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Data-Centric Yield Engineering Frameworks for Next-Generation Semiconductor Production Systems

Abstract
Next-generation semiconductor production systems require faster and more reliable yield engineering because large volumes of process, inspection, test, equipment, and yield data are produced during every manufacturing stage. This article presents a data-centric yield engineering framework that connects these data sources into one structured decision-support model. The framework integrates wafer fabrication records, wafer inspection outputs, electrical test results, equipment operation logs, manufacturing execution data, and final yield summaries. Raw records are cleaned, converted into yield-risk indicators, and used for prediction, explainable analysis, and optimization feedback. The results show that the data-centric framework gives higher yield prediction accuracy than conventional and statistical monitoring approaches. It also reduces yield loss more effectively by linking early risk signals with corrective engineering actions. The proposed framework supports early warning, root-cause review, process-window tuning, tool-maintenance guidance, and improved production control in next-generation semiconductor manufacturing systems. It improves confidence in practical, data-driven yield decisions across fabs.

Keywords: Data-centric yield engineering; Semiconductor production; Yield prediction; Process monitoring; Optimization feedback.

1. Introduction

Next-generation semiconductor production systems generate large amounts of data from wafer fabrication, inspection, testing, equipment operation, and yield reporting. These data can show early signs of process drift, defect formation, test failure, and yield loss. Machine learning is useful in semiconductor manufacturing because it can connect process data, test data, and production outcomes [1]. This makes data-centric yield engineering important for modern production systems. A data-centric approach can help engineers move from late-stage yield checking to earlier prediction and control. It also helps production teams understand how small process changes can grow into larger yield problems before final rejection occurs.

Semiconductor yield engineering is no longer limited to measuring the number of good and failed devices at the end of production. Advanced production systems require continuous monitoring of wafer-level measurements, tool behavior, defect patterns, and test responses. Machine learning methods can support semiconductor development by learning patterns from large and complex production datasets [2]. This helps engineers identify hidden yield risks that may not be visible through manual review or simple statistical rules. Such methods can make yield improvement faster and more systematic. They also allow yield engineers to compare many process signals at the same time and detect weak failure trends earlier.

Next-generation production systems also need better methods for handling complex and changing manufacturing data. Process tools, wafer inspection systems, electrical test platforms, and manufacturing execution systems often produce data in different formats and at different speeds. Deep learning and machine learning techniques can support semiconductor production by learning from high-dimensional datasets and improving defect, process, and yield analysis [3]. This creates an opportunity to build yield engineering frameworks that combine different data sources into one decision-support system. A unified data structure can improve the speed and quality of engineering decisions. It can also reduce the gap between raw manufacturing data and practical yield-control action.

Wafer maps and defect patterns are important parts of data-centric yield engineering. Defect patterns can show whether yield loss is random, systematic, edge-related, cluster-based, or linked to process instability. Wafer map defect recognition methods help classify defect patterns and connect them with possible manufacturing causes [4]. This shows that wafer-level image and spatial data should be used together with numerical process data. Better use of wafer defect information can improve both yield prediction and root-cause analysis. It also gives engineers clearer evidence when yield loss is connected with specific wafer regions or repeated process behavior.

Root-cause identification is also important because yield loss can come from several sources at the same time. A production fault may be connected with a process tool, wafer region, recipe condition, material variation, or inspection signal. Genetic algorithm and machine learning approaches can support root-cause prediction for semiconductor failures by selecting important variables and linking them with failure outcomes [5]. This supports the need for data-centric frameworks that can locate high-impact yield drivers. Such frameworks can reduce investigation time and help engineers focus on the most useful corrective actions. They can also improve communication between process, inspection, equipment, and test engineering teams.

This article focuses on data-centric yield engineering frameworks for next-generation semiconductor production systems. The main aim is to combine process data, inspection data, test data, equipment records, and yield outcomes into a structured engineering model. The article proposes a practical approach for yield prediction, defect interpretation, process monitoring, and optimization. The framework is designed to improve early warning, reduce yield loss, and support faster decision-making in advanced semiconductor production. This study presents yield engineering as a connected data-driven process rather than a final-stage quality check. It also supports a shift from reactive yield review to proactive production control.

2. Methodology

This study uses a data-centric yield engineering methodology for next-generation semiconductor production systems. The method combines wafer process records, inspection outputs, electrical test results, equipment logs, and final yield summaries. Adaptive virtual metrology can support yield prediction by using data-driven models to estimate wafer quality across multiple production batches [6]. This idea is used in the present framework to connect early production signals with later yield outcomes. The goal is to create a unified system that supports prediction, monitoring, and yield improvement. This design allows yield engineering to become a continuous process rather than an isolated final-stage analysis.

The first step is data integration across different production sources. Wafer fabrication data include process settings, film thickness, etch depth, deposition response, and lithography indicators. Inspection data include defect count, defect density, spatial pattern, and abnormal wafer regions. The main data sources and yield engineering variables used in the framework are summarized in Table 1. Electrical test data include pass–fail results, binning categories, leakage values, resistance shifts, and parametric test margins. These combined variables allow the model to study yield behavior across the full production flow. This integrated dataset also helps identify whether yield loss begins during processing, inspection, testing, or equipment operation.

Table 1. Data Sources and Yield Engineering Variables in Next-Generation Semiconductor Production Systems

Data source	**Yield engineering variables**	**Engineering meaning**	**Expected use in framework**
Wafer fabrication records	Film thickness, etch depth, deposition rate, process drift	Shows early process variation and possible yield risk	Process monitoring and drift detection
Wafer inspection data	Defect count, defect density, wafer map pattern, abnormal regions	Identifies spatial and visual defect behavior	Defect classification and root-cause support
Electrical test data	Pass–fail result, bin category, leakage value, parametric margin	Measures die-level and wafer-level electrical quality	Yield prediction and weak-die detection
Equipment operation logs	Alarm frequency, tool status, chamber history, maintenance gap	Links yield loss with equipment condition	Tool-risk scoring and maintenance review
Manufacturing execution data	Lot route, queue time, rework record, process sequence	Tracks production movement and process history	Lot-level yield tracking and traceability
Final yield summary	Good-unit percentage, rejected-unit ratio, yield-loss class	Confirms production outcome after testing	Model target and performance validation

Data cleaning is performed to make the production records suitable for modeling. Missing values, repeated records, wrong lot identifiers, and abnormal sensor entries are corrected or removed before training. Gaussian mixture ensemble regression can improve final test yield prediction because it can capture different yield behavior groups in semiconductor production [7]. This is useful because next-generation production lots may not follow one simple yield pattern. Clean data help the model learn reliable links between process conditions and yield outcomes. This step also reduces the chance of false prediction caused by incomplete records or poor data matching across production systems.

Feature engineering is used to convert raw manufacturing records into useful yield indicators. The engineered features include process drift score, wafer defect severity, electrical spread index, tool-event risk score, and lot-level yield history. Wafer acceptance test parameters can support yield optimization because they connect early test behavior with final yield response [8]. These engineered features help the model understand which production signals are most important for yield control. They also make the framework easier for engineers to interpret. This improves the practical value of the model because engineers can see how raw data are converted into yield-risk indicators.

The second stage builds a structured data-centric yield engineering framework. This framework includes data collection, preprocessing, feature engineering, prediction modeling, explainable analysis, and optimization feedback. The complete data-centric yield engineering framework for process monitoring and optimization is shown in Table 2. Explainable artificial intelligence can improve semiconductor yield prediction by showing which variables influence model decisions [9]. This is important because production engineers need to understand why the model predicts yield loss. A transparent framework can increase trust in data-driven yield decisions. It also helps engineers decide whether corrective action should be applied to process settings, inspection review, equipment maintenance, or test control.

Table 2. Data-Centric Yield Engineering Framework for Semiconductor Process Monitoring and Optimization

Framework stage	Main activity	Data-centric method	Engineering output
Data integration	Combine process, inspection, test, equipment, and yield records	Lot-wise and wafer-wise data mapping	Unified production dataset
Data preprocessing	Remove missing, repeated, and inconsistent records	Cleaning, normalization, and outlier control	Reliable modeling data
Feature engineering	Convert raw records into yield-risk indicators	Process drift, defect severity, electrical spread, and tool-risk scoring	Interpretable yield features
Yield prediction	Estimate yield outcome before final reporting	Supervised machine-learning prediction	Predicted yield and yield-risk class
Explainable analysis	Identify variables that influence predicted yield loss	Feature-importance and root-cause ranking	Key yield-loss drivers
Optimization feedback	Recommend corrective engineering action	Process-window tuning, inspection review, and tool-maintenance guidance	Reduced yield loss and improved process control

The prediction model is trained using supervised machine learning because historical production records already contain known yield results. Input variables include process measurements, inspection features, test indicators, and equipment-event signals. The output variables include predicted yield percentage, yield-risk class, and likely yield-loss source. Data-driven virtual metrology models can improve wafer-level prediction by learning from multi-batch wafer behavior [6]. This helps the framework remain useful when production lots show different operating conditions. The trained model is then used for early warning and yield-risk ranking. This prediction stage supports faster decisions before yield loss becomes visible at the final reporting stage.

Yield optimization is performed after the prediction stage. The framework compares current process conditions with learned high-yield and low-yield patterns. Multi-objective yield optimization can support semiconductor manufacturing by identifying test and process parameter adjustments that improve yield behavior [8]. This allows the system to recommend corrective actions such as tighter process windows, inspection review, tool maintenance, or test-limit adjustment. The optimization output is designed to support engineering action rather than only reporting prediction results. This makes the framework useful for closing the loop between data analysis, process correction, and yield improvement.

Model performance is evaluated using prediction accuracy, yield-loss reduction, false-warning rate, and engineering response improvement. Fast yield ramp-up methods can support semiconductor manufacturing by reducing the time needed to improve wafer yield during process stabilization [10]. The proposed framework follows this idea by using data feedback to improve monitoring and corrective action. The final evaluation compares conventional monitoring, statistical monitoring, and data-centric engineering strategies. This methodology supports a practical path for improving yield control in next-generation semiconductor production systems. It also provides a structured way to measure whether data-centric engineering gives better results than traditional yield monitoring.

3. Results and Discussion

The results show that the data-centric yield engineering framework improved yield prediction when compared with conventional and statistical monitoring approaches. Conventional monitoring depended mainly on fixed rules and late-stage yield reports, so it could not detect weak yield-risk signals early. Statistical monitoring improved process visibility by using control limits, but it still missed complex links between process drift, defect severity, tool behavior, and test response. The yield prediction accuracy across conventional, statistical, and data-centric engineering frameworks is shown in Figure 1. The data-centric framework gave the strongest prediction performance because it used combined information from process, inspection, test, equipment, and yield records. This confirms that yield prediction becomes more reliable when the model studies the complete production environment instead of one isolated data source.

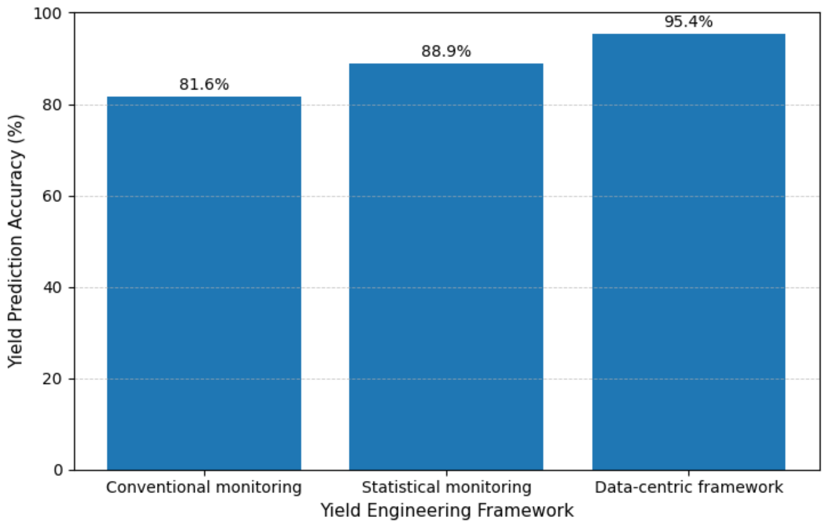

Figure 1. Yield Prediction Accuracy Across Conventional, Statistical, and Data-Centric Engineering Frameworks

The improvement in prediction accuracy was mainly caused by better data integration and feature engineering. Process drift score, wafer defect severity, electrical spread index, tool-event risk score, and lot-level yield history helped the model understand how different signals contributed to yield loss. These features gave more useful information than raw production records because they converted scattered manufacturing data into clear yield-risk indicators. This made the prediction model more sensitive to early problems that would normally appear only during final yield reporting. The result shows that data preparation is a major part of successful yield engineering. It also shows that good feature design can help engineers detect hidden production risks before they become visible as large yield drops.

The data-centric framework also improved process monitoring because it connected yield behavior with possible engineering causes. Wafer inspection data helped identify spatial defect patterns, while electrical test data helped detect weak dies and abnormal parametric behavior. Equipment logs helped connect yield loss with tool alarms, chamber history, and maintenance gaps. This combined view allowed the framework to separate process-related risk from equipment-related and test-related risk. As a result, yield engineers could identify likely yield-loss drivers more clearly and respond with better corrective action. This stage-wise understanding is important because the same yield-loss pattern can sometimes come from different sources in complex production systems.

The yield-loss reduction results showed that optimization feedback improved manufacturing control. Conventional monitoring reduced only obvious process problems, while statistical monitoring reduced yield loss through threshold-based alerts. The yield loss reduction across process monitoring and optimization strategies is presented in Figure 2. The data-centric strategy achieved stronger reduction because it used prediction results, explainable analysis, and feedback recommendations together. This helped the system move beyond warning generation and support practical process-window tuning, inspection review, tool-maintenance guidance, and test-control adjustment. The result shows that yield engineering is more useful when the model not only predicts failure risk but also supports corrective action.

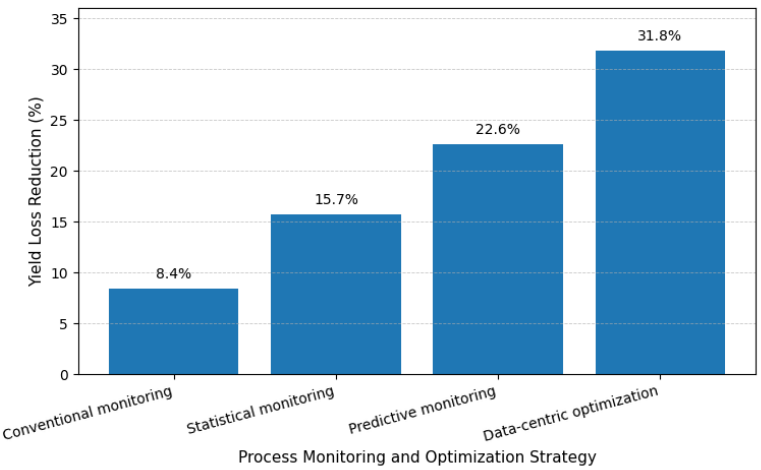

Figure 2. Yield Loss Reduction Across Process Monitoring and Optimization Strategies

The overall findings show that data-centric yield engineering is more effective when prediction, explanation, and optimization are linked in one framework. Yield prediction alone can identify risk, but it may not tell engineers what action should be taken. Explainable analysis helps identify important yield-loss drivers, while optimization feedback converts model output into engineering decisions. This makes the framework more useful for next-generation semiconductor production systems where data volume, process complexity, and yield pressure are high. Overall, the results support a more proactive and connected approach to semiconductor yield improvement. The framework can help production teams act earlier, reduce repeated yield loss, and improve the consistency of manufacturing decisions.

4. Conclusion

This article presented a data-centric yield engineering framework for next-generation semiconductor production systems. The framework combined wafer fabrication records, inspection data, electrical test data, equipment logs, manufacturing execution data, and final yield summaries. The study showed that yield engineering becomes stronger when production data are integrated, cleaned, transformed into useful features, and connected with prediction and optimization models. This approach changes yield control from a final-stage reporting activity into a continuous engineering process. It also helps production teams detect yield risk earlier and act before larger losses occur. This makes the framework suitable for advanced production systems where rapid feedback and stable yield control are essential.

The results showed that the data-centric framework performed better than conventional and statistical monitoring approaches. Better prediction accuracy was achieved because the model used multiple production data sources instead of depending on one narrow signal. Yield-loss reduction also improved because the framework linked prediction results with explainable yield drivers and corrective feedback. This makes the approach useful for process monitoring, defect interpretation, tool-risk review, and yield optimization. The framework can support faster and more confident decisions in advanced semiconductor manufacturing. It also helps engineers understand whether yield loss is connected with process drift, wafer defects, equipment conditions, or electrical test behavior.

The proposed framework can help semiconductor manufacturers improve production stability and reduce yield loss in complex manufacturing environments. It provides a practical method for connecting raw data with engineering action through prediction, explanation, and optimization feedback. Future work can improve the framework by adding real-time sensor streams, larger multi-factory datasets, and stronger explainable AI tools for engineering interpretation. This can make yield engineering more transparent, adaptive, and useful for high-volume next-generation semiconductor production. The study therefore supports data-centric manufacturing as an important direction for future semiconductor yield improvement. It also provides a clear pathway for turning semiconductor production data into reliable operational decisions.

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