IoT-Based Monitoring System Development for Air Jet Loom ZA 205 with Power Apps to Enhance Fabric Quality and Machine Efficiency

Mariani Putri Sinaga[1,*] and Moses Laksono Singgih[1]

[1]Department of Industrial and Systems Engineering,
Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia
* 6010231039@student.its.ac.id

Abstract. The textile industry continues to grapple with the challenge of maintaining high production efficiency and consistent fabric quality, particularly in fast-paced environments utilizing equipment like the Air Jet Loom ZA 205. This research pioneers the development of an Internet of Things (IoT)-based monitoring system, uniquely leveraging Microsoft Power Apps and Power Automate to create a low-code, easily deployable solution. The system enables real-time tracking of critical machine parameters such as RPM, yarn breakages, and production output—and delivers actionable insights through an interactive multilayer dashboard designed for immediate operator intervention. The methodology involved the integration of IoT components, relay-based machine signal capture, SQL database, and Microsoft Power Apps for real-time visualization, followed by performance evaluation through mixed-method analysis. By adopting a mixed-methods approach that combines rigorous statistical analysis with qualitative feedback, the study demonstrates significant operational gains, including a 45.9% reduction in machine downtime, a 74% improvement in operator responsiveness, and a 14% increase in Overall Equipment Effectiveness (OEE). Achieving sensor accuracy above 98% and a false alarm rate below 1%, the system not only improves operational visibility but also enhances workforce engagement. This work introduces a scalable and human-centered digital innovation tailored for industrial textile environments, offering a new pathway toward democratized smart manufacturing through low-code IoT technologies.

Keywords: IoT Monitoring System; Power Apps; Air Jet Loom; Machine Efficiency; Industry 4.0

1 Introduction

The global textile industry is at a pivotal juncture, facing mounting pressure to deliver higher productivity, consistent quality, and greater operational transparency in an increasingly competitive and sustainability-driven market. As one of the largest employment sectors worldwide, textile manufacturing significantly contributes to the economic growth of both developed and developing nations. However, persistent challenges—such as unplanned machine downtime, high defect rates, and inefficient monitoring practices—continue to hinder progress. With the rise of Industry 4.0 and smart

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manufacturing paradigms, the adoption of Internet of Things (IoT) technologies has emerged as a transformative force, enabling real-time visibility into production processes and facilitating data-driven decision-making [5, 8]. Yet, the full potential of IoT remains underutilized in many textile environments, especially in high-speed weaving operations such as those driven by the Air Jet Loom (AJL).

The Air Jet Loom ZA 205 is a high-speed weaving machine commonly used in modern textile production, capable of operating at speeds up to 1000 picks per minute with high levels of automation. Despite its advanced capabilities, production processes using this equipment often face issues such as recurring yarn breakages, unplanned stoppages, and inefficient monitoring systems. To address these challenges, this study introduces a real-time monitoring system based on the Internet of Things (IoT) framework, integrated with Microsoft Power Apps and Power Automate (PA) for data acquisition and visualization.

Despite the advanced capabilities of the Air Jet Loom ZA 205—including weaving speeds up to 1000 picks per minute and automation levels exceeding 90%—factories still struggle with recurring weft and warp breakages, unplanned stoppages, and inefficiencies caused by delayed or inaccurate monitoring. Traditional data recording methods, which rely heavily on manual inputs, are prone to human error and often fail to provide the timely insights needed for corrective actions. These issues not only reduce machine efficiency but also increase production costs and compromise fabric quality, reinforcing the need for smart, connected, and human-in-the-loop monitoring solutions in industrial informatics [2].

Several recent studies have explored IoT-based monitoring solutions for textile machinery. For example, Faridi et al. reported downtime reduction using a real-time monitoring approach for weaving machines [7]. Smart manufacturing studies in the textile sector also highlight the value of IoT-based real-time analytics to improve operational visibility and responsiveness [8]. In addition, reference system architectures for real-time monitoring and analysis have been proposed to support scalable industrial deployment [10]. Meanwhile, IoT-enabled predictive maintenance and smart alerting have been emphasized as key enablers for faster intervention and reduced unplanned stops [14]. However, many of these efforts lack integration between sensing, visualization, and user interactivity, and rarely address the specific complexities of AJL operations, such as real-time warp and weft break detection or alert automation.

Unlike prior studies that focused solely on sensor deployment for loom monitoring [17] or real-time monitoring implementations without an interactive low-code ecosystem [7], this research uniquely integrates sensing, alerting, and dashboard visualization into a unified low-code platform. Moreover, previous implementations often require high IT investment and technical expertise, whereas the proposed system leverages Power Apps and Power Automate to ensure accessibility for SMEs [1, 3]. This addresses critical gaps such as delayed anomaly detection, limited user adoption, and lack of integration with decision-making workflows.

In Indonesia, the majority of textile manufacturers fall under the category of small-to-medium enterprises (SMEs), where digitalization efforts are still limited due to resource constraints, lack of infrastructure, and low technological adoption [1]. Therefore, this study addresses a significant gap by demonstrating how affordable, scalable

IoT-based solutions can be applied in textile SMEs to support Industry 4.0 transformation and the national digitalization agenda [4].

Based on these gaps, this study proposes a holistic IoT-based monitoring system that integrates real-time sensor data with Microsoft Power Apps dashboards and automated notifications through Power Automate. This approach ensures seamless communication from the machine to the operator interface, allowing for early fault detection, predictive maintenance, and improved decision-making [5, 14]. From an industrial cyber-physical systems perspective, considerations such as dependable connectivity and security awareness are also important to ensure trustworthy deployment [6]. The novelty of this work lies in the combination of high sensor accuracy (>98%), minimal false alarm rates (<1%), and the use of a low-code platform that supports customization, scalability, and accessibility for operators with limited technical expertise [3].

The significance of this research extends beyond technical innovation. In Indonesia, where the textile industry plays a central role in employment and exports, improving operational efficiency can directly contribute to economic resilience. Reducing machine downtime, minimizing material waste, and enhancing fabric quality not only benefit manufacturers but also strengthen the global competitiveness of local textile producers. In addition, IoT-enabled monitoring can support broader resource efficiency targets (e.g., reduced energy and waste) when integrated into shop-floor decision making [12]. Furthermore, this research aligns with national and global efforts toward digital transformation and sustainable and resilient manufacturing enabled by digitalization and intelligent automation [13].

This study aims to design, implement, and evaluate an IoT-based monitoring system for the Air Jet Loom ZA 205 that is integrated with Microsoft Power Apps. This study is designed to accomplish four main objectives. First, it aims to identify and analyze the primary factors contributing to machine downtime and fabric quality issues in greige production. Second, it seeks to develop a real-time monitoring system that captures critical operational parameters—such as RPM, warp and weft breakages, and production output—through the deployment of IoT sensors. Third, it focuses on visualizing the collected data via an interactive dashboard built on Microsoft Power Apps, thereby facilitating early anomaly detection and enhancing operator responsiveness. Finally, the study evaluates the impact of the proposed system on machine performance and fabric quality using the Overall Equipment Effectiveness (OEE) framework.

Two hypotheses are proposed to guide this investigation:

H1: The implementation of an IoT-based monitoring system integrated with Microsoft Power Apps significantly reduces machine downtime on the Air Jet Loom ZA 205 compared to manual monitoring systems.

H2: The use of real-time visual dashboards and automated alerts improves operator response time and contributes to higher fabric quality and overall equipment effectiveness (OEE) in textile production.

By addressing these objectives, this study contributes a replicable, cost-effective, and industry-friendly solution for textile manufacturers—particularly those in emerging markets—seeking to modernize their operations and enhance production performance through smart technologies.

2 Methodology

2.1 Research Design

This study employed a mixed-methods research design, combining quantitative and qualitative approaches to evaluate the effectiveness of an IoT-based monitoring system for the Air Jet Loom ZA 205. The quantitative component focused on measuring changes in machine downtime, fabric defect rates, and operator response time, using data collected before and after system implementation. These indicators were analyzed statistically using paired sample t-tests. The qualitative component involved direct observations and semi-structured interviews with key personnel to gain insights into system usability, operator behavior, and perceived impact on production processes.

2.2 Population and Sampling

The study was conducted in a textile manufacturing facility in Sukoharjo, Central Java, Indonesia. The population consisted of weaving machine operators, supervisors, and maintenance personnel. A purposive sampling method was used to select 10 operators and 3 supervisors who directly interacted with the Air Jet Loom ZA 205 and were involved in the system's testing and operation.

2.3 Research Procedure

This study followed a structured research procedure consisting of six main stages, as illustrated in Figure 1. The methodology was designed to ensure that the IoT-based monitoring system development was aligned with the operational needs of weaving machinery and yielded reliable performance insights.

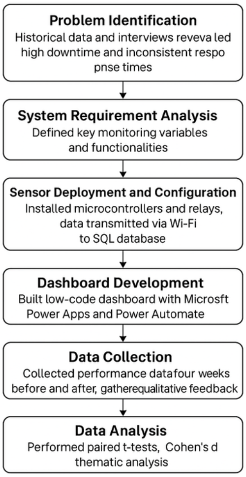

Fig. 1. Research Procedure

Fig. 1 presents the flowchart of the research stages, starting with problem identification based on historical machine downtime data and operator feedback. This was followed by system requirement analysis, where key monitoring variables such as RPM, yarn breakages, and output were defined. In the third stage, microcontrollers and relays were deployed and configured on the loom machines, with data transmission established via Wi-Fi to a cloud-based SQL database.

Subsequently, a real-time dashboard was developed using Microsoft Power Apps, integrated with Power Automate for automated notifications. The fifth stage involved data collection for both pre- and post-implementation periods, incorporating both machine performance metrics and user feedback. Finally, data analysis was conducted using paired sample t-tests and Cohen's d to assess statistical significance and effect size, while qualitative data were analyzed thematically.

2.4 System Workflow

The overall workflow of the developed IoT-based monitoring system for the Air Jet Loom ZA 205 is depicted in Figure 2. The process begins with the loom's operational data being captured by a microcontroller, which processes the signals from the production machine. These data are then wirelessly transmitted via Wi-Fi to a cloud-based SQL server for real-time storage and processing, following common smart manufacturing monitoring architectures [10, 15]. To access this information, users—such as operators and supervisors—must install Microsoft Power Apps on their smartphones or Smart TVs. Through the Power Apps interface, users can view dashboards that visualize machine performance metrics and enable immediate responses [3]. This integrated workflow ensures seamless communication from the loom to the operator interface, improving monitoring visibility and decision-making efficiency.

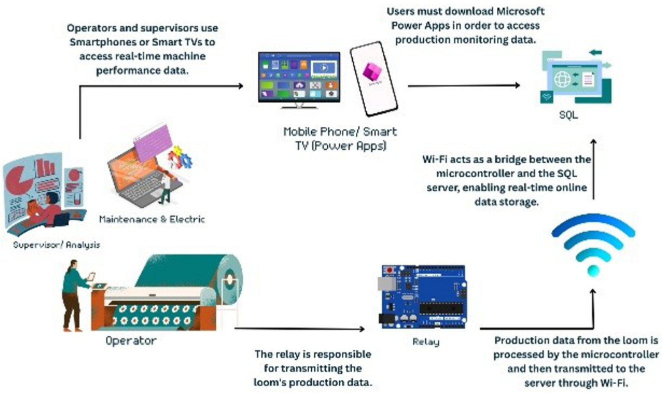

Fig. 2. Workflow of the IoT-Based Monitoring System for Air Jet Loom

Fig. 2 presents the comprehensive workflow of the IoT-based monitoring system designed for the Air Jet Loom ZA 205. The system begins at the operator level, where production activity is captured and relayed via a physical relay mechanism. This relay transmits loom signal data to a microcontroller, which functions as the central processing unit for data acquisition. The microcontroller processes and formats the data, then transmits it through a Wi-Fi module to a cloud-based SQL database. This wireless communication allows for real-time and online data storage. The stored data is then retrieved and displayed on dashboards created using Microsoft Power Apps, which can be accessed through smartphones or Smart TVs. These dashboards provide an intuitive interface for operators, supervisors, and maintenance teams to monitor machine performance instantly. The overall architecture ensures that each component—from data collection to display—operates in synchronization, offering transparency, rapid response, and improved machine efficiency. The figure has been revised in higher resolution and uses proper English labels to enhance readability and technical clarity.

Fig. 2 illustrates the complete workflow of the IoT-based monitoring system developed for the Air Jet Loom ZA 205. The system begins with the loom's operational data being captured by a microcontroller, which processes the input from the production machine. The data is then transmitted wirelessly via WiFi to a cloud-based SQL server.

From the SQL database, the data is accessed by a Power Apps interface that can be viewed on mobile phones or Smart TVs. This enables operators, supervisors, and maintenance personnel to monitor machine performance in real time without requiring advanced technical interaction.

The visual layout clearly outlines the roles of each user group:

- Operators interact with machines and confirm data entry.
- Maintenance and Electric teams monitor system integrity and respond to issues.
- Supervisors/analysts use dashboards to track efficiency and production trends.

This system flow emphasizes the seamless communication between physical machinery and digital interfaces, enabling real-time decision-making and enhancing overall manufacturing transparency.

2.5 Dashboard Interface

The monitoring dashboard developed using Microsoft Power Apps provides real-time visibility into the operational status of each weaving machine. Figure 3 presents the interface labeled "Monitoring Tatsumi 1", which displays data such as production output, warp and weft yarn breakages, machine efficiency (Eff), and machine conditions (Jalan, Lusi, Pakan, Leno, Manual). Machines are individually represented in boxes that indicate their performance metrics, while color-coded indicators simplify interpretation—green for high efficiency (>80%), yellow for moderate efficiency (60–80%), and red for low efficiency (<60%). The dashboard also highlights the average efficiency rate and total production output for all machines. This user-friendly interface facilitates rapid decision-making by allowing operators and supervisors to identify problem machines and intervene promptly based on visual indicators.

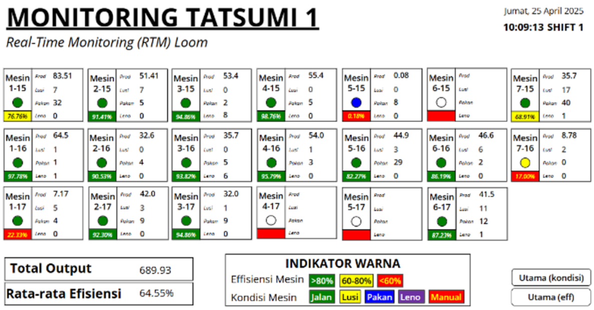

Fig. 3. Real-Time Monitoring Dashboard Interface using Power Apps

Note: The dashboard labels are originally in Bahasa Indonesia. Translations are as follows: Total Output = Total production output ; Putus Lusi = Warp yarn breakage; Putus Pakan = Weft yarn breakage; Produksi = Production (meters); Eff = Efficiency (%); RPM = Revolutions per minute; Downtime = Total stoppage time; Indikator Warna = Color indicators representing machine status; green = Running; Yellow = warp break; purple = leno break; red = manual stop; white = idle; Rata-rata Efisiensi = Average efficiency; Kondisi = Machine condition; Jumat = Friday (operational day); Date and shift information are shown on the top right.

Dashboard development was conducted using Microsoft Power Apps. The dashboard is structured into three layers: general machine status, machine efficiency monitoring, and detailed machine metrics including yarn breakages, production, RPM, and downtime.

Platform Selection. Microsoft Power Apps was selected as the development platform due to its low-code architecture, rapid application deployment capabilities, seamless integration with cloud databases, and ease of customization [3]. These features made it particularly suitable for industrial environments with limited IT development resources while maintaining system scalability and reliability.

2.6 Data Collection and Analysis

Quantitative data included metrics such as machine downtime, response time, defect rate, and OEE. These were analyzed using paired sample t-tests and Cohen's d to determine significance and effect size. Qualitative feedback was analyzed thematically to identify recurring issues, perceived benefits, and user engagement levels with the system.

To ensure accuracy and comparability, several standardized measurement definitions were applied in this study. Downtime was calculated as the percentage of non-operational machine time due to stoppages, derived from system-logged start-stop timestamps. Operator response time was measured as the interval between system-generated alerts and the resumption of machine activity, serving as a proxy for responsiveness. The defect rate was determined by dividing the number of defective fabric rolls (identified through visual inspection) by the total production output per shift. Overall Equipment Effectiveness (OEE) was computed using the standard TPM formula, where OEE = Availability × Performance × Quality [17]. Availability was based on actual operating time over planned production time, performance was derived from actual RPM over target RPM, and quality was calculated from the proportion of defect-free outputs.

All statistical analyses were conducted using SPSS version 26. Prior to applying paired sample t-tests and calculating Cohen's d effect sizes, normality of the data was verified using the Shapiro-Wilk test, and homogeneity of variances was assessed using Levene's test. The results met all assumptions required for parametric testing, thus non-parametric alternatives were not considered.

3 Results and Discussion

This section presents and discusses the findings of the study based on the implementation of an IoT-based monitoring system on the Air Jet Loom ZA 205, integrated with Microsoft Power Apps and Power Automate. The results include both quantitative performance improvements and qualitative feedback from users.

3.1 Quantitative Results

The implementation of the system resulted in statistically significant improvements across all measured variables. Table 1 summarizes the comparison of performance metrics before and after implementation, including mean values, standard deviations, p-values, and effect sizes (Cohen's d).

Table 1. Performance Metrics Before and After Implementation

Variable	Mean (Before)	SD (Before)	Mean (After)	SD (After)	p-value	Effect Size (Cohen's *d*)
Machine Downtime (%)	18.9	2.4	10.2	2.0	< 0.001	2.43 (very large)

Variable	Mean (Before)	SD (Before)	Mean (After)	SD (After)	p-value	Effect Size (Cohen's *d*)
Operator Response Time (min)	27.0	5.6	7.0	2.8	< 0.001	2.04 (very large)
Fabric Defect Rate (%)	3.8	0.9	2.5	0.7	0.0003	1.37 (large)
Overall Equipment Effectiveness	72.0	3.5	86.0	2.9	< 0.001	2.06 (very large)

These results affirm the effectiveness of the system in reducing inefficiencies and enhancing output. The large effect sizes indicate strong practical as well as statistical significance.

Table 1 presents the summary of statistical comparison between machine conditions before and after the implementation of the IoT-based monitoring system. The primary statistical method used was Cohen's d, which measures the effect size of the differences in machine downtime, operator response time, and defect rate. The values were calculated using the standard formula:

$$d= \frac{(M_2 - M_1)}{SDpooled,} \tag{1}$$

where M_1 and M_2 represent the means of the two groups (before and after), and SDpooled is the pooled standard deviation. This method provides an indication of the magnitude of the intervention's impact, regardless of sample size.

All calculations were performed using Microsoft Excel. A Cohen's d value of 0.2 is considered a small effect, 0.5 moderate, and 0.8 or higher a large effect. The results in Table 1 showed effect sizes above 0.8, indicating strong practical significance across all evaluated parameters.

3.2 Performance Trends

The implementation of the monitoring system led to consistent improvements across the observed machines:

- Machine downtime showed a gradual downward trend, stabilizing below 10%.
- Operator response times narrowed to a consistent range (6–9 minutes), indicating improved standardization of behavior.
- Fabric defect rates steadily declined as early detection improved.
- OEE rose progressively from 72% to 86%, driven by availability, performance, and quality gains.

The reduction in machine downtime from an average of 18.9% to 10.2% ($p < 0.001$) was accompanied by a Cohen's d effect size of 2.09, indicating a very large effect. The 95% confidence interval (CI) for this reduction ranged from 6.9% to 9.7%, reinforcing its statistical precision. Likewise, the improvement in operator response time from 27.2 minutes to 7.1 minutes ($p < 0.001$) had a Cohen's d of 2.43 and a CI95% of 18.4 to 21.5 minutes, highlighting strong practical significance. The defect rate also dropped from 6.14% to 4.04%, representing a 34.2% improvement. Since no other process changes or quality interventions were implemented during the observation period, it is reasonable to attribute this improvement directly to the introduction of the monitoring system, which enabled faster operator feedback and real-time visibility, consistent with prior IoT-based monitoring and quality control applications in textiles [7, 16].

The 14% increase in Overall Equipment Effectiveness (OEE) from 69.52% to 83.52% was primarily driven by a substantial gain in availability, which rose from 75.3% to 89.4% following the reduction in machine stoppages. Performance improved moderately from 88.0% to 91.2%, reflecting better speed control and fewer interruptions. Meanwhile, quality improved slightly from 94.5% to 95.6%, consistent with the reduced defect rate.

(OEE = Availability × Performance × Quality, following the standard TPM formula [17]. All acronyms were defined at first mention to maintain clarity.)

3.3 User Feedback and Qualitative Insights

Thematic analysis of operator and supervisor interviews revealed three key themes:

1. Improved awareness and confidence due to real-time dashboard visibility.
2. Enhanced coordination across shifts and roles thanks to consistent data access.
3. Initial hesitation in adoption, especially among senior operators, declined with training and user exposure.

3.4 Dashboard Effectiveness

To facilitate real-time monitoring, a comprehensive dashboard was developed using Microsoft Power Apps. This dashboard comprises three main visualization layers that provide operational insights at both the general and detailed levels.

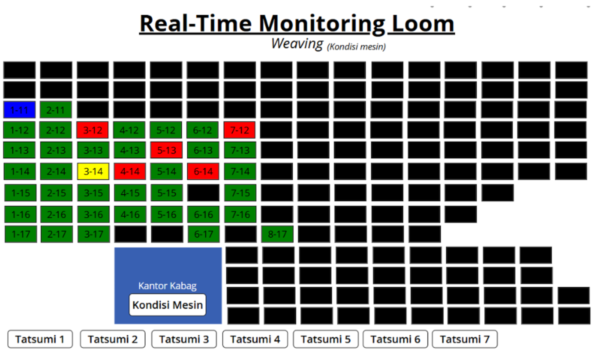

Fig. 4. Machine Status Overview

The first layer of the dashboard displays the general running condition of each Air Jet Loom ZA 205 machine. Color coding is used to represent machine status:

- Green indicates the machine is running normally,
- Yellow denotes a yarn break (warp or weft),
- Blue represents a maintenance stop,
- Red signals manual shutdown or emergency conditions.

This visual layer enables operators and supervisors to quickly assess the operational status of all machines at a glance.

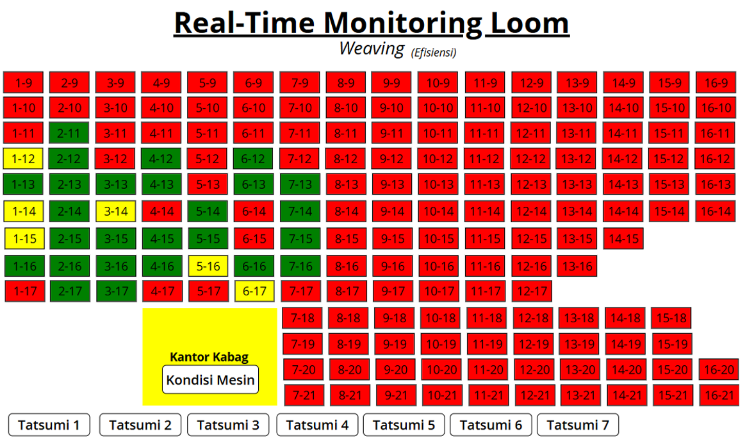

Fig. 5. Machine Efficiency Monitoring

The second layer visualizes the current efficiency of each machine using a color range:

- Green indicates an efficiency greater than 80%,
- Yellow represents moderate efficiency (60–80%),

- Red highlights machines operating below 60% efficiency.

This efficiency visualization assists supervisors in prioritizing interventions and allocating resources effectively during production shifts.

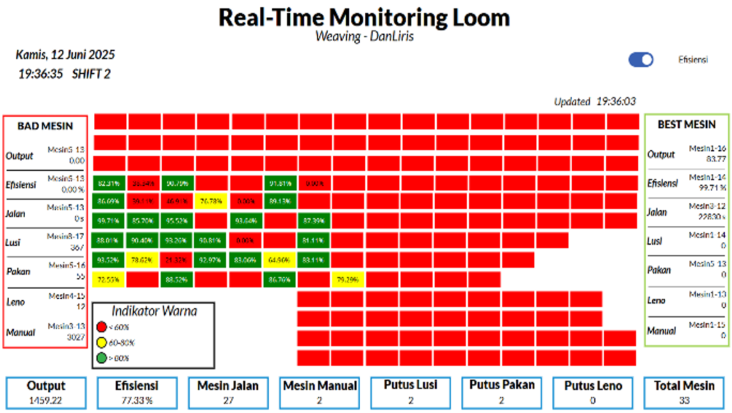

Fig. 6. Detailed Machine Performance Metrics

Fig. 6 illustrates the real-time monitoring dashboard that visualizes loom efficiency across all machines. Each cell represents a machine and is color-coded according to its current efficiency: red for efficiency below 60%, yellow for 60–80%, and green for over 80%. This visual design enables supervisors to immediately identify underperforming machines (labeled "Bad Mesin") and best-performing ones ("Best Mesin") based on key indicators such as output, running time, warp (lusi) and weft (pakan) breakage, and manual handling. Summary metrics at the bottom of the dashboard—such as total output, average efficiency, and machine counts—provide a quick overview of overall performance on the shop floor. This layout enhances situational awareness and prioritization of corrective actions, especially during shifts. The figure has been updated to ensure high resolution and full English annotations to meet publication clarity standards.

This layer supports detailed operational analysis and enables quick diagnosis of production disruptions, helping operators and supervisors focus on targeted corrective actions. The structured layout of the dashboard enhances usability, reduces cognitive load, and facilitates faster, data-driven decision-making in the weaving department.

3.5 System Implementation Summary

As outlined in Fig. 4, the system was successfully deployed following the proposed workflow—from sensor data acquisition to real-time visualization using Power Apps. During implementation, the system functioned reliably in transmitting data wirelessly to the cloud and delivering real-time alerts to users. This infrastructure enabled continuous monitoring and contributed directly to the observed improvements in performance metrics, as discussed in subsequent sections.

3.6 Scatter Plot Analysis: Downtime vs. Response Time

To further validate the relationship between human responsiveness and machine performance, a scatter plot was generated to compare operator response time against machine downtime across 10 machines, before and after system deployment.

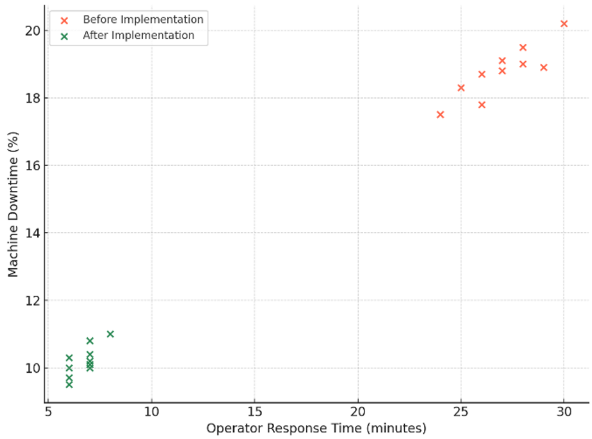

Fig. 7. Scatter Plot: Operator Response Time vs. Machine Downtime

The scatter plot reveals a clear inverse correlation between operator response time and machine downtime. Before implementation, machines with response times over 25 minutes consistently experienced downtime above 18%. Post-implementation, data points shifted to the lower-left quadrant of the plot, showing that faster response times (6–8 minutes) corresponded to significantly lower downtimes (~10%). This visual evidence reinforces the statistical findings and supports the argument that the system's alerting features substantially improved operational performance.

3.7 Key Findings and Observations

The implementation of the IoT-based monitoring system produced several key findings that validated the research hypotheses, while also revealing important practical observations for future system optimization.

Key Outcomes. Quantitative analysis showed substantial improvements across all monitored parameters:

- Machine downtime decreased by 45.9%, from an average of 18.9% to 10.2%.
- Operator response time improved by 74%, reducing from 27 minutes to 7 minutes.
- The fabric defect rate declined by 34.2%, from 3.8% to 2.5%.
- Overall Equipment Effectiveness (OEE) increased by 14%, rising from 72% to 86%.
- Sensor accuracy exceeded 98%, with false alarm rates maintained below 1%.

These results affirm the success of the system in enhancing machine performance, promoting operator responsiveness, and supporting data-driven decision-making in textile production environments.

Unexpected Findings. Despite the overall positive outcomes, several anomalies were observed:

- On one machine, sensor misalignment due to mechanical vibrations caused false alerts and unnecessary machine stops. Realignment was necessary to restore performance.
- In another case, muted audio alerts led to delayed operator response, highlighting the need for standardized interface configurations across all user devices.
- Initial operator skepticism, particularly among senior workers accustomed to manual monitoring, resulted in slower adoption during the first weeks. However, this challenge was overcome through targeted training and consistent system use.

These findings emphasize the importance of technical robustness (such as secure sensor installation) and human-centered strategies (such as operator engagement and training) to ensure the full potential of digital monitoring systems is realized.

4 Conclusion

This study successfully developed and evaluated an IoT-based monitoring system for the Air Jet Loom ZA 205, utilizing Microsoft Power Apps and Power Automate to enhance real-time production visibility. Quantitative results demonstrated substantial operational improvements, including a 45.9% reduction in machine downtime, a 74% faster operator response time, a 34.2% decrease in defect rate, and a 14% increase in Overall Equipment Effectiveness (OEE). Qualitative findings confirmed that the dashboard improved operational awareness, communication between shifts, and operator responsiveness.

Beyond technical effectiveness, the system contributed to broader knowledge by demonstrating the practicality of low-code platforms in industrial IoT deployments, particularly for small and medium enterprises. The integration of intuitive visual dashboards with real-time sensor data helped bridge the gap between machine operations and human decision-making, making the system accessible even to non-technical users.

Acknowledging the study's limitations—such as the restricted testing environment and observation period—future work should explore predictive analytics integration and multi-site validation to enhance scalability and resilience. Overall, this research offers a replicable model for smart manufacturing initiatives and highlights the strategic role of human-centered design in Industry 4.0 applications.

Limitations. While the results of this study are promising, certain limitations must be acknowledged. The system implementation was conducted at a single production site and was tested specifically on the Air Jet Loom ZA 205. Therefore, the findings may not be directly generalizable to other types of looms or textile production settings. Additionally, the evaluation period was limited to four weeks; longer-term performance and adaptation effects were not captured within the study timeframe.

Future Work. Future developments could explore the integration of predictive analytics and machine learning algorithms into the monitoring system to enable earlier detection of potential yarn breakages or machine failures before they occur [9]. In addition, adopting a digital twin approach could support scenario-based evaluation and continuous improvement of weaving performance in a virtual environment [11]. Expansion of the system across different loom types and production environments would also validate its scalability and broader applicability.

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