Research Article

Prognostics, Health Assessment, and Modelling of Material Removal Rate by EDM for Al 6061 and AISI 304 via Cockroach Swarm and Fruit Fly Optimization Approaches

Senthil Kumaran Selvaraj,1 Jayakumar Kaliappan,2 Natarajan Muthuswamy,3 S. Ramesh Kumar,4 and Muralimohan Cheepu5

1Department of Manufacturing Engineering, School of Mechanical Engineering, Vellore Institute of Technology (VIT), Vellore 632 014, Tamil Nadu, India
2School of Computer Science and Engineering, Vellore Institute of Technology (VIT), Vellore 632014, Tamil Nadu, India
3School of Mechanical Engineering, Vellore Institute of Technology (VIT), Vellore 632 014, Tamil Nadu, India
4School of Mechanical Engineering, SASTRA Deemed to be University, Thanjavur 613401, India
5Super-TIG Welding Co.,Ltd., Busan, Republic of Korea

Correspondence should be addressed to Senthil Kumaran Selvaraj; senthilkumaran.s@vit.ac.in

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Micro-electric discharge machining (Micro-EDM) is deployed for machining hard-to-machine materials, such as various grades of titanium alloys, heat-treated alloy steels, composites, tungsten carbides, and so forth. Mild steel is known for its easy machinability. However, conventional machining of mild steel can often lead to the built-up edge formation on the tool. There is a minimal focus on machining ductile materials using nonconventional machining processes. This is due to the rapid work hardening in cold forming conditions. In the present study, the aluminium alloy 6061 and mild steel AISI 304 were taken as a work piece. Input pulse on factors considered as three levels and orthogonal array utilized to optimize the EDM parameters. Numerical results confirm the influence of input parameters in the response. The highest MRR is obtained at \( T_{\text{on}} = 40 \mu s \) and \( T_{\text{off}} = 4 \mu s \), and the least MRR is acquired at \( T_{\text{on}} = 20 \mu s \) and \( T_{\text{off}} = 3 \mu s \). The fruit fly algorithm and the cockroach swarm algorithm were used to predict the optimal minimized MRR value. The experimental results show that the cockroach swarm algorithm was performing better than the fruit fly algorithm in the MRR minimization process.

1. Introduction

Nontraditional machining processes were developed since the 1930s. Due to industrialization and as a result of war, methods that include less workforce and that give high precision are the need of the hour. This process is capable of producing high precision, highly accurate size, and shapes can machine sturdy materials such as tungsten alloys, Inconel alloys, heat-treated alloys, and metal matrix composites [1]. Wire EDM was developed in the 1960s and 1970s as an innovative process for making dies from hardened steel [2]. It is a kind of EDM in which a thin wire is utilized to machine electrically conductive material. The addition of EDM to the methods of machining has created an optimal process of manufacturing extremely complicated products that are independent or self-reliant of the properties of the material [3]. This is due to the integrity of the potential of EDM to cheaply produce products, which are hard and complicated to be done by the conventional machining processes. Output factors such as TW, MRR, and SR are significant indicators of machining performance. Highly extensive research is taking place in the recently regarding the optimization of parameters. Die sinker EDM can be utilized to machine intricate cavities and structures in tools.
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and dies, for example, moulds for plastic injection and dies for metal stamping [4]. The process starts with machining a graphite electrode to create a “positive” of the required complex cavity or structure. Then, the electrode is brought in contact with the workpiece, creating sparks on the surface of the workpiece as the gap is closed by the surface features [5]. The plus points of dry EDM are lower tool wear, higher precision, no fire hazard, no toxic fume generation, narrower discharge gap length, and the possibility of arbitrary machining directions. Disadvantages, however, include low material removal rates and poor process stability [6].

Material removal rate (MRR) is the ratio of the volume of material removed and the time of machining. An alternate definition of the material removal rate is to consider an “instantaneous” MRR (independent of time), which is the speed of removal of material area moves through the workpiece [7]. The MRR keeps changing during the process because the depth of the cut is not constant. This is important in specific scenarios, such as whether the forces of cutting and the produced product and the strains in the tool are considered. The varying quantity of MRR along the attenuating shaft implies that the CF and, therefore, the strains also vary according to the process [8].

Surface roughness (SR) is a part of the texture of the surface of an object. It is defined as the changes in the direction of the normal vector of an actual object surface from the ideal object surface. If the changes in the normal vector are substantial, then we have a rough surface. If the deviations are negligible, then we have a smooth surface [9]. In surface science, roughness is defined as the large-frequency, low-wavelength part of the surface being measured. However, in practical scenarios, we need to know the value of both the magnitudes of the amplitude and the frequency to confirm whether a surface is viable [10].

Roughness plays a crucial part in finding how an actual object would interlude within its surroundings. Rough surfaces generally wear rapidly and have higher coefficients of friction than surfaces that are smooth [11]. Roughness sometimes acts as a great foreteller of the quality of a mechanically produced part, since surface defects might create some nucleation sites where cracks initiate or corrosion starts [12]. It can also conclude that roughness may further result in adhesion. In general terms, instead of the descriptors that are specific to scale, cross-scale ones like fractality of the surface give much better and meaningful results of the mechanical interactivity at surfaces with the static friction and contact stiffness [13]. Tool wear (TW) is an essential factor as it affects and alters the shape of the final product and also its dimensional accuracy. Tool wear is directly related to the metal’s melting point, or we can say the material. Further, tool wear is directly influenced by the precipitation and collection of carbon in dielectric from the surface of the electrode during the sparking process. Deepak et al. discussed the input parameters of wired EDM on machining of Al 6061 reinforced with SiC and summarized material removal rate influenced by input parameter. Optimization algorithms can play a good role in tuning the parameters to reduce the wear [14], [15]. Current, pulse-on, voltage, and wire speed proportionally increase the MRR, and it decreases with pulse-off and rotational speed after certain limit [16]. Another study found current and pulse-on and played a significant role in out-of-roundness while machining. Discharge current, pulse-on time, pulse-off time, gap voltage, and dielectric pressure contributed to 70.46%, 9.66%, 5.84%, 0.06%, and 0.23%, respectively, as influential parameters [17]. In machining of HCHCR steel, hybrid optimization utilization improved the quality of machining by having better MRR and surface roughness [18]. Patel et al. discussed the influence of electrodes in MRR and found aluminium electrode as best to machine the mild steel with EDM technique. Analysis of heat-affected zone reveals the distribution of heat on work piece during machining process [19]. Taguchi grey analysis with $L_{23}$ orthogonal array EDM machining of titanium alloy with copper electrode was studied. Hybrid factor enhanced the analysing part to identify the contribution of input parameters like current, pulse time, and voltage to obtain the better responses such as surface roughness and MRR [20]. Mixing of graphite, Si, and W powders in the dielectric improved the performance of machining of steel. SEM analysis ensured the material migration during the EDM machining; the concentration of powder has been optimized to obtain good surface finish [21].

The literature has identified and discussed about the machining parameters of EDM and how they influence the operation and the output such as surface roughness. However, the optimization process for input parameters has been limited. To bridge input parameters with optimized techniques to obtain the optimum responses, a step is attempted in this study. The primary aim of this work is to vary and optimize the machining conditions and parameters for aluminium alloy (6061) and mild steel AISI 304 grade through cockroach swarm and fruit fly optimization approaches.

2. Materials and Methods

2.1. Materials Used. The materials used as workpieces are aluminium alloy and mild steel. The aluminium grade is Al 6061, and mild steel grade is AISI 304. The EDM machine was ELECTRONICA’s C-425 die sinker machine with a PSR 35 pulse generator and is shown in Figures 1(a) and 1(b).

The chemical composition for Al 6061 and AISI 304 was performed by the X-ray spectroscopy (XPS) and shown in Tables 1 and 2, respectively. The Vickers micro-hardness testing is adopted to measure the hardness of Al 6061 and AISI 304. The hardness is taken at 1 kgf with dwell time of 10 s. 30 HV and 200 HV are the micro-hardness value for Al 6061 and AISI 304, respectively.

2.2. Material of Tool. The copper electrode was used to machine the workpiece metals. It is cut from a long copper rod of 10 mm in diameter, as shown in Figure 2(a) and 2(b). The copper electrode is used as it is proven to produce better surface roughness values. However, the copper electrode has a lower heating value. The copper electrode used is shown in Figure 2(a).
2.3. Technologies and Software Used. MINITAB 19 was utilized to perform DOE (design of experiments) and ANOVA (analysis of variance), as shown in Table 3.

The design of experiments is a design model that helps in analysing the variation of response factors when the input factors or design factors are varied. This helps in providing an ideal and hypothesized condition for experiments and can give credible and dependable results if used correctly. ANOVA is used to test the difference and influence of several independent or dependent factors or variables on one
response variable. It helps us to determine the effect of every input factor on the output factor. It also helps us identify the most significant parameter of any process.

2.4. Design of Experiments. The concept of the Taguchi’s design of experiments was used, and the L9 orthogonal array was selected. The parameters that are to be varied were chosen; they were pulse-on time and pulse-off time. These parameters were given three levels each, and experiments are done accordingly. The design factors and values of each level are shown below in Table 4.

The Taguchi L9 orthogonal array aids us in carrying out the experiments statistically and scientifically, to produce reliable results. The array is shown in Table 5.

2.5. Methodology. Firstly, the workpiece is thoroughly cleaned to remove surface impurities. Surface impurities may affect the quality of machining. It may also hinder the removal and surface roughness. Then, the workpiece is placed on the worktable and screwed into position using an Allen key, as shown in Figure 3. The work holding device ensures that the work metal does not move during the machining process; this will provide proper and accurate machining. The copper electrode of the 10 mm diameter is securely fastened into the electrode holder. The electrode holder has a collet setup and is screwed tight with the help of a spanner.

The die-sinking EDM machine is switched ON, and the type or mode of die sinking is determined. It could be either dry mode or submerged mode [22]. Then, the position coordinates, namely, the y-coordinate of the tool, is calibrated according to the workpiece thickness. The other two coordinates, the x-coordinate and y-coordinates, are also adjusted using the position controls. The electrode is then lowered to the work metal while maintaining a minuscule gap between the tool tip and work metal. Then, the sparking process is started by pressing the “SPARK” button, as shown.

Table 3: A typical Minitab software was used for experiment analysis.

| One-way ANOVA: MRR vs pulse-off time |
|--------------------------------------|
| Model summary                        |
| $S$ $\quad$ $R$-sq $\quad$ $R$-sq(adj) $\quad$ $R$-sq(pred) |
| $0.0001728$ $\quad$ $4.00\%$ $\quad$ $0.00\%$ $\quad$ $0.00\%$ |

| Means |
|-------|
| $N$   |
| pulse-off time |
| $3$   |
| $0.000260$ |
| $0.000181$ |
| $(0.000016, 0.000504)$ |
| $3$   |
| $0.000328$ |
| $0.000169$ |
| $(0.000084, 0.000572)$ |
| $3$   |
| $0.000278$ |
| $0.000034$ |
| $(0.000034, 0.000522)$ |

| Sl. no. | Pulse-on time | Pulse-off time | MRR     |
|---------|---------------|---------------|---------|
| 1       | 20            | 3             | 0.0000632 |
| 2       | 20            | 3             | 0.0001421 |
| 3       | 20            | 5             | 0.0000964 |
| 4       | 30            | 3             | 0.0002981 |
| 5       | 30            | 4             | 0.0003718 |
| 6       | 30            | 5             | 0.0003101 |
| 7       | 40            | 3             | 0.0004198 |
| 8       | 40            | 4             | 0.0004712 |
| 9       | 40            | 5             | 0.0004276 |

Table 4: Design factors and their levels.

| Factors                  | Symbol  | Level 1 | Level 2 | Level 3 |
|--------------------------|---------|---------|---------|---------|
| Pulse-on time (ms)       | $T_{on}$| 20      | 30      | 40      |
| Pulse-off time (ms)      | $T_{off}$| 3       | 4       | 5       |

Table 5: L9 orthogonal array for EDM parameters.

| Pulse-on time (coded) | Pulse-off time (coded) | Pulse-on time (actual) | Pulse-off time (actual) |
|-----------------------|------------------------|------------------------|------------------------|
| 1                     | 1                      | 20                     | 3                      |
| 1                     | 2                      | 20                     | 4                      |
| 1                     | 3                      | 20                     | 5                      |
| 2                     | 1                      | 30                     | 3                      |
| 2                     | 2                      | 30                     | 4                      |
| 2                     | 3                      | 30                     | 5                      |
| 3                     | 1                      | 40                     | 3                      |
| 3                     | 2                      | 40                     | 4                      |
| 3                     | 3                      | 40                     | 5                      |
in Figure 4. The workpiece was machined for a specific amount of time, 60 seconds for each run in our experiment. After that, the sparking is turned off. The workpiece is then removed from the work holding device and is checked for determining the amount of material loss. This value will help us determine the material removal rate.

The same procedure is repeated for the required number of trials; in our experiment, it is nine runs for each workpiece material. The experimentation process also includes the recording of corresponding values for pulse-on time and pulse-off time. Parameters like gap current and gap voltage are established as a result of the movement of electrode, sparking at the electrode, and the machining process. As the machining time is kept at a constant value of 60 seconds, the analysis of the removal rate is simplified.

2.6. Machining. The machining resulted in the formation of craters on the surface of the metals, aluminium, and mild steel. The samples obtained after machining are shown Figures 5 and 6.

3. Results and Discussions

The material removal rates for aluminium and mild steel for different pulse-on time and pulse-off times are shown in Tables 6 and 7, respectively.

3.1. Effect of Pulse-On Time on MRR of Aluminium. The experiments performed on the aluminium alloy, Al 6061, were done according to the Taguchi’s concepts of design of experiments. The input parameters were varied to determine the optimal values for the desired removal rate.

In our experiment, three levels of each input factor were chosen. For pulse-on time, the 3 levels chosen were as follows:

(i) Level 1: 20 μs
(ii) Level 2: 30 μs
(iii) Level 3: 40 μs

Upon varying these parameters, according to the above-mentioned levels, some interesting results were obtained; the results are shown in Table 8.

For a pulse-on time of 20 ms, for different levels of increasing pulse-off time, we can observe that the removal rate is 0.0001351 g/sec for a pulse-off time of 3 μs. Then, as the pulse-off time increments, the rate drops to 0.0000870 g/sec, but as it increases further, the MRR increases to 0.0001872 g/sec. So, at a pulse-on time of 20 μs, the removal rates are minimal and not very useful in metal erosion. For pulse-on time of 30 μs, for different levels of pulse-off time, we can observe that the removal rate ranges are higher than that of the previous level. The MRR ranges from 0.0002598 g/sec to 0.0003416 g/sec. The highest MRR is obtained at 4 μs, and the least is collected at 5 μs. The removal rates increase...
with incrementing pulse-off time, for the same pulse-on time, up to a specific value; then, it reduces with more increase. For a pulse-on time of 40 μs, for differing levels of pulse-off time, we can observe that removal rate ranges are very much higher than those of the previous levels. The ranges of removal rates are from 0.0003876 g/sec to 0.0004352 g/sec. The highest MRR is obtained at 4 μs, and the least is achieved at 5 μs. A similar pattern was exhibited at level 2 of pulse-on time. The removal rates increase initially with increment in pulse-on time and then reduce on further increase in pulse-on time.

3.1.1. One-Way ANOVA: MRR vs. Pulse-On Time for Aluminium. The pulse-on time parameter was taken as the input factor, and the MRR was considered as a response factor. The significance level was taken as α = 0.05. The null hypothesis tells us that all means are equal. On performing the analysis of variance, for rate vs. pulse-on time, it was found that the P value obtained was 0.019, and the degrees of freedom are 2, as shown in Table 9. As the P value < α, we can say that the difference between means is statistically significant. This means that we can reject the null hypothesis, which tells us that all ways are equal. One factor is significantly affecting the results than the other factors.

The mean values and standard deviation at 95% confidence limits are shown in Table 10. At 30 μs, we obtain the east standard deviation; this suggests that the values are closed to the central measures.

Different plots for rates vs. pulse-on time, namely, the interval plot, individual value plot, and the boxplot, are shown in Figures 7(a)–7(c), respectively. From the interval plot, we can observe that the mean value for a pulse-on time of 20 μs is that least and is the highest for the pulse-on time of

| Pulse-on (actual) | Pulse-off (actual) | Pulse-on (coded) | Pulse-off (coded) | MRR       |
|------------------|-------------------|------------------|------------------|-----------|
| 20               | 3                 | 1                | 1                | 0.0001351 |
| 20               | 4                 | 1                | 2                | 0.0000870 |
| 20               | 5                 | 1                | 3                | 0.0001872 |
| 30               | 3                 | 2                | 1                | 0.0002598 |
| 30               | 4                 | 2                | 2                | 0.0003416 |
| 30               | 5                 | 2                | 3                | 0.0002709 |
| 40               | 3                 | 3                | 1                | 0.0003876 |
| 40               | 4                 | 3                | 2                | 0.0007364 |
| 40               | 5                 | 3                | 3                | 0.0004352 |

Table 6: MRR values for aluminium.

| Pulse-on (actual) | Pulse-off (actual) | Pulse-on (coded) | Pulse-off (coded) | MRR       |
|------------------|-------------------|------------------|------------------|-----------|
| 20               | 3                 | 1                | 1                | 0.0000632 |
| 20               | 4                 | 1                | 2                | 0.0001421 |
| 20               | 5                 | 1                | 3                | 0.0000964 |
| 30               | 3                 | 2                | 1                | 0.0002981 |
| 30               | 4                 | 2                | 2                | 0.0003718 |
| 30               | 5                 | 2                | 3                | 0.0003101 |
| 40               | 3                 | 3                | 1                | 0.0004198 |
| 40               | 4                 | 3                | 2                | 0.0004712 |
| 40               | 5                 | 3                | 3                | 0.0004276 |

Table 7: MRR values for mild steel.

| Pulse-on (actual) | Pulse-off (actual) | Pulse-on (coded) | Pulse-off (coded) | MRR |
|------------------|-------------------|------------------|------------------|-----|
| 20               | 3                 | 1                | 1                | 0.0000870 |
| 20               | 4                 | 1                | 2                | 0.0001421 |
| 20               | 5                 | 1                | 3                | 0.0000964 |
| 30               | 3                 | 2                | 1                | 0.0002981 |
| 30               | 4                 | 2                | 2                | 0.0003718 |
| 30               | 5                 | 2                | 3                | 0.0003101 |
| 40               | 3                 | 3                | 1                | 0.0004198 |
| 40               | 4                 | 3                | 2                | 0.0004712 |
| 40               | 5                 | 3                | 3                | 0.0004276 |

Table 8: MRR at different levels of pulse-on time.

| Pulse-on (actual) | Pulse-off (actual) | Pulse-on (coded) | Pulse-off (coded) | MRR |
|------------------|-------------------|------------------|------------------|-----|
| 20               | 3                 | 1                | 1                | 0.0001351 |
| 20               | 4                 | 1                | 2                | 0.0000870 |
| 20               | 5                 | 1                | 3                | 0.0001872 |
| 30               | 3                 | 2                | 1                | 0.0002598 |
| 30               | 4                 | 2                | 2                | 0.0003416 |
| 30               | 5                 | 2                | 3                | 0.0002709 |
| 40               | 3                 | 3                | 1                | 0.0003876 |
| 40               | 4                 | 3                | 2                | 0.0007364 |
| 40               | 5                 | 3                | 3                | 0.0004352 |

Table 9: One-way ANOVA: MRR vs. pulse-on time for aluminium.

Table 10: Mean and standard deviation at different pulse-on times for aluminium.

| Pulse-on time/pulse-off time (μs) | 20 μs | 30 μs | 40 μs |
|-----------------------------------|-------|-------|-------|
| 3                                 | 0.0001351 | 0.0002598 | 0.0003876 |
| 4                                 | 0.0000870 | 0.0003416 | 0.0007364 |
| 5                                 | 0.0001872 | 0.0002709 | 0.0004352 |

| Source | DF  | Adj SS | Adj MS | F value | P value |
|--------|-----|--------|--------|---------|---------|
| Pulse-on | 2  | 0.000000 | 0.000000 | 8.32    | 0.019   |
| Error   | 6  | 0.000000 | 0.000000 |         |         |
| Total   | 8  | 0.000000 | 0.000000 |         |         |

Means

| Pulse-on | N | Mean | StDev | 95% CI |
|----------|---|------|-------|--------|
| 20       | 3 | 0.000136 | 0.000050 | (−0.000027, 0.000300) |
| 30       | 3 | 0.000291 | 0.000044 | (0.000127, 0.000454) |
| 40       | 3 | 0.000520 | 0.0001189 | (0.000356, 0.000683) |

Pooled StDev = 0.000115837
40 ms. This implies that as the pulse-on time increases, the removal rate experiences a significant change. It is also found that the ranges of removal rates for each pulse-on time are very similar. From the individual value plot, we observe that the means for each level of pulse-on time, 20 μs, 30 μs, and 40 μs, are 0.000136 g/sec, 0.000291 g/sec, and 0.000520 g/sec, respectively. From the boxplot, we can see that the values of removal rates at 20 μs are around mean. However, in the case of 30 μs and 40 μs, the values are more towards the lower limit, that is, lesser than the mean value.

3.2. Effect of Pulse-Off Time on MRR of Aluminium. The experiments performed on the aluminium alloy, Al 6061, were done according to the Taguchi’s concepts of design of experiments. The input parameters were varied to determine the optimal values for the desired removal rate. In our experiment, three levels of each input factor were chosen. For pulse-off time, the 3 levels selected were as follows: Level 1: 3 μs, Level 2: 4 μs, and Level 3: 5 μs. Upon varying these parameters, according to the levels mentioned above, some impressive results were obtained; the results are shown in Table 11.

For a pulse-off time of 3 μs, for different levels of increasing pulse-on time, we can observe that the material removal rate is 0.0001351 g/sec for a pulse-on time of 20 μs.

Then, as the off-time pulse increments, the rate increments to 0.0002598 g/sec, as it increases further the MRR increases to 0.0003876 g/sec. So, at a pulse-off time of 3 μs, the removal rates gradually increase on incrementing pulse-on time. At the same pulse-on time value, the removal rates increments initially reduce with increasing pulse-off time. For a pulse-off time of 4 μs, for different levels of increasing pulse-on time, we can observe that the material removal rate is 0.0000870 g/sec for a pulse-on time of 20 μs. Then, as the pulse-off time increases, the MRR increases to 0.0003416 g/sec, and it expands further the MRR increases to 0.0007364 g/sec. So, at a pulse-off time of 4 μs, the removal rates gradually increase on increasing pulse-on time and have maximum values when compared to 3 μs and 5 μs. At the same pulse-on time value, the removal rate increments initially the decrement with increasing pulse-off time. For a pulse-off time of 5 μs, for different levels of incrementing pulse-on time, we can

| Pulse-off time/pulse-on time (μs) | 3 μs | 4 μs | 5 μs |
|------------------------------------|-----|-----|-----|
| 20                                 | 0.0001351 | 0.0000870 | 0.0001872 |
| 30                                 | 0.0002598 | 0.0003416 | 0.0002709 |
| 40                                 | 0.0003876 | 0.0007364 | 0.0004352 |

Table 11: MRR at different levels of pulse-off time.
observe that the material removal rate is 0.0001872 g/sec for a pulse-on time of 20 μs. Then, as the off-time pulse increases, the MRR increases to 0.0002709 g/sec, and as it expands further, the MRR increases to 0.0004352 g/sec. So, at a pulsed on-time of 5 μs, the removal rates gradually increase on increasing pulse-on time.

### 3.2.2. Effect of Pulse-On Time on MRR of Mild Steel

The experiments performed on mild steel, AISI 304, were done according to the Taguchi concepts of design of experiments. Input parameters were varied to determine the optimal values for the desired removal rate. In our experiment, three levels of each input factor were chosen. For pulse-on time, the 3 levels selected were as follows: Level 1: 20 μs, Level 2: 30 μs, and Level 3: 40 μs. Upon varying these parameters, according to the levels mentioned above, some impressive results were obtained; the results are shown in Table 14.

For a pulse-on time of 20 μs, for different levels of increasing pulse-off time, we can observe that the removal rate is 0.0000632 g/sec for a pulse-off time of 3 μs. Then, as the pulse-off time increases the removal rate increments to 0.0001421 g/sec, as it increases further the MRR drops to 0.0000964 g/sec. So, at a pulse-on time of 20 ms, removal rates are minimal and not very effective in metal erosion. For a pulse-on time of 30 μs, for different levels of pulse-off time, we can observe that removal rate ranges are higher than that of the previous level. The MRR ranges from 0.0001421 g/sec to 0.0003718 g/sec. The highest MRR is obtained at 4 μs, and the least is obtained at 3 μs. A similar pattern was exhibited at level 2 of pulse-on time. The material removal rates increase initially with an increase in pulse-off time and decrease with further increment in pulse-off time. Generally, higher pulse-on time leads in higher removal rate.

### Table 12: One-way ANOVA: MRR vs. pulse-off time for aluminium.

| Source | DF | Adj SS | Adj MS | F value | P value |
|--------|----|--------|--------|---------|---------|
| Pulse off | 2  | 0.000000 | 0.000000 | 0.28 | 0.766 |
| Error | 6 | 0.000000 | 0.000000 | - | - |
| Total | 8 | 0.000000 | - | - | - |

### Table 13: Means and standard deviation at different pulse-off times for aluminium.

| Pulse-off | N | Mean | StDev | 95% CI | Pooled StDev |
|-----------|---|------|-------|--------|--------------|
| 3         | 3 | 0.000261 | 0.000126 | (-0.000043, 0.000565) | 0.000215194 |
| 4         | 3 | 0.000388 | 0.000327 | (0.000084, 0.000692) | - |
| 5         | 3 | 0.000298 | 0.000126 | (-0.000006, 0.000602) | - |

Pooled StDev = 0.000215194
3.2.3. One-Way ANOVA: MRR vs. Pulse-On Time for Mild Steel. The pulse-on time parameter was taken as the input factor, and MRR was taken as a response factor. The significance level was taken as $\alpha = 0.05$. The null hypothesis tells us that all means are equal. On performing the analysis of variance, for removal rate vs. pulse-on time, it was found that the $P$ value obtained was 0.001, and the degrees of freedom are 2, as shown in Table 15. As the $P$ value $< \alpha$, we can say that the difference between the means is statistically significant. This means that we can reject the null hypothesis, which tells that all means are equal. One factor is significantly affecting the results than the other factors.

![Interval Plot of MRR vs Pulse off](image)

*The pooled standard deviation is used to calculate the intervals.*

![Individual Value Plot of MRR vs Pulse off](image)

![Boxplot of MRR](image)

**Figure 8:** (a) Interval plot of MRR vs pulse-off time for aluminium. (b) Individual value plot of MRR vs pulse-on time for aluminium. (c) Box plot of MRR vs pulse-off time for aluminium.

| Pulse-on time/pulse-off time ($\mu$s) | 20 $\mu$s | 30 $\mu$s | 40 $\mu$s |
|--------------------------------------|-----------|-----------|-----------|
| 3                                    | 0.0000632 | 0.0002981 | 0.0004198 |
| 4                                    | 0.0001421 | 0.0003718 | 0.0004712 |
| 5                                    | 0.0000964 | 0.0003101 | 0.0004276 |

**Table 14: MRR at different levels of pulse-on time.**

| Source       | DF | Adj SS   | Adj MS   | $F$ value | $P$ value |
|--------------|----|----------|----------|-----------|-----------|
| Pulse-off    | 2  | 0.000000 | 0.000000 | 68.75     | 0.000     |
| Error        | 6  | 0.000000 | 0.000000 |           |           |
| Total        | 8  | 0.000000 |          |           |           |

**Table 15: One-way ANOVA: MRR vs. pulse-on time for mild steel.**
The mean values and standard deviation at 95% confidence limits are shown in Table 16. At 20 μs, we obtain the least standard deviation; this suggests that the values are close to the central measures.

Different plots for removal rate vs. pulse-on time, namely, the interval plot, individual value plot, and the boxplot, have been shown in Figures 9(a)–9(c), respectively. From the interval plot, we can observe that the mean value for a pulse-on time of 20 μs is that least and is the highest for the pulse-on time of 40 ms. This implies that as the pulse-on time increases, the removal rate experiences a significant change. It is also found that the ranges of removal rates for each pulse-on time are very similar. From the individual value plot, we observe that the means for each of pulse-on time, 20 μs, 30 μs, and 40 μs, are 0.000101 g/sec, 0.000327 g/sec, and 0.000440 g/sec, respectively. From the boxplot, we can see that the values of removal rates at 20 μs are around mean. However, in the case of 30 μs and 40 μs, the values are

**Table 16: The mean and standard deviation in mild steel for different pulse-on times.**

| Pulse-on time | N | Mean     | StDev  | 95% CI               |
|---------------|---|----------|--------|----------------------|
| 20            | 3 | 0.000101 | 0.000040 | (0.000050, 0.000152) |
| 30            | 3 | 0.000327 | 0.000040 | (0.000276, 0.000378) |
| 40            | 3 | 0.000440 | 0.000028 | (0.000389, 0.000490) |

Pooled StDev = 0.0000360573

---

The pooled standard deviation is used to calculate the intervals.

**Figure 9:** (a) Interval plot of MRR vs pulse-on time for mild steel. (b) Individual value plot of MRR vs pulse-on time for mild steel. (c) Boxplot of MRR vs pulse-on time for mild steel.

---

**Table 17: Factor information for mild steel.**

| Method                   | Factor coding (−1, 0, +1) | Factors | Type  | Levels | Values |
|--------------------------|---------------------------|---------|-------|--------|--------|
| Factor information       |                           | Pulse-on time | Fixed | 3      | 20, 30, 40 |
|                          |                           | Pulse-off time | Fixed | 3      | 3, 4, 5   |
more towards the lower limit, that is, lesser than the mean value.

The fit summary shows that model used is statistically significant for the removal rate analysis. The results represented in the ANOVA format for the quadratic model are given in Tables 17 and 18. This model is being developed at a 95% level of confidence. There is only a 0.01% possibility that a “model value” as significant as F value could occur due to signal noise.

The mathematical relationship for correlating various process variables and the rate of machining is obtained as follows: 

\[
MRR = -0.000289 + 0.000188 \text{ pulse-on time}_{20} + 0.000038 \text{ pulse-on time}_{30} + 0.000039 \text{ pulse-off time}_{4} - 0.000029 \text{ pulse-off time}_{3} - 0.000011 \text{ pulse-off time}_{5}.
\]

### 3.3. Effect of Pulse-Off Time on MRR of Mild Steel

The experiments performed on mild steel, AISI 304, were done according to the concepts of the design of experiments. Input parameters were varied to determine the optimal values for the desired removal rate. In our experiment, three levels of each input factor were chosen. For pulse-off time, the three levels selected were as follows: Level 1: 3 \(\mu\)s, Level 2: 4 \(\mu\)s, and Level 3: 5 \(\mu\)s upon varying these parameters; according to the levels mentioned above, some impressive results were obtained, and the result is shown in Table 19.

For a pulse-off time of 3 \(\mu\)s, for different levels of incrementing pulse-on time, we can observe that the material removal rate is 0.0000632 g/sec for a pulse-on time of 20 \(\mu\)s. Then, as the pulse-on time increases, the MRR increases to 0.0001421 g/sec, and as it increases further, the MRR increases to 0.0004198 g/sec. So, at a pulse-off time of 3 \(\mu\)s, the removal rates are minimal and not very effective in metal erosion. For a pulse-off time of 4 \(\mu\)s, for different levels of pulse-on time, we can observe that the removal rate ranges are higher than that of the previous level. The MRR ranges from 0.0001421 g/sec to 0.0004712 g/sec. The highest MRR is obtained at 40 \(\mu\)s, and the least is obtained at 20 \(\mu\)s. The removal rates increase with increasing pulse-on time for the

### Table 18: ANOVA model for mild steel.

| Source            | DF | Adj SS         | Adj MS         | F value  | P value |
|-------------------|----|----------------|----------------|----------|---------|
| Pulse-on time     | 2  | 0.000000       | 0.000000       | 1079.45  | 0.000   |
| Pulse-off time    | 2  | 0.000000       | 0.000000       | 45.11    | 0.002   |
| Error             | 4  | 0.000000       | 0.000000       |          |         |
| Total             | 8  | 0.000000       | 0.000000       |          |         |

### Model summary

| Source  | SS        | R-Sq | R-sq(adj) | R-sq(pred) |
|---------|-----------|------|-----------|------------|
| Pulse-on time | 0.000000 | 99.82% | 99.64% | 99.10%       |

### Coefficients

| Team      | Coef    | SE coef | T value | P value | VIF |
|-----------|---------|---------|---------|---------|-----|
| Constant  | 0.000289| 0.000003| 95.25   | 0.000   | 1.33|
| Pulse-on time | 20     | 0.000004| -43.91  | 0.000   | 1.33|
| Pulse-off time | 3      | 0.0000029| -6.66   | 0.003   | 1.33|
| Pulse-off time | 4      | 0.000039| 9.20    | 0.001   | 1.33|

### Table 19: MRR at different levels of pulse-on time.

| Pulse-off time/pulse-on time (\(\mu\)s) | 3 \(\mu\)s | 4 \(\mu\)s | 5 \(\mu\)s |
|----------------------------------------|------------|------------|------------|
| 20                                     | 0.0000632  | 0.0001421  | 0.0000964  |
| 30                                     | 0.0002981  | 0.0003718  | 0.0003101  |
| 40                                     | 0.0004198  | 0.0004712  | 0.0004276  |

### Table 20: One-way ANOVA: MRR vs. pulse-off time for mild steel.

| Source      | DF | Adj SS    | Adj MS    | F value | P value |
|-------------|----|-----------|-----------|---------|---------|
| Pulse-off time | 2  | 0.000000  | 0.000000  | 0.13    | 0.885   |
| Error       | 6  | 0.000000  | 0.000000  |         |         |
| Total       | 8  | 0.000000  |           |         |         |
same pulse-off time. For a pulse-off time of 5 μs, for different levels of pulse-on time, we can observe that the removal rate ranges are very much lesser than those of the previous levels. The ranges of removal rates are from 0.000964 g/sec to 0.0004276 g/sec. The highest MRR is obtained at 40 μs, and the least is obtained at 20 μs. A similar pattern was exhibited at all the levels of pulse-off time. The material removal rates increase initially with increment in pulse-off time and then decrease with further increment in pulse-off time for the same pulse-on time.

3.3.1. One-Way ANOVA: MRR vs. Pulse-Off Time. The pulse-off time parameter was taken as the input factor, and MRR was taken as a response factor. The significance level was taken as α = 0.05. The null hypothesis tells us that all means are equal. On performing analysis of variance, for MRR vs. pulse-off time, it was found that P value obtained was 0.885, and the degrees of freedom are 2, as shown in Table 20. As the P value >α, we can say that the difference between the means is not statistically significant. This means that we must accept the null hypothesis, which tells that all means are equal. This factor does not significantly affect the results; the other factor has a significant influence on the response parameter.

The mean values and standard deviation at 95% confidence limits are shown below in Table 21. At 3 μs, we obtain the least standard deviation; this suggests that the values are closed to the central measures.

Different plots for MRR vs. pulse on time are shown in Figures 10(a)–10(c), namely, the interval plot, individual value plot, and the boxplot, respectively. From the interval plot, we can observe that the mean value for a pulse-off time of 3 ms is that least and is the highest for the pulse-off time of 4 ms. This implies that as the pulse-off time increases, the removal rate experiences a significant increment and then decreases with further increase. It is also found that the ranges of removal rates for each pulse-on time are very similar. From the individual value plot, we observe that the means for each level of pulse-off time, 3 μs, 4 μs, and 5 μs, are 0.000260 g/sec, 0.000328 g/sec, and 0.000278 g/sec, respectively. From the boxplot, we can see that the values of removal rates for each level of pulse-off time are leaning towards higher side of the mean.

3.4. MRR Optimization Using Fruit Fly and Cockroach Swarm Optimization Algorithms. Optimization techniques, or algorithms, are used to find the solution to the problem specified in linear and nonlinear constrained optimization problems. The optimization algorithm [23, 24] aims at finding the combination of design variable values that results in the best objective function value, while satisfying all the equality, inequality, and side constraints.

The main disadvantage of the Taguchi method is that the results obtained are only relative and it does not exactly indicate what parameter has the highest effect on the performance characteristic value. Since orthogonal arrays do not test all variable combinations, this method should not be used where all the relationships between all variables are needed. Whenever the process parameters obtained are contradicted to each other due to different mechanisms affecting various qualities, many studies devised a new experiment design methodology to optimize multiple quality characteristics simultaneously by integrating Taguchi method with other techniques [25]. It will provide accurate results for the robust design of products and process.

ANOVA is a statistically decision-making tool, which helps in testing the significance of all main factors. ANOVA method was utilized to understand the percentage of contribution of each parameter.

\[\text{Pooled StDev} = 0.0000360573\]

3.4.1. Fruit Fly Optimization Algorithm (FOA). Fruit fly optimization algorithm (FOA) is also a kind of bio-inspired optimization algorithm. The design problems in any field require the help of the optimization algorithm to enrich or obtain the solution. Pan had introduced this FOA algorithm. Fruit fly uses its apheresis and vision capability to find its food. Initially, the fruit fly’s apheresis organ smells the scent of its food; this organ was able to smell the food even 40 km away. Once it comes a little bit closer to the food, it then uses its vision capability to reach the food. Pan [14] applied it for the financial distress data of Taiwan’s enterprise. In this paper, the optimization function was used to find both the maximal and minimal values. The functionality of the algorithm is tested for the varying population strength and other characteristics. This paper also had verified the optimization capability of FOA, for which the financial distress data of 100 companies are taken as the test data. Three methods are taken for comparison study, and they are fruit fly Algorithm optimized general regression neural network (FOAGRNN), general regression neural network (GRNN), and multiple regression (MR). The experimental results have proved that FOA has very well optimized the spread value of the GRNN network parameter, and the classification prediction capability of the GRNN is also enhanced.

Travelling salesman problem is a classic NP-hard, combinatorial optimization problem. Iscan and Gunduz [24] had applied FOA for travelling salesman problem with
some modifications in the vision phase. There are no changes in the apheresis phases. Two different methods are developed in the vision phase. The first 30% of the best solutions from apheresis phase is in the half of the city arrangement matrix, which is updated. If this first phase was not able to get nearer to the optimal solution, then the second half of the city arrangement matrix is randomly fitted.

Fruit fly is a seven-step process. Similar to any optimization algorithm, we need to initialize the population count and the total number of iterations. The initial fruit fly location is \((X_0, Y_0)\), and the fruit flies are initialized by giving them the random direction and distance for the search of food using apheresis by an individual fruit fly. Since the food location cannot be known, the distance to the origin is thus estimated.

Energy conservation is a significant industrial problem. Xia [23] proposed the improved fruit fly optimization algorithm withmatch pursuit method was used to decompose and reconstruct the detection signal for the accurate decomposition of heat exchange fouling ultrasonic detection signal. IFOA can avoid local extremums. The experimental results have proven that the residual energy of IFOA-MP method decomposition is much lesser than FOA-MP.

The first step in FOA is population initialization. The \(X_0\) and \(Y_0\) are the initial fruit fly position. Next, the fruit fly population set is created using equation (1). \((X_i, Y_i)\)

\[
X_i = X_0 + \text{rand} \\
Y_i = Y_0 + \text{rand}
\]  

(1)

The next step is the calculation of smell concentration judgment value \(s\). The value of \(s\) is calculated by finding the distance \(D\) using the formula in equation (2) and then finding the reciprocal of distance \(D\) using

\[
D(i) = \sqrt{x(i)^2 + y(i)^2},
\]  

(2)

\[
s[i] = \frac{1}{D(i)}.
\]  

(3)

We substitute the calculated smell concentration judgment value \(S\) into smell concentration judgment function (i.e., our fitness function). We find the smell concentration value (i.e., fitness function value) of the individual location of the fruit fly. We find out the fruit fly with maximal or minimal smell value as per the requirement of our optimization problem. This is termed as “smellBest.” Store the position index of this Fruit fly as \(X(\text{bestIndex})\) and \(Y(\text{bestIndex})\). Next, the vision phase starts, where the fruit fly flies towards that location with the best fitness function value.
3.4.2. Cockroach Swarm Optimization Algorithm (CSO).

Inspired by the social behaviour exhibited by cockroaches in looking for food, scattering, and escaping of light, Zhoa Hui developed the cockroach swarm optimization algorithm (CSO) [24] in the Year 2010. The cockroach is an insect, which belongs to Blattodea. Termites also come under this group. Cockroach likes to live in dark and moist places. Cockroaches quickly learn about its surroundings using its sensitive antennae. From its swarming and chasing habits, we can conclude that it can communicate with each other effectively. The cockroaches can survive from its predators easily with its well-executed dispersing habit. It can quickly any small change in the environment; hence, its survival rate is high.

When the cockroach population undergoes a food shortage, they start exhibiting their ruthless habit. That is, the cockroaches will start eating each other for their survival. The bigger one eats the smaller ones, and the stronger one eats the weaker one. The CSO was framed from the habits mentioned above of cockroaches.

Many methods are available with travel planning problems, and many models were developed. The travel planning algorithm finds out the efficient use of transport
modes to complete his complete travel plan. The CSO approach is applied in this paper [25] to solve the travel planning problem. The output of this method was compared with PSO, CSO, and Dijkstra’s algorithm and found that the results were much improved.

The very first step of any optimization algorithm is initializing the population size, iteration count, and parameter values. The CSO algorithm has to execute three procedures at each iteration to solve any optimization problem. The three methods are chase-swarming, dispersing, and ruthless behaviour. The first executed process is the chasing swarm procedure; in this, the cockroaches place into the local best solution (Pi) and form small swarms. Afterward, the individual cockroaches move individually forward to the global optimum (Pg), as Figure 12 describes this process. In the chase-swarming procedure, in the new cycle, each individual (Xi) moves to the strongest cockroaches carrying the local best solutions (Pi) and form small swarms. The cockroaches next move forward to the global optimum (Pg) within its visual scope. The problem here is diverse searching, which is missed. So, the dispersing process is initiated at the random time interval. At regular intervals, each individual (Xi) is dispersed randomly so that the searching diversity is maintained. There is a need to replace the poor-performing cockroaches with the better-performing cockroaches for a better search of optimization solution.

The ruthless behaviour comes into play now. The cockroaches producing lower optimization results are replaced with better cockroaches. This process is equivalent to the phenomenon of eating weaker cockroaches in the case of inadequate food availability.

The set of equations used in the CSO implementation is given as follows.

Equations (4)–(6) are used for the chase swarming behaviour. Each X(i) will chase the local optimum(Opt) individual P(i) within its visual scope; When an individual is the best one within its visual scope, it will chase the global optimum individual Pg [24]. Equations (4) and (5) are used to find the optimum (Opt) value within the initial population named as P(i). The global optimum found is referred to as Pg. Using Equation (6), chasing swarm behaviour is operated.

\[
P(i) = \text{Opt}[X(j) | X(i) \neq j, j = 1, 2, \ldots, N] \quad \& \quad (i = 1, 2, \ldots, N),
\]

\[
Pg = \text{Opt}(X(i), i = 1, 2, \ldots, N),
\]

\[
X'(i) = \begin{cases} 
X'(i) + \text{step.rand.}(P(i) - X(i)), & X(i) \neq P(i) \\
X(i) + \text{step.rand.}(Pg - X(i)), & X(i) = P(i). 
\end{cases}
\]

Equation (7) is for dispersing behaviour.

\[
X' = X(i) + \text{rand}(1, D), i = 1, 2, \ldots, N.
\]

Equation (8) exhibits ruthless behaviour.

\[
X(k) = Pg.
\]

In solving the optimization problems, the very first step is to identify the design parameters. In our problem statement, the design parameters are identified as pulse-off at 3, 4, and 5 microseconds and pulse-on at 20, 30, and 40 microseconds. Next, the optimization problem has to be represented in the mathematical equation, and this serves as our objective function. Here, we have framed two equations. In equation (9), the MRR calculation is given for aluminium. In equation (10), the MRR calculation is given for mild steel. The optimization function was to minimize the MRR.

\[
\text{MRR (aluminium)} = 0.000082 + 0.0 \text{ Pulse} - \text{ on (actual)}_{20} + 0.000154 \text{ Pulse} - \text{ on (actual)}_{30} + 0.000383 \text{ Pulse} - \text{ on (actual)}_{40} + 0.0 \text{ Pulse} - \text{ off (actual)}_{3} + 0.000127 \text{ Pulse} - \text{ off (actual)}_{4} + 0.000037 \text{ Pulse} - \text{ off (actual)}_{5},
\]

\[
\text{MRR (mild steel)} = 0.00072 + 0.0 \text{ Pulse} - \text{ on (actual)}_{20} + 0.000226 \text{ Pulse} - \text{ on (actual)}_{30} + 0.0 \text{ Pulse} - \text{ off (actual)}_{3} + 0.000068 \text{ Pulse} - \text{ off (actual)}_{4} + 0.000018 \text{ Pulse} - \text{ off (actual)}_{5}.
\]

\[
0.000339 \text{ Pulse} - \text{ on (actual)}_{40}.
\]

The boundary condition for the design parameters to be used in the optimization process is given in Table 22.

3.4.3. Result Using Fruit Fly. The optimization process was first done using a fruit fly. For the fruit fly algorithm, the number of iterations and the population size is initialized, and it is given in Table 23. The optimized MRR and its optimized input parameter values for aluminium are given in Table 24. The optimized MRR value for aluminium is obtained as 0.000239, while for the mild steel, it is received as...
The optimized input parameter values are tabulated in Table 25.

3.4.4. Result Using Cockroach. For the cockroach algorithm, the initial parameter to be initialized is the number of cockroaches (population size) and number of iterations, visual scope is set as visibility range, and step length is a fixed value. The values initialized are given in Table 24. The MRR minimization for the aluminium is obtained as 0.000221, and other respective parameter values are given in Table 25.

---

**Table 22: Boundary conditions used to run the algorithm.**

| Condition | Value |
|-----------|-------|
| 20 ≤ A ≤ 30 | Pulse-on (actual) |
| 30 ≤ B ≤ 40 | Pulse-on (actual) |
| 40 ≤ C ≤ 50 | Pulse-on (actual) |
| 3 ≤ D ≤ 4 | Pulse-off (actual) |
| 4 ≤ E ≤ 5 | Pulse-off (actual) |
| 5 ≤ F ≤ 6 | Pulse-off (actual) |

**Table 23: Initial parameters of fruit fly.**

| Parameter | Value |
|-----------|-------|
| MAX-iterations | 75 |
| Population size | 25 |

**Table 24: Initial parameters of cockroach.**

| Parameter | Value |
|-----------|-------|
| Number of cockroaches | 50 |
| Number of iterations | 80 |
| Visibility range | 3 |
| Step length | 2 |

**Table 25: Comparison between the values predicted using fruit fly and cockroach algorithms with the experimental values for aluminium.**

| Parameter | Experiment | Fruit fly | Cockroach |
|-----------|------------|-----------|-----------|
| Pulse-on (actual) | 20 | 20.0 | 24.92 |
| Pulse-on (actual) | 30 | 39.64 | 30.44 |
| Pulse-on (actual) | 40 | 44.66 | 41.28 |
| Pulse-off (actual) | 3 | 3 | 3.84 |
| Pulse-off (actual) | 4 | 4 | 4.87 |
| Pulse-off (actual) | 5 | 5 | 5.39 |
| MRR | 0.000316 | 0.000214 | 0.000214 |

---

**Algorithm 1: Cockroach swarm optimization algorithm.**

According to the cockroach behaviour models, we give the steps of CSO algorithm as follows:

**Step 1:** Initialize algorithm parameters.

- **Initialize** Step (a fixed value),
  - N (Number of population)
  - D (Number of parameter in design problem);

**Step 2.a:** Generate an initial set of cockroach population

\[ X(i) = (x_{i1}, x_{i2}, \ldots, x_{iD}) \]  
(i = 1, 2, . . . , N) within feasible region randomly.

**Step 2.b:** Search for \( P(i) \) and Pg by equations (4) and (5).

**Step 3:** Apply equation (6) and operate chase-swarming behaviour.

\[ X(i) \leftarrow X'(i) \text{, update Pg, where } X'(i) \text{ is the superior individual cockroach.} \]

**Step 4:** With equation (7) carrying out the dispersing behaviour. If the new position \( X'(i) \) superior than the original location \( X(i) \), then \( X(i) \leftarrow X'(i) \); otherwise, return to the original location \( X(i) \). Update Pg.

**Step 5:** With equation (8) carrying out ruthless behaviour.

**Step 6:** Check whether the iteration count condition is reached? If reached display output, otherwise, return to step 2.
The MRR result for the mild steel is obtained as 0.000215, and its individual input parameter values are given in Table 26.

### Table 26: Comparison between the values predicted using fruit fly and cockroach algorithms with the experimental values for mild steel.

| Parameters            | Experiment | Fruit fly | Cockroach |
|-----------------------|------------|-----------|-----------|
| Pulse-on (actual)_20  | 26         | 27.90     | 22.39     |
| Pulse-on (actual)_30  | 37         | 39.45     | 30.54     |
| Pulse-on (actual)_40  | 40         | 40.0      | 41.64     |
| Pulse-off (actual)_3   | 3          | 3         | 3.83      |
| Pulse-off (actual)_4   | 4          | 4         | 4.91      |
| Pulse-off (actual)_5   | 5          | 5         | 5.42      |
| MRR                   | 0.000289   | 0.000221  | 0.000215  |

3.4.5. **Comparison of the Results Obtained Using Fruit Fly and Cockroach Algorithms with the Experimental Values.**

The deviation between the MRR value for aluminium obtained using the laboratory experiment, Fruit fly algorithm and the cockroach algorithm are calculated. The deviation values are represented in percentage and plotted as a graph, shown in Figure 13. The value deviations are seen only for the pulse-off, and cockroach algorithm result was deviated from the experimental and fruit fly values.

From Tables 25 and 26, it is found that the cockroach algorithm is performing better than the fruit fly algorithm in optimizing the MRR of aluminium and mild steel.

Figure 14 shows the deviation graph of the MRR of mild steel values found using laboratory experiments compared with fruit fly and cockroach algorithms. For the pulse-on stage, the deviation between the experiment result and cockroach is slightly higher, but for the pulse-off and MMR, there is no much difference. Fruit fly algorithm values are not much deviated from the experimental values.

### 4. Conclusion

The experiment focused on analysing the influence of pulse-on and pulse-off time in material removal rate (MRR). Taguchi grey analysis was employed for optimization. The conclusion is summarized as follows:

The $P$ value for each ANOVA was found. Numerical results suggest that if $\alpha$ is higher than the $P$ value, then the input factor has a significant impact on the response, and if $\alpha$ is lesser than the $P$ value, then the input factor has no to negligible effect on the response of the machining process, in our case of MRR.

For selecting optimum values for pulse-on time and pulse-off time for a specific application, the required surface finish or other output characteristics are determined, and the acceptable range of MRR for that particular application is chosen. For this range of MRR, it can select the input parameters accordingly.

For aluminium Al6061, the values of MRR range from 0.0000870 g/sec to 0.0007364 g/sec. The highest MRR is obtained at $T_{on} = 40 \mu s$ and $T_{off} = 4 \mu s$, and the least MRR is acquired at $T_{on} = 20 \mu s$ and $T_{off} = 4 \mu s$. For mild steel, AISI 304, the values of MRR range from 0.0000632 g/sec to 0.0004712 g/sec.

The highest MRR is obtained at $T_{on} = 40 \mu s$ and $T_{off} = 4 \mu s$, and the least MRR is acquired at $T_{on} = 20 \mu s$ and $T_{off} = 3 \mu s$. The cockroach swarm algorithm performs a
superior prediction of the optimized MRR value in comparison with the fruit fly algorithm.

Abbreviations

EDM: Electrical discharge machining
MRR: Material removal rate
Ton: Pulse-on
Toff: Pulse-off
SR: Surface roughness
FOA: Fruit fly optimization algorithm
CSO: Cockroach swarm optimization algorithm

Appendix

Pseudocode for fruit fly algorithm

//default parameters settings
Set maxIterations Set popSize
Set SmellMin = 100

//random initial fruit fly swarm location
Assign XAxis a rand value Assign YAxis a rand value

//iterative optimization start
Do until maxIterations reached
  //give the random direction and distance for the search of food using
  //ophresis by an individual fruit fly.
  for each cockroach(i) in
    popSize calculate X(i) = XAxis + 2 * rand() – 1
    Normalize, Normalize X(i) within the boundary
    values Calculate Y(i) = YAxis + 2 * rand() – 1
    Normalize X(i) within the boundary values
    Calculate D(i) = (X(i)2 + Y(i)2)0.5
    Calculate S(i) = 1/D(i);
    smell(i) = FitnessFun(S(i));
  end
  [bestSmell, bestIndex] = min(smell) Check if
  bestSmell < smellMin
  Replace bestsmell with smellMin
  Store the XAxis, Yaxis value of bestindex.
Function int FitnessFun(x)
  sol = 0.01 + 0.00646 * x + 2.5 * x + 0.02 * x

Data Availability

All data are included within the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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