Neural Comput & Applic (2013) 23:1539–1550
DOI 10.1007/s00521-012-1103-2

ORIGINAL ARTICLE

Parameter optimization of etching process for a LGP stamper

**Wen-Chin Chen · Yi-Chia Tai · Min-Wen Wang ·
Hsiang-Cheng Tsai**

Received: 28 April 2012 / Accepted: 19 July 2012 / Published online: 1 August 2012

Abstract This study proposes a two-stage system to optimize the etching process parameter for making a light guide plate (LGP) stamper. The multi-quality characteristics of the parameter settings include depth and uniformity of the microstructures formed in the LGP stamper. The control factors to conduct the process are etching temperature, specific gravity, spray pressure, transfer speed, and oscillating rate. The first stage is to conduct signal-to-noise (S/N) ratio optimization using Taguchi orthogonal array experiments. After conducting the etching process in microstructure, the experimental data can be translated and tested by back-propagation neural networks in order to create S/N ratio and the other quality characteristics predictors. In addition, the S/N ratio predictor and genetic algorithms are used together to obtain combinations of settings and to find the maximized process parameters on S/N ratios. As a result, the quality variance could be minimized. The second stage demonstrates quality characteristics optimization by pushing the process qualities to the targeted specifications. The analysis of variance (ANOVA) is employed to determine the significant control factors. Then, a statistical analysis using the aforementioned quality predictor, S/N ratios predictor, and particle swarm optimization is implemented to simulate the targeted specifications and then find a suitable specifications combination and the most stable and qualified process.

Keywords Light guide plate · Stamper · Etching process · Taguchi orthogonal array · Back-propagation neural networks · Genetic algorithms · Particle swarm optimization

1 Introduction

In recent years, products in the thin film transistor liquid crystal display (TFT-LCD) industry have pursuit to become thinner and lighter and the market also demands for medium- and large-size TFT-LCDs. To achieve this goal, the light guide plate (LGP) of the backlight module must become thinner and needs to be illuminated evenly and effectively. Typical small and medium TFT-LCD LGPs are injection molded. Since the LGPs duplicate the patterns on the stampers, the fabrication of the molding stampers is an important process especially in the medium-size LGPs. There are different steps for making the stampers, such as electroforming, laser cutting, precision cutting, UV-LIGA, and the combination of photolithography and etching process. Currently, most of the stampers are fabricated with the combination of photolithography and etching processes. However, the determination for the parameter settings of the etching process still relies on the engineers' experience and intuition. Normally, engineers use trial-and-error and numerous design of experiment (DOE) to generate suitable and reliable parameter settings, which leads to spending a large amount of time, manpower, and cost. If the etching process parameters could not be controlled properly, problems such as stamper failure and large

W.-C. Chen · H.-C. Tsai
Department of Industrial Management, Chung Hua University,
707 Wu Fu Rd., Sec.2, Hsinchu 300, Taiwan

Y.-C. Tai
Ph.D. Program of Technology Management, Chung Hua
University, 707 Wu Fu Rd., Sec.2, Hsinchu 300, Taiwan

M.-W. Wang (✉)
Department of Mechanical Engineering,
National Kaohsiung of Applied Sciences,
415 Chien Kung Road, Kaohsiung 807, Taiwan
e-mail: mwwang@kuas.edu.tw

variation in microstructures will occur. Since the stampers cannot be re-worked if there are defects, they become wastes. In order to increase the yield and reduce the cost, the parameter setting of etching process control factors is even more critical. Thus, a two-stage parameter optimization system will be proposed to optimize the etching parameter settings of multi-quality characteristics (i.e., the depth and the uniformity of microstructure) of LGP stamper in this research.

Since there are varieties of materials and chemical etching solutions used in the etching process for LGP stampers, many researchers dedicated themselves to study the interactions between different kinds of chemical etching solutions and materials, and on the related physical phenomena in the etching process. Zhuang et al. [1] conducted related researches utilizing wet etching process with three different materials (GaN, AlN, and SiC); they discovered that under the temperature of around 75 °C, all etching solutions have similar etching rate on GaN and AlN. At this temperature, there is practically no etching solution can etch GaN effectively. KOH and NaOH are the only two of few etching solutions, which have better etching effects on GaN under high temperature. Although appropriate combinations of etching solutions and materials can be found through the analysis of materials, the correlation between process parameters and product quality still cannot be assured. An inappropriate set of process parameters will result in product defects and unstable processes. In the past, many researchers have used trial-and-error to conduct experiment on exploring the correlation between process parameters and product quality. Sheu [2] found that the etching rate is theoretically proportional to temperature. The higher the temperature the higher the etching rate, while the surface roughness and the nanostructures morphology deteriorated. But surface roughness can be improved by additional ultrasonic agitation of the solution. Shue demonstrated that the optimization linewidth of the silicon nanofabrication can be reduced down to 20 nm by using higher aqueous temperature over 30 °C and orientation-dependent etching (ODE) technique with ultrasonic agitation. Kim et al. [3] applied the wet etching process to fabricate photonic quantum ring (PQR) laser. The critical process control factors for this etching process included etching solution volume ratio, temperature, stirring magnitude, and etching time, and the etched surface roughness after the etching process was studied. Wilke et al. [4] optimized a fabrication technique for manufacturing microneedle arrays in standard silicon wafer [(100) orientation] using potassium hydroxide (KOH) wet etching. He simulated the etching process with the SIMODE software and designed a mask for the microneedle array using the result from the simulation. The processing environment such as etching parameters and etch bath conditions on the formation of silicon microneedle was studied. Sakwe et al. [5] used KOH etching solution to find the optimized process parameters for etching of n-type and p-type silicon carbides. According to the experiment results, temperature is the vital process control factor; the optimal etching temperature and etching time were 530 °C/5 and 500 °C/5 min for n-type and p-type SiC, respectively. Chen et al. [6] proposed an optimization photolithography process for LGP stamper. In this photolithography process, the critical controlling factors are oven temperature, baking time, roller temperature, exposure energy, and development speed. Taguchi orthogonal array for experiments was used to find appropriate process parameters that would fit the characteristics of the targeted quality level. The experiment proved that both diameter and uniformity qualities can be met with the best combination of parameters with this method.

In the above researches, correlation between process parameters and quality goal were obtained by trial-and-error or design of experiment, and a better combination of process parameters could be achieved. However, the process parameters obtained from these experiments are from the original DOE levels and they are of discrete type, and the optimal combination of process parameters cannot be found. Hence, one must, combining experimental design, predictor, and application of related optimized theories, use numerical simulation to study the optimal combination of process parameters [7, 8]. Han et al. [9] utilized genetic algorithm to find the best parameter setting for semiconductor etching process and used this parameter setting as input data for RBFN prediction. The etching rate and selectivity of Al, and the etching rate, tooth angle, and side surface roughness of Si were used as outputs. A prediction model was created to improve the etching process. GA-RBFN was then compared with statistics feedback model. This research results demonstrated GA-RBFN to be more effective comparing to other methods. Chen et al. [10] created a model with back-propagation neural networks (BPNN) using fourteen Si substrate dry etching process parameters as inputs and the maximum, minimum, and averaged values of etching depth measured from etching process as outputs. This system, eventually, was proven to predict the etching depth effectively. Chen et al. [11] also investigated the optimization parameters for plastic injection process. The data gathered from Taguchi orthogonal array were applied to back-propagation neural networks to create a quality predictor. The authors then combined genetic algorithm to find the optimal injection process parameters. The experiment indicated that when limiting the range of process parameters within $\pm 1/2$ Taguchi's experiment standard from the optimal S/N ratio, the parameter combination derived from genetic algorithms and quality predictor gave better part quality than the parameter combination obtained from Taguchi experiment. The research by Chen et al. [12] on the optimization of LED lens design utilized the optical-simulation software, TracePro, to conduct an optical analysis. BPNN was employed to build a quality predictor for the optical lenses. The optimization system can analyze the LED's viewing angle and luminance uniformity rapidly and accurately. It also offered the global optimal solution with the combination of utilizing both genetic algorithm and back-propagation neural networks.

However, in the previous studies, researchers only focused on optimizing the process parameters for better quality, but did not assess the stability of process. Therefore, the stability and quality of the etching process could not be achieved to the optimal condition. This paper proposes a two-stage optimization system for the etching process for fabricating stainless LGP stamper with ferric chloride etchant. The first stage is to optimize the S/N ratio. We employ the S/N ratio predictor, along with simulation of genetic algorithm, to search for optimal combination of process parameters. This increases the quality consistency and improves the stability of the process. In the second stage, the quality predictor and S/N ratio predictor are used together with particle swarm optimization to search for the optimal combination of process parameters. The combination of process parameters obtained by the proposed system not only made the entire process more stable, but also attained the compliance of LGP microstructure to the designated size specification (depth and uniformity). As well, it cuts down the time and cost required for LGP design to production process.

2 Design of a two-stage optimization system

This study proposes a two-stage system to explore the optimization parameters of etching process for a LGP stamper. Technologies including Taguchi method, back-propagation neural networks (BPNN), genetic algorithm (GA), and particle swarm optimization (PSO) are integrated in this two-stage parameter optimization system. In the first stage, the deviation of product quality is minimized. In the second stage, the product quality is improved to approach the target value and the process is stabilized as well. For the LGP stamper etching process, the quality characteristics are the etching depth and uniformity of microstructure formed in the stamper.

The following process and measurement equipment are utilized in this study: oven, spray etcher, de-taping system, 3D optical measurement system, and microfigure measuring instrument. Quality characteristics of the experiment are microstructure depth of LGP etching process and uniformity of the entire microstructure. Controlling factors of the experiment are temperature, specific gravity, spray pressure, transfer speed, and oscillating rate. The experiment utilizes $L_{27}(3^5)$ Taguchi orthogonal array for the etching process. In the first stage, data gathered from the orthogonal array experiment are used to train and test the back-propagation neural networks to become an S/N ratio predictor and a quality predictor of the etching process. The S/N ratio predictor is combined with genetic algorithm to find a combination of process parameters, which yields the maximum S/N ratio. This combination of process parameters is within the parameter standard set by the Taguchi experiment and has the smallest quality deviation. In the second stage, the BPNN quality predictor is combined with the particle swarm optimization (PSO). The optimal process parameters found in the first stage are used as initial values. The control factors are found through ANOVA. The optimal combination of process parameters, which meets quality requirement and yields minimum quality variance, is found through this BPNN quality predictor and PSO analysis. The target of microstructure depth is 19 μm, with acceptable range between 18 and 19 μm. Measurements are taken in eight regions (Fig. 1). Ten thousand points are measured for each region. The difference between target value and each measured value is calculated. All differences are averaged to represent the uniformity. This method of measurement ensures uniformity. The uniformity is calculated with the following equation:

$$U = \frac{1}{8 * 10000} \times \sum_{i=1}^{8} \sum_{j=1}^{10000} \left| H_{ij} - H_t \right| \quad (1)$$

where H_{ij} is the measured depth of LGP stamper microstructure, H_t is the target depth of LGP stamper microstructure, U is the uniformity of LGP stamper, i is the index of the measured region, and j is the index of the measured point.

The main purpose of this research is to find the best combination of process parameters for the LGP stamper etching process and to control the quality of LGP

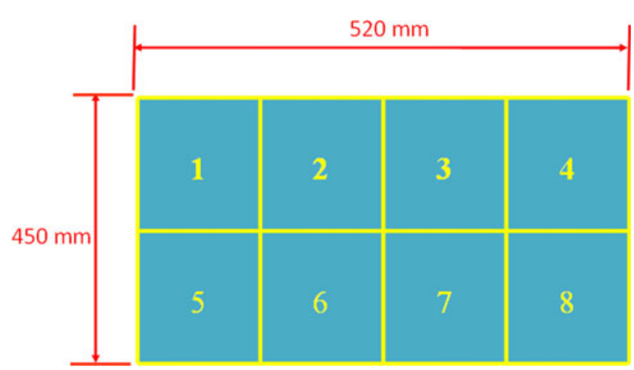


Fig. 1 Schematic picture of the 8 zones of the stamper

stamper within a specific tolerance. Hence, the production process will be stabilized and the failure rate will be reduced. The flowchart of this study is illustrated in Fig. 2.

2.1 Taguchi experiment

The target quality of this research is based on product specifications and requirements from the manufacturers. It specifies diameter and uniformity as product quality characteristics. After exploration of articles and discussions with many experts and engineers, this research sets 5 experiment factors as temperature (°C), specific gravity, spray pressure (kgf/m^2), transfer speed (m/min), and oscillating rate (times/min). After consulting the field engineers and observation of experiment results, the standard ranges of these experiment factors are specified. Temperature ranges from 40 to 50 °C. Specific gravity ranges from 1.48 to 1.49. The standard range of spray pressure is 1–3 (kgf/m^2). The standard range of transfer speed is 1–2 (m/min). As for oscillating rate, the standard range is 2–4 times per minute. The experiment has 5 factors and each factor has 3 levels, so an $L_{27}(3^5)$ orthogonal array is chosen. This research is conducted by experiment of multi-quality characteristics, so different S/N ratio equations for different quality characteristics are used. Depth and uniformity of microstructure after etching are quality characteristics of this experiment. For the depth quality characteristic, the equation of nominal-the-better is used, and it is:

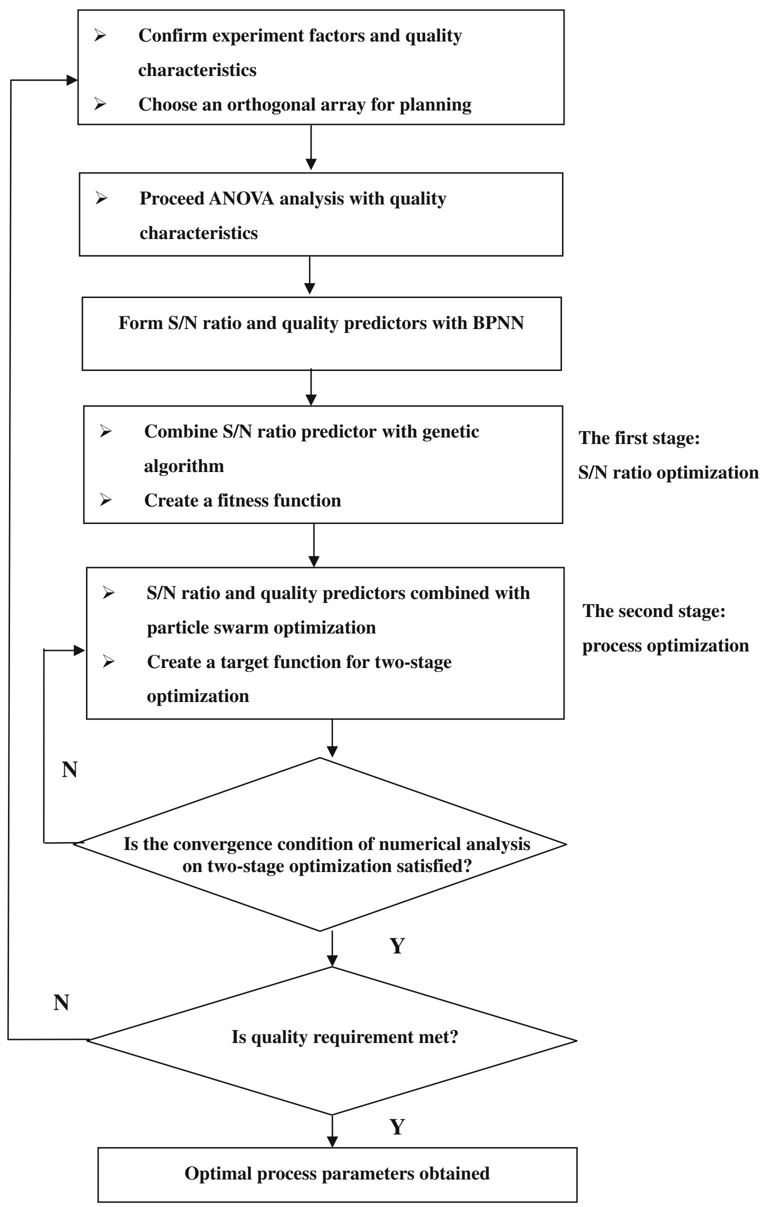


Fig. 2 Flowchart of the research

$$S/N = -10 \times \log\left(\frac{S^2}{\bar{y}^2}\right) \tag{2}$$

where $\bar{y}$ is the average value and S^2 is the square of standard deviation. As for the uniformity quality characteristic, the equation of smaller-the-better characteristic is used. The equation is:

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

where y_i is the response value of a specific treatment under i replications, and n is the number of replications.

2.2 The first stage: S/N ratio optimization

Because the optimal parameter combination found by the Taguchi method is a discontinuous local best solution, it is not easy to find the best parameter combination for multi-quality characteristics. Therefore, this research proposes a two-stage system to explore the optimization parameters of etching process for a LGP stamper. In the first stage, this study optimizes S/N ratio, so that the S/N ratio of target depth and uniformity can reach the maximum values. First, data gathered from Taguchi experiment are used for back-propagation neural networks (BPNN) training. Five parameter combinations, within standard range of Taguchi experiment, are produced randomly for BPNN testing. After several iterations of training and testing, convergence error reaches the preset value. An S/N ratio predictor ($\mathrm{BPNN_{S/N}}$), which complies with the real process, is established. The inputs to the S/N predictor include transfer speed, spray pressure, specific gravity of etching solution, oscillating rate, and temperature. The outputs are S/N ratio of microstructure depth and uniformity. The target value of S/N ratio for each quality characteristic is set to the S/N ratio of each quality characteristic in Taguchi experiment. Using the S/N ratio predictors ($\mathrm{BPNN_{S/N}}$) combined with GA, the best combination of process parameters can be obtained after numerical simulations. This combination of process parameters minimizes variance of product quality. The process parameters are all within the parameter standard specified by Taguchi experiment. The fitness function of GA is defined as follows:

$$\begin{aligned} &\operatorname{Min} F_1(X) = \sum_{i=1}^{2} (\mathrm{SN}_{oi} - \mathrm{SN}_{ti})^2 \\ &\text{s.t.} \\ &\mathrm{LSR}_m \le x_m \le \mathrm{USR}_m \quad m = 1, 2 \ldots 5 \end{aligned} \tag{4}$$

where $X = (x_1, x_2, x_3, x_4, x_5)$ is the control parameter, SN_{oi} is the output $\mathrm{BPNN_{S/N}}$ of i response, and SN_{ti} is the target S/N ratio of i response. x_m is the notation of process parameter m. LSR_m and USR_m are lower and upper search range of process parameter m, respectively. The setting method of LSR_m and USR_m is listed as follows:

$$\mathrm{LSR}_m = \mathrm{Min}(\mathrm{PS}_{im}) - \frac{H_m}{2}$$

$$\mathrm{USR}_m = \mathrm{Max}(\mathrm{PS}_{im}) + \frac{H_m}{2}$$

where PS_{im} is the process parameter setting value of parameter m, which let the S/N ratio of response i be highest, and H_m is the factor level's equal range of parameter m in Taguchi experiment.

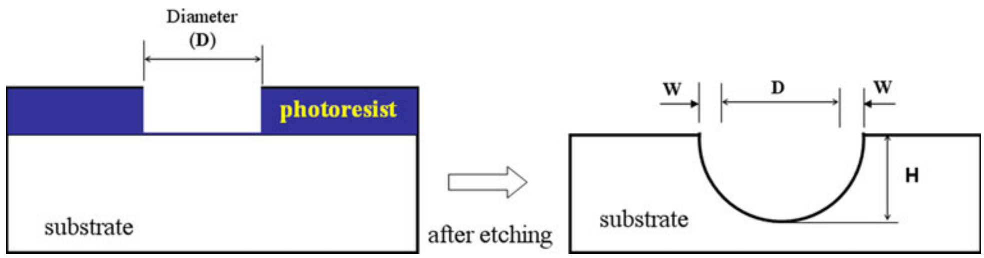
2.3 The second stage: process optimization

In the first stage, S/N ratio has been optimized to reduce process variance, but target values of quality characteristics have not yet achieved. Therefore, in this stage, data obtained from Taguchi experiment $L_{27}(3^5)$ are utilized to find quality characteristic value, $\bar{y}$, which is then trained with BPNN. After training, it is tested with the previous 5 sets of parameter combination, which was randomly produced in the experiment. With the above procedures, a quality predictor ($\mathrm{BPNN_{PQ}}$) is established, which matches the real etching process. ANOVA is applied based on data measured from the depth and uniformity experiment. The purpose of ANOVA is to understand the contribution and sensitivity of each factor to depth and uniformity. The optimized parameter combination resulted from the first stage is used as the initial values of numerical model in the second stage. Through ANOVA analysis on sensitivity and quality characteristics, those factors which have more significant influence on depth and uniformity are adjusted. Using the $\mathrm{BPNN_{PQ}}$ and $\mathrm{BPNN_{S/N}}$ combined with PSO to execute the numerical analysis, the best combination of process parameters is obtained, which reduces the process quality variance and makes the product quality to the target value. The objective function of PSO is as following:

$$\begin{aligned} &\operatorname{Min} F_2(X) = \sum_{i=1}^{a} (\mathrm{SN}_{oi} - \mathrm{SN}_{ti})^2 + (y_{p1} - y_t)^2 \\ &\operatorname{Min} y_{p2} \\ &\text{s.t.} \\ &\mathrm{LSR}_m \le x_m \le \mathrm{USR}_m \quad m = 1 \cdots c \end{aligned} \tag{5}$$

where $X = (x_1, x_2, x_3, x_4, x_5)$ is the control parameter, SN_{oi} is the output $\mathrm{BPNN_{S/N}}$ of i response, and SN_{ti} is the target S/N ratio of i response; and y_{p1} is the output value from the $\mathrm{BPNN_{PQ}}$ (depth), y_{p2} is the output value from $\mathrm{BPNN_{PQ}}$ (uniformity), and x_m is the process parameter indexed by m. The optimized parameter combination resulted from the first stage is used as the initial values in the PSO search model. LSR_m and USR_m are lower and upper search range

Fig. 3 Illustration of the etched microstructure dimensions



of process parameter m, respectively. The setting method of LSR_m and USR_m is listed as follows:

$$LSR_m = \mathrm{Min}(PS_m) - \frac{H_m}{2}$$

$$USR_m = \mathrm{Max}(PS_m) + \frac{H_m}{2}$$

where PS_m is the initial setting value of parameter m, H_m is the factor level's equal range of parameter m in Taguchi experiment.

3 Experiment results and analysis

3.1 Experiment materials and equipment

The material for the stamper used in the experiment is SUS430BA stainless steel plate (450 mm × 550 mm × 0.8 mm). For the wet etching process, the etchant is ferric chloride solution. To measure the diameter and the depth of the etched microstructures, a Mohr non-contact 3D optical measuring system (OMS 600, Germany) and an ET-4000 microfigure measurement instrument (Kosaka Laboratory Ltd., Japan) were used in this study, respectively.

Prior to the etching experiment, the stainless steel substrates were prepared through photoresist coating, soft baking, exposure, development, and hard baking processes. The microstructures with an averaged diameter of 44.7 μm were formed on the resist layers over the substrate. For this anisotropic etching process, etching starts perpendicular to the substrate surface at beginning, then etching goes vertically and laterally and causes undercutting the resist layer as shown in Fig. 3. For the equipment and etchant used in this study, the etch ratio, etched depth H to the lateral etching width, is close to 2:1 according to the experience of Material and Chemical Research Laboratories of Industrial Technology Research Institute (MRRL/ITRI).

3.2 Experiments and ANOVA

In this section, an experiment in LGP stamper etching process is conducted and analyzed. The parameters of control factors are equally divided into three levels within the specified range, as shown in Table 1. Taguchi experiment is implemented using $L_{27}(3^5)$ orthogonal array. Runs No. 1 to No. 27 are Taguchi experiment data and No. 28 to No. 32 are random selected parameters within the level range. Experimental data and statistical data of depth and uniformity are shown in Tables 2 and 3. As for the quality characteristics, the 22nd set has the highest depth S/N ratio as shown in Table 2. The 20th set has the highest uniformity S/N ratio as shown in Table 3. Process parameters for highest depth and uniformity S/N ratio are listed in Table 4. Based on the data obtained from the experiment, ANOVA analysis is applied to depth, uniformity, and sensitivity, respectively. According to the ANOVA Tables 5 and 6, the significance of factors among quality characteristics can be realized. With this analysis, the process parameters which significantly affect depth and uniformity are obtained and the best Taguchi parameters can be chosen. For the factors, which have significant influence on depth or uniformity, their standard values are chosen as standard values of Taguchi's best parameter combination. For the factors, which have significant influence on both depth and uniformity or have no significant influence on both depth and uniformity, the average of two standard values is taken and set it to be the standard value of Taguchi's best parameter combination. Therefore, the optimal process parameter settings obtained from the Taguchi method and ANOVA are etching temperature = 50, specific gravity = 1.4825, spray pressure = 2, transfer speed = 1.75, and oscillating rate = 2.5. In Tables 7 and 8, when the P value is smaller than 0.05, temperature, spray pressure, and transfer speed can all significantly affect depth and uniformity.

3.3 The first stage: S/N ratio optimization

In this research, the optimization program is written with MATLAB 2007. The S/N ratio predictor ($BPNN_{S/N}$) is built using BPNN. Taguchi experiment data are used for

Table 1 List of parameters

	Temperature (°C)	Specific gravity	Spray pressure (kgf/m^2)	Transfer speed (m/min)	Oscillating rate (rate/min)
Level 1	40	1.48	1	1	2
Level 2	45	1.485	2	1.5	3
Level 3	50	1.49	3	2	4

Table 2 Experimental results of depth

No.	Y1 (μm)	Y2 (μm)	Y3 (μm)	AVG (μm)	SD	S/N ratio	Sensitivity
1	9.045	8.930	8.910	8.962	0.073	41.767	19.048
2	8.642	8.091	8.558	8.430	0.297	29.066	18.514
3	8.870	8.050	8.908	8.609	0.485	24.987	18.693
4	7.192	8.390	8.258	7.947	0.657	21.650	17.989
5	7.233	6.767	7.540	7.180	0.389	25.314	17.116
6	7.473	7.225	7.525	7.408	0.160	33.297	17.393
7	6.125	6.067	6.167	6.119	0.050	41.715	15.734
8	6.100	5.867	6.100	6.022	0.135	33.007	15.594
9	6.269	6.200	6.364	6.278	0.082	37.665	15.956
10	3.905	8.040	7.888	6.611	2.345	9.003	16.123
11	5.963	7.700	5.867	6.510	1.032	15.998	16.216
12	7.700	8.000	8.217	7.972	0.259	29.750	18.029
13	15.360	15.730	15.525	15.538	0.185	38.468	23.828
14	15.418	14.850	14.750	15.006	0.360	32.390	23.524
15	15.445	14.955	14.992	15.131	0.273	34.863	23.596
16	7.507	6.900	7.154	7.187	0.305	27.447	17.127
17	7.108	7.200	7.364	7.224	0.129	34.941	17.175
18	6.264	6.242	6.425	6.310	0.100	35.991	16.000
19	14.300	14.717	14.617	14.544	0.218	36.504	23.253
20	18.207	18.392	17.718	18.106	0.348	34.324	25.155
21	14.017	14.717	14.308	14.347	0.352	32.214	23.134
22	6.775	6.808	6.809	6.797	0.019	50.861	16.647
23	6.755	6.908	6.967	6.877	0.110	35.953	16.747
24	6.850	6.009	6.640	6.500	0.438	23.435	16.248
25	15.875	15.033	15.050	15.319	0.481	30.058	23.703
26	15.108	15.575	15.683	15.456	0.306	34.080	23.781
27	16.000	15.564	15.450	15.671	0.290	34.644	23.901
28	6.175	6.817	6.842	6.611	0.378	24.858	16.398
29	4.392	3.982	3.955	4.109	0.245	24.496	12.268
30	6.950	7.158	6.933	7.014	0.125	34.955	16.918
31	17.040	16.417	16.283	16.580	0.404	32.266	24.390
32	9.400	9.133	9.200	9.244	0.139	36.471	19.317

Table 3 Experimental results of uniformity

No.	U1	U2	U3	AVG	SD	S/N ratio	Sensitivity
1	10.955	11.070	11.090	11.038	0.073	−20.858	20.858
2	11.358	11.909	11.442	11.570	0.297	−21.269	21.265
3	12.608	11.950	11.092	11.883	0.761	−21.517	21.490
4	12.808	11.610	11.742	12.053	0.657	−21.635	21.616
5	12.767	13.233	12.460	12.820	0.389	−22.162	22.156
6	13.150	12.775	12.475	12.800	0.338	−22.147	22.143
7	13.875	13.933	13.758	13.856	0.089	−22.833	22.832
8	13.900	14.133	13.900	13.978	0.135	−22.909	22.909
9	13.731	13.800	13.636	13.722	0.082	−22.749	22.749
10	16.095	11.960	12.112	13.389	2.345	−22.666	22.468
11	14.038	12.300	14.133	13.490	1.032	−22.626	22.588
12	12.300	12.000	11.783	12.028	0.259	−21.606	21.603
13	17.250	4.270	4.475	8.665	7.436	−21.152	16.761
14	4.582	5.150	5.250	4.994	0.360	−13.991	13.958
15	4.555	5.045	5.008	4.869	0.273	−13.763	13.743
16	12.493	13.100	12.846	12.813	0.305	−22.155	22.152
17	12.892	12.800	12.636	12.776	0.129	−22.128	22.128
18	13.736	13.758	13.575	13.690	0.100	−22.728	22.728
19	5.700	5.283	5.383	5.456	0.218	−14.744	14.733
20	1.793	1.625	2.282	1.900	0.341	−5.712	5.504
21	5.983	5.283	5.692	5.653	0.352	−15.062	15.037
22	13.225	13.192	13.191	13.203	0.019	−22.413	22.413
23	13.245	13.092	13.033	13.123	0.110	−22.361	22.361
24	13.150	13.991	13.360	13.500	0.438	−22.611	22.605
25	4.125	4.967	4.950	4.681	0.481	−13.452	13.383
26	4.892	4.425	4.317	4.544	0.306	−13.169	13.140
27	4.000	4.436	4.550	4.329	0.290	−12.747	12.718
28	13.825	13.183	13.158	13.389	0.378	−22.538	22.533
29	15.608	16.018	16.045	15.891	0.245	−24.024	24.022
30	13.050	12.842	13.067	12.986	0.125	−22.270	22.269
31	2.960	3.583	3.717	3.420	0.404	−10.741	10.650
32	10.600	10.867	10.800	10.756	0.139	−20.633	20.632

BPNN training and testing. Input to BPNN is 5 control factors including temperature, specific gravity, spray pressure, transfer speed, and oscillating rate. Outputs from $BPNN_{S/N}$ are depth and uniformity S/N ratios. BPNN has a hidden layer containing 8 neurons. Sigmoid function is used for the activation function. There are 27 training data and 5 testing data. The range of normalization is from 0.1 to 0.9. After 2,427 iterations of training, the training and testing RMSE values are 0.0031 and 0.032, respectively. In the first stage, GA is combined with $BPNN_{S/N}$ to optimize etching process parameters. Two Taguchi's best combinations of the process parameters are used as the initial values. According to Sect. 2.2, the parameter searching range is listed in Table 9. The size of mating pool is 100. The crossover procedure is the one-cut-point method. The mating rate is 0.8. The mutation procedure is single point mutation with mutation rate set to 0.6. The convergence threshold is 1.0000e-005 or 100,000 iterations. The fitness function of GA is defined as the following:

$$\begin{aligned}
&\operatorname{Min} F_1(X) = (SN_{o1} - 50.861)^2 + (SN_{o2} + 5.712)^2 \\
&\text{s.t.} \\
&47.5 \le x_1 \le 50 \\
&1.48 \le x_2 \le 1.4875 \\
&1 \le x_3 \le 3 \\
&1.25 \le x_4 \le 2 \\
&2 \le x_5 \le 3.5
\end{aligned} \tag{6}$$

Table 4 Process parameters of highest depth and uniformity S/N ratio

No.	Temperature	Specific gravity	Spray pressure	Speed	Oscillating rate	AVG	SD	S/N
20	50	1.48	3	1.5	3	1.900	0.341	−5.712
22	50	1.485	1	2	2	6.797	0.019	50.861

Table 5 Quality characteristics—depth—ANOVA

Source	*df*	Seq SS	Adj MS	*F*	*P*
Temperature	2	121.544	60.772	86.69	0.000
Specific gravity	2	4.176	2.088	2.98	0.079
Spray pressure	2	108.598	54.299	77.46	0.000
Speed	2	189.848	94.924	135.41	0.000
Oscillating rate	2	0.389	0.194	0.28	0.761
Error	16	11.216	0.701		
Total	26	435.771			
		R-Sq = 97.43 %		R-Sq (adj) = 95.82 %	

Table 6 Quality characteristics—depth uniformity—ANOVA

Source	*df*	Seq SS	Adj MS	*F*	*P*
Temperature	2	127.747	63.874	53.68	0.000
Specific gravity	2	5.888	2.944	2.47	0.116
Spray pressure	2	91.907	45.953	38.62	0.000
Speed	2	161.19	80.595	67.73	0.000
Oscillating rate	2	1.978	0.989	0.83	0.453
Error	16	19.034	1.19		
Total	26	407.744			
		R-Sq = 95.33 %		R-Sq (adj) = 92.41 %	

Table 7 Sensitivity—depth—ANOVA

Source	*df*	Seq SS	Adj MS	*F*	*P*
Temperature	2	74.685	37.343	91.30	0.000
Specific Gravity	2	4.715	2.358	5.77	0.013
Spray Pressure	2	62.751	31.375	76.71	0.000
Speed	2	146.312	73.156	178.87	0.000
Oscillating rate	2	0.043	0.021	0.05	0.949
Error	16	6.545	0.409		
Total	26	295.05			
		R-Sq = 97.78 %		R-Sq (adj) = 96.40 %	

where $X = (x_1, x_2, x_3, x_4, x_5)$ is the control parameter, SN_{o1} is the depth S/N ratio predicted by $\mathrm{BPNN}_{\mathrm{S/N}}$, SN_{o2} is the uniformity S/N ratio predicted by $\mathrm{BPNN}_{\mathrm{S/N}}$, 50.861 is the target depth S/N ratio, and −5.712 is the target uniformity S/N ratio. x_1 is the etching temperature, x_2 is the specific gravity, x_3 is the spray pressure, x_4 is the transfer speed,

Table 8 Sensitivity—depth uniformity—ANOVA

Source	*df*	Seq SS	Adj MS	*F*	*P*
Temperature	2	179.938	89.969	24.76	0.000
Specific gravity	2	8.988	4.494	1.24	0.317
Spray pressure	2	137.758	68.879	18.96	0.000
Speed	2	172.701	86.35	23.77	0.000
Oscillating rate	2	7.74	3.87	1.07	0.368
Error	16	58.126	3.633		
Total	26	565.25			
		R-Sq = 89.72 %		R-Sq (adj) = 83.29 %	

and $x5$ is the oscillating rate. The optimal process parameters achieved by $\mathrm{BPNN}_{\mathrm{S/N}}$ combined with GA are listed in Table 10.

3.4 The second stage: process optimization

In this research, BPNN is used to construct the quality predictor ($\mathrm{BPNN}_{\mathrm{PQ}}$). Taguchi experiment data are used for BPNN training and testing. Input to BPNN is 5 control factors including temperature, specific gravity, spray pressure, transfer speed, and oscillating rate. Outputs from BPNN are measured values of depth and uniformity. BPNN has a hidden layer containing 9 neurons. Sigmoid function is used for the activation function. There are 27 training data and 5 testing data. The range of normalization is from 0.1 to 0.9. After 3,360 iterations of training, the training and testing RMSE values are 0.0033 and 0.042, respectively. In this stage, ANOVA analysis is applied to the quality characteristics: depth, uniformity, and sensitivity. Controlling factors with significant influences on the process are chosen as adjustment factors for numerical analysis in this stage. From Tables 5, 6, 7, and 8, etching temperature, spray pressure, and transfer speed have more

Table 9 The searching range in GA

Range	Temperature	Specific gravity	Spray pressure	Transfer speed	Oscillating rate
Upper	50	1.4875	3	2	3.5
Lower	47.5	1.48	1	1.25	2

Table 10 Optimal parameters in the first stage

	Temperature	Specific gravity	Spray pressure	Transfer speed	Oscillating rate
$BPNN_{S/N}$ + GA optimization parameters	49.9398	1.48	1.005	1.4375	2.65

notable influence on depth and uniformity. In addition, temperature, spray pressure, and speed have more notable influence on sensitivity of depth and uniformity. Therefore, in this stage, only temperature, spray pressure, and transfer speed are adjusted to make quality to our target value. In the second stage, the parameters of etching process are optimized using PSO combined with $BPNN_{PQ}$ and $BPNN_{S/N}$. The first optimal parameter combination achieved in the first stage is used as the initial value of PSO. The result of ANOVA analysis indicates that etching temperature, spray pressure, and transfer speed need to be adjusted. Specific gravity and oscillating rate can be fixed. The objective function of PSO is listed below.

$$\begin{aligned}
&\text{Min}\, F(X) = (\text{SN}_{o1} - 50.861)^2 \\
&\qquad + (\text{SN}_{o2} + 5.712)^2 + \left(y_{p1} - 18.106\right)^2 \\
&\text{Min}\, y_{p2} \\
&\text{s.t.} \\
&40 \le x_1 \le 50 \\
&1 \le x_3 \le 3 \\
&1 \le x_4 \le 2
\end{aligned} \tag{7}$$

where SN_{o1} is the depth S/N ratio predicted by $BPNN_{S/N}$ after denormalization, SN_{o2} is the uniformity S/N ratio predicted by $BPNN_{S/N}$ after denormalization, y_{p1} is the depth predicted by $BPNN_{PQ}$ after denormalization, y_{p2} is the uniformity predicted by $BPNN_{PQ}$ after denormalization, 50.861 is the target depth S/N ratio, −5.712 is the target uniformity S/N ratio, 18.106 is the target depth, x_1 is the etching temperature, x_3 is the spray pressure, and x_4 is the transfer speed. The target of this research is 19 μm. In Taguchi experiment, depth closest to the target is 18.106 μm. The acceptable range in reality is between 18 and 19 μm. The etch ratio of microstructure, H:W, after etching process should be around 2:1. Therefore, the target value of depth for the two-stage optimization is 18.106 μm. The minimum threshold value for uniformity is 1.9. The controlling factors for numerical analysis are etching temperature, spray pressure, and transfer speed. Via $BPNN_{S/N}$ and $BPNN_{PQ}$ combined with the particle swarm algorithm, the optimal process parameters can be obtained using numerical analysis. The optimal process parameters are listed in Table 11.

3.5 Relation between process parameters and quality characteristics

There exists a very complicated nonlinear relationship between process parameters and quality characteristics. In the second stage, through ANOVA analysis, the controlling factors, which have significant influences on process, are chosen as the adjustment factors for numerical simulation. Variable factors of process parameters are etching temperature, spray pressure, and transfer speed. The quality predictor ($BPNN_{PQ}$) is utilized to predict the output quality and to explore the relationship between quality characteristics and process parameters. The run charts are illustrated in Figs. 4, 5, 6, 7, 8, and 9. From Figs. 4 and 5, at a fixed transfer speed of 1.05 m/min, when the etching temperature was raised to about 43 °C, etching depth reaches a more stable state and spray pressure has more significant influence on uniformity. At lower etching temperatures, spray pressure must be reduced to get better uniformity. At higher etching temperatures, spray pressure must be increased for better uniformity. From Figs. 6 and 7, when spray pressure is fixed at 1.03 kgf/m^2, lower temperature and faster speed will result in better depth and uniformity. From Figs. 8 and 9, when the temperature is fixed at 50 °C, speed has more influence on depth and uniformity than spray pressure. Through analysis of correlation between process parameters and quality characteristics, it should be noted that speed and spray pressure have more influence on the qualities than other parameters. When it comes to adjustment of process parameters, speed and spray pressure should be considered first, and speed should be adjusted before spray pressure.

4 Results and discussion

To demonstrate the effectiveness of the proposed two-stage optimization system, this research performed three

Table 11 Optimal parameters in the second stage

	Temperature	Specific gravity	Spray pressure	Speed	Oscillating rate
$BPNN_{PQ}$ + PSO optimization parameters	50	1.48	1.03	1.05	2.65

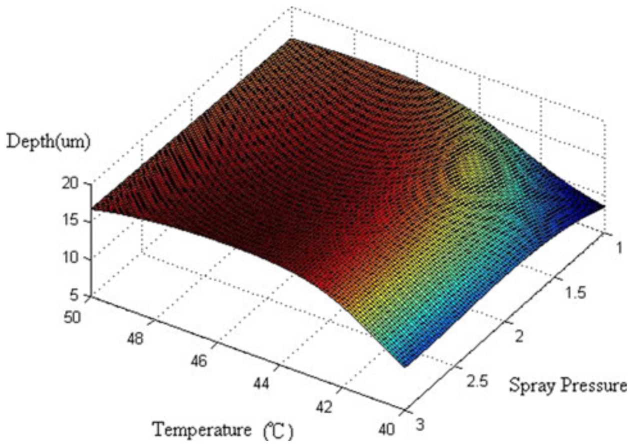


Fig. 4 Run chart of temperature and spray pressure versus depth

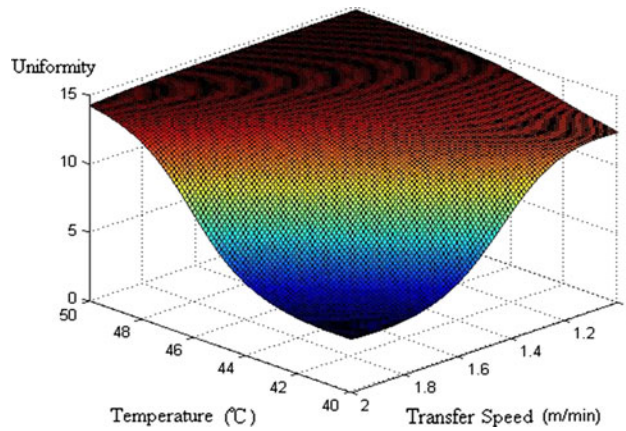


Fig. 7 Run chart of temperature and speed versus uniformity

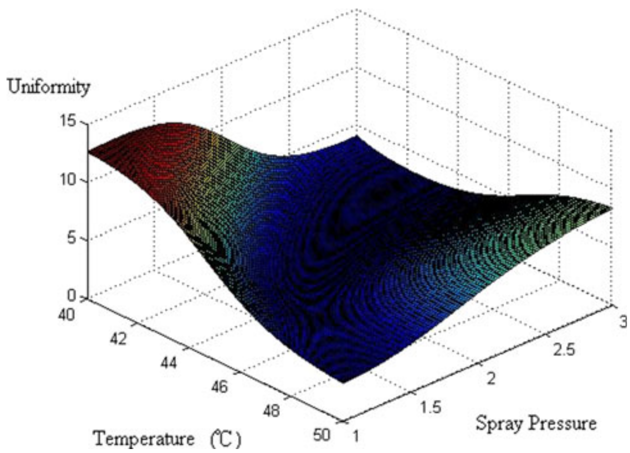


Fig. 5 Run chart of temperature and spray pressure versus uniformity

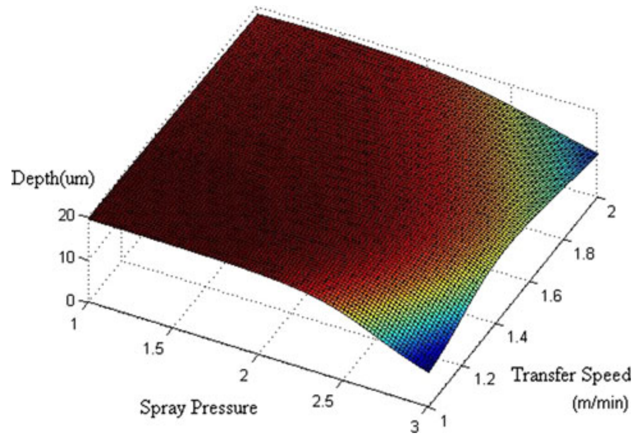


Fig. 8 Run chart of spray pressure and speed versus depth

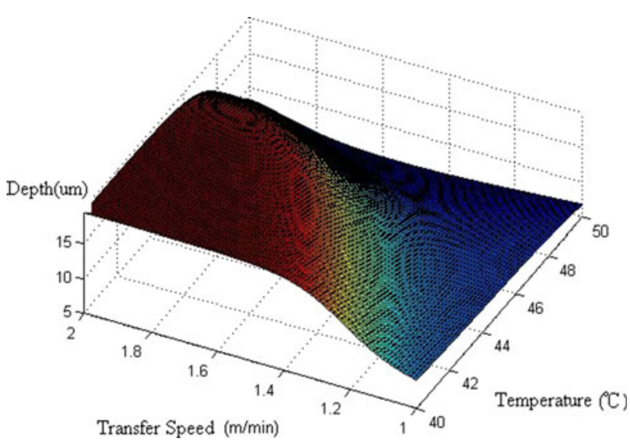


Fig. 6 Run chart of temperature and speed versus depth

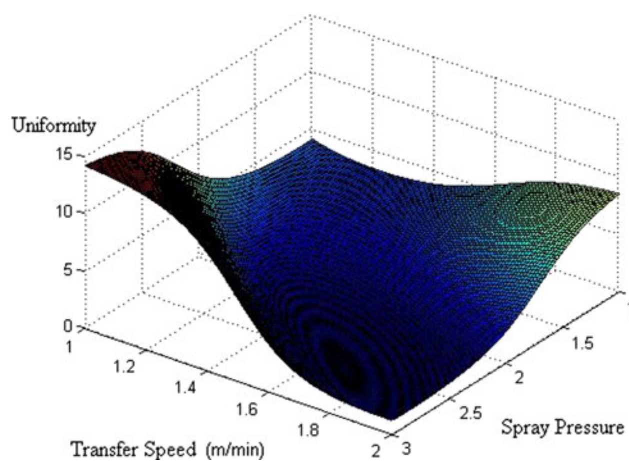


Fig. 9 Run chart of spray pressure and speed versus uniformity

confirmation experiments. One experiment utilized preliminary initial process parameter settings obtained from the Taguchi method. The other two experiments utilized the optimal initial process parameter settings obtained from the first stage and the second stage. Due to the limitation of equipment precision, the settings of optimal parameters must take this limitation into consideration with an appropriate round-off. The optimal parameters and machine settings are listed in Table 12. Etching experiment is performed 25 times for each parameter setting. The measured values for depth and uniformity are listed in Table 13. Regarding the uniformity quality characteristic, the best result is obtained after the second-stage optimization. The average value of uniformity decreases from 9.6312 to 1.6392, and the standard deviation also drops from 0.18 to 0.0698. Uniformity is improved about 83 %. As for the depth quality characteristic, the average value 18.37 after the second-stage optimization is closer to the target value than the average value 10.3688 of Taguchi method. Standard deviation decreases from 0.1801 to 0.0698. After the two-stage optimization, depth is closer to the target value, uniformity is better, and process is also

Table 12 Optimal process parameters and settings of machine's parameters

	Etching temperature	Specific gravity	Spray pressure	Transfer speed	Oscillating rate
Taguchi method optimization parameters	50	1.4825	2	1.75	2.5
Machine setting	50	1.48	2	1.75	2.5
The first-stage optimization parameters	49.9648	1.48	1.0039	1.4413	2.7
Equipment setting	50	1.48	1	1.44	2.7
The second-stage optimization parameters	50	1.48	1.03	1.05	2.7
Machine setting	50	1.48	1.03	1.05	2.7

Table 13 Depth and uniformity values measured in experiment

Taguchi method optimization parameters			First-stage optimization parameters			Second-stage optimization parameters		
No.	Depth	Uniformity	No.	Depth	Uniformity	No.	Depth	Uniformity
1	10.23	9.77	1	13.17	6.83	1	18.436	1.54
2	10.2	9.8	2	13.2	6.8	2	18.34	1.68
3	10.2	9.8	3	13.23	6.77	3	18.43	1.57
4	10.5	9.5	4	13.23	6.77	4	18.436	1.53
5	10.2	9.8	5	13.17	6.83	5	18.323	1.7
6	10.9	9.1	6	13.23	6.77	6	18.432	1.56
7	10.23	9.77	7	13.2	6.8	7	18.421	1.6
8	10.2	9.8	8	13.2	6.8	8	18.36	1.65
9	10.2	9.8	9	13.33	6.67	9	18.34	1.69
10	10.3	9.7	10	13.2	6.8	10	18.323	1.7
11	10.2	9.8	11	13.27	6.73	11	18.326	1.69
12	10.43	9.57	12	13.17	6.83	12	18.321	1.72
13	10.47	9.53	13	13.33	6.67	13	18.3	1.7
14	10.4	9.6	14	13.23	6.77	14	18.33	1.69
15	10.33	9.67	15	13.33	6.67	15	18.43	1.56
16	10.63	9.37	16	13.27	6.73	16	18.423	1.59
17	10.27	9.73	17	13.2	6.8	17	18.43	1.57
18	10.73	9.27	18	13.37	6.63	18	18.31	1.71
19	10.23	9.77	19	13.3	6.7	19	18.33	1.7
20	10.3	9.7	20	13.33	6.67	20	18.43	1.58
21	10.4	9.6	21	13.2	6.8	21	18.35	1.67
22	10.4	9.6	22	13.17	6.83	22	18.5	1.5
23	10.47	9.53	23	13.27	6.73	23	18.3	1.7
24	10.37	9.63	24	13.17	6.83	24	18.3	1.71
25	10.43	9.57	25	13.33	6.67	25	18.21	1.67
AVG	10.3688	9.6312	AVG	13.244	6.756	AVG	18.3652	1.6392
SD	0.1801	0.18	SD	0.0638	0.0638	SD	0.066725	0.0698

more stable. Process capability index (C_{pk}) is an important index for the evaluation of process stability. Normally, the minimum threshold value is 1.33. If it is <1.33, the process is ineffective and has higher defect rate. However, for the small volume production, C_{pk} is not an appropriate index. Nevertheless, from the calculation of C_{pk} value and experiment, depth after the two-stage optimization is closer to the target value, standard deviation drops to 0.0698, and C_{pk} value is 1.825. As a conclusion, it proves that, after the two-stage optimization of this research, not only quality is closer to the target value, but also the process capability is improved a lot.

In the etching process of LGP stamper, the expected etch ratio is 2:1 according to MCRL/ITRI's experience. After the process parameters optimization in the second stage, the average diameter of microstructure measured from the etching process experiments is 61.5 μm. The average depth of microstructure is 18.3652 μm. The average diameter of microstructure formed on the resist layer after photolithography process is 44.7 μm. So the etch ratio of the optimal etching process is about 2:0.92, which is very close to the expected ratio, 2:1.

5 Conclusion

During the etching process of LGP stampers, the setting of parameters usually requires the presence of experienced engineers. Intuitions from previous experiences and use of trial-and-error or Taguchi method are often applied to determining the suitable process parameters. This method takes a large amount of time and cost, and the process parameters found are not optimal. In this research, based on two quality characteristics, depth and uniformity, etching experiments with Taguchi method are conducted to find the initial process parameters. Experiment data are utilized to construct the S/N ratio predictor and the quality predictor. Through the S/N ratio predictor combined with GA, the process reaches a stable status. The quality predictor combined with the PSO is used for the second-stage optimization. Through numerical analysis, the process parameters, which are stable and close to the target specification of quality characteristics, are effectively obtained. Twenty-five experiments based on the process parameters obtained from the proposed two-stage optimization system are performed. The results show that the quality characteristic, depth, is closer to the target value. Uniformity and process capability are also significantly improved. The etch ratio is about 2:0.92, very close to theoretical etch ratio of the etching process (2:1).

Acknowledgments The authors would like to thank Material and Chemical Research Laboratories of Industrial Technology Research Institute in Taiwan for providing equipment and technical support.

References

1. Zhuang D, Edgar JH (2005) Wet etching of GaN, AlN, and SiC: a review. Mater Sci Eng 48:1–46
2. Sheu JT, You KS, Wu CH, Chang KM (2001) Optimization of KOH wet etching process in silicon nanofabrication. In: Proceedings of the 2001 1st IEEE Conference on Nanotechnology, M1.2 Nano-Mater I, pp 213–217
3. Kim MJ, Kim DK, Lee SG, Kown OD (2004) Wet etching fabrication of photonic quantum ring laser. J Appl Phys 96:4742
4. Wilke N, Mulcahy A, Ye SR, Morrissey A (2005) Process optimization and characterization of silicon microneedles fabricated by wet etch technology. Microelectron J 36:650–656
5. Sakwe SA, Muller R, Wellmann PJ (2006) Optimization of KOH etching parameters for quantitative defect recognition in n-and p-type doped SiC. J Cryst Growth 289:520–526
6. Chen WC, Chen HP, Chen XH (2010) Optimization of photolithography process for a LGP molding stamper. In: International conference on engineering and business management. Chengdu, China, pp 4626–4629
7. Gandomi AH, Alavi AH (2012) A new multi-gene genetic programming approach to nonlinear system modeling. Part I: materials and structural engineering problems. Neural Comput Appl 21(1):171–187
8. Smrekar J, Pandit D, Fast M, Assadi M, De S (2010) Prediction of power output of a coal-fired power plant by artificial neural network. Neural Comput Appl 19(5):725–740
9. Han D, Moon SB, Park K, Kim B, Lee KK, Kim NJ (2005) Modelling of plasma etching process using radial basis function network and genetic algorithm. Vaccum 79:140–147
10. Chen WC, Lee HI, Deng WJ, Liu KY (2006) The implementation of neural network for semiconductor PECVD process. Expert Syst Appl 32(4):1148–1153
11. Chen WC, Chen CT, Chou SC (2010) A two-stage optimization system for the plastic injection molding. In: International conference on engineering and business management. Chengdu, China, pp 1600–1603
12. Chen WC, Lai TT, Wang MW, Hung HW (2011) An optimization system for LED lens design. Expert Syst Appl 38(9):11976–11983