南　　華　　大　　學

資訊管理所

碩士論文

# LCD-TFT 製程整合性良率分析

***An Integrated Yield Analysis for LCD-TFT Manufacturing Process***

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指導教授： 謝昆霖

中華民國　九十五 年　十二 月 二十一 日

# 南　華　大　學

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## 碩 士 學 位 論 文

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# LCD-TFT 製程整合性良率分析
# An Integrated Yield Analysis for LCD-TFT Manufacturing Process

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# LCD-TFT 製程整合性良率分析

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## 摘　　要

製程改善能力是當前 TFT-LCD 製造商競爭力的決定性因素之一，但直到現今，還沒有任何適當的理論被提出用以改善 TFT-LCD 工業的良率問題，然而經驗證從良率模式所獲得的資訊（例如，domain knowledge 或 parameter effect）對於 TFT-LCD 的製造商實能夠提供有用的建議和改善方案，也就是說，良率模式的建構與製程參數的影響性，對於 TFT-LCD 產業的良率分析而言，將會是一個必需被重視的課題。

在此篇論文中，我們提出了結合類神經網路與迴歸分析之技術以達成良率模式的建構，並在實例說明中，套用一臺灣臺南科學園區的 TFT-LCD 製造商的實際生產資料，用以驗證我們所提出的模式。

關鍵字：良率模式；液晶顯示器（LCDs）；類神經網路（ANNs）；逐步迴歸

***An Integrated Yield Analysis for LCD-TFT Manufacturing Process***

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ABSTRACT

The ability to improve yield in manufacturing process is an important competitiveness determinant for TFT-LCD factories. Until now, no any suitable theories were proposed to address the yield problem in TFT-LCD industry. However, the information (e.g. the domain knowledge or the parameter effect) obtained from the yield model will provide useful recommendations and improvements to those manufacturers. That is, the model construction and parameter effect for yield analysis will be a necessary issue to be addressed.

In this study, we proposed a procedure incorporating the artificial neural networks (ANNs) and stepwise regression techniques to achieve the model construction and parameter effect. Besides, an illustrative case owing to

TFT-LCD manufacturer at Tainan Science Park in Taiwan will be applied to verifying our proposed procedure.

Keywords: Yield model; Liquid crystal displays (LCDs); Artificial neural networks (ANNs); Stepwise regression

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# 1. Introduction

The market for liquid crystal displays (LCDs) is known as a growing rapidly and impacting new fields. The primary applications of LCDs include personal digital assistants (PDAs), cellular phones, digital cameras, computers, notebooks, flat panel TVs and various computer game units. During the past several years, the market for LCDs has grown at over 20% on average per annum. The speculative demand increase has driven capacity expansion, particularly in South Korea, Japan and Taiwan (Su *et al*., 2004).

The price for LCD products is significantly reduced due to both the technology maturity and ample manufacturing capacity. The downward pricing trend further promotes LCD applications. LCDs can be divided into three major products including TN (twisted nematic), STN (super twisted nematic) and TFT (thin film transistor). The most widely used LCD for high information content display is the TFT-LCD. In the TFT-LCD each picture pixel is controlled using a thin film transistor. The TFT-LCD panel has a sandwich structure (Singer, 1994) consisting of two glass plates with liquid-crystal material in between. The bottom substrate is the TFT array. The top substrate is the color filter plate. Color filter glasses are usually purchased from outside vendors.

The manufacturing technology, capital investment and industrial

infrastructure are key factors affecting LCD industry competition (Liu and Lee, 1997; Su *et al*., 2004). The ability to improve yield in the manufacturing process is an important competitiveness determinant for LCD factories due to the significant yield loss ranging from 5 to 25%. This loss is attributed to three major manufacturing sectors: the array, cell and module assembly processes. The yield loss from the array process is one of the most critical steps. To increase array process yield, more conforming LCD panels must be produced from one glass substrate. However, no any suitable theories were proposed to study the real yield problem and the possible opportunity of improvement to manufacturing process will be omitted. In order to survival during the competitive environment, how to mine the useful information from the "know how or domain knowledge" of manufacturing process will be an important issue to all enterprises. Hence, most manufacturers provide more resources to study such issue. Besides, a flexible model construction in TFT-LCD industry should be another consideration due to the initial development stage of yield analysis. From the systematical viewpoint, several parameters (e.g. the setting of process condition) will significantly affect the result of yield model. How to keep the knowledge about the effect on yield for those parameters will be also another importance issue. From the considerations mentioned above, we will apply the artificial neural networks (ANNs) into the yield model construction due to there were many successful applications; and the necessary statistical technique will also be applied into the analysis of parameter effect. A procedure to achieve the model construction and parameter effect for yield analysis in

TFT-LCD industry was proposed in this study. In order to verify the rationality and feasibility of our approach, an illustrative example owing to TFT-LCD manufacturer at Tainan Science Park in Taiwan will be also chosen in this study.

# 2. Background Information

## 2.1 Stepwise model-building technique

Stepwise model-building techniques for regression designs with a single dependent variable had been described in numerous sources (e.g., see Darlington, 1990; Hocking, 1966, Lindeman, Merenda, and Gold, 1980; Morrison, 1990; Neter, Wasserman, and Kutner, 1985; Pedhazur, 1982; Stevens, 1986; Younger, 1985).

The basic procedures of Stepwise model-building will involve:

(1) Identifying an initial model.

(2) Repeatedly altering the model at the previous step by adding or removing a independent variable (or process parameters) in accordance with the "stepping criteria".

(3) Terminating the search when stepping is no longer possible given the stepping criteria, or when a specified maximum number of steps has been reached. The details on the use of stepwise model-building procedures will be given as follows:

A. The initial model can be defined as Step 0. The initial model

always includes the regression intercept (unless the No intercept option has been specified with respect to the real requirement). As for the backward stepwise and backward removal methods, the initial model also includes all effects specified to be included for the analysis. The initial model for these methods is therefore the whole model. For the forward stepwise and forward entry methods, the initial model only includes the regression intercept (unless the No intercept option has been specified.). The initial model may also include 1 or more effects specified to be forced into the model. If j is the number of effects specified to be forced into the model, the first j effects specified to be included are entered into the model at Step 0 . Any such effects are not eligible to be removed from the model during subsequent Steps. Effects may also be specified to be forced into the model when the backward stepwise and backward removal methods are used. As in the forward stepwise and forward entry methods, any such effects are not eligible to be removed from the model during subsequent Steps.

B. The forward entry method is a simple model-building procedure. At each Step after Step 0, the entry statistic is computed for each effect eligible for entry in the model. If no effect has a value on the entry statistic which exceeds the specified critical value for model entry, then stepping is

terminated, otherwise the effect with the largest value on the entry statistic is entered into the model. Stepping is also terminated if the maximum number of steps is reached.

C. The backward removal method is also a simple model-building procedure. At each Step after Step 0, the removal statistic is computed for each effect eligible to be removed from the model. If no effect has a value on the removal statistic which is less than the critical value for removal from the model, then stepping is terminated, otherwise the effect with the smallest value on the removal statistic is removed from the model. Stepping is also terminated if the maximum number of steps is reached.

D. The forward stepwise method employs a combination of the procedures used in the forward entry and backward removal methods. At Step 1 the procedures for forward entry are performed. At any subsequent step where 2 or more effects have been selected for entry into the model, forward entry is performed if possible, and backward removal is performed if possible, until neither procedure can be performed and stepping is terminated. Stepping is also terminated if the maximum number of steps is reached.

E. The backward stepwise method employs a combination of the procedures used in the forward entry and backward removal

methods. At Step 1 the procedures for backward removal are performed. At any subsequent step where 2 or more effects have been selected for entry into the model, forward entry is performed if possible, and backward removal is performed if possible, until neither procedure can be performed and stepping is terminated. Stepping is also terminated if the maximum number of steps is reached.

F. Either critical F values or critical p values can be specified to be used to control entry and removal of effects from the model. If p values are specified, the actual values used to control entry and removal of effects from the model are 1 minus the specified p values. The critical value for model entry must exceed the critical value for removal from the model. A maximum number of Steps can also be specified. If not previously terminated, stepping stops when the specified maximum number of *Steps* is reached.

## 2.2 Backpropagation Neural Network Model (BPNN)

A neural network consists of a number of simple, highly interconnected processing elements or nodes and is a computational algorithm that processes information by a dynamic response of its processing elements and their connections to external inputs. A neural network can model the non-linear relationship between the system's input and system's output. The non-linear relationship or the interaction effect among several variables can be kept in the structure of hidden layer of a neural network model. Restated, it can be learned by passing the training pairs through the network. Among the several conventional supervised learning neural models including the perceptron, backpropagation neural network (BPNN), learning vector quantization (LVQ), and counter propagation network (CPN), the BPNN model is frequently used (Ko *et al*., 1998; Neural Ware, 1990; Hsieh, 2001; Hsieh, 2006) and, therefore, it will be selected herein. A BPNN consists of three or more layers, including an input layer, one or more hidden layers, and an output layer. Detailed descriptions of the algorithm can be found in various sources (Neural Ware, 1990; Rumelhart *et al*., 1986). The following is a brief description.

To develop a backpropagation neural network, the training and testing data set are firstly collected. The data sets consist of both the input parameters and the resulting output parameters. The backpropagation

learning algorithm employs a gradient- or steepest- heuristic that enables a network to self organize in ways that improve its performance over time. The network first uses the input data set to produces its own output. This forward pass through the backpropagation network begins as the input layer receive the input data pattern and passes it to the hidden layer. Each processing element (PE) calculates an activation function in first summing the weighted inputs. This sun is then used by an activation function in each node to determine the activity level of the processing node. The output generated by the network is compared to the known target value. If there is no difference, no learning takes place. If a difference exists, the resulting error term is propagated back through the network, using a gradient- or steepest- descent heuristic to minimize the error term by adjusting the connection weights. The equation (Neural Ware, 1990; Rumelhart *et al*., 1986) utilized to adjust the weights following the presentation of an input/output pair for the output layer k is:

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

where

$\Delta W_{kj}$ = the change to be made in the weight from the j-th to k-th unit following the presentation of an input pattern,

$\delta_k$ =the error signal for unit k after the presentation of an input pattern,

$O_j$ = the j-th element of the output pattern produced by the presentation of an input pattern,

$\eta$ = the learning rate that governs how fast the network will encode a set of input/output patterns.

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

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

where

$\Delta W_{ji}$ = the change to be made in the weight from the j-th to i-th unit following the presentation of an input pattern,

$\delta_j$ =the error signal for unit j after the presentation of an input pattern,

$O_i$ =the i-th element of the output pattern produced by the presentation of an input pattern,

$\eta$ = the learning rate that governs how fast the network will encode a set of input/output patterns.

As for the training phase, a signal input pattern is presented and the network adjusts the set of weights in all the connecting links such that the

desired output is obtained at the output node. On accomplishing the adjustment, the next pair of input and output target value is presented and the network learns that association.

# 3. Proposed approach

Generally, a particular relationship will exist among the input variables and output variables of a system, e.g. the functional relationship or statistical relationship. From mathematical viewpoint, the logical relationship can be constructed by modeling techniques. Generally, system's output can be viewed as a function of system's input. Hsieh (2006), Hsieh & Tong (2001), Su and Hsieh (1998), Ko *et al*. (1998) had applied the BPNN to model this logical relationship to achieve quality optimization. Hence, we will apply it into our approach. Besides, the parameter effects to output variable (i.e. yield) can also provide the recommendation to process improvement. Hence, such information must be collected along with the yield model construction. After reviewing the related techniques, e.g. the conventional experimental design, stepwise regression analysis, analysis of variance (ANOVA), the stepwise regression analysis had been used for many real applications. In this study, we will apply it into our integrated approach. The detailed procedure of the integrated approach will be given as follows.

## 3.1 Step1. Determine the input/output variables of system and collect data.

Yield can be viewed as the response variable (or the output variable of a system) to our proposed modeling approach. According to the real manufacturing processes, the analyzers can decide the independent variables (or the related input variables which will affect the output of a system) depending their real considerations or judgments. After discussing with the senior engineers, the defect count of several layers (or it can be denoted as manufacturing process) can be taken as the input variables to our proposed procedure. The reason is that a larger defect count will lead to a significant yield loss from the historical experience. That is, the relationship among yield and defect count of different layer (or manufacturing process) can be represented as:

$$\text{Yield} = f(\text{defect count}_{\text{layer1}}, \text{defect count}_{\text{layer2}}, \ldots, \text{defect count}_{\text{layer n}}) \qquad (1)$$

Where the sequence of layer will be denoted as *layer 1*→ *layer 2* →…→ *layer n*. Linear relationship will be the simple one to represent the statistical relationship. However, it does not generally demonstrate the real relationship well due to that most cases are non-linear relationship, especially for the manufacturing process. That is, the conventional regression

analysis is not suitable method to directly construct the model. Hence, the modeling power of ANNs will let it be a suitable technique and it will be selected herein.

## 3.2 Step2. Construct the yield model by using BPNN model.

**Step2-1.**Randomly select the data from the historical record to form the training and the testing data set of BPNN. The ratio of the testing/training set is frequently recommended as 1/4 (Neural Ware, 1990; Hsieh & Tong, 2001; Hsieh, 2006).

**Step 2-2.** As for the training phase of BPNN to the prediction issue, the RMSE (Root of the Mean Square Error) value of the training and testing dataset will be an evaluation index since comparing the different network's architectures (Neural Ware, 1990). The architecture with the minimum training RMSE and testing RMSE values at the same time will be selected to be the feasible architecture.

**Step 2-3.** After the feasible architecture been obtained, we will retrain the selected neural networks to arrive at the steady state (i.e. the RMSE value will not make any change or less than a pre-designed error value or arrive at a training epoch) by

combining the above training and testing set in Step 2-1 into a training set. Finally, we can obtain the optimum yield model for the corresponding problem. Restated, the obtained yield model can be adjusted with the different architectures or different conditions in the future.

## 3.3 Step3. Screen out the effect of all parameters by using stepwise regression analysis.

After the model being constructed well, we can verify the feasibility and rationality to the choice of input variables. Next, we can study the effect for each parameter on the yield. Herein, we will only take the characteristics for the priority of effects on yield even though the linear model can be constructed via stepwise regression analysis. As for the detailed procedure about performing stepwise regression analysis can be referred to Darlington (1990), Hocking (1966), Lindeman *et al*. (1980), Morrison (1990), Neter *et al*. (1985), Pedhazur (1982), Stevens (1986), Younger (1985). After performing the stepwise regression analysis, we can obtain the recommendations about the important effect for those input variables to yield.

## 3.4 Step4. Make necessary recommendations.

According to the model construction and the parameter effect, we can provide more useful information about TFT-LCD manufacturing processes to those practitioners. The choice of model's input variables can be verified depending on the model construction, and the effect priority on yield can also be obtained via the stepwise regression analysis. The information can improve the focus of the manufacturing control and the practitioners can pay more attentions to the significant processes. Besides, the know-how about the manufacturing process can also be kept via yield model construction. In the future, we can incorporate the information to construct the feasible expert systems.

# 4. Illustrative example

A TFT-LCD manufacturer's data at Tainan Science Park in Taiwan will be taken as an example to demonstrate our proposed procedure. Basically, TFT-LCD manufacturing processes can be mainly divided into three parts (in Figure 1) and they can be described as follows:

## 4.1 TFT-LCD manufacturing processes introduction

### 4.1.1 **Array assembly process (Array)**:

It will grow thin films on glass substrates and produce thin film transistors (TFT). The Array manufacturing processes are similar with the one frequently seen in semiconductor processes.

### 4.1.2 **Cell assembly process (Cell)**:

The matching process for the Array completed TFT plate with color filter (CF) will be made in this process. After assembly of the TFT plate and color filter, inject liquid crystal and seal the assembly. Attach polarizer with the assembly.

4.1.3 **Module assembly process (Module):**

This process will attach additional polarizer and insert driving IC joints. Then, it will complete assembly of glass plate with back light unit and Cell completed plate.

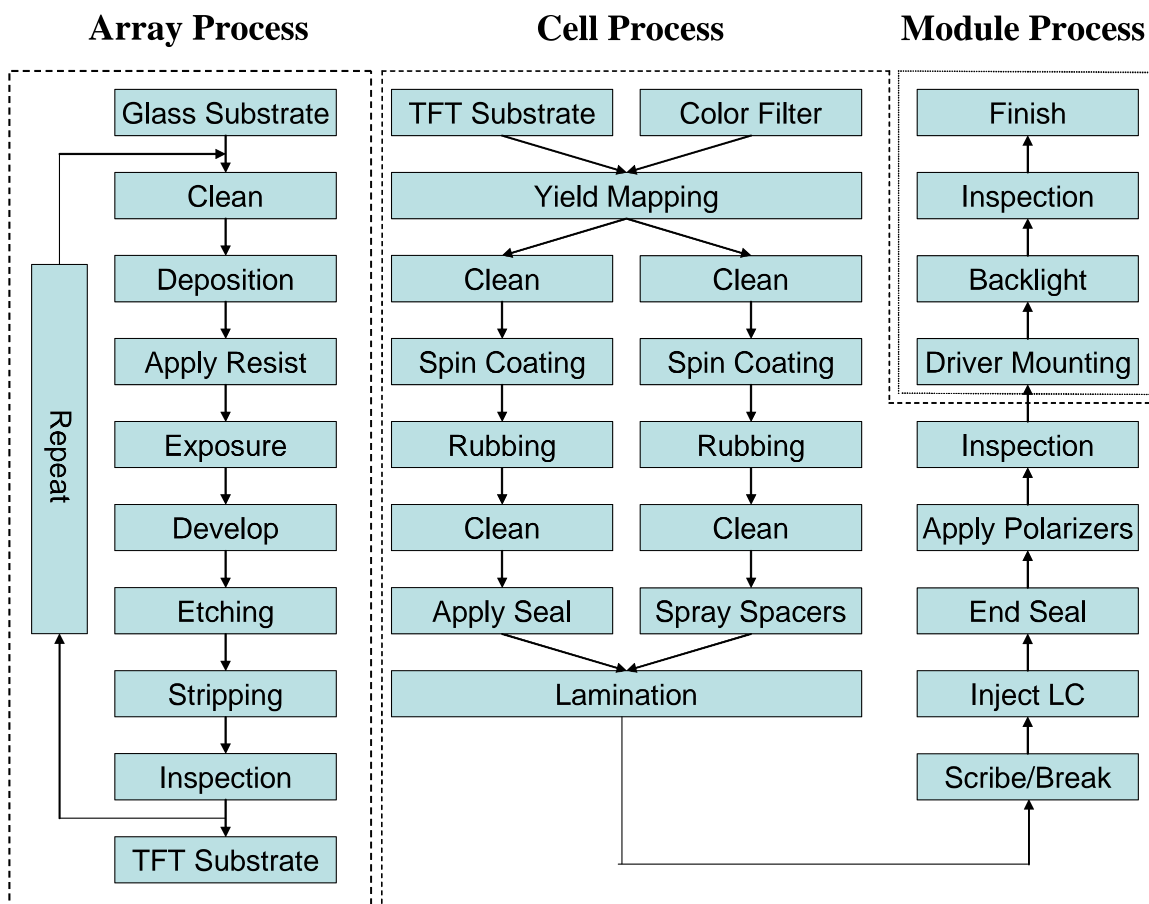


Figure 1. TFT-LCD manufacturing processes.

The TFT-LCD structural as figure 2.

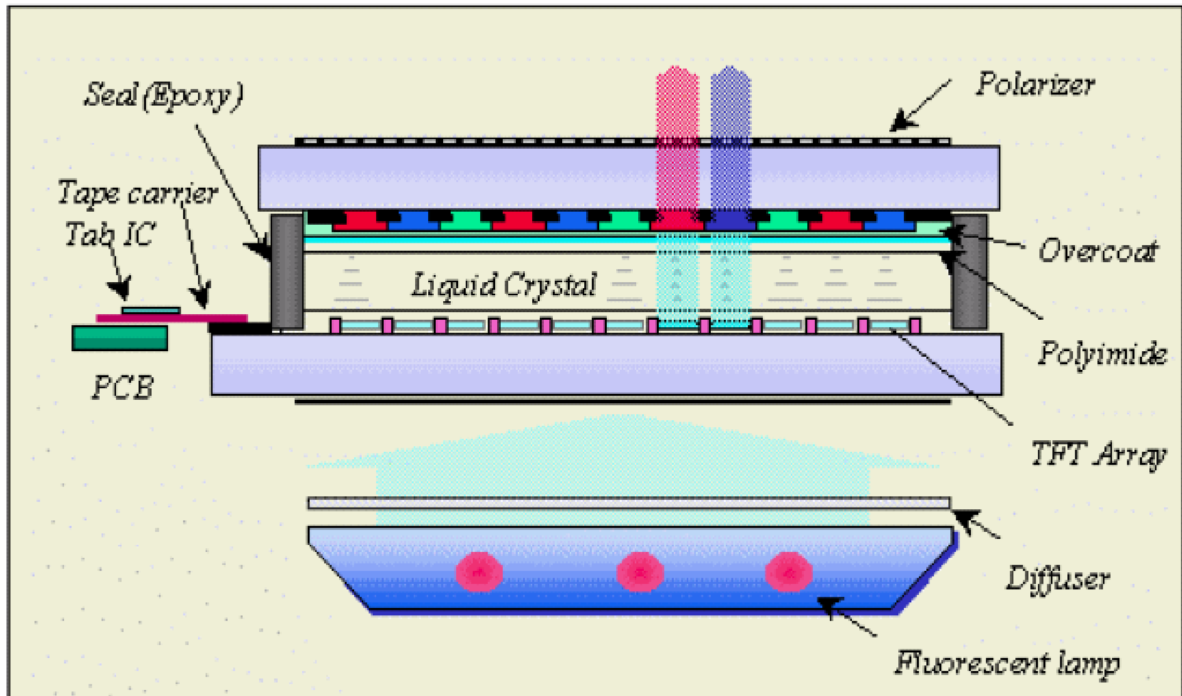


Figure 2. TFT-LCD structural .

The case of data are collected from AOI (Automatic Optical Inspection) inspection and array electrical measurement of Array manufacturing which section is the most complex and precise during TFT-LCD manufacturing process. Hence, we will focus on such case. There are nine steps in Array manufacturing. Introduction of each process and applied chemical materials as follows:

## 4.2 TFT-LCD array manufacturing process introduction

**Glass substrate:** Purchased glass substrates are processing through Array manufacturing after unpacking and preliminary cleaning by deionizer water and sanitizer (detergent).

**Cleaning:** Glass substrate needs to process through detailed cleaning procedure to expel impure materials remain from previous process.

**Thin film:** Utilize high energy electrons from electric plasma to provide collision with gas molecule. Produce solid state deposition on the heated surface of the glass substrate by chemical reaction.

**Photo-resist coating:** Evenly coat the glass substrate with photo-resist materials by rotating the substrate.

**Exposure:** Expose the glass substrate with Stepper. Use ultraviolet ray to duplicate pattern from the mask to the photo-resist substrate.

**Development:** Remove the exposed photo resist with developed liquid.

**Etching:** Remove portion that is not covered or protected by photo resist with physical or chemical reaction. There are dry etch and wet etch.

**Resist remove:** Remove photo resist with photo resist removal

liquid.

**Test**: Inspect post etch pattern. Do thin film electrical measurement and TFT characteristic measurement.

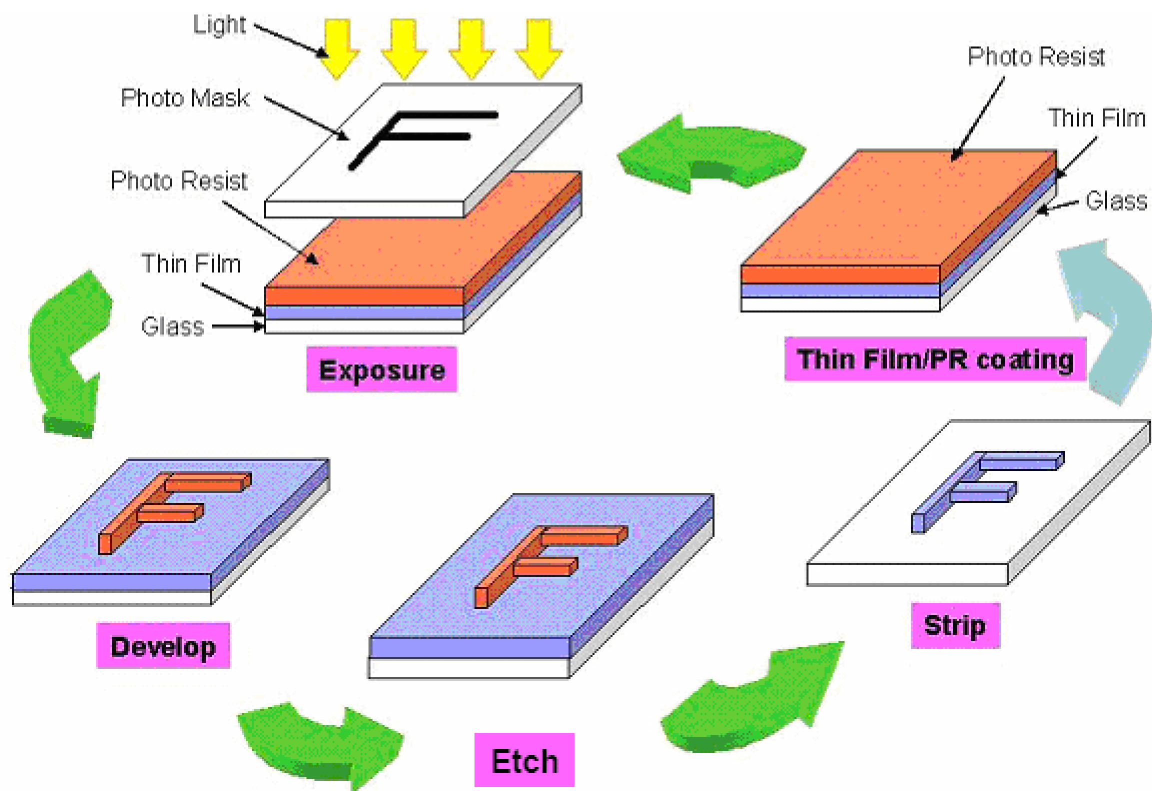


Figure 3. TFT-LCD Array manufacturing processes.

## 4.2 Yield model verification

Due to the real requirement, it will need to repeat (5) or (7) times (layers) of the above steps in the manufacturing of TFT. In this study, totally one hundred and fifty data will be collected from the historical records. Each data will include several input parameters obtained from the processes for a glass, i.e. the defect count for AOI inspect in Gate layer (denoted as defect 1), the defect count for the in line repair and defect judge-1 (denoted as defect 2), the defect count of AOI inspect in IN layer (denoted as defect 3), the defect count of AOI inspect in M2 layer (denoted as defect 4), the defect count for the in line repair and defect judge-2 (denoted as defect 5), the defect count of AOI inspect in ITO layer (denoted as defect 6), the defect count of electronic testing for Array (denoted as defect 7), the defect count of array repair (denoted as defect 8) and the output parameter (the yield value of each glass). The reason for that those parameters will be chosen due to the previous experience for the issue having effect on the yield. From the collected data, we can obtain the correlation values for each parameters and the yield in Table 1. From Table 1, we can find out that the correlation values for each parameter and the yield are negative, and it will denote the rationality.

|  | yield | defect1 | defect3 | defect3 | defect4 | defect5 | defect6 | defect7 | defect8 |
|---|---|---|---|---|---|---|---|---|---|
| yield | 1 |  |  |  |  |  |  |  |  |
| defect1 | -0.16002 | 1 |  |  |  |  |  |  |  |
| defect3 | -0.21016 | 0.99995 | 1 |  |  |  |  |  |  |
| defect3 | -0.16925 | -0.06718 | -0.06719 | 1 |  |  |  |  |  |
| defect4 | -0.07841 | -0.00561 | -0.00514 | 0.15204 | 1 |  |  |  |  |
| defect5 | -0.10966 | 0.00945 | 0.00979 | 0.22056 | 0.77626 | 1 |  |  |  |
| defect6 | -0.31132 | 0.04746 | 0.04766 | 0.40938 | 0.13356 | 0.20959 | 1 |  |  |
| defect7 | -0.16623 | -0.07019 | -0.06967 | 0.21274 | 0.14748 | 0.24711 | 0.242 | 1 |  |
| defect8 | -0.19454 | -0.04759 | -0.04706 | 0.20168 | 0.14493 | 0.24677 | 0.24176 | 0.98291 | 1 |

Table 1. The correlation value for the yield and each parameter.

Besides, the yield of a glass will be computed as (the number of good panels on a glass/the number of panels on a glass). Firstly, we must divide those data into two parts: the training dataset and the testing dataset. Herein, we will take about fifteen data to be the testing dataset and the remainder part will be taken as the training dataset according to Hsieh (2006), Hsieh and Tong (2001). Next, we can perform the model construction and parameter effect. To simplify the operation of modeling, we will take a software (the Neural Professional Plus II) will be chosen herein. Among those models of ANNs, BPNN will be chosen to model the relationship of this problem. The numbers of input parameter and output parameter are 8 and 1 and the number of PES (Process elements) for the input and output layer of BPNN will be determined as 8 and 1. Then, we will apply the try-and-error technique to determine the optimum number of PEs for the hidden layer of BPNN. According to the recommendation (Hsieh, 2006; Neural Professional Plus II, 1990), the

average number of the input's PEs and output's PEs will be set as the initial state, i.e. the number of PEs for the hidden layer equals to 5. Then, the BPNN model will be used to construct the modeling relationship according to the BPNN's architecture as 8-5-1. Besides, several parameters about the software will also need to set, e.g. the learning rate, the momentum, the learning epoch, the transfer function and so on. After reviewing several basic architectures, we decide to set learning rate as 0.2, momentum as 0.8, the learning epoch as 50000 with a hyper tangent transfer function. Restated, we can make the necessary comparison for the different architectures according to the training/testing RMSE values when the training epoch being arrived. Table 2 will list the results of training/testing RMSE for several architectures. From Table 2, we can find out that the RMSE values of Training will gradually decrease with along the PEs number of hidden layer increasing. However, the RMSE values of testing will be initially decrease and then increase when the PEs number of exceeding 12. Hence, the optimum yield model will be determined as BPNN with 8-10-1 architectures. Figure 4 will depict graphically the yield model based on BPNN model.

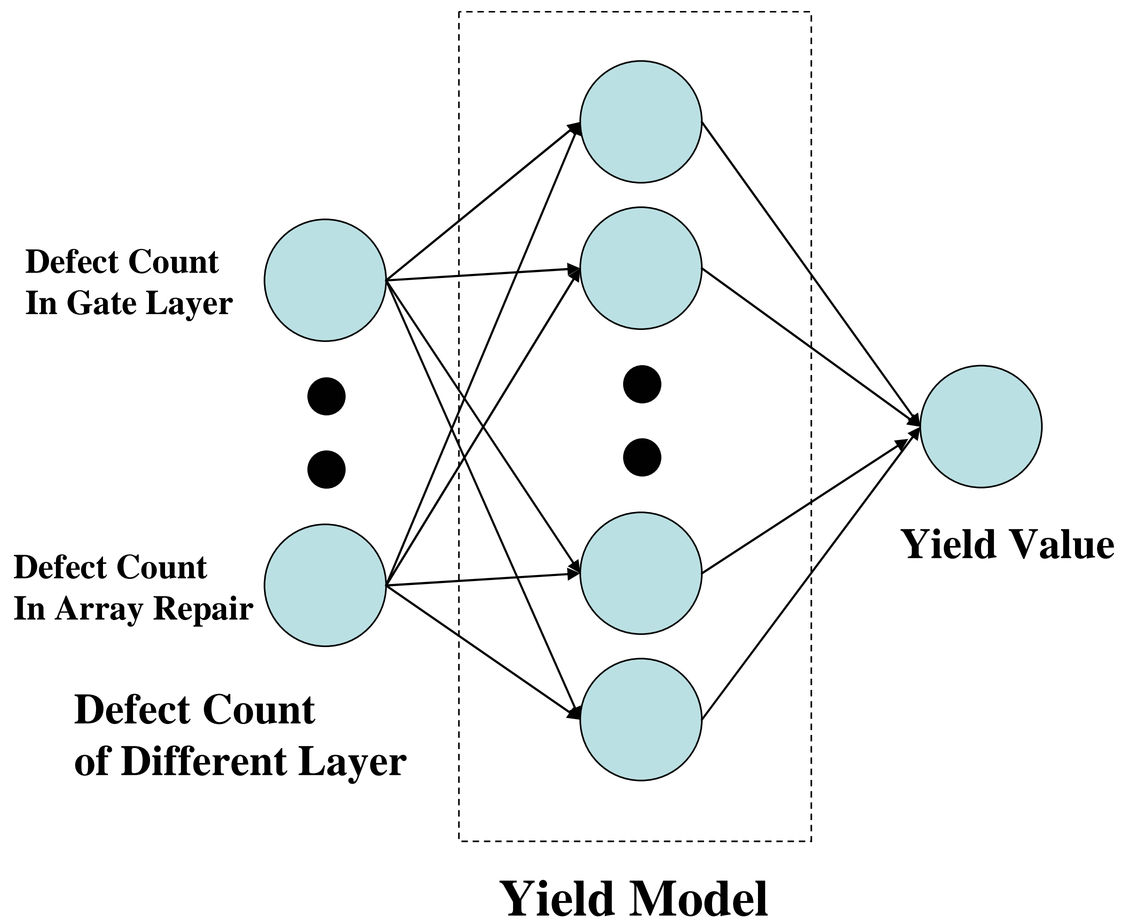


Figure 4. The diagram for yield model based on BPNN model.

| Architectures | Training RMSE | Testing RMSE | Decision-making |
|---|---|---|---|
| 8-2-1 | 0.2486 | 0.3482 | |
| 8-5-1 | 0.1938 | 0.2109 | |
| 8-8-1 | 0.1456 | 0.1544 | |
| 8-10-1 | 0.1128 | 0.1286 | * |
| 8-13-1 | 0.0956 | 0.1372 | |
| 8-16-1 | 0.0914 | 0.1396 | |

Table 2. The comparison table for the different structures of BPNN.

From Figure 5, we can find out that the actual yield will be significant close to the predicted yield depending on the line diagram. Due to verify it, we also apply the correlation analysis to computing the correlation coefficient $r$ to be as 0.8618. It will represent to have a larger similarity degree between actual and predicted yield. It obviously demonstrated the effectiveness of the model construction. Next, we will combine the initial training data and testing data into a whole training data. Those data will be applied to retraining the chosen optimum yield model to achieve a stable state. Herein, we use a simple condition to performing such retraining, i.e. we set the training epoch as 50000.

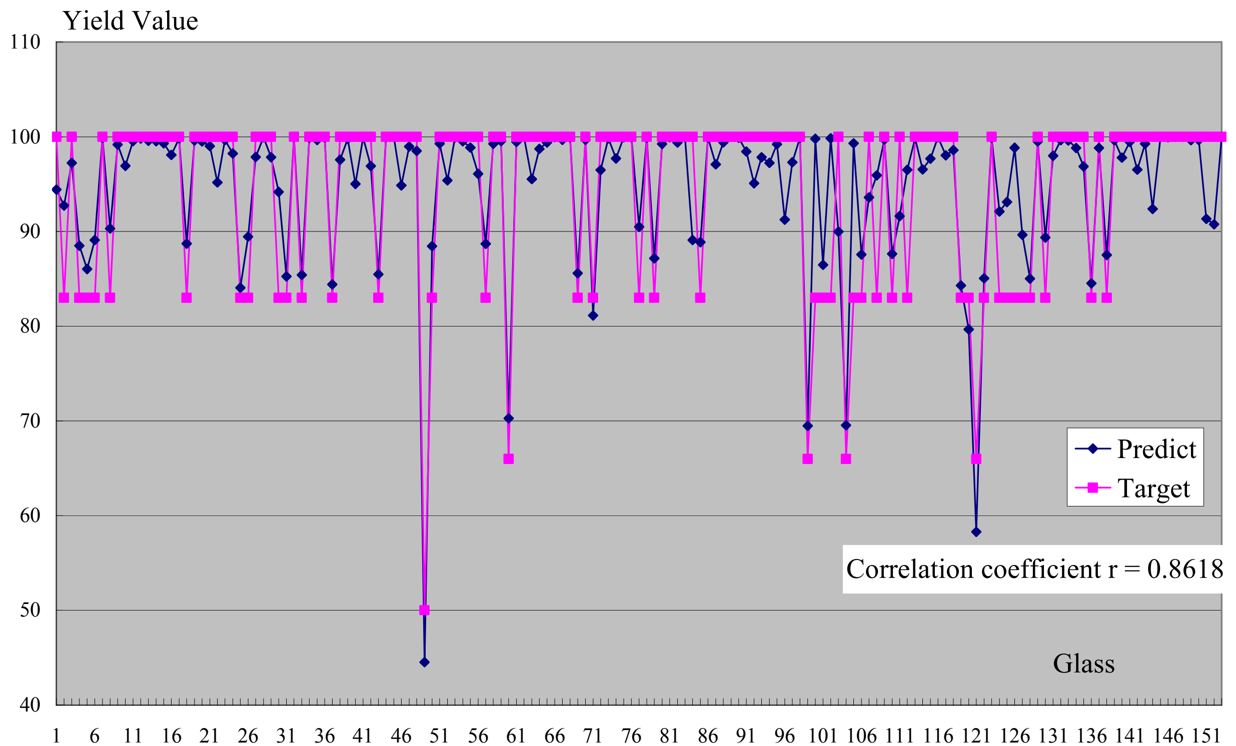


Figure 5. The comparison diagram for the actual and the predicted yield value.

Then, we will screen out the effect priority on yield for those input parameters, i.e. the defect count for different layer. The statistical software (SPSS 12.0) will be applied to simplify the analysis operation. The stepwise model-building technique, the forward stepwise technique, is then taken to study such issue. After performing the stepwise model-building procedure, we can find out that the priority of effect for all input parameters on yield will be listed as (<u>the defect count of AOI inspect in ITO layer→the defect count for AOI inspect in Gate layer→the</u>

defect count for the in line repair and defect judge-1→the defect count for the in line repair and defect judge-2→the defect count of AOI inspect in M2 layer→the defect count of AOI inspect in IN layer→the defect count of array testing→the defect count of array repair and defect judge). The $R^2$ of such linear model is about 0.3988 and it can be explained as almost 40% of variation can be explained well by using this linear model. Herein, we can find out that the AOI inspect in ITO layer will be the critical layer with the significant effect on the yield of glass. From the engineering judgment, it will denote that the practitioners or engineers must perform the necessary detailed analysis, e.g. the clustering effect for those defects on a glass or material analysis, to this critical layer. Restated, the practitioners must pay more attention to such critical layer. The yield will be improved when the critical being managed or controlled from the viewpoint of 80/20 rule.

# 5. Concluding remarks and recommendations

After applying a real example to demonstrate the proposed procedure, we find out that the yield analysis will make the practitioners to understand their domain knowledge or manufacturing core. The advantage of the proposed procedure can be summarized as:

(1) The yield model can be constructed based on the real manufacturing consideration without any mathematical equation or computation. Such non-formula model will rapidly provide the related information to the engineers. Subsequently, the engineers can make more detailed analysis via referring to it.

(2) The yield model can be viewed as an adjustable structure and the practitioners can determine the input variables according to their manufacturing process. Then, the yield model can be constructed by taking the historical manufacturing data.

(3) The effect priority for all input parameters on the response variable can be obtained. Restated, the critical layer can be mined via the proposed approach. After the critical layers being obtained, the practitioners can make the decision about the resource's investment or distribution.

These three remarks will point the rationality and feasibility of the proposed approach. However, in the future, how to make more detailed analysis to those critical layers will be worthy issue to be studied. Besides, how to incorporate the yield model for the different TFT-LCD products into an integrated system will be also discussed in the future.

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