Advances in Technology Innovation, vol. 4, no. 4, 2019, pp. 211-221

An Intelligent Optimization System of Micro Electroforming Process for the Mesh Filter

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Received 12 April 2019; received in revised form 19 May 2019; accepted 17 July 2019

Abstract

This research integrates the Taguchi method, analysis of variables (ANOVA), back-propagation neural networks (BPNN), and hybrid PSO-GA to develop an intelligent optimization system of micro electroforming process for the mesh filter. From the outset of discussions with engineers in terms of past related literature survey of the micro electroforming process, the quality characteristics of product and control variables can be well ascertained, then transforming the problem of multiple quality characteristics into a single quality characteristic via the Taguchi method and ANOVA. However, the optimal parameter settings (solution) through the Taguchi experimental planning is still belong to a discrete optimal solution which is impossible to meet the process stability and quality goals. Therefore, this study first identifies the initial weight of BPNN，using hybrid PSO-GA with multilayer perceptron (MLP)，in order to improve training efficiency and precision of BPNN. Furthermore, the study constructs the signal-to-noise (S/N) ratios (BPNNS/N) and quality predictors (BPNNQ) based on hybrid PSO-GA and BPNN with the experimental data. The optimal parameter settings are obtained through a combination of BPNNS/N and BPNNQ with modified PSO-GA. Finally, confirmation experiments are performed to assess the effectiveness of the proposed system. The results show that the proposed system can create the best performance, and the optimal parameters not only enhance the stability in the micro electro forming process but also effectively improve the product quality.

Keywords: Taguchi method, BPNN, PSO-GA, micro electroforming, MLP

1. Introduction

Recently the technology of micro electroforming process has been widely used, and The mesh process can be mainly divided into the photolithography process and the micro electroforming process, having been widely used recently. And the process parameter control directly affects product quality and cost. The photolithography process consists of three main components: coating photoresist, exposure, and development. In order to obtain higher resolution, some baking and cooling steps are also adopted in the photolithography process. In the current technology, of photolithography process, entirely seven steps are required in the process: cleaning the substrate, pre-baking, coating the photoresist, soft-baking, exposure, development, and hard-baking. When the photolithography process parameters are not well controlled, defects such as the

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excessive image size variation, poor transfer rate, and even transfer failure may occur; therefore, the photoresist must be stripped and the previous process repeated until the inspection is completed. Then, the semi-finished mold core formed by photolithography is subjected to a micro-electroforming process. The micro electroforming process consists of five main components: electroforming, photoresist stripping, finished stripping, cleaning and hard baking. As to the current technology of electrochemical micro-electroforming process for making molds, when the process parameters are not well controlled, problems such as the product forming failure and excessive size variation will be directly caused and hence the loss due to the fact that the product will not pass the quality inspection and cannot be reworked. Therefore, to improve yield and reduce cost, the parameter setting of the micro electroforming process control factors are even more important.

Since the micro electroforming process can be applied to a variety of materials, and there are many types and formulations of chemical electroforming fluids, many scholars are devoted to studying the interaction between various chemical electroforming fluids and materials and the related physical phenomena in the process [1-8]. However, through the analysis of the materials, a suitable combination of electroforming liquid and materials, a better process and product quality, and the better process parameters combination all can be obtained. If an inappropriate combination of process parameters is used, it can lead to product defects and excessive process variations. In the past, some scholars adopted the Taguchi experimental design method to explore the correlation between process parameters and quality [9-11].However, the Taguchi experimental design is a discrete method for solving single quality characteristics, and only the local optimal solution of the pre-selected parameter level can be obtained specific to a single quality characteristic, but not the global continuous optimal solution. Therefore, it is necessary to combine the experimental design, smart predictors and applications of related theories for optimization to search for the best combination of process parameters by numerical simulation and prediction[12-14].The above studies only focused on optimizing the process parameters for product quality characteristics, but they did not assess the stability of the process in the micro electroforming process. Therefore, this study proposes an intelligent optimization system to find optimal process parameters of multiple quality characteristics in the micro electroforming process. Firstly, the Taguchi method is used to determine the best combination of parameter settings by calculating the signal-to-noise (S/N) ratio from the experimental data. The highest S/N ratio value is employed to decide the best settings for quality responses. Significant factors are determined through Analysis of Variance (ANOVA). The S/N ratio predictor (BPNNSN) and quality predictor (BPNNQ) are constructed by BPNN. In the first stage optimization, BPNNS/N is coupled with GA in order to minimize the variations of the process. In the second stage optimization, the optimal parameter settings are obtained via a combination of BPNNS/N, BPNNQ and hybrid GA-PSO. Finally, two confirmation experiments are conducted to assess the effectiveness of the proposed intelligent optimization system. This study focuses on not only the optimal process parameters to improve the multiple qualities, but also the stability of the process to enhance the productivity. The research has been motivated by the current development of AI, Big Data, internet of things (IoT) and cloud computing worldwide in general, which especially play their important roles in the future industrial automation systems.

2. Research Methodologies

In this study, an intelligent optimization system is proposed for the micro electroforming process of the mesh filter. The research integrates the Taguchi method, ANOVA, BPNN, the improved hybrid PSO-GA, statistical process control and other related technologies to obtain the optimization for multi-objective micro-electroforming process. And it has enabled product quality to be maintained within acceptable quality ranges and made the micro electroforming process more stable.

Firstly, based on the literature reviews and discussions with engineers on the influence of process parameters to their quality characteristics, the control parameters and level are selected for the Taguchi orthogonal table experiment. Then the electroforming experiment is proceeded in the customized electroforming tank for the research. The micro electroforming workpiece is the mesh filter. In order to ensure that the product can be supplied to the manufacturer's required size specifications, a discussion with the manufacturer is proceeded, obtaining a product diameter of 555±3μm and a deviation of quantity specification within 5% of the product thickness. Therefore, the quality characteristics are set to the diameter roundness and thickness uniformity. After literature reviews and discussions with a number of experts and engineers, the control factors selected for the experiments are the temperature of the electroforming liquid, current density, cathode size, the distance between the anode and the cathode, and oscillating rate. To acquire more accurate data, the study has to consider the lesser number of experimental control factors and standards, so the Taguchi L_{18} (2^1 x 3^4) orthogonal table is used for the experiment, in which the temperature of the casting liquid is set at two levels and the remaining control factors are set at three levels. However, the Taguchi experimental design is a discrete method for solving single quality characteristics, and only the local optimal solution of the pre-selected parameter level can be obtained specific to a single quality characteristic, but not the global continuous optimal solution. In addition, since the combination of process parameters obtained from the Taguchi experimental planning cannot meet both the stability of the micro electroforming process and the best quality of the product, a two-stage optimization must be carried out.

The first stage is to obtain the measurement data of the diameter and thickness of the mesh filter by experiments. Next, for the Taguchi data analysis, the problem of multi-objective quality characteristics needs to be transformed into a single quality characteristic, so that the based-on data can be further analyzed accordingly. The data analysis includes factor response graph analysis and variance analysis, and the relationships between the S/N ratios and the quality characteristics of the experimental control factors can be known. Using the S/N ratio factor reaction map, we can find important control factors that have a significant impact on the quality characteristics and classify the control factors to optimize the two steps of the Taguchi process. Firstly, the step uses the first type factor to modulate the S/N ratios to the maximum value for the purpose of reducing the process variation. Secondly, the step adjusts the second type of factor level to approximate the average value of the quality characteristic to the target value. Finally, the third type of factor is used to reduce production costs. Based on the steps, a set of optimal process parameters of Taguchi can be obtained, which can be used as the initial value of the optimization of the second stage. Through the factor response analysis and the analysis of the variance, the significant control factors found will be adjusted as the basis of the subsequent solution parameters.

In the second stage, the parameter combination obtained by the Taguchi experimental planning is used as the basis to establish the S/N ratio predictor (BPNNS/N) and quality predictor (BPNNQ). However, the initial weight value of the BPNN is often generated in a random manner, and the initial weight value affects the network training speed and prediction accuracy; therefore, this study uses the improved hybrid PSO-GA combined with multilayer perceptron (MLP) to obtain and preserve the initial weight required for BPNN. This method not only improves the training speed of BPNN, but also increase the predictive power of it. In this stage, the process parameter combination obtained in the first stage is used as the initial value, and the S/N ratio predictor and the quality predictor are combined with the hybrid PSO-GA for global search to find the process parameters that best meet the quality specifications and the most stable quality. The mesh microstructure diameter size target is 555 μm, and the acceptable thickness deviation is within 5%. For the diameter roundness, the measurement method is divided into twenty areas, as shown in Fig. 1. The measurement of five points in each area is averaged, thus the measurement can better determine the exact roundness of diameter. Formula for roundness is as shown in Eq. 1.For the thickness uniformity, the measurement method is divided into 20 points for the inner and outer regions, as shown in Fig. 2, taking the percentage of thickness deviation inside and outside.

$$\mathrm{D}=\frac{1}{20\times 5}\times\sum_{i=1}^{20}\sum_{j=1}^{5}\mathrm{D}_{ij} \tag{1}$$

D_{ij} is the measured value of the mesh microstructure diameter; D is the diameter roundness of the mesh quality characteristics; measuring area has 20 measuring points in five zones; and j is the number of measuring points. The main purpose of this study is to find out the optimal process parameter combination of the micro electroformed mesh, so that its quality is within the desired range, and the product tends to stabilize and reduces the non-performing rate. The thickness uniformity is shown as Eq. 2.

$$\mathrm{T} = \frac{1}{T_{Max} - T_{Min}} \cdot \frac{1}{4 \times 5} \times \sum_{i=1}^{4} \left| \sum_{j=1}^{5} TO_{ij} - \sum_{k=1}^{5} TI_{ij} \right| \tag{2}$$

T is the thickness uniformity of the mesh quality characteristics as shown in Equation 2. The maximum thickness measurement value is T_{Max} =*Max* (TO_{ij} , TI_{ij}); the minimum value is T_{Min} =*Min* (TO_{ij} , TI_{ij}); TO_{ij} is the thickness measurement of the outer ring; TI_{ij} is the thickness measurement of the inner ring; *i* is the measuring area; and *j* is the number of measurement points.

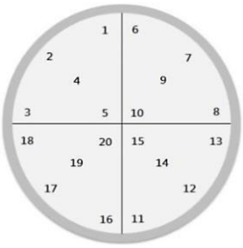

Fig. 1 Schematic diagram of mesh diameter measurement

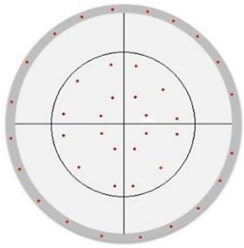

Fig. 2 Schematic diagram of mesh thickness

3. Results and Discussion

3.1. Taguchi Experiment

In this study, the micro electroforming product is the mesh filter. In order to ensure that the product can be supplied to the manufacturer's required size specifications, a discussion with the manufacturer is proceeded, obtaining a product diameter of 555±3μm and a deviation of quantity specification within 5% of the product thickness. The quality characteristics are diameter roundness and thickness deviation. In addition, the experimental control factors are defined as following five experimental control factors: temperature of the electroforming liquid (TL) (℃), current density (CD) (A/ dm^2), cathode size (CS) (dm^2), the distance between the anode and the cathode (DAC) (cm), and oscillating rate (OR) (rate/min). The range of adjustment parameters and the control factor level settings are shown in Table 1. The five experimental control factors in this study uses $L_{18}(2^1 \times 3^4)$ orthogonal table. As shown in Table 2, the micro electroforming is performed on a customized experimental machine, and the data of the diameter roundness and the thickness deviation are obtained by measurement, and the S/N ratios are calculated. The diameter roundness adopts the first type formula of the eyesight characteristic, and the thickness deviation adopts the small characteristic formula. 18 groups from No.1 to No.18 are the Taguchi experimental data; 5 groups from No. 19 to No. 23 are randomly generated. For the quality characteristic of diameter, the equation of Type I formula of the nominal-the-best is used as shown in Eq. 3. As for a deviation of quantity specification within 5% of the product thickness, the smaller-the-better is used as shown in Eq. 4. The experimental product is shown in Fig. 3.

$$S/N = -10\log\frac{\sum_{i=1}^{n}(y_i - m)^2}{n} = -10\log[(\bar{y} - m)^2 + S^2] \tag{3}$$

$$S/N = -10\log\frac{\sum_{i=1}^{n} y_i^2}{n} = -10\log(\bar{y}^2 + S^2) \tag{4}$$

where y_i is the response value of a specific treatment under I replications, *n* is the number of replications, $\bar{y}$ is the average of all y_i values, and *S*is the standard deviation of all y_i values.

Table 1 Showing different crystal growth methods, growth time and approximate sizes of the grown crystal

Experimental control factors	Range	Level 1	Level 2	Level 3
TL	40-50	40	50	-
CD	1-5	1.00	3.00	5.00
CS	1-4	1.00	2.25	4.00
DAC	9-12	9.0	10.5	12.0
OR	20-52	20	36	52

Table 2 The results of the diameter and thickness deviation of the Taguchi experiment

No	**Average diameter (X) (μm)**	**Thickness deviation (Y) (%)**	**σ(X)**	**σ(Y)**	**S/N ratiofor X**	**S/N ratio for Y**
1	554.310	0.0237	0.1114	0.0018	3.1114	32.4771
2	554.447	0.0303	0.2542	0.0017	4.3085	30.3453
3	555.780	0.0271	0.1100	0.0020	2.0726	31.3317
4	554.330	0.0139	0.2128	0.0016	3.0610	37.0848
5	554.837	0.0315	0.1332	0.0015	13.5251	30.0174
6	555.117	0.0295	0.0907	0.0020	16.6066	30.5767
7	553.903	0.0106	0.1570	0.0022	-0.8895	39.2921
8	555.467	0.0326	0.1986	0.0025	5.8971	29.7218
9	555.347	0.0292	0.1986	0.0019	7.9694	30.6632
10	554.257	0.0171	0.2194	0.0012	2.2136	35.3380
11	554.690	0.0308	0.3568	0.0019	6.5092	30.2133
12	555.700	0.0303	0.0954	0.0024	3.0181	30.3316
13	554.380	0.0081	0.1153	0.0018	4.0044	41.6647
14	554.807	0.0391	0.1069	0.0012	13.1148	28.1516
15	555.067	0.0303	0.1097	0.0024	17.8310	30.3329
16	553.923	0.0072	0.1222	0.0014	-0.6972	42.6330
17	554.577	0.0321	0.1914	0.0023	6.6586	29.8436
18	554.833	0.0367	0.2775	0.0024	9.7959	28.6889
19*	554.767	0.0282	0.1168	0.0016	11.6699	30.9735
20*	555.550	0.0219	0.2117	0.0012	4.5930	33.1608
21*	555.107	0.0408	0.1570	0.0020	14.4356	27.7712
22*	554.740	0.0359	0.1153	0.0024	10.9205	28.8752
23*	553.997	0.0074	0.2084	0.0019	-0.2124	42.3435

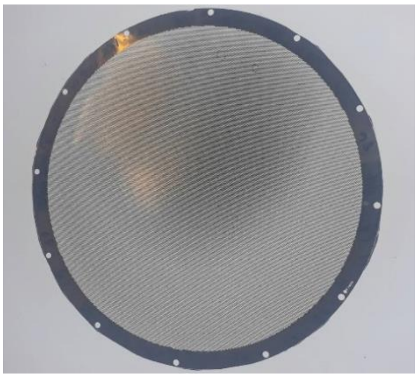

Fig. 3 The experimental product

3.2. Variation of pH value in the water storage tank

This study aims to find an optimal combination of process parameters that meet the multi-objective quality. However, Taguchi's experimental design belongs to a single quality response and discrete optimization method, and only can derive local optimal solution of pre-selected parameter level value for a single quality characteristic. Therefore, it is necessary to first transform and integrate the problem of multiple quality objectives of diameter and thickness deviation into a problem of single quality objective, and then to conduct subsequent data analysis based on the experimental data. Data analysis includes factor response analysis and ANOVA in order to understand the relationships between experimental control factor pairs of S/N ratio and quality characteristics. S/N ratio response chart can identify important control factors with more significant effects on S/N ratios, while the use of quality characteristics response chart can screen control factors with more significant effects on quality characteristics. The Taguchi optimization process parameter combination can be used as the initial value for subsequent optimization, while the significant control factors found by factor response analysis and ANOVA are chosen as the basis for adjusting the process parameters for subsequent optimization. The method is to integrate the individual offsets of the quality characteristics of the diameter and thickness deviation into a total offset to achieve a single target quality. The calculation of the integrated diameter and thickness deviation into a single target quality is as follows [15]:

(1) The calculation of the total offset

Taking the Taguchi experimental product as an example, the diameter size of the experimental product is measured as X, and the target value of the quality characteristic is 555μm, so the diameter offset is X-555μm; The thickness deviation measurement is Y, and the target value of the quality characteristic is 0%, so the measured value is the thickness deviation offset. Thus, the same measurement unit (X-555) and Y are assumed to be two vectors, so the vector sum Z is its total offset. The calculation is as follows:

$$\text{Total offset } Z = ((X - 555)^2+Y^2)^{1/2} \tag{5}$$

(2) The calculation of the total standard deviation

In the Taguchi experiment, if the standard deviation of a certain group of diameter is σ(X), and the standard deviation of thickness is σ(Y), then the total standard deviation σ(X+Y) is as follows

$$\sigma(X+Y) = \sqrt{\sigma^2(X)+\sigma^2(Y)+2\cdot\operatorname{cov}(X,Y)} \tag{6}$$

(3) Conduct factors response analysis via ANOVA and main effects plot

The S/N ratio response factor table of integrating into a single quality and the main effects plot for S/N ratios of total bias are demonstrated in the study. The factor response chart shows that a set of Taguchi optimal process parameter combination can be obtained to meet the multiple quality characteristics. This study will denote the minimum process variation and optimal quality characteristic, and the optimal parameter combination of Taguchi experiment and ANOVA.

Table 3 ANOVA of the total offset - quality characteristics

	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution	Significant
TL	1	0.00999	0.00999	0.00999	0.34	0.578	0.64%	No
CD	2	0.39617	0.39617	0.19808	6.67	0.020	25.40%	Yes
CS	2	0.78652	0.78652	0.39326	13.24	0.003	50.42%	Yes
DAC	2	0.07188	0.07188	0.03594	1.21	0.347	4.61%	No
OR	2	0.05761	0.05761	0.02880	0.97	0.420	3.69%	No
Error	8	0.23764	0.23764	0.02971	-	-	15.24%	-
Total	17	1.55980	-	-	-	-	-	-
S = 0.172352, R-Sq = 84.76%, R-Sq(adj) = 67.62%								

This integrated diameter and thickness deviation offset becomes the total offset, which is a quality characteristic of single target quality. Since the smaller the value is, the better the result will be, the S/N ratio chooses the smaller-the-better formula. For the ANOVA of the total offset of quality characteristics, the significant influence factors are selected according to the contribution. First, the two control factors of cathode size (50.42%) and current density (25.40%) are spotted, as shown in Table 3. The above two control factors have a significant influence on the quality characteristics and can provide the basis for subsequent optimization of the adjustment process parameters. The optimal parameter combination of the Taguchi method is shown in Table 4.

Table 4 Optimal parameter combination

Optimal Parameter	TL	CD	CS	DAC	OR
	50	3.00	4.00	9	20

3.3. Using MLP combined with hybrid PSO-GA to find the initial weight of BPNN

As a consequence of using the Taguchi experimental analysis, the optimal combination of parameters obtained is the discrete parameter combination established by the original Taguchi experimental design, and the quality may not reach the target value. Therefore, the research uses the backpropagation neural network (BPNN) to construct the S/N ratio predictor and quality predictor, combining the improved hybrid PSO-GA optimized in this study. Moreover, in terms of the Taguchi experimental analysis, the optimized combination of parameters is used as the initial value of the algorithm search. Furthermore, it is hoped to find a set of continuous type of best combination of parameters that can achieve process stability and quality objectives. However, when the traditional BPNN is in sample training, the initial weight is often generated randomly, and it will affect the training speed and accuracy of the neural network. Therefore, this study proposes to use the improved PSO-GA combined with MLP to solve the initial weight value of BPNN and to find a better set of adaptation as the initial weight value of BPNN. The study uses BPNN to build the S/N ratio predictor and quality predictor, using the improved PSO-GA combined with MLP to find the better initial weight for the S/N ratio predictor and quality predictor respectively.The objective function is defined in Eq. 7.

$$\text{Min } f(\mathrm{W}) = \frac{1}{36}\sum_{p=1}^{18}\sum_{k=1}^{2}(d_k^p - y_k^p(\mathrm{W}))^2 \tag{7}$$

where p represents number of pth sample, k represents kth quality characteristic, d_k^prepresents the target value of BPNN indexed by k , $y_k^p(W)$ represents the output value of MLP indexed by k, W is MLP's weights. Through using MLP and Eq. 7 with the modified PSO-GA to solve optimization weights, better weight values can often be found.

3.4. Establishing S/N Ratio Predictor and Quality Predictor

The study uses BPNN to establish the S/N ratio predictor and quality predictor. The input values of the S/N ratio predictor and quality predictor are the normalized values of the 18 groups of parameters of the Taguchi experiment, and the output value of the predictor is the normalized value of the S/N ratio and the average value of the quality characteristics in the Taguchi experiment. In addition, the 19th to 23rd groups in the Taguchi experiment are used as the testing data of BPNN. In order to enable BPNN to training convergence, this study adopts the weighting solution of MLP-PSO-GA, stated in the previous section, as the initial value of BPNN for training. The S/N ratio predictor training uses 1053 generations, training RMSE to be 0.0004940, and testing RMSE to be 0.0259. The quality predictor takes 968 generations; the training RMSE is 0.00082261, and the test RMSE is 0.0253. The error of the predicted value of the two predictors is analyzed within the acceptable range by comparing the error between the predictors and the actual values.

3.5. Two-stage process parameter optimization

In the first stage, the experiment focuses on maximizing the S/N ratio. The constructed S/N ratio predictors are combined with a GA to identify the process parameter combination with the minimum variance and the most robust process so that the S/N ratio values of diameter roundness (mm) and thickness deviation must be maximized. The Taguchi optimal parameter combination is used as the initial value to carry out the full range global search for the six control factors. The fitness function of GA is presented as follows:

$$\begin{aligned} &Max\ SNod,\ SNot \\ &s.t. \\ &40 \leq x1 \leq 50,\ 1 \leq x2 \leq 5,\ 1 \leq x3 \leq 4,\ 9 \leq x4 \leq 12,\ 20 \leq x5 \leq 52, \end{aligned} \tag{8}$$

where X(x_1, x_2, x_3, x_4, x_5) is the process parameter(control factor), SN_{od} is the S/N ratio of diameter predicted by de-normalized $BPNN_{S/N}$, and SN_{ot} is the S/N ratio of thickness deviation predicted by de-normalized $BPNN_{S/N}$. Five control factors are temperature of the electroforming liquid *(x_1)*, current density (x_2), cathode size *(x_3)*, the distance between the anode and the cathode *(x_4)*, and oscillating rate *(x_5)*. This numerical analysis is to conduct the global search for all control factors and obtained the process parameter combination of the first stage multi-objective S/N ratio maximization. The optimal parameter combinations are: $x_1=49.582$, $x_2=2.152$, $x_3=3.545$, $x_4=9.004$, and $x_5=51.912$.

$$\begin{aligned} &Min\ F_2(x) = (y_{od} - 555)^2 \\ &Max\ SN_{od},\ SN_{ot} \\ &s.t. \\ &y_{ot} \leq 0.01 \\ &8 \leq x_2 \leq 28,\ 62 \leq x_3 \leq 78 \end{aligned} \tag{9}$$

where X(x_2,x_3)is the process parameter (control factor), y_{od} is the output value of diameter quality predictor after de-normalization, and y_{ot} is the output value of thickness deviation quality predictor after de-normalization, and 555 is the target value of diameter quality characteristic, and 0.01 is the target value of thickness deviation quality characteristic as smaller as possible. The main control factors are $x_2$is current density and x_3 is cathode size. By conducting a global search for the two significant control factors of the second stage, and combining $BPNN_{S/N}$ and $BPNN_Q$ with modified PSO-GA, this study can obtain the process parameter combination meeting the multi-objective quality and minimizing variation. The optimal process parameter combination is shown in Table 5.

Table 5 Optimal parameter combination (two-stage process)

	TL	CD	CS	DAC	OR
Optimal Parameter	49.582	2.002	3.85	9.004	51.912

3.6 Confirmation of experiment and discussion

Due to the accuracy set by the operating machine, the optimized parameter values must be rounded up according to the limits set by the machine. The finally confirmed experimental parameters are shown in Table 6. The experimental data will be confirmed according to the above-mentioned quality evaluation methods, and the comprehensive evaluation and comparison tables of the quality of the diameter and thickness will be separately compiled, as shown in Table 7 and Table 8. The product quality characteristics and ideal functions of this study are based on the manufacturer's requirements for product quality. The diameter roundness specification is 555 ±0.3 μm (target value: 555 μm, tolerance: ±3 μm), and the thickness deviation specification is 5% and expectedly smaller. (Target value: 0μm). Additionally, for the diameter quality characteristics, the multi-quality optimized Cpk value is 1.69, which is much larger than the 0.70 of the Taguchi method, and the average diameter value is also the closest to the target value. The standard deviation of 0.058 is also lower than 0.132 of the Taguchi method. It is found that the two-stage optimization is better. Moreover, for the thickness quality characteristics, after the two-stage optimization, the thickness deviation is reduced from the Taguchi method, 0.0281, to 0.0191; the standard deviation is also reduced from 0.0075 of the Taguchi method to 0.0036. It can be seen that after the two-stage optimization, not only the diameter is closer to the target value, but also the thickness deviation is reduced, and the process is more stable. The results show that the two-stage optimization is better in the comprehensive evaluation of each quality.

Table 6 Optimal parameters and machine settings

	TL	CD	CS	DAC	OR
Taguchi + ANOVA	50	3.00	4.00	9	20
Machine settings	50	3.00	4.00	9	20
Two-stage optimization	49.582	2.002	3.850	9.004	51.912
Machine settings	50	2.00	4.00	9	52

Table 7 A comprehensively evaluation & comparison table of diameter quality

	C_{pk}	Average	Standard deviation
Taguchi + ANOVA	0.70	554.980	0.132
Two-stage optimization	1.69	555.004	0.058

Table 8 A comprehensively evaluation & comparison table of thickness quality

	Average	Standard deviation
Taguchi + ANOVA	0.0281	0.0075
Two-stage optimization	0.0191	0.0036

3.7. Process Parameters and Quality Characteristics Analysis

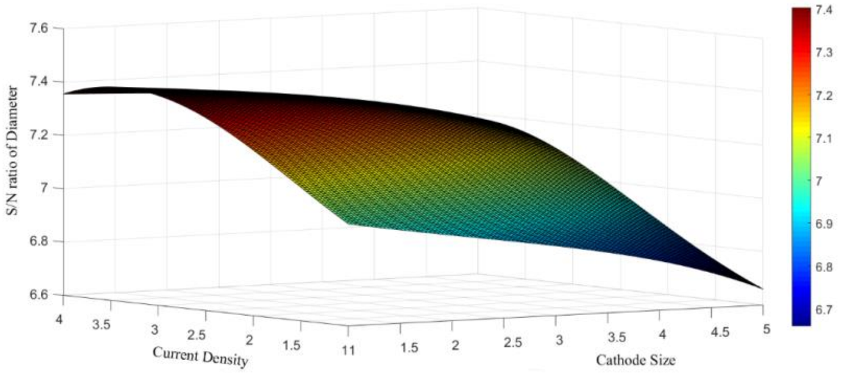

Fig. 4 The effect of current density and cathode size on diameter S/N ratio

This section discusses the relationship between process parameters and quality characteristics. The process parameter control factors of this experiment are the temperature, current density, cathode size, distance between cathode and anode, and oscillating rate. According to previous investigation, the current density and cathode size are the most significant factors for the process parameters in this research; therefore, this study uses those factors as variation factors for more in-depth analysis. The cathode size, the cathode-anode distance, and the oscillating rate are fixed according to the optimum parameters of the Taguchi experimental analysis, and their values are 50° C, 9 cm and 20 times / min respectively. When the S/N ratio predictor and the quality predictor are used as the variation factors for the predicted current density and the cathode size, the output of the predictor is shown in Figs. 4 to 7. As what is shown from Figures 4 and 5, for the diameter roundness S/N ratio, the smaller the value of the current density and the larger the value of the cathode size are, the greater the influence on the S/N ratio is. Therefore, if it is desired that the diameter roundness S/N ratio can achieve better results, the current density and cathode size parameters are respectively lowered and increased to perform better. For the thickness deviation S/N ratio, the smaller the current density and the larger the cathode size are, the greater the influence on the thickness S/N ratio is. It is clearly observed that the current density interacts with the cathode size. Therefore, if a thickness S/N ratio is desired to obtain a better result, the adjustment of the current density should be considered, followed by the cathode size. In addition, as seen from Fig. 6 and Fig. 7, if the value of the current density is lower and the value of the cathode is higher, the influence on the diameter roundness and thickness deviation is more obvious. Thus, if the product process requires a larger size, the parameters with lower current density adjustment and higher cathode size adjustment can obtain better results. The diameter quality characteristic required for this experiment in this research is 555μm; and the thickness quality characteristic is the smaller the better. According to the trend graph of the diameter quality predictor, the drop point is between the current density of 1~2 A/dm^2 and the cathode size is about 3~4 dm^2, and according to the trend graph of the thickness quality predictor, the drop point is about between 1~3 A/dm^2 (current density) and 3.5~4 dm^2(cathode size). Therefore, in this study, the optimal parameters of the S/N ratio predictor and the quality predictor are obtained by the hybrid PSO-GA. The best parameters are current density 2.00 A/dm^2 and cathode size 4 dm^2.

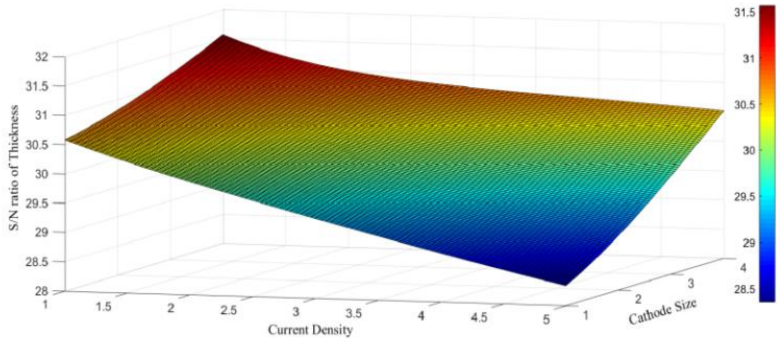

Fig. 5 The effect of current density and cathode size on thickness S/N ratio

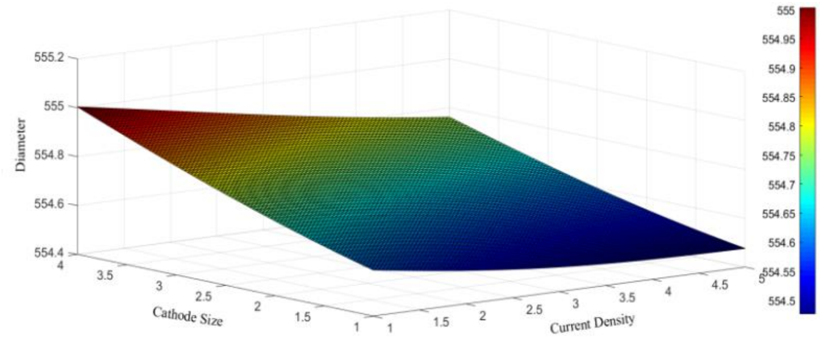

Fig. 6 The effect of current density and cathode size on the diameter

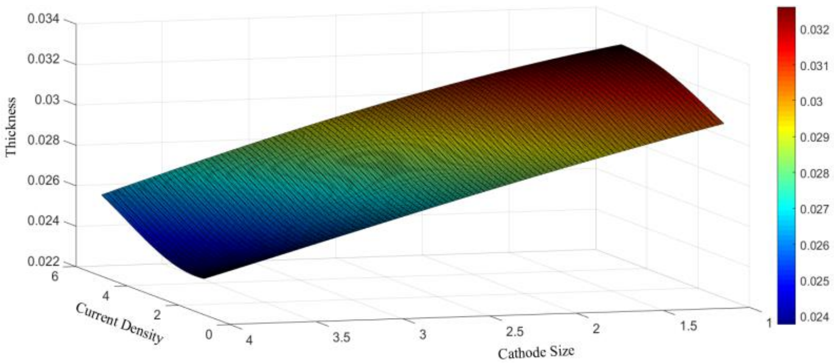

Fig. 7 The effect of current density and cathode size on thickness

4. Conclusions

The micro electroforming technology has been widely adopted, and the industry has higher and more requirements for the product precision. How to set appropriate process parameters to meet the quality requirements and improve the production efficiency and process stability often bothers the engineers. Therefore, if the optimal process parameters can be found, it will improve product quality and reduce costs. To this end, this research studies the intelligent optimization system of the micro electroforming process parameters for the mesh filter, using the systematic optimization method to effectively find the optimal combination of process parameters. After the actual verification, for the diameter quality characteristics, the multi-quality optimized C_{pk} value is 1.69, which is much larger than the 0.70 of the Taguchi method, and the average diameter value is also the closest to the target value. The standard deviation of 0.058 is also lower than 0.132 of the Taguchi method. For the thickness quality characteristics, the thickness deviation is reduced from the Taguchi method, 0.0281, to 0.0191; the standard deviation is also reduced from 0.0075 of the Taguchi method to 0.0036. Therefore, Accordingly, the results suggest that t he proposed intelligent optimization system not only makes the diameter closer to the target value but also reduces the thickness deviation and makes the process more stable.

Conflicts of Interest

The Authors would like to thank Material and Chemical Research Laboratories of Industrial Technology Research Institute (ITRI) in Taiwan for providing equipment and technical support.

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