Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

Deep Learning Based Metal Removal Rate Investigation on Superni 90 Super Alloy Using Al 7178 Tool on Die-Sink Edm

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Abstract Aluminum being the light material, its alloy materials are used in most of the aerospace and automotive fields. From the Literature it is observed, that a tool material of AL 7178 for the Electro Discharge Machining Process is not adopted though it is favorable material for tool. In this work an attempt is made to investigate the various input parameters of Electro Discharge Machining Process which affects the Material Removal Rate (MRR), Surface Roughness (SR) and Tool Wear rate (TWR) For the experimentation AL 7178 is employed as tool material for machining of Nickel based alloy (Superni90). The investigation of the experimentation is compared with conventional tool material of Copper (Cu). And it is observed that AL 7178 yields that AL 7178 is superior performance. Further results of the experimentation machine learning and Deep learning models are developed for better understanding of the process with AL 7178 tool for real life applications which can minimize the cost of experimentation. Apart from these studies, an attempt is made to see the accuracy of geometry of the material removal on the workpiece with respect to tool geometry by using image analysis concept avialble in Mat Lab Software.

Keywords: Electric discharge machining, Aerospace And Automotive Fields, Current (I), Voltage (V), Tool Wear Rate (TWR), Material Removal Rate (MRR), Pulse on Time (Ton), Pulse off Time (Toff), Surface Roughness (SR), % error, Deep Learning.

1. Introduction

Modern technology has led to an explosion of lightweight materials, particularly in the realms of aerospace and automobile. The research on new high-strength aluminum alloys is being undertaken by numerous countries and corporations, the aim is to decrease the weight of the materials as much as possible, while still maintaining the stability of mechanics and corrosion resistance for the overall structure, in order to substitute traditional materials such as iron.

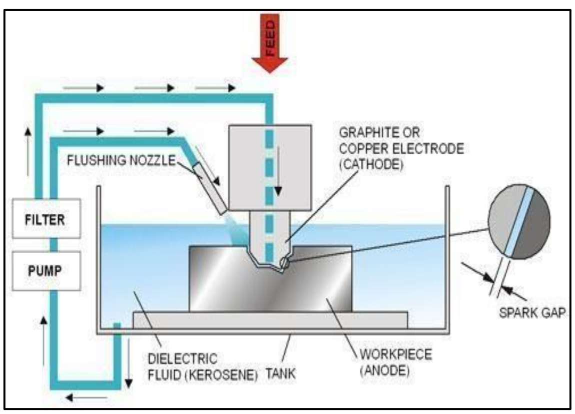
In recent years, a great deal of novel materials that are widely used in space exploration, firearms, and nuclear manufacturing sectors have been produced. Because these materials are stronger, harder, more resilient to heat, and resistant to wear, they cannot be manufactured usingconventional machining methods. This development of unique metal removal processes has led to the creation of newer machining procedures, also referred to as unconventional machining procedures.

The processes can produce intricate and detailed shapes on the workpiece and are unaffected by the strength, hardness, toughness, or brittleness of the materials. Heat treatment can be used to strengthen Al 7XXX alloys, which are primarily composed of the Zn element. The alloy Al-Zn- Mg, which contains magnesium, is a weldable and high-strength aluminum alloy with excellent thermal deformation characteristics and a broad quenching range. By applying the appropriate heat treatment, it is possible to achieve increased strength, enhanced welding capabilities, and improved corrosion resistance.

Incorporating Cu into the Al-Zn-Mg alloy results in the creation of the Al-Zn-Mg-Cu alloy. This alloy demonstrates enhanced strength when compared to Al 2XXX alloys, which is why it is commonly Referred to as an ultra-high-strength aluminum alloy, this material exhibits similar yield and tensile strengths, leading to a remarkably high specific strength. However, its plasticity and high-temperature strength are somewhat lacking. It is best suited for use as a load-bearing structural component at or below room temperature or below 120ºC. It is easily processed, provides good corrosion resistance, and exhibits high toughness.

1.1. Electrical Discharge Machining

EDM is a non-traditional and non-contact machining technique that finds application in industries like manufacturing, aerospace, automotive, communication, and biotechnology for creating highly precise products. The process, as illustrated in the figure, is specifically designed for machining hard and brittle conductive materials, as it is able to melt any electrically conductive material, regardless of its hardness. EDM is a type of thermal machining that involves removing material from the workpiece through the thermal energy generated by the electric spark. In a dielectric medium, such as kerosene, deionized water, or another appropriate fluid, the tool and the workpiece are fully submerged. The system's non-contact characteristic, along with its nearly force-free machining capability, enables the gentle and precise shaping of electrode materials to create extremely hard, fragile, or thin workpieces.



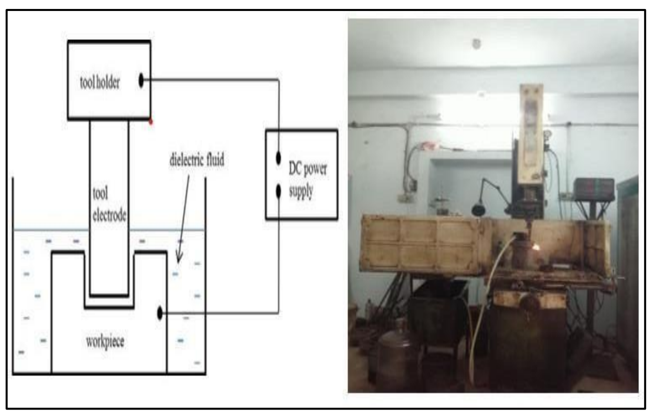


Figure 1. Electrical Discharge Machining **Figure 2. . EDM Process**

1.2. Work piece Material Superni90 Super Alloy

Super alloys are characterized by their outstanding mechanical strength, resistance to creep under high temperatures, stable surface properties, and exceptional corrosion and oxidation resistance. These corrosion-resistant super alloys find widespread application in extreme environments where both heat and corrosion resistance are crucial for maintaining the integrity of the end product. Various industries, including chemical and petrochemical processing, aero- engines, power generation facilities, and the oil and gas sector, extensively utilize these specialized super alloys.

Nickel-based superalloys are classified as high-performance alloys with a notable nickel content. Variances among these superalloys are typically observed in their material composition, tailored to exhibit distinct properties based on their intended applications.

2. Experimentation

The Experimentation consists of the following steps.

- Testing the AL 7178 for electrical conductivity and to establish its usability as tool material.
- Preparation of the samples.
- Experimentation on the EDM process.
- Measurement of MRR, TR, and SR Surface Roughness.

2.1. Electrical Conductivity

Conductivity of electricity is the capacity of a substance to conduct an electric current, particularly in the case of an electrolyte in solution. It is a measure of electrical conduction and demonstrates a material's capability to transmit a current.In the field, conductivity is measured using a portable probe. It is usually a component of the pH and temperature meter, allowing us to monitor all three parameters at once. The temperature adjustment to 25°C will be carried out by the meter software. Potassium chloride solution with a known conductivity is used as a reference to confirm the calibration of the probe. Conductivity of electrodes is measured by equipment named TECHNOFOUR CONDUCTIVITY METER TYPE 979 which is shown in figure.

Figure 3. Electrical Conductivity

2.2. Preparation of the samples

The Preparation of the samples involves stir casting and Machining of the casted products to make it ready for experimentation on EDM process.

Stir Casting

In the stir casting process, the melt is continuously stirred, leading to continuous exposure of the melt surface to the atmosphere and subsequent oxidation of the aluminum melt. Coal, blower, crucible, furnace, and other materials are needed to melt the Al 7178 alloy. The temperature within the furnace is raised to 800°C, while the melting point of Aluminum 7178 is 660°C.

In this present study, An ideal mixture of copper and aluminum alloy was reinforced in order to study the tolls at various EDM settings. The product was manufactured with a stirring system-equipped resistance furnace. The stirring process was run at a consistent 100 rpm for ten to fifteen minutes, while the casting temperature was maintained at 750±5°C. The mixing apparatus utilized in this phase was a driving motor with a rotational speed within the 100rpm range. In the process of removing moisture-induced surface impurities, balanced aluminum 7178 alloys were melted in a graphite crucible, while copper particles and aluminum alloy were heated in a muffle furnace set at 900oC for approximately one hour. The gradual and continuous addition of ceramic particles Al2O3 into the molten metal, coupled with continuous stirring at 100 rpm, was performed to produce metal matrix composites using the stir casting technique.

The experiments were performed on EDM, EDM oil is selected as dielectric. The material is selected as Superni90 having dimension of 120mm diameter and 10mm thickness. Aluminum 7178 alloy. With the optimum composition of AL7178 material as electrode and Nickel based Super Alloy - Superni 90 for machining investigations and optimization of process parameters.

Figure 4. Process of Stir Casting and Al 7178 casted Tools **Figure 5. Working process of EDM machining**

A. Material Removal Rate (MRR)

The MRR is defined as the material weight difference of the workpiece before and after machining divided by the machining time.

MRR = $[(W_{wpbm} - W_{wpam})/(t*\rho)]$ mm3/min

W_{wpbm} – Workpiece weight Before machining W_{wpam} – Workpiece weight After machining

t - Machining period Time 10min

B. Tool Wear Rate (TWR)

To calculate the Tool Wear Rate (TWR), one must divide the change in weight of the tool before and after machining by the time taken for machining.

TWR = $[(W_{etbm}–W_{etam})/(t*\rho)]$ mm^3/min

W_{etbm} – Electrode weight Before machining W_{etam} – Electrode weight After machining

t - Machining period Time 0min ρ – Density of Tool material

C. Experimentation on Superni90

The work material selected for experimental investigation is a super alloy which has wide applications in defense with commercial name as Superni90. The electrode material chosen for machining on work material is Al7178 and copper and the experiment done according to the procedure. Researchers conduct experiments across a wide range of disciplines, usually with the aim of gaining insights into a specific process or system. An experiment involves conducting a trial or a series of trials in which deliberate changes are made to the input variables of a process or system to facilitate the observation and identification of the factors influencing changes in the output. The process of

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

choosing the quantity of trails and operating parameters for them, which are necessary and sufficient for precisely answering the problem, is known as experiment design.

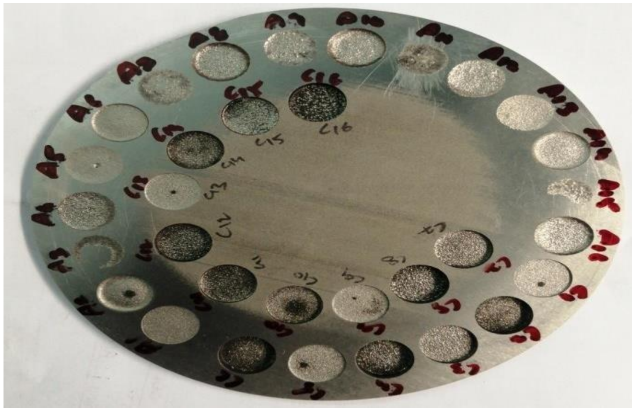


Figure 6. Experimentation on Superni90 work material with Aluminum and copper as Electrodes using EDM

D. Linear Regression

Image processing is an advancing technology that focuses on enhancing images and extracting valuable data. This method involves performing operations on images to improve their quality or extract useful information. Image analysis plays a vital role in characterizing porous substances structurally and finds applications in diverse fields. The structural features of materials can be described through statistical and morphological aspects, including dimensions, shapes,and topological properties. MATLAB is commonly utilized for image processing to assess the accuracy of diameters.

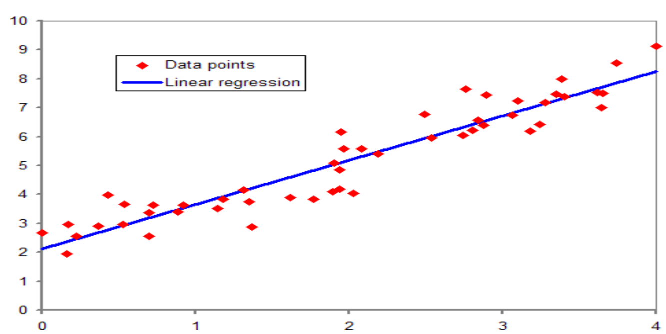


Figure 7. Linear Regression

E. Deep Learning

A machine learning technique called deep learning combines representation learning with artificial neural networks. It can take three forms: semi-supervised, unsupervised, or supervised. Application of Sophisticated artificial intelligence frameworks, including convolutional neural networks, recurrent neural networks, deep reinforcement learning, deep neural networks, and deep belief networks, has produced results that are on par with or even better than human expert performance in a number of domains.

Deep learning utilizes numerous layers within the network, hence the term "deep." Previous studies have illustrated that a universal classifier can be established by utilizing a nonpolynomial activation function with a single hidden layer of unlimited width. In contrast, deep learning emphasizes the use of an infinite number of narrow layers, allowing for optimal implementation and practical application while maintaining theoretical universality under mild conditions. The efficiency, trainability, and interpretability of these layers may differ significantly from connectionist models based on physiological principles.

F. Results

The Tool Material Al7178 is performed on the workpiece material i.e., Superni90 super alloy on EDM process.

The obtained values of Surface Roughness (SR), Material Removal Rate (MRR) and Tool Wear Rate (TWR) for the Aluminum alloy 7178 Metal matrix composite and copper which are performed on Superni90 super alloy on Electrical Discharge Machining are listed in table.

Current(I) (amp)	T_on(μ sec)	T_off(μ sec)	V(v)	MRR (g/h)	TWR(g/h)	SR
4	100	50	30	29.34	1.08	2.45
12	100	50	30	638.14	12.19	2.66
4	1000	50	30	66.01	0.36	0.401
12	1000	50	30	95.35	1.79	4.87
4	100	100	30	73.35	1.79	3.82
12	100	100	30	366.75	3.58	3.54
4	1000	100	30	22.00	1.79	2.22
12	1000	100	60	520.78	5.38	5.18
4	100	50	60	66.01	2.15	3.433
12	100	50	60	777.51	3.94	3.46
4	1000	50	60	73.35	3.58	2.19
12	1000	50	60	95.35	2.87	4.109
4	100	100	60	51.34	0.72	2.695
12	100	100	60	388.75	5.73	2.75
4	1000	100	60	65.28	1.08	2.39
12	1000	100	60	462.10	5.38	3.47

Sl no	Current(I)	T_on	T_off	V	MRR(g/h)	TWR(g/h)	SR
1	4	100	50	30	344.74	0	4.42
2	12	100	50	30	2171.15	0	4.45
3	4	1000	50	30	29.34	0	1.782
4	12	1000	50	30	2369.19	0	4.7
5	4	100	100	30	403.42	0	3.848
6	12	100	100	30	1745.72	0.111607	4.253
7	4	1000	100	30	1173.59	0	2.84
8	12	1000	100	60	1635.70	0	4.051
9	4	100	50	60	946.21	0	3.138
10	12	100	50	60	916.87	0	2.616
11	4	1000	50	60	601.47	0	2.309
12	12	1000	50	60	2046.45	0	3.32
13	4	100	100	60	36.67	0	2.917
14	12	100	100	60	784.84	0	3.79
15	4	1000	100	60	777.51	0	2.43
16	12	1000	100	60	1239.61	0	3.198

Figure 8. Experimental values of (MRR, TWR, SR) for Al7178 tool on Superni90

Figure 9. Experimental values of (MRR, TWR, SR) for Copper tool on Superni90

Development of Machine Learning algorithms and Evaluation of Al7178 and Copper using Python

By using Python programming language, we are developed 5 Predictive models which are Linear regression, Rigid regression, Decision trees, Random Forest, Gradient Boosting.

Firstly, import all the required modules and data sets to the programming code to access and it will describe the data in background according to the output requirements with the code we have given to it. We shown the process step by step with images below.

- Model building for Optimum Al7178 & Copper (Cu)

```
for key, value in models.items():
    model = value
    model.fit(X_train, y_train)
    scores[key] = model.score(X_test, y_test)
```

```
# after feature election
scores_frame = pd.DataFrame(scores, index=["Accuracy Score"]).T
scores_frame.sort_values(by=["Accuracy Score"], axis=0 ,ascending=False, inplace=True)
scores_frame
```

	Accuracy Score
Decision tree	0.965154
Gradient boosting	0.953279
Random forest	0.560431
Ridge	0.062913
Linear Regression	0.054554

```
#Creat test and train data
from sklearn.model_selection import train_test_split
X_train_cu, X_test_cu, y_train_cu, y_test_cu = train_test_split(X_c,y_c, test_size=0.45, random_state=16)
print(X_train_cu.shape)
print(X_test_cu.shape)

(8, 4)
(8, 4)
```

```
for key, value in models.items():
    model = value
    model.fit(X_train_cu, y_train_cu)
    scores[key] = model.score(X_test_cu, y_test_cu)
```

```
# after feature election
scores_frame = pd.DataFrame(scores, index=["Accuracy Score"]).T
scores_frame.sort_values(by=["Accuracy Score"], axis=0 ,ascending=False, inplace=True)
scores_frame
```

	Accuracy Score
Gradient boosting	0.580312
Random forest	0.491047
Decision tree	0.414728
Ridge	0.180221

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

Figure 10. Models developed for Al7178 by using Python programming language

Figure 11. Models developed for Cu by using Python programming language

For Al7178 data we Build above 5 ML algorithms those five we got Decision tree (96%) and Gradient boosting (95%) havemuch better accuracy compere to all other models. For Cu data we Build above 5 ML algorithms those five we got Random Forest (49%) and Gradient boosting (58%) have much better accuracy compere to all other models.On comparing the above two cases of Al7178 and Copper of 5ML algorithms the results obtained for Al7178 [Decision tree (96%) and Gradient boosting (95%)] is higher when compared to copper [Random Forest (49%) andGradient boosting (58%)]. According to the data we have taken this is not a good accuracy with this small dataset

.3. GEOMETRIC ANALYSIS

The trueness of the diameter is analyzed by imageprocessing in MATLAB.

The evaluation of this image processing can be performed using MAT Lab software. The six images which are obtained using MATLab for surface roughness are named as crop image, Black & white, Histogram, Normalized, Normalized Histogram and Binary.

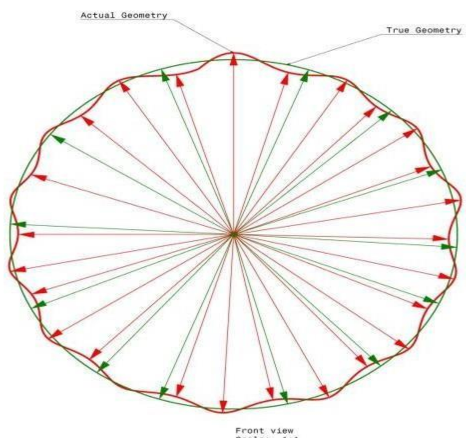


Figure 12. 2D image of centroid location

Case-1 Electrode Al7178

Current(I) (amp)	T_on(μ sec)	T_off(μ sec)	V(v)	MRR (g/h)	TWR(g/h)	SR
4	100	50	30	29.34	1.08	2.45
12	100	50	30	638.14	12.19	2.66
4	1000	50	30	66.01	0.36	0.401
12	1000	50	30	95.35	1.79	4.87
4	100	100	30	73.35	1.79	3.82
12	100	100	30	366.75	3.58	3.54
4	1000	100	30	22.00	1.79	2.22
12	1000	100	60	520.78	5.38	5.18
4	100	50	60	66.01	2.15	3.433
12	100	50	60	777.51	3.94	3.46
4	1000	50	60	73.35	3.58	2.19
12	1000	50	60	95.35	2.87	4.109
4	100	100	60	51.34	0.72	2.695
12	100	100	60	388.75	5.73	2.75
4	1000	100	60	65.28	1.08	2.39
12	1000	100	60	462.10	5.38	3.47

Figure 13(a)

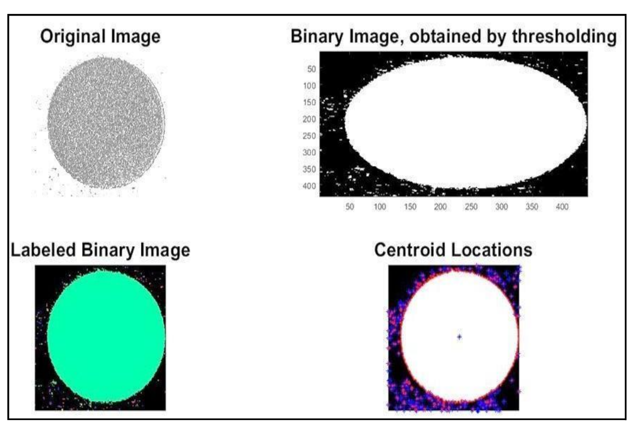
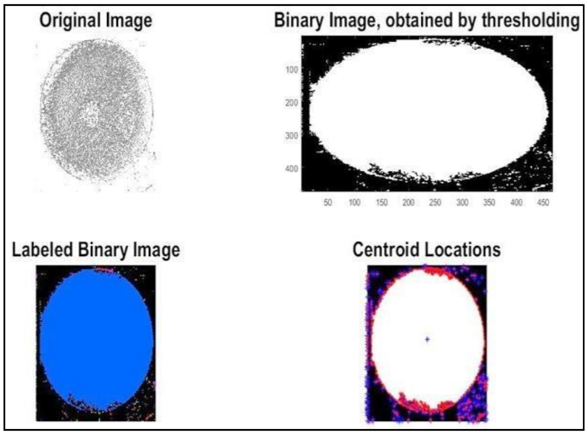


Figure 13(b)

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)



Current(I)	T_on	T_off	V	MRR	Avg mean(radius)	% error	standard deviation
4	100	50	30	29.34	4.966	0.69	0.05
12	100	50	30	638.14	5.11	2.354	0.21
4	1000	50	30	66.01	-	-	-
12	1000	50	30	95.35	4.79	4.26	0.14
4	100	100	30	73.35	4.94	1.1	0.07
12	100	100	30	366.75	5.11	2.19	0.14
4	1000	100	30	22.00	5.03	0.66	0.1
12	1000	100	60	520.78	5.85	14.6	0.4
4	100	50	60	66.01	5.58	10.53	0.12
12	100	50	60	777.51	5.22	4.23	0.26
4	1000	50	60	73.35	5.77	13.47	0.66
12	1000	50	60	95.35	5.03	0.7	0.13
4	100	100	60	51.34	5.39	7.2	0.14
12	100	100	60	388.75	5.2	3.9	0.24
4	1000	100	60	65.28	-	-	-
12	1000	100	60	462.10	5.04	0.9	0.311

Figure 13(c) **Figure 13(d)**

Figure 13(a). Experimental values of (MRR, TWR, SR) for Al7178 tool on Superni90 Figure 13(b) & Figure 13(c). Images obtained by performing trails for Optimum Al7178 Figure 13(d). Geometric analysis for Al7178 tool

Similarly, all fourteen trails are performed for Optimum Al7178 using MATLab to obtain the percentage error of fourteen trails.

Sl no	Current(I)	T_on	T_off	V	MRR(g/h)	TWR(g/h)	SR
1	4	100	50	30	344.74	0	4.42
2	12	100	50	30	2171.15	0	4.45
3	4	1000	50	30	29.34	0	1.782
4	12	1000	50	30	2369.19	0	4.7
5	4	100	100	30	403.42	0	3.848
6	12	100	100	30	1745.72	0.111607	4.253
7	4	1000	100	30	1173.59	0	2.84
8	12	1000	100	60	1635.70	0	4.051
9	4	100	50	60	946.21	0	3.138
10	12	100	50	60	916.87	0	2.616
11	4	1000	50	60	601.47	0	2.309
12	12	1000	50	60	2046.45	0	3.32
13	4	100	100	60	36.67	0	2.917
14	12	100	100	60	784.84	0	3.79
15	4	1000	100	60	777.51	0	2.43
16	12	1000	100	60	1239.61	0	3.198

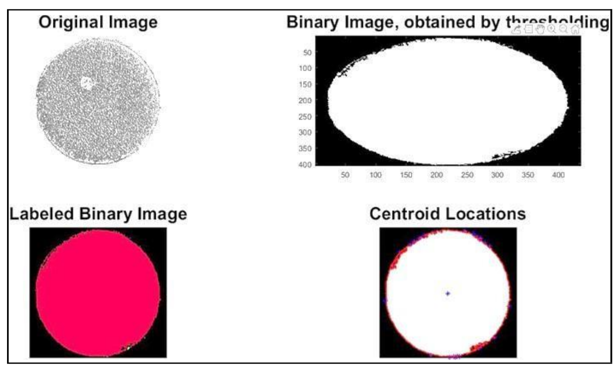
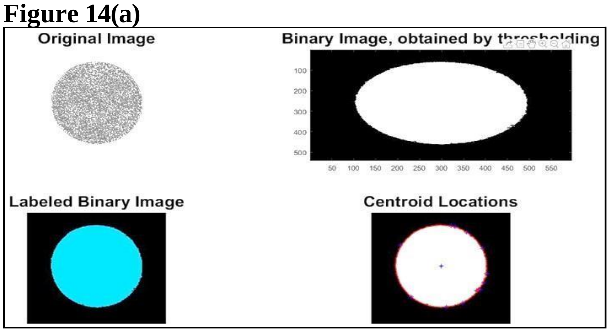


Figure 14(a) **Figure 14(b)**



Sl no	Current(I)	T_on	T_off	V	MRR	Avg mean(radius)	% error	standard deviation
1	4	100	50	30	344.74	5.4	7.81	0.09
2	12	100	50	30	2171.15	5.18	3.54	0.06
3	4	1000	50	30	29.34	5.42	8.19	0.122
4	12	1000	50	30	2369.19	5.2	5.6	0.1
5	4	100	100	30	403.42	5.3	6.3	0.13
6	12	100	100	30	1745.72	5.44	8.6	0.14
7	4	1000	100	30	1173.59	5.49	9.45	0.113
8	12	1000	100	60	1635.70	5.12	2.55	0.192
9	4	100	50	60	946.21	5.413	7.94	0.11
10	12	100	50	60	916.87	5.016	0.32	0.08
11	4	1000	50	60	601.47	5.29	5.7	0.087
12	12	1000	50	60	2046.45	5.27	5.35	0.007
13	4	100	100	60	36.67	5.3	5.8	0.073
14	12	100	100	60	784.84			
15	4	1000	100	60	777.51	5.3	5.8	0.073
16	12	1000	100	60	1239.61	5.4	9.4	0.151

Figure 14(a). Experimental values of (MRR, TWR, SR) for copper tool on Superni90 Figure 14(b) & Figure 13(c). Images obtained by performing trails for copper Figure 14(d). Geometric analysis for copper tool

Similarly, all fourteen trails are performed for copper tool using MATLab to obtain the percentage error of fourteen trails

4. Conclusion

From the experimental data and results obtained from the analysis the following conclusions may be drawn.

- Al7178 was 70% lighter weight than copper. So with same dimensions of tool (10cm length, 10mm diameter) copper weight was 100grams and Al7178 was 40grams material we required.

- MRR Performance of Copper tool was slightly high compere to Al7178, but geometric accuracy of Al7178 is good.

- Tool wear rate also max in Al7178 but, wisely using this `Al7178 tool it can reduce the cost and improve the Profits of the company/Production. Al7178 can use for low depth operation, and like finishing operations it gives most efficient results.

- Used to build the Machine Learning (ML) and Deep learning (DL) models, predict the output variables such as MRR, TWR, and SR for unknown value of Input variables. ML and DL models are proposed to reduce the cost of experimentation.

- An attempt is made to see the accuracy of geometry of the material removal on workpiece

with respect to tool geometry. With help of MATLAB toolbox the images of the workpiece is imported to MATLAB to calculate the accuracy of the machining process for all set of experiments.

5. Acknowledgement

The success of my project is a result of the hard work and technical expertise of many individuals, and I am grateful for their contributions. I would like to express my deep appreciation to my supervisor, **Dr. L. Siva Rama Krishna, Professor** & Department of Mechanical Engineering, Osmania University, for his guidance and suggestions throughout the project. I would like to express my deep appreciation to my co-supervisor, **Dr. S. Gajanana, Professor** & Dean of the Department of Mechanical Engineering, MVSR, for his guidance and suggestions throughout the project.

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