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Optimizing Main Process Parameters When Conducting Powder-Mixed Electrical Discharge Machining of Hardened 90CrSi

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Abstract: In the current study, an optimization process of powder-mixed electrical discharge machining (PMEDM) process when machining cylindrically shaped parts made of hardened 90CrSi steel is reported. In this study, SiC powder was mixed into the Diel MS 7000 dielectric solution. Additionally, graphite was chosen as the electrode material. The multi-objective functions were minimizing the surface roughness (SR) and electrode wear rate (EWR) and maximizing the material removal rate (MRR). The used input parameters of the optimization process included the powder concentration, the pulse-on time, the pulse-off time, the pulse current, and the servo voltage. A combination between the Taguchi method and the grey relation analysis (GRA) method with the support of Minitab R19 software was used to design the experiment and analyze the results. It was found that the optimal set of process parameters that can satisfy the above responses are Cp of 0.5 g/L, Ton of 8 µs, Toff of 8 µs, IP of 5 A, and SV of 4 V.

Keywords: EDM; PMEDM; surface roughness; Taguchi method; ANOVA; SiC powder

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1. Introduction

In order to remove the materials on the surfaces of mechanical parts made of difficult-to-cut materials, research communities and industry have successfully applied electrical discharge machining (EDM), an advanced machining process. Additionally, EDM is also able to generate complicated geometrical shapes. This operation has shown its advantages compared to those of traditional machining processes such as grinding [1–14]. In recent decades, EDM has been widely utilized in the automotive industry, aerospace, mold, and die made of conductive materials irrespective of the physical properties of machined materials. Nevertheless, it is noticed that the machinability of the EDM process is crucially limited by the low removing speed of materials or by the low material removal rate (MRR), bad surface quality, and the quick acceleration of tool wear. To solve the weakness of EDM, powder-mixed electrical discharge machining (PMEDM) has been proposed [15–21]. In this context, fine powder is mixed with the dielectric to satisfy the properties of EDM, e.g., high precision, better surface quality, and improving material removal rate.

It has been proven that the added powder has a strong effect on the dielectric fluid increase in the MRR [1,6,22]. W.S. Zhao et al. [6] conducted the experimental evaluation to test the influences of PMEDM on machining efficiency compared with traditional EDM operation. The surface roughness and machining efficiency resulting from both PMEDM and traditional EDM were measured and compared. It was revealed that the machining efficiency of PMEDM was smaller than that of traditional EDM. Inversely, in terms of the surface roughness, PMEDM exhibited a much smaller value than that generated by traditional EDM. This can be explained by the fact that in the case of PMEDM, the discharge gaps and passage are normally bigger than those of EDM machining, hence pulse discharge energy is much lost in discharge gaps. Moreover, ejecting force of discharge on the melted materials is reduced by extended discharge gaps. Finally, these reasons significantly impact the lower efficiency of PMEDM machining when compared to that of traditional EDM. On the other hand, the similar discharge parameters, and evenly distributed and "large and shadow" shaped etched cavities make better machining quality of PMEDM. With a similar purpose, Jeswani et al. [1] quantitatively investigated the effectiveness of mixing the powder into the traditional EDM process to increase MRR and reduce EWR. It has been found that adding 4 g of fine graphite powder per little of kerosene causes to augment MRR by 60%. This might be due to the reduction in the breakdown voltage of the kerosene dielectric generated by adding the powder. The advantages of PMEDM compared to traditional EDM machining have also been documented in other studies [10,17,23].

It should be noticed that PMEDM and traditional EDM processes have different machining characteristics, some parameters may be suitable to the former, but unreasonable to the latter. Hence, in order to get the proper set of parameters that can much better improve the advantages of PMEDM, there have been research works dealing with the optimization process [18,20,23–25]. Kanssal et al. [21] applied the response surface method to plan and analyze the experiments for optimizing the process parameters such as pulse-on time, duty cycle, peak current, and concentration of the silicon powder. The responses in this study are minimizing surface roughness and maximizing the material removal rate. It shows that peak current factor and concentration are the most influential parameters on MRR and SR. The reliability of the proposed method is confirmed by a small error percentage between predictions and experiments. In another study [20], the authors have similar conclusions about the most influential factors of the peak current and the concentration of the silicon powder. However, in this study, the responses selected were machining rate (MR), SR, and tool wear rate (TWR). The important impact of powder-mixed concentration was documented in some studies [5,17,23]. Regarding the materials of mixed powder, some kinds have been adopted in the research community such as SiC, silicon carbide, titanium, and aluminum [17,20,23,25]. When comparing the effectiveness of each mixed powder material, Narumiya et al. [2] reported that under suitably mastered machining conditions, surface quality resulting from aluminum and graphite powders is better than that generated by silicon powder in the dielectric. However, there have been few studies dealing with comparing the capability of each mixed powder material. The Taguchi method, analysis of variance (ANOVA), and response surface method have been widely adopted to optimize the process parameters in PMEDM machining [17,20,21,24] when single responses are required. However, in several studies, it is reported that the Taguchi method is combined with GRA [15] to solve the multi-objective responses. Recently, there have been a few studies on PMEDM when processing cylindrically shaped parts [15,26,27]. They have contributed to improving productivity and accuracy when machining tablet-shaped punches (Figure 1).

From the above analysis, it can be seen that there have been many studies on PMEDM so far. However, there has been no research on the optimization of the PMEDM process when machining cylindrically shaped parts with the use of graphite electrodes. Moreover, solving PMEDM with the multi-objective function is a crucial requirement in practice, but there have been few studies dealing with this issue type until now. In this work, an optimization process will be conducted to find the set of optimal main process parameters which can minimize SR and EWR, and maximize MRR. The input parameters are the powder concentration, the pulse-on time, the pulse-off time, the pulse current, and the servo voltage. The PMEDM cylindrical-shaped workpiece and the gray relation analysis (GRA) method combined with the Taguchi method for simultaneously solving multi-objective functions with the support of Minitab R19 software are used to design the experiment and analyze the results. The materials of mixed powder to the dielectric are SiC. The optimal set of main process parameters will be confirmed by experiments.

Figure 1. Tablet-shaped punches made by the EDM process [15].

2. Experimental Setup and Optimization Methodology

2.1. Experimental Setup

The specimens in this study are prepared in a cylindrical shape and made of 90CrSi tool steel. The graphite electrodes, SiC powder with 100 nm size, and Diel MS7000 dielectric solution are adopted. The PMEDM process is conducted by a Sodick A30 EDM machine. The setup of the experiment is presented in Figure 2. The chosen input parameters and their investigated levels are listed in Table 1. Except for servo voltage with two levels, other parameters are investigated by three levels.

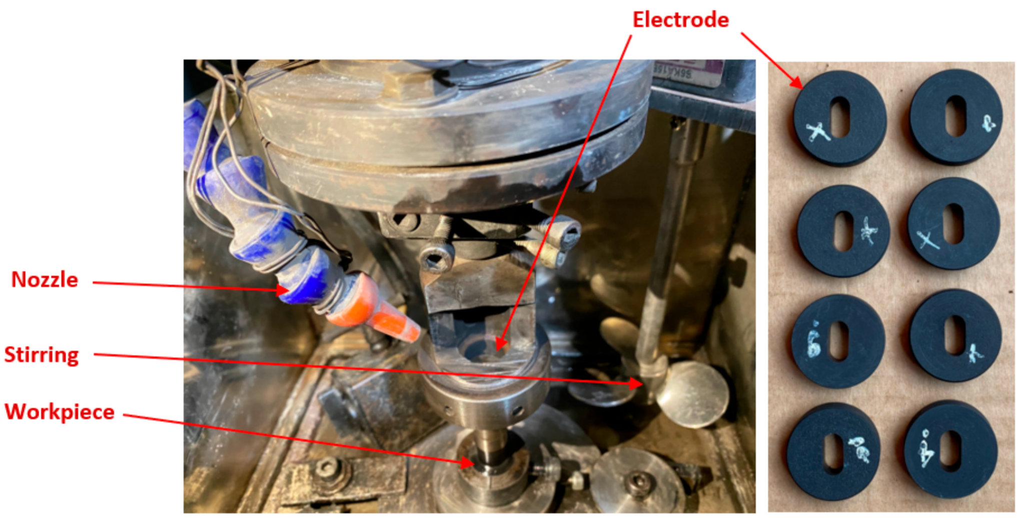

Figure 2. Experimental setup of PMEDM machining.

Table 1. Input factors and their levels.

No.	Input Parameters	Code	Unit	Level		
				1	2	3
1	Powder concentration	Cp	g/L	0	0.5	1
2	Pulse-on time	T_{on}	μs	8	12	16
3	Pulse-off time	T_{off}	μs	8	12	16
4	Servo current	IP	A	5	10	15
5	Servo voltage	SV	V	4	5	-

The Taguchi method and Minitab R19 software are utilized to design the experiment plans and analyze the results in which the design of L18 (2ˆ1 + 3ˆ4) is selected. For this reason, it has a total of 18 tests. The experimental results for each run are measured three times and presented in Table 2.

Table 2. Input parameters and experimental results.

No.	Input Factors					Ra (μm)			MRS (g/h)			EWR (g/h)		
	Cp	Sp	Ton	Toff	SV	Trail 1	Trail 2	Trail 3	Trail 1	Trail 2	Trail 3	Trail 1	Trail 2	Trail 3
1	0.0	8	8	5	4	2.009	2.135	1.979	0.751	0.715	0.726	0.0541	0.0553	0.0533
2	0.0	12	12	10	4	2.947	3.005	2.832	1.238	1.531	1.263	0.0577	0.0527	0.0559
3	0.0	16	16	15	4	7.635	7.776	7.701	3.916	3.973	3.779	0.0465	0.0440	0.0474
4	0.5	8	8	10	4	1.998	2.100	2.109	0.779	0.813	0.806	0.0888	0.0895	0.0991
5	0.5	12	12	15	4	4.863	4.887	5.011	7.064	7.171	6.974	0.0146	0.0149	0.0141
6	0.5	16	16	5	4	6.954	6.837	6.998	0.826	0.802	0.812	0.3197	0.3257	0.3153
7	1.0	8	12	5	4	1.889	2.022	1.985	1.403	1.400	1.390	0.0312	0.0295	0.0292
8	1.0	12	16	10	4	2.798	2.649	2.867	3.932	3.813	3.716	0.1434	0.1451	0.1440
9	1.0	16	8	15	4	4.554	4.537	4.598	4.385	4.188	4.661	0.0387	0.0398	0.0390
10	0.0	8	16	15	5	3.602	3.519	3.582	7.043	6.976	6.890	0.0059	0.0063	0.0061
11	0.0	12	8	5	5	4.789	4.952	4.782	1.987	1.879	1.965	0.2015	0.1946	0.1895
12	0.0	16	12	10	5	3.689	3.758	3.721	1.428	1.411	1.445	0.0713	0.0632	0.0675
13	0.5	8	12	15	5	2.951	2.856	2.801	6.990	7.053	7.258	0.0050	0.0045	0.0052
14	0.5	12	16	5	5	4.001	4.177	4.199	2.087	2.563	2.335	0.1995	0.1965	0.1969
15	0.5	16	8	10	5	2.864	2.898	2.965	1.158	1.360	1.226	0.1935	0.1909	0.1922
16	1.0	8	16	10	5	1.687	1.635	1.701	1.976	2.230	2.058	0.0389	0.0418	0.0409
17	1.0	12	8	15	5	3.467	3.597	3.632	7.212	7.016	7.086	0.0298	0.0278	0.0290
18	1.0	16	12	5	5	3.002	2.960	2.895	2.420	2.655	2.618	0.1157	0.1179	0.1161

2.2. Optimization Methodology

The Taguchi method is a useful tool of experimental design and analysis. The experimental design introduced by Taguchi involved orthogonal arrays to organize the parameters that affect the process and the levels that need to be changed. The Taguchi method does not test for all possible combinations, but only a few. This testing will generate a key set of data that can determine which factors have the most impact on product quality with minimal testing to save time and money. However, the original Taguchi method has been designed to optimize a single performance characteristic. The treatment of many performance characteristics by the Taguchi method needs further investigation. In this study, MRR is a "higher-the-better" performance characteristic. Nevertheless, SR and EWR are "lower-the-better" performance characteristics. Consequently, an improvement of one performance characteristic may lead to a deterioration of another. Therefore, optimizing multiple performance characteristics is much more complex than optimizing a single performance characteristic. In this research, GRA is purposely applied to investigate the multiple performance characteristics in the PMEDM process.

GRA has been widely applied to evaluate the degree of relationship between sequences based on the gray relational grade. This method has also been applied to optimize the control parameters with multi-responses through the gray relational grade. Gray relational analysis is widely used to combine all the considered performance characteristics into a single value that can be used as the single characteristic in optimization problems. This advantage is impossible to obtain in other methods. The process of combination between Taguchi method and GRA will be detailed in the next part.

3. Multi-Objective Optimization

The responses in this study are minimizing SR and EWR, and maximizing MRR. As previously mentioned, with the single utilization of the Taguchi method it is impossible to get the multi-objective optimization with three requirements, hence, the GRA method and Taguchi method will be applied to simultaneously optimize the three above-stated targets. According to this combination, firstly the S/N ratio of SR, EWR, and MRR should be determined:

$$\text{For the maximum MRR}: S/N = -10\log_{10}(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}) \tag{1}$$

$$\text{For the minimum SR and EWR}: \ S/N = -10\log_{10}(\frac{1}{n}\sum_{i=1}^{n}y_i^2) \tag{2}$$

The average values of S/N ratios of three responses are exhibited in Table 3.

Table 3. Average values and S/N of SR, EWR, and MRR.

No.	Input Factors					Ra (μm)		EWR (g/h)		MRR (g/h)	
	Cp	Ton	Toff	Ip	SV	Mean	S/N	Mean	S/N	Mean	S/N
1	0.0	8	8	5	4	2.0410	−6.2016	0.05425	25.3114	0.73061	−2.7320
2	0.0	12	12	10	4	2.9280	−9.3340	0.05546	25.1148	1.34409	2.4522
3	0.0	16	16	15	4	7.7040	−17.7346	0.04594	26.7522	3.88944	11.7920
4	0.5	8	8	10	4	2.0690	−6.3178	0.09246	20.6692	0.79922	−1.9511
5	0.5	12	12	15	4	4.9203	−13.8406	0.01452	36.7577	7.06941	16.9860
6	0.5	16	16	5	4	6.9297	−16.8147	0.32022	9.8902	0.81356	−1.7941
7	1.0	8	12	5	4	1.9653	−5.8723	0.02996	30.4660	1.39784	2.9090
8	1.0	12	16	10	4	2.7713	−8.8585	0.14417	16.8225	3.82036	11.6351
9	1.0	16	8	15	4	4.5630	−13.1851	0.03918	28.1370	4.41144	12.8666
10	0.0	8	16	15	5	3.5677	−11.0481	0.00609	44.3001	6.96939	16.8628
11	0.0	12	8	5	5	4.8410	−13.6998	0.19523	14.1865	1.94347	5.7639
12	0.0	16	12	10	5	3.7227	−11.4173	0.06734	23.4239	1.42822	3.0947
13	0.5	8	12	15	5	2.8693	−9.1576	0.00493	46.1269	7.10034	17.0222
14	0.5	12	16	5	5	4.1257	−12.3119	0.19765	14.0820	2.32829	7.2484
15	0.5	16	8	10	5	2.9090	−9.2758	0.19222	14.3239	1.24793	1.8666
16	1.0	8	16	10	5	1.6743	−4.4781	0.04050	27.8478	2.08814	6.3624
17	1.0	12	8	15	5	3.5653	−11.0437	0.02885	30.7931	7.10457	17.0291
18	1.0	16	12	5	5	2.9523	−9.4043	0.11656	18.6689	2.56452	8.1581

In order to analyze gray relation based on the S/N ratio, the value of this ratio should be converted into a series compared to unitless quantities. Hence, the data have to be normalized. The determined values of S/N ratios are normalized by using Z_i where $0 \leq Z_i \leq 1$ and:

$$Z_i = \frac{S/N_i - \min(S/N_i, i = 1,2,\ldots,n)}{\max(S/N_i, i = 1,2,\ldots,n) - \min(S/N_i, i = 1,2,\ldots,n)} \quad (3)$$

where n is the number of experimental runs (n = 18). The calculated values of normalized Z_i are shown in Table 4.

Table 4. The calculated values of normalized Z_i.

TT	S/N			*Zi*		
				Ra	**EWR**	**MRS**
	Ra	**EWR**	**MRS**	**Reference Values**		
				1.000	**1.000**	**1.000**
1	−6.2016	25.3114	−2.7320	0.8700	0.5744	1.0000
2	−9.3340	25.1148	2.4522	0.6337	0.5799	0.7377
3	−17.7346	26.7522	11.7920	0.0000	0.5347	0.2650
4	−6.3178	20.6692	−1.9511	0.8612	0.7025	0.9605
5	−13.8406	36.7577	16.9860	0.2937	0.2586	0.0022
6	−16.8147	9.8902	−1.7941	0.0694	1.0000	0.9525
7	−5.8723	30.4660	2.9090	0.8948	0.4322	0.7145
8	−8.8585	16.8225	11.6351	0.6696	0.8087	0.2730
9	−13.1851	28.1370	12.8666	0.3432	0.4965	0.2106
10	−11.0481	44.3001	16.8628	0.5044	0.0504	0.0084
11	−13.6998	14.1865	5.7639	0.3044	0.8814	0.5701
12	−11.4173	23.4239	3.0947	0.4765	0.6265	0.7051
13	−9.1576	46.1269	17.0222	0.6470	0.0000	0.0003
14	−12.3119	14.0820	7.2484	0.4091	0.8843	0.4949
15	−9.2758	14.3239	1.8666	0.6381	0.8776	0.7673
16	−4.4781	27.8478	6.3624	1.0000	0.5044	0.5398
17	−11.0437	30.7931	17.0291	0.5047	0.4232	0.0000
18	−9.4043	18.6689	8.1581	0.6284	0.7577	0.4489

The gray relation coefficient $y_j(k)$ is identified by the following equation:

$$y_i(k) = \frac{\Delta_{\min}(k) + \zeta.\Delta_{\max}(k)}{\Delta_i(k) + \zeta.\Delta_{\max}(k)} \; i = 1,\, 2, \ldots,\, n \quad (4)$$

where n is the number of tests (n = 18); k is the number of output responses (k = 3); $\Delta_i(k)$ is the absolute value of reference value determined by: $\Delta_i(k)$ = $||Z_0(k) - Z_i(k)||$; it is the absolute value of the difference between $Z_0(k)$ (reference value $Z0(k) = 1$) and $Z_i(k)$) (Z-value of the i^{th} experiment of the k^{th} target). $\Delta_{min}(k)$ is the minimum value of $i(k)$; max(k) is the maximum value of $i(k)$; ζ is the discriminant coefficient, determined in the range $0 \leq \zeta \leq 1$, in experimental research ζ = 0.5.

The degree of gray relation can be calculated through the average gray relation value of the output objectives:

$$\overline{y_i} = \frac{1}{k}\sum_{j=0}^{k} y_{ij}(k) \quad (5)$$

where y_{ij} is the gray relation value of the j^{th} output aims in the i^{th} experiment. The determined results of gray relation value y_i and the average gray relation value $\overline{y_i}$ of the experiments are shown in Table 5.

Table 5. Values of Δ_i *(k)* and GRA of responses $\overline{y_i}$.

TT	Δi (k)			Grey Relation Values y			$\overline{y_i}$
	Ra	EWR	MRS	Ra	EWR	MRS	
1	0.1300	0.4256	0.0000	0.794	0.540	1.000	0.778
2	0.3663	0.4201	0.2623	0.577	0.543	0.656	0.592
3	1.0000	0.4653	0.7350	0.333	0.518	0.405	0.419
4	0.1388	0.2975	0.0395	0.783	0.627	0.927	0.779
5	0.7063	0.7414	0.9978	0.415	0.403	0.334	0.384
6	0.9306	0.0000	0.0475	0.350	1.000	0.913	0.754
7	0.1052	0.5678	0.2855	0.826	0.468	0.637	0.644
8	0.3304	0.1913	0.7270	0.602	0.723	0.407	0.578
9	0.6568	0.5035	0.7894	0.432	0.498	0.388	0.439
10	0.4956	0.9496	0.9916	0.502	0.345	0.335	0.394
11	0.6956	0.1186	0.4299	0.418	0.808	0.538	0.588
12	0.5235	0.3735	0.2949	0.489	0.572	0.629	0.563
13	0.3530	1.0000	0.9997	0.586	0.333	0.333	0.418
14	0.5909	0.1157	0.5051	0.458	0.812	0.497	0.589
15	0.3619	0.1224	0.2327	0.580	0.803	0.682	0.689
16	0.0000	0.4956	0.4602	1.000	0.502	0.521	0.674
17	0.4953	0.5768	1.0000	0.502	0.464	0.333	0.433
18	0.3716	0.2423	0.5511	0.574	0.674	0.476	0.574

4. Result and Discussions

In order to ensure consistency among the output parameters, the average gray relation values should be higher-the-better. Therefore, the multi-objective function can be considered as a single objective function with the output being the average gray relation values. Taguchi method is applied to estimate the effects of the PMEDM process parameters on the average gray relation values. For that reason, the S/N ratio of $\overline{y_i}$ can be calculated by Equations (1) and (2), and this series is analyzed by the ANOVA shown in Table 6.

Table 6. Effects of process parameters on average gray relation values.

Analysis of Variance for Means							
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**	**C (%)**
SV	1	0.010914	0.010914	0.010914	7.41	0.026	3.64
Cp	2	0.008339	0.008339	0.004170	2.83	0.118	2.78
Ton	2	0.022758	0.022758	0.011379	7.73	0.014	7.59
Toff	2	0.023649	0.023649	0.011825	8.03	0.012	7.88
IP	2	0.222483	0.222483	0.111241	75.53	0.000	74.18
Residual Error	8	0.011783	0.011783	0.001473			3.93
Total	17	0.299927					

Model Summary		
S	**R-Sq**	**R-Sq(adj)**
0.0384	96.07%	91.65%

There is the fact that the influencing degree of each parameter is represented by its *p*-value shown in Table 6. This means that one parameter has static significance when its *p*-value is minor to a confidence level of 0.05. Based on the results presented in Table 6, it is seen that P-values of IP, T_{off}, T_{on}, SV, and C_p are 0.000, 0.012, 0.014, 0.02, and 0.118, respectively. Except for the case of C_p having a *p*-value higher than 0.05, the remainder have static significance. The influencing order of process parameters on the average gray relation values $\overline{y_i}$ is peak current (IP) of 74.18% (with the strongest influence), pulse-off time (T_{off}) of 7.88%, pulse-on time (T_{on}) of 7.59%, servo voltage (SV) of 3.64%, and finally powder concentration (C_P) of 2.78%, which can be considered as non-static significance. This influencing order can be shown in tabular form as in Table 7.

Table 7. Influencing order of input parameters on the average gray relation values.

Response Table for Means					
Level	**SV**	**Cp**	**Ton**	**Toff**	**IP**
1	0.5963	0.5557	0.6144	0.6177	0.6546
2	0.5470	0.6021	0.5274	0.5291	0.6458
3		0.5571	0.5731	0.5681	0.4145
Delta	0.0492	0.0463	0.0871	0.0886	0.2401
Rank	4	5	3	2	1
average gray relation values: 0.572					

It is realized that from Table 7 the influence order of input parameters on the average gray relation values are IP, T_{off}, T_{on}, SV, and Cp. Moreover, this influence can be graphically described by using the main effects plot for means as exhibited in Figure 3.

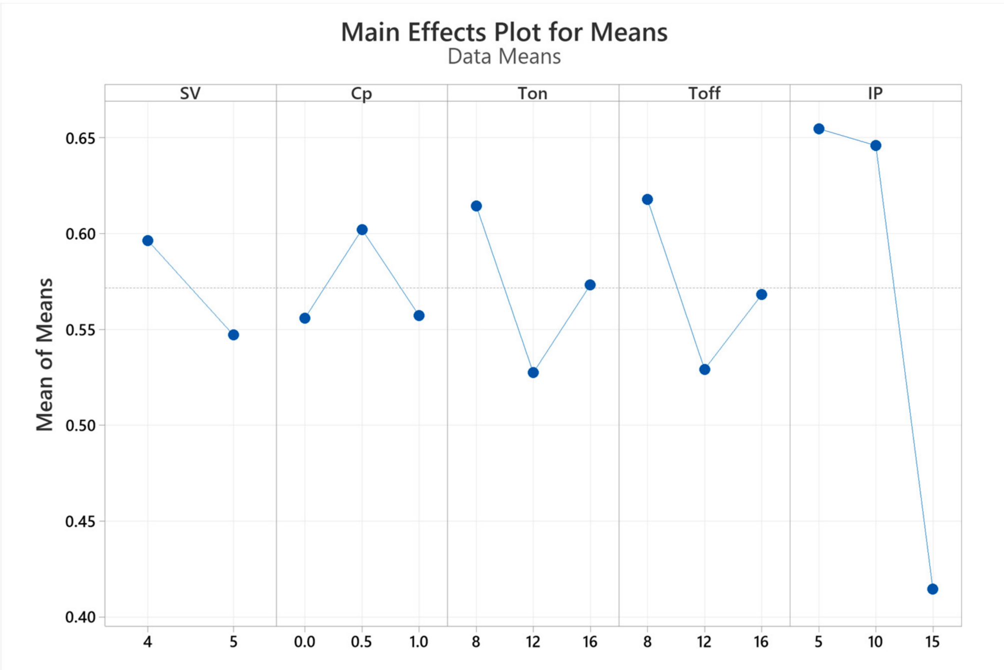

Figure 3. The effects of input parameters on the average gray relation values.

In order to achieve a clearer understanding of the evolution of input parameters and the average gray relation values, the next part discusses the results presented in Figure 3. It is noticed that when SV is increased from 4 V to 5 V, the values of $\overline{y_i}$ are reduced. For the powder concentration parameter, compared to unmixed powder (traditional EDM) the powder concentration of 0.5 g/L leads to an increase in $\overline{y_i}$. Nevertheless, $\overline{y_i}$ is reduced when the powder concentration reaches 1 g/L. Regarding the two parameters of T_{on} and T_{off}, both have a similar varying tendency, e.g., when they are increased from 8 µs to 12 µs,

$\overline{y_i}$ lessens. However, $\overline{y_i}$ increases when T_{on} and T_{off} come to 16 µs. Finally, for Pear current parameter, $\overline{y_i}$ slightly decreases when IP is varied from 5 A to 10 A, and $\overline{y_i}$ significantly declines when IP reaches 15 A. This is the factor with the strongest impact on $\overline{y_i}$.

It is noted that to determine the optimal set of process parameters, the effects of noise through the values of the S/N ratio should be considered. As the objective function of this study, in order to achieve the largest average gray relation value, the largest S/N value for each input parameter means that at that survey level it is less affected. The influence of the input parameters on the S/N ratio is described in Table 8.

Table 8. Effect of parameters on the S/N ratio of the mean gray relation values.

Analysis of Variance for SN Ratios							
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**	**C (%)**
SV	1	1.763	1.763	1.7627	6.37	0.036	2.40
Cp	2	1.219	1.219	0.6096	2.20	0.173	1.66
Ton	2	3.919	3.919	1.9596	7.08	0.017	5.34
Toff	2	4.687	4.687	2.3436	8.46	0.011	6.39
IP	2	59.589	59.589	29.7946	107.61	0.000	81.19
Residual Error	8	2.215	2.215	0.2769			3.02
Total	17	73.392					
Model Summary							
S			**R-Sq**			**R-Sq(adj)**	
0.5262			96.98%			93.59%	

As in the earlier analysis, the parameters have a statistical significance when their P-values are bigger than the confidence level of 0.05. Similarly, the influence order of parameters is identically observed as those presented in Table 6 where except for Cp, the others have statistical significance on the response. According to the analysis results in Table 8, IP parameters also have the greatest influence on the S/N ratio with 81.19%, followed by the influence of the following parameters: T_{off} (6.39%), T_{on} (5.34%), SV (2.4%), and C_p (1.66%), respectively. The influence order of the input parameters and the S/N ratio at the survey levels are shown in Table 9. Table 9 also shows that the influence order of input parameters is IP, T_{off}, T_{on}, SV, and Cp, respectively. At the same time, the S/N ratio of the input parameters through the survey levels is also clearly shown in Figure 4. From this chart in Figure 4, it is possible to determine the S/N value of each survey level of the input parameters and determine the maximum S/N value.

Table 9. Order of influence of input parameters S/N ratio of mean gray relation value.

Response Table for Signal to Noise Ratios					
Larger is better					
Level	**SV**	**Cp**	**Ton**	**Toff**	**IP**
1	−4.775	−5.330	−4.546	−4.435	−3.746
2	−5.400	−4.726	−5.685	−5.681	−3.856
3		−5.207	−5.033	−5.147	−7.660
Delta	0.626	0.603	1.139	1.246	3.913
Rank	4	5	3	2	1

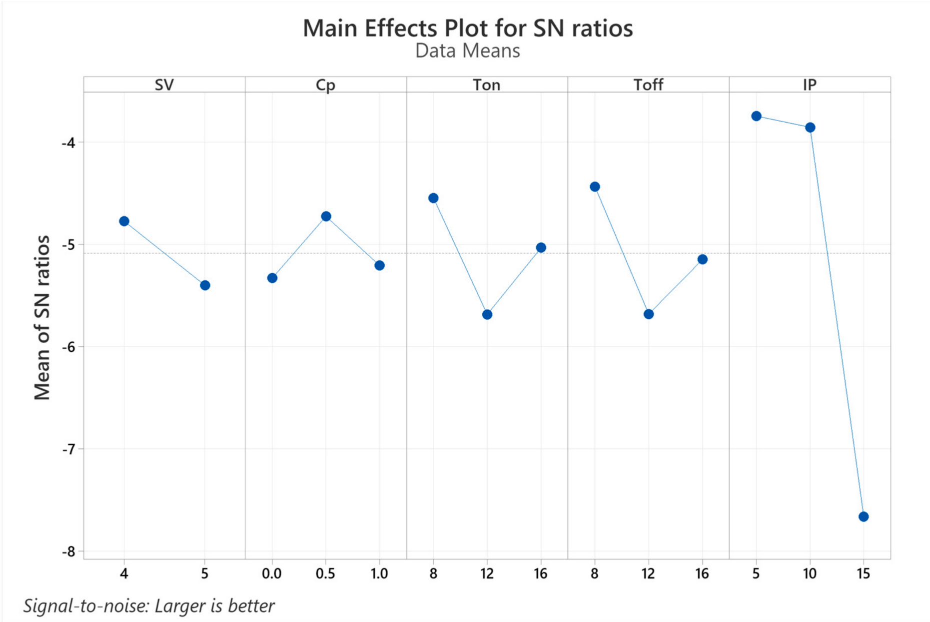

Figure 4. Effect of parameters on the S/N value of $\overline{y}$.

As analyzed above, the parameter set with the highest S/N value $\overline{y}$ for each input parameter is the most reasonable set of parameters. From the chart in Figure 4, the trend of influence of each input parameter on the S/N value is shown and the multi-objective optimal parameter set is determined, specifically in Table 10.

Table 10. The optimal set of the process parameters for PMEDM machining.

TT	Input Factors	Code	Unit	Level	Optimal Value
1	Powder concentration	C_p	g/l	2	0.5
2	Pulse-on time	T_{on}	µs	1	8
3	Pulse-off time	T_{off}	µs	1	8
4	Peak current	IP	A	1	5
5	Servo voltage	SV	V	1	4

4.1. Validating the Optimal Set of Main Process Parameters

In order to confirm the optimal values of input parameters, experiments were conducted. The experimental values of SR, MRS, and EWR are presented in Table 11. It is observed that the error percents showing variation between predictions and experiments are small. For example, for SR the predicted and experimental values are 2.456 µm and 2.324 µm, respectively. This difference corresponds to the error percent of 5.38. The highest error percent belongs to EWR by 6.62%. For these results, it can be concluded that the suggested model is significantly confirmed and reliable.

Table 11. Comparison of the optimal response values given predictions and experiments.

Input Factors					Predict Value			Experiment Value			Error (%)		
SV	**Cp**	**Ton**	**Toff**	**IP**	**Ra**	**MRS**	**EWR**	**Ra**	**MRS**	**EWR**	**Ra**	**MRS**	**EWR**
4	0.5	8	8	5	2.456	1.63	0.099	2.324	1.702	0.092	5.38	4.42	6.62

4.2. Evaluating the Reliability of the Proposed Experimental Method

The experimental model is evaluated through error distribution charts as shown in Figure 5. It can be seen that in the normal distribution error distribution chart, the errors of the experimental points corresponding to the blue points on the distribution chart around the normal distribution line (red solid color line) indicate that the error is small. Histogram reveals the frequency of errors shows that the errors appear in the range −0.1 to 0.1, accounting for a large proportion. The remaining two graphs show the random distribution of experimental errors, which means that the built model is largely influenced by the selected input parameters and is not affected by the order of the experiment.

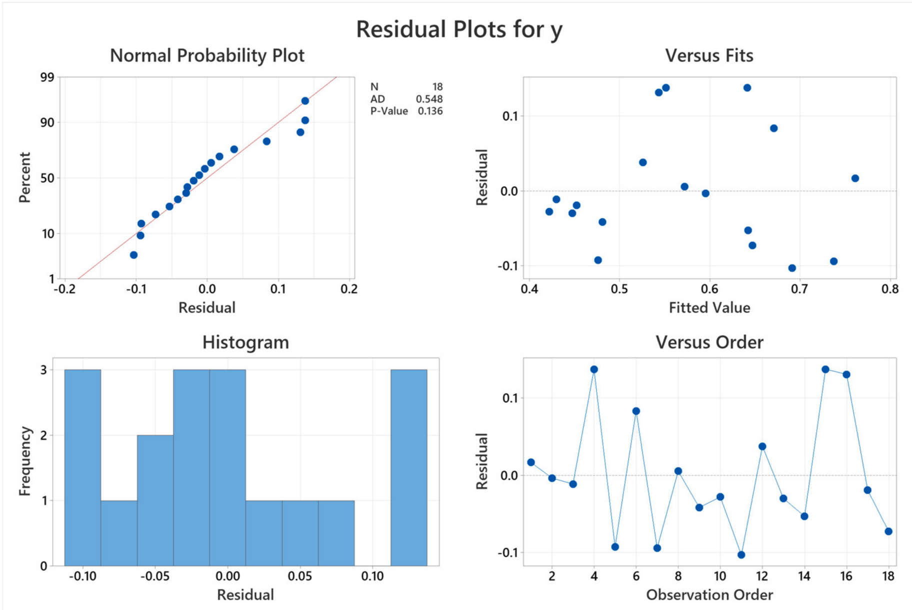

Figure 5. Residual plots for $\overline{y}$.

4.3. Evaluation of Mode Fit

The appropriateness of the experimental model verified by the Anderson–Darling method in Figure 6 shows that the data corresponding to the experimental points (blue dots) are in the region bounded by two upper and lower bounds with the standard deviation of 95%. The P-value of 0.150 is greater than the value of $\alpha = 0.05$. This indicates that the applied experimental model is suitable.

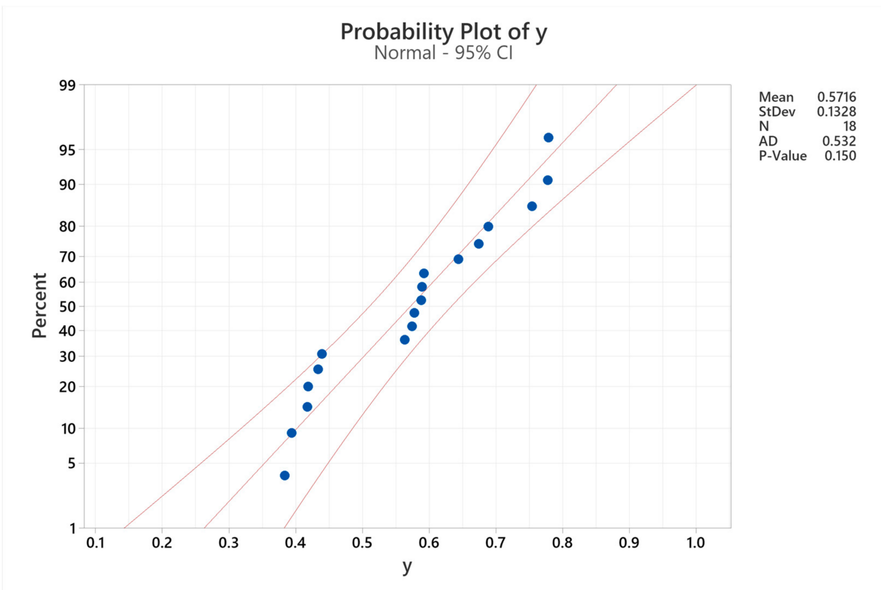

Figure 6. Probability graph of the fit of the experimental model for $\overline{y}$.

5. Conclusions

The optimal set of process parameters that can minimize surface roughness, electrode wear rate, and maximize material removal rate is found in this study. Powder-mixed electrical discharge machining (PMEDM) with SiC powder-mixed-dielectric of hardened 90CrSi steel is conducted. The used input parameters of the optimization process are the powder concentration, the pulse-on time, the pulse-off time, the pulse current, and the servo voltage. A combination of the Taguchi method and the grey relation analysis (GRA) method with the support of Minitab R19 software was used to design the experiment and analyze the results. The following conclusions can be made:

1. The results reveal that peak current has the strongest influence by 74.18% on the responses, pulse-off time (T_{off}) by 7.88%, pulse-on time (T_{on}) by 7.59%, servo voltage (SV) by 3.64%, and finally, powder concentration (C_P) by 2.78% follow.
2. Thanks to the use of GRA, the three initial objective functions such as minimizing SR and EWR and maximizing MRR can be optimized through an average gray relation value of GRA to find an optimal set of input parameters. The optimal parameters of PMEDM are a powder concentration of 0.5 g/L, a pulse-on time of 8 µs, a pulse-off time of 8 µs, a peak current of 5 A, and a servo voltage of 4 V.
3. Experiments were carried out to confirm the optimal values of input parameters. It is revealed that the difference between the predicted values and experimental values of the responses is small. Hence, the proposed model is significantly confirmed and reliable.
4. The appropriateness of the experimental model is verified by the Anderson–Darling method. It shows that the applied experimental model is suitable.

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Nomenclature

PMEDM	Powder-mixed electrical discharge machining
EDM	Electrical discharge machining
SR	Surface roughness
EWR	Electrode wear rate
MMR	Material removal rate
GRA	Gray relation analysis
ANOVA	Analysis of variance
Cp	Powder concentration
T_{on}	Pulse-on time
T_{off}	Pulse off time
IP	Servo current
SV	Servo voltage
$y_j(k)$	Gray relation coefficient
$\overline{y_i}$	Average gray relation value

References

1. Jeswani, M.L. Effect of the addition of graphite powder to kerosene used as the dielectric fluid in electrical discharge machining24. *Wear* **1981**, *7*, 133–139. [CrossRef]

2. Narumiya, H.; Mohri, N.; Saito, N.; Otake, H.; Tsnekawa, Y.; Takawashi, T.; Kobayashi, K. EDM by powder suspended working fluid. In Proceedings of the 9th ISEM, Nagoya, Japan, 10–14 April 1989; pp. 5–8.
3. Mohri, N.; Saito, N.; Higashi, M.; Kinoshita, N. A New Process of Finish Machining on Free Surface by EDM Methods. *CIRP Ann.* **1991**, *40*, 207–210. [CrossRef]
4. Wong, Y.S.; Lim, L.C.; Rahuman, I.; Tee, W.M. Near-mirror-finish phenomenon in EDM using powder-mixed dielectric. *J. Mater. Process. Technol.* **1998**, *79*, 30–40. [CrossRef]
5. Tzeng, Y.F.; Lee, C.Y. Effects of Powder Characteristics on Electrodischarge Machining Efficiency. *Int. J. Adv. Manuf. Technol.* **2001**, *17*, 586–592. [CrossRef]
6. Zhao, W.S.; Meng, Q.G.; Wang, Z.L. The application of research on powder mixed EDM in rough machining. *J. Mater. Process. Technol.* **2002**, *129*, 30–33. [CrossRef]
7. Ho, K.H.; Newman, S.T. State of the art electrical discharge machining (EDM). *Int. J. Mach. Tools Manuf.* **2003**, *43*, 1287–1300. [CrossRef]
8. Kumar, A.; Maheshwari, S.; Sharma, C.; Beri, N. Research Developments in Additives Mixed Electrical Discharge Machining (AEDM): A State of Art Review. *Mater. Manuf. Process.* **2010**, *25*, 1166–1180. [CrossRef]
9. Mondal, S.; Paul, C.P.; Kukreja, L.M.; Bandyopadhyay, A.; Pal, P.K. Application of Taguchi-based gray relational analysis for evaluating the optimal laser cladding parameters for AISI1040 steel plane surface. *Int. J. Adv. Manuf. Technol.* **2012**, *66*, 91–96. [CrossRef]
10. Prayogo, G.S.; Lusi, N. Application of Taguchi technique coupled with grey relational analysis for multiple performance characteristics optimization of EDM parameters on ST 42 steel. In *AIP Conference Proceedings*; AIP Publishing LLC: Melville, NY, USA, 2016; p. 020061.
11. Raut, V.; Gandhi, M.; Nagare, N.; Deshmukh, A. Application of Taguchi Grey Relational Analysis to optimize the process parameters in wire electrical discharge machine. *Int. J. Innov. Sci. Eng. Technol.* **2016**, *3*, 108–115.
12. Muthuramalingam, T.; Saravanakumar, D.; Babu, L.G.; Huu Phan, N.; Pi, V.N. Experimental Investigation of White Layer Thickness on EDM Processed Silicon Steel Using ANFIS Approach. *Silicon* **2019**, 1–7. [CrossRef]
13. Markopoulos, A.P.; Papazoglou, E.-L.; Karmiris-Obratański, P. Experimental Study on the Influence of Machining Conditions on the Quality of Electrical Discharge Machined Surfaces of aluminum alloy Al5052. *Machines* **2020**, *8*, 12. [CrossRef]
14. Le, V.T.; Banh, T.L.; Tran, X.T.; Nguyen, T.H.M.; Le, V.T. Studying the microhardness on the surface of SKD61 in PMEDM using tungsten carbide powder. *Int. J. Mod. Phys. B* **2020**, *34*, 2040164. [CrossRef]
15. Tran, T.-H.; Nguyen, M.-C.; Luu, A.-T.; Do, T.-V.; Le, T.-Q.; Vu, T.-T.; Tran, N.-G.; Do, T.-T.; Vu, N.-P. Electrical Discharge Machining with SiC Powder-Mixed Dielectric: An Effective Application in the Machining Process of Hardened 90CrSi Steel. *Machines* **2020**, *8*, 36. [CrossRef]
16. Le Xuan, H.; Tran Thanh, H.; Vu Ngoc, P. A Study on Modelling Surface Finish in Electrical Discharge Machining Tablet Shape Punches Using Response Surface Methodology. *J. Environ. Sci. Eng. B* **2017**, *6*. [CrossRef]
17. Long, B.T.; Phan, N.H.; Cuong, N.; Jatti, V.S. Optimization of PMEDM process parameter for maximizing material removal rate by Taguchi's method. *Int. J. Adv. Manuf. Technol.* **2016**, *87*, 1929–1939. [CrossRef]
18. Ojha, K.; Garg, R.K.; Singh, K.K. Parametric Optimization of PMEDM Process using Chromium Powder Mixed Dielectric and Triangular Shape Electrodes. *J. Miner. Mater. Charact. Eng.* **2011**, *10*, 1087. [CrossRef]
19. Kansal, H.K.; Singh, S.; Kumar, P. Technology and research developments in powder mixed electric discharge machining (PMEDM). *J. Mater. Process. Technol.* **2007**, *184*, 32–41. [CrossRef]
20. Kansal, H.K.; Singh, S.; Kumar, P. Performance parameters optimization (multi-characteristics) of powder mixed electric discharge machining (PMEDM) through Taguchi's method and utility concept. *IJEMS* **2006**, *13*, 209–216.
21. Kansal, H.K.; Singh, S.; Kumar, P. Parametric optimization of powder mixed electrical discharge machining by response surface methodology. *J. Mater. Process. Technol.* **2005**, *169*, 427–436. [CrossRef]
22. Uno, Y.; Okada, A. Surface Generation Mechanism in Electrical Discharge Machining with Silicon Powder Mixed Fluid. *Int. J. Electr. Mach.* **1997**, *2*, 13–18.
23. Singh, P.; Kumar, A.; Beri, N.; Kumar, V. Influence of electrical parameters in powder mixed electric discharge machining (PMEDM) of hastelloy. *J. Eng. Res. Stud.* **2010**, *1*, 93–105.
24. Al-Khazraji, A.; Amin, S.A.; Ali, S.M. The effect of SiC powder mixing electrical discharge machining on white layer thickness, heat flux and fatigue life of AISI D2 die steel. *Eng. Sci. Technol. Int. J.* **2016**, *19*, 1400–1415. [CrossRef]
25. Razak, M.A.; Abdul-Rani, A.M.; Nanimina, A.M. Improving EDM Efficiency with Silicon Carbide Powder-Mixed Dielectric Fluid. *Int. J. Mater. Mech. Manuf.* **2015**, *3*, 40–43. [CrossRef]
26. Ky, L.H.; Danh, B.T.; Cuong, N.V.; Hong, T.T.; Vinh, N.T.; Nguyen, T.Q.D.; Le, T.P.T.; Cuong, N.M. Effect of input parameters on electrode wear in PMEDM cylindrical shaped parts. In *Key Engineering Materials*; Trans Tech Publications Ltd.: Bäch, Switzerland, 2020; pp. 136–142.
27. Hong, T.T.; Cuong, N.V.; Danh, B.T.; Ky, L.H.; Linh, N.H.; Lien, V.T.; Vinh, N.T.; Cuong, N.M. Multi-Objective Optimization of PMEDM Process of 90CrSi Alloy Steel for Minimum Electrode Wear Rate and Maximum Material Removal Rate with Silicon Carbide Powder. In *Materials Science Forum*; Trans Tech Publications Ltd.: Bäch, Switzerland, 2021; pp. 51–58.