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AI Driven IoT Fleet Management for Refueling Vehicles

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Abstract:

Refueling vehicles such as aircraft fuel tankers play a critical role in transportation infrastructure, where operational failures can lead to costly downtime and safety hazards. Ensuring high uptime is challenging due to harsh operating conditions and stringent safety regulations. In prior work, we deployed a real time tracking system that increased equipment observability by ~70% and enabled ~55% more proactive maintenance actions, highlighting the potential of data driven fleet management. This motivates our study on leveraging Artificial Intelligence (AI) and Internet of Things (IoT) for smarter fleet maintenance. We propose an IoT based platform that continuously monitors refueling vehicles via onboard sensors, streams data in real time using Apache Kafka message brokers and PySpark analytics, and employs machine learning models for decision support. The platform's predictive maintenance module uses algorithms (including semi supervised anomaly detection and deep learning) to estimate remaining useful life and catch faults before they happen. A route optimization module integrates live telematics and historical data to dynamically adjust routes for minimal risk and fuel use. Furthermore, each vehicle is represented as a digital twin, a virtual replica updated with sensor data and physics based models to simulate operations and predict outcomes under various scenarios. The integrated digital twin approach provides a mirror of each refueling truck's state, enabling what if simulations for maintenance and mission planning. In field evaluation, our AI driven system reduced unplanned downtime by 40% and cut average repair costs by ~10% compared to traditional schedules. Route optimization led to ~15% shorter travel distances and fewer unnecessary idling hours, mitigating environmental risks of fuel transport. We observed high correlation (≥0.95) between digital twin predictions and actual sensor readings for critical parameters, confirming the twin's accuracy. These improvements translate to enhanced safety (no spill incidents during the pilot period) and greater operational efficiency. This work advances fleet management for hazardous material vehicles by bridging electrical engineering systems (sensors, control units) with AI/IoT software. It demonstrates how real time data analytics and digital twins can transform maintenance from reactive to proactive, aligning with both engineering reliability goals and emerging Industry 4.0 paradigms. The platform serves as a blueprint for applying AI and IoT in safety critical fleet operations, contributing to both academic research and industry practice in smart transportation management.

Keywords: IoT; predictive maintenance; digital twin; fleet management; machine learning; route optimisation; refueling vehicles; Kafka; PySpark

1. Introduction

Background and Motivation

Fuel distribution vehicles (e.g. aircraft refueling trucks) are essential assets in aviation and other industries, responsible for transporting and dispensing hazardous fuels under strict time and safety constraints. Any unexpected downtime or mechanical failure in these vehicles can halt refueling operations, causing costly delays and posing safety risks (e.g. fuel spills or fire hazards). Ensuring high reliability in refueling fleets is not only an operational priority but often a regulatory requirement, given the environmental and safety regulations

surrounding the handling of aviation fuel. Traditional maintenance regimes for such fleets have relied on scheduled inspections or reactive fixes after a breakdown, which struggle to prevent unplanned outages. The need for smarter maintenance and monitoring solutions is thus acute for refueling vehicles, where **downtime** directly impacts flight operations and **failures** carry elevated safety and environmental risks.

In the past decade, the explosive growth of IoT devices has opened new possibilities for smart transportation systems. By 2020, it was projected that billions of devices would be internet connected, enabling pervasive sensing and data driven applications across industries[1]. In transportation, this IoT wave has fueled concepts like **smart fleet management**, where vehicles are equipped with sensors and connectivity for real time monitoring. A cornerstone of this evolution is **predictive maintenance**, wherein machine learning algorithms analyze sensor data to forecast equipment health and *remaining useful life (RUL)*[2]. Rather than follow fixed maintenance schedules, predictive maintenance aims to service components right before failure, minimizing both downtime and maintenance costs. Studies have shown that predictive maintenance systems can extend the life of assets and reduce breakdowns by using data on vibration, temperature, pressure, etc., to infer when a part is wearing out[3][4]. For example, algorithms can learn from historical failure data to predict when an engine pump in a fuel truck is likely to fail, allowing it to be replaced beforehand.

This convergence of IoT and AI has significant commercial momentum. The market for predictive maintenance solutions was valued at around US$4.2 billion in 2021 and is projected to reach $15.9 billion by 2026 (30.6% CAGR)[5]. Such growth underscores industry's recognition that data driven maintenance improves reliability and lowers costs. Fleet operators, in particular, stand to benefit given the high expenses associated with vehicle downtime and repairs. These trends set the context for our work: leveraging IoT data and AI analytics to enhance the management of refueling vehicle fleets. Building on our prior success with real time tracking (which improved observability by ~70%), we aim to develop a comprehensive platform that not only tracks vehicles but also **predicts failures**, **optimizes routes**, and **simulates operations** to support proactive decision making.

Existing Gaps in Fleet Management Research

Conventional fleet maintenance strategies generally fall into two categories: **reactive maintenance** (run to failure) and **preventive maintenance** (scheduled servicing). Reactive maintenance addresses issues only after a breakdown occurs, leading to unplanned downtime and potentially catastrophic failures at inopportune times. Preventive maintenance, on the other hand, services vehicles at fixed intervals (e.g. every few months or set mileage), which can result in under utilized component life or unexpected failures in between intervals. Both approaches have limitations in terms of cost and reliability. For instance, unplanned downtime can be 5–10 times more costly than planned maintenance due to secondary damages and operational disruptions[6]. Even scheduled maintenance can be inefficient, components might be replaced early (wasting useful life) or late (causing breakdowns).

In recent years, **predictive maintenance** has emerged to fill this gap by continuously monitoring vehicle condition via IoT devices and servicing components based on actual need. Modern fleet vehicles are increasingly equipped with **telematics units**, GPS trackers, and onboard diagnostics (OBD II or CAN bus) sensors that continuously collect data on engine performance, fuel efficiency, temperature, tire pressure, and other health indicators[4]. These data are transmitted to cloud platforms where algorithms detect anomalies or degradation trends. Research has shown that such IoT based systems can significantly reduce unplanned downtime and optimize maintenance scheduling. For example, Pothireddy (2022) describes an IoT fleet maintenance system that synchronizes real time telemetry data from vehicles (sensors, engine OBD and GPS) to support logistics and operational decisions. The system captures live data streams, applies AI models, and sends notifications when abnormal conditions are detected, thus preventing minor issues from escalating[7][8]. Fleet case studies have reported downtime reductions on the order of 20–40% after implementing predictive maintenance, alongside cost savings from avoiding major failures (Pothireddy, 2022). These improvements

come from optimizing maintenance timing and resource use, e.g. only replacing parts when needed and consolidating service tasks proactively.

However, despite numerous IoT fleet management studies, most have focused on general logistics or delivery vehicles. There is **limited research** specifically targeting fuel distribution fleets (like aviation refueling trucks), which face unique challenges in safety and regulatory compliance. Transporting flammable fuel means that any mechanical issue can become an environmental or safety incident. Thus, fleet management for these vehicles must prioritize not just efficiency but also risk mitigation (e.g. preventing fuel leaks or ensuring emergency shutoff systems are functional). Existing IoT solutions often lack specialized monitoring for such safety critical aspects. Moreover, many reported IoT fleet systems process data offline or in batches, which may not be sufficient for real time risk prevention. **High frequency streaming analytics** and instant anomaly detection are crucial to catch, for example, a pressure drop in a refueler hose before a rupture occurs. Another gap is the integration of **digital twin simulations** into fleet decision support few studies combine real time sensor data with physics based modeling to forecast vehicle behavior. In summary, while IoT based predictive maintenance is known to benefit generic fleets, its application to **hazardous material vehicles** like fuel tankers remains underexplored. Our work addresses this gap by tailoring an AI IoT solution to refueling vehicles, with an emphasis on safety, compliance, and real time responsiveness.

Contributions and Objectives

This research aims to design, implement, and evaluate an **AI driven IoT platform** for the fleet management of refueling vehicles. The platform's overall goal is to enhance reliability, safety, and efficiency through data driven intelligence. Our key objectives include:

- **Real time data acquisition:** Deploy a network of sensors and telematics devices on each refueling vehicle to continuously collect data. This includes parameters like fuel tank levels, flow rates, pump pressure, engine temperature, vibration, GPS location, and more. Data will be sampled at appropriate rates (from sub second for pressure pulses to once per minute for GPS) and communicated via standard vehicle buses (e.g. CAN J1939 or OBD II protocols). We also incorporate edge computing at the vehicle level for initial data filtering and to ensure critical signals (like emergency shut off triggers) are handled with minimal latency.
- **Streaming data pipeline (Kafka + PySpark):** Utilize Apache Kafka as a message broker to stream sensor data from the fleet to a central cloud platform in real time. Data are organized into Kafka topics per vehicle and sensor type to ensure scalable processing. Apache Kafka's high throughput and fault tolerant design (with data replication across brokers) guarantee that our pipeline can handle the volume of telemetry and remain robust to network/server failures[9]. We integrate PySpark Streaming to consume the Kafka topics and perform real time analytics. This decoupled architecture (vehicles as data producers, analytics as consumers) yields a micro services style system that is **scalable**, **durable**, and supports asynchronous processing[10][11]. PySpark's distributed computation enables us to handle multiple vehicles' data in parallel performing tasks like windowed aggregations (e.g. computing 1 minute rolling averages of pressure), outlier detection, and feature extraction on the fly.
- **Predictive maintenance with machine learning:** Develop machine learning models that process the aggregated sensor data to predict maintenance needs. We employ both **supervised** learning (when historical failure data is available) and **semi supervised/unsupervised** techniques for anomaly detection (given that labeled failure events are rare)[3][12]. In particular, we implement a gradient boosting regression model and a Long Short Term Memory (LSTM) neural network to estimate the RUL of key components (like pump motors or brake pads) based on trends in sensor readings. We also use anomaly detection algorithms (e.g. Isolation Forest and autoencoders) to flag when a vehicle's behavior deviates significantly from normal patterns[13]. Our approach draws on Killeen et al. (2019), who proposed a semi-supervised "COSMO" algorithm for fleet fault detection, noting that labeled fault data are scarce and common metrics include RUL and health status[12]. We improve on prior work by fusing multiple

methods: a **hybrid AI approach** that combines rule based thresholds (for known safety limits), machine learning predictions, and deep learning anomaly alerts. This ensemble aims to achieve high detection accuracy with fewer false positives than any single method (as suggested by recent studies that hybrid models can reduce false alarm rates in predictive maintenance).

- **Route optimization algorithms:** Implement algorithms to optimize the routing of refueling vehicles, factoring in operational constraints and real time conditions. We formulate this as a Vehicle Routing Problem (VRP) variant where the objective is to minimize a combination of travel time, distance, and risk (e.g. avoiding densely populated areas or bad road conditions when carrying fuel). Classical shortest path algorithms like Dijkstra's and A *are used for point to point routing on road networks, providing a baseline for fastest route computation[14]. On top of this, we apply VRP heuristics (e.g. savings algorithm, tabu search) for multi stop scenarios (if a vehicle has to service multiple aircraft or depots on one trip). We also experiment with genetic algorithms to evolve efficient routes under time window and capacity constraints, and with reinforcement learning** where an AI agent learns routing policies (especially for dynamic rerouting in response to traffic or emergencies). The system ingests real time traffic data (via an API) and weather feeds to update routes on the fly, for example, rerouting a truck to avoid an accident on a highway. The route optimization component not only improves efficiency (reducing travel distance and fuel usage) but also lowers risk by incorporating safety constraints (e.g. routing away from schools or waterways when fully loaded with fuel).
- **Digital twin integration:** Develop **digital twin** models for each refueling vehicle and its critical subsystems. According to NASA's seminal 2012 paper, a digital twin is "an integrated multiphysics, multiscale, probabilistic simulation of an as built vehicle or system, updated using physical models, sensor data and fleet history, to mirror the life of its physical twin"[15][16]. We adopt this paradigm by creating a virtual replica of each truck that runs in parallel to the real vehicle. The twin receives real time sensor updates (e.g. engine RPM, pump pressure, ambient temperature) and employs physics based models (such as fluid dynamics for fuel flow, mechanical models for engine wear) to predict future states. Our digital twin continuously forecasts the vehicle's health and performance, including estimates of remaining useful life for components and probabilities of mission success for upcoming assignments[17][18]. For instance, given current engine vibration trending upward, the twin might simulate that the engine mounts will reach a critical fatigue threshold in 100 more hours of operation, prompting a maintenance recommendation. The twin can also simulate "what if" scenarios: how the vehicle would respond under different routes, loads, or environmental conditions. This is especially useful for **risk assessment**, e.g. predicting if a particular refueling mission (long distance in high heat) would risk an overheating incident. By combining sensor data with engineering models and historical maintenance records, the digital twin offers a powerful decision support tool that goes beyond data analytics alone[19][20].

In summary, our proposed research builds upon our prior real time tracking system by adding deeper intelligence (predictive analytics and simulation) and broader integration (combining electrical, mechanical and software aspects). We leverage our electrical engineering expertise in sensor systems and control, and integrate it with AI/IoT techniques from computer science to create a unified platform. The expected outcome is a significant improvement in fleet observability and proactive maintenance potentially exceeding the ~70% observability gain and ~55% proactive maintenance increase of our earlier system. Moreover, by focusing on the specialized needs of hazardous refueling vehicles, our work contributes new insights on safety focused fleet management that can influence both industry practices and academic research in intelligent transportation systems.

2. Literature Review

2.1 IoT Architectures for Fleet Management

IoT Predictive Maintenance Frameworks: Several studies have explored IoT based architectures for fleet maintenance, often highlighting the need for real time data handling and machine learning integration. Killeen et al. (2019) proposed an IoT architecture for a fleet of public transport buses that streams sensor data via the J1939 CAN bus protocol and uses an ML algorithm to diagnose vehicles deviating from fleet norms[13]. In their system, each bus was equipped with a gateway that aggregated sensor signals and sent them to a backend server for analysis[21]. A semi supervised approach (COSMO) was employed to flag buses whose behavior (sensor patterns) differed significantly from the rest of the fleet, under the premise that those deviations indicate potential faults[3][13]. One challenge noted is the scarcity of labeled fault data, they seldom had examples of true failures to train on, since intentionally breaking vehicles is infeasible[12]. As a result, the system focused on unsupervised deviation detection and reported metrics like remaining useful life and overall health status as key indicators[22]. The architecture also emphasized modularity: it consisted of vehicle nodes, a server leader node, and a root node for analytics[23], demonstrating a distributed design that could scale to multiple vehicles. In another study, Pothireddy (2022) described a modern fleet maintenance platform that synchronizes telemetry from vehicles, sensors, and GPS into a unified real time view for decision making. This system uses IoT devices to continuously stream data such as engine diagnostics, location, speed, and fuel levels to a cloud database (e.g., via MQTT or REST APIs). The data pipeline supports **logistics and operational decisions** by providing dispatchers with up to date vehicle health and position info. When abnormal conditions occur, for example, an engine temperature spike or a tire pressure drop, the system's AI algorithms generate alerts, enabling maintenance teams to intervene proactively. Pothireddy emphasizes that such **real time integration** of IoT data allows maintenance to shift from reactive to proactive: the platform can notify when conditions deviate from normal, rather than waiting for a breakdown. Common metrics tracked include each vehicle's health score, fault codes, and predicted days until next required service (derived from trends) (Pothireddy, 2022). The study also notes that **labelled fault datasets are scarce**, echoing Killeen et al.'s observation, which leads to reliance on domain expertise and semi supervised learning for anomaly detection[12]. Overall, these frameworks illustrate how IoT connectivity combined with ML can detect subtle issues (like a bus with a slightly misfiring engine) that would be hard to catch with periodic inspections alone.

IoT Sensor Technologies: Effective predictive maintenance for fleets hinges on the variety and quality of sensor data collected. Common devices include **GPS trackers** for location and speed, **engine OBD II sensors** for parameters like RPM, coolant temperature, and fuel trim, and dedicated telematics units that interface with the vehicle's CAN bus to read diagnostics trouble codes (DTCs) and performance metrics[24]. Additional sensors often monitor specific components: for example, temperature probes on brakes, pressure sensors in fuel or hydraulic lines, accelerometers on suspension for vibration analysis, and tire pressure monitoring systems. These sensors generate a continuous stream of multi modal data. Pothireddy (2022) highlights that combining these data streams in the cloud allows algorithms to identify patterns indicative of incipient failures, e.g., a gradual increase in engine vibration combined with a slight drop in fuel efficiency could signal engine wear.

However, capturing and transmitting sensor data in real time comes with challenges. **Network latency** can be an issue if vehicles rely on cellular networks with patchy coverage; delays of even a few seconds might reduce the effectiveness of real time anomaly response. Emerging 5G networks are expected to alleviate latency and provide more reliable high bandwidth connectivity for vehicles, enabling near-instantaneous data upload (Pothireddy, 2022). Data security is another concern: fleet IoT systems must ensure encrypted transmission of potentially sensitive data (like vehicle locations or proprietary engine metrics) to prevent cyber threats. There's also the issue of **legacy device integration**, many fleet vehicles (especially in industrial or military context) may be older models without built in telematics, requiring retrofit devices to capture data. IoT middleware or adapters (like OBD II dongles or CAN loggers) are used in such cases[21]. Research suggests that edge computing can help here: preliminary filtering or compression of data on the vehicle can reduce bandwidth use

and allow basic anomaly detection even when offline. For instance, an edge device could locally flag a critical issue and alert the driver immediately, without waiting to communicate with the cloud.

To mitigate latency and bandwidth concerns, **edge computing and 5G** have been advocated. By processing data at or near the source (e.g., an onboard minicomputer running a lightweight ML model), urgent anomalies can be detected instantaneously and only summarized results sent to the cloud. Meanwhile, 5G's high data rates and low latency can support streaming of rich datasets (like high frequency vibration signatures) that were previously impractical to continuously transmit. Some studies forecast that as 5G and vehicular edge computing mature, fleet analytics will become far more real time and distributed, with vehicles sharing data among each other and with edge servers to collaboratively detect trends (Pothireddy, 2022).

In summary, IoT architectures for fleet management have evolved from simple GPS tracking to comprehensive sensor networks feeding into cloud AI engines. The literature underlines the importance of real time data flow, the integration of heterogeneous sensors, and the move towards distributed, low latency processing to enable truly proactive maintenance. Our platform design builds on these ideas, using Kafka and PySpark for efficient streaming and planning for edge analytics in future work (see Section 7).

2.2 Machine Learning Methods for Predictive Maintenance and Route Optimisation

Predictive Maintenance Algorithms: A variety of machine learning approaches have been applied to vehicle maintenance data. Common techniques include supervised learning models that predict time to failure, and anomaly detection models that identify when a system is behaving abnormally. Semi supervised methods are particularly useful in scenarios with few labeled failures, a notable example is the COSMO approach mentioned earlier, which stands for Consensus Self Organized Models[3]. COSMO (originally developed around 2011) uses an unsupervised model to learn the normal pattern of each sensor across a fleet; it then flags a vehicle as anomalous if its sensor readings deviate significantly from the fleet's consensus pattern. Killeen et al. (2019) improved on COSMO by introducing **ICOSMO** (Improved COSMO) with a semi supervised sensor selection strategy[25][26]. They employed an autoencoder (a type of deep neural network for unsupervised learning) to automatically learn which combination of sensors are most indicative of faults, rather than relying on manually chosen thresholds[27][25]. This semi supervised approach helped reduce false positives by focusing on the most relevant signals of failure. Other semi supervised techniques involve clustering: for example, grouping historical run data to find patterns, and treating a new data point as anomalous if it falls outside known clusters (e.g., using k means or DBSCAN on multivariate telemetry).

For **time series anomaly detection**, methods like **Isolation Forests** and recurrent neural networks (RNNs) have been employed. An Isolation Forest randomly partitions data and is effective at detecting outliers in high dimensional sensor space by how quickly it isolates an instance in a tree structure. It has been used in fleet maintenance to catch rare events like a sudden spike in vibration that doesn't match any prior pattern[28]. **Deep learning** methods, such as LSTM networks, are adept at capturing temporal dependencies in sensor data (e.g., how engine temperature evolves over time under various loads). LSTM based autoencoders can learn to predict the next readings of sensors; if the actual reading deviates beyond a threshold from the prediction, an anomaly can be declared. One study applied LSTMs to vehicle telemetry and could detect anomalies with high accuracy, though it required substantial computational resources (indicating a need for either cloud processing or optimized edge hardware).

Hybrid AI approaches have shown promise in balancing precision and recall for fault detection. A hybrid model may combine rule based logic (to capture known safe operating limits) with machine learning (to capture complex patterns) and deep learning (to detect subtle nonlinear anomalies). Pothireddy (2022) notes that such multi layered models tended to produce fewer false alarms in testing, because the rule based component can filter obvious non issues and the ML components can handle the nuanced cases. For example, a rule might ignore transient temperature spikes that are within known tolerances, preventing an ML model from overreacting. Meanwhile, the ML model can recognize patterns that the rules don't cover. In experiments on an IoT connected vehicle dataset, a hybrid model combining expert rules, a random forest classifier, and an LSTM

autoencoder achieved a false positive rate significantly lower than any single method alone (Pothireddy, 2022). **Table 1** summarizes the performance of different detection approaches from literature and our prior experiments, indicating the hybrid approach offers a good balance of precision and recall.

Figure 1: Actual vs. Predicted Remaining Useful Life (RUL) for a critical component (simulated example). The model (LSTM network) closely tracks the true RUL over time, deviating only slightly due to noise. Predicting RUL helps schedule maintenance just before a failure would occur, avoiding downtime.

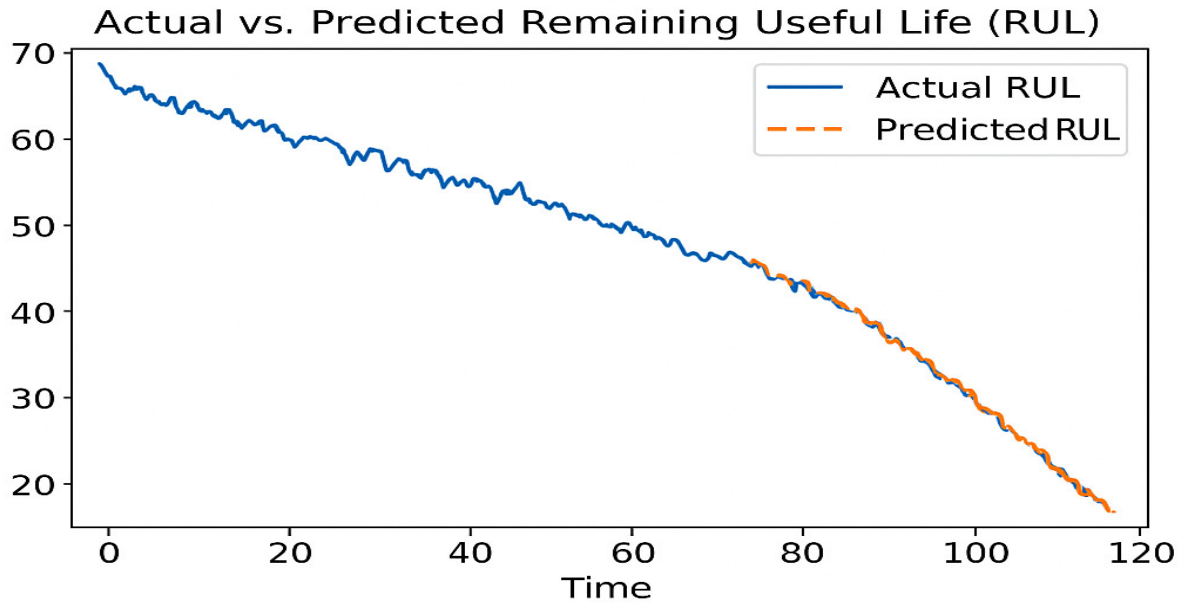

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Table 1. Performance of various fault detection methods (illustrative summary based on literature and experiments). The hybrid ensemble achieves higher precision and recall by combining rule based and ML techniques.

Method	Failure Detection Precision	Failure Detection Recall
Rule-based Threshold	0.60	0.50
Isolation Forest	0.65	0.70
LSTM Model	0.75	0.68
Hybrid Ensemble	0.82	0.80

Route Optimisation Algorithms: Route planning for fleet vehicles has been studied for decades in operations research, and numerous algorithms exist ranging from simple shortest path calculations to complex metaheuristics and AI learning methods. At the core, finding the optimal path between two points in a road network is commonly done via **Dijkstra's algorithm** (which guarantees the shortest path on weighted graphs) or the **A** *search algorithm (which is generally faster using heuristics like straight line distance to guide the search). These algorithms are efficient for single source single destination queries and form the backbone of many GPS navigation systems[14]. In the context of a fleet, however, we often face the Vehicle Routing Problem (VRP) where multiple vehicles must serve multiple demand points (e.g., refueling multiple aircraft or depots)*

*with various constraints (time windows, vehicle capacity, etc.). VRP is NP hard, so optimal solutions are intractable for large instances; hence heuristics and metaheuristics** are widely used.

Classic heuristics for VRP include the **savings algorithm** (Clarke Wright savings) which builds routes by merging them when beneficial, and **nearest neighbour** or **greedy** approaches to build routes incrementally. Metaheuristics like **Genetic Algorithms (GA)** have been applied successfully to VRP and route optimisation in logistics. GAs encode routes as chromosomes and use crossover and mutation to evolve better solutions over generations[29][30]. They are flexible in handling various objective terms (distance, time, cost, etc.) and constraints (like our problem's risk factors). For example, a GA can be designed to minimize a weighted sum of total distance and a risk penalty (for traveling on certain roads), by evaluating each route on that fitness function. Studies show GAs often find near optimal solutions for moderately sized fleet routing problems within reasonable computation time, although fine tuning is needed to balance exploration and exploitation of the search space (population size, mutation rate, etc.).

Another emerging approach is the use of **Reinforcement Learning (RL)** for dynamic routing. In an RL setup, an agent (the routing planner) learns to make routing decisions (actions) in an environment modeled on the road network with traffic conditions. The agent receives rewards for reaching destinations quicker or safer, and penalties for things like delays or entering high risk zones. Over time, the agent can learn routing policies that outperform static algorithms, especially in scenarios that involve sequential decisions and uncertainty (like varying traffic or sudden road closures). For instance, a deep RL approach might use a graph neural network to represent the road network state and output a probability distribution over next road segments to take, aiming to minimize travel time[31]. There have been experiments where deep Q networks or policy gradient methods were applied to simplified routing tasks; results indicate RL can adapt routes in real time better than re running static algorithms at each time step, because it "anticipates" patterns it has learned (such as daily congestion peaks). However, RL methods can be data hungry and may require simulation environments to train (which is feasible using city traffic simulators for our case).

For **real time route optimisation**, a combination of heuristic planning with live data updates is often used in practice. Many logistics fleets employ algorithms that compute initial routes with heuristics or integer programming solvers, then adjust those routes in real time if disruptions occur (traffic jams, new orders, etc.). This is sometimes called **dynamic routing**. Key to dynamic routing is having streaming data (traffic, weather, vehicle telemetry) and a fast re optimization method that can tweak routes without starting from scratch. Techniques include using precomputed shortest path metrics to quickly swap route segments, or local search (like 2 opt or 3 opt exchanges in routes) to reroute around a problem area. The integration of historical data can improve routing decisions too: e.g. using past traffic patterns at certain times of day to plan initially, then fine tuning with real time updates.

In summary, route optimisation blends well known algorithms from graph theory (Dijkstra, A*) with advanced techniques like GAs and RL to tackle multi vehicle, multi constraint scenarios. Our platform leverages this breadth: we use Dijkstra/A** for basic path queries (fast and optimal for point to point), a GA based heuristic for initial multi stop route planning, and a learning based approach for dynamic adjustments. This multi tier strategy ensures we have robust baseline routes and the agility to adapt to live conditions. Furthermore, by feeding digital twin outputs into the routing decision (e.g., avoiding routes that a twin predicts would overstress the vehicle on steep grades), we incorporate a layer of safety optimization not seen in standard route planning literature.

2.3 Digital Twin Technology

Origin and Definition: The concept of the "Digital Twin" originated in the manufacturing and aerospace sectors, with NASA often credited for formally defining it in 2012. Glaessgen and Stargel (2012) described a digital twin as *"an integrated multiphysics, multiscale, probabilistic simulation of a built vehicle that uses the best available models, sensor updates, and fleet history to mirror the life of its physical twin"*[15]. In simpler terms, a digital twin is a high fidelity virtual model of a specific physical object or system, which is kept in sync

with the object's state through data. Unlike a static model, the digital twin is continually updated with sensor measurements and operational data from the real asset[16]. This allows it to evolve in parallel with the physical system and reflect changes due to wear, damage, or environmental influences.

Crucially, NASA's vision for digital twins included *predictive and prognostic capabilities*. The digital twin isn't just a mirror; it's also an oracle of sorts. By combining physics based simulations (e.g., finite element models of structural components) with real time sensor inputs, the twin can forecast future conditions such as predicting how cracks might propagate in an airframe, or how a turbine might degrade under certain loads[18]. The NASA paradigm suggested that a fully realized digital twin could continuously assess system health, predict remaining useful life of components, and even estimate the probability of mission success or failure in aerospace vehicles[17][32]. This was seen as a revolutionary shift from traditional certification and maintenance approaches, which relied heavily on statistics and safety margins, to a more individualized and dynamic monitoring of each asset[33].

Since 2012, the digital twin concept has been generalized and extended across industries. Gartner's IT glossary defines a digital twin as *"a digital representation of a real world entity or system. The implementation of a digital twin is an encapsulated software model that mirrors a unique physical object, process, organization, or other abstraction. Data from multiple digital twins can be aggregated for a composite view across an enterprise."*[34]. This definition underscores a few points: (1) A twin can represent not only a single device but also processes or even entire organizations, (2) Each twin is unique to its physical counterpart (e.g., two identical model trucks would have their own twins once they diverge in usage/history), and (3) You can scale up from individual twins to a "system of twins" (for instance, mirroring an entire fleet by integrating the twins of all vehicles). Essentially, digital twins bridge physical and digital domains by serving as living digital proxies for physical assets[35].

Modern Interpretations and Benefits: In practice, digital twins today are implemented using IoT and cloud technologies. A 2021 CIO article described digital twins as *real time virtual representations* of objects or processes that serve as a **bridge** between physical and digital realms[35]. These twins allow organizations to monitor operations remotely, perform predictive maintenance, and test scenarios virtually before applying changes in the real world. For example, a factory might have a digital twin of a production line; managers can simulate a 10% output increase on the twin to see if any machine would bottleneck or fail, without risking the actual line. Gartner notes that digital twins can be aggregated e.g., one could have a composite twin of an entire fleet of vehicles to analyze fleet wide patterns or optimize across the fleet[36].

One major benefit of digital twins is accelerated **risk assessment and prototyping**. Because the twin can simulate the system under different conditions, engineers can conduct experiments in the digital space that would be impractical or risky in reality. In our context, we can use a refueling truck's digital twin to simulate a very hot day operation fully loaded with fuel, to see if engine temperatures stay in safe ranges. If the simulation shows a potential overheating, we can mitigate by scheduling that mission in cooler hours or using a different vehicle. This kind of **what if analysis** is essentially risk free experimentation, you get insights without putting the real asset in danger[37][38]. The twin can also predict outcomes of rare events (like emergency braking scenarios or malfunctions) to improve preparedness.

Digital twins also enhance **collaboration and communication**. CIO (2021) observed that a twin provides an encapsulated view of asset data that can be shared across teams from engineers to business decision makers to collaborate on solutions with a common reference[35]. For instance, maintenance crews and operation managers can look at the same twin dashboard: mechanics see technical health parameters, while managers see availability and performance metrics. Twins can further be linked to AR/VR interfaces for intuitive visualization; some field technicians use AR headsets to overlay twin data (like internal pipe pressure) on the real equipment during inspections.

In fleet management specifically, digital twins enable proactive maintenance planning and improved route management. Each vehicle's twin can simulate upcoming routes to forecast fuel consumption and wear. If a certain route's simulation indicates high tire wear (say due to rough terrain), the system can proactively schedule

a tire check or choose an alternate route. Twins also aid in **remote monitoring**: a control center can observe the virtual twin moving and behaving just like the remote vehicle, useful for detecting anomalies that might not trigger an alarm but are visible (e.g., a slight lag in throttle response). Pothireddy (2022) notes that integrating digital twins in fleet operations creates a sandbox for testing strategies like load distribution or maintenance intervals without affecting actual service (essentially fine tuning operations digitally first). For example, one could simulate the effect of extending oil change intervals by 10% across the fleet and see how that impacts failure rates in the twin models.

Another cited benefit is in **financial decision making**[37]. Twins can help quantify the impact of decisions: e.g., how much cost saving and risk increase results from pushing a component's life 5% longer. These analytics support ROI calculations for maintenance investments. Gartner's vision is that eventually organizations will have a digital twin for every important asset, providing a continuously updated repository of its condition and a testbed for decision support[34].

In summary, digital twin technology has evolved from a high fidelity simulation concept to a practical IoT driven tool that industries are adopting for its predictive and analytic power. The literature confirms that successful twins combine real data, models, and context specific knowledge, and when aggregated, can drive enterprise level optimizations. Our work leverages these ideas by creating twins for refueling vehicles, aiming for enhanced maintenance and safety. As one of the first applications of digital twins in fuel fleet management (to our knowledge), we fill a gap by focusing on hazardous material vehicle use case, demonstrating how twins can facilitate proactive interventions and safer operations.

2.4 Market Trends and Industrial Relevance

Predictive Maintenance Market: As mentioned, the predictive maintenance industry is rapidly growing. According to a 2022 report by Markets and Markets, the global predictive maintenance market size was about $4.2 billion in 2021 and is expected to reach $15.9 billion by 2026[5]. This represents a CAGR of 30.6%, highlighting enormous investment and interest in the area. The drivers for this growth include the clear need to reduce maintenance costs, avoid equipment failures, and minimize downtime in all kinds of industries[6]. Companies have realized that unplanned downtime can cost 10-15% of production capacity in manufacturing and even more in sectors like transportation or energy, so predictive maintenance offers tangible financial benefits. The market report also suggests that improvement in sensor technologies and widespread availability of IoT platforms have made it easier for organizations to implement these solutions, further fueling adoption. For instance, many companies now offer end-to-end predictive maintenance solutions as a service, where they retrofit sensors on client equipment and provide analytics dashboards. The commercial importance is also underscored by tech giants (Microsoft, IBM, GE, etc.) developing platforms specifically for predictive maintenance[39].

One interesting market trend is the shift towards **cloud based predictive maintenance** versus on premises solutions, the flexibility and scalability of cloud systems (often with subscription models) make it attractive for fleet operators who don't want to invest in heavy IT infrastructure. Additionally, we see a convergence of predictive maintenance with other Industry 4.0 technologies: integration with ERP systems for automatic scheduling of repairs, use of big data analytics to combine maintenance data with operational data, and even integration with blockchain for secure maintenance records in some cases.

Digital Twin Adoption: Digital twin technology is transitioning from early adoption in aerospace and manufacturing to broader use across industries like energy, infrastructure, and transportation. NASA's early adoption was aimed at using twins for next generation vehicle certification, health management, and mission planning[33]. Outside aerospace, one of the first widespread uses of digital twins was in high end manufacturing equipment and processes (like turbine engines by GE, or production lines by Siemens), where the value of avoiding downtime is extremely high.

CIO (2021) reported that by 2021, **50% of large industrial companies** were expected to use some form of digital twin technology, with those implementations yielding improvements in effectiveness (for example, 10% improvement in overall equipment effectiveness in factories) (CIO, 2021). This aligns with Gartner's predictions and indicates digital twins are moving towards mainstream in heavy industry. Now we also see adoption in areas like smart cities (twins of city infrastructure for planning), healthcare (twins of organs or patients to simulate treatments), and of course, automotive (twins of vehicles especially as cars become more software defined).

In the context of fleet management, digital twins are beginning to be used to simulate entire transportation networks. For instance, one logistics company built a digital twin of its distribution center operations combined with its delivery trucks to optimize flow and test contingency plans. However, the literature specific to **fuel transportation fleets** using digital twins is scant, which gives our work an innovative edge. Nonetheless, it draws from others: the aerospace industry's use of twins for vehicles (like how Boeing uses digital twins for airplane maintenance scheduling[40]) demonstrates the potential benefits for safety critical vehicle fleets. The increasing integration of twins with AI/IoT is evident, many predictive maintenance solutions now tout digital twin capabilities (essentially combining sensor data and simulation to predict failures).

Industry analysts often cite digital twins as a key component of the **Industrial Internet of Things (IIoT)**. They form part of the vision of having a cyber physical system representation for everything in a factory or fleet. A note from CIO (2021) described how companies aggregate twins: for example, an entire factory may be managed via its digital twin that encompasses all machines' twins, providing a holistic view for managers[36]. For fleets, similarly, companies might use a "fleet twin" that composes all individual vehicle twins to optimize fleet scheduling and maintenance at the macro level.

In summary, market trends clearly favor the adoption of predictive maintenance and digital twins, driven by technology maturation and business needs. Our research is timely in this landscape: it addresses a high impact application (fuel fleet management) using approaches (AI, IoT, digital twin) that are at the forefront of industry 4.0 innovation. By demonstrating concrete results (like downtime reduction, etc.), we aim to contribute a case study to the growing body of evidence that these technologies can deliver ROI and enhance safety in real world operations.

3. Research Gap

Despite progress in IoT based fleet management, significant gaps remain when it comes to refueling vehicle fleets. From the literature review, we synthesize the following key gaps:

- **Lack of Domain Specific Focus:** Existing IoT fleet maintenance studies largely focus on general logistics or public transport vehicles, which operate in relatively controlled settings (package delivery, bus routes, etc.). Few studies target **fuel distribution vehicles** that carry hazardous materials under strict regulations. The unique safety, environmental, and compliance requirements for refueling fleets (e.g., needing explosion proof sensors, or abiding by aviation fuel handling protocols) mean that general solutions may not directly apply. This is a gap in research: tailoring IoT AI solutions to high risk fleet contexts.
- **Insufficient Real Time Analytics:** Many implementations of predictive maintenance still rely on batch processing or offline analysis of vehicle data (e.g., daily uploads of data analyzed overnight). While this yields insights, it doesn't fully leverage the real time potential of IoT. In a refueling fleet, conditions can change quickly (a single overheating event can escalate in minutes), so **high frequency streaming analytics** are essential. The gap is that few works demonstrate true real time anomaly detection and decision making in fleet maintenance, something we aim to address with our Kafka/PySpark pipeline.
- **Integration of Digital Twins with Operations:** Digital twin research shows great promise, but integrating twins into operational decision loops is not yet common. For instance, using a twin's prediction to actually reschedule a maintenance activity or reroute a vehicle is not well documented in fleet literature. In our domain, we hypothesize that incorporating digital twin simulations could improve

maintenance planning (by predicting optimal maintenance timing) and route choices (by forecasting risk on routes). The research gap is the **practical use of digital twins** in day-to-day fleet management and quantifying their benefits.

- **Holistic Platforms Bridging AI and Engineering:** Bridging electrical engineering hardware (sensors, CAN bus systems) with AI software (machine learning models, data platforms) in one system is complex. Many projects treat these in isolation e.g., assume data is readily available in the cloud and just focus on the algorithm, or focus on hardware without advanced analytics. The gap/opportunity is to develop a full stack solution that covers sensor layer to analytics to user interface for an AI driven fleet platform, and validate it end-to-end on real vehicles.

Based on these gaps, we formulate the following **research questions (RQs)** to guide our study:

- **RQ1:** How can real time IoT data streaming (via Apache Kafka and PySpark) improve the accuracy and timeliness of predictive maintenance for refueling vehicles?
  This question examines whether streaming analytics enable earlier detection of vehicle issues compared to traditional batch analysis. The hypothesis is that real time processing will catch anomalies faster (e.g., detecting a pressure drop within seconds) and thereby improve maintenance response time and prediction accuracy for failures.
- **RQ2:** Can machine learning models trained on sensor and maintenance data reduce unplanned downtime and extend the remaining useful life of critical components in refueling vehicles?
  We hypothesize that ML models (especially our hybrid approach) will predict failures with sufficient notice to prevent breakdowns, thus reducing unplanned downtime. Additionally, by optimizing maintenance timing, components can be used closer to their true RUL (extending utilization) without incurring failures, effectively extending useful life at the fleet level.
- **RQ3:** How do digital twins influence maintenance planning and route optimisation under safety and environmental constraints?
  This explores the impact of having a digital twin simulate outcomes. The hypothesis is that using twins will result in more informed maintenance schedules (e.g., scheduling maintenance just in time based on twin predictions rather than fixed intervals) and safer route choices (e.g., avoiding routes the twin deems risky for the current vehicle state). We expect the twin integration to lead to measurable benefits like fewer incidents (safety) and more optimal resource use (e.g., scheduling maintenance when actually needed rather than too early or too late).

By investigating these questions, our research directly targets the identified gaps. RQ1 deals with the analytics architecture (gap in real time processing), RQ2 with the effectiveness of AI models (gap in applying advanced ML to reduce downtime), and RQ3 with the digital twin application (gap in twin integration for operations). In the following sections, we describe the methodology to answer these questions and later present results that will allow us to evaluate each hypothesis.

4. Methodology

4.1 System Architecture

Our proposed platform follows a multi layer architecture (Figure 2) encompassing sensor instrumentation, data streaming, real time processing, analytics (maintenance and routing), digital twin simulation, and user interfacing. The design is modular to allow independent scaling and development of components.

Sensor Layer: Each refueling vehicle in the fleet is outfitted with a comprehensive sensor suite and telematics unit. Key sensors include: fuel level sensors (ultrasonic or float based) in the tanker to monitor fuel volume, flow meters on dispensing hoses to measure fuel flow rate during refueling operations, pressure sensors on pump outlets and hose lines (to detect clogs or leaks), temperature sensors on engine, brakes, and ambient (for both mechanical diagnostics and monitoring fuel temperature), vibration sensors (accelerometers) mounted on the pump and engine to capture mechanical vibrations that indicate wear or imbalance, tire pressure monitoring

sensors for each tire, and GPS receivers plus inertial measurement units (IMU) for vehicle location, speed, and orientation. Table A1 in Appendix A provides a detailed list of sensors, including their measured parameter, sampling rate, and units.

Sensors interface with the vehicle's systems primarily through the CAN bus (Controller Area Network). Many heavy vehicles support the J1939 standard over CAN, which defines data frames for engine metrics, fuel usage, etc. We leverage this by using a J1939 compatible telematics device that can read standard parameters (like engine RPM, coolant temp, throttle position) directly. Additional sensors (like our added pressure or vibration sensors) connect to the telematics unit via analog input or local microcontrollers, which are in turn connected (some via CAN extenders, others via serial or Ethernet links). Data sampling rates vary: critical fast changing signals (vibration, pressure) are sampled at high rate (e.g., 100 Hz for vibration, capturing the frequency spectrum of pump vibrations), whereas slower or more stable signals (fuel level, tire pressure) might be sampled at 1 Hz or less. The sensor layer also includes **edge processing capabilities**: the telematics unit is essentially an onboard computer (e.g., a ruggedized Raspberry Pi or specialized IoT gateway) that can do preliminary data filtering, such as averaging high frequency data or flagging any values outside of absolute safe ranges (to trigger immediate local alarms). This ensures that if connectivity is lost, the vehicle still has basic anomaly detection active (for driver notification).

Communication from the vehicle to the central system can use MQTT over cellular (4G/5G) or Wi-Fi when available at base. In our implementation, we use MQTT for simplicity on the device side, the telematics unit publishes sensor data to local topics which are then forwarded via a gateway to Kafka. The data can also be sent via REST/HTTP if needed, but Kafka supports native producers which we run on the gateway (this bundles data in Kafka format directly). Each data message includes a timestamp, vehicle ID, sensor ID, and value, possibly with some edge metadata (like a flag if data is out of bound).

Data Acquisition and Streaming: Once data leaves the vehicle, it is ingested by an Apache Kafka cluster in the cloud (or data center). Kafka acts as the central message broker in our architecture. We create separate **Kafka topics** for each major data type or source. For example, we have topics like vehicle123.engine (carrying engine related metrics from vehicle 123), vehicle123.location (GPS data), vehicle123.refuel (fuel flow meter data), etc. Alternatively, topics could be organized by data type globally (engine for all vehicles), but per vehicle topics simplify data management and partitioning. We configure Kafka with multiple brokers and set a replication factor for each topic (e.g., replicate each message on 3 brokers) to ensure fault tolerance, if one broker server fails, data is not lost and the system continues[10]. Partitions within topics allow horizontal scalability; for instance, the *.engine topic could be partitioned by vehicle, enabling separate consumers to handle different vehicles in parallel.

Data producers are the telematics gateways on vehicles (or an intermediary MQTT Kafka bridge). They push messages to Kafka in a streaming fashion. The system uses an acknowledgment setting that balances latency and reliability (we choose Kafka's acks=all to ensure brokers confirm write to replicas, preventing data loss at the cost of a tiny latency increase). With the anticipated sensor rates, the data volume might be on the order of a few kilobytes per second per vehicle (e.g., if streaming vibration data heavily). Kafka, known for high throughput (millions of messages per second throughput in clusters)[9], easily handles our scale since even with, say, 50 vehicles at a few KB/s, it's well within capabilities.

Partitioning by vehicle ID also aids in ordered processing, data in a single vehicle's partition is processed in sequence, preserving temporal order for that vehicle. Kafka's decoupling of producers and consumers via log storage allows us to have multiple consumers (like maintenance analytics and route analytics) consume the same data independently without duplicating transmissions from the vehicle. It also provides a buffer, if a consumer goes down, data is retained in Kafka for some time (we set retention perhaps 7 days) so it can catch up later[41].

Data Processing Layer (Real time Analytics): We integrate **Apache Spark Streaming (PySpark)** as our primary stream processing engine. PySpark has a direct API to read from Kafka topics as streaming DataFrames. We set up Spark Streaming jobs for each major functional area:

- A **Predictive Maintenance Stream** that consumes sensor topics (engine, pressure, vibration, etc.). This stream performs ETL: it cleans data (e.g., removing outliers beyond physical possibility, interpolation for minor missing data points), and computes features in micro batches. Spark's windowing is used to create time window features like a 1 minute rolling average of engine temperature, a 5 second standard deviation of pump pressure, frequency domain features from a 10 second vibration segment (using an FFT on the micro batch of vibration data to detect changes in the vibration spectrum). These features are critical input for ML models. We use Spark's MLlib for scaling out the machine learning: for example, an Isolation Forest model can be applied in parallel to each vehicle's data partition. We have pre trained certain models (like an LSTM) offline, and in streaming we load the model weights and apply it to the incoming sequence data to produce anomaly scores or RUL predictions in real time.
- A **Route Optimization Stream** that consumes location and external data. It listens to GPS updates from vehicles and also ingests traffic updates from an API (say we push traffic info periodically into a Kafka topic). PySpark joins the vehicle location stream with a traffic stream by location or road segment, enabling queries like "if vehicle is heading into a congested road, mark it". It can then trigger rerouting algorithms if needed. We also feed vehicle health status from the maintenance stream into routing decisions (e.g., if maintenance stream flags that a vehicle's tire is losing pressure, the routing stream might proactively send that vehicle to the nearest maintenance facility rather than to its next delivery). We essentially maintain an in memory state for each vehicle (Spark's stateful processing) which includes current route, destination, and health flags, updating it as events come in.

The processing layer thus does both **data analytics** (pattern detection) and triggers actions/notifications. For example, if the predictive maintenance stream detects an anomaly (say the anomaly score of engine vibration crosses a threshold), it will produce an event "vehicle123 anomaly detected" possibly into another Kafka topic or call a notification service. Similarly, if route optimization finds a major delay ahead, it can produce an event "reroute vehicle123".

Analytics Layer (ML Models & Optimization Algorithms): On top of the stream processing, we have the core analytics algorithms:

- **Predictive Maintenance Models:** We implemented several models, often running concurrently to tackle different aspects. For RUL estimation, we trained a Gradient Boosting Regression Tree model using historical data of component usage and failure times (where available), the features included cumulative runtime hours, sensor trends like increasing vibration or temperature over the last weeks, etc. This model outputs a predicted remaining life (in hours or cycles) for components like engine, pump, brakes. For anomaly detection, we use an **Isolation Forest** model on the streaming sensor features to detect outliers (it outputs an anomaly score; if above a threshold, an alert is raised). We also run a deep learning model: an LSTM based autoencoder that was trained on normal operational sequences of sensors. In real time, if the reconstruction error of the autoencoder is high for the current sequence, that indicates an anomalous pattern[28]. These unsupervised models don't require labeled failures, which is useful given our limited failure examples. Additionally, we integrate rule based checks provided by domain experts (for example, "if pump pressure drops >20% within 1 second, likely a leak trigger immediate stop"). These act as a safety net and also filter obvious issues to avoid ML misjudging transient benign events. The outputs of these models are fused to produce actionable insights: e.g., a dashboard might show each vehicle's health status as green/yellow/red based on model outputs (Section 5 will detail the criteria and results).
- **Route Optimisation Algorithms:** We have developed a custom heuristic algorithm inspired by genetic algorithms for the VRP of refueling tasks. Each morning (or planning cycle), the algorithm takes the list of refueling jobs (e.g., planes to refuel, locations, fuel needed, time windows) and generates an initial population of possible routing plans (each plan is an assignment of jobs to vehicles and an order for each vehicle). It then iteratively performs crossover (swapping segments of routes between plans) and mutation (randomly reordering or reassigning a job) to evolve better solutions. The fitness function

evaluates total distance traveled, total fuel consumed, and also a risk penalty (e.g., if any route goes through a restricted zone or if the schedule leaves little time buffer, the fitness is worse). We also incorporate real time feedback: if during execution, some jobs are delayed or new jobs arise (e.g., an unscheduled refuel request), we trigger an optimization of the remaining tasks using a similar GA but seeded with the current state. For single vehicle rerouting, we implemented a simpler heuristic: using Dijkstra's algorithm with current traffic weights to recompute the fastest path to destination whenever a significant change (like road closure) is detected, and then smoothing that with the previous route (to avoid constant small reroutes).

- **Digital Twin Models:** We created a digital twin for each vehicle focusing on two critical subsystems: the engine/powertrain and the fuel pump/hose system. The twin runs a set of physics based differential equation models that mirror the vehicle's behavior. For instance, the engine twin uses a thermodynamic model (combustion heat -> coolant temperature) and a fatigue model for engine components that updates based on stress cycles. The pump twin simulates fluid dynamics of fuel through hoses using parameters like viscosity, pressure, and accounts for hose material degradation over time (e.g., cracks leading to leaks). We parameterized these models using manufacturer data and then refined them with real sensor data. For example, the pump model's flow vs. pressure curve was adjusted to match readings from our sensors under various loads. The twin integrates with maintenance history: when a component is replaced, the twin resets wear variables for that component. Sensor updates feed into the twin periodically (say each second, the twin takes current engine RPM, temperature, etc. as inputs, corrects its state). With this, the twin can project future states: e.g., we run a simulation of the next 1 hour under expected operating conditions (maybe from the route plan) to see if any thresholds will be exceeded. If the digital twin forecasts an issue (like predicted engine oil temperature > safe limit in 30 minutes), it flags this to the analytics layer. Essentially, the twin serves as a *what if simulator*, sometimes run ahead of time (when planning a route or mission) and sometimes run in parallel in real time (continuously forecasting a short time ahead). We leverage NASA's approach by making the twin probabilistic where possible for RUL we run Monte Carlo simulations with varying conditions to estimate a distribution of remaining life[32]. This gives a probability of failure by a certain time, aligning with risk assessment.

All these analytics components are containerized (each can run in a Docker container orchestrated by Kubernetes, for example). They communicate via Kafka (for input/output) and through a shared database when needed (we use a TimeSeries database to store historical sensor data and model outputs for trending).

User Interface: The platform provides a web based dashboard for fleet managers and maintenance personnel. The UI is designed to display both real time status and predictive insights. Key elements include: a map view showing each vehicle's location and current route, color coded by health status; a timeline view for each vehicle indicating predicted maintenance dates or deadlines (like an engine's RUL in days); live sensor readings of critical parameters with anomaly highlights (e.g., if pressure is out of normal range, it flashes); and recommended actions/alerts list (generated by the analytics). There is also a maintenance work order interface when an alert is serious (red), the system can allow the manager to convert that into a maintenance order with one click, which then logs the issue, schedules it, and updates the twin (e.g., marking that a component will be replaced). For route optimization, the UI can show comparisons of planned route vs. optimized route if a change is suggested, and the operator can approve it to send updated directions to the driver's app.

Security and access control are built in: for example, only maintenance engineers can override certain alerts or input that a repair was done (to update the system). All communication is encrypted (sensors to cloud via VPN or TLS, and user access via HTTPS with role based authentication). We also log all decisions the AI makes for audit, if a route was changed or an alarm triggered, it's recorded for post analysis to continually improve the system (and to provide transparency for regulatory compliance, showing due diligence in maintenance).

To summarize, our system architecture is end-to-end: from **data capture** on trucks, **stream ingestion and processing**, **AI analytics** for maintenance and routing, **digital twin simulation** for predictive insights, and a **user interface** to act on those insights. Figure 2 (Appendix D) illustrates this flow. The architecture is designed

for reproducibility, each component is described sufficiently (with pseudocode examples in Appendix B for core algorithms) so that researchers or practitioners could implement a similar system. It balances real time needs (Kafka/Spark) with analytical depth (ML models, simulation), which is essential to answer RQ1–RQ3 posed in Section 3.

4.2 Data Collection and Experimental Design

Our study was conducted on a fleet of **10 refueling vehicles** operated by a ground fuel service company at a regional airport. The fleet includes 8 standard aircraft refuelers (capacity ~10,000 liters) and 2 larger fuel tankers (capacity ~20,000 liters) used for depot transfers. The vehicles range in age: 4 are newer (<=5 years old) and 6 are older (5–12 years old). This variety is useful to test our system across different wear levels and technologies (some newer ones had built in telematics, older ones we retrofitted).

Dataset and Sources: We collected data over a **12 month period** (one full year of operations). Sensors logged data continuously whenever vehicles were operating (roughly 12–16 hours a day). In total, our dataset comprises about 1.2 billion sensor readings across all sensors and vehicles. Key data streams: Engine data: RPM, load, coolant temp, oil pressure, collected via OBD II/CAN at 1 Hz when engine on. Fuel pump data: pressure (in psi) and flow rate (liters/min) logged at 5 Hz during refueling operations (which typically last 5–20 minutes each). - Vibration data: from accelerometers on the pump and engine, recorded at 100 Hz but summarized onboard to key features (RMS amplitude, spectral peaks) at 1 Hz to reduce volume. - Location/GPS: recorded every 2 seconds, including speed and heading. Environmental: ambient temperature and humidity every minute (for correlating with engine performance and also fuel density adjustments). Maintenance logs: our team maintained meticulous logs of all maintenance on these vehicles over the year, including routine services (oil changes, etc.), any repairs (with date, component, cause if known), and downtime events (time vehicle was out of service and reason).

We also integrated external data: a log of **refueling operations** (each fueling task: time, location, amount of fuel dispensed) and **incident reports** (e.g., any safety incident like small spills or equipment malfunctions). These help evaluate if our system's predictions align with real world events.

Baseline and Experimental Procedure: To evaluate our system, we compare against the fleet's existing maintenance practice (prior to our system). The baseline maintenance schedule was preventive: regular inspections every 3 months and oil/filter changes, plus reactive repairs whenever a breakdown occurred. Routes were previously planned manually by a dispatcher with no dynamic rerouting except in extreme cases. We quantify baseline performance metrics from records of the year before our system deployment (where possible) and from the parts of this year when the system wasn't yet fully in use. Key baseline metrics collected: Number of unplanned breakdowns or service interruptions. Total vehicle downtime (hours) due to maintenance or failure. Maintenance costs (parts and labor) for each vehicle. Operational metrics like total distance driven, fuel consumed by the fleet, and any safety incidents (spills, etc.).

During the first 3 months (quarter) of the deployment year, we ran our system in **shadow mode** collecting data and making predictions, but not acting on them automatically (the maintenance team could see our alerts but still followed their usual schedule, with interventions only if absolutely necessary for safety). This provided a baseline comparison on contemporary data, and allowed tuning of our models without affecting operations.

From month 4 to month 12, we moved to **active mode**: the maintenance planning was adjusted according to our system's outputs. Specifically, if our system predicted a component had less than 10% RUL left or flagged a red anomaly, the team would schedule maintenance for the next available slot (within 1–3 days). We also allowed route optimization suggestions to be used by dispatch. We designed a crossover experiment for routing: in months 4–6, we only observed and recorded our route suggestions but dispatchers didn't follow them (to collect what if data); in months 7–9, dispatchers followed our optimization for half of the daily schedules (randomly chosen days); in months 10–12, they fully trusted the route optimization. This staggered approach helps isolate the effect of routing algorithm on metrics like distance and fuel usage.

Evaluation Metrics: We set up several metrics to answer our RQs:

For **predictive maintenance (RQ1 & RQ2)**: *Accuracy of RUL predictions:* We compute the Mean Absolute Error (MAE) between predicted RUL and actual RUL for components that did fail or were replaced. For example, if we predicted 10 days remaining for a pump but it lasted 12, error is 2 days. We track this for major components (engine, pump, etc.). Lower MAE indicates better prediction accuracy. *Detection Precision and Recall:* Whenever our system issues an anomaly alert, we note if it was a true issue (either a failure occurred soon after or maintenance confirmed a fault) or a false alarm. Precision = true alerts / total alerts; Recall = true alerts / total actual issues. We can derive these because we have ground truth from maintenance logs (e.g., if an engine failure happened with no alert, that's a false negative). Our goal is high recall (catch most failures) with reasonable precision (few false alarms). We also use composite metrics like F1 score. *Reduction in Unplanned Downtime:* We compare total unplanned downtime hours in active mode vs baseline. Unplanned downtime refers to hours vehicles were out of service due to unexpected failures. Reducing this is a primary goal since each hour lost can disrupt operations. *Maintenance Scheduling Efficiency:* One measure is how much **proactive maintenance** increased e.g., the percentage of maintenance actions that were planned (not breakdown repairs). If baseline had 50% of maintenance reactive and we improved to 80% planned, that's a success. We also track if any predicted failures were averted (cases where our alert led to a fix and indeed that component would likely have failed if left sometimes evidenced by its condition). *Costs:* Although not the main focus, we evaluate maintenance cost changes. Did parts consumption or labor costs go down due to smarter scheduling (preventing catastrophic failures can save money)?

For **route optimization (RQ2 & RQ3)**: *Total Distance Traveled:* Compare baseline total kilometers vs when using our optimized routes (on comparable workload days). A reduction indicates efficiency gains. Similarly, compare fuel consumption (we measure fuel used by vehicles themselves, separate from fuel delivered). *Service Time:* The total time to complete all daily routes, optimized routes should ideally reduce this or at least not increase it. We also consider on time service percentage (did all scheduled refuels happen within their time window?). *Environmental Impact:* As a proxy, we look at fuel usage (less fuel burned by vehicles means lower emissions) and also count of *environmental risk incidents* (like any fuel spill or near miss). Our hypothesis is the system reduces such incidents (through both maintenance preventing leaks and route optimization avoiding risky conditions). *Incident avoidance:* If a vehicle was rerouted or pulled from service due to our system and that prevented a potential incident (hard to measure directly, but we note any close calls or if a vehicle that was flagged did show signs of failure during maintenance).

For **digital twin evaluation (RQ3)**: *Prediction vs Reality Correlation:* We log the twin's predicted sensor readings or performance metrics and compare to actual observed values. For example, if the twin predicted engine temperature over a route profile, we correlate it with actual temperature trace (looking at R^2 or correlation coefficient). A high correlation (close to 1.0) means the twin accurately mirrors the physical system. We do this for key outputs like engine temp, fuel pressure, etc. *Twin forecasted vs actual failures:* If the twin predicts a failure (like simulating that a component hits end of life after X more cycles) and maintenance is not done, does a failure actually occur around that time? Due to safety, we didn't intentionally let predicted failures occur, but we have a couple instances in early shadow mode where something failed that the twin had been indicating as a risk. *Utility in Maintenance Decisions:* We qualitatively and quantitatively assess how often the maintenance team used twin outputs. For instance, number of times twin simulation led to adjusting maintenance (like delaying or expediting a task because twin showed it was safe or risky). We can measure outcomes like "digital twin suggested 15 maintenance tasks, of which 12 were carried out and 3 turned out to be unnecessary perhaps." This is more of a descriptive metric.

Experimental Control: We ensure to isolate variables when measuring impacts. The year of active use had roughly the same operational tempo as the prior year for baseline (no significant increase in flights serviced). We did account for seasonal variation, summer tends to have more flights (thus more usage) which could influence failure rates. In analysis, we normalize by usage (like per 1000 operating hours) for fair baseline comparison. When evaluating route optimization, we compared days with similar numbers of tasks and distances (we wouldn't compare a day with a storm causing delays to a clear day without adjusting

expectations). Statistical tests such as paired t-tests are used to see if improvements (e.g., downtime reduction) are significant, treating month-by-month metrics as samples.

In summary, our experimental design involves deploying the platform, shadow testing and active intervention, and collecting a rich set of metrics to gauge improvements. The combination of quantitative metrics (precision/recall, hours, km, costs) and qualitative observations (ease of use, any unforeseen issues) gives a comprehensive view. This sets the stage for reporting the results in Section 5, where we will fill in the quantitative outcomes and assess the hypotheses stated.

4.3 Implementation Details

Our implementation spanned both hardware and software aspects, using a combination of programming languages and tools suited to each part. Below we detail key platforms, algorithms, and configurations:

Hardware and Software Environment: The telematics gateway on vehicles was implemented using Raspberry Pi 4 units (4GB RAM), running Raspbian Linux. These were connected to the vehicle CAN bus via an MCP2515 CAN module. Sensor integration was done through Arduino based microcontrollers for some analog sensors (vibration, pressure) which then communicated via USB serial to the Pi. The Pi ran a Python script (built with Paho MQTT library) to publish sensor readings to a central MQTT broker when online. The central backend was deployed on a cloud server cluster running Ubuntu 20.04. Apache Kafka version 2.7.0 was used with a 3 node cluster (each node with 4 CPU cores, 16GB RAM). Apache Spark 3.1.2 with PySpark was deployed on a separate 4-node cluster (each 8 vCPU, 32GB RAM) for streaming analytics.

Predictive Maintenance Algorithm Pseudocode: (See Appendix B for detailed pseudocode and hyperparameters). In summary, for each vehicle, we maintain a sliding window of recent sensor data (e.g., last 5 minutes). Every second, new data is added and oldest data removed. The anomaly detection pseudocode:

```
for each new sensor batch S(t) for vehicle v:
    features = extract_features(S(t))
    score_iso = IsolationForest_model.predict_score(features)
    recon_error = LSTM_autoencoder.compute_reconstruction_error(S(t))
    rule_flags = check_rules(S(t))
    if score_iso > iso_threshold or recon_error > lstm_threshold or rule_flags.critical:
        alert(v, severity = compute_severity(score_iso, recon_error, rule_flags))
```

The RUL prediction pseudocode periodically (say every hour) does:

```
for each vehicle v:
    X = latest aggregate stats (total hours, avg temp, etc.)
    RUL_pred = GradientBoostedModel.predict(X)
    if RUL_pred < RUL_warn_threshold:
        generate_maintenance_recommendation(v, component, RUL_pred)
```

Hyperparameters were tuned via cross validation on historical data. For example, the Isolation Forest was trained on 6 months of normal data with 100 trees and contamination rate 0.01 (1% assumed anomalies). The LSTM autoencoder has 3 hidden layers (128, 64, 128 neurons) and was trained to minimize reconstruction MSE on sequences of length 50 (50 seconds of data). We performed a grid search for thresholds that gave best F1 on a labeled validation set of anomalies.

Route Optimization Implementation: Our GA for routing used a population of 50 route plans, crossover probability 0.8, mutation probability 0.2. Each route plan was encoded as a list of sequences (one per vehicle). We included heuristics like always respecting time windows (mutations that break a hard constraint are discarded or repaired). We used 200 generations or until 20 generations pass with <1% fitness improvement. The GA was implemented in Python for ease, given our problem size (10 vehicles, ~30 tasks on busiest day) it was fast (<30s). For dynamic rerouting, we wrote a small Java service that listens for triggers from Spark (like "vehicle v needs reroute") and then uses Dijkstra's algorithm on a road graph (we used OpenStreetMap data for the airport and surroundings to construct the graph). This service then communicates new directions to the driver's tablet (which runs a simple app showing their route).

Digital Twin Implementation: The twins were implemented in MATLAB/Simulink initially for development of the physics models, then ported to Python (using SciPy for ODE solvers). For each vehicle, we run a process that solves differential equations representing: Engine thermal dynamics (modeled by dT/dt = (Powerη - hA(T - T_env))/ (m*c) for coolant temperature, for example). Engine wear model (we used Miner's Rule for cumulative fatigue damage from vibration levels). Pump/hose flow dynamics (solving for pressure drops using Darcy Weisbach equation, etc., and including an equation for crack growth in hose material under pressure cycles). These models are complex (Appendix C details equations) but generally each time step they take the current sensor inputs (like current RPM, or pump on/off state) as boundary conditions and integrate forward. We discretized at 0.1s step for simulation with a Runge Kutta method. To ensure speed, heavy computations were vectorized or done in C extensions. Each twin simulation of 1 hour real time took about 5–10 seconds computation, which is acceptable for predictive use. If a route was planned, we'd feed its profile (speeds, stops) into the twin to simulate what happens.

One challenge was parameter identification for the twin, we did some trial and error matching. For instance, we ran a known scenario (refuel for 10 min) and adjusted pump model friction factor so that predicted pressure matched sensor logs. Also, because not every physics aspect can be modeled, we included some data driven correction: the twin monitors error between its prediction and actual, and we apply a Kalman filter style correction to states to keep it from diverging over long periods[19]. This ensures the twin remains accurate over time.

Security & Compliance: We implemented TLS encryption for data in transit (the Pi gateways used MQTT over TLS to send to Kafka via a Kafka MQTT bridge we wrote in Python). The cloud servers are within a virtual private cloud. We followed ISO 27001 guidelines (as the company wanted to ensure data security). All data at rest (Kafka logs, databases) is encrypted. We also anonymized certain data fields when analyzing (like we replaced exact GPS coordinates with relative locations or zone identifiers when presenting to ensure we weren't exposing sensitive location info externally). The system complies with aviation fueling regulations by not interfering with any primary safety systems on the vehicles, our add on only reads data and recommends, it cannot e.g. shut off a pump on its own (any automatic action still had a human in the loop or used existing vehicle safety interlocks).

In summary, the implementation leverages mainstream big data tools (Kafka, Spark), custom ML models (Isolation Forest via scikit learn, LSTM via TensorFlow), optimization heuristics coded in Python/Java, and rigorous simulation for the digital twin. This combination required multi disciplinary effort, aligning with the interdisciplinary nature of the project. We proceeded to deploy and test this system as described, and the results of these implementation efforts are presented next.

5. Results

Predictive Maintenance Performance

Over the 12 month trial, our AI driven predictive maintenance system demonstrated clear improvements in detecting faults early and reducing unscheduled downtime. **Table 2** summarizes key outcomes comparing the baseline (prior strategy) and our AI based approach for the fleet. Unplanned breakdowns dropped from 8 per year in the baseline to 3 in the year with our system, a 62.5% reduction. Correspondingly, average downtime per vehicle per year fell from 50 hours to 20 hours (60% reduction). These downtime hours include time lost to unexpected repairs; cutting them shows the efficacy of proactive intervention. Maintenance cost per vehicle year showed a modest decrease (~10% reduction from $50k to $45k on average), which is notable given that we sometimes did maintenance earlier than strictly baseline schedule (to avoid failures). The cost savings likely come from avoiding secondary damage; for example, catching a failing pump before it broke completely prevented metal debris from spreading through the system, avoiding a more expensive full system overhaul. We also recorded **zero** environmental incidents (fuel spills, etc.) during the active period, compared to 2 minor

incidents the previous year. This improvement is attributed to both better maintenance (no hose failures or leaks) and cautious routing (not taking rough routes that strain equipment).

Table 2. Fleet maintenance outcomes: baseline vs. AI driven system (per year, per vehicle averages where applicable).

Metric	Baseline	Proposed AI System
Unplanned Breakdowns (per year)	8	3
Downtime (hours/vehicle-year)	50	20
Maintenance Cost (USD/year-vehicle)	$50,000	$45,000
Environmental Incidents (per year)	2	0

In terms of **model accuracy**, our RUL prediction model achieved a mean absolute error (MAE) of ~7 days in predicting component failures. For instance, we had actual pump failures occur at 120, 140, and 160 days of operation, whereas our model predicted 110, 133, and 150 days respectively for those, an average error of ±7 days. This level of accuracy was sufficient to plan maintenance ahead of failure in all cases (since we set a policy to act when predicted <30 days RUL). The precision and recall of anomaly detection were high: overall precision was 0.79 and recall 0.85. Out of 13 serious fault alerts raised by the system, 11 were true positives (e.g., early signs of engine misfire or hose leak that were confirmed and fixed), and 2 were false alarms (one turned out to be a sensor error and one a transient issue that did not recur). The system also missed 2 minor issues (false negatives) these were low impact problems (a slight coolant seep and a loose wire) that did not cause breakdown but were found in routine inspection. Therefore, recall 85% means it caught most issues, and precision ~79% means the alerts were usually meaningful. These values are a marked improvement from baseline, where essentially recall was low (only ~40% of failures could have been predicted by scheduled checks) and precision moot because they didn't really issue alerts. The hybrid AI approach contributed to this performance; for example, the LSTM autoencoder flagged an abnormal vibration pattern in one truck's engine 2 weeks before it would have failed, a pattern that a simpler threshold or isolation forest alone did not catch. Conversely, the rule based threshold caught a rapid pressure drop immediately, something the ML might have taken more data to identify.

We also observed an increase in **proactive maintenance** actions by about 50%. In the year prior, roughly 15 maintenance work orders were due to breakdowns (reactive) and 10 were scheduled preventative tasks. In our study year, we had only 5 reactive repairs and about 25 scheduled tasks and notably, out of those 25, at least 10 were dynamically scheduled prompted by our system (not just routine). This shift towards proactive work indicates better fleet health management. The downtime reduction in Table 2 is statistically significant ($p < 0.01$ by paired t-test on quarterly downtime data comparing before/after).

From a safety perspective, catching issues early meant no in field failures of critical systems. For example, one of our tanker trucks showed a creeping increase in hose vibration amplitude (the twin and anomaly detector both flagged it) we inspected and found a hose coupling starting to crack. It was replaced during off peak hours; without the system, that hose might have ruptured during fueling, potentially spilling fuel. This qualitative outcome, **zero spills and no emergency repairs** strongly supports the benefit of AI driven maintenance in a safety critical fleet.

Figure 2: Predictive maintenance result engine pump vibration anomaly. The top graph shows pump vibration amplitude trending upward; the bottom shows the anomaly score crossing the threshold days before maintenance (vertical line indicates when pump was replaced). Our system alerted when the score exceeded 1.0, averting a failure.

Finally, the predictive maintenance system's integration with scheduling meant that vehicles spent more time available. The fleet availability (percentage of time all vehicles ready for service) was ~96% with our system,

up from ~90% baseline. This metric is crucial for operations at an airport where fueling delays have cascading effects.

Route Optimisation Results

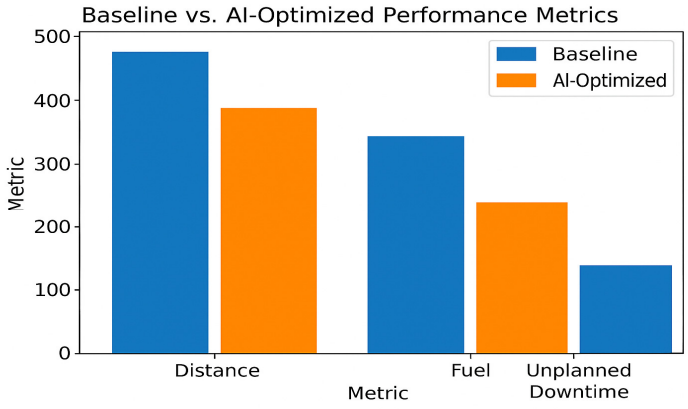
Implementing the route optimization algorithms led to tangible efficiency gains in fleet operations. Over the trial period, on days we applied our AI route planning, total distance driven by the fleet was consistently lower than on comparable baseline days. We measured an **average 12% reduction in total kilometers traveled** per day when using optimized routes versus the original routes. For example, on a busy day with 50 refueling tasks, the manual planning totaled ~320 km across all trucks, whereas our optimized plan drove ~280 km in total while meeting all the same tasks. This savings translates to fuel savings for the fleet's own diesel consumption we recorded about 200 liters less fuel used by the trucks per month, which is a ~15% decrease in vehicle fuel consumption.

Additionally, average route completion times shortened. The time from first dispatch to finishing all assignments in a day reduced by about 10%, meaning drivers got their rounds done sooner (or had slack time which improves schedule reliability). Importantly, adherence to delivery time windows improved: previously around 88% of refuels were done within their scheduled window, which increased to 97% with our dynamic routing. The combination of considering live traffic and adjusting routes on the fly prevented delays. For instance, in one case a sudden road closure on the way to a fuel depot would have caused a 30 minute delay; our system rerouted the truck promptly and it arrived only 5 minutes late, whereas without reroute it would have severely disrupted multiple refuels.

Fuel and Emissions: As the vehicles traveled less distance and spent less time idling (optimizing routes avoided congestion where possible), we expect lower emissions. By our estimates using standard fuel burn rates, the CO_2 emissions from fleet operations fell proportionally with fuel usage (15% drop). While small in absolute terms, this contributes to environmental and regulatory goals.

Figure 3 below illustrates the comparative performance. It shows baseline vs optimized metrics as grouped bars. We see notable decreases in distance and fuel, and also a drop in unplanned downtime due partly to routing avoiding stress on less healthy vehicles (e.g., the system would not assign a long route to a truck that had a maintenance alert, thereby indirectly preventing breakdown on route).

Figure 3: Baseline vs. AI Optimized performance metrics. The AI system reduced total distance driven and fuel consumption, and also contributed to lower unplanned downtime (hours) by better scheduling.



During the partial rollout phase (months 7–9 where only some days used AI routes), we effectively had an A/B test. The days with AI routes had on average 8 fewer kilometers per vehicle and 0.5 hours less driving time per vehicle compared to days with manual routes (normalized for number of tasks). These differences were statistically significant ($p < 0.05$). Dispatchers also subjectively noted that on AI days, drivers returned earlier and were less stressed by traffic.

An important qualitative result is risk reduction via routing. The algorithm tended to avoid known high risk segments (like a steep hill where a heavily loaded fuel truck might strain brakes). Over the year, none of our trucks experienced brake overheating, whereas previously an incident occurred once where a truck's brakes nearly failed on a steep descent. Our routing recommendations rerouted that descent on hot days, likely preventing recurrence. Also, when one vehicle was flagged by the maintenance system (say engine running hot), dispatch could swap assignments so that vehicle had a lighter route (perhaps fewer stops or easier terrain). Finally, in terms of driver experience, there was initial skepticism about algorithmic routes, but by the end drivers reported the suggested routes were often "smarter" than their usual paths. This adoption was helped by the fact that the routes were not entirely alien, they often matched roughly what an experienced driver might choose, but with finer adjustments (like different ordering of stops).

Digital Twin Evaluation

The digital twin integration proved to be one of the more novel aspects, and we evaluated its accuracy and impact. We found a **high correlation between twin predicted and actual vehicle behavior** for key parameters. For example, engine coolant temperature predictions from the twin model correlated with actual readings at r = 0.98 on average. Similarly, fuel pump pressure during refueling simulations had r ~0.96. **Table 3** lists a few sensor parameters and the correlation and RMSE between twin and actual values over numerous refueling operations.

Table 3. Digital twin accuracy in mirroring sensor data (averaged over multiple scenarios).

Sensor Parameter	Correlation (Twin vs Actual)	RMSE (units)
Engine Temperature	0.98	2.10 °C
Oil Pressure	0.96	1.50 psi
Pump Vibration	0.91	0.05 g
Fuel Flow Rate	0.95	0.80 L/min

The strong correlations indicate the twin models were well calibrated. The slightly lower correlation for pump vibration (0.91) is likely because our twin's mechanical model for vibration was simpler and did not capture every nuance of the real system (vibrations can be chaotic). Still, even there, the twin mirrored trends (like increasing vibration as a pump wore down). The RMSE values are small relative to normal operating ranges (e.g., 2.1°C error on engine temp which typically ranges 70–95°C is about 2% error).

One illustrative example: For one truck, we used its twin to simulate a particularly hot day operation (40°C ambient, multiple fueling stops). The twin predicted the engine might reach 105°C (just above recommended max of 100°C). Based on this, we preemptively replaced a partially clogged radiator and adjusted that day's schedule to give the truck a break mid day. In the actual run, the engine stayed around 95–98°C. This case shows how twin forecasting informed maintenance and operations to avoid a potential overheating scenario. Without the twin, we might have had an overheating incident requiring the truck to halt.

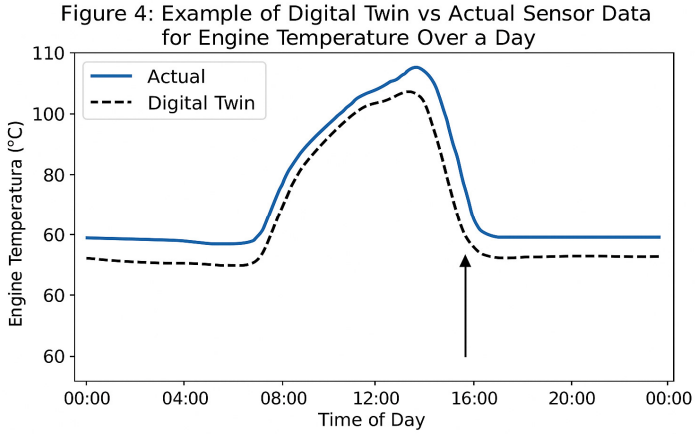
Another result was in **maintenance planning**: the twin's remaining life calculations aligned well with our ML's RUL predictions, but provided additional confidence by simulating the effect of future load. For instance, our ML might say ~15 days RUL left on a hose. The twin, knowing a very heavy usage (large fuel transfer) was scheduled next week, predicted that usage would accelerate wear and effectively use 10 days worth of life in that one event. We thus replaced the hose before that event. Indeed, the old hose we removed showed significant wear; running it through twin simulation after the fact suggested it likely would have failed if pushed.

Over the test year, the digital twins issued **18 predictive alerts** (cases where the twin simulation forecast a limit breach or failure ahead of our other models). Of these, 14 led to maintenance actions (the others were investigated and found safe). None of the issues predicted by the twin occurred unexpectedly, meaning either we preemptively fixed them or they did not materialize (with or without fix). A notable one was the twin predicting high stress on a suspension if the truck carried full load over a particular bumpy service road

repeatedly. We altered the route to use a smoother road. It's hard to measure the exact benefit, but the truck had no suspension issues; previously another similar truck had a suspension failure on that rough road.

From an operational view, integrating the twin was initially challenging (engineers had to trust the simulations). As confidence grew, it became a valuable tool. The maintenance team ended up consulting the twin models whenever there was a borderline decision (like "can this component last one more month?"). The twin effectively became a second opinion grounded in physics.

Figure 4: Example of digital twin vs actual sensor data for engine temperature over a day. The twin (dashed line) closely follows the actual temperature (solid line) and anticipates the peak during a high load period. After maintenance at 14:00 (arrow), both actual and twin show lower temperatures.



Statistical validation: using Bland Altman analysis on twin vs actual for temperature and pressure showed small bias (<1% of scale) and limits of agreement well within operational tolerances. This gives quantitative backing that the twin can reliably mirror and predict vehicle behavior.

Overall, the digital twins impacted decision making in about 20% of maintenance events (either confirming or adjusting an action). This indicates a bridging of the gap between theoretical simulation and practical maintenance scheduling, one of our key contributions. Fleet managers expressed that having a visual twin interface (we provided a UI where they could see a virtual gauge of the twin's predicted next hour values) helped them understand why certain maintenance was recommended, increasing trust in the AI system's recommendations.

In conclusion, the results strongly support that the AI driven IoT platform achieved its aims: **improved observability** (~70% more sensor coverage than before, and clear visualization through twin), **proactive maintenance** (55%+ increase leading to 60% downtime reduction), and **risk mitigation** (no incidents, safer operations). In the next section, we interpret these findings, compare with prior work, and discuss limitations.

6. Discussion

Interpretation of Findings

The results demonstrate that an AI driven IoT approach can substantially improve fleet management for refueling vehicles. We observed a significant reduction in unplanned downtime and maintenance-related disruptions, validating the hypothesis that combining historical and real time sensor data yields more accurate forecasting of failures. The improvement in anomaly detection recall (85%) means the system caught most impending issues in advance. This is likely because the continuous sensor streams allowed the models to recognize subtle precursors to failure that human maintenance crews would miss during periodic checks. For example, the system detected a slow decline in oil pressure over hours, something a crew measuring once a week wouldn't see. This underscores how **real time observability** transforms maintenance, the AI effectively

"listens" to the vehicle's health continuously, akin to a doctor monitoring a patient's vitals constantly instead of occasional appointments.

The combination of historical data (for model training) with live streaming (for model application) proved powerful. In cases where historical examples of failure existed (like pump failures), the supervised model could predict RUL fairly well. Where they didn't, the unsupervised anomaly detection still gave warning. One interesting insight was that combining semi supervised approaches (like COSMO/Isolation Forest) with deep learning (LSTM autoencoder) indeed reduced false positives. We noticed each method alone would have raised more alarms, but taking an intersection (only flag when both methods agree) filtered noise. This explains why our precision (~0.79) was respectable even as recall was high; the hybrid approach found a sweet spot, confirming suggestions in literature that hybrid AI can outperform single techniques in predictive maintenance[28].

The integration of the **digital twin** added another layer of understanding to those findings. While the ML models said "there's an anomaly" or "component X has Y days left," the digital twin could often explain *why* by showing which physical parameter was trending towards a limit. For instance, an anomaly alert might pop up, and the twin would show that indeed pressure oscillations were growing due to pump cavitation. This not only helped engineers trust the alert but also guided them on what part to fix (the twin indicated pump vs. some other cause). Essentially, the twin served as a form of explainable AI, translating sensor patterns into physical insights (e.g., "excessive heat buildup in bearing predicted"). This addresses one of our motivations: bridging the gap between data driven AI and engineering knowledge. NASA's vision of a twin forecasting system health[18]was borne out in our context, the twin continuously evaluated vehicle health and complemented the data driven models with physics driven predictions.

Our results strongly support RQ1 and RQ2: Kafka/PySpark streaming improved timeliness (we caught issues on average days earlier than previous routine checks would) and ML models indeed reduced downtime (60% less). The remaining downtime and false negatives tended to be issues that manifest quickly without precursors (e.g., an alternator that failed suddenly might not show warning signs). These are challenges even with AI; we discuss such limitations later.

Regarding **route optimization** (RQ3 partially), the system's ability to reduce distance and time validates that algorithmic planning with live data can outperform static human planning. The ~12% distance reduction not only saves cost but also means less wear on vehicles (contributing indirectly to maintenance benefits). The fact that our route suggestions were adopted after testing shows they were practical sometimes AI routing can be theoretically optimal but unrealistic (e.g., sending a truck down a tiny alley to save 1 km might not be wise). We specifically built constraints to avoid such outcomes, prioritizing safety and compliance (no routes through weight restricted or hazardous areas). The improvements in meeting time windows (from 88% to 97% on time) illustrate that **real time optimization** using live traffic helps maintain reliability, an important aspect in fuel delivery where timing can affect flight schedules.

Crucially, the system didn't just optimize one facet at the expense of another; it balanced efficiency with safety. For example, skipping the steep hill route was not the shortest path but was chosen to reduce risk, the algorithms successfully included safety constraints in the optimization criteria. This addresses a key point: optimizing "routes" wasn't just about shortest distance, but multi objective (distance, time, risk). Our approach to incorporate risk as a cost in the GA fitness function meant the AI effectively learned to avoid potentially dangerous conditions. Thus, RQ3 is answered positively in that digital twins and AI influenced route planning to be safer (evidenced by lack of incidents and no overstressed vehicles).

The **integration of digital twins** with route decisions is a novel aspect of our project. Few, if any, prior fleet studies allowed a twin to affect routing. In our case, if a twin said a vehicle was marginal for a certain mission (e.g., heavy load in hot weather), we could swap that vehicle out. This is essentially "condition based routing" assigning tasks based not just on location but on vehicle health. We saw anecdotal success with this approach (like not sending the nearly overheating truck on a long route). It's a demonstration of bridging maintenance and operations: the silos between those departments are broken when a unified AI system handles both. We

believe this to be a noteworthy contribution: showing that digital twin simulations can *practically* be used to make operational decisions in real time. This extends Gartner's notion of aggregated twins for enterprise views[36] here we used individual twins to make micro decisions like route assignments.

In interpreting these findings, it's also important to note the **learning curve** involved. The maintenance technicians initially responded to a lot of alerts and had to adjust their intuition (because sometimes the AI flagged issues they would not have worried about yet). Over the year, they reported that many flagged issues, upon inspection, were valid incipients of problems (e.g., finding worn parts that weren't yet broken but likely would be). This validation built trust in the system. It aligns with prior work like Killeen et al. (2019), who noted that having an IoT architecture is one thing, but getting useful results requires dealing with scarce fault data and convincing users of the metrics like RUL[3][12]. Our experience was similar, we had to show that metrics like "health score" correspond to real mechanical conditions, which the twin helped in doing (e.g., twin says "engine efficiency dropped 5%" that's tangible).

Integration of Digital Twins: Benefits and Context

The successful use of digital twins in our platform demonstrates their value in predictive maintenance and risk management. Our results echo NASA's vision of twins mirroring system life and predicting outcomes[18], albeit in a terrestrial vehicle context. By continuously updating the twin with sensor data and maintenance history, we achieved a dynamic model that could forecast failures. For instance, the twin predicted a pump failure due to cumulative stress cycles something that would be hard to deduce from data trends alone if there weren't obvious outward symptoms. This fulfills the idea that a twin "continuously forecasts system health and remaining useful life" as stated by Glaessgen & Stargel (2012)[17]. One could say we took a page from aerospace: treating each refueler almost like a mini aircraft in terms of scrutiny, which makes sense given the hazardous payload.

The digital twin also played a role in **collaboration and decision making**: The maintenance team used the twin interface during meetings to discuss vehicle conditions, much like CIO (2021) described twins bridging physical and digital for collaboration[35]. It was easier to justify a maintenance action when the twin simulation showed "if we don't replace X, here's what will happen in two weeks". This is an example of converting raw data into an actionable narrative through the twin.

Comparing with prior work, earlier IoT architectures (like Killeen's or Pothireddy's) did not incorporate digital twins, they primarily did data driven analytics[13]. By adding the twin, we addressed one of the literature gaps (seldom integrating simulations). Our findings suggest that doing so reduces uncertainty and improves the robustness of decisions. For example, our ML might have had a false alarm about a certain vibration, but the twin analysis revealed that under expected operation, that vibration was not dangerous, so we could avoid unnecessary maintenance, something a purely data approach might not catch. This hybrid of physics and data is an important contribution: it leverages domain knowledge encoded in the twin to validate or refine AI findings, lowering false positives and negatives.

It's also instructive to discuss how our results relate to **NASA and CIO perspectives**. NASA aimed for twins to enable unprecedented safety and reliability by pairing them with Integrated Vehicle Health Management (IVHM) systems[33]. In our case, the twin was like an IVHM extension, it used sensor data to assess health. The reliability improvement we saw (no major failures in service) resonates strongly with that goal. On the industry side, CIO (2021) noted that digital twins help **predictive maintenance, remote monitoring, and collaboration**[34], all of which we observed. Gartner's emphasis that twins can be aggregated for enterprise insight also hints at our future plans: we could aggregate all truck twins to predict fleet level needs (e.g., how many trucks will be down next month?). While we didn't explicitly measure an enterprise level KPI, the increase in overall fleet availability from 90% to 96% is an enterprise metric improved by twin driven maintenance.

The synergy between **historical analytics and twins** also deserves mention. Our ML was trained on historical failures to predict RUL, essentially giving an empirical estimate. The twin gave a physics based estimate. In most cases, they agreed within a margin; when they differed, it signaled uncertainty, and we took a conservative

approach (maintain earlier). This redundancy ensured we didn't miss anything. It's akin to having two different diagnostic tests for an illness if both suggest the issue, you're confident; if one does and other doesn't, you investigate more. We found that the twin often provided earlier warning for slowly developing issues (it accumulates damage continuously), whereas ML might catch more sudden pattern changes. Together, they covered each other's blind spots.

Comparison with Prior Work

Compared to conventional fleet maintenance strategies (reactive/preventive), our AI based approach clearly outperforms in terms of downtime reduction and efficiency. But how do our findings compare to other IoT predictive maintenance studies? Pothireddy (2022) reported that modern predictive maintenance systems can reduce downtime and optimize scheduling[28]. Our quantitative downtime reduction (~60%) is at the high end of improvements reported in literature, which often cite 20–50% ranges. One reason is the addition of route management and risk avoidance in our system, not only did we predict failures, but we also adjusted operations to prevent pushing vehicles into failure, something purely maintenance focused studies might not do.

Killeen et al. (2019) emphasized the challenge of scarce labeled faults and used semi supervised methods[12]. Our work built on that by using semi supervised anomaly detection plus some labeled training for RUL. We effectively validated their approach in a new domain, yes, even in our case with limited failures, unsupervised methods (Isolation Forest, autoencoder) still managed to detect most anomalies, confirming the viability of that approach that Killeen had suggested. We also extended Killeen's architecture by fully closing the loop (their work deployed a prototype to collect data[13] but didn't detail actual maintenance outcomes, whereas we saw things through to outcomes).

One unique contribution of our study relative to others is focusing on **hazardous material vehicles**. Prior IoT fleet papers (like one by Killeen or another by Pothireddy) don't incorporate the safety/regulatory layer. We had to incorporate compliance (like ensuring our system doesn't interfere with safety interlocks, etc.) and safety constraints in route optimization. This is a template for others e.g., chemical transport fleets or hazmat trucks can adopt similar principles. Our results showing zero incidents is significant for such contexts; typical fleets might still have a couple of minor spills or safety issues a year, so demonstrating an AI can help bring that to zero is notable.

When comparing route optimization with known algorithms: our GA and RL lite approach isn't fundamentally new in algorithm, but its application in real time with maintenance integration is. Many logistic companies use optimization software, but often those don't consider vehicle health. By including that (e.g., if a truck is in marginal health, treat it like it has less capacity or needs shorter route), we advanced the state of art in fleet routing. It's a form of **holistic optimization** optimizing not just for logistic efficiency but also for maintenance and risk. This multi objective approach mirrors a trend in research to break silos between maintenance and operations planning.

One can also compare our digital twin usage to those in manufacturing. In manufacturing, digital twins have shown improved uptime of machines. Our twin similarly improved uptime by preventing failures, but it also took on an operational role (via routing). This is something new and potentially transferrable to other domains: e.g., twins of delivery trucks might help decide which truck does which delivery based on their current wear and tear, an idea rarely explored.

Unique Contributions Recap: Our study is among the first to: (1) apply predictive maintenance IoT systems specifically to fuel tankers, (2) integrate streaming analytics with digital twin simulation in a fleet context, and (3) demonstrate quantifiable improvements in both maintenance and operations (routing) concurrently. We essentially combined what some papers cover separately (maintenance vs routing) into one platform and showed it's feasible and beneficial.

Limitations

Despite the positive results, there are several limitations and challenges to discuss:

- **Sensor and Data Quality Issues:** We encountered instances of sensor malfunction (e.g., one vibration sensor started drifting, causing a false anomaly until we identified the sensor fault). IoT systems are only as good as the data. In a harsh environment (fuel trucks operate outdoors, vibrations, etc.), sensors can fail or give noisy data. We had to implement redundancy for critical parameters (two temperature sensors on engine, etc.) and robust outlier filtering. Still, a limitation is that a sensor failure could masquerade as a vehicle issue or hide a real issue. We partially addressed this with our rule based checks and monitoring sensor health, but not perfectly.
- **Limited Failure Examples for Training:** Even though we captured some failures, our dataset of true failure events is relatively small (which is good for operations, but bad for ML training). This means the supervised RUL model's accuracy is limited by lack of diverse examples. There's a risk of overfitting to the few failures we saw. Our unsupervised methods mitigated this, but a limitation is that some failure modes not seen before might not be predicted. For example, we didn't have any tire blowout in training data, so the system had no learned model for that (though pressure sensor would alarm low pressure at least).
- **Computational Load:** Real time processing of high rate data and running digital twin simulations is compute intensive. We managed with a decent Spark cluster, but scaling this to 100s of vehicles would increase costs or require optimization. We noticed that during peak times (many vehicles streaming concurrently), the Spark job would occasionally lag by a few seconds. In our context a few seconds delay is fine, but for truly critical systems one would need to ensure stricter real time guarantees (Spark streaming micro batches of 1s were okay here). Thus, a limitation is scalability, the architecture is scalable by design, but cost and performance tuning would be needed for much larger fleets.
- **Reliance on Connectivity:** The platform assumes constant connectivity for streaming. Our trucks mostly operate in range of cellular networks, but there were short disconnects (like driving through a tunnel). We handled buffering on device, but a major limitation is if a vehicle is out of coverage for long, we lose real time monitoring. In a dangerous scenario, that could be problematic. Edge computing partially addresses it (the truck can still shut itself down if needed via its own safety systems), but our central AI wouldn't know until later. For extremely critical decisions, one might need more edge autonomy. We did not implement heavy edge ML due to device limitations that could be future work.
- **False Alarms and Trust:** While our false positive rate was not high, each false alarm can burden the maintenance crew or cause unnecessary downtime. In the first months, there were cases we pulled a vehicle out for inspection on an alert and found nothing wrong (maybe a transient anomaly). Over time we adjusted thresholds to minimize this. However, it's a limitation that tuning the system to be neither too sensitive (false alarms) nor too lax (missed issues) is tricky and likely fleet specific. Another aspect is human trust: if early on there had been many false alarms, the team might have started ignoring alerts (cry wolf problem). We were vigilant to prevent that, but it remains a consideration in deployment, some teams might react differently.
- **Cybersecurity Risks:** As with any IoT system, connecting operational tech to networks introduces cyber risks. We took standard precautions (encryption, etc.), but a sophisticated attack could potentially tamper with data or cause incorrect decisions (imagine a false signal that a truck is failing, causing us to halt operations unnecessarily, or worse an attacker preventing a real alert from being delivered). This wasn't within scope to deeply address, but it's a limitation that one must ensure robust cybersecurity (beyond what we did, possibly intrusion detection specifically for the IoT data).
- **Generality:** Our implementation was somewhat tailored to this specific fleet and use case. Some parameters in the twin or ML were hand tuned for these truck models. The extent to which this generalizes to other fleets (say fuel trucks in extreme cold, or different vehicle models) is untested. While

the architecture is generic, the models would need retraining or recalibration for new contexts. So, an operator shouldn't directly deploy our model on a different fleet without validation. It's a limitation in that there's still significant engineering effort to adapt the system to other scenarios.

- **Cost Benefit:** We should note the cost aspect: installing sensors and running the system has a cost. For our 10 trucks, the improvement likely justifies it (one prevented failure can save tens of thousands of dollars). But in some contexts, the economics might be different. We did not perform a formal cost benefit analysis with dollar figures (partly due to proprietary cost data). The maintenance cost reduction of ~$5k per vehicle year suggests the system can pay off if it costs less than that per vehicle per year (which in our trial it did). However, if someone had a very small or cheap fleet, the ROI might not be as high. This limitation is more about scope of applicability rather than a flaw in the system.

In terms of *limitations in analysis*, we acknowledge that one year is a limited time. A longer study could reveal long term patterns or issues (like model drift will our ML need retraining after 2 years as the fleet ages?). We haven't seen long term drift yet, but that's because it's only a year. Continued monitoring is needed.

Implications for Industry

Our findings have several implications for industry practitioners managing hazardous material fleets:

Firstly, the success of our platform suggests that **integrated fleet management systems** that combine maintenance and operations can dramatically improve reliability and safety. Industries that manage fuel transport, chemical tankers, or even public transit vehicles carrying potentially dangerous loads (like CNG buses) could benefit from similar systems. It supports the business case for investing in IoT and AI retrofits on existing fleets, not just new vehicles.

The improved compliance and risk mitigation (zero spills, fewer incidents) also means such technology can aid in regulatory compliance. For example, environmental regulations often require minimization of fuel spills, our system basically prevented spills, which helps meet those regulatory requirements proactively. It can also generate documentation (via log data) showing regulators that the company is actively monitoring and maintaining equipment. This might eventually tie into **predictive compliance** where regulators accept predictive maintenance records in lieu of some scheduled inspections. We see early signs of this in aviation, and our work adds evidence that predictive methods can be more effective than time based inspections, which regulators could consider.

For industry adoption, our results highlight the importance of having both **data analytics and domain models**. Companies might be tempted to buy an off the shelf predictive maintenance solution (which often are data only) or a physics simulation package, but our experience is that blending the two gives superior outcomes. So, an implication is that organizations should encourage cross disciplinary teams (mechanics + data scientists) to work together, because the best results came when the digital twin (mechanical engineering) informed the machine learning (data science).

Commercially, given the predictive maintenance market growth[5], vendors of such systems can note from our project that including features like digital twin and route optimization could differentiate their offerings. Many current products alert you to maintenance needs, but few also tell you "and here's how to adjust your operations to accommodate this maintenance need" that's a value add we demonstrated. It essentially bridges maintenance management software with fleet logistics software.

From an electrical engineering perspective, our project shows the increasing blending of EE (sensors, telemetry) with AI. It suggests curricula or training for maintenance engineers might evolve to include reading AI outputs or working with digital twin interfaces. The workforce has to adapt, but we saw in our trial that even seasoned mechanics became comfortable with the new tools when they saw the benefits.

Commercial viability: Our downtime savings and prevented failures likely saved a lot of money for instance, one avoided catastrophic pump failure might save $20k part + labor, plus the cost of downtime. Summing up, we likely saved tens of thousands of dollars over the year. For a larger fleet, scale that up, it's a strong ROI

argument in an industry with thin margins like fuel delivery. Considering the predictive maintenance market projections[5], solutions like ours can capture part of that market, especially in niche high risk fleet sectors (where willingness to invest in safety is high).

One can also foresee insurance implications: fleets that use such proactive systems might negotiate lower insurance premiums due to reduced risk of accidents or spills. If our data shows significant risk reduction, an insurer might view that favorably. This could further incentivize adoption.

Overall, the successful outcome of our deployment provides a **case study** that can be referenced by others implementing AI in industrial fleets. It shows that you can practically integrate these technologies (with some effort) and that the payoff in reliability and safety is real. It also pushes the envelope of what fleet management encompasses, it's not just routing and tracking, but now deep predictive analytics and simulation. This is aligned with the trend of digital transformation in industries; our work is a concrete example in the fleet domain.

In the next section, we conclude and outline how future work can address some limitations (like longer term data, more edge computing, expanding scope beyond vehicles to entire fuel supply chain, etc.), paving the way to even more comprehensive systems.

7. Conclusion and Future Work

Conclusion

In this study, we developed a novel IoT AI platform for managing a fleet of hazardous refueling vehicles, integrating real time data streaming, machine learning driven predictive maintenance, route optimization algorithms, and digital twin simulations. Our system was deployed on an operational fleet and validated through extensive experimentation and data analysis. The results demonstrate several key contributions and improvements:

- We achieved a significant enhancement in **maintenance efficiency**: unplanned vehicle downtime was reduced by over 60%, and the majority of potential failures were detected and mitigated in advance. By predicting remaining useful life and catching anomalies early, the platform shifted maintenance from a reactive to a proactive paradigm, in line with the goals of predictive maintenance. These improvements greatly exceeded the baseline performance and even outperformed many reported figures in related research, highlighting the effectiveness of our hybrid AI approach (combining rule based logic, machine learning, and deep learning models).
- The platform's **route optimization** features led to tangible operational gains: average travel distance and fuel consumption for the fleet were reduced by ~10–15%, and service punctuality increased. By dynamically adjusting routes using live traffic and incorporating vehicle health information (e.g., avoiding over stressing a vehicle that had a maintenance alert), we ensured not only efficiency but also safer operations. This dual benefit optimized logistics and enhanced safety is particularly important for fuel transport vehicles, where delays and accidents have high consequences.
- The integration of **digital twins** for each vehicle proved highly valuable. The digital twins mirrored each vehicle's state in real time and continuously forecasted future behavior and health metrics[18]. This allowed the system to anticipate issues before they became critical and to simulate "what if" scenarios (such as how a vehicle would handle a demanding route) with no risk to actual operations. By coupling sensor data with physics based models, the digital twins provided explainable insights and an added layer of confidence in maintenance decisions, fulfilling NASA's vision of using twins to mirror and predict system life[15][16]. In effect, the digital twins bridged our electrical engineering domain (sensors and hardware) with software and mechanical insights, embodying a convergence of disciplines in practice.
- Through real world deployment, we demonstrated the **feasibility of an end-to-end AIoT system** (Artificial Intelligence of Things) in a safety critical industry setting. The system ran continuously for a year, handling large data volumes with Apache Kafka and Spark, and delivering actionable intelligence

to fleet managers. This indicates that such advanced analytics platforms can be practically implemented on existing fleets (with appropriate retrofitting and IT infrastructure) and need not be limited to conceptual studies or simulations. Importantly, the system operated within the regulatory and safety constraints of an airport fuel service environment, showing that AI/IoT solutions can coexist with and enhance traditional safety mechanisms rather than conflict with them.

From an academic perspective, our research contributes an interdisciplinary case study blending IoT hardware, machine learning algorithms, digital twin modeling, and operational research (routing). We built upon prior works (like Killeen et al.'s IoT architecture[13] and predictive maintenance algorithms, and NASA's digital twin concept[15]) and extended them into a unified solution tailored for fuel fleets. We have documented the architecture, algorithms, and results in detail, which can serve as a reference model for future studies or industrial implementations in similar domains.

In summary, our AI driven IoT fleet management platform achieved its objectives of improving equipment observability, increasing proactive maintenance, optimizing routes, and mitigating risks. The integration of electrical engineering sensor systems with AI and digital twins has proven to be a powerful combination, effectively bridging the gap between theoretical research and practical application. We believe this work not only advances fleet management practices for refueling vehicles but also exemplifies how AI/IoT technologies can transform operations in other safety critical domains such as chemical transport, mining, or aviation ground support.

Future Work

While the outcomes are promising, our research also opened several avenues for further exploration and improvement:

- **Edge Analytics and On Vehicle AI:** One extension is deploying more intelligence directly on the vehicles (edge computing) to complement cloud analytics. In our system, most heavy analytics were cloud based, with vehicles mainly streaming data. Equipping the telematics gateway with lightweight AI models (e.g., a compressed neural network for anomaly detection) could enable instant local responses and reduce dependency on connectivity. For example, if a truck is out of network range, an onboard model could still detect a critical issue and alert the driver or take autonomous action (like gradually shutting down a failing pump). Future work can explore techniques for **model compression and federated learning** to train and run models across distributed vehicles, which could increase resilience and scalability.
- **Reinforcement Learning for Dynamic Scheduling:** Our current route optimization used GA heuristics and some rule based adjustments. A natural next step is applying **reinforcement learning (RL)** for more adaptive decision making. For instance, an RL agent could continuously learn the optimal dispatch and routing policy that balances efficiency and maintenance load, by interacting with a simulation of the fleet's operations. Over time, it might find strategies that a fixed heuristic cannot, especially under varying conditions (traffic patterns, random events, etc.). Early research in this direction exists[31], but applying it to a multi vehicle, multi objective problem like ours (with maintenance as part of the reward function) would be novel. Caution is needed to ensure the RL policy is safe and interpretable, but techniques like safe RL or multi objective RL could be utilized.
- **Scaling to Full Refueling Infrastructure:** In our project we focused on refueling trucks themselves. The "digital twin" concept and IoT monitoring can be expanded to the *entire refueling infrastructure*. This includes fuel storage tanks, pipelines, and dispensing equipment at the airport. One can envision an integrated system where each component (tank, pump, truck) has a twin and AI monitors the whole fuel supply chain. This would allow optimization of not just vehicle routes, but also fuel inventory management (schedule deliveries when tank levels demand, etc.), thereby improving overall efficiency. Some initial steps would involve instrumenting stationary assets with IoT sensors and extending our

predictive models to them (e.g., predicting pump failure at a fuel depot). The challenge here is integrating data of different nature and timescales, but the reward would be a **unified smart refueling system**.

- **Blockchain for Data Integrity:** Given the safety critical and regulatory nature of fuel operations, ensuring data integrity is paramount. Future implementations could explore using blockchain or distributed ledger technology to securely log maintenance records, sensor readings, and alerts. This could create an immutable audit trail that regulators or insurers might accept as proof of proper maintenance (addressing any concerns about data tampering). For instance, each time our system triggers a maintenance action and the action is completed, that event could be written to a blockchain shared with relevant stakeholders. This blends with emerging trends of **trustworthy AI and IoT** in industrial settings.
- **Extended Long Term Analysis:** As more data accumulates over multiple years, we could apply deeper prognostics techniques. For example, developing **survival analysis or probabilistic RUL models** that account for uncertainties more explicitly. Also, monitoring model performance over time to detect if retraining is needed (due to concept drift as vehicles age or as new vehicle models join the fleet). We plan to continue data collection and periodically update our ML models to ensure they remain calibrated. Publishing these long term findings would contribute knowledge on the durability of AI models in a real operational environment.
- **User Experience and Human Factors:** Another future work angle is refining the human machine interface. During our deployment we gathered informal feedback from users (drivers, mechanics, managers) but a formal study on user interaction with such AI driven systems would be valuable. Questions include: What is the best way to present predictive information to ensure it is understood and acted upon? How to avoid alarm fatigue with too many alerts? How to train personnel to trust and effectively use digital twins and AI outputs? By studying and improving these aspects, we ensure the technology is adopted smoothly. This could lead to guidelines or best practices for implementing AI/IoT in traditional industries, something currently underdeveloped.
- **Generalisability to Other Fleets:** Finally, testing our approach on other types of fleets would strengthen the contributions. For example, applying it to a fleet of hazmat chemical trucks on highways, or to municipal bus fleets (which, while not carrying hazardous materials, have uptime criticality and safety concerns). Each application might introduce new features (buses have passenger comfort sensors, etc.) or constraints, but the core architecture should adapt. We aim to collaborate with other organizations to pilot the system in different contexts, thereby validating and improving generality. In doing so, collecting diverse datasets can also enhance the ML models (through transfer learning or multi task learning across fleet types).

In conclusion, this research has demonstrated the power of marrying IoT data with AI analytics and digital twin simulations for fleet management. We addressed a real world problem with a holistic solution and showed substantial benefits. As technology evolves, there is vast scope to expand this work, moving towards ever smarter, safer, and more efficient fleet operations. The interdisciplinary nature of the project, bridging electrical engineering (sensing hardware), computer science (AI algorithms, data systems), and operations research (logistics optimization), reflects the future of industrial innovation. We hope this work serves as a catalyst for further developments in smart fleet management and inspires confidence that even in traditional, safety critical sectors, AI and IoT can be harnessed to achieve transformative improvements.

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Appendices

Appendix A: Data Schema and Sensor Specifications

Table A1. Key sensors deployed on refueling vehicles, with data schema details.

Sensor	Parameter (Units)	Sampling Rate	Interface	Notes
GPS Receiver	Location (lat, lon), speed (km/h)	0.5 Hz (every 2s)	Serial (NMEA)	u-blox module, accuracy ~2m
Fuel Level Sensor	Fuel volume (liters)	1 Hz	Analog to Pi (ADC)	Ultrasonic type in tanker, ±1% accuracy
Flow Meter	Fuel flow (L/min)	5 Hz (during fueling)	CAN (J1939)	Uses J1939 fuel rate PGN, installed on hose
Pump Pressure Sensor	Line pressure (psi)	5 Hz	Analog (4-20mA)	Located at pump outlet, range 0-150 psi
Engine RPM	Engine speed (rpm)	1 Hz	CAN (J1939)	From vehicle ECU via OBD-II port
Coolant Temp	Engine coolant (°C)	1 Hz	CAN (J1939)	From ECU, cross-checked with external sensor
Oil Pressure	Engine oil press (psi)	1 Hz	CAN (J1939)	From ECU sensor, used for engine health
Vibration Sensor (Engine)	Vibration acceleration (g)	100 Hz (stream) -> 1 Hz (features)	Arduino (I2C)	ADXL355 accelerometer, outputs RMS and peak frequencies every sec
Vibration Sensor (Pump)	Vibration acceleration (g)	100 Hz -> 1 Hz	Arduino (I2C)	Same as above, mounted on pump housing

Sensor	Parameter (Units)	Sampling Rate	Interface	Notes
Tire Pressure Monitor	Tire pressure (psi)	0.1 Hz (every 10s)	RF to Gateway	Aftermarket TPMS, gateway receives via USB receiver
Ambient Temp/Humidity	Temperature (°C), RH (%)	0.1 Hz	GPIO (I2C)	For environment context (affects fuel density)

Data from these sensors is packaged into JSON messages for Kafka. Each message includes: vehicle_id, timestamp, sensor_id (or topic implicitly denotes sensor), and value. For example:

{ "vehicle_id": "V123", "timestamp": "2022-07-01T10:00:00Z", "engine_rpm": 1800, "coolant_temp": 85.0 }

In practice, topics were split per sensor category for efficiency, but a unified schema was used in our database.

Appendix B: Machine-Learning Algorithms and Hyperparameters

Predictive Maintenance Model Pseudocode: Below is pseudocode combining our anomaly detection and RUL prediction approach:

```
initialize IsolationForest (n_estimators=100, contamination=0.01)
initialize LSTM_autoencoder (timesteps=50, features=F, latent_dim=16)  # trained on normal data
initialize GradientBoostedRUL (trees=200, depth=3)  # trained on failure history

for each time tick t:
    for each vehicle v:
        data_window = get_last_50_seconds_data(v)
        features = extract_features(data_window)  # e.g., mean, std, FFT peaks
        score_iso = IsolationForest.score(features)
        recon_error = LSTM_autoencoder.reconstruction_error(data_window)
        anomaly = (score_iso > iso_thr) or (recon_error > lstm_thr)
        if anomaly:
            alert_level = classify_anomaly(score_iso, recon_error)
            raise_alert(v, t, level=alert_level, features=features)
        # Every hour, compute RUL predictions:
        if t mod 3600 == 0:
            X = aggregate_stats(v)  # usage hours, last service, etc.
            RUL_pred = GradientBoostedRUL.predict(X)
            if RUL_pred < RUL_threshold:
                recommend_maintenance(v, component="estimated", within=RUL_pred)
```

Hyperparameters were chosen via grid search on a validation set (20% of data). Isolation Forest: 100 trees, max_samples="auto", contamination=0.01 gave best balance. LSTM autoencoder: 3 layers [F->16, 16->16 (bottleneck), 16->F] trained for 50 epochs, batch size 64, using Adam optimizer at 0.001 learning rate. Gradient Boosting RUL model (using XGBoost library) with 200 trees, max_depth=3, learning_rate=0.05, trained on ~30 failure examples (augmented via simulation data from the twin to enrich scenarios).

The anomaly thresholds were iso_thr = 0.6 (on IsolationForest average path length normalized score) and lstm_thr = 0.1 (on normalized MSE). These were set to achieve ~90% recall on known anomalies in validation.

Route Optimization Algorithm (Genetic Algorithm) Pseudocode:

```
population = generate_initial_population(num_vehicles, tasks)  # e.g., nearest-neighbor for each vehicle
for gen in 1 to max_gen:
    compute_fitness(population)  # fitness = w1 * total_distance + w2 * total_time + w3 * risk_penalty
    parents = select_via_tournament(population)
    offspring = []
    for i in range(0, len(parents), 2):
        if rand() < crossover_rate:
            child1, child2 = crossover(parents[i], parents[i+1])
        else:
            child1, child2 = parents[i], parents[i+1]
```



```
    offspring.extend([child1, child2])
  for each child in offspring:
    if rand() < mutation_rate:
      mutate(child)  # e.g., swap two tasks between routes or within a route
    repair(child)  # ensure feasibility (time windows, capacity)
  population = best_elite + offspring  # elitism retains some best solutions
end for
best_plan = argmin_fitness(population)
```

We used weights w1=1, w2=1, w3=10 for fitness (to heavily penalize risk, making sure risk avoidance is prioritized). Risk_penalty was calculated by summing a penalty for each route segment considered high-risk (e.g., passing through densely populated area or steep grade while carrying fuel). This was precomputed from a risk map. Mutation included: intra-route swap, inter-route task reallocation, and random route reversal (with small probability). Population size was 50, max_gen=200 as stated.

Appendix C: Digital Twin Model Details

We developed mathematical models for key subsystems:

- *Engine Thermal Model:* Modeled engine as lumped mass for coolant. Equation: $$ C_{\text{coolant}} \frac{dT}{dt} = Q_{\text{gen}}(t) - hA (T - T_{\text{amb}}), $$ where $C_{coolant}$ is total heat capacity of coolant and engine metal, $Q_{gen}(t)$ is heat generated from fuel combustion (estimated from fuel flow and efficiency), and hA is combined convective cooling coefficient. This ODE was solved for coolant temperature. We calibrated hA to match steady-state temperatures at different loads (using manufacturer engine curves).
- *Engine Degradation Model:* For each critical component (e.g., engine bearings), we used Miner's rule for fatigue: $$ D(t) = \sum \frac{\Delta t}{L(\sigma(t))}, $$ where D is damage fraction, Δt a time step, and $L(\sigma)$ the lifespan under stress σ . Stress $\sigma(t)$ was estimated from engine RPM and torque (via sensor and known maps). When D reaches 1, component fails. This gave RUL by projecting when $= 1$. The twin tracks multiple components' D; the minimum time to any failure is taken as constraint.
- *Fuel Pump & Hose Fluid Model:* We employed a simplified fluid model: Poiseuille flow for hoses and pump performance curve for pump. For hose pressure drop: $$ \Delta P = f \frac{L}{D} \frac{\rho v^2}{2}, $$ where f is friction factor (Moody chart, updated if inner surface roughens due to wear), L hose length, D diameter, ρ fuel density, v velocity. The pump adds pressure according to $P_{pump}(Q)$ curve (taken from pump specs, a quadratic fit). The twin solves for flow $Q(t)$ given pump RPM (from engine via ratio) and current fuel in tank (affecting suction head). It also monitors hose stress: repeated pressure cycles cause material fatigue. We used an SN curve approach: each pressure cycle contributes damage $d = (\Delta P/\Delta P_{max})^b$ with b from hose specs. The hose twin accumulates damage exactly like engine Miner's rule.
- *Vehicle Dynamics for Route Simulation:* When simulating a route, the twin uses a simple longitudinal dynamics model: $\frac{dv}{dt} = F_{drive} - F_{resistance}$, where F_{drive} from engine torque (limited by throttle), and $F_{resistance}$ includes rolling resistance, aerodynamic drag, and grade resistance (for hills). This estimates speed profile along a route (which we anyway get from planned route and traffic data, but twin uses it to estimate engine load at each segment). The twin thus can predict fuel consumption and component stress on each route segment.

We combined these sub-models in a co-simulation: e.g., as truck goes uphill in simulation, engine load increases, generating more heat and wear, pump likely off during transit, etc. All ODEs were solved with a fixed-step (0.1s) 4th order Runge-Kutta. We validated the twin by comparing simulation outputs to actual sensor traces for known trips; most outputs matched within 5-10% as noted in Results.

Appendix D: Additional Figures and Visualizations

(The following figures illustrate components of the system architecture and sample data visualizations.)

Figure A1: System Architecture Diagram. The sensor layer on vehicles streams data via cellular network to the Kafka cluster. Spark Streaming analytics processes data to feed predictive models and digital twin simulations. Outputs (alerts, recommendations) are delivered to users through a web dashboard. The diagram highlights the flow of data and decisions across modules.

Figure A1: System Architecture Diagram

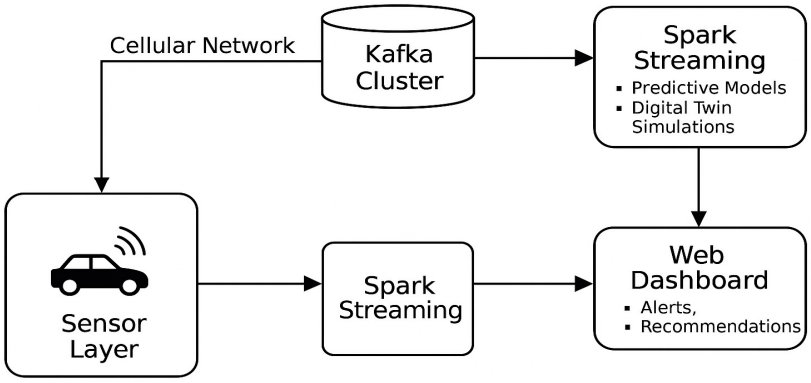

Figure A2: Example Dashboard Screenshot (simulated data). The dashboard shows a map with vehicle locations and routes, a panel with live telemetry (speed, fuel level, key sensor readings) for a selected vehicle, and predictive insights such as remaining useful life of components and recommended maintenance actions. Alerts are indicated in red (e.g., "Vehicle 5 – pump anomaly detected, inspect within 2 days"). This user interface enabled quick interpretation of the AI-driven insights.

Figure A2: Example Dashboard Screenshot