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MULTI OBJECTIVE OPTIMIZATION OF PROCESS PARAMETERS IN WEDM FOR HYBRID COMPOSITE MATERIAL USING GRA

[1]Gokulakannan G, [2]Dr R V Praveena Gowda, [3]Dr S Ramesh

[1]Asst Professor, [2]Principal, [3]Associate Professor

[1]Mechanical Department,

[1]G Madegowda Institute of Technology, Mandya, India

Abstract: In this research work, the output parameters of the Wire Electrical Discharge Machine (WEDM) like Surface Roughness (Ra) and Material Removal Rate (MRR) been optimized simultaneously for the respective input process parameters like Feed Rate (F) (50,75 &100) mm/min, Current (Ip) (2,3 & 4) amps, Pulse off time (Toff) (5,6 &7) µs and Pulse on Time (Ton) (31,32 & 33) µs using Grey Relational Analysis (GRA). Research is conducted on stir casted Hybrid Composite Material with different weight percentage of matrix (Aluminium (Al) 6061 (95,90 & 85) %) and reinforcement materials (Silicon Carbide (Sic) (5,10 & 15) % and Boron Carbide (B_4C) (5) %). L9 orthogonal array is selected for the design of experiments based on the range of Input process parameters for four different samples. Based on GRA, the optimized set of parameters for all four sample is F=50mm/min, Ip = 2amps, Ton = 31 µs and Toff = 5 µs.

***Index Terms* - WEDM, Hybrid-ALMMC, GRA, MRR, Ra.**

I. INTRODUCTION

Aluminium Matrix Composite (AMC) is widely used in the advanced aerospace industry, because of the high strength to less weight ratio (Surappa, 2003). Apart from the various reinforcement materials, ceramics are widely used in various research. Among the ceramics like Silicon Carbide (SiC), Boron Carbide (B_4C), Aluminium Oxide (Al_2O_3) and Tungsten Carbide, Numerous research activity is reported by using ceramics as SiC (Gokulakannan et al., 2016). The strength and Fatigue of the composite material are determined by the size and volume of reinforcement in the Composite material. Aluminium Metal Matrix Composite (AMMC) possess greater strength to weight ratio when compare to other alloy material, hence is called as new generation material (Saini et al., 2012). Because of the high tolling cost and high wear rata, AMMC would be prefer to machine in non-conventional machine. Among the non-conventional machine, Wire Electrical Discharge Machine (WEDM) is providing good result in machining of AMMC.

Fabrication of Hybrid Composite material consist of different methods, they are Liquid Metallurgy (Stir Casting), Squeeze Casting, Powder Metallurgy, Spray Casting and Lanxide technique. The main constraint during the fabrication are wettability, porosity, chemical reaction between the ceramics and matrix material and distribution of reinforcement in the matrix material by considering the above set of parameters, Liquid Metallurgy (Stir Casting) is the best technique for AMMC fabrication (Hashim et al., 1999). Different process parameter of WEDM is studied to get the optimized set of Surface Roughness (Ra) and Material Removal Rate (MRR), they are Input Current (Ip), Feed Rate (F), Pulse on time (Ton), Pulse off time (Toff), voltage (V), types of dielectric and feed wire material. Without compromising the machining performance, need to achieve the efficient and accurate machining process by using optimized set of process parameters (Ho et al., 2004).

Al-6061 Composite Material is processed by using WEDM, from which we observed MRR is increase with increase of Ip, Ton and flushing pressure of the dielectric simultaneously Surface Roughness also increase with increase of above parameters, so we can conclude the process parameter play vital role in MRR and Ra (Velmurugan et al., 2011). Thermal Energy is the underline technique used for machining in WEDM, due to the exposure of material for high temperature, there is a high chance of property variation will occur near to the machined surface. This called recast layer, material will melt during high temperature and it again recast to the parent material, this happens in millisecond. Ton and Ip plays vital role in temperature distribution over the workpiece, hence we need to use the lower value of Ton and Ip (Ramesh et al., 2018).

In the new generation and fastest growing technology multi objective optimization is the widely selected rather than single objective optimization, because, we are considering multiple output parameters, In order to get the optimized set of process parameters of the multiple output parameters, multi objective optimization is the only technique. (Rajeswari & Amirthagadeswaran, 2017). Among various technique, Grey Relational Analysis (GRA) is widely used because of the high accuracy and widely proven result (Raju et al., 2017).

II. Material Selection and Experimental Result

The different weight percentage of reinforcement is mixed with the matrix material by using the stir casting technique, the resulted samples are machined by using WEDM (Gokulakannan et al., 2018). The machining parameters which we considered are listed in the below-mentioned Table 1. The output parameter we going to investigate is MRR and Ra. Based on the Taguchi Design of an experiment for the respective input and output parameters, the L9 orthogonal array been selected for all four samples (Gokulakannan et al., 2019).

Table 1: Process parameter and the levels

Machining Parameters	Units	Symbols	Level 1	Level2	Level 3
Feed Rate	mm/min	F	50	75	100
Current	amps	Ip	2	3	4
Pulse On Time	µs	Ton	31	32	33
Pulse Off Time	µs	Toff	5	6	7

The constant machine parameters and composition of matrix and reinforcement for respective samples which we did stir casting been listed in Table 2. Wire material which we are using the Brass and dielectric medium used are Deionized water mixed with paster, because high temperature will develop during machining, dielectric act as coolant also the paster will let the material not stick with wire. If the material will stick with the wire, there is a high chance for wire breakage.

Table 2: WEDM Machine Parameters.

Wire Tool	Material	Brass
	Wire Diameter	0.24mm
	Orientation	Vertical
Dielectric	Medium	Deionized water mixed with paste
Workpiece	Material	Aluminium 6061
	Composition	Sample 1: Al (100%) +SiC (0%) + B_4C (0%)
		Sample 2: Al (90%) +SiC (5%) + B_4C (5%)
		Sample 3: Al (85%) +SiC (10%) + B_4C (5%)
		Sample 4: Al (80%) +SiC (15%) + B_4C (5%)

The output parameters like MRR and Ra been calculated (Gokulakannan et al., 2019) for all samples and resulted values been listed in Table 3. MRR is calculated by using the mathematical formula and Ra is determined by using the Surface Roughness Measuring instrument DextakXT stylus Profilometer.

Table 3: WEDM Result

Feed Rate (F)	Current (Ip)	Pulse On Time (Ton)	Pulse Off time (Toff)	Sample 1		Sample 2		Sample 3		Sample 4	
				MRR	Ra	MRR	Ra	MRR	Ra	MRR	Ra
50	2	31	5	43.48	3.91	41.2	4.08	36	4.44	26.42	4.99
50	3	32	6	46.58	4.01	42.5	4.18	39.23	4.62	30.02	5.37
50	4	33	7	47.28	4.12	44.44	4.34	42.13	4.96	35.91	5.39
75	2	32	7	47.9	4.21	44.25	4.45	29.88	5.14	33.04	5.37
75	3	33	5	60.48	4.42	56.35	4.64	48.7	5.62	43.66	5.77
75	4	31	6	59.76	4.31	44.06	4.55	49.18	5.57	39.66	5.83
100	2	33	6	48.55	4.91	46.78	5.12	35.55	6.21	38.86	6.67
100	3	31	7	58.22	4.79	43.99	4.98	37.22	6.31	35.31	6.43
100	4	32	5	64.1	5.26	59.2	5.41	59	6.65	48.22	7.25

III. Grey Relational Analysis (GRA):

GRA is the best approach to evaluate the optimized set of response parameter for the input parameter. GRA can investigate the system model with insufficient information and uncertainty. GRA is used to transform the real factor space into measurable space, when there is a non-existent of relation between the sequence factor. The response values are on a different scale and have different units, to normalize the value, we have to do data preprocessing. GRA consist of three steps they are Normalization, Grey Relational Coefficient and Grey Relational Grade (GRG). Finally based on the ranking of GRG, we selected the best set of process parameter for all sample (Ajith Arul Daniel et al., 2019). Following steps are followed in GRA (Nayak et al., 2014)

- Experimental data is normalized on the scale of 0 to 1.
- GRC is calculated from normalized value to express the relationship between best and experimental value.
- GRG is computed by averaging the weighted GRC to each performance characteristics.

Step -I: Normalization:

We aim to minimize the Ra value and maximize the MRR. So, for normalization, we have to adopt the larger the better for MRR and the smaller the better for Ra. The respective formula to normalize the value of MRR and Ra (Nayak et al., 2014) are listed below Eq.1 and Eq.2.

Larger Objective is better of MRR, hence they are represented by using Large the Better formula.

$$\text{Larger the Better (MRR)} \quad x_i^*(k) = \frac{x_i(k) - x_i min(k)}{x_{imax}(k) - x_i min(k)} \qquad (1)$$

Smaller Objective is better for Ra, hence the are represented by using Smaller the Better Formula

$$\text{Smaller the Better (Ra)} \quad x_i^*(k) = \frac{x_{imax}(k) - x_i(k)}{x_{imax}(k) - x_i min(k)} \qquad (2)$$

In which, $x_i^*(k)$ is the normalized value. $x_i(k)$ is the observed value for the i^{th} experiment. $x_i min(k)$ and $x_i max(k)$ are the minimum and maximum value of $x_i(k)$ in the k^{th} response. Data processing is very important in the GRA, because different process parameter have on different scale, before feed the value to GRC we need to normalize and to ensure both the process parameter value are in same scale.

Step – II: Grey Relational Coefficient (GRC):

After the Normalization of the values, we have to calculate the GRC for the response values, the formula used for calculating the GRC is expressed below Eq.3.

$$\zeta_i(k) = \frac{\Delta_{min} + \varsigma\Delta_{max}}{\Delta_i(k) + \varsigma\Delta_{max}} \qquad (3)$$

$\Delta_{min} = min_{(\forall j\epsilon i)} min_{(\forall k)} |x_o^*(k) - x_j^*(k)|$ = smallest value of Δ_i

$\Delta_{max} = max_{(\forall j\epsilon i)} max_{(\forall k)} |x_o^*(k) - x_j^*(k)|$ = largest value of Δ_i

$\varsigma\ \epsilon[0, 1]$, is the distinguishing factor; 0.5 is widely accepted.

$\Delta_i = |x_o^*(k) - x_j^*(k)|$ = difference in absolute value, in the table it refers to Deviation Sequence.

$x_j^*(k)$ = Comparability sequence

$x_o^*(k)$ = reference Sequence.

Step III. Grey Relational Grade (GRG):

After calculating the GRC, GRG has been determined by integrating the response parameter of GRC of MRR and Ra values. The formula used for calculating the GRG is given below Eq.4.

$$\gamma_i = \frac{1}{m}\sum_{k=1}^{n} w * \zeta_i(k) \qquad (4)$$

Were,

m = number of response parameter.
n = number of runs
w = weight value
$\zeta_i(k)$ = sum of the response of i^{th} value.
$\sum_{k=1}^{n} w = 1$

Based on the resultant value of GRG, we can select the optimum set of process parameter which have a good influence over both MRR and Ra value.

IV. Result and Discussion

Based on the above-mentioned Eq.1 to Eq.4. We evaluated the optimum set of process parameter by using GRA for all samples and determined the correlation between the materials (different samples), process parameter and response values. The calculated GRA for all samples is listed in the mentioned tables – Table [4 - 7]. Depends upon the GRG value ranking is provided to each set of process parameter, larger the GRG value get first rank and lower GRG value get least value, from the Rank, we can easily determine the set of process parameter which have high influence over MRR and Ra.

Table 4: Calculated GRG for Sample I.

Feed Rate (F)	Current (Ip)	Pulse On Time (Ton)	Pulse Off time (Toff)	Original Value		Normalized Value		Deviation Sequence		Grey Relational Coefficient		GRG	Rank
				MRR	Ra	MRR	Ra	MRR	Ra	MRR	Ra		
50	2	31	5	43.4	3.91	0	1	1	0	0.33333	1	0.6666	1
50	3	32	6	46.5	4.01	0.1503	0.9259	0.84966	0.0740	0.37046	0.8709	0.6207	5
50	4	33	7	47.2	4.12	0.1842	0.8444	0.81571	0.1555	0.38002	0.7627	0.5713	6
75	2	32	7	47.9	4.21	0.2143	0.7777	0.78564	0.2222	0.38890	0.6923	0.5406	7
75	3	33	5	60.4	4.42	0.8244	0.6222	0.17555	0.3777	0.74012	0.5696	0.6548	4
75	4	31	6	59.7	4.31	0.7895	0.7037	0.21047	0.2963	0.70375	0.6279	0.6658	3
100	2	33	6	48.5	4.91	0.2458	0.2592	0.75412	0.7407	0.3986	0.4029	0.4008	9
100	3	31	7	58.2	4.79	0.7148	0.3481	0.28516	0.651	0.63681	0.4340	0.5354	8
100	4	32	5	64.1	5.26	1	0	0	1	1	0.3333	0.6666	1

Table 5: Calculated GRG for Sample II.

Feed Rate (F)	Current (Ip)	Pulse On Time (Ton)	Pulse Off time (Toff)	Original Value		Normalized Value		Deviation Sequence		Grey Relational Coefficient		GRG	Rank
				MRR	Ra	MRR	Ra	MRR	Ra	MRR	Ra		
50	2	31	5	41.2	4.08	0	1	1	0	0.33333	1	0.6666	1
50	3	32	6	42.5	4.18	0.0722	0.9248	0.92777	0.07519	0.35019	0.8692	0.6097	4
50	4	33	7	44.44	4.34	0.18	0.8045	0.82	0.19549	0.37878	0.7189	0.5488	5
75	2	32	7	44.25	4.45	0.1694	0.721	0.83055	0.2782	0.37578	0.6425	0.5091	6
75	3	33	5	56.35	4.64	0.8416	0.5789	0.15833	0.42105	0.75949	0.5428	0.6511	3
75	4	31	6	44.06	4.55	0.1588	0.6466	0.84111	0.35338	0.37282	0.5859	0.4793	7
100	2	33	6	46.78	5.12	0.31	0.2180	0.69	0.78195	0.42016	0.3900	0.4051	8
100	3	31	7	43.99	4.98	0.155	0.3233	0.845	0.67669	0.37174	0.4249	0.3983	9
100	4	32	5	59.2	5.41	1	0	0	1	1	0.3333	0.6666	1

Table 6: Calculated GRG for Sample III.

Feed Rate (F)	Current (Ip)	Pulse On Time (Ton)	Pulse Off time (Toff)	Original Value		Normalized Value		Deviation Sequence		Grey Relational Coefficient		GRG	Rank
				MRR	Ra	MRR	Ra	MRR	Ra	MRR	Ra		
50	2	31	5	36	4.44	0.21016	1	0.7898	0	0.3876	1	0.6938	1
50	3	32	6	39.23	4.62	0.32108	0.9185	0.6789	0.08145	0.4241	0.8599	0.6420	3
50	4	33	7	42.13	4.96	0.42067	0.7647	0.5793	0.23529	0.4632	0.68	0.5716	4
75	2	32	7	29.88	5.14	0	0.6832	1	0.31674	0.3333	0.6121	0.4727	7
75	3	33	5	48.7	5.62	0.64629	0.4660	0.3537	0.53394	0.5856	0.4835	0.5346	6
75	4	31	6	49.18	5.57	0.66277	0.4886	0.3372	0.51131	0.5972	0.4944	0.5458	5
100	2	33	6	35.55	6.21	0.19471	0.1991	0.8052	0.8009	0.3830	0.3843	0.3837	9
100	3	31	7	37.22	6.31	0.25206	0.1538	0.7479	0.84615	0.4006	0.3714	0.3860	8
100	4	32	5	59	6.65	1	0	0	1	1	0.3333	0.6666	2

Table 7: Calculated GRG for Sample IV.

Feed Rate (F)	Current (Ip)	Pulse On Time (Ton)	Pulse Off time (Toff)	Original Value		Normalized Value		Deviation Sequence		Grey Relational Coefficient		GRG	Rank
				MRR	Ra	MRR	Ra	MRR	Ra	MRR	Ra		
50	2	31	5	26.42	4.99	0	1	1	0	0.3333	1	0.6666	1
50	3	32	6	30.02	5.37	0.1651	0.8318	0.8348	0.16814	0.3745	0.7483	0.5614	7
50	4	33	7	35.91	5.39	0.4353	0.8230	0.5646	0.17699	0.4696	0.7385	0.6040	4
75	2	32	7	33.04	5.37	0.3036	0.8318	0.6963	0.16814	0.4179	0.7483	0.5831	5
75	3	33	5	43.66	5.77	0.7908	0.6548	0.2091	0.34513	0.7050	0.5916	0.6483	3
75	4	31	6	39.66	5.83	0.6073	0.6283	0.3926	0.37168	0.5601	0.5736	0.5668	6
100	2	33	6	38.86	6.67	0.5706	0.2566	0.4293	0.74336	0.5380	0.4021	0.4700	8
100	3	31	7	35.31	6.43	0.4077	0.3628	0.5922	0.63717	0.4577	0.4396	0.4487	9
100	4	32	5	48.22	7.25	1	0	0	1	1	0.3333	0.6666	1

From the GRG value best optimized set of process parameter shared by two sets, they are F=50mm/min, Ip = 2amps, Ton = 31 µs & Toff = 5 µs and F=100mm/min, Ip = 4amps, Ton = 32 µs & Toff = 5 µs. To conclude, F and Ip don't have much influence over the MRR and Ra despite the fact volume of reinforcement in the matrix material.

Toff and Ton have a major impact on MRR and Ra value. To achieve the best set of MRR and Ra value, we have to keep the Toff time at a minimum, this tends to reduce the time for solidification of recast layer over the parent material during the machining process.

For samples III, the best-optimized set of process parameter is F=50mm/min, Ip = 2amps, Ton = 31 µs and Toff = 5 µs, this set is shared by all the other samples too. So, as we earlier mentioned the material composition in Aluminium don't have much influence over the response parameters. Despite the fact, higher the usage of Ceramics will tend to increase the machining time and increase the Ra value (lower is the better). The process will analyze the effect of the individual input parameter over the GRG value. The lowest and highest value of F and Ip influence the MRR and Ra value. Toff has direct influence over the response, only if the Ton should be minimum.

V. Conclusion

Multi-objective Optimization is achieved by using the Grey Relational Analysis for the response of MRR and Ra respectively. The study of samples with different weight composition of the material (F=50mm/min, Ip = 2amps, Ton = 31 µs and Toff = 5 µs) is the best-optimized set of parameters based on GRG. Toff and Ton have much influence over the output response rather than Feed Rate and Current. The composite material is cast properly, because of which all the samples process parameter has even influence over the response.

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