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RSM model to evaluate material removal rate in EDM of Ti-5Al-2.5Sn using graphite electrode

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Abstract. The usage of electrical discharge machining (EDM) is increasing gradually owing to its capability to cut precisely, geometrically complex material regardless hardness. Many process parameters greatly affect the EDM performance and complicated mechanism of the process result the lag of established theory. Hence, it becomes important to select the proper parameter set for different machining stages in order to promote efficiency. In view of these barriers, it is attempted to establish a model which can accurately predict the material removal rate (MRR) of titanium alloy by correlating the process parameter. Effect of the parameters on MRR is investigated as well. Experiment is conducted utilizing the graphite electrode maintaining negative polarity. Analysis and modelling is carried out based on design of experiment as well as response surface methodology. The agreeable accuracy is obtained and thus the model can become a precise tool setting the EDM process cost effective and efficient. Moreover, high ampere, short pulse-off time and low servo-voltage combined with about 250 µs pulse-on time generate the highest MRR.

1. Introduction

In EDM, the tool (anode) and the work piece (cathode) are immersed in a dielectric medium separated from each other by a small gap of the order of about 5-100 µm [1]. A controlled spark is generated between the two electrodes by applying a voltage (~200V) which breaks down the dielectric medium causing the voltage falls to about 25-30 V (discharge voltage) and the current to rise to a constant value set by the operator [2]. During machining electrons start flowing from cathode to anode which ionizes the dielectric medium and form a plasma channel between the cathode and anode. Some of the electrodes materials are melted and vaporized resulting material removal owing to intense heat generated in the plasma. The growth of the plasma channel, energy sharing between electrodes, process of vaporization, formation of recast layer, plasma-flushing efficiency, and temperature sensitivity of thermal properties of the work material are a few physical phenomena that render the machining process highly complex and stochastic [3]. The mathematical consideration of all these complex phenomena is very difficult. Therefore, mathematical prediction of material removal rate when compared with the experimental results shows wide variation.

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Many process parameters greatly affect the electrical discharge machining performances. Consequently, it becomes important to select properly the process parameter set for different machining stages in order to promote efficiency [4]. Although, the desired process parameters can be determined based on experience or handbook values, it is a great challenge to ensure that the selected parameters are perfect for a particular material and environment.

In EDM process, parameter selection are often far from the optimum and at the same time selecting optimization parameters is costly and time consuming [5]. To improve the production rate and to decrease the dependence on experience, it is necessary to establish an optimization model in EDM process. A number of works has been carried out in modelling division using different types of material such as copper–steel (EN-8), die Steel, CK45 steel, C40 steel, Tungsten Carbide, tool steel 1.2714, AISI D2 tool steel, Ti-6Al-4V, Ti-15-3, etc. [5-16]. However, until now no study is noticed in electrical discharge machining considering titanium alloy Ti-5Al-2.5Sn workpiece and graphite tool.

In these circumstances, this paper aims to develop a mathematical model for material removal rate of titanium alloy Ti-5Al-2.5Sn based on design of experiment (DOE) and response surface methodology. The selection of this material was made taking into account its wide range of applications in airframes, jet engines, steam turbine blades, aircraft engine, compressor blades, missile fuel tanks and structural parts, etc. [17]. Four process parameters namely, peak current, pulse-on time, pulse-off time and servo-voltage are taken into account as input parameters of the model. The experimental work is performed as DOE utilizing graphite electrode as tool with negative polarity. Besides, the influence of the process parameters on material removal rate is investigated as well as attempt is made to estimate the maximum MRR.

2. Experimental procedure

The experiments were carried out utilizing a numerical control programming electrical discharge machine known as ‘‘LN power supply AQ55L”. The EDM has the provisions of movement in three axes such as longitudinal (X-axis), lateral (Y-axis) and vertical direction of electrode (Z-axis) and has also a rotary U-axis with maximum rpm ±40. In this research, titanium alloy Ti-5Al-2.5Sn was taken into consideration as workpiece material and cylindrical graphite tool was applied in order to machine the workpiece. Process parameters namely, peak current, pulse-on time, pulse-off time and servo-voltage were selected in accordance with the literature review as well as preliminary experiment to connect these parameters with output criteria MRR. Pulse-on time refers the duration of time in which the current is allowed to flow whilst pulse-off time is the duration of time between the sparks per cycle [18] and [19]. Each cycle has an on-time and off-time that is expressed in units of microseconds. Since all the work is done during on-time, the duration of these pulses and the number of cycles per second (frequency) are important.

Peak current is the amount of power used in discharge machining, measured in units of amperage, and is the most important machining parameter in EDM [20]. Peak current (I_p) is the maximum current during spark. Servo-voltage is a reference voltage that can be set by operator. If the average gap voltage is higher than the servo reference voltage the feed speed increases. In contrast, the feed speed decreases or the electrode is retracted when the average gap voltage is lower than the servo reference voltage. MRR is an important indicator of the efficiency and cost effectiveness of the electrical discharge machining technique [9]. Material removal rate (mm^3/min) is calculated by measuring the average amount of material removed and the machining time as follows [6]:

$$\mathrm{MRR}\ (\mathrm{mm^3/\,min}) = \frac{\text{reduction in weight of workpiece(g)}}{\text{density of workpiece } (\mathrm{g/mm^3}) \times \text{machining time(min)}} \tag{1}$$

It can also be expressed as

$$MRR = \frac{1000 \times W_w}{\rho_w \times t} \tag{2}$$

$$W_w = W_1 - W_2 \tag{3}$$

where W_w is the weight loss of the workpiece in gm
W_1 is initial weight of work piece
W_2 is final weight of work piece
ρ_w is the density of the workpiece material (density of Ti-5Al-2.5Sn is 4.41 g/cm^3)
t is the machining time in minutes.

A well-designed experimental plan can substantially reduce the number of experiments [7]. This is the why; experimental design via central composite design of response surface methodology (RSM) was developed with an attempt to formulate the mathematical relations using smallest number of experiments possible. The coded levels for all process parameters used are displayed in table 1. The listing of experimental parameters is scheduled in table 2. Each experiment was conducted for fixed period, 40 minutes. A new set of the workpiece and graphite tool were applied for each run and total 62 experimental run, including one replication were carried out according to the design of experiment. The other process parameters were kept constant during experiments. In order to evaluate the amount of material removal the workpiece was weighed before and after machining using a digital single pan balance (maximum capacity=210 gm, precision=0.1 mg).

Table 1. Machining parameters and their levels.

Process parameters	Designation	Level 1	Level 2	Level 3	Level 4	Level 5
		-2	-1	0	1	2
Peak Current, I_p (A)	X_1	1	8	15	22	29
Pulse-on time, T_{on} (μs)	X_2	10	95	180	265	350
Pulse-of time, T_{off} (μs)	X_3	60	120	180	240	300
Servo-voltage, S_v (V)	X_4	75	85	95	105	115

Table 2. Experimental settings.

Working parameters	Description
Work piece material	Ti-5Al-2.5Sn
Size of work piece	22 mm × 22 mm × 20 mm
Electrode material	Graphite
Size of electrode	ϕ 20 mm × 50 mm (length)
Electrode polarity	Negative
Dielectric fluid	Commercial Kerosene
Applied voltage	120 V
Flushing pressure	0.15 MPa
Machining time	40 Minute

3. Modelling using RSM

The design of experiments (DOE) technique is a powerful work tool which allows us to model and analyse the influence of determined process variables over other specified variables, which are usually known as response variables. These response variables are unknown functions of the former design variables, which are also known as design factors. Response surface methodology is an interaction of mathematical and statistical techniques for modelling and optimizing the response variable models involving quantitative independent variables [8]. Through the use of the response surface methodology of DOE and applying regression analysis, the modelling of the desired response to several independent input variables can be gained.

In RSM, the independent process parameters can be represented in quantitative form as:

$$Y = f(X_1, X_2, X_3, \ldots X_n) \pm \varepsilon \tag{4}$$

where Y is the response MRR, f is the response function, ε is the experimental error, and X_1, X_2, X_3, . . ., X_n are independent variables.

The form of f is unknown and may be very complex. Therefore, RSM aims at approximating f by a suitable lower ordered polynomial in some region of the independent process variables. If the response can be well modelled by a linear function of the independent variables, the equation (4) can be written as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots\dots\dots + \beta_n X_n + \varepsilon \tag{5}$$

In the case of present study whilst the number of the independent variables is four, the linear equation is formed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 \mathrm{X}_2 + \beta_3 \mathrm{X}_3 + \beta_4 \mathrm{X}_4 \tag{6}$$

On the other hand, the second-order model is normally used when the response function is nonlinear. However, if the model is not well fitted by the linear function then a higher order polynomial such as the quadratic model can be used. In the present study, both the linear model and second-order (quadratic model) model have been studied. The experimental values are analysed and the mathematical model is then developed that illustrate the relationship between the process variable and the output.

The mathematical model based on a second-order polynomial is given as follows:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_i^2 + \sum_{i,j=1, i \neq j}^{n} \beta_{ij} X_i X_j + \varepsilon \tag{7}$$

where Y is the corresponding response, X_i is the input variables, X_i^2 and X_iX_j are the squares and interaction terms, respectively, of these input variables. β_o, β_i, β_{ij} and β_{ii} are the unknown regression coefficients. In this work, equation (7) can be rewritten according to the four variables used as:

$$\begin{aligned} Y = {} & \beta_0 + \beta_1 X_1 + \beta_2 \mathrm{X}_2 + \beta_3 \mathrm{X}_3 + \beta_4 \mathrm{X}_4 + \beta_{11} \mathrm{X}_1^2 + \beta_{22} \mathrm{X}_2^2 + \beta_{33} \mathrm{X}_3^2 + \beta_{44} \mathrm{X}_4^2 \\ & + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{14} X_1 X_4 + \beta_{23} X_2 X_3 + \beta_{24} X_2 X_4 + \beta_{34} X_3 X_4 \end{aligned} \tag{8}$$

where X_1, X_2, X_3, and X_4 are four input variables as peak current (I_p), pulse-on time (T_{on}), pulse-off time (T_{off}) and servo-voltage (S_v), respectively.

4. Results and discussion

4.1 Mathematical model

In this work, RSM is utilized for determining the relations between the various EDM process parameters with the various machining criteria and exploring their effects on the material removal rate. After knowing the values of the measured response, the values of the different regression coefficients of mathematical equation are estimated. The mathematical model based on the response surface methodology is developed by utilizing test results obtained through the entire set of experiments.

Both linear and non-linear regression models were examined and the acceptance was based on high to very high coefficients of correlation (R) calculated as well as model adequacy. The first-order and second-order mathematical equation are executed using the same experimental data. It is essential to check the adequacy of the fitted models, because an incorrect or under-specified model can lead to confusing evaluation of the response. It can be verified whether the model is under specified by checking the fit of the model. The model adequacy checking includes the test for significance of the regression model, model coefficients, and lack of fit. Analysis of variance (ANOVA) as shown in table 3 and table 4 was performed in support of both linear and non-linear model owing to the aforesaid motives.

It is observed that the standard error, S (0.206950) for quadratic equation is smaller than the value of S (2.04202) for linear equation. Then again, the value of R^2, R^2-adjusted and R^2-predicted in the table 4 are greater than that of table 3. The lower value of S and higher value of R^2 shows the adequacy of the model. Consequently, the regression model with quadratic terms is more adequate and significant over the model with linear terms.

Furthermore, if the p-value of residual error is less than the α-level, it means that the model does not accurately fit the data. The p-value for the lack-of-fit in the case nonlinear model is 0.095, which is larger than 0.05 (i.e. α=0.05, or 95% confidence). Hence, the lack-of-fit term is insignificant as it is desired. The fit summary recommended that the second order model is statistically significant for analysis of MRR.

Table 3. Analysis of variance for single order model of MRR.

Source	Degree of freedom	Sum of squares	Mean squares	F-ratio	P
Regression	14	1025.74	256.434	61.50	0.000
Linear	4	1025.74	256.434	61.50	0.000
Residual error	16	108.42	4.170		
Lack-of-Fit	10	108.30	5.415	285.59	0.000
Pure Error	6	0.11	0.019		
Total	30	1134.15			
Standard deviation (S) = 2.04202					
R^2 = 90.44%					
R^2-adjusted = 88.97%					
R^2-predicted = 85.41%					

Table 4. Analysis of variance for second order model of MRR.

Source	Degree of freedom	Sum of squares	Mean squares	F-ratio	P
Regression	14	1133.47	80.962	1890.38	0.000
Linear	4	1025.74	256.434	5987.49	0.000
Square	4	89.36	22.339	521.59	0.000
Interaction	6	18.38	3.063	71.51	0.000
Residual error	16	0.69	0.043		
Lack-of-Fit	10	0.57	0.057	3.01	0.095
Pure Error	6	0.11	0.019		
Total	30	1134.15			
Standard deviation (S) = 0.206950					
R^2 = 99.94%					
R^2-adjusted = 99.89%					
R^2-predicted = 99.70%					

Finally, the second order model of MRR can be obtained as follows putting the values of the coefficients that obtained through response surface methodology.

$$\begin{aligned} MRR = {} & 4.93853 + 1.28459 I_p + 0.0480985 T_{on} - 0.0591216 T_{off} - 0.127086 S_v \\ & + 0.0321069 I_p^2 - 8.58835\times10^{-5} T_{on}^2 + 6.58753\times10^{-5} T_{off}^2 + 8.94884\times10^{-4} S_v^2 \\ & + 3.80572\times10^{-4} I_p T_{on} - 8.90482\times10^{-4} I_p T_{off} - 0.0131805 I_p S_v + \\ & 3.31059\times10^{-5} T_{on} T_{off} - 2.31268\times10^{-4} T_{on} S_v + 3.28692\times10^{-4} T_{off} S_v \end{aligned} \tag{9}$$

4.2 Confirmation test

The developed model is also validated through confirmation test and the results are presented in table 5. It is apparent that the error between the observed value and predicted value of MRR is in the range of 1.82-9.19% having a mean error as 4.29%. Accordingly, the developed regression model is demonstrated to be a practical and effective way for the evaluation of tool wear rate in EDM process.

Table 5. EDM conditions in verification test.

Peak current (A)	Pulse-on time (µs)	Pulse-off time (µs)	Servo-voltage (V)	MRR (mm^3/min)		Error (%)
				Experimental	Predicted	
15	180	120	85	9.7939	9.9726	-1.82
29	320	120	85	31.0053	31.5841	-1.87
5	95	120	85	1.5230	1.3830	9.19
					Average	4.29

4.3 Effect of process parameters on MRR

An attempt is also made to investigate the effect of the input parameters as peak current, pulse-on time, pulse-off time and servo-voltage on material removal rate. The figure 1–3 shows the influences of the process parameters. It is obvious in the figure 1 that the increase of peak current increases the material removal rate. This is due to the fact that increasing peak current increases the discharge energy which results more material removal. Thus, material removal more increases with peak current and the similar observation was found in the research of Lee and Li [21] and Singh et al. [22]. The material removal rate increases as the pulse-on time increase up to certain value of on time (250 µs) hereafter the MRR decreases with on time. At too long pulse duration, the spark intensity is decreased in the discharge spots because of the expansion of the plasma channel [23]. Accordingly, the long pulse-on time lowers the material removal rate.

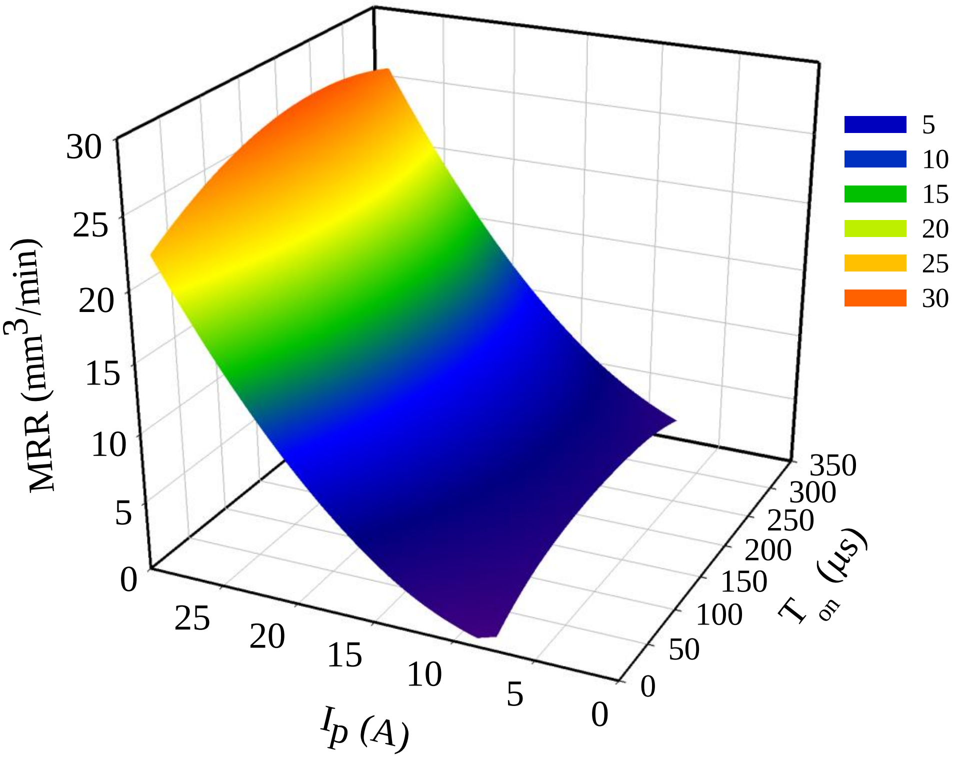

Figure 1. 3-D surface plot of the effect of I_p and T_{on} on MRR.

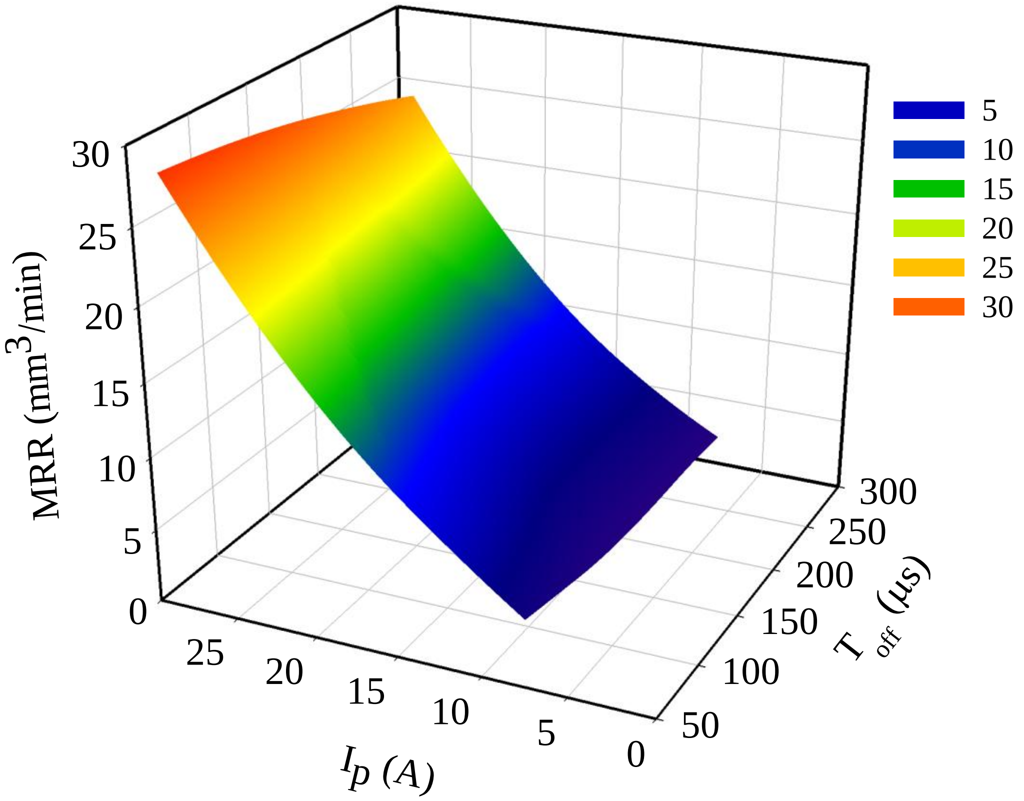

Figure 2. 3-D surface plot of the effect of I_p and T_{off} on MRR.

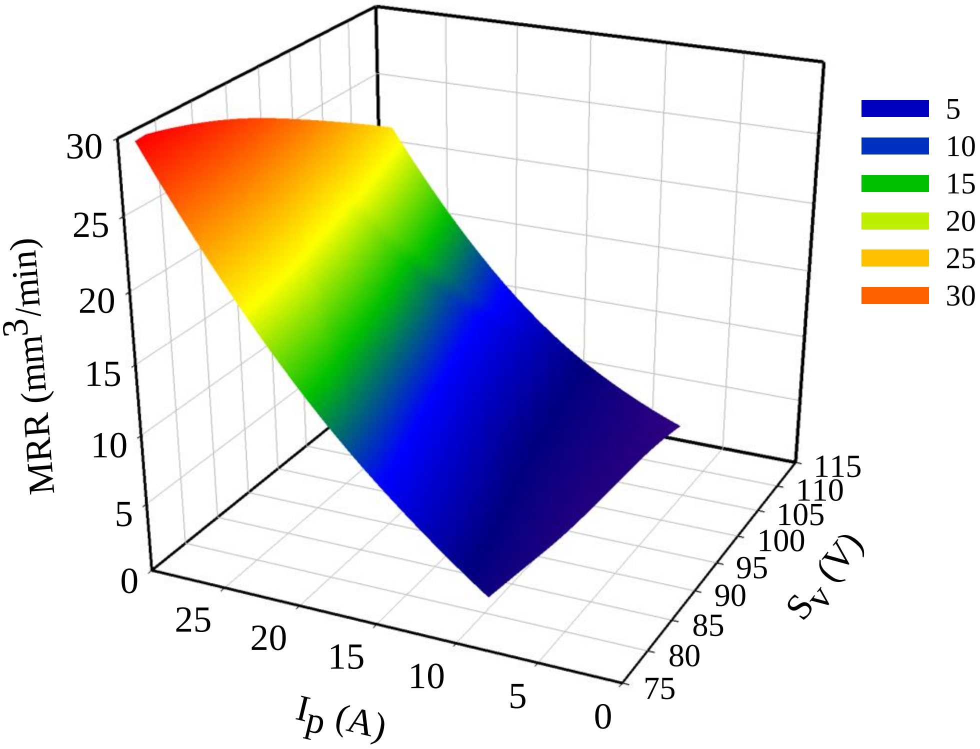

Figure 3. 3-D surface plot of the effect of I_p and S_v on MRR.

It is perceived from figure 2–3 that the increase of pulse-off time as well as servo-voltage reduces the material removal rate. The pulse off time is the time during which no energy is applied to the workpiece surface. Therefore, the short pulse off time create accessibility the application of heat energy on the workpiece surface for long duration and consequently the material is eroded at faster rate [24]. The short pulse-off time combined with lower servo-voltage generates the maximum material removal rate. Electrode's speed towards the workpiece together with gap width depends on servo-voltage. Longer ignition delay is occurred when the average gap voltage is higher than the servo reference voltage. On the contrary, when the average gap voltage is lower than the servo reference voltage results a smaller ignition delay. In another word, the high servo-voltage causes longer ignition delay and lower servo-voltage reduces the ignition delay. Therefore, as servo-voltage increase the ignition delay increases reducing the material removal rate and the controversy is also true. Han and Kunieda [25] and Kunieda et al. [20] also found the similar effect of servo-voltage on material removal.

5. Conclusions

This study is accomplished for the development of MRR model aiming to make the EDM cost effectiveness. The developed model is checked through the ANOVA henceforward confirmation test is performed to test the validity of the model. The result from analysis of variance exhibits that the model having satisfactory fitness. The confirmation test reveals the error from 1.82% to 9.19 with a mean error as 4.29% which is acceptable as less than 10%. Thus, the RSM model can be used tool to predict the MRR successfully making the EDM technique as cost effective and efficient. Moreover, the influences of the parameter is investigated and observed that peak current and pulse-on time have almost the similar effect and the converse response is apparent in the case of pulse-off time and servo-voltage. High ampere combined with short off-time and low servo-voltage yield maximum MRR while the pulse-on time is about 250 μs.

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