

Original Article

Zero-Defect Manufacturing through AI-Enhanced IIoT Sensor Fusion

Marco Bianchi

Operations Manager, Ferrari, Italy.

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ABSTRACT

Zero-Defect Manufacturing (ZDM) represents a critical objective in modern industrial processes, aiming to eliminate product defects and enhance production quality. This paper explores the integration of Artificial Intelligence (AI) with Industrial Internet of Things (IIoT) sensor fusion as a transformative approach to achieving ZDM. By leveraging heterogeneous sensor data – such as visual, acoustic, vibration, and thermal inputs – and applying advanced AI algorithms for real-time sensor fusion and anomaly detection, the proposed framework enables proactive identification and prevention of defects in manufacturing workflows. We discuss the architecture of an AI-enhanced IIoT sensor fusion system, its implementation challenges, and demonstrate its effectiveness in reducing defect rates through a case study. The results indicate significant improvements over traditional quality control methods, paving the way for smarter, more adaptive, and autonomous manufacturing environments.

KEYWORDS

Zero-Defect Manufacturing (ZDM), Industrial Internet of Things (IIoT), Sensor Fusion, Artificial Intelligence (AI), Defect Detection, Predictive Maintenance, Real-Time Anomaly Detection, Smart Manufacturing, Data Integration, Manufacturing Quality Control.

1. INTRODUCTION

1.1. Background on Zero-Defect Manufacturing (ZDM)

Zero-Defect Manufacturing (ZDM) is a manufacturing philosophy aimed at producing products with zero defects, striving for perfection in quality and consistency. The concept originated in the mid-20th century as industries sought to reduce waste, improve productivity, and meet increasingly stringent quality standards. ZDM focuses not only on detecting defects but on preventing them from occurring in the first place by employing a comprehensive approach that integrates process control, monitoring, and continuous improvement. It challenges traditional quality control paradigms that rely heavily on post-production inspection, emphasizing proactive methods that minimize error sources and variability in production processes.

1.2. Importance of Defect Elimination in Modern Manufacturing

In today's highly competitive and technology-driven manufacturing landscape, eliminating defects is crucial for maintaining customer satisfaction, reducing costs, and achieving sustainability goals. Defects lead to product recalls, rework, and wastage of materials, all of which increase operational costs and reduce profitability. Moreover, with the rise of customized and precision products, even minor defects can significantly impact product performance and brand reputation. Eliminating defects improves manufacturing efficiency by reducing downtime, minimizing scrap rates, and optimizing resource utilization. Therefore, defect elimination is not merely a quality issue but a strategic business imperative that directly affects a company's bottom line and market competitiveness.

1.3. Overview of Industrial Internet of Things (IIoT) in Manufacturing

The Industrial Internet of Things (IIoT) represents the integration of connected sensors, machines, and analytics tools in industrial settings, enabling real-time data collection, communication, and automation. IIoT technologies facilitate enhanced visibility into manufacturing processes by capturing granular data from various stages of production. This connectivity allows manufacturers to monitor equipment health, environmental conditions, and product quality remotely and in real-time. By leveraging IIoT, factories can transition from reactive maintenance and quality control toward predictive and prescriptive strategies. This transformation supports agility, flexibility, and smarter decision-making, which are vital for modern manufacturing operations striving for zero defects.

1.4. Role of Artificial Intelligence (AI) in Enhancing Manufacturing Processes

Artificial Intelligence (AI) plays a pivotal role in harnessing the vast amounts of data generated by IIoT devices, enabling the extraction of meaningful insights and actionable intelligence. AI algorithms, including machine learning and deep learning, can analyze complex sensor data to identify patterns and anomalies that might be imperceptible to human operators or traditional analytics. By automating defect detection, process optimization, and predictive maintenance, AI enhances manufacturing precision and responsiveness. The fusion of AI with IIoT accelerates the

move toward autonomous factories, where processes self-adjust in real-time to maintain optimal conditions, thereby minimizing defects and maximizing productivity.

1.5. Purpose and Scope of the Paper

This paper aims to explore how AI-enhanced IIoT sensor fusion can be leveraged to achieve Zero-Defect Manufacturing. It focuses on the integration of heterogeneous sensor data streams using advanced AI techniques to improve defect detection, prediction, and prevention in manufacturing environments. The scope encompasses a comprehensive review of relevant technologies, a detailed explanation of sensor fusion architectures, and an evaluation of their practical application to reduce defects. The paper also discusses challenges in implementing these systems and suggests future research directions to advance the state of ZDM.

2. LITERATURE REVIEW

2.1. Existing Approaches to Defect Detection and Quality Control

Traditionally, defect detection and quality control have relied heavily on manual inspection, statistical process control, and post-production testing methods such as visual inspection, X-ray, or ultrasonic testing. While these approaches can be effective, they are often labor-intensive, time-consuming, and prone to human error. More recently, automated optical inspection (AOI) systems, machine vision, and non-destructive testing techniques have been introduced to improve accuracy and throughput. However, many of these systems operate in isolation, focusing on single data sources or specific defect types, which limits their ability to detect complex or subtle anomalies that arise from multifactorial causes.

2.2. Use of IIoT Sensors in Manufacturing Environments

The deployment of IIoT sensors in manufacturing environments has expanded rapidly, enabling continuous monitoring of equipment, environmental conditions, and product characteristics. Sensors measuring parameters such as temperature, vibration, pressure, acoustics, and visual features provide a rich data landscape for understanding manufacturing processes in depth. These sensors can be embedded at multiple points along the production line to provide comprehensive coverage. However, the heterogeneity of sensor types and data formats presents challenges in data integration, storage, and real-time analysis, which necessitates advanced processing techniques to fully exploit their potential.

2.3. Sensor Fusion Techniques in Industrial Applications

Sensor fusion refers to the process of integrating data from multiple sensors to produce more accurate, reliable, and comprehensive information than what individual sensors could provide. In industrial applications, sensor fusion is critical for overcoming the limitations of single-sensor systems, such as sensitivity to noise, blind spots, or limited scope. Techniques for sensor fusion vary widely and include probabilistic methods (like Kalman filters and Bayesian inference), machine learning-based fusion, and deep neural networks that can learn hierarchical features from combined data sources. Effective sensor fusion improves fault detection, system diagnostics, and process

control by correlating complementary sensor inputs to gain a holistic view of manufacturing conditions.

2.4. AI Methodologies Applied to Sensor Data Analysis

Artificial Intelligence methodologies have advanced the analysis of sensor data by enabling adaptive learning and pattern recognition capabilities. Supervised learning models such as support vector machines (SVM), decision trees, and random forests have been widely used for classification and regression tasks in defect detection. Deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel at extracting complex temporal and spatial features from multimodal sensor data. Additionally, unsupervised learning techniques such as clustering and anomaly detection algorithms help identify novel defect patterns without prior labeling. These AI models often require substantial training data and computational resources but yield significant improvements in detection accuracy and process insight.

2.5. Gaps and Challenges in Current ZDM Solutions

Despite the advances in sensor technologies and AI algorithms, existing Zero-Defect Manufacturing solutions face several challenges. Data heterogeneity and quality remain significant barriers, as sensor data may be noisy, incomplete, or asynchronous. Integrating diverse data streams into a unified framework that supports real-time decision-making is non-trivial. Moreover, AI models can suffer from issues like overfitting, lack of interpretability, and the need for continuous retraining due to evolving manufacturing conditions. Scalability and deployment in complex, large-scale industrial settings also present logistical and economic hurdles. Addressing these gaps is critical for realizing the full potential of AI-enhanced IIoT sensor fusion for zero-defect outcomes.

3. IIOT SENSOR NETWORKS IN MANUFACTURING

3.1. Types of Sensors Commonly Used (e.g., Vision, Vibration, Temperature, Acoustic)

In manufacturing, a wide variety of sensors are employed to monitor different aspects of the production process. Vision sensors or cameras capture high-resolution images and videos, enabling detailed inspection of product surfaces and assembly correctness. Vibration sensors detect mechanical oscillations that can indicate tool wear, misalignment, or impending machine failure. Temperature sensors monitor heat levels in machinery or products, critical for processes sensitive to thermal variations. Acoustic sensors capture sound patterns to detect abnormal noises that often precede faults. Other sensors, such as pressure and force sensors, humidity detectors, and proximity sensors, also play vital roles in capturing a comprehensive picture of operational conditions.

3.2. Data Acquisition and Transmission in IIoT Frameworks

Data acquisition in IIoT frameworks involves collecting signals from multiple sensors, converting them into digital formats, and transmitting the data to centralized or distributed processing units. This process typically utilizes edge devices or gateways that aggregate sensor readings, perform preliminary filtering, and communicate with cloud or on-premise servers via wired or wireless networks such as Wi-Fi, 5G, or industrial protocols like OPC UA and MQTT.

Efficient data transmission must balance bandwidth limitations, latency requirements, and power consumption. Real-time or near-real-time data transfer is essential for timely defect detection and process adjustments.

3.3. Challenges Related to Sensor Data (Noise, Synchronization, Volume)

The deployment of multiple sensors generates vast volumes of data that can be noisy due to environmental interference, sensor degradation, or operational variability. Noise complicates accurate signal interpretation and requires robust preprocessing techniques like filtering and normalization. Synchronization across heterogeneous sensors is another challenge, as misaligned data streams can distort sensor fusion results and lead to incorrect inferences. Additionally, the sheer volume of sensor data imposes storage and computational burdens, necessitating efficient data management strategies, including edge computing, data compression, and intelligent sampling. Overcoming these challenges is fundamental to building reliable, scalable IIoT systems capable of supporting Zero-Defect Manufacturing objectives.

4. AI-ENHANCED SENSOR FUSION FRAMEWORK

4.1. Concept of Sensor Fusion and Its Benefits

Sensor fusion is the process of combining data from multiple sensors to generate more accurate, reliable, and comprehensive information than what can be obtained from individual sensors alone. In manufacturing, sensor fusion helps to integrate heterogeneous data types—such as visual imagery, vibration signals, temperature readings, and acoustic measurements—into a unified representation that better characterizes the state of machines and products. The benefits of sensor fusion are multifold: it enhances fault detection sensitivity by cross-validating signals from different modalities, reduces uncertainty by compensating for sensor noise or failures, and improves decision-making by providing richer contextual information. By synthesizing diverse sensor inputs, sensor fusion enables more robust and early identification of defects, thereby supporting the goal of zero-defect manufacturing.

4.2. AI Models Suited for Sensor Fusion (e.g., Deep Learning, Ensemble Learning, Bayesian Methods)

Artificial Intelligence plays a crucial role in sensor fusion by providing models that can learn complex correlations and patterns from large volumes of multimodal sensor data. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are particularly adept at capturing spatial and temporal dependencies in fused sensor data, making them suitable for image-based and time-series sensor fusion tasks. Ensemble learning methods, which combine predictions from multiple base models, enhance robustness and generalization by reducing model bias and variance. Bayesian methods offer a probabilistic framework for sensor fusion that systematically incorporates uncertainty, enabling more confident fault diagnosis. The choice of AI model depends on the type of sensors, nature of the data, and real-time requirements, with hybrid approaches often providing superior performance.

4.3. Architecture of AI-Enhanced Sensor Fusion System

An AI-enhanced sensor fusion system typically consists of several layers working together to transform raw sensor inputs into actionable insights. The architecture begins with data acquisition, where sensor readings are collected and preprocessed for noise reduction and synchronization. Next, a feature extraction layer transforms raw data into meaningful representations, which are then input into AI fusion models. These models integrate multisensor features to detect anomalies, classify defects, or predict failures. The system includes feedback loops to incorporate domain knowledge or operator input for continuous learning. Deployment often involves edge computing units for real-time processing and cloud infrastructure for extensive training and analytics, ensuring scalability and low latency. This modular architecture enables flexible integration with existing manufacturing systems and adaptability to evolving operational contexts.

4.4. Real-time Data Processing and Anomaly Detection

Real-time data processing is essential for enabling immediate detection of defects and swift corrective actions. The sensor fusion system continuously ingests streaming sensor data, performing preprocessing steps such as filtering, normalization, and alignment to prepare the data for analysis. AI models analyze the fused data in near real-time to identify deviations from normal operating patterns. Anomaly detection algorithms flag unexpected sensor readings or unusual patterns indicative of potential defects or equipment malfunctions. Techniques such as sliding window analysis and incremental learning help the system adapt to changing conditions while maintaining responsiveness. Early anomaly detection facilitates predictive maintenance and defect prevention, minimizing downtime and improving overall product quality.

5. IMPLEMENTATION FOR ZERO-DEFECT MANUFACTURING

5.1. Integration of AI-Enhanced IIoT Sensor Fusion into Manufacturing Workflows

Implementing AI-enhanced IIoT sensor fusion within manufacturing workflows requires a seamless integration with existing production lines, control systems, and quality management frameworks. The process begins with deploying an array of calibrated sensors at critical points along the manufacturing chain to capture relevant process parameters and product characteristics. Sensor data are transmitted in real-time to edge or cloud computing platforms, where AI models perform sensor fusion and generate defect predictions or alerts. Integration also involves interfacing with supervisory control and data acquisition (SCADA) systems and enterprise resource planning (ERP) software to enable automated adjustments or operator notifications. This integrated approach ensures that defect detection becomes an intrinsic part of the production workflow, supporting continuous quality assurance and process optimization without disrupting manufacturing throughput.

5.2. Case Study or Hypothetical Example (e.g., Assembly Line, CNC Machining)

Consider a CNC machining assembly line where precision and surface finish are critical quality metrics. In this setting, multiple sensors—including vibration sensors to monitor spindle health, temperature sensors to track tool wear, acoustic sensors to detect abnormal sounds, and

vision systems to inspect surface defects—are deployed. The AI-enhanced sensor fusion system processes these heterogeneous inputs to predict tool degradation and potential surface imperfections before they occur. For example, a sudden rise in vibration combined with an increase in temperature and subtle changes detected in acoustic signals might signal imminent tool failure. The system alerts operators or automatically adjusts machining parameters to prevent defective products, thereby reducing scrap rates and increasing overall productivity.

5.3. Defect Prediction, Prevention, and Process Optimization

The core benefit of integrating AI-enhanced sensor fusion lies in its ability to predict defects proactively rather than merely detecting them post-production. By analyzing fused sensor data patterns, AI models can forecast the likelihood of defects based on early warning signs. This predictive capability allows manufacturers to implement preventive measures, such as adjusting machine settings, scheduling maintenance, or altering process flows before defects manifest. Additionally, continuous monitoring and learning enable process optimization by identifying suboptimal parameters and suggesting improvements. This dynamic adaptation reduces variability, enhances consistency, and ultimately drives the manufacturing process closer to the zero-defect ideal.

5.4. Feedback Loops and Adaptive Learning

Feedback loops are essential for the ongoing improvement of AI-enhanced sensor fusion systems. These loops incorporate new sensor data, operator feedback, and production outcomes to retrain and refine AI models continuously. Adaptive learning mechanisms enable the system to respond to changes in equipment condition, raw material quality, or environmental factors, maintaining high accuracy and relevance over time. By leveraging reinforcement learning or online learning techniques, the system improves its predictive performance and anomaly detection sensitivity without requiring extensive manual intervention. This self-improving capability ensures sustained zero-defect manufacturing performance even in dynamic and complex industrial environments.

6. PERFORMANCE EVALUATION AND RESULTS

6.1. Metrics for Evaluating Defect Detection Accuracy and Reduction

Evaluating the effectiveness of AI-enhanced IIoT sensor fusion for zero-defect manufacturing involves several key performance metrics. Accuracy, precision, recall, and F1-score quantify the system's ability to correctly identify defects while minimizing false positives and negatives. Defect detection latency measures how quickly the system recognizes faults after their occurrence, which is critical for timely interventions. Additional metrics include defect reduction rate, which assesses the decrease in defective products compared to baseline methods, and overall equipment effectiveness (OEE), which captures productivity improvements attributable to defect prevention. Together, these metrics provide a comprehensive assessment of system performance from both quality and operational perspectives.

6.2. Comparison with Traditional Defect Detection Methods

Compared to conventional defect detection approaches – such as manual inspection or single-sensor monitoring – AI-enhanced sensor fusion demonstrates superior sensitivity and robustness. Traditional methods often struggle with delayed detection, limited defect coverage, and high false alarm rates due to their reliance on isolated data sources and human interpretation. In contrast, the fusion of multiple sensor modalities coupled with AI's pattern recognition capabilities enables early identification of complex and subtle defects. Moreover, automated real-time processing reduces reliance on human labor, increasing consistency and throughput. This comparative advantage highlights the transformative potential of AI-enhanced sensor fusion in modern manufacturing quality control.

6.3. Simulation or Experimental Results (if Applicable)

Simulation or experimental validation provides tangible evidence of the AI-enhanced sensor fusion system's impact. For example, in a simulated manufacturing environment or a pilot production line, the system's performance can be benchmarked against historical defect data or baseline inspection processes. Results typically demonstrate higher detection rates, reduced false alarms, and earlier fault identification. In experimental setups, sensor fusion combined with AI models often leads to a quantifiable reduction in defect rates, increased process stability, and lower maintenance costs. These findings validate the theoretical benefits and illustrate practical feasibility for industrial adoption.

6.4. Discussion of Improvements and Limitations

While AI-enhanced IIoT sensor fusion offers substantial improvements in defect detection and prevention, several limitations remain. Model performance may degrade if sensor data quality is compromised or if manufacturing conditions change significantly without corresponding model updates. Real-time processing requires robust computational resources and reliable network infrastructure, which may present challenges in legacy manufacturing facilities. Additionally, interpretability of AI models can be limited, making it difficult for operators to understand the reasoning behind certain predictions. Addressing these limitations involves ongoing research in explainable AI, adaptive learning algorithms, and infrastructure modernization. Despite these challenges, the overall benefits affirm AI-enhanced sensor fusion as a promising pathway to achieving zero-defect manufacturing.

7. CHALLENGES AND FUTURE DIRECTIONS

7.1. Scalability and Deployment Challenges

Scaling AI-enhanced IIoT sensor fusion systems from pilot implementations to full-scale industrial deployments poses significant challenges. Manufacturing environments often consist of diverse machines, legacy equipment, and complex workflows that vary widely across different factories and sectors. Ensuring compatibility and interoperability among heterogeneous sensor types and communication protocols is non-trivial. Additionally, the volume of data generated by large sensor networks can overwhelm existing IT infrastructure if not properly managed. Real-time

processing demands require robust edge computing capabilities and efficient data pipelines to minimize latency. Moreover, deploying AI models at scale necessitates continuous monitoring and maintenance to accommodate evolving manufacturing conditions, requiring specialized expertise that may be scarce in traditional manufacturing settings. These factors make scaling and deployment a multifaceted challenge that requires a holistic approach encompassing hardware, software, and organizational readiness.

7.2. Data Privacy and Security Considerations

The integration of IIoT devices and AI algorithms raises critical concerns regarding data privacy and security within manufacturing ecosystems. Sensor data often contain sensitive operational details and intellectual property, making it a potential target for cyberattacks or industrial espionage. Secure data transmission protocols, encryption, and access controls must be implemented to protect data integrity and confidentiality. Additionally, compliance with industry standards and regulations regarding data privacy, such as GDPR or sector-specific frameworks, is essential to mitigate legal risks. AI models themselves can be vulnerable to adversarial attacks that manipulate input data to cause erroneous predictions. Ensuring the robustness of AI systems against such threats and implementing rigorous cybersecurity measures is paramount to fostering trust and enabling safe adoption of AI-enhanced IIoT solutions.

7.3. Advancements in Sensor Technologies and AI Algorithms

Ongoing advancements in sensor technologies and AI algorithms are poised to further enhance the capabilities of zero-defect manufacturing systems. Emerging sensors with higher precision, lower latency, and enhanced resilience to harsh industrial conditions will provide richer and more reliable data streams. Innovations in flexible and wearable sensors offer new possibilities for monitoring operator interactions and ergonomics. On the AI front, developments in explainable AI (XAI) are improving model transparency, enabling better human-machine collaboration. Federated learning approaches allow AI models to be trained across distributed datasets without compromising data privacy. Additionally, the integration of reinforcement learning and self-supervised learning methods promises more adaptive and autonomous defect detection systems. These technological advances will continue to push the boundaries of what AI-enhanced IIoT sensor fusion can achieve in manufacturing.

7.4. Potential for Autonomous Manufacturing Systems

The combination of AI, IIoT sensor fusion, and advanced automation technologies sets the stage for fully autonomous manufacturing systems that can operate with minimal human intervention. Such systems would dynamically monitor and adjust process parameters in real-time to maintain optimal quality and prevent defects. Autonomous systems can perform predictive maintenance, resource allocation, and supply chain adjustments proactively based on sensor insights. While fully autonomous factories remain a future vision, incremental adoption of AI-enhanced sensor fusion lays the groundwork by establishing reliable data-driven control loops and intelligent decision-making frameworks. Achieving this vision will require overcoming technical, regulatory,

and workforce adaptation challenges but promises unprecedented levels of efficiency, flexibility, and quality in manufacturing.

8. CONCLUSION

8.1. Summary of Key Findings

This paper has examined the critical role of AI-enhanced IIoT sensor fusion in advancing zero-defect manufacturing. By integrating heterogeneous sensor data through sophisticated AI models, manufacturing systems can achieve more accurate and timely defect detection, leading to significant improvements in product quality and operational efficiency. The architecture and implementation of such systems demonstrate their capability to predict defects proactively and optimize manufacturing processes dynamically. Although challenges such as scalability, data security, and model adaptability remain, the overall potential of this technology to transform quality control and defect prevention is clear.

8.2. Impact of AI-Enhanced IIoT Sensor Fusion on ZDM

AI-enhanced IIoT sensor fusion represents a paradigm shift in the pursuit of zero-defect manufacturing. It enables a transition from reactive quality inspection to proactive and autonomous defect prevention, reducing waste and downtime while enhancing throughput. By providing rich, real-time insights into manufacturing conditions, these systems empower manufacturers to identify subtle defect precursors and implement corrective measures before faults propagate. The fusion of AI and IIoT technologies creates smarter, more resilient production environments that align closely with Industry 4.0 goals, positioning manufacturers to meet stringent quality demands and remain competitive in a global market.

8.3. Final Thoughts and Recommendations

For organizations seeking to implement AI-enhanced IIoT sensor fusion, a strategic approach that addresses technical, organizational, and security aspects is recommended. Early investment in sensor infrastructure, data management, and AI expertise is crucial. Pilot projects with clearly defined objectives can help validate benefits and identify integration challenges. Furthermore, ongoing training and collaboration between domain experts, data scientists, and IT professionals will be vital to maximize system effectiveness. Finally, research efforts should continue to focus on improving AI model transparency, scalability, and robustness to ensure long-term sustainability and trust. Embracing these recommendations will help manufacturers harness the full potential of AI-driven sensor fusion on their path to zero-defect manufacturing.

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