TESTER ANOMALY DETECTION WITH MACHINE LEARNING MODEL PREDICTION

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ABSTRACT

Material processing complexity due to wafer-to-wafer variation has been one of the major challenges at Western Digital. Maximization of wafer usage is critical to meet the growing demand. This paper presents how the application of Fourth Industrial Revolution (4IR) technologies plays a significant role in addressing the challenges in the Testing Process.

Using the old method of detection, problematic testers are still recurring affecting high quantity of parts being defected and re-tested. This is due to delay in pulling out of bad testers from the machine, late triggering due to manual checking of Technicians from the thousands of Statistical Process Control (SPC) charts attended and validated daily.

Through the application of machine learning models for early and accurate detection of problematic testers and the elimination of manual monitoring activities by technicians, it efficiently detects out-of-control testers faster, thus preventing the production of high defects and re-testing. It also includes a tester auto-eject function when any of the machine learning models detect an out-of-control tester. Additionally, the model features auto-detection and auto-notification functions that determine if there's a change in the process, such as new specifications or new process changes.

1. 0 INTRODUCTION

Dynamic Performance Testing (DPT) is a testing process that screen out-of-specification magnetic head. Each machine has 5 testers and each tester measure 1 magnetic head.

The main objective of this system is for the early and accurate detection of problematic testers and the elimination of manual monitoring activities on the production floor.

High tester-to-tester variation can be due to mis-tests or abnormal parametric measurements. The mis-test phenomenon occurs when a test is aborted due to a tester mechanical problem, either during initial resistance checking or during loading to the disk, resulting in incomplete parametric data. Mis-test parts are identified using error codes. All parts tagged as mis-tests from initial DPT measurements will be re-tested and evaluated with other DPT machines after sorting. This process requires additional resources such as tool capacity, manpower, and materials.

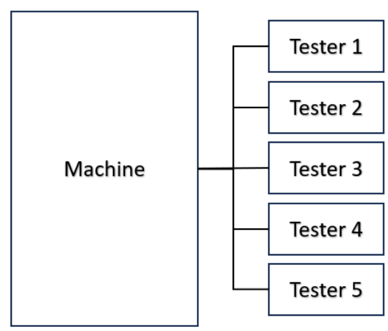

Figure 1. Illustration of DPT Machine and Testers

On the other hand, parametric variations occur when tester perform differently compared to other tester from the same machine. This can be driven by poor calibration and other abnormal tester conditions. Both scenarios contribute to high tester-to-tester variation, affecting yield.

Before the implementation of this system, mis-test detection mainly focused on the count or combination of certain error codes produced by each tester. With this method, detection is ineffective, resulting in numerous occurrences of testers without findings in Failure Analysis (FA). Another detection method is through SPC charts, wherein technicians manually check and validate out-of-control testers, leading to delays in pulling out testers.

2. 0 REVIEW OF RELATED WORK

In this study, the following concepts in anomaly detection were explored:

To detect problematic testers due to non-parametric error codes, the project investigated the concept of moving probability, also known as dynamic or evolving probability.

This concept refers to the likelihood of an event occurring, which changes over time or based on certain conditions.

The local outlier factor (LOF) is an algorithm introduced by Markus M. Breunig, Hans-Peter Kriegel, Raymond T. Ng, and Jörg Sander in 2000 within the realm of anomaly detection[2]. It aims to identify anomalous data points by assessing the local deviation of each point in relation to its neighboring points. This approach is rooted in the concept of local density, where the proximity of a data point to its k nearest neighbors is utilized to estimate its density. By comparing the density of a point to that of its neighbors, regions of similar density can be discerned, while points exhibiting notably lower density are flagged as outliers.

Another anomaly detection concept used in this study is Principal Component Analysis (PCA). Karl Pearson is credited with the development of PCA in 1901. PCA is commonly used for data preprocessing for use with machine learning algorithms. It can extract the most informative features from large datasets while preserving the most relevant information from the initial dataset. This reduces model complexity, as the addition of each new feature negatively impacts model performance, a phenomenon commonly referred to as the 'curse of dimensionality.

3.0 METHODOLOGY

The system developed to address problematic testers is commonly known as Tester Anomaly Detection (TAD). TAD is composed of 4 different algorithms, Flaggy, Local Outlier Factor (LOF), Yield Parametric Ratio (YPR) and Principal Component Analysis (PCA).

3.1 Flaggy

One persistent problem the TAD system has addressed is to reduce the occurrences of mis-tested magnetic head due to tester mechanical defects. Mechanical defects are problems because of tester's physical condition, or testing machine setup problems such as alignment issues, contact issues, and other electrical issues. Flaggy checks occurrences of at least 5 mis-tested parts out of ten consecutive tests in a moving 10 detection window.

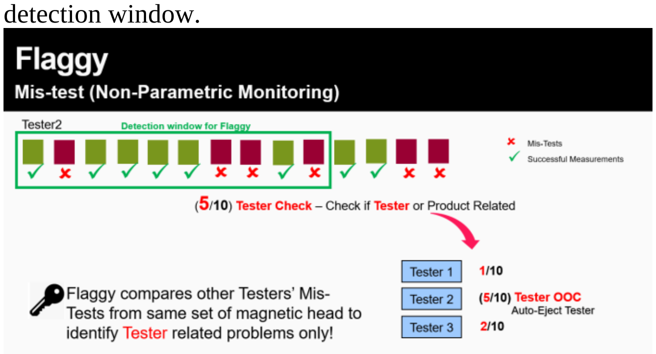

Figure 2. X denote mis-tested parts while the check symbol indicates that the measurements were taken successfully.

3.2 Local Outlier Factor (LOF)

To address parametric problems, the team needed to ascertain whether errors stemmed from inaccurate measurements by out-of-control testers or were product-related. Given that products processed in a single machine originated from the same job, it was reasonable to assume that parametric measurements at a given time would not deviate significantly from each other. Hence, the Local Outlier Factor (LOF) and Yield-Parametric Ratio (YPR) were developed to compare parametric measurements and tester yields at the machine level.

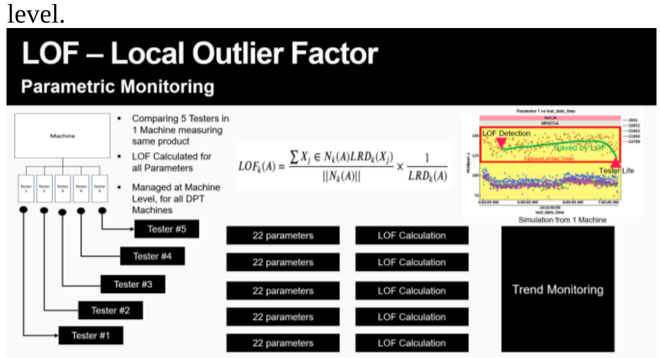

Figure 3. In the illustration above, clearly the highlighted tester behaves differently. The application of LOF algorithm, would capture this much earlier in the tester's life preventing the exposure of other magnetic head to this problematic tester.

LOF compares parametric measurements captured by each of the 5 testers to those of the other testers in the same machine. It starts off by calculating the LOF value for every parameter measurement in a 15-minute time range. It is based on a concept of a local density, where locality is given by k nearest neighbors whose distance is used to estimate the density. By comparing the local density of an object to the local densities of its neighbors, we can identify regions of similar density, and points that have a substantially lower density than their neighbors. The algorithm then uses these LOF values to spot outlier behavior of a tester in comparison with the other testers in the same machine.

3.3 Yield Parametric Ratio (YPR)

YPR or Yield Parametric Ratio is similar to LOF, but instead of parametric measurements, it compares parametric yield of each tester to the yield of all other testers in the same machine. Parametric yield is calculated by getting the ratio of parts tested within the parameter spec limit and total number of parts tested. We calculate this for all parameters in each tester. Like what the LOF does, the algorithm then uses these YPR values to spot outlier behavior of a tester in comparison with other testers in the same machine. Capturing problematic testers that would have exposed more parts, causing issues otherwise.

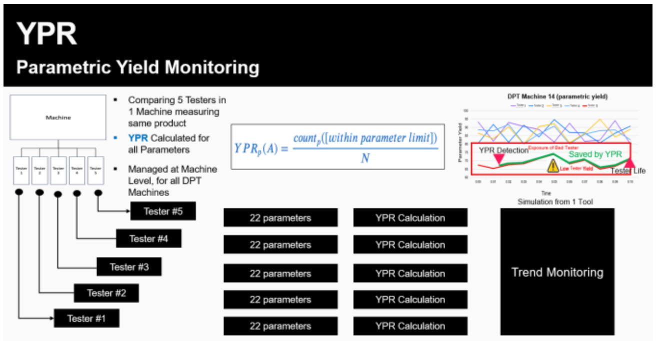

Figure 4. Illustration of how YPR detect outlier tester.

3.4 Principal Component Analysis (PCA)

Principal Component Analysis or PCA which checks parametric measurements of all testers. The algorithm performs principal component analysis to reduce the dimensionality of the dataset as we are processing all data from production testers.

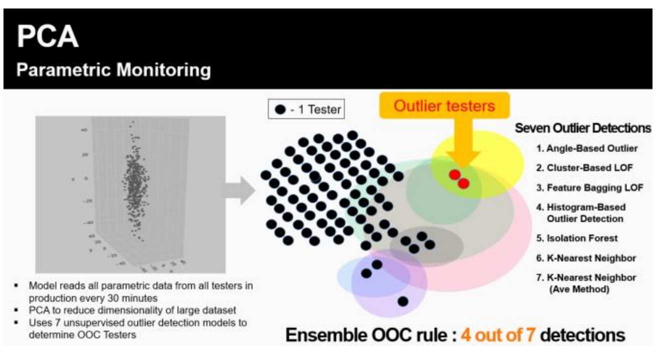

Figure 5. Illustration how PCA detects outlier tester.

In the above illustration, one dot is a tester that is plotted in a 2-dimensional space representing all its electrical parameters. Then, 7 unsupervised learning algorithms[3] are performed to identify outlier testers. These are:

- Angle-based outlier
- Cluster-based LOF
- Feature Bagging LOF
- Histogram-Based Outlier Detection
- Isolation Forest
- K-Nearest Neighbor
- Average method K-Nearest Neighborhood.

If at least 4 out of these 7 algorithms identify a tester as an outlier, the tester is considered out of control.

3.5 Implementation

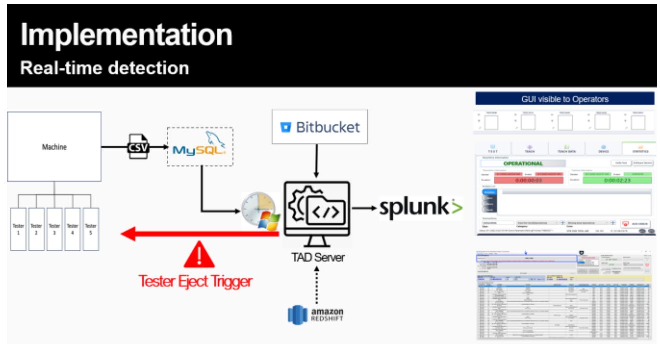

Figure 6. TAD Infrastructure

Testing produces a CSV file output after each test which is then loaded to Real-time Parametric Monitoring or RTPM database which is the main data source of the detection algorithms.

The algorithms are triggered through Windows Tasks Scheduler and when an anomalous tester is detected, the TAD server sends a signal to the machine by inserting a record to a data table in RTTC database to eject that tester out of the machine automatically, thus preventing possible further incorrect or invalid test results.

To implement the machine learning models, the team setup a MySQL database where all the test parametric values get stored in real time. These data are then use by the TAD server for model inferencing. Essentially, applying the algorithms discussed earlier.

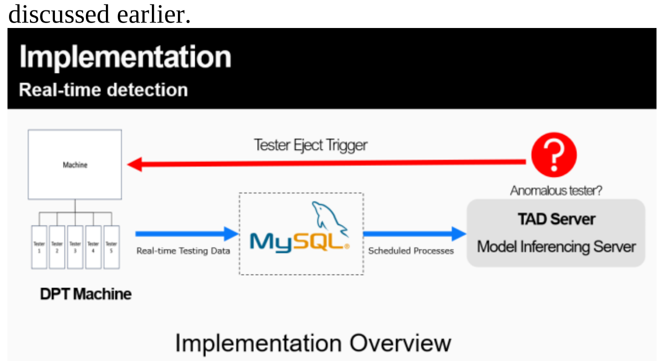

Figure 7. Implementation Overview

3.6 Splunk Visualization

Alongside the Machine Learning Models implemented on the production floor, Splunk dashboards aim to monitor the health of machine learning models. One of these is the Model Accuracy Summary, which shows the Detection Accuracy Level per Product. Within the dashboard, users can select the product they wish to check. The bar chart displays how many testers each model detected, while the line chart represents the detection accuracy. For each model, a summary of findings is also provided, indicating where specific tester part defects occur, thus enabling accurate improvement efforts.

Figure 8. Model Report Dashboard for Detection Accuracy. Detection accuracy refers to the proportion of testers with findings correctly identified by the Machine Learning Model out of the total number of testers detected by the model.

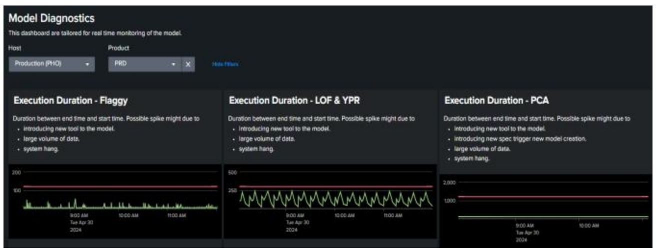

Figure 9. Model Diagnostic Dashboard for Model Performance Visualization

Figure 9 depicts another dashboard called the Model Resource Performance visualization, designed to monitor server performance, and ensure that each model operates within the normal running time per batch.

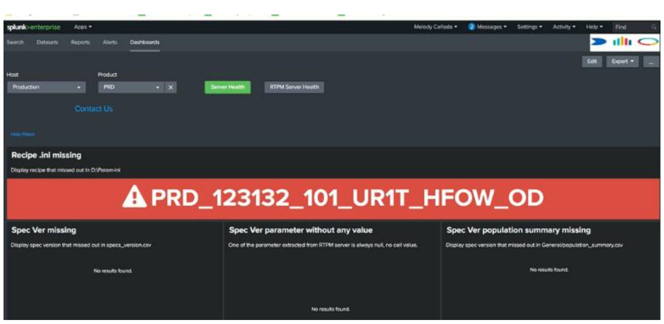

Figure 10. Model Configuration Dashboard

Another visualization is dedicated to detecting any new specifications or recipes introduced in production that require inclusion in the model configuration. Figure 10 provides an example of an alerted recipe.ini file that has not yet been added to the model configurations.

All these visualizations have an auto-notification feature that alerts the Test Team about changes in the model.

4.0 RESULTS AND DISCUSSION

Upon the implementation of this Machine Learning models, Below problems were addressed.

4.1 Reduced High Tester-to-Tester Variation

The initiative to address delayed triggering in problematic testers has yielded impressive results, notably reducing mis-tests by 58%. This improvement is attributed to the successful implementation of a real-time detection system for tester problems. The introduction of this system not only enhances the efficiency and accuracy of our testing processes but also contributes to significant resource savings. With fewer mis-tests, there's a reduced need for re-testing, leading to savings in tool capacity, manpower, and materials. This streamlined approach not only optimizes our operational efficiency but also translates into tangible cost savings, further reinforcing the value of investing in technological advancements for process improvement.

4.2 Elimination of Manual Monitoring

The introduction of this system marks a significant advancement by removing the necessity for manual monitoring tasks previously undertaken by technicians to identify and resolve issues with problematic testers. Prior to the system's implementation, technicians were required to dedicate a substantial portion of their time, nearly 70%, towards meticulously managing a vast array of approximately 1800 Statistical Process Control (SPC) charts each day. These charts were essential for scrutinizing the performance of the numerous testers utilized in the production process. This labor-intensive process not only consumed valuable time but also posed a considerable challenge in promptly addressing emerging issues and ensuring the smooth operation of the production line. With the adoption of automated monitoring and detection capabilities provided by the new system, technicians can now redirect their focus towards more strategic tasks, thereby enhancing efficiency, accuracy, and overall productivity within the manufacturing environment.

4.3 Improve Detection Accuracy

By enhancing detection accuracy, the system is able to identify genuine tester issues more effectively, resulting in a significant improvement from detecting issues in only 32% of testers to identifying problems in over 90% of testers with findings. This substantial increase in accuracy ensures that a higher percentage of potential issues are captured and addressed, thereby enhancing overall quality control and reducing the likelihood of defective products reaching the market.

Table 1. Summary of KPI Improvement

KPI	Unit	%Improvement from Baseline
Material Damage Rate	%	58%

Detection Accuracy	%	181%
Labor Productivity	%	75%

5.0 CONCLUSION

The adoption of Fourth Industrial Revolution (4IR) technologies within our manufacturing site represents a transformative step towards enhancing efficiency, productivity, and yield. By integrating cutting-edge technologies such as automation, Internet of Things (IoT), artificial intelligence (AI), and data analytics into our operations, we're revolutionizing traditional manufacturing processes. This technological evolution enables us to streamline operations, optimize resource utilization, and minimize downtime through predictive maintenance and real-time monitoring. Additionally, leveraging AI and advanced analytics enhances decision-making capabilities, enabling us to identify and address inefficiencies proactively. As a result, our manufacturing site experiences improved throughput, reduced cycle times, and increased overall yield. The adaptation of 4IR technologies not only enhances our competitive edge but also positions us for sustained growth and success in the rapidly evolving manufacturing landscape.

6.0 RECOMMENDATIONS

It is recommended that the learnings and improvements made in this project be disseminated to other similar processes to enhance detection capability, efficiency, and productivity.

7.0 ACKNOWLEDGMENT

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8.0 REFERENCES

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9.0 ABOUT THE AUTHORS

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