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# Energy Consumption Modeling for EDM Based on Material Removal Rate

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**ABSTRACT** In recent years, the energy problem has caused widespread concern in the manufacturing industry. The energy consumption in traditional turning and milling processes has been widely studied. However, there are few studies on the energy consumption of the EDM (Electric Discharge Machining) process, which is also widely used. This article proposed a modeling method for the energy consumption model of EDM based on the discharge between electrodes. The proposed model is composed of processing energy consumption caused by electrode-to-electrode discharge and no-load energy consumption of the machine tool. Based on the discharge principle of EDM and the relationship between EDM machining parameters and MRR (Material Removal Rate), an energy consumption model for EDM machining is established. In this article, validation experiments are designed for important machining parameters, and the prediction accuracy of the theoretical model established in this article is higher than 96%. The energy efficiency in electric machining is also analyzed, and the influence relationship between energy consumption and machining parameters is revealed, which can effectively reduce the energy consumption of electric spark punching.

**INDEX TERMS** EDM, MRR, energy consumption modeling, energy efficiency.

## I. INTRODUCTION

Modern manufacturing industry generally has great impact on the consumption of resources and the destruction of the environment [1]. Low-energy-consumption and high-efficiency processing plays an important role in green and sustainable manufacturing [2]–[6]. At present, most studies tend to monitor the energy consumption of machining processes or establish the prediction model of the energy consumption by experimental methods [7]–[8]. Currently, many countries have made systems and policies for energy conservation and emission reduction [9]–[11]. As a widely used special processing technology, EDM can process all conductive materials that are difficult to machine and is not limited by the shape of the parts. However, it has a series of technological problems such as high energy consumption, relatively low processing efficiency and poor processing environment. Singh and Sharma [12] and other scholars [13]–[17] have conducted in-depth research in the field of green EDM, analysis of machining mechanisms and improvement of the machining

environment. Pellegrini and Ravasio [18] defined a sustainability index on energy consumption and have applied it to a micro-electrical discharge machining (micro-EDM) process in drilling operations. Gamage and de Silva [19] analyzed and explained the fluctuations of energy consumption in the process of wire breakages for machine tool design and operating practices. Wu *et al.* [20] designed and proposed a high-efficiency green pulse power supply with high energy in sustainable and high-efficiency EDM milling. In the final experiment, the energy efficiency of this pulsed power supply was improved by more than 200%. The energy efficiency  $E_e$  and removal efficiency  $Re$  of micro EDM were theoretically analyzed by Zahiruddin and Kunieda [21]. Similarly, many researchers have attempted the use of new green materials and media [22]–[24] in electrical processing, which has improved the quality of the processing environment, effectively reduced energy consumption and improved the processing efficiency in actual production. Other scholars have reduced energy consumption by controlling the pulse power or improving the processing technology [25–28], which is easy to achieve in actual processing and reduces power consumption to some extent.

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Zhen *et al.* [29] analyzed the energy characteristics of WEDM based on a nonpulse energy consumption unit and established the prediction model of nonpulsed auxiliary energy consumption and feed energy. The accuracy of the prediction model was 96%. Balogun and Mativenga [30], Liu and Liu [31], and Tuo *et al.* [32] established an energy consumption model based on the CNC machine tool system by analyzing the connotation and characteristics of the energy consumption of the machine tool. They analyzed and calculated the energy consumption of each axis and each subsystem. The corresponding information is fed back to the control system for energy saving improvement and regulation. Mori *et al.* [33] and Diaz *et al.* [34] classified the machining states of machine tools into the basic state, idle state and machining state and tested the power of several states to obtain the total energy consumption. Branham *et al.* [35] studied the energy consumption system of the machine tool from the perspective of thermodynamics and regarded the machine tool as an open system. They calculated the reduction value of the input and output of the machine tool during its operation as the energy consumption of the processing system. However, this method is limited because the thermodynamic properties of different materials are difficult to control and calculate.

Scientific and accurate prediction of energy consumption plays a very important role in energy saving optimization of processing. At present, the research on the energy saving of hole EDM drilling mainly focuses on the pulse power control strategy. In this article, the film hole EDM of turbine blades is used as the background to study the variation law of power in the drilling process. The paper will analyze the relationship between power and material removal rate and other parameters and establish a model of energy consumption prediction. Through experimental comparison, the model can reduce the energy consumption and enhance the processing efficiency.

**II. ENERGY CONSUMPTION MODEL OF EDM**

The total energy consumption model of EDM is composed of standby energy consumption and processing energy consumption, which can be expressed as:

$$P_{total} = P_{standby} + P_{processing} \tag{1}$$

where the standby energy consumption ( $P_{standby}$ ) is related to the performance of the machine tool. The processing energy consumption ( $P_{processing}$ ) is determined by factors such as the workpiece material, electrode material, and processing parameters.

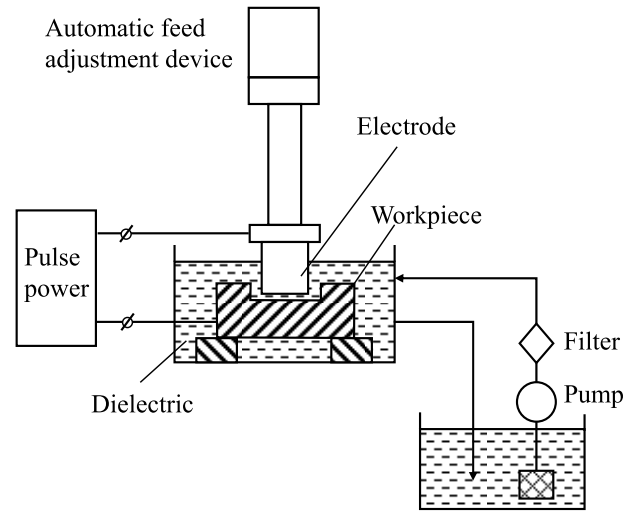
Due to the unique processing characteristics of EDM, the machine tool in the unprocessed state does not generate electrical discharge between the electrode and the material, so the standby energy consumption of the machine tool is constant. In other words, when the machine tool is in the unprocessed state, the total machine tool energy consumption is the standby energy consumption of the machine tool.

The processing energy consumption in the EDM process is essentially generated by the discharge reaction between

the electrode and the material being processed. In the following part, the energy consumption of EDM is theoretically modeled.

**A. INTER-ELECTRODE DISCHARGE ENERGY MODEL FOR EDM**

Electrical discharge processing refers to a method of machining a workpiece in a certain medium by the electric erosion of a pulse discharge between a tool electrode and a workpiece electrode, as shown in Figure 1.



**FIGURE 1. Schematic of EDM.**

Energy is generated at the moment of the pulse discharge. The principle of EDM is to remove the material by the energy of the pulse discharge between the electrode and the material being processed.

Therefore, according to the principle of pulse discharge, the energy of a single pulse can be expressed as:

$$W_M = \int_0^{t_e} u(t) i(t) dt \tag{2}$$

where  $u(t)$  is the time-varying voltage (V) in the discharge gap;  $i(t)$  is the time-varying current (A) in the discharge gap;  $t_e$  is the discharge time of a single pulse time ( $\mu s$ );  $W_M$  is a single pulse energy (J).

**B. PROCESSING ENERGY CONSUMPTION MODEL OF EDM**

According to the single pulse energy model, the energy of EDM machining over a period of time can be calculated and expressed as:

$$E_{processing} = \sum W_M \tag{3}$$

Then, the processing energy consumption of EDM can be expressed as

$$P_{processing} = \frac{E_{processing}}{t} = \frac{\sum W_M}{t} \tag{4}$$

### C. MATERIAL EROSION MODEL FOR EDM

The process of converting the energy of the discharge into the energy of removing the material is lossy, i.e., there is a problem of the conversion rate, which is difficult to measure. The model of material removal can be calibrated. The positive and negative material removal of a single pulse of EDM can be expressed as:

$$\begin{cases} q_a = K_a W_M \varphi \\ q_c = K_c W_M \varphi \end{cases} \quad (5)$$

where  $q_a$  and  $q_c$  are the total removed quantities of the positive electrode and negative electrode;  $W_M$  is the single pulse energy;  $K_a$  and  $K_c$  are process coefficients related to the electrode materials, pulse parameters, working fluid, etc.;  $\varphi$  is the effective pulse utilization rate.

The total amount of material removed from the positive and negative electrodes is the amount of removed material MR:

$$MR = q_a + q_c = (K_a + K_c) f \varphi \sum W_M \quad (6)$$

Then, the material removal rate MRR can be expressed as:

$$MRR = (K_a + K_c) \varphi \frac{\sum W_M}{t} = (K_a + K_c) \varphi P_{processing} \quad (7)$$

### D. TOTAL ENERGY CONSUMPTION MODEL OF EDM

The EDM processing power obtained from the EDM material erosion model can be expressed as:

$$P_{processing} = \frac{MRR}{(K_a + K_c) \varphi} \quad (8)$$

By substituting Equation 8 into Equation 1, we obtain the total energy consumption model of EDM:

$$P_{total} = P_{idle} + P_{processing} = P_{standby} + \frac{MRR}{(K_a + K_c) \varphi} \quad (9)$$

Make  $K = \frac{1}{(K_a + K_c) \varphi}$ ;  $K$  is the specific energy coefficient of material removal rate and single pulse energy; the unit is  $W/mm^3$ , which is related to the workpiece material and machine tool performance and effective pulse utilization.

Replace  $\frac{1}{(K_a + K_c) \varphi}$  in the formula with  $K$ , so that  $K = \frac{1}{(K_a + K_c) \varphi}$ ;  $K$  is the specific energy coefficient of material removal rate and single pulse energy; the unit is  $W/mm^3$ . It is related to the workpiece material, machine performance and effective pulse utilization.

In summary, the total energy consumption model of EDM can be expressed as:

$$P_{total} = P_{standby} + K \cdot MRR \quad (10)$$

where MRR is related to the processing parameters and can represent the exponential function of current, pulse width and pulse:

$$MRR = I^a t_{on}^b t_{off}^c \quad (11)$$

In short, the flowchart below shows the logic of the energy consumption model for the EDM drilling process.

## III. EXPERIMENT DETAILS FOR MODEL CALIBRATION AND VALIDATION

### A. EXPERIMENTAL DESIGN

The EDM experiments were performed on High-speed small-hole EDM machine tool DD703, and the workpiece material was #45 steel with a thickness of 3 mm. The diameter of the electrode in the processing experiment was 0.8 mm, and the dielectric was kerosene. The model was calibrated using orthogonal tests, and the processing parameters are listed in table 1.

TABLE 1. Processing parameters of Experiment 1.

	1	2	3	4
I(A)	3	5	8	11
$t_{on}(\mu s)$	10	30	60	90
$t_{off}(\mu s)$	10	30	60	90

In total, 16 experiments were performed in Experiment 1. To ensure the accuracy of the experiment, three repeated experiments were performed for each parameter, and the average value was obtained.

### B. MEASURING

The power data during the experiment were recorded by a HIOKI PW3360 power meter with a sampling frequency of 1 Hz. The machining times of individual holes are also recorded.

The energy consumption under different working conditions and the energy consumption during processing were monitored in real time. Specific experimental data were stored for subsequent modeling and analysis.

### C. MODEL CALIBRATION

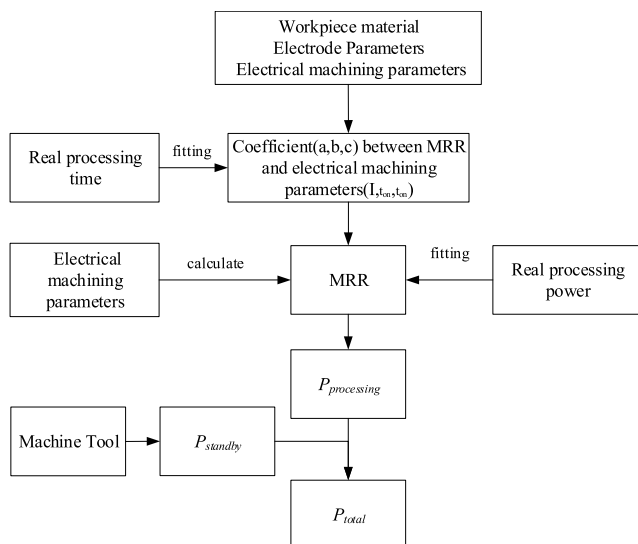
First, this section will calibrate the standby energy consumption ( $P_{standby}$ ) of the machine tool in the experiment. When the machine tool is in the start-up state, the energy consumption of the machine tool is measured in the noncutting state. Since the motor does not react with the workpiece, the standby energy consumption at this time is constant. The standby energy consumption ( $P_{standby}$ ) can be expressed as:

$$P_{standby} = 99.8W$$

According to equation (10), the EDM power can be calculated by the material removal rate. It is necessary to record the processing time under different processing parameters to determine the material removal rate under the current parameters. The processing time under different processing parameters in Experiment 1 is provided in table 2. The volume of the holes is obtained through the geometric parameters of the workpiece, and the material removal rate is calculated according to the definition.

**TABLE 2.** Processing time, material removal rate and processing power for different processing parameters in experiment 1.

No.	I(A)	t <sub>on</sub> (μs)	t <sub>off</sub> (μs)	t <sub>processing</sub> (s)	MRR(mm <sup>3</sup> /s)	P <sub>processing</sub> (W)
1	3	10	10	21	0.0718	23.7
2	3	30	30	116	0.0130	4.0
3	3	60	60	351	0.0043	1.3
4	3	90	90	612	0.0025	0.7
5	5	10	30	61	0.0247	9.0
6	5	30	10	15	0.1005	30.7
7	5	60	90	342	0.0044	1.2
8	5	90	60	211	0.0071	2.0
9	8	10	60	101	0.0149	5.5
10	8	30	90	188	0.0080	2.3
11	8	60	30	50	0.0301	10.1
12	8	90	10	12	0.1256	41.0
13	11	10	90	125	0.0121	4.1
14	11	30	60	77	0.0196	5.3
15	11	60	30	37	0.0407	11.1
16	11	90	10	8	0.1884	55.8

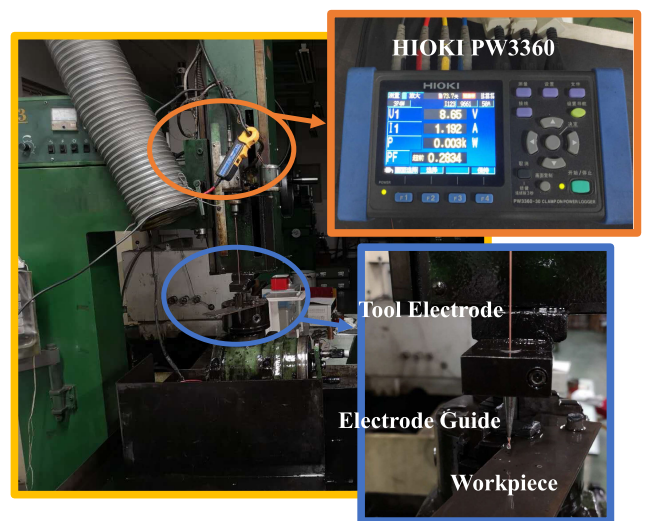


**FIGURE 2.** Flowchart of the EDM energy consumption calculation.

Using these experimental data, the relationship between MRR and processing energy consumption can be established, as shown in Figure 4. Then, the specific energy coefficient  $K = 307.45$  of the MRR and the energy of a single pulse are obtained by the least square method.

Therefore, the total energy consumption model of EDM can be expressed as:

$$P_{total} = P_{standby} + 307.45MRR$$



**FIGURE 3.** Experimental setup.

MRR can be calibrated with experimental data using formula (11) and expressed as:

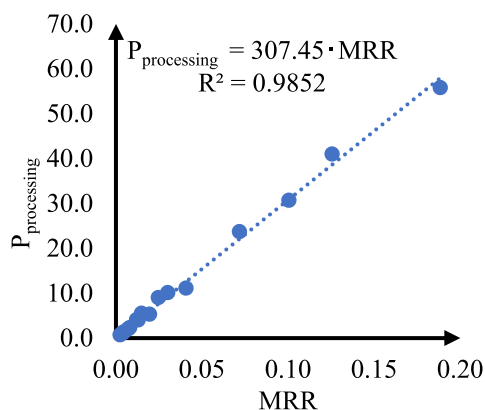
$$MRR = I^{0.9930} t_{on}^{-0.1897} t_{off}^{-1.3998}$$

Table 3 shows the experimental values of MRR and the processing power and the predicted values and errors of the model.

Table 3 shows that the average prediction errors of the MRR and processing power are 5.41% and 4.96%,

**TABLE 3.** Measured and predicted values and errors of the MRR and processing power.

No.	MRR(mm <sup>3</sup> /s)	MRR*(mm <sup>3</sup> /s)	Error	P <sub>processing</sub> (W)	P* <sub>processing</sub> (W)	Error
1	0.0718	0.0766	6.69%	23.7	23.6	0.42%
2	0.013	0.0134	3.08%	4	4.1	2.50%
3	0.0043	0.0044	2.33%	1.3	1.4	7.69%
4	0.0025	0.0023	8.00%	0.7	0.7	0.00%
5	0.0247	0.0273	10.53%	9	8.4	6.67%
6	0.1005	0.1033	2.79%	30.7	31.8	3.58%
7	0.0044	0.0042	4.55%	1.2	1.3	8.33%
8	0.0071	0.0068	4.23%	2	2.1	5.00%
9	0.0149	0.0165	10.74%	5.5	5.1	7.27%
10	0.008	0.0076	5.00%	2.3	2.3	0.00%
11	0.0301	0.031	2.99%	10.1	9.5	5.94%
12	0.1256	0.1337	6.45%	41	41.1	0.24%
13	0.0121	0.0128	5.79%	4.1	4	2.44%
14	0.0196	0.0184	6.12%	5.3	5.7	7.55%
15	0.0407	0.0426	4.67%	11.1	13.1	18.02%
16	0.1884	0.1835	2.60%	55.8	57.9	3.76%
Average error			5.41%			4.96%



**FIGURE 4.** Relationship between MRR and processing power.

respectively. The prediction accuracy of the model can be considered acceptable.

**IV. EXPERIMENTAL RESULTS AND DISCUSSION**

**A. MODEL VALIDATION**

For the obtained EDM energy consumption model, experimental verification is necessary. According to the data in Experiment 1, Table 4 lists the measured value (P<sub>total</sub>), predicted value (P\*<sub>total</sub>) of the total power, and prediction error of the model. The draw prediction error of the proposed model is only 2.13%, which indicates that the model can achieve good prediction accuracy.

**TABLE 4.** Measured value (P<sub>total</sub>), predicted value (P\*<sub>total</sub>) of the total power and model prediction error (Experiment 1).

No.	P <sub>total</sub> (W)	P* <sub>total</sub> (W)	Error
1	121.7	123.4	1.40%
2	107	103.9	2.90%
3	99.3	101.2	1.91%
4	97.7	100.5	2.87%
5	111	108.2	2.52%
6	129.7	131.6	1.46%
7	103.2	101.1	2.03%
8	104	101.9	2.02%
9	103.5	104.9	1.35%
10	103.3	102.1	1.16%
11	112.1	109.3	2.50%
12	144	140.9	2.15%
13	101.1	103.8	2.67%
14	103.3	105.5	2.13%
15	110.1	112.9	2.54%
16	153.8	157.7	2.54%
Average error			2.13%

To further validate the proposed model, a second set of experiments (Experiment 2) was performed using different processing parameters from Experiment 1. Table 5 lists the



**TABLE 5. Processing parameters in experiment 2. MRR, measured and predicted values and errors of the total energy consumption.**

No.	I(A)	t <sub>on</sub> (μs)	t <sub>off</sub> (μs)	MRR(mm <sup>3</sup> /s)	MRR*(mm <sup>3</sup> /s)	Error	P <sub>total</sub> (W)	P* <sub>total</sub> (W)	Error
1	4	20	20	0.0351	0.0339	3.42%	109.0	110.2	1.11%
2	4	50	50	0.0081	0.0079	2.47%	96.8	102.2	5.53%
3	4	80	80	0.0036	0.0037	2.78%	104.9	100.9	3.85%
4	7	20	50	0.0171	0.0164	4.09%	109.7	104.8	4.45%
5	7	50	80	0.0068	0.0071	4.41%	101.6	102	0.39%
6	7	80	20	0.0431	0.0454	5.34%	117.9	113.8	3.49%
7	10	20	80	0.0125	0.0121	3.20%	100.5	103.5	2.97%
8	10	50	20	0.0718	0.0707	1.53%	120.1	121.5	1.17%
9	10	80	50	0.0171	0.0179	4.68%	107.5	105.3	2.04%
Average error						3.55%			2.78%

processing parameter settings, measured value (MRR), predicted value (MRR\*) of the material removal rate under each processing parameter, and prediction error of the model. The average prediction error of the MRR model is only 3.55%, which shows the model can reach good prediction accuracy. Similarly, Table 5 lists the total measured value (P<sub>total</sub>), predicted value (P\*<sub>total</sub>), and prediction error of the model. The average prediction error of the proposed energy consumption model is only 2.78%, which indicates that the model can accomplish very high prediction accuracy. In different experiments, for different processing parameters, the prediction accuracy of the energy consumption model exceeds 97%, which indicates the effectiveness of the proposed energy consumption model.

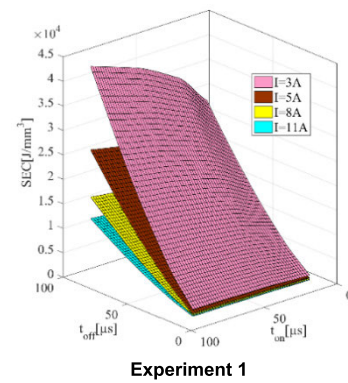
**B. ENERGY EFFICIENCY ANALYSIS**

As verified in the previous sections, the proposed model can provide accurate power predictions under new processing conditions. In addition, the model considers most processing parameters (I, t<sub>on</sub>, t<sub>off</sub>, etc.) when calculating the MRR. It is not necessary to perform actual machining experiments to accurately predict the energy efficiency of EDM processes under different cutting conditions. Therefore, the model can be used as a reliable platform to optimize the parameters of the clean manufacturing process.

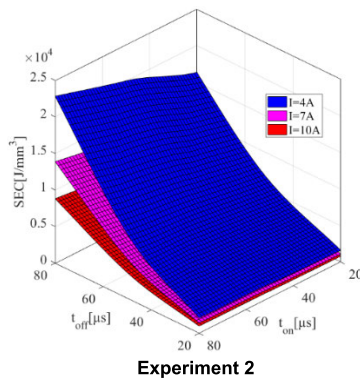
In this section, the effects of three processing parameters (I, t<sub>on</sub> and t<sub>off</sub>) on the energy efficiency of EDM of the #45 steel are thoroughly studied through simulation experiments with the proposed model.

The specific energy consumption (SEC) is used to indicate the energy efficiency of the EDM hole process (SEC can be expressed as  $SEC = \frac{P_{total}}{MRR}$ ). A smaller SEC corresponds to a higher energy efficiency.

I, t<sub>on</sub> and t<sub>off</sub> are used to simulate the hole processing process in a certain range. The results are shown in Figure 5 and 6. The 3D surface is composed of ton, toff and



**FIGURE 5. SEC map for the EDM process of #45 steel.**



**FIGURE 6. SEC map for the EDM process of #45 steel.**

SEC under different currents. The following observations are worth noting:

- 1) At the same I, t<sub>on</sub> and t<sub>off</sub>, when I increases, the energy efficiency will be higher. Due to the increase in phase pulse energy caused by a large current, the processing efficiency increases.

**TABLE 6.** SEC measured value (SEC), predicted value (SEC\*) and model prediction error in Experiment 1.

No.	SEC(J/mm <sup>3</sup> )	SEC*(J/mm <sup>3</sup> )	Error
1	1695.7	1610.2	5.04%
2	8235.1	7775.9	5.58%
3	23125.2	22783.5	1.48%
4	39671.2	43124.5	8.70%
5	4492.4	3958.4	11.89%
6	1290.8	1273.7	1.33%
7	23417.2	24180.5	3.26%
8	14559.4	14923.5	2.50%
9	6935.7	6348.2	8.47%
10	12885.1	13432.5	4.25%
11	3718.8	3523.7	5.25%
12	1146.5	1053.7	8.09%
13	8384.8	8074.2	3.70%
14	5277.4	5730.9	8.59%
15	2702.8	2651.8	1.89%
16	816.3	837.3	2.56%
Average error			5.16%

2)At the same current, the effect of a larger pulse width on the SEC is not significant. The reason is that although the larger pulse width increases the discharge time, the effect of electrical corrosion does not significantly improve.

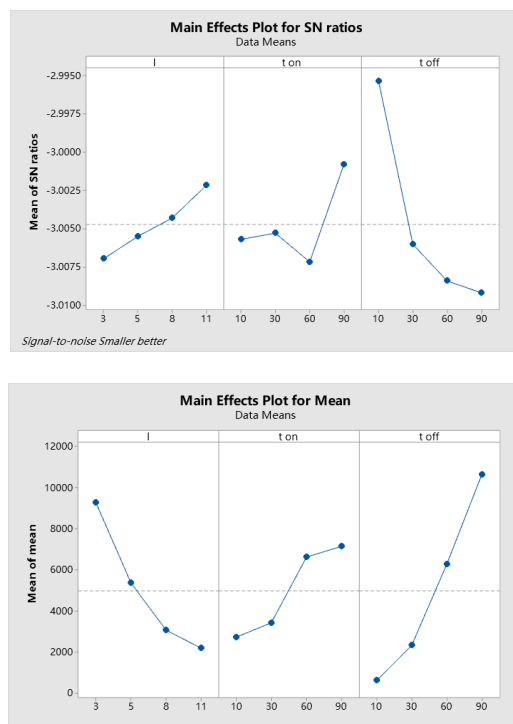
3)At the same current, smaller pulses will increase the energy efficiency. The reason is that the smaller pulses reduce the discharge gap, reduce the invalid processing time, improve the MRR, and effectively improve the processing efficiency.

The data of Experiment 1 and Experiment 2 are used to prove the accuracy of the model’s prediction of the SEC. The draw prediction error of the proposed energy consumption model is only 5.16%. Similarly, Table 7 lists the actual measured value (SEC), predicted value (SEC\*) of the SEC and prediction error of the model for each parameter in Experiment 2. The draw prediction error of the proposed energy consumption model is only 5.27%, which indicates that the proposed model achieves high prediction accuracy.

To study the effects of the current, pulse width and pulse duration on SEC, this article uses range analysis and Taguchi analysis. Figures 7 and 8 show the main effects of the current, pulse width, and pulse duration on SEC for the processing parameters of Experiment 1 and Experiment 2, respectively. Figures 7 and 8 show that when the input current increases, the SEC will decrease; when the interpulse increases, the SEC will increase, and the effect of the change in pulse width on

**TABLE 7.** SEC measured value (SEC), predicted value (SEC\*) and model prediction error in Experiment 2.

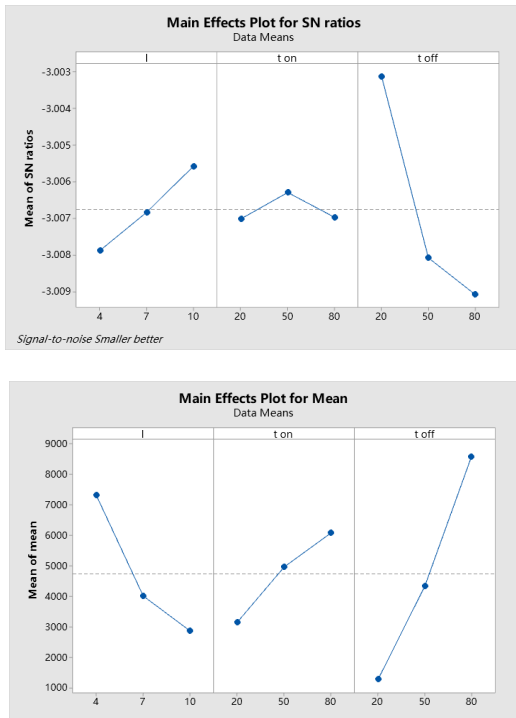
No.	SEC(J/mm <sup>3</sup> )	SEC*(J/mm <sup>3</sup> )	Error
1	3105.1	3250.7	4.69%
2	11956.1	12936.7	8.20%
3	29149.7	27270.3	6.45%
4	6413.8	6390.2	0.37%
5	14941.7	14366.2	3.85%
6	2735.8	2506.6	8.38%
7	8041.2	8553.7	6.37%
8	1672.6	1718.5	2.74%
9	6286.3	5882.7	6.42%
Average error			5.27%



**FIGURE 7.** Plot of the S/N ratios for Taguchi L16 orthogonal array (Experiment 1).

the SEC is not monotonous. The SEC does not increase with the pulse width.

In summary, the contrast between numerical research and actual experimental results clearly proves the validity and dependability of the model. Because the model has higher accuracy and reliability, the numerical research performed by the numerical model is more efficient. At the time of optimizing the energy efficiency of the EDM process, no actual machining experiments are required, which saves material



**FIGURE 8.** Plot of the S/N ratios for Taguchi L9 orthogonal array (Experiment 2).

and time. Hence, it can greatly promote energy-saving manufacturing and cleaner production.

## V. CONCLUSION

The EDM process is widely used in hole processing and manufacturing, especially in the processing of small holes.

1) By investigating the properties of hole EDM drilling of #45 steel, the mechanisms of EDM machining in high-temperature alloy processing were studied. Due to the characteristics of the material removed by the discharge of the EDM, the problem of energy consumption during processing is prominent.

2) To improve the energy efficiency, an accurate and reliable electrical discharge machining (EDM) consumption model based on MRR is proposed. It consists of the no-load power and machining discharge power of a machine tool. The proposed model has been validated for different experimental parameters.

3) Since the model can be used to analyze the energy efficiency with various processing parameters, it also provides an excellent platform to optimize processing parameters for energy efficiency. The use of numerical simulation instead of experimental processing to optimize energy utilization greatly reduces cost and promotes the development of green and clean manufacturing.

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