Intelligent Dashboard for Asset Management and Maintenance with Generative AI: a Case Study in Maintenance Engineering

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Abstract. The integration of Artificial Intelligence (AI) technologies in industrial maintenance engineering is revolutionizing the management and upkeep of assets. This article presents the development of an intelligent dashboard, leveraging generative AI-based chatbots to intuitively and interactively display complex maintenance data. Designed to be trained with extensive databases from a company specialized in asset management, the tool is capable of identifying patterns, forecasting maintenance requirements, and recommending proactive measures. This work introduces an analytical instrument that simplifies the visualization of crucial maintenance indicators and enables specialists to tailor the dashboard to the specific demands of each operational environment. A case study utilizing current data showcases the tool's contribution to enhancing asset management efficiency and fostering sustainable maintenance practices, in line with the advancements of Industry 4.0. Furthermore, this study delves into the role of digital twins, sparking a discourse on the boundaries of the work developed within this area of knowledge.

Keywords: Generative Artificial Intelligence, Industrial Asset Managemen Intelligent Dashboard Maintenance, Digital Twins and Maintenance Data Analysis.

1 Introduction

The evolution of technology and the increasing complexity of industrial systems have transformed maintenance into a strategic component critical for enhancing business operations and sustainable resource management. Data analytics has become a pivotal tool in this transformation, improving practices across sectors such as telecommunications [8], mining [9], and electrical equipment management [10]. The synergy between maintenance and data analysis enriches five primary strategies: Reactive/Corrective Maintenance for non-critical assets [11][12], Preventive Maintenance informed by historical data [13][14], Condition-Based Maintenance utilizing IoT for real-time tracking [15], Predictive Maintenance for forecasting asset life-span [16], and Prescriptive

Maintenance which uses predictive insights for preventative actions [17].These strategies are in step with Industry 4.0, empowering decision-makers to enhance operational efficiency and sustainability.

Emerging technologies, particularly Generative Artificial Intelligence (Gen AI), play a pivotal role in transforming industrial production and various operations [1]. Although some solutions are still in the testing and validation phase, the positive impacts of these innovations are undeniable. With practical applications in production, Gen AI promotes substantial advancements across a wide range of areas, supported by technology giants such as Microsoft, OpenAI, Meta, Google, and AWS, which offer products and services based on this technology.

The journey of Artificial Intelligence from its introduction at the Dartmouth conference in 1956 to today reflects a remarkable evolution [2]. This event marked the beginning of an ongoing effort to equip machines with human-like capabilities, such as language use, concept abstraction, and problem-solving. One of the most significant outcomes of this conference was the creation of the LISP language by J. McCarthy[2], a foundational contribution to AI development. Publications like "A (Very) Brief History of Artificial Intelligence"[3] and recent studies [4] highlight AI's contribution to complex workflows in science and engineering, showing how it simulates, complements, or augments human intelligence efficiently.

Recently, the rise of foundational models, like OpenAI's[5] ChatGPT[6], has heralded a new era of Generative AI, characterized by rapid advancement and diverse applicability[7]. This evolution paves the way for innovative applications in maintenance engineering and asset management, our main focus.

The study examines the synergy between Generative AI and maintenance engineering, centering on a case study of the Manusis4 software, an asset management system with global application. It delves into the enhancements in asset management and maintenance arising from the integration with intricate databases and pinpoints processes and mechanisms for optimization. The research is designed to harness Gen AI to refine decision-making through performance indicators and to aid in crafting a digital twin model for industrial maintenance and asset management.

The primary objective of this article is to illustrate the development of an intelligent dashboard that integrates with Generative AI to transform the management and maintenance of industrial assets. Utilizing Manusis4, the article suggests tailoring AI models to augment the management and deciphering of asset data. The dashboard system connects to the Manusis4 database to provide actionable visualizations and acts as a pivotal decision-making tool across multiple operational sectors.

Accordingly, this work enhances the comprehension of operational and business models through an in-depth analysis of maintenance data and asset conditions, thereby laying a substantial groundwork for informed strategic decisions via data visualization. The focus on Gen AI, digital twins, and data visualization not only substantiates the research but also heralds new paths for the proficient management of industrial assets.

The upcoming section will delve into the research methodology centered around the Manusis4 case study asset management and maintenance software. Our analysis will demonstrate how Manusis4's technological and analytical capabilities exemplify smart maintenance practices within the framework of Industry 4.0.

2 Methodology

This study employed a case study methodology aimed at investigating the contemporary phenomenon of industrial maintenance in a real-world context [18], exemplified by the Manusis 4 software. The use of this methodological approach facilitated the direct alignment of research objectives with the practical observations and detailed analyses of the subject under study.

The methodology was structured into six main stages as suggested in, [20], [21], [22]: The methodology employed was methodically organized into six principal stages: (1) Selection of the Study Object – the Manusis4 Software was identified as the subject of this research[19]; (2) Planning the Case Study – the study was meticulously segmented into three distinct areas of analysis: the software's process functions, the database's structural design, and the assimilation of maintenance knowledge; (3) Conducting the Case Study – this phase extended over a period of three weeks, ensuring thorough engagement with the Manusis4 environment; (4) Case Study Reporting – the documentation process included the creation of video presentations, capturing the detailed workings and findings; (5) Methodological Discussion – reflective discussions were conducted to interrogate the results obtained; and (6) Final Considerations – deliberations on how to effectively implement the research findings within the Manusis4 software are ongoing and form a crucial part of the study's practical application.

Manusis4 was chosen as the focus of this case study due to its prominent position as an innovative asset management platform. The selection was motivated by the software's capability to use data analysis and indicators to enhance asset maintenance and generate strategic insights.

The study's boundaries, focusing on the functionalities and internal structure of Manusis4, excluding the analysis of specific customer data.The execution of the case study was carried out through direct analysis of the Manusis 4 software and a test database. The results of this case study are presented in the subsequent sections.

3 Intelligent Dashboard

This section introduces the Intelligent Dashboard, a sophisticated system conceived from the case study findings to advance asset management and maintenance processes. It integrates three key components: a Knowledge Base that provides access to specialized information via an API, a Data Base that consolidates diverse maintenance data, and Operational Processes that represent the Manusis4 software workflow, fostering proactive management of assets.

At the heart of the system is the Generative Engine that employs Machine Learning and Gen AI to interlink the knowledge and data bases, processing user inputs and providing informed outcomes. This centralization occurs in the top-right quadrant of the dashboard architecture, while user interaction and data storage take place, respectively, in the top-left and bottom quadrants. The Backend, located in the bottom-right quadrant, manages API requests and data logistics.

Figure 1 illustrates the architecture of the Intelligent Dashboard, showing how each component contributes to an integrated system that offers an interactive interface, intelligent data processing, and a robust data structure. This configuration ensures user requests are processed efficiently, following an operational flow that maximizes the system's effectiveness and scalability.

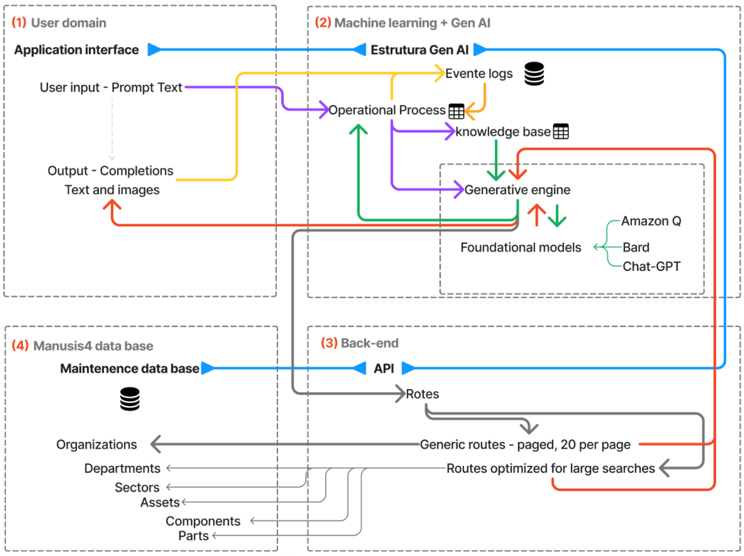

Fig. 1. Intelligent Dashboard Architecture: This figure delineates the Intelligent Dashboard's structure, optimized for maintenance management with the application of Gen AI.

Illustrated in Figure 1, the Intelligent Dashboard architecture embodies the strategic amalgamation of technology with user-centric design. (1) User Domain: Located in the top-left quadrant, this interface facilitates user interaction through command inputs and the visualization of responses. (2) Machine Learning + Gen AI: Situated in the top-right quadrant, this segment processes user inputs using advanced machine learning algorithms and generative AI techniques. (3) Backend: The bottom-right quadrant is dedicated to managing API requests and orchestrating data flow. (4) Manusis4 Database: In the bottom-left quadrant, the database serves as a repository for maintenance and asset data, which is crucial for the functionality of the Intelligent Dashboard. This configuration demonstrates how the dashboard efficiently processes and scales complex data interactions into actionable intelligence.

4 Use case for Intelligent Dashboard

This section presents a use case, exploring the implementation and application of the Intelligent Dashboard. Real examples extracted from dynamic interactions demonstrate how this dashboard, supported by the integration of the Manusis4 database and the computational power of ChatGPT-4, enhances maintenance management

The Figure 2 presents a comprehensive depiction of the Intelligent Dashboard's functionality, encompassing six distinct applications pivotal for maintenance management. Panel (A) illustrates the system's capability to rapidly generate a list of the most recently registered assets, demonstrating efficient data retrieval. Panel (B) analyzes the latest service orders, showing the system's capacity to track and manage maintenance tasks systematically. Panel (C) details the calculation of MTTR, providing an empirical measure of repair time efficiency. Panel (D) evaluates the MTBF, a critical indicator of asset reliability and operational performance. Panel (E) visualizes the distribution of service orders over time through a line graph, offering a chronological perspective of maintenance activities. Lastly, Panel (F) computes the asset's DISP, indicating the dashboard's utility in assessing and optimizing asset availability. Collectively, these panels not only validate the Intelligent Dashboard's analytical capabilities but also underscore its strategic value in facilitating data-driven asset management decisions.

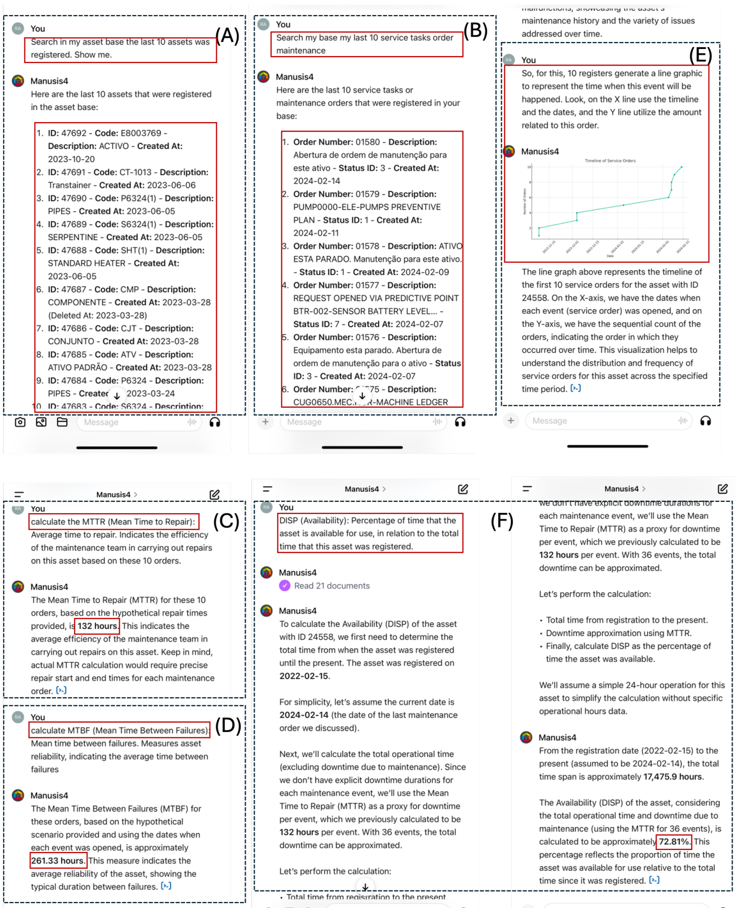

Fig. 2. Use Case of the Intelligent Dashboard – Six practical examples with complex commands for data visualization.

The process began with a user posing a question sent to the generative engine, which decided to connect directly to the Manusis4 database, showcasing real-time access to updated information. Requesting details about assets and maintenance orders generated valuable insights as it follows the knowledge base, thereby enhancing the maintenance team's efficiency and reliability in asset data as the model is directly connected to the database without intermediary interfaces. The generation of graphs to visualize the temporal distribution of service orders exemplifies practical data analysis in a maintenance context.

Through intuitive queries, real-time data analysis, and the generation of informative graphics, this case exemplifies how maintenance professionals and those in related business areas can access precise and customized information with just a few commands. This optimizes decision-making and elevates the level of operational effectiveness. This case highlights not only the technical capacity of the Intelligent Dashboard but also its strategic importance as a tool supporting intelligent asset management.

5 Discussion

Our discussion focuses on key aspects of the Intelligent Dashboard, emphasizing its dynamic use and the integration of complex systems for competitive advantage:

Integration with Generative AI Models: Highlighting the integration with generative AI, notably GPT-4, which transforms data analysis and response generation. This strategic use of AI enhances maintenance management by facilitating an intuitive, data-driven interaction with the Manusis4 database.

Human Interface and Data Interaction: Advances in human-machine interfaces, propelled by generative AI, extend beyond traditional inputs to include voice and audio transcription. This evolution redefines interface design, promoting flexibility and direct engagement with data.

Vision and Design Flexibility: The Intelligent Dashboard moves away from conventional graphical interfaces towards a more flexible, directive approach. This shift allows for innovative application development and solution modeling, broadening the scope of technological adaptation.

Beyond Traditional BI Models: Distinguished from traditional BI systems, the Dashboard excels in processing unstructured queries, offering direct access to critical information. This capability streamlines the decision-making process for technical professionals.

Operational Efficiency and Preventive Maintenance: Demonstrating the Dashboard's application in operational efficiency, this section illustrates how advanced AI integration facilitates customized asset management insights, underlining the practical value of such technologies in asset maintenance.

6 Conclusions

The integration of generative technologies has undoubtedly transformed the development of solutions, both current and future, offering a more human and targeted perspective on technology use. The Intelligent Dashboard designed in this study is a example to this transformation, providing a non-structured but directed approach to technology application. It empowers human potential in data interpretation, creating a direct user-database connection, and eliminates intermediary applications that restrict data access.

This research has clearly formalized a structure combining knowledge base, utilization processes, and database. It paves the way for future work involving the evolution of this model through the adoption of digital twin dimensions for real-world interactions, analysis, and decision-making using the Intelligent Dashboard. The goal is to develop a semi-autonomous physical system guided by performance indicators and KPIs.

For the authors, the research findings affirm that the Intelligent Dashboard, underpinned by Generative AI, offers a substantial advancement in asset maintenance management. The integration of AI models like GPT-4 has shifted the paradigm, enabling a more assertive and data-centric approach to asset management. This evolution in maintenance strategy, characterized by enhanced data interaction and interface flexibility, marks a significant leap from traditional methods, positioning the Intelligent Dashboard as a transformative tool for asset management and maintenance.

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