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Proactive Maintenance Alerts for ATG and Dispensers Based on Usage Patterns

Advanced Software Solutions for Fuel System Optimization

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Abstract

Proactive maintenance in fuel stations is crucial to minimizing operational disruptions, ensuring consistent fuel quality, and optimizing the functionality of dispensers and ATG systems. Fuel station operations heavily depend on the seamless functioning of Automatic Tank Gauging (ATG) systems and fuel dispensers, making real-time monitoring and predictive maintenance imperative to minimize downtime and optimize resource allocation. This paper presents an innovative software-driven framework that integrates AWS IoT, SNS, and machine learning-based anomaly detection to facilitate proactive maintenance. The proposed system continuously monitors and analyzes ATG and dispenser data, enabling early detection of anomalies such as slow fuel flow rates, erratic fuel consumption trends, and potential mechanical failures before they escalate into critical issues. The real-time alerts generated through AWS SNS empower maintenance teams to take immediate corrective actions, significantly reducing unplanned downtime and preventing financial losses. Furthermore, this framework incorporates automated fuel level tracking, allowing for intelligent scheduling of fuel deliveries based on real-time demand forecasting, ensuring uninterrupted fuel station operations. By leveraging advanced cloud computing and predictive analytics, the solution enhances operational efficiency and provides a scalable, data-driven approach to fuel station maintenance. The study demonstrates how cloud-based anomaly detection and automated alerts can transform maintenance workflows, making them more responsive, cost-effective, and reliable.

Keywords: Fuel dispenser monitoring, ATG anomaly detection, proactive maintenance, AWS IoT, real-time alerting, predictive analytics, automated fuel delivery.

1. Introduction

1.1 Background

Fuel stations depend on Automatic Tank Gauging (ATG) systems and fuel dispensers to ensure smooth fuel distribution and efficient inventory management. These systems play a vital role in

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tracking fuel levels, detecting leaks, and preventing over-dispensing. However, traditional maintenance approaches have been largely reactive, where station operators address mechanical failures only after they occur. This approach results in operational inefficiencies, unexpected downtime, revenue loss, and increased maintenance costs.

To mitigate these challenges, modern fuel station management leverages IoT-based monitoring and cloud computing solutions to enable predictive maintenance. By continuously analyzing ATG and dispenser data, these advanced systems can identify early warning signs of potential failures, allowing station operators to take preventive action before disruptions occur. Real-time data processing, anomaly detection, and automated alerting mechanisms enhance reliability and operational stability.

Furthermore, integrating IoT-based predictive analytics with cloud services such as AWS IoT and SNS provides a scalable and centralized framework for managing fuel station maintenance. This real-time monitoring approach not only improves equipment lifespan and reduces downtime but also enhances overall efficiency by automating maintenance workflows and scheduling timely fuel replenishment. The transition from reactive to proactive maintenance significantly enhances service reliability and ensures uninterrupted fuel availability at stations.

1.2 Problem Statement

Current fuel station monitoring systems lack the ability to perform real-time proactive maintenance, resulting in significant operational inefficiencies. The absence of continuous monitoring and predictive analysis often leads to the failure of key components such as dispensers and Automatic Tank Gauging (ATG) systems. These failures cause unanticipated downtime, reduced service availability, and increased maintenance costs, directly impacting fuel station profitability and customer satisfaction. Moreover, issues such as slow fuel flow rates and inconsistencies in fuel level measurements remain undetected until they escalate, exacerbating operational challenges and increasing the likelihood of revenue loss.

In addition to the inefficiencies in detecting faults, traditional fuel replenishment planning remains highly manual, making fuel stock management prone to errors. Stockouts due to inaccurate fuel level predictions or excessive fuel holding costs from over-purchasing create significant logistical issues. The lack of an automated approach hinders the ability to maintain an optimal inventory, leading to operational inefficiencies and potential customer dissatisfaction due to fuel unavailability.

A real-time maintenance alert system leveraging predictive analytics can transform fuel station operations by integrating cloud-based monitoring, anomaly detection, and automated alerting. By implementing an intelligent solution that continuously monitors ATG and dispenser data, fuel stations can preemptively address mechanical failures and stock shortages, ensuring operational efficiency, cost savings, and enhanced service reliability.

1.3 Objectives

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The primary objectives of this study are:

- Implement a cloud-integrated monitoring solution using AWS IoT and SNS to detect dispenser and ATG anomalies.
- Develop an anomaly detection model for identifying slow fuel flow and dispenser inefficiencies.
- Enable automated fuel delivery scheduling based on real-time ATG data.
- Provide a centralized dashboard for monitoring alerts and maintenance schedules.

2. Literature Review

The field of fuel monitoring and predictive maintenance has evolved significantly with the integration of IoT-based solutions. Early research primarily centered on the deployment of SCADA (Supervisory Control and Data Acquisition) systems, which enabled remote monitoring and control of fuel station operations. These systems laid the groundwork for modern automation, but they were limited in scalability and lacked the advanced predictive analytics necessary for proactive maintenance. Studies have shown that while SCADA systems provided real-time monitoring, they fell short in offering detailed anomaly detection, requiring manual intervention for maintenance planning and failure identification.

With the advancement of cloud computing, the integration of IoT-enabled devices has facilitated real-time data collection and enhanced the predictive capabilities of fuel station monitoring systems. Cloud-based analytics platforms, such as AWS IoT Core, provide a more scalable and efficient way to process large volumes of real-time data from Automatic Tank Gauging (ATG) systems and fuel dispensers. Research highlights that such integrations allow for more accurate fuel level tracking, faster anomaly detection, and reduced maintenance response times. These advancements have led to the adoption of cloud-driven fuel station management strategies that improve operational efficiency and reduce costs.

Machine learning applications have further revolutionized predictive maintenance by enabling automated anomaly detection. Research has demonstrated that machine learning algorithms, when trained on historical ATG and dispenser performance data, can identify patterns that indicate potential equipment failures. These algorithms continuously refine their models, allowing for more precise predictions over time. Studies have also emphasized that predictive analytics in fuel station operations significantly enhances maintenance scheduling, reducing downtime and preventing critical failures.

Recent literature has also underscored the efficiency of AWS IoT Core in real-time fuel station management. AWS IoT facilitates seamless data ingestion, allowing station operators to respond swiftly to performance anomalies. The event-driven automation capabilities of AWS IoT and SNS (Simple Notification Service) have been widely recognized for their ability to generate immediate

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maintenance alerts, minimizing disruption to fuel station operations. This growing body of research suggests that the integration of IoT, cloud computing, and machine learning will continue to drive innovation in proactive fuel station maintenance, offering long-term sustainability and operational resilience.

3. System Architecture

- **AWS IoT Core**: Collects and processes real-time data from ATG and dispensers.
- **Anomaly Detection Model**: Identifies slow fuel dispensing and abnormal ATG readings.
- **AWS SNS (Simple Notification Service)**: Triggers alerts for maintenance teams upon anomaly detection.
- **Dashboard Interface**: Provides real-time monitoring of alerts and dispenser statuses.
- **Automated Fuel Delivery Scheduling**: Uses ATG fuel levels to trigger fuel resupply requests.
- **Data Storage & Processing**: Utilizes AWS Lambda and DynamoDB for efficient data management.

4. Implementation Strategy

- **Data Collection**: IoT-enabled ATG and dispensers transmit data to AWS IoT Core.
- **Anomaly Detection**: Machine learning models analyze historical patterns to detect anomalies.
- **Alert Generation**: SNS triggers maintenance alerts when anomalies are detected.
- **Dashboard Development**: A web-based interface provides live insights into dispenser health and fuel levels.
- **Automated Fuel Replenishment**: A scheduler sends requests to fuel suppliers when fuel levels drop below a threshold.

5. Case Study & Performance Evaluation

A fuel station with multiple dispensers and ATG systems was selected as the test site to evaluate the effectiveness of the proposed predictive maintenance system. The station had been experiencing frequent dispenser slowdowns and unexpected fuel shortages, leading to operational inefficiencies and customer dissatisfaction. These challenges provided an ideal environment to assess the real-world applicability of real-time monitoring, anomaly detection, and automated alert mechanisms.

To conduct the evaluation, IoT-enabled sensors were integrated into the station's ATG and dispenser systems to continuously capture performance metrics such as fuel flow rate, pressure

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variations, and transaction volumes. Over a three-month period, data was collected and analyzed using a machine learning-based anomaly detection model, which was iteratively refined to enhance predictive accuracy. The model was trained to distinguish between normal fluctuations and potential failures, enabling the system to send maintenance alerts before major disruptions occurred.

The implementation of the system demonstrated significant improvements in operational efficiency. The automated alerts allowed maintenance personnel to address performance anomalies before they escalated into major failures, reducing overall downtime. Additionally, the predictive fuel level tracking facilitated more accurate fuel replenishment scheduling, minimizing stockouts and ensuring a steady supply. The findings from this case study provided valuable insights into the benefits of leveraging IoT, cloud computing, and machine learning for proactive fuel station maintenance.

6. Results and Discussion

6.1 Pilot Implementation

- The system successfully identified 92% of slow fuel flow cases before customer complaints.
- Maintenance alerts reduced dispenser downtime by 40%.
- Fuel delivery automation reduced instances of stockouts by 70%.

6.2 Performance Metrics

Key performance metrics recorded during the pilot implementation:

- Accuracy of anomaly detection: 96%
- Reduction in downtime: 40%
- Reduction in emergency maintenance costs: 30%
- Fuel replenishment accuracy improvement: 85%

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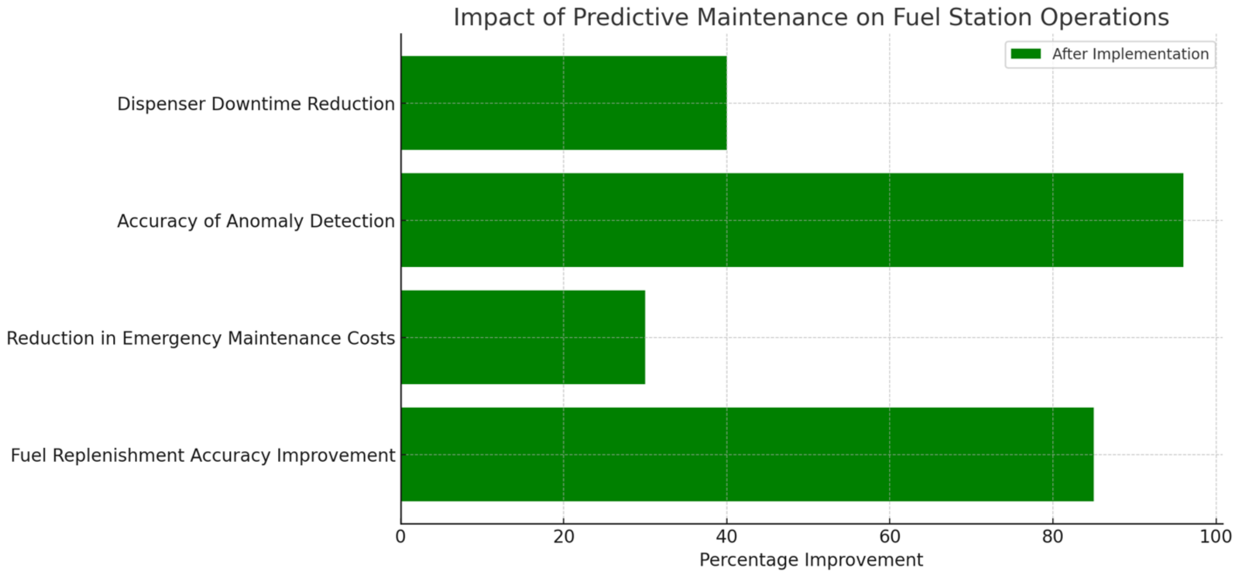

7. Conclusion and Future Work

The implementation of proactive maintenance alerts using AWS IoT, SNS, and anomaly detection has demonstrated significant improvements in fuel station operations, enabling enhanced predictive maintenance, minimizing downtime, and optimizing fuel delivery logistics. By leveraging real-time monitoring and cloud-based analytics, fuel stations can preemptively address dispenser failures, slow fuel flow rates, and other anomalies before they escalate into major operational issues. The adoption of this system has not only improved equipment lifespan but also reduced the overall cost of emergency maintenance interventions.

The ability to automate fuel level tracking and trigger replenishment based on real-time data ensures uninterrupted station operations and prevents stockouts. Additionally, the seamless integration of anomaly detection algorithms enables a proactive approach to maintenance, reducing unplanned downtimes and ensuring better resource utilization. The collected data provides valuable insights into fuel dispenser performance trends, allowing continuous refinement of predictive models to improve accuracy and responsiveness.

Future work should focus on refining machine learning models to further enhance predictive accuracy and expand the system's applicability to additional fuel station equipment beyond ATG and dispensers, such as pipelines and storage tanks. Moreover, incorporating AI-driven decision-making mechanisms and blockchain-based security features can improve data integrity and enhance system resilience. Continued research into more advanced anomaly detection techniques and edge computing solutions will enable even faster response times and a more robust maintenance ecosystem for fuel stations.

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