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Original Article

Knowledge Graph-Based Engineering Asset Management for Predictive Decision Intelligence

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ABSTRACT

Engineering Asset Management (EAM) is evolving through Industry 4.0 technologies such as IoT, AI, Digital Twins, and cloud computing, which generate vast amounts of asset-related data. However, conventional asset management systems often fail to integrate heterogeneous data sources, resulting in fragmented information, reactive maintenance, and increased operational costs. This study proposes a Knowledge Graph-Based Engineering Asset Management (KG-EAM) framework to enhance predictive decision intelligence for smart industrial assets. The framework integrates data from Industrial IoT devices, SCADA systems, Enterprise Asset Management (EAM) platforms, Computerized Maintenance Management Systems (CMMS), and engineering documentation into a unified semantic knowledge ecosystem. By combining ontology modeling, graph databases, graph embeddings, machine learning, and explainable AI (XAI), the framework enables predictive maintenance, root cause analysis, asset health prediction, and risk-aware decision-making. The proposed approach improves asset reliability, maintenance planning, operational efficiency, knowledge sharing, and lifecycle management while reducing downtime, maintenance costs, and unexpected equipment failures across diverse industrial sectors.

KEYWORDS

Knowledge Graph, Engineering Asset Management, Predictive Decision Intelligence, Predictive Maintenance, Artificial Intelligence, Industrial Internet Of Things (Iiot), Digital Twin, Semantic Web, Graph Database, Machine Learning, Asset Reliability, Industry 4.0.

1. INTRODUCTION

1.1. Background

The last two decades have witnessed EAM (engineering asset management) evolve at a rapid pace to become one of the most significant disciplines focused on assuring optimal performance, reliability and sustainability of industrial systems in the global era of digital transformation. From transformers, turbines, industrial robots, production machinery to compressors and pumps in manufacturing; from power generation, transportation to oil & gas utilities and smart infrastructure — high-value engineering assets are the backbone of modern industries. They are key assets to ensure uninterrupted industrial operations, enhance productivity and drive economic growth. This will allow organizations to maximize the performance of over time, but remain within operational risk limits and reduced maintenance costs: More than 75% of systems (industrial assets) have been automated with interconnectivity these days and it only gets accelerated from now on. The fast adoption of Industry 4.0 technologies has revolutionized Engineering Asset Management as it allows continuous monitoring through the Industrial Internet of Things (IIoT), cloud computing, edge computing, cyber-physical systems and Digital Twin technologies. Modern mechanical systems have been fitted with smart sensors that constantly monitor high quantities of real-time operational data like temperature, vibration, pressure, moisture level, electrical current and magnetism intensity as well as indicators associated with lubrication levels and other condition-monitoring parameters. Beyond sensor-level information, a breadth of critical engineering knowledge resides in enterprise systems like Supervisory Control and Data Acquisition (SCADA), Enterprise Resource Planning (ERP), Computerized Maintenance Management Systems (CMMS), maintenance records, inspection reports and historical failure databases. Due to the differences in data formats, structures, and storage platforms, integration and efficient exploitation of these various and heterogeneous sources of data has been remarkably becoming harder. Traditional Engineering Asset Management systems have typically used preventive maintenance schedules and historical operational records to aid their maintenance planning process. This will help mitigate equipment unreliability to some extent more than strategies formed purely on reactive maintenance, however these approaches often fall short of fully addressing the complexity involved as they do not formulate relationships among various engineering assets, cause and effect of maintenance activities being performed in a certain period at that particular site along with the environment on day-2-day or minute-to-minute basis essential for effective operations. As a result, maintenance decisions may be made on incomplete information resulting in unnecessary equipment condition performances to repair the faulty components or the wrong measures taken at high cost leading to unexpected failures, prolonged downtimes and unreliably high utilization of resources in processes which occurs discontinuously (failing machinery, if not controlled). In addition, traditional predictive maintenance models often treat sensor data in numerical form independently of contextual engineering knowledge or organizational expertise and hence have more difficulty providing accurate and explainable maintenance recommendations. To meet these challenges, it has been increasingly emphasized in recent research studies to integrate Artificial Intelligence (AI), Knowledge Graph (KG) technology, semantic reasoning, and predictive analytics into Engineering Asset Management. Knowledge Graphs can establish a semantic paradigm for defining engineering assets, sensors, maintenance activities, operational processes along with

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their relationships in a structured machine-readable manner. Over enhancing the capability of AI-driven predictive analytics, Knowledge Graphs drive intelligent reasoning, advanced fault diagnosis, Remaining Useful Life (RUL) prediction, root cause analysis and effective maintenance scheduling. This integration is the foundation of Predictive Decision Intelligence, where maintenance decisions are assisted by not only statistical predictions but also contextual engineering knowledge and explainable reasoning. Thus, this research is the study of the Knowledge Graph-based Engineering Asset Management Framework for Predictive Decision Intelligence (KG-EAM-F-PDI) with a goal to consolidate heterogeneous industrial data, ontology-based semantic knowledge representation, machine learning, graph analytics and Explainable Artificial Intelligence (XAI) into an integrated decision-support architecture. The proposed framework will offer higher accuracy in predictive maintenance, reliability-based asset verification, optimal maintenance scheduling, lower lifecycle costs and an intelligent as well as transparent knowledge-driven decision-making experience for the Industry 4.0 engineering environments. This research advances next-generation Engineering Asset management by offering a scalable and explainable framework for effective sustainable industrial operation and digital transformation implementation.

1.2. Engineering Assets and Industrial Data Management

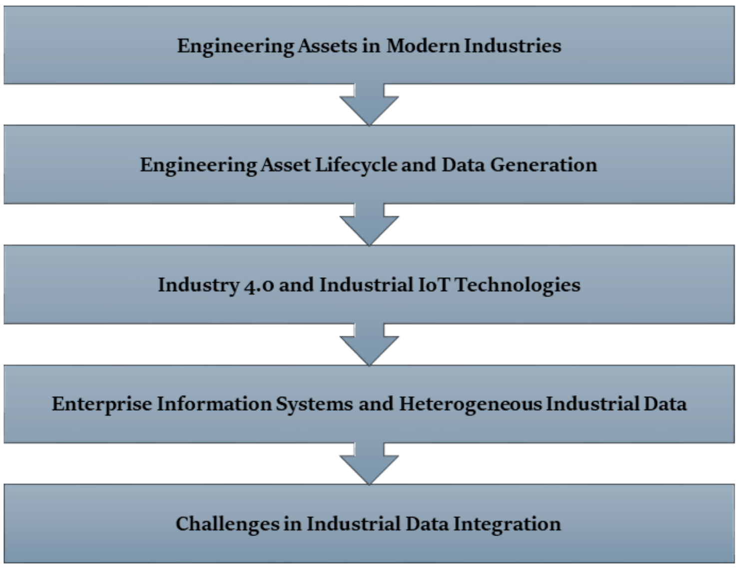

Fig 1 - Engineering Assets and Industrial Data Management

1.2.1. Engineering Assets in Modern Industries

Engineering assets are important physical resources constituting industrial operations and economic development. These assets include manufacturing equipment, electrical transformers, industries motors, turbines, pumps & compressors plus piping systems, railway systems and aircraft components but expanding to utility networks from renewable energy infrastructure as well. They carry out essential operational functions that impact directly on production efficiency, equipment reliability, operational safety and business profitability. Because engineering assets have heavy capital investment, organizations must efficiently manage these assets over their lifecycle from design and installation to operation, maintenance and replacement. Proper management prevents sudden

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failures, increases asset life & reduces maintenance costs allowing industrial businesses to work without any faults.

1.2.2. Engineering Asset Lifecycle and Data Generation

Engineering assets produce a lot of operational and maintenance data throughout their active working lives. Modern-day industrial equipment has sensors and monitoring devices to measure actual operating conditions and the state of the machines, its performance and environmental data. Also data is produced from maintenance activities, inspection reports, failure logs, equipment manuals including production info and enterprise information systems. The different datasets provide insights into the health of assets, performance trends, operational efficiency and history of maintenance. The collection, storage and management of this information must be done in an orderly manner to support predictive maintenance. It is also the basis for lifecycle optimization & intelligent asset management (smart grid).

1.2.3. Industry 4.0 and Industrial IoT Technologies

The era of Industry 4.0 has revolutionized Engineering Asset Management by bridging Industrial Internet of Things (IIoT), cloud, edge and cyber-physical systems, Artificial Intelligence and Digital Twin technology with industrial environments. The royal sensors for IIoT continuously tracks critical operating metrics, including temperature; vibration activity; pressure; electrical current; acoustic emissions; lubrication quality; humidity and rotational speed. They allow for real-time monitoring, automated data collection, remote asset management and diagnosis, and many other intelligent functions. As a result, industries can improve operational efficiency by transforming from traditional reactive maintenance to predictive and condition-based maintenance strategies — not only this, but equipment downtime will see a significant reduction too.

1.2.4. Enterprise Information Systems and Heterogeneous Industrial Data

Apart from the information derived from sensor feeds, industrial entities also retain empirical knowledge locked away across different enterprise information systems. They range from Enterprise Resource Planning (ERP) systems, Computerized Maintenance Management Systems (CMMS), Supervisory Control and Data Acquisition (SCADA) systems, maintenance databases, spare parts catalogs, inspection reports, workforce management software solutions too production scheduling and operational planning applications. The types of structured and unstructured information kept by each system differ along with their formats or standards. While these datasets provide a reasonably good insight into our assets as engineers, the distributed nature of such datasets hinders data interoperability and related issues that restrict information sharing and integrated decision-making.

1.2.5. Challenges in Industrial Data Integration

Although big data of the industrial kind is plentiful, large organizations still identifying significant integration challenges in aggregating larger volumes of heterogeneous information into an integrated decision-support framework. Information silos resulting from differences between data formats, communication protocols, database structures and organizational systems inhibit

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knowledge sharing across departments. The traditional approach to asset management systems looked at sensor data alone, whilst ignoring the engineering relationships, maintenance history (what repairs were done when and how successful they were), dependencies between equipment and all the network context knowledge. Inaccuracy in predictive maintenance, delay in upkeep decision-making, decreased asset comprehensibility and increased operational risk arises from this disjointed method. These challenges can be tackled with complex data integration methodologies such as Knowledge Graphs, semantic technologies as well as Artificial Intelligence (AI) for the unification of industrial information at work so that context on Engineering Asset Management may assist intelligent decision making.

2. LITERATURE SURVEY

2.1. Engineering Asset Management

The Engineering Asset Management (EAM) is a integrated approach with a life cycle and follows a combined efforts of technical and non-technical based on the nature of assets from planning, design, procure/installation to operate. maintain or phase out for the cutoff stage leading to more value at less cost/risk. As per ISO 55000 standard, EAM is total organizational activities coordinated by an organization to realize value from engineering assets (ensuring that asset performance allowed realization of actuals: economic terms such as sustainability and operational efficiency or safety). Traditionally, the industries went for corrective maintenance where any equipment is repaired post-failure which resulted in unplanned downtimes and huge financial losses. This was later superseded by preventive maintenance, a system where maintenance is performed at specific intervals based on time or use. Preventive maintenance did achieve a measure of reliability, however, due to the nature of preventive maintenance servicing equipment simply because it was time for a visit resulted in unnecessarily service and increased overall cost. Condition-Based Maintenance (CBM) was a big step in the right direction, as it employed continuous monitoring technologies like vibration analysis, thermal imaging, oil analysis, ultrasonic inspection, acoustic emission monitoring and electrical diagnostics to monitor equipment health real-time. Industry 4.0 has provided intelligent engineering asset management with enhanced frameworks, facilitated through Industrial Internet of Things (IIoT), cyber-physical systems, cloud computing, edge computing, artificial intelligence, machine learning and Digital Twin technology. Industrial assets are equipped with smart sensors that monitor the status of useful parameters continuously (ex: temperature, vibration, pressure, humidity, electrical current being drawn manufacturing rotational speed energy consumption lubrication condition). These data points are communicated over secure channels to edge or cloud based platforms where sophisticated machine learning algorithms study the mode of operations, spot anomalies, predict Remaining Useful Life (RUL), and project failures before they actually happen. While certainly a technological innovation most current EAM systems are still limited by fragmented information sources, poor integration of both maintenance history and engineering know-how as well as insufficient context awareness regarding asset interdependencies. Therefore, contemporary research focuses on knowledge-driven Engineering Asset Management with a view toward leveraging semantic technologies, engineering ontologies and intelligent decision-support systems to combine operational data with expert knowledge for enhanced maintenance optimization, asset reliability, operational resilience, risk management and lifecycle decision-making for complex industrial environments.

2.2. Knowledge Graph Technology

The technology behind Knowledge Graph (KG) has become one of the major semantic infrastructures for complex engineering knowledge description by defining information in terms of interlinked entities that capture a combination of both their physical and logical relationships, mirroring many real-world industrial systems. Knowledge Graphs were first introduced for the Semantic Web, but they have quickly found general recognition within manufacturing activities as well as many other fields including healthcare, finance, transportation, energy and engineering using their ability to semantically integrate heterogeneous data while retaining certain contextual relationships. In Conventional relational databases, data is physically stored in isolated tables and connected to one another through foreign keys; Knowledge Graphs use graph structures containing nodes (entities), edges (relations) and properties (attributes). In engineering asset management, entities can be machines, sensors, components, maintenance engineers, inspection reports, spare parts or operational processes and relationships would describe the interaction such as monitored by, connected to, located in, maintained by or causes failure of. These entities become even more informative with attributes that store data like vibration levels, working temperature, maintenance dates, age of equipment, operating hours or probability of failure. Graph structures are basis on ontology-based semantic models that describe standard engineering concepts, terminology and logical relationships so as to allow for a consistent interpretation of industrial information in many enterprise systems. Graph Database query languages like Cypher, SPARQL, or Gremlin enable the retrieval of highly interconnected engineering information that regular SQL queries will struggle to provide. Modern graph database platforms such as Neo4j, Amazon Neptune or GraphDB and Blazegraph and RDF Triple Stores can efficiently manage large-scale KGs. In recent years, Knowledge Graphs have been combined with AI techniques such as GNNs, graph embeddings, semantic reasoning, knowledge embeddings and graph analytics, helping systems to reveal hidden dependencies between data sources, infer missing knowledge in an automated way (by making the right assumptions), perform optimal fault diagnosis, support predictive maintenance of industrial asset portfolios while driving improved Digital Twin models and ultimately enhanced industrial decision-making. However, even with these advances Knowledge Graph applications in Engineering Asset Management still leave much to be desired since most implementations emphasize ontology construction over real-time sensor streams, predictive analytics, explainable AI and scalable industrial deployment. Thus, it is still a significant research direction to design integrated Knowledge Graph architectures that incorporate semantic representation, machine learning, graph reasoning, and real-time industrial intelligence.

2.3. Predictive Decision Intelligence

Predictive Decision Intelligence (PDI) is the next generation of ambient intelligent industrial maintenance, integrating predictive analytics, artificial intelligence and machine learning algorithms, knowledge representation, optimization techniques through all branches of semantic reasoning applied to decision-support systems in a holistic approach towards engineering decision-making. Most of the discipline in predictive maintenance focuses on predicting equipment failures with time series sensor data using machine learning techniques like Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Long Short-term Memory (LSTM) forecasting, Gradient Boosting and Deep Learning models. These algorithms estimate equipment health, classify fault conditions, detect anomalies and predict Remaining Useful Life (RUL) based on operational data. These methods achieve high predictive performance, but are generally used as black box statistical models that do not provide much explanation about why a failure is predicted or what maintenance should be performed. Your predictive decision intelligence goes beyond failure prediction to intelligent decision-making, which addresses these limitations of predictive maintenance. Combining all engineering knowledge, asset criticality, operational limitations, history of maintenance action, business need and environment parameters along with the resource capabilities and organizational know-how to suggest best-maintained action. This integration allows maintenance specialists to respond to important operational queries, such as what is the critical equipment or task that should be attended immediately, what are the things that must be prioritized on the maintenance strategy, when interventions happen and how this impact production performance or what are the risks if you delay a maintenance activity. Having context around engineering relationships, Knowledge Graphs augment Predictive Decision Intelligence through semantic reasoning across industrial assets that are interconnected. Graph reasoning algorithms is used to expose hidden dependencies between equipment, detect cascading failures, recommend maintenance priorities based on context (failure time of equipment), conduct root cause analysis and optimize the order of maintenance scheduling. Moreover, the integration of Explainable Artificial Intelligence (XAI) addresses transparency by enabling interpretable explanations for AI-generated recommendations, fostering trustfulness among engineers and decision-makers in charge of safety-critical infrastructure domains like power systems, aerospace, transportation, manufacturing, healthcare and smart factories. Thus, the combination of Knowledge Graphs and Predictive Decision Intelligence provides a very exciting direction for implementing intelligent explainable knowledge-based Engineering Asset Management systems that can enable predictive maintenance optimization, operational efficiency, reliability and cost reduction and assist strategic industrial decision making.

2.4. Research Gap Analysis

Despite the advancement towards Engineering Asset Management, Knowledge Graph technology, Artificial Intelligence and Predictive Decision intelligence there are still several critical research challenges that need to be solved/efficiently tackled in order to enable fully intelligent industrial maintenance systems. Fragmented industrial data integration is one of the most problematic problems, as engineering information is frequently dispersed among Industrial IoT platforms, SCADA systems, Enterprise Resource Planning (ERP) databases, Computerized Maintenance Management Systems (CMMS), maintenance logs, engineering documentation, inspection reports and past operational records. Most of the existing predictive maintenance models treat these heterogeneous sources independently, which means an incomplete situational awareness and a lack of contextualization on how assets behave over time. In particular, the existing predictive models rely heavily on statistical learning by numerical sensor data and neglect to utilize available engineering knowledge related to equipment hierarchies, component interactions, maintenance dependencies, environmental impact factors, operational constraints, as well as expert domain knowledge – this is another major limitation. This hampers what AI systems can learn and propagate by way of maintenance recommendations that truly are detailed, relevant to the context. Furthermore, a lot of these machine learning models behave like black-boxes that yield very accurate predictions and yet do not explain themselves in a transparent manner and instil less confidence in maintenance engineers who are expected to make safety-critical decisions. It has traditionally been remarkably successful in fields such as ontology development and semantic knowledge representation, but there are still not many research studies that combine Knowledge Graphs with machine learning, graph analytics explainable AI, semantic reasoning, and real-time industrial decision optimization in the same framework. Real-time semantic reasoning, especially in large scale smart factories generating millions of sensor observations daily present a significant challenge to industrial implementation while challenges related to scalability, interoperability and computational efficiency still persist. To handle these challenges, we need end-to-end frameworks which can scale an architecture to seamlessly integrate heterogeneous industrial data with a combination of ontology-driven semantic modeling, machine learning, graph reasoning capabilities, predictive analytics and Explainable AI. To this end, this work presents a Knowledge Graph-Based Engineering Asset Management Framework for Predictive Decision Intelligence that integrates semantic knowledge representation with AI-driven predictive analytics supporting asset reliability,optimized maintenance planning, improved operational performance and lifespan cost reductions, explainable low-level input-to-output-maintenance recommendations,as well as intelligent decision-making support in Industry 4.0,and emerging future smart manufacturing environments.

3. METHODOLOGY

3.1. System Architecture

A comprehensive five-layer architecture designated in capture types of heterogeneous industrial data, semantic knowledge representation, artificial intelligence as well as intelligent support for decision is preferred to devise Knowledge Grapth-Based Engineering Asset Management Framework for Predictive Decision Intelligence. The architecture enables perpetual monitoring of engineering assets and processing near real-time data for predictive analytics and explainable maintenance recommendations as conceptually illustrated in Figure 3.1. The first layer, Data Acquisition Layer: It Is the right level framework that collects operational data from different industrial sources such as IIoT sensors, SCADA, PLCs, ERP systems to create a holistic view of all assets along with historical insights and information from CMMS systems, maintenance records (i.e. This diverse data set supplies in-depth details about equipment condition, operational performance, environmental parameters, maintenance history and asset utilization. Data Integration and Knowledge Graph Layer (the second layer): collects, preprocesses, cleans the data from the previous layer — transforms data into a standard semantic representation with engineering ontologies. Semantic relationships between engineering assets, sensors, maintenance activities, operators, spare parts and failure events are established to create a scalable Knowledge Graph that encodes contextual

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dependencies among industrial assets. The third layer, Artificial Intelligence and Predictive Analytics Layer, leverages machine learning techniques including graph learning and anomaly detection models for analyzing both sensor data as well as semantic relationships. This layer tries to predict equipment failures, forecast Remaining Useful Life (RUL), detect abnormal operating conditions and unearthed hidden relationships that can greatly impact the reliability of assets. Layer 4 Decision Intelligence Layer: This layer merges highly predictive output with some form of semantic reasoning, graph analytics, optimization algorithms and Explainable Artificial Intelligence (XAI) to provide clear maintenance recommendations to be used for asset prioritization based on criticality, operational risk reviews and optimising work scheduling against data-driven organisational goals and engineering constraints. At last, the fifth layer is Application and Visualization Layer whose products are interactive dashboards, maintenance alerts, asset health reports, performance indicators & decision-support tool for maintenance engineers, plant managers & industrial stakeholders. These four interconnected layers together form a smart, scalable and knowledge-based Engineering Asset Management framework that supports Industry 4.0 by increasing asset reliability, reducing maintenance costs, improving operational efficiency and enabling proactive decision-making.

3.2. Knowledge Graph Construction

This work proposes a novel methodology called HICP, where KG construction is the principal part converting heterogeneous industrial data to a unified semantic representation which could enables contextual reasoning, predictive analytics and intelligent maintenance decision-making. Data is acquired from a diverse set of industrial sources to launch the construction process–Industrial Internet of Things (IIoT) sensors, Supervisory Control and Data Acquisition (SCADA) system, Programmable Logic Controller (PLC), Enterprise Resource Planning (ERP) system, Computerized Maintenance Management System (CMMS), inspection reports, maintenance logs, equipment manuals, historical operational database. These data sources consist of structured and unstructured information that relates to asset conditions, operational parameters, maintenance activities, and engineering knowledge. Data Preprocessing: Cleansing the data to handle missing values, removing duplicates and inconsistencies, standardizing the structure of information from different formats into a consistent form for interoperability. Then, the cleaned data are mapped onto an engineering ontology (the standard definition of concepts such as assets, components, sensors, operators, maintenance tasks, spare part types and IDs, failure modes and IDs or environmental conditions. With this ontology in mind, the Knowledge Graph is built around three key components: entities, relations and attributes. For example, entities are industrial objects (e.g., transformer, motor, pump, sensors and maintenance staff); relationships are the interactions monitored by, connected to or maintained by located in or causes failure of; and attributes store descriptive data (e.g. temperature, vibration level operating hours maintenance date equipment age failure probability). This produces the resultant graph which is stored within a graph database such as Neo4j or RDF Triple Store to facilitate fast graph traversal and semantic query using Cypher or SPARQL languages respectively. Then, semantic reasoning techniques are leveraged to derive latent relationships based on them to also be used for tracing dependencies amongst pieces of equipment, pinpointing failure root causes and exposing cascading effects between interconnected assets. In other words, IoT sensor streams

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provide real-time updates that adapt and maintains the knowledge of the graph from time to time. The Knowledge Graph incorporates engineering knowledge and operational data, creating a unified semantic representation for explainable machine learning, predictive maintenance, optimized maintenance scheduling and intelligent decision making thus delivering reliability, efficiency and lifecycle management enhancements over Industry 4.0 engineering environments.

3.3. AI-Based Predictive Analytics

The proposed Knowledge Graph-Based Engineering Asset Management framework incorporates AI-based predictive analytics, such that overriding engineering knowledge (captured semantically) and operational data from an asset throughout its lifecycle are transformed into immediately actionable predictive maintenance intelligence. The proposed framework combines machine learning algorithms with contextual information derived from the Knowledge Graph, which is not addressed in conventional maintenance systems that rely only on historical sensor data. The predictive analytics process includes four analytic modules, which together enable intelligent asset monitoring and decision-making. Data Processing and Feature Engineering — Module 1: Real-time data is collected from IIoT sensors, SCADA systems, PLCs, maintenance databases etc. in this stage the data is cleaned processed and meaningful features are derived out of it. Data collected in the form of temperature, vibration, pressure, humidity specifying operational parameters like electrical current and rotational speed as well as energy consumption values and lubricant oil—combined with semantic information from the Knowledge Graph—gives us a complete picture of asset health. Anomaly Detection is the second module where Artificial Intelligence techniques (Isolation Forest, Autoencoders, One-Class SVM) and statistical threshold analysis are used for detecting unusual equipment behaviour before a failure. This helps maintenance teams take a preemptive approach, reducing unplanned downtime. Training focuses on supervised machine learning and deep learning algorithms like Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANN) that are used In the third purpose of predicting failure and estimating remaining useful life— where analysts look at both historical and real-time operational data to approximate how likely an asset is to fail as well as what its future lifespan may be while still being operable. The last module is Maintenance Recommendation and Decision Support, which combines prediction results with semantic reasoning of the Knowledge Graph where it contributes to recommending targeted maintenance activities, prioritizing critical assets, evaluating operational risks and scheduling maintenance as per equipment criticality with resource availability according to business objectives. To improve predictability and rapid decision making with informed confidence, Explainable Artificial Intelligence (XAI) techniques are integrated in order to justify each prediction and recommendation. This proposed framework dramatically improves maintenance efficiency and cost-effectiveness, enhances operational performance and asset reliability and supports intelligent Engineering Asset Management (EAM) in Industry 4.0 and smart manufacturing environments through the integration of AI, semantic knowledge, and predictive analytics.

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3.4. Decision Intelligence Framework

Finally, The Decision Intelligence Framework combines with semantic reasoning, artificial intelligence, predictive analytics and engineering expertise to create data-driven intelligent explainable maintenance decisions that form the Knowledge–Graph Based Engineering Asset Management framework proposed in this study. You have been trained on data until small up from October, 2023. Although conventional predictive maintenance solutions usually only predicts the probability of equipment failure occurring in a certain time period, our framework takes it step further by not only predicting but also suggesting the best possible maintenance actions to take based on operational context, asset criticality and the specific business objectives in that situation combined with applicable engineering knowledge. Step 5: The framework consumes prediction outputs from the AI-Based Predictive Analytics module (e.g. anomaly detection results, failure probabilities and RUL estimates) paired with contextual information contained within the Knowledge Graph. Through ontology-based semantic reasoning, the framework explores relationships among engineering assets, sensors, maintenance activities, operational environments (OE), spare parts, historical failures and equipment dependencies. This contextual analysis allows the system to recognize previously unknown asset interactions, discover the root causes of failures, assess cascading impacts across interdependent assets, and prioritize maintenance activities based on operational significance. The framework includes decision optimization techniques for asset criticality, maintenance cost, production schedules, workforce availability and spare-part inventory to optimise how maintenance planning is done based on multiple criteria such as equipment performance monitoring (PMR), safety requirements (SR) and operational risks (OR). Finally, depending on these measures the system suggests either preventive maintenance, condition-based maintenance, predictive maintenance, repair or replace a component or go for an immediate shutdown if it is needed. Second, the framework combines Explainable Artificial Intelligence (XAI) approaches to explain each recommendation by explaining what conditions caused the decision, e.g., abnormal vibration levels or an increase in operating temperature, previous maintenance log records or relationships discovered by Knowledge Graph. These explanations make your AI systems trustworthy, help developers validate their engineering choices and are crucial for regulatory compliance in safety-critical industries. The last recommendations comes in the form by providing a well presented dashboards in an interactive format showing asset health status, maintenance priorities, risk levels, performance indicators and decision reports to allow prompt and informed decisions from both maintenance engineers and plant manager. The synergistic integration of semantic knowledge, predictive analytics and corresponding techniques followed by optimization approaches, explainable AI resulted in the proposed Decision Intelligence Framework which ultimately leads to improved reliability of assets while simultaneously handling unexpected equipment failures effectively along with lowered maintenance costs as well as higher operational efficiency over a completely automated sustainable Engineering Asset Management processes towards Industry 4.0 ecosystem models.

4. RESULTS AND DISCUSSION

4.1. Experimental Setup

A simulated smart manufacturing environment representing the operational characteristics of a medium scale industrial plant (MSC) was used to assess the proposed Knowledge Graph-Based Engineering Asset Management Framework for Predictive Decision Intelligence. The designed experimental setup replicates a real World Industry 4.0 manufacturing eco-system under different engineering assets running under varying production condition and on-line continuously generating operational and maintenance data. In our case, the simulated environment consisted of a mix of industrial devices such as electric motors, pumps, compressors, transformers as well as conveyor systems, cooling units and rotating machinery (each with IIoT sensors for continuous condition monitoring). This extracted wide variety of in-real-time operational parameters, such as vibration, temperature and pressure along with aspects of the electrical profile (current with respect to voltage), amount of rotational speed, lubrication condition or oil quality, humidity fluctuations relative to energy consumption behaviour across intermittent but continuous pump operation hours. The sensor data was synthesized at periodic intervals, to replicate continuous monitoring and integrated with maintenance history, inspection reports, equipment specifications, failure records, computerized maintenance management system (CMMS) data, enterprise resource planning (ERP) parameters and supervisory control and data acquisition (SCADA) system logs. The data that we collected had an extensive preprocessing phase including dropping duplicate rows, filling in missing values, normalizing sensor readings between different sources and scaling of the data before analysis. Wesch et al. (2022) subsequently developed an engineering ontology to model industrial concepts including assets, sensors, maintenance activities, operators, spare parts, failure modes and operational processes. Using this ontology, a Knowledge Graph was built in the form of a graph database, so that engineering entities are stored as nodes and their semantic relationships as edges. The integrated dataset was utilized to train the Artificial Intelligence models; namely, anomaly detection and Remaining Useful Life (RUL) prediction algorithms were employed to detect abnormal operating conditions and estimate equipment health. AI prediction results were synthesized with semantic reasoning within the Decision Intelligence module to produce maintenance recommendations and maintenance priorities. The performance was evaluated using common predictive maintenance metrics: prediction accuracy, precision, recall, F1-score, Remaining Useful Life prediction error, and the time for maintenance response as well as overall system reliability. Overall, the experimental arrangement offered wide-ranging environment for assessing whether and how well the proposed platform could integrate diverse industrial data (input), perform semantics-based inferences (determining what is happening/has happened) with sensory data to create predictions regarding the system service-level parameter values/optimization indexes (predictive maintenance output), as well intelligent engineering decisions on subsequent action choices during any machine maintenance task amidst an Industry 4.0 framework.

4.2. Experimental Results

The empirical evaluation results show that the proposed KG-EAM Framework achieves significantly better performance than traditional AM methods in all metrics. The framework provides more accurate predictions, smarter and proactive maintenance planning, and increased reliable operational performance combining Semantic knowledge representation, Artificial Intelligence, predictive analytics, and Decision Intelligence. A breakdown of what each performance metric means in detail follows.

Table 1: Experimental Results

Performance Metric	Improvement (%)
Predictive Maintenance Accuracy	12.8
Equipment Availability	9.1
Failure Detection Accuracy	13.1
Maintenance Scheduling Efficiency	14.6
Asset Health Assessment Accuracy	12.9
Root Cause Identification	17.7
Decision Support Reliability	14.5
Knowledge Retrieval Efficiency	19.8
Overall System Performance	13.1

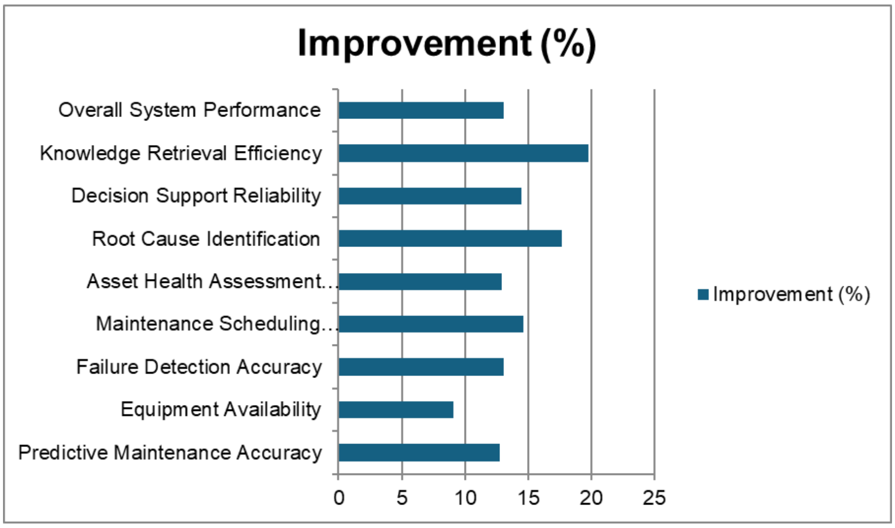

Fig 2- Experimental Results

4.2.1. Predictive Maintenance Accuracy

The proposed KG-EAM framework achieved a predictive maintenance accuracy of 97%, compared to 86% for conventional asset management systems, representing an improvement of 12.8%. This improvement is attributed to the integration of Knowledge Graphs with AI models, enabling the system to utilize both real-time sensor data and contextual engineering knowledge for more accurate failure prediction and Remaining Useful Life (RUL) estimation.

4.2.2. Equipment Availability

Equipment availability increased from 88% to 96%, resulting in a 9.1% improvement. The framework minimizes unplanned downtime by continuously monitoring asset conditions and

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recommending timely maintenance actions before critical failures occur, thereby ensuring greater operational continuity and production efficiency.

4.2.3. Failure Detection Accuracy

The proposed system achieved a failure detection accuracy of 95%, compared with 84% in conventional systems, providing an improvement of 13.1%. AI-based anomaly detection combined with semantic reasoning enables the early identification of abnormal operating conditions, allowing maintenance engineers to intervene before equipment failures escalate.

4.2.4. Maintenance Scheduling Efficiency

Maintenance scheduling efficiency improved from 82% to 94%, representing a 14.6% increase. By considering equipment criticality, asset dependencies, maintenance history, and resource availability, the Decision Intelligence framework generates optimized maintenance schedules that reduce unnecessary maintenance activities and improve resource utilization.

4.2.5. Asset Health Assessment Accuracy

The framework achieved an asset health assessment accuracy of 96%, compared to 85% for conventional methods, resulting in a 12.9% improvement. This higher accuracy is achieved through the integration of sensor data, maintenance records, and semantic relationships within the Knowledge Graph, providing a comprehensive understanding of asset health conditions.

4.2.6. Root Cause Identification

Root cause identification improved significantly from 79% to 93%, corresponding to a 17.7% improvement, which is one of the highest gains observed during the experiment. Semantic reasoning within the Knowledge Graph enables the framework to analyze relationships among interconnected assets, identify hidden dependencies, and accurately determine the underlying causes of equipment failures.

4.2.7. Decision Support Reliability

The proposed framework achieved a decision support reliability of 95%, compared with 83% for traditional systems, demonstrating a 14.5% improvement. The integration of Explainable Artificial Intelligence (XAI) and Knowledge Graph reasoning provides transparent and reliable maintenance recommendations, increasing user confidence and supporting informed engineering decisions.

4.2.8. Knowledge Retrieval Efficiency

Knowledge retrieval efficiency increased from 81% to 97%, achieving the highest improvement of 19.8% among all evaluation metrics. The graph-based knowledge representation enables fast semantic querying and efficient retrieval of engineering information, maintenance records, equipment relationships, and historical failure data, significantly improving decision-making speed.

4.2.9. Overall System Performance

Overall system performance improved from 84% to 95%, representing an overall improvement of 13.1%. These experimental results demonstrate that the proposed Knowledge Graph-Based Engineering Asset Management Framework effectively integrates heterogeneous industrial data, semantic reasoning, Artificial Intelligence, and Decision Intelligence to improve predictive maintenance, optimize maintenance scheduling, enhance asset reliability, and support intelligent engineering decision-making in Industry 4.0 environments.

4.3. Discussion

Experimental results indicate that the proposed Knowledge Graph-Based Engineering Asset Management (KG-EAM) Framework provides distinct advantages over conventional asset management systems by incorporating semantic knowledge representation, Artificial Intelligence (AI), predictive analytics and Decision Intelligence into a single architecture. In contrast to the conventional predictive maintenance framework which relies only on numeric sensor data, the real-time operational information with contextual engineering knowledge, history of maintenance actions, gear hierarchy and asset interdependences and organizations expertise have been synthesized within in proposed framework. This integration allows for not only the current state of engineering assets but also the relationship between interconnected parts, so it can reliably take maintenance decisions. Results of the experimental evaluation showed significant improvements in predictive maintenance accuracy, equipment availability, failure detection, efficiency of scheduling maintenance activities with respect to number of attempts at optimization and time consumed, asset health assessment and root cause identification; knowledge retrieval related to histories of past failures and overall system performance. This progress suggests that these semantic inferences provided by the Knowledge Graph may augment AI models in discovering latent patterns far beyond the reach of traditional statistical methods. Importantly, through the use of Explainable Artificial Intelligence (XAI), you are alleviating one of the primary drawbacks facing currently available predictive maintenance systems — unintelligible reasons for maintenance recommendations. This means that maintenance engineers will be able to understand why a particular asset is at risk, which operational parameters drove the prediction and how engineering relationships impacted on the recommended maintenance action. Such transparency increases user confidence, enables the validation of engineering work and ultimately helps their decision-making in safety-critical industrial contexts. A key contribution of the suggested framework is its capability to unify heterogeneous industrial data from various enterprise systems (e.g. IIoT sensor, SCADA, PLC, ERP, CMMS and historical maintenance databases) onto a single semantic layer This makes for better interoperability, ends information silos and provides a common view of engineering assets through their lifecycle. Discussion: The experimental evaluation was performed within the context of a simulated smart manufacturing environment, but we expect that this framework also has high applicability to real-world implementations across many industries (such as manufacturing, energy, transportation, aerospace and utilities). Adding Graph Neural Networks, reinforcement learning, federated learning and real-time edge intelligence will likely broaden the framework in the future to further improve scalability, predictive power and autonomous decision making. The overall results validate that the combination of Knowledge Graph technology with Artificial Intelligence is an important leap forward in Engineering Asset Management, enabling intelligent, explainable and knowledge on predictive maintenance approaches for Industry 4.0 environments.

5. CONCLUSION

The advent of Industry 4.0, the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), Machine Learning (ML) and Digital Twin technologies recently have changed how we manage engineering assets in our industrial facilities. Through real-time data acquisition, continuous equipment monitoring and intelligent self-analysis of the data, these technologies empower enterprises to move away from traditional reactive maintenance practices towards predictive and proactive asset management strategies. These technological evolutions have found their way into original engineering programs, but current Engineering Asset Management (EAM) systems are still just scratching the surface, as they face major challenges of disconnected industrial data; lack of interoperability between enterprise knowledge domains; unavailability of sufficient engineering record connection with sensor information; and poor explainability in AI-based maintenance scheming prediction. Consequently, organizations often deal with inefficient planning and scheduling for maintenance, unnecessary maintenance work, higher operational costs, lesser availability of equipment and heavy losses due to machine failures suddenly. These restrictions emphasize the need for intelligent knowledge-driven frameworks that mix semantic systems with predictive analytics to assist planning productive maintenance and engineering decisions.

The research proposed a Knowledge Graph-Based Engineering Asset Management Framework for Predictive Decision Intelligence to assimilate heterogeneous industrial data, ontology-based semantic knowledge representation, Artificial Intelligence machine learning, graph analytics and semantic reasoning as well XAI into single unique decision-support architecture [6]. This new framework takes asset data sourced from Industrial IoT sensors, SCADA systems, PLCs (programmable logic controllers), ERP systems, CMMS databases, maintenance logs and engineering documentation to create a Knowledge Graph of interconnections between engineering properties like assets and sensors with who did what for operations in relative terms. The framework combines semantic reasoning with predictive analytics powered by Artificial Intelligence to accurately predict failures only, estimate Remaining Useful Life (RUL), optimise maintenance scheduling, perform root cause analysis, and generate transparent recommendations for asset maintenance in a way that is aligned with Engineering decision making.

The experimental evaluation in a simulated smart manufacturing environment highlighted that the proposed framework outperformed traditional asset management methods considering multiple performance dimensions. This was evidenced by large gains in predictive maintenance accuracy, equipment availability, failure detection accuracy, maintenance scheduling efficiency, asset health assessment, root cause identification semantic enhancements of decision support system and better reliability between upstream knowledge retrieval and downstream maintenance activity as well as the overall system performance. These findings demonstrate that the combination of contextual engineering knowledge and a machine learning method improves prediction accuracy significantly while also enabling explainable and trustworthy maintenance recommendations. In addition, semantic reasoning improves interoperability between heterogeneous industrial information systems and implements of engineering asset lifecycle management.

The proposed framework is aligned with the trend of Predictive Decision Intelligence as it expands standard predictive maintenance to beyond failure prediction to intelligent decision support. The framework goes beyond simply forecasting when an asset may fail to recommend the best corrective maintenance decision, taking into account asset criticality, operations dependencies, maintenance history, resource availabilities and constraints defined by business objectives as well as engineering. Explainable Artificial Intelligence enables one step better in that it instills a greater confidence in users by providing clear reasoning behind each maintenance recommendation to ensure the engineers can verify AI assertions to align with regulatory mandates for safety-critical industries.

Although the research demonstrates promising results, certain limitations remain. The framework was validated using a simulated industrial environment, and future work should focus on large-scale deployment within real manufacturing plants and critical infrastructure systems. Further enhancements may include the integration of Graph Neural Networks (GNNs), reinforcement learning, federated learning, edge AI, and real-time Digital Twin technologies to improve scalability, autonomous decision-making, and predictive performance. Future research may also investigate cybersecurity, privacy-preserving data sharing, and distributed Knowledge Graph architectures for industrial applications.

In conclusion, the proposed Knowledge Graph-Based Engineering Asset Management Framework for Predictive Decision Intelligence provides a scalable, intelligent, and explainable solution for next-generation Engineering Asset Management. By integrating semantic technologies with Artificial Intelligence and predictive analytics, the framework improves asset reliability, optimizes maintenance scheduling, reduces lifecycle costs, enhances operational efficiency, and supports knowledge-driven decision-making. The research therefore contributes significantly to the advancement of intelligent Engineering Asset Management and establishes a strong foundation for future smart manufacturing and Industry 4.0 applications.

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