Intelligent Fault Detection and Classification in Semiconductor Manufacturing Using Statistical Learning Techniques

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Abstract

Semiconductor manufacturing requires early identification of equipment and process faults to reduce wafer loss and production delay. This study presents an intelligent fault detection and classification framework based on statistical learning techniques. Historical process data were collected from normal and faulty wafer-processing cycles and converted into features describing pressure, gas flow, radio-frequency power, temperature, timing, alarms, and maintenance condition. Linear discriminant analysis, support vector machine, and random forest models were developed and compared. Random forest achieved the highest accuracy of 94.3%, followed by the support vector machine and linear discriminant analysis. Pressure instability showed the strongest classification performance, while timing and equipment faults remained more difficult because they developed gradually and shared features with process drift. The proposed framework can support faster diagnosis, lower false alarms, improved maintenance planning, and more reliable semiconductor production through data-driven monitoring and fault classification.

Keywords: semiconductor manufacturing; fault detection; statistical learning; process monitoring; fault classification

1. Introduction

Semiconductor manufacturing includes many connected operations such as deposition, lithography, etching, cleaning, implantation, and polishing. A small equipment failure or process change can create faults that affect a large number of wafers. These faults may appear as abnormal sensor readings, unstable operating conditions, equipment alarms, or repeated defect patterns on wafer maps. Some faults develop slowly and remain unnoticed during the early stages of production. Early fault detection is therefore important because delayed identification can increase wafer loss, production delay, equipment downtime, maintenance cost, and final product rejection.

Large semiconductor factories generate continuous data from sensors, production tools, inspection systems, maintenance records, and wafer tests. Wafer-map analysis has been used to recognize common failure patterns and compare similar defects across large manufacturing datasets [1]. Regression-based learning has also supported the identification of defect patterns from wafer-level information [2]. Predictive models have been applied to equipment data to detect possible machine faults before serious process failure occurs [3]. Statistical learning can process many related variables at the same time and identify abnormal behaviour that may not be visible through manual inspection. These methods show that manufacturing data can provide useful evidence for both fault detection and fault classification.

Fault classification is more difficult than simple abnormality detection because different failures can produce similar changes in process measurements. A pressure fault, gas-flow problem, or power variation may create overlapping sensor patterns, making direct diagnosis difficult. Convolutional learning has been used to separate fault types and support diagnosis in semiconductor production [4]. Equipment fault fingerprints have also been extracted from batch-process data to identify the variables linked to abnormal operating conditions [5]. This study develops an intelligent framework that uses statistical learning techniques to detect process faults, classify their likely type, and identify the process features that contribute most strongly to each fault condition. The framework is intended to support faster engineering decisions and reduce the effect of equipment faults on wafer quality.

2. Methodology

Historical manufacturing data were collected from semiconductor process tools operating under both normal and faulty conditions. Each record represented one complete wafer-processing cycle and included sensor measurements, equipment events, tool identity, recipe information, maintenance condition, and inspection outcome. The dataset contained normal production runs and labelled fault cases confirmed by engineers or equipment records. Information from several production periods was included to capture normal equipment variation and different fault conditions. Records with missing wafer identification, incomplete process cycles, unavailable fault labels, or major sensor-data loss were removed before model development.

The selected process variables included chamber pressure, temperature, gas-flow rate, radio-frequency power, process duration, endpoint time, vibration, alarm count, and wafers processed since cleaning. Statistical features were calculated from every process cycle to describe the mean, standard deviation, maximum, minimum, range, slope, and time outside the normal operating limit. Differences between the current cycle and a stable reference cycle were also calculated to represent process drift. Wafer-map classification has shown that process faults can be represented through spatial defect information [6]. Transfer learning has been used to improve semiconductor defect classification when only a limited number of labelled examples are available [7]. The main variables and fault groups used in this study are presented in Table 1.

Table 1. Statistical process features, fault categories, and classification variables used for intelligent fault detection in semiconductor manufacturing

Fault category	Main process features	Typical abnormal behaviour	Classification label	Diagnostic meaning
Pressure instability	Chamber pressure mean, range, and slope	Rapid pressure rise or repeated fluctuation	F1	Possible vacuum or valve problem
Gas-flow fault	Gas-flow deviation and imbalance	Flow outside the recipe range	F2	Mass-flow controller or supply issue
Power variation	Radio-frequency power mean and variation	Unstable plasma-power delivery	F3	Generator or matching-network problem
Thermal fault	Temperature average and rate of change	Slow heating, overheating, or poor control	F4	Heater, sensor, or cooling problem
Timing and equipment fault	Process time, endpoint time, alarms, and chamber age	Delayed endpoint or repeated interruptions	F5	Tool aging, contamination, or maintenance need

Raw process data were cleaned before statistical features were extracted. Duplicate records, impossible sensor readings, and values outside valid engineering ranges were removed. Short missing sensor intervals were filled through interpolation, while process records with long missing periods were excluded. Numerical features were standardized using the mean and standard deviation calculated from the training dataset. Tool, recipe, maintenance state, and chamber identity were converted into categorical codes. Multitask learning has shown that measurements from different semiconductor tools and chambers can share common information while maintaining equipment-specific behaviour [8]. The data were therefore grouped by tool and recipe during training and validation to prevent normal equipment differences from being incorrectly identified as faults.

Three statistical learning models were developed and compared: linear discriminant analysis, support vector machine, and random forest. Linear discriminant analysis provided a simple statistical baseline, while the support vector machine was used to separate fault classes within a high-dimensional feature space. Random forest was selected because it can capture nonlinear relationships, manage interactions among variables, and rank the importance of process features. Feature-learning and transfer-learning methods have improved semiconductor fault classification by extracting useful patterns from limited or complex datasets [9], [10]. The records were divided chronologically into training, validation, and testing sets to represent practical production use. Model performance was evaluated using accuracy, precision, recall, F1-score, false-alarm rate, and a multiclass confusion matrix.

3. Results and discussion

The three statistical learning models were tested using unseen semiconductor process records that were not included during training. Linear discriminant analysis achieved an overall classification accuracy of 84.2%, while the support vector machine reached 90.6%. Random forest gave the best performance with an accuracy of 94.3%. It also produced the highest precision, recall, and F1-score among the tested models. The improved result was mainly due to its ability to handle complex relationships among sensor variables and equipment conditions. These findings show that nonlinear learning methods were more suitable for separating fault classes that had similar process and sensor patterns.

Figure 1 compares the precision, recall, and F1-score obtained for the five semiconductor fault classes. Pressure instability achieved the strongest and most balanced performance, with all three measures reaching 97.1%. Gas-flow faults and power variation also produced stable results, with F1-scores of 93.6% and 93.5%, respectively. Thermal faults showed high recall at 95.7%, but lower precision indicated that some normal or other fault cases were incorrectly assigned to this class. Timing and equipment faults showed high precision but lower recall, which means that the model identified this class accurately when predicted but missed some actual cases. These differences show that the classification system performed well overall, while slow-developing equipment faults still require more representative training data.

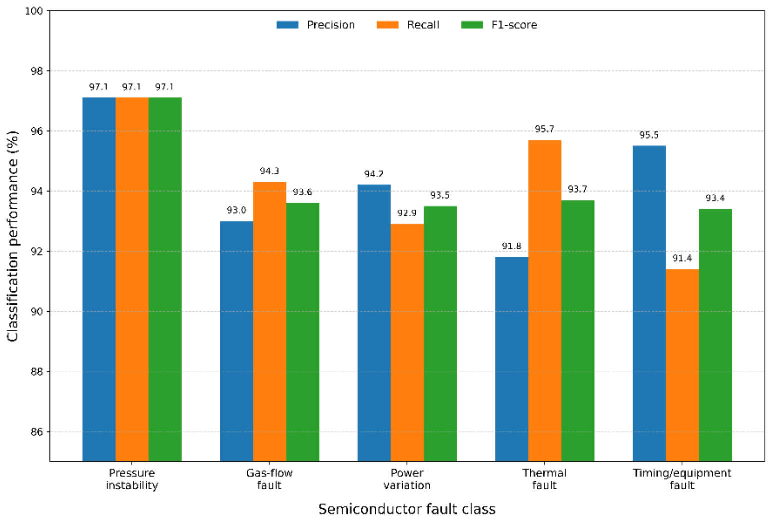

Figure 1. Classification performance of statistical learning techniques across semiconductor fault categories

Feature-importance analysis showed that chamber-pressure variation, gas-flow imbalance, radio-frequency power deviation, temperature slope, endpoint delay, and alarm frequency were the strongest indicators of process faults. Random forest performed well because it could combine these variables and detect nonlinear relationships between equipment behaviour and fault type. The low false-alarm rate suggests that the model could distinguish real faults from acceptable process variation without creating many unnecessary warnings. This is important in semiconductor factories because frequent false alarms can interrupt production and reduce engineer confidence in automated monitoring systems. However, model performance may decrease when new recipes, equipment tools, or previously unseen fault types are introduced, so regular retraining and process-specific validation are required.

4. Conclusion

This study developed an intelligent fault detection and classification framework for semiconductor manufacturing using statistical learning techniques. Process sensor data, equipment information, maintenance conditions, and statistical cycle features were used to classify five major fault categories. Among the tested models, random forest achieved the best overall performance, followed by the support vector machine and linear discriminant analysis. The results confirm that statistical learning can support early fault identification and improve the interpretation of complex manufacturing data. The framework also provides useful information about the process variables responsible for each predicted fault, allowing engineers to understand the model results more clearly.

The proposed framework can help process engineers reduce wafer loss, shorten fault diagnosis time, and improve equipment maintenance decisions. It can also support continuous production monitoring by identifying the variables most strongly linked to pressure, gas-flow, power, thermal, and timing faults. Early warning of these conditions may allow corrective action before a large number of wafers are affected. Future work should include data from more production tools, recipes, product types, and manufacturing sites to improve model reliability. Online learning, automated feature updating, and real-time sensor integration may further strengthen the use of intelligent fault detection in semiconductor production.

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