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IMPLEMENTATION OF CONDITION-BASED MAINTENANCE (CBM) WITH FMEA APPROACH TO IMPROVE PRODUCTIVITY OF THE AUTO INSERT MACHINE IN ELECTRONIC COMPONENT MANUFACTURING

Irkham Syifaul Qulub

Mercu Buana University. Jakarta, Indonesia.

irkhamsyifaul@gmail.com

Abstract:

This study explores the implementation of Condition-Based Maintenance (CBM) integrated with Failure Mode and Effects Analysis (FMEA) on the *Auto Insert Connectors FFC* machine, a critical asset in the assembly process of Flexible Flat Cable (FFC) connectors within the electronic components manufacturing industry. The machine plays an essential role in ensuring precision and consistency during the insertion of connector materials, making its reliability a key factor in overall production efficiency. The primary objective of this research is to optimize the maintenance process by transitioning from a preventive maintenance approach to a condition-based strategy utilizing real-time sensors and monitoring systems. FMEA was employed to identify critical failure modes and calculate Risk Priority Numbers (RPNs) for key machine components, which guided the strategic installation of sensors for continuous performance monitoring. Compared to conventional preventive maintenance methods, the implementation of CBM resulted in a 69.75% reduction in inspection time, indicating a substantial improvement in maintenance efficiency. The findings conclude that integrating CBM with real-time data and FMEA significantly enhances operational productivity and minimizes machine downtime. This approach demonstrates strong potential for broader application across various high-precision industries, particularly electronics, automotive, and mining, where equipment reliability is essential to maintaining competitiveness.

Keywords: condition-based maintenance (CBM); failure mode effects analysis (FMEA); manufacture electronic component.

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1. General information

The COVID-19 pandemic has heightened global economic uncertainty, including in Indonesia (Greig et al., 2020). In 2023, Indonesia's Gross Domestic Product (GDP) reached IDR 20,892.4 trillion, growing at 5.05% a slight decline from 5.31% in 2022 (Badan Pusat Statistik, 2023). Despite this slowdown, the manufacturing sector, particularly electronics, continues to be a vital driver of economic growth, recording a 1.06% year-on-year increase supported by Industry 4.0 technologies such as 5G connectivity (Kementrian PPN, 2023). Translating this national trend into the microeconomic context, one electronic components manufacturer located in Bekasi specializing in terminal insulation and electrical connectors has been contributing significantly to the industry with an average monthly output of 40 million units. However, between April and December 2023, the company experienced a consistent production shortfall of approximately 1 million units per month. The shortfall is largely associated with limited operational availability of the Auto Insert machine, which plays a crucial role in ensuring product precision and assembly quality.

Although the Auto Insert machine is integral to the production process, its operational performance is suboptimal. On average, the machine achieves a running time of only 63%, while experiencing 37% downtime. Running time refers to the percentage of scheduled production time during which the machine is actively operating, whereas downtime includes periods when the machine is idle due to planned or unplanned events. A notable portion of this downtime is attributed to daily checks and manual inspection routines necessary yet time consuming activities that lack sufficient automation or efficienc. In response, the company has set a target to increase machine running time to at least 80% to close the production gap and meet growing demand.

To address this challenge, a Condition-Based Maintenance (CBM) strategy supported by early-detection sensors offers a promising solution for minimizing downtime. When combined with Failure Mode and Effects Analysis (FMEA), CBM enables the early identification of potential machine failures, ensuring greater process stability and predictive accuracy (Pierce et al., 2018). By systematically analyzing failure modes and their respective risks, FMEA serves as a foundation for determining critical components to monitor.

*Corresponding author: Irkham Syifaul Qulub, irkhamsyifaul@gmail.com

This research introduces an innovative approach through the comprehensive integration of CBM and FMEA on the Auto Insert machine. Despite its potential, this approach has not yet been widely adopted in Indonesia's electronic component manufacturing sector. Through its implementation, this study aims to enhance machine reliability, reduce downtime, and optimize production efficiency ultimately strengthening the company's competitiveness in both domestic and global markets.

2. Materials and Methods

2.1. Materials

2.1.1. Maintenance

Maintenance refers to a series of actions aimed at keeping or repairing machinery to ensure it remains in optimal condition (Nursanti et al., 2019). Proper maintenance prevents downtime, improves machine performance, and reduces the risk of unexpected failures. Routine maintenance activities include inspections, lubrication, repairs, and spare parts adjustments (Nursanti et al., 2019). Machine performance degradation can be caused by natural deterioration or accelerated deterioration due to incorrect operation or lack of maintenance.

Although maintenance is often seen as a cost burden, regular maintenance actually reduces the risk of costly major repairs. Preventive and predictive maintenance can improve production efficiency and extend machine lifespan (Nursanti et al., 2019). Maintenance is classified into several types:

1. Planned Maintenance, scheduled maintenance aimed at preventing damage (including Preventive, Corrective, and Predictive Maintenance).
2. Unplanned Maintenance, emergency maintenance due to sudden failures.
3. Autonomous Maintenance, maintenance performed by operators with basic training, following 5S principles (Nursanti et al., 2019).

The primary goals of maintenance are to analyze early damage, extend machine life, maintain product quality, prevent excessive wear (Shagluf et al., 2014). The main function of maintenance is to extend the economic life of machines and ensure equipment is always ready for use in optimal condition (Nursanti et al., 2019).

2.1.2. Condition-Based Maintenance (CBM)

According to Wang et al. (2016), maintenance strategies can be divided into two main types: reactive maintenance and proactive maintenance.

The classification of these strategies is shown in Figure 1 Condition-Based Maintenance (CBM) is part of proactive maintenance, specifically in the predictive maintenance subcategory. This means CBM is performed at the right time and only when necessary, based on actual equipment condition (Wang et al., 2016).

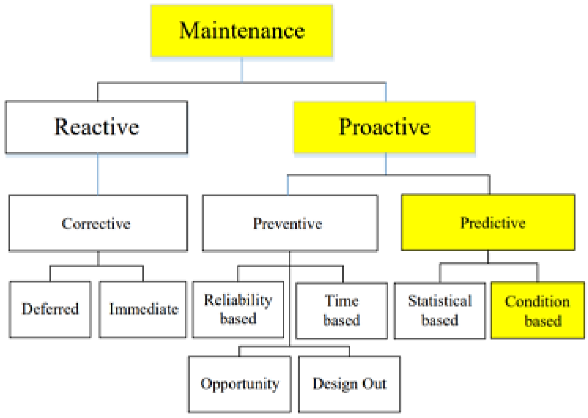


Figure 1: Maintenance Strategy Classification.

CBM focuses on predicting the degradation process of a product. It assumes that abnormalities develop gradually, from normal to abnormal conditions (Fu et al., 2004). CBM recommends maintenance based on data obtained from equipment measurements. Jardine et al. (2006) outline three key stages in CBM implementation: data acquisition, data processing, and maintenance decision-making.

The data acquisition stage involves collecting failure diagnosis and prognosis data, including event data (failures and repairs) and condition measurement data from sensors (e.g., temperature, vibration). Data processing involves data cleaning and analysis to interpret optimal results (Xu & Kwan, 2003). Maintenance decisions are divided into prognosis (predicting failures) and diagnosis (identifying failures after they occur) (Jardine et al., 2006). Prognosis typically involves predicting Remaining Useful Life (RUL), a key factor in CBM decision-making (Almeida et al., 2015).

Key techniques in CBM include:

1. Condition Monitoring, uses sensors to detect physical changes in equipment (Pierce et al., 2018).
2. Non-Destructive Testing, methods like ultrasonic testing and infrared thermography detect internal equipment issues.
3. Data Analysis, software and algorithms analyze data to identify failure patterns and trends (Pierce et al., 2018).
4. Real-Time Monitoring Systems, integrates monitoring tools like SCADA with Computerized Maintenance Management Systems (CMMS) for proactive maintenance suggestions (Pierce et al., 2018).

Additionally, CBM can use alarm-based systems for equipment monitoring without real-time data, which is more affordable and easier to implement (Yoon et al., 2023).However, alarm-based CBM systems have limitations, such as delayed response and lack of predictive data (Yoon et al., 2023).

2.1.3. Failure Modes Effect Analysis (FMEA)

Failure Mode and Effect Analysis (FMEA) is a systematic method for identifying and evaluating potential failures in a system, process, or product (McDermott et al., 2017). FMEA aims to identify failure modes, assess their impacts, and design actions to mitigate these risks. Originally developed for the aerospace and military industries, it is now widely used in various sectors such as manufacturing and healthcare (Stamatis, 2003). FMEA involves identifying three main components:

1. Failure Mode, how a failure can occur.
2. Effect, the impact of the failure on the system or end user.
3. Cause, the underlying cause of the failure.

Each failure mode is assigned values based on severity, occurrence, and detection. The combination of these values results in the Risk Priority Number (RPN), which is used to prioritize corrective actions (McDermott et al., 2017). The RPN formula is:

$$RPN = S \cdot O \cdot D \tag{1}$$

Three components are evaluated: Severity (S), Occurrence (O), and Detection (D). Severity measures the impact of failure, Occurrence assesses its frequency, and Detection evaluates the ability to identify it. These factors combine to form the Risk Priority Number (RPN), guiding corrective action priorities. RPN values range from 1 (lowest risk) to 1000 (highest risk). The higher the RPN value, the greater the priority for corrective action. Types of FMEA (McDermott et al., 2017):

1. Design FMEA (DFMEA), analyzes potential failures in product design before production begins.
2. Process FMEA (PFMEA), focuses on analyzing failures in the production process.
3. System FMEA, analyzes potential failures in the system as a whole.
4. Service FMEA (SFMEA), analyzes risks in services or after-sales support.
5. Software FMEA, analyzes software failures and their impact on system functionality.

FMEA is widely used by the automotive and manufacturing industries to improve product and process quality and reliability.

2.1.4. Why-Why Analysis

Why-Why Analysis is a problem-solving method used to identify the root cause of an issue by repeatedly asking the question "why," typically five times or more, until the primary cause is identified. This technique helps uncover hidden causes and ensures that the solution addresses the root problem, rather than just its symptoms (Naranje et al., 2019).

2.1.5. Plan-Do-Check-Action (PDCA)

PDCA is a management cycle used to drive continuous improvement in various processes and systems (Ghatorha et al., 2022). The cycle consists of four steps:

1. Plan, in this stage, problems or improvement opportunities are identified, and specific objectives are set. Then, an action plan to achieve those objectives is developed based on data analysis and appropriate strategies.
2. Do, this step involves implementing the plan that has been developed. The process is carried out according to the plan, and data or information is collected to assess the results of the implementation.
3. Check, after implementation, the results of the actions taken are evaluated and compared to the initial goals. During this stage, data is analyzed to determine if improvements have been achieved or if there are discrepancies that need to be addressed.
4. Act, based on the evaluation results, corrective actions are taken if discrepancies are found, or successful processes are expanded or standardized. The cycle then starts again with planning further improvements, ensuring continuous improvement.

2.1.6. Predictive Maintenance and Data-Driven Technologies

Predictive Maintenance (PdM) is an advanced form of Condition-Based Maintenance (CBM) that utilizes predictive algorithms and machine learning to estimate the Remaining Useful Life (RUL) of components. This approach enables more effective maintenance planning by anticipating failures before they occur.

One of the commonly used techniques in PdM is the Long Short-Term Memory (LSTM) neural network, which is effective in processing time-series data. A study by Zeng & Liang (2023) demonstrated that deep learning approaches using LSTM networks offer high accuracy in RUL prediction of lithium-ion batteries, supporting more informed decision-making in maintenance operations.

Furthermore, a hybrid model that combines Convolutional Neural Networks (CNN), LSTM, and attention mechanisms has shown improved prediction accuracy for complex systems such as aero-engines. According to Wu et al. (2022), this method significantly outperforms traditional prediction models in estimating RUL.

2.1.7. Integration of Industry 4.0 Technologies in Maintenance Systems

The digital transformation driven by Industry 4.0 technologies has shifted maintenance paradigms from reactive to predictive. Technologies such as the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI) facilitate large-scale data collection and analysis, enabling more accurate and timely maintenance decisions.

Ucar, Karakose, and Kırımça (2024) emphasized that AI plays a critical role in PdM applications, particularly in enabling real-time equipment monitoring and predictive failure analysis based on historical data trends.

Additionally, the incorporation of Edge Computing into maintenance systems allows for local data processing at the device level, reducing latency and improving responsiveness to machine conditions (Bala et al., 2024). Highlighted that the integration of AI with edge technologies provides a robust framework for predictive maintenance while addressing design and implementation challenges.

2.1.8. The Impact of CBM and Predictive Maintenance on Productivity (OEE)

The implementation of CBM and Predictive Maintenance strategies has shown positive impacts on productivity, often measured through the Overall Equipment Effectiveness (OEE) metric. OEE evaluates equipment performance based on three core components: Availability, Performance, and Quality.

Dobra and Jósvai (2022) presented that machine learning models used for cumulative and rolling horizon OEE prediction can improve operational efficiency and reduce unplanned downtime.

Moreover, AI-driven predictive maintenance systems significantly enhance OEE by minimizing unexpected breakdowns and optimizing equipment performance. According to a report by Mohan et al. (2023), AI-powered PdM solutions can considerably improve OEE, supporting continuous improvement and cost reduction in industrial operations.

2.2. Methods

The research methodology used in this study is the PDCA (Plan-Do-Check-Act) cycle, applied to enhance the effectiveness of Condition-Based Maintenance (CBM). In the Plan phase, the first step is to identify machine operational time, followed by root cause analysis using the Why-Why Analysis method. Next, an analysis is conducted on the machine components with high and low priority using the Failure Mode and Effect Analysis (FMEA) method to determine areas that require more attention. Based on this analysis, a CBM implementation plan is developed. In the Do phase, CBM is implemented according to the plan formulated in the previous phase, focusing on machine maintenance based on the actual conditions detected. After implementation, in the Check phase, an evaluation is carried out to assess the results of the CBM application, comparing the machine performance after maintenance. Finally, in the Act phase, if the evaluation results show that CBM has yielded positive outcomes, CBM is implemented across all machines to maintain low downtime and enhance overall operational efficiency. Thus, the PDCA cycle is expected to improve machine maintenance quality and support more efficient production processes. Here is the breakdown of the implementation process following the PDCA methodology:

2.2.1. Plan

This research began by collecting data through field studies and literature on the implementation of Condition-Based Maintenance (CBM) using the Failure Mode and Effect Analysis (FMEA) approach on the Auto Insert machine in the electronic component manufacturing process. The primary focus of this research was on the Auto Insert Connectors FFC machine in the Assembly department, which has frequently experienced high downtime.

The initial data collected included an analysis of the company profile and the machine's operational time distribution, which can be seen in Table 1.

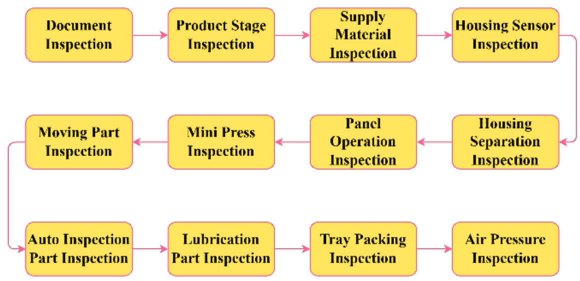


Figure 2: Sequence of Inspection Activities for the Auto Insert Connectors FFC Machine.

Figure 2 shows the mapping of maintenance activities carried out by this company, a Japanese electronic components manufacturer located in the MM2100 Industrial Estate, Cikarang Barat, with a long history of producing high-quality connectors.

Based on Table 1, the machine's operational time distribution shows key activities such as production (code 111), daily checks (code 124S), and inspections (code 122).

Table 2 presents the root cause analysis results using the Why-Why Analysis method, which identified that the high daily check time was the main cause of the downtime. The lengthy manual inspection became the priority for optimization. The subsequent FMEA analysis

Table 1: Distribution of Operational Time for the Auto Insert Machine.

Machine	Running	Planned Down Time				Break Down Time			
		111	121	122	124C	124E	122	126	1294
Total FE Machine	259294	7165	36135	20508	23032	11920	19445	7895	15400

Table 2: Why-Why Analysis Based on the Operational Time Distribution of the Auto Insert Machine.

Analysis	Question (Why)	Answer	Detail
Why 1	Why has Running Time not reached 80% as targeted by the company?	Due to high downtime	Caused by various other company activities
Why 2	Why is downtime high?	Due to a lot of time spent on daily checks and other maintenance processes	Inspection and maintenance processes are lengthy
Why 3	Why does Daily Check take a long time?	Because the procedure is done one by one in detail	The procedure involves many steps, requiring high precision and attention
Who	Who is involved in the Daily Check process?	Maintenance Staff	Maintenance staff conduct checks daily
What	What activities cause a long Daily Check time?	Checking all components	Checking every component daily takes a longer time
Where	Where is the Daily Check performed?	On the Auto Insert Connectors FFC machine	Checks are performed on the components of this machine
How	How is the Daily Check process carried out?	Done manually, involving physical component checks	This process requires a long time for each component checked daily
	Solution	Implement CBM using sensors on the Auto Insert Connectors FFC machine	Target to reduce Daily Check time (1245)

identified priority and non-priority machine inspection activities. High-priority activities (RPN>100) will continue to be performed manually, while non-priority activities (RPN<100) will be handled using CBM. Example of RPN Calculation:

FMEA was conducted to evaluate potential failures in the Auto Insert FFC machine's Daily Check activity. The Risk Priority Number (RPN) is calculated by multiplying Severity (S), Occurrence (O), and Detection (D) scores, which determine the priority of corrective actions. The following is an example of the RPN calculation:

- Lamp & LED Display: RPN = 5 × 7 × 5 = 175
- Stroke/Guide Transfer: RPN = 7 × 4 × 5 = 140
- Separation Movement: RPN = 8 × 6 × 4 = 192

FMEA Results and Focus for Improvement:

Table 3: FMEA Results.

No.	Activity	Result
1	Before Activity	PRIORITY
2	Product Stage	NON-PRIORITY
3	Supply Material	NON-PRIORITY
4	Sensor Housing	NON-PRIORITY
5	Housing Separation	NON-PRIORITY
6	Panel Operation	PRIORITY
7	Mini Press	NON-PRIORITY
8	Movement Inspection	PRIORITY
9	Auto Inspect Part	NON-PRIORITY
10	Lubrication Part	NON-PRIORITY
11	Tray Packing Part	PRIORITY
12	Others (Air Pressure)	NON-PRIORITY

According to Table 3 the FMEA results for non-priority activities will implement CBM. The planned solution includes adding automatic sensors to monitor the actual machine component conditions, such as lubrication, sliders, and tray pathways. The goal is to reduce manual inspection time, improve machine reliability, and extend machine lifespan.

Table 4: CBM Implementation Plan.

No.	Activity	CBM Implementation Plan
1	Before Activity	-
2	Product Stage	Addition of product path detection sensor
3	Supply Material	Addition of inspection sensor
4	Sensor Housing	Inspection will be done while the machine is running by the operator
5	Housing Separation	Addition of inspection sensor
6	Panel Operation	-
7	Mini Press	Implementation of cleanliness sensor
8	Movement Inspection	-
9	Auto Inspect Part	Addition of monitoring system
10	Lubrication Part	Addition of lubrication detection sensor
11	Tray Packing Part	-
12	Others (Air Pressure)	Use of automatic sensor

Table 4 shows the CBM implementation plan, including various prioritized activities and RPN calculations to determine the stages of CBM application on the machine.

2.2.2. Do

a. CBM Implementation Process

The implementation of Condition-Based Maintenance (CBM) involves a systematic approach that integrates real-time monitoring with predictive maintenance strategies. This process includes sensor installation, data collection, and the development of a responsive system to ensure optimal machine performance and reduced downtime.

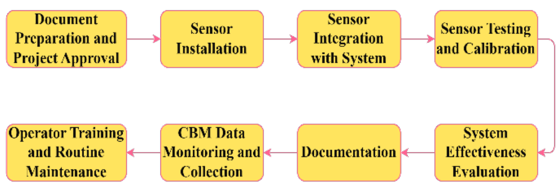


Figure 3: CBM Implementation Flow.

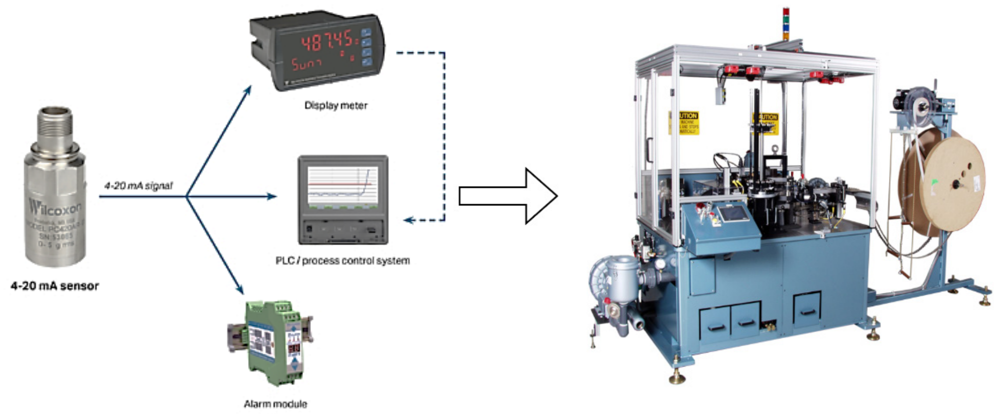


Figure 4: Sensor Installation.

Figure 3 illustrates the flow of CBM implementation. The CBM project aims to maintain machine condition by using sensor technology to monitor essential parameters. The implementation stages include planning, sensor installation, system integration, testing, and operator training. The CBM process aims to reduce machine failures and improve operational efficiency.

b. Sensor Installation on the Machine

The installation of sensors on the machine plays a crucial role in the CBM implementation process. Critical components, such as lubrication systems, tray pathways, and air pressure systems, are equipped with sensors to monitor their real-time conditions. These sensors provide continuous data, enabling early detection of potential issues and facilitating proactive maintenance.

According to Figure 4, various types of sensors are installed at strategic points on the Auto Insert FFC machine to enable real-time condition monitoring and early failure detection. For the product pathway and housing separation, *photoelectric sensors* and *fiber optic sensors* are used to detect the presence and alignment of components with high accuracy. In the mini press section, *displacement sensors* (such as linear encoders) are applied to monitor pressing movement precision, while *vision sensors* are installed for automatic part inspection to classify conforming and non-conforming products. For the lubrication system, *flow sensors* and *pressure sensors* are used to ensure the proper delivery of lubrication oil. Additionally, *pneumatic pressure sensors* monitor air pressure in auxiliary systems, and *vibration sensors* are positioned near critical mechanical components to detect anomalies that may indicate wear or imbalance.

The placement of each sensor follows a logical layout based on the critical control points (CCP) of the machine's operation areas most susceptible to failure or those requiring precise control. Calibration of the sensors is carried out periodically using reference standards and calibration tools recommended by the sensor manufacturers. Validation of sensor data is performed through comparison with manual measurements and known reference values to ensure consistency and accuracy before the data is used for analysis or dashboard visualization.

c. Sensor Integration with the System

The integration of sensors with the system is designed to enable real-time monitoring and data collection, ensuring proactive maintenance and improved machine performance. Each sensor is connected to a centralized system that facilitates seamless data analysis and decision-making.

Figure 5 illustrates how the installed sensors are connected to monitoring and control software platforms that enable real-time data tracking and analysis. The system utilizes R for advanced statistical analysis and machine learning-based anomaly detection, while Microsoft Excel is employed for initial data processing, logging, and manual reporting. Power BI serves as the primary visualization tool, presenting interactive dashboards that display sensor trends, machine status, and alert systems for operators and engineers. These platforms are integrated with the company's central information system, allowing seamless data sharing between production monitoring, maintenance planning, and enterprise resource planning (ERP) systems. This integrated approach supports faster and more informed maintenance decision-making, minimizes unplanned downtime, and ultimately extends the operational life of the machine.

d. CBM Dashboard Design

The CBM dashboard is designed to provide a comprehensive overview of machine performance and sensor data in real-time. It integrates inputs from installed sensors, displaying critical parameters such as lubrication levels, tray pathway status, and air pressure. The dashboard's user-friendly interface enables maintenance teams to monitor machine conditions effectively, identify anomalies quickly, and implement timely corrective actions, ensuring optimized machine uptime and productivity.

Figure 6 shows the design of the CBM dashboard used to monitor machine conditions in real-time. This dashboard provides essential information to the maintenance team to detect issues early and perform maintenance as needed.

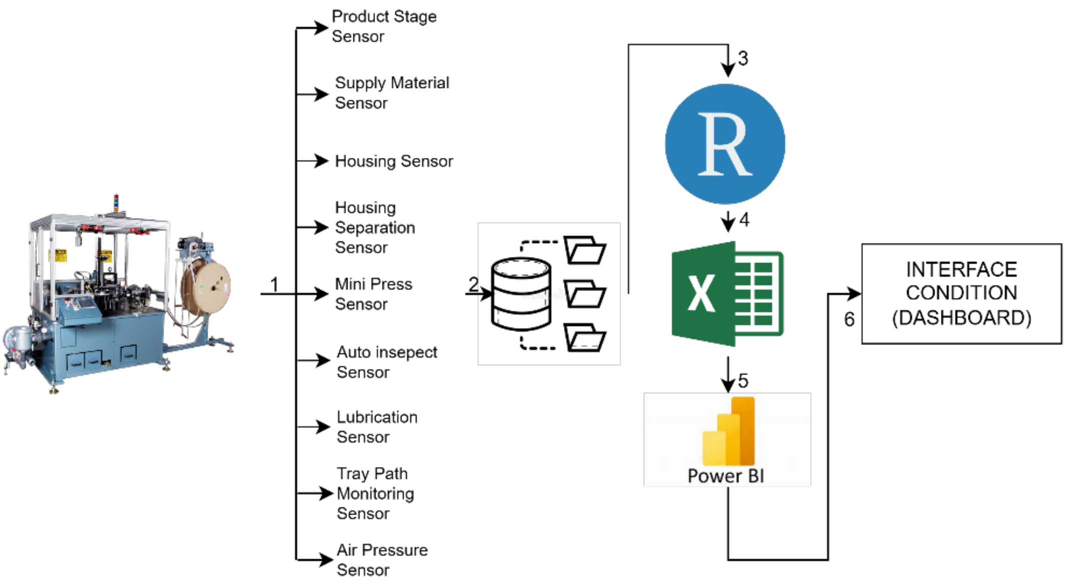
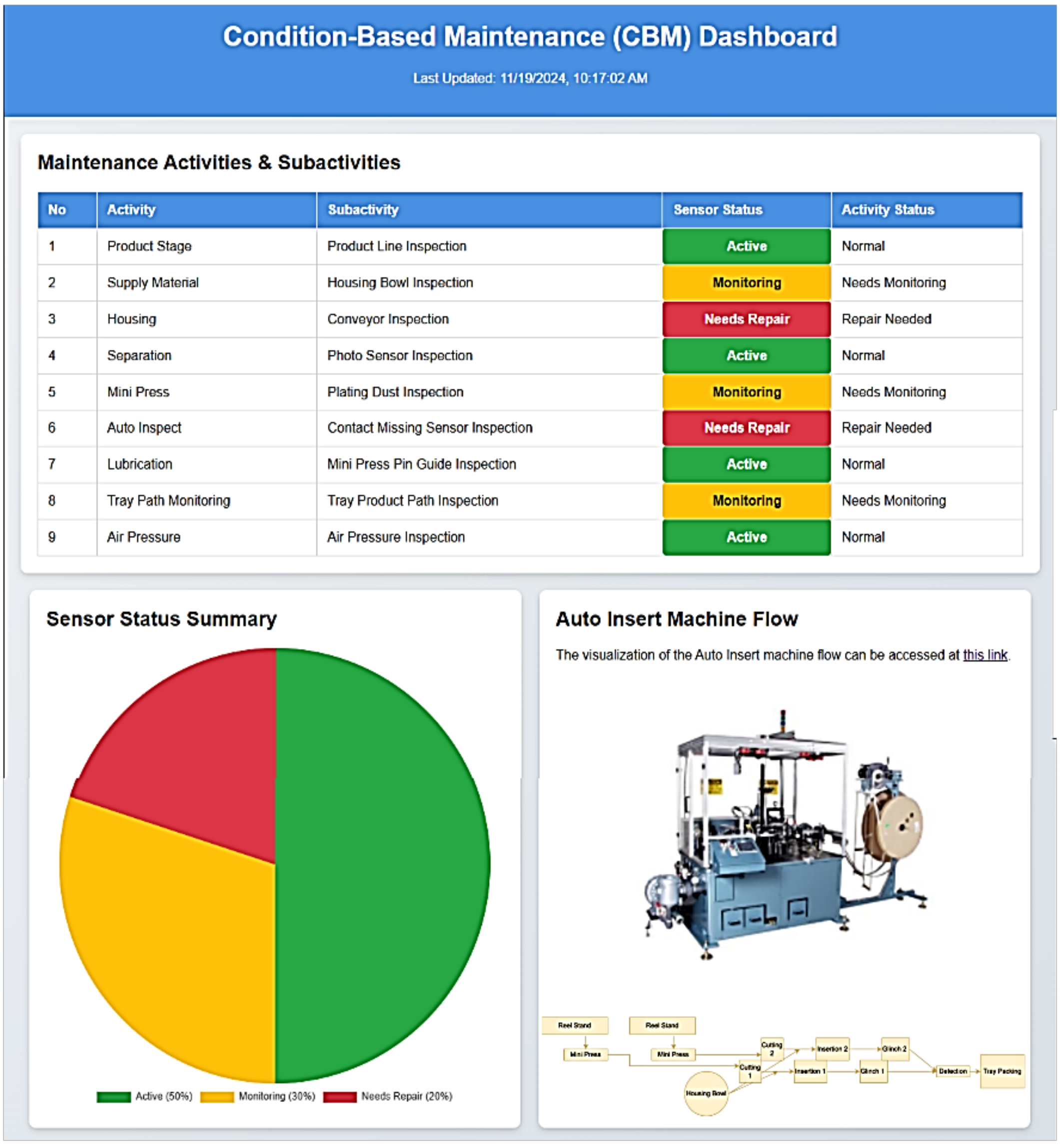


Figure 5: Sensor Integration Scheme with the System.



No	Activity	Subactivity	Sensor Status	Activity Status
1	Product Stage	Product Line Inspection	Active	Normal
2	Supply Material	Housing Bowl Inspection	Monitoring	Needs Monitoring
3	Housing	Conveyor Inspection	Needs Repair	Repair Needed
4	Separation	Photo Sensor Inspection	Active	Normal
5	Mini Press	Plating Dust Inspection	Monitoring	Needs Monitoring
6	Auto Inspect	Contact Missing Sensor Inspection	Needs Repair	Repair Needed
7	Lubrication	Mini Press Pin Guide Inspection	Active	Normal
8	Tray Path Monitoring	Tray Product Path Inspection	Monitoring	Needs Monitoring
9	Air Pressure	Air Pressure Inspection	Active	Normal

Figure 6: CBM Dashboard Design.

2.2.3. Check

After CBM implementation, an evaluation is conducted to check the effectiveness of the system that was applied:

a. Comparison Before and After CBM Implementation

The comparison highlights the significant improvements achieved through CBM implementation, focusing on reduced inspection time, enhanced operational efficiency, and minimized downtime. These changes demonstrate the effectiveness of integrating condition-based strategies into the maintenance process.

According Table 5 evaluation results showed that after CBM implementation, the inspection time decreased significantly from 52 minutes and 20 seconds (3140 seconds) to 15 minutes and 50 seconds (950 seconds). This indicates that using automatic sensors to monitor machine conditions in real-time has reduced the time needed for manual inspections.

b. Daily Inspection Standards

The existing inspection standards table includes all major components, such as the operation panel, mini press, and CBM dashboard. Each item in the inspection checklist now has clear evaluation parameters to ensure proper examination of each component.

c. Efficiency Improvements

The reduction in inspection time is most noticeable in areas that previously took longer, such as stroke and tray packing. With CBM implementation, monitoring in these areas has become more efficient, allowing operators to focus more on other critical components and improving overall productivity.

2.2.4. Act

a. Expansion of CBM Implementation

Based on the successful implementation of CBM on the Auto Insert Connectors FFC machine, the company decided to expand the use of the CBM system to other machines in the Assembly department. This expansion is expected to improve inspection time efficiency and overall productivity across the entire production line.

b. Integration into Maintenance SOPs

The results of CBM implementation have been integrated into the company's Standard Operating Procedures (SOPs). These SOPs include sensor installation and maintenance procedures, the use of dashboards for machine condition monitoring, and ongoing training for operators and technicians to optimize condition-based maintenance.

c. Feedback and Continuous Improvement

CBM implementation provides an opportunity to gather feedback from the maintenance team. This feedback is used to refine and improve the CBM system, ensuring its effectiveness and identifying potential improvements that can be applied to other machines.

With these steps, the company aims to maintain machine reliability across all production lines, reduce downtime, and continuously improve operational efficiency.

3. Result

3.1. Experimental Results and Interpretation

This section presents the outcomes of implementing Condition-Based Maintenance (CBM) on the Auto Insert Connectors FFC machine. The results demonstrate significant improvements in operational efficiency, reduced downtime, and optimized maintenance procedures through real-time monitoring and sensor-based analysis.

According to Figure 7, a bar chart illustrating performance metrics before and after the implementation of Condition-Based Maintenance (CBM), the average daily machine inspection time decreased from 52 minutes and 20 seconds (3140 seconds) to 15 minutes and 50 seconds (950 seconds), representing a 69.75% reduction. This reduction was calculated based on the

Table 5: Before and After CBM Implementation.

Before			After		
No.	Point Activity	Time	No.	Point Activity	Time
1	Document Inspection	02 min	1	Document Inspection	02 min
2	Product Stage Inspection	06 min	2	-	0 min
3	Supply Material Inspection	07 min	3	-	0 min
4	Sensor Housing Inspection	07 min	4	-	0 min
5	Mini Press Inspection	01 min	5	Mini Press Inspection	01 min
6	Housing Separation Inspection	01 min	6	-	0 min
7	Lubrication Inspection	07 min	7	-	0 min
8	Auto Inspection	06 min 50 sec	8	-	0 min
9	Movement Inspection	08 min	9	Movement Inspection	06 min 50 sec
10	Tray Packing Inspection	05 min	10	Tray Packing Inspection	3 min
11	Air Pressure Inspection	01 min 30 sec	11	-	0 min
12	-	-	12	CBM Dashboard Inspection	3 min
	Total Time	52 min 20 sec		Total Time	15 min 50 sec

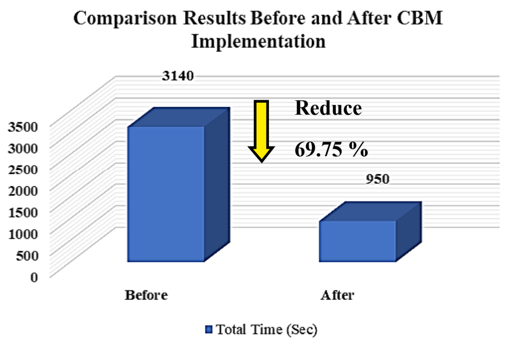


Figure 7: Comparison Results Before and After CBM Implementation.

average of 10 inspection cycles conducted before and after the implementation of CBM to ensure data reliability and minimize observational bias.

Further statistical analysis using a paired t-test confirmed that the difference in inspection time was statistically significant, with a p-value of 0.0014 at a 95% confidence level. Additionally, the 95% confidence interval for the mean difference ranged from -2310 seconds to -1845 seconds, reinforcing that the observed improvement was not due to random variation.

An initial Failure Mode and Effects Analysis (FMEA) was conducted to identify components with the highest failure risk. The “Separation Movement” had the highest Risk Priority Number (RPN) of 192, followed by the “Slider Follower” (RPN = 168) and “Tray Packing” (RPN = 160). Based on these results, sensors were strategically installed to monitor the most critical components in real time.

These sensors were integrated into a real-time monitoring system capable of continuous data acquisition. The system was connected to a custom-designed Power BI dashboard, providing maintenance personnel with immediate access to machine condition data. This enabled quicker diagnostics and preventive action, significantly reducing manual intervention and improving machine responsiveness.

3.2. Experimental Conclusions

The integration of CBM, supported by sensor technology and real-time data visualization, demonstrated significant improvements in maintenance operations. Beyond the reduction in inspection time, the system facilitated a transition from reactive to preventive maintenance, thereby minimizing unplanned downtime.

The improvements were observed consistently over a four-week trial period, reinforcing the reliability and effectiveness of the CBM system. As a result, the company plans to extend this approach to additional machines within the assembly department and incorporate it into official Standard Operating Procedures (SOPs).

This research underscores the strategic importance of adopting condition-based approaches in modern industrial settings, particularly in the high-precision manufacturing sector. The integration of FMEA, sensor technology, and real-time monitoring not only enhances machine reliability and reduces costs but also supports long-term operational resilience.

4. Discussion

The implementation of Condition-Based Maintenance (CBM) on the Auto Insert Connectors FFC machine in this study successfully reduced daily inspection time by over 69.75%, demonstrating significant improvements in operational efficiency. These findings offer a novel perspective compared to prior studies that focused on alternative maintenance and system improvement methods, such as Failure Mode and Effects Analysis (FMEA), Reliability Centered Maintenance (RCM), and the 5S methodology.

For instance, Banghart et al. (2018), in a collaborative study between Embry-Riddle Aeronautical University and Mississippi State University, utilized FMEA and RCM to analyze system failures in aerospace systems. They identified a key limitation in the form of subjectivity in FMEA classification, which impacted the consistency of risk assessment outcomes. This limitation suggests that traditional approaches relying heavily on human judgment may lack scalability and repeatability challenges that the current study seeks to mitigate through sensor-based, real-time condition monitoring, enabling more objective and timely decision-making.

Similarly, Aucasime-Gonzales et al. (2020) addressed low production efficiency in a manufacturing company by proposing a waste reduction model aimed at minimizing setup time and enhancing maintenance management to improve Overall Equipment Effectiveness (OEE). The model resulted in a 13% increase in OEE, a 22.5% reduction in setup time, increased changeover capacity, outsourcing of 37 activities, and an 80% improvement in the operators’ knowledge index..

Kipchumba et al. (2024) further contributed to this area by using FMEA and Fishbone Diagram methodologies to identify failures in the textile manufacturing sector, exposing inefficiencies in scheduling and prolonged downtimes. In contrast, this study emphasizes proactive detection through condition-based inspections, effectively reducing downtime through automated alerts and real-time system feedback. The CBM approach eliminates the need for extensive manual diagnosis, streamlining response times and improving machine availability.

Likewise, Prawira et al. (2018) implemented the 5S methodology in the mining industry to reduce equipment downtime and boost productivity. While effective, their approach involved a broader scope of organizational and workspace improvements. In contrast, the present study concentrates on equipment-level optimization, utilizing CBM and FMEA specifically to enhance the operational productivity of the Auto Insert machine.

When compared with CBM studies in automotive, aerospace, and heavy manufacturing sectors, this research distinguishes itself by targeting the unique challenges of electronic component manufacturing, which demands higher sensitivity to failure, shorter production cycles, limited physical space (space constraints), and more frequent inspection requirements. These factors necessitate a more granular and responsive maintenance system. Unlike heavy industry machines that can tolerate broader maintenance intervals, the Auto Insert Connectors FFC machine operates under tight dimensional and operational tolerances, making real-time monitoring and rapid response essential.

Despite the successful outcomes, this study presents certain limitations. First, the analysis is restricted to a single machine type and brand, which may not represent the full diversity of equipment in other electronic manufacturing environments. Second, scalability remains a challenge; implementing similar CBM systems across different machines may require custom sensor setups and software adaptations. Third, the effectiveness of CBM depends on operator familiarity, meaning staff training is essential. Additionally, not all enterprises have uniform system architectures, which may hinder full integration with existing enterprise systems (e.g., ERP or MES platforms). Addressing these limitations will be crucial for broader adoption.

The implications of this research underscore the scalability and efficiency of CBM in reducing downtime and enhancing machine productivity in precision manufacturing. Future research could explore cross-industry applications of CBM by integrating advanced technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) for predictive diagnostics. Additionally, the development of a standardized CBM implementation framework could bridge the gap between theoretical advancements and practical applications, facilitating broader adoption across diverse manufacturing environments.

5. Conclusion

This study demonstrates that the implementation of Condition-Based Maintenance (CBM) with sensor integration and real-time monitoring on the Auto Insert Connectors FFC machine significantly reduced daily inspection time by 69.75%. The findings confirm that CBM enhances the efficiency of maintenance processes, enables early failure detection, and proactively reduces machine downtime. The primary contribution of this research lies in its practical validation of CBM within a high-precision electronic component manufacturing environment, addressing industry-specific constraints such as limited spatial allowances, high inspection frequency, and sensitivity of components to operational anomalies.

Beyond immediate operational improvements, this study lays a foundation for scalable, data-driven maintenance frameworks in similar manufacturing contexts. Future work could explore the integration of Artificial Intelligence (AI) and Machine Learning (ML) to develop predictive analytics models capable of forecasting failures based on historical sensor patterns. Additionally, the use of edge computing could enable localized, real-time decision-making directly on the machine, minimizing latency and improving system responsiveness. These technological advancements would further enhance the reliability and adaptability of CBM, supporting autonomous maintenance ecosystems that align with the goals of Industry 4.0 and smart manufacturing.

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Author Contributions

Study design (Irkham Syifaul Qulub), data collection (Irkham Syifaul Qulub), analysis (Irkham Syifaul Qulub, Muhammad Kholil, Uly Amrina), writing (Irkham Syifaul Qulub), critical review (Muhammad Kholil, Uly Amrina).

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Grammarly in order to assist with initial drafting and sentence editing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Almeida, A.T., Cavalcante, C.A.V., Alencar, M.H., Ferreira, R.J.P., de Almeida-Filho, A.T., Garcez, T.V. (2015). Multiobjective and Multicriteria Decision Processes and Methods. In: *Multicriteria and Multiobjective Models for Risk, Reliability and Maintenance Decision Analysis*. International Series in Operations Research & Management Science, vol 231. Springer, Cham. https://doi.org/10.1007/978-3-319-17969-8_2

Aucasime-Gonzales, P., Tremolada-Cruz, S., Chavez-Soriano, P., Dominguez, F., & Raymundo, C. (2020). Waste Elimination Model Based on Lean Manufacturing and Lean Maintenance to Increase Efficiency in the Manufacturing Industry. In *IOP Conference Series: Materials Science and Engineering* (Vol. 999). IOP Publishing Ltd. https://doi.org/10.1088/1757-899X/999/1/012013

Badan Pusat Statistik. (2023). *Statistik Indonesia 2023*. https://www.bps.go.id/id/publication/2023/02/28/18018f9896f09f03580a614b/statistik-indonesia-2023.html

Bala, A., Rashid, R.Z.J.A., Ismail, I., Oliva, D., Muhammad, N., Sait, S.M., Al-Utaibi, K.A., Amosa, T.I., & Memon, K.A. (2024). Artificial intelligence and edge computing for machine maintenance—review. *Artificial Intelligence Review, 57*(5), Article 119. https://doi.org/10.1007/s10462-024-10748-9

Banghart, M., Babski-Reeves, K., Bian, L., & Strawderman, L. (2018). Subjectivity in failure mode effects analysis (FMEA) severity classification within a Reliability Centered Maintenance (RCM) context. *International Journal of Aviation, Aeronautics, and Aerospace*, *5*(1). https://doi.org/10.15394/ijaaa.2018.1191

Dobra, P., & Jósvai, J. (2022). Assembly Line Overall Equipment Effectiveness (OEE) Prediction from Human Estimation to Supervised Machine Learning. *Journal of Manufacturing and Materials Processing*, *6*(3). https://doi.org/10.3390/jmmp6030059

Fu, C., Ye, L., Liu, Y., Yu, R., Iung, B., Cheng, Y., & Zeng, Y. (2004). Predictive Maintenance in Intelligent-Control-Maintenance-Management System for Hydroelectric Generating Unit. *IEEE Transactions on Energy Conversion*, *19*(1), 179–186. https://doi.org/10.1109/TEC.2003.816600

Ghatorha, K. S., Sharma, R., & Singh, G. (2022). Lean Manufacturing Through PDCA: A Case Study of a Press Manufacturing Industry. In *Lecture Notes on Multidisciplinary Industrial Engineering: Vol. Part F41*. https://doi.org/10.1007/978-3-030-73495-4_12

Greig, P. R., Dixson, T., & McCorkell, S. (2020). A process for daily checks when using anaesthetic machines to ventilate the lungs of COVID-19 patients: the 'domino switch' technique. In *Anaesthesia* (Vol. 75, Issue 7). https://doi.org/10.1111/anae.15098

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. In *Mechanical Systems and Signal Processing* (Vol. 20, Issue 7). https://doi.org/10.1016/j.ymssp.2005.09.012

Kementrian PPN. (2023). *Perkembangan ekonomi Indonesia dan dunia*. https://perpustakaan.bappenas.go.id/e-library/file_upload/koleksi/migrasi-data-publikasi/file/Update_Ekonomi/Ekonomi_Makro/2023/Laporan%20Perkembangan%20Ekonomi%20Indonesia%20dan%20Dunia%20Triwulan%20III%202023.pdf

Kipchumba, B. B., Chemweno, P., Ochola, J., & Nganyi, E. O. (2024). Statistical mapping and data collection of critical equipment failures in the weaving section of textile manufacturing. *Engineering Reports*, *6*(3). https://doi.org/10.1002/eng2.12743

McDermott, R. E., Mikulak, R. J., & Beauregard, M. R. (2017). THE BASICS OF FMEA, 2nd Edition. In *The Basics of FMEA, 2nd Edition*. https://doi.org/10.1201/b16656

Mohan, R., Roselyn, J. P., & Uthra, R. A. (2023). LSTM based artificial intelligence predictive maintenance technique for availability rate and OEE improvement in a TPM implementing plant through Industry 4.0 transformation. *Journal of Quality in Maintenance Engineering*, *29*(4). https://doi.org/10.1108/JQME-07-2022-0041

Naranje, V., Naranje, A., & Salunkhe, S. (2019). Improving process performance with world-class manufacturing technique: A case in tea packaging industry. In *Lecture Notes in Mechanical Engineering*. https://doi.org/10.1007/978-981-13-2718-6_8

Nursanti, E., Avief Suaidy, Sibut, & Kertaningtyas Mariza. (2019). *Maintenance Capacity Planning Efisiensi & Produktivitas*. Dream Litera Buana. www.dreamlitera.com

Pierce, K., Gopal Gopalkrishnan, Chris Crosby, David Thomason, Curt Hertler, Matt Miller, Zsolt Oros, Regional Account Manager Roland Wedgwood, & Claessens. (2018). *A Guidebook to Implementing Condition-Based Maintenance (CBM) Using Real-time Data* (2nd ed.). OSIsoft, LLC.

Prawira, A. Y., Rahayu, Y., Hamsal, M., & Purba, H. H. (2018). A Case Study: How 5S Implementation Improves Productivity of Heavy Equipment in Mining Industry. *Independent Journal of Management & Production*, *9*(4), 1184–1202. https://doi.org/10.14807/ijmp.v9i4.826

Shagluf, A., Longstaff, A., & Fletcher, S. (2014). Maintenance strategies to reduce downtime due to machine positional errors. In J. T. Farinha & D. Galar (Eds.), *Proceedings of Maintenance Performance Measurement and Management (MPMM) Conference 2014* (pp. 111–118). Universidade de Coimbra. https://doi.org/10.14195/978-972-8954-42-0

Stamatis, D. H. (2003). Failure Mode Effects Analysis: FMEA from Theory to Execution (2nd Edition). *American Society for Quality*.

Ucar, A., Karakose, M., & Kırımça, N. (2024). Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends. In *Applied Sciences (Switzerland)* (Vol. 14, Issue 2). https://doi.org/10.3390/app14020898

Wang, K., Dai, G., & Guo, L. (2016). *Intelligent Predictive Maintenance (IPdM) for Elevator Service Through CPS, IOT&S and Data Mining*. https://doi.org/10.2991/iwama-16.2016.1

Wu, T., Zhao, T., & Xu, S. (2022). Prediction of Remaining Useful Life of the Lithium-Ion Battery Based on Improved Particle Filtering. *Frontiers in Energy Research*, *10*. https://doi.org/10.3389/fenrg.2022.863285

Xu, R., & Kwan, C. (2003). Robust isolation of sensor failures. *Asian Journal of Control*, *5*(1). https://doi.org/10.1111/j.1934-6093.2003.tb00093.x

Yoon, D., Ashok, P., van Oort, E., Annaiyappa, P., Industries, N., & Abe, S. (2023). Field Validation of Scalable Condition-Based Maintenance (CBM) of Mud Pumps. *SPE - International Association of Drilling Contractors Drilling Conference Proceedings*. https://doi.org/10.2118/212564-MS

Zeng, J., & Liang, Z. (2023). A Deep Gaussian Process Approach for Predictive Maintenance. *IEEE Transactions on Reliability*, *72*(3). https://doi.org/10.1109/TR.2022.3199924