

FUSION AI: A Knowledge-Driven AI Employee for Engineering Problem Solving in Tyre Manufacturing

Bhumika M¹, Chethan R¹

¹Automotive Europe, L&T Technology Services, India

Abstract - Manufacturing engineers often spend significant time searching fragmented technical documents, consulting experienced personnel, investigating failures, and preparing reports. This study presents FUSION AI, a knowledge-driven engineering intelligence framework proposed for tyre manufacturing. The system combines retrieval-augmented generation, an engineering knowledge base, structured reasoning, and workflow automation to support machine-issue investigation, root cause analysis, FMEA, CAPA, validation, and engineering report generation. Unlike a generic conversational assistant, FUSION AI is designed around manufacturing-specific knowledge and established engineering decision methods. The proposed framework also connects engineering investigations with operational indicators such as downtime, machine availability, production recovery, scrap, and revenue. The presentation-based demonstration indicates potential reductions in investigation, knowledge-retrieval, and documentation time, although these figures are illustrative and require validation through industrial testing. The framework provides a foundation for human-centric AI-assisted engineering within Industry 5.0.

Key Words: Artificial Intelligence; Smart Manufacturing; Retrieval-Augmented Generation; Root Cause Analysis; Industry 5.0

1. INTRODUCTION

Modern tyre manufacturing depends on a large body of engineering knowledge, including machine manuals, standard operating procedures (SOPs), inspection standards, failure reports, FMEA records, and lessons learned. The difficulty is often not the absence of information, but finding the right information when a production problem occurs. Knowledge-management research has similarly identified the need to make distributed production knowledge accessible and reusable within cyber-physical manufacturing systems [6].

The problem considered in this work is the time required to investigate a machine or process abnormality. The FUSION AI presentation describes a conventional sequence involving manual searches through SOPs and technical documents, consultation with experienced engineers, review of previous reports, root cause analysis (RCA), and report preparation. An indicative investigation time of 15 days and more than 5,000 scattered documents are reported in the presented manufacturing scenario. Prolonged investigation can also extend downtime and contribute to production, delivery, and revenue losses.

Artificial intelligence offers a possible way to reduce this burden. Machine-learning methods are already established in manufacturing applications such as condition monitoring and predictive maintenance [10], [11]. However, diagnosing an

existing failure requires more than detecting an abnormal condition. Engineers must relate observed symptoms to process knowledge, equipment information, previous failures, and established problem-solving methods [9].

Large language models (LLMs) can process and summarize technical information, but general-purpose models lack access to organization-specific engineering knowledge. Retrieval-Augmented Generation (RAG) addresses this limitation by retrieving relevant external information to support model responses [1], with domain-specific approaches showing potential in smart manufacturing [5].

FUSION AI proposes to combine this capability with structured engineering methods. The framework uses organizational knowledge to support RCA, FMEA, validation, CAPA, and automated reporting. Its aim is not to replace engineering judgment, but to make relevant knowledge easier to access and reduce repetitive investigation and documentation work. This human-centric approach is consistent with the principles of Industry 5.0 [13], [14].

2. LITERATURE REVIEW

Manufacturing organisations generate large volumes of technical knowledge through SOPs, maintenance records, FMEA documents, inspection standards, and previous failure reports. Managing and reusing this knowledge remains a practical challenge, particularly when information is distributed across different documents and systems. Knowledge Management 4.0 approaches have therefore focused on making engineering knowledge accessible within cyber-physical production environments [6]. Knowledge graphs have also been investigated to connect manufacturing information and improve knowledge retrieval and reuse [7], [8].

Recent research has examined the use of large language models (LLMs) in smart manufacturing. Their ability to interpret technical text and support engineering tasks makes them suitable for applications such as fault diagnosis and manufacturing assistance [3], [4]. However, general-purpose LLMs may not contain the specific equipment, process, and organisational knowledge required for reliable engineering decisions. Retrieval-Augmented Generation (RAG) addresses this limitation by retrieving relevant information from an external knowledge base before generating a response [1]. Domain-specific RAG has shown potential for manufacturing question-answering and technical knowledge retrieval [5].

Root cause analysis remains another important area. Conventional methods such as 5-Why, Fishbone analysis, FMEA, and fault-tree analysis provide structured approaches for investigating failures [9], [15]. AI can assist these methods by reducing information-search effort and connecting failure symptoms with existing engineering knowledge. At the same

time, predictive-maintenance research shows the growing role of machine learning in identifying equipment conditions and supporting maintenance decisions [10], [11].

Industry 5.0 places greater emphasis on human-machine collaboration rather than complete replacement of engineers [13], [14]. This provides the basis for FUSION AI, which combines organisational knowledge retrieval with structured engineering analysis and reporting.

3. PROPOSED FUSION AI FRAMEWORK

FUSION AI is proposed as an engineering support system for tyre manufacturing, with the aim of reducing the time spent searching for technical information and preparing investigation reports. The framework uses an engineering knowledge base containing SOPs, machine manuals, previous RCA reports, FMEA records, inspection standards, and lessons learned. These sources provide the technical context required for investigating a machine or process issue.

The system combines retrieval-augmented generation (RAG) with an engineering reasoning layer. When an engineer reports a problem, FUSION AI identifies the relevant information from the knowledge base and uses it to support the investigation. RAG is particularly suitable for this purpose because the generated response can be grounded in retrieved organisational information rather than relying only on the language model's internal knowledge [1], [5].

The investigation follows established engineering practices, including 5-Why analysis, Fishbone analysis, Pareto analysis, Fault Tree Analysis, and FMEA [9], [15]. The system can also suggest validation activities and corrective and preventive actions (CAPA). Once the investigation is completed, the collected findings and supporting references are used to generate an engineering report.

The framework also includes workflow automation for storing reports and retaining investigation knowledge. This creates a feedback loop in which previous engineering investigations can become useful references for future problems. Knowledge-based approaches and knowledge graphs have similarly been explored for improving knowledge reuse in manufacturing environments [6]–[8].

FUSION AI is therefore positioned as an engineering assistant rather than a replacement for engineers. The final decisions and validation of corrective actions remain with engineering personnel, consistent with the human-centric approach promoted under Industry 5.0 [13], [14].

4. ENGINEERING INVESTIGATION AND DECISION PROCESS

The proposed FUSION AI framework structures an engineering investigation around the information available for a particular machine or process issue. The engineer first provides the observed symptoms and relevant operating details. FUSION AI then retrieves related machine documentation, SOPs, previous failure records, and other engineering references from the knowledge base [1], [5].

The retrieved information is used to support a systematic root cause investigation. Techniques such as 5-Why analysis and Fishbone analysis help organise possible causes, while Pareto

analysis and Fault Tree Analysis can be used where the available evidence supports further prioritisation [9]. FMEA provides an additional method for examining failure modes, their effects, and associated risks [15].

The framework does not treat the first identified cause as the final answer. Proposed causes require engineering validation using available process data, inspection results, or physical checks. This distinction is important because manufacturing failures can result from interactions between equipment condition, process parameters, materials, and operating practices. Previous research on AI-assisted RCA similarly highlights the need to combine automated analysis with established industrial problem-solving methods [9].

Following validation, FUSION AI can assist in documenting the confirmed cause, recommended corrective and preventive actions, and supporting evidence. The resulting report can include the investigation summary, RCA findings, FMEA information, critical quality parameters, CAPA, recommendations, and references. This standardised documentation also allows the outcome of one investigation to become part of the organisation's engineering knowledge for future cases.

5. SYSTEM ARCHITECTURE AND IMPLEMENTATION

FUSION AI is organised into four main layers: engineering input, intelligence, automation, and output. The engineer provides the machine or process issue, while the intelligence layer connects the query with the engineering knowledge base and performs the required analysis. The presentation identifies RAG, a reasoning engine, and the knowledge base as the main components of this layer.

The knowledge base is central to the framework because manufacturing investigations depend heavily on organisation-specific information. Machine manuals, SOPs, previous RCA reports, FMEA records, and lessons learned can be indexed and retrieved when required. This approach follows the basic principle of RAG, where external knowledge is retrieved to support language-model responses [1]. Knowledge graphs can further improve the connection between machines, processes, failure modes, and engineering records [7], [8].

The automation layer connects the investigation with practical engineering documentation. In the proposed architecture, workflow automation is used to generate and store engineering reports through tools such as Google Docs and Google Drive. The presentation also proposes retaining completed investigations as organisational knowledge, allowing future engineers to refer to earlier cases.

This architecture keeps the engineer involved in the investigation while reducing repetitive information retrieval and documentation work. It also provides a foundation for later integration with factory systems, including IoT, MES, ERP, computer vision, predictive maintenance, and digital twins, as outlined in the proposed roadmap.

6. MANUFACTURING COMMAND CENTER AND PERFORMANCE MONITORING

The proposed framework extends engineering support beyond individual failure investigations by providing a common view of manufacturing and engineering performance. The FUSION AI dashboard presented in the source includes machine status, production status, downtime, scrap, investigation time, MTTR, machine availability, OEE, quality indicators, and engineering alerts.

These indicators help connect technical problems with their operational consequences. For example, prolonged equipment downtime can affect production output and delivery performance, while recurring process failures may contribute to increased scrap. Monitoring such measures alongside engineering investigations can help engineers understand whether corrective actions are improving plant performance. OEE and equipment availability are also commonly used to assess manufacturing performance, while predictive-maintenance research has demonstrated the value of combining equipment information with analytical methods [10], [11].

The presentation provides an illustrative demonstration in which the command centre reports 87% machine utilisation, 81% OEE, reduced downtime, lower scrap, and recovered revenue. These values are explicitly identified as illustrative figures and should not be interpreted as experimentally validated results.

The dashboard therefore serves primarily as a decision-support layer. Its value lies in bringing engineering investigation and operational indicators into the same view, allowing engineers and management to assess problems in terms of both technical causes and manufacturing impact.

7. EXPECTED BENEFITS AND INDUSTRIAL IMPACT

The main expected benefit of FUSION AI is a reduction in the time required for engineering investigation and documentation. The proposed workflow brings document retrieval, RCA, FMEA, CAPA, validation, and report preparation into a single process. This can reduce the need for engineers to repeatedly search through separate sources or manually compile information from previous investigations. Similar knowledge-retrieval approaches have been explored for domain-specific manufacturing applications [5].

The presentation compares a conventional investigation period of 15 days with a proposed duration of 2 days. It also presents reductions in knowledge-search time and report-generation time, with report preparation shown as taking less than one minute. These figures represent the proposed system's demonstration rather than measured industrial results.

Beyond time savings, the framework can support organisational knowledge retention. Engineering experience contained in previous RCA reports, lessons learned, and technical documentation can remain accessible when experienced personnel move to other roles or leave the organisation. This addresses a recognised knowledge-management challenge in manufacturing environments [6], [7].

The presentation also estimates improvements in machine availability, scrap reduction, engineering productivity, and MTTR, including a projected annual revenue saving of ₹12 crore. These values are explicitly described as illustrative and would require validation under actual operating conditions. Therefore, the principal contribution of the proposed framework is not a claimed financial result, but a structured approach for applying engineering knowledge and AI assistance to manufacturing problem-solving.

8. IMPLEMENTATION ROADMAP

The proposed FUSION AI framework can be implemented progressively rather than introducing all manufacturing integrations at once. The presentation defines an initial MVP focused on engineering knowledge retrieval, investigation support, RCA, and automated reporting. This provides a practical starting point for evaluating the system with real engineering cases.

The next stage can connect FUSION AI with machine and factory data through IoT systems. Such integration would allow investigation support to use actual operating conditions alongside documented engineering knowledge. Predictive maintenance is another proposed extension, building on established applications of machine learning for equipment monitoring and maintenance decision-making [10], [11].

The roadmap also includes computer vision, digital twins, ERP, and MES integration. These additions could gradually expand the system from document-based engineering assistance toward a broader manufacturing decision-support platform. Digital twins, in particular, provide a route for connecting physical factory operations with digital representations across the product and factory lifecycle [16].

The final stage described in the presentation is a “factory digital brain,” where engineering knowledge, operational data, and manufacturing systems are connected. Such an implementation would require careful validation, data governance, cybersecurity, and continued involvement of engineering personnel. The roadmap should therefore be viewed as a development direction rather than evidence that all proposed capabilities have already been implemented.

9. DISCUSSION

FUSION AI addresses a practical gap between the availability of manufacturing knowledge and its use during day-to-day engineering investigations. Conventional problem-solving methods such as RCA and FMEA already provide a structured basis for failure investigation [9], [15]. The proposed framework does not replace these methods; instead, it uses AI to help engineers find relevant information, organise the investigation, and document the outcome.

The use of RAG is particularly relevant because manufacturing knowledge is often specific to individual machines, processes, and organisations. Retrieving information from an engineering knowledge base can provide the language model with context that would not be available from its general training [1], [5]. Knowledge graphs can further support relationships between

equipment, processes, failure modes, and historical cases [7], [8].

A key consideration is the reliability of the information used by the system. An incorrect or outdated SOP, incomplete failure record, or poorly documented previous investigation could lead to an unsuitable recommendation. For this reason, engineering validation remains necessary before corrective actions are implemented. This is also consistent with the human-centred direction of Industry 5.0, where AI is intended to support human expertise rather than remove it from the decision process [13], [14].

The proposed framework therefore has greater relevance as an engineering decision-support system than as a fully autonomous maintenance system. Its effectiveness will ultimately depend on the quality of the knowledge base, integration with manufacturing data, retrieval accuracy, and validation using real industrial cases.

10. LIMITATIONS AND VALIDATION REQUIREMENTS

The proposed FUSION AI framework has several limitations that need to be addressed before industrial deployment. Its performance depends strongly on the quality and completeness of the engineering knowledge base. Missing, outdated, or inconsistent maintenance records can affect the relevance of retrieved information and, consequently, the quality of the investigation.

Another limitation is that an LLM-based system may produce a technically plausible response without sufficient supporting evidence. RAG can reduce this problem by grounding responses in retrieved documents, but retrieval quality remains an important factor [1], [5]. Manufacturing fault diagnosis also involves physical conditions and process interactions that may not be fully represented in textual records [4], [9].

The framework therefore requires validation using actual machine failures and historical investigation cases. Performance should be assessed using measures such as retrieval accuracy, RCA agreement with experienced engineers, investigation time, report-generation time, and the quality of recommended CAPA. Human review should remain part of the validation process, particularly for safety- or quality-critical decisions.

The financial and operational values presented in the FUSION AI demonstration should also be treated cautiously. The presentation identifies the reported improvements in downtime, scrap, MTTR, productivity, and revenue as illustrative values rather than measured results. Consequently, the proposed benefits require controlled industrial evaluation before they can be used as evidence of system effectiveness.

11. DISCUSSION

The proposed framework provides a starting point for broader integration of AI with manufacturing engineering. The immediate scope is to strengthen the engineering knowledge base and connect FUSION AI with plant data so that

investigations can use both documented knowledge and current machine conditions. The presentation identifies IoT integration, computer vision, predictive maintenance, digital twins, ERP, and MES as potential extensions.

Integration with predictive-maintenance systems could allow the framework to move from responding to reported failures toward supporting earlier identification of equipment problems. Predictive-maintenance research has already established the use of machine-learning methods for condition monitoring and maintenance planning [10], [11]. Computer vision could similarly extend the system to inspection and quality-related applications, where image-based information can complement existing process records.

Digital-twin integration offers another possible direction. A digital representation of factory equipment and processes can provide a connection between engineering knowledge and the physical manufacturing environment [16]. Combining this information with historical investigations could support more context-specific engineering decisions.

In the longer term, integration with ERP and MES systems could connect engineering investigations with production, quality, and operational data. The presentation describes this broader direction as a “factory digital brain.” Achieving this level of integration would require reliable data structures, system interoperability, cybersecurity, and appropriate human oversight.

12. CONCLUSION

FUSION AI presents a practical framework for applying AI to engineering problem-solving in tyre manufacturing. The proposed system combines retrieval-augmented generation with an engineering knowledge base and established methods such as RCA and FMEA [1], [9], [15]. Its main purpose is to reduce the time engineers spend searching for technical information and preparing investigation reports while retaining engineering review and validation.

The framework also provides a way to retain knowledge from previous investigations and make it available for future cases, addressing a common challenge in manufacturing knowledge management [6], [7]. The proposed integration with IoT, predictive maintenance, computer vision, MES, ERP, and digital twins provides scope for further development.

The performance and financial improvements presented in the demonstration are illustrative and require validation using real industrial data. Overall, FUSION AI is best considered a human-centred engineering support framework that can make existing manufacturing knowledge easier to access, apply, and preserve. This aligns with the broader objectives of Industry 5.0, where technology is intended to strengthen human capabilities within industrial systems [13], [14].

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