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

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Abstract

The present study focuses on γ titanium aluminide wire electrical discharge machining (WEDM). It is challenging to choose the optimal machining parameter combinations for improved cutting efficiency and accuracy in WEDM because of the many process variables and complex stochastic process processes. Generally speaking, there isn't a single ideal combination that will provide both the best surface finish quality and the quickest cutting speed. The information was chosen for this purpose from a review of the literature. The endeavor to develop an appropriate machining method for attaining the maximum process criterion yield is described in this research. Differential evolution, a stochastic optimization technique, has been used to describe the machining process. The three most significant factors that have been used as process performance indicators are cutting speed, surface roughness, and wire offset. Six distinct control parameters—pulse on time, pulse off time, peak current, wire tension, dielectric flow rate, and servo reference voltage—can be used to forecast the response characteristics. After calculating the R2, R2, and R2 values to see if the model is realistic, the potential models' constraints are examined. For the maximum cutting speed, minimal surface roughness, and minimum wire offset, the optimization values are 3.02 mm/min, 2.36 µm, and 0.13 mm, respectively. It is shown that the optimization method satisfies real-world needs and that the machining model is appropriate.

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

Introduction

Wire electrical discharge machining (WEDM) has become more popular in recent years. A variety of press tools, molds, and even electrodes for use in other EDM operations may be produced using wire EDM. Nowadays, wire EDM is widely used in almost every conductive material machining application, including the automotive, medical, and aerospace sectors. It is thought to be particularly appropriate for high precision, intricate contour machining, and materials that are difficult to remove using traditional techniques [1].

There have also been several efforts to mimic the process. A factor model has been developed by Scott et al. [2] to evaluate the process performance according to the various control circumstances. The process was further improved by adding the idea of a not-dominated point. Liao et al. [3] developed a mathematical model by using regression analysis and then addressed the optimization issue with a workable directed method. Karthikeyan et al. [4] used a complete factorial design to simulate EDM for processing carbide silicone particle composites, and the analysis of variance method was used to confirm the model's relevance. The WEDM finish-cutting process was

optimized by Huang et al. [5]. The gap width, surface roughness, and white layer depth of the machined workpiece surface are measured and assessed. The Taguchi quality design technique and numerical analysis indicate that two important factors influencing the machining performance are the pulse-on time and the distance between the wire perimeter and the workpiece surface.

In order to improve the cutting speed, surface roughness, and wire offset input parameters in wire electrical discharge processing, we used a novel technique to the modeling design-optimization process. Regression analysis and the Box-Behnken design were used to determine the proportion of outputs in this method, which was structured based on a review of the literature [6]. Multiple nonlinear neuro-regression analysis, encompassing linear, non-linear, and their rational forms for the outputs, was first thoroughly studied. Second, in order to provide realistic values, the prospective models' bounds were examined. Lastly, a rigorous implementation of stochastic search techniques was carried out.

1. Materials and methods

1.1. 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, 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, R^2 and R^2. This procedure evaluates whether the selected models satisfy the many criteria which are necessary for reality [7-9].

1.2. 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.

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/cm²)**	**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/cm²)**	**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

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

Conclusions

In the current study, γ titanium aluminide alloy was wire electrically discharged machined, and an innovative optimization technique was suggested to find the best set of control parameters. The WEDM process model is built using a stochastic optimization technique. A number of optimization models were examined during the training phase. One model has been shown to be able to predict each output more accurately. The wire offset value has been assessed as a metric of process performance for better dimensional control, together with surface polish and cutting speed. A model was created that will allow one to choose the best model that will maximize cutting speed while, within certain bounds, maintaining the necessary surface smoothness. Furthermore, the model can optimize the machining process (under multi-constraint situations) while keeping the internal corner radius and surface roughness within predetermined bounds. The study results and the developed technical recommendations in the area of γ titanium aluminide alloy machining will also help manufacturing engineers in today's manufacturing sectors solve a number of challenging issues.

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