White Paper

Optimizing Shopfloor Production via AI – An Overview of 3 Use Cases

IMPRINT

Publisher

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Status

File: Optimizing Shopfloor Production via AI – An Overview of 3 Use Cases
February 17th, 2025 – Version 1.0

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1   Introduction

Artificial Intelligence (AI) is gradually reshaping shopfloor production by enabling data-driven decision-making and driving improvements in manufacturing processes. It enables manufacturers to address challenges and optimize their operations through advanced analytical capabilities. By analyzing diverse production data, such as machine performance metrics, operational parameters, and quality inspection results, intelligent systems can uncover inefficiencies, recommend corrective actions, and streamline workflows. The results include enhanced product consistency, minimized production downtime, and better resource utilization. They also reduce the need for manual supervision and make equipment more reliable, leading to smoother and more cost-efficient production.

This paper explores three key use cases in the context of machinery where advanced technologies significantly impact established processes: quality control, predictive quality, and condition monitoring. Each use case addresses a different stage of production, offering distinct ways to improve performance and reliability on the shopfloor.

Quality control ensures products meet required standards by detecting defects during production. Traditional methods, such as visual inspections and sampling, often miss subtle or internal defects, leading to inefficiencies and higher costs. Advanced quality control systems overcome these challenges with real-time monitoring, identifying issues early to reduce waste, minimize rework, and improve consistency. This focus on resolving defects during production sets the stage for predictive quality, which goes a step further by preventing defects before they occur.

Predictive quality focuses on preventing defects by analyzing production data and adjusting process parameters in real time. This approach ensures consistent product quality and addresses potential issues early, even during design and setup, to reduce defects later in the process. Unlike quality control, which detects and resolves defects during production, predictive quality avoids defects at their source. This proactive focus naturally connects to condition monitoring, which ensures the machinery supporting these processes operates reliably.

Condition monitoring ensures the reliability and efficiency of machinery by continuously monitoring performance data, such as temperature, pressure, and vibration. The focus here is on the machinery, whereas predictive quality targets the product itself. By analyzing this data, advanced systems detect early signs of wear or anomalies, allowing for timely interventions that prevent unplanned downtime and extend equipment lifespan.

2 Use Case: Quality Control

2.1 Overview & Motivation

In modern manufacturing, ensuring that products meet required quality standards is critical to avoiding costly disruptions, inefficiencies, and customer dissatisfaction. Quality control identifies and addresses defects during the production process to ensure products meet specifications and are suitable for use. When this process falls short, defective products may require rework or scrapping, causing delays and additional expenses. Industries such as automotive, aerospace, and steel manufacturing face particular challenges, as even small defects can affect safety, increase costs, and reduce product reliability.

Historically, manufacturers have relied on techniques such as visual inspections, statistical sampling, and non-destructive testing to manage quality. While these methods have been useful, they are often slow, labor-intensive, and prone to human error. Subtle or internal defects, such as material inconsistencies or surface flaws, can easily go undetected, leading to quality problems further along in production.

Modern quality control systems use real-time monitoring and advanced data analysis to address these limitations. Technologies like video feed analysis and pattern recognition enable manufacturers to detect anomalies early, ensuring issues are resolved before they escalate. These systems also reduce reliance on manual inspections, improving consistency and freeing up resources for other tasks.

By improving defect detection and reducing waste, advanced quality control ensures smoother production processes and helps manufacturers meet quality standards more efficiently.

2.2   Technical Insights

Modern approaches to quality control rely on advanced techniques such as anomaly detection and computer vision to address technical challenges during production.

Anomaly detection works by comparing product quality of the currently relevant part against the patterns exhibited by the overall production to establish an anomaly score. If this score passes a threshold the part is assumed to be defective which allows for timely interventions by the operator or assistance system.

Computer vision introduces a powerful method for inspecting visual data, using high-resolution cameras and advanced algorithms to identify defects. Unlike conventional image processing, which focuses on simpler features, computer vision systems analyze detailed visual patterns and can address more complex defects, such as irregularities in textured surfaces or layered materials. These systems can also incorporate multi-dimensional analysis by combining visual data with other inputs, such as process parameters, to uncover subtle defects that might otherwise go unnoticed.

A key aspect of these technologies is the ability to unify diverse sources of data into a coherent framework. By combining imaging data, production parameters, and historical trends, these methods provide a structured approach to understanding deviations in the manufacturing process. For example, integrating information about surface conditions with operational data allows for a deeper understanding of defect origins and helps refine detection criteria.

These technical methods are continuously refined through the use of iterative training processes. Algorithms are trained on extensive datasets to handle variable conditions in production, such as changing product shapes or material properties. This iterative approach ensures the systems can adapt to the complexities of modern manufacturing environments while maintaining consistency and precision.

3 Use Case: Predictive Quality

3.1 Overview & Motivation

Predictive quality is a proactive approach to maintaining product standards by identifying potential defects before they occur. Using data from previously manufactured parts combines two key principles: analyzing current process parameters to estimate the quality of the product being produced and predict and adjust future parameters to prevent or mitigate defects if a process or quality anomaly is detected. This dual focus enables manufacturers to address quality issues systematically, ensuring consistent results throughout production.

Traditional quality management often reacts to defects after they appear, relying on inspections and rework to maintain standards. Predictive quality, however, is integrated directly into the production process. By monitoring real-time data and comparing it with historical trends, systems can anticipate quality risks and take corrective actions during production. For instance, in electronics manufacturing, the condition of solder joints is monitored to predict and prevent potential failure points, ensuring that critical components meet reliability criteria. This concept also applies to industries such as automotive and aerospace manufacturing, where material consistency and structural integrity are essential to product performance.

Predictive quality shifts the focus from detecting problems to preventing them, embedding quality management into the production process itself. This approach not only improves process control but also minimizes disruptions caused by defects, ensuring that production remains efficient and products meet high-quality standards from the outset.

3.2   Technical Insights

Predictive quality relies on advanced analytical models that use production data to anticipate and prevent defects before they occur. These models evaluate real-time production parameters, such as temperature, pressure, and material composition, in combination with historical data from previous production cycles. By identifying correlations and patterns, these methods predict when and where quality deviations are likely to arise, allowing for proactive adjustments during production.

A key technical aspect of predictive quality is its ability to integrate data from diverse sources, such as operational sensors, material analysis, and environmental factors. This combination provides a more comprehensive understanding of the conditions that impact product quality. For instance, in metal production, data on stress behaviors and thermal conditions are combined to predict the likelihood of internal flaws such as cracks or warping, ensuring material integrity during high-stress operations.

Another important approach involves parameter optimization based on predictive insights. By analyzing the relationships between input parameters and final product quality, predictive quality systems refine operational settings dynamically. For example, in extrusion processes, flow rates and cooling conditions are adjusted in real time to prevent dimensional inconsistencies or surface defects. This capability extends to complex processes, where even minor changes in settings can significantly affect the final outcome.

Iterative model training plays a critical role in ensuring predictive quality systems remain reliable across different production environments. Algorithms are continuously updated using data from ongoing production, enabling them to adapt to variations in material properties, equipment wear, or environmental conditions. This ensures the models remain accurate and effective over time, even as production conditions evolve.

By focusing on these technical aspects, predictive quality provides manufacturers with a structured, data-driven approach to maintaining consistent standards across production cycles.

4 Use Case: Condition Monitoring

4.1 Overview & Motivation

Condition monitoring focuses on ensuring the reliability and efficiency of machinery by addressing potential issues before they escalate into failures. Traditional maintenance methods, such as fixed schedules or reactive repairs, often lead to inefficiencies - either through unnecessary maintenance or unplanned downtime caused by undetected problems. Condition monitoring overcomes these limitations by analyzing real-time data from machines to identify early warning signs of wear or irregularities, allowing for timely and precise interventions.

In modern manufacturing, where equipment must operate continuously under demanding conditions, maintaining machine health is critical. This approach is particularly important in industries where the performance of machinery directly impacts production quality and timelines. In sectors such as automotive, aerospace, and heavy manufacturing, even minor equipment failures can lead to significant operational delays and financial losses. Condition monitoring ensures that critical machinery remains reliable, reducing the risk of unexpected breakdowns and optimizing production processes.

By replacing reactive practices with proactive maintenance strategies, condition monitoring supports seamless production and helps manufacturers adapt to the increasing complexity and demands of modern industrial systems.

4.2 Technical Insights

Condition monitoring is built on the continuous monitoring and analysis of machine performance data to detect potential failures early. The process starts by identifying the

most critical components that are prone to wear or malfunction. Once these components are determined, key telemetry variables, such as vibration levels, temperature, and power consumption, are monitored to gain a detailed understanding of the machine's condition.

A critical step in condition monitoring is establishing a baseline for normal operating conditions. Algorithms analyze data collected during the machine's optimal performance to define this reference. Deviations from the baseline, such as unexpected increases in vibration or shifts in power usage, are flagged as potential warning signs. These signals help identify issues before they escalate into major failures.

Another key concept is the segmentation of operational data into "episodes," which are defined periods of machine activity. For machines with clear operational cycles, such as industrial robots or presses, an episode corresponds to a single cycle. For continuous processes, like extruders, episodes are defined by consistent time intervals. This segmentation enables the system to monitor performance trends and detect even subtle changes in machine behavior over time.

By focusing on these processes, condition monitoring provides a structured approach to identifying and addressing potential issues, ensuring machinery remains reliable and production stays uninterrupted.

5   Challenges & Limitations

Integrating advanced technologies into manufacturing processes presents several challenges that need to be addressed. One key issue across all use cases is the quality and availability of data. Production environments often generate data that is noisy, incomplete, or scattered across isolated systems. Ensuring this data is clean, organized, and accessible is critical for effective implementation. In many cases, existing infrastructure struggles to handle the volume and variety of data produced on the shop floor - additional engineering is required to unify sources, including supplier data.

Another challenge lies in the limited coverage of sensors. While many machines are equipped with programmable logic controllers (PLCs) that provide useful information, older equipment often lacks sufficient digital sensors to collect critical data. Retrofitting these machines with modern sensors is often necessary to close gaps in data collection. Even with sufficient infrastructure, achieving full coverage of all relevant parameters is difficult, which can leave important areas unmonitored.

The complexity of modern manufacturing environments also adds to the difficulty. Many factories have already been optimized through manual adjustments, making it harder to highlight the benefits of advanced systems. This is especially true in environments with high product variety and low production volumes, where variability introduces additional challenges for data collection and analysis.

Collaboration between stakeholders, including process engineers, operations teams, and maintenance staff, is essential for success. Misalignment in priorities or communication can slow progress and hinder adoption. Over time, issues like changes in operating conditions or data drift may affect the accuracy of predictive models, requiring ongoing refinement to maintain reliability.

Finally, ensuring system security and workforce readiness is crucial. As manufacturing systems become more interconnected, cybersecurity risks increase. Protecting data and infrastructure is vital to maintaining operational integrity. At the same time, many organizations face a lack of personnel trained to manage and operate advanced technologies. Training programs and support structures are necessary to help employees adapt to new systems and processes.

6   Step-By-Step – How to Make Use of AI NOW?

Adopting AI in manufacturing requires a clear understanding of your current state and a structured, iterative approach. Depending on your situation, you can begin at different points, but identifying where you stand is crucial to ensure success. The following steps outline the process to guide you from readiness assessment to full implementation.

1.   Assess Your Current Readiness

The first step is to evaluate where you are today. This includes identifying business objectives and determining whether your data and infrastructure are ready to support AI. Key considerations include the quality, availability, and structure of your data and the capacity of your operational technology to handle AI solutions. Securing management support is essential, whether through leadership alignment or convincing business cases. If expertise in this area is limited, external help may be valuable.

2. Define Use Cases and Success Criteria

Identifying a specific use case where AI can provide measurable value is critical. This step involves aligning stakeholders on project goals, selecting relevant key performance indicators (KPIs), and determining controllable and uncontrollable parameters. Data exploration at this stage helps establish relationships between variables and process outcomes, ensuring a strong foundation for AI development.

3. Prepare Data and Modernize Infrastructure

AI relies on clean, well-organized data from reliable sources. Many systems may require harmonizing datasets across different silos or retrofitting older equipment with sensors to capture critical parameters. Establishing a unified, IoT-enabled data layer ensures seamless integration and provides the framework needed to support AI applications.

4. Develop and Validate a Proof of Concept

A proof of concept (PoC) is essential to demonstrate feasibility and potential return on investment. This phase includes testing algorithms, analyzing performance, and iteratively refining models based on experimental results. The process not only validates the AI's potential but also builds confidence among stakeholders.

5. Integrate and Operationalize

For AI to provide value, it must be seamlessly integrated into existing systems. This step involves linking AI solutions to operational workflows, setting up dashboards for actionable insights, and ensuring long-term sustainability which support deployment, monitoring, and scalability.

6. Continuously Improve and Scale

AI systems require ongoing refinement to remain effective. Continuous updates based on new data and insights allow the system to adapt to changing production environments. Successful implementations can then be scaled across production lines or facilities, maximizing the impact of AI solutions.

Conclusion

The integration of advanced approaches like quality control, predictive quality, and Condition monitoring represents a pivotal step toward smarter and more efficient production processes. These technologies address the key challenges faced by industries today, from enhancing product quality to ensuring equipment reliability and optimizing production workflows.

However, achieving the full potential of these advancements requires collaboration. Challenges such as unifying data silos, ensuring interoperability, and addressing skills gaps are too significant for any single company to overcome alone. This is why the Open Industry 4.0 Alliance exists. We are committed to bringing manufacturers, technology providers, and stakeholders together to create shared solutions. By aligning efforts, we enable companies to adopt these innovations more effectively and with greater impact.

At the Open Industry 4.0 Alliance, our principles focus on openness, interoperability, and practical implementation. We believe that by working together, industries can break down barriers, develop resilient and interconnected systems, and unlock new opportunities for growth and innovation. Our mission is to support businesses in navigating this transformation, providing frameworks and guidance to ensure a seamless and sustainable transition. Together, we can shape the industries of tomorrow, ensuring progress, resilience, and shared success.