Development of a Smart Monitoring System for Bottle Breakage Detection in Production Lines

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Abstract *— This project presents the development of a smart monitoring system for bottle breakage in production lines. The system aims to improve operational efficiency by analyzing production data and detecting abnormal breakage patterns. The proposed solution integrates data analytics and statistical methods to monitor breakage rates, generate alerts, and support maintenance decisions. Additionally, the system incorporates location-based thresholds to provide flexible and scalable monitoring across different production areas. By transforming raw production data into actionable insights, the system enables real-time monitoring and enhances decision-making processes in manufacturing environments. This work is aligned with Industry 4.0 principles, promoting the use of intelligent and data-driven systems to optimize industrial operations.*

Keywords *— Anomaly Detection, Bottle Breakage Detection, Industry 4.0, Predictive Maintenance, Smart Monitoring System.*

INTRODUCTION

The manufacturing industry increasingly relies on data-driven technologies to improve efficiency, reduce defects, and optimize production processes [1]. In modern production lines, particularly in bottle filling and packaging operations, maintaining product quality while minimizing operational losses is a critical challenge.

One of the most common issues in these environments is bottle breakage during production. These events can lead to material waste, production delays, and increased maintenance requirements. Although breakage data is often collected, many existing systems lack the ability to analyze this information effectively and provide actionable insights. With the emergence of Industry 4.0, manufacturing systems are evolving toward more intelligent and automated environments. Technologies such as artificial intelligence, data analytics, and real-time monitoring enable companies to improve decision-making and enhance operational performance [2].

This project proposes the development of a smart monitoring system for bottle breakage in production lines. The system integrates data analytics and statistical methods to detect anomalies, generate alerts, and support maintenance decisions. By transforming raw production data into actionable insights, the system aims to improve efficiency, reduce downtime, and enhance overall process control.

LITERATURE REVIEW

Recent research has highlighted the importance of data-driven approaches in modern manufacturing systems. Industry 4.0 introduces the integration of digital technologies, data analytics, and intelligent systems to improve production efficiency and operational performance [2].

Anomaly detection techniques have been widely used to identify abnormal patterns in industrial environments. These methods allow systems to detect deviations from normal behavior without requiring labeled data, making them suitable for real-world manufacturing applications [3].

In addition, predictive maintenance has become a key strategy for reducing downtime and improving machine performance. By analyzing historical data, it is possible to anticipate failures and take preventive actions, overcoming the limitations of traditional reactive and preventive maintenance approaches [4].

Machine learning models have also been successfully applied for defect detection in industrial processes. These models can identify complex patterns in production data and achieve high accuracy in classifying defective and non-defective products. Furthermore, explainable AI techniques enable better understanding of model decisions, improving transparency and supporting decision-making processes [5].

Statistical Process Control (SPC) methods provide a strong foundation for monitoring production processes. These techniques allow the identification of variability and the detection of abnormal conditions using control limits and statistical analysis [6].

Finally, data analytics plays a crucial role in transforming raw production data into actionable insights. Modern manufacturing systems use dashboards, real-time monitoring, and different levels of analytics (descriptive, diagnostic, predictive, and prescriptive) to improve decision-making and operational efficiency [1].

Based on these studies, it is evident that combining anomaly detection, predictive maintenance, statistical analysis, and data analytics can significantly enhance manufacturing processes. This project builds upon these concepts to develop a smart monitoring system for bottle breakage in production lines.

PROBLEM

In bottle production lines, breakage events occur frequently due to factors such as machine misalignment, contamination, or improper handling. Although these events are typically recorded, current monitoring systems provide limited support for decision-making.

Operators are required to manually interpret breakage data to determine whether corrective actions, such as machine adjustments or cleaning procedures, are necessary. This process can lead to delays, inconsistent decisions, and increased operational losses.

Additionally, many systems rely on static thresholds that do not adapt to different production conditions or locations within the production line. This lack of flexibility reduces the effectiveness of monitoring systems and limits their ability to detect abnormal patterns in real time.

Therefore, there is a need for a smart monitoring system that not only records breakage events but also analyzes data dynamically, detects anomalies, and provides automated alerts and recommendations. Such a system would improve operational efficiency, reduce downtime, and enhance production performance.

METHODOLOGY

The proposed Smart Monitoring System was developed as a data-driven solution to monitor bottle breakage in production lines. The system integrates data input, statistical analysis, and real-time visualization to support maintenance decision-making.

The architecture of the system consists of three main components: a web-based user interface developed using Flask, a SQLite database for data storage, and a dashboard for visualization using Chart.js. Figure 1 shows the local execution of the system using Flask, enabling user interaction through a web-based interface.

Figure 1
Flask Application Running Locally

The system operates by recording production events. Each event represents a data input provided by the user, including batch number, production stage, total bottles produced, and broken bottles. Unlike traditional systems that rely on batch-level analysis, this approach enables continuous monitoring through event-based data collection.

The system calculates two key metrics:

- Breakage Rate (Event-Level): Breakage Rate = Broken Bottles / Total Bottles. This metric represents the condition of the system at a specific moment.
- Accumulated Rate (System-Level): Accumulated Rate = Total Broken Bottles / Total Produced Bottles (cumulative). This metric evaluates the long-term performance of the machine and is used for decision-making.

The system uses predefined thresholds to classify machine status:

- NORMAL: Accumulated Rate < 0.005
- WARNING: $0.005 \leq$ Accumulated Rate ≤ 0.01
- CRITICAL: Accumulated Rate > 0.01

Based on these thresholds, the system generates maintenance recommendations:

- WARNING → Schedule Preventive Maintenance
- CRITICAL → Perform Corrective Maintenance

Additionally, the system calculates Quantity Between Failures (QBF), which measures the number of units produced between failure events:

- QBF = Accumulated Total – Last Failure Point

When a CRITICAL condition is detected, the accumulated counters are reset, simulating a maintenance intervention. Batch numbers are included for traceability purposes only and do not affect system calculations, ensuring that decision-making is based solely on accumulated statistical behavior.

RESULTS

The system was tested using simulated production data representing multiple events across different stages of the production line. Figure 2 summarizes the recorded production events and corresponding system responses. Figure 3 shows the user input interface of the system.

Figure 2

Summary of Production Events and System Responses

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Windows PowerShell
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Install the latest PowerShell for new features and improvements! https://aka.ms/PSWindows

PS C:\Users\hirbe> cd "C:\Users\hirbe\OneDrive\Desktop\smart-monitoring-system"
PS C:\Users\hirbe\OneDrive\Desktop\smart-monitoring-system> python view_data.py
(1, '05082026_001', 'rinser', 500, 25, 0.05, 0, 0, 0.05, 'CRITICAL', 'Perform Corrective Maintenance', 500.0)
(2, '05082026_001', 'filler', 1000, 2, 0.002, 1000, 2, 0.002, 'NORMAL', 'Continue Normal Operation', None)
(3, '05082026_001', 'rinser', 1000, 3, 0.003, 1000, 3, 0.003, 'NORMAL', 'Continue Normal Operation', None)
(4, '05082026_001', 'filler', 1000, 15, 0.015, 2000, 17, 0.0085, 'WARNING', 'Schedule Preventive Maintenance', 2000.0)
(5, '05082026_001', 'filler', 1000, 25, 0.025, 0, 0, 0.014, 'CRITICAL', 'Perform Corrective Maintenance', 1000.0)
PS C:\Users\hirbe\OneDrive\Desktop\smart-monitoring-system>
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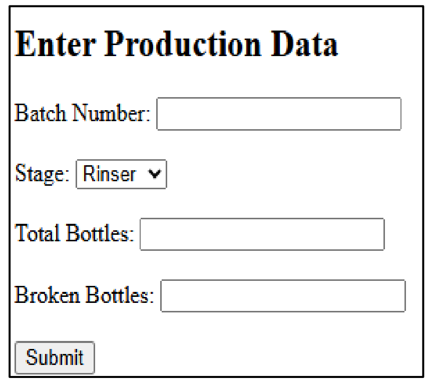

Figure 3

User Input Interface

The user interface of the system allows operators to input key production data in a structured and intuitive manner. Specifically, users can enter the batch number, select the production stage, and provide the total number of bottles processed along with the number of broken bottles. This input mechanism enables real-time data collection at the event level, supporting continuous monitoring rather than relying solely on batch-level analysis.

Once the data is submitted, the system automatically processes the input and calculates essential performance indicators. These include the breakage rate for the current event, the accumulated breakage rate across multiple events, and the system status classification (NORMAL, WARNING, or CRITICAL). In addition, the system generates maintenance recommendations and calculates the Quantity Between Failures (QBF), providing valuable insights into machine reliability and operational performance.

This approach ensures that users receive immediate feedback based on both current and historical data, allowing for more informed decision-making. By combining real-time input with accumulated analysis, the system is capable of identifying early signs of degradation and supporting proactive maintenance strategies, improving overall efficiency in production environments.

The results demonstrate that the system correctly evaluates both event-level and accumulated performance. For example, a single event with a high breakage rate may not immediately trigger a critical condition if the accumulated rate remains within acceptable limits. Figure 4 presents the system behavior under normal conditions.

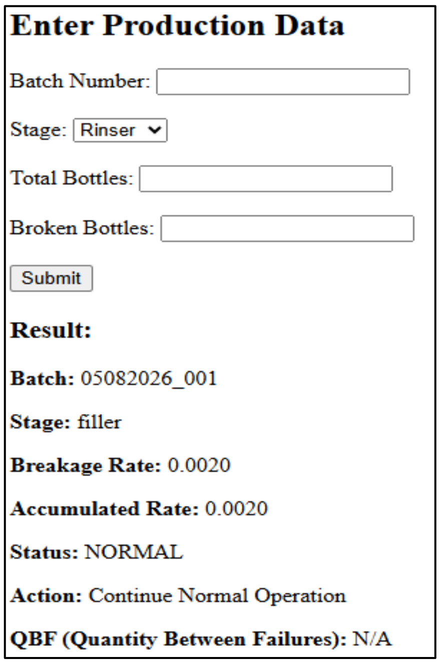

Figure 4
System Output in NORMAL State

However, as multiple events accumulate, the system begins to identify degradation patterns that are not evident at the individual event level. Instead of reacting to isolated fluctuations, the system evaluates the accumulated breakage rate to determine whether performance is deteriorating over time. This allows for a more stable and reliable assessment of machine condition.

Figure 5 illustrates the system entering a warning condition as the accumulated breakage rate increases and approaches the predefined threshold. This transition reflects a shift from normal operation to a state that requires attention, even if individual events may not appear critical on their own.

At this stage, the accumulated breakage rate enters the warning range, indicating that the system is experiencing consistent degradation. As a result, the system recommends preventive maintenance to address potential issues before they escalate into critical failures.

This proactive response is essential in industrial environments, as it allows operators to intervene early, reducing the risk of unplanned downtime and improving overall system reliability. Figure 6 shows the system reaching a critical condition as the accumulated breakage rate surpasses the predefined threshold, triggering corrective maintenance and initiating a reset of accumulated values to simulate machine recovery after intervention.

The system identifies a critical condition when the accumulated breakage rate exceeds the predefined threshold. At this point, corrective maintenance is triggered, and the accumulated counters are reset to simulate system recovery after intervention.

The QBF metric provides additional insight into machine reliability by indicating how many units were produced before a failure condition occurred.

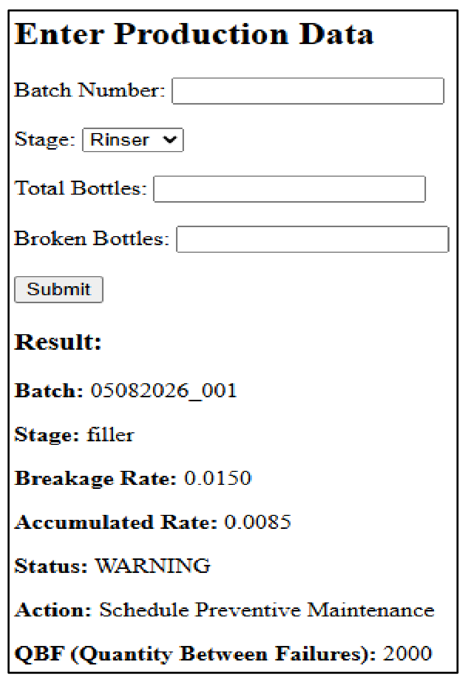

Figure 5
System Output in WARNING State

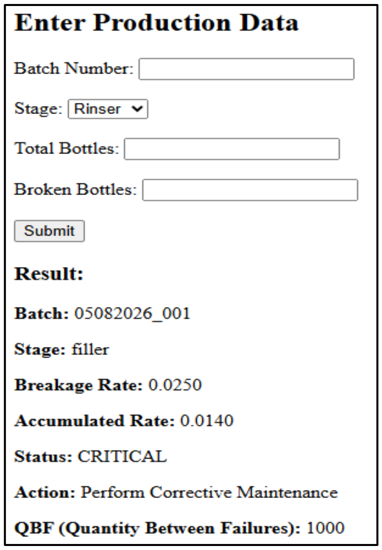

Figure 6
System Output in CRITICAL State

The dashboard allows users to visualize performance trends over time. Each data point represents an event, enabling fine-grained monitoring of machine behavior. Figure 7 presents the visualization of system performance over time, highlighting the relationship between event-level breakage and accumulated system behavior.

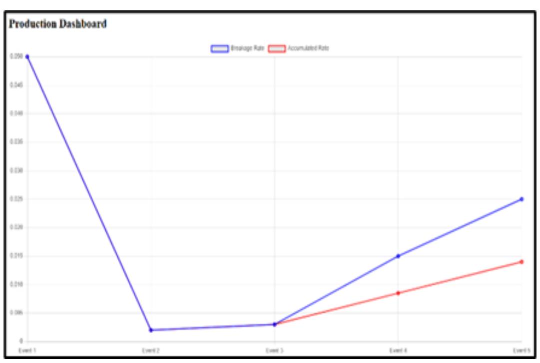

Figure 7
Production Performance Dashboard

The blue line represents the breakage rate at the event level, while the red line represents the accumulated breakage rate, reflecting the overall trend of system performance over time.

The results further demonstrate that the system effectively distinguishes between short-term variability and long-term performance trends. While individual events may present fluctuations in breakage rate, the accumulated rate provides a more stable and reliable indicator of system behavior. This allows the system to avoid overreacting to isolated anomalies while still identifying meaningful degradation patterns over time.

From an operational perspective, this capability is particularly valuable in industrial environments, where premature or unnecessary maintenance actions can lead to increased costs and production interruptions. By relying on accumulated performance rather than isolated events, the system supports more consistent and data-driven decision-making, improving both efficiency and reliability.

Furthermore, the integration of visualization through the dashboard enhances the interpretability of system behavior. Users can clearly observe how the breakage rate evolves over time and how it impacts the accumulated rate, providing intuitive insight into machine condition. This visual representation reinforces the system's ability to support proactive maintenance strategies and continuous monitoring.

Discussion

The results indicate that the proposed system provides significant improvements over traditional monitoring approaches.

Unlike static threshold systems, this solution evaluates accumulated performance, allowing for more accurate detection of abnormal behavior. This reduces false alarms caused by isolated events and improves decision consistency.

The integration of QBF introduces a reliability-based perspective, which is commonly used in industrial environments to assess machine performance.

The use of event-based monitoring allows the system to react in near real-time, providing continuous feedback rather than waiting for batch completion. Additionally, the system aligns with Industry 4.0 principles by incorporating data analytics, real-time monitoring, and automated decision support, which collectively enhance decision-making capabilities and improve operational efficiency in modern manufacturing environments.

In addition to improving decision-making accuracy, the system introduces a structured approach to performance evaluation that can be easily adapted to different production environments. By relying on accumulated metrics rather than isolated events, the system provides a more consistent and scalable framework for monitoring machine behavior across various production stages.

Another important contribution of this system is its ability to bridge the gap between raw production data and actionable insights. In many industrial settings, data is collected but underutilized due to the lack of analytical tools. This solution demonstrates how relatively simple statistical logic combined with real-time processing can significantly enhance the value of production data.

Furthermore, the event-based monitoring approach enables greater flexibility compared to traditional batch-based systems. Since each event is evaluated independently while still contributing to accumulated performance, the system can detect gradual degradation patterns earlier. This allows for more timely interventions, reducing the likelihood of severe failures and improving overall production stability.

However, the current system has limitations. It relies on manually entered data and does not yet integrate machine sensors or automated data acquisition. Future improvements may include machine learning models for predictive maintenance and anomaly detection.

Conclusion

This project presented the development of a Smart Monitoring System for bottle breakage detection in production lines. The system integrates statistical analysis, real-time monitoring, and decision logic to evaluate machine performance and support maintenance actions. By combining event-level data with accumulated performance metrics, the solution provides a more comprehensive understanding of system behavior.

The results demonstrate that the system is capable of distinguishing between short-term variability and long-term degradation patterns. This distinction allows for more accurate identification of abnormal conditions, reducing false alarms caused by isolated events. Additionally, the incorporation of the QBF metric introduces a reliability-based perspective, enabling operators to better assess machine performance over time and make informed maintenance decisions.

Overall, the proposed system contributes to the advancement of data-driven monitoring approaches in industrial environments. By leveraging simple yet effective analytical techniques, the solution enhances operational efficiency, supports proactive maintenance strategies, and aligns with Industry 4.0 principles. Future improvements may include the integration of machine learning models, automated data acquisition, and advanced analytics to further strengthen the system’s capabilities.

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