A Framework for Semi-Automated Fault Detection Configuration with Automated Feature Extraction and Limits Setting

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***Abstract*—In today's microelectronics manufacturing facilities, fault detection (FD) is pervasive as the primary advanced process control (APC) capability in use. The current approach to FD, while effective, has a number of shortcomings that impact its cost and effectiveness. The highest among these is the cost in time and resources associated with the largely manual methods used for partitioning and extraction of features of interest in individual traces. Additionally, once these features are extracted, feature-based univariate analysis (UVA) is the primary method used for process monitoring and FD, which fails to incorporate process variable correlations in detecting faults and quality issues. On the other hand, current multivariate analysis (MVA) approaches, such as principal component analysis (PCA), partial least squares (PLS), and their variants, focus on threshold setting in a multivariate space so that they cannot provide direct limit settings on raw (sensor) parameters for decision-making support during online process monitoring. Also, in bypassing feature identification and extraction, the subject matter expert (SME) is largely left out of the loop in MVA analysis; thus, information on the relationship between univariate features and faults is not captured. Furthermore, it is difficult to visualize and understand multivariate limits due to the high dimensionality of the data produced in microelectronics manufacturing processes. Finally, slow and normal process changes often occur in real processes, which can lead to false alarms during implementation when using models trained from offline samples. Thus, a need exists for an FD method that leverages the existing feature-based UVA and provides (1) a method for automated signal partitioning and feature extraction that allows for SME input, (2) an MVA mechanism which considers correlation among parameters and is adaptive to the normal process drift, (3) an automatic approach for limiting UVA features that captures the correlation among parameters, and (4) a methodology for easily viewing these capabilities so that an SME is able to view, understand, and continue to contribute to the FD optimization process. This capability has been developed and successfully applied to microelectronics manufacturing data sets and is proposed as a key component to future microelectronics smart manufacturing systems.**

Keywords—Fault Detection, Advanced Process Control, Subject Matter Expert, Direct Limit Setting, Univariate Analysis, Multivariate Analysis.

I. Introduction

Today's semiconductor manufacturers deal with a huge number of high level production challenges to keep profitable in the increasingly competitive global environment[1]. Key among these challenges are yield and throughput optimization[2]. Advanced process control (APC) was proposed in the 1990s as a key tool to help address these challenges and has been an integral component of microelectronics manufacturing for at least the past two decades[3, 4]. APC capabilities include the solutions such as online equipment, process fault detection (FD) and classification (FDC), and run-to-tun (R2R) control, which are pervasive in microelectronics manufacturing facilities[5]. These solutions leverage the data collection throughout the fabrication process and provide certain flexibility and re-configurability in the configurable control workflows to deal with the variability among processes, various products, and process dynamics[6, 7]. As a testament to their effectiveness, FD and R2R control techniques are now used on just about every front-end process to minimize scrap, improve product quality, detect quality degradation, and potentially determine when the equipment needs to be shut down for maintenance[2, 8, 9].

While existing APC approaches are effective, a number of issues with developing, deploying, and maintaining APC capabilities have surfaced. These issues arise due in large part to the complexity and dynamic nature of the microelectronics production process, combined with increased APC capabilities. Specifically, the shortcomings of today's FD solutions that impact their cost and effectiveness are summarized as below.

a) **High cost in time and resources in configuring solutions**: Existing approaches for FD include largely manual

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methods used for partitioning and extracting features, which lead to the high cost in time and resources associated with these manual operations. Fig. 1 summarizes the problems and concerns caused during the procedure of partitioning a typical manufacturing trace data, extracting and selecting features, and optimizing operations.

b) **Failure to consider the process variables correlations**: Once the features are extracted, feature-based univariate analysis (UVA) is the primary method for process monitoring and FD in today's microelectronics manufacturing facilities. However, feature-based UVA fails to use the process variable correlations in detecting fault and quality issues.

c) **Lack of direct limit setting on raw parameters**: The current multivariate analysis (MVA) methods used in FD focus on threshold setting in the projected reduced dimension space, which is effective for anomaly detection, but it fails to provide a mechanism for direct limit settings on raw parameters to support decision-making during online process monitoring[10].

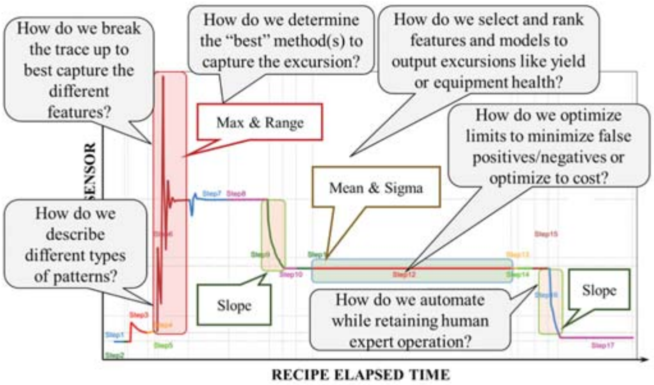

Fig. 1. An example of the approach and challenges of today's highly manual methods of UVA FD configuration.

The move to smart manufacturing (SM) solutions in microelectronics manufacturing leverages integrating physical and cyber capabilities up and down the supply chain, taking advantage of manufacturing data for increased adaptability and flexibility, while providing methods for incorporating subject-matter-expertise in solutions[11, 12].

The emergence of SM results in the ability to improve existing capabilities which are pervasive in microelectronics manufacturing, including FD[2]. Specifically, SM trends can be used to improve existing FD capabilities in the following ways:

a) **Supervision**: In the operation of traditional FD and FDC, the manufacturing data from the equipment is analyzed with the aid of quality data to determine whether the parameters are anomalous; this is referred to as "unsupervised" analysis. With the integration of SM capabilities, quality data can be incorporated to support both reactive FD and predictive "supervised" analysis. Semi-supervised and supervised scenarios exist in the new FD and FDC capabilities, in which the supervised data is used for model training to provide a high level of supervision[13, 14].

b) **Correlation of parameters**: A large number of FD solutions focus on UVA analysis, in which each parameter is analyzed individually. Meanwhile, other parts of FD solutions only focus on MVA techniques that fully explore the parameter correlations[15]. Integrating SM provides new decision-making support and process monitoring solutions to leverage UVA and MVA techniques based on different scenarios.

c) **Integration of subject matter expert (SME)**: Many traditional FD systems have components that are purely statistical or data-driven where SME is available, but not used (e.g., mean and variance analysis of signals). In the improved FD with SM, the incorporated SME can be as simple as selecting parameters prior to data-driven analysis, selecting features among the candidates, fine tunning models, or more complicated methods, such as developing model frameworks[16].

This paper proposes a framework for semi-automated FD configuration with automated extraction and limits setting. This framework addresses the issues of time, cost, and accuracy associated with today's FD approaches while being capable of leveraging the emerging SM solutions in microelectronics manufacturing. Specifically, the framework provides a level of configuration automation to the the existing feature-based UVA and highlights an MVA mechanism for process control and direct limit setting on raw parameters and a method for viewing these limits. A new mechanism is also proposed that allows the limits to automatically adapt to normally occurring process drifts. Applying the framework and solution to a public microelectronics manufacturing dataset illustrates its effectiveness in reducing FD setup time for feature partitioning, feature extraction, and limits setting, as well as its ability to provide improved quality results.

II. The Proposed Framework

This paper presents a framework for adaptive multivariate limits setting and visualization for FD in microelectronics manufacturing. The framework includes solutions for semi-automatic trace segmentation, feature identification, and feature extraction, followed by a systematic adaptive limit-setting and visualization. The proposed framework has several advantages over the previous work: (1) provides a level of configuration automation to leverage feature-based UVA and MVA mechanisms; (2) provides limits automatically adapt to the occurring process drifts; and (3) addresses the issues of time, cost, and accuracy with SM solutions. The proposed framework has been shown effective when applied to a public dataset and datasets generated by our trace generator tool[17].

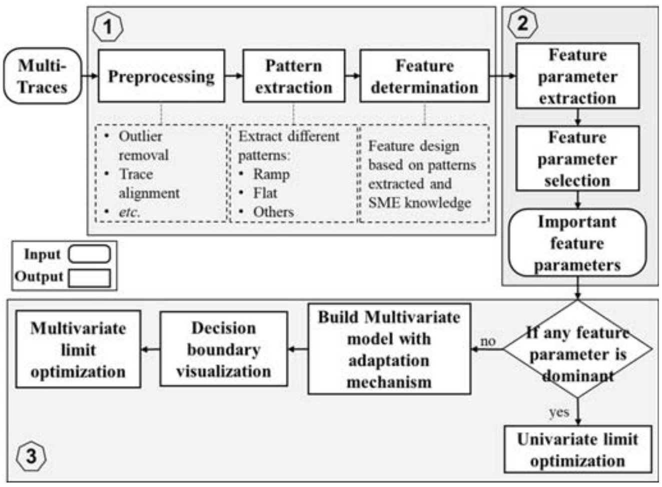

Fig. 2. An overview of the application to FD

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A high-level overview of the proposed framework is described in Fig. 2, which mainly includes three major steps.

Step 1 - Pattern extraction and determination from traces: A set of trace data from wafer runs is used to partition and determine the patterns contained in the traces. Different patterns in the traces are detected by its pattern extraction algorithm. The trace segmentation techniques in this step further improve on the initial achievements that have been presented at the 29th, 30th, and 31st APC conferences [17-20]. Within each trace segment, expert knowledge is leveraged to finalize the pattern set of interest. For example, the patterns such as ramp and flat are recognized by the pattern extraction processing. Either every single pattern or the combination of different contingent patterns will be taken as patterns of interest for further analysis. Fig. 3 illustrates the output of Step 1.

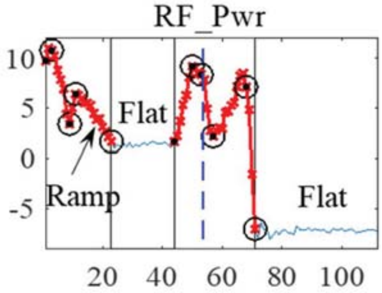

Fig. 3. An example of trace data with flat and ramp segments. During the procedure of partitioning the trace data, the ramps, and flats are recognized as patterns.

Step 2 - Feature parameter extraction and selection: The major task of Step 2 is to determine the distributions of features that describe the patterns determined in Step 1 and to select the important feature parameters. For example, the slope, length, width, and height are extracted to depict a ramp pattern. In addition, the solution provides a method for an SME to be employed to depict and/or fine tune the properties of certain patterns, as shown in Fig. 4. The statistical parameters are mainly used to summarize the important features in the recognized patterns, including maximum, minimum, range, standard deviation and mean, *etc*. After the feature parameter extraction is completed, the important features are selected based on criteria, such as receiver operating characteristic (ROC) curve analysis. This selection can occur in an unsupervised setting.

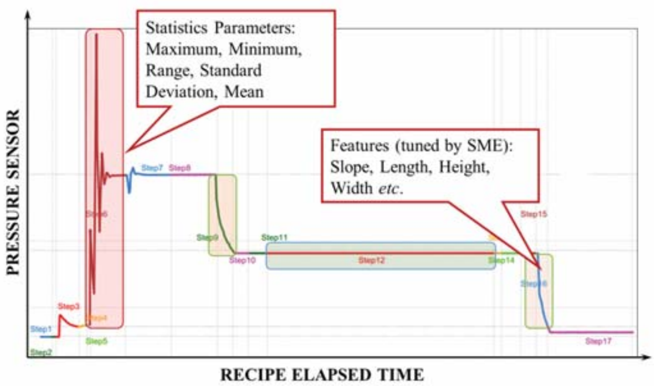

Fig. 4. An example of feature parameter extraction. Features such as slope, length, width, and height are used to depict the segments. An SME is also employed to tune the features. Statistical feature parameters are extracted based on the feautres.

Step 3 - FD model development, adaptive multivariate limit setting, and visualization of model: Once the important feature parameters are selected, the FD model and corresponding multivariate limit setting mechanism are developed based on Support Vector Machine (SVM). In the analysis pipeline in Step 3, a check is performed first to find out if dominant feature parameters exist that fully differentiate faulty from healthy traces individually, which is equivalent to finding a suitable parameter for UVA. If a dominant feature exists, the FD model and its visualization can be reduced to a single feature analysis with limits, found in existing FD capabilities (see Fig. 5 for an illustration). If no decisive parameters are found, multiple parameters are selected based on their importance ranking obtained in Step 2, and the multivariate FD model is established. To realize better visualization, understanding, and SME decision-making integrated support, the multivariate limit determined by the FD model is projected and shown in lower-dimensional views (usually 2D as shown in Fig. 6). In this view areas of "normal" and "faulty" are defined where the classification can be determined exclusively by the two variables being shown or plotted in the visualization. Additionally, a "grey area" is also defined where the classification cannot be determined soley by the two variables being shown.

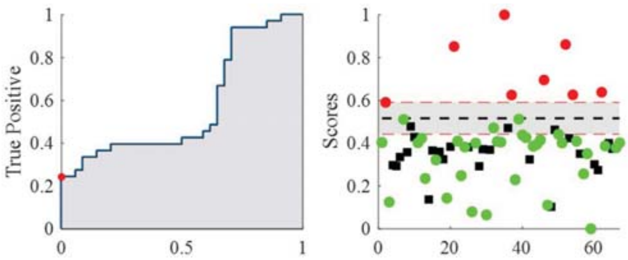

Fig. 5. An example of a univariate model with limits plot. The area under curve is used to determine the True and False Positives.

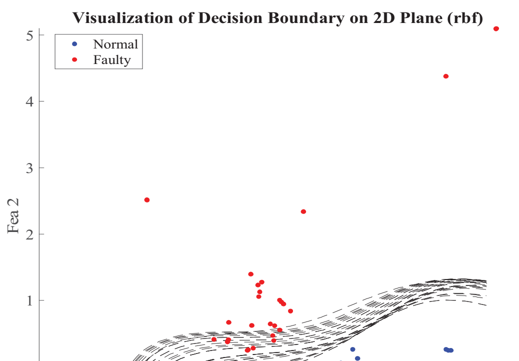

Fig. 6. A typical example for "Grey Area." "Fea 1" and "Fea 2" are referred to the selected two features. The curves represent the decision boundaries, referred as "Grey Area." The data outside the Grey Area can be determined by Fea 1 and Fea 2 as normal or faulty, while the data within the Grey Area can't, and it has to be determined by a 3rd feature.

In addition to auto limit generation and visualization, a model adaptation mechanism is incorporated to address any data drift in processes and treat it as anomalous or normal. The adaptation mechanism incorporates a moving window, data filtering, and incremental modeling methods.

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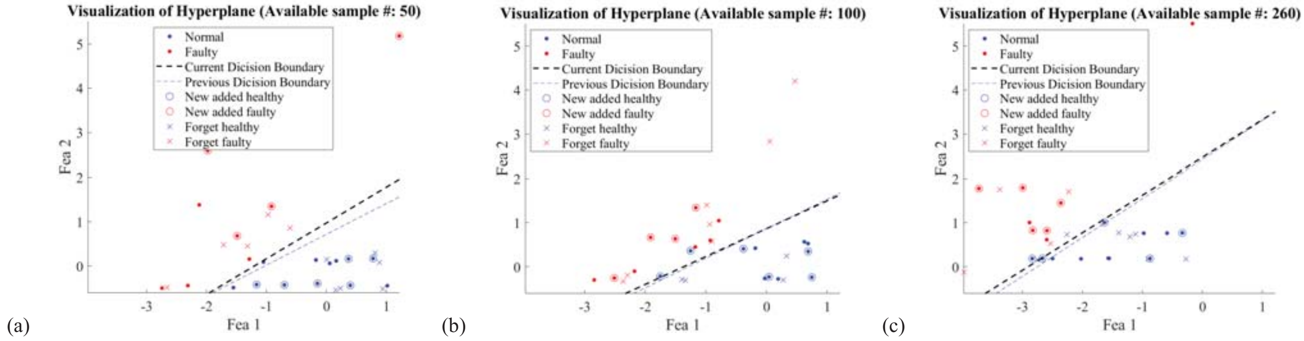

Fig. 7. Results of auto limit when the modeling option is: SVM (linear) + sliding window with EWMA filtering for different available sample numbers.

III. Experimental Results

The proposed framework of adaptive multivariate limits setting and visualization approach is validated on a public etcher data set provided by Eigenvector Research Inc[21]. The result indicates that the developed methods are capable to build the multivariate limit effectively and update the multivariate limit adaptively during the manufacturing process.

In this public dataset, there are 128 wafer runs in total. The sensors are summarized in TABLE I. There are 19 sensor signals measured from the etching tools, except piecewise constant included.

TABLE I. Data Description of The Etcher Data

# of Runs/Wafers	**128 (107 Normal, 21 Faulty)**
# of Experiments	3 (3 Regimes)
List of Variables	1. Time; 2. Step Number; 3. BCl3 Flow; 4. Cl2 Flow; 5. RF Btm Pwr; 6. RF Btm Rfl Pwr; 7. Endpt A; 8. He Press; 9. Pressure; 10. RF Tuner; 11. RF Load; 12. RF Phase Err; 13. RF Pwr; 14. RF Impedance; 15. TCP Tuner; 16. TCP Phase Err; 17. TCP Impedance; 18. TCP Top Pwr; 19. TCP Rfl Pwr; 20. TCP Load; 21. Vat Valve

After the procedure of preprocessing and pattern extraction, five statistics from each trace segment are extracted as features, which are maximum value, minimum value, peak-to-peak value, and standard deviation. Given that there are only 128 samples in total in this public dataset, the sample size is extended by three times by adding drifts to the samples in order to make sure that the sample size is enough to demonstrate the model adaptation capability.

The multivariate auto limit-setting and visualization procedure consists of several options, which are listed below.

SVM kernel: linear or radial basis function (RBF).

Adaptation option: sample accumulation or sliding window.

Filtering mechanism: exponentially weighted moving average (EWMA) or none.

To fully validate the proposed framework, Fig. 7 and Fig. 8 illustrate two different cases of option combinations for the model settings respectively, which are summarized in TABLE II. Each model setting includes three sub-figures in order to demonstrate the changing process of the decision boundaries as the sample size enlarges.

TABLE II. Results with Different Modeling Options

	SVM kernel		**Adaptation option**		**EWMA**	
	Linear	RBF	Sample accumulation	Sliding window	No	Yes
Fig. 7	✓			✓		✓
Fig. 8		✓	✓			✓

To illustrate the decision boundaries intuitively, Fig. 7 and Fig. 8 show the FD model and multivariate limit projection and visualization on lower dimension. In each case, three important parameters are chosen for FD modeling. The multivariate limit is projected to a parameter-pair 2D plane by varying the 3rd parameter, which results in the changing decision boundary.

In each case showed in Fig. 7 and Fig. 8, it can be observed that the multivariate limit adapts when new samples are available during the process. Specifically, the decision boundaries in Fig. 7 are straight lines while the boundaries in

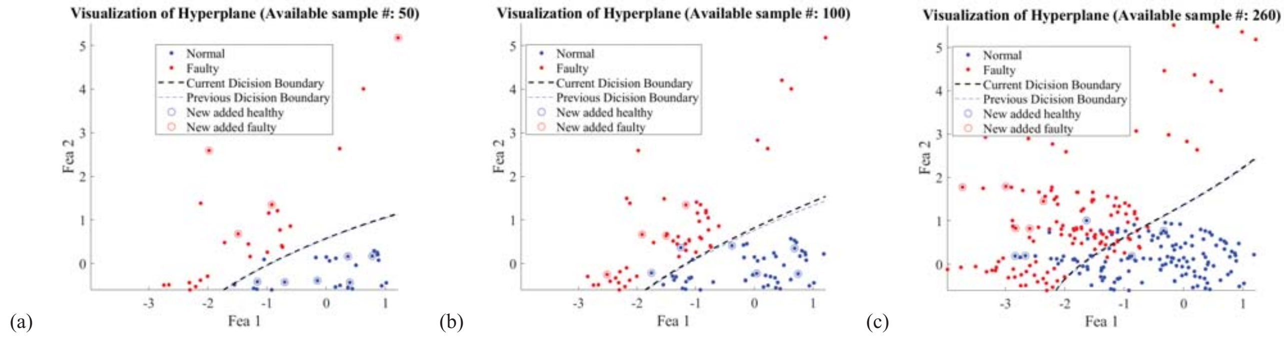

Fig. 8. Results of auto limit when the modeling option is: SVM (RBF) + samples accumulation with EWMA filtering for different available sample numbers.

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Fig. 8 are curves. The reason is that the SVM kernel used for Fig. 7 is a linear kernel while the SVM used for Fig. 8 employs a non-linear (RBF) kernel.

In Fig. 7 and Fig. 8, the employment of EWMA filtering results in the changing trend of the decision boundaries. A more obvious example is demonstrated in Fig. 6, in which the decision boundaries generated by the SVM with RBF kernel divide the graph into three parts. In Fig. 6, the area between all the decision boundaries is referred to the "grey area," where the two displayed parameters cannot be used alone to determine the classification (e.g., good or bad). Thus, the graph in Fig. 6 contains three areas: (1) an area where the sample is determined to be normal solely by the two parameters displayed, (2) an area where the sample is determined to be faulty or abnormal solely by the two parameters displayed, and (3) a "grey" area where additional parameters must be evaluated to determine the classification of the sample. By choosing different parameter pairs, the projections of variate limit are different.

IV. Summary

This paper proposes a multivariate FD framework for adaptive limit-setting and visualization in microelectronics manufacturing processes. The proposed framework enhances and expands the capabilities of a traditional FD system by integrating the concept of SM, and it improves the capabilities of supervision, the combination of UVA and MVA techniques, and the incorporation of SME. The main contributions of the proposed FD framework include (1) leveraging the existing base of feature-based UVA, (2) providing a mechanism to determine the correlation among parameters, (3) providing a mechanism to understand and, as necessary, reject normal process drift, (4) providing for automatic calculation of limits and UVA features that capture correlation among parameters, and (5) providing a method for simple viewing of these capabilities so that an SME can view, understand, and continue to contribute to the FD optimization process.

In future work, field evaluations with more testing data will be conducted. Methods for integration with FD applications will be studied and developed. Approaches to common segmentation across multiple sensors will be investigated. Also, full-trace analysis without segmentation will be evaluated and incorporated into the solution as necessary.

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