



O.R. Applications

Optimization of TQFP molding process using neuro-fuzzy-GA approach

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Abstract

This paper focuses on an integrated optimization problem that involves multiple qualitative and quantitative responses in the thin quad flat pack (TQFP) molding process. A fuzzy quality loss function (FQLF) is first applied to the qualitative responses, since the molding defects cannot be simply represented by the relationship between molding conditions and mathematical models. Neural network is then used to provide a nonlinear relationship between process parameters and responses. A genetic algorithm together with exponential desirability function is employed to determine the optimal parameter setting for TQFP encapsulation. The proposed method was implemented in a semiconductor assembly factory in Taiwan. The results from this study have proved the feasibility of the proposed approach.

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Keywords: Thin quad flat pack; Fuzzy quality loss function; Neural network; Exponential desirability function; Genetic algorithms

1. Introduction

The manufacturing of integrated circuits has become the heart of the electronic industry that is now the second largest basic industry (behind agriculture) and the fastest expanding manufacturing industry in the world. In the past, product is the only determinant of the profitability of a semiconductor company. However, over the last decade, the ever-increasing competition had led to the need for IC companies to also be able to

manufacture their products in an efficient and cost effective manner. Increasingly, these companies have turned to data intensive operational modeling and analysis tools and techniques because of their potential to significantly improve the bottom line performance [14].

Recently, IC packages have been diversified due to increasing handy or high performance electronic applications, which require smaller body, lightweight, and high I/O connection. Thin quad flat pack packages (TQFP) are applied to accommodate higher I/Os and faster production cycle times. The TQFP assembly process includes wafer mounting, die sawing, die bonding, wire bonding, molding, marking, plating, trimming and forming, and electrical functional testing.

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This study presents an integrated optimization approach of neural networks, generic algorithms, exponential desirability function, and fuzzy theory for solving multiple qualitative and quantitative response problems in the molding process of TQFP.

2. The molding process of TQFP

TQFP packages are plastic die encasements with lead contact distribution around the perimeters of the packages and can be referred to as “Gull Wing” packages due to the shape of the very fine contact leads (≤ 0.5 mm pitches) (Fig. 1). TQFP can be seen in a wide area of applications includes mobile communications, portable consumer electronics, portable computers, and PCMCIA cards with pin counts ranging from 44 leads to 256.

The TQFP molding process is used to provide mechanical support, connect and distribute signals, dissipate and distribute power, and insulate electricity. The quality of the molding process depends on the appropriate process parameter settings such as mold temperature, clamp pressure, transfer time, transfer pressure, cure time, and heat-plate temperature (Table 1).

Three types of TQFP molding defects that are most often encountered during operation and their characteristics are considered in this study (Table 2). However, optimization of multiple responses with qualitative and quantitative characters has received little attention in engineering fraternity. Complexity in decision-making is an issue concerning parameter design for the TQFP molding process. The excessive numbers of operation alternatives exist in the manufacturing system,

Table 1
TQFP molding process parameters

Parameter	Definition
Mold temperature	Temperature in the mold dies, controlling viscosity and cure rates of the mold compound
Clamp pressure	Pressure between upper and bottom mold dies keeping from molding compound linkage
Transfer time	Operation time for filling molding cavities
Transfer pressure	Operation pressure in molding cavities
Cure time	Cure time for solidifying the compound in the cavities
Heat-plate temperature	Preheating temperature for lead frames before moving molding compound into cavities

Table 2
TQFP molding defects and their characteristics

Defect type	Characteristic
Void (y_1)	Linguistic
Resin bleed (y_2)	Linguistic
Warpage (y_3)	Numeric

which makes the selection of appropriate parameter combinations a difficult task. An alternative methodology exploring the relationship between parameters and identifying the optimal setup values is an example of experimental design, that is, the Taguchi method. Although applying the Taguchi method can successfully identify the optimal parameter settings in the factorial design, the real optimal parameter values in the complete explored region cannot be guaranteed [11]. It is not unusual in most semiconductors manufacturing processes where engineers have to deal with multiple responses. Phadke [10] applied the Taguchi method with engineer’s judgement to the selection of the optimal parameters in a VLSI manufacturing system with multiple responses. By human judgement, the validity and feasibility of the experimental results cannot be assured. Furthermore, the design and analysis of multiple responses that involve not only quantitative but also qualitative characteristics have received little attention in the related literature. To make up for this shortfall, an integrated optimization approach for

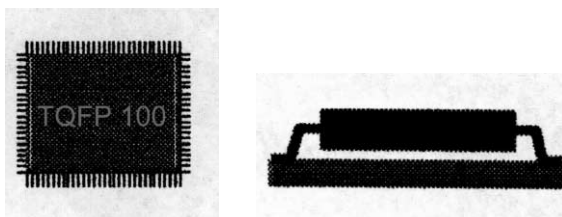


Fig. 1. The outline photographs of the TQFP package.

multiple responses by using fuzzy theory, neural network, exponential desirability function, and genetic algorithms in the TQFP molding process is proposed in this paper.

The rest of this paper is organized as follows. A brief description of fuzzy quality loss function, neural network, genetic algorithms, and exponential desirability functions is provided first. An integrated procedure for optimizing the TQFP molding process is presented in the next section. Then an experimental design for the implementation of proposed procedure is illustrated, followed by a benchmark of the proposed procedure and Taguchi method. Concluding remarks are made in the end.

3. Background information

This section will briefly introduce some portions of fuzzy quality loss function, neural network, genetic algorithms and exponential desirability function used in this study.

3.1. Fuzzy quality loss function

The quality loss is the most widely used technique of evaluating the quality performance [8]. The concept of Taguchi’s loss function is applied to formulating the quality loss of the linguistic data in terms of the membership function. It is shown that operating a process at the minimum of the quality loss function has the additional benefit of minimizing sensitivity of the product to noise variation in the design parameter settings, leading to robust designs automatically [1]. In this study, we develop an approach by minimizing fuzzy quality loss function (FQLF) of qualitative responses. The FQLF value is calculated based on the quality loss of the categories of the qualitative response. The FQLF can be formed as [5]

$$FQLF = \sum_{u \in U} [(u - u_{target})^2 * \bar{\mu}(u)], \tag{1}$$

$$\bar{\mu}(u) = r_A * u_A(u) + r_B * u_B(u) + r_C * u_C(u) + \dots, \tag{2}$$

$$r_i = \frac{n_i}{\sum_{i \in \text{fuzzy term}}^{\forall i} n_i}, \tag{3}$$

where u_A, u_B, u_C, \dots represent the membership function of the fuzzy terms A, B, C ; u_{target} denotes the target value of the qualitative response. r_A, r_B, r_C, \dots are the related frequency of fuzzy terms A, B, C, \dots in the experiment, and n_i is the count owing to the i th fuzzy term.

3.2. Neural network

Basically, a neural network approach can typically be constructed without any assumption about the functional form of the relationship between predictors and responses [13]. In addition to learning and extracting the process behavior from previous operating information, this approach can also be used as a model for process optimization. The neural network approach holds a major advantage over the statistical method in that the neural network is explicitly nonlinear through hidden layers. Neural networks have recently emerged as a highly promising alternative to physically based models and statistical methods of semiconductor process modeling. Fig. 2 displays the general structure of a feedforward multilayer neural network used for semiconductor process modeling that is typically trained via back-propagation [9].

3.3. Exponential desirability function

The desirability function approach attempts to transform a multiresponse problem into a single response problem by mathematical transformation [3]. Kim and Lin [7] developed an approach based

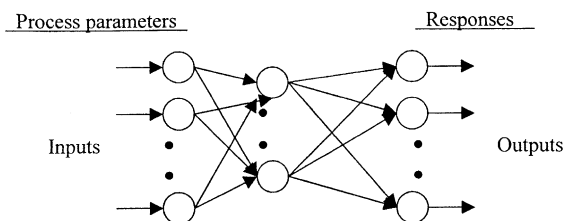


Fig. 2. Topology of the back-propagation neural network.

on maximizing exponential desirability functions that do not require any assumptions regarding the form or degree of the estimated response models. Such an approach is robust to the potential interdependency between response variables. Their approach aims to identify the settings of the input variables to maximize the degree of overall satisfaction with respect to all the responses. The exponential desirability function has been extensively used to simultaneously optimize several responses. The exponential desirability function can be formed as [7]

$$d(z) = \begin{cases} \frac{\exp(t) - \exp(t|z|)}{\exp(t) - 1} & \text{if } t = 0, \\ 1 - |z| & \text{if } t \neq 0. \end{cases} \quad (4)$$

3.4. Genetic algorithms

For solving optimization problems, genetic algorithms have been investigated recently and shown to be effective at exploring a large and complex space in an adaptive way guided by the equivalent biological evolution mechanism [4,6]. Many conventional optimization methods start from one point in the search area and then move sequentially to achieve the optimal solution, thereby operating rather locally and highly prone to falling inside a coincidental local optimum. GAs perform a global, random, and parallel search for an optimal solution using simple computations. Generally speaking, GAs start the search with a population of randomly generated design candidates known as the first generation. Once the first generation is generated, GAs produce subsequent generations based on three operators of reproduction, crossover, and mutation in an iterative way.

4. Proposed optimization procedure

This study proposes an integrated optimizing algorithm of the parameter settings in the TQFP molding process that involves multiple qualitative and quantitative responses. The proposed approach consists of three major stages. The first stage of the procedure defines the linguistic fuzzy

term, defective category, and membership function for each qualitative response. The value of fuzzy quality loss function is then computed in the organized experiment. The next stage involves using a BP network to derive the relationship model between input parameters and output responses. Notably, the trained network can accurately predict the behavior of the feasible parameter combinations. Thus, tuning the input parameters in the trained network allows us to obtain the corresponding responses. The exponential desirability function is then used to transform the multiple responses into a single response. During the third stage, GA is applied to obtain the optimum degree of satisfaction (λ). Herein, the chromosome represents the possible solution. Each gene in the chromosome represents the value of the input parameter. For example, a manufacturing process has three input parameters M , N , and O . The value of the three parameters (M , N , O) can be represented by a chromosome, respectively. The essential genetic operators during the iterative procedure can be found in the previous section. These operations are conducted to obtain the optimal response, which is evaluated by the fitness function. Therefore, the optimal parameters concerning the problem can be obtained. Fig. 3 schematically depicts the proposed optimization procedure. The detailed procedure is summarized as follows:

- Step 1.* Define the qualitative and quantitative responses. Determine the control factors and their levels.
- Step 2.* Identify the linguistic fuzzy sets, categories, and membership functions for qualitative responses.
- Step 3.* Conduct the experimental design.
- Step 4.* Collect the data and compute FLQF value of each qualitative response.
- Step 5.* Develop a BP network model to obtain the relationship between input parameters and output responses.
- Step 6.* Apply the exponential desirability function to transforming the multiple responses into a single one. The trained network with a modified single response is referred to as a fitness function.

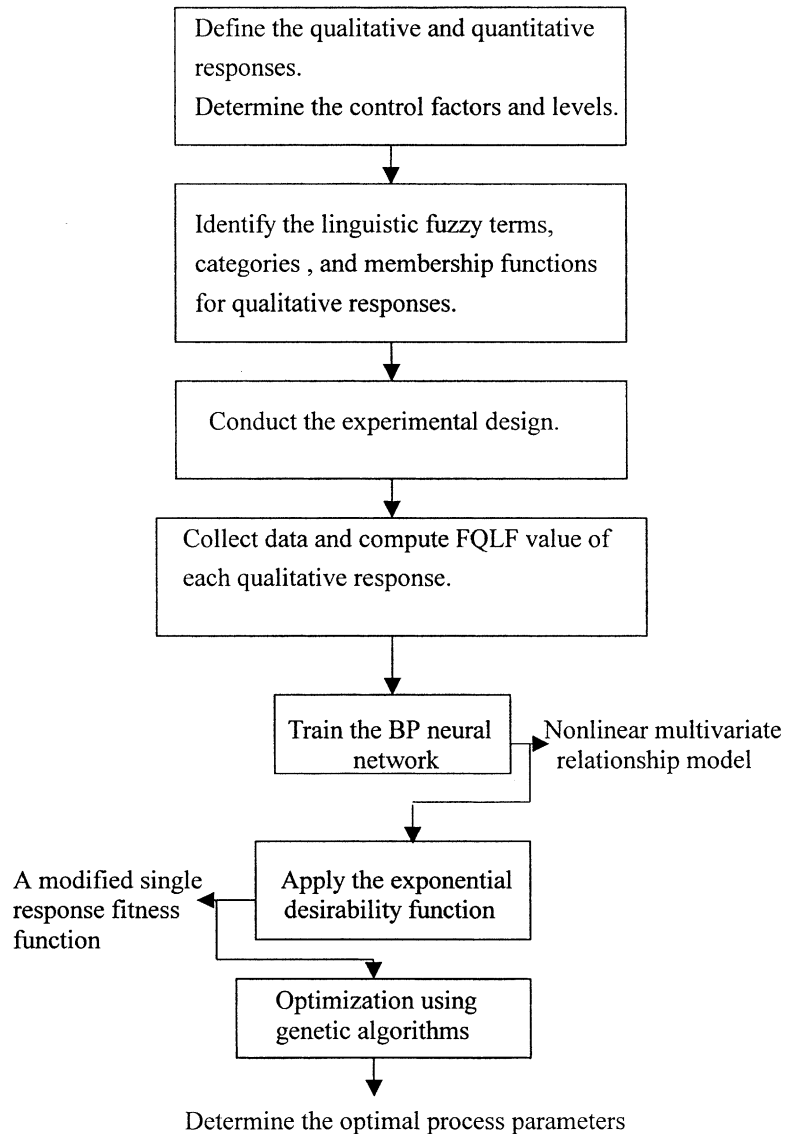


Fig. 3. The proposed procedure for determining the optimal molding parameters.

- Step 7.* Set the GA operating conditions (e.g. population size, generation size, parameter number, crossover rate, and mutation rate).
- Step 8.* Create an initial population by randomly selecting the value of the input parameters.
- Step 9.* Repeat steps 10–14 until the stopping condition is reached.

- Step 10.* Calculate the fitness value by inputting the parameter values to the fitness function.
- Step 11.* Select the parameter values according to the computed responses.
- Step 12.* Crossover the fitness parameter values.
- Step 13.* Mutate the parameter values to yield the next generation.

Step 14. Obtain the current optimal parameter values.

Step 15. Obtain the optimal parameter settings.

5. Implementation

5.1. Conduction of the experiment

This study focuses on three types of TQFP molding defects, i.e., void, resin bleed and warpage, which are most often encountered during the operation. In order to optimize the molding process with respect to each response, an engineering experiment on the 1.4 mm TQFP100 molding process is conducted. Table 3 lists the process parameters and values for each level. Thirty-six trials (36 strips of lead frames) are conducted by a well-structured orthogonal array L_{18} .

A universal set of $u \subseteq U = \{1, 2, 3, 4, 5\}$ is defined based on process engineer’s experience as the categories of defect significance of void and resin bleed from $u = 1$ (the worst grade) to $u = 5$ (the best grade). Thus, the target value of the two qualitative responses is 5 for each. The membership functions of both fuzzy sets A (good) and B (serious) with respect to defects of void and resin bleed according to the impact on the final quality can be given as:

For void:

$$A = \langle \text{good} \rangle = \frac{0.1}{1} \oplus \frac{0.2}{2} \oplus \frac{0.4}{3} \oplus \frac{0.7}{4} \oplus \frac{1.0}{5},$$

$$B = \langle \text{serious} \rangle = \frac{1.0}{1} \oplus \frac{0.9}{2} \oplus \frac{0.3}{3} \oplus \frac{0.1}{4} \oplus \frac{0}{5}.$$

Table 3
Parameters level setting

Parameter	Level 1	Level 2	Level 3
Mold temperatue (x_1)	150	175	200
Clamp pressure (x_2)	1500	1800	2100
Transfer time (x_3)	3.0	6.0	9.0
Transfer pressure (x_4)	300	600	900
Cure time (x_5)	50	70	90
Heat-plate temperature (x_6)	70	100	130

For resin bleed:

$$A = \langle \text{good} \rangle = \frac{0}{1} \oplus \frac{0.1}{2} \oplus \frac{0.7}{3} \oplus \frac{0.9}{4} \oplus \frac{1.0}{5},$$

$$B = \langle \text{serious} \rangle = \frac{1.0}{1} \oplus \frac{0.8}{2} \oplus \frac{0.5}{3} \oplus \frac{0.2}{4} \oplus \frac{0.1}{5}.$$

Tables 4–6 list the membership value of each category corresponding to each element in the universal set U by applying Eqs. (2)–(5) to the qualitative responses to void and resin bleed, respectively. The FQLF of each run for the qualitative defects of void and resin bleed is computed by Eq. (1). The experimental data (as shown in Table 7) are then used to construct the relationship model between parameters and responses through the neural network training.

Table 4
Definition of the categories of the qualitative characteristics

Category	Linguistic description of defects
I	[very][good]
II	[good]
III	[not][good][and][not][serious]
IV	[serious]
V	[very][serious]

Table 5
The membership functions with respect to the category of void

Category of response	Element of the universal set u				
	1	2	3	4	5
I	0.01	0.04	0.16	0.49	1
II	0.1	0.2	0.4	0.7	1
III	0	0.1	0.6	0.3	0
IV	1	0.9	0.3	0.1	0
V	1	0.81	0.09	0.01	0

Table 6
The membership functions with respect to the category of resin bleed

Category of response	Element of the universal set u				
	1	2	3	4	5
I	0	0.01	0.49	0.81	1
II	0	0.1	0.7	0.9	1
III	0	0.2	0.3	0.1	0
IV	1	0.8	0.5	0.2	0.1
V	1	0.64	0.25	0.04	0.01

Table 7
Experimental data

Test no.	Void (FQLF, 40 ea/2 strips)	Resin bleed (FQLF, 40 ea/2 strips)	Warpage (mil, two strips)	
			S_1	S_2
1	13.9	13.4	3.2	3.5
2	18.1	22.7	4.1	3.9
3	15.5	14.8	3.1	3.3
4	5.8	3.9	1.8	1.4
5	3.7	5.6	2.6	3.0
6	10.1	5.0	0.5	0.6
7	3.4	3.7	0.9	0.5
8	6.1	4.3	1.3	1.1
9	4.1	4.3	1.4	1.2
10	18.3	19.5	3.9	3.6
11	21.8	21.5	3.0	3.2
12	6.9	4.8	2.6	2.7
13	17.4	20.9	2.0	1.8
14	13.3	15.0	2.7	2.9
15	3.1	3.2	0.4	0.3
16	8.0	7.4	2.0	1.8
17	3.7	11.1	2.6	2.5
18	3.4	5.8	1.9	2.1

5.2. Determination of the fitness function

The BP neural network is used to develop the required model. Eighty percent of the patterns for training and 20% for testing are randomly selected from Table 7. Fig. 4 displays the detailed neural

network architecture which the structure 6-4-3 is selected under the best convergence criterion of the root of mean square (RMSE).

In this study, all of the responses y_1 , y_2 and y_3 belong to the smaller-the-better type. Herein, the exponential desirability function is used to solve the multiresponse problem. We have

$$\lambda = \min(d_1, d_2, d_3), \tag{5}$$

where d_i is calculated from Eq. (4). The engineering management agrees on employing convex exponential desirability functions for y_1 , y_2 and y_3 with $t = -3, -1$, and -2 , respectively, according to their importance. Therefore, λ is set as the fitness function of the GA, which will be further explored in the next section.

5.3. Optimization using genetic algorithms

Each input parameter in the TQFP molding process is normalized to a value between 0 and 1 and combined with others into one string. That is, the input parameters listed in Table 3 are transformed into the chromosome representation $(x_1, x_2, x_3, \dots, x_6)$ in a string. Strings are randomly generated to form the initial population. When GA is applied to optimize the TQFP molding parameter selection, the essential operators, including reproduction, crossover and mutation should

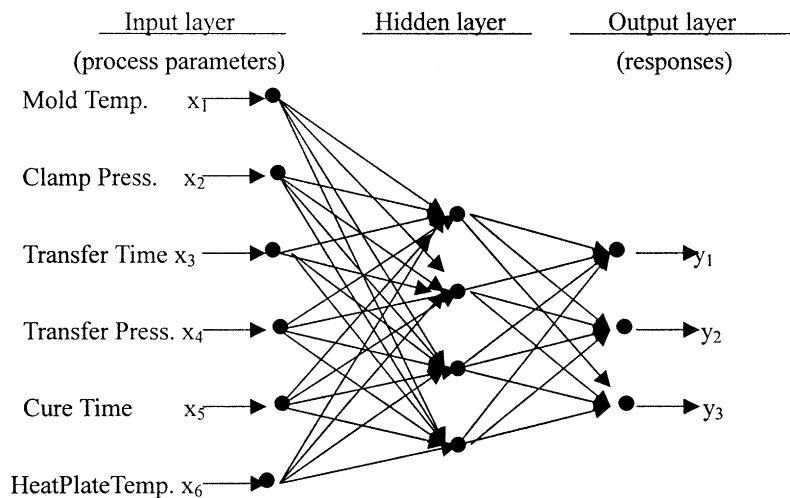


Fig. 4. Parameters-to-responses BP neural network.

Table 8
Implementation results of GA

Item	Data
The largest λ value in 20 runs	0.9021
The smallest λ value in 20 runs	0.8531
Average λ value	0.8819

be determined in advance. Herein, a roulette wheel approach is adopted as the selection procedure. The crossover rate and mutation rate are set as 0.5 and 0.01, respectively. Fifty strings are randomly generated to establish the initial population. Notably, 6000 generations were processed.

The above information is used and the GA is executed 20 runs. Table 8 summarizes the implementation results. A greater value of λ implies a better degree of satisfaction in terms of compromised solution. The largest λ value is 0.9021 and its optimum chromosome is (181, 1733, 4, 791, 88, 97). It indicates the optimal setting for the six process parameters.

6. Confirmation experiment and benchmark

Many practitioners have applied Taguchi’s approach and sound engineering knowledge with experience to tackling multiresponse problem [12]. This study finally conducted a comparison between the Taguchi method and the proposed approach under the optimum conditions. The analysis of the 18 original trials shown in Table 3 by using the Taguchi method results in the optimal settings for six control factors are as listed in Table 9. For benchmarking purpose, the Taguchi method and the proposed approach are again applied to the analysis of 40 strips (20 units per strip) for each at an IC assembly site. Table 10 compares the implementation results and reveals the superior

Table 9
Optimum parameters identified by the proposed approach and Taguchi approach

	x_1	x_2	x_3	x_4	x_5	x_6
The proposed approach	181	1733	4	791	88	97
Taguchi’s approach	200	2100	6	600	90	100

quality of the proposed approach over Taguchi’s approach.

According to the comparison in Table 10, the proposed approach reveals better performance more than 3.5% and 5.6% on the void and resin bleed, respectively.

This study also employed the *t*-tests of the mean values for warpage between the two approaches, respectively; the *t* statistics are -5.46 with a *P* value of 0.00001. Thus, there are strong evidences to indicate that the means for warpage by the proposed approach are better than the means by the Taguchi’s approach.

7. Conclusion

This study is presents an integrated optimization approach of neural networks, generic algorithms, exponential desirability function, and fuzzy theory for solving multiple qualitative response problems, which has received little attention among the engineering fraternity. Fuzzy set theory incorporates imprecision and subjectivity into the model formulation and solution process. The method of formalizing linguistic evaluation based on fuzzy sets proposed by Zadeh [2,15] is used in this study for providing more flexibility in presentation by defining each qualitative response. This study applies the fuzzy quality loss function (FQLF) to represent the value of each qualitative

Table 10
A comparison between the Taguchi’s approach and the proposed approach

	Probabilities by categories (void)					Probabilities by categories (resin bleed)					Warpage (mil)	
	I	II	III	IV	V	I	II	III	IV	V	\bar{x}	<i>s</i>
Proposed approach	0.88	0.11	0.01	0.0	0.0	0.94	0.06	0.0	0.0	0.0	1.4	0.3
Taguchi’s approach	0.85	0.12	0.03	0.0	0.0	0.89	0.11	0.0	0.0	0.0	2.1	0.5

response. Therefore, operating a process at the minimum of the FQLF has the additional benefit of minimizing sensitivity of the product to noise variation in the design parameters setting, leading to robust designs automatically.

The results of the study have demonstrated that the proposed methodology can be applied as a very effective approach to optimizing multiple responses in the TQFP molding process. These settings facilitate process engineers in achieving acceptable process control during the production. In addition, the improvement in process performance enables factories to more easily manufacture products with superior quality in the IC assembly industry.

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