Optimization of relative wear ratio during EDM of titanium alloy using advanced techniques

Neeraj Agarwal¹ · Nitin Shrivastava¹ · M. K. Pradhan²

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Abstract

This study presents the relative wear ratio (RWR) optimization of Titanium alloy 685 for electric discharge machining (EDM). Titanium alloys are widely used in modern industry due to its excellent engineering property like high strength to weight ratio, corrosion resistance. There is difficulty in the machining of titanium alloy with conventional machining processes, hence EDM used to machine titanium alloy. The objective is to maximize the material removal rate (MRR) while the tool wear rate (TWR) should be minimized. The machined surface is an exact replica of the tool face. If TWR increases then the quality of the machined surface deteriorate. A new term introduces a RWR which represents the ratio of MRR to the TWR. The high value of RWR is desired to improve the quality of the machined surface. In this paper RWR is optimized. Response surface model used to develop a regression model of RWR. Optimization of RWR is done by advanced optimization techniques, Jaya Algorithm, teaching-learning-based optimization and response optimizer. Parameters optimization of peak current (I_p), pulse on time (T_{on}), duty factor (t) and voltage (V) done in this study to maximize RWR.

Keywords EDM · Electric discharge machining · Modelling · Optimization · Advanced optimization · Relative wear ratio (RWR) · Titanium alloy 685 · Jaya Algorithm

1 Introduction

Nowadays there are requirements of advanced materials like superalloys, Titanium alloy, ceramic, etc with excellent engineering property like hardness, strength, high strength to weight ratio, etc. Due to the hardness of these materials, machining is extremely difficult and even sometimes not possible to machine, with conventional machining processes. These materials can be machined by unconventional machining processes like Electrical Discharge Machining (EDM), Electro-Chemical Machining (ECM), Laser Beam machining (LBM), etc [1, 2]. EDM is most popular because of its machining capabilities and comparatively low cost. EDM is a nonconventional machining process, which is used to machine extremely hard material [3–5]. There are two electrodes, one is a workpiece and the other

is the tool electrode. Two electrodes are completely submerged in a dielectric fluid. A gap is maintained between two electrodes. Voltage is gradually applied between two electrodes. Due to this potential difference, there is a series of sparking takes place between two electrodes (one is a workpiece and the other is known as a tool/electrode). Due to this sparking, some material from the surface of the workpiece is melt and flushed away from the machining area [6] and some material from the tool surface also removed [7]. There are many control parameters of electrical discharge machining (EDM). Peak current (I_p) is the maximum current flow between electrodes, pulse on time (T_{on}) is the time interval during each spark, duty factor (t) is the percentage of the ratio between pulse duration and total cycle time, voltage (V) is applied a potential difference between both electrodes [8].

✉ Neeraj Agarwal, neeraj.bhopal@gmail.com | ¹University Institute of Technology, Rajiv Gandhi Proudhyogiki Vishwavidyalaya, Bhopal, India. ²Maulana Azad National Institute of Technology, Bhopal, India.

Higher material removal rate (MRR) is desirable, but higher MRR also leads to a higher tool wear rate (TWR). High TWR deforms the tool shape, which affects the machining quality of the workpiece. Because the machined surface is an exact replica of the tool surface. This limitation can be overcome by maximizing the relative wear ratio (RWR). RWR is the ratio of MRR to TWR (in other words $RWR = MRR/TWR$). There is a challenge to maximize RWR. Qudeiri Jaber E. Abu et al. reviewed the EDM machinability of Titanium alloy [9]. Relative wear ratio is a very important term for electrical discharge machining (EDM). A higher value of RWR ensures a better quality of EDM machining. To understand the behavior of the process, it is required to develop a model between the process parameters and response measure. Muthuramalingam and Mohan reviewed on the influence of various electrical process parameters in the EDM process [10]. Ghoreishi and Atkinson used RSM to develop a regression model for MRR, TWR, and SR during UAEDM of tool and die steel [11]. Pradhan and Biswas used RSM to development of the model and work on multi-objective optimization of MRR and surface roughness [12]. EDM has many control parameters like peak current, discharge voltage, pulse on-time, pulse-off time, electrode polarity, electrode gap, dielectric [13]. Four important control parameter Peak current (I_p), discharge voltage (V), pulse on time (T_{on}) and duty factor (t) is selected as control parameter; RWR is selected as quality measures. To prepare the empirical model, thirty experiments were conducted using a design of experiment with central composite design (CCD) [14]. Once the model is prepared, the developed model is used for optimization.

Optimization is the process of finding the best result within the given resources. Rajesh and Dev optimize MRR and surface roughness (R_a) on the EDM process [15]. Kao et al. optimized electrode wear ratio (EWR), MRR and R_a [16]. Tarng et al. find the optimum level of control parameters in wire electrical discharge machining [17]. Many researchers applied different optimization techniques like Genetic Algorithm (GA), simulated annealing (SA), particle swarm analysis (PSA) and many more. These optimization techniques have algorithm-specific parameters and complicated in nature. Rao invented an optimization algorithm, known as Jaya algorithm in 2016. Jaya algorithm is an advanced optimization technique and simpler to implement, further, it requires fewer parameters. Jaya Algorithm is successfully used in constrained optimization as well [18–20]. Teaching–learning–based optimization (TLBO) is an advanced optimization technique that is based on the process of teaching and learning of a student [21, 22].

In this paper, RWR has been optimized, through advanced optimization technique Teaching learning based optimization (TLBO) and Jaya Algorithm. RWR optimization of Titanium alloy 685 is discussed in this research

Fig. 1 Workpiece

Table 1 Control parameters and their ranges

Parameter	Level 1	Level 2	Level 3
I_p (Ampere)	4	6	8
T_{on} (μ seconds)	50	100	150
Duty Factor (%)	25	37.5	50
V (Volt)	40	70	100

paper. No work has been reported on EDM machinability of Titanium alloy 685. Many researchers worked on the optimization of MRR and surface roughness but very few research work reported on RWR optimization. The researcher involves maximizing MRR only (this also maximizes TWR with poor machining quality especially for complicated tool shape). This paper maximizes MRR while TWR is minimized simultaneously.

2 Experimental setup

Titanium alloy 685 is selected as a workpiece and a copper rod of 10 mm diameter is selected as an electrode. Thirty experiments were conducted as per the design of experiments (DOE) shown in Table 2. Four important parameter I_p , T_{on} , t , and V are selected as control parameters. Table 1 shows the corresponding range of variables. Each experiment was conducted for thirty minutes. The workpiece is shown in Fig. 1. The material removal rate (MRR) and tool wear rate (TWR) is recorded for each experiment. The MRR is calculated as following

Table 2 Experimental details

Exp.	Ip (Amp)	Ton (μ s)	t (%)	V (V)	RWR
1	4	50	25	40	7.4365
2	4	50	50	40	7.9299
3	4	150	25	40	21.4429
4	4	150	50	40	34.4082
5	4	100	37.5	70	31.2013
6	4	50	25	100	6.8743
7	4	50	50	100	9.5447
8	4	150	25	100	15.7667
9	4	150	50	100	28.2391
10	6	100	37.5	40	9.8320
11	6	50	37.5	70	5.2024
12	6	100	25	70	8.6039
13	6	100	37.5	70	10.0938
14	6	100	37.5	70	9.2377
15	6	100	37.5	70	8.8455
16	6	100	37.5	70	10.4862
17	6	100	37.5	70	9.2038
18	6	100	37.5	70	9.6536
19	6	100	50	70	11.8069
20	6	150	37.5	70	15.2702
21	6	100	37.5	100	9.6188
22	8	50	25	40	3.2859
23	8	50	50	40	4.3258
24	8	150	25	40	8.1091
25	8	150	50	40	13.1414
26	8	100	37.5	70	6.5890
27	8	50	25	100	3.2556
28	8	50	50	100	9.3455
29	8	150	25	100	9.8446
30	8	150	50	100	13.4870

$$MRR = \frac{M_{fw} - M_{iw}}{T_p} \quad (1)$$

where M_{fw} = Final weight of workpiece after machining, M_{iw} = Initial weight of workpiece, T_p = Time period of machining in minutes.

The TWR is calculated as following

$$TWR = \frac{E_{fw} - E_{iw}}{T_p} \quad (2)$$

where E_{fw} = Final weight of tool electrode after machining, E_{iw} = Initial weight of electrode, T_p = Time period of machining in minutes.

Relative wear ratio (RWR) is the ratio of MRR to TWR. RWR is calculated for each experiment and inserted into Table 2 to show the experimental result.

RWR is calculated as following

$$RWR = \frac{MRR}{TWR} \quad (3)$$

3 Modelling and optimization

3.1 Modelling

In response surface methodology, The relation between the quality measures and process control parameters is express as following:

$$y = f(x_1, x_2, x_3, x_4, x_5, \dots, x_n) \quad (4)$$

where $x_1, x_2, x_3, x_4, x_5, \dots, x_n$ are input parameters and y is output response. With plotting the response 'y', a surface is obtained which is known as response surface. Function of 'y' may be very complicated and unknown. The RSM aims is to approximating f by a suitable lower order equation. A second order regression model is represented as following:

$$y = b_0 + \sum_{i=1}^p b_i x_i + \sum_{i=1}^p b_{ii} x_i^2 + \sum_i \sum_j b_{ij} x_i x_j \quad (5)$$

where b_0 is constant and all b' are regression coefficient.

Response surface methodology (RSM) used to develop a regression model. Commercial statistical software Minitab 18 is used to develop a regression model as following.

$$\begin{aligned} RWR = & 39.4 * 21.62 * Ip + 0.669 * V + 0.235 * Ton \\ & - 0.027 * t + 1.699 * Ip * Ip - 0.00516 * V * V \\ & + 0.0186 * Ip * V - 0.0273 * Ip * Ton \\ & - 0.000659 * V * Ton + 0.00238 * Ton * t \end{aligned}$$

3.2 Optimization using Jaya Algorithm

Jaya algorithm is an advanced optimization technique and found suitable for engineering optimization. Figure 2 shows flow diagram of Jaya Algorithm.

Step 1: Initial population is generated randomly with in the range as per Table 1

Step 2: The objective is to maximize RWR as per equation 6. The highest value of RWR, considered as best and lowest RWR considered as worst. Candidate 4 having best value of RWR and corresponding variables of candidate 4 have $Ip_best = 4.9262$, $Ton_best = 142.7235$, $t_best = 47.38632$, $V_best = 71.1816$. Candidate 5 having minimum RWR, hence $Ip_worst = 4.8570$, $Ton_worst = 67.9034$, $t_worst = 39.2846$, $V_worst = 51.5042$.

Fig. 2 Flow diagram of Jaya Algorithm

Now Consider two random numbers $r_1 = 0.7332$, $r_2 = 0.4231$. Calculate the new value of all parameters candidate as per equation (7). All values of newly calculated parameters should be within the range as per Table 1. If new values fall below the lower limit then assign a lower limit to a new variables value. If new values of variable go beyond the upper limit of variables then assign an upper limit to the given variable as per Table 1.

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}(X_{j,best,i} - |X_{j,k,i}|) - r_{2,j,i}(X_{j,worst,i} - |X_{j,k,i}|)$$

$$\begin{aligned} \text{Candidate 1 } l_p &= 7.7104 + 0.7332(4.9262 - |7.7104|) \\ &- 0.4231(4.8570 - |7.7104|) = 6.8764 \end{aligned}$$

$$\begin{aligned} \text{Candidate 2 } l_p &= 4.1532 + 0.7332(4.9262 - |4.1532|) \\ &- 0.4231(4.8570 - |4.1532|) = 4.4222 \\ \text{Candidate 3 } l_p &= 4.0926 + 0.7332(4.9262 - |4.0926|) \\ &- 0.4231(4.8570 - |4.0926|) = 4.3804 \\ \text{Candidate 4 } l_p &= 4.9262 + 0.7332(4.9262 - |4.9262|) \\ &- 0.4231(4.8570 - |4.9262|) = 4.9555 \\ \text{Candidate 5 } l_p &= 4.8570 + 0.7332(4.9262 - |4.8570|) \\ &- 0.4231(4.8570 - |4.8570|) = 4.9077 \\ \text{Candidate 1 } T_{on} &= 112.6811 + 0.7332(142.7235 - |112.6811|) \\ &- 0.4231(67.9034 - |112.6811|) = 153.6536326 \quad (= 150 \text{ because maximum } T_{on} = 150) \\ \text{Candidate 2 } T_{on} &= 85.3170 + 0.7332(142.7235 - |85.3170|) \\ &- 0.4231(67.9034 - |85.3170|) = 134.77514 \end{aligned}$$

Table 3 Initial solution

Can.	Ip	Ton	t (%)	V	RWR
1	7.7104	112.6811	49.9706	45.6465	11.4634
2	4.1532	85.3170	47.0505	97.7998	15.7032
3	4.0926	101.5753	41.7021	62.5484	23.0844
4	4.9262	142.7235	47.8632	71.1816	24.7406
5	4.8570	67.9034	39.2846	51.5042	9.8303

Table 4 New values of all parameter and corresponding objective function RWR (first iteration)

Can.	Ip	Ton	t (%)	V	RWR
1	6.8764	150.0000	50.0000	61.8904	18.0981
2	4.4222	134.7751	50.0000	97.8713	22.5136
3	4.3804	45.9918	47.2422	73.5511	29.4930
4	4.9555	150.0000	50.0000	79.5073	25.4826
5	4.9077	122.7613	45.5744	65.9316	21.0654

Candidate 3 Ton = $101.5753 + 0.7332(142.7235 - |101.5753|) - 0.4231(67.9034 - |101.5753|) = 103.6817411$

Candidate 4 Ton = $142.7235 + 0.7332(142.7235 - |142.7235|) - 0.4231(67.9034 - |142.7235|) = 174.3798843$ (= 150 because maximum Ton = 150)

Candidate 5 Ton = $67.9034 + 0.7332(142.7235 - |67.9034|) - 0.4231(67.9034 - |67.9034|) = 122.7614973$

Candidate 1 t = $49.9706 + 0.7332(47.8632 - |49.9706|) - 0.4231(39.2846 - |49.9706|) = 52.9467$ (= 50 because maximum t = 50)

Candidate 2 t = $47.0505 + 0.7332(47.8632 - |47.0505|) - 0.4231(39.2846 - |47.0505|) = 50.9321$ (= 50 because maximum t = 50)

Candidate 3 t = $41.7021 + 0.7332(47.8632 - |41.7021|) - 0.4231(39.2846 - |41.7021|) = 47.2422$

Candidate 4 t = $47.8632 + 0.7332(47.8632 - |47.8632|) - 0.4231(39.2846 - |47.8632|) = 51.4928$ (= 50 because maximum t = 50)

Candidate 5 t = $39.2846 + 0.7332(47.8632 - |39.2846|) - 0.4231(39.2846 - |39.2846|) = 45.5744$

Candidate 1 V = $45.6465 + 0.7332(71.1816 - |45.6465|) - 0.4231(51.5042 - |45.6465|) = 61.8904$

Candidate 2 V = $97.7998 + 0.7332(71.1816 - |97.7998|) - 0.4231(51.5042 - |97.7998|) = 97.8710$

Candidate 3 V = $62.5484 + 0.7332(71.1816 - |62.5484|) - 0.4231(51.5042 - |62.5484|) = 73.5510$

Candidate 4 V = $71.1816 + 0.7332(71.1816 - |71.1816|) - 0.4231(51.5042 - |71.1816|) = 79.5071$

Candidate 5 V = $51.5042 + 0.7332(71.1816 - |51.5042|) - 0.4231(51.5042 - |51.5042|) = 65.9316$

Now insert calculated new value into Table 4.

Table 5 Updated values of all variables and corresponding RWR (first iteration)

Can.	Ip	Ton	t (%)	V	RWR
1	6.8764	150	50	61.8904	18.0981
2	4.4222	134.7751	50	97.8713	22.5136
3	4.3804	145.9918	47.2422	73.5511	29.493
4	4.9555	150	50	79.5073	25.4826
5	4.9077	122.7613	45.5744	65.9316	21.0654

Table 6 New values of all variables for second iteration

Can.	Ip	Ton	t (%)	V	RWR
1	5.6138	147.9726	48.605	67.7887	21.5808
2	4	133.1297	48.605	100	24.9066
3	4	144.065	45.9165	79.1568	31.7298
4	4	147.9726	48.605	84.9635	32.1518
5	4	121.4175	44.2905	71.7286	28.0169

Table 7 Updated values of all variables and corresponding RWR for second iteration

Can.	Ip	Ton	t (%)	V	RWR
1	5.6138	147.9726	48.605	67.7887	21.5808
2	4	133.1297	48.605	100	24.9066
3	4	144.065	45.9165	79.1568	31.7298
4	4	147.9726	48.605	84.9635	32.1518
5	4	121.4175	44.2905	71.7286	28.0169

Step 3: Compare every candidate and select with better RWR (objective function). Candidate 1 from Table 4 has better objective value compare to candidate 1 of Table 3, hence inserted into Table 4 as candidate 1. Similarly candidate 2, 3, 4, and 5 of Table 4 has also better RWR as compare to candidate 2, 3, 4, 5 of Table 3, hence candidate 2, 3, 4 and 5 of Table 3 inserted into Table 5. First iteration is over.

Step 4: Consider Table 5 as input to second iteration. Consider $r1 = 0.5058$, $r2 = 0.4807$ and repeat the same procedure as per step 2 and step 3. Table 6 represent new value of all variables. Now compare each candidate from Table 5 and Table 6. Select better RWR for each candidate and insert into Table 7.

3.3 Optimization using TLBO algorithm

Teaching-learning-based optimization (TLBO) is two-phase optimization algorithm, first is teacher phase and second is the learner phase. Figure 3 shows flow diagram of TLBO Algorithm.

Fig. 3 Flowchart of TLBO algorithm

Step 1: Initial population is randomly generated in between upper bound and lower bound of variables as shown in Table 1. Calculate the mean of all variables.

Step 2: Objective is to maximize RWR as per equation 6. Candidate 2 has maximum RWR value hence selected as teacher. Value of $l_p = 4.8153$, $Ton = 85.5584$, $t = 33.0294$,

$V = 46.5677$ selected as teacher's variables value. Calculated mean value of l_p , Ton , t and V are 6.2326, 87.24592, 34.22178, 67.04024 respectively. Consider four random numbers $r_1 = 0.6476$, $r_2 = 0.9520$, $r_3 = 0.1991$ and $r_4 = 0.0000$ for l_p , Ton , t and V respectively. The difference mean values of l_p , Ton , t and V calculated as following.

Fig. 4 Effect of various control parameters on RWR **Table 8** Initial population

Can.	Ip	Ton	t (%)	V	RWR
1	5.8033	75.6442	30.6602	40.7974	2.7112
2	4.8153	85.5584	33.0294	46.5677	10.8899
3	6.1957	76.3754	30.6019	83.3591	5.7567
4	7.6135	135.5253	30.5221	99.1143	6.7809
5	6.7352	63.1263	46.2953	65.3627	6.9415
Mean	6.2326	87.24592	34.22178	67.04024	6.2326

Table 9 New values of the input variables and the objective function (teacher phase)

Can.	Ip	Ton	t (%)	V	RWR
1	4.8854	74.0377	30.4228	40	6.5787
2	4	83.9519	32.792	40	15.5988
3	5.2778	74.7689	30.3645	75.9497	8.7602
4	6.6956	133.9188	30.2848	91.7049	7.9195
5	5.8174	61.5198	46.058	57.9533	6.6744

Difference mean (Ip) = $0.6476 \times (4.8153 - 6.2326)$
 Difference mean (Ton) = $0.9520 \times (85.5584 - 87.24592)$
 Difference mean (t) = $0.1991 \times (33.0294 - 34.22178)$
 Difference mean (V) = $0.0000 \times (46.5677 - 67.04024)$

The values of difference mean (Ip) is added to all parameter of Ip (first column) similarly difference mean (Ton) is added to all values of Ton (second column), difference mean (t) is added to all values of t and difference mean (V) is added to all values of V of Table 8. Thus Table 9 is prepared shows the new values of all variables.

Step 3: Now compare Tables 8 and 9 for better values of RWR. The better value of RWR is placed in Table 10 for each candidate. Table 9 has a better RWR value for each candidate as compared to Table 8. Hence select all

Table 10 Updated values of the variables and the objective function based on best of two (teacher phase)

Can.	Ip	Ton	t (%)	V	RWR
1	4.8854	74.0377	30.4228	40	6.5787
2	4	83.9519	32.792	40	15.5988
3	5.2778	74.7689	30.3645	75.9497	8.7602
4	6.6956	133.9188	30.2848	91.7049	7.9195
5	6.7352	63.1263	46.2953	65.3627	6.9415

candidate from Table 9 and inserted into Table 10. The teacher phase is over now.

Step 4: Learner phase is started now. Every learner (candidate) has to interact with any other learner (candidate) and every learner interacts with anyone learner. Here, the interaction between learner 1 and learner 2, learner 2 and learner 3, learner 3 and learner 4, learner 4 and learner 5 and interaction between learner 5 and learner 1 is considered. Consider random numbers $r5 = 0.3653$, $r6 = 0.1889$, $r7 = 0.2440$ and $r8 = 0.5060$ for Ip, Ton, t and V respectively.

After a comparison between learner 1 and learner 2, learner 2 has better RWR hence

(Ip) new for learner 1 = $4.8854 + r5 \times (4 - 4.8854) = 4.5621$
 (Ton) new for learner 1 = $74.0377 + r6 \times (83.9519 - 74.0377) = 75.9102$
 (t) new for learner 1 = $30.4228 + r7 \times (32.792 - 30.4228) = 31.0009$
 (V) new for learner 1 = $40 + r8 \times (40 - 40) = 40$

Similarly calculated new values of all variables of candidate 2, candidate 3, candidate 4, and candidate 5 is inserted into Table 11. It is noted that the new value of variables should be within the range of input as per Table 1. If the value falls below lower limit the assign lower bound and if

Table 11 New values of the variables and the objective function (learner phase)

Can.	Ip	Ton	t (%)	V	RWR
1	4.5621	75.9102	31.0009	40	9.1741
2	4	85.6863	33.3843	40	16.0114
3	5.7955	85.9405	30.3451	83.9219	7.2491
4	6.6811	147.2893	26.3784	100	5.0965
5	7.4107	61.0655	50	78.1963	8.7936

it goes beyond the upper limit then assign an upper limit to the variable.

Step 5: Now compare Tables 10 and 11 for better values of $f(x)$ and better value of $f(x)$ is placed in Table 12 for each candidate. Learner phase is over now. Iteration one is over.

Step 6: Table 12 would be input to next iteration and repeat step 2,3,4 and step 5. Continue procedure for 100 iterations and report optimum solution.

3.4 Optimization using Minitab 18

Response optimizer of commercial software Minitab 18 optimizes response measures RWR = 35.5719 and corresponding four control parameters are $I_p = 4$ A, $V = 62.4242$ V, $Ton = 150$ μ seconds and $t = 50$ %.

4 Discussion

MRR increases with the increase of peak current (I_p), but TWR also increases with I_p increases [10]. Many authors maximize MRR with compromise to TWR and quality. The quality of the machined surface deteriorates if TWR has a higher value. Hence in this study, we consider RWR ($RWR = MRR/TWR$) optimization. This optimization ensures to maximize MRR while the quality of the machined surface maintained at the best level. This section discusses the effect of four control parameters individually on RWR. Figure 4 shows the effect of all parameters on RWR value. RWR decreases with the increment of peak current (I_p),

Table 12 Updated values of the variables and the objective function based on fitness comparison (learner phase)

Can.	Ip	Ton	t (%)	V	RWR
1	4.5621	75.9102	31.0009	40	9.1741
2	4	85.6863	33.3843	40	16.0114
3	5.2778	74.7689	30.3645	75.9497	8.7602
4	6.6956	133.9188	30.2848	91.7049	7.9195
5	7.4107	61.0655	50	78.1963	8.7936

Table 13 Optimum result

Algorithm	Ip	Ton	t (%)	V	RWR
Jaya Algorithm	4	150	50	62.4614	35.6021
TLBO	4	150	50	62.4564	35.6021
Response Opt.	4	150	50	62.4242	35.5719

RWR increases with the increases of pulse on time (Ton), RWR increases with the increases of duty factor (t) and the optimum value of voltage (v) observes at $V = 62.4242$ V, as shown in Figure 4.

5 Results

Optimization results are shown in tabular form. Table 13 shows the comparison and result produced by the different optimization algorithm.

6 Conclusion

The optimization of RWR using response surface modeling, Jaya Algorithm and teaching-learning-based optimization algorithm (TLBO) has been done. All three optimization methods show the same result. Maximum RWR is 35.6021 at an optimum level of $I_p = 4$ amp, $Ton = 150$ μ s, duty factor $t = 50$ % and $V = 62.4614$ V.

Jaya Algorithm converges the optimization quickly in just 15 iterations and found suitable for engineering optimization. RWR decreases with the increase of peak current, RWR increases with the increases of Ton and duty factor (t) while the optimum value of voltage (V) observed at 62.4614 V.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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