optimum combination of machining parameters with the most minimal value of Ra. The minimum surface roughness value (2.2949$\mu m$) of the experiment was obtained at the combination of 150$\mu s$ of pulse on time, 90$\mu s$ of pulse off time, 10A of peak current and 60V of servo voltage. GSO optimization estimated the minimum surface roughness (2.2751$\mu m$) of linear model at the combination of 163.0319$\mu s$ of pulse on time, 87.9741$\mu s$ of pulse off time, 10.7982A of peak current and 58.9041V of servo voltage. While the 2FI model estimated the minimum value of Ra (2.0287$\mu m$) at the combination of 188.6636$\mu s$ of pulse on time, 86.6291$\mu s$ of pulse off time, 10.0605A of peak
current and 59.3569V of servo voltage. Thus, it can be concluded that the 2FI model gives the most minimal value of Ra compared to the linear model and experimental result.

| Method       | Optimum machining parameters | Minimum Ra (µm) |
|--------------|------------------------------|-----------------|
|              | A (µs) | B (µs) | C (A) | D (V) |                       |
| Experimental | 150    | 90     | 10    | 60    | 2.2949                 |
| Linear model | 163.0319 | 87.9741 | 10.7982 | 58.9041 | 2.2751 |
| 2FI model    | 188.6636 | 86.6291 | 10.0605 | 59.3569 | 2.0287 |

6. Conclusion

In this study, the effects of the pulse on time (ON), pulse off time (OFF), peak current (IP) and servo voltage (SV) on the Ra of die sinking EDM was studied by using integrated regression and glowworm swarm optimization algorithm. The experimental data were collected from AG40L Sodick electrical discharge machine with full factorial design of experiment with added four center points. The validity of the linear and 2FI models of Ra was performed by using ANOVA and F test. Then, both models were applied as the objective function for the GSO optimization process. Statistical analysis was used as to discuss the results from the optimization process. From this integrated study, the following conclusions are made:

- Ra has found to be most minimum at the run no. 11 (2.2949µm) which the combinations of the cutting parameters are 150µs of pulse on time, 90µs of pulse off time, 10A of peak current and 60V of servo voltage.
- The predicted Ra values match the experimental values reasonably well, with R-squared of 0.608 and 0.835 for linear model and 2FI model, respectively.
- Based on the confirmation test, 2FI model of Ra gives slightly lower of the percentage error compared to the linear model of Ra.
- 2FI model of Ra predicted value of Ra (2.0287µm) much lower rather than the linear model (2.2751µm).
- For optimization process, it can be summarized that the 2FI model of Ra gives the most minimal value of Ra compared to the linear model and experimental result.

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