Optimizing Multiple Quality Characteristics of Wire Electrical Discharge Machining via Taguchi method-based Gray analysis for Magnesium Alloy

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ABSTRACT

This paper demonstrates the optimizing process of multiple quality characteristics for Wire Electrical Discharge Machining (WEDM) of magnesium alloy parts via the Taguchi method-based Gray analysis. The modified algorithm adopted here was successfully used for both detraining the optimum settings of machine parameters and for combining multiple quality characteristics into one integrated numerical value called Gray relational grade. Multiple quality characteristics required include: (1) material removal rate and (2) surface roughness following WEDM. This work machines magnesium alloy parts under controlled machine parameter settings, and measures the above quality characteristics. The optimized machine parameter settings clearly improve quality characteristics of the machined workpiece compared to quality levels achieved for initial machine parameter settings. Material removal rate changes from 41.10 to 113.57 mm^2/min and surface roughness on the workpiece changes from 2.69 to 3.13 μmRa (target value 3 μmRa).

Keywords: multiple quality characteristics, Taguchi method, Gray theory, wire electrical discharge machining (WEDM), magnesium alloy

以田口式實驗計畫法與灰色分析應用於鎂合金之線切割放電加工多重品質特性優化之研究

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摘　要

本文提出一多重品質特性之優化方法，透過田口式方法為基礎的灰色分析並應用於鎂合金之線切割放電加工(WEDM)研究。此一修改後之優化方法，成功地應用於參數優化設置並結合多重品質特性為一個綜合的評估數值，稱為灰色關聯度。本研究之線切割放電加工多重品質特性需求包括：(1) 材料去除率和 (2) 加工表面粗糙度等。經由本研究之優化參數之研究，相較於初步的參數設置，明顯的提高加工品質特性水準，材料去除率的從 41.10 提升到 113.57 mm^2/min 和表面粗糙度由 2.69 至 3.13 μmRa (目標設定為 3 μmRa)。

關鍵詞：多重品質特性，田口式實驗計畫法，灰色理論，線切割放電加工 (WEDM)，鎂合金

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I. INTRODUCTION

Magnesium alloy has been employed to manufacture 3C (computer, communication, and consumer electronics) products. As such, processing magnesium alloy has become a concern for all manufacturers involved in precision machining. Magnesium alloy used in mechanical engineering is limited primarily by the hexagonal close packed (HCP) arrangement of magnesium atoms. This particular mode involves only one slip plane and three slip directions, so Vlack [1] claims that the probability of slip by the magnesium alloy material at room temperature is lower to other metals, causing to reduce the ductility of the magnesium alloy and also to make it difficult to shape. Therefore this study presents the application of WEDM to process magnesium alloy and derives optimal machining condition, with a view to providing references for academic and industrial researchers. Manufacturing managers must optimize quality characteristics through research, design and setting parameters during the WEDM process. Manufacturing managers have used the Taguchi method in the machining process to determine optimal machining parameters with a single quality characteristic. Some analytic methods are too difficult to implement, while others are too simplistic for real life use. Determining optimal machining parameters for multiple quality characteristics is much more complicated than optimizing a single quality characteristic. This paper presents an efficient method for determining the optimal process parameters for multiple quality characteristics, through integrating the Gray theory with the Taguchi method for magnesium alloy.

II. ADOPTED METHODOLOGY

This study constructs experiments using the L18 orthogonal array of the Taguchi method. Analysis of variance and F tests obtain the optimal single quality index. This research integrates the respective single quality characteristic index with the Gray theory to weight and construct the optimal multiple quality characteristic index. Figure 1 explains the process of changing an optimal single quality characteristic index to an optimal multiple quality characteristics index.

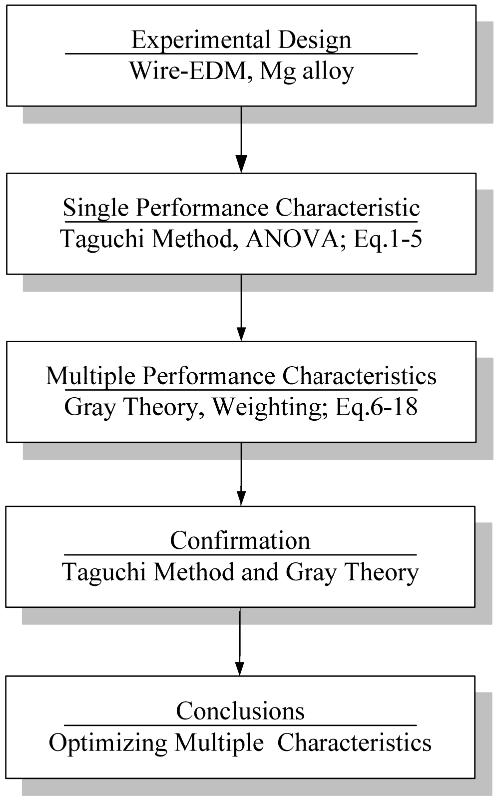

Fig. 1. Flow Chart of Optimal Multiple Quality Characteristics.

2.1 Experiment Design Using the Taguchi Approach

The Orthogonal Array forms the basis for the experimental analysis in the Taguchi Method [2]. Manufacturing managers select the experiment parameter factors and their corresponding levels. Then the analysis of variance (ANOVA) method manipulates the experimental results to determine the effect of each parameter versus the objective function. The experiment procedures are described as follows:

(i) Select parameter factor selection based on the required quality objective.
(ii) Determine parameter factor level.
(iii) Calculate total degree of freedom and suitable Orthogonal Array selection, based on parameter factors and levels.
(iv) Proceed with the practical experiment, based on the Orthogonal Array variable factor layout.

(v) Obtain experimental results and then compute the ANOVA for Signal-to-Noise Ratio (S/N Ratio) and the contribution.
(vi) Select the optimal parameter factor level combination.
(vii) Use the optimal parameter level combination to proceed with the confirmation experiment.

The basic method for the Taguchi method parameter design converts the objective parameter to the S/N Ratio, treated as the quality characteristics evaluation index. The least variation and the optimal design are obtained by means of the S/N Ratio. The final step actually conducts the experiment to confirm experiment success.

Benefits of the S/N Ratio include increasing the factor weighting effect, decreasing mutual action, simultaneously processing the average and variation, and improving engineering quality. The higher the S/N Ratio, the more stable the achievable quality. Depending on the required objective characteristics, different calculation methods can be applied as follows:

Where the objective optimal value is smaller, the Smaller-the-Better (SB) method applies, such as in surface roughness and dimension accuracy error.

$$\eta = -10\log\left[\frac{1}{n}\sum_{k=1}^{n} y_k^2\right] \tag{1}$$

Where the objective optimal value is larger, the Larger-the-Better (LB) method applies, such as in material removal rate and tensile strength.

$$\eta = -10\log\left[\frac{1}{n}\sum_{k=1}^{n} y_k^{-2}\right] \tag{2}$$

Where the objective optimal value is particular (preferable), the Nominal-the-Better (NB) method applies, such as in coating depth and others.

$$\eta = -10\log\left[\frac{1}{n-1}\sum_{k=1}^{n}(y_k-\mu)^2\right] \quad \mu = \frac{1}{n}\sum_{k=1}^{n} y_k \tag{3}$$

where η : Signal-to-Noise Ratio (S/N Ratio); y_k: the k-th result of the experiment; n: the repeated number of the k-th experiment.

After selecting optimal process parameter levels, the final step predicts and verifies the objective function. The predicted optimum value of the S/N Ratio (η_{pred}) is [3]:

$$\eta_{pred} = m + \sum_{j}^{p}\left[\left(m_{i,j}\right)_{\max} - m\right] \tag{4}$$

where $\left(m_{i,j}\right)_{\max}$ is the S/N Ratio of optimum level i of parameter j, m is the overall mean of the S/N Ratio and p is the number of parameters affecting the objective function. Furthermore, in order to judge experimental value closeness of the S/N Ratio (η_{expt}) with that of the predicted value (η_{pred}), this work determines the confidence interval (CI) of η_{pred} for the optimum process parameter level combination at the 95 percent level. The CI is given by [4]:

$$CI = \sqrt{F_{(1,v_e)} V_e \left(\frac{1}{n_{eff}} + \frac{1}{n_{ver}}\right)} \tag{5}$$

where $F_{(1,v_e)}$ is the F value for 95 percent confidence interval; v_e is the degree of freedom for error; V_e is the mean square of error; $n_{eff} = \frac{N}{1+v}$, N= total trial number in Orthogonal Array and v= degree of freedom of p factors; n_{ver} is the confirmatory test trial number. If the prediction error $|\eta_{pred} - \eta_{expt}|$ is within the CI value, then the optimum factor level combination and additive model for factor effects in this experiment are valid.

2.2 Gray Theory

2.2.1 Gray Relation Generating

The Gray theory investigates a system model with uncertain and insufficient information [5-10]. The Gray Relational Analysis among sequence groups requires that all sequences satisfy comparability conditions, for instance, non-dimension, scaling, and polarization attributes. If comparability does not exist within sequences, the Gray Relationship generating approach can be adopted to transform the original sequence factor space into measurable space, generating a comparable sequence with three different comparability types as follows,

(i) The Larger-the-Better (LB): the larger objective value is better and the property can be represented as the following equation,

$$x_i^*(k) = \frac{x_i^{(0)}(k) - \min x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)} \tag{6}$$

(ii) The Smaller-the-Better (SB): the smaller objective value is better,

$$x_i^*(k) = \frac{\max x_i^{(0)}(k) - x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)} \tag{7}$$

(iii) The Nominal-the-Better (NB): the value closer to the objective value OB is better,

$$x_i^*(k) = 1 - \frac{\left|x_i^{(0)}(k) - OB\right|}{\max\left\{\max x_i^{(0)}(k) - OB; OB - \min x_i^{(0)}(k)\right\}} \tag{8}$$

where $x_i^*(k)$ is the value after the Gray Relation generating process and min $x_i^{(0)}(k)$, max $x_i^{(0)}(k)$ denotes the minimum and maximum of $x_i^{(0)}(k)$ respectively.

The Gray Relational Grade in the Gray Relational Analysis is defined as the relative degree between two sequences. Only one sequence $x_0(k)$ selected as the reference sequence is called the localized Gray Relational Grade, i.e., one sequence exists in the Gray Relation space { $P(X)$; Γ },

$$x_i(k)=(x_i(1), x_i(2), \cdots\cdots, x_i(k)) \in \boldsymbol{X}$$

where $i=0, 1, 2\cdots\cdots, m \in \boldsymbol{N}$; $k=1, 2, \cdots\cdots, n \in \boldsymbol{N}$, i.e.,

$$x_0(k)= (x_0(1), x_0(2), \cdots\cdots, x_0(k))$$

$$x_1(k)= (x_1(1), x_1(2), \cdots\cdots, x_1(k))$$

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$$x_m(k)= (x_m(1), x_m(2), \cdots\cdots, x_m(k)) \tag{9}$$

2.2.2 Entropy Weighting

Entropy Weighting employs the entropy concept to determine the relative weighting factor for each attribute. Computing entropy value through the selected case effect for each attribute determines the uncertain deliverable degree of information for the entire decision making process. Then comparing the entropy value for each attribute calculates the relative importance among all attributes, or the relative weighting factor. The relative weighting factors obtained by entropy weighting apply evaluated attribute information among all selected cases, not including the artificial subjective factor of decision maker; hence, Entropy Weighting belongs to the objective-weighting factor. Entropy Weighting is introduced as follows [10-13]:

(i) Compute each attribute's summation value for all sequences, D_k

$$D_k = \sum_{i=1}^{m} x_i(k) \tag{10}$$

(ii) Compute the normalization coefficient K

$$K = \frac{1}{0.6487n} \tag{11}$$

where n represents the number of quality characteristics, or attributes

(iii) Find the entropy for the specific attribute, e_k

$$e_k = K\sum_{i=1}^{m} W_e(z_i) \tag{12a}$$

where

$$W_e(z_i) = z_i e^{(1-z_i)} + (1-z_i)e^{z_i} - 1 \tag{12b}$$

$$z_i = \frac{x_i(k)}{D_k} \tag{12c}$$

(iv) Compute the total entropy value, E:

$$E = \sum_{k=1}^{n} e_k \tag{13}$$

(v) Determine the relative weighting factor, λ_k,

$$\lambda_k = \frac{1}{n-E}\left|(1-e_k)\right| \tag{14}$$

(vi) Using the normalization method, each attribute weight, or quality characteristic, can be calculated as

$$\omega_j = \frac{\lambda_k}{\sum_{k=1}^{n} \lambda_i} \tag{15}$$

2.2.3 Gray Relational Grade

The major calculation processes include the following:

(i) Endow the weighting factor: According to the Gray Relation generating data, the weighting factors of each attribute are given.

(ii) After selecting the weighting factor, the following equation is computed

$$\Delta_{0i}(k) = \left|x_0(k) - x_i(k)\right| \tag{16}$$

where $i=1, 2,\cdots, m,\quad k=1, 2, \cdots, n\quad j \in i$

x_0 represents the weighting factor for each attribute; hence, $x_0(k)$ and $x_i(k)$ are the reference (ideal) sequence and the specific relative sequence respectively.

(iii) Calculate the Gray Relational Grade Γ_j through the following equation

$$\Gamma_j = \frac{\Delta_{min} + \Delta_{max}}{\Delta'_j + \Delta_{max}} \tag{17}$$

where $\Delta_j' = \frac{1}{n}\sum_{i=1}^{n}\Delta_{0i}(k)$ and $\Delta_{\min}$, $\Delta_{\max}$ are constants as

$$\Delta_{min} = \overset{min}{\forall j} \in \overset{min}{\forall k}\left|x_0(k) - x_j(k)\right| \tag{18a}$$

$$\Delta_{max} = \overset{max}{\forall j} \in \overset{max}{\forall k}\left|x_0(k) - x_j(k)\right| \tag{18b}$$

III. DESIGN AND VERIFICATION OF THE EXPERIMENT

This section demonstrates usability of the multiple quality indexes model and verifies machining parameters design in a real life environment by the experimental design and implementation of Wire Electrical Discharge Machining [14-17].

3.1 Principles of Wire Electrical Discharge Machining

The WEDM metal removal involves the complex erosion effect from electric sparks generated by a pulsating direct current power supply. The sparks generate between two closely spaced electrodes under the influence of dielectric liquid. The applied voltage creates an ionized channel between the nearest points of the workpiece and the wire electrode in the initial stage. Actual discharge in the next stage takes place with heavy current flow, causing gradually decreasing resistance of the ionized channel. High current intensity further ionizes the channel and generates a powerful magnetic field. The magnetic field compresses the ionized channel, resulting in localized heating. Transforming electron kinetic energy into heat raises electrode temperature above the normal boiling point of the workpiece, even with short duration sparks. The high energy density erodes partial material from both the wire electrode and workpiece by local melting and vaporizing, forming the dominant erosion process.

3.2 Experimental Design

This study performs experiments on a FANUC W1 CNC Wire Electrical Discharge Machining, and uses a negatively polarized brass wire with a diameter of 0.25 mm as the tool. Quality measure characteristics include

Material Removal Rate (MRR) and Surface Roughness (SR). These characteristics are affected by six machining parameters: (1) wire feed rate, (2) pulse-on time, (3) pulse-off time, (4) no load voltage, (5) servo voltage, and (6) wire tension.

Developing an empirical model capable of predicting quality characteristics for further optimization, as listed in Table 1, requires an experiment which selects a reasonable set of parameters as inputs while other parameters affecting quality characteristics of the process are fixed. The WEDM limits available input parameters, designed with three levels - small, medium and large denoted by 1, 2 and 3. The inputs and fixed parameters listed in Table 2 are chosen from manufacturing experience, experts' opinions, literature survey, etc.

Table 1. Experimental Measure

Measure Performance Value	Experimental Conditions
● MRR: Material Removal Rate（mm^2/min） ＝Feed Rate × Workpiece Thickness ● SR: Surface Roughness (μmRa)	● Workpiece Material: AZ31B ● Workpiece Thickness: 15 mm ● Wire: Brass, Diameter 0.25 mm ● Workpiece and Flow Space: 0.3mm

Table 2. Factors and levels

Symbol	Factors	Unit	Level 1	Level 2	Level 3
[A]	Wire Feed Rate (F_w)	Step	6	10	--
[B]	Pulse-On Time (τ_{on})	μs	5	6	7
[C]	Pulse-Off Time (τ_{off})	μs	30	40	50
[D]	No Load Voltage (H_v)	Step	5	6	8
[E]	Servo Voltage (V_s)	V	45	50	55
[F]	Wire Tension (T_w)	gf	300	600	1000
Fixed Setting	Water Flow	Step	10		
	Resistive of Water	$\times 10^4 \Omega$-cm	2.5		
	Feed Rate Override	%	100		

3.3 The Single Quality Characteristic Combination

The optimization process for a single quality index is described as follows:

(i) Construct the process parameters using the L_{18} Orthogonal Array, which anticipates material removal rate as the Higher-the-Better, HB. On the other hand, surface roughness is the Nominal-the-Better, NB (3μmRa) in this study. The suitable condition, recorded data and the evaluated experimental value and response (S/N) Ratio are shown in Table 3.

(ii) To implement the experiment based on the L18 Orthogonal Array, statistic analysis of variance evaluates each parameter significance and F-test according to Table 4 and Table 5.

3.4 The Combination of Multiple Quality Characteristics

Selecting the highest S/N Ratio from single quality characteristics cannot directly obtain optimization of multiple quality indexes, owing to the interrelations between higher S/N Ratio quality characteristics and lower S/N Ratios. This section develops methodology for handling multiple quality characteristics as follows.

Table 3. Single performance characteristic index and S/N Ratio

No.	Control Parameters						Experimental Value			
	F_w	τ_{on}	τ_{off}	H_v	V_s	T_w	MRR mm^2/mm	MRR dB	SR μmRa	SR dB
1	6	5	30	5	45	300	19.50	25.80	2.52	-8.04
2	6	5	40	6	50	600	15.00	23.52	2.68	-8.56
3	6	5	50	8	55	1000	19.20	25.67	2.76	-8.83
4	6	6	30	5	50	600	45.00	33.06	3.08	-9.79
5	6	6	40	6	55	1000	35.70	31.05	3.37	-10.56
6	6	6	50	8	45	300	61.50	35.78	3.88	-11.83
7	6	7	30	6	45	1000	111.00	40.91	4.24	-12.54
8	6	7	40	8	50	300	120.00	41.58	4.25	-12.57
9	6	7	50	5	55	600	39.75	31.99	4.32	-12.71
10	10	5	30	8	55	600	26.70	28.53	3.75	-11.52
11	10	5	40	5	45	1000	15.90	24.03	2.33	-7.36
12	10	5	50	6	50	300	11.25	21.02	2.76	-8.85
13	10	6	30	6	55	300	42.75	32.62	3.29	-10.36
14	10	6	40	8	45	600	72.75	37.24	3.46	-10.81
15	10	6	50	5	50	1000	30.30	29.63	3.22	-10.16
16	10	7	30	8	50	1000	156.15	43.87	4.13	-12.32
17	10	7	40	5	55	300	45.75	33.21	4.33	-12.73
18	10	7	50	6	45	600	65.55	36.33	3.78	-11.55

Table 4. F test and contribution of material removal rate

Parameter (A)	*Degree (f_A)*	*Square Sum (S_A)*	*Variance (V_A)*	F_{A0}	$F_{0.05}$	$F_{0.01}$	*Contribution (%)*
[A]	1	0.46	0.46	3.26	5.99	13.75	0.13
[B]	2	538.08	269.04	1896.29**	5.14	10.93	73.87
[C]	2	49.95	24.98	176.04**	5.14	10.93	6.86
[D]	2	112.32	56.16	395.81**	5.14	10.93	15.42
[E]	2	24.27	12.14	85.54**	5.14	10.93	3.33
[F]	2	2.61	1.30	9.20*	5.14	10.93	0.36
Error	6	0.85	0.14				

Note: An F_{A0} value that exceeds the $F_{0.01}$ value is **"extremely significant"**, and is indicated by **. An F_{A0} value that is less than the $F_{0.01}$ value, but exceeds the $F_{0.05}$ value is **"significant"**, and is indicated by *.

Table 5. F test and contribution of surface roughness

Parameter (A)	*Degree (f_A)*	*Square Sum (S_A)*	*Variance (V_A)*	F_{A0}	$F_{0.05}$	$F_{0.01}$	*Contribution (%)*
[A]	1	0.002	0.002	0.003	5.99	13.75	0.01
[B]	2	37.705	18.853	21.053**	5.14	10.93	79.15
[C]	2	0.339	0.170	0.189	5.14	10.93	0.71
[D]	2	4.575	2.287	2.554	5.14	10.93	9.60
[E]	2	2.271	1.136	1.268	5.14	10.93	4.77
[F]	2	0.950	0.475	0.530	5.14	10.93	1.99
Error	6	5.373	0.895				

Note: An F_{A0} value that exceeds the $F_{0.01}$ value is "extremely significant", and is indicated by **. An F_{A0} value that is less than the $F_{0.01}$ value, but exceeds the $F_{0.05}$ value is "significant", and is indicated by *.

Table 6. Gray relational grade of multiple quality characteristics

No	Gray Relationship Generating		Gray Relational Analysis		Absolute value of the difference between sequences (Δ_{0i})		Gray Relational Grade	
	MRR	SR	Weighting via Gray coefficient				Γ_j	Rank
			MRR 0.481	SR 0.519				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	0.057	0.639	0.027	0.332	0.454	0.187	0.618	13
2	0.026	0.759	0.012	0.394	0.469	0.125	0.636	9
3	0.055	0.820	0.026	0.425	0.455	0.094	0.654	7
4	**0.233**	**0.940**	**0.112**	**0.488**	**0.369**	**0.031**	**0.722**	**1**
5	0.169	0.722	0.081	0.375	0.400	0.144	0.656	6
6	0.347	0.338	0.167	0.176	0.314	0.343	0.612	14
7	0.688	0.068	0.331	0.035	0.150	0.484	0.621	12
8	0.751	0.060	0.361	0.031	0.120	0.488	0.631	11
9	0.197	0.008	0.095	0.004	0.386	0.515	0.535	18
10	0.107	0.436	0.051	0.226	0.430	0.293	0.590	15
11	0.032	0.496	0.015	0.257	0.466	0.261	0.588	16
12	0.000	0.820	0.000	0.425	0.481	0.094	0.644	8
13	0.217	0.782	0.105	0.406	0.377	0.113	0.679	4
14	0.424	0.654	0.204	0.339	0.277	0.179	0.695	3
15	0.131	0.835	0.063	0.433	0.418	0.086	0.673	5
16	1.000	0.150	0.481	0.078	0.000	0.441	0.702	2
17	0.238	0.000	0.115	0.000	0.367	0.519	0.540	17
18	0.375	0.414	0.180	0.215	0.301	0.304	0.632	10

Table 7. Gains of S/N of multiple performance characteristic indexes

Items	Performance Characteristics			
	MRR		SR	
	Initial	Practice	Initial	Practice
Level	A2/B2/C2/D2/E2/F2	A2/B2/C1/D3/E2/F3	A2/B2/C2/D2/E2/F2	A2/B2/C1/D3/E2/F3
Original Value	41.10	113.57	2.69	3.13
S/N (dB)	32.28	41.11	10.17	17.72
Gain of S/N (dB)	8.83		7.55	

(i) Convert the optimal combination equation (6)~(8) of single quality index as shown in Table 6.

(ii) Organize the above optimized single quality index (MRR and SR) by the Gray relationship analysis, normalized between zero and one, resulting from the dimensionless factor in Table 6, column 2, 3.

(iii) Gray relationship generating, and then, weighting via the Gray coefficient equation (10)~(15), resulting from individual characteristic weighting in Table 6, column 4, 5.

(iv) Practice the equation (16)~(18) and the optimal combination of multiple quality indexes as listed in Table 6, column 8.

(v) Determine the optimal combination of multiple quality characteristic indexes from the response diagram in Fig. 2. A2/B2/C1/D3/E2/F3：F_w 10 step, τ_{on} 6 μs, τ_{off} 30 μs, H_v 8 Step, V_s 50 V, and T_w 1000 gf.

Table 8. Verification test of Gray relational grade

No	Gray Relationship Generating		Gray Relational Analysis		Absolute value of the difference between sequences (Δ_{0i})		Gray Relational Grade	
	MRR	SR	Weighting via Gray coefficient				Γ_j	Rank
			MRR 0.483	SR 0.517				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	0.057	0.639	0.028	0.330	0.456	0.187	0.617	14
2	0.026	0.759	0.013	0.392	0.471	0.124	0.635	10
3	0.055	0.820	0.027	0.424	0.457	0.093	0.653	8
4	**0.233**	**0.940**	**0.113**	**0.486**	**0.371**	**0.031**	**0.720**	**2**
5	0.169	0.722	0.082	0.373	0.402	0.144	0.655	7
6	0.347	0.338	0.168	0.175	0.316	0.342	0.611	15
7	0.688	0.068	0.333	0.035	0.151	0.482	0.620	13
8	0.751	0.060	0.363	0.031	0.121	0.486	0.630	12
9	0.197	0.008	0.095	0.004	0.388	0.513	0.534	19
10	0.107	0.436	0.052	0.225	0.432	0.291	0.588	16
11	0.032	0.496	0.016	0.256	0.468	0.260	0.587	17
12	0.000	0.820	0.000	0.424	0.483	0.093	0.642	9
13	0.217	0.782	0.105	0.404	0.378	0.113	0.678	5
14	0.424	0.654	0.205	0.338	0.278	0.179	0.694	4
15	0.131	0.835	0.064	0.431	0.420	0.085	0.672	6
16	1.000	0.150	0.483	0.078	0.000	0.439	0.702	3
17	0.238	0.000	0.115	0.000	0.368	0.517	0.539	18
18	0.375	0.414	0.181	0.214	0.302	0.303	0.631	11
19	**0.706**	**0.902**	**0.341**	**0.466**	**0.142**	**0.051**	**0.843**	**1**

(vi) Comparing with initial S/N gains results in: MRR 8.83 dB, and SR 7.55 dB as shown in Table 7.

(vii) Confirm the predicted results:

Method I.

Compare the experiment with the optimal suggested control parameters with the predicted value. The predicted S/N Ratio using Equation (4) for parameter level combination (A2/B2/C1/D3/E2/F3) is -2.29 dB. Using Equation (5), for the optimal process parameter settings, η_{expt} is -1.48 dB. Hence, the prediction error is 0.81 dB, within the CI value of ± 1.69 dB under 95 percent confidence interval, thus justifying the adequacy of the additivity of the multiple quality model.

Method II.

By using No. 19 data (MRR 113.57 mm^2/min, SR 3.13 μmRa) from Table 7, together with the No. 1~18 data from Table 3, one additional iteration proceeds the Gray Relational Analysis in order to verify combination rank for multiple quality characteristics. The results for multiple quality characteristics, compared to the Table 6, are shown in Table 8, in which No. 19 data, by verification test from multiple quality characteristics, ranks number one for both Gray Relational Analysis. This indicates that integration design for multiple objective experimental parameters is remarkably feasible.

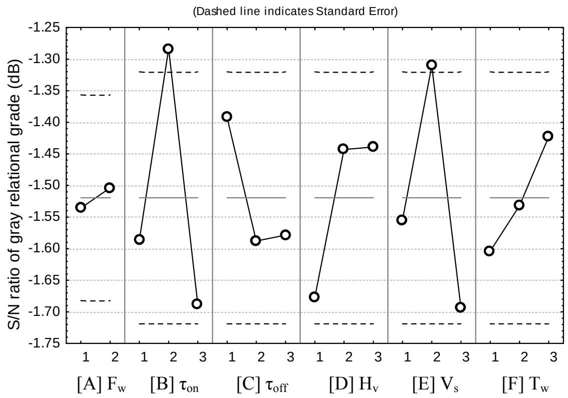

Fig. 2. Response diagram of multiple performance characteristics [Revel optimal combination factor: A2/B2/C1/D3/E2/F3].

IV. CONCLUSIONS

This paper optimizes multiple quality characteristics of WEDM machined magnesium alloy parts using the Taguchi method-based Gray analysis. The Gray Relational Grade calculation helps quantify the integrated quality of multiple quality characteristics required in the WEDM process. The complex interactions in WEDM involve wire feed rate, pulse-on time, pulse-off time, no load voltage, servo voltage, and wire tension. This research successfully optimized the WEDM process, by calculating the Gray Relational Grade and using the Taguchi experimental design for determining machining parameters. Accordingly, the optimal combination of machining parameters for the WEDM process include wire feed rate of 10 step, with pulse-on time of 6 μs, pulse-off time of 30 μs, no load voltage of 8 step, servo voltage of 50 V, and wire tension of 1000 gf. Compared with initial gains of Signal-to-Noise Ratio for material removal rate, and surface roughness are 8.83, and 7.55 dB, respectively. The material removal rate changes from 41.10 to 113.57 mm^2/min and surface roughness on the workpiece changes from 2.69 to 3.13 μmRa.

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REFERENCES

[1] Van Vlack, L. H., Elements of Materials Science and Technology, 5th Edition, Addison Wesley, California, 1985.

[2] Roy, R. K., Design of Experiments Using the Taguchi Approach: 16 Steps to Product and Process Improvement, in: Wiley Interscience, New York, 2001.

[3] Phadke, M. S., Quality Engineering Using Robust Design, Prentice Hall, Englewood Cliffs, NJ, 1989.

[4] Ross, P. J., Taguchi Techniques for Quality Engineering, McGraw-Hill, New York, 1996.

[5] Lin, J. L., Wang, K. S., Yan, B. H., and Tarng, Y. S., "Optimizing of the Multi-Response Process by Taguchi Method with Grey Relational Analysis", The Journal of Grey System, Vol.10, No.4, pp. 355-370, 1998.

[6] Lin, J. L., Wang, K. S., Yan, B. H., and Tarng, Y. S., "A Study of the Grey-Based Taguchi Method for Optimizing the Multi-Response Process", The Journal of Grey System Vol.11, No.3, pp. 257-277, 1999.

[7] Pan, L. K, Wang, C. C., Wei, S. L., Sher, H. F., "Optimizing multiple quality characteristics via Taguchi method-based Grey analysis", Journal of Materials Processing Technology, Vol. 182, Issue 1-3, pp. 107-116, 2007.

[8] Fung, C. P., "Manufacturing process optimization for wear property of fiber-reinforced polybutylene terephthalate composites with grey relational analysis", Wear, Vol. 254, No. 3-4, pp. 298-306, 2003.

[9] Tsai, H. C., Hsiao, S. W., Hung, F. K., "An image evaluation approach for parameter-based product form and color design. Computer-Aided Design", Vol. 38, No. 2, pp. 157-171, 2006.

[10] Wang, C. C., Lin, T. W., Hu, S. S., "Optimizing the rapid prototyping process by integrating the Taguchi method with the

Gray relational analysis", Rapid Prototyping Journal, Vol. 13, No. 5, pp. 304-315, 2007.

[11] Liu, X. W., Han, S. L., "Ranking fuzzy numbers with preference weighting function expectations. Computers & Mathematics with Applications", Vol. 49, No. 11-12, pp. 1731-1753, 2005.

[12] Liu, X., "Parameterized defuzzification with maximum entropy weighting function--Another view of the weighting function expectation method. Mathematical and Computer Modelling", Vol. 45, No. 1-2, pp. 177-188, 2007.

[13] Milani, A.S., Shanian, A, El-Lahham, C., "A decision-based approach for measuring human behavioral resistance to organizational change in strategic planning", Mathematical and Computer Modelling, Vol. 48, Issues 11-12, pp. 1765-1774, 2008.

[14] Chiang, K. T, Chang, F. P., "Optimization of the WEDM process of particle-reinforced material with multiple performance characteristics using grey relational analysis", Journal of Materials Processing Technology, Vol. 180, Issue 1-3, pp. 96-101, 2006.

[15] Dokania, A. K., Pelle, M., Kruit, P., "Fabrication of miniaturized Schottky emitter by wire electrical discharge machining (WEDM)", Microelectronic Engineering, Vol. 85, No. 5-6, pp. 1031-1034, 2008.

[16] Yan, B. H., Tsai, H. C., Huang, F. Y., Lee, L. C., "Examination of wire electrical discharge machining of Al2O3p/6061Al composites", International Journal of Machine Tools and Manufacture, Vol. 45, No. 3, pp. 251-259, 2005.

[17] Tsai, T. C., Horng, J. T., Liu, N. M., Chou, C. C., Chiang, K. T., "The effect of heterogeneous second phase on the machinability evaluation of spheroidal graphite cast irons in the WEDM process", Materials & Design, Vol. 29, No. 9, pp. 1762-1767, 2008.