出國報告(出國類別：出席國際研討會發表論文)

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摘要

本次出國之目的爲參加於日本神戶市(Kobe, Japan)舉行之2009 年IEEE機器人與自動化國際研討會(2009 IEEE International Conference on Robotics and Automation, ICRA 2009)，並發表學術研究論文。ICRA 2009國際研討會之主題爲”Robotics and IRT (Information and Robotics Technology) for Livable Societies.”本次會議共有從46個國家，1626篇技術論文(Technical Papers)及36段長影片(Long Video)投稿，審查結果僅696篇技術論文及16段長影片獲接受於本次大會發表，接受率分別僅約42.8%及44.4%。本次大會於98年5月12日、13日及17日共排定有26個機器人與自動化相關之Workshops與Tutorials，並舉辦三場全體出席的大會演講(Plenary Talks)、一場科學論壇(Science Forum)、一場工業論壇(Industrial Forum)與一場公民論壇(Citizen’s Forum)。本次大會也利用5月14日至16日3天時間，於同一時間分13平行場次(Parallel Tracks)，共有149場次(Sessions)，將所有論文利用口頭方式公開發表。本人在本次會議發表論文乙篇「發展一個產品品質錯誤偵測機制(Developing a Product Quality Fault Detection Scheme)」，被安排於5月14日下午工廠自動化(Factory Automation)場次報告。

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一、目的

本次出國之目的爲參加於日本神戶市(Kobe, Japan)舉行之2009 年IEEE機器人與自動化國際研討會(2009 IEEE International Conference on Robotics and Automation, ICRA 2009)，並發表學術論文乙篇，經費來源爲行政院國家科學委員會補助國內專家學者出席國際學術會議經費。

二、過程

本次2009年IEEE 機器人與自動化國際研討會(ICRA 2009)於98年5月12日至17日在日本神戶市(Kobe, Japan)舉行。ICRA 2009國際研討會之主題爲”Robotics and IRT (Information and Robotics Technology) for Livable Societies.”本次會議共有從46個國家，1626篇技術論文(Technical Papers)及36段長影片(Long Video)投稿，審查結果僅696篇技術論文及16段長影片獲接受於本次大會發表，接受率分別僅約42.8%及44.4%。

本次大會於98年5月12日、13日及17日共排定有26個機器人與自動化相關之Workshops與Tutorials，並舉辦三場全體出席的大會演講(Plenary Talks)、一場科學論壇(Science Forum)、一場工業論壇(Industrial Forum)與一場公民論壇(Citizen’s Forum)。本次大會也利用5月14日至16日3天時間，於同一時間分13個平行場次(Parallel Tracks)，共有149場次(Sessions)，將所有論文利用口頭方式公開發表。本人在本次會議發表論文乙篇「發展一個產品品質錯誤偵測機制(Developing a Product Quality Fault Detection Scheme)」，被安排於5月14日下午工廠自動化(Factory Automation)場次報告，論文資料如下：

（中文題目：發展一個產品品質錯誤偵測機制）

Yi-Ting Huang, Fan-Tien Cheng, and Min-Hsiung Hung, “Developing a Product Quality Fault Detection Scheme,” in *Proceedings of 2009 IEEE International Conference on Robotics and Automation*, Kobe, Japan, pp. 927-932, May 12-17, 2009.

三、心得

本次大會之特色除了3 場邀請之專題演講(Invited Plenary Talks)外，也舉辦機器人競賽(Robot Challenge)，從世界各地來之學生隊伍，帶著他們的機器人到會場參加比賽。此外，大會也安排有展示攤位，展覽各式機器人、發展軟體等。本次國際學術會議，國內有多位的專家學者參加，包括：台大電機系羅仁權教授與傅立成教授、交通大學電控系胡竹生教授與楊谷洋教授、成大製造所鄭芳田教授等人。其中台大電機系羅仁權教授獲邀於5月12日工業論壇(Industrial Forum)中發表演講。

整體而言，本次大會相當成功。除了參加人數眾多外，各項舉辦之競賽與活動也為大家所讚許，值得國內舉辦國際研討會時參考。

四、建議事項

最後，感謝國科會提供經費補助國內專家學者出席國際研討會，也期盼國內學者能繼續積極參與國際學術活動並發表論文，以期提升我國之國際學術地位。

五、攜回資料名稱及內容

1. Proceedings CD of 2009 IEEE International Conference on Robotics and Automation.

附錄：「發展一個產品品質錯誤偵測機制(Developing a Product Quality Fault Detection Scheme)」論文內容

2009 IEEE International Conference on Robotics and Automation
Kobe International Conference Center
Kobe, Japan, May 12-17, 2009

Developing a Product Quality Fault Detection Scheme[1]

Yi-Ting Huang[2], *Student Member*, *IEEE*, Fan-Tien Cheng, *Fellow*, *IEEE*, and
Min-Hsiung Hung, *Senior Member, IEEE*

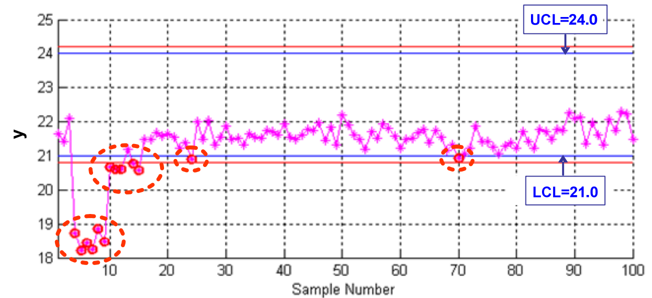
Abstract—**In current semiconductor and TFT-LCD factories, periodic sampling is commonly adopted to monitor the stability of manufacturing processes and the quality of products (or workpieces). As for those non-sampled workpieces, their quality is usually monitored by such as a fault-detection-and-classification (FDC) server. However, this method may fail to detect defected products. For example, a workpiece with all the individual manufacturing process parameters being in-spec may still result in out-of-spec product quality. Under this circumstance, unless this certain defected workpiece is selected for sampling by chance, it cannot be detected by simply monitoring the manufacturing process parameters collected from the production equipment. To solve the abovementioned problem, this research proposes a product quality fault detection scheme (FDS), which utilizes the classification and regression tree to implement a model for identifying the relationship between process parameters and out-of-spec products. Through this model, each set of normal manufacturing process parameters can be real-time and on-line examined to detect failure or defected products.**

Index Terms—**Fault Detection Scheme, Classification and Regression Tree, Virtual Metrology.**

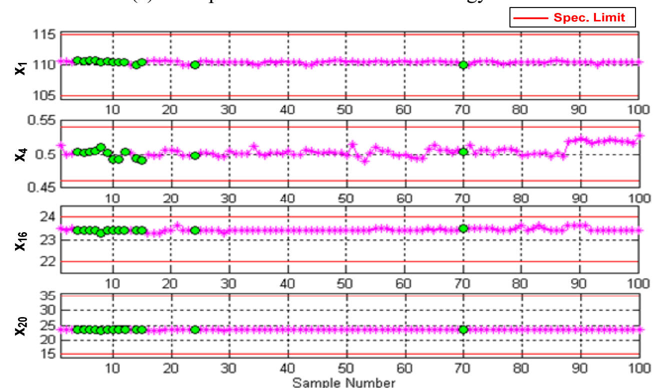
I. Introduction

In current semiconductor and TFT-LCD factories, periodic sampling is commonly adopted to monitor the stability of manufacturing processes and the quality of products (or workpieces). As for those non-sampled workpieces, their quality is usually monitored by such as a fault-detection-and-classification (FDC) server. However, this method may fail to detect defected products. For example, a workpiece with all the individual manufacturing process parameters being in-spec may still result in out-of-spec product quality. Under this circumstance, unless this certain defected workpiece is selected for sampling by chance, it cannot be detected by simply monitoring the manufacturing process parameters collected from the production equipment.

A TFT-LCD photolithography process is taken as the illustrative example. Fig. 1(a) presents the real metrology data of some selected samples and their control limits (upper control limit (UCL) = 24, lower-control-limit (LCL) = 21). As shown in Fig. 1, we can easily observe 13 out-of-spec (OOS) metrology data, in samples No. 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 24 and 70, respectively. However, further investigations show that all the 24 corresponding process data of these 13 samples are within the specifications, as shown in



(a) Examples for OOS Product Metrology Data.



(b) Selected Process Data Corresponding to the Metrology Data Shown in (a).

Fig. 1 Product Quality OOS Example.

Fig. 1(b), where only x_1, x_4, x_{16}, x_{20} of those 24 corresponding process data are displayed.

To resolve the problem mentioned above, this research proposes a product quality fault detection scheme (FDS), which utilizes the normal process data collected from production equipment to perform on-line and real-time product quality monitoring. When an OOS workpiece is detected, the proposed scheme will alarm the process engineers to perform subsequent analysis or measurement of the failure or defected products.

To implement the FDS, first we need to collect corresponding sets of historical metrology and process data to build a fault detection model (FD model). Note that the collected metrology data must include both in-spec and out-of-spec ones for building a complete model. Besides, the collected process and metrology data must be preprocessed to ensure their data quality for avoiding deterioration in the FD model.

To on-line and real-time evaluate the quality of the collected process and metrology data for the FDS, the automatic data quality evaluation methods proposed by the authors [1] are adopted in this research.

Many studies related to product and process quality evaluations have been carried out in the past [2], [3], [4], [5],

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[6], [7]. However, with the fast development of manufacturing technologies, new inspection techniques are needed. Taking the semiconductor industry for example, the semiconductor technology roadmap proposed by the International SEMATECH [8] shows that the manufacturing process nowadays is getting more and more complex. There are more factors that are influential to the quality of products, and many process parameters are correlated. Given this situation, the traditional single-variate statistical process control methods [9] are no longer sufficient for the current semiconductor industry. Instead, the multivariate statistical analysis [10] and data mining technology [11] are demanded for making data-driven decisions. In this way, the causes or hidden information of process abnormalities can be effectively discovered based on the professional knowledge of process engineers and the experience rules.

In view of the current status, a data mining technique called the "classification and regression tree (CART)" [12], [13] is adopted by the proposed FDS to construct a model for identifying the relationship between process parameters and in-spec or OOS products. As such, the FDS will be able to on-line and real-time detect failure or defected products. The FDS is different from the conventional statistical methods (e.g. one-way plots [14], ANOVA analysis[14], etc.) which do not efficiently address the problem of confounding effects from multiple factors. Therefore, the FDS is more applicable in handling and detecting OOS products resulted from special process parameter combinations.

The remainder of this paper is organized as follows. Section 2 explains the mechanism of the proposed product quality FDS. Section 3 presents an illustrative example of the photolithography equipment in a TFT-LCD factory in Taiwan. Section 4 discusses the advantages and disadvantages of FDS in comparison with the virtual metrology system (VMS) [1], [15], [16], [17]. and proposes an integrated scheme with FDS+VMS. Finally, Section 5 provides a summary and conclusions.

II. PRODUCT QUALITY FAULT DETECTION SCHEME

The complete product quality FDS proposed in this paper is mainly composed of two models, namely the data quality evaluation model and the FD model as shown in Fig. 2. First, when a set of process data is collected, the DQI_X will be calculated to define whether this process data is abnormal (e.g. exceeds the control limits) or not. If true, a warning message requesting further analysis and confirmation will be sent to the process engineers; otherwise, this process data will be forwarded to and applied by the FDS to conduct on-line and real-time monitoring of product qualities. During this procedure, the FDS will notify the engineers to perform real measurement when OOS workpieces are detected. On receiving the real metrology data, the metrology data quality evaluation module will perform real-time evaluation via DQI_y to identify abnormalities resulted from measurement errors or other external factors (such as particle pollution). If abnormalities exist, a warning message will be sent to ask the engineers to confirm the quality of the metrology data. Finally, all the normal corresponding data sets will be forwarded to the FD model to perform re-training and execute the pruning process. The details of Fig. 2 including data collection, data quality evaluation (DQI_X and DQI_y models) and FD model are explained as follows.

1) Data Collection

This procedure starts with collecting the historical metrology data. Then, the process data which correspond to the collected metrology data are searched. If the corresponding process data are found, the complete set of process and metrology data will be included; otherwise, the metrology data with no accompanying process data will be deleted. The above steps should be executed until the collected historical data sets are enough for building the FD model. To establish a complete model for on-line and real-time FDS, the quality of all the collected process and metrology data sets must be normal, and the metrology data must include both in-spec and OOS ones. Also, with more OOS samples collected for building the FDS model, the relationship or rules between process parameters and OOS products can be described more specifically. After all the required historical metrology data and process data are collected, data cleaning processes should be performed manually to screen out the abnormalities of process and metrology data.

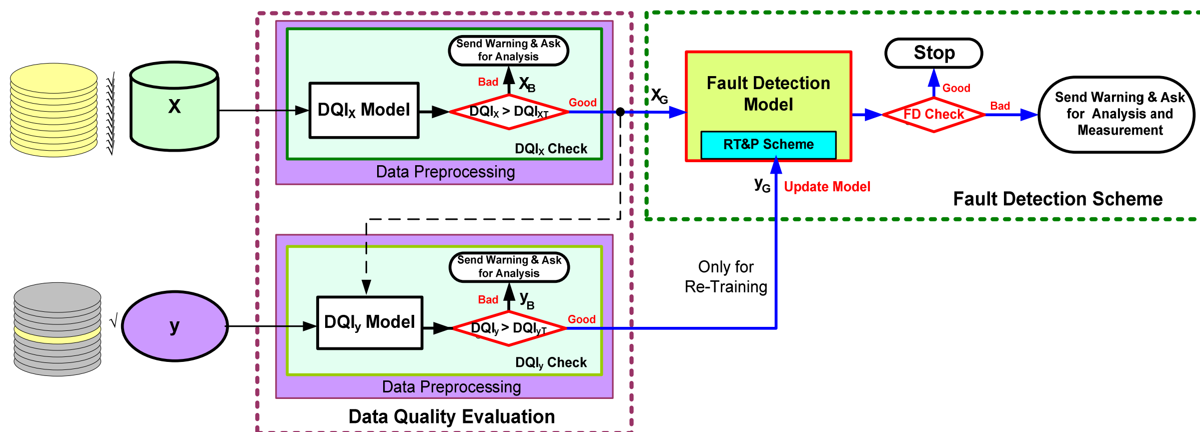


Fig. 2 Real-time and On-line Product Quality Fault Detection Scheme with Data Quality Evaluation.

2) Data Quality Evaluation

After collecting enough number of normal historical data sets, the initial DQI_X and DQI_y models can be constructed. Since the standardized process data generated by the DQI_X model must be utilized to create the first DQI_y model, the DQI_X model should be built first [1]. The DQI_X and DQI_y models are summarized as follows. Firstly, principal component analysis (PCA) is applied to analyze all the collected equipment process data; then Euclidean distance is utilized to unify all the principal components into a single index denoted process data quality index (DQI_X) for evaluating the quality of process data. Secondly, adaptive resonance theory 2 (ART2) and normalized variability (NV) are applied to define the metrology data quality index (DQI_y) for appraising the quality of metrology data. The thresholds of both DQI_X and DQI_y are also defined accordingly.

3) Fault Detection Model

The FD model is created after the DQI_X and DQI_y models, since the data used for constructing the FD model need to be checked by DQI_X and DQI_y first. To begin with, the metrology data (y) are divided in to 3 quality classes according to the product quality control limits, i.e. the upper control limit (UCL) and the lower control limit (LCL). The 3 quality classes are: (1) Class 0: the metrology data (y) is within the control limits ($y \geq LCL$ and $y \leq UCL$); (2) Class -1: the metrology data (y) is lower than LCL ($y<LCL$); and (3) Class 1: the metrology data (y) exceeds UCL ($y>UCL$).

Next, the quality classes with the corresponding process data are utilized by the classification and regression trees (CART) [12] for constructing the FD model. The FD model can discover process-data combination rules that are influential to the quality of products. Also, through the procedure mentioned above, the process data are classified in to a tree-like structural detection model.

A CART is a binary decision tree which adopts the GINI Index (IBM Intelligent Miner) as the branch criteria [12]. Each parent node in a CART can be split into 2 child nodes, and the data set is partitioned into mutually exclusive sub-datasets in each split. The more homogeneous the data in a sub-dataset are, the more samples we can find in a class.

The constructed FD model must be able to carry out on-line and real-time product quality detection and maintain 90% and above accuracy by avoiding too many false alarms (FAs) and/or miss detections (MDs). For the semiconductor and TFT-LCD industries, MDs are much more serious than FAs. Therefore, a practical FD mechanism should have a low MD rate. Considering this requirement, a re-training & pruning scheme (RT&P scheme) is designed in the FD model. The RT&P scheme adopts the concept of the minimum-cost for pruning the relatively insignificant rules in a model tree to avoid model overfitting. In the FD model, the RT&P scheme mainly functions to prune off leaf nodes with a few samples to reduce FAs. However, over-pruning of the model tree might also increase the frequency of MD. Therefore, the RT&P scheme sets up the cost for each error detection: MD costs 2, FA costs 1, and correction detection (CD) costs 0. Next, the RT&P scheme computes the cost of the model trees using the latest data for modeling and a10-fold cross-validation [11]. The cost of the model trees are evaluated through the combination and arrangement to find the best number of leaf nodes of pruning which has the minimum-cost. Finally, construct a new FD model by the best number of leaf nodes. The above are the procedures for implementing the first FD model. The on-line re-training and pruning procedures of FD model are presented in the “RT&P Scheme” block in Fig. 3 and detailed below.

Step 1. Collect a corresponding set of process and metrology data, which must be examined by DQI_X and DQI_y respectively and confirmed as normal data (X_G, y_G). Then, convert the metrology data y_G into the corresponding class values (-1, 0, or 1) and send the metrology data class values associated with the process data (X_G) to the FD model.

Step 2. Calculate the cost of the tree model using the latest data for modeling and by 10-fold cross-validation.

Step 3. Evaluate the cost of the model trees through the combination and arrangement to find the best number of leaf nodes of pruning which has the minimum-cost.

Step 4. Construct a new FD model base on the best number of leaf nodes.

Step 5. Replace the old FD model in the FDS with the newly constructed one.

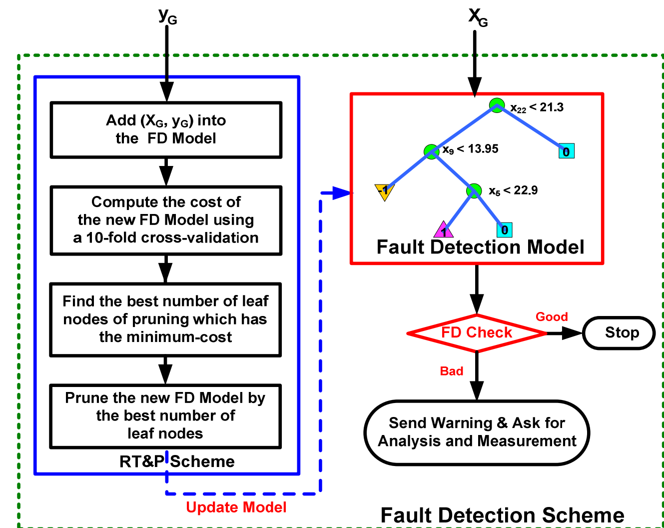


Fig. 3 Re-Training and Pruning (RT&P) Scheme in FDS.

III. Illustrative Example

A piece of photolithography equipment in a TFT-LCD factory in Taiwan is taken as the illustrative example. This experiment involves 315 sets of corresponding real metrology data and process data collected during the latest 6 months. Among those 315 data sets, the first 119 sets are used to construct the FD model, while the rest 196 sets are applied for on-line and real-time verification of the FDS. Furthermore, the first 119 data sets include 8 sets of y>UCL (Class 1) data,

TABLE I
FDS EXPERIMENTAL RESULTS

196 testing samples	Without Pruning					With Pruning				
	Case	CD	FA	MD	Accuracy	Case	CD	FA	MD	Accuracy
Free-Running Mode	#1	174	21	1	0.888	#2	183	13	0	0.933
Re-Training Mode	#3	193	2	1	0.985	#4	195	1	0	0.995

23 sets of y<LCL (Class -1) data, and 88 sets of normal (Class 0) data. On the other hand, the rest 196 sets of verification data contains 5 sets of Class -1 data and 12 sets of Class 1 data. Of course, all the data sets are checked and verified by the DQI_y and DQI_X.

To evaluate the capability of FDS, an experiment including two modes (the free-running mode and re-training mode) is designed to compare the detection accuracy. And, each mode has two cases (with and without pruning). The difference of the two modes is that the re-training mode will re-train the FD model once each newly collected data is received. As such, Cases 1 and 2 belong to the free-running mode while Case 3 and 4 are the re-training mode. Cases 1 and 3 utilize the simple re-training scheme (without pruning) while Cases 2 and 4 apply the RT&P scheme to build the first FD model and perform the re-training process.

Table 1 presents the experimental results of the 4 cases. The detection accuracy for all the 4 cases is above 88%. However, Case 1 has the lowest accuracy owning to too many FAs and 1 MD. As presented in Fig. 4 and Table 2, the first FD model of Case 1 consists of 8 rules and 3 classes (Classes -1, 0, 1) along with their corresponding relationships with the process data. Thus, the FD model of Case 1 can be applied to identify the quality of products in 3 categories. In Case 1, most of the examples can be correctly detected, however it still has 21 FAs and 1 MD. The incorrect detection examples are depicted in Fig. 5. The dotted red circle in Fig 5(a) marks the rule that causes MD in sample #46. The dotted red circles

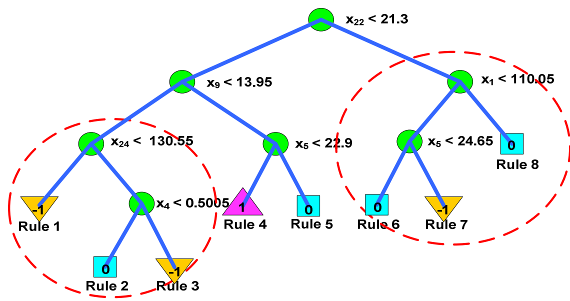


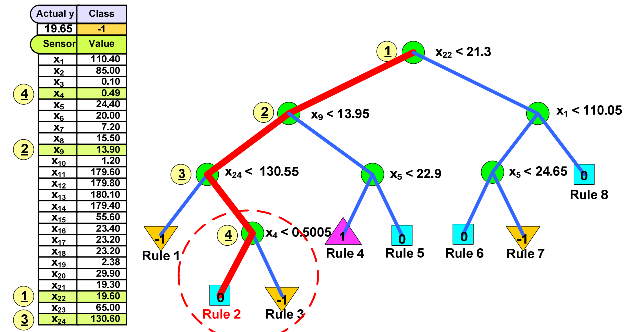
Fig. 4 The First FD Model of Cases 1 and 3 (without Pruning)

TABLE II
THE FIRST FD MODEL OF CASES 1 AND 3 CONSIST OF 8 RULES

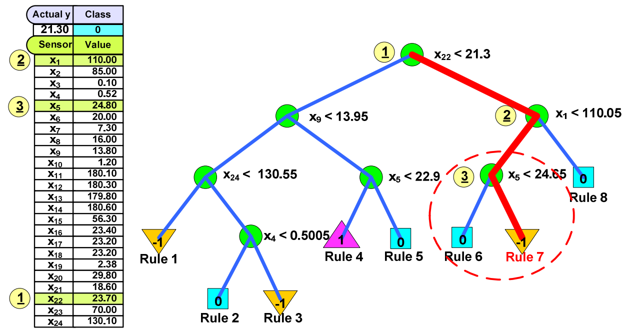
Rule 1	If $x_{22} < 21.3$ and $x_9 < 13.95$ and $x_{24} < 130.55$ then Class = -1
Rule 2	If $x_{22} < 21.3$ and $x_9 < 13.95$ and $x_{24} \geq 130.55$ and $x_4 < 0.5005$ then Class = 0
Rule 3	If $x_{22} < 21.3$ and $x_9 < 13.95$ and $x_{24} \geq 130.55$ and $x_4 \geq 0.5005$ then Class = -1
Rule 4	If $x_{22} < 21.3$ and $x_9 \geq 13.95$ and $x_5 < 22.9$ then Class = 1
Rule 5	If $x_{22} < 21.3$ and $x_9 \geq 13.95$ and $x_5 \geq 22.9$ then Class = 0
Rule 6	If $x_{22} \geq 21.3$ and $x_1 < 110.05$ and $x_5 < 24.65$ then Class = 0
Rule 7	If $x_{22} \geq 21.3$ and $x_1 < 110.05$ and $x_5 \geq 24.65$ then Class = -1
Rule 8	If $x_{22} \geq 21.3$ and $x_1 \geq 110.05$ then Class = 0

in Figs. 5(b) and 5(c) locate the rules that cause false alarms in samples #25 and #130. As stated before, the first FD model of Case 1 requires pruning to prevent the model from overfitting. From Figs. 5(a), 5(b), and 5(c), we can conclude that the circled parts in Fig. 4 are the places that require pruning.

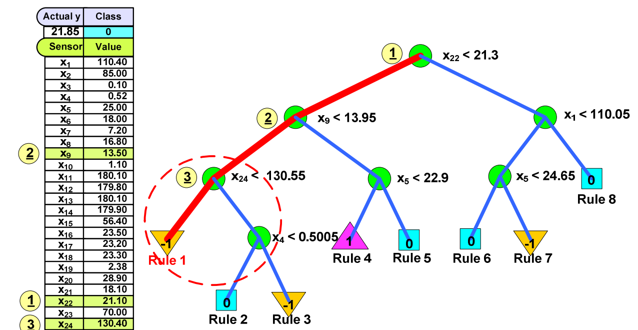
Case 2 uses the same free-running model for data verification as Case 1, and further adopts the RT&P scheme as shown in Fig. 3 to prune the initial FD model. The cost curve of the first FD model with pruning by 10-fold cross



(a) MD Occurs for Test Sample 46 (Actual Class = -1, Detected Class = 0).



(b) FA Occurs for Test Sample 25 (Actual Class = 0, Detected Class = -1).



(c) FA Occurs for Test Sample 130 (Actual Class = 0, Detected Class = -1).

Fig. 5 Incorrect-Detection Examples of Case 1.

validation is shown in Fig. 6. Figure 6 indicates that the lowest cost happens when the number of leaf nodes is equal to four (4). Therefore, the first FD model of Case 2 (with pruning), which has only four rules, is shown in Fig. 7 and Table 3.Observing Table 1, it is clear that the re-training mode can reduce FAs significantly when comparing with the free-running mode (Case 1 vs. Case 3 and Case 2 vs. Case 4). Besides, the pruning scheme can further enhance the detection accuracy (Case 1 vs. Case 2 and Case 3 vs. Case 4). In conclusion, Case 4 is the most accurate one (with 99.5% accuracy) and, therefore, will be adopted for deployment.

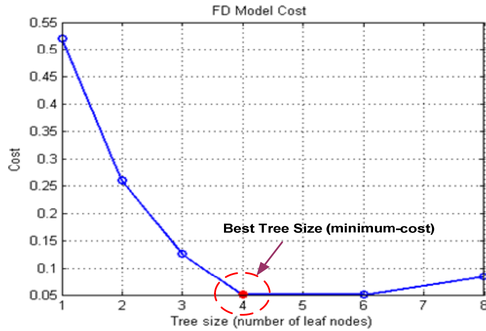


Fig. 6 The Cost Curve of the First FD Model with Pruning by 10-Fold Cross Validation.

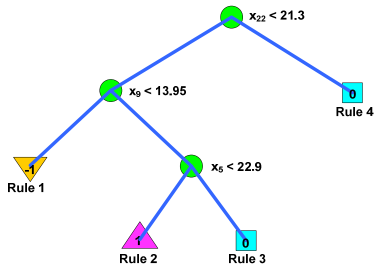


Fig. 7 The First FD Model of Cases 2 and 4 (with Pruning).

TABLE III
THE FIRST FD MODEL OF CASES 2 AND 4 CONSIST OF 4 RULES

Rule 1	If $x_{22} < 21.3$ and $x_9 < 13.95$ then Class = -1
Rule 2	If $x_{22} < 21.3$ and $x_9 \geq 13.95$ and $x_5 < 22.9$ then Class = 1
Rule 3	If $x_{22} < 21.3$ and $x_9 \geq 13.95$ and $x_5 \geq 22.9$ then Class = 0
Rule 4	If $x_{22} \geq 21.3$ then Class = 0

IV. DISCUSSION

The FDS is capable of detecting OOS products with normal process parameters. Therefore, it can be applied to perform on-line real-time inspection of product failures and achieve workpiece-to-workpiece (W2W) fault inspection. From the illustrative example presented in Section 3, we can conclude that with enough sample data for modeling, the inspection accuracy of FDS is greater than 90%. Nevertheless, the FDS is unable to output a product quality conjecture value. On the other hand, the virtual metrology system (VMS) proposed by the authors [1], [15], [16], [17] can on-line real-time conjecture the virtual metrology (VM) value of a workpiece and generate the reliance index (RI) and global similarity index (GSI) for indicating the reliance level of the corresponding VM values. However, the VMS cannot detect OOS products with normal process parameters.

If the FDS and VMS can be combined as shown in Fig. 8, then the two schemes can take from the long and add to the short such that the overall detection accuracy of abnormal and OOS products can be enhanced. Observing Fig. 8, when a set of process data enters the VMS, the DQI_X will check whether it is a normal process data. If it is a normal process data, it will be forwarded to the FDS for on-line and real-time product quality evaluation. Meanwhile, through the conjecture model of VMS, the phrase-I VM conjecture value (VM_I) along with the accompanying RI/GSI values are also generated. In this way, the un-sampled workpieces' product quality can be inspected and the corresponding VM values with RI/GSI can also be conjectured by adopting the FDS+VMS scheme.

Moreover, on receiving the real metrology data, the DQI_y will be applied to check whether it is normal. If the collected metrology data is normal, it will be sent with its corresponding process data to the FDS and VMS for tuning and re-training purposes. Also, the Phrase-II VM conjecture value (VM_{II}) along with its RI/GSI values can be generated to enhance the conjecture accuracy of VM.

By applying the illustrative example mentioned in Section 3, the effects of the FDS+VMS scheme is analyzed and presented in Fig. 9. The pink blocks indicate where the OOS products occur. Observing Fig. 9, we can see that VM_I approximately follows the actual metrology value with some

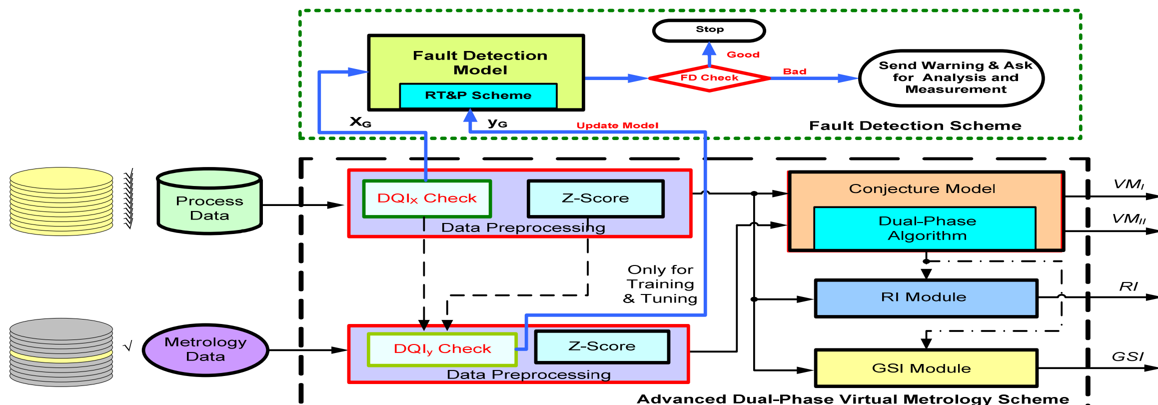


Fig. 8 Integrated Scheme with FDS + VMS.

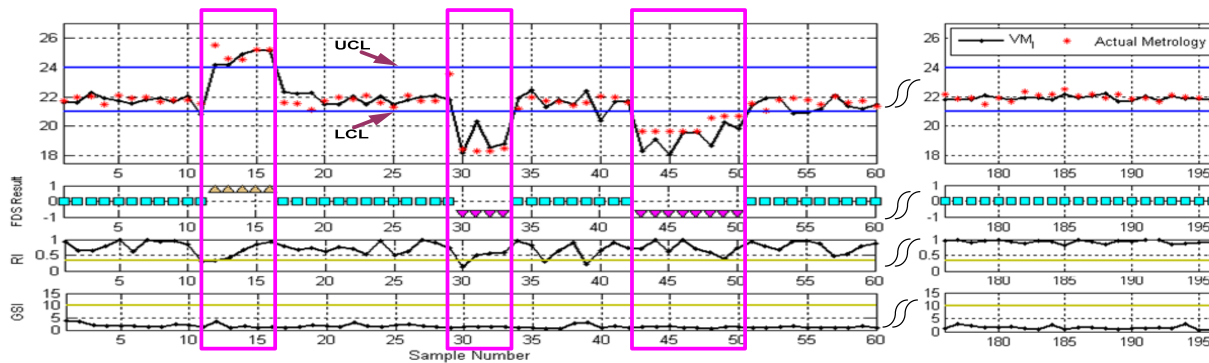


Fig. 9 Experimental Results of the FDS+VMS Scheme.

conjecture errors. On the other hand, the accompany RI/GSI values of VM_I demonstrate no significant out-of-threshold warning signs due to the fact that the corresponding process data are all in-spec. Therefore, it can be concluded that the FDS can be applied to achieve better OOS product detection rate when the process parameters are all within the specifications.

V. Summary and Conclusions

This paper proposes a product quality FDS, which can effectively detect OOS products with in-spec process parameters. The FDS adopts the CART to build the model for specifying the relationship between process data and in-spec as well as OOS products. A re-training & pruning scheme (RT&P scheme) which adopts the concept of the minimum-cost for pruning is designed within the FD model to prevent overfitting. With correct process data, the FD model can identify defected or failure products on-line and in real time. When detecting OOS products, the proposed scheme will warm the engineers to take necessary actions in time, which will prevent producing massive OOS products. In data preprocessing, the FDS adopts the DQI_X and DQI_y to prevent bad quality process or metrology data from affecting the accuracy of FD models. However, since the main purpose of FDS lies in product quality detection, it is unable of outputting a product quality conjecture value. Therefore, by integrating the FDS with the VMS, the overall capability of product quality monitoring and evaluation as well as W2W APC support can be achieved.

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