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Applying Residual Control Charts to Identify the False Alarms in a TFT-LCD Manufacturing Process

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Abstract: Statistical Process Control (SPC) is widely applied to monitor and improve highly integrated and automated manufacturing processes. Adopting proper SPC charts and corresponding detection mechanisms is crucial for a TFT-LCD manufacturing process. This study conducts an empirical study of highly complex TFT-LCD manufacturing processes to identify the most suitable SPC method. The TFT-LCD manufacturing process is generally divided into three main procedures, namely Array Engineering to create the TFT array, Cell Engineering to join the TFT array, liquid crystal and color filter together, and Module Engineering to integrate PCB and semiconductor chips into final products. The crucial step in Cell Engineering is injecting the liquid crystal into the layer between the TFT array and color filter substrates and the thickness of the layer is the main control target. Applying traditional Shewhart and EWMA control charts to real TFT-LCD manufacturing data reveals a significant false alarm rate, and these false alarms can adversely impact manufacturing efficiency. Based on time series analysis, this study proposes a residual control chart using an AR(1) model to avoid false alarms that could obstruct TFT-LCD manufacturing flow. The results of the proposed approach provide a useful guideline for improving the TFT-LCD manufacturing.

Keywords: Statistical process control, control chart, residual, time series, TFT-LCD.

1 Introduction

With the increasing complexity of high-tech manufacturing processes, process control efficiency and accuracy can determine enterprise competitiveness. Owing to the capital-intensive and highly automated nature of the TFT-LCD industry, it is crucial to adopt proper process control mechanisms in order to improve the process quality. As a consequence, statistical process control (SPC) techniques are widely used in TFT-LCD manufacturing industry in order to detect and eliminate the process disturbances.

In the optical network, the optical signal is converted to the electrical signal, an electrical signal is converted to an optical signal at the entry point and then remains in the optical domain throughout the network until it is received at the far end and converted back to an electrical signal [5]. WDM optical networks offer huge transmission capacity. To ensure high-speed WDM network transmission capacity, there must be a good switching technology. In addition, a good routing technology is an important factor to ensure high-speed broadband WDM networks [6]. WDM can take advantage of the huge fiber bandwidth, so that transmission capacity than the single-wavelength transmission increased several times or more. Using WDM technology, originally used only a single wavelength of light as the carrier channel into several channels of different wavelengths of light while transmitting in the fiber, which fiber optic communications capacity doubled.

The Shewhart type of control charts, the best known SPC control charts, divides the process variation into two types: chance causes resulting from inevitable environment variation and assignable causes resulting from some human or machine error [1]. Once the process is detected as out-of-control by using the Shewhart chart,

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process investigation is implemented to identify and remove the corresponding assignable cause. Although the Shewhart chart can effectively detect abrupt process variations, the magnitude of small variations resulting from certain types of assignable causes are infrequently detected with the proper promptness. Therefore, different types of control charts are proposed to deal with the small variations.

The cumulative sum (CUSUM) control method was introduced with the accumulation of the historic output information to detect when the system is out-of-control [2]. To combine the efficiency of the Shewhart chart, many studies proposed the combined methodology which utilized both the Shewhart and CUSUM charts to obtain better results [3,4,5].

The exponentially weighted moving average (EWMA) control method was introduced by assigning collected data different weights based on their timing sequential property [6]. By adjusting the weights, EWMA can trade the accuracy of the CUSUM chart against the efficiency of the Shewhart chart. The EWMA was used to create the self correlated model of the output data and using the prediction error for further process control [7]. Additionally, it was concluded that when $0.05 \leq \lambda \leq 0.25$, the EWMA chart can be proven relatively effective compared with other values [8]. The EWMA was used to predict manufacturing cost and optimize process control performance [9]. Furthermore, the double sampling method was proposed together with the EWMA control chart to monitor the process variations [10].

However, in the highly complex processes, such as TFT-LCD manufacturing, the feature of autocorrelation has been attracting increasing research attention. Approaches based on time series analysis, originally proposed by Box and Jenkins [11,12] are widely applied to handle the autocorrelated process. It was found that autocorrelation of the sampling data reduces the effectiveness of control charts for the high sampling rate in the manufacturing process [13]. Consequently, they proposed using the ARIMA model to construct geometric moving average (GMA) and geometric moving range (GMR) charts to improve quality control. Also, it was found that the time series approach should be applied when using automatic sampling to reduce the influence of the autocorrelation [14,15]. It was concluded the sample data is highly autocorrelated for the cases involving a shorter sampling interval [16,17].

To monitor the highly autocorrelated process, a novel control method to propose to adjust the control limits to compensate for the influence of autocorrelation [18]. Moreover, it was found that the existence of autocorrelation significantly reduced control effectiveness and increased false alarm rates [19].

Recently, a growing number of investigations have adopted series analysis, and various empirical studies have been proposed. It was developed the ARIMA-EGARCH model to improve short term forecasting of electricity prices [20]. The ARIMA model was applied to semiconductor manufacturing by adjusting the process ingredients. The ARIMA analysis was used to assess business activity performance.

This study focuses on highly complex and automatic TFT-LCD manufacturing processes. Applying traditional Shewhart and EWMA control charts to real TFT-LCD manufacturing data may result in high false alarm rates, and these false alarms can damage manufacturing efficiency. Consequently, this study utilizes the time series approach to model the sampling data and develop a effective residual control chart. The residual control chart is able to help to reduce the false alarms, and thus, the process improvement can be achieved.

2 TFT-LCD Manufacturing Process

WDM TFT-LCD related products are affecting daily life for everyone. Notebook PCs, monitors, TVs, mobile phones and numerous other consumer products use TFT-LCD as the display component. Although TFT-LCD is so popular and almost universal, the TFT-LCD manufacturing process is so complex and capital-intensive that only a few manufacturers with superior manufacturing efficiency and quality control can survive. Two of the top five TFT-LCD manufacturers, AUO and CMO-Innolux, are located in Taiwan, and this empirical study is practical.

The TFT-LCD manufacturing process can be divided into three main procedures, namely Array Engineering to create the TFT array, Cell Engineering to join the TFT array, liquid crystal and color filter, and Module Engineering to integrate PCB and semiconductor chips into final products. One of the most important TFT-LCD manufacturing steps in Cell Engineering is injecting the liquid crystal into the layer between the TFT array and color filter substrates in order to form a sandwich, as shown in Fig. 1. Transistor switches control the TFT arrays spread with picture elements, called pixels. The color filter substrate provides and determines the color of each pixel. The layer between the color filter and the TFT array, known as the Gap, represents the injection room and is the main focus of this study.

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To maintain the quality, the Gap height should be measured and analyzed using micrometers ($um, 10^{-6}m$) as the measurement unit. A Gap that is too thick can result in air bubbles and a gap is too thin can influence liquid crystal behavior and damage injection yield. Consequently, a control limit should be set on the Gap size, and once the measurement exceeds the limit, assignable causes should be identified and removed in order to improve the process.

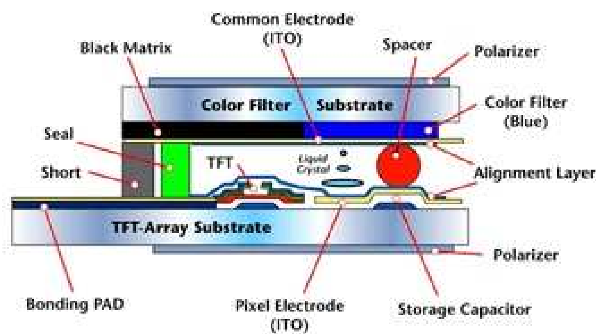

Fig. 1: The cross-sectional view of the TFT-LCD

Table 1: Data obtained from the Gap process

Sample No.	Time	Gap	Sample No.	Time	Gap
1	13:26	3.2574	18	13:59	3.2766
2	13:28	3.2460	19	14:02	3.2820
3	13:31	3.2586	20	14:04	3.2916
4	13:32	3.2864	21	14:05	3.2788
5	13:34	3.2822	22	14:07	3.2794
6	13:36	3.2808	23	14:09	3.2658
7	13:38	3.2684	24	14:11	3.2506
8	13:40	3.2542	25	14:13	3.2464
9	13:42	3.2576	26	14:15	3.2502
10	13:44	3.2522	27	14:24	3.2528
11	13:46	3.2534	28	14:26	3.2558
12	13:48	3.2616	29	...	...
13	13:50	3.2550	30	...	...
14	13:51	3.2536	...	...	...
15	13:53	3.2450	...	...	...
16	13:55	3.2460	500	10:42	3.2518
17	13:57	3.2484			

3 Simulation Results: X-MR and EWMA Control Charts

Table 1 lists the actual sampling data for the Gap measurement process. The sampling interval is two minutes and all the data are automatically measured using automatic instruments. To avoid high time dependency because of the high sampling frequency, only the first of each of the five samples is analyzed below.

For the X-MR Shewhart control charts, the control limits for the X chart can be derived as follows:

$$\begin{aligned} UCL_X &= \overline{X} + 3\frac{\overline{MR}}{d_2}, \\ CL_X &= \overline{X}, \\ LCL_X &= \overline{X} - 3\frac{\overline{MR}}{d_2}, \end{aligned} \quad (1)$$

where $\overline{MR}$ denotes the average of the moving samples and d_2 is set to be 1.128.

Fig. 2 shows that four disturbances can be identified based on X-MR control chars during the manufacturing of these 100 observations. However, after investigating the liquid crystal injection process and checking the final product quality of the Cell Engineering procedure, the manufacturing process during these 100 observations was found to be stable and normal. That is, all four out-of-control signals can be attributed to false alarms.

Fig. 3 plots the EWMA control chart based on the parameter $\lambda = 0.2$. Although the EWMA control chart could deal with the accumulating fine variation, numerous false alarms are also found. For the highly complex and automatic TFT-LCD manufacturing process, false alarms of the process control are costly, and can seriously obstruct the manufacturing flow.

4 Simulation Results: Time Series Methods

For the time series methods, this study separates the sampling data into two groups. The first group comprises 80 samples which are used for time series model build-up, and the second group comprises 20 samples used to verify the constructed model.

Four possible models, namely AR(p), MA(q), ARMA(p,q) and ARIMA(p,d,q), are applied for model

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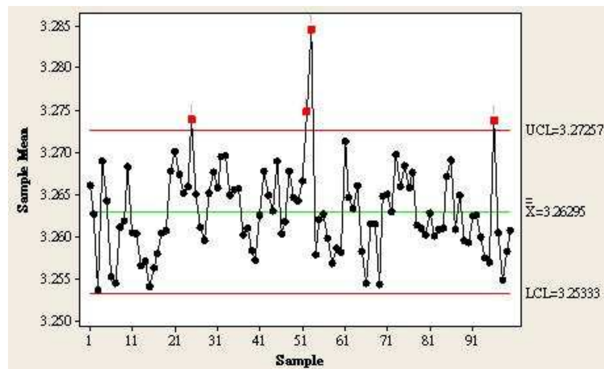

Fig. 2: The false alarms in the X chart

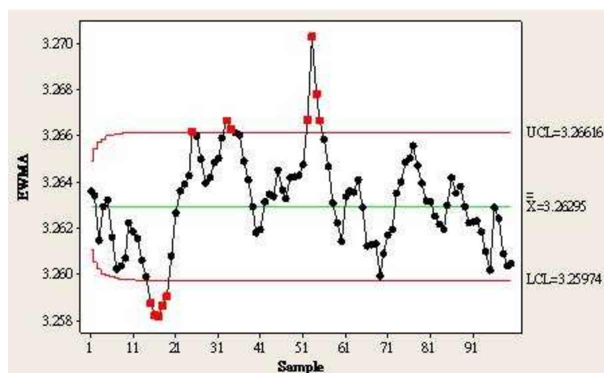

Fig. 3: The false alarms in the EWMA chart

fitting and four types of data, namely Type 1 (d=0, D=0), Type 2 (d=1, D=0), Type 3 (d=0, D=1) and Type 4 (d=1, D=1) are used as input data for fitting. Using SAS 9.2 for simulations, Type 3 and Type 4 are further analyzed because of their lower AIC and SBC indices as shown in Table 2.

The prediction capability of the models is compared using three criteria. The three criteria include mean absolute difference (MAD), mean square error (MSE) and mean absolute percentage error (MAPE), and they are shown in the following equations.

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|e_t|, \quad (2)$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(e_t)^2, \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{Y_t} \times 100, \quad (4)$$

where e_t stands for the residual at time t.

Table 3 lists the simulation results. This study finds that the Type 3 model with AR(1) is the most suitable model for the sample data shown in (4.1).

$$y_t = \delta + \phi_1 y_{t-1} + y_{t-12} - \phi_1 y_{t-13} + a_t, \quad (5)$$

where y_t denotes the output of time t, δ represents the mean value of the output, ϕ_1 is a constant and a_t denotes white noise resulting from the manufacturing process.

Also, Using the Type 3 AR(1) model, a residual control chart can be obtained, as shown in Fig. 4. The residual values for the last 20 samples are reported in Table 4. By observing Fig. 4, we noticed no signal has occurred. It implies that the fault which occurred in an X chart is, in fact, a false alarm. Consequentially, the process personnel can ignore this alarm signal.

Table 2: Analysis of model fitting for types 1 to 4

Type	AIC	SBC	STD Error
1	-621	-614	0.00488
2	-601	-591	0.00526
3	-482	-477	0.00688
4	-472	-459	0.00684

Table 3: Comparison of the prediction capabilities for type-3 and type-4 models

Criteria	Type-3 (d=0, D=1)	Type-4 (d=1, D=1)
MAD	0.002392	0.007057
MSE	0.000011	0.000096
MAPE	7.334%	21.620%

5 Conclusion

Effective and efficient process control is crucial to success in the highly competitive TFT-LCD manufacturing industry. This study analyzes real TFT-LCD manufacturing data and finds that the time series approach can significantly reduce the false alarm rate. Through model fitting, the AR(1) model is adopted and the residual control chart can provide better results than the traditional Shewhart and EWMA charts. The

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simulation results also demonstrate that the TFT-LCD manufacturing process is highly autocorrelated because of high sampling frequency. This conclusion provides a useful guideline for improving the TFT-LCD manufacturing process. Since there are other types of manufacturing processes, the possibility to use the same procedure to other processes deserves further direction.

Table 4: The residual values for last 20 samples

Time	y_t	Fitted y_t	Residual
t_{81}	3.26284	3.25380	0.00904
t_{82}	3.26008	3.26842	-0.00834
t_{83}	3.26080	3.26298	-0.00218
t_{84}	3.26100	3.26105	-0.00005
t_{85}	3.26708	3.26886	-0.00178
t_{86}	3.26912	3.26479	0.00433
t_{87}	3.26084	3.26979	-0.00895
t_{88}	3.26484	3.26250	0.00234
t_{89}	3.25952	3.26714	-0.00762
t_{90}	3.25928	3.25786	0.00142
t_{91}	3.26244	3.26001	0.00243
t_{92}	3.26256	3.26082	0.00174
t_{93}	3.25992	3.26389	-0.00397
t_{94}	3.25744	3.25881	-0.00137
t_{95}	3.25688	3.25965	-0.00277
t_{96}	3.27376	3.25929	0.01447
t_{97}	3.26048	3.27264	-0.01216
t_{98}	3.25484	3.26624	-0.01140
t_{99}	3.25824	3.25462	0.00362
t_{100}	3.26072	3.26371	-0.00299

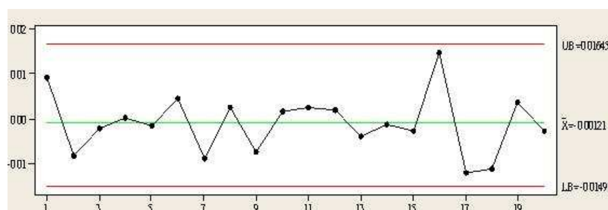

Fig. 4: The residual chart for the last 20 samples

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