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Application of the Taguchi method for the optimization of visual inspection parameters for multi-layer ceramic capacitors

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Abstract. Multi-Layer Ceramic Capacitors (MLCC) are extensively used as important components of various electric and electronic products. Generally, electronic consumer products, such as mobile phones and digital TVs, contain at least 150 MLCCs, which are manufactured in batches of millions of units. Automated inspection machines have replaced manual optical inspection of MLCC units. To improve the quality of optical inspection in this automated operation, the Taguchi method is used to formulate an experimental layout of machines using five important parameters that describe practical manufacturing processes. In this study, not only is the parameter design for machines that automatically inspect MLCC optimized, but also significant parameters that influence the quality of optical inspection of the MLCCs are obtained. Experimental results illustrate the effectiveness of the method.

1. Introduction

Multi-Layer Ceramic Capacitors (MLCC) are extensively used in computers, communications, and consumer electronic (3C) products such as mobile phones, notebook computers, LCD TVs and tablet PCs because of their small size, large capacitance and high stability [1]. The length, width and height of each MLCC are 1.0, 0.5 and 0.5 mm, respectively. Each batch of production consists of anywhere from hundreds to millions of units. To improve their quality and the production efficiency, automated inspection machines have replaced optical inspection machines to inspect them for defects of products. The automated inspection machine adjusts parameter settings for three products, but the settings of the machines are set by inspectors based on personal experience, without the application of consistent standards or criteria. If parameters are set too strictly, then non-defective products will be categorized as defective, and the false-negative error rate is increased. If parameters are set too loosely, then, the error that defines the rate of identification of defective products as non-defective may also be increased. Therefore, the parameter settings of an optical inspection machine significantly affect production yield.

In previous studies of MLCCs, Yang et al. [2] developed a Tabu-search simulation optimization method for solving the problem of scheduling in a flow shop with multiple processors. A practical case study of an MLCC manufacturing plant is presented to illustrate the proposed solution methodology. Yang et al. [3]

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also developed a genetic algorithm-based simulation method for solving a multi-attribute combinatorial dispatching decision problem for a flow shop with multiple processors. Kuo et al. [4] proposed two multiple-criteria decision-making methods; one for ranking preferences by similarity to ideal solutions, and the other, an analytic hierarchy process, for solving a combinatorial dispatching rule problem associated with an MLCC manufacturing system. Cho et al. [5] developed a simple and cost-effective method for fabricating discrete component-embedded printed circuit boards.

With respect to investigations that involve the application of the Taguchi method specifically, George et al. [6] applied the method to formulate an experimental layout for establishing the ranking of predominance. Macodiyo and Soyama [7] utilized the Taguchi method to identify critical factors to improve the fatigue strength of chrome-molybdenum steel and to efficiently optimize cavitation peening. Hung et al. [8] used the Taguchi method to discover the combination of production levels of control factors to provide low production loss and reduce production variance. Nalbant et al. [9] applied the Taguchi method to study the performance characteristics of the turning operations of AISI 1030 steel bars. Chou et al. [10] used the Taguchi method to determine the optimal operating conditions for improving the roundness and surface roughness of the work pieces. Kim et al. [11] applied the Taguchi method to optimize experimental conditions for the preparation of bimodal Ag nanoparticles in a semi-batch reactor. Tzou et al. [12] used the method to optimize the thermal conductivity of 1050 aluminum substrates with Cu or Ag thin films that were formed under various sputtering conditions. Ozcelik [13] utilized the Taguchi experimental method to examine the effect of injection parameters on the mechanical properties of specimens with a weld line of polypropylene during plastic injection molding. Yiamsawas et al. [14] used the Taguchi method to examine the factors that promote the growth of zinc oxide nanocrystals. Lin et al. [15] utilized the method to improve the quality of processes for coating thin-film transistor liquid-crystal display panels with polyimide. Bilici [16] utilized the Taguchi method to optimize friction stir spot welding parameters of polypropylene. The Taguchi method has been extensively used to optimize the parameters of this process [17-20].

The above review of current literature clearly shows that no one has used the Taguchi method to set inspection parameters to evaluate the quality of MLCCs. Therefore, this work uses the Taguchi method to optimize the parameter settings of automated optical inspection machines to reduce the error rate of inspection and to increase the throughput of the inspection process.

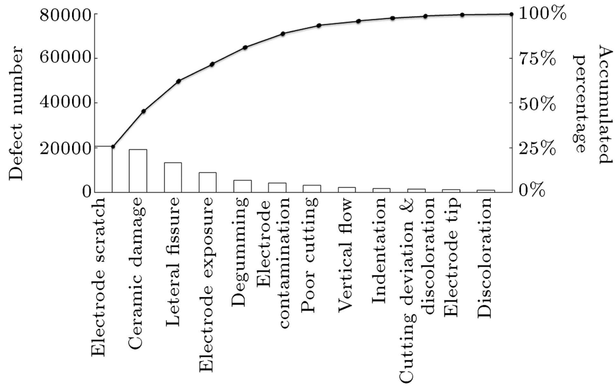

Figure 1. MLCC visual defect Pareto analysis.

2. Case study

Company Y, located in Kaohsiung, Taiwan, is one of the three largest global passive component manufacturers. Its products include resistor covers, inductors and capacitors. Its annual throughput of MLCCs is approximately 30 billion units. The MLCCs that are manufactured by this company can be grouped into categories, X7R, X5R, and Y5R, based on their sensitivity to temperature. Products of all three types are very small. They are typically used in high-capacitance and high-voltage products. Their small size and the large batch size demand automated optical inspection rather than manual visual in all instances of inspection. Figure 1 shows the Pareto analysis of optically or visually identified defects. The analysis used 82677 sets of inspection data that were obtained from the internal quality control system (Compostar CNET) from January 2011 to December 2011, as shown in Figure 1.

Based on the analysis of Figure 1, the five most common causes of optical defects are: scratching of the electrode (20616 defects or 25%), ceramic damage (19302 defects or 23%), lateral fissure (13284 defects or 15%), electrode exposure (8934 defects or 11%), degumming (5433 defects or 7%), and others (15108 defects or 19%) in that order (Figure 2). Table 1 presents the types of MLCC products manufactured by Company Y.

In Table 1, the visual defect type is related to the product properties. For X5R products, the major visual defect types are electrode exposure and electrode scratch; for X7R products, the major visual defect types are lateral fissure and electrode scratch; for Y5V products, the major visual defect types are ceramic damage and electrode scratch. An MLCC is constructed from two or more alternating layers of ceramic and a metal, which act as electrodes. The composition of the ceramic material determines its electrical behavior. Accordingly, some visible defects may change the capacitance of the MLCC and cause it to be functionally defective. Company Y currently utilizes three types of optical inspection equipment.

Ceramic damage   Electrode scratch   Lateral fissure   Degumming   Electrode exposure

Figure 2. MLCC visual defect types.

Table 1. Statistical analysis for product types and defect types.

Defect types	Electrode scratch		Ceramic damage		Lateral fissure		Electrode exposure		Degumming		Others		Sum %
X5R	3141	29%	1020	9%	804	7%	3180	29%	738	7%	1972	18%	100%
X7R	9411	23%	6996	17%	10974	27%	2901	7%	2862	7%	7261	18%	100%
Y5V	8064	26%	11286	36%	1506	5%	2853	9%	1833	6%	5875	19%	100%
Sum of defect numbers	20616	–	19302	–	13284	–	8934	–	5433	–	15108	–	82677

Two are the Japanese O and K types, and the third is the Y type, which was developed in Taiwan. The Japanese K type equipment is used in 80% of optical inspections; the Taiwanese Y type equipment is used in 13%, and the Japanese O type equipment is used in 7%. This study concerns the setting of the parameters of the Japanese K type optical inspection equipment (machine), as it is the most frequently used, but the results of this study can be easily extended to any optical inspection equipment.

The optical inspection machine identifies defects by radiating the surface of an MLCC with a light source, scanning it linearly with an optical lens, and then identifying the defect from the variation of brightness of the color of the surface of the MLCC. The optical inspection machine depends on various parameter settings to inspect different products. The purpose of inspection is to minimize the error rate of inspection, which is defined by Eq. (1), given the inspection of S products:

$$\varepsilon = \frac{G_b + B_g}{S}, \tag{1}$$

where:

ε Error rate (%);

G_b Number of defective products among the products identified as non-defective;

B_g Number of non-defective products among the products identified as defective products;

S Total die number in experiment batch.

An inspector typically adjusts the particular parameter settings of an optical inspection machine, according to the products to be inspected. Overly strict or loose parameter settings increase the error rate of inspection. The next section will introduce the Taguchi experimental design and analysis that are used in the present study.

3. The experiment

In this study, 500 MLCCs of each of the three types, X5R, X7R, and Y5V, are used. Out of the 500 MLCCs of each product type, 400 are non-defective and the rest are defective. The Japanese K type optical inspection machine is used to determine the equipment setup parameters that affect optical inspection. Based on discussions with on-site engineers, equipment technicians and field operators, five critical parameters of optical inspection are identified. They are (1) The brightness of the light source in lm; (2) The distance from the pixels to axis in pixels, used to specify the distance from one point to another along a straight line on the surface of a product; (3) Relative variation of the gray scale of pixels; (4) The pixel defective area ratio, which is the ratio of visual defects to the surface area of the MLCC; (5) The color of the light source; red (R), green (G) or blue (B).

Consistent with the Taguchi method for designing experiments, each of the above five control factors are set at one of three levels, as shown in Table 2. Experiments and studies, as well as experience in optical inspection at Company Y, have demonstrated the absence of any interaction among the factors. The mixed orthogonal array in the Taguchi method was $L_{18}(2^1 \times 3^7)$ (see Table 3).

4. Data analysis

4.1. Taguchi design and analysis of variance

In this study, the error rate of inspection is minimized, consistent with a "the-smaller-the-better" quality char-

Table 2. Visual control factor and level.

Code	Parameter	Unit	Level 1	Level 2	Level 3
A	Light source brightness	l m	100	120	140
B	Axis pixel distance	pixel	10	15	20
C	Pixel scale variation ratio	—	10	20	30
D	Pixel defective area ratio	%	2	5	10
E	Light source type	—	R	G	B

Table 3. Experimental layout using $L_{18}(2^1 \times 3^7)$.

		A	B	C	D	E		
Trial no.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

acteristic, as defined by Taguchi. The most appropriate Signal-to-Noise ratio (SN ratio) that must be maximized for this Taguchi quality characteristic, as explained by Ross [21], is:

$$\eta = -10. \log_{10} \left(\frac{1}{n} \sum_{i=1}^{n} y_i^2 \right), \tag{2}$$

where n is the number of measurements in a trial (and in this experiment, $n = 1$), and y_i is the ith measurement made in a trial. In this study, Minitab software is used to compute ε and the SN ratio in all trials. For each trial, ε and the SN ratio are calculated for X5R, X7R and Y5V products, as indicated in Table 4.

The SN ratio response of each control factor-level for X5R-X7R and Y5V products are calculated and recorded in Tables 5 through 7, respectively.

Analysis of variance (ANOVA) is performed to determine whether the experimental factors significantly influence the SN quality characteristics of the three products, X5R, X7R and Y5V. The ANOVA for SN ratios of X5R, X7R and Y5V products are calculated and recorded in Tables 8 through 10, respectively. The F ratio was computed, and a level of significance of was used to set the upper limit on the probability of Type I error in all tests of hypotheses associated with the ANOVA tables. As seen in Tables 8, 9 and 10, the significant parameters for the X5R and X7R products are A, B, C and E; for Y5V products, they are A, D and E.

4.2. Confirmation tests

The predicted SN of the aspect ratio and standard deviation, using the optimal level of each factor, are calculated from the following equation [22]:

$$\hat{\eta} = \eta_m + \sum_{i=1}^{q} (\overline{\eta}_i - \eta_m), \tag{3}$$

where η_m is the total of the mean SN ratios, $\overline{\eta}_i$ is the mean SN ratio when factor i is at its optimal level, and q is the number of process parameters that significantly influence the performance characteristic. From Table 4, $\eta_m = 15.24$ for X5R; $\eta_m = 16.29$ for X7R; and $\eta_m = 15.22$ for Y5V. The optimal parameter combination for X5R is A2B1C1E2; the optimal parameter combination for X7R is A1B3C2E1; the optimal parameter combination for Y5V is A2D3E3. The calculations are as follows:

$$\begin{aligned} \hat{\eta}_{X5R} =& 15.24 + (16.33 - 15.24) + (15.8 - 15.24) \\ &+ (16.11 - 15.24) + (17.11 - 15.24) = 19.63, \end{aligned}$$

$$\begin{aligned} \hat{\eta}_{X7R} =& 16.29 + (17.45 - 16.29) + (1675 - 16.29) \\ &+ (17.08 - 16.29) + (17.72 - 16.29) = 20.13, \end{aligned}$$

$$\begin{aligned} \hat{\eta}_{Y5V} =& 15.22 + (16.26 - 15.22) + (16.97 - 15.22) \\ &+ (16.73 - 15.22) = 19.52. \end{aligned}$$

Table 11 presents the results of the confirmatory experiments using the optimal inspection parameters for X5R, X7R and Y5V products. The predicted machining performance is close to the actual machin-

Table 4. Error rate and SN ratio for various MLCCs.

Trial no.	A	B	C	D	E	X5R $\varepsilon\%$	X5R SN ratio	X7R $\varepsilon\%$	X7R SN ratio	Y5V $\varepsilon\%$	Y5V SN ratio
1	100	10	10	2	R	19.8%	14.07	12.2%	18.27	23.8%	12.47
2	100	15	20	5	G	16.0%	15.92	13.6%	17.33	19.0%	14.42
3	100	20	30	10	B	23.0%	12.77	15.6%	16.14	14.2%	16.95
4	120	10	10	5	G	9.4%	20.54	18.2%	14.80	18.8%	14.52
5	120	15	20	10	B	18.0%	14.89	16.4%	15.70	8.2%	21.72
6	120	20	30	2	R	20.2%	13.89	14.2%	16.95	20.0%	13.98
7	140	10	20	2	B	19.2%	14.33	16.8%	15.49	19.2%	14.33
8	140	15	30	5	R	21.4%	13.39	14.6%	16.71	20.8%	13.64
9	140	20	10	10	G	14.8%	16.59	17.8%	14.99	16.8%	15.49
10	100	10	30	10	G	15.6%	16.14	15.2%	16.36	16.2%	15.81
11	100	15	10	2	B	19.6%	14.15	16.4%	15.70	18.6%	14.61
12	100	20	20	5	R	22.0%	13.15	9.0%	20.92	19.6%	14.15
13	120	10	20	10	R	16.8%	15.49	13.4%	17.46	15.6%	16.14
14	120	15	30	2	G	13.6%	17.33	19.2%	14.33	19.4%	14.24
15	120	20	10	5	B	16.2%	15.81	16.0%	15.92	14.2%	16.95
16	140	10	30	5	B	19.4%	14.24	18.8%	14.52	16.2%	15.81
17	140	15	10	10	R	16.8%	15.49	15.8%	16.03	16.4%	15.70
18	140	20	20	2	G	15.6%	16.14	16.6%	15.60	22.6%	12.92

Table 5. Response of SN ratio to each level for X5R products (larger is better).

Level	A	B	C	D	E
1	14.37	**15.80**	**16.11**	14.99	14.37
2	**16.33**	15.20	14.99	**15.51**	**17.11**
3	15.03	14.73	14.63	15.23	14.25
Max-Min	1.96	1.08	1.48	0.52	2.86
Rank	2	4	3	5	1

Table 6. Response of SN ratio to each level for X7R products (larger is better).

Level	A	B	C	D	E
1	**17.45**	16.15	15.95	16.06	15.58
2	15.86	15.97	**17.08**	**16.7**	15.57
3	15.56	**16.75**	15.84	16.11	**17.72**
Max-Min	1.9	0.78	1.25	0.64	2.15
Rank	2	4	3	5	1

Table 7. Response of SN ratio to each level for Y5V products (larger is better).

Level	A	B	C	D	E
1	14.74	14.85	14.96	13.76	**16.73**
2	**16.26**	**15.72**	**15.62**	14.92	14.57
3	14.65	15.08	15.07	**16.97**	14.35
Max-Min	1.61	0.88	0.66	3.21	2.38
Rank	3	4	5	1	2

ing performance. For X5R products, the increase in the SN ratio from the initial values of the inspection parameters to the optimal values of the inspection parameters is 4.4, corresponding to a 6.2% reduction in error rate. For X7R products, the increase in the SN ratio from the initial values of the inspection parameters to the optimal values of the inspection parameters is 4.89, corresponding to a reduction in error rate of 6.8%. For Y5V products, the increase in the SN ratio from the initial values of the inspection parameters to the optimal values of the inspection parameters is 6.02, corresponding to a reduction in error rate of 8.2%.

5. Conclusions

The main contribution of this study is the use of the Taguchi method to determine efficiently the optimal combination of optical inspection parameters for MLCC, using as few experiments as possible. The experimental results support the following conclusions.

1. The type and brightness of the light source are two

Table 8. ANOVA table for SN ratios of X5R products.

Factors	SS[a]	DF[b]	MS[c]	*F*	*P*-value	Pure sum of square	Percent contribution	Significant
A	11.925	2	5.9627	19.49	0.001	11.313	19.85	Yes
B	3.497	2	1.7486	5.72	0.034	2.885	5.06	Yes
C	7.173	2	3.5866	11.72	0.006	6.561	11.51	Yes
D	0.821	2	0.4106	1.34	0.321	0.209	0.37	No
E	31.430	2	15.7152	51.36	0	30.818	54.08	Yes
Error	2.142	7	0.3060			5.201	9.13	
Total	56.989	17				56.989	100.00%	

[a]SS: Sum of Square; [b]DF: Degree of Freedom; [c]MS: Mean Square.

Table 9. ANOVA table for SN ratios of X7R products.

Factors	SS[a]	DF[b]	MS[c]	*F*	*P*-value	Pure sum of square	Percent contribution	Significant
A	12.454	2	6.2270	37.84	0	12.125	29.35%	Yes
B	2.02	2	1.0100	6.14	0.029	1.691	4.09%	Yes
C	5.692	2	2.8460	17.29	0.002	5.363	12.98%	Yes
D	1.507	2	0.7535	4.58	0.053	1.178	2.85%	No
E	18.481	2	9.2405	56.15	0	18.152	43.94%	Yes
Error	1.152	7	0.1646			2.798	6.77%	
Total	41.306	17				41.306	100.00%	

[a]SS: Sum of Square; [b]DF: Degree of Freedom; [c]MS: Mean Square.

Table 10. ANOVA table for SN ratios of Y5V products.

Factors	SS[a]	DF[b]	MS[c]	*F*	*P*-value	Pure sum of square	Percent contribution	Significant
A	9.833	2	4.9165	6.78	0.023	8.383	11.73%	Yes
B	2.488	2	1.244	1.72	0.247	1.038	1.45%	No
C	1.481	2	0.7405	1.02	0.408	0.031	0.04%	No
D	31.743	2	15.8715	21.90	0.001	30.293	42.40%	Yes
E	20.822	2	10.411	14.36	0.003	19.372	27.12%	Yes
Error	5.074	7	0.7249			12.323	17.25%	
Total	71.441	17				71.441	100.00%	

[a]SS: Sum of Square; [b]DF: Degree of Freedom; [c]MS: Mean Square.

Table 11. Results of the confirmation experiment for X5R, X7R and Y5V products.

	Initial inspection parameters	Optimal inspection parameters		Prediction	Improvement
		Experiment	Confirmation		
X5R parameters	A3B3C3D1E2	A2B1C1D2E2	A2B1C1D2E2	A2B1C1E2	
ε%	15.6%	9.4%	8.9%		6.2%
SN ratio	16.14	20.54	21.01	19.63	4.4
X7R parameters	A3B2C1D3E1	A1B3C2D2E1	A1B3C2D2E1	A1B3C2E1	
ε%	15.8%	9.0%	9.1%		6.8%
SN ratio	16.03	20.92	20.81	20.13	4.89
Y5V parameters	A3B2C1D3E1	A2B2C2D3E3	A2B2C2D3E3	A2D3E3	
ε%	16.4%	8.2%	8.3%		8.2%
SN ratio	15.7	21.72	21.61	19.52	6.02

very important parameters in reducing the mean error rate and the variation in the error rate, for any MLCC product.

2. ANOVA yields the importance of each control factor as the percentage contribution to the sum of the squares of the variation in the response. For the X5R MLCC, the type of light source contributes 54.08%; its brightness contributes 19.85%; the variation ratio of the gray scale of the pixels contributes 11.51%, and the distance between axis and pixels contributes 5.06%. For the X7R MLCC, the respective contributions are 43.94%, 29.35%, 12.98%, and 4.09%. For the Y5V MLCC, the contributions are 42.40% for pixel defective area ratio, 27.12% for the color of light source, and 11.73% for the brightness of the light source.

3. The optimal parameter combination for inspecting X5R is a green light source, a light source brightness of 120 lm, a pixel gray scale variation ratio of ten, and an axis-pixel distance of ten pixels. The optimal parameter combination for inspecting X7R is a red light source, a light source brightness of 100 lm, a pixel gray scale variation ratio of 20, and an axis-pixel distance of 20 pixels. The optimal parameter combination for inspecting Y5V is a blue light source, a light source brightness of 120 lm, and a pixel defective area ratio of 10%.

4. The error rate of optical inspection is reduced from 16% to 7.07%, corresponding to a reduction of 44%.

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