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Electrochemical Machining of AISI 202 using AgNO3 mixed electrolyte and its Optimization

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Abstract - Electrochemical Machining (ECM) process is one of the unconventional machining processes, widely used to machine the poor machinable materials without inducing any internal stresses on the machined surfaces. This paper attempts to explore the impacts of $AgNO_3$ with normalities of N/10 and N/50 mixed $NaNO_3$ electrolytes in ECM of AISI 202-Austenitic Stainless Steel. This material is highly utilized in Petroleum and Gas turbine industries. The major influencing parameters of applied voltage, tool feed rate and electrolyte discharge rate with three levels each have been chosen to study their effects on Material Removal Rate (MRR) of electrochemically machined AISI 202 work specimens. The experimental results proved that $AgNO_3$ (N/50) solution significantly improves the performance of ECM in terms of obtaining better MRR AISI 202 due to develop the consistent current density across the Inter Electrode Gap (IEG). The mathematical models of MRR was developed and the optimum range of values of chosen influencing parameters were obtained using Multi Objective Genetic Algorithm (MOGA). The MOGA results have given the wider range of optimum values of chosen influencing parameters and select the optimum values based on the priority of customer requirements within the chosen objectives. The confirmatory experiments revel that the deviation of experimental results from the MOGA predicted results are found to be 2-3%.

Keywords - ECM, AISI 202, MRR, MOGA

I. INTRODUCTION

Highly competitive manufacturing environments expect from the researchers community to develop a newer combination materials with salient features of high hardness, high strength light weight etc. However, most of the combination of newer materials alloys generally poor machinable to conventionally existing machining techniques. Electrochemical Machining (ECM) is one of the unconventional machining techniques usually preferred by most of the industries to machine the poor machinable materials and its alloys due to machining is done with free from-thermal cracks, thermal fatigue and tool wear [1,2]. Despite these advantages of ECM, achievement of better Material Removal Rate (MRR) and average surface roughness (R_a) together is highly challengeable. So, this research work attempts to investigate the reasons and identify the ways to achieve better MRR of the selected work specimen Austenitic Stainless Steel [3] (AISI 202 Grade) and find the optimum values of chosen influencing parameters using Multi Objective Genetic Algorithm (MOGA).

II. EXPERIMENTATION

ECM setup consists of machining chamber, control panel and electrolyte tank as shown in figure 1. Electrolyte flow is controlled by a digital flow meter with two digit accuracy (make: Endress+Hauser) and pressure gauge is equipped to monitor the flow pressure.

Fig 1. ECM Set-up

The selected major influencing parameters of applied voltage, tool feed rate and electrolyte discharge rate with three levels each and full factorial experiments, totally 27 * 3 = 81, are conducted using plain Sodium Nitrate ($NaNO_3$) aqua, Silver Nitrate with Normality of 10 ($AgNO_3$ [N/10]) mixed $NaNO_3$ aqua and Silver Nitrate with Normality of 50 ($AgNO_3$ [N/50]) mixed $NaNO_3$ aqua electrolytes. Austenitic Stainless steel –AISI 202 is tedious to machine by conventional machining processes due to formation of chromates. AISI 202 shows excellent heat and corrosion resistance with sound mechanical properties over the range of temperature, hence, it is widely preferred for Petroleum and Gas turbine Industries. The chemical composition is given in Table 1.

Table 1. Chemical composition of AISI 202

Element	**C**	**Cr**	**Mn**	**Ni**	**Mo**	**P**	**S**	**Co**	**Fe**
Wt %	0.107	13.98	9.75	0.189	0.0162	0.052	0.005	0.033	73.7

ECM tool electrode was made of Copper due its higher electrical conductivity and completely insulated in order to minimize the stray current effect on the machined specimen [4]. The electrolyte properties of electrical conductivity, concentration, temperature and turbidity were monitored and consistently maintained by manually using water test rig equipment. The loss of weight is measured the difference between before and after machining of material and found the MRR with respect to machining time as 3-minute. Inter Electrode Gap (IEG) of 0.5 mm was initially set for machining [5-8]. The plan for full factorial design is given in Table 2.

Table 2. Plan for Full factorial design for each category

S.No	Applied Voltage (V)	Tool feed rate (mm/min)	Electrolyte discharge rate (lit/min)	S.No	Applied Voltage (V)	Tool feed rate (mm/min)	Electrolyte discharge rate (lit/min)
1	15	0.32	8	15	12	0.54	8
2	12	0.32	8	16	15	0.10	8
3	18	0.10	8	17	15	0.10	10
4	15	0.54	10	18	18	0.54	12
5	18	0.32	12	19	15	0.54	8
6	18	0.32	10	20	15	0.10	12
7	15	0.54	12	21	12	0.54	12
8	18	0.32	8	22	15	0.32	12
9	18	0.10	12	23	12	0.10	8
10	15	0.32	10	24	12	0.10	10
11	12	0.10	12	25	12	0.32	10
12	12	0.54	10	26	12	0.32	12
13	18	0.54	10	27	18	0.54	8
14	18	0.10	10	-	-	-	-

Silver Nitrate ($AgNO_3$) solution – 500 ml with normalities of 10 and 50 (N/10 & N/50) were chosen to mix with $NaNO_3$ aqua solution. $AgNO_3$ is chemically corrosive in nature and silver ions strengthen the ionisation rate of flow resulting in improved MRR. The identified mechanisms of material removal from the results of experiments are listed as below:

1. Anodic dissolution according to Faraday's laws
2. Passivating layer improves the current density across the IEG resulting in better surface finish
3. $AgNO_3$ solution creates corrosive environment across the machining gap, which enhances the anodic dissolution rate
4. Silver ions improve the electrical conductivity of electrolyte.

III. OPTIMIZATION

Optimization of ECM process parameters helps to achieve efficient working of the process and reduces the machining cost. It is observed from literature reviews that most of researches in optimization of ECM parameters have been carried out by considering either MRR or surface roughness. From practical point of view, considering two objectives simultaneously gives an optimal solution which is highly desirable. So, an attempt has been made to find the optimum MRR of ECM. In order to study the effect of the ECM parameters on MRR , a second-order polynomial RSM mathematical model can be developed as shown in Equation (1).

$$Y_u = b_0 + \sum_{i=1}^{n} bi\, x_{iu} + \sum_{i=1}^{n} b_{ii}\, x^2_{iu2} + \sum_{i<j} b_{ij}\, x_{iu} x_{ju} \qquad \text{--- (1)}$$

where Y_u is the corresponding response created by various process variables of ECM and 1, 2, …, n are the coded levels of n controlling machining parameters. The terms b_0, b_1, etc., are the second-order regression coefficients. The second term under the summation sign of this polynomial equation is attributable to linear effect, whereas the third term corresponds to higher-order effect; the fourth term of the equation includes the interactive effect of the process parameters [10]. The MINITAB software Version 16 is used for regression and graphical analysis of the data obtained. The optimum values of selected variables are obtained by solving the regression equation and generate the mathematical models for the chosen objectives. The consistency of the developed models was checked by confirmatory experiments and the deviation is found to be within 7 %. Subsequently, the fitness function was generated for the criteria as Maximize MRR using the developed mathematical models. This fitness function was applied to Multi-Objective Genetic Algorithm (MOGA) for finding the range of optimum values for the chosen criteria [11]. Genetic Algorithms have proven to be a useful approach to address a wide a variety of optimization problems. Being a population-based approach, GA is well suited to solve the multi-objective optimization problems. In this work, multi-objective genetic algorithm is applied to solve the multi-objective OPF problem. Figure 3 shows the flow chart of the GA based algorithm for solving the optimization problem. The major advantage of this work is, industrial experts have the freedom to pick-up

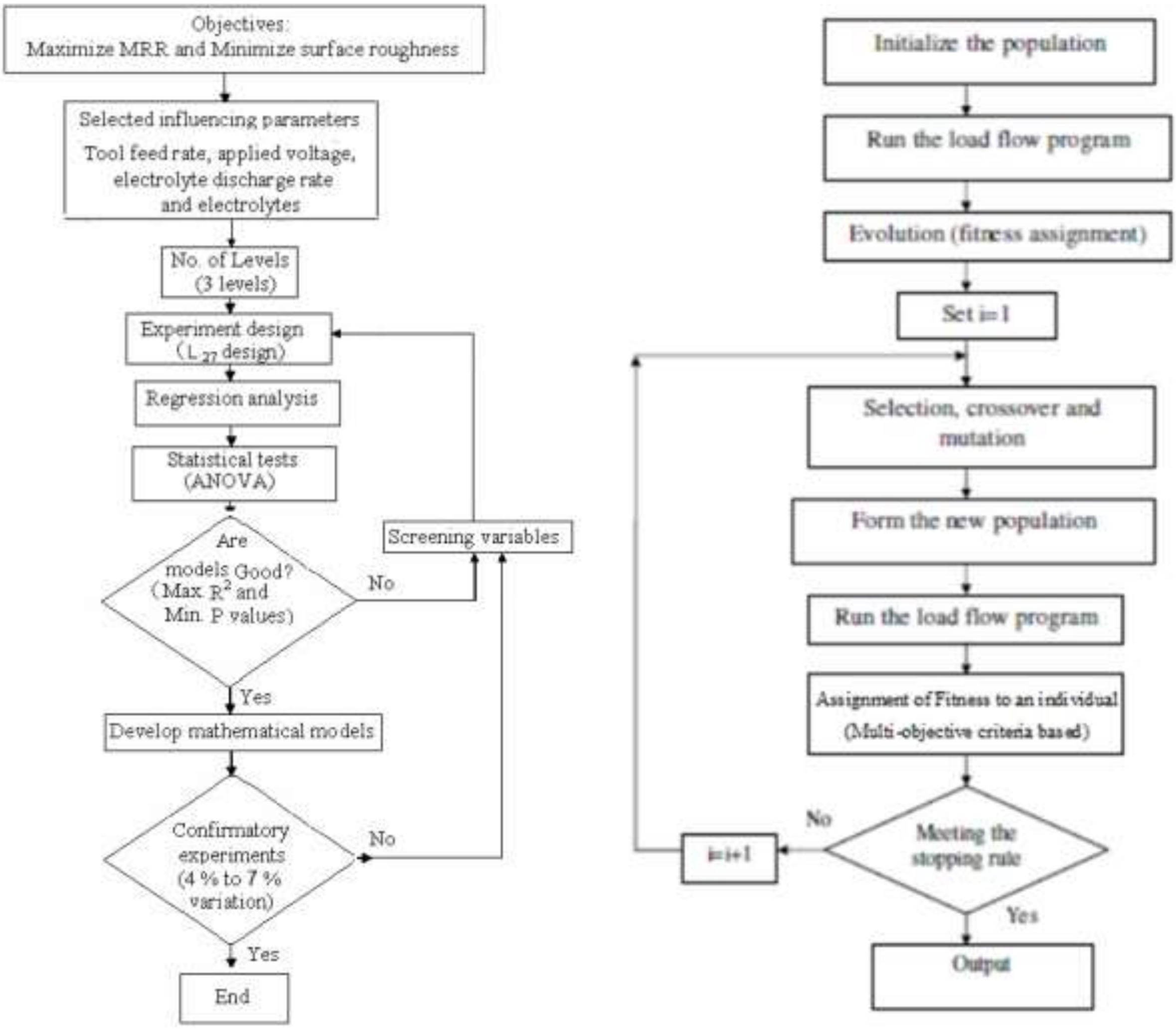

Fig 2. Flow chart for MOGA

optimum values of chosen influencing parameters from the available ranges of obtained solution with respect to customer requirements. Over all machining cost could be minimized by the way of selecting appropriate optimum values i.e. most of the machined components require only moderate surface roughness, so there will be chances to obtain maximum MRR. The main difference between a conventional GA and a MOGA lies in the assignment of fitness to an individual. The rest of the algorithm is the same as that in a classical GA. In a MOGA, first, each solution is checked for its domination in the population. In this way, non-dominated solutions are assigned a rank equal to 1, since no solution would dominate a non-dominated solution in a population. Once the ranking is performed, a raw fitness to a solution is assigned based on its rank.

To perform this, first the ranks are sorted in the ascending order of magnitude. Then a raw fitness is assigned to each solution by using a linear mapping function. Usually, the mapping function is chosen so as to assign the fitness between N (for the best rank solution) and 1 (for the worst rank solution). Thereafter, the solutions of each rank are considered at a time and their raw fitness's are averaged. This average fitness is now called the assigned fitness to each solution of the rank. This emphasizes the non-dominated solutions in the population. In order to maintain the diversity among non-dominated solutions, niching among solutions of each rank are introduced. For this investigation, among the selected electrolytes, $AgNO_3$ (N/50) mixed $NaNO_3$ aqua solution yielded better MRR and Ra of electrochemically machined AISI 202 specimen, hence the above optimization work was carried out for the above mentioned electrolyte combinations and the results are discussed.

IV. RESULTS AND DISCUSSIONS

Experiments have been conducted for investigating the impacts of $AgNO_3$ solution on MRR in AISI 202. Figure 3 shows the impacts of AgNO3 solution (N/10 & N/50) at 12 V, which are clearly identified through variations in MRR of AISI 202 under the same operating conditions. Also, the results reveal that electrolyte discharge rate plays a vital role in obtaining the better performance of ECM especially at 10 lit/min, because of developing the consistent current density across the gap as well as limited escapement of charged ions from the IEG. $AgNO_3$ also creates the corrosive environment at the machining gap resulting in faster removal of materials from the anode Despite this realistic environment, $AgNO_3$ solution acts as a catalyst for maintaining the current density (Amps/cm^2) as well as oxidizing agent while machining. It is observed that 10 lit/min of discharge rate improves the performance in terms of MRR. In ECM, whenever the applied tool feed rate not supposed to be equal to dissolution rate, there will be a chance of short-circuiting between anode and cathode yielding in non-removal of material. This was happened at 12 lit/min and 0.54 mm/min conditions, hence, lower values of MRR obtained in all three aqua electrolyte solution.

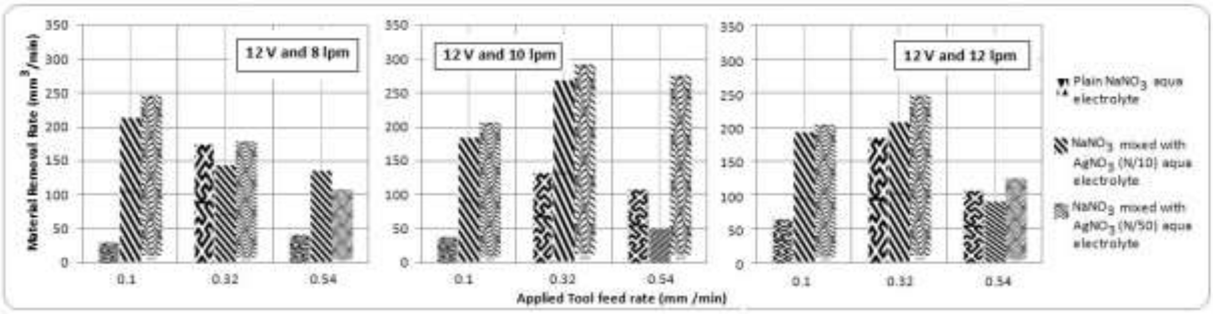

Fig. 3 Effect of $AgNO_3$ on MRR of AISI 202 at 12 V

The effect of $AgNO_3$ at 15 V is shown in figure 4. The $AgNO_3$ (N/50) performs better at 8 lit/min than that of other chosen conditions. Higher applied voltage increases the current rating at the machining gap especially at lower discharge rate. However, the chosen machining time is 3 minutes hence, initial performance of ECM of AISI 202 is better. The maximum MRR of 308.034 mm^3/min is obtained under 15 V, 0.1 mm/min and 8 lit/min conditions. The $AgNO_3$ significantly played a role for enhancing the performance of ECM in terms of yielding better MRR.

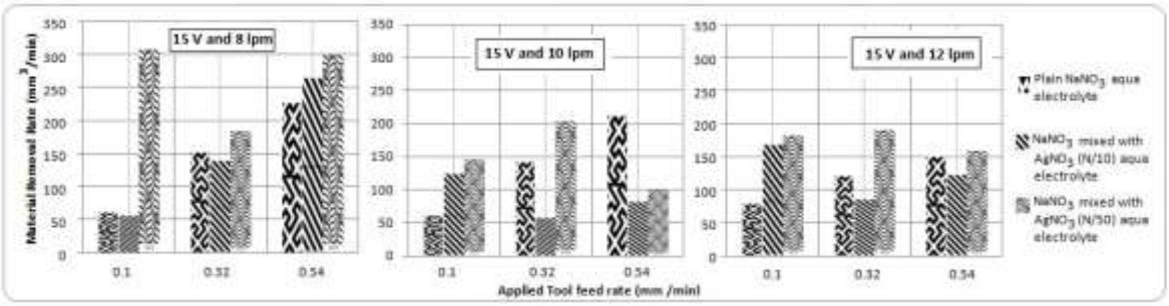

Fig. 4 Effect of $AgNO_3$ on MRR of AISI 202 at 15 V

Figure 5 also reveals the impacts of $AgNO_3$ with normality of N/10 and N/50 that $AgNO_3$ (N/50) acts vibrantly to obtain better MRR at 8 and 10 lit/min conditions. However, the role of tool feed rate at 10 lit/min condition are not so significant because of inconsistent
maintaining of IEG.

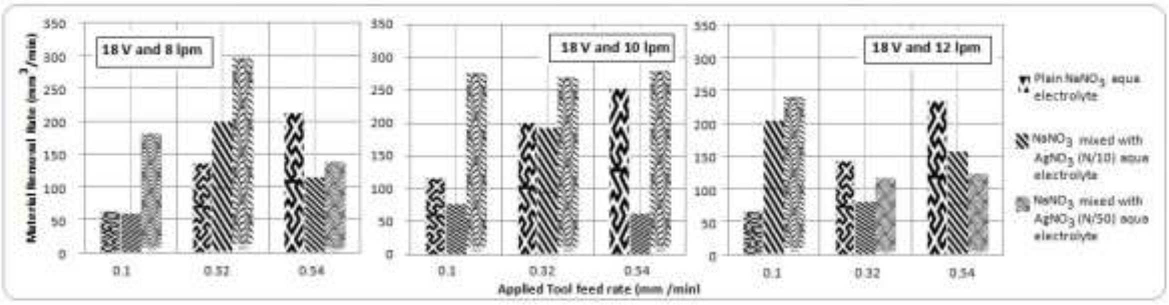

Fig. 5 Effect of $AgNO_3$ on MRR of AISI 202 at 18 V

Highly complicated inclusive factors of material homogeneity and its electro-chemical equivalent weight are involved in the mechanism of material removal in ECM. The developed mathematical model for MRR using $AgNO_3$ (N/50) mixed $NaNO_3$aqua electrolyte is given in Equation 2.

MRR = -520.423 – 24.036* Applied voltage + 239.169* Tool feed rate + 190.709* Electrolyte discharge rate + 1.651* Applied voltage* Applied voltage – 410.186 * Tool feed rate * Tool feed rate – 8.104* Electrolyte discharge rate * Electrolyte discharge rate – 1.063* Applied voltage * Tool feed rate – 2.447* Applied voltage * Electrolyte discharge rate – 5.754* Tool feed rate * Electrolyte discharge rate

----- (2)

The Equation (2) elaborates the relationship among the chosen major influencing parameters of applied voltage, tool feed rate and electrolyte discharge rate in respect of their linear effects, square effects and interaction effects.

The confirmatory experiments were conducted for ensuring the consistency of develop mathematical models and the deviation from the predicted is found to be within 7 % only. The above models have been used to generate the fitness function for MOGA in order to identify the range of optimum values of selected influencing parameters. The basic advantage of this optimization is achieving of maximum using MOGA results. The obtained MOGA results are presented in the table 3. Figure 6 shows the number of iterations and convergent of optimal solution using $AgNO_3$ (N/50) mixed $NaNO_3$ aqua electrolyte.

Table 3. MOGA Optimization Results

S.No	Applied Voltage (V)	Tool feed rate (mm/min)	Electrolyte discharge rate (lit/min)	Generated MRR (mm3/min)
1	17.89	0.10	8.27	247.669
2	18.00	0.20	8.94	257.816
3	17.98	0.10	11.99	179.250
4	17.99	0.11	11.96	181.986
5	17.99	0.10	10.97	220.719
6	17.95	0.10	8.01	243.749
7	17.99	0.12	11.67	195.802
8	17.97	0.11	11.43	204.645
9	17.96	0.11	11.11	216.453
10	17.91	0.10	9.00	252.059
11	17.95	0.16	8.52	254.610
12	17.96	0.10	11.25	211.638
13	17.98	0.10	11.99	179.250
14	17.98	0.11	11.83	187.984
15	17.98	0.11	11.83	187.938
16	17.92	0.14	8.32	251.221

The MOGA results categorically reveal that higher applied voltage and lower tool feed rate always preferred to obtain the better MRR of electrochemically machined AISI 202 while using $AgNO_3$ (N/50) mixed $NaNO_3$ aqua electrolyte. Higher electrolyte discharge rate yields logical MRR due to flush-out the residues and high oxidation at the machining gap. On the other side, higher MRR requires lower electrolyte discharge because of improved current density. The confirmatory experiments were conducted to identify the genuinity of MOGA results. From the table 3, serial number 8 and 16 data were taken to conduct the confirmatory experiments and the results of deviation are given in table 4.

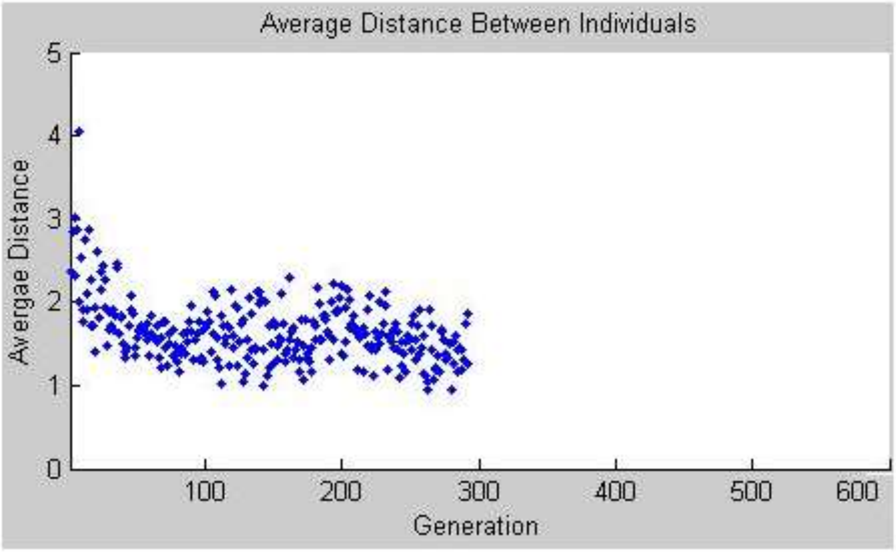

Fig 6 . MOGA Iteration and its convergent solution

Table 4. MOGA –Confirmatory experiments results

S.No	V	F (mm/min)	Q (lit/min)	Generated MRR (mm^3/min)	Confirmatory experimental MRR (mm^3/min)
1	17.97	0.11	11.43	204.645	198.420
				Deviation is 3.04 %	
2	17.92	0.14	8.32	251.221	245.545
				Deviation is 2.25 %	

V- Applied Voltage, F- Tool feed rate, Q- Electrolyte discharge rate

V. CONCLUSIONS

The experiments have been conducted on AISI 202-Austenitic Stainless Steel using aqua of plain $NaNO_3$, $AgNO_3$ (N/10) mixed $NaNO_3$ and $AgNO_3$ (N/50) mixed $NaNO_3$ electrolytes to investigate the effects of $AgNO_3$ solution. Subsequently, the relationship in the form of mathematical models was established among the chosen influencing factors of applied voltage, tool feed rate and electrolyte discharge rate. In order to obtain the optimum ranges of chosen influencing parameters, Multi Objective Genetic Algorithm has been applied and the range of values was obtained. Based on the experimental investigation, the following conclusions are drawn.

1. Silver Nitrate solution ($AgNO_3$) significantly improves the MRR of AISI 202.

2. $AgNO_3$ (N/50) mixed $NaNO_3$ aqua electrolyte enhances the current density across the machining gap resulting in improved MRR.
3. Relationship among the major influencing parameters of applied voltage, tool feed rate and electrolyte discharge rate were established through mathematical models.
4. The developed model consistency is estimated through the results of confirmatory experiments.
5. For obtaining the better MRR , Multi Objective Genetic Algorithm was applied. The MOGA results reveal that higher applied voltage and lower tool feed rate always preferred to obtain the better MRR of electrochemically machined AISI 202 while using $AgNO_3$ (N/50) mixed $NaNO_3$ aqua electrolyte.
6. It is identified from the MOGA results that lower discharge rate is preferred to obtain higher MRR.
7. The genuinity of MOGA results were evaluated by confirmatory experiments and found the deviation is 2-3% only.

VI. ACKNOWLEDGEMENT

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