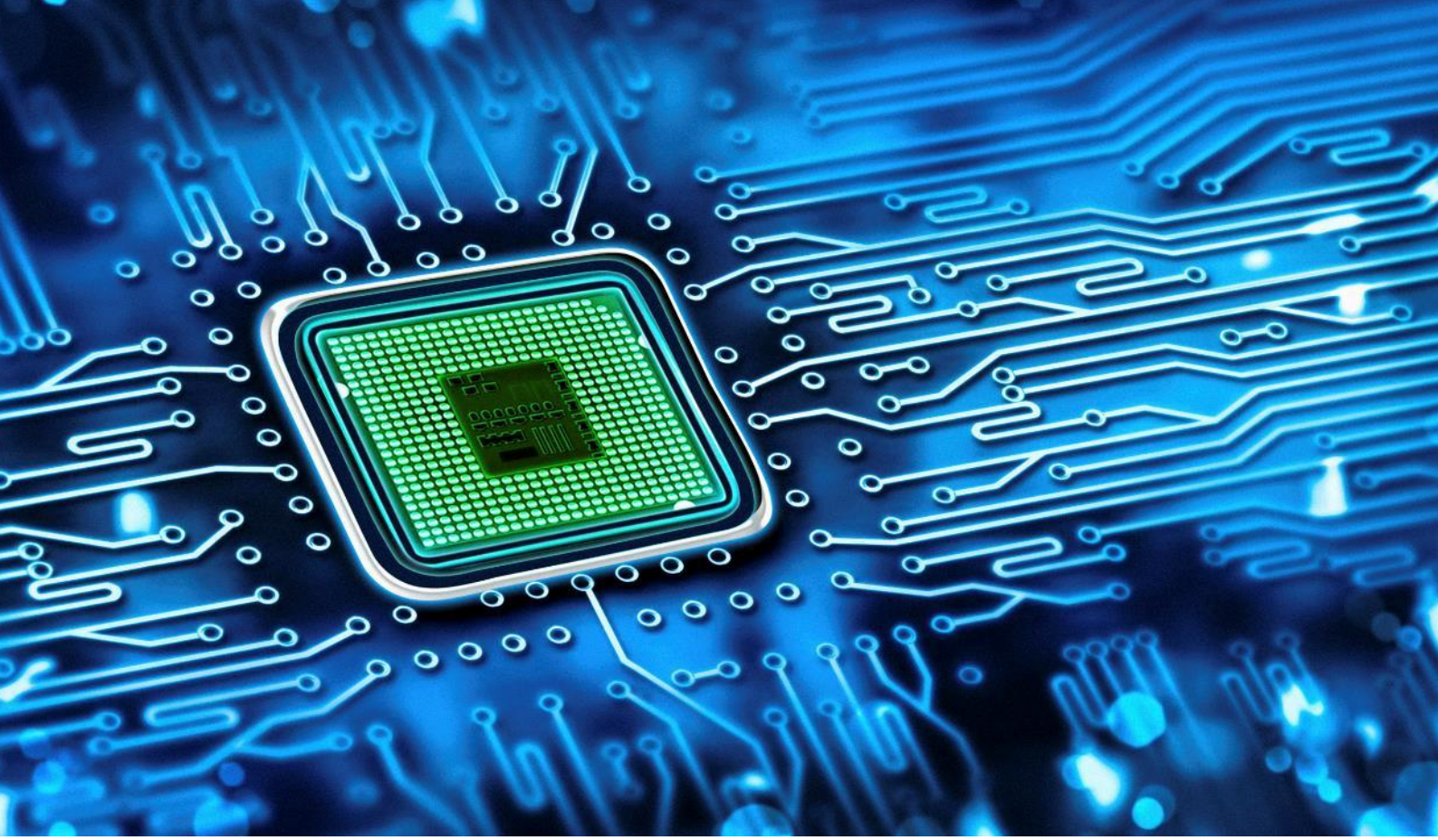


ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN SEMICONDUCTOR AND ELECTRONICS PRODUCTION

Industrial AI conquers the shopfloor

Artificial intelligence (AI) and machine learning (ML) have been successfully introduced into many industrial applications and provide significant benefits in terms of manufacturing yield and cost. Faced with increasing pressure to speed up time to market, manufacturing flexibility, and product output, the semiconductor and electronics industry will benefit from applying AI/ML at the operator, equipment, and process levels.

SIEMENS

INDUSTRIAL MACHINE LEARNING

Beyond the adoption barrier

Over the last decade, the rise of Big Data and AI created a hype which led to enormous business expectations. Following the first successful use cases and applications in the semiconductor and electronics industry, AI/ML is now set to establish itself as a valuable technology along the whole value chain.

Industry meets AI

A recent McKinsey article[1] identifies semiconductor manufacturing as the use-case domain where AI/ML will deliver the most value in terms of impact on earnings – about 40% of the total business impact across all analyzed verticals. AI/ML can reduce costs, improve yields, and increase a fab's throughput. The authors of the article estimate that, over the long term, AI/ML will decrease manufacturing costs (both cost of goods sold and depreciation) by up to 17%. However, in the same publication, a survey of semiconductor-device makers shows that only about 30% of respondents stated that they are already generating value through AI/ML.

Data challenges in industrial environments

One adoption barrier that complicates the transfer of a promising Proof-of-Value (PoV) into an industrial-grade application of AI is the nature of the industrial shopfloor. ML models typically rely on static historical extracts of generally dynamic data for training. But data may change rapidly, sometimes in an unknown and undetected manner once models are implemented in production. So a model's predictive performance and reliability is likely to decrease over time. This poses the challenge of keeping models up to date with both high performance and reliability to generate the promised value. Emerging solutions for continuous monitoring and testing of ML systems can resolve this technical challenge, paving the way for a more widespread application of AI/ML in semiconductor and electronics manufacturing.

AI/ML as a tool to tackle future challenges

AI/ML proves to be a valuable tool in optimizing the entire manufacturing value chain. AI/ML can be applied at various stages throughout the process and on various levels:

- Operator level
  AI/ML can aid and/or guide the operator during manual tasks. The AI/ML application will help identify errors or defects, support the correct execution of work instructions, and document the work result.
- Equipment level
  When deployed close to the machine, the AI/ML application can monitor or reevaluate process results – for instance, to assess product or process quality or to improve automatic inspection procedures. This can help improve important KPIs such as Overall Equipment Effectiveness (OEE) and First Pass Yield (FPY).
- Process level
  AI/ML can also assist or replace process-control routines at the automation level. This approach can help optimize processes for specific material or equipment properties and optimize process performance in multivariate settings.

[1] Scaling AI in the sector that enables it: Lessons for semiconductor-device makers, McKinsey & Company, 2021

OPERATOR LEVEL AI/ML USE CASE

Industrial visual inspection

AI/ML helps detect placement and completeness in existing manual assembly and packaging stations.

The challenge: preventing assembly and packaging errors during manual processes

Despite a steadily increasing automation level, many operations in the electronics industry still rely on manual procedures. As with all manual operations, these processes are prone to human error. Digital tools such as work instructions and checklists can support the operators in completing their tasks but have the downside of interfering with the manual process. Traditional machine vision systems that monitor the manual process can work without interference, but training them for the variability present in manual operations is complex. Therefore, manual operations often lead to rework and faulty products and shipments, which in turn lead to costly product recalls and dissatisfied customers.

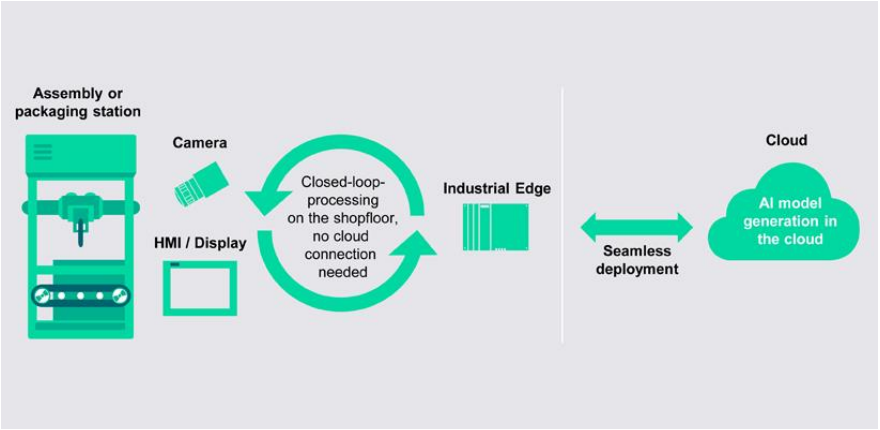
The solution: detecting placement and completeness through AI/ML-aided visual inspection

An AI/ML solution can aid the operators by monitoring the packaging or assembly process and detecting missing or wrong components. To do so, the AI/ML algorithm is trained with process visuals of correct and incorrect packaging or assembly. The AI/ML system can also learn to recognize stacked or partially hidden components of a package or assembly (e.g., a user manual placed both beneath and on top of the product) or irregularly shaped objects, such as power cords. Moreover, changes in the process can easily be integrated in the AI/ML system through retraining the AI/ML algorithm.

The benefits: lower nonconformity costs

The visual inspection system helps employees deliver high quality and error-free manual labor by immediately recognizing any mistakes and giving visual guidance to correct them. Documenting placement and completeness is easy. Overall, AI/ML visual inspection will drastically reduce the consequential costs of traditional visual inspections as well as the costs of rework, penalties, handling, and replacement or return shipping – and will prevent loss in brand recognition and customer satisfaction.

Manual procedures are typically used where automated operations are too costly or difficult to implement – for example in high-mix, low-volume assembly lines. Another area that relies on manual operations is the packaging of products, accessories, and documents for shipping.



EQUIPMENT LEVEL AI/ML USE CASE

False call reduction

AI/ML helps increase FPY of the Automated Optical Inspection (AOI) test step in SMT lines through false call detection.

The challenge: reduce nonconformance costs of false calls

AOI systems are commonly used on the shopfloor to inspect and detect faulty products. AOI systems can detect a wide range of defects, such as open circuits, scratches, stains, and issues in the soldered joints. If the AOI machine detects an error, the product needs to go through manual inspection to determine its actual quality. The ability to detect real errors depends on the settings of the machine. Data screenings of leads and pilot customers show that up to 95% or even 99% of all failures identified by an AOI system are false calls. Unnecessary manual inspections not only interrupt the manufacturing workflow but also are prone to errors and never 100% effective. Depending on the environment and testing conditions, manual testing by operators can have an error rate of up to 30%. Therefore, reducing false calls and the resulting manual inspections is a powerful lever to reduce nonconformance costs.

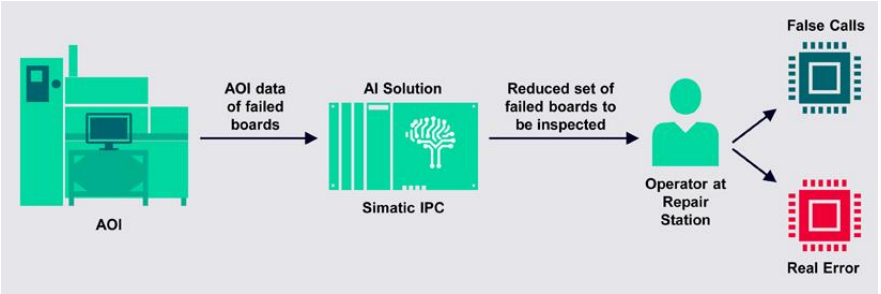
The solution: AI identifies false calls

An AI/ML-based approach can help detect false calls by analyzing the tabular data provided by AOI machines installed in SMT lines along with manual inspection findings recorded whenever a PCB is found to be faulty. The solution consists of two parts: the local installation on the shopfloor and a cloud-based service for model generation and updates. The local installation connects to the respective AOI machine and receives the measurements from the test equipment for every product inspected. The ML model predicts the probabilities of AOI machine outputs indicating a false call or a real error. A dashboard presents the findings to the operator in charge of inspecting PCBs at the SMT line. Training of the ML model and monitoring of the ML model's performance run on a cloud-based back end.

The benefits: significant reduction of manual inspections

The AI/ML solution evaluates and visualizes the real-time shopfloor data and makes recommendations for manual testing. Whenever a false call is detected, the operator can skip the manual handling and inspection efforts. In this way, AI/ML can reduce up to 50% of manual efforts for inspection and material handling, leading to a 15% increase in FPY of the whole AOI production step.

Automated quality inspection is a vital instrument for validating production quality. But all test equipment causes false calls. AI/ML solutions can help reduce these false calls significantly.



PROCESS LEVEL AI/ML USE CASE

Optimizing monocrystalline growth

AI/ML helps to continuously optimize the temperature control needed for monocrystalline silicon production.

The challenge: achieving and maintaining ingot quality

Monocrystalline silicon ingots are usually produced with the Czochralski process in crystal grower furnaces. One key parameter for controlling the crystallization process is the temperature of the silicone melt. Typically, PID controllers are used to control the melt temperature, but they are not an ideal solution. The monocrystalline silicon production process has a significant thermal inertia – that is, the temperature change is not immediately noticeable after tuning the heating power. Due to this physical system characteristic, well-trained and experienced operators permanently oversee the crystal grower furnaces and manually adjust the temperature control. Even with top-skilled operators, this often leads to diameter errors that require the whole ingot to be scraped or reworked. Quality concerns prevent higher productivity, since trying to pull the ingot with a higher speed usually affects the diameter negatively. This issue limits attempts to shorten the ingot production times.

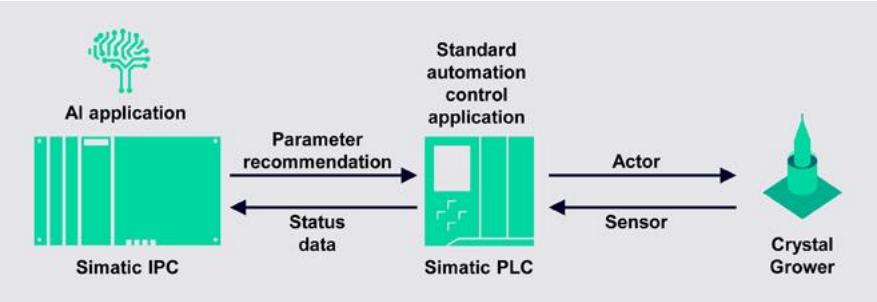
The solution: an autonomous optimization system based on AI

Using an AI/ML solution can help overcome the problem of the delayed response associated with the thermal inertia of the crucible. The AI/ML model is trained with historical production data to learn the best strategy for optimizing the temperature control and thus producing ingots with the lowest possible variance in diameter. Because process characteristics vary for each furnace, a model is fit to a specific furnace. The solution runs locally on the production floor and can be operated via a local HMI. The retraining process runs automatically after a specified number of production batches, or operators can manually trigger it. System updates and monitoring can be done remotely, making the whole commissioning and maintenance process much easier and more flexible.

The benefits: significant improvements in process quality and performance

First installations in the production of monocrystalline ingots for solar wafers have demonstrated that this AI/ML solution can significantly reduce ingot diameter errors and increase production speed, with substantial savings and greater production quantity. It also reduces the risk of relying on specialized operators to control and monitor the process, which in turn helps to reduce operational costs.

The AI solution setup can be added to standard automation PLC applications, optimizing the temperature control with data from each mono-Si crystal grower.



More information

You can find more information on AI/ML in semiconductor and electronics production online:

Artificial Intelligence in Industry

AOI SMT Machine False-Call Reduction

To learn about the Digital Enterprise portfolio for the electronics industry, visit our Website:

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