Parameter Optimization for Microlens Arrays Fabrication Using Genetic Algorithms

Chui-Yu Chiu, Yung-Kang Shen+, Po-Chou Shih*, Yi-Hsian Chou**

**National Taipei University of Technology, Taipei 110, Taiwan*

+Bio-Medical Nano/Micro Forming Laboratory, School of Dental Technology, College of Oral Medicine, Taipei Medical University, Taipei 110, Taiwan

Email: cychiu@ntut.edu.tw

Abstract - As a work of bionics, microlens arrays are an application of micro-optics, which are used in daily life. They are commonly applied in the backlight diffusion and enhancement of flat panel display backlights, optical fiber couplings, and wave-front detection. Numerous processes have been developed to enhance the precision, but few of them can be applied in mass production. In this study, the experimental data of three processes were used for exploration and discussion. With relatively few experimental results, this study used a back-propagation neural network (BPN) to construct a prediction model, and then applied a genetic algorithm (GA) in the global optimum search. The above process was used to find the optimal process parameter combination to assist the enhancement of the optical microlens array replication process.

Keywords - Microlens Array, Optimization Process; Genetic Algorithm; BPN

I. INTRODUCTION

Applications for optimal film can be found in almost any place where there is light. Examples include glare resistant lamps, different types of glasses, camera lenses, vehicle window insulation, FPDs (flat panel displays), and even banknote anti-counterfeit measures. In 2002, the Taiwan government proposed the Two Trillion Double-star Plan, setting a goal of reaching 1 trillion NTD in both the semi-conductor and FPD industries by 2006. Governmental support has promoted the fast growth of optics-related industries, and it is one of the major factors that have allowed Taiwan to rival South Korea in FPD production capacity.

FPD backlight modules are not technologically different from general fluorescent lights. The strip light sources can present the backlight effect of even lights because of the layers of optical film; this is an application of a microlens array. However, the light utility rate is extremely low, at around 5%, due to layers of consumption. The other 95% of the light source causes energy waste as well as an increase in the FPD operating temperature, thus shortening its service life.

Hence, microlens arrays have been applied in FPDs to achieve energy efficiency. Composed of numerous two-dimensional arrays, a microlens array changes the direction of light travel by optical conceptual design. Each lens refracts the incoming light to avoid blocking the transistor and line, focusing the lights on the opening of the liquid crystal layer. Thus, the light appears only in that spot, which improves the light source utilization.

Stimulated by consumer market demands, manufacturers have need to reduce product sizes while being careful not to affect product functionality, in order to make multi-functional, lightweight, highly portable and good-looking products. This has led to increasing demands for microlens arrays. The system integration of microlens arrays and MEMS is diversified, and they have been applied in optical communications, medical, surveying, astronomy and other research fields, including FPD light source diffusion and enhancement, optical coupling, and wave front detection.

When a product requires mass production, it will attract more studies on its process. Numerous process optimization methods have been widely applied in various industries. Through working out the optimal process parameter combinations, companies are expected to be more effective in the manufacturing process and achieve higher product quality demands. This is one of the major reference factors to judge the competitiveness of various enterprises.

The above industrial developments have resulted in a substantial increase in the demand for optical products. The traditional optical technology of using glass as the manufacturing material cannot fully satisfy consumer demands. Plastic optical components that light weight, have a low cost, wide raw material options and high reproducibility have received attention and have been rapidly developing. However, due to the microlens array product size and accuracy requirements, the commonly used injection molding technology for general plastic products needs to be modified and improved. There are a number of emerging manufacturing method; however, when the size is reduced to the nanometer level, setting the parameters to precisely present the detailed design of a microlens array surface using plastic materials becomes a major problem.

Numerous studies have used the experimental design or Taguchi quality engineering technology to reduce experiment times and costs to find the optimal process parameter combination. Taking advantage of the solution-finding characteristics of a BPN in cases of information insufficiency may be able to additionally reduce experiment times and costs for process parameter optimization, providing the same effects with the increased elasticity of a rapid response while using fewer resources.

Neural networks and GAs have been used in finding solutions to numerous academic and real-world problems and have been proved as reliable for application in numerous situations. The reproduction of successful models can provide the appropriate process parameter combinations without doing experiments; thus increasing the probability of getting correct parameter combinations and reducing the costs and needed resources for experimentation.

II. THE APPLICATION OF NEURAL NETWORKS IN MICROLENS ARRAYS

Hung et al. [1] used the data obtained by the Taguchi L28 orthogonal array experiment for BPN training with a network prediction error smaller than 1%. It could reduce the variance of microlens caused by the hot-flowing process parameters by 58%. Many of the above studies have used neural networks to get better prediction models with complete information. However, this study attempted to find the optimal solution under a certain accuracy level with less information, by taking advantage of applying neural networks in character recognition.

III. THE APPLICATION OF GA IN MICROLENS ARRAY PROCESSES

Gomes and William [2] used GA, without increasing the error rate of wavefront detection, to achieve the same target error tolerance, using a microlens array of 10 properly calculated microlens in position instead of the original microlens array of 36 microlens. GA has been confirmed as having a good solution-finding quality in problems for various fields, as well as in the studies above. However, discussions on the quality attribute of transliteration are rare, and this study explored this respect.

IV. RESEARCH METHOD FOR MICROLENS ARRAY MANUFACTUING OPTIMIZATION

This study discussed process optimization with transliteration as the subject using three processes of mass production capabilities, including micro-injection molding, micro-injection compression molding and micro hot embossing.

The data used in this study consisted of three parts, including data for micro-injection molding, micro-injection compression molding, and micro hot embossing. The data were provided by Kang-yung Shen from the experiments on Taguchi quality engineering technology. The diameter of the microlens was 150μm and there were two heights, 11.35μm and 31.67μm, respectively. The total number of microlens was about 200x200.

The micro-injection molding and micro-injection compression molding processes used two types of forming materials: PMMA and PC. The PMMA brand was Asahi Kasei -DELPET80NH, and the PC brand was Mitsubishi - H3000R. Micro hot embossing also used two types of PMMA and PC raw materials: MSK-PMR2 and GE-T2FOQ, both of which were optical level thin films. The thickness of the PMMA was 0.8mm, and the three types of PC materials had a thickness of 0.38mm, 0.25mm, and 0.18mm, respectively.

The four types of process parameters for the three processes are as shown in the following table:

Table 1 process parameters

parameter\level	micro-injection molding	micro-injection compression molding	Micro hot embossing
parameter A	mold temperature	mold temperature	mold temperature
parameter B	molten plastic temperature	molten plastic temperature	Compression pressure
parameter C	injection speed	injection speed	Compression time
parameter D	dwell pressure	injection speed	mold temperature

In the micro-injection molding process, the four parameters of the PC and PMMA materials, including the mold temperature, molten plastic temperature, injection speed and dwell pressure, were set at three different levels, as shown in Tables 2 and 3:

Table 2 micro-injection molding process parameter level of the PC material

parameter\level	level Ⅰ	level Ⅱ	level Ⅲ
A. mold temperature (℃)	100	110	120
B. molten plastic temperature (℃)	300	310	320
C. injection speed (mm/s)	180	190	200
D. dwell pressure (MPa)	160	180	200

Table 3 micro-injection molding process parameter level of the PMMA material

parameter\level	level Ⅰ	level Ⅱ	level Ⅲ
A. mold temperature (℃)	70	80	90
B. molten plastic temperature (℃)	240	250	260
C. injection speed (mm/s)	120	140	160
D. dwell pressure (MPa)	100	120	140

In the micro-injection compression molding process, the four parameters of the PC and PMMA materials, including the mold temperature, molten plastic temperature, injection speed and compression speed, were set at three different levels, as shown in Tables 4 and 5:

Table 4 Micro-injection compression molding process parameter level of the PC material

parameter\level	level Ⅰ	level Ⅱ	level Ⅲ
A. mold temperature (℃)	100	110	120
B. molten plastic temperature (℃)	300	310	320
C. injection speed (mm/s)	180	190	200
D. dwell pressure (MPa)	8	16	24

Table 5 Micro-injection compression molding process parameter level of the PMMA material

parameter\level	level Ⅰ	level Ⅱ	level Ⅲ
A. mold temperature (℃)	70	80	90
B. molten plastic temperature (℃)	240	250	260
C. injection speed (mm/s)	120	140	160
D. dwell pressure (MPa)	8	16	24

In the micro hot embossing process, the four parameters of the PC and PMMA materials, including the mold temperature, imprinting pressure, compression time and ejection temperature, were set at three different levels, as shown in Tables 6 and 7:

Table 6 Micro hot embossing process parameter level of the PC material

parameter\level	level Ⅰ	level Ⅱ	level Ⅲ

A. mold temperature (℃)	180	190	200
B. molten plastic temperature (℃)	3.13	4.17	5.21
C. injection speed (mm/s)	30	60	90
D. dwell pressure (MPa)	50	60	70

Table 7 Micro hot embossing process parameter level of the PMMA material

parameter\level	level Ⅰ	level Ⅱ	level Ⅲ
A. mold temperature (℃)	130	140	150
B. molten plastic temperature (℃)	3.13	4.17	5.21
C. injection speed (mm/s)	30	60	90
D. dwell pressure (MPa)	50	60	70

Using the Taguchi orthogonal array, as shown in Table 8, L9 (34). This study conducted nine tests of each process using different materials and thicknesses, with five samples in each test. Combined with the optimized parameter combinations found by the Taguchi quality technology, verification tests were conducted with five samples in each case, for a total of 50 batches of data, as shown in Appendix A.

Table 8 L9 (34) Taguchi orthogonal array

Experiment	Parameter A	Parameter B	Parameter C	Parameter D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

A. BPN Construction

This study used the data of the above experiments after reduction for network training, and searched its optimized parameter combinations at the subsequent stages. A BPN is a type of monitoring learning network structure. After pair data training, BPN was used in the calculation of the transliteration estimated value.

Since the input information of this study was four-dimensional, the number of input layer neurons was set as four and the output parameter was set as one. The number of the output layer neurons was therefore one. The hidden layer in the middle has no certain standard regarding the number, and as a network with one hidden layer can solve most problems, it was set as one layer. The number of neurons referring to the setting of NHN=(no. of input* no. of output)0.5 was set as two. The overall network structure was a 4-2-1 network architecture.

The input layer was linearly converted to output the addition of the multiplication of the input value and the weight. The hidden layer and the input layer were non-linearly converted after the addition of the input value and the weight using the sigmoid function.

B. GA Model Construction

After the completion of the prediction mechanism composed of a BPN, this study used a genetic algorithm to construct a solution-finding model for the optimal value to search the combination of optimal process parameters.

This study used a real number coding scheme by setting Level 1 of the Taguchi experiments as the lower bound and Level 3 as the upper bound. The random values of the four parameters produced within the lower and upper bounds were used as the initial parent population to be placed in a chromosome with a length of 4, and the values were subsequently changed according to the rules. The coding scheme is as shown in Figure 1.

85.492	249.738	144.357	136.875

Figure 1 Real number coding diagram

C. Fitness Function Value Calculation

The fitness function value calculation was based on the BPN structure, and it was normalized before being input into the network. The equations used are as follows:

where xi stands for the value after the normalization of zi, zmax and zmin stand for the maximum and minimal value of the data group of zi, and λ1 and λ2 represent the predicted range of the data after normalization. The range was [0.1, 0.9] in this study. The normalized data were then input into the above mentioned network structure after training, to find the output values after the weight and function conversion of the network.

V. *RESULTS AND DISCUSSION*

This study used Borland C++ Builder 6.0 as the complier to write the program for finding the solution. The program was mainly composed of two parts. The first part was the proper prediction model obtained by training the BPN for a 4-2-1 network architecture. In the second part, the model was input as the rule for the calculation of the fitness function to find the optimal process parameter combination using GA.

The solution-finding equipment was an Intel Core2 Due T9600 (2.8GHz) CPU, 4G of memory, and Windows 7 home edition (32-bit) OS. In this setting, it took about 0.5 seconds to find the BPN solution for 1000 generations, and it took about 4.5 seconds for to find the solution for 1000 generations using GA.

A. Data Setting

The solution-finding equations used three different data amounts, including six groups of 30 batches, seven groups of 35 batches, and eight groups of 40 batches for discussion. For the six groups of 30 batches, No. 1, 2, 3, 4, and 5 of the Taguchi quality technology L9 orthogonal array and the No. 7 experimental data combination were used for experiment. For the seven groups of 35 batches of data, No. 1, 2, 3, 4, 5, and 6 of the Taguchi quality technology L9 orthogonal array and the No. 7 experimental parameter combination were used. For the eight groups of 40 batches of data, No. 1, 2, 3, 4, 5, 6, and 7 of the Taguchi quality technology L9 orthogonal array and the No. 8 experimental parameter combination were used. The matching of different data amounts and the experimental groups are as shown in Table 9.

Table 9. Solution-finding calculation data and experimental groups

Data Set	experimental group
6	1、2、3、4、5、7
7	1、2、3、4、5、6、7
8	1、2、3、4、5、6、7、8

B. Parameter Setting

The learning rate of the BPN training was set as 0.5, the momentum of inertia was set as 0.5, and the samples without excessive training during the training process were selected, namely, the weight combination of the lowest point before the rebound of the testing sample's MSE was selected coupled with the 4-2-1 network architecture as the basis for the subsequent prediction. The BPN network architecture is as shown in Figure 2, and the selection of the weight combination is as shown in Figure 3.

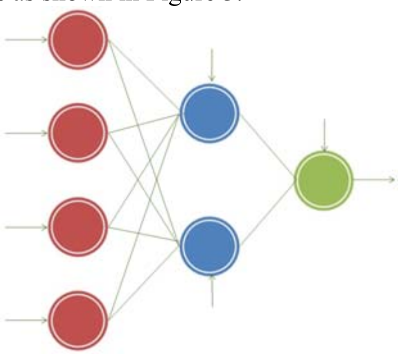

Figure 2. BPN network architecture

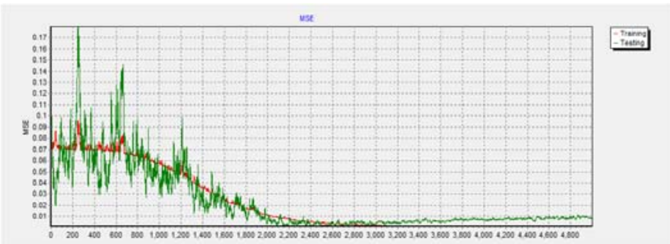

Figure 3. BPN training weight combination selection

The GA population was set as 100, the number of replications was set as 80, the crossover rate was set as 0.5, and the mutation rate was set as 0.001 for the calculation of 1000 generations to find the solution.

VI. CONCLUSIONS

This study classified the actual Taguchi experimental data of different processes and materials into six, seven and eight groups, respectively, for the training of the prediction network model of the BPN. The model was then used as the tool for finding the solution to the GA fitness function for GA optimization.

The calculation data showed that, overall, the solution-finding results of using eight groups of data were better than the results of using seven or six groups of data, in terms of the network prediction. However, the differences between the results of using seven groups of data for solution-finding training and using eight groups of data were slight, in terms of the network prediction accuracy. In some cases of process and material combinations, the network prediction accuracy of using seven groups of data was higher than that of using eight groups of data. Using six groups of data for training was considerably lower than that of using eight or seven groups of data for training, in terms of the network prediction accuracy. In addition to a rising error rate, the obtained process parameter combination was either different from the optimization process parameter combination obtained using the Taguchi quality technology or was in an unstable state.

In the data analysis model integrating the proposed BPN and GA, using seven groups of data for training the solution-finding can minimize the experimental times and costs while keeping the quality stable.

When using seven groups of data for solution-finding training, as suggested in this study, the experimental time can be reduced by 22.22%, reducing the experimental costs and time consumption while keeping a stable quality. As far as the research data of this study was concerned, the maximum network error rate obtained using seven groups of data for training was 5.89%, which was acceptable.

In the proposed data analysis method, when the levels of the Taguchi experiments have no significant impact on the experimental results, the obtained optimization process combination may not be the same as the optimization parameter combination obtained using the Taguchi quality technology. However, the microlens transliteration results obtained by the two data analysis methods are very close.

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