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Performance analysis of sensors in a mechatronic system for transformer magnetic core lamination cutting within an automated production line

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ABSTRACT

Transformer magnetic core lamination cutting is a critical process in transformer manufacturing, directly affecting product quality and production efficiency. This paper presents an analysis of the sensor systems employed on an automated cutting line for silicon-steel transformer magnetic core laminations. The study identifies the types and roles of sensors used across the line's key subsystems (uncoiler, feeder, cutting station, and stacker) and evaluates their performance relative to industrial requirements. The findings indicate that conventional inductive, optical (e.g., photoelectric), and magnetic sensors, together with rotary encoders, provide the necessary feedback for automation, cutting precision (±0.1 mm), and control. However, they offer limited self-diagnostic capabilities, increasing downtime during troubleshooting. To enhance reliability and enable predictive maintenance, the integration of advanced "smart" sensors with real-time communication (e.g., EtherCAT, IO-Link) is recommended. The results demonstrate how sensor selection and placement influence cutting accuracy and system downtime and suggest improvements such as leveraging servo-drive feedback and IoT-based monitoring to optimize sensor usage. Practical insights are provided for improving automated production lines in accordance with modern industrial and Industry 4.0 trends, aiming to increase operational efficiency, reduce maintenance costs, and ensure high product quality.

KEYWORDS

Transformer core lamination, Automated cutting line, Industrial sensor systems, Inductive and optical sensors, Rotary and absolute encoders, Sensor diagnostics, Predictive maintenance, Smart sensors, Real-time communication (EtherCAT, IO-Link), Industry 4.0 in manufacturing.

1. INTRODUCTION

The cutting of transformer core laminations is a critical stage in production, as precision directly affects core assembly and electrical performance. In modern automated lines, various types of sensors—including inductive, optical, magnetic, and rotary encoders—are essential for monitoring positions, speeds, and material presence. These sensors enable programmable logic controllers (PLCs) to maintain accuracy and promptly respond to process anomalies. Sensor feedback ensures proper strip alignment, material tension, and synchronized operation across different subsystems of the line. While traditional sensors typically provide basic binary signals, they often lack diagnostic capabilities, limiting their usefulness for predictive maintenance or rapid troubleshooting, as described in [1], [2]. To address this, new generations of sensors—commonly referred to as "smart sensors"—are capable of local signal processing, self-monitoring, and communication via protocols such as IO-Link or EtherCAT [3].

The concepts of Industry 4.0 emphasize the importance of real-time data acquisition, interconnected systems, and advanced analytics in manufacturing [3]. In this context, sensors are not merely control devices, but key sources of operational data that enable machine learning, predictive maintenance, and optimization [4].

Studies have shown that intelligent sensor systems significantly reduce unplanned downtime and improve process reliability in industrial environments [5]. This paper analyzes the sensor configuration of an automated transformer magnetic core cutting line, focusing on performance, limitations, and upgrade potential. The study addresses three key questions: (1) which sensors are currently used and how they affect process performance; (2) what weaknesses exist in the sensor system; and (3) how it can be improved to support real-time monitoring and predictive maintenance. The goal is to provide practical recommendations aligned with Industry 4.0 trends and advanced manufacturing needs. The authors participated directly in the design and implementation of the control software and sensor integration for the cutting line, which provides the practical basis for the presented analysis.

2. MECHATRONIC SYSTEM FOR TRANSFORMER MAGNETIC CORE LAMINATION CUTTING

2.1. Automated Cutting Line Overview

The analyzed system is an automated line for cutting and stacking grain-oriented electrical steel sheets used in transformer magnetic cores, as shown in Fig. 1.

Figure 1: Automated transformer magnetic core cutting line

It processes steel coils, typically 0.23–0.35 mm thick, into precise lamination shapes, shown in Fig. 2, suitable for step-lap stacking configurations, shown in Fig. 3, which help reduce magnetic core losses and acoustic noise [6].

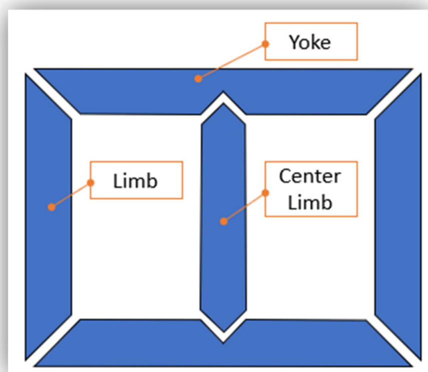

Figure 2: Lamination shapes

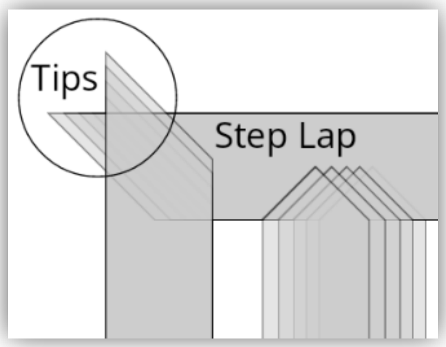

Figure 3: Step-lap stacking configurations

Key components of the line, shown in Fig 4, include a multi-head coil unwinding system, slack loop section, servo-driven feeder, cutting station, evacuation conveyor, and stacker. The coil unwinding system operates under controlled tension, while the loop section – monitored by sensors – buffers material flow and prevents misfeeds. The feeder is equipped with a measuring wheel and a rotary encoder (e.g., Heidenhain ERN 480 [7]), enabling high positioning precision (±0.1 mm) during strip advancement.

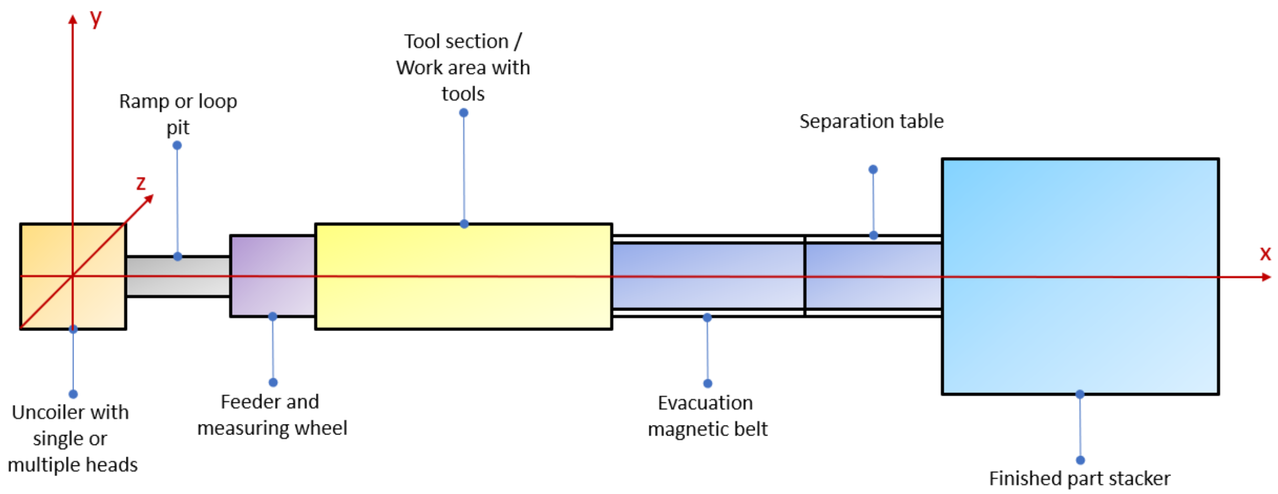

Figure 4: Key components of the transformer magnetic core cutting line

The cutting unit performs punching and notching operations using hydraulic and pneumatic actuators. Strip presence, position, and tool status are monitored using inductive sensors such as the Pepperl+Fuchs NBB5-18GM50-E2-V1 [8]. These sensors provide reliable binary feedback to the PLC regarding material and actuator positions [2].

After cutting, the laminations are transferred by a magnetic conveyor to the stacking unit. Optical sensors (e.g., Pepperl+Fuchs ML6-8-H-40 [9]) are used to detect lamination presence, stack height, and misalignment conditions. These sensors are mounted in adjustable brackets for optimal field-of-view, enabling flexibility for different lamination sizes. Diverters and pneumatic actuators direct laminations into designated core sections, with magnetic reed sensors (e.g., models designed for pneumatic cylinders [10]) used to confirm actuator end positions and ensure mechanical synchronization.

All sensors are connected to a central PLC-based control system that manages signal processing, safety interlocks, and motion logic. Additionally, feedback from servo drives—such as real-time torque, position deviation, and error status—can be leveraged for advanced process diagnostics and predictive maintenance strategies, offering deeper insight than discrete sensors alone [3].

2.2. Sensor Identification and Data Collection

For this study, the sensor configuration of the cutting line was documented through machine design analysis and on-site inspection. Each sensor's type, location, and function were identified, and technical specifications were verified using manufacturer datasheets to assess suitability [1]. The system primarily employs inductive and photoelectric sensors for material and part detection, rotary encoders for motion feedback, and magnetic reed sensors for actuator monitoring. Table 1 provides an overview of the key sensors by section, including their roles and, where relevant, model references observed on the machine, Fig. 4.

Sensor integration into the control system was evaluated through documentation review and system observation. Binary sensors (inductive, optical, magnetic) are connected to the PLC's digital inputs, while encoders interface with high-speed counters or servo drives. Notably, the coil unwinding unit uses an EtherCAT-connected absolute encoder—such as the Sick AFM60A [12]—for multi-turn position feedback, enabling seamless integration and high-resolution monitoring.

Incremental encoders, such as the feeder encoder, are linked via servo drives or counter modules depending on operating mode. These encoders typically operate with a resolution of 2048 PPR (pulses per revolution), which meets the required control precision for ±0.1 mm strip advancement [7]. Sensor specifications—including detection range, response time, and environmental tolerance—were analyzed to identify potential performance issues or integration mismatches. For example, inductive sensors such as the NBB5-18GM50-E2-V1 have a nominal sensing range of 5 mm, which can be limiting in dynamic or misaligned conditions [8].

Control logic tied to sensor inputs was also reviewed, including emergency stop conditions triggered by loop instability, sheet jams, or detection loss. Common failure scenarios—such as inductive sensor offset due to vibration, or lens contamination in optical sensors—were identified as significant contributors to downtime [11]. These failure modes were analyzed to evaluate system robustness and potential areas for redundancy.

No experimental changes were made during this study; the work remains analytical. However, the insights gained provide a strong foundation for proposing sensor upgrades and control strategy enhancements that could be implemented and validated in future work.

Table 1: Summary of main sensors used in the transformer magnetic core cutting line.

Picture	Line Section	Sensor (Type & Model)	Function / Purpose
	Uncoiler	Rotary Absolute Encoder (Sick AFM60A-S4EB018x12 EtherCAT)	Monitor rotation angle of active uncoiler head (multi - head position tracking for coil selection). Enables precise control of unwinding and automatic head switching.
	Uncoiler drive	Rotary Incremental Encoder (SEW Eurodrive ES7S)	Measure uncoiler head rotation speed and relative position. Used for tension control and synchronization when absolute position is not required.
	Ramp or Loop pit	Photoelectric Sensor (Diffuse) (Pepperl+Fuchs OBT200-18GM70-E5-V1)	Detect loop height/strip presence in the entry slack loop. Controls uncoiler speed to maintain proper loop; long sensing range (up to 200 mm) handles loop motion.
	Feeder and measuring wheel	Rotary Incremental Encoder (Heidenhain ERN 480)	High-precision measurement of strip length feed by the measuring wheel. Provides feedback to ensure each lamination is cut to the exact programmed length (resolution up to 5000 PPR).
	Tool section	Inductive Proximity Sensor (NBB5-18GM50-E2-V1)	Detect the presence of the steel strip entering the cutting station. Short-range (5 mm nominal) sensor confirms the strip is properly fed; also used to detect strip misfeeds or end-of-coil.
	Stacker	Photoelectric Sensor (Background suppression) (Pepperl+Fuchs ML6 series)	Precisely detect presence and height of stacked laminations. Ignores background reflections and reliably detects laminations for stopping the stacker or initiating stack changeover.
	Whole line	Magnetic Cylinder Sensor (FESTO SMT-8M-A reed switch)	Sense piston position (extended/retracted) on pneumatic cylinders. Confirms diverter or guide position. Non-contact sensors improve safety and sequencing.

3. PERFORMANCE ANALYSIS

3.1. Current Sensor System Performance

The automated cutting line employs a combination of sensor types, each selected to meet specific operational and environmental demands. The system architecture is designed to ensure high-precision control of motion and sequencing throughout the cutting process.

Inductive proximity sensors represent the dominant technology in the line, particularly in the cutting and alignment sections. Their robustness against oil, metal dust, and mechanical vibration makes them a practical choice for industrial applications with harsh conditions [1], [8]. These sensors detect the presence of the steel strip or mechanical flags with a typical nominal sensing range of 5 mm, and reliably operate at switching frequencies up to 2 kHz. Shielded variants are applied in locations where electromagnetic interference (EMI) is expected, while unshielded types are used where a wider sensing field is required. Throughout multiple operation cycles, no false triggering or signal loss was recorded, confirming their suitability for repetitive high-speed tasks according to the manufacturer's datasheet [8].

Photoelectric sensors are strategically placed where inductive sensors are either ineffective or spatially impractical. A diffuse-mode optical sensor in the slack loop section monitors the vertical position of the looped strip to regulate coil unwinder speed and prevent slack buildup. In the stacking area, a background suppression sensor detects the presence of lamination sheets regardless of background reflectivity, minimizing errors due to ambient light or frame reflections [3], [9]. These sensors offer a response time of around 1.5 ms, which is sufficient for real-time loop compensation. However, they do require regular lens cleaning to maintain performance, especially in dusty environments [5].

Rotary encoders provide high-resolution feedback critical for position tracking. An incremental encoder installed on the coil unwinder delivers relative angular displacement information, enabling the PLC to monitor coil unwinding dynamically. Unlike absolute multi-turn encoders, it does not retain position after power loss, which requires homing upon startup [7]. On the measuring wheel, an incremental encoder with a resolution of up to 5000 pulses per revolution ensures sub-millimeter length accuracy during strip feeding. This encoder is tightly integrated into the servo control loop, enabling fast and stable feedback. Cutting precision within ±0.1 mm is consistently achieved, and the servo system includes error monitoring that halts the machine if deviation thresholds are exceeded [4], [7], [12].

Magnetic reed sensors are mounted on the cylinders controlling diverter gates and other pneumatic actuators. These sensors confirm cylinder stroke completion and ensure that mechanical movements occur in the intended sequence [10]. Their simple on-off nature makes them ideal for basic interlocks in safety-critical steps, despite lacking self-diagnostic capabilities. Still, no failure incidents were observed during prolonged operation, indicating their reliability in this specific setup, consistent with findings in [11].

3.2. Observed Limitations and Reliability Issues

Although the current sensor system meets essential automation requirements and ensures high-precision operation under stable conditions, several limitations have been observed that affect long-term reliability, maintainability, and integration potential within modern manufacturing paradigms.

Lack of Diagnostics: Most of the installed sensors are discrete binary devices, such as inductive proximity and reed sensors, which lack built-in diagnostic capabilities. These devices provide only basic presence confirmation without monitoring internal health states such as output signal degradation, contamination, or wiring issues [2], [11]. Consequently, potential faults remain undetected until a malfunction occurs—often triggering an unplanned stop. Since the PLC only receives basic high/low input states, maintenance technicians must rely on manual inspection and deduction, which increases downtime and complicates root cause analysis [5].

Discrete Feedback Only: The system relies primarily on threshold-based digital signals. For example, loop tension is monitored using a single-point diffuse photoelectric sensor, which only indicates the presence of material at a specific level. An analog sensor, such as a distance-measuring laser or ultrasonic unit, could enable continuous feedback and support more refined control strategies [3], [12]. Similarly, inductive sensors can confirm metal object presence but provide no indication of gradual wear, skew, or rubbing—conditions that could lead to silicon steel material defects if not detected early.

Environmental Sensitivity: The photoelectric sensors installed in the loop control and stacker sections are highly susceptible to dust, vapor, and reflective interference. Accumulated contamination on the optics can result in reduced sensitivity or false detections [9], [12]. While inductive sensors are more resistant to contaminants, they operate within a limited range and require precise alignment with metallic targets. Vibrations or mechanical shifts over time may alter sensor position, leading to missed detections or inconsistent switching [1], [8].

Functional Range Limits: Each sensor type used in the system has inherent limitations. Inductive sensors detect only metallic objects and at short distances—typically under 10 mm. This makes them unsuitable for detecting plastic or composite parts, or for applications requiring longer-range detection. Optical sensors, while capable of longer sensing ranges and material flexibility, are sensitive to surface reflectivity and changes in ambient lighting, which can distort measurements or generate false positives [2], [13].

Lack of Smart Communication: With the exception of the EtherCAT-connected absolute encoder, none of the sensors on the line offer intelligent communication protocols such as IO-Link or fieldbus integration. As a result, there is no possibility for real-time sensor diagnostics, parameterization, or automatic device identification [13]. These smart features are now standard in Industry 4.0 environments and are instrumental in enabling predictive maintenance strategies, reducing commissioning time, and improving data traceability [5], [13].

Reactive Maintenance Dependency: Due to the binary and passive nature of the sensors, the system depends entirely on reactive maintenance. Faults are typically discovered only after they disrupt production. For instance, in one observed case, a small metal fragment became lodged near an inductive sensor, causing it to remain in the "on" state continuously. As a result, a critical step in the sequence failed to initiate, halting the entire line. Resolving the issue required manual inspection and physical removal of the object—an avoidable scenario if the sensor had internal state monitoring or signal quality reporting [11], [13].

Summary and Recommendations: While the current sensor configuration is functionally adequate for basic automation and has demonstrated solid reliability under controlled conditions, it lacks the intelligence and flexibility expected in modern, data-driven production systems. Integrating smart sensors with diagnostic capabilities, adding analog or continuous feedback where appropriate, and adopting communication-enabled devices could significantly enhance operational robustness and reduce unplanned downtime [5], [13].

Although the current system primarily supports reactive maintenance, certain preventive measures are feasible within the existing configuration. Scheduled sensor cleaning, periodic calibration of photoelectric devices, and replacement of inductive sensors after predefined operating hours can reduce the probability of sudden failures. However, the absence of diagnostic feedback limits the effectiveness of such preventive strategies compared to systems with integrated smart sensors.

4. DISCUSSION

4.1. Enhancing sensor capabilities and integration

The analysis of the existing system revealed clear opportunities for enhancement through the adoption of smart sensor technologies aligned with Industry 4.0 principles. One of the key recommendations is to replace conventional binary sensors with intelligent devices that support communication protocols such as IO-Link or EtherCAT. Unlike legacy sensors, smart sensors can deliver extended diagnostic information—including signal quality, internal temperature, contamination levels, and supply voltage stability—which is critical for implementing predictive maintenance strategies [5], [14].

Although the sensor system does not feature predictive maintenance or built-in health diagnostics, its overall reliability and simplicity contribute to stable long-term operation. The selected sensor technologies are mature, field-proven, and well-supported by manufacturers, which is a significant advantage for system maintainability and spare part logistics, [12]. Future improvements may include integration of smart sensors with diagnostic and communication capabilities, enabling advanced fault detection and maintenance scheduling [5], [13]. With smart sensor integration, preventive maintenance can be gradually replaced by predictive strategies, where diagnostic data and communication protocols allow early fault detection and proactive intervention.

By using IO-Link-capable sensors, real-time condition monitoring and remote parameterization become possible. For instance, an optical IO-Link sensor could continuously monitor light intensity and automatically alert operators when lens contamination causes signal degradation. Similarly, replacing the binary loop control sensor with a laser distance sensor using EtherCAT could provide continuous analog feedback, enabling precise strip control through PID or fuzzy logic algorithms in the PLC [12], [14]. This would eliminate the limitations of discrete detection and improve dynamic loop regulation.

The control of this machine is based on Beckhoff industrial PCs and the EtherCAT real-time communication protocol [16], with the topology shown in Fig. 5. In this architecture, all motor drives and distributed I/O nodes are already connected to the EtherCAT network. The control software is implemented in Beckhoff's TwinCAT environment, utilizing advanced technologies such as complex motion control, high-integrity TwinSAFE safety systems, and a modern HMI interface for intuitive operation. This configuration allows the seamless addition of EtherCAT-compatible devices—such as sensors, encoders, and other slave modules—at any point in the network. Furthermore, due to the wide range of available I/O modules, IO-Link masters can be integrated, enabling connection of any IO-Link–capable devices. In addition, interface modules are available for conversion to other real-time communication standards, such as PROFIBUS, PROFINET, SERCOS, or CANopen, providing high flexibility in system expansion and interoperability.

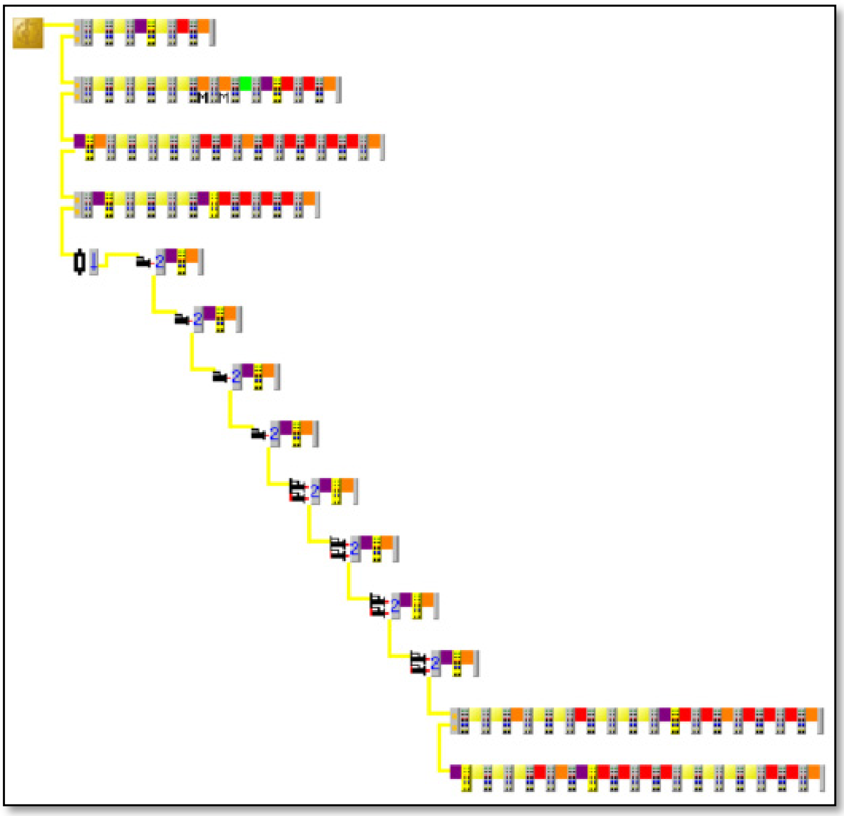

Figure 5: EtherCAT topology for transformer magnetic core lamination cutting line

Remote configuration offers another significant operational benefit. In the current system, adjusting detection thresholds or changing sensor sensitivity requires manual access—often involving production stoppages and mechanical intervention. With smart sensors, such adjustments can be performed remotely via software, reducing setup time when switching between materials or product variants and minimizing the risk of human error [14], [15].

Beyond sensor hardware, existing data from EtherCAT servo drives can be better leveraged. In addition to monitoring key parameters such as motor torque, velocity, and temperature, these drives also provide valuable information related to energy consumption, including DC bus voltage and current, main supply voltage, brake resistor load, and instantaneous power usage, as illustrated in Fig. 6. Such telemetry serves as a set of virtual indicators of both mechanical and electrical conditions. For example, a gradual increase in feeder motor torque may suggest increased resistance due to strip misalignment, blade dulling, or roller contamination, while abnormal power draw or DC bus fluctuations can indicate issues such as bearing wear, misalignment, or electrical faults. By implementing logic in the PLC to track these trends or detect threshold violations, the available drive data can be repurposed into "soft sensors" for early fault detection and predictive maintenance [4], [15].

Figure 6: On-line monitoring of energy consumption and electrical health parameters from EtherCAT servo drives for feeder axis [17]

Another promising approach is inferential sensing, which uses mathematical models to estimate physical quantities. For example, instead of installing a physical sensor to measure coil diameter, it can be inferred from encoder pulses and total fed length. This method reduces hardware complexity and cost while maintaining accuracy sufficient for control purposes [13], [15]. Such approaches have been validated in modern production systems and can be highly effective when combined with periodic recalibration.

Environmental conditions must also be considered. In dusty or oily environments, optical sensors often suffer from reduced reliability. Replacing or supplementing them with ultrasonic sensors—whose measurements are immune to surface reflectivity and airborne particulates—can improve robustness. Although ultrasonic sensors typically have lower resolution, their tolerance to contamination makes them suitable for gross loop detection or backup systems [2], [14]. Alternatively, modern optical sensors equipped with auto-teach functions and contamination alarms can self-calibrate and notify operators when their effectiveness is compromised, further improving maintenance responsiveness.

As a longer-term improvement, the integration of industrial vision systems should be considered. Camera-based systems can be used for real-time monitoring of strip edge position, surface defects, or lamination orientation. Combined with machine learning algorithms, these systems allow for adaptive quality control and closed-loop corrections. Although not part of the current line, their implementation is increasingly common in high-end transformer core production environments [3], [15].

In summary, by upgrading to smart sensors, utilizing existing drive and encoder data more effectively, introducing hybrid sensing methods, and considering future integration of vision and inferential technologies, the automation system can achieve a higher level of reliability, maintainability, and scalability. These enhancements align with the broader goals of digital transformation and Industry 4.0 readiness.

4.2. Towards predictive maintenance and Industry 4.0

Enhancing the sensor system of the transformer core cutting line not only improves immediate functionality but also lays a robust foundation for implementing predictive maintenance (PdM)—a key component of modern Industry 4.0 frameworks. Predictive maintenance aims to forecast and prevent equipment failures by analyzing historical and real-time trends in sensor, actuator, and drive data, moving the maintenance strategy from reactive to proactive [5], [13].

Rather than waiting for critical faults, PdM systems monitor patterns such as gradual torque increases, shifting position feedback, or declining sensor signal strength. These deviations often indicate early signs of wear, contamination, or misalignment. When detected in time, corrective actions can be scheduled during planned downtimes, avoiding unplanned halts and reducing repair costs [15].

To enable this transition, it is necessary to implement a centralized platform for data acquisition and analytics. This can be realized through a SCADA system, edge computing unit, or a cloud-integrated Manufacturing Execution System (MES) that consolidates machine, sensor, and production data using modern industrial protocols such as MQTT or OPC UA [14]. A representative case study is the MESWARM platform [17], [18], developed as a modular and Industry 4.0–oriented Manufacturing Execution System architecture, as illustrated in Fig. 7. In this architecture, IoT modules collect real-time data from PLCs, drives, and smart sensors, while production management modules handle scheduling, resource allocation, and performance tracking. Adaptive logic and service management modules process events to trigger predictive maintenance actions, and integration with AI and document management subsystems enables long-term trend analysis and knowledge retention. The system supports deployment in both public and private clouds, ensuring scalability, remote accessibility, and secure configuration management.

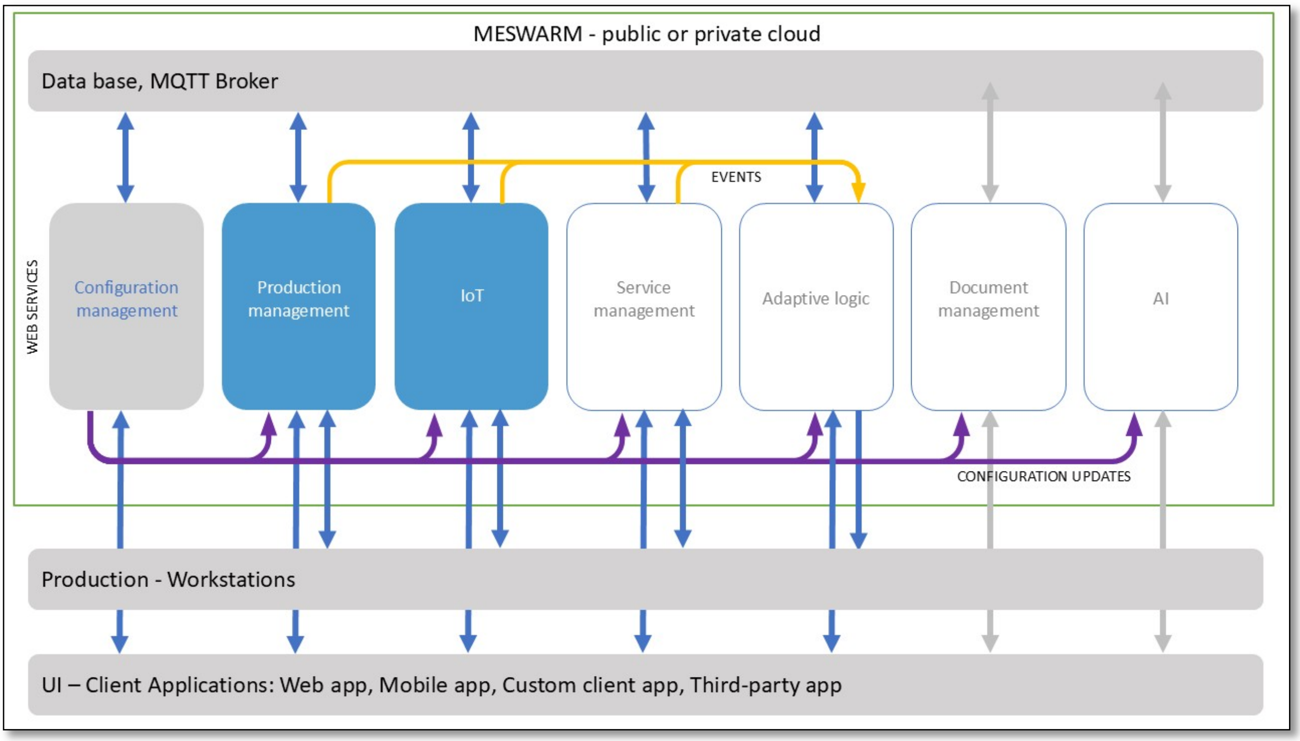

Figure 7: MESWARM: Industry 4.0–oriented architecture

By linking SCADA-level monitoring with MES-level analytics, the transformer core cutting line can benefit from unified dashboards where operators view live equipment status, engineers receive trend-based maintenance alerts, and managers can evaluate cross-line performance. An example MESWARM dashboard [17, 18], Fig 8, illustrates how real-time sensor data, historical trends, and predictive alerts are presented in a single interface. Such visualizations allow rapid identification of deviations—such as increased torque, declining sensor signal strength, or encoder jitter—and enable maintenance actions to be scheduled before faults occur. This integrated approach not only facilitates predictive maintenance but also aligns the production environment with broader Industry 4.0 ecosystems, including ERP and digital twin integration.

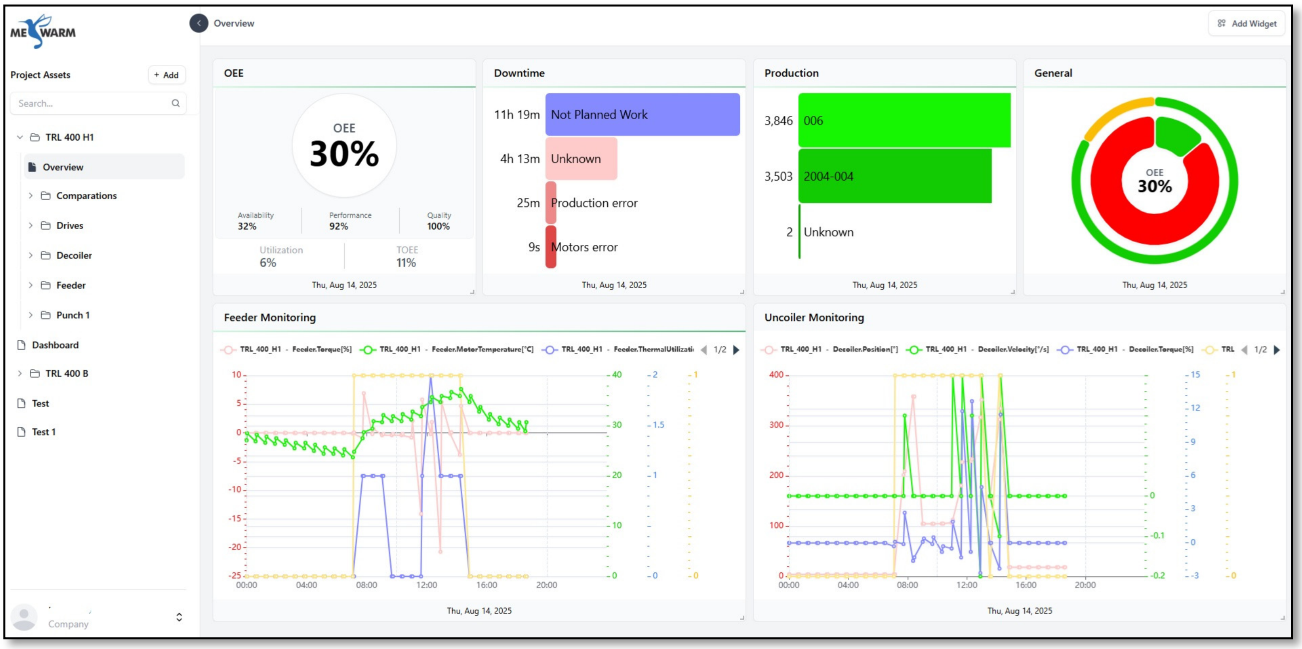

Figure 8: MESWARM: Dashboard example [17]

Smart sensors with IO-Link or EtherCAT interfaces play a crucial role in this strategy. Unlike conventional binary devices, these sensors can provide diagnostic data, such as detection counters, signal-to-noise ratios, and internal temperature. Monitoring such parameters over time enables detection of sensor degradation trends, such as sensitivity loss due to dust accumulation on photoelectric lenses [14]. Servo drives further enhance PdM readiness by offering telemetry data—torque curves, position errors, overloads, thermal behavior—which, when interpreted correctly, act as virtual sensors indicating the machine's physical health [4], [13].

Inferential sensing methods also contribute to maintenance simplification. For example, instead of physically measuring the coil diameter with an additional sensor, the system can estimate it using encoder feedback and total feed length. This approach reduces hardware complexity, minimizes failure points, and aligns with lean maintenance principles. Research confirms that such estimations, when supported by initial calibration, maintain high accuracy across operational cycles [13].

Connectivity is another critical enabler. In a smart factory environment, sensor data can be transmitted securely to cloud-based platforms for centralized monitoring across multiple production lines. This allows identification of cross-line anomalies, long-term drift, or systemic sensor degradation. Furthermore, advanced platforms can even trigger automated spare part orders or generate maintenance tickets when thresholds are exceeded [14]. However, increased connectivity introduces systemic complexity. Potential issues such as unstable network links, software bugs, or incorrect configuration must be mitigated through failsafe system design. For instance, IO-Link sensors should revert to default binary output in the event of protocol failure, ensuring continuity of core functions [14].

Looking forward, the adoption of multifunctional sensors, such as dual-channel encoders, multi-range proximity sensors, or embedded vision cameras, offers potential for consolidation of hardware. These devices can simultaneously perform multiple tasks, reduce wiring and installation effort, and simplify maintenance diagnostics. Although such sensors may have higher initial cost, their long-term value lies in reducing downtime, cabling complexity, and troubleshooting time especially in flexible production systems where rapid adaptation is essential [12].

In summary, by adopting predictive maintenance strategies grounded in intelligent sensing, advanced analytics, and streamlined connectivity, the transformer core cutting line can move toward a more reliable, maintainable, and digitally integrated future. This evolution not only addresses existing shortcomings but also strategically prepares the system for integration into Industry 4.0 ecosystems, including MES, ERP, and digital twin technologies.

5. CONCLUSIONS

This paper analyzed the sensor system implemented in an automated transformer magnetic core lamination cutting line, focusing on its operational performance and upgrade potential. The existing configuration, consisting of inductive proximity sensors, photoelectric sensors, magnetic reed switches, and rotary encoders, has proven reliable in practice, as confirmed through continuous operation of the real cutting line, where precise cutting results and consistent process sequencing were observed across all segments.

Despite its proven functionality, several limitations were identified. The lack of built-in diagnostics and communication interfaces restricts the system to reactive maintenance, where issues such as contamination or mechanical misalignment are discovered only after faults occur. Additionally, photoelectric sensors were found to be sensitive to environmental factors such as dust accumulation and variable surface reflectivity, which can compromise detection reliability.

To improve system resilience and support the transition towards Industry 4.0 practices, the implementation of smart sensors is recommended. These sensors enable real-time condition monitoring, remote parameter configuration, and improved fault diagnostics, contributing to shorter downtime and enhanced process control. Furthermore, the system can leverage data already available in servo drives and encoders—such as torque, temperature, or load feedback—to create virtual diagnostic tools based on programmable logic. This approach aligns with lean engineering principles by enhancing observability without adding hardware complexity.

Initial improvement steps could include replacing key binary sensors with intelligent counterparts, enabling PLC-based data logging, and implementing basic software-based fault detection algorithms. Such measures can serve as pilot initiatives for evaluating technological and economic feasibility before adopting a full-scale smart sensing solution.

In summary, although the current sensor system satisfies the functional requirements of the cutting process, its gradual transformation toward intelligent sensing and integrated diagnostics offers a clear path toward increased reliability, reduced maintenance effort, and readiness for future smart manufacturing applications. The contribution of the authors lies not only in the analytical evaluation but also in their direct involvement in the development and integration of the initial system, which strengthens the practical relevance of the findings.

6. ACKNOWLEDGEMENTS

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