Optimal process parameters design for a wire bonding of ultra-thin CSP package based on hybrid methods of artificial intelligence

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Abstract
Purpose – The aim of this research is to combine the Taguchi method and hybrid methods of artificial intelligence, to use them as the optimal tool in wire bond designing parameters for an ultra-thin chip scale package (CSP) package, and then construct a set of the optimal parameter analysis flow and steps.
Design/methodology/approach – The hybrid methodology of artificial Intelligence was used in order to identify the optimum parameters design for a wire bonding of ultra-thin CSP package. This paper employed desirability function to integrate two quality characteristics (loop height and wire pull strength) into a single quality indicator to construct a well-trained neural network prediction system with hybrid genetic algorithm.
Findings – The processes parameters of low-loop of micro HDD driver IC were optimized with GA, thereby achieving the objective of improving process yield and robustness design of micro HDD driver IC.
Practical implications – The engineers could quickly obtain the optimal production process parameter with the demand of multi-quality characteristics, and enhance the assembly quality and yield of driver IC of micro HDD.
Originality/value – This paper applies the design of experiments approach to a lower wire loop processes parameters design, and improves the process yield and robustness design of micro HDD driver IC.

Keywords Artificial intelligence, Programming and algorithm theory, Surface mount technology

Paper type Research paper

1. Introduction

In IC packaging patterns, gold wire package is one of the main packaging technologies at present, occupying about 90 percent of the total demand. The wire bonding process is mainly used to transmit signals among components. For the IC package products with a high unit price, the quality of wire bonding process has the greatest effect on the post-process and the yield loss of products, occupying about 40 percent (Su and Chiang, 2003). In recent years, the portable electronic communication products become increasingly thinner, which makes IC chip package body thinner as well. Meanwhile, the demand for the stacked die package, such as chip scale package (CSP) and wafer level package micro package technology are have gradually matured. Thus, IC package manufacturers in Taiwan, in designing new products, have to develop the processing technology and the production flow for new products to satisfy the demands of customers for the design specifications of products.

Nowadays, with the increase of the demand for the consumptive digital equipment market, the high-capacity micro HDD (larger than 20 GB) has become the main storage media of the portable digital products. Driver IC is the key electronic component of micro HDD. Driver IC functions as anti-mechanical shock and read head control, and driver IC is responsible of the performance and effectiveness of micro HDD. To satisfy the design of thinner, smaller and low profile of micro HDD, the vertical dimension of driver IC becomes thinner and thinner. This study focuses on the vertical dimension of driver IC in the specification of 0.65 mm. There are two chips in the driver IC: ASIC die is for logical control and memory die is responsible for read-and-write for buffer memory. There are 180 I/O leads in the CSP package, and the structure includes mold compound, silicon die, rigid substrate and copper trace materials, where the substrate also serves as the connection between die and motherboard. The die is the signal generator and it controls all activity for the device. In other words, the CSP technology is being developed to achieve miniaturized packaging systems with improved space limitations. The advantages to using a CSP over direct chip attach include: easier handling, more protection for the chip, simpler board assembly and reduced total package costs (Baliga, 1998).

The CSP manufacturing processes of micro HDD driver IC are described as follows: wafer back-grinding ⇒ wafer saw ⇒ die attach ⇒ wire bonding ⇒ molding ⇒ marking ⇒ post mold cure ⇒ solder paste printing ⇒ re-flow ⇒ singulation ⇒ packing. The main assembly sizes of micro

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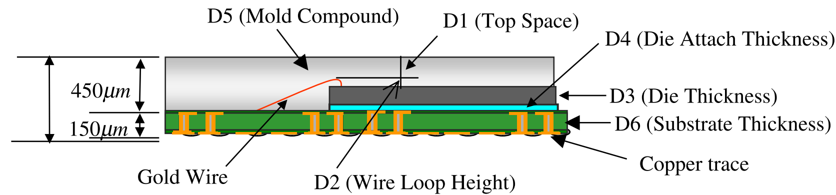
Figure 1 CSP packaging structure for micro HDD driver IC



HDD driver IC are shown in Figure 1. The symbols D1, D2, D3, D4, D5 and D6, respectively, stand for the top space from gold wire to the border of components, the distance between gold wire and silicon chip, die thickness, die attach thickness, mold compound thickness and substrate thickness. In fact, the space in the micro HDD is quite limited. Since, portable device are to be lighter, thinner, shorter and smaller, there is not much space for the IC package. Each package should be controlled in tight tolerance. Otherwise, it will be a micro HDD assembly issue. A vertical dimension (*Z*-axis) control of driver IC is crucial owing to the limited space in micro HDD. In addition, the mold thickness is one of the key materials and it is the major dimension to keep the overall package height ("D5" dimension in Figure 1). The second key material dimension is substrate thickness and it is a very importance process control item for the CSP assembly, under cost constrains, this study uses a rigid substrate carrier and its material dimension specification is 150 μm ("D6" dimension in Figure 1).

Although the total thickness of driver IC package body is 0.65 mm, D5 (the mold compound thickness) is only 450 μm for assembly space. If the die thickness (125 μm) and die attach thickness (30 μm) are also considered, the distance from the chip to the upper edge of the package body is only 295 μm (D1 + D2). However, in the present CSP packaging process, the height of gold wire is usually designed as 130 $\sim$ 200 μm. Thus, the space from the upper edge of gold wire to the outer side of package body becomes smaller (D1). Especially, after the molding process, because of the effect of warpage, gold wire is exposed out of package body, which would influence the assembly yield rate. In order to avoid this situation, we have to design the gold wire height of driver IC wire bonding process (D2) as 60 $\sim$ 100 μm. In order to satisfy the demand in design and take the quality of bonding process into consideration, in this study, the loop height specification (60 $\pm$ 15 μm) and the gold wire pull strength (over 2 gf) were defined as two key quality characteristics.

In this study, the Taguchi method of parameter design using the static characteristic was employed for the robust design of CSP on a substrate carrier with less than 0.65 mm package height. And to probe into the overall output performance of lower loop processes, this paper employed desirability function (Derringer and Suich, 1980) to integrate two quality characteristics (loop height and pull strength) into a single quality indicator to construct a well-trained neural network prediction system with hybrid genetic algorithm (HGA). Finally, the processes parameters of low loop of micro HDD driver IC were optimized with GA, thereby achieving the objective of improving process yield and robustness design of micro HDD driver IC.

2. Literature review

In previous researches on wire bonding process, the parameters used to measure the loop height and the quality characteristic of wire bonding process include: ball height, ball size, pull strength, shear strength, the height of heat affected zone (HAZ). The so-called height of HAZ refers to the area where the structure changes because the wire bonding is heated, after the process of electrical flame-off (EFO). In fact, wire bonding loop height has a close connection with wire bonding loop process technology, while the forming of wire bonding is mainly affected by the materials and looping parameters of wire bonding. Therefore, proper looping parameters cannot only effectively reduce the loop height, but also increase the reliability of wire bonding quality (Hu *et al.*, 1995; Ohno *et al.*, 1991).

The previous researches on the forming of gold wire track, loop height and gold wire strength showed that the control factors affecting the quality of wire bonding included: gold wire (its shape, materials, length, and radius), discharge strength (the length of HAZ), the design of lead frame (leads' width, thickness and length), the materials of lead frame, shape of wire loop (the width and length of wire loop, turns and the position of turn), the pull wire parameters of wire bonder, etc. The correlative process parameters are: wire bonder, types of bonding probe, temperature of wire bonding, time of wire bonding, bonding force, bonding speed, ultrasonic power, bonding time, free air ball size, loop length, loop height, etc. (Chen and Lin, 2000; Tsao, 2000; Su and Chiang, 2003). The widely-used statistical research methods are: design of experiment (DOE) (Groover *et al.*, 1994), response surface methodology (RSM) (Shu, 1992), finite element method (Liu *et al.*, 2004; Chaudhry and Barez, 1998) and Taguchi method (Chen, 2000). The advantage of using the Taguchi method is in the reduction of both production cost and time. It concerns minimizing the effect of uncertainty or variation in design parameters (Phadke, 1989). Taguchi developed procedures that apply orthogonal arrays of statistically designed experiments to efficiently obtain the best model with the fewest possible experiments. However, most Taguchi procedures have been applied to analyzing only linear systems under the assumption of the addition of individual factor effects (Tong *et al.*, 1997). Because of the complexity of the nonlinear relationship between input parameters of wire bound process and the multi-quality characteristics' measurement, the optimal wire bound process parameter combinations remain uncertain (Wong *et al.*, 1997). In other words, the Taguchi method is not a panacea to all parameter design problems. Some scholars advised to solve this problem with RSM, but RSM could not completely solve the problems with multi-quality characteristics.

In recent years, artificial neural networks (ANNs) have been developed to mimic the behavior of biological neural

nets, and have successfully solved problems through generalization of a limited quantity of training data, overall trends in functional relationships (Sandro, 2000; Schalkoff, 1997). ANNs have been used in a wide range of applications and proven to be effective in performing complex functions in various fields. ANNs can be constructed to perform classification (Raimundo and Narayanaswamy, 2001), approximate equations (Joo *et al.*, 2001), and predict values (Freeman and Skapura, 1991; Kim *et al.*, 2005; Wong *et al.*, 1997; Su and Chiang, 2003). In predictive modeling, the objective is to map a set of input patterns onto a set of output patterns. In recent years, many researches have been conducted based on the Taguchi-neural network for electronic packages and in predicting the wire bond quality characteristics (Chen and Lin, 2000; Lo and Tsao, 2002; Tsao, 2000; Liau and Chen, 2005). Through the use of the Taguchi-neural network model, the prediction model between IC wire bond process parameters and multiple quality characteristics was generated (Su and Chiang, 2003; Liau and Chen, 2005). However, building an optimal prediction model with multiple quality characteristics is complicated by the presence of many training factors. Training factors typically involved in building a Taguchi-neural network model may include: the hidden neuron, training tolerance, initial weight distribution, and function gradient. The most difficulty problem often arises from the nature of randomness in the initial weight distribution (Kim and Park, 2001). GA is widely used to search for optimized parameters to satisfy given constraints (Goldberg, 1989). The advantage of the GA approach is that it can handle arbitrary kinds of constraints and objectives. When solving multi-objective (process parameters) problems, GA provides many satisfactory solutions in terms of the objectives, and then allows the decision maker to select the best alternative (Grefenstrtte, 1986).

3. Prediction model of multi-quality characteristics

This section is to build the experimental factors of wire bonding of driver IC through the Taguchi method and construct two importance quality characteristics. Next, the levels of experimental factors are normalized as the predict variables for wire bonding neural network (WBNN), and the loop height and pull strength from Taguchi experiments are set as the output of WBNN to construct the nonlinear network models. The WBNN is evaluated and selected with respect to the root mean-squared error (RMSE) functions. Then, the optimal prediction model of WBNN is obtained by HGA.

3.1 Taguchi experiment design

Conventionally, engineers apply the Taguchi method to conduct parameter design in a variety of industrial practices. The Taguchi experiments have been successfully applied on the optimum design of IC packages processes. Orthogonal arrays have been developed to accomplish experiment designs with a number of arrays. This method using signal-to-noise ratios (SN ratio) takes both the mean and the variability into account. The orthogonal arrays are designated by the notation L (L for Latin squares) with a subscript, the SN ratio (η) is an index of robustness in experimental processing, and the definition of SN ratio for STB and LTB response are as follows:

$$\text{Smaller the better}: \quad SN_{STB} = -10\log_{10}(MSD) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \qquad (1)$$

$$\text{Larger the better}: \quad SN_{LTB} = -10\log_{10}(MSD) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \qquad (2)$$

where y_i is the ith observation and n is the number of observation in each combination and s is the deviation of all observations in each combination, respectively. According to the definition of SN ratio in Taguchi method (Phadke, 1989), the larger SN ratio means the better product quality with less product loss. In the study, 27 trails are conducted by a well-structured orthogonal array $L_{27}(3^{10})$ to attain lower loop height and bounding pull strength. The ten control factors included in Taguchi experiments are power, search speed, EFO current, search height, loop angle, main heat, torch time, loop speed, bond time and bond force. For each parameter, three levels are chosen to cover the range of interest. The control factors with chosen levels are listed in Table I.

3.2 Hybrid genetic algorithm

In the HGA phase, there are two separate stages: to building a WBNN and then to construct an optimal prediction model of WBNN. First, we choose to use NNs method to building a WBNN because it handles nonlinearity associated with the data well. The widely used algorithms of NN in approximate model are the back propagation neural networks (BPNNs). BPNNs have accomplished this task by learning from a series of data sets related to the system and then applying what was learned to approximate or predict the corresponding output. Processing elements (PEs) are the neurons in a BPNN. The most successful BPNN learning model till now is the least mean square (LMS) algorithm, due to its high-prediction accuracy having been excellently proven. Main components of information processing in the neural networks are: inputs, weights, summation function (weighted average of all input data going into a PE, transformation function and outputs. In this study, we employ a three-layered BPNN that includes an input layer, a hidden layer and an output layer to construct

Table I The control factors with three levels for the Taguchi experiment

Control factors	Variables	Level 1	2	3
Power (mA)	*A*	60	70	80
Search speed (mil/ms)	*B*	5	10	15
EFO current (mA)	*C*	32	45	60
Search height (mil)	*D*	4	5	6
Loop angle (deg)	*E*	8	12	16
Main heat (°C)	*F*	150	155	160
Torch time (ms)	*G*	1	3	5
Loop speed (μm/sec)	*H*	20	30	40
Bond time (ms)	*J*	35	37	40
Bond force (mg)	*K*	9	10	12

the WBNN prediction model. Example of steps involving WBNN process is as follows:

1. The input layer, the levels of experimental factors are normalized by equation (1) to be served as the predict variables for WBNN:

$$V_{\text{new}} = \left[\frac{V_{\text{old}} - \mu}{\sigma}\right] \tag{3}$$

   where μ is the mean and σ is the standard deviation of the training set. It normalizes the inputs and targets so that they will have zero mean and unity standard deviation.
2. The hidden layers of neurons with nonlinear activation functions (tan-sigmoid) allow the network to learn nonlinear relationship, and the output layer provides the response (loop height and pull strength) of the WBNN to the activation patterns applied to the input layer.
3. The LMS algorithm is employed, and 80 percent observations are used for training and remaining 20 percent observations are used for testing.
4. The WBNN are evaluated and selected with respect to the RMSE functions as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{p=1}^{m}\sum_{j=1}^{n}(T_j^p - Y_j^p)}{m \times n}} \tag{4}$$

   where m is the number of test sample, n is the number of neuron, the T_j^p and Y_j^p represent the desired and calculated outputs of the jth output neuron for the pth test sample. The WBNN simulation was performed using MATLAB® software.

GA is a function-related optimization tool most commonly used to resolve the problem of solution space and calculate global optimal solution. So, it is a method of searching target function limit. Though GA is a random search mode, it often searches and amends space to generate reasonable solutions according to cumulative information of every generation of population. During optimization process of GA, possible solution chromosome is composed of genes. In general, every gene is represented by a series of binary strings, which complete the evolution through selection, crossover and mutation. Firstly, GA enables encoding of variables, and then expresses the search space in the form of encoding. Population size represents the number of every generation of chromosome. In the case of excessively small size, GA will be converged too quickly, often leading to poorer solution owing to insufficient information of population. Fitness function in GA process, also called target function, is used to decide the degree of fitness of a chromosome under an environmental condition, namely, measuring the performance of every chromosome (Holland, 1992; Murthy and Chowdhury, 1996).

Because the parameter space of WBNN in network weight and bias was big, for GA, it would take a long time to calculate the time in analyzing the optimal WBNN network parameters. If GA calculus was generational deficiency, what we found still was not the best parameter solution. Hybrid GA used GA to find the optimal point in advance, and then, according to the present weights and biases, trained the prediction system with the deepest decent in the traditional optimization methods, such as EBP (error back propagation). Thus, the optimal network weight and bias parameter could be obtained and the prediction model of multi-quality characteristics could be more efficient. The optimal prediction model of WBNN was obtained by HGA, achieved through the procedures of executing HGA is simplified as follows:

1. The fitness function was chosen and the fitness function of this paper was expressed by equation (4).
2. The initial conditions of GA were set to include the following parameters: the number of chromosomes, the number of evolution, mating rate, mutation rate, etc.
3. The weight and bias parameters of WBNN were used as the initial solutions.
4. The solutions of the weight and bias parameters were substituted into WBNN and RMSE of the fitness function was calculated.
5. Proper solutions were chosen to conduct mating.
6. Based on the results of mating, mutation was conducted to produce the next group of candidate solutions.
7. According to the solutions after mutation, the response values were worked out and the best filial generation was produced.
8. The best solution of the filial generation was temporarily set as the optimal solution. If it satisfied the end condition of the algorithm, we would go on with the next step; otherwise, we should go back to Step 4.
9. The optimal prediction network model of WBNN process quality was solved.

3.3 Optimal parameter design

Because the wire bonding process of micro HDD driver IC belonged to multi-quality characteristics, and in order to seek the optimal parameter set values satisfying the two quality characteristics and avoid the contradiction in choosing the process parameter levels in Taguchi experiment, this research changed the multi-response values into the single-response values with desirability function and then, through GA, solved the best level combination of the overall quality characteristic control parameter.

In the two quality characteristics discussed in this research, loop height belonged to the nominal-the-better characteristic, while wire bonding strength was the larger-the-better characteristic. Their desirability function transformations were, respectively, shown in formulas (5) and (6):

$$p(y_i) = \begin{cases} 0, & \text{USL} < y \\ \left[\frac{y_i - \text{LSL}}{T - \text{LSL}}\right]^r, & \text{LSL} \leq y \leq T \\ \left[\frac{y_i - \text{LSL}}{T - \text{LSL}}\right]^v, & T \leq y \leq \text{USL} \\ 0, & y < \text{LSL} \end{cases} \tag{5}$$

$$p(y_i) = \begin{cases} 1, & y_{\max} \leq y \\ \left[\left|\frac{y_i - \text{LSL}}{y_{\max} - \text{LSL}}\right|\right]^r, & \text{LSL} \leq y \leq y_{\max} \\ 0, & y < \text{LSL} \end{cases} \tag{6}$$

In the above formulae, p was the desired value of each quality characteristic; y was the experimental output value; i was the individual quantity of the quality characteristics of applied desirability function; T was the expected quality output; $y_{\max}$ was the maximum value that could actually be achieved; the size of r and v could be designed according to individual quality characteristic and the higher value showed that when

T is farther, the reduction velocity of desired value would be larger; USL and LSL, respectively, stood for the upper and lower limits of tolerated error; the total desired value was the geometric average of all individual desired values, as shown in formula (7):

$$P = (p_1 \times p_2 \times \cdots \times p_n)^{1/n} = \left(\prod_{i=1}^{n} p_i \right)^{1/n} \qquad (7)$$

The optimal parameter design of wire bounding of driver IC packaging process, achieved through the procedures of executing GA is simplified as follows:

1. The fitness function was chosen and the fitness function of this paper was expressed by equation (7).
2. The initial conditions of GA were set to include the following parameters: the number of chromosomes, the number of evolution, mating rate, mutation rate, etc.
3. The level of a group of control factors was randomly chosen as the initial solution.
4. The level of control factors or the optimal solution of GA was substituted into the fitness function and then the total desirability function value was calculated (P).
5. Proper solutions were chosen to conduct mating.
6. Based on the results of mating, mutation was conducted to produce the next group of candidate solutions.
7. According to the solutions after mutation, the response values were worked out and the best filial generation was produced.
8. The best solution of the filial generation was temporarily set as the optimal solution. If it satisfied the end condition of the algorithm, we would go on with Step 9; otherwise, we should go back to Step 4.
9. The optimal level combination of process parameters was solved.

4. Results and discussions

The orthogonal array used in the study is $L_{27}(3^{10})$ with three repetitions of each quality characteristic for each combination. There are a total of 162 observations in our study. Based on the results of the Taguchi experiment, the data set contained ten input variables (control factors) and two target variables (η). After Taguchi configuration experiment, for the measured values of each experimental combination, the η_i^q of their loop height and wire bonding strength were, respectively, worked out with the formulae of the nominal-the-better characteristic and the larger-the-better characteristic. The unit was decibel (dB); thereinto, i was the experimental combination ($i = 1, 2, \ldots, 27$), q was the quality characteristic ($q = 1, 2$). The results of Taguchi experiment showed that the maximum value of η in the quality characteristic of loop height was $\eta_{22}^1 = 42.22\,\text{dB}$; the average loop height: $= 63.67\,\text{mil}$; the effectiveness of each experimental factor was shown in Figure 2. According to the results of Taguchi experiment, the optimal factor level combination of loop height should be: $A_2\, B_2\, C_2\, D_2\, E_1\, F_3\, G_2\, H_2\, J_1\, K_3$.

In addition, for the quality characteristic of wire bonding strength, the maximum η in Taguchi experiment was $\eta_{17}^2 = 15.89\,\text{dB}$, $\bar{y}_{17}^2 = 6.23\,\text{gf}$; the effectiveness of experimental factors was shown in Figure 3. According to the results of Taguchi experiment, the optimal factor level combination of wire bonding strength should be: $A_2\, B_3\, C_3\, D_2\, E_1\, F_3\, G_3\, H_1\, J_2\, K_1$. The results of Taguchi experiment also showed that the loop height of wire bonding did not accord with the quality characteristic of wire bonding strength in the optimal level combination.

This research normalized the data obtained from the experimental results of Taguchi's orthogonal array and then used them as the training data constructing WBNN network model. The data set containing the total 27 observations of experimental data was divided into 24 observations for the training group and three observations for the test group, which would be used to train and construct WBNN network. The WBNN model constructed in this research was shown in Figure 4; thereinto, the number of neurons on the input layer was set as ten process parameters (control factors); there were six neurons on the hide layer; in transfer function, sigmoid function was adopted; in addition, there were six neurons on output layer, and the first three output values (y_1, y_2 and y_3) were the quality outputs of loop height, while the last three output values (y_4, y_5 and y_6) were the quality outputs of wire bonding strength; the transfer function of output layer was linear function; in error function, the RMSE statistical index of equation (4) was used to evaluate the learning quality of network.

After the neural network framework was decided, the training data were input to conduct training. The training results were shown in Figure 5 in which the horizontal coordinate stood for the times of learning and the vertical coordinate represented the convergence errors. The convergence value of RMSE had reached 0.11083. When the neural network training had been finished, the test data could be input to confirm the effectiveness of network learning. Table II displayed the test results of WBNN model. The error between predictive value and target value inferred by the network was very low, indicating that the constructed WBNN prediction model could fully embody the quality prediction of wire bonding process.

The experimental data in this research were obtained by planning each experimental combination and repeating three times based on $L_{27}(3^{10})$ orthogonal arrays, so each combination had six experimental data. The purpose was to take the variability of process into consideration so as to make the accuracy of the prediction model constructed by the neural network closer to the actual production process. Table III displayed the specifications of all quality characteristics of wire bonding process.

Therefore, this research would produce six desired values. The closer to 1 the desired values were, the closer to the target values of quality characteristics they became. Among the two quality characteristics in this research, the loop height was the more important, so the r value of desirability function was set as 2; the r value of wire bonding strength was set as 1; the entire desired value (P) was the geometric average of individual desired values. Hereby, the fitness function of genetic algorithm would help solve the optimal process function value with the total desired value being the target, as shown in formula (5).

The process of solution itself might be a nonlinear optimization problem, while GA algorithm, through the operational methods (such as the replication, exchange and mutation of chromosomes), executed the analysis of optimization in the parameter field represented by chromosomes. In this process, it would be affected by number of clusters, probability of exchange and probability of mutation as well as fitness function. That was why the genetic

Figure 2 Results of Taguchi experimental analysis for the loop height

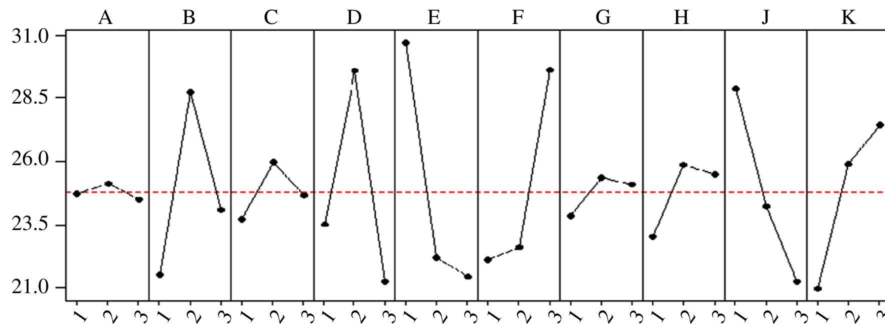


Figure 3 Results of Taguchi experimental analysis for the wire strength

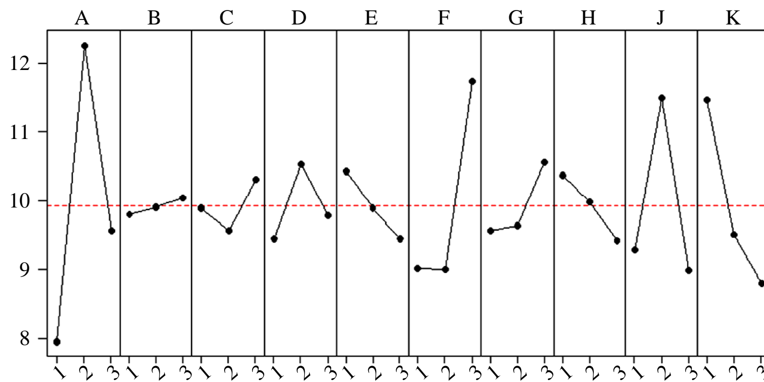


Figure 4 The WBNN architecture for micro HDD driver IC

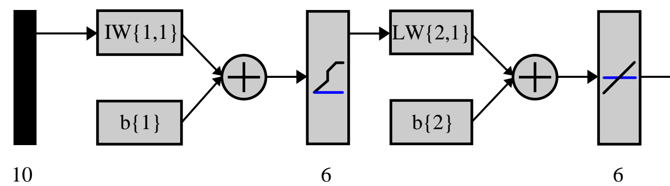


Figure 5 The training RMSE for WBNN model

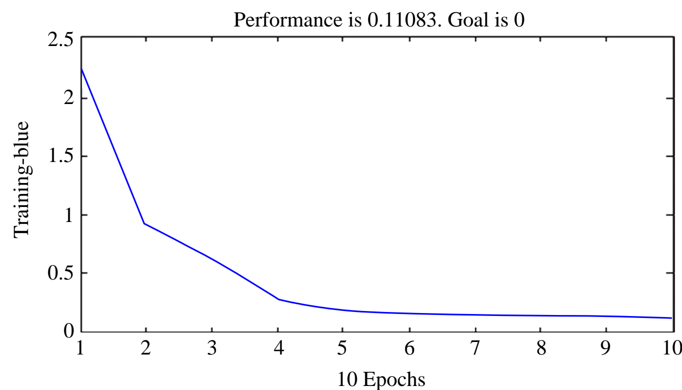


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Table II The prediction errors for WBNN models

	Prediction			Target			Prediction error		
y_1	59.724	62.286	61.894	61.2	62	63	1.476	−0.286	1.106
y_2	60.461	60.286	59.908	60	60	58	−0.461	−0.286	−1.908
y_3	60.700	60.848	59.870	60	61	61	−0.7	0.152	1.13
y_4	1.9315	4.2343	2.5774	2.2	4.33	2.6	0.2685	0.0957	0.0226
y_5	3.8159	2.9706	1.7077	3.6	3	1.6	−0.2159	0.0294	−0.1077
y_6	2.8158	3.4998	2.0787	2.78	3.5	2.1	−0.0358	0.0002	0.0213

Table III The specifications of wire bond quality characteristics

Quality characteristic	LSL	*T*	USL
Loop height (mil)	45	60	75
Wire bonding strength (gf)	2	10	–

algorithm could not independently decide the optimal parameter value. Some researchers (Holland, 1992) advised to use the proper method in choosing parameters. When the matrix was small, larger mating rate and mutation rate could be chosen to prevent premature convergence; when the matrix was big, smaller mating rate and mutation rate could be chosen to save operation time. This research adopted the simplest and the widely-used roulette wheel selection. The matrix was set as 100, the mating rate 0.95, the mutation rate 0.01 and the generations of genetic evolution were 100. Through 30 runs of operation with genetic algorithm, the maximum desired value was 0.979, as shown in Table IV. Additionally, the ten optimal parameter values found with GA were, respectively, 68.68, 14.24, 27.68, 6.44, 15.95, 155.14, 1.89, 27.83, 39.29 and 3.72, as shown in Table V.

After the optimal process parameter value was input to the neural prediction system, the obtained predictive loop height value and the wire bonding strength value were, respectively, 60.22 mil and 9.50 gf; the optimal process parameter would be provided to the engineering workers on the scene to execute confirmation experiment and the evaluation results of its prediction system were listed in Table VI. The confirmation experiment value of loop height was 59.51 and the relative error was 1.19 percent; the confirmation experiment value of wire bonding pull strength was 8.84 gf and the relative error was 7.46 percent. From the results of experiment, the small relative error showed the optimal parameter value solved in this research could effectively achieve the requirements of quality specifications.

Table IV Statistical result of GA's optimal desired value (*P*)

Genetic algorithm 30 runs	Entire desired value (*P*)
Maximum value (*D*)	0.979
Minimum value (*D*)	0.846
Average	0.931
Standard deviation	0.047

5. Conclusions

Because the appearance size of micro HDD driver IC became increasingly thinner, the follow-up packaging process was made even more difficult. Especially, in the wire bonding process of CSP package, the insufficient wire bonding strength and weak control of loop height would affect the yield rate of products. In order to satisfy the requirements of quality specifications, such as the low wire bonding height of thin package of 0.65 mm, wire bonding strength, etc. this research combined the Taguchi method and hybrid methods of artificial intelligence, used them as the optimal tool in designing parameters, and then constructed a set of the optimal parameter analysis flow and steps. Thus, engineers could quickly obtain the optimal production process parameter with the demand of multi-quality characteristics, and enhance the assembly quality and yield of driver IC of micro HDD.

Table V The optimal parameter levels for wire bonding of micro HDD driver IC

Process factors	A	B	C	D	E	F	G	H	J	K
Genetic values	−0.16	1.02	−1.54	1.74	1.19	4.84	−0.66	−0.26	0.93	2.67
Factors level	68.68	14.24	27.68	6.44	15.95	155.14	1.89	27.83	39.29	13.72

Table VI The Comparison between the WBNN prediction and confirmation experimental results

	Loop height (mil)	Wire strength (gf)
WBNN prediction	60.22	9.50
Confirmation experiment	59.51	8.84
Prediction error (percentage)	1.19	7.46

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