Machine Learning-based Analytics for Early Detection of HPFF Leaks

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SUMMARY

The High-Pressure Fluid Filled (HPFF) system is designed to provide a reliable and efficient means of power delivery in densely populated urban areas. The HPFF system utilizes cables which are insulated by a high-pressure dielectric fluid. The fluid enhances electrical insulation and aids in heat dissipation. Despite its advantages, the HPFF system suffers from the risk of fluid leaks, which could pose significant environmental hazards. Detecting leaks within HPFF systems presents a formidable set of challenges, including the underground placement of these cables beneath urban centres or critical infrastructure, the vast lengths of cable involved and the subtle nature of early-stage leaks demand highly sensitive detection mechanisms capable of continuous monitoring over large areas, and the complexity is further compounded by the need to distinguish between normal operational fluctuations and signs of a genuine leak, requiring advanced analytics and comprehensive data interpretation. The challenges of leak detection in HPFF systems necessitate innovative approaches that can leverage real-time data, sophisticated analytics, and automated alert systems to ensure environmental protection, system integrity, and operational continuity.

In this study, we have proposed a series of advancements in the detection and management of leaks within HPFF transmission systems, marking a substantial leap forward in operational efficiency and environmental protection. The system takes advantage of pressure variation data to calculate pump starts, overcoming the limit of no pump start sensor installed. Recognizing that excessive pump starts could indicate a system anomaly, possibly a leak, we leveraged this insight to develop a reliable anomaly detection framework. Then we have developed a machine learning-based method to dynamically adjust alert thresholds to detect anomaly. To augment our anomaly detection capabilities, we crafted a data visualization dashboard that serves as a powerful cross-check tool. Utilizing these tools and methodologies, our engineers have achieved a remarkable reduction in leak detection times—from the traditional span of traditionally several days to a few hours. This acceleration in detection capability not only enables data-driven infrastructure management but also underscores our commitment to environmental protection and sustainability.

KEYWORDS

Anomaly Detection, Data Analytics, High-Pressure Fluid Filled Cable, Machine Learning.

1. Introduction

High-Pressure Fluid-Filled (HPFF) cable systems are critical components in the underground transmission network, responsible for safely transporting high-voltage electricity across vast distances. These cables are insulated with paper or polypropylene and filled with a pressurized insulating fluid, which is critical for preventing electrical discharges and ensuring the longevity of the cable system. These systems have been in use for decades due to their reliability and efficiency in maintaining electrical insulation. The pressurized fluid in HPFF cables serves to maintain a constant dielectric environment within the cable, preventing breakdowns in insulation due to electrical stress. These cables are typically buried underground, and their maintenance is vital to avoid system failures that could cause power outages or environmental hazards due to oil leaks.

One of the primary issues in HPFF cable systems is fluid leakage. Leaks can occur due to mechanical damage, corrosion, or the natural aging of components such as seals and joints. Even small leaks can have significant consequences, including insulation degradation, reduced cable lifespan, and, in severe cases, environmental contamination. Many HPFF systems in operation today were installed decades ago, and the aging infrastructure poses increasing risks of failure. As these systems age, they become more susceptible to leaks, which makes developing reliable detection and maintenance strategies a priority for utility companies.

Historically, leakage detection in HPFF systems has relied on visual inspections and manual pressure monitoring. Periodic inspections along the cable route allowed maintenance teams to identify obvious signs of leakage. Pressure drops in the system were another key indicator, prompting repairs if pressure loss exceeded acceptable thresholds. However, these methods are both labor-intensive and relying on huge capital investment for hardware upgrade. Several studies have explored the use of acoustic sensors to detect fluid leaks in HPFF systems. Acoustic sensing works by identifying the sound waves generated as pressurized fluid escapes through cracks or holes in the cable. In [1], the study demonstrated that acoustic sensing could locate even small leaks with high accuracy, providing a valuable early warning system. More recently, Xiaoyi et al. introduced a network of acoustic sensors that enable continuous monitoring, reducing reliance on periodic inspections [2]. Thermal imaging has also been explored as a method for detecting leaks, particularly when the escaping fluid results in temperature anomalies along the cable's surface. Mahmoud et al. showed how infrared cameras could detect these temperature differentials, providing a non-invasive method to identify leaks that may not be visible through traditional means [3]. In [4], the use of hydrocarbon sensors to detect the presence of insulating fluid in the soil surrounding the cables was explored. This method has been particularly useful for detecting environmentally hazardous leaks, as even trace amounts of oil can be detected with high sensitivity, allowing for rapid response before the leak escalates. Fiber optic sensing is one of the most promising recent advancements in HPFF leakage detection. Fiber optics can monitor changes in both temperature and pressure along the cable, providing real-time feedback on the system's integrity. In recent years, machine learning has emerged as a tool for improving leakage detection. By analysing historical data, including pressure readings, acoustic sensor outputs, and environmental factors, machine learning algorithms can predict the likelihood of leaks before they occur. Wojciech et al. highlighted how this approach significantly reduced false alarms while providing earlier detection of potential issues, thus improving maintenance efficiency and system reliability [5].

In this study, we have pioneered a series of advancements in the detection and management of leaks within HPFF transmission systems, marking a substantial leap forward in operational efficiency and environmental protection. The system takes advantage of pressure variation data to calculate pump starts, overcoming the limit of no pump start sensor installed. Recognizing that excessive pump starts could indicate a system anomaly, possibly a leak, we leveraged this insight to develop a reliable anomaly detection framework. Then we have developed a machine learning-based method to dynamically adjust alert thresholds to detect anomaly. To augment our anomaly detection capabilities, we crafted a data visualization dashboard that serves as a powerful cross-check tool. Utilizing these tools and methodologies, our engineers have achieved a remarkable reduction in leak detection times - from the traditional span of traditionally several days to a few hours. This acceleration in detection capability not only demonstrates our leading role in developing data-driven infrastructure management but also underscores our commitment to environmental protection and sustainability.

2. System Overview

The HPFF leak early detection system has three parts, pump start calculation, machine learning-based dynamic threshold setting, and a comprehensive PowerBI dashboard.

2.1 Innovative Use of Pressure Variation Data

In the proposed HPFF monitoring and alert system, we have developed an approach to use line oil pressure for estimating the pump start events. This process involves monitoring the variation in oil pressure and applying a structured analysis to detect unusual patterns in pump operation.

The first step involves monitoring the line oil pressure. As shown in the left curve in Figure 1, the variations in pressure over time can be observed. The pressure fluctuates from 158 PSI to 202 PSI, which typically indicates a pump start. To quantify pump activity, we calculated the number of pump starts within four-hour or daily intervals. This method provided a granular view of pump activity and captured the patterns over time. The middle graph in Figure 1 illustrates the results of this calculation, showing the frequency of pump starts. Once we have established a baseline of pump starts based on four-hour or daily intervals, we apply an anomaly detection mechanism. The goal is to identify sudden increases in the frequency of pump starts, which may indicate system anomalies or malfunctions. Using a rolling window approach, we evaluated the daily sum of pump start and compared it to a pump start threshold, which can be calculated by a machine learning (ML) method.

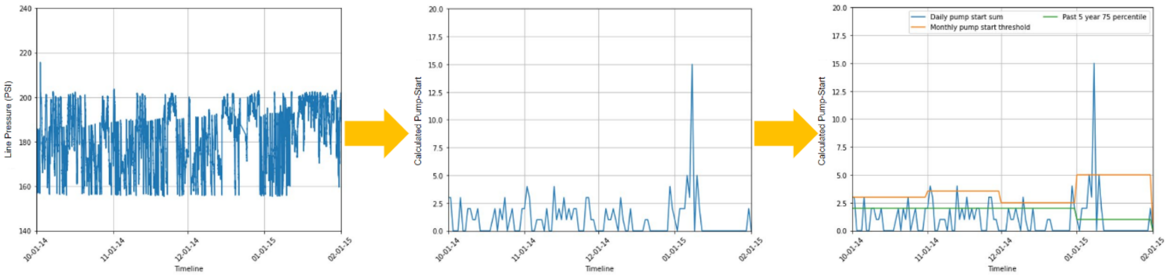

Figure 1. Process of calculating the pump start from line pressure variations.

2.2 Machine Learning-Based Dynamic Threshold Setting

To calculate the threshold, we have developed a ML-based method. Given that pump start events can be influenced by various factors such as elevation changes, temperature fluctuations, seasonal variations, load dynamics, and concurrent pump operations, it is critical to implement a flexible threshold that adapts to these variables. The diagram in Figure 2 outlines the overall workflow.

The process begins with data collection from multiple sensors, stored in a PI Historian database. The data includes oil line pressure, oil level, line current, and oil temperature. This diverse set of data provides a holistic view of the factors influencing the pump's behaviour. Before analysing the data for pump start detection, it undergoes pre-processing to ensure accuracy and reliability. Then the machine learning model considers multiple influencing factors, such as, elevation changes, temperature fluctuations, seasonal variations, load dynamics, and concurrent pump operations. By analysing the historical data alongside these variables, the ML model calculates a dynamic, real-time threshold for pump starts.

The output of the machine learning model is a dynamic threshold that adapts over time. The graph shows two thresholds:

a. **Rolling monthly threshold (orange)**: This threshold is calculated based on the recent history of pump start behaviour, allowing for short-term fluctuations.
b. **History-based monthly threshold (green):** This threshold is derived from long-term historical data, providing a stable reference point for detecting significant deviations.

Together, these thresholds allow for the detection of anomalies that may indicate potential issues in the HPFF system. Any sudden or unexplained increase in pump start frequency that exceeds these thresholds is flagged for further investigation.

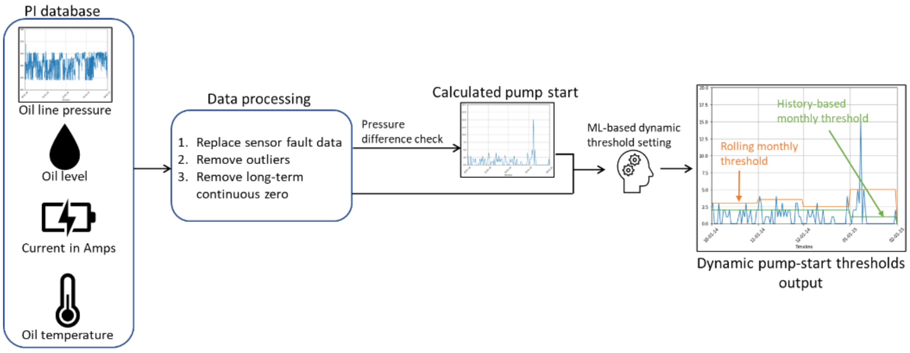

Figure 2 – Diagram of ML-based Dynamic Threshold Setting

2.3 Development of a Comprehensive PowerBI Dashboard:

To augment our anomaly detection capabilities, a PowerBI dashboard that serves as a powerful cross-check tool has been developed. By integrating tank level data, temperature readings, and load change information, this dashboard provides operation engineers with a 360° view of system operation. This integration of diverse data streams into a unified interface empowers engineers to rapidly ascertain whether an identified anomaly is indicative of a leak.

Figure 3 shows the first page of the dashboard serves as a central hub for summary information, which provides a broad yet detailed view of the HPFF system's health over a 90-day period. Key features include:

a. **Oil Pressure**: A visual representation of the oil pressure across each line for quick identification of pressure trends.
b. **Pressure-Derived Pump Start**: Insights into pump start counts derived from pressure data.
c. **Load Changes Visualization**: Load variations over time, highlighting how shifts in demand impact system pressure.
d. **Temperature Variation Tracking**: Temperature data across the system.
e. **Pump Plant Tank Oil Variations**: Observation of oil level trends in pump plant tanks.

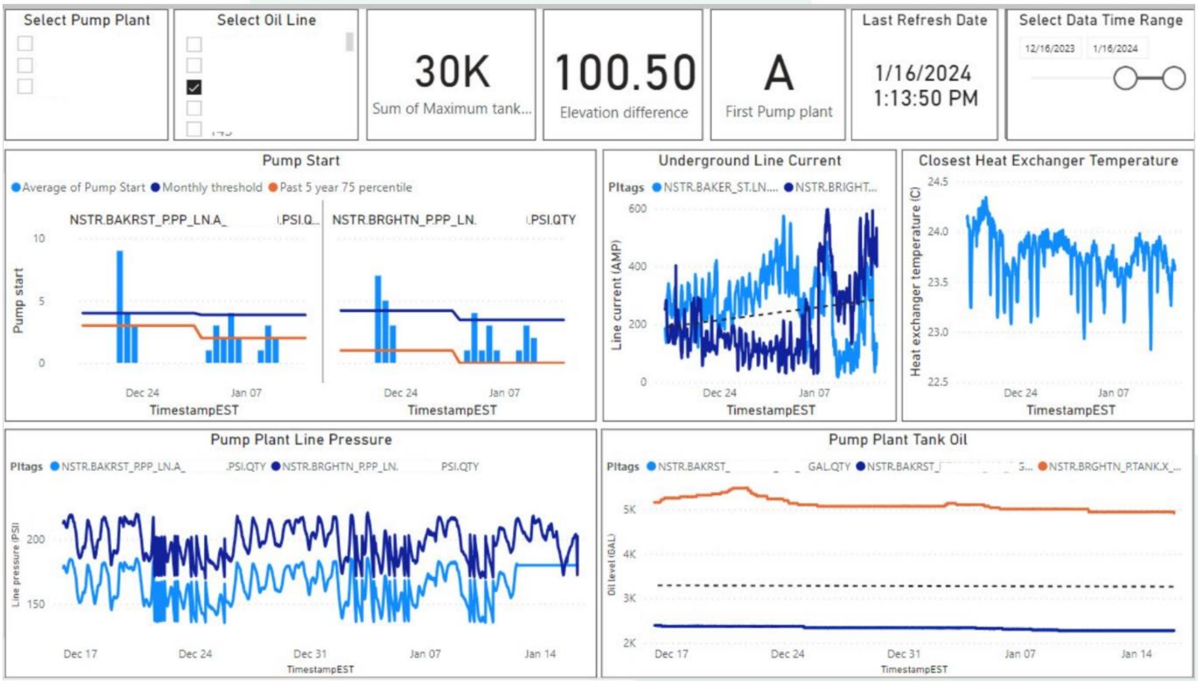

Figure 3 – Summary information of HPFF pipeline/network

The second page, as shown in Figure 4, shows the critical task of anomaly detection and verification.

Figure 4 – Anomaly detection and crosscheck

The features are:

a. **4-Hour, 24-Hour and 10-Day Alert Counts**: Immediate access to recent alert statistics, enabling trend analysis and prioritization of investigative efforts.
b. **Anomalies Ranking Table**: A prioritized list of detected anomalies, ranked by severity or potential impact.
c. **Pump-Plant Line Pressure Trend**: Detailed tracking of pressure trends over time.

d. **Tank Oil Trend Analysis**: Insights into oil level changes in tanks, which may indicate leaks or system integrity issues.
e. **Pump Start Trend Visualization**: Examination of pump start frequencies, highlighting operational anomalies that may suggest leaks or mechanical issues.

Together, these pages form a comprehensive monitoring solution that enhances the operational efficiency and contributes to early detection and response to potential leaks.

3. Demonstrated in Practice: Effective Application on a Recent Leak

Since its implementation, the proposed leak detection method has been rigorously tested, proving its value by facilitating the identification of a leak event as shown in Figure 5. On that morning, the developed monitoring system flagged a potential leak within the HPFF system, triggered by irregular pump start patterns, which automatically notified the operational engineers. Upon receipt of this notification, the team quickly undertook a verification process, leveraging the PowerBI dashboard to scrutinize oil tank variation data, line load changes, in conjunction with the initial pump start irregularities. This comprehensive review process allows for a nuanced analysis of system behaviour, ensuring that alerts are validated with corroborating operational data. The detailed examination led to the quick identification of the issue, and the operation team was able to take swift action not only to resolve the issue effectively but also to prevent what could have been a significant oil leak.

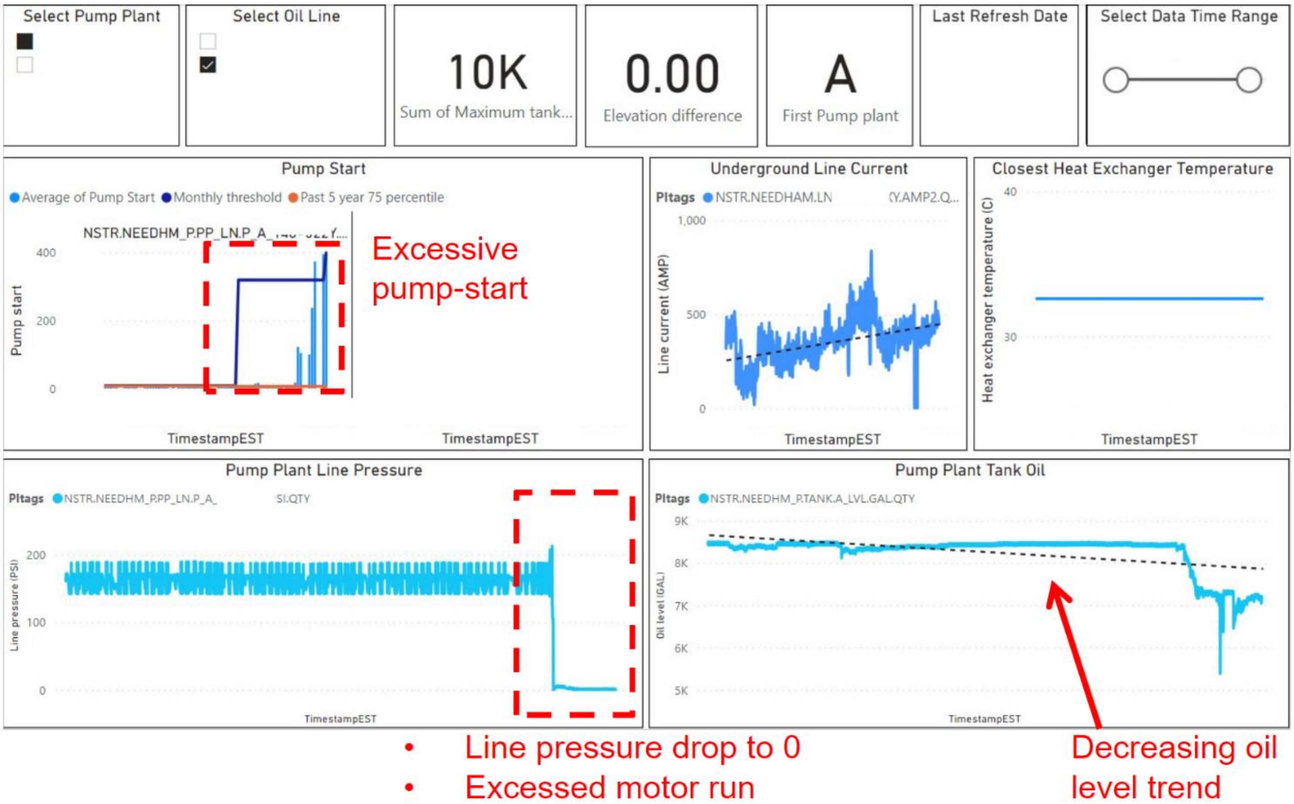

Figure 5 – Verification in a leak event

This event serves as a powerful example of the efficacy of the proposed leak detection method. The ability to detect, validate, and respond to anomalies with such speed and precision significantly reduced the risk of oil leakage and its associated environmental impacts. Furthermore, this incident highlights the importance of integrating sophisticated analytics with operational expertise, a synergy that is central to our approach.

4. Environmental Impact

The advancements in leak detection within HPFF systems embody a significant stride towards mitigating environmental risks associated with high-voltage power transmission. The cornerstone of our environmental impact is the dramatic reduction in leakage detection time—from traditionally several days to a few hours. This expedited detection process significantly limits the volume of dielectric fluid that can leak into the environment, thereby reducing the potential for soil and water contamination. The introduction of the ML-based dynamic threshold method and comprehensive dashboard for the anomaly detection has provided a data-driven foundation to quantify environmental benefits. While specific metrics of prevented incidents and resource savings are continually being compiled and analysed, the overarching trend indicates a significant positive impact. Reduced leakage volumes, decreased use of clean-up resources, and the avoidance of potential regulatory penalties are concrete indicators of our system's environmental benefits. The project exemplifies how technological innovation can be harmoniously aligned with environmental stewardship, setting a new benchmark for the industry in the pursuit of eco-friendly energy solutions.

5. Conclusions

In this study, we have proposed an approach to leak detection and management in HPFF transmission systems, significantly improving both efficiency and environmental safeguards. Our solution utilizes pressure variation data to infer pump starts, bypassing the need for a dedicated sensor, and recognizing that a spike in pump starts can signal potential system issues, such as leaks. Building on this insight, we created a robust framework to identify anomalies in real-time. To enhance the accuracy of our detection, we integrated ML algorithms that automatically adjust alert thresholds based on evolving data patterns. Additionally, we developed an interactive dashboard for data visualization, offering engineers a streamlined way to validate system performance and cross-check for anomalies. As a result of these innovations, we can dramatically reduce the time it takes to detect leaks, shrinking it from days to just hours. This faster detection not only optimizes system reliability but also underscores our commitment to protecting the environment through sustainable practices.

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