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A COMPREHENSIVE FRAMEWORK FOR IOT-DRIVEN PREDICTIVE MAINTENANCE: LEVERAGING AI AND EDGE COMPUTING FOR ENHANCED EQUIPMENT RELIABILITY

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The convergence of the Internet of Things (IoT), Artificial Intelligence (AI), and Edge Computing has advanced predictive maintenance (PdM). The main two benefits of this integration are to enable real-time monitoring and proactive equipment management across industries. This paper presents a comprehensive framework for IoT-driven PdM, using AI-powered analytics and Edge Computing to enhance equipment reliability, reduce operational downtime, and optimize maintenance costs. Based on a comprehensive study of the previous work, we proposed a framework that integrates six key steps to use IoT, AI, and edge computing in preventive maintenance. The steps are IoT sensors and devices for data acquisition, Edge and cloud computing for efficient processing, AI-driven predictive analytics for fault detection, automated decision-making and alert systems, remote monitoring and automated control, and continuous learning for system optimization. The paper discussed the advantages of the proposed approach, such as reduced costs, and improved instrument utilization. However, challenges such as cybersecurity concerns, integration complexities, and computational resource requirements are also presented. A case study involving the implementation of an IoT-based PdM system for water tank trucks in a Civil Defense Directorate demonstrates the effectiveness of the proposed framework in real-world applications. Results show that real-time data analytics and predictive modeling improve problem detection accuracy, enabling prompt intervention and minimizing expensive mechanical breakdowns. This study proposes a systematic approach to AI-enabled PdM adoption, enabling scalable and cost-effective industrial maintenance strategy optimization.

Keywords: Internet of Thing, predictive maintenance, PdM, machine learning

HIGHLIGHTS

- A six-step framework integrating IoT, AI, and Edge Computing is proposed to optimize predictive maintenance across industrial sectors.
- A real-world case study on water tank trucks demonstrates improved fault detection accuracy and reduced downtime through AI-powered PdM.
- The proposed system enables 30–40% cost savings and up to 40% enhancement in asset availability by enabling real-time diagnostics and proactive maintenance actions.

1 Introduction

The Internet of Things (IoT) transformed industrial operations, particularly in the realm of maintenance practices. The traditional reactive and preventive maintenance strategies are associated with unnecessary operating costs and unplanned downtime. Predictive maintenance (PdM), on the other hand, applies real-time data capture with advanced Artificial Intelligence (AI) and Edge Computing to anticipate possible failures and optimize maintenance schedules for asset longevity and operation performance [1,2]. In contrast, condition-based maintenance (CBM) uses real-time monitoring of equipment parameters—such as temperature, vibration, and pressure—to detect signs of deterioration and schedule interventions only when necessary [3]. While CBM reacts to current equipment states, PdM extends this by forecasting future failures using predictive analytics.

PdM relies on connected IoT sensors built into factory machinery, permitting real-time monitoring of critical parameters such as temperature, pressure, vibration, and power usage. Sensor data is processed using machine learning (ML) algorithms that detect anomalies and predict component failure before it actually happens. This data-driven predictive layer is what differentiates PdM from both preventive and condition-based approaches. The convergence of IoT and AI towards PdM has been widely accepted worldwide to reduce equipment failure rates by up to 50% and maintenance costs by 40% [4-5]. Good-quality data is at the center of the excellence of AI-enabled predictive maintenance systems. Redundant sensors of critical parameters to enable cross-validation and fault location are employed in most current PdM implementations to prevent the dangers of noisy, missing, or corrupted sensor data. Data validation methods such as outlier detection, smoothing filters, and real-time integrity checks are employed to identify and correct anomalies prior to feeding data into machine learning algorithms. Edge computing platforms typically conduct early data preprocessing on-site, not only reducing latency but also ensuring that only validated data is transmitted for further processing. These processes significantly enhance the robustness and reliability of the PdM system, particularly in dynamic industrial environments.

Recent case studies have demonstrated the actual benefits of PdM over traditional preventive maintenance (PM) methods in industrial usage. Cheikh et al. [6], for example, employed Monte Carlo simulations under varying maintenance regimes and concluded that PdM reduced downtime and maintenance costs significantly with improved overall system reliability versus PM. Specifically, the study highlighted that PdM helped achieve 30–40% reduction in unplanned downtime and improved mean time between failures (MTBF) due to the ability to identify faults earlier and schedule optimized. Such comparative standards bear witness to the operational value of PdM, particularly in cases where equipment availability is mission-critical and reactive maintenance is costly.

Edge Computing is a crucial element of the PdM model by providing real-time processing at the point of origin, reducing latency, and optimizing bandwidth use. In contrast to traditional cloud-based solutions, which demand high latency in data transfer, Edge Computing ensures real-time response time and is therefore a favorite in the industry among mission-critical industrial applications. Experiments have shown that PdM enabled by Edge-AI significantly enhances operational uptime, reduces machine failures, and improves industrial process efficiency [7].

Furthermore, the integration of AI into PdM enables more precise failure prediction and flexibility through learning mechanisms. Advanced AI models like convolutional neural networks (CNNs) and Long Short-Term Memory (LSTM) networks continuously revise their prediction functions against history and real-time data, improving the accuracy of fault detection over time [8]. Studies have also shown that Reinforcement Learning (RL) can be used to optimize maintenance activity scheduling, dynamically changing maintenance schedules to achieve minimum disruption and maximum cost-effectiveness [9].

Although it has its advantages, IoT-based PdM is faced with various challenges such as data security problems, integration with legacy industrial systems, and the need for high computing capacity. Edge Computing offers a solution by processing data locally and minimizing dependency on cloud servers, improving cybersecurity and lowering infrastructure expenses [10]. Another critical challenge is the dependability of IoT sensors in hostile industrial environments. Sensors may experience calibration drift, physical degradation, or environmental noise over time when exposed to extreme temperatures, humidity, vibration, or chemicals. It will result in inaccurate or noisy data and then compromise the quality of predictive models and can generate false alarms or undetected failures. To mitigate these risks, regular sensor calibration, redundancy in sensor deployment, and the use of signal filtering and self-diagnostic algorithms are recommended. Maintenance planning must also account for sensor reliability as a variable, such that predictive outputs are cross-checked with physical inspection or secondary data streams where feasible.

This paper presents an end-to-end IoT-based PdM solution with a focus on AI and Edge Computing integration towards optimizing equipment reliability. Based on a review of current state-of-the-art solutions and industry best practices, this study aims to provide a systematic methodology for the implementation of AI-based PdM systems across industries. Numerous industry reports and case studies indicate that the implementation of PdM can achieve a substantial return on investment (ROI) within 12 to 24 months, depending on the complexity and scope of implementation. For instance, Tau at al. [11] reported that firms that have implemented PdM programs averaged operational cost savings of up to 30%, along with 25–40% enhancement in asset availability by reducing unplanned downtime. These economic benefits accrue from enhanced failure prediction, optimization of maintenance schedules, and less spare part consumption. Further, the investments in PdM systems are front-loaded, with long-term benefits like extended equipment life and better safety, making PdM economically attractive to industries that have thin operational margins.

A successful transition from traditional maintenance practices to predictive maintenance requires a systematic roadmap that harmonizes technological advancements, upskilling of employees, and phased deployment. Companies are advised to start with pilot projects on high-priority equipment using IoT sensors to gain near-term return on investment and build internal adoption. Developing data acquisition infrastructure and integrating it with AI models for anomaly detection forms the next step, while gradually phasing out reactive and time-based maintenance procedures. Moreover, fostering interdepartmental collaboration—especially among IT, operations, and maintenance units—is critical for data governance and implementation success. Studies suggest that combining real-time condition monitoring with explainable AI not only reduces downtime but also builds confidence among technicians previously accustomed to rule-based systems [12-13].

The integration of PdM fundamentally changes the role of the maintenance teams, from conventional reactive fix to data-based decision-making. The maintenance personnel now must interpret sensor readings, understand machine learning predictions, and interact with AI-driven dashboards. To meet this challenge, upgrading accordingly is essential. Organizations tend to respond with formal training programs for the operation of IoT devices, data analysis, and the basics of AI, internally or through partnership with technical schools. It has been proven that companies adopting PdM successfully are more likely to adopt hybrid modes of training—complementing experiential learning with online training programs-to bridge the skill gap and leverage workers' trust in new technologies [14]. This shift not only boosts efficiency in the workforce but also boosts employee engagement through broadening their technological capabilities.

2 Materials and methods

In this section, we present the materials and methods by detailing the proposed framework to use IoT in preventive maintenance. The framework outlines each methodological step necessary for integrating IoT, AI, and edge computing into predictive maintenance strategies. The integration between the IoT and the use of AI in industrial operations has transformed maintenance strategies, making PdM a reality. PdM utilizes IoT sensors, edge computing, cloud processing, AI-powered predictive analytics, automated maintenance, and continuous learning to establish a self-sustaining system that ensures equipment reliability. Each step in the PdM framework plays a crucial role in ensuring a smooth transition from data collection to decision-making and execution. The authors conducted a thorough review and analysis of references [15-51] to establish a comprehensive methodology or a general framework for integrating IoT into PdM. From this analysis, a structured approach to IoT-based PdM was developed and is summarized in the following model. This model consists of six sequential execution steps, as illustrated in Fig. 1.

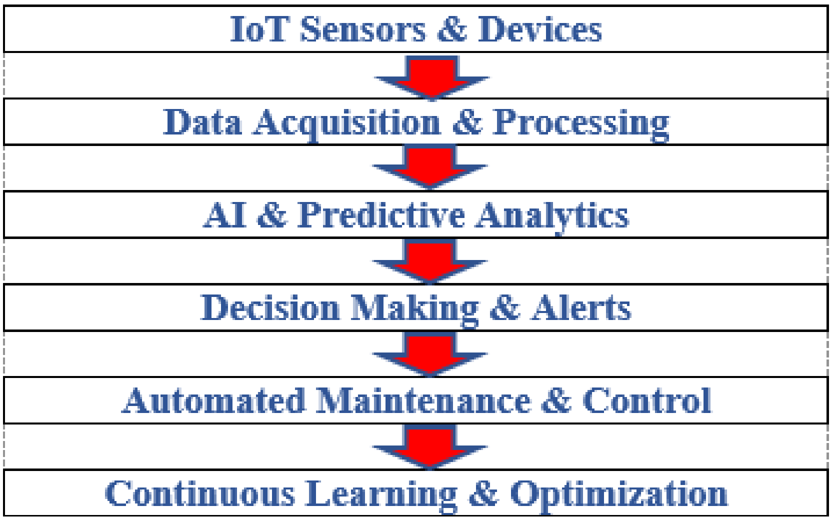

Fig. 1. Framework for Utilizing IoT in PdM

2.1 First step. IoT Devices and sensors for data collecting for PdM

PdM relies on data collection utilizing sensors to monitor equipment/systems performance. Common in conventional maintenance systems, reactive or planned maintenance may lead to unexpected issues, increased operating expenses, and unscheduled downtime. Conversely, IoT-driven PdM allows businesses to constantly gather and assess sensor data, hence enabling proactive asset management. Modern maintenance strategies therefore heavily rely on IoT sensors as this shift increases operating efficiency, lowers failures, and optimizes maintenance schedules [15].

Data collection powered by IoT begins with the installation of advanced sensors on critical machinery and infrastructure. These sensors detect key factors like temperature, pressure, vibration, humidity, electrical consumption, and infrared signals to identify performance variances. While vibration sensors—for example—are extensively used in rotating machinery to identify misalignments or bearing faults, temperature sensors help monitor overheating concerns in mechanical and electrical systems.

Once acquired, sensor data is delivered via wireless communication protocols such Message Queuing Telemetry Transport (MQTT), Zigbee, LoRaWAN, and NB-IoT therefore ensuring real-time data delivery to cloud-based or edge-computing platforms. Edge computing is very necessary for pre-processing and local level filtering of raw sensor data, hence boosting response times and reducing network congestion. Whereas, cloud computing offers large amounts of data storage and advanced AI-based analytics for predictive modelling [16]. These systems recognize patterns and abnormalities through digital twin simulations and ML algorithms and hence predict trouble before it begins. The technology automatically provides alarms and automates repairs to prevent costly breakdowns whenever an impending issue is realized.

2.1.1 Step's Benefits

There are several benefits of IoT sensors incorporated in PdM that help improve asset performance and reliability. Some of the key benefits are less downtime and failure avoidance since regular monitoring enables maintenance staff to identify issues before they become worse. Studies have established IoT-based PdM has the potential to reduce overall maintenance costs by 40% and reduce equipment failure by 30–50% [17].

PdM through IoT improves energy efficiency since real-time monitoring witnesses' industrial machinery working at optimum levels of performance, hence conserving energy wasted unnecessarily. In industrial large-scale establishments, where power-guzzling machinery which operates continuously like motors and turbines [18], IoT sensors help unveil inefficiencies and maximizing the utilization of power. Moreover, remote monitoring software enables businesses to track multiple sites through a single dashboard, thereby reducing the need for regular on-site visits and boosting employee productivity.

2.1.2 Challenges and Difficulties

Adoption of IoT-based PdM raises certain problems that must be addressed even with its advantages if efficient deployment relies on it. One of the primary concerns is data overload as industrial IoT (IIoT) devices generate massive volumes of real-time data demanding efficient storage, processing, and management. Strong cloud infrastructure and big data analytics are required if we are to deal with the data effectively [19].

IoT sensors and connected devices exposed to ransomware attacks, data breaches, and hacking makes cybersecurity issues very crucial as well. PdM is powered by sensitive equipment data, so secure communication protocols and blockchain-based authentication need to be used in order not to allow unauthorized access. Moreover, connectivity issues at remote industrial sites might impact real-time data transmission, thereby impacting PdM activities maybe delays. Finally, small and medium businesses (SMEs) which are searching for PdM platforms [15] observe their funding being impeded by the initial costs of rolling out IoT sensors and AI analytics platforms.

2.1.3 Examples of This Step's Implementation

Several industries have successfully implemented IoT-based PdM to enhance operational productivity and reduce equipment failure. In the manufacturing sector, companies such as Siemens and General Electric (GE) employ vibration sensors and temperature sensors to monitor production line equipment with the objective of identifying mechanical faults at early stages. Research conducted by Candón Fernández et al. [20] has reported that IoT-based PdM in manufacturing has raised production uptime by over 20%.

In the motor vehicle sector, fleet operators have used predictive telemetry systems to monitor vehicle performance and manage maintenance schedules. Lysenko and Лисенко [21] put across that IoT-enabled fleet monitoring solutions have lowered vehicle downtimes by 35% and reduced maintenance costs. Likewise, in smart cities, IoT sensors have been embedded into bridges, water pipes, and power grids to avoid structural collapse and maximize urban infrastructure maintenance [22]. In healthcare, AIoT (AI + IoT) is being used to monitor and maintain vital medical equipment, such as MRI scanners and ventilators. Real-time IoT monitoring hospitals have experienced improved equipment lifespan and patient care efficiency [23].

2.1.4 Step2. Data Acquisition & Processing (Edge & Cloud Computing) in PdM

Currently, modern-day organizations greatly depend on PdM, which allows them to forecast the equipment failure before it occurs, thereby reducing costs of maintenance and downtime. The practice greatly depends on edge and cloud computing technologies and data acquisition and processing. Edge computing allows near-sourcing processing of real-time data, hence reducing latency and allowing instant decision-making. Cloud computing allows companies to efficiently analyze large volumes of data using scalability and enhanced predictive analysis. Merging two technologies allows companies to advance their PdM models, thereby providing smooth data flow from IoT sensors to actionable insights [24].

From data acquisition from sensors to real-time analysis and cloud-based ML models, PdM encompasses various phases in data collection and processing. First gathering real-time data on critical parameters like temperature, vibration, pressure, and power consumption, IoT sensors deployed in industrial equipment then consolidate Edge computing devices first level of processing continuously feed data from such sensors.

Edge computing plays a very important role when it comes to filtering and processing data at the point of origin. Edge devices instead of pushing large amounts of raw data to the cloud, they monitor sensor data in real-time and recognize early indications of equipment malfunction. In the event of a potential weakness, immediate alerts may be sent to maintenance personnel so they can take action before disasters occur. This reduces decision-making latency that burdens network bandwidth [25].

Sophisticated cloud-based AI-powered analytics allow companies to compare real-time data and historical trends simultaneously for better failure prediction. Information then forwarded to cloud computing architectures, which hold and manage through ML, is stored and held when it needs a more intense examination. Large industrial use heavily relies on cloud computing because data from vast locations can be classified and viewed at the same time.

2.1.5 Step's Benefits

Inserting edge and cloud computing in PdM has a variety of advantages that boost industrial efficiency and reliability. The primary gain is the ability to identify anomalies in real-time. Edge computing is useful in helping firms detect machine malfunctions in a timely way and consequently avert catastrophic machine failure. It is mostly important in high-risk sectors such as manufacturing, health care, and transportation because a fault in detecting could cause financial loss and risk [26].

The two other significant advantages are cost-saving and bandwidth utilization efficiency. Edge computing conserves cloud storage and processing costs over sending enormous data to cloud servers because it allows only important and pertinent data to be sent. This is quite helpful in far-flung industrial locations where the network bandwidth might be constrained. Moreover, the scalability and flexibility of cloud computing enable businesses to manage many industrial plants from a centralised platform, thereby offering perfect data access and analysis [27]. Edge devices also promote cybersecurity and data privacy. Sensitive data is processed locally at the edge and is not sent out to third-party cloud servers, thereby reducing the cyber threat. Nonetheless, when cloud computing is applied for deterrence of unauthorized access and leakage of data, strong encryption techniques and AI-based security capabilities are just inevitable

2.1.6 Challenges and Difficulties

Although edge and cloud computing have numerous benefits in PdM, their integration is not without issues. One such significant issue is the significant initial investment in the usage of IoT sensors, edge devices, and cloud analytics tools. SMEs would risk having a hard time transitioning over from traditional schedules in maintenance on the basis of financial restrictions.

One of the greatest issues would be problems with information protection. Cloud infrastructure could enable ransomware threats, data breaches, and attacks to gain access within them. PdM involves the sharing of proprietary industrial information, and companies would need to have high-grade protection features such as end-to-end encryption and blockchain-driven validation in order to safeguard their resources [28].

Another issue is the connectivity and network constraint. While PdM relies on a consistent stream of information, in remote factory conditions, network disconnections would compromise real-time monitoring. While there is research on how to leverage private business networks and 5G networks as a solution, having a consistent connection remains challenging, especially in locations with inferior infrastructure [25].

The complexity in integrating the information is ultimately a major hurdle. Those factory floors with aging infrastructure and diverse ecosystems are not capable of integrating edge computing, cloud infrastructure, and analytics based on AI in a seamless PdM solution. They are required to provision employees with standardized information formats, train them, and harness API-driven solutions [24] in a bid to obtain seamless communication among multiple maintenance systems

2.1.7 Examples of This Step's Implementation

Most industries have leveraged edge and cloud computing in an effective manner to drive PdM. Firms like Siemens and General Electric (GE) have integrated edge-based AI analytics into production. By doing this, they have reduced equipment failures by 25% and improved operational uptime [24]. With real-time processing of edge sensor data, these companies have optimized machine performance and minimized unplanned downtime.

PdM is applied in autonomous vehicle and fleet technology in the automotive sector. Edge computing and AI algorithms are used to monitor vehicle performance and battery health, enabling remote diagnostics and predictive fault detection. PdM in vehicle fleets has seemingly increased vehicle lifespan and decreased maintenance costs by thirty percent.

PdM based on edge and cloud computing in the healthcare field has brought corresponding innovations in medical device reliability. Hospitals utilizing AI-driven PdM have observed a 40% increase in system availability, ensuring that critical medical equipment such as MRI scanners and ventilators remain operational at all times [28].

2.2 Step 3. AI & Predictive Analytics in PdM: Anomaly Detection & ML Models

AI-driven predictive analytics revolutionize maintenance by enabling real-time monitoring, anomaly detection, and failure prediction, reducing unexpected breakdowns and costs. But proactive, Condition-Based Maintenance (CBM) made possible by AI alters the approach, therefore improving asset reliability and operating efficiency. Large dataset analysis, anomaly detecting, and pre-start failure prediction all rely heavily on ML models; therefore, ensuring best equipment performance and reducing downtime [24].
Data collection and preprocessing begin with IoT sensors placed on industrial equipment monitoring temperature, vibration, pressure, and electrical signals. Data quality and efficiency are improved by edge computing cleaning sensor data to eliminate duplicates and extraneous data [29].

Anomalies are detected using AI. Random Forest, SVM, and ANNs are supervised learning models that detect whether equipment is working well or failing early. Without labeled failure data, K-Means clustering and Autoencoders find operational deviations. Advanced methods include LSTM networks and Deep Learning models like CNNs analyze time-series sensor data to discover minute irregularities that may indicate problems.

Following anomalies is when predictive analytics and failure forecasts take front stage. AI systems employ historical and real-time sensor data to estimate the remaining useful life (RUL) of machine components. Predictive algorithms like Recurrent Neural Networks (RNNs) and Gradient Boosting Machines (GBMs) help maintenance teams to plan repairs ahead rather than waiting for a breakdown by means of exact estimates on when a component is likely to fail [30].

Finally, AI-driven maintenance optimization and decision-making ensure that discovered anomalies sendoff real-time alerts and automated repair orders. Digital twin technology—which creates virtual representations of physical assets-helps to maximize maintenance procedures and hence lower unnecessary intervention by replicating real-world performance and failure scenarios [31]. AI models also continuously learn and improve by methods of reinforcement learning (RL), wherein maintenance strategies are dynamically adjusted based on fresh data inputs [32].

AI based PdM introduces far greater computation than traditional CBM methods. While CBM relies on threshold-tracking monitoring and rule-based reasoning, PdM incorporates continuous data ingestion from high-frequency IoT sensors and then performs complex processing with machine learning (ML) or deep learning models. These include real-time anomaly detection, model retraining and training, and multivariate trend analysis-all of which involve high memory, computation, and most likely GPU acceleration. Deep neural networks like LSTM and CNN architectures for time-series forecasting, for instance, are computationally heavy and most likely require edge-cloud hybrid deployment to satisfy the constraints of latency and bandwidth. But this enhanced demand is counterbalanced by the higher accuracy and earlier detection of failure that PdM can provide, and that results in fewer false alarms and more optimally scheduled maintenance.

2.2.1 Step's Benefits

PdM provides several advantages with AI-powered analytics. Some of the main benefits include reduced downtime and increased reliability of assets. Detection of abnormalities at an early stage enables AI-powered maintenance processes enhance equipment life and minimize unplanned downtime by as much as 50%.

Even more value comes from lower maintenance expenses. Conventional maintenance routines tend to involve unnecessary servicing, thereby wasting resources. Predictive analytics using AI streamlines maintenance schedules, thereby eliminating unnecessary interventions and achieving up to 40% savings on operational expenses. Moreover, AI models provide real-time fault detection and reaction, thus assuring that any problems are corrected before they become significant breakdowns and so improving the general system dependability and safety.

Across industry, energy, transportation, and healthcare, PdM motivated by AI is also flexible and scalable. AI models can process enormous amounts of sensor data from many industrial sites, therefore offering centralized monitoring and prediction insights for several operating scenarios [33].

2.2.2 Challenges and Difficulties

Use of AI-based PdM has challenges even though it has advantages. One of the significant challenges is high data dependency and model complexity. AI models' accurate predictions rely on vast, quality data. Industries without historical failure data, however, might not be able to create efficient AI models [30].

Cyber threats and data privacy are yet another intimidating factor. PdM AI-based systems rely on cloud computing, hence are susceptible to cyber-attacks like data breaches, sensor spoofing, and unauthorized access. Industries must utilize strong encryption, threat detection based on AI, and blockchain-based security solutions to protect confidential maintenance data.

Moreover, particularly for small and medium-sized businesses (SMEs), high computational capacity and infrastructure costs pose financial challenges. PdM with AI relies on strong computer resources, cloud infrastructure, and AI-specialized expertise [32] and is costly to deploy and maintain.

Most companies hold back on using AI-powered maintenance solutions due to the "black-box" nature of deep learning models, where the decision-making processes are not easily accessible. The resolution of this challenge entails integrating explainable AI (XAI) methods, which provide insight into how AI models predict outcomes [33].

2.2.3 Examples of This Step's Implementation

AI-driven industrial PdM has been employed by companies like Siemens and GE to keep equipment in plants in operation, hence reducing failures by thirty% while increasing the efficiency of operations [34]. Through the detection of defects in renewable energy plants and power grids by helping the energy sector, anomaly detection using AI has provided more efficient energy distribution and reduction of costly outages [30]. Particularly in the case of hospital equipment monitoring, AI-driven PdM has also benefited the healthcare industry. AI-driven PdM for MRI machines, ventilators, and infusion pumps has helped minimize equipment downtime thus ensuring uninterrupted healthcare provision and patient safety [32]. ML-based anomaly detection of engine aircraft has minimized flight failures and optimized flight maintenance schedules, thus improving passenger safety and operational reliability [31].

2.3 Step 4. Decision Making & Alerts in PdM: Fault Detection and Maintenance Planning

PdM has evolved as a transformational tool for raising asset dependability and reducing downtime by using real-time monitoring, predictive analytics, and automated decision-making systems. This approach depends much on alert generation and decision-making as they ensure early problem discovery, proactive maintenance scheduling, and maximum asset performance. Among traditional maintenance methods, reactive and preventive maintenance might lead to unexpected failures or unnecessary repairs. AI-powered PdM instead integrates ML models, IoT sensor data, and advanced analytics to provide real-time fault identification and intelligent maintenance planning, therefore guaranteeing both operational efficiency and cost savings.

Using decision-making and alert systems in PdM follows a systematic approach comprising real-time data collection, anomaly detection, automated alerts, and optimum maintenance schedule.

First in this approach is real-time data collection and defect spotting. Industrial IoT sensors constantly monitor critical equipment variables like temperature, vibration, pressure, and electrical current. Processing these data pieces are AI-based anomaly detection models-which uncover early symptoms of failure by comparing real-time sensor readings against prior operational data. Detecting deviations that lead to probable flaws largely rely on ML techniques such random forests, deep learning networks, and support vector machines (SVMs) Sui et al. [32].

The device instantly generates an alert informing maintenance staff about a found anomaly. The degree of the discovered flaw defines the priority of these alerts, thereby ensuring that non-critical issues are scheduled for regular maintenance while serious failures are handled immediately. Usually sent via email alerts, smartphone dashboards, SMS, or direct connection with industrial control systems, notifications allow maintenance workers [35] to respond quickly.

Once alerts are raised, PdM scheduling and decision-making take center stage. AI models allow businesses to strategically develop interventions by calculating the remaining useful life (RUL) of machine components. By use of operational logs, maintenance histories, and failure trends, decision support systems (DSS) identify the most reasonably priced maintenance schedule. This ensures that important maintenance tasks are finished before equipment issues start, therefore avoiding needless service [34].

At finally, lifetime learning and adaptive optimization ensure that PdM systems improve with time. AI models increase their fault detection accuracy and maintenance planning recommendations by continuously reviewing new sensor data. Real-time operational data allows reinforcement learning techniques to dynamically alter their decision-making strategies [36]. PdM systems may therefore be used.

2.3.1 Step's Benefits

For many different industries, PdM provides several significant benefits thanks to its mix of real-time alert systems and AI-powered decision-making. Two most major advantages are early fault identification and fewer downtime. PdM is shown to cut unplanned downtime by up to 50%, therefore ensuring that equipment remains operational and productive. By seeing and resolving problems before they become major failures, businesses may save valuable production time and costly repairs [37].

Two other major benefits are still reduced costs and better maintenance scheduling. Conventional methods of maintenance either over-maintain equipment (source of superfluous costs) or under-maintain it (cause of unexpected failures). AI-driven PdM reduces these inefficiencies and resulting in up to 35% savings in maintenance expenditures while extending asset lifespan by guaranteeing that maintenance activities are conducted only when needed [38].

Moreover, real-time alerts, AI-powered decision-making tools, and avoidance of hazardous equipment failures enhance worker safety. In industries such nuclear power, chemical processing, and aviation in avoiding catastrophic failures and maintaining regulatory compliance, AI-driven PdM is very vital [39]. Furthermore, very scalable is PdM driven by AI, which fits numerous industries like manufacturing, healthcare, energy, and transportation. AI tools let firms centrally monitor and manage PdM plans by analyzing massive amounts of sensor data from many industrial sites [40].

2.3.2 Challenges and Difficulties

Although warning systems and AI-driven decision-making offer numerous advantages, certain problems that need to be addressed if they are to be most effective.

One of the hardest challenges are false positives and alert fatigue. Should a PdM system generate too many alarms-including false alarms-maintenance workers may get overwhelmed and ignore or dismiss significant signals. Constant training and fine-tuning are necessary for AI models to help to lower this issue so that alarms only go off for real-time failures or high-risk anomalies [41].

Another great challenge is cybersecurity connected to cloud-based PdM systems. Dependant on AI analytics managed on cloud systems, PdM is vulnerable to cyberattacks, data breaches, and illicit manipulation. To address these problems industries, have to implement robust cybersecurity systems like end-to--end encryption, blockchain-based authentication, and intrusion detection systems [42].

Combining AI-driven PdM with conventional industrial equipment presents even another challenge. Many businesses still run older equipment without IoT capabilities, which makes real-time data monitoring and automated warning usage difficult. Solutions include IoT-enabled industrial innovations, edge computing, and sensor retrofitting [43] will help to define smooth PdM integration.

Moreover, difficult are high computer requirements and infrastructure expenses, particularly for SMEs (small and medium-sized companies). Smaller businesses might find it financially onerous to have high processing capabilities and cloud infrastructure required by AI-based PdM solutions. By means of hybrid edge-cloud computing systems, data processing may be efficiently distributed and operational costs [44] saved.

2.3.3 Examples of This Step's Implementation

Some firms have efficiently used AI-powered decision-making and alert systems to boost PdM performance.

AI-driven PdM in manufacturing by companies like Siemens and General Electric (GE) helps to continually monitor production equipment in real time, therefore reducing downtime by thirty%. AI-powered DSS optimize machine performance, hence ensuring continuous production [34]. PdM has raised the reliability of sectorally used medical imaging equipment, ventilators, and infusion pumps. Hospitals have seen a 40% drop in medical equipment failures by means of PdM grounded on AI, therefore ensuring continuous healthcare services and patient safety [45]. AI-powered PdM for smart grid systems has improved sectoral energy distribution reliability, hence reducing outages and energy losses. Predictive warnings enable energy companies to design proactive infrastructure maintenance, hence ensuring ongoing supply of power [43]. AI-driven PdM in airplanes has reduced engine failures, therefore enabling airlines to optimise their maintenance schedules and increase passenger safety [36].

Step 5. Automated Maintenance & Control: Remote Monitoring and Repairs in PdM

Automated maintenance and control systems are changing industrial management of equipment maintenance, issue identification, and repairs. Remote monitoring technologies, IoT sensors, and AI allow industries to now autonomously diagnose and manage operations free from human participation. Included in PdM systems, automated control systems provide self-healing characteristics, problem detection, and real-time monitoring. These advances enhance resource consumption, reduce downtime, increase general equipment efficiency [46] and reduced downtime. Automated maintenance and control systems combining real-time monitoring, remote diagnostics, and AI-driven decision-making help to provide PdM and automatic fixes.

Starting the process with remote monitoring, IoT sensors and edge computing devices continually collect real-time data from industrial machines, HVAC systems, energy grids, or transportation networks. These sensors provide the data needed for cloud-based analytics systems tracking critical running parameters like temperature, vibration, pressure, and energy consumption. After that, AI based anomaly detection technologies search this data for early warning signs of probable failures.

Oncean anomaly is discovered, automated maintenance systems run relying on predefined protocols. A minor flaw might cause the system to remotely adjust settings, recalibrate parameters, or initiate free from human intervention self-repair mechanisms. Automated work orders generated for more severe issues guide maintenance personnel or trigger robotic repair systems. In critical environments like smart grids or water treatment plants, remote monitoring and control systems may isolate problematic components, reroute power, or switch on backup systems to prevent widespread failures [47]. Programmable Logic Controllers (PLCs) and Supervisor Control and Data Acquisition (SCADA) operate completely automated PdM often in concert with AI-driven predictive analytics. By allowing remote personnel to monitor, diagnose, and even repair assets from centralized control centers, these technologies help to reduce the need for on-site inspections and human interventions.

2.3.4 Step's Benefits

Many diverse industries benefit much from the use of automated maintenance and control systems in PdM. Two primary advantages are better efficiency and fewer downtime. By adopting real-time remote monitoring and automated maintenance, industries may find problems before they start, therefore reducing unexpected equipment downtime by 40–50%. This is very useful in key sectors such manufacturing, transportation, and energy production where equipment failures may cause major disruptions.

Another great benefit comes from savings in maintenance activities. Conventional approaches of maintenance demand scheduled repairs, frequent inspections, and reactive repairs resulting in excessive labor costs. Automated maintenance systems assist to reduce maintenance-related expenditures by 30–40% by means of optimal repair schedules and resource allocation [48].

A major benefit is also improved risk and safety control. Structural defects, pressure leaks, or overheating-among other real-time hazards-allow automated control systems to quickly respond to halt safety incidents. In areas such aviation, chemical processing, and healthcare, where maintenance failures might have catastrophic consequences, this is especially crucial [32].

Remote monitoring and automatic maintenance also enable companies to remain flexible and expandable. Large-scale industrial operations including smart cities, automated industries, and utility networks gain from centralized maintenance management-where AI-driven systems coordinate maintenance tasks across many sites, so reducing the demand for on-site personnel-where centralized maintenance management benefits.

2.3.5 Challenges and Difficulties

Adoption of automated maintenance and control systems in PdM presents several challenges that companies have to handle even with their advantages.

One of the main challenges is high first investment costs. Robotic maintenance systems, IoT sensors, and AI-powered monitoring platforms all need a large financial outlay for adoption. Long-term cost savings are rather significant even if small and medium-sized firms (SMEs) may find it difficult to justify the first expenditures of automation [49].

Still another major difficulty are cybersecurity concerns and data privacy considerations. Dependent largely on cloud-based data processing and remote connectivity, automated maintenance systems are prone to cyberattacks, hacking attempts, and data breaches. Cybersecurity technologies include end-to--end encryption, blockchain-based authentication, and AI-driven threat detection [32] help to defend industrial assets from cyberattacks.

Moreover, making adoption of automated maintenance systems difficult are issues of technical complexity and integration. Many industries still rely on legacy equipment without IoT connectivity; hence it is challenging to mix modern automation technologies with more old equipment. Under research are concepts such edge computing, sensor retrofitting, and hybrid AI-cloud integration to address this disparity.

Another challenge comes from too depending too much on automation and probable system failures. While automation drastically lowers human participation, AI-driven systems face the risk of misreading anomalies or ignoring appropriate maintenance activities. Industries must set additional control systems, human monitoring systems, and fail-safe mechanisms to ensure consistent operations and therefore lower this risk [50].

2.3.6 Examples of This Step's Implementation

Some industries have employed remote monitoring and automated maintenance very well to enhance PdM strategies.

AI-powered robotic maintenance systems have been used in the industrial sector by companies such Siemens and General Electric (GE), therefore reducing plant downtime by thirty%. By means of real-time IoT monitoring and autonomous maintenance, these solutions provide continuous production with little human intervention.

In smart energy grids, AI-based automated control systems monitor power transmission networks and electrical substations, spotting flaws and automatically rerouting electricity to stop outages. PdM methods have reduced maintenance costs and improved grid reliability by 25% in renewable energy plants [47].

Moreover, embraced by the medical industry is automated maintenance for technical tools. MRI scanners, ventilators, infusion pumps, and remote diagnostics controlled by AI have grown more dependable by means of self-repair technologies, therefore ensuring that hospitals experience 40% fewer equipment failures [50].

AI-powered remote monitoring in the transportation sector is used by autonomous railway and aviation maintenance systems to examine tracks, diagnose aircraft engine problems, and automate repairs, thereby reducing downtime and enhancing passenger safety [49].

2.4 Step 6. Continuous Learning & Optimization in PdM: Model Refinement and Security Updates

PdM drives modern industrial processes today as it enables businesses to spot equipment failures before they start. Conversely, static predictive models are less effective at spotting new types of mistakes and changing with the times to fit operational environments. Here is where constant education and optimization have application. Using adaptive ML models, real-time feedback loops, and regular security updates, PdM systems may improve cybersecurity, predict, and boost accuracy. Maintaining effective and in line with evolving industry needs depends on constant updating and improving predictive models [26]. Maintenance plans remain such this way.

Always learning and optimizing in PdM

Constant learning in PdM comprises of security enhancements to prevent cyberattacks, real-time feedback integration, and little model improvement.

Beginning with dynamic model training and ongoing data collection, the IoT sensors capture real-time data on equipment health including temperature, pressure, vibration, and energy use among other factors. AI driven PdM systems look at this data and find early failure tendencies. But when new patterns emerge, existing models must be changed using fresh training data. Conventional batch learning models often find it difficult to match this demand, hence online learning systems-which continuously improve predictions as new data floods in—must be adopted [51].

Reinforcement learning (RL), which helps PdM models adjust their decision-making depending on real-time performance feedback, is another key technique in continuous learning. Evaluating cost, risk, and operational constraints, RL-based systems dynamically optimize maintenance schedules so that repairs are performed at the most effective time [52].

Natural basis for PdM optimization is security updates. Dependent more and more on cloud computing, IoT networks, and AI-driven analytics, PdM systems are susceptible to hacks, sensor spoofing, and data breaches. Companies utilize automated security patches, blockchain authentication, and anomaly-based intrusion detection [51] to guard maintenance data and prevent unauthorized modifications.

2.4.1 Step's Benefits

For many different industries, using security updates and continuous learning in PdM has great advantages.

Among the key benefits are less false alarms and improved prediction accuracy. Constant improvement of ML models allows PdM systems to adapt new failure patterns, hence lowering the risk of false positives—unneeded maintenance-and false negatives-missed failures. From this, more consistent failure projections and better maintenance decisions ensue [27].

Two other significant advantages are still cost management and effective maintenance scheduling. Driven by AI, PdM regularly alters its maintenance plans based on real-time operational data, therefore ensuring only necessary repairs. By up to 40% this reduces needless downtime and maintenance expenses [52].

Still another great benefit is enhanced data integrity and cybersecurity. Regular security updates protect PdM systems against cyberattacks, fraud data injections, and unauthorized access. Blockchain security, end-to--end encryption, and AI-powered intrusion detection will enable industries to ensure that PdM data remains accurate and secure [51].

Furthermore, continuous schooling enhances scalability and adaptability, which makes PdM useful in manufacturing, energy, healthcare, and aerospace among other areas. Adaptive models may provide dependability even in dynamic industrial environments by self-optimizing based on real-time operational conditions [53].

Longer equipment lifespan and efficiency are ultimately quite beneficial. Constant enhancement of PdM systems helps to lower unnecessary asset wear and tear, thus extending their running lifespan. Research using continuously updated PdM systems demonstrate asset lifespan rises between 20 and 30%.

2.4.2 Challenges and Difficulties

Although security improvements in PdM and ongoing education offer numerous advantages, their implementation causes significant challenges.

Two main challenges are significant computer costs and infrastructure requirements. Components of ongoing education include frequent model retraining, cloud computing, and real-time data analysis-all of which need for high-performance computer resources. Small and medium-sized companies (SMEs) may find implementing adaptive AI-driven PdM systems difficult with relation to early expenditures [26].

Data quality and sensor drift are yet another challenge. While AI models rely on consistent, high-quality sensor data, calibration drift, ambient noise, and sensor degradation may distort readings and provide false maintenance predictions. If industries want to address this issue, they must invest in sensor diagnostics, recalibration techniques, and redundancy systems [51].

Cybersecurity is still a big problem even if PdM systems are becoming connected with IoT networks and cloud systems. By altering sensor data, targeting adversarial attacks on AI models may assist to generate false maintenance alerts. Reducing these risks demands for using anomaly detection algorithms, blockchain-based authentication, and safe AI training [52].

Interpretability of AI models adds even another challenge. Many PdM systems-especially those developed on deep learning and neural networks-function as black-box systems, which makes it challenging for maintenance teams to know how predictions are generated. Using explainable AI (XAI) techniques will improve openness and aid to establish trust in PdM decisions [52].

2.4.3 Examples of This Step's Implementation

Many businesses have cleverly implemented continuous learning and optimization into their PdM strategies.

PdM systems based on reinforcement learning in manufacturing are used by companies like Siemens and Bosch to dynamically modify maintenance plans depending on evolving operational conditions. These AI-driven technologies have reduced machine failures by thirty percent; they have also increased industrial production [27].

Continuous learning AI models have been used by hospitals to monitor MRI scanner, ventilator, and robotic surgical equipment performance. By producing a 35% drop in medical device failures, these adaptive PdM systems have guaranteed continuous patient care and guaranteed that equipment breakdowns are projected [53].

AI driven constant optimization has benefited the energy sector. This has bearing on maintaining the smart grid. By means of self-learning fault detection systems, dynamic modifications in maintenance schedules for renewable energy installations and power substations serve to reduce outages and increase grid efficiency [52].

Constantly updating relying on real-time aircraft performance data in aerospace and aviation, AI-driven PdM models enable airlines to optimize engine maintenance and decrease in-flight breakdowns [51].

3 Results and discussion

In this section, the results and discussion are provided through an in-depth case study. The case study demonstrates the application of the proposed framework and discusses the outcomes, practical implications, and observed benefits in a real-world setting. The case study implementation relied on a layered architecture combining IoT sensors, Edge AI modules, and a cloud-based analytics dashboard to support real-time monitoring and predictive alerts. The PdM program described in the case study is designed to enhance the reliability and operational efficiency of water tank trucks belonging to Jordan's Civil Defense Directorate. The fleet, responsible for emergency response operations such as firefighting and disaster relief, has to be available for operation at all times to enable quick deployment. Any unexpected breakdown of these vehicles can have a major impact on emergency response times. To mitigate this risk, the study integrated a IoT-driven PdM system that monitors critical vehicle parts in real time to facilitate early fault detection and timely maintenance interventions.

The heart of this system is the On-Board Diagnostics II (OBD II) reader, which has been integrated right into the cars. The system collects real-time data from an array of sensors installed around the truck, including those monitoring the gear transmission system, condition of the clutch, and efficiency of diesel injection. The information is transferred via Wi-Fi to the Microsoft Azure cloud platform to enable constant, secure, and remote access to maintenance staff. As indicated in Figure 2, this cloud-based system provides seamless data flow from the vehicle's onboard computer to the maintenance center for comparison with normal operating parameters.

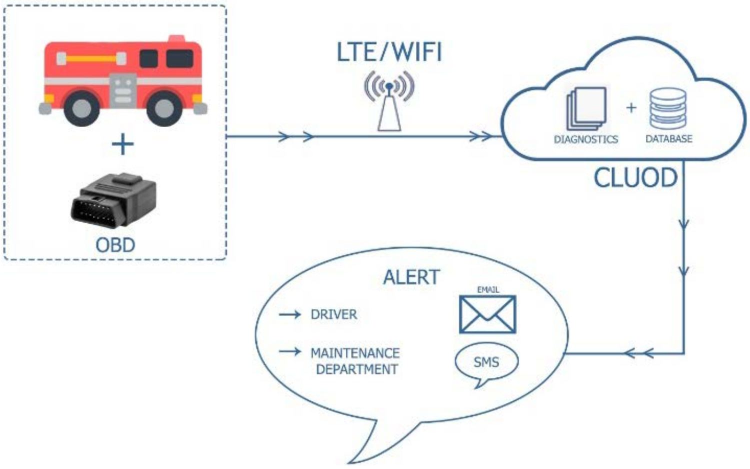

Fig. 2. The Architecture of the system

One of the advantages of this system is its real-time anomaly detection and alert system. The moment a fault is sensed—be it faulty engagement of gears, excessive clutch wear, or anomalous fuel injection pressure—the driver and maintenance are alerted at once by SMS to the driver and email to maintenance. Such speedy alerting implies that immediate remedial action is feasible before more damage is caused and potential for complete mechanical breakdown. The system incorporates ML algorithms in it that search through old and new data regularly and predict impending failures most likely to occur beforehand.

The model focuses on three critical components of the car:

1. Gear Transmission System: Identifies misuse of gears, which results in excessive wear and eventual mechanical breakdown.
2. Clutch Wear Monitoring: Tracks usage of clutch plates and generates warnings when they should be replaced.
3. Diesel Injection System: Monitors pressure fluctuations to identify fuel pump or injector issues before they affect performance.

One of the most important findings in the case study was the impact of improper gear selection on vehicle wear and breakdowns. As Figure 3 displays, the evidence revealed that 36% of move-off occurrences occurred in higher gears (gear 5 or 6), leading to over-stress in the transmission system. This chronic error resulted in early gear failure, which went unnoticed until total breakdown had occurred. Application of the OBD II-based monitoring system allowed early detection of the problem, thereby enabling maintenance crews to notify drivers and prevent similar failures in the future.

The data collected from the sensors was processed using a cloud-based analytics platform, which utilized time-series analysis and threshold-based alert mechanisms to detect anomalies. In the instance of clutch wear, data analysis showed progressive clutch plate wear to be a major cause of vehicle downtime. Figure 4 indicates the way that wear on the clutch increases with age, and how the absolute travel distance of the clutch plate increases from 24mm to 50mm as it ages. When the distance approaches 60mm, an automatic warning is initiated so that the driver can schedule for maintenance before the clutch becomes non-operational. This preventive approach increases the lifespan of the clutch system by many folds, keeping downtime to a bare minimum.

In addition, the system provides a report of diesel injection performance, a criterion influencing the efficiency of vehicles. According to Figure 5, the model regularly monitors fuel injection pressure to ensure optimum combustion conditions. A reduction of diesel pressure indicates that there can be an issue with the fuel pump, filter, or injectors, and if this situation is not cured, engine performance may be depreciated. By detecting and repairing such issues in advance, the system avoids fuel wastage and reduces long-term maintenance.

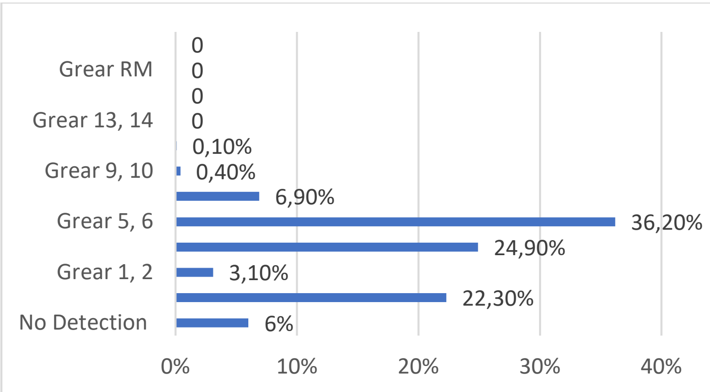

Fig. 3. The percentage of moving – off in the truck gear

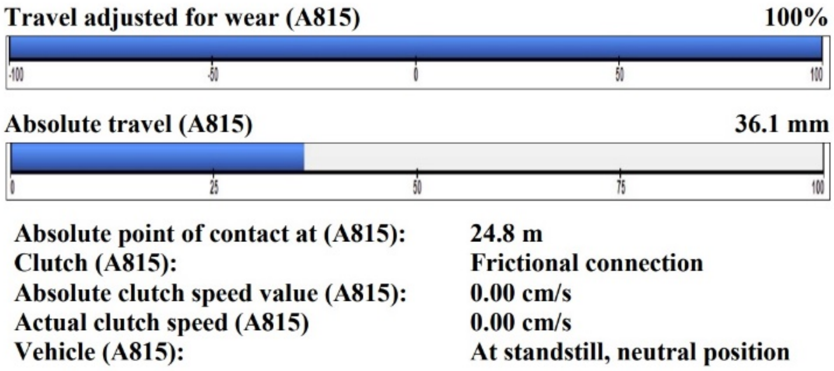

Fig. 4. The absolute travel and the wear in clutch system

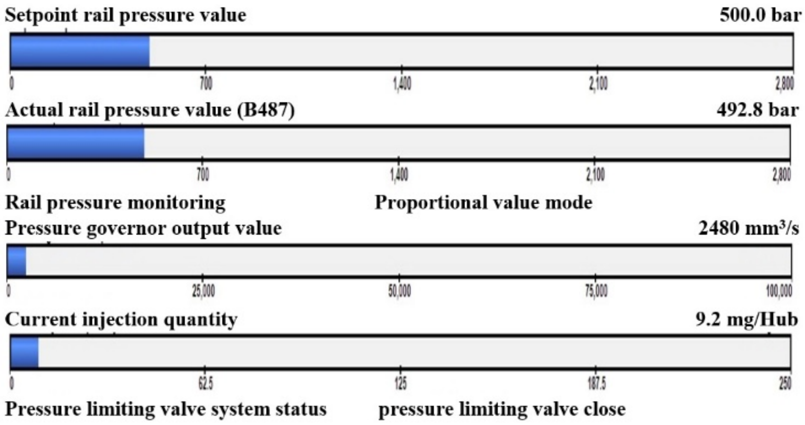

Fig. 5. Different pressures in the vehicle's diesel system

The following discussion provides a step-by-step analysis of how the introduced framework was applied in the case study.

3.1 Step 1.

The first step of the framework is the acquisition of data through IoT sensors, which continuously monitor vehicle health parameters in real-time. The case study depicts the effectiveness of the step by mounting an OBD II reader on the vehicle, whereby permanent recording of critical operational data is facilitated. The system specifically monitors gear usage, clutch wear, and diesel injection performance, which are primary determinants of the reliability of water tank trucks.

One of the significant issues found during the data collection process was driver error in gear shifting, where truck drivers tended to initiate moving the vehicle in higher gears (5 and 6) instead of the optimal lower gears. As seen in Figure 3, 36% of the move-off incidents were recorded in gear 5 or 6, placing unnecessary stress on the vehicle's transmission system, accelerating wear, and making failure more likely. Without real-time monitoring, this fault went undetected to the maintenance department until a complete breakdown. The capability of driver error detection and measurement by IoT-based monitoring underlines the need for real-time data capture for PdM.

3.2 Step 2.

Once data is collected, the storage, processing, and transmission of the data is the second necessity. In the case study, the OBD II reader wirelessly transmits real-time data to the Microsoft Azure cloud platform, which is indexed and scanned for anomalies. The cloud technology enables immediate access to the vehicle diagnostics for maintenance professionals to actively monitor the health of fleets.

The importance of data processing is demonstrated in the study of the clutch system. Data collected from different vehicles showed a correlation between driving patterns and clutch wear, where improper gear shifting caused the clutch to deteriorate earlier. This information was essential in predicting clutch failure and issuing early warnings to drivers and maintenance staff. The system further improved the response times, such as in the case study, where clutch wear was foreseen in advance and thus prevented costly mechanical damage. Such foresight was not only crucial in determining the reliability of vehicles but also applied to optimize the maintenance schedule by reducing unnecessary downtime.

3.3 Step 3.

Step three of the methodology involves applying predictive analytics and ML to detect anomalies and forecast failures. To implement the solution, we used condition-monitoring sensors connected via a wireless network to an IoT platform, enabling real-time data acquisition and fault prediction. The case study applied historical data and real-time data to pick up on wear patterns in the clutch system. As shown in Figure 4, the absolute travel of the clutch plate increases as a function of time as the system wears from the initial value of 24 mm to 50 mm and beyond. When this value reaches 60 mm, the system automatically sends an SMS alert to the driver and an email alert to the maintenance team. This predictive aspect is such that clutch replacement is scheduled before failure and consequently prevents operational downtime.

Additionally, ML algorithms were applied to study how driving behaviors impact component wear. Data-driven analysis in Table 1 revealed that gears were shifted in high gear excessively to get the vehicle in motion, leading to excessive wear in transmission and clutch components. By these abusive driving behaviors being detected, drivers were warned and informed to modify their behavior, and considerable lowering of component wear and maintenance costs was realized.

Table 1. The wear of moving – off in each gear

GEARBOX	Number of Moving-off Manoeuvers	Moving-off Wear (KWs)	Shifting Wear (kWs)
Grear R	2775	10704451	427028
Grear 1, 2	969	4009480	45402
Grear 3, 4	3351	41658441	5382209
Grear 5, 6	2177	35415069	22839182
Grear 7, 8	368	9724307	29096354
Grear 9, 10	39	47035	41824704
Grear 11, 12	8	0	5492807
Grear 13, 14	8	25581	40857555
Grear 15, 16	1	0	18158718
Grear RM	0	0	0
Grear DM	0	0	0

3.4 Step 4.

The fourth step of the model is to generate alerts and notify maintenance decisions by means of real-time diagnostics. The case study demonstrates this with an automated alert system that notifies drivers and maintenance personnel when critical levels are reached.

For instance, in the diesel injection system, fuel pressure deviations were being monitored and analyzed in real-time. As depicted in Figure 5, the system constantly tracks injection pressure levels and identifies unusual fluctuations, which could indicate issues with the fuel pump, filter, or injectors. In any moment when pressure falls below an optimal level, an immediate alert is triggered, allowing for swift intervention. This procedure ensures that issues are addressed before the engine fails, thereby improving overall car efficiency and fuel mileage.

3.5 Step 5.

Step five is maintenance response automation, which allows vehicles to self-diagnose and schedule servicing according to predictive data. The case study illustrates this with great effect through clutch wear monitoring. The system is continuously measuring clutch plate thickness and, as soon as it detects excessive wear, auto-schedules maintenance. This prevents unexpected vehicle downtime and has repair work done at optimum intervals rather than sticking to rigid maintenance schedules.

Further, OBD II reader real-time diagnosis enabled maintenance groups to recognize the trend of gear abuse on various trucks and develop fleetwide driver training programs. This proactive intervention strategy not only extended vehicle component life, but also contained overall maintenance costs and production downtime.

3.6 Step 6.

The final step in the framework ensures that PdM system gets better continuously with adaptive analytics and ML. The case study indicates how previous breakdowns were used to enhance predictive models so that the system could detect gearbox issues 55,000 km in advance as opposed to before.

One of the most notable improvements attained was the reduction of gearbox failure from occurring at 65,000 km to being detected at 10,000 km. This was made possible through the ability of the system to learn from experiences, detect patterns in driver behavior, and provide real-time feedback to correct faulty habits. Besides, the notifications and warnings became more focused as the system refined its models of failure prediction so that it only provided the most critical alerts. This reduced alert fatigue and allowed maintenance crews to focus on priority interventions.

4 Conclusions

Using IoT, AI, and Edge Computing in PdM allows real-time monitoring, precise failure prediction, and fast decision-making, revolutionizing industrial maintenance. The research offered a framework that incorporates IoT data collecting, Edge and cloud computing for fast processing, AI-based predictive analytics, automated maintenance control, and continuous learning for system improvement. These solutions may decrease equipment downtime, optimize maintenance schedules, cut operating costs, and improve asset dependability and performance.

Jordan's Civil Defense Directorate's IoT-based PdM case study proved its efficacy. Real-time monitoring of critical vehicle components and AI-driven predictive analytics increased fleet availability, defect identification, and intervention. It was shown that PdM decreases unexpected failures, increases asset lifetime, and improves operational efficiency. In spite of its benefits, cybersecurity threats, hefty initial investment, and legacy system integration complexity prevent widespread use. These difficulties necessitate secure communication protocols, cost-effective IoT solutions, and smooth interoperability between industrial infrastructures and PdM technologies. This research offers a scalable and cost-effective strategy for using AI-driven PdM to optimize maintenance operations. The incorporation of sophisticated AI models like reinforcement learning and digital twin simulations could improve predicted accuracy and adaptive maintenance tactics in future research. Industry may move toward smarter, self-sustaining maintenance ecosystems that enhance productivity and asset usage by enhancing PdM frameworks.

The specific scientific contribution of this study lies in demonstrating the practical integration of IoT-enabled predictive maintenance within civil defense fleet operations, highlighting measurable improvements in operational efficiency and reliability. By employing real-time monitoring and data analytics, this work advances the application of predictive maintenance in critical service sectors and provides a replicable model for similar fleet-based systems.

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7 Conflict of interest statement

The authors declare that they have no conflicts of interest in relation to the work described in this manuscript.

8 Author contributions

Conceptualization, Mohammad M. Hamasha and Qais Albedoor; methodology, Mohammad M. Hamasha and Qais Albedoor; writing-original draft preparation: Mohammad M. Hamasha and Qais Albedoor; edit the draft: Ahmad Qamar and Fateh Berrah; supervision: Sa'd Hamasha and Haneen Ali.

9 Availability statement

The data are available based on request.

10 Supplementary materials

No supplementary materials

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