To Improve the Atomic Force Microscopic (AFM) Printing Process of Liquid Crystal Display (LCD)

Jui-Chin Jiang
Dept. of Industrial and Systems Engineering
Chung Yuan Christian University
Chung-Li City, Taiwan 32023
Email: jcjiang@cycu.edu.tw

Tai-Ying Lin
Dept. of Industrial and Systems Engineering
Chung Yuan Christian University
Chung-Li City, Taiwan 32023
Email: lty0858@vnu.edu.tw

Abstract: - Six Sigma is to introduce DMAIC (Define, Measure, Analyze, Improve, Control) in manufacturing process to improve product quality and reduce defect products. At the improvement stage, the Mahalanobis-Taguchi System, given its capability of classification and feature selection, is integrated to reduce the redundant testing items in the testing procedure, and provide a test flow of better economic benefits. The important variables screened by the Reduced Model in MTS are C_2, C_5 and the classification accuracy rate is 99.73%. The Atomic force microscopic thickness average has been reduced from $707.38\,\overset{\circ}{A}$ to $701.16\,\overset{\circ}{A}$. The standard deviation is reduced from 45.76 to 8.73, PCI is raised from 0.73 to 3.81, process accuracy is improved from 0.07 to 0.012, and process performance is improved from 0.67 to 3.76. Finally, this study confirmed that the new process parameters can reduce the alignment film thickness variance, and enhance the overall LCD chromaticity yield.

Key-Words: - Process Capability Index (PCI), Six Sigma, Mahalanobis-Taguchi System(MTS), Classification, Atomic Force Microscopic, Liquid Crystal Display (LCD)

1 Introduction

The increasing demand for small and medium sized panels for 3C electronic products leads to the improvement of product yield and equipment capacity utilization. Thus, how to use existing production facilities to meet rapid changes of market demands has become a major issue to multi-panel factories. During the TFT LCD manufacturing process, the alignment of liquid crystal molecules on the glass panel is the major bottleneck. Improving the process yield is the major concern. The Six Sigma design and flow control minimize the possible errors in the flow operations. The Mahalanobis-Taguchi System (MTS) is a new diagnosis and prediction technology for multi-variable data with capabilities of classification and feature selection [1] [8]. The application of the Six Sigma approach integrated with the MTS can help enterprises to achieve the highest quality and efficiency, the lowest cost, the shortest operation time, the biggest profit, and all-around customer satisfaction.

2 Literature Review

2.1 Six Sigma

Six Sigma is an approach developed by Dr. Mike J. Harry of Motorola in 1980s. Since 1987, the Motorola company has implemented the Six Sigma, and used the statistical quality control to improve management process in order to control the defect rate below 3.4 in 1 million products. The result was a culture of quality that permeated Motorola and led to a period of unprecedented growth and sales. The crowning achievement was being recognized with the Malcolm Baldrige National Quality Award in 1988 [3]. Although invented at Motorola, Six Sigma has been experimented with by Allied Signal and Perfected at General Electric (GE). The successful implementation of Six Sigma by GE, which has obtained huge cost savings, induced the fervor of pursuing Six Sigma around the world since it afterwards.

Six Sigma is a methodology that provides business with the tools to improve the capability of their business processes. For Six Sigma, a process is the basic unit for improvement. A process could be a product or a service process that a company provides to outside customers, or it could be an internal process within the company, such as billing or production process. In Six Sigma, the purpose of process improvement is to increase performance and decrease performance variation. This increase in performance and decrease in performance variation will lead to defect reduction and improvement in profits, to employee morale and quality of product, and eventually to business excellence [19].

Overall, Six Sigma is a top-down approach that is led by the company Chief Executive Officer, and the roles of the Champion, Master Black Belt, Black Belt, and Green Belt usually organizes the infrastructure of a Six Sigma project. The Six Sigma methodology that is most widely used is known as DMAIC (Define, Measure, Analyze, Improve and Control). DMAIC offers a structured and disciplined methodology for solving business problems and enables a business to achieve extremely low non-conformance rates [7]. The Six Sigma tool kit includes a variety of techniques, primarily from statistical data analysis and quality improvement. Many tools are familiar from the era of total quality management; others are more recent and sophisticated [2].

2.2 Process Capability Index (PCI)

Process capability indices (PCIs) can provide numerical measure on whether a process is capable of producing items meeting the quality requirement preset in a factory. Then the production department can trace and improve a poor process so that the quality level can be enhanced and the requirements of the customers can be satisfied. Therefore, PCIs can be viewed as effective and excellent means of measuring product quality and performance. Some basic capability indices that have been widely used in the manufacturing industry include C_p, C_a and C_{pk}, explicitly defined as follows1–3 [6][11][12][13]:

$$C_p = \frac{USL - LSL}{6\sigma} \tag{1}$$

$$C_a = 1 - \frac{|\mu - m|}{d} \tag{2}$$

$$C_{pk} = \min\left\{\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right\} \tag{3}$$

where USL and LSL are the upper and the lower specification limits, respectively, μ is the process mean, σ is the process standard deviation, $m = (USL + LSL)/2$ is the mid-point of the specification interval, and $d = (USL - LSL)/2$ is half the length of the specification interval.

The index C_p measures the overall process variation relative to the specification tolerance, therefore it only reflects process potential (or process precision). The index C_a measures the degree of process centering, which alerts the user if the process mean deviates from its target value. Therefore, the index C_a only reflects process accuracy. The index C_{pk} takes into account the magnitude of process variation as well as the degree of process centering, which measures process performance based on yield (proportion of conformities).

2.3 MTS

MTS is a diagnosis and prediction technology developed for multivariate data. Taking Mahalanobis distance of variable correlation to measure the multivariate system [10][16], it implements the system optimization process by principles of robust engineering. A typical multivariate diagnosis system is as shown in Figure 1, where $X_1, X_2, X_3, ..., X_k$ denotes k variable, providing information for decision-makers in making decisions; input signal (M) is the true value of system status. In general, signal factors and system output have interactive relationships, the noise factors vary from the use environment, and are uncontrollable that may affect the system and result in deviation. In the multivariate diagnosis system, the decision-maker cannot observe each variable independently to make correct decisions due to the potential, unknown correlation. Hence, when constructing the system, the decision-maker should take the relationship structure between variables into consideration.

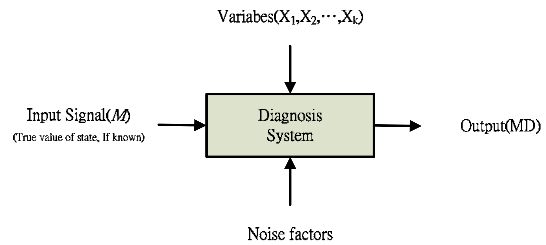

Fig. 1 Modified multidimensional diagnosis system

Mahalanobis distance is proposed by Indian statistician P. C. Mahalanobis in 1936. Mahalanobis distance (MD) is a distance measure that is based on correlations between variables and the different patterns that can be identified and analyzed with respect to a reference population. MD is a discriminant analysis tool [16], Traditionally, the MD methodology has been used to classify observations into different groups. The following is the formula used to calculate MDs:

$$MD_j = D_j^{\,2} = \frac{1}{k} Z_{ij}^{\,T} C^{-1} Z_{ij} \qquad (4)$$
$$i = 1,2,...,k,\; j = 1,2,...,n$$

Where,

k	is the number of data sets,
i	is the number of variables ($i = 1,2,...,k$)
j	is the number of samples ($j = 1,2,...,n$)
Z_{ij}	is the standardized vector of the example
x_{ij}	is the value of the ith characteristic in the jth observation
m_i	is the mean of the ith characteristic
s_i	is the standard deviation of the ith characteristic
T	is the transpose of the standard vector
C^{-1}	is the inverse of the correlation matrix

In the next phase, orthogonal arrays (OAs) and signal-to-noise (SN) ratios are used to screen the important variables. Applying OAs, each variable is assigned to one column and set with two levels: using and not using this variable. The SN ratio, the larger-the-better SN ratio is frequently suggested [15][16], obtained from the abnormal MDs is used as the response for each run of OA. The importance of each variable is evaluated by calculating the “effect gain.” If the gain corresponding to a variable is positive, the variable may be considered as worth keeping; otherwise, it should be removed. Finally, a “reduced model measurement scale” is established using the important variables. Then, an appropriate threshold to discriminate between the normal group and the abnormal examples are determined for future diagnosis.

3 Research Results

3.1 Define

At present, small and medium sized LCD is mostly used on mobile phones. The customer demands on display panel products focus on portability, display quality, lightweight, and power saving. Since the uniform membrane thickness of the Atomic force microscopic will affect the overall display of LCD chromaticity, the overall improvement of small chromaticity differences is an important technology in LCD products.

3.2 Measure

The key quality feature of the Atomic force microscopic printing process is the membrane thickness uniformity. The ideal target value is $700\,\mathring{A}$, thicker or thinner printing membrane thickness will result in insufficient color saturation and poor display quality, or even inability to display. Hence, it is a the-nominal-the-best feature that needs to be improved.

3.3 Analyze

The analysis of the impact of the a Atomic force microscopic printing thickness uniformity on LCD chromaticity should define performance objectives, identify variance sources, and calculate the process capability before improvement in order to provide a reference to future process improvement.

Define performance goals: the key quality feature of the Atomic force microscopic printing process is the membrane thickness uniformity. The original $700\,\mathring{A} \pm 100\,\mathring{A}$ is improved to find out the optimal level of the process parameters to reduce the variance of Atomic force microscopic printing thickness uniformity and the original evenness tolerance. Furthermore, the variance is reduced to enhance process capability, making the membrane thickness tolerance satisfying the Six Sigma requirements.

Confirm variance sources: using the Cause and Effect Chart to determine the factors of printing parameters affecting the printing thickness uniformity of the Atomic force microscopic. Four possible factors, including the convex point arrangement, convex point diameter, exposure energy, exposure time, are summarized as the controllable factors of the experiment.

Establish process capability: record items including the quality feature control item (membrane thickness uniformity), target value ($700\,\mathring{A}$), measurement tool (surface roughness instrument), the control method ($\overline{X}$ and R control diagrams), control frequency (sampling twice per day, and the sample size is five) in the QC engineering table. The operating staffs conduct sampling test daily and observe for 9 working days to obtain 18 groups of samples and 90 observation values as shown in Table 1. The obtained data are summarized to calculate the control diagrams of $\overline{X}$ and R , the shown in Figure 2 and Figure 3, and the relevant parameters of the control diagram are A2=0.577, D3=0, D4=2.114, d2=2.326, the central line of R control diagram is $\overline{R}=106.44$, the control upper limit is $D_4\overline{R}=225.01$, the control lower limit is $D_3\overline{R}=0$, $\overline{X}$ control diagram's central line $\overline{\overline{X}}=707.38$, the control upper limit is $UCL=\overline{\overline{X}}+A_2\overline{R}=768.80$, the control lower limit is $LCL=\overline{\overline{X}}-A_2\overline{R}=645.96$, by the central line of $\overline{X}$ control diagram. The deviation of the central value of the Atomic force microscopic printing thickness is insignificant, the upper specification limit of membrane thickness USL is $800\ \mathring{A}$, the lower specification limit LSL is $600\ \mathring{A}$, hence, the membrane thickness tolerance is 200, the estimated standard deviation of membrane thickness is $\hat{\sigma}=\frac{\overline{R}}{d_2}=45.76$, $\hat{C}_P=0.73$, $\hat{C}_a=0.07$, $\hat{C}_{pk}=0.67$, the $\hat{C}_{pk}$ is relatively low. Hence, the Taguchi method will be applied to reduce variance to improve membrane thickness uniformity.

Table 1 The raw data

Sample	Variables 1	2	3	4	5	$\overline{x}$	R
1	737	752	729	715	659	718.4	93
2	685	662	672	611	638	653.6	74
3	656	704	710	712	684	693.2	56
4	686	660	671	624	669	662.0	62
5	774	749	714	681	718	727.2	93
6	660	682	610	702	693	669.4	92
7	660	814	635	711	738	711.6	179
8	668	695	740	727	729	711.8	72
9	657	749	783	760	796	749.0	139
10	729	701	648	754	738	714.0	106
11	774	635	804	660	682	711.0	169
12	785	760	709	678	738	734.0	107
13	668	615	685	723	741	686.4	126
14	774	711	727	646	651	701.8	128
15	675	829	650	726	753	726.6	179
16	693	720	765	752	754	736.8	72
17	835	810	759	728	738	774.0	107
18	676	650	661	614	659	652.0	62
						$\overline{\overline{X}}=707.38$	$\overline{R}=106.44$

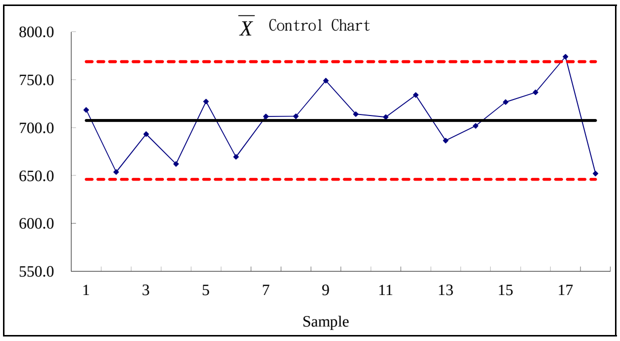

Fig. 2 $\overline{X}$ Control Chart

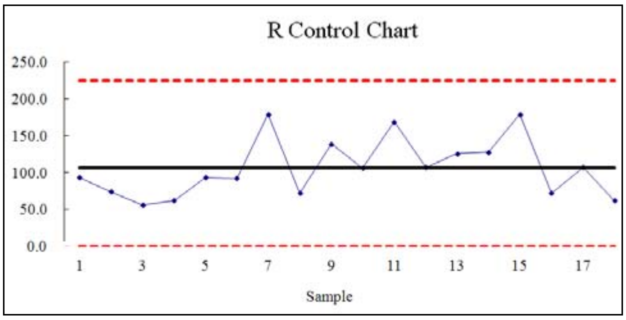

Fig. 3 R Control Chart

3.4 Improve
3.4.1 Implementation of MTS
The Mahalanobis-Taguchi System (MTS) is a diagnostic and forecasting technique for multivariate data. The test measures the ITO (Indium Tin Oxide) glass of the process parameters, and the membrane thickness at five measuring points in the upper, lower, left, right and the center of the printing area as the testing attributes. The products that pass the 5 tests are considered normal samples. The data were randomly sampled and split into training and test sets. The training set used to construct a measurement scale contained 150 normal and 30 abnormal examples, where as the test set used to demonstrate the capability of the scale contained 50 normal and 10 abnormal examples.

Phase 1: Construct a "Full Model Measurement Scale" with MS as the Reference

The attribute values, means, and standard deviation of the normal group were collected, calculated, and the results are shown in Table 2 and, then, the standardized values of the 5 attributes were computed and shown in Table 3. We used the standardized attribute values in Table 3 to compute the inverse of the correlation matrix of the normal group in Table 4. Finally, the Mahalanobis distance of normal samples are calculated. The Mahalanobis distance of the first example of the normal group was calculated as follows:

$$MD_1 = \left\{ \frac{1}{5} \begin{bmatrix} 1.539 & 1.497 & \cdots & 1.217 \end{bmatrix}_{1\times 5} * \begin{bmatrix} 1.49 & 0.11 & \cdots & -0.46 \\ 0.11 & 1.47 & \cdots & 0.11 \\ \vdots & \vdots & \ddots & \vdots \\ -0.46 & 0.11 & \cdots & 1.31 \end{bmatrix}_{5\times 5} \begin{bmatrix} -0.24 \\ -0.61 \\ \vdots \\ -0.60 \end{bmatrix}_{5\times 1} \right\}$$

$$= 1.077$$

The MD of each example of the normal group is shown in Table 3.

Table 2 Attribute Value, Mean and SD of the Normal Group

Attribute / Sample	C_1	C_2	C_3	C_4	C_5
1	745	744	708	794	746
2	685	745	735	742	682
3	635	674	692	785	612
⋮	⋮	⋮	⋮	⋮	⋮
148	685	662	668	685	698
149	685	663	657	664	669
150	682	673	681	682	675
$\overline{x_i}$	690.61	693.50	694.10	698.86	698.46
s_i	35.33	33.72	35.05	39.39	39.05

Table 3 Standardized Attribute Value and MD of the Normal Group

Attribute / Sample	C_1	C_2	C_3	C_4	C_5	MD
1	1.539	1.497	0.396	2.415	1.217	1.077
2	-0.158	1.526	1.166	1.095	-0.421	0.911
3	-1.573	-0.578	-0.060	2.186	-2.214	1.092
⋮	⋮	⋮	⋮	⋮	⋮	⋮
148	-0.158	-0.933	-0.744	-0.351	-0.011	1.147
149	-0.158	-0.904	-1.058	-0.884	-0.754	1.072
150	-0.243	-0.607	-0.373	-0.427	-0.600	1.183

Table 4 Inverse of the Correlation Matrix of the Normal Group

Attribute / Sample	C_1	C_2	C_3	C_4	C_5
C_1	1.490	0.105	0.142	-0.736	-0.459
C_2	0.105	1.466	-0.524	-0.487	0.109
⋮	⋮	⋮	⋮	⋮	⋮
C_4	-0.736	-0.487	-0.696	1.964	0.074
C_5	-0.459	0.1099	-0.448	0.074	1.310

Phase 2: Validate the Measurement Scale

The 30 abnormal samples in the training set are standardized, and their Mahalanobis distances are calculated. If the measurement scale constructed in phase 1 is good, the MDs of the abnormal examples will be larger than that of the normal group. It is obvious that the MDs of the abnormal samples are indeed larger than that of normal groups, and it appears that the measurement scale is effective.

Phase 3: Screen important variables

The five attributes as the control factors, each of which is set as two levels, level 1 was inclusive of the factor, and level 2 was exclusive of the factor, and the control factors are configured in $L_8(2^7)$ the orthogonal array. We will use assigned variables to calculate MD in each run, and then acquire the SN ratio from these MDs. SN ratio is defined as a tool to measure the accuracy of the measurement scale. The allocation of the factors in the OA and the SN ratios are shown in Table 5. take Run 1,for instance . The SN ratio was calculated as follows:

$$\eta_1 = -10 \cdot \log_{10}\left[\frac{1}{30} \cdot \left(\frac{1}{1.077} + \cdots + \frac{1}{1.183}\right)\right]$$
$$= 13.6458$$

Table 5 Factors Allocation and SN Ratios

Run	C_1	C_2	C_3	C_4	C_5			MD_1	…	MD_{30}	SN ratio η (dB)
	1	2	3	4	5	6	7				
1	1	1	1	1	1	1	1	21.974	…	27.425	13.645
2	1	1	1	2	2	2	2	21.838	…	21.442	16.762
3	1	2	2	1	1	2	2	15.670	…	26.057	14.177
4	1	2	2	2	2	1	1	9.4141	…	14.597	13.823
5	2	1	2	1	2	1	2	21.831	…	18.010	14.784
6	2	1	2	2	1	2	1	23.357	…	25.618	17.638
7	2	2	1	1	2	2	1	13.635	…	15.618	13.151
8	2	2	1	2	1	1	2	10.320	…	17.905	14.309

For the known variables X_i , we use $\overline{SN^+}$ to represent the average SN ratio from all the experimental results when X_i is included as a variable. On the contrary, $\overline{SN^-}$ represents the average SN ratio from all the experimental results when X_i is excluded as a variable. A "gain" represents the difference between these two values, i.e. $\overline{SN^+}$ - $\overline{SN^-}$. If the "gain" is positive, keep the variable; if not, then exclude it. Take attribute C_1 as an example, the effect gain was calculated as follows:

$$\overline{SN^+} = \frac{1}{4}(13.6458 + 16.7628 + 14.1773 + 13.8231)$$
$$= 14.60225$$

$$\overline{SN^-} = \frac{1}{4}(14.7844 + 17.6384 + 13.1512 + 14.3098)$$
$$= 14.97095$$

Phase 4: Diagnose or predict future observations with important variables

Take the case of gain > 0, the remainder attributes are C_1, C_3, and C_4, and we used the normal group with these 5 attributes to develop a reduced model measurement scale. For this reduced model with 3 attributes, using 1.724 to be the threshold resulted in 99.73 percent classification accuracy on the training set. Finally, to verify the classification capability of the reduced model, the test set was utilized.

3.4.2 Determine the Control Factors and Levels. The Taguchi parametric design approach is used to conduct experimental planning to select four control factors of Atomic force microscopic thickness uniformity, including the convex point arrangement, convex point diameter, exposure energy, and exposure time. The experiment has two two-level factors and three three-level factors. $L_{18}(2^1 * 3^7)$ orthogonal array is used for the experiment. The summary of four factors and their levels is shown in Table 6. After identifying the optimal level of process parameters, the variance in the Atomic force microscopic printing membrane thickness uniformity is reduced to considerably improve the printing membrane thickness uniformity of the Atomic force microscopic. Each group of experiments uses four pieces of ITO glass under the same process parametric conditions. The membrane thickness value is measured at two measuring points at the lower and central area of each piece of ITO glass. Hence, each group of experiments has 8 observation values and 18 types of tests to result in 144 observation values of the Atomic force microscopic printing membrane thickness. The obtained membrane thickness measurement values are as recorded as shown in Table 7 for data analysis.

Table 6 Control factors and their level

Factor	Level		
	1	2	3
Convex point arrangement	Square arrangement	Regular triangle arrangement	
Convex point diameter	35 μ m	40 μ m	45 μ m
Exposure energy	35mw/cm^2	40mw/cm^2	45mw/cm^2
Exposure time	100sec	110sec	120sec

Table 7 Experimental data

Run	C_1	C_2	C_3	C_4			Measurement piece 1		…	Measurement piece 4		$\bar{y}$ (Å)	s	η (dB)
	1	2	3	4	…	8	Lower point	Central point	…	Lower point	Central point			
1	1	1	1	1	…	1	744	746	…	685	795	726.250	54.652	22.467
2	1	1	2	2	…	2	785	703	…	765	745	749.875	25.542	29.354
3	1	1	3	3	…	3	745	682	…	674	755	718.000	35.185	26.194
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
16	2	3	1	3	…	2	682	655	…	682	663	671.750	10.525	36.099
17	2	3	2	1	…	3	685	665	…	670	673	671.625	8.618	37.834
18	2	3	3	2	…	1	648	664	…	649	649	658.625	9.6056	36.722
												$\bar{\bar{y}}$ =693.799		$\bar{\eta}$ =30.387

Table 8 Responses of average η values (dB) at all levels

Factor	Average η Values (dB) at All Levels		
	1	2	3
Convex point arrangement	24.646	36.128	
Convex point diameter	30.666	30.557	29.939
Exposure energy	29.509	31.969	29.683
Exposure time	29.412	30.904	30.846

Table 9 Responses of average valued of membrane thickness at all levels

Factor	Average valued of membrane thickness at all levels		
	1	2	3
Convex point arrangement	697.431	690.167	
Convex point diameter	725.541	687.688	668.167
Exposure energy	686.542	704.792	690.063
Exposure time	690.313	698.167	692.917

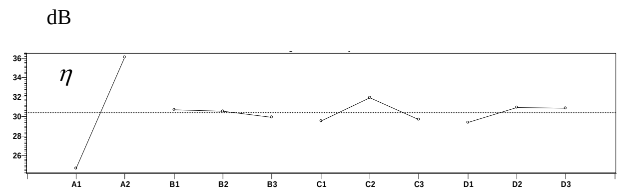

Fig. 5 The factor effects of average η values (dB)

3.4.3 Optimal level combinations and expected improvement effects.

According to the factor effects of average η values (dB) as shown in Figure5 and Table 8, the optimal parametric level is A2C2. The factor effects of the printing membrane thickness values as shown in Table 9. The $\bar{\eta}_{A_1}$ and $\bar{y}_{A_1}$ were calculated as follows:

$$\eta = 10\log(\frac{\bar{y}}{s})^2 = 10\log(\frac{726.25}{54.652})^2 = 22.47$$

$$\bar{\eta}_{A_1} = \frac{1}{9}(\eta_1 + \eta_2 + \eta_3 + \eta_4 + \eta_5 + \eta_6 + \eta_7 + \eta_8 + \eta_9)$$
$$= 24.646\,(dB)$$

$$\bar{y}_{A_1} = \frac{1}{9}(\bar{y}_1 + \bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5 + \bar{y}_6 + \bar{y}_7 + \bar{y}_8 + \bar{y}_9)$$
$$= 697.431\ \mathring{A}$$

The expected improvement effects of the Atomic force microscopic printing thickness uniformity: the current printing membrane thickness specification value is $700 \pm 100\ \mathring{A}$, process average value is $707.38\ \mathring{A}$, the process deviation is $\sigma = 45.76$, $\eta = 10\log(707.38/45.76)^2 = 23.78$, the estimated value of process capability indicator $C_{pk} = C_p|1 - C_a| = 0.67$, and the estimated η (η_{opt}) at the optimal level is

$$\eta_{opt} = (\bar{\eta}_{A_2} - \bar{\eta}) + (\bar{\eta}_{C_2} - \bar{\eta}) = \bar{\eta}_{A_2} + \bar{\eta}_{C_2} - \bar{\eta}$$
$$= 37.71(dB)$$

Expected improvement effects

$$\Delta\eta = \eta_{opt} - \eta_{old} = 37.71 - 23.78 = 13.93(dB)$$

$$\left(\frac{\sigma_{opt}}{\sigma_{old}}\right)^2 = 10^{\frac{-\Delta\eta}{10}} = 0.04, \frac{\sigma_{opt}}{\sigma_{old}} = 0.2$$

The optimal level variance is reduced to below 4% of the existing level, and the standard deviation is reduced to 0.2 times of the original. The average estimated value of the optimal factor combinations is

$$\bar{y}_{opt}(A_2C_2) = \bar{y}A_2 + \bar{y}C_2 - \bar{y} = 701.16\ \mathring{A}$$

3.5 Control

Improvement performance: regarding the improvement benefits by Taguchi parametric optimization, the Atomic force microscopic thickness average has been reduced from $707.38\ \mathring{A}$ to $701.16\ \mathring{A}$, which slightly vary from the estimated process average value of the optimal factor combination $A_2B_3C_2D_2$. The error is acceptable as it is closer to the target value $700\ \mathring{A}$ than $707.38\ \mathring{A}$ before improvement. The standard deviation is reduced from 45.76 to 8.73, PCI is raised from 0.73 to 3.81, process accuracy is improved from 0.07 to 0.012, and process performance is improved from 0.67 to 3.76.

Table 10 Comparison of Control Charts to Improvement Performance

Control Chart	The uniform membrane thickness of the Atomic force microscopic									
	$\bar{X}$ Control Chart			R Control Chart			Standard deviation	Process Capability Indices	Process accuracy	Performance indicators of process capability
	UCL	CL	LCL	UCL	CL	LCL	$\hat{\sigma} = \frac{\bar{R}}{d_2}$	$\hat{C}_P$	$\hat{C}_a$	$\hat{C}_{pk}$
Before improvement	768	707	645	225	106	0	45.76	0.73	0.07	0.67
After improvement	713	701	689	45	20	0	8.73	3.81	0.012	3.76

4 Conclusion

MTS is the diagnosis and prediction technology developed for the multivariate data. It is not only can product robust and fine results in processing classification problems, but also eliminate unimportant feature variables to reduce system cost or speed up data processing. This study integrated MTS with the Six Sigma DMAIC model to identify customer demands on LCD and the core process-alignment membrane printing process. The Six

Sigma is used for optimizing the process parameters, and the Taguchi method is applied to use the orthogonal array and S/N ratio as tools in order to understand the impact of various factors and identify the optimal process parameter combinations. Finally, by MTS analysis, the ITO glass testing attributes were reduced from the 5 items to 2 items with high remaining accuracy rate. Meanwhile, with the new parametric level-papillary arrangement was changed into regular triangle arrangement, the exposure energy was changed from 35mw/cm^2 to 40mw/cm^2 to improve dB value by 13.93dB, and reduce the standard deviation to 0.2 times of the original, raise the process capability performance index C_{pk} from 0.69 to 3.76. The results suggested that the new process parameters obtained in this experiment can reduce the alignment membrane thickness variance, reducing the evenness tolerance. The application of the new parameter combination in the assembly line has considerably improved the LCD overall chromaticity and contrast yield to enhance LCD competitiveness accordingly.

References:

[1] Bovas, A. and Asokan Mulayath, V., Discussion - A Review and Analysis of the Mahalanobis-Taguchi System, *Technometrics*, Vol.45, No.1, 2003, pp. 22-25.

[2] Breyfogle, F. W., *Implementing Six-Sigma: Smarter Solutions Using Statistical Methods*, John Wiley & Sons, Inc., New York, 1999.

[3] Breyfogle, F. W., Cupello, J. M., and Meadows, B., *Managing Six-Sigma*, John Wiley & Sons, Inc., New York, 2001.

[4] Brue, G., *Six Sigma for Managers*, McGraw-Hill, New York, 2002.

[5] Eckes, G., *Making Six Sigma Last: Managing the Balance Between Cultural and Technical Change*, John Wiley & Sons, New York, 2001.

[6] Gunter, B.H., The use and abuse of Cpk, *Quality Progress*, Vol.22, No.3, 1989, pp. 108-109.

[7] Harry, M. and Schroeder, R., *Six Sigma: The Breakthrough Management Strategy Revolutionising the World's Top Corporations*, Doubleday, New York, 2000.

[8] Hawkins, D.M., Discussion - A Review and Analysis of the Mahalanobis-Taguchi System. *Technometrics*, Vol.45, 2003, pp. 25-29.

[9] Henderson, K.M. and Evans, J.R., Successful implementation of Six Sigma: benchmarking General Electric Company. *Benchmarking: An International Journal*, 2000, Vol.7, No.4, 2000, pp. 260–281.

[10] Jugulum R., Taguchi G., Taguchi S., and Wilkins J., Discussion of A review and analysis of Mahalanobis-Taguchi System, *Technometrics*, Vol.45, No.1, 2003, pp. 16-21.

[11] Kane VE., Process capability indices. Journal of Quality Technology, Vol.18, No.1,1986, pp.41–52.

[12] Pearn WL, Kotz S, Johnson NL., Distributional and inferential properties of process capability indices. *Journal of Quality Technology*, Vol.24, No.4, 1992, pp. 216–231.

[13] Pearn WL, Lin GH, Chen KS., Distributional and inferential properties of the process accuracy and process precision indices. *Communications in Statistics: Theory and Methods*, Vol.27,No.4, 1998, pp. 985–1000.

[14] Smith, Dick, Jerry Blakeslee and Richard Koonec, *Strategic Six Sigma: Best Practices from the Executive Suite*, John Wiley & Sons, New York, 2002.

[15] Taguchi, G., Chowdhury, S. and Wu, Y., *The Mahalanobis Taguchi System*, McGraw-Hill, New York, 2001.

[16] Taguchi, G. and Jugulum, R., *The Mahalanobis-Taguchi Strategy: A Pattern Technology System*, John Wiley & Sons, 2002.

[17] Woodall, W. H., Koudelik, R., Tsui, K. L., Kim, S. B., Stoumbos, Z. G. and Carvounis, C. P., A Review and Analysis of the Mahalanobis-Taguchi System, Technometrics, Vol.45, 2003, pp. 1-15.

[18] Wright, P. A., A process capability index sensitive to skewness. *Journal of Statistical Computation and Simulation*, Vol.52, 1995, pp. 195-203.

[19] Yang, K. and El-Haik, B., *Design for Six Sigma: A Roadmap for Product Development*, McGraw-Hill, New York, 2003.