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Optimizing the IC wire bonding process using a neural networks/genetic algorithms approach

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A critical aspect of wire bonding is the quality of the bonding strength that contributes the major part of yield loss to the integrated circuit assembly process. This paper applies an integrated approach using a neural networks and genetic algorithms to optimize IC wire bonding process. We first use a back-propagation network to provide the nonlinear relationship between factors and the response based on the experimental data from a semiconductor manufacturing company in Taiwan. Then, a genetic algorithms is applied to obtain the optimal factor settings. A comparison between the proposed approach and the Taguchi method was also conducted. The results demonstrate the superiority of the proposed approach in terms of process capability.

Keywords: Integrated circuit (IC), wire bonding, neural networks, back-propagation network, genetic algorithms

1. Introduction

The packaging of integrated circuit (IC) chips often affects significantly overall electrical performance, reliability, and cost. In recent times, the major cause of failure in IC packaging has been the wire bonding (Fig. 1) (Rich, 1999). To prevent the facilities from producing unreliable products, failure in semiconductor packaging, especially in wire bonding, must be eliminated. Wire bonding today is applied throughout the semiconductor industry as a means of connecting the chips, the substrates and the output pins. Wire bonding designs include ultra fine pitch and cavity-up, which can dissipate heat from the die through the substrate and interconnect. Because of the intrinsic design, bond pads and outer-lead pads of IC packages are technically difficult to bond. Moreover, most wire bonding processes are designed for high I/O counts, normally reaching up to 500 leads. As a result, these processes demand both fine-pitch ($\leq 85\,\mu$m) wire bonding and require long wire lengths, straight loops as well as small first and second bond areas. With the requirements of high I/O count, fine pitch wire bonds, and long wire lengths, wire bonding in an IC assembly becomes critical. Optimizing a manufacturing process for the wire bonding technology requires a thorough study of all parameters relating to wire bonding.

Wire bonding is used throughout the semiconductor industry as a means of interconnecting the dies, substrates and I/O pins. Figure 2 depicts the mechanism of wire bonding. The wire bonding process begins with targeting the capillary on the bond pad and then positions above the die with a ball of which it is formed on the end of the wire. The capillary descends, forcing the ball in contact with the die. An inside cone, or radius, grips the ball and forms the bond. In a thermosonic system, ultrasound vibration is then applied. After the ball is bonded to the die, the capillary raises to the position of loop height. The clamps are open and the wire is free to feed out the end of the capillary. The lead of the device is positioned under the capillary, which is then

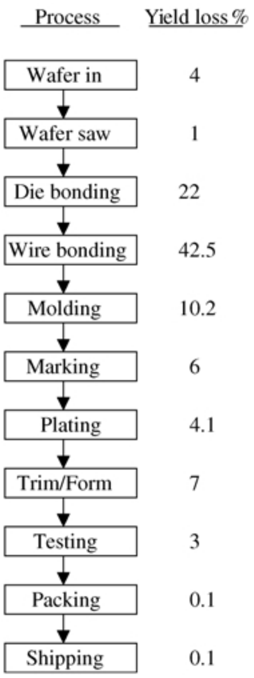

Fig. 1. Flow chart and its corresponding yield loss for IC assembly.

lowered to the lead. The wire is fed out the end of the capillary, forming a loop. The capillary deforms the wire against the lead producing a wedge-shaped bond, which has a gradual transition into the wire. The capillary then raises away from the lead and leaves the stitch bond. At a pre-set height the clamps are closed, while the capillary is still rising with the bonding lead. This prevents the wire from feeding out the capillary and pulls at the bond. The wire will break at bond's thinnest cross section. A new ball is formed on the tail of the wire, which extends from the end of the capillary. A hydrogen flame or an electronic spark may be used to form the ball. The cycle is completed to be ready for the next ball bond.

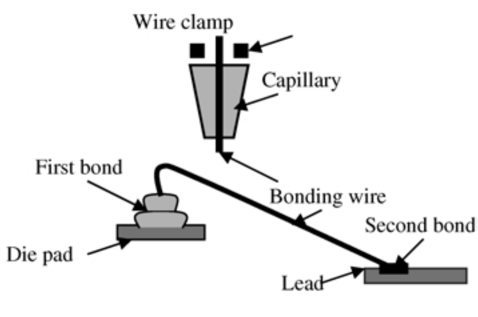

Fig. 2. The mechanism of wire bonding process.

The objective of wire bonding operation is to develop a high yield interconnect and low wire sweep process with a sufficient long-term reliability to satisfy customers. Wire bonding failures can attribute to many different causes, however, considerable evidence indicates that insufficient bonding strength is one of the main causes. Figures 3 and 4 show some defect pictures of wire bonding. To achieve a high standard of performance and quality for wire bonding, it is necessary to accurately identify and control appropriate parameters with respect to bonding process.

The task of the process engineers is to identify and control these parameters to obtain the desired wire bonding quality based on either their experience or equipment vender's recommendation to optimize response factors (e.g., maximum ball shear strength). Therefore, many industry practitioners have made their efforts in setting up tests to model actual field conditions and to find the cause-effect relationship of design to performance. However, their knowledge is limited in terms of providing a nonlinear relationship between control parameters and responses and searching for the optimum parameter settings. This task is complicated and difficult because wire bonding is a coupled multivariable system, which makes the adjustment of any single parameter inevitable without affecting the other ones within the system. Therefore, this multivariate operation reveals the necessities of having an intelligent system to be used for evaluating the process and determining the best adjustments (Tay and Bulter, 1997.)

Conventionally, engineers apply the Taguchi method to conduct parameter design in a variety of industrial practices. The Taguchi method offered a revolutionary concept, but the dramatic success of this methodology lies in the implementation of combining statistical design of experimental methods with a deep understanding of process problems. The usage of Taguchi's approach in the area of semiconductor manufacturing has been proven to be very beneficial to process modeling, optimization and control. For example, Phadke (1989) used the Taguchi method to study the surface defects and thickness of a polysilicon deposition process used in a VLSI circuit technology. However, the Taguchi method is not a panacea to all parameter design problems. It has certain limitations when used in practice, that is, the

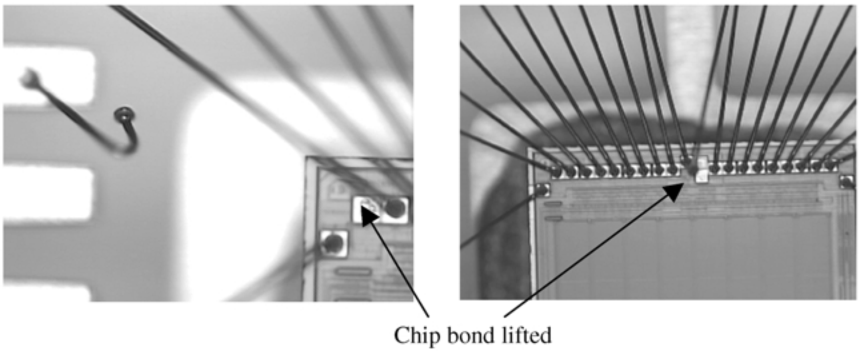

Fig. 3. Some defects of lifted chip bond.

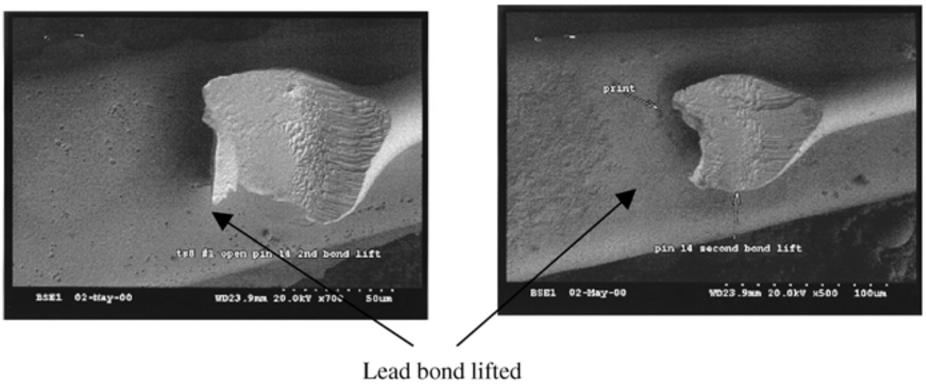

Fig. 4. Some defects of lifted lead bond.

optimal solutions obtained still remain uncertain (Goh, 1993; Dabade and Ray, 1996; Chao and Hwang, 1997). Those drawbacks are summarized as follows:

(1) The Taguchi method can only obtain the optimal solution within the specified level of control factors. Once the parameter setting is determined, the range of optimal solution is constrained concurrently.

(2) The Taguchi method is unable to find the real optimal values when the specified parameters have continuous in nature, because it only addresses the discrete control factors.

(3) The Taguchi method lacks of efficiency to deal with interactions among parameters.

This study presents an integrated technique not only to explore empirical models between process parameters and response via neural networks, but also to optimize the process through certain parameter settings using genetic algorithms for IC wire bonding process. A comparison through confirmatory trials between the Taguchi method and the proposed approach with respect to the response is conducted as well.

This paper is organized as follows. A brief description of neural networks and genetic algorithms is made. The next section proposes an integrated procedure for optimizing IC wire bonding process. An experimental design for the implementation of proposed approach and the Taguchi method is then illustrated; followed by a comparison between the proposed procedure and the Taguchi method in terms of process performance. Finally, a concluding remark is provided.

2. Modeling and optimization approach

2.1. *Neural networks*

Due to the breakthrough of neural networks technology, there has been an increasing amount of research application of neural network in the last decade. Neural networks are beginning to be used for modeling of complex manufacturing processes, usually for process and quality control (Coit *et al.*, 1998). Often times, these models are used to identity optimal process setting. In fact, neural networks possess a unique capability of learning arbitrary nonlinear mappings between noisy sets of input and output patterns (Lee *et al.*, 2000). Basically, a neural network approach can usually be constructed without requiring any assumptions being made concerning the functional form of the relationship between factors and responses (Stern, 1996). Besides, it learns and extracts the process behavior from the past operating information. It can also be used as a model for process optimization. The principal strength of a neural network outperforms the statistical method due to the fact that the neural network is explicitly nonlinear through hidden layers. It is a more general mapping procedure with respect to which a specific function format is not required in model building (Chang and Su, 1995; Chen *et al.*, 1999). Therefore, this advantage particularly fits for the highly complex process of IC wire bonding.

Recently, neural networks have emerged as an attractive alternative to physically construct models used for optimizing semiconductor processing. The general structure of a feedforward, multilayer neural network is shown in Fig. 5 after its being trained via back-propagation to be used in this study. The back-propagation networks have already been applied to a wide range of problems (speech synthesis, pattern recognition, etc.) and have demonstrated good results in most cases (Lipmann, 1987). A back-propagation network, once trained, can be evaluated very quickly—an advantage during the optimization phase. Recent overviews of applications to neural networks in manufacturing were compiled by Zhang and Huang (1995), and they have cited usages of neural networks from various factories such as milling, metal cutting, injection molding, arc welding and spray painting. In addition, Liao and Chen (1998) presented not only several MLP training algorithms for manufacturing process modeling but also three methods for process optimization. In their work, the transformation method is used to convert a constrained objective function into an unconstrained one and then used as the error function at the process optimization stage. More related applications can be found in (Tay and Butler, 1997; Chiu *et al.*, 1997; Liao and Chen, 1998; Chen *et al.*, 1999; Lee *et al.*, 2000; Chen and Liu, 2000).

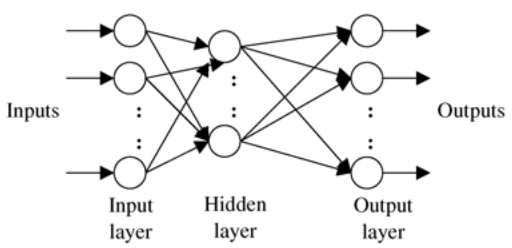

Fig. 5. Topology of a back-propagation neural network.

The back-propagation learning algorithm employs a heuristic with descending gradient to enable a network to self-organize in such a way that it improves its performance over a period of time. The training of a back-propagation network involves three stages: the feedforward of the input training data, the calculation and back-propagation of the associated error, and the adjustment of the connected weights. The equation utilized to adjust the weights following the presentation of an input/output pair for the output layer k is (Brainmaker, 1989):

$$\Delta W_{kj} = \eta \delta_k O_j$$

where ΔW_{kj} is the change to be made in the weight from the jth to kth unit following the presentation of an input pattern; η the learning rate that governs how fast the network will encode a set of input/output patterns; δ_k the error signal for unit k after the presentation of an input pattern; and O_j the jth element of the output pattern produced by the presentation of an input pattern.

The back-propagation rule for changing weights following the presentation of an input/output pair for the hidden layer j is

$$\Delta W_{ji} = \eta \delta_j O_i$$

where ΔW_{ji} is the change to be made in the weight from the ith to kth unit following the presentation of an input pattern; η the learning rate that governs how fast the network will encode a set of input/output patterns; δ_j the error signal for unit j after the presentation of an input pattern; O_i the ith element of the output pattern produced by the presentation of an input pattern.

2.2. *Genetic algorithms (GAs)*

Genetic algorithms (GAs) are optimization techniques based on the concepts of natural selection and genetics (Goldberg, 1989). Many conventional optimization methods start from one point in the search area and then move step by step with the intention of achieving the optimum, thus operating rather locally. Therefore, they are sensitive to falling inside a coincidental local optimum. In contrast, GAs counteract the entrapment in a local optimal solution by learning the principles of natural genetics and natural selection to conduct procedure of searching and optimization. They perform a global, random, and parallel search for an optimal solution with simple computations. The studies by Huang and Adeli (1994), Sette *et al.* (1997), Hsu and Su (1998) have demonstrated the superior capability regarding the optimum search using GAs.

GAs use the randomized operators operating on a population of candidate solution to generate a new population of candidates in the search space (Goldberg, 1989). In this paper, since large dimensions are involved in the parameters-to-responses function and the fact that a mathematical formulation is not available, this study applies genetic algorithms to optimize the complicated production system. Three essential operators, i.e., reproduction, crossover, and mutation, are used in GAs to evolve the possible solution. They are described as follows:

2.2.1. *Reproduction*

The main parameters must first be identified and coded as genes in the form of a string of finite length called a chromosome. The initial population of chromosomes can be randomly selected to ensure that the population is diverse. Reproduction is a process in which individual strings (chromosomes) are copied according to their fitness values. The higher the fitness values, the more will chromosomes have a higher number of offspring in the succeeding generation. Once a string has been selected for reproduction, an extract replica is made out of it. This string is then entered into a tentative new population for further operation performed by genetic operator.

2.2.2. *Crossover*

Having randomly initialized the population, the GAs will try to evolve the population to find the best solution. The crossover operation is applied to two parent structures selected probabilistically from the population. That is, a random point along the parent strings is chosen and designated as the crossover point. A new population with same size is created this way from the ''old'' population. Reproduction and crossover provide GAs with considerable flexibility and direct the search toward areas having better optimal values.

2.2.3. *Mutation*

The mutation operator is a simple one-unit operation on a single population member; it can be seen as a random walk through the whole string space. Using it cautiously can prevent a genetic system from premature death or stalling. Hence, a child inherits all bits from one parent up to the crossover point, and inherits all remaining bits from the other parent. Having done that, the GAs may also flip a small number of bits in the children to mimic the randomizing effect of biological mutation (Sette *et al.*, 1997).

3. Proposed approach for the IC wire bonding optimization

This section proposes an integrated neuro-genetic algorithm capable of optimizing the parameters setting in the IC wire bonding process. The proposed approach consists of two stages. The first stage involves using a BP network to derive the relationship model between input parameters and output responses. Note that the trained network can accurately predict the behavior of possible parameter combinations. Thus, tuning the input parameters in the trained network allow us to obtain the corresponding response. At the second stage, GAs are applied to obtain the optimum parameters setting. Herein, the chromosome is used to represent the possible solution. Each gene in the chromosome represents the value of the input parameter. For example, a manufacturing process has three input parameters X, Y, and Z. A chromosome can represent the value of the three parameters (X, Y, Z), respectively. The essential genetic operations are conducted to obtain the optimal response, which is evaluated by the fitness function. Therefore, the optimal parameters of the problem can be obtained. Figure 6 schematically depicts the proposed optimiza-

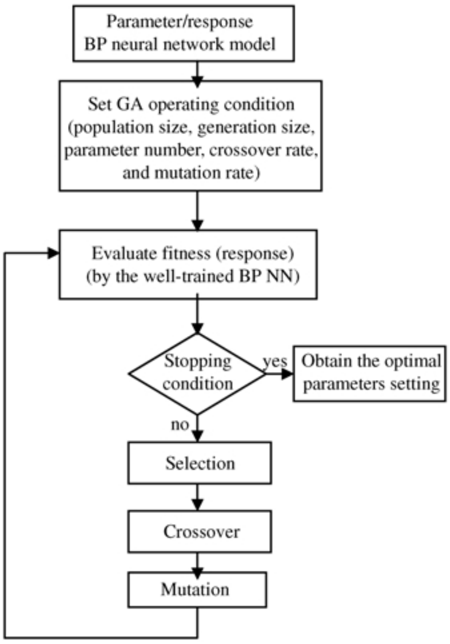

Fig. 6. Schematic diagram of the proposed procedure.

tion procedure. The detailed procedure is summarized as follows:

Step 1. Collect the input parameters and the corresponding responses.

Step 2. Develop a BP network model to obtain the relationship between input parameters and output response. The trained network is referred to as a fitness function.

Step 3. Set the GA operating conditions (e.g., population size, generation size, parameter number, crossover rate, and mutation rate).

Step 4. Create an initial population by randomly selecting the value of input parameters.

Step 5. Repeat steps 6–10 until the stopping condition is reached.

Step 6. Calculate the fitness value by inputting the parameter values to the fitness function.

Step 7. Select the parameter values according to the computed response.

Step 8. Crossover the fitness parameter values.

Step 9. Mutate the parameter values to yield the next generation.

Step 10. Obtain the current parameter values as the optimal condition.

Step 11. Obtain the optimal parameter settings.

Table 1. Control factors and their levels

Factor	*Level 1*	*Level 2*	*Level 3*
USG Delay (A)	10	15	20
Ramp up (B)	0	6	12
Contact threshold (C)	25	35	45
Power (D)	30	40	50
Force time (E)	0	15	30
Force ramp time (F)	0	10	20
Ramp down (G)	0	25	50
Initial force (H)	0	15	30

4. Experiments and results

4.1. *Training of neural networks*

In this study, eight controllable factors were selected to optimize the wire bonding strength. Table 1 lists these factors and their alternative levels. An engineering experiment on the 52 μm fine pitch wire bonding process was conducted. In order to measure the bonding strength, a small hook is placed in the center of the wire span between the substrate and the lead frame and pulled up in a direction normal to the bonding plane. Then, the wire is pulled to failure and a pull force value recorded. Twenty-seven trials with six replications were performed by a well-structured orthogonal array $L_{27}(3^{13})$. Table 2 summarizes the data of signal-to-noise ratio for these 27 trials. The experimental data are then employed for constructing the relationship model between parameters and responses through the BP neural network. Functionally, 80% (approximately 130 samples) are used for training the neural network while the remaining 20% (approximately 32 samples) are used for testing.

Table 3 shows several options of the neural network architecture in which the structure 8-4-1 under the best convergence criterion of root of mean square (RMSE) is selected to obtain a better performance. The topology of the 8-4-1 network with a 0.30 learning rate and a momentum of 0.80 is depicted in Fig. 7.

4.2. *Optimization with genetic algorithms*

In this study, the response (bonding strength) is the larger-the-better (LTB) type and the required value is at least 30 g. Herein, we used the GAs to optimize the back-propagation neural network function. Each input

Table 2. Summary of experiment data

Experiment no.	*Factors*								*Bonding strength*	
	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*Average*	*S/N (dB)*
1	1	1	1	1	1	1	1	1	25.62	28.09
2	1	1	1	1	2	2	2	2	33.35	30.41
3	1	1	1	1	3	3	3	3	39.49	32.34
4	1	2	2	2	1	1	1	2	37.92	31.55
5	1	2	2	2	2	2	2	3	27.30	28.55
6	1	2	2	2	3	3	3	1	30.01	29.49
7	1	3	3	3	1	1	1	3	34.13	30.61
8	1	3	3	3	2	2	2	1	36.01	31.11
9	1	3	3	3	3	3	3	2	39.00	31.76
10	2	1	2	3	1	2	3	1	32.00	30.08
11	2	1	2	3	2	3	1	2	36.02	31.08
12	2	1	2	3	3	1	2	3	29.29	29.23
13	2	2	3	1	1	2	3	2	27.50	28.77
14	2	2	3	1	2	3	1	3	29.91	29.46
15	2	2	3	1	3	1	2	1	36.23	31.15
16	2	3	1	2	1	2	3	3	37.30	31.41
17	2	3	1	2	3	1	2	2	36.29	31.16
18	2	3	1	2	3	1	2	2	32.39	30.14
19	3	1	3	2	1	3	2	1	35.06	30.86
20	3	1	3	2	2	1	3	2	28.25	28.99
21	3	1	3	2	3	2	1	3	31.67	29.95
22	3	2	1	3	1	3	2	2	28.84	29.15
23	3	2	1	3	2	1	3	3	34.49	30.73
24	3	2	1	3	3	2	1	1	36.51	31.18
25	3	3	2	1	1	3	2	3	28.38	29.03
26	3	3	2	1	2	1	3	1	28.22	28.94
27	3	3	2	1	3	2	1	2	36.91	31.30

Note: Average $= \frac{1}{n}\Sigma_{i=1}^{n} y_i$, $S/N_{\mathrm{LTB}} = -10\ \log_{10}\left(\frac{1}{n}\Sigma_{i=1}^{n}\frac{1}{y_i^2}\right)$, $i = 1, 2, \ldots, 6$.

parameter in the wire bonding process is normalized to the value between 0 and 1 and they are combined into one string. For example, the input parameters listed in Table 1 are transformed into the chromosome representation $(A, B, C, \ldots, H)$ in a string. Strings are randomly generated to form the initial population. When GAs are applied to optimize the wire bonding parameter selection, the essential operators including reproduction, crossover, and mutation should be determined in advance. Herein, a roulette wheel approach is adopted as the selection procedure. The crossover rate and mutation rates are set as 0.5 and 0.01, respectively. Fifty strings are randomly generated to establish the initial population. Notably, 3000 generations were processed. The above information is used and the GAs are executed twenty runs. Table 4 summarizes the implementation results with the largest fitness value being 42.3, and the optimum chromosome is (19.8, 0.35, 45, 50, 29.8, 20, 47.6, 22.7). These settings are the optimal condition for eight process parameters.

Table 3. Options for neural networks

Architecture	*RMSE*	
	Training	*Testing*
8-3-1	0.08221	0.11911
8-4-1	0.06431	0.09253
8-5-1	0.07082	0.10772
8-6-1	0.10676	0.10365
8-7-1	0.11883	0.11329

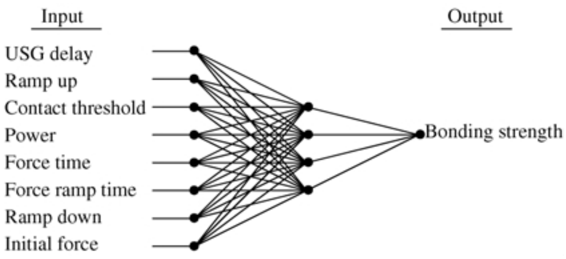

Fig. 7. The BP network topology of the IC wire bonding process.

Table 4. Implementation results of GAs

Item	*Data*
The largest fitness value in 20 runs	42.3
The smallest fitness value in 20 runs	39.7
Average fitness value	40.6
Standard deviation	0.58

4.3. *Optimization using the Taguchi method*

Many practitioners have previously applied Taguchi's approach along with their engineering experience to tackle the optimization problem of wire bonding process. The *SN* values for each trial that was listed in Table 2 can be used to calculate the effect of each factor's level. According to the response graph shown in Fig. 8, the optimum levels of factors can be set as $A_1B_2C_3D_3E_3F_1G_3H_1$.

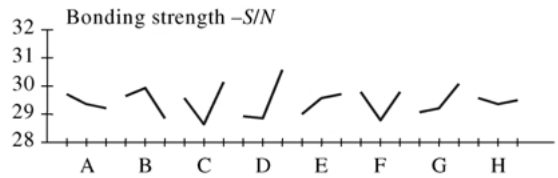

Fig. 8. Factors effects on *S*/*N* ratio.

4.4. *The comparison*

This study finally conducted a comparison between the Taguchi method and the proposed approach using the optimum conditions respectively. Table 5 summarizes the results from confirmatory trials using optimal parameter settings obtained by both the Taguchi method and the proposed approach. According to the results listed in Table 5, the proposed approach achieves a better performance by more than 24.5% in terms of short term process capability. The feasibility of the proposed approach was conducted at a semiconductor assembly line in Taiwan to optimize the parameters of an IC wire bonding process. The yield rate obtained after implementing the optimal parameter settings under mass production could increase from 98.9% to an average of around 99.99%. That is, there has been a reduction of 10,900 DPPM (defect parts per million). The annual cost saving was expected to exceed 630,000 US dollars, whereas the expenditure for the experiment was below USD 1000.

5. Conclusions

Up till now, the major cause of failure in IC packaging has been attributed to wire bonding. Engineers conventionally apply the Taguchi method to optimize the process; however, the Taguchi method has some limitations in practice. For example, this method can only get the optimal solution uncertainty in discrete values. This paper presents an integrated approach of a neural networks and genetic algorithms for the IC wire bonding optimization problem. A back-propagation network is first used to develop the nonlinear multivariate relationship model between factors and the response. Then, a genetic algorithms is applied to obtain the optimal factor settings of wire bonding

Table 5. A comparison of the proposed approach and the Taguchi method

	Results of the proposed approach	*Results of the Taguchi method*
1. Optimal factors settings	(19.8, 0.35, 45, 50, 29.8, 20, 47.6, 22.7)	(10, 6, 45, 50, 30, 0, 50, 0)
2. Sample size of comparison	40	40
3. Mean and Std. deviation	(41.5, 2.15)	(40.5, 2.45)
4. Short term process capability (C_{pk})	1.78	1.43

process. Advantages of neural networks are their easy-and-quick capability to explore a nonlinear multivariate relationship between parameters and responses. Moreover, GAs are known for their robustness and effectiveness of overall search capabilities.

This paper also conducts a comparison, using real experimental data from an IC assembly company in Taiwan, between the proposed approach and the Taguchi method. The results demonstrate superiority and feasibility of the proposed approach in terms of process capability. Future study may include (1) to compare the proposed approach with Liao and Chen's method, and; (2) to apply other local search methods such as simulated annealing, ant and tabu search algorithms.

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