# Data-Driven Approaches to Yield Prediction in Semiconductor Manufacturing

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Semiconductor yield prediction forecasts the number of functional chips resulting from a wafer after completing the fabrication process. It systematically analyses extensive data collected during production - including process parameters, equipment performance metrics, environmental conditions, etc. By leveraging this data, manufacturers can identify potential defects, predict yield outcomes and implement proactive measures to optimise production processes.

The evolution of yield prediction methodologies has shifted from traditional statistical process control techniques to advanced data-driven models. Modern approaches incorporate sophisticated analytics, machine learning (ML) algorithms and big data frameworks. These tools enable precise, dynamic and scalable yield forecasting - allowing manufacturers to manage process variability proactively and enhance yield rates, while also maintaining a competitive edge in an increasingly complex semiconductor landscape.

As semiconductor manufacturing processes become increasingly intricate and data-intensive, more advanced data-driven methodologies will emerge as indispensable yield prediction tools. These approaches are set to enhance predictive accuracy and uncover hidden patterns/correlations within large datasets that traditional methods might overlook. Thus, it is essential to understand the key data-driven methodologies transforming yield prediction, highlighting their principles, applications and impact on semiconductor manufacturing efficiency. Then, these should be adopted into daily manufacturing and product development flows.

## Data-driven methodologies for yield prediction

Data-driven yield prediction in semiconductor manufacturing can be broadly classified into basic, advanced and hybrid methodologies - reflecting the evolution from traditional statistical techniques to cutting-edge integrated models.

- Basic approach - This relies on traditional statistical techniques, such as regression models, analysis of variance and statistical process control (SPC). It helps identify relationships between process parameters and yield, monitoring process stability, so as to detect anomalies. It can likewise be handy for establishing baseline process performance, understanding historical trends and supporting root cause analysis during yield excursions. However, while effective for essential process monitoring, it struggles with the high-dimensional data, non-linear interactions and dynamic process variations that are typical in modern semiconductor environments. This limits its predictive accuracy in complex manufacturing scenarios.

- Advanced approach - Here advanced statistical techniques and ML models are leveraged in order to address the complexities of modern fabrication processes. Multivariate statistical process control enhances traditional SPC by monitoring multiple correlated variables, enabling the detection of subtle process shifts in operations like photolithography. Bayesian inference offers probabilistic forecasts by integrating prior knowledge with real-time data, while survival analysis predicts time-to-failure for components, supporting proactive maintenance. ML models elevate yield prediction through supervised learning (e.g. random forests) for defect density prediction in chemical vapour deposition (CVD), unsupervised learning for anomaly detection and deep learning for wafer defect classification plus time-series forecasting. A notable example is CuLitho by NVIDIA, which

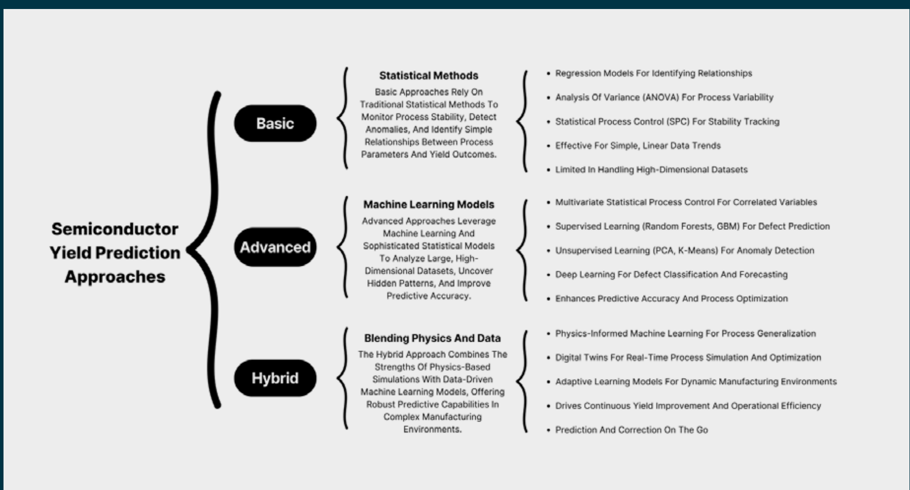


Figure 1: The 3 approaches to semiconductor yield prediction

uses GPU-accelerated deep learning to optimise photomask designs, significantly enhancing yield prediction for advanced semiconductor nodes.

- Hybrid approach – This integrates physics-based models with ML techniques to enhance predictive accuracy and process optimisation. Physics-informed machine learning (PIML) combines domain-specific knowledge with data-driven algorithms, improving model generalisation in complex processes like extreme ultra-violet (EUV) lithography, where optical simulation data is merged with ML to predict overlay errors and boost yield in sub-3nm nodes. Additionally, digital twins create real-time virtual replicas of manufacturing processes, enabling continuous monitoring, scenario testing and proactive yield optimisation without disrupting actual production. Companies like Applied Materials and TSMC integrate hybrid models into advanced process control systems to drive continuous yield improvements at scale.

## Challenges in data-driven yield prediction

Data-driven yield prediction in semiconductor manufacturing presents several technical and operational challenges that can impact the accuracy, reliability and efficiency of predictive models. These challenges stem from the intricacy of semiconductor processes, the vast volumes of data generated and the dynamic nature of manufacturing environments. Understanding and addressing these challenges is crucial for developing robust predictive models and optimising manufacturing performance.

Tackling these issues requires a multi-disciplinary strategy that blends semiconductor process expertise with data science and artificial intelligence (AI). Manufacturers can fully unlock the potential of data-driven yield prediction by adopting advanced data preprocessing techniques, leveraging explainable AI (XAI), optimising computational resources and ensuring continuous model adaptation. Overcoming these hurdles will also improve predictive accuracy, increase manufacturing efficiency, reduce costs and enhance product quality in semiconductor fabrication.

## What next for semiconductor yield prediction?

As semiconductor production continues to evolve, the future of yield prediction will be shaped by integrating more sophisticated data-driven methodologies, real-time analytics and automation. Emerging technologies like AI, which can potentially enable on-device data processing, will play a critical role in reducing latency and enhancing real-time decision-making at the equipment level. XAI will become increasingly important, providing greater transparency into complex models and fostering trust in data-driven decisions among process engineers and stakeholders.

Additionally, self-adaptive learning systems, capable of continuously retraining models with new data, will improve the robustness and accuracy of yield predictions, especially in dynamic manufacturing environments where process changes are frequent. The growth of digital twins will also redefine process optimisation, allowing for real-time simulation, predictive maintenance and scenario testing without impacting upon production lines.

Furthermore, as semiconductor nodes shrink below 2nm and process complexities increase, the demand for cross-disciplinary collaboration between data scientists, process engineers and materials scientists will intensify further. The convergence of AI with advanced metrology tools will create more comprehensive data ecosystems, driving reactive and prescriptive predictive models, as well as proactively guiding process adjustments. Ultimately, the next frontier for yield prediction lies in building autonomous manufacturing ecosystems where predictive models are deeply integrated with process control systems. This will enable fabs to keep competitive by achieving higher yield rates, reduced operational costs and faster time-to-market.

| Challenge | Description | Potential Solutions |
|---|---|---|
| **Data quality issues** | Missing values, noise, outliers and inconsistencies from equipment malfunctions, sensor errors, or logging issues can obscure meaningful patterns. | Advanced preprocessing, data validation protocols, and robust data cleaning techniques. |
| **High dimensionality** | Numerous variables (process parameters, equipment metrics, environmental conditions) can lead to overfitting and poor generalisation. | Dimensionality reduction, feature selection algorithms and regularisation methods. |
| **Model interpretability** | Complex models like deep neural networks operate as 'black boxes' - making it hard to understand prediction drivers. | XAI techniques, such as SHAP and LIME, can enhance transparency and stakeholder trust. |
| **Real-time processing** | Low-latency yield predictions are required in high-throughput environments, posing technical challenges with large data volumes. | Edge computing, optimised model architectures and distributed computing frameworks. |
| **Data integration and heterogeneity** | Diverse data sources (equipment logs, sensors, metrology tools) with varying formats and quality complicate unified modelling. | Standardised data pipelines, data fusion techniques and consistent data governance practices. |
| **Dynamic process variability** | Frequent changes in equipment, processes and materials can render models trained on historical data less effective. | Continuous model retraining, transfer learning and adaptive learning techniques will maintain model relevance. |
| **Resource constraints** | Advanced models require significant computational resources for training and deployment. | High-performance computing, efficient algorithm design and model compression enable resource optimisation. |
| **Evolving data tools** | Rapid advancements in data tools can lead to integration challenges, compatibility issues and increased complexity in managing data workflows. | Adoption of flexible, scalable data platforms, continuous tool evaluation and seamless integration strategies with existing systems. |

Table 1: Resolving data-driven yield prediction issues