Tool Health Monitoring

IE3100M Systems Design Project (AY2017/2018) | Department of Industrial Systems Engineering and Management

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Wafer Fabrication Process

Semiconductor production entails the fabrication of wafers that comprise of precise layers which together, form an electrical circuit. Recipes dictate the tools needed to manufacture a specific type of wafer.

Recipe → Tool-Wafer combination

Sensors monitor the health of tools in real-time. At the end of the entire fabrication process, random sampling of wafers checks for violation of specifications or wafer dimensions. Sensor and sampling data are used to uphold the quality level of manufactured wafers.

Sensor Data + Sampling Data = Quality Assurance

Project Overview

Problem Description

Currently, faults are mainly detected using conventional statistical process controls methodologies which is insufficient because of its inability to predict potential faults in advance. The aim of this project is to identify sensor signals, or a set of few signals, that will correlate strongly with wafers that fail eventually at the random sampling stage. A successful establishment of correlation gives Micron the confidence to erect a set of rules that operators can use to predetermine which in-line tool or wafers will fail eventually in advance.

Statistical Process Control → Data Analytics

Key Objectives

- To be able to prep and analyze data using various algorithms whilst reducing impact of white noise
- Find the best possible methodology that will provide the most efficient detection rate and the lowest false alarm rate
- Constantly feedback to data science team, the various results and effectiveness of the algorithms

Key Skills

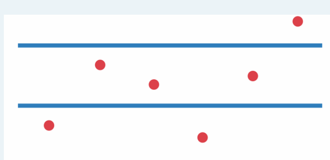
- In-depth knowledge of *Python programming*
- An understanding of Statistical Process Controls
- Aptitude in data analytics
- Data Visualization techniques

Methodologies

Data Interpretation → Generate Benchmark Performance Criteria → Data Preparation → Data Analysis → Results & Recommendations

Benchmark

To determine which wafers are faulty, 3σ limits are constructed for the sampling data. Wafers falling outside the limits constitutes a faulty wafer.



3 Sigma Limits

Out of the 27000 wafers sampled, 151 wafers are found to violate the limits. Further analysis shows only 23 of the 151 bad wafers exist in the sensor data. Sampling data is a 6-month dataset while sensor data is a 1-month dataset. Hence, these 23 wafers are taken as the benchmark.

Benchmark: 23 wafers

Proposed Methods

Variance Criteria

Time Series

Data Preparation

Grouping by recipe and sensor

There are a total of 87 sensors. Each sensor measures a small part of a tool's health, eg. Temperature. Furthermore, different recipes manufacture different types of wafers. Therefore, sensor data need to be pre-processed and categorized into distinct recipe-sensor group before conducting any analysis.

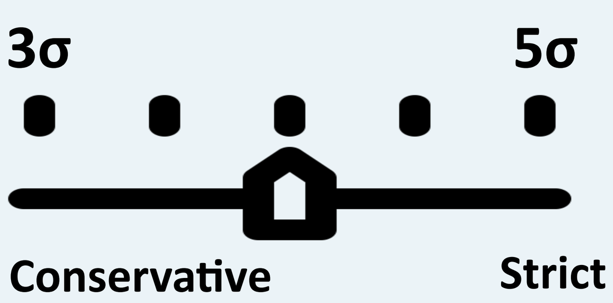
An example of a tool with sensors

Variance Criteria

- Adopting the principles from statistical process control, sigma limit charts are constructed based on the mean and standard deviation of every sensor.
- A sensor, or a combination of 2 sensors, will be flagged as potential predictive indicators if they fall outside the sigma limits across all recipes.
- Sensors showing null or zero readings are removed first to reduce white noise. Sigma limits are then constructed for the remaining 66 effective sensors out of the 87 benchmarks.

Sigma Limits Sliding Scale

- Instead of using a fixed sigma limit, a range of 3 to 5σ limits are imposed on each limits chart plotted.
- Low sigma limits produces high catch rates but also high false alarm rate. Conversely, large sigma limits reduces false alarm rates but also reduce catch rate.



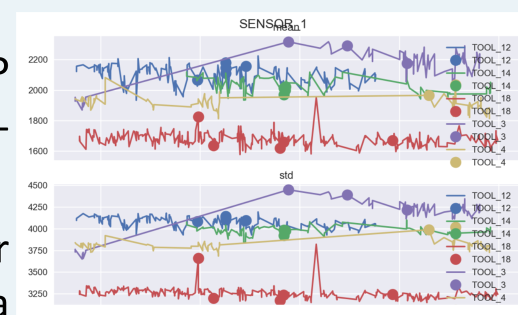
Reducing False Alarm Rate

By Tool	✓	✓	✗	✗
By Step ID	✓	✗	✓	✗

- Further grouping of dataset by tool and step ID serves to reduce the false alarm rate by recognizing differences across tools and steps
- A "second-pass" criteria is also implemented. In this criteria, a wafer is considered to violate sigma limits only if at least 2 sensors and/or under 2 step ID there are cases of violation of limits. The rationale is that if a certain tool or sensor is faulty, it is likely that it will violate under more than one condition.

Time Series

Change Point (CP) Algorithm



Sample time series

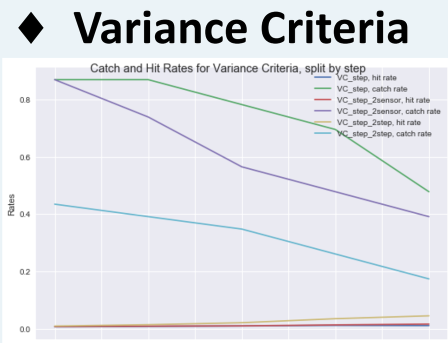
- Process shifts are indicative of a deviation from the norm and CP Algorithm attempts to identify these points in a time series dataset.
- Changes in the probability distribution along the time series for the means and standard deviations of wafers will register as a change point.
- A drift in the sampling data would reflect a change to the critical dimension (defect).
- If the time of the drifts in the sampling data (wafer health) correspond to that of the sensor

Moving Average

- The Change Point methodology could be further improved by imposing an additional measure: Moving Average pre-processing.
- This pre-processing stage allows for the smoothing of the time series sequences along various time periods of 5 data points.
- Because of this smoothing effect, the effects of drifts relative to noise is amplified thereby, increasing the sensitivity of the Change Point methodology.

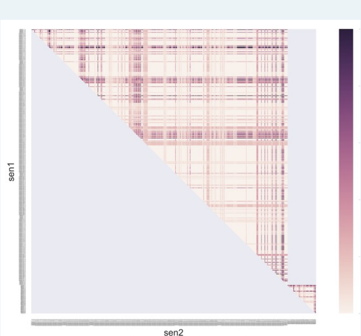
Results & Conclusion

Variance Criteria



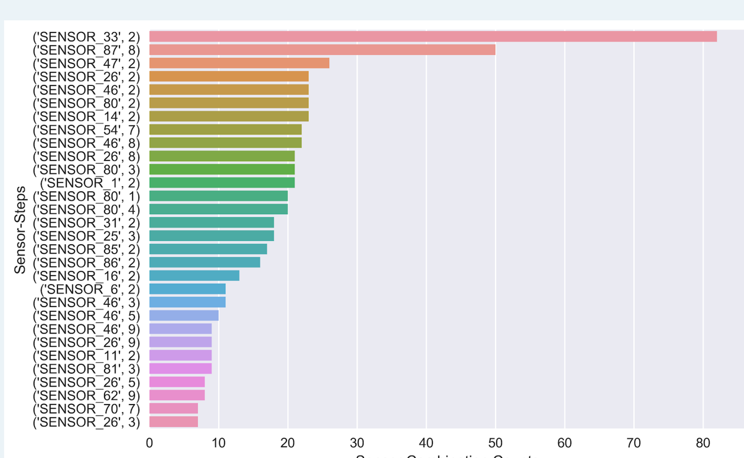
- When categorising by process steps, the second-step second-pass criteria was necessary to reduce false alarm rate, as the hit rate became non-negligible with higher sigma levels only with the second-pass filter regardless of tool differences.

- Certain sensor pairs suffer higher hit-rate than others. A heat map is used to investigate which sensor often comes up as a faulty sensor. The two axis are a list of all the 66 sensors. A dark line for a particular sensor indicates that this sensor often appears in sensor pairs which are flagged as out of limits. This is an indication that the violations are not random.



Heat Map

- A summary of the sensors that frequently appears in sensor-pairs that violates sigma limits are plotted in the chart below
- It also appears that violations occur frequently at steps 2, 8 and 9.



Change Point Algorithm

- It is found that the drifts detected by the change point algorithm in sampling data does not correlate to the violations set-up in the benchmark data
- Inconclusive data is likely because sampling data is a small proportion of the entire data population, the sparsity of data renders the CP algorithm unable to detect change points predictively or unable to detect change points altogether

Conclusion

- Variance Criteria is more effective than Change Point Algorithm
- Physical attributes of sensors, if given, will improve the grouping of datasets for analysis on a more homogeneous sample
- Change-point algorithm can investigate relationship between tool drifts and wafer defects given complete sensor dataset