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AI-Driven Andon System for Smart Manufacturing Production Recommendations

Divya Shah*, Shivani Budhkar**, Abhishek Sharma***, Shubham Gugale****, Gaurav Patil*****

*(MCA Department, PES Modern College of Engineering, Pune, India
Email: work.divyashah@gmail.com)
** (MCA Department, PES Modern College of Engineering, Pune, India
Email: shivanibudhkar@gmail.com)
***(TATA Motors Digital.AI Labs, Pune, India
Email: royalabhisheksharma@gmail.com)
****(TATA Motors Digital.AI Labs, Pune, India
Email: s.k.gugale@gmail.com)
*****(TATA Motors Digital.AI Labs, Pune, India
Email: gaurav.patil.ds1@gmail.com)

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Abstract:

Traditional Andon systems in manufacturing environments primarily function as real-time visual alert mechanisms for production interruptions and downtime events. However, they lack intelligent analytical capabilities and proactive decision-support mechanisms required in modern smart manufacturing ecosystems.

This research proposes an AI-driven intelligent Andon system that integrates natural language processing, text-to-SQL query generation, and real-time production analytics to transform conventional reactive alert systems into intelligent recommendation platforms. The system enables users to interact through a chatbot interface, where the chatbot processes manufacturing questions and creates corresponding database queries for information retrieval, which are executed on a centralized production database. Results are dynamically presented in textual, tabular, or graphical formats to support rapid decision-making.

Beyond downtime monitoring, the proposed framework incorporates automated root cause analysis (RCA) by correlating production loss data with quality metrics, machine performance indicators, and material-related factors. By identifying recurring failure patterns and operational bottlenecks, the system generates actionable production recommendations to improve efficiency and reduce loss time.

The proposed approach enhances transparency, reduces manual reporting effort, and supports data-driven decision-making in smart manufacturing environments. The developed approach enables smarter production supervision through automated analysis, interactive querying, and intelligent operational recommendations.

Keywords — **Andon system, smart manufacturing, Industry 4.0, NLP, Text-to-SQL, root cause analysis**

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I. INTRODUCTION

The rapid evolution of Industry 4.0 and smart manufacturing technologies has transformed modern production systems through interconnected machines, real-time data collection, and advanced analytics[4].

Manufacturing environments generate large volumes of operational data from machines, sensors, production lines, and quality monitoring systems. However, effectively utilizing this data for improving efficiency, reducing downtime, and supporting decision-making remains a challenge.

One of the widely used mechanisms for monitoring production activities is the Andon system. Traditionally, Andon systems act as visual signaling tools that notify operators about machine failures, abnormalities, or production interruptions[1]. While effective for real-time alerting, these systems are largely reactive and lack analytical capabilities to identify root causes or long-term performance trends.

With increasing system complexity, there is a need for intelligent solutions that can analyze production data and provide actionable insights. At the same time, accessing production databases requires knowledge of structured query languages (SQL), limiting usability for non-technical users. This creates a gap between data availability and its practical use in decision-making.

Recent advancements in Artificial Intelligence (AI), Natural Language Processing (NLP), and Large Language Models (LLMs) provide new opportunities to address this challenge[3]. The Text-to-SQL paradigm enables natural language queries to be automatically converted into structured database queries[10], allowing users to interact with data more intuitively.

In this context, this research proposes an AI-driven intelligent Andon system that integrates natural language interfaces, automated Text-to-SQL query generation, and real-time production analytics. The system enables users to interact with manufacturing data through a chatbot interface, with results presented in textual, tabular, and graphical formats.

Furthermore, the framework incorporates automated Root Cause Analysis (RCA) by correlating production loss events with machine performance, quality metrics, and operational factors[7]. This enables the identification of recurring patterns and supports generation of actionable production recommendations.

Overall, the proposed approach transforms traditional Andon systems into intelligent decision-support tools, contributing to smart manufacturing environments aligned with Industry 4.0 principles.

II. LITERATURE REVIEW

Andon systems are widely used in manufacturing for real-time monitoring and rapid response to production abnormalities. These systems provide visual alerts to notify operators about machine failures or production disruptions. However, conventional Andon systems are primarily reactive and lack advanced analytical and decision-support capabilities.

Liu, Wang, and Li proposed an IoT-based Andon system that enables real-time data transmission from machines to centralized systems, improving visibility and communication in manufacturing processes[1]. Similarly, Zhang and Kumar developed an Industrial IoT-based Andon system for production monitoring and automated alerts, though their approach mainly focuses on data collection rather than intelligent analysis[2].

With the advancement of Industry 4.0, artificial intelligence has been increasingly integrated into manufacturing systems. Smith and Lee demonstrated how AI-driven analytics can enhance production management and support predictive decision-making[3]. Wang and Zhao further highlighted the role of cyber-physical systems in enabling automated monitoring, predictive maintenance, and adaptive control in smart manufacturing environments[4].

Recent studies have applied machine learning techniques to analyze production data and detect inefficiencies. Patel and Singh reviewed time-series pattern recognition methods for identifying anomalies and operational trends[5], while Chen and Gupta explored AI-based predictive maintenance models to reduce unexpected equipment failures[6].

Root Cause Analysis (RCA) has also gained attention in manufacturing research. Rocha and Perez showed that machine learning techniques can improve root cause identification in zero-defect manufacturing[7]. Johnson and Martens further demonstrated the effectiveness of AI-assisted RCA in improving defect detection and reducing production errors in industrial settings[8].

Natural Language Processing (NLP) has been increasingly used to simplify interaction with complex databases. Gupta and Roy proposed neural approaches for Text-to-SQL generation, enabling natural language queries to be converted into structured database queries[10]. Ortiz and Fernandez reviewed Natural Language Interfaces to Databases, highlighting their ability to improve accessibility for non-technical users[11].

Lee and Zhou introduced a neurosymbolic causal analysis framework that combines machine learning with causal reasoning for deeper understanding of manufacturing processes[9].

Overall, existing research demonstrates significant progress in IoT-based monitoring, AI-driven analytics, predictive maintenance, root cause analysis, and natural language interfaces. However, most approaches address these components independently. Limited work focuses on integrating conversational AI with Andon systems for automated analysis and recommendation generation, highlighting a gap addressed by the proposed system.

III. RESEARCH GAP AND CHALLENGES

Despite advancements in smart manufacturing, industrial IoT, and AI-based production analytics, several limitations persist in current manufacturing monitoring systems. Traditional Andon systems primarily function as real-time alert mechanisms for machine failures and production interruptions. While they improve operational awareness, they lack advanced analytical capabilities required to extract meaningful insights from production data.

Although IoT-based Andon systems enhance real-time monitoring and data collection, they mainly focus on status tracking and alert generation rather than intelligent analysis of production loss patterns or root causes. As a result, production engineers often rely on manual analysis of large datasets, which is time-consuming and prone to errors.

Another major limitation is the restricted accessibility of production data for non-technical users. Most systems require knowledge of SQL for data retrieval, creating a barrier for operators and managers and limiting effective data utilization.

Furthermore, existing approaches such as predictive maintenance, machine learning-based root cause analysis, and natural language interfaces are often developed independently. Limited research has focused on integrating conversational AI with manufacturing monitoring systems to enable intuitive data interaction along with analytical insights.

Identifying root causes of production losses also remains challenging due to the involvement of multiple interrelated factors such as machine performance, material quality, and operator efficiency. Existing systems often fail to effectively correlate these factors, making it difficult to generate actionable recommendations.

Therefore, a research gap exists in developing intelligent Andon systems that integrate monitoring, analytics, natural language querying, and root cause analysis. The proposed system addresses this gap by enabling conversational interaction and providing actionable production insights.

IV. RESEARCH METHODOLOGY

A. Data Collection

The data used in this research consists of manufacturing production analytics generated using a simulated SQL database. Due to confidentiality constraints associated with real industrial data, a synthetic dataset was created to replicate real-world production line operations.

The dataset includes key production parameters such as production quantity, machine performance indicators, downtime events, quality rejection counts, and operator-wise production metrics. The data was generated using structured SQL scripts to ensure realistic manufacturing scenarios.

The generated manufacturing dataset is maintained within a relational database platform to support fast retrieval, filtering, and production analysis operations. Initial preprocessing steps including removal of inconsistent entries and standardization of values were performed to improve data quality before analysis.

B. Proposed Methodology

The developed framework operates through multiple processing stages that combine conversational AI, database query creation, production data evaluation, and automated recommendation support for manufacturing analysis.

Production-related requests are entered through a conversational web interface that accepts user instructions in plain language. The conversational inputs are analyzed using an LLM-supported language processing module that identifies user requirements and generates corresponding database queries for data retrieval. The generated database instructions are processed against the manufacturing dataset to obtain the required operational information.

Retrieved production records are examined to detect operational trends including equipment downtime behavior, shift-level output variation, utilization efficiency, and quality-related abnormalities. Analytical findings are presented using descriptive summaries, structured tables, and graphical visualizations for easier understanding.

The framework also evaluates production loss conditions by examining relationships between equipment behavior, material conditions, and

operator-level performance factors. Based on these insights, the system generates actionable recommendations for improving production efficiency and reducing downtime.

Overall, the workflow converts conversational production requests into actionable manufacturing insights through automated analytical processing.

V. IMPLEMENTATION AND DESIGN

A. Implementation Environment

The proposed AI-driven Andon system was implemented using a client-server architecture. The backend was developed in Python for AI processing, NLP tasks, and database connectivity, while the frontend was designed as a conversational web interface for user-friendly query interaction.

A centralized relational database platform was utilized to store synthetic production data generated through SQL scripts, including metrics such as production performance, downtime events, and quality indicators.

The AI processing layer utilized Large Language Models (LLMs) to convert natural language requests into runnable SQL statements using prompt-engineered inference.

B. System Implementation Workflow

The system follows a multi-stage execution pipeline:
Step 1 — User Query Input:
Users interact through a chatbot interface by submitting production-related requests using natural language.
Step 2 — Query Processing:
The language model interprets user requests using intent detection, entity recognition, and query structuring to generate valid SQL queries and structured outputs.
Step 3 — SQL Execution:
Generated SQL statements are processed within the production database, retrieving structured production data.
Step 4 — Data Analytics:
The retrieved data is analyzed using statistical methods to identify trends such as downtime patterns, production variations, and machine utilization.
Step 5 — Visualization:
Results are presented in textual, tabular, and graphical formats (e.g., bar charts, line graphs) to improve interpretability.
Step 6 — Recommendation Generation:
The system performs basic root cause analysis and generates recommendations such as maintenance scheduling and process optimization.

C. System Implementation Workflow

The system was tested using multiple query scenarios, including production efficiency, downtime analysis, machine performance, and quality evaluation. SQL query correctness and output accuracy were verified manually.
Performance was evaluated based on:
• Query generation accuracy
• Response time
• Visualization correctness
• Recommendation relevance

D. Tools And Technologies
• Python for backend and AI processing
• Large Language Models for NLP and query generation
• Relational database for data storage and SQL execution
• Web-based chatbot interface for user interaction
• Visualization libraries for graphical outputs.

E. Advantages
• Reduces manual querying effort
• Enables natural language interaction
• Provides intelligent production insights
• Supports data-driven decision-making

VI. RESULTS AND DISCUSSION

The proposed AI-driven Andon framework was tested using various simulated manufacturing analysis scenarios on a synthetic manufacturing dataset. The system successfully demonstrated the ability to interpret user-defined conversational inputs and convert them into properly formatted SQL statements commands for retrieving relevant production data.
The results indicate that the proposed framework is capable to effectively generate accurate query outputs and present them in multiple formats, including textual summaries, tables, and visualizations. The use of natural language interaction simplifies access to production data, enabling users to retrieve insights related to downtime analysis, production performance, and quality metrics without requiring technical expertise in SQL.
Visualization of results helped in identifying key production trends such as dominant downtime causes, shift-wise performance variations, and quality-related issues. These insights improve understanding of operational inefficiencies and support faster analysis compared to traditional reporting methods.

Fig 1: Total Production Quantity

Fig 2: Daily Production Trend over time

Additionally, the system demonstrated the capability to generate basic production improvement recommendations by analysing patterns in the retrieved data. This supports proactive decision-making by highlighting potential areas for maintenance and process optimization.
However, system performance depends on query accuracy and data quality, and real-world deployment would require further optimization.
Overall, the results confirm that integrating natural language processing with production analytics improves accessibility and supports efficient decision-making in manufacturing systems.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This research presented an AI-driven Andon system that integrates natural language processing, Text-to-SQL query generation, and production analytics to enhance traditional manufacturing monitoring systems. The proposed approach enables users to interact with production databases using natural language, eliminating the need for technical query knowledge.

The system retrieves and analyzes production data, presenting insights in text, tables, and visualizations, while supporting data-driven decision-making through root cause analysis.

Overall, the proposed system transforms conventional Andon systems from reactive alert mechanisms into intelligent decision-support tools, contributing to the advancement of smart manufacturing environments.

B. Future Work

Future research can focus on integrating real-time production data using IoT-based systems to enable live monitoring and analysis. Advanced machine learning techniques can be incorporated to improve predictive capabilities, such as forecasting machine failures and optimizing production processes.

Further enhancements may include improved root cause analysis using advanced algorithms, multilingual support for wider accessibility, and cloud-based deployment for scalable manufacturing analytics. Integration with enterprise systems such as ERP platforms can also be explored to support automated decision-making and resource planning.

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