Cycle Time Forecasting Models for Defect Inspection Process in TFT-LCD Module Assembly

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***Abstract*—Because most of the procedures in defect inspection process of TFT-LCD module assembly are examined manually through human vision, cycle time estimation for this particular process is complicated and usually deviated from actual observations considerably in practice. Hence, this study would like to apply the approaches of Bayesian network, linear discriminant analysis, and logistic regression to develop reliable prediction models for defect inspection cycle time. Potential explanatory variables like work-in-process, throughput, yield, and number of product mixes are considered for model construction. Applicability of these approaches is validated through an empirical study of TFT-LCD factory. From the perspective of prediction accuracy and flexibility, findings of this study suggest that logistic regression is a better choice for cycle time estimation than Bayesian network and discriminant analysis.**

***Index Terms*—Cycle time prediction, Bayesian networks, Discriminant analysis, Logistic regression**

I. Introduction

Reliable cycle time estimation is critical for manufacturers to schedule production and to respond to customer's inquiry about order delivery. However, the task of forecasting is challenging due to the complexities of production processes. For example in the TFT-LCD (Thin Film Transistor Liquid Crystal Display) industry, manufacturing of TFT-LCD panel has to go through three main processes: array, cell, and module assembly. In the array process, transistors are fabricated on a glass substrate and then pass to the cell process for joining front and back substrates with liquid crystal. At last, panel undergoes core procedures including chip on glass, printed circuit board (PCB), PCB inspection, silicon dispenser, assembly, and defect inspection during the module assembly process to complete the final product [7]. Usually the accuracy of cycle time is no problem for the processes of array and cell because these processes are mostly operated by machines and their cycle time information can be retrieved from manufacturing execution system directly. But the cycle time estimation for module assembly process could be troubled because its defect inspection procedure has to be visually examined by operators and therefore its cycle time information is not available from information systems. With the assistance of instruments, staffs need to use their eyes to check the appearance specifications, electrical specifications, and exterior specifications of TFT-LCD panels listed in Table 1 [6]. All of the appearance specifications (active area, bezel, connector, flexible print circuit board, label, solder, screw, and white sheet) and exterior specifications (dimensions, weight, display tolerance, and panel gap for exterior specifications) are required to be controlled by visual inspection. Even during the electrical examination, operators still have to visually detect panel flaws such as bright dots, dark dots, adjacent dots, or display non-uniformity (mura) by comparing the images produced from pattern generator, video board, or luminance colorimeter with the limited samples provided by customers [13]. Although research has developed several methods to test panel defects through machines automatically without manual operations [13][15][18][25], most of defect inspections are manually operated in practice to ensure product quality. Consequently, estimation of defect inspection cycle time in module assembly process is typically evaluated by experienced staff who is responsible for the corresponding processes. This kind of guess work is easily deviated from actual observations and thus affects on-time delivery rate. Hence, how to develop a suitable cycle time prediction model for this particular process has been an important issue in TFT-LCD industry.

Table 1: Checklist of Defect Inspection Station

Inspection	*Specification*
Appearance	Active area, Bezel, Connector, Flexible print circuit board, Label, Solder, Screw, White sheet
Electrical	Adjacent dot defect, Bright dots, Dark dots, Display non-uniformity or Mura, Total dots defect
Exterior	Display tolerance, Outside dimension (vertical), Outside dimension (horizontal), Outside dimension (thickness), Panel gap, Weight

Source: Chen [6]

The objective of this study is to apply Bayesian network (BN), discriminant analysis (DA), and logistic regression (LR) to construct forecasting models for defect inspection cycle time in TFT-LCD module assembly process. Here in this study, the defect inspection cycle time is a categorical

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variable because TFT-LCD manufacturers usually report this information in a 6-hour block. Comparisons of prediction results are also discussed to find out which approach can best explain this manually operated process. In fact, approach of BN, DA, or LR has its own advantages in forecasting analysis. The strength of Bayesian network approach is its learning capability of model structure and parameters through accumulating data. Besides, BN is able to handle incomplete data or different data types by Bayesian methodology. Meanwhile, discriminant analysis is a mathematical technique that does not involve with any kind of bias. For prediction purpose of DA, linear discriminant functions are derived first from initial data set with known groups and then are used to determine group membership for new observations. On the other hand, (ordinal) logistic regression is a class of regression models including cumulative logit model, proportional odds model, continuation ratio model, etc. Unlike other logit models that need to alter ordinal variables into dichotomization of ordered responses, ordinal LR can perform logistic regression on an ordinal response variable without further transformations. Because there is lack of research addressing BN, DA, and LR simultaneously for cycle time prediction of defect inspection process, this paper would like to investigate the applicability of these approaches in TFT-LCD industry. One major difference between this study and other simulation research is that all of our models are based on the data collected from manufacturing execution system without making any further parameter assumptions. Hence in the next section, the potential explanatory variables of defect inspection cycle time are explored first. Methodology of BN, DA, and LR for this study is then discussed in section III. To evaluate the practicability of our proposed approaches, a TFT-LCD panel factory was selected as our case study. Results of prediction analyses from this sample factory are later analyzed in section IV. Finally, conclusions about the applicability of BN, DA, and LR for defect inspection cycle time in TFT-LCD industry are discussed.

II. Explanatory Variables of Cycle Time

Because there are not many literatures addressing the issue of defect inspection cycle time, this study tried to survey the potential predictors of defect inspection cycle time through investigating the factors that affect production processes in the electronics industry. The relationships among cycle time, work-in-process (WIP), and throughput was first documented in 1961 by John Little. According to Little's Law, the ratio of WIP to cycle time equals throughput at a given WIP level. Buzacott [3] also indicated that WIP and cycle time are convex increasing functions of throughput. Srivarsan and Kempf [22] stated a useful approach for throughput time modeling in a semiconductor wafer fabrication factory, where throughput time of a process is defined as the sum of the step throughput times over all the steps that constitute that process. Predictors such as process time, transport time, variable availability of resource, machine and operator dedications, non-product lots, batching and setups, WIP management policies, lots on hold and rework lots were used to estimate factory throughput time. To compute the expected lot cycle time, Zargar [26] constructed an equation that is composed of machine setup time, number of wafers in a lot, process time, rework time, and probability that a wafer fails as the potential factors. Lee et al. [17] introduced a planning model with the consideration of cycle time and production capacity in semiconductor wafer fabrication. The objective of this linear programming model is to satisfy the given demand while maintaining proper level of WIP inventory. Under the capacitated loading procedure, their model has to find the behaviors of cycle time and the level of WIP, which satisfies the due dates of the demand under the capacity constraints. Results suggested that capacity, WIP, and cycle time were highly correlated in the planning of wafer production. Raddon and Grigsby [20] developed a forecasting model for throughput time, where throughput time is defined as the cumulative time for completion of a work cycle including wait time and processing time. According to their model analysis, utilization over availability, theoretical throughput time, number of tools, and number of steps in line were considered as possible predictors of throughput time.

Additionally, recent study from Chen, George, and Tardif [5] introduced a two-segment piecewise linear function with explanatory variable WIP to predict cycle time. In addition, a data driven discrete event simulation model was discussed by Sivakumar and Chong [21]. This model is used to control input variables for cycle time reduction in semiconductor backend manufacturing system, where variables include maintenance schedules, yield, rework, units per hour, batch process time, down time, shift pattern, set-up time matrix and product mix variety. Meanwhile, a cycle time estimation model for design stage, resource planning stage, and manufacturing stage of printed circuit board was developed by Haberle and Graves [8]. According to their findings, possible factors affecting the design phase cycle time include redesign, in-circuit test, and board type. In the stage of resource planning, board type, number of signal layers, and part lead form are the potential drivers of cycle time estimation. To access the cycle time of manufacturing stage, board function and number of layers were used as the predictor variables. Moreover, Hung and Chang [10] found out that the hours of a small time period, number of machine in work station, the total workload arrival to work station, the queue amount of work station, the capacity of work station, and the loading rate of work station are highly correlated to the flow time prediction. Haller, Peikert, and Thoma [9] presented a methodology to manage cycle time by closely monitoring and limiting the WIP. Findings suggested that yield, product qualification, and equipment qualification could be directly influenced by cycle time. Beeg [2] described a successfully implemented method to predict future wafer fab cycle time under different job loading situations. In his study, variables such as equipment uptime, equipment utilization, number of process steps running in the work center, process speed, theoretical fastest cycle time per step, current cycle time per step, number of tools, and number of processed wafers were applied for cycle time estimation. Finally, Backus et al. [1] mentioned that factors like WIP at specific operations, lot priority, and product type can be used to build up a predictive model for cycle time in semiconductor manufacturing. From the above literature review, possible drivers of cycle time estimation in different situations of electronics manufacturing processes are summarized. These variables were referred as the potential explanatory variables of defect inspection cycle time for the BN, DA, and LR models used in this study.

III. Prediction Models

Before explaining the details of prediction models applied in this paper, selection of predictor variables is discussed first. Due to the manually operated nature of defect inspection in TFT-LCD panel manufacturing, cycle times of individual inspection procedures are generally short and operator-dependent. The checklist shown in Table 1 also indicates data complexity and unavailability in defect inspection station. To resolve this situation, variable selections started with the consideration for those data that can be retrieved from manufacturing execution systems. Because the production stations before defect inspection are mostly conducted by machines, their data can be collected from systems and thus their corresponding variables became the candidates of cycle time predictors. In addition, if we assumed that there are no significant differences among the outputs of operators in defect inspection station, the characteristics of products like volume and complexity before entering the defect inspection station may affect the performance of inspection. As a result, variables like WIP (W), throughput (T), yield (Y), and number of product mixes (P) are considered as the predictors of defect inspection cycle time (CT) according to the literature review in previous section and the on-site interviews with the experienced staffs of TFT-LCD factories. Here, weekly data was collected in order to be consistent with the interval of scheduling and planning in TFT-LCD plants. Based on the selected predictors, methodology of Bayesian network, discriminant analysis, and logistic regression was used to develop prediction models of defect inspection cycle time. Test observations were also collected to examine predictive accuracy. Brief introduction of these approaches are described as follows.

A. *Bayesian Network*

A Bayesian network is a form of probabilistic graphical model that has many advantages that other techniques do not have. For example, the uncertain graphical representation of BN model can be validated through observed knowledge. Even if the prior beliefs regarding conditional probabilities are unreliable, their information can be updated through the collection of new data. As some of the cycle time estimation methods may need detailed information or assumptions on corresponding procedures and parameters, BN approach on the other hand can handle these problems through parameter learning or structural learning from accumulating data. Because we do not have strong prior knowledge regarding model structure or conditional probabilities, approach of Bayesian network may demonstrate its strength under the situations of this study.

To construct a BN model for prediction, qualitative and quantitative configurations have to be specified first. At the qualitative stage of BN construction, we have to outline a directed acyclic graph with nodes and directed arcs, where nodes denote variables of interests and directed arcs between nodes imply conditional dependences among variables. Although variable in BN can be continuous, this study only considers the discrete variables. Because WIP, throughput, yield and product mixes are the explanatory variables in this study, direct arcs are drawn from these predictor nodes to the node of cycle time in the qualitative graph of BN model as shown in Figure 1, where symbol W, T, Y, P, and CT denote WIP, throughput, yield, number of product mixes, and cycle time respectively. Even if these conditional relationships are assumed, structural learning of BN can be adopted for further refinements of graphical representation. Here in this study, algorithm of necessary path condition [23] was applied to perform the updating mechanism of qualitative specification. Further removal or addition of directed arcs may happen through the processes of structural learning.

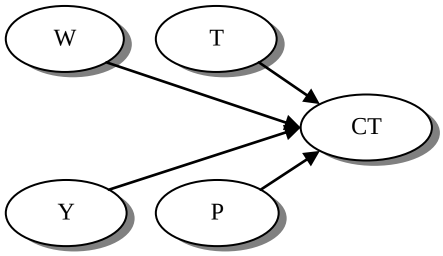

Figure 1: Prior BN Model for Cycle Time Estimation

At the quantitative level of Bayesian network construction, conditional probability distributions are used to encode beliefs among variables or uncertain events of variables. Since there is no prior knowledge regarding the characteristics of conditional probabilities, this study applied expectation-maximization algorithm [16] to approximate the conditional probability distributions based on the collected observations. This approximation approach can avoid the bias of subjective judgment. After completing the qualitative and quantitative configurations of Bayesian network model, this study utilized the probability updating algorithm from Jensen, Lauritzen, and Olesen [12] to make inferences. In the following discussion of Bayesian network application, the conditional probabilities of explanatory variables given the evidences of cycle time and the conditional mean of cycle time given the evidences of explanatory variables were analyzed to understand the behavior of defect inspection cycle time. Additionally, the final updated BN model can be also used to make predictions through computing the posterior probabilities of cycle time given the evidence of explanatory variables. Staff can report the prediction results of defect inspection cycle time through either the perspective of posterior probability distribution or the viewpoint of posterior expected value.

B. *Discriminant Analysis*

Discriminant analysis is a classic statistical method that can be used to assign observations into mutually exclusive and exhaustive groups based on a set of measurable attributes. DA technique is appropriate when dependent variable is categorical. Although there are different methods to conduct DA, this study adopted the approach of linear discriminant analysis to distinguish between three or more groups. In order to perform such analysis, this research assumed that groups can be separated by a linear combination of explanatory variables and all groups have the same covariance matrix. According to the objectives of this study, cycle time of defect inspection is defined as the group variable. Besides, explanatory variables include WIP, throughput, yield and product mixes. Because defect inspection cycle time is a categorical variable, discriminant analysis is suitable for this study.

The procedures of DA can be demonstrated from the simplest form with two-group only. A standardized linear discriminant function D defined in (1) has to be calculated first to distinguish between two groups:

$$D = \sum_{j=1}^{p} r_j z_j \ , \qquad (1)$$

where subscript j denotes the j-th predictor variable, p is the number of predictor variables, r_j is the standardized regression coefficient, and z_i is the standardized explanatory variables. The assignment of an observation in DA depends on whether its D score is larger than 0 or not. Although we can apply D to assign objects into groups, classification functions S_i defined in (2) are often considered for situation with three or more groups:

$$S_i = c_i + \sum_{j=1}^{p} w_{ij} x_j \ , \qquad (2)$$

where subscript i denotes the i-th group, c_i is a constant term for the i-th group; x_j is the observed value of the j-th variable for the respective case, and w_{ij} is the discriminant weight of the j-th variable for the i-th group. Detailed derivations of w_{ij} and c_i can be referred by [24]. Each case belongs to the group for which it has the highest classification score. In addition, we can also have the posterior probability of an observation belonging to each class by computing the corresponding Mahalanobis distances. The posterior probability that a case belongs to a certain class is basically proportional to the Mahalanobis distance from that group centroid. This study would examine how well the current classification functions predict group category of observations through the classification matrix, where the numbers of correctly classified cases and misclassified cases are reported. Based on the above information, this study finally predicts the group membership of test observations by evaluating their corresponding posterior probabilities.

C. Logistic Regression

Like discriminant analysis, logistic regression is a useful classification tool for analyzing data that includes categorical response variables. Logistic regression is somehow more preferable than discriminant analysis because it is less affected by the basic regression assumptions like multivariate normality and equal variance-covariance matrices across groups. As the response variable of this study could have more than 2 groups, proportional odds model [19] was applied to make classification. This approach assumes that the effect of predictors has to be constant across all possible cut-offs for the ordered responses. Suppose that we have I groups and that $\pi_i(\mathbf{x})$ denote response probabilities at value for a set of predictor variables $\mathbf{x}$, where $i = 1, 2, \ldots, I$-1. We also define the cumulative probabilities $F_i(\mathbf{x})$ as

$$F_i(\mathbf{x}) = P(Y \le i \mid \mathbf{x}) \ , \qquad (3)$$

where Y is the response variable. Then the cumulative logit function logit($F_i(\mathbf{x})$) and proportional odds model $L_i(\mathbf{x})$ can be formed as follows:

$$\mathrm{logit}(F_i(\mathbf{x})) = \log\left(\frac{F_i(\mathbf{x})}{1 - F_i(\mathbf{x})}\right), \qquad (4)$$

$$L_i(\mathbf{x}) = \alpha_i + \boldsymbol{\beta}_i' \mathbf{x} = \mathrm{logit}(F_i(\mathbf{x})) \ , \qquad (5)$$

where α_i is the intercept and $\boldsymbol{\beta}_i$ is the vector of regression coefficients that is approximated by maximum likelihood approach. Deviance and Pearson goodness-of-fit statistics are also calculated to test model fitness. If the p-values of the above tests are larger than the significance level, the proportional odds model can be used to classify test observations. McCullagh [19] has detailed discussion about the proportional odds model.

IV. Empirical Analysis

In this section, the application of Bayesian network, discriminant analysis, and logistic regression is illustrated by using each method to construct cycle time prediction models for the defect inspection process in a TFT-LCD panel manufacturing plant. According to the methodology described in section III, a total of 91 weekly data regarding cycle time, WIP, throughput, yield, and number of product mixes was retrieved from the manufacturing execution systems of sample factory. The final 13 observations (one season's data) were used as the test sample to compare the prediction accuracy of respective model. Response variable (defect inspection cycle time) is classified into 4 groups: (1) less than 6 hours, (2) between 6 hours and 12 hours, (3) between 12 hours and 18 hours, and (4) more than 18 hours. This categorization is consistent with the on-site requirements of cycle time reporting. Although the other predictor variables are metric data, approach of discrete BN model has to transform these predictors into categorical variables. Based on the specification defined by plant engineers, each explanatory variable is further categorized in to 4 conditions: (1) low, (2) medium-low, (3) medium-high, and (4) high. On the other hand, analysis of discriminant analysis and logistic regression still uses the metric data of predictor variables without transformations. After discussing the prediction model for each approach, comparisons among these models are also analyzed for model recommendation of defect inspection cycle time.

A. Bayesian Network

One of the advantages from BN approach is its capability to learn model structure or parameters even if we have no prior knowledge regarding our problem. Hence, algorithm of necessary path condition was applied to learn graphical model of BN. Result of structural learning is depicted in Figure 2, where all of original arcs are still remained in the updated model except an addition directed arc from "Product Mix" to "Yield". This not only implies that our initial dependent assumptions regarding cycle time and predictor variables are consistent with actual observations, but also indicates that there is a conditional dependent relationship existing between

"Product Mix" and "Yield" from observed data. This slightly adjusted graphical model is later used for statistical inference and cycle time prediction.

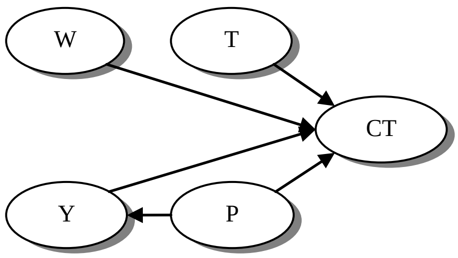

Figure 2: Posterior BN Model

In addition to the structural learning of BN model, expectation-maximization algorithm was also applied to perform parameter learning for updating prior conditional probabilities. Posterior probabilities of *P*(Cycle Time | WIP, Throughput, Yield, Product Mix), *P*(Yield | Product Mix), *P*(WIP), *P*(Product Mix), and *P*(Throughput) were calculated after parameter learning. Their posterior marginal probability distributions are shown in Table 2, where cells in table demonstrate the results of probabilities *P*(Variable = *i* | Observed Data), where *i* = 1, 2, 3, 4 for the response variable and *i* = "Low", "Medium-Low", "Medium-High", and "High" for the predictor variables. Here we can see that the posterior marginal probabilities of cycle time = 1, 2, 3, 4 given observed data are 0.34, 0.37, 0.16 and 0.13 respectively. It means that around 70% of defect inspection cycle time is less than 12 hours in this TFT-LCD factory. Meanwhile, more than 50% of the WIP happened in the condition of "Medium-Low", which is significantly higher than the other conditions of WIP. For the explanatory variables of Throughput and Yield, around 70% of the conditions occur in "Medium-Low" or "Medium-High". On the other hand, the posterior probabilities of Product Mix = "Low", "Medium-Low", "Medium-High", and "High" are 0.20, 0.35, 0.23, and 0.22 respectively. It indicates that the distribution of Product Mix is spread out more evenly than the ones of other predictors. These posterior marginal probabilities can help us understand the likely distributions of variables from the view point of Bayesian approach.

Table 2: Posterior Marginal Probability Distributions

	1	2	3	4
Cycle Time	0.34	0.37	0.16	0.13
	Low	Medium-Low	Medium-High	High
WIP	0.22	0.54	0.15	0.09
Throughput	0.19	0.37	0.32	0.12
Yield	0.14	0.33	0.40	0.13
Product Mix	0.20	0.35	0.23	0.22

Based on the results of structural learning and parameter learning, conditional probabilities given evidence can be used to make statistical inference in BN model. Here we start with the examination of expected cycle time given the evidence of observed individual predictor variable. To compute the probability given evidence, updating algorithm from Jensen, Lauritzen, and Olesen [12] was adopted to perform this task. Table 3 summarizes the computation result of cycle time expectation E[CT | Evidence, Ψ], where evidence is the observed individual predictor variable and Ψ denotes the updated BN model after structural learning and parameter learning. Let us use the situation of WIP as example to examine the behavior of cycle time. When we observed evidence of WIP = "Low", its corresponding expected cycle time is 2.13. Meanwhile, expected cycle time reaches its highest value 2.58 when WIP is observed as "High". It implies that staff of defect inspection station may report expected cycle time somewhere near the upper bound of 12 hours when they observed evidence of WIP = "High". Moreover, all of the expected cycle times shown in Table 3 are around category "2". It suggests that the expectation of cycle time is more likely less than 12 hours but higher than 6 hours given any evidence from the individual predictor variable. Information of Table 3 can provide the staff of defect inspection station with helpful reference if they have limited available data but have to report cycle time estimation for customers instantly. Although this study just demonstrates the situation with only one observed predictor, people can compute the expected cycle time given the evidence of more than one predictor variable for further insight.

Table 3: Expected Cycle Time Given Evidence

Evidence		WIP	Through-put	Yield	Product Mix
Low	μ	2.13	2.33	2.26	1.96
	σ	1.11	1.02	1.07	1.05
Medium-Low	μ	1.86	2.01	1.90	2.04
	σ	0.86	0.94	1.01	1.00
Medium-High	μ	2.44	1.92	2.09	2.19
	σ	1.02	0.98	0.91	0.91
High	μ	2.58	2.28	2.28	2.12
	σ	1.07	1.07	1.08	1.02

μ: mean, σ: standard deviation

Next, the posterior probability of predictor variable given the evidence of cycle time, *P*(Predictor | CT, Ψ), can be also used to analyze cycle time behavior from Bayesian perspective. Summary of this inference is shown in Table 4. For the situation of WIP, posterior probabilities of WIP = "Low", "Medium-Low", "Medium-High", and "High" are 0.25, 0.60, 0.09, and 0.06 respectively when the observed evidence of cycle time = 1. It means that the volume of WIP is likely in "Medium-Low" level when the observed cycle time is less than 6 hours. The above statement is still true when the evidence of cycle time is between 6 hours and 18 hours. As the observed cycle time increases, Table 4 also indicates that the standard deviation (σ) of WIP is getting higher and the probability distribution of WIP is more dispersed over the possible values of cycle time. However, we are unable to have a better understanding of cycle time performance from the expected values (μ) of WIP given the evidence of cycle time because their differences are not significant. In the mean time, the discussion for predictor Throughput is skipped here because its posterior probability distribution given evidence of cycle time has similar behavior as WIP. For the case of predictor variable Yield, its posterior probability distribution given the evidence of cycle time = '3' or '4' is slightly more centralized than the ones from WIP and Throughput. Besides, the posterior probability of Yield = 'Medium-High" is as high as 50% when the observed cycle time is between 6 to 12 hours. Finally, we can also find out that the probability distributions of Product Mix given the evidences of cycle time are more evenly distributed comparing to the results from WIP, Throughput, and Yield,. The information in Table 4 can help the staff of defect inspection station to look out the critical predictors if they wish to control their defect inspection cycle time within reasonable timeframe.

Table 4: Posterior Probability of Predictor Variable Given Evidence of Cycle Time

	CT	< 6 hrs	6 ~ 12 hrs	12 ~ 18 hrs	> 18 hrs
W	1	0.25	0.16	0.23	0.30
	2	0.60	0.64	0.35	0.29
	3	0.09	0.15	0.23	0.25
	4	0.06	0.05	0.19	0.16
	μ	1.96	2.09	2.37	2.28
	σ	0.75	0.71	1.03	1.06
T	1	0.15	0.16	0.33	0.24
	2	0.36.	0.43	0.31	0.31
	3	0.39	0.30	0.23	0.28
	4	0.10	0.11	0.13	0.17
	μ	2.44	2.37	2.17	2.39
	σ	0.85	0.88	1.03	1.03
Y	1	0.13	0.11	0.19	0.19
	2	0.44	0.28	0.26	0.30
	3	0.31	0.51	0.38	0.32
	4	0.12	0.10	0.17	0.19
	μ	2.42	2.60	2.54	2.50
	σ	0.85	0.82	0.99	1.00
P	1	0.26	0.16	0.17	0.21
	2	0.38	0.33	0.34	0.34
	3	0.15	0.29	0.27	0.21
	4	0.21	0.22	0.22	0.24
	μ	2.31	2.56	2.54	2.48
	σ	1.08	1.00	1.01	1.08

The above discussion used different angles such as expected cycle time given evidence and posterior probability of predictor variable given evidence of cycle time to examine the applicability of BN approach. Because the model after structural learning and parameter learning is mainly used to make inference, summary of classification accuracy for initial data is not addressed here. Prediction quality of BN model will be discussed later with other approach through a test sample.

B. *Discriminant Analysis*

As described in section III, approach of linear discriminant function analysis was also applied to predict class membership based on a linear combination of the explanatory variables. Hence, the linear discriminant functions have to be estimated first in DA. Because we have 4 groups for response variable, the coefficients of their respective linear discriminant functions are shown in Table 5. This result was then applied to compute the posterior probability that a case belongs to a certain class. Summary of classification for initial data (without test sample) is displayed in Table 6. Cases are assigned to the group with the highest posterior probability. According to the analysis result of Table 6, the linear discriminant analysis correctly identified 46 of 78 cycle time observations. The overall proportion of correct classification is only 59% in this study. The problem of classification accuracy is probably caused by the mismatch of group 2, where only 13 of 36 observations are accurately classified. However, linear discriminant analysis provides with excellent hit ratios for the group of "3" and "4". Hence, staff of defect inspection station should be cautious about the classification results of linear discriminant analysis if defect inspection cycle time generally falls between 6 hours and 12 hours. To identify test sample of TFT-LCD plant, this study also computed the linear discriminant functions associated with each group from the results of Table 5 and identified the new case as being of a particular group depending upon which discriminant function value is higher. Results of classification for test samples are later discussed with the results from other approaches.

Table 5: Coefficients of Linear Discriminant Functions for Groups

Factor \ Group	1	2	3	4
Constant	-5064.3	-5066.4	-4995.7	-4643.4
WIP	0.0	0.0	0.0	0.0
Throughput	0.0	0.0	0.0	0.0
Yield	116.7	116.8	115.8	111.3
Product Mix	-0.5	-0.5	-0.5	-0.5

Table 6: Summary of Classification

Into Group \ True Group	1	2	3	4
1	22	16	0	0
2	8	13	1	0
3	0	7	9	0
4	0	0	0	2
Subtotal	30	36	10	2
Num of Correct	22	13	9	2
Proportion	0.733	0.361	0.900	1.000
Total	78			
Num of Correct	46			
Proportion	0.590			

C. *Logistic Regression*

Because the response variable of this study has more than 2 groups, proportional odds model was adopted to make classification. Estimated coefficients, z-values, and *p*-values of proportional odds model for this study are shown in Table 7, where const(i) is the estimated intercept of proportional odds model for group i, i = 1, 2, 3. There is no need to estimate an intercept for group 4 since the cumulative probability for the last response value is 1. All of the regression coefficients are approximated by maximum likelihood approach. Here, the estimated coefficient for WIP is -0.0007 with a *p*-value of 0. It suggests that there is sufficient evidence to conclude that WIP affects cycle time. Similarly, the *p*-value of Yield is also smaller than the significance level 0.05, which implies the importance of Yield factor on cycle time. However, there is insufficient evidence to conclude that Throughput and Product Mix have significant effects upon defect inspection cycle time because their respective *p*-values are 0.271 and 0.218. Thus, only WIP and Yield are critical predictors of defect inspection cycle time in this empirical study. Before utilizing this model for classifying test samples, the suitability of the proportional odds model should be checked by the following goodness-of- fit tests.

Table 7: Logistic Regression Table

	Coefficient	z	*p*-value
Const(1)	-47.3231	-2.28	0.022
Const(2)	-42.4551	-2.07	0.039
Const(3)	-36.4901	-1.82	0.068
WIP	-0.0007	-5.76	0.000
Throughput	0.0000	1.10	0.271
Yield	0.5632	2.35	0.019
Product Mix	-0.0047	-1.23	0.218

Table 8 first summarizes the test result of null hypothesis that all the coefficients associated with predictors equal zero. The test statistic G = 14.713 with a *p*-value of 0.000 implies that there is at least one estimated coefficient that is different from zero. Results of Pearson and deviance goodness-of-fit tests were also summarized in Table 8. In this study, there is insufficient evidence to claim that the proportional odds model does not fit the data adequately because the *p*-values for both tests are larger than the significance level 0.05. Therefore, the proportional odds model shown in Table 7 is appropriate for explaining cycle time estimation and was used to compare with other approaches with test observations.

Table 8: Goodness-of-Fit Tests

Test	G	DF	*p*-value
All slopes are zero	92.058	4	0.000
Test	χ^2	DF	*p*-value
Pearson	109.65	266	1.000
Deviance	113.51	266	1.000

DF: Degrees of Freedom

D. *Comparison of Prediction Accuracy*

Applying the above discussed BN, DA, and LR models, one season's data is used to evaluate their respective prediction quality. Table 9 demonstrates the comparisons of cycle time predictions among BN, DA, and LR. From the perspective of proportion correct, logistic regression model correctly identified 10 of 13 cycle time observations. Comparing with the prediction result from DA with only 8 correctly classified cases, LR yields better prediction result than DA. However, the prediction results from BN are somehow different than the other approaches. Due to the limitation of initial data, posterior probability of cycle time given the evidence of WIP, Throughput, Yield, and Product Mix from BN model is not sensitive for situations that have not occurred in the initial data. As a result, instead of showing the classification result from BN approach by assigning object to the group with highest posterior probability, the posterior means (μ) and standard deviations (σ) given evidences of all predictors are displayed in Table 9. Although the accuracy percentage is not available for BN model, staff of defect inspection station could still report cycle time estimation through the information of μ and σ. These statistics can also help us computing the values of mean square deviation (MSD) and mean absolute deviation (MAD), which are used to compare the prediction quality here. According to the results from Table 9, LR has the lowest values of MSD and MAD among the three prediction models discussed in this study. Approach of BN has the second lowest value 0.25 on MSD but has the highest score 0.4231 on MAD. Hence, proportional odds model best explains the prediction of defect inspection cycle time in this TFT-LCD plant based on the data of test samples.

Table 9: Comparisons of Cycle Time Predictions among BN, DA, and LR

[1]Obs.	Actual	BN		DA	LR
		μ	σ		
1	3.0	3.0	0.00	3.0	3
2	2.0	2.5	1.12	3.0	3
3	2.0	3.0	0.00	3.0	2
4	3.0	2.5	1.12	3.0	3
5	3.0	2.5	1.12	3.0	3
6	3.0	3.0	0.00	4.0	3
7	2.0	2.5	1.12	3.0	2
8	3.0	2.5	1.12	3.0	2
9	3.0	2.5	1.12	3.0	3
10	3.0	3.0	0.00	3.0	3
11	3.0	2.5	1.12	2.0	2
12	2.0	2.5	1.12	2.0	2
13	2.0	2.5	1.12	2.0	2
Proportion Correct		[2]NA		0.6154	0.7692
[3]MSD		0.2500		0.3846	0.2308
[4]MAD		0.4231		0.3846	0.2308

[1]Obs.: Observation; [2]NA.: Not Available;
[3]MSD: Mean Square Deviation;
[4]MAD: Mean Absolute Deviation

V. CONCLUSIONS

Because almost all of the procedures in TFT-LCD defect inspection process are examined manually through human vision, cycle time estimation from the experienced staff is generally deviated considerably from actual observation. Hence, this paper illustrates how to adopt the approaches of Bayesian network, discriminant analysis, and logistic regression to construct prediction models for this particular process. To validate the applicability of these three models, case study of a TFT-LCD panel factory was conducted. According to the comparison results of prediction analysis, logistic regression demonstrates its superior prediction ability in all corresponding measurements. Although TFT-LCD panel manufacturers could still apply any of these three models for their cycle time estimation, logistic regression seems to be a better tool than the other models based on the findings of this study. Besides, logistic regression has two more advantages over the discriminant analysis in practical application. First, logistic regression is more flexible than discriminant analysis when the regression assumptions are not met. Second, logistic regression is as straightforward as multiple regression because it has similar statistical tests and can incorporate metric and nonmetric variables. While Bayesian network also has its own advantages like learning mechanism and explicit model representation, its prediction capability is limited in this empirical test due to the problem of insufficient samples. Future research may collect more data to further check the prediction results of Bayesian network approach. We can also check the application of quadratic discriminant function instead of linear discriminant function. Additionally, only four predictor variables are considered here for model construction, it's worthy of note to explore more potential variables for defect inspection cycle time. Finally, as logistic regression demonstrates its superior prediction quality in this study, we may improve the prediction accuracy by applying other specialized models of logistic regression such as cumulative logit model or adjacent-category logits. Manufacturers can also further adjust the proposed prediction models to accord with their production environments and data availability.

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