Decision Support for IC Molding Parameter Settings Using Grey Relational Analysis and Neural Network

Yu-Min Chiang, Chung-Hsien Chou, Yung-Yuan Chuang

Department of Industrial Engineering and Management, I-Shou University
No. 1, Sec. 1, Syuecheng Rd., Dashu Township, Kaohsiung County, 840, Taiwan, R. O. C

Abstract

In order to be competitive in the semiconductor manufacturing industry, quality improvement and yield enhancement have received increasing attention. The research focuses on the molding process of Integrated Circuit (IC) assembly. The defects often occurred in molding process include hole, vein, crack, and floss. In order to raise the yield of molding process, the study applies the Taguchi method combined with grey relational analysis to find out the most appropriate molding parameters with multiple quality characteristics. The study further adopts a back-propagation neural network to estimate the optimal process parameters. Results show that the proposed approach can improve the quality of the molding process.

Keywords: Multiple quality characteristics, Taguchi method, grey relational analysis, neural network

1. Introduction

Semiconductor industry has become apparent as one of the most important industries in Taiwan. As the rapid progress of semiconductor fabrication, the downstream assembly companies have to develop robust and reliable processes with high yield to become competitive in the global environment. The assembly of integrated circuit (IC) chips influences significantly overall electrical performance and product reliability.

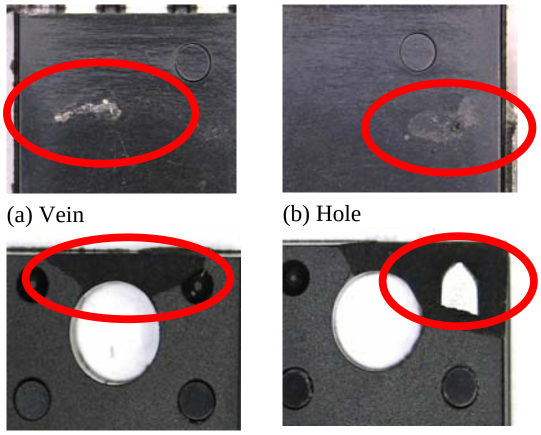
Recently, engineers in a variety of industries have applied the Taguchi method to design and improve the product or process performance [1, 2]. The Taguchi method is a systematic application of design and analysis of experiments for the purpose of designing and improving product quality and is also called parameter design [3]. It uses the orthogonal array to set up the experiment for the advantages of less number and elastic disposition of experiment, and optimizes the process parameters by the analysis of signal to noise (SN) ratio table and graph to improve the robustness of products. Though the Taguchi method is a powerful tool for improving productivity, it has certain limitations when used in practice. Su and Chiang [4] induced three major drawbacks about employing the Taguchi method. For example, the Taguchi method can only obtain the optimal solution within the specific level of control factors. They therefore utilized a neural network combined with genetic algorithm to optimize IC wire bonding process.

Another limitation of the traditional Taguchi method is it only can be used to optimize a single performance characteristic. Some researchers tried to solve the problem with multiple quality characteristics by the grey relational analysis [2, 5-7]. The method transformed multiple quality characteristics into grey relational grade, and then optimized the process parameters by analyzing the grey relational grade.

However, the tasks of parameter setting to obtain the desired quality are often taken by the process engineers based on their experience or equipment vendor's suggestion. In this work, an integrated decision support approach for IC molding parameter settings using the grey-based Taguchi method and the neural network is proposed to improve yield.

2. Decision Support for IC Molding Parameter Settings

The research focuses on the molding process of IC assembly and its purpose is to improve the yield. To investigate the importance of parameter settings, the study first applied the Taguchi method to find out the suitable process parameters by a minor number of experiments. The quality characteristics of molding process include hole, vein, crack, and floss, as shown in Fig. 1. As the molding process has multiple quality characteristics, we can't use the traditional Taguchi method to obtain the optimal process parameters. Instead, the research applies the grey relational analysis to integrate the multiple quality characteristics into a single index called grey relational grade. The paper further adopts a neural network to obtain the optimal solution beyond the specified level of control factors. Fig. 2 schematically depicts procedures of the proposed parameter settings decision support approach. Details of the three main methods are described in the following sub-sections.



(a) Vein (b) Hole

(c) Floss (d) Crack

Fig. 1: Defects of molding process

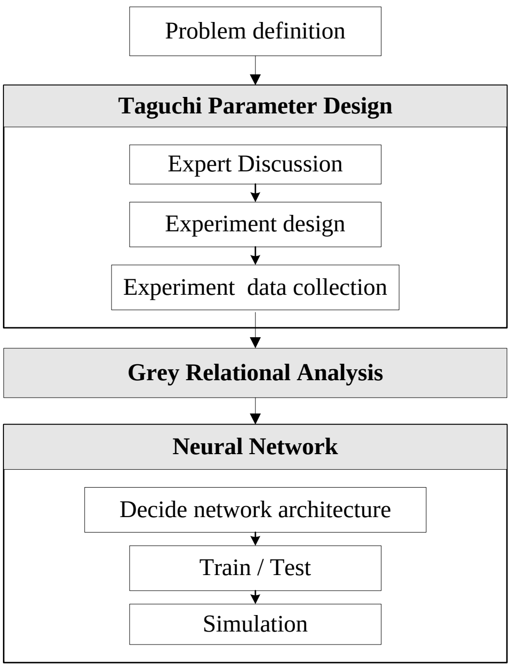


Fig. 2: Procedures for Parameter Settings

2.1. Taguchi parameter design

Five parameters of molding process were identified by expertise as the ones having the most impact. These five parameters are molding temperature, injection pressure, clamp pressure, shaft speed, and resin preheating temperature. Table 1 lists these control factors and their alternative levels. This study identified three noise factors which are temperature, humidity, and the molding compound. The molding quality is measured by the four types of defects as shown in Fig. 1.

Table 1: Control Factors and Their Levels

Control factors	Level		
	1	2	3
A: Molding Temperature (℃)	175	180	185
B: Injection Pressure (kgf/cm^2)	85	90	95
C: Clamp Pressure (kgf/cm^2)	110	120	130
D: Shaft Speed (m/sec)	12	17	22
E: Resin Preheating Temperature (℃)	90	95	100

According to the Taguchi quality design concept, an $L_{27}(3^5)$ orthogonal array was chosen to carry out the experiments. The same experiment was conducted under two trials with different levels of noise factors.

The quality characteristics in this work all belong to the smaller-the-better (STB) type. In the Taguchi parameter design, the SN (signal to noise) ratio is used to determine the deviation of the quality characteristic from the desired value. A higher SN ratio means the better performance. For the STB type of quality characteristic, the SN ratio is calculated by the following equation.

$$\eta = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_{ij}^2\right) \quad (db), \quad j = 1,\ldots,4. \qquad (1)$$

Where η = SN ratio transformation, measured in db

n = number of outer array combinations used for each inner array combination

y_i = i-th observed value of the quality characteristic j.

The optimal parameter of each quality characteristic is chosen after the analysis of the response table and the response graph.

2.2. Grey relational analysis

The grey system theory avoids the inherent defects of conventional, statistical methods and only requires a limited data to estimate the behavior of an uncertain system [8]. The theory is especially suitable for the data with uncertain, multi-inputs, and discrete properties. The steps of the grey relational analysis are as follows.

Step 1: Normalizing the original data.
Step 2: Calculating the grey relational coefficient.
Step 3: Calculating the grey relational grade.

In this paper, the grey relational grade is used to estimate the relative importance of multiple quality characteristics. The weight of the element (or attribute) is determined by the expert's experience.

2.3. Neural network

Since the Taguchi method can only obtain the best parameters solution within the specified level of control factors, it has certain limitations. To predict the behavior of any possible parameter combinations, the research uses a back-propagation (BP) network to derive the relationship model between input parameters and output quality characteristic. Therefore, the optimal solution beyond the specified level of control factors in the Taguchi experiments can be found. The detailed procedure is summarized as follows:

Step 1: Collect the input parameters and the corresponding output responses of the Taguchi experiments.

Step 2: Develop a BP network model. Apply the Taguchi method to determine the suitable network parameters like the number of hidden neurons, learning rate, momentum..., and so on.

Step 3: Prepare all possible input parameters combinations and use the built BP network to simulate the output responses.

Step 4: Find the optimal parameter combinations from the network simulated results.

3. Experiments and Results

3.1. Taguchi experiments

In this study, five control factors were selected to optimize the molding process. Twenty seven experiments with two noise factor trials were conducted by a $L_{27}(3^5)$ orthogonal array. The four response variables were recorded after one mold that contains 192 pieces of IC finished. Fig. 3 shows the response graph of the four quality characteristics. It can be observed from Fig. 3 that the best parameter combination of different quality characteristics has conflicts. For example, Level 3 of control factor C performs best in quality characteristic Hole but it's the worst solution for Floss. Therefore, it needs further analysis to find a parameter combination that can decrease the four types of defects simultaneously.

3.2. Grey relational analysis

After discussed with the domain experts, we set the weights of the four quality characteristics (Table 2). Among the four types of defects, Hole is the most one that need to be improved. Part of the results of the grey relational analysis is illustrated in Table 3.

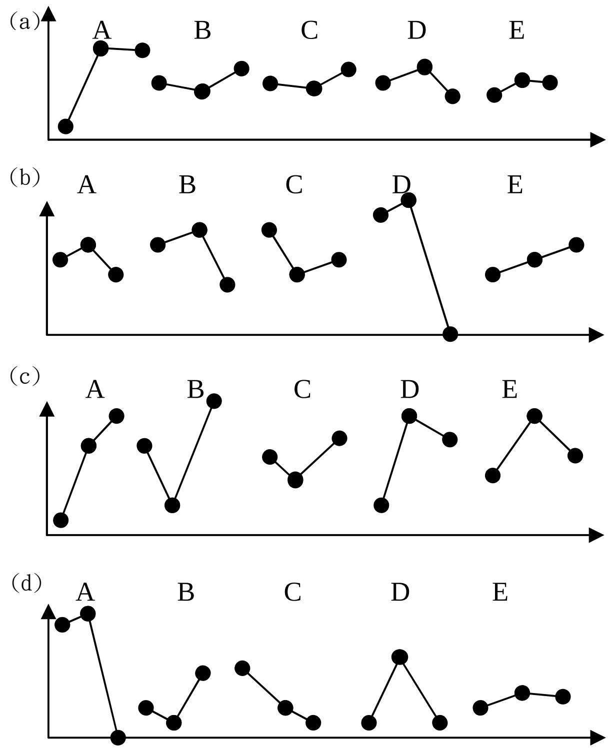


Fig. 3: Response Graph of four quality characteristics
(a) Hole (b) Vein (c) Crack (d) Floss

Table 2: The weights of four quality characteristics

Quality	Hole	Vein	Crack	Floss
Weight	0.4	0.2	0.3	0.1

Table 3: The grey relational grade (GRG) of each experiment

Experiment # (parameter combination)	GRG
1 ($A_1B_1C_1D_1E_1$)	0.85844
⋮	⋮
17 ($A_2B_3C_1D_2E_2$)	1
18 ($A_2B_3C_1D_2E_3$)	1
⋮	⋮
27 ($A_3B_3C_2D_1E_3$)	0.92059

From the result of the grey relational analysis, we obtained two optimal parameter combinations: $A_2B_3C_1D_2E_2$ and $A_2B_3C_1D_2E_3$. While the control factor E had little effect on the four types of defects, we dropped it from the control factors and conducted the confirmation experiment. Under the parameter combination $A_2B_3C_1D_2$, only one Hole and no other types of defects occurred in the molding process. The outcome verifies the performance of the proposed approach.

3.3. Optimization with a BP neural network

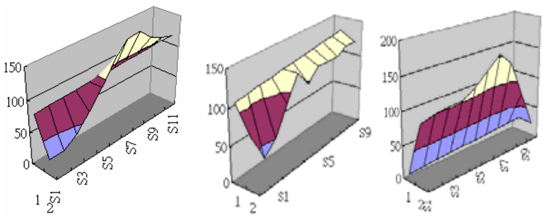
The research utilized the results of the Taguchi experiments for training a BP network to obtain the relationship between input parameters and output responses. For every control factor (*A~D*), we set 11 levels, so there are total 14641 parameter combinations. The simulated results show there are 4180 combinations that generate the minimal count of defects. Table 4 lists the numbers of parameter setting that has optimal responses under factor A's best settings (180 and 181). Fig. 4 shows the process window of factor A and the other factors. Suppose the factor A (molding temperature) is set as 180℃, the research suggests setting the injection pressure (factor B) as 92 kgf/cm^2, clamp pressure (factor C) as 119 kgf/cm^2, and clamp speed (factor D) as 18 m/sec. The results therefore provide engineers a decision support about molding parameters settings.

Table 4: The number of parameter setting that has optimal responses under factor A's best settings.

Factor A	number	Factor B	number	Factor C	number	Factor D	number
175	65	85	25	110	72	12	94
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
179	471	89	91	119	120	16	116
180	518	90	125	121	97	17	134
181	519	91	145	123	114	18	154
182	506	92	148	125	112	19	135
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
185	334	95	114	130	118		

4. Conclusions

The study proposed a decision support system for parameter settings by using the grey-based Taguchi method and the neural network to decrease the four types of defects occurred in the IC molding process. The experimental results validate that using the parameter combination obtained from the grey-based Taguchi method can simultaneously decrease the count of hole, vein, crack, and floss. It relatively reduces the opportunities of repair and rework of IC molding process and then raises the yield. The parameter settings of complicated multiple quality characteristics can be greatly simplified through this approach with reproducibility and feasibility. The paper also developed a BP neural network to derive the multivariate relationship model between input parameters and output responses to complement the limitations of Taguchi method. The generated process windows can benefit engineers in choosing a good parameter combination.



(a) A-B (b) A-C (c) A-D

Fig.4 The process window of factor *A* vs. the other factors

5. References

[1] M. S. Phadke, ***Quality Engineering using robust design***. NJ: Prentice-Hall, 1989.

[2] Y. S. Tarng, S. C. Juang, and C. H. Chang, "The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hardfacing," *Journal of Materials Processing Technology*, Vol. 128, No. 1-3, pp. 1-6, 2002.

[3] G. S. Peace, ***Taguchi Methods: A Hand-on Approach***. MA: Addison-Wesley, Reading, 1993.

[4] C. T. Su and T. L. Chiang, "Optimizing the IC wire bonding process using a neural networks/genetic algorithms approach," *Journal of Intelligent Manufacturing*, Vol. 14, No. 2, pp. 229-238, 2003.

[5] C. B. Chen, C. T. Lin, C. W. Chang, and C. P. Ho, "Grey relation for solving multi-quality characteristics problems of Taguchi methods," *Journal of Technology*, Vol. 15, No. 1, pp. 25-33, 2000.

[6] L. I. Tong and C. H. Wang, "Optimizing Multi-Response Problem in the Taguchi Method by Grey Relation Analysis," *Journal of the Chinese Institute of Industrial Engineer*, Vol. 17, No. 2, pp. 147-156, 2000.

[7] Y. M. Chiang and H. H. Hsieh, "Yield improvement for color filter by applying Taguchi method and the grey relational analysis," *Proceedings of the 35th International Conference on Computers and Industrial Engineering*, Istanbul, Turkey, Vol. 1, pp. 447-452, 2005.

[8] J. Deng, "Introduction to grey system," *Journal of Grey System*, Vol. 1, No. 1, pp. 1–24, 1989.