Prediction model of recast layer thickness in die-sinking EDM process on Ti-6Al-4V machining through response surface methodology coupled with least squares support vector machine

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Abstract

Ti-6Al-4V is widely applied in frontier for its excellent properties such as a high strength-weight ratio, great heat stability and exceptional corrosion resistance. Electrical discharge machining (EDM) is suitable for machining titanium alloys, because it is the technical that removal materials by discharge energy and non-contact in processing progress. The recast layer is formed by the solidification of molten metal on the machined surface during the EDM process. In the present investigation, a hybrid approach using Least squares support vector machines (LS-SVM) and response surface methodology (RSM) for predication the recast layer thickness is proposed. Experimental plan is performed by response surface method with 20 experimental runs. The different machining parameters of pulse current, pulse on-time, and pulse off-time are selected as input factors. The white layer thickness (WLT) is response variable. The LSSVM method is applied to construct the predication model based on the orthogonal experiment swatches. The randomly 15 experimental runs were utilized to train the LS-SVM model to predict the WLT. Finally, support vector machine is used to compare with the proposed method. The proposed model can be good performance in prediction of white layer thickness of the complex EDM process.

Keywords: Electrical discharge machining, Least squares support vector machines, Response surface methodology, Recast layer

1 Introduction

Electrical discharge machining (EDM) is directly to use the electrical energy and heat energy to fabricate the workpiece. In the machining process, the material is wiped out of the workpiece just by a succession of electrical discharges occurring between the workpiece and the electrode which is not contacted with each other and produce local and instantaneous high temperatures [1]. EDM is used widely in machining special structure and complex shape parts in aerospace and nuclear sector by reason of it can machine every conductive material effectively and economically with no obvious mechanical cutting force, which has no limit on the hardness, brittleness tenacity and melting point of the workpiece material. Its typical applications include the processing of cooling holes on turbine blades and fuel nozzles [2, 3]. Because the material is removed by melting and vaporization, the resolidified/recast layer is inevitable to produce on the top surface of the workpiece by subsequently resolidifies and cools at a high rate. When the recast layer is observed by scanning electron microscope, the layer is white and can be called the white layer. It contains numerous pock marks, globules, cracks and microcracks and will influence the fatigue life of parts. Various researchers have made a great deal work to optimize and reveal the relationship between the input parameters and output parameters like metal removal rate (MRR), tool wear rate (TWR), and surface finish. However, the efforts are less concentrated towards the white layer thickness and tool wear ratio. According to the research of Ti-6Al-4V alloy machining by EDM about recast layer/white layer is less. Because of the Ti-6Al-4V alloy properties such as high strength-to-weight ratio, high temperature stability and good corrosion resistance are classified as difficult-to-cut materials [4]. However, the Ti-6Al-4V alloy is commonly used in the important industries such as aerospace; the recast layer/white layer machined by EDM will have a great effect on the finished workpiece.

Some investigations have been conducted on MRR, EW and WLT in the EDM/micro-EDM process. H. Ramasawmy [5] made an attempt to investigate the relationship between the EDM process factors (current and pulse on time) and the thickness of the white layer. It correlates the thickness of the white layer with 3D surface roughness parameters and reveals a better correlation between the average thick ness of the white layer and the spatial parameters. Ahmet [6] carried out the experiments to machine the Ti-6Al-4V with different electrode materials (graphite, electrolytic copper and aluminium) using the process parameters (pulse current and pulse

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duration). It was noted that the value of material removal rate, surface roughness, electrode wear and average white layer thickness increase accompanying with the increasing current density and pulse duration. Among the different electrode materials, the graphite electrode is best choice on material removal rate, electrode wear and surface crack density although the poorer surface finish. Unfortunately, this experiment just reveals the relationship between the average white layer thickness and the process parameters with no mathematic model. Ulas caydas and ahmet hascalik [7] made an attempt to model electrode wear and recast layer thickness through response surface methodology (RSM) in a die-sinking EDM process. Analysis of variance (ANOVA) was applied to study and pointed out the pulse current was the most important factor related to the EW and WLT, but the pulse off time is not important factor. B. Jabbaripour [8] changed the main machining parameters just as pulse current, pulse on time and open circuit voltage during EDM tests. Analysis of variance (ANOVA) was done and revealed the current and voltage have significant effect on the MRR, the current. In the same way the pulse on time, voltage and current have significant effect on the tool wear ratio. It was reported that the recast layer thickness has great relationship with the pulse energy based on pulse on time and pulse current variations. Zhang [9] performed support vector machine (SVM)/genetic algorithm (GA) to settle of the optimal micro-EDM processing (discharge pulse, pulse on time, pulse off time, capacitance, electrode rotating speed, and servo reference speed) to minimum processing time and electrode wear. It was reported that a new multi-objective optimization GA based on the idea of non-dominated sorting had a great performance on the micro-EDM processing. Tzeng and Chen [10] applied response surface methodology and genetic algorithm approach to model and optimize EDM process parameters for SKD61. Meanwhile the result had been compared with the SVM and BPNN/GA. Somashekhar [11] established the parameter optimization model to analyse the material removal of Micro-EDM by making use of the artificial neural network (ANN). The genetic algorithms (GAs) have been applied to optimize the best process parameters.

In this study, 20 experiments were carried out which was based on the design of response surface methodology, the least squares support vector machines and response surface methodology were proposed and applied to model and optimize EDM processing parameters for Ti-6Al-4V. Simultaneously, a mathematical predictive model based on the statistical learning theory was selected to predict the white layer thickness (WLT). The WLT was observed through scanning electron microscope. Finally, the comparison of the different approaches of LS-SVM/RSM and SVM were also conducted.

2 Description of the experimentation

2.1 MATERIAL

Ti-6Al-4V is a widely material applied to the aerospace, automotive and biomedical for its excellent properties in mechanical and thermal. The composition of the Ti-6Al-4Vis89.464wt%Ti, 6.08wt%Al, 4.02wt%V, 0.22wt%Fe, 0.18wt%O, 0.02wt%C, 0.01wt%N, 0.053wt%H. The hardness of Ti-4Al-6V is 600, the yield strength of it is 745MPa and elastic modulus is 113GPa.

2.2 EXPERIMENTAL INSTALLATIONS

The series of experiment were performed on a die-sinking EDM machine of type MITSUBISHI ELECTRIC-EX22 shown in Figure 1 and the model was FP60E of 8.7 KVA machine unit input. The electrode was made of a pure cylindrical copper (99.9% Cu) rod 500 μm in diameter and 15 mm in height, which machined was shown in Fig.2, and Commercial grade EDM oil (specific gravity = 0.763, freezing point $= 94^{\circ}C$) was used as a dielectric fluid.

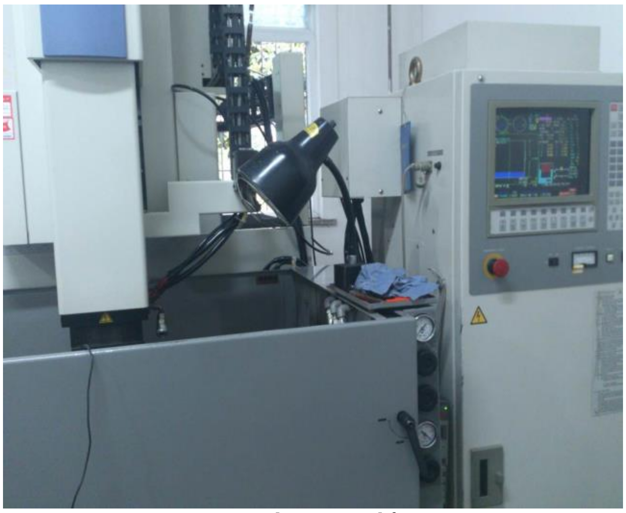

FIGURE 1 Experimental set-up used for experimentation

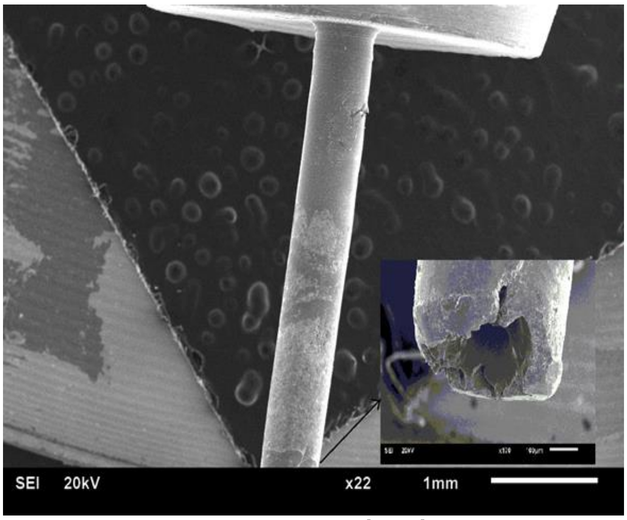

FIGURE 2 Copper electrode

2.3 EXPERIMENTAL PARAMETERS AND DESIGN

The white layer thickness produced by the EDM is mainly affected by the process parameters like discharge current, pulse on time and pulse off time. The proper selection of the process parameters which include the lower discharge current and longed pulse on time can cause a less recast layer thickness. In this study, experiments were planned using face-centred design with three variables that is based on a response surface methodology. The design of machining parameters and their levels for the CCD used was shown in Table 1. The pulse on time (t_i), pulse off time (t_s) and discharge current (I_p) were selected as the input parameters for the EDM process.

TABLE 1 Design scheme of machining parameters and their levels

Parameters	Unit	Symbol	Levels		
			-1	0	1
Pulse on time(t_i)	μs	X_1	32	64	96
Pulse off time(t_s)	μs	X_2	64	96	128
Discharge current (I_p)	A	X_3	3	6	9

2.4 RESPONSE VARIABLES EVALUATION

The white layer thickness after the EDM operation was observed using scanning electron microscope (JSM-7500F) with high magnification. The average thickness is measured by the image process software (Image-Pro version 6.0). The average white layer thickness is calculated at 34.20 μm in Fig.3.

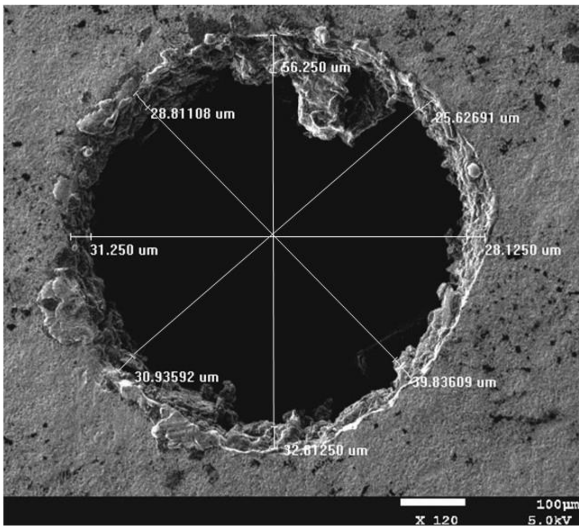

FIGURE 3 Micro-holes corresponding to $I = 9A$, $t_s = 128\mu s$ and $t_i = 96\mu s$

3 Analysis method

3.1 EXPERIMENTAL DESIGN WITH RSM

The response surface method is by constructing a clear form of implicit polynomials to approximate expression function, which use a limited test by regression analysis to fit the analytical expression to replace the real response surface. Response surface method is an interaction of mathematical and statistical techniques for modelling and analysis of machining parameters in the EDM process which contains the discharge current, pulse on time and pulse off time in order to obtain the relationship to the WLT. In this study, the central composite design (CCD) is used to finish the experimental design.

In general, the response of the system and design factors $(x_1, x_2, \cdots, x_n)$ can be represented as following:

$$y = f(x_1, x_2, \cdots x_n) + \varepsilon , \tag{1}$$

where y is the response of the system, f is the response function (or response surface), $x_1, x_2, \cdots x_n$ are the independent input variables and ε is the fitting error. In present, most of all use the quadratic model to demonstrate the second-order effect of each variable and the two-way to find the interaction between combinations of these design factors. The quadratic model of y can be written as follows:

$$y = \alpha_0 + \sum_{i=1}^{n} \alpha_i x_i + \sum_{i=1}^{n} \alpha_{ii} x_i^2 + \sum_{i<j}^{n} \alpha_{ij} x_i x_j + \varepsilon , \tag{2}$$

where α_0 is constant, α_i, α_{ii} and α_{ij} are the coefficients of linear, quadratic and cross product terms, respectively. For three variables (n=3), the experimental runs number is 20, which consists 2^3 factor points, 6 axial points and six centre points. Table 2 shows that the central composite design composes three input variables; X_1 (Pulse on time), X_2 (Pulse off time) and X_3 (Discharge current).

TABLE 2 Design layout and experiment results

Run	Coded factors			Actual factors			
	X_1	X_2	X_3	t_i	t_s	I_p	WLT_{actual}
1	0	0	0	64	96	6	14.64
2	-1	1	1	32	128	9	28.67
3	1	-1	1	96	64	9	31.24
4	1	0	0	96	96	6	16.24
5	0	0	-1	64	96	3	13.04
6	0	-1	0	64	64	6	14.33
7	1	-1	-1	96	64	3	13.22
8	1	1	-1	96	128	3	15.93
9	0	0	0	64	96	6	14.64
10	0	0	0	64	96	6	14.64
11	0	0	1	64	96	9	29.90
12	0	1	0	64	128	6	20.01
13	0	0	0	64	96	6	14.64
14	0	0	0	64	96	6	14.64
15	-1	-1	-1	32	64	3	11.16
16	0	0	0	64	96	6	14.64
17	-1	1	-1	32	128	3	13.78
18	1	1	1	96	128	9	34.20
19	-1	-1	1	32	64	9	28.40
20	-1	0	0	32	96	6	13.96

3.2 DATA ANALYSIS USING RSM

The design expert software (version 7.0.0) is used to design and analysis the process parameters of the response equation, and subsequent analysis of variance (ANOVA) was assessed. In this study, the analysis of variance (ANOVA) is utilized to summary the above tests performed and analyse the results of the experimental runs. As per this technique, the response variable WLT was evaluated by the F-test of ANOVA shown in Table 3, respectively. The model should be considered to be significant when the p-values were less than 0.05 and 0.001 when using 5% and 1% significance levels. In the Table 3, the p-values are less than 0.05 which indicate that the model for WLT is significant. In the same way, the effect of the discharge current, pulse on time and pulse off time were significant which can be seen in the Table 3. It can be seen that the effects of X_1, X_2, X_3, X_2^2 and X_3^2 were statistically significant. In the model WLT, the discharge current (X_1) played the important role in the machining process.

TABLE 3 Analysis of variance for WLT (RLT)

Source	Sum of squares	Degrees of freedom	Mean square	f-value	Prob.>F	
Model	1006.58	9	111.84	129.10	<0.0001	significant
X_1	22.08	1	22.08	25.49	0.0005	
X_2	20.28	1	20.28	23.41	0.0007	
X_3	727.27	1	727.27	839.50	<0.0001	
$X_1 X_2$	0.97	1	0.97	1.12	0.3158	
$X_1 X_3$	2.16	1	2.16	2.50	0.1451	
$X_2 X_3$	0.55	1	0.55	0.64	0.4436	
X_1^2	0.46	1	0.46	0.53	0.4847	
X_2^2	7.60	1	7.60	8.78	0.0142	
X_3^2	97.77	1	97.77	112.86	<0.0001	
Residual	8.66	10	0.87			
Lack of fit	8.66	5	1.73			
Pure Error	0.000	5	0.000			
Correlation total	1015.25	19				
R^2=0.9915						

3.3 LEAST SQUARES SUPPORT VECTOR MACHINES (LS-SVM)

As a new learning machine, Support Vector Machine based on statistical learning theory proposed by Vapnik [12] is known as an excellent tool for the classifying regression problems of good generalization. In the following, the learning theory has been developed by many researchers and it has various types and Least square support vector machine (LS-SVM) is widely used in the pattern recognition and nonlinear regression. In this paper, we briefly introduce the principle of LS-SVM:

For a given training set of S data points $\{x_k, y_k\}_{k=1}^{l}$, $x_k \in R^m$, $y_k \in R$, x_k is the input data and y_k is the output data. A nonlinear function φ is utilized to map the input data x to high dimensional feature space G and linear approximation in this space. By statistical theory, this function can be written as follow:

$$f(x) = w^T \varphi(x) + b\,. \tag{3}$$

In Equation (3) where w is weight vector and b is deviation value.

LS-SVM utilizes the quadratic loss function to transform the inequality constraints to equality constraints. Then the following optimization problem is formulated:

$$\min J(w,e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{k}^{n} e_i^2\,, \tag{4}$$

$$\text{s.t. } y_i = w^T \varphi(x_i) + b + e_i \quad i = 1, 2, \cdots n\,, \tag{5}$$

where the regularization factor is γ and e_i is the difference between the desired and the actual output.

In order to solve this constrained optimization, a Lagrangian is constructed:

$$L(w,b,e,a) = J(w,e) - \sum_{i=1}^{p} (w^T \varphi(x_i) + b + e_i - y_i)\,, \tag{6}$$

where α_i is Lagrangian multiplier.

According to the optimization theory, the conditions are given by:

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0, \to w = \sum_{i=1}^{p} \alpha_i \varphi(x_i) \\ \dfrac{\partial L}{\partial b} = 0, \to \sum_{i=1}^{p} \alpha_i = 0 \\ \dfrac{\partial L}{\partial e_i} = 0, \to \alpha_i = \gamma e_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \to w^T \varphi(x_i) + b + e_i - y_i = 0 \end{cases}, \tag{7}$$

From Equation (7), the following linear equations can be obtained after elimination of the variables w and e:

$$\begin{bmatrix} 0 & \vec{1}^{T} \\ \vec{1} & \Omega+\gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ a \end{bmatrix}=\begin{bmatrix} 0 \\ y \end{bmatrix}, \tag{8}$$

where $y=[y_1,\cdots y_n]^T$, $\vec{1}=[1,\cdots,1]^T$, $\alpha=[\alpha_1,\cdots,\alpha_P]^T$, $\Omega_{ij}=\varphi(x_i)^T\varphi(x_j)=K(x_i,x_j)$, $i,j=1,2,\cdots,p$.

The resulting LS-SVM model can be evaluated as follows:

$$f(x)=\sum_{i=1}^{p}\alpha_i K(x_i,x_j)+b, \tag{9}$$

where b and α_i are the solutions to Equation (8) and $K(x_i,x_j)$ is the kernel function which meet Mercer condition. In LS-SVM, the kernel function is different and has many choices. In this work, the radial basis function (RBF) is selected as the kernel function with its stronger learning ability.

RBF kernel functions as follows:

$$K_{RBF}(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right), \tag{10}$$

where σ^2 is the kernel function parameter.

3.3.1 Data pre-processing

Data pre-processing is the method of transferring the original sequence to a comparable sequence which method is applied to cancel the difference of the orders of magnitude. After data pre-processing, the data is adjusted to between a range of 0 and 1. In general, the data normalizations include two kinds. In this study, the origin data is normalized as in the Equation (11).

The larger-the-better

$$x_k=\frac{x_k-x_{\min}}{x_{\max}-x_{\min}}, \tag{11}$$

The mean variance method

$$x_k=\frac{x_k-x_{mean}}{x_{\mathrm{var}}}. \tag{12}$$

3.3.2 The LSSVM regression model establishment and test

In order to establish the LS-SVM regression model, the Matlab software (version R2012b) is used to estimate the LS-SVM model. Hence, the mathematical modelling of EDM process is needed. Many empirical, statistical and regression techniques have been used in literature [13-16]. The data pre-processing and normalization are very important for training and testing. The 15 groups are randomly selected as the training data and used to establish the training model and the remaining 5 groups are adopted as the testing samples. When the regression model is applied to model the EDM machining process, the kernel function should be selected firstly which can be suitable for the nonlinear and complex EDM process. In this paper, the Gaussian function kernel is chosen as the kernel function which has better performance comparing with the other linear kernel. The Gaussian function is expressed in Eq.8 which has less hypermeter that influences the complexity than the polynomial kernel. The predict data after the LS-SVM model is reversed to origin data. In order to make the LS-SVM has great performance; the best set of hyperparameters such as γ and σ^2 are found by using the grind search and leave-one-out cross-validation method [17, 18] where γ is the regularization parameter and σ^2 is the kernel function parameter. The mean squared error is adopted as the model error by using leave-one-out method. The evaluation function correlation coefficient R^2 is utilized to discuss the predict accuracy of the LS-SVM model.

$$MSE=\frac{\sum_{i=1}^{N}e_i^2}{N}, \tag{13}$$

$$R^2=1-\sum_{i=1}^{N}\left(\frac{Y-X}{X}\right)^2, \tag{14}$$

where the N is the experimental number, Y is the testing data and X is the predict result of the model.

After repeated tests, the regularization parameter γ and the kernel function parameter σ^2 are chosen as 43201.2 and 120.764 for the LS-SVM model by using the proposed parameter chosen method. Then the LS-SVM model is trained by using training data and the remaining 5 groups is selected as the testing data. The experimental white layer thickness is compared with the LS-SVM model predict result in Figure 4. That $MSE=4.55653$ and $R^2=0.997029$. The comparison results between the original and predict values are shown in Table 4. From the Table 4, the trained LS-SVM model has small output errors and can correctly reflect the causality between inputs and outputs. Comparing with the RSM method, the R^2 can reflect the LS-SVM method having great performance.

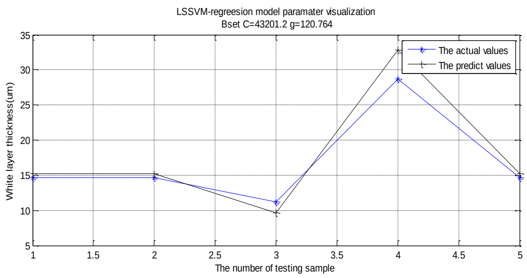

FIGURE 4 The predicted white layer thickness versus the actual white layer thickness

TABLE 4 LSSVM model test result using the remaining five groups of parameter combinations

Initial no	t_i	t_s	I_p	WLT_{actual}	$WLT_{predicted}$	Residual
1	64	96	6	14.64	15.23	-0.59
9	64	96	6	14.64	15.23	-0.59
15	32	64	3	11.16	9.65	1.51
17	32	128	9	28.67	32.84	-4.17
10	64	96	6	14.64	15.23	-0.59

4 Result and discussion

4.1 OBSERVATION OF THE MACHINED MICRO-HOLE

Figure 5 and 6 show the micrographs in the 120 magnification that can be observed the micro-hole finish of Ti-6Al-4V after EDM processing. Figure 5 displays the micro-hole finish under the EDM with a discharge current of 9A, a pulse on time of 32 μs and a pulse off time of 128 μs. Similarly, Fig. 6 displays the micro-hole finish under the EDM with a discharge current of 9A, a pulse on time of 64 μs and a pulse off time of 96 μs.

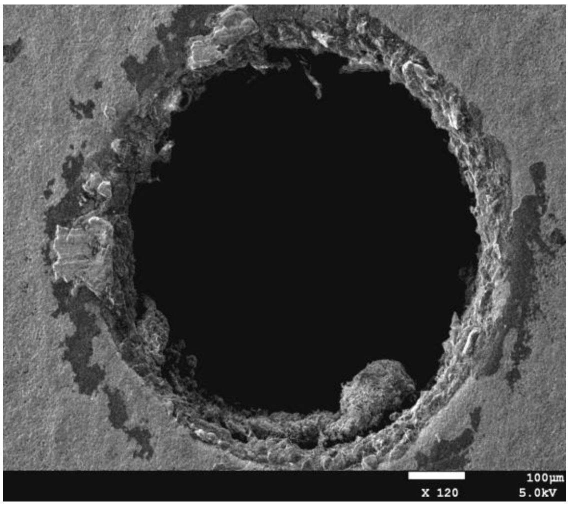

FIGURE 5 Micro-holes corresponding to $I=9A$, $t_s=128\mu s$ and $t_i=32\mu s$

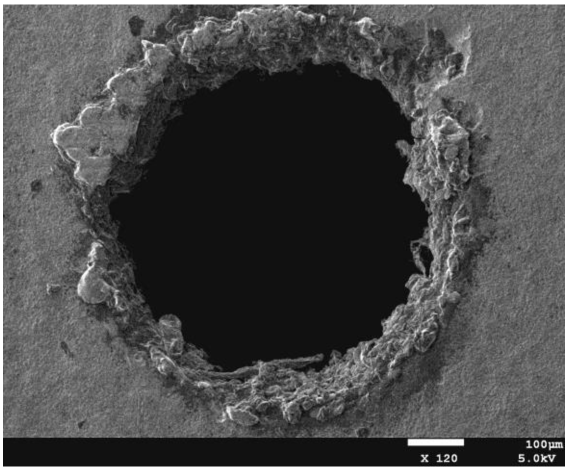

FIGURE 6 Micro-holes corresponding to $I=9A$, $t_s=96\mu s$ and $t_i=64\mu s$

4.2 COMPARING WITH SINGLE SUPPORT VECTOR MACHINE

According to the data in the Table 2, the SVM is applied to model the nonlinear EDM processing and the Gaussian function kernel is selected as kernel function. K-fold Cross Validation (K-CV) is employed to select the best set of hyperparameters such as C and g. In the K-CV method, the training set has been divided to groups. Each subset is selected as the validation set and the remaining set as the test set. Basic pairs of (C and g) are tried and the best coefficient and are chosen as 2.8284 and 0.0625 after repeated tests. The selection result of the SVR parameter (3D view) is shown in Figure 7. For example, the growing sequences of adjustment parameters as:

$$C=e^{-4},e^{-2},\cdots,e^{4} \quad g=e^{-4},e^{-2},\cdots,e^{4}, \tag{15}$$

The MSE is selected as the evaluation index as in the Equation (13) and the evaluation function correlation coefficient R^2 as in the Equation (14).

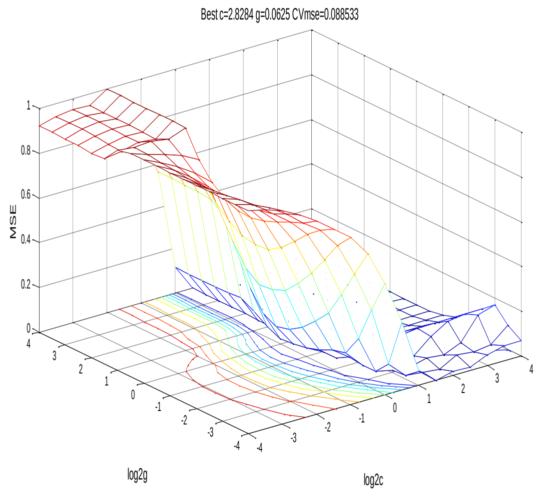

FIGURE 7 The result of SVR parameters (3D view)

When the training model of WLT is finished, the remaining random 5 groups of processed data is applied to test the performance of the model. The comparison result between the original and test values are shown in Figure 8, in which the MSE is 0.14742 the R^2 value is 0.89136.

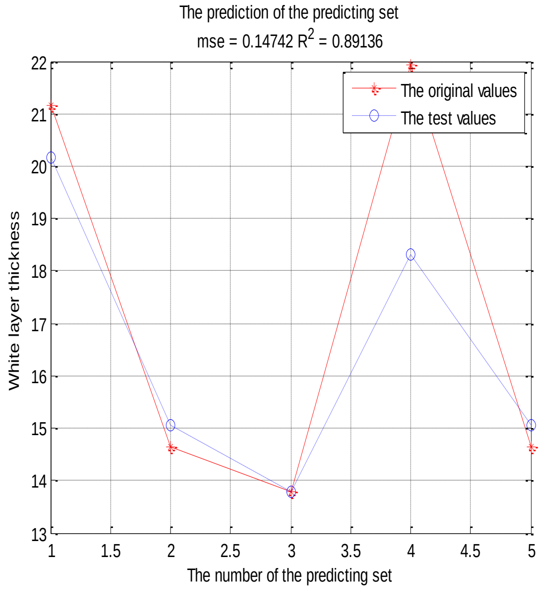

FIGURE 8 The comparison of the original and test values

4 Conclusions

In this study the white layer thickness in the die-sinking EDM process on Ti-6Al-4V was predicted by response surface methodology coupled with least squares support vector machine for the machining parameters. According to the implementation results obtained in the illustrative example, the conclusions are as follows:

1 Response surface methodology is utilized to design the economical experiment and ANOVA indicated that the EDM parameter of discharge current is the most significant factors for white layer thickness. According to the result, the discharge energy increasing lead to the white layer thickness increased. Accompany with the increasing discharge current, the removed material from the machined surface is more when the pulse on time is a constant. The value of the pulse on time increase leading to the WLT increasing because of more discharge energy is transformed to surface of workpiece during a single pulse. The pulse off time is significant and the reason will be that the flushing away by dielectric fluid the less volume of molten particles are re-solidified that leads to induce of WLT when the value of the pulse off time increasing.

2 The LS-SVM is found to give reasonably good prediction accuracy for WLT in the die-sinking EDM machining on the Ti-6Al-4V with the pure cylindrical copper electrode. It gives better prediction results in the experimental runs than just using the SVM method. The LS-SVM model, the predict accuracy is better.

3 According to the LS-SVM model, the result can express the higher discharge current can lead to the higher white layer thickness .However, the longer pulse off time can lead to the lower white layer thickness.

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