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Research Article

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Modeling and optimum design for wire electrical discharge machining of γ titanium aluminide alloy

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Abstract

Wire electrical discharge machining (WEDM) of γ titanium aluminide is the subject of the current research. Due to the large number of process variables and sophisticated stochastic process mechanisms, selecting the best machining parameter combinations for increased cutting efficiency and accuracy is a difficult task in WEDM. In general, there is no perfect combination that can produce the fastest cutting speed and the finest surface finish quality at the same time. For this purpose, the data were selected from a literature study. This study describes an attempt to devise a suitable machining technique for achieving the highest possible process criteria yield. To model the machining process, a stochastic optimization method, differential evolution, has been performed. Cutting speed, surface roughness, and wire offset are the three most important criteria that have been used as indicators of process performance. The response characteristics can be predicted as a function of six different control parameters, namely pulse on time, pulse off time, peak current, wire tension, dielectric flow rate, and servo reference voltage. The limitations of the candidate models are checked after the $R^2_{training}$, $R^2_{testing}$ and $R^2_{valiadtion}$ values are calculated to reveal whether the model is realistic. Optimization results are 3.02 mm/min, 2.36 μm, and 0.13 mm for the maximum cutting speed, the minimum surface roughness, and minimum wire offset, respectively. It is shown that the machining model is suitable and that the optimization technique meets practical requirements.

Keywords:* γ *titanium aluminide; modeling; optimization; wire EDM.

1. Introduction

In recent years, the use of wire electrical discharge machining (WEDM) has increased dramatically. Wire EDM has a wide range of applications, including the production of various press tools, molds and even electrodes for use in other EDM processes. Wire EDM is currently commonly applied in the aerospace, automotive, and medical industries, as well as in almost every other conductive material machining application. It is considered especially suitable for machining complex contours, for high accuracy and for materials that are not amenable to conventional removal methods [1].

Several attempts to model the process have also been made. Scott et al. [2] have created a factor model to assess the process performance in accordance with the varied control conditions. By introducing the concept of a not-dominated point, the procedure was further optimized. By using regression analysis and subsequently resolving the optimization problem with a viable directional approach, the Liao et al. [3] built a mathematical model. EDM was modeled by Karthikeyan et al. [4] with a full factorial design for processing carbide silicone particle composites and the models significance was verified using the analysis of variance technique. Huang et al. [5] attempted to optimize the WEDM finish-cutting operation. The machined workpiece surface's gap width, surface roughness, and white layer depth are all measured and evaluated. The pulse-on duration and the distance between the wire perimeter and the workpiece surface are two major parameters impacting the machining performance, according to the Taguchi quality design approach and numerical analysis.

We took a new approach to the modeling design-optimization process to optimize the cutting speed, surface roughness, and wire offset input parameters in wire electrical discharge processing. This approach was organized based on a literature study [6] using the Box-Behnken design and regression analysis to obtain the percentage of outputs. First, a detailed study was conducted on multiple nonlinear neuro-regression analysis, including linear, non-linear and their rational forms for the outputs. Second, the boundaries of candidate models were checked to produce realistic values. Finally, a stochastic search methods were implemented methodically.

2. Materials and methods

2.1. Modeling

To assess the accuracy of the predictions during the modeling phase, a hybrid method including regression analysis is used. All data is divided into three groups in this approach, with the first portion being used for training,

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the second for testing, and the third for validation. By modifying the regression models and coefficients during the training phase, the goal is to reduce the errors between the experimental and predicted values.

Following that, the testing stage is used to achieve the prediction results by reducing the effects of regression model inconsistencies. This procedure yields information about the candidate models' ability to anticipate. Third, checking the boundedness of candidate models for prescribed values is critical in determining whether or not the model is realistic. In this case, the maximum and minimum values of the models in the given interval for each design variable are calculated after acquiring the right models in terms of $R^2_{training}$, $R^2_{testing}$ and $R^2_{validation}$. This procedure evaluates whether the selected models satisfy the many criteria which are necessary for reality [7-9].

2.2. Optimization

Substantially, the optimization of a structure may be described as obtaining the best design by minimizing the specified single or multi-objective that corresponds to all of the constraints. There are two types of optimization techniques: traditional and nontraditional. Traditional optimization techniques work for only continuous and differentiable functions, such as constrained variation and Lagrange multipliers. In engineering design problems, traditional optimization techniques cannot be used because of their specificity. In these cases, stochastic optimization methods such as genetic algorithms (GA), particle swarm (PS), and simulated annealing (SA) are favorable. Because of the nature of stochastic methods, the exact solution cannot be obtained and using more than one method with a different phenomenological basis for the same optimization problem increases the reliability of the solution [7].

2.3 Problem definition

The optimal design of cutting speed, surface roughness, and wire offset in a wire electrical discharge machining was organized as follows, using the references [8-11]. The data shown in Table 1 were selected from the reference study [6]. They modeled the electrical discharge process input parameters with Box-Behnken design and regression analysis.

- Ten to twenty candidate functional structures were proposed to model the data of the wire electrical discharge process system and were evaluated in terms of the limitation of functions, $R^2_{training}$, $R^2_{testing}$ and $R^2_{validation}$ values.
- One optimization scenario was introduced by using the obtained suitable models and these problems were solved by four different direct search methods.

2.4. Optimization Scenario

Scenario

In this optimization problem, the objective function defines the cutting speed, surface roughness and wire offset, all design variables are assumed to be real numbers, and the search field is continuous. For this case, 0.8 µs < Pulse on time (T_{on}) < 1.6 µs, 14 µs < Pulse off time (T_{off}) < 30 µs, 120 A < Peak current (I_p) < 220 A, 900 V< Servo reference voltage (SV) < 1380 V,2 gm < Wire tension (WT) < 10 gm,7 kg/cm^2< Dielectric flow rate (discharge pressure) (FR) < 10 kg/cm^2. The main purpose is to maximize cutting speed, minimize surface roughness and wire offset. Mathematically, the boundaries of the objective function can also be obtained with this approach.

3. Results and discussion

Various regression models for cutting speed, surface roughness, and wire offset design in electrical discharge machining have been tested using $R^2_{training}$, $R^2_{testing}$ and $R^2_{validation}$ in the literature. In the reference study [6], Box-Behnken design and regression analysis were used to model outcomes input parameters.

In the present study, more than 20 different regression models with six parameters have been tested, and the most proper ones are listed in Table 2. And additionally with respect to these models predicted outputs and prediction error has been shown in Table 1.

The maximum cutting speed (3.02 mm/min) was obtained for the following optimal conditions;

Pulse on time (T_{on}):1.6 µs, Pulse off time (T_{off}):14 µs, Peak current (I_p):220 A, Servo reference voltage (SV):900 gm, Wire tension (WT):2 V, Dielectric flow rate (discharge pressure) (FR):7 kg/cm^2.

Table 1. *Input parameters, experimental results, adjusted value and error for training data* [6]

	Input Parameters						Responses			Predicted Values			Error		
Experiment Number	T_{on} (µs)	T_{off} (µs)	I_p (A)	WT (gm)	SV (V)	FR (kg/cm^2)	Machining Speed (mm/min)	Average R_a (µm)	Wire Offset (mm)	Machining Speed (mm/min)	Average R_a (µm)	Wire Offset (mm)	Machining Speed (mm/min)	Average R_a (µm)	Wire Offset (mm)
1	1.1	14	120	900	2	7	2.67	2.77	0.142	2.42553	2.6586	0.142529	9.2%	4.0%	0.4%
2	1.1	20	170	1140	6	8.5	2.15	2.78	0.148	1.7869	2.6499	0.146767	16.9%	4.7%	0.8%
3	1.1	30	220	1380	10	10	1.38	2.78	0.15	1.37839	2.6598	0.150725	0.1%	4.3%	0.5%
4	1.6	14	120	1140	6	10	2.24	2.85	0.147	2.45339	2.8647	0.148745	9.5%	0.5%	1.2%
5	1.6	20	170	1380	10	7	2.12	2.81	0.147	2.24005	2.9867	0.149615	5.7%	6.3%	1.8%
6	1.6	30	220	900	2	8.5	2.08	2.97	0.151	2.32903	2.9721	0.150505	12.0%	0.1%	0.3%
7	0.8	14	170	900	10	10	1.84	2.33	0.151	1.73582	2.3688	0.148929	5.7%	1.7%	1.4%
8	0.8	20	220	1140	2	7	1.69	2.48	0.146	1.65183	2.5191	0.144681	2.3%	1.6%	0.9%
9	0.8	30	120	1380	6	8.5	0.98	2.3	0.141	0.939057	2.4498	0.141104	4.2%	6.5%	0.1%
10	1.1	14	220	1380	6	7	2.1	2.82	0.151	2.17147	2.6315	0.147892	3.4%	6.7%	2.1%
11	1.1	20	120	900	10	8.5	1.56	2.64	0.148	1.81435	2.6592	0.146644	16.3%	0.7%	0.9%
12	1.1	30	170	1140	2	10	1.78	2.78	0.146	1.60498	2.6776	0.145485	9.8%	3.7%	0.4%
13	1.6	14	170	1380	2	8.5	2.58	2.87	0.148	2.65672	2.9012	0.147745	3.0%	1.1%	0.2%
14	1.6	20	220	900	6	10	2.56	2.92	0.156	2.3741	2.9354	0.154032	7.3%	0.5%	1.3%
15	1.6	30	120	1140	10	7	2.25	3.03	0.15	1.99165	2.9868	0.147087	11.5%	1.4%	1.9%
16	0.8	14	220	1140	10	8.5	1.69	2.39	0.148	1.70961	2.3783	0.149635	1.2%	0.5%	1.1%
17	0.8	20	120	1380	2	10	1.14	2.3	0.14	1.27845	2.4672	0.14122	12.1%	7.3%	0.9%
18	0.8	30	170	900	6	7	1.07	2.42	0.14	1.33865	2.4921	0.14386	25.1%	3.0%	2.8%

Table 1(cont.). *Input parameters, experimental results, adjusted value and error for testing and validation data* [6]

	Input Parameters						Responses			Predicted Values			Error		
Experiment Number	T_{on} (µs)	T_{off} (µs)	I_p (A)	WT (gm)	SV (V)	FR (kg/cm^2)	Machining Speed (mm/min)	Average R_a (µm)	Wire Offset (mm)	Machining Speed (mm/min)	Average R_a (µm)	Wire Offset (mm)	Machining Speed (mm/min)	Average R_a (µm)	Wire Offset (mm)
19	1.6	30	170	900	2	10	2.24	3.16	0.151	2.21872	2.9626	0.149116	1.0%	6.2%	1.2%
20	0.8	20	170	1380	6	8.5	1.14	2.55	0.139	1.2765	2.4496	0.144315	12.0%	3.9%	3.8%
21	0.8	14	220	1140	2	8.5	2.1	2.31	0.145	1.88906	2.406	0.146223	10.0%	4.2%	0.8%
22	1.6	14	170	900	2	7	2.9	2.84	0.152	2.97953	2.9436	0.147989	2.7%	3.6%	2.6%
23	1.6	14	220	900	6	8.5	2.87	2.72	0.15	2.777	2.8741	0.149263	3.2%	5.7%	0.5%
24	1.1	30	220	900	6	8.5	1.65	2.62	0.15	1.70465	2.6599	0.153329	3.3%	1.5%	2.2%

Table 2. *Results of the Neuro-regression models*

Models			$R^2_{Training}$			$R^2_{Testing}$			$R^2_{Validation}$		
Output 1	**Output 2**	**Output 3**	**Output 1**	**Output 2**	**Output 3**	**Output 1**	**Output 2**	**Output 3**	**Output 1**	**Output 2**	**Output 3**
897.012 +2.66282 ArcTan[x1]-15.6669 ArcTan[x2]+31.3301 ArcTan[x3]-583.628 ArcTan[x4]-0.493013 ArcTan[x5]-3.92331 ArcTan[x6]	$-28389.7+3.48657/(1+e^{x1})+85229.3/(1+e^{-x2})-28389.7/(1+e^{-x3})-28389.7/(1+e^{-x4})-0.232106/(1+e^{-x5})-59.9122/(1+e^{-x6})$	$0.127465+0.00589561\ x1-0.0000698996\ x2+0.0000502358\ x3-2.84728{*}10^{-6}\ x4+0.000426472\ x5+0.00074837\ x6$	0.9850	0.9968	0.9997	0.9558	0.8999	0.998	0.9844	0.8043	0.9743

Table 3. *Results of optimization problems for the selected models.*

Outputs	Aim	Constraints	Results	Suggested Design
Output 1	Maximize	0.8 < x1 < 1.6, 14 < x2 < 30, 120 < x3 < 220, 900 < x4 < 1380, 2 < x5 < 10, 7 < x6 < 10	3.02141	x1=1.6, x2=14, x3=220, x4=900, x5=2, x6=7
Output 2	Minimize	0.8 < x1 < 1.6, 14 < x2 < 30, 120 < x3 < 220, 900 < x4 < 1380, 2 < x5 < 10, 7 < x6 < 10	2.36884	x1=0.8, x2=14, x3=210.748, x4=900.001, x5=10, x6=10
Output 3	Minimize	0.8 < x1 < 1.6, 14 < x2 < 30, 120 < x3 < 220, 900 < x4 < 1380, 2 < x5 < 10, 7 < x6 < 10	0.138276	x1=0.8, x2=30, x3=120, x4=1380, x5=2, x6=7

When the table is examined, it is seen that different optimum values emerge for each output. This is an indication that the engineering parameters to be maximized or minimized have different dynamics from each other. For this reason, it reveals how important the different optimization definitions made within the scope of this study are. The minimum surface roughness R_a (2.36 μm) was obtained for the following optimal conditions;

Pulse on time (T_{on}):0.8 μs, Pulse off time (T_{off}):14 μs, Peak current (I_p):210.74 A, Servo reference voltage (SV):900.001 gm, Wire tension (WT):10 V, Dielectric flow rate (discharge pressure) (FR):10 kg/cm^2. The minimum wire offset (0.13 mm) was obtained for the following optimal conditions; Pulse on time (T_{on}):0.8 μs, Pulse off time (T_{off}):30 μs, Peak current (I_p):120 A, Servo reference voltage (SV):1380 gm, Wire tension (WT):2 V, Dielectric flow rate (discharge pressure) (FR):7 kg/cm^2. They are also shown in Table 3. These tables (Table 1, Table 2, Table 3, Table 4) have been prepared to show that we have successfully created the model for outputs and implemented them into the project properly. Results are suitable with intervals of our inputs

3. Conclusions

In the present research, wire electrical discharge machining of γ titanium aluminide alloy has been carried out, and an advanced optimization strategy has been proposed to determine the optimal combination of control parameters. A stochastic optimization method is used to construct the WEDM process model. During the training process, several optimization models were studied. It has been found that one model can provide a better prediction for each output.

The wire offset value, together with surface finish and cutting speed, have been evaluated as measurements of process performance for improved dimensional control. A model was developed that will enable one to select the optimum model that will result in maximum cutting speed while maintaining the required surface finish within limits. Additionally, the model is also capable of optimizing the machining process (under multi constraint conditions) while maintaining the surface roughness as well as the internal corner radius within specified limits. The findings of the research and the created technical guidelines in the field of γ titanium aluminide alloy machining will also contribute in the resolution of a variety of hard problems faced by manufacturing engineers in today's manufacturing sectors.

Declaration of Interest

The authors declare that there is no conflict of interest.

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