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An Examination of an Integrated Platform for Pipeline Management and Detection of Theft/Leaks based on Industry 4.0

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Abstract

This paper delves into the transformative implications of Digital Twin (DT) technology on pipeline management within Industry 4.0, emphasizing its pivotal role in ensuring integrity, efficiency, and leak detection for oil, gas, and water transportation. The proposed pipeline management platform adopts a conceptual DT architecture, integrating key components such as the Asset Administration Shell (AAS), Admin-Shell-IO, Node-RED, Apache StreamPipes, SimCenter, MATLAB, and Ignition software.The platform focuses on automation, operational optimization, safety, and regulatory compliance through this integration. To achieve these goals, the paper introduces the Modified Real-Time Transient Modeling (MRTTM) framework, which aims to swiftly and accurately detect and locate leaks. Furthermore, the operational procedure of this framework involves three key stages. In the "Data Collection" phase, sensor data are monitored by observing nodes. In the subsequent "Detection" stage, leaks are identified, and in the concluding "Decision-making" module, the exact magnitude and location of the leakage are determined using MRTTM. Leveraging a hybrid approach that combines the Extended Kalman Filter (EKF), Real-Time Transient Modeling (RTTM), and machine learning algorithms, the framework offers accurate insights into the pipeline's operational status. Moreover, machine learning models, including K-nearest neighbors (KNN) and support vector machines (SVM), enhance anomaly detection precision, allowing for early identification and localization of potential leaks.Ultimately, the proposed framework brings several key benefits to pipeline management, including early anomaly detection, real-time data integration, predictive maintenance, and regulatory compliance. By identifying potential leaks and anomalies early on, operators can take measures to prevent failures, respond quickly to disruptions, and comply with environmental and safety regulations.

Keywords: Pipeline Management; Theft/Leak Detection; Industry 4.0; Digital Twin; Asset Administration Shell; Modified Real-Time Transient Modelin.

Introduction

The most important strategy for reviving industries in the oil and gas sector is digital transformation. Real-time frontier organizational information, historical operating statistics, predictive analysis, forecasting, and execution are crossed by the journey to digital transformation. They are components of the next industrial revolution that include the visualization, evaluation, and improvement of all aspects of the industrial process with a 360-degree view of the digital value chain [1]. Using technological platforms provides opportunities to improve operator performance, reduce energy consumption, and increase the efficiency of crucial products. Enhanced online activity management is made possible by these platforms, and it substantially affects energy consumption, process performance, and efficiency optimization for both manufacturing and process plants [2]. Meanwhile, Industry 4.0 is a revolutionary force that unifies automation, Big Data analytics, Cyber-Physical Systems (CPS), the Internet of Things (IoT), and automation through a cloud-based architecture [3]. In addition, technology, industries, social dynamics, and operational procedures are all expected to undergo radical change in this game-changing period, mainly due to increased connection and intelligent automation.

The idea of a "Digital Twin" or a synchronized virtual depiction of physical assets, is central to the concept of Industry 4.0. When combined with state-of-the-art communication technology, these virtual equivalents of their physical counterparts provide a range of

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advantages, including real-time awareness, granular control, intelligent decision-making, and two-way information flow [4]. Applying the DT technology in Industry 4.0 transforms traditional production and operating models. It opens up novel possibilities for enhanced productivity and intelligent decision-making in modern industrial environments. The advent of this digital revolution into previously unheard-of industries such as oil and gas indicates a new era of unparalleled prospects for performance optimization, energy efficiency, and operational enhancements.

The Reference Architecture Model for Industry 4.0 (RAMI 4.0) is one of the popular foundations for Industry 4.0's development. It functions as an organized and thorough three-dimensional model that addresses the intricacies of Industry 4.0 and promotes understanding among its constituents. Moreover, an essential part of planning and arranging the execution of Industry 4.0 projects is RAMI 4.0 [5]. In addition, managing physical assets in Industry 4.0 is the primary function of AAS, which is a fundamental element of the RAMI 4.0 framework [6]. On the other hand, the asset, communication, information, and function layers are among the layers of the RAMI 4.0 structure that AAS functions across. In addition, it offers an information structure that is strong enough to support the flow of data between digital assets by providing a meta-data model.

AAS allows synchronized virtual equivalents of physical assets by arranging the information flow among assets, including tools, supplies, software, and documents. This greatly aids in the digital transformation of industries. RAMI 4.0 and AAS work together to create an integrated framework that simplifies the digital representation of physical assets. This increases data sharing and operational efficiency in the Industry 4.0 ecosystem. To explore this subject in greater detail, future research might look into real-world case studies, improvements made to AAS functionalities, difficulties encountered during implementation, and the growing role that AAS serves in many fields.

Typically, the pipeline is made of carbon steel and is the primary cause of pipeline accidents, described as metal failure, cracking, external interference, dents and mechanical damage, material, manufacturing or construction, and geotechnical hazards [7]. Performance estimation allows systematic leak detection system (LDS) knowledge and Figurs out how components cause issues, as well as performance observation using historical performance evaluation and/or testing of LDS performance to help decide LDS performance [8]. Specific criteria and permits are essential for guaranteeing AAS deployment's efficacy and compliance in pipeline management and leak detection. The following particular guidelines and authorizations are necessary for this area:

Adhering to the American Petroleum Institute (API) standards, e.g., API 1130 for computational pipeline monitoring, is crucial for effective pipeline management and leak detection [9]. Ensuring compliance with safety measures like ASME B31.8 is vital for safeguarding pipeline operations during the design, construction, and maintenance phases [10]. Upholding environmental regulations, as established by entities like the Environmental Protection Agency (EPA), specifically regarding leak prevention and detection, is imperative. Protecting pipeline systems from cyber threats necessitates cybersecurity standards, such as the National Institute of Standards and Technology (NIST) Cybersecurity Framework [11]. Adhering to data privacy regulations, including the General Data Protection Regulation (GDPR) and similar laws, is essential when handling sensitive pipeline operation data [12]. Obtaining approval from regulatory authorities is often a legal requirement, contingent on the pipeline's location and characteristics. Complying with interoperability standards is crucial for the seamless interaction of AAS components with various monitoring and control systems. Addressing patents and intellectual property rights is pivotal when deploying exclusive technology for pipeline management and leak detection.

To implement pipeline management and leak detection systems effectively, seeking guidance from industry associations, regulatory bodies, and legal experts is crucial. Determining the required standards and permissions is vital, considering variables like location, pipeline type, and associated technologies.

This paper's literature review aims to arrive at an achievable solution by analyzing pertinent research and relevant approaches. The objective is to create this solution focusing on digital transformation by fusing both conventional and novel technologies with applications. Also, the research methodology aims to offer a theoretical solution for using the AAS in Asset Performance Management (APM) when implementing a DT, and a paper [13] is cited to explain this further. Concerning papers [14-16], the investigation of AAS's application in Industry 4.0 is also covered. Also, the use of DT in the management of pipelines and leakages is available in papers [17-19]. Additionally, the utilization of Node-RED in pipeline management and leak detection is highlighted, with references to articles [20, 21]. In [21] and [22], an efficient, standardized method for exchanging maintenance data within the Operation and Maintenance framework of process plants, elevating their capabilities as DTs, is introduced.

In pipeline asset management and data analysis, the Kalman filter is a powerful tool for tracking fluid flow and detecting potential leaks [22]. This recursive estimation algorithm effectively mitigates uncertainties inherent in the data and the dynamics of the pipeline system by updating its state estimates with new and previous measurements. Conversely, RTTM provides a dependable approach to leak identification [23]. Moreover, RTTM is a mathematical model-based leak detection technology that utilizes real-time fluid flow, pressure, and temperature measurements to detect and locate pipeline leaks. Continuously comparing the actual operating conditions of the pipeline to a simulated "virtual pipeline" model, RTTM identifies discrepancies that could indicate a leak. The MRTTM framework, as presented in this paper, represents a substantial advancement over traditional RTTM, particularly in leak detection. By integrating machine learning algorithms, such as KNN and SVM, with real-time adaptive capabilities, MRTTM demonstrates superior responsiveness to dynamic pipeline conditions. As outlined in [24], this enhanced responsiveness is crucial for effective leak detection in complex pipeline systems. Unlike RTTM, which primarily relies on modeling fluid dynamics and detecting deviations in pressure and flow profiles, MRTTM leverages the EKF to mitigate the challenges posed by sensor noise and operational variability. This enables MRTTM to filter out noise and swiftly respond to transient conditions, such as sudden leaks, enhancing detection speed and accuracy. Furthermore, MRTTM's utilization of a leakage pattern bank allows it to adapt to diverse pipeline conditions and fluid types, increasing its versatility and effectiveness. The framework's dynamic adaptability and incorporation of machine learning models facilitate more precise leak localization compared to the more static approach of RTTM. In addition, AAS complements these technologies by providing a centralized repository for asset data. This centralized platform empowers the EKF to gain comprehensive insights into the pipeline's operational status, enabling the accurate identification and localization of potential leaks.

It has integrated machine learning algorithms into the proposed hybrid methodology to further advance the precision of leak detection in pipelines. This approach incorporates well-established models such as SVM [25] and KNN [26]. These models are crucial in identifying anomalies within the pipeline data, particularly in analyzing patterns and deviations observed in flow rate and pressure measurements. Integrating SVM and KNN enhances the system's capability to pinpoint potential leak locations with heightened precision. While hybridization of SVM, KNN, and EKF increases computational complexity, it substantially enhances detection accuracy in complex, nonlinear scenarios. To mitigate the computational burden, techniques like dimensionality reduction or parameter optimization can be employed to optimize the balance between speed and accuracy. Hybridization is often essential when individual models fail to fully address the intricacies of the problem. While the integration of machine learning, specifically KNN and SVM, is well-aligned with the proposed DT-based platform, and the explanation of their role in anomaly detection is clear, a more quantitative evaluation is warranted. Including performance metrics like accuracy, precision, recall, and F-score would provide a more robust assessment of these model's effectiveness in detecting leaks. For a more detailed discussion, please refer to [24].

In addition to incorporating SVM and KNN, we introduce two additional cutting-edge techniques, namely Long Short-Term Memory (LSTM) [27] and Convolutional Neural Network (CNN) [28], to introduce advanced methodologies to our readership. While our primary focus in this section revolves around utilizing SVM and KNN in leak detection, the introduction of LSTM and CNN aims to broaden the scope of potential techniques that can be explored in the field. The combination of AAS, EKF, and machine learning presents a comprehensive solution for asset management, data analysis, and accurate leak detection in pipelines. This synergistic integration leverages the strengths of each technology to achieve optimal performance in pipeline monitoring and anomaly identification.

The research highlights a significant innovation in integrating technologies for managing pipelines and addressing issues such as leakage and theft. While previous studies have examined these technologies independently, this paper introduces a novel approach leveraging the DT conceptual architecture. Notably, the research identifies a gap in existing literature, noting the absence of cases where these technologies have been integrated. This signifies a pioneering effort to bring together disparate aspects of pipeline management and compliance with regulatory standards through the unified framework of a DT, demonstrating a unique and promising direction for future developments in this field.

The motivation for compiling the present study was the specifications for integrated pipeline management and theft/leak detection systems using DTs and related technologies and the requirements for use. Using the proposed framework, operators are guided to align with setup allocation and reduce operating expenses based on the pipeline's integrity, efficiency, and convenience. Information-sharing frameworks, systems, implementations, resource management, security, and flexible applications must be built on open standards to be precise, flexible, and responsive. This makes it easier to do enterprise at different levels, connect field systems to corporate operations, and integrate operational control, information management, energy management, real-time process automation, and data safety with international data protection protocols [27]. This concept aims to streamline the control and surveillance of critical pipeline networks, enhancing management, efficiency, and cost-effectiveness [28, 29]. For the oil and gas sectors in all project phases—construction, operation, or repair—this advanced pipeline management offers a lot of promise.

The remaining section of the paper is arranged as follows: Section 2 includes a description of the role of DT's and related technologies, advanced pipeline management and leak detection, as well as an assessment of problems. Section 3 introduces the Concept of advanced pipeline management and leak detection platform developed by author and related methodology in the proposed framework. Section 4 concludes the study by offering the paper's findings, advantage of concept and suggestions for future research.

Materials and Methods

In today's complex industrial landscape, managing pipelines—particularly in the oil, gas, and water sectors—has become increasingly sophisticated and data-driven. The advent of Digital Twin (DT) technology has significantly transformed this domain. When applied to pipeline management and leak detection, DTs provide unprecedented benefits. The following introduces the components and functional structure of this innovative approach.

Digital Twin

The DT paradigm is a computational process model that supports smart objects attached to sensors, and IoT can be used to monitor and control system status in real-time in combination with machine learning and advanced analysis. National Aeronautics and Space Administration (NASA) was the first experimenter in space technology with the DT pairing technology predecessor [30]. DT systems allow the full life-cycle control of physical assets, starting with the design and length of the product or operation. As the asset's lifetime continues, a digital copy is updated in real-time [31]. One invention that's revolutionizing a number of industries is the idea of "DT's," which has a special bearing on leak detection and pipeline management. DT's provide a thorough picture of industrial processes and go beyond conventional operations in the context of digital transformation. DT's, which function as replicas of actual assets and allow for real-time monitoring and control of pipeline systems, are primarily powered by IoT, sensors, and machine learning. These virtual models constantly change in time with the pipeline's life cycle, enabling complete life-cycle control and an in-depth analysis of every component of the pipeline. The process of creating DT's is intricate and involves several key stages, such as data collection, data representation, and hybrid analytics models [32]. This leads to precise reflections of pipeline elements, accurate real-time data collection, and advanced analysis capabilities for pipeline management, facilitating deliberate decision-making. When advanced data processing, machine learning algorithms, and predictive analytics are integrated into platforms, the effectiveness of DT's in detecting leaks is significantly increased. These developments allow real-time data from sensors and inspections to be updated continually into high level models, improving pipeline integrity by revealing hidden breaches.

Due to their potential to completely transform industries by producing replicas of real products, DT's have drawn a lot of fascination. The core architecture is what makes them effective, especially when it comes to big data and AI pipeline integration. The following architecture is proposed by Big Data Value Association (BDVA) [33]:

- **Data Acquisition/Collection**: In order to create realistic virtual representations, real-time data from IoT devices must be gathered at this stage of the process. It makes it possible to acquire extensive data for pipeline management, which is essential for leak detection.
- **Data Representation**: Transforming gathered data into a digital format requires modeling and organizing it using flexible computer-generated frameworks.
- **Hybrid and Cognitive Analytics Models**: These sophisticated analytics models improve decision-making by providing in-depth analysis, predictive, and intelligent features [34].
- **Action/Interaction, Visualization, and Access**: DT's enable users to make well-informed decisions by offering actionable insights, interactive interfaces, visual representations, and readily available real-time data.

Because of its dynamic nature, the DT concept may be tailored to fit the various needs of different sectors and can change to meet new requirements. In addition, DT's' encompassing architecture, which includes accurate representation, strong data collecting, cognitive analytics, and user-friendly interfaces, has a profound effect on a variety of industries and increases their potential for transformation [35]. The proposed DT architecture outlines the operational functioning of the software within the integrated pipeline management framework. Furthermore, innovations such as advanced data processing, machine learning algorithms, and predictive analytics are incorporated into DT frameworks to enhance their capabilities in handling big data and AI-driven pipeline design. Moreover, these applications further amplify the influence of DTs across various sectors. In addition, to ensure data quality and reliability, preprocessing steps like missing data handling, outlier detection, normalization, filtering, and data reconciliation [36] are essential. Missing data points, resulting from sensor failures or communication errors, should be addressed through interpolation or imputation. Furthermore, outlier detection is crucial for identifying sensor malfunctions or external disruptions that might falsely indicate leaks. Normalization ensures that data from sensors measuring different physical quantities can be effectively compared in the machine learning models.

Furthermore, data reconciliation is employed to improve the accuracy and consistency of generated data within the pipeline monitoring system. This reconciled data is crafted to emulate real-world sensor data attributes, including missing values, measurement errors, outliers, and noise-induced variability. By using reconciled data with such realistic characteristics, the DT framework ensures that training and operational data accurately mirror real-world conditions, thus strengthening model robustness and reliability. The concept presented in Fig. 1 emphasizes an extensive and multifaceted infrastructure that is necessary for preserving the existence of DT's.

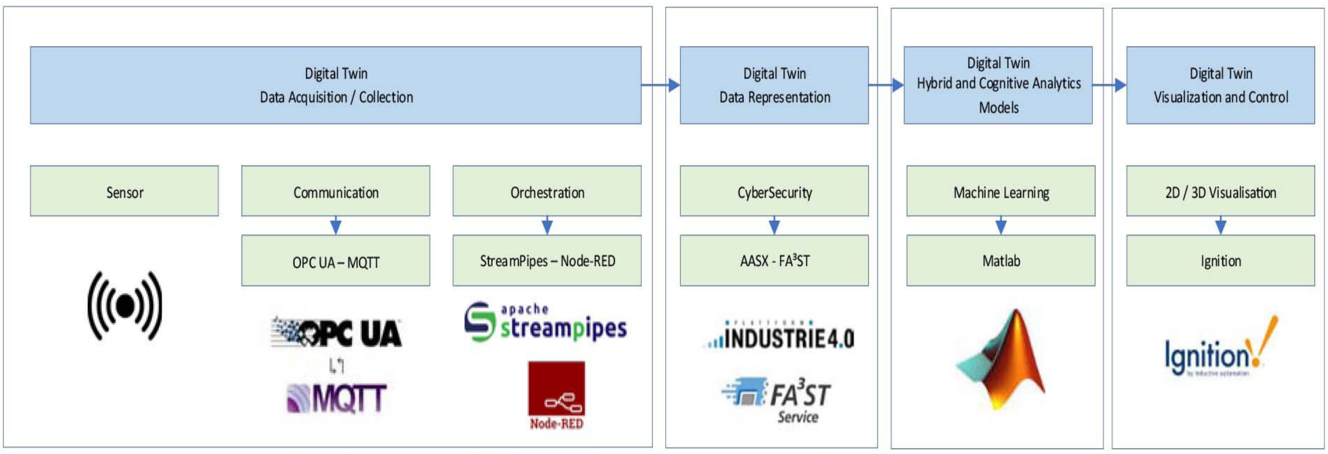


Fig. 1 Conceptual DT architecture for the integrated Pipeline management.

The application of a conceptual DT for integrated pipeline management offers a robust framework to analyze and mitigate potential risks swiftly and efficiently. By integrating precise engineering data and instrument information, it allows for proactive hazard identification, compliance assessment, and quick response strategies to prevent or minimize potential incidents. This advanced platform's adaptability and access to diverse datasets are key factors in ensuring swift, compliant, and effective pipeline management across various sectors, from oil and gas to water resources.

Asset Administration Shell

One of core ideas of the industry 4.0 is the AAS. Within this ecosystem, AAS represents a methodically constructed, standardized data envelope of a particular asset or component. For the smooth operation of an AAS, data sharing, regulatory compliance, and interoperability, a variety of standards and permissions must be followed. Important conditions for putting AAS into practice include following ISO standards such as ISO 22400 and ISO 15926; adhering to Industry 4.0 principles; following data privacy and security laws such as the GDPR; getting asset owners' consent; meeting interoperability requirements; taking care of patents and intellectual property rights; and possibly obtaining regulatory approvals, especially for safety-critical systems or assets [37]. For complete compliance in AAS implementation, it is imperative to communicate with industry experts and legal specialists as the specific requirements and approvals may differ based on the corporation, use case, and assets involved.

The Header and the Body are the two primary parts of the AAS data model, as shown in Fig. 2 The important function of the Header is to indicate the depicted Asset and the AAS and to provide basic context. The Body, on the other hand, explores the finer points of the digital representation, defining Submodel Elements like Properties that identify particular properties of the Asset and Submodels of the Asset that depict hierarchical structures inside the AAS. External reference Concept Descriptions are used to help determine the Submodels and Properties related with the Asset and to build the structure and relationships within the AAS. Moreover, the correlation across several AASs is determined at the level of the Asset or Submodel, which makes it easier to depict intricate assets, their characteristics, and connections inside the AAS framework [38]. DT's can integrate data seamlessly thanks in large part to Admin-Shell-IO. It provides the methods and instruments required to connect various sensors and devices to the DT, guaranteeing effective data gathering, processing, and analysis. This data integration is quite important, especially when it comes to pipeline systems. It is essential for real-time pipeline infrastructure monitoring and the early identification of anomalies and leakage. DT's may efficiently collect and handle data from several sources by utilizing Admin-Shell-IO [40]. This helps to proactively identify possible problems in pipeline systems, which improves operational efficiency and safety.

On the other hand, considering Industry 4.0 as a whole, this AAS structure is essential for creating a DT of physical assets, which enables efficient data exchange, asset management, and asset modeling in the technological domain. Additionally, a Java-based software toolbox called FA³ST, which stands for "Fraunhofer Advanced AAS Tools for DT's," is designed especially for the creation and administration of DT's that follow AAS principles. For developers, this all-inclusive software suite is essential since it provides all the tools needed to swiftly create and manage DT's that meet AAS criteria [41]. Conceptual architecture of the FA³ST Service can be seen in Fig. 3 The high-level schematic diagram in Fig. 3 outlines the FA³ST service library's components and interfaces, emphasizing extensibility and customization. At the heart of the AAS Metamodel lies a Digital Twin (DT) representation with its attributes and functionalities. The south-bound side introduces an Asset Connection extension to facilitate connections with various AAS systems, while the north-bound side employs a Protocol Endpoint extension to establish API endpoints for interactive DT engagement. The FA³ST service provides HTTP/REST and Open Platform Communications Unified Architecture (OPC UA) endpoints formatted to align with the I4.0 Language specification. Moreover, the Handler component handles mediation and synchronization responsibilities and accommodates diverse serialization formats and data storage systems via extension points. Furthermore, FA³ST seamlessly integrates with Apache StreamPipes, empowering DTs with real-time stream processing capabilities. In addition, apache StreamPipes offers a user-friendly visual editor, and FA³ST incorporates a DT source and sink component. For more comprehensive insights, including a code example and integration with Apache StreamPipes, refer to [42].

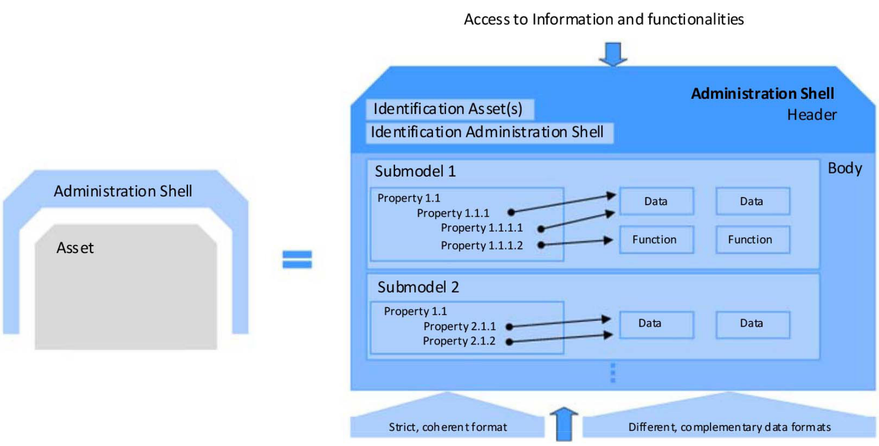


Fig. 2 General structure of an Administration Shell [39].

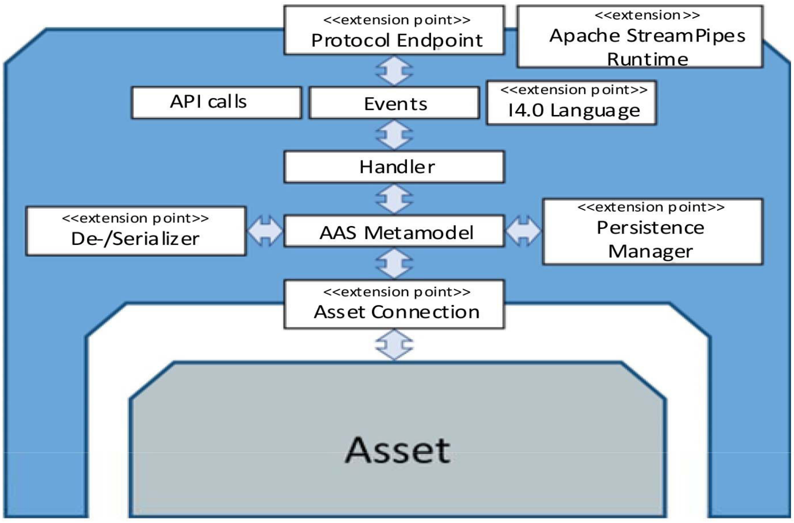


Fig. 3 High-level schematic diagram of FA³ST service [41].

Automation and Analytics

Solutions designed for advanced data analysis and process automation include Apache StreamPipes and Node-RED. Node-RED stands out as a technology that has changed the way workflows are automated and the IoT is integrated. Due to its user-friendly interface, large node library, and strong community support, it is a platform of choice for developers, organizations, and IoT players who are looking to create and optimize workflows. Node-RED is still at the forefront of technology, enabling users to develop interconnected systems and applications with simplicity [42]. The goal of the IIoT toolset Apache StreamPipes is to make data exploration, analysis, and communication easier. It offers a low-code or no-code approach to application creation, making it suitable for both technical and non-technical users. Working with IoT data and getting insightful information is made easier through way [43].

These platforms are quite helpful in streamlining operations when it comes to DTs for pipeline management. Node-RED provides a graphical programming environment for creating automation processes, whereas Apache StreamPipes is more focused on analytics and data processing. Operators can make informed judgments and more precisely estimate maintenance requirements by automating processes and evaluating the vast amounts of data provided by DT's.

Simulation and Visualization

Siemens' SimCenter is a complete software suite that makes testing and simulation more straightforward across a range of sectors, including pipeline management. It gives engineers the ability to create digital models that replicate the characteristics of pipelines in a variety of scenarios. In order to enable predictive maintenance and risk assessment, this technology is especially important for anticipating how pipelines may respond to stress, pressure changes, or other influencing factors [44]. SimCenter helps operators anticipate maintenance needs and potential risks by realistically simulating real-world pipeline scenarios. This helps operators understand how these systems function and potentially fail under different circumstances. By providing information about stress locations, structural flaws, or probable failure modes, it optimizes pipeline operation and helps put preventive measures in place to improve efficiency and safety.

The Ignition software developed by Inductive Automation presents a holistic solution for SCADA, HMI, and dashboard creation. It empowers operators to oversee and regulate equipment, access live data, and craft interactive dashboards to bolster decision-making. Within the realm of pipeline oversight, Ignition software furnishes a robust framework for visualizing data and effectively managing systems [45]. Utilizing Ignition software in managing pipelines significantly aids in leak detection and operational effectiveness:

Ignition software provides a framework for data gathering, real-time monitoring, and alarm management in pipeline installations when used in conjunction with AAS. Also, it strengthens anomaly identification through integration with machine learning algorithms, enabling timely detection and reactions to possible leaks. In addition, the ability of Ignition software to produce reports and guarantee compliance with regulations is a crucial aspect of pipeline management.

On the other hand, in this paper, a pipeline leak detection system is proposed using EKF and AAS using MATLAB software. Although MATLAB provides a user-friendly environment for algorithm development, its execution speed can limit real-time capabilities in pipeline leak detection applications. The EKF and AAS algorithms were switched to Python in order to maximize computational performance, integrate, and lower implementation costs. This choice leverages Python's extensive library ecosystem—such as TensorFlow, Scikit-Learn, and NumPy—that enhances both computation speed and machine learning support. Comparative tests showed that Python reduced the average processing time by approximately 30%, making it better suited for real-time deployment. The system uses the EKF to detect anomalies, anticipate possible leaks, and pinpoint their location. It gathers real-time data from sensors along the pipeline and compares it with pipeline metadata. The system also integrates a digital twin to provide a detailed representation of the pipeline and enable dynamic simulations. This approach enables real-time monitoring, predictive anomaly detection, and centralized data management for effective pipeline integrity monitoring

and leak prevention.
In brief, pipeline management and leak detection have changed as a result of the combination of DT technology, AAS, Admin-Shell-IO, Node-RED, Apache StreamPipes, SimCenter, and Ignition software. Real-time monitoring, early anomaly identification, data-driven insights, and effective operations are made possible by these technologies. Leak detection and pipeline management appear to have a bright future considering to the significant growth of these techniques and technology.

The Proposed Framework

The operation of large pipeline networks, which are essential to the oil and gas, water management, and utility industries, requires accuracy, alertness, and state-of-the-art technology solutions. The management of pipelines has undergone a significant transformation thanks to the integration of advanced tools such as ASSX for data integration, SimCenter software for modeling and simulation, MRTTM [24] for pipeline leak detection system application, and the Ignition platform by Inductive Automation with SCADA and HMI. OPC UA protocol has further enhanced the integration of these technologies. Moreover, OPC UA is a machine-to-machine (M2M) communication protocol employed in industrial automation that facilitates data exchange and communication across disparate devices and systems, establishing a standardized and interoperable communication environment. This paper delves into these integrated technologies and elucidates their role in optimizing pipeline operations.
The workplace has been significantly impacted by the integration of AAS, which is a key element in the administration and harmonization of many data sources. The production of AAS in AASX format marks the start of this systematically process. A pipeline leak detection system can be effectively managed using an AAS, which serves as a digital representation of the physical assets. The AAS can incorporate sub-models to capture various aspects of the system, such as technical data, operational data, and documentation.
The accuracy of the converted AAS-based neutral equipment maintenance data was verified by importing it into the AASX package explorer, a C#-based open-source tool for editing AAS data. This tool operates on Windows 10 and later operating systems. By comparing the imported neutral data with the original Process Equipment Diagnosis System (PEDS (data, it was confirmed that the conversion process accurately preserved the IDs, assembly relationships, and properties of process/equipment/components. Fig. 4 shows a screenshot of the AASX Package Explorer displaying a sample asset's details.

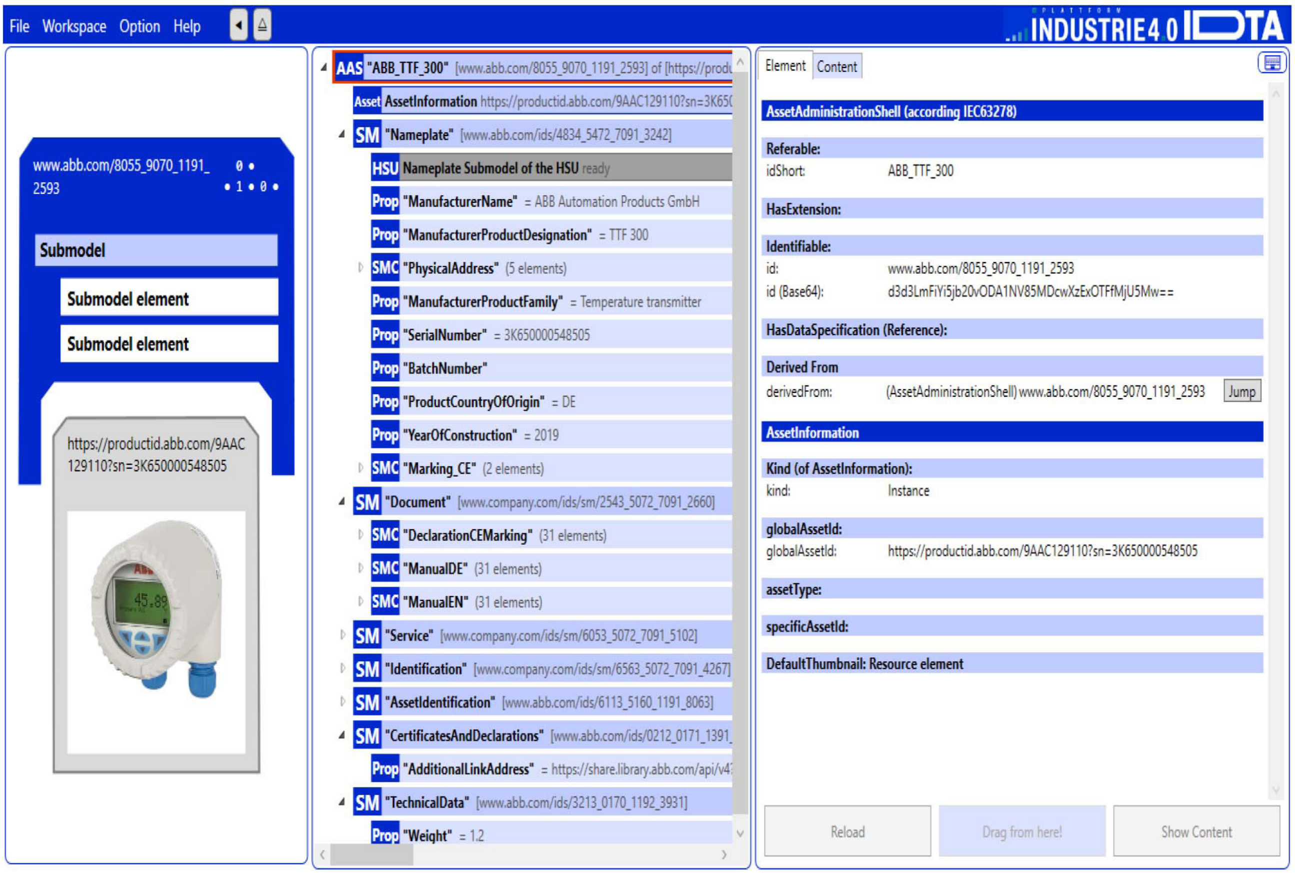


Fig. 4 The AASX Package Explorer displaying a sample asset's details.

The workflow of AAS and AASX in industrial operations is explained, with a focus on their integration, data management, and communication with other systems. The process begins with the development of AAS, which is then sent to an AASX Server, which serves as a centralized location for organizing and obtaining AAS-related data. REST/API-enabled data flow guarantees seamless, two-way data interchange with external systems. A popular IoT messaging protocol called MQTT helps to improve the industrial data environment by facilitating the feeding of data to AASs through Python scripts. Data must be transferred from the AASX Server to Apache StreamPipes, an Intelligent IIoT toolkit, in the last stage. This platform makes it quicker to integrate and use AAS data, which improves industrial process efficiency. It also offers an intuitive interface for data connectivity, analysis, and application creation.
Additionally, an architecture diagram in Fig. 5 shows the system's configuration and data flow. This procedure makes it possible for pipeline management data to be transmitted efficiently and for AASs and MQTT data to be combined seamlessly. In order to support Industry 4.0 developments, it is essential to integrate AASs into IoT networks in conjunction with Apache StreamPipes to provide effective data storage and analysis for pipeline management as well as detection of leaks in industries.
Pipeline leak detection can be improved by integrating AAS with Node-RED. It enables real-time monitoring. Node-RED is a useful tool in this context since it is a flow-based development tool for visual programming and Internet of Things applications. This is how pipeline leak detection may be done with AAS and Node-RED. There are a few key steps involved in integrating AAS with Node-RED for pipeline management. The first step is to create an AAS, which functions as a DT and stores important details about the materials, design, and historical data of the pipeline. This is the cornerstone of efficient management. After that, sensors are incorporated into the pipeline and linked to Node-RED, allowing for the real-time data collection of vital parameters like temperature, pressure, and flow rates—all of which are necessary for leak detection. Node-RED can initiate alerts and notifications upon detecting abnormalities, rapidly informing pertinent persons or systems about any issues. Moreover, Node-RED can access past data kept in the AAS, which helps with anomaly identification and offers insights into the pipeline's long-term health. By combining historical and real-time data, predictive maintenance enables the scheduling of repairs or maintenance tasks prior to the occurrence of a leak. Furthermore, Node-RED can effortlessly interface with SCADA systems, if that's the case, improving pipeline visibility and control overall. To ensure the security of AAS data, stringent security measures should be implemented to restrict access to authorized users, safeguarding critical information and maintaining the integrity of the pipeline management system. This combination of Node-RED's data processing and workflow automation capabilities with the strength of AAS for asset-related information description and communication allows for quick reactions to possible leaks. The cooperative application of these technologies provides an efficient asset management procedure, supporting safety protocols by quickly detecting and addressing pipeline irregularities. The integration of these technologies serves as a crucial instrument in assuring the security and effectiveness of pipeline systems throughout diverse industrial environments. It also helps with effective real-time detection and establishes a proactive and flexible framework.
The use of SimCenter software for modeling and simulation has resulted in a substantial change in the understanding and administration of pipeline systems. Operators can assess different operating situations, anticipate possible problems, and practice responses to a range of conditions by simulating whole transmission lines. This capacity increases overall operational efficiency by enabling predictive maintenance and reducing unplanned operational disruptions.
Whenever it pertains to pipeline integrity, using algorithms such as RTTM is critically important. RTTM examines variations in electrical conductivity to help identify anomalies in the pipeline, including leaks or faults. It does this by utilizing real-time transient modeling. These algorithms improve the precision and efficacy of anomaly detection when combined with SimCenter's simulations and the data aggregated by ASSX, strengthening the structural integrity and safety of the pipelines.

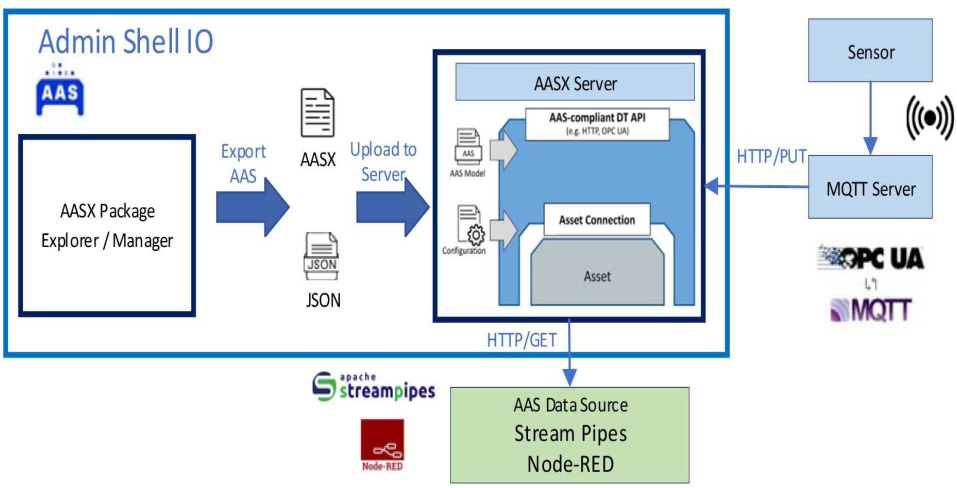


Fig. 5 The architecture using Admin Shell IO, StreamPipes and Node-RED.

Meanwhile, machine learning has been applied to boost accuracy assurance. SimCenter is used to simulate different leakage scenarios in different circumstances for this purpose. These requirements are implemented, as shown in Fig. 6, by first segmenting the pipeline into many imaginary parts and generating a fake leak for each one independently. Secondly, three different varieties of low, medium, and high leakage are developed for each leakage. The mass flow rate from the leakage, the inlet and outlet pressure, and the inlet and outlet flow are eventually taken into account in all of the scenarios that are run under the same parameters. A database called the Leakage Pattern Bank holds the potential leak situations for a certain pipeline. These simulations take into account the mass flow rate, inlet and outlet pressure, and flow from the leaks that are kept in the Leakage Pattern Bank, a database of potential leak situations. Using a data-driven DT technique combined with machine learning greatly improves accuracy and validates the RTTM method. SimCenter performs a key role in testing and validating various scenarios by running a variety of leak scenarios.

The points that follow are the main procedures for putting in place a pipeline leak detection system that uses EKF and AAS: The first step of the system's operation is the collection of pipeline metadata and sensor data. The AAS, which offers a centralized store for all pipeline data, is then merged with this data. The state vector, transition matrix, and process noise covariance matrix will be added to the EKF model configuration. The reason for this structure can be found in [46]. Next, the EKF leak detection algorithm is put into practice. This algorithm uses the measurement update step and prediction step to continually evaluate sensor data and update its state estimations. Moreover, the algorithm also identifies anomalies in the pipeline's behavior and estimates the location of potential leaks. Leak detection alerts are then generated and sent to operators or system administrators. In addition, the system continuously monitors the pipeline for potential leaks and provides real-time anomaly detection and centralized data management

The digital twin can also be used for dynamic simulations, which allow the EKF to evaluate the impact of potential leaks on the pipeline's behavior and prioritize leak detection efforts. The pipeline model, the Kalman filter, and the simulation results when a leak occurs are contrasted and compared in Fig. 7. The head pressure (H_{in} -H_{out}) and flow rate (Q_{in}-Q_{out}) at the beginning and end of pipeline are also shown. An effective and dependable method for detecting pipeline leaks is EKF. With it to function properly, essential parameters are needed:

A state vector that depicts the dynamic state of the pipeline, including the pressure and flow rate at each point along the pipeline, is needed by the EKF. All EKF estimates are based on this vector. The pipeline's dynamics and operating conditions are taken into consideration as the transition matrix outlines how the pipeline's state changes over time. Moreover, this matrix ensures that the EKF's predictions correctly represent the actual behavior of the pipeline. This matrix subsequently represents the uncertainty in the pipeline's state estimates through the inclusion of measurement uncertainties and sensor noise. This uncertainty is factored into the EKF's prediction process, which results in more accurate leak detection. The EKF works by continuously analyzing sensor data and updating its state estimates using the measurement update step. This step ensures that the filter adapts to new measurements and reflects real-time conditions. The EKF also predicts the pipeline's future state based on its current state and the transition matrix, enabling proactive leak detection and early warning.

When the EKF identifies unusual behavior in a pipeline, it utilizes its understanding of the pipeline's structure and dynamics, along with the detected anomaly, to estimate the probable location of a leak. This estimation assists operators in pinpointing the leak and taking necessary actions. To detect anomalies, the EKF continuously contrasts predicted pipeline behavior with actual sensor readings. Significant discrepancies trigger anomaly flags, often indicating leaks through sudden pressure or flow rate drops.

While both RTTM and Kalman filter effectively detect pipeline leaks, their approaches differ. RTTM employs a virtual pipeline model to identify discrepancies that signal leaks, excelling in early detection, accurate localization, and continuous monitoring. Kalman filter utilizes a recursive statistical approach to estimate pipeline states and detect anomalies, demonstrating robustness in handling noisy data and adaptability to changing conditions. The optimal choice is depended on specific needs. These two different leak detection techniques are compared in Fig. 8, with the goal of locating an actual leak that is known to be at a distance of 4500 meters. RTTM and Kalman filter with normal distribution approaches are the techniques being assessed. The leak location is accurately identified using RTTM, with a high degree of alignment with the real position. However, the Kalman filter performs effectively in leak estimates, suggesting that leak detection occupations are an ideal match for it.

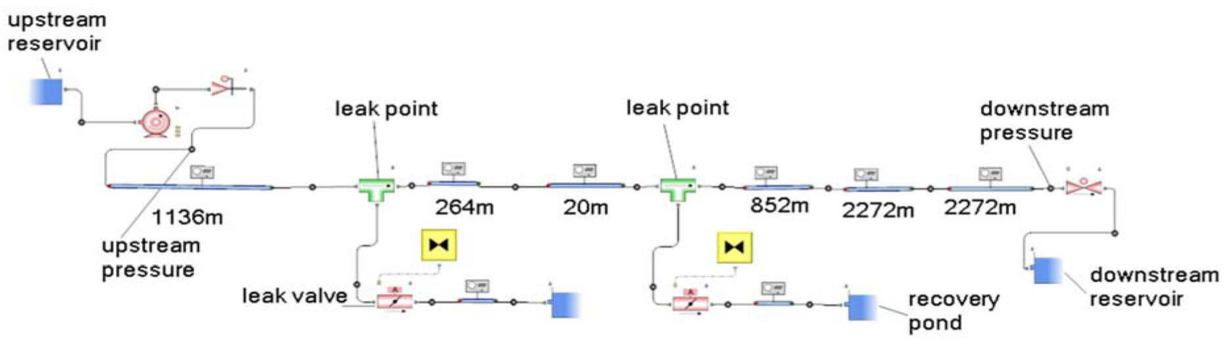
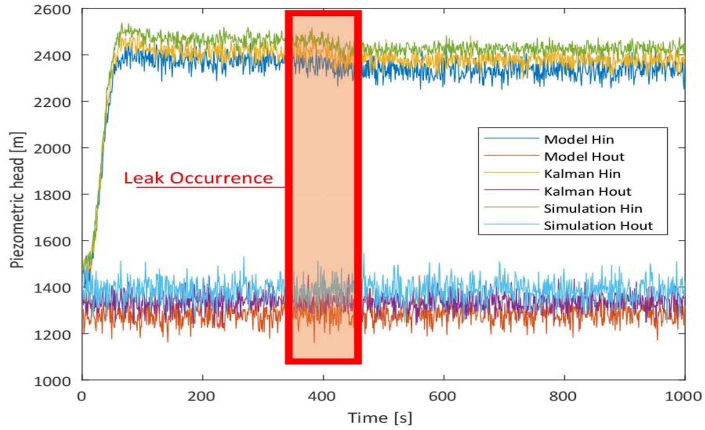


Fig. 6 Pipeline Simulation Design with two fictitious leaks by SimCenter software.



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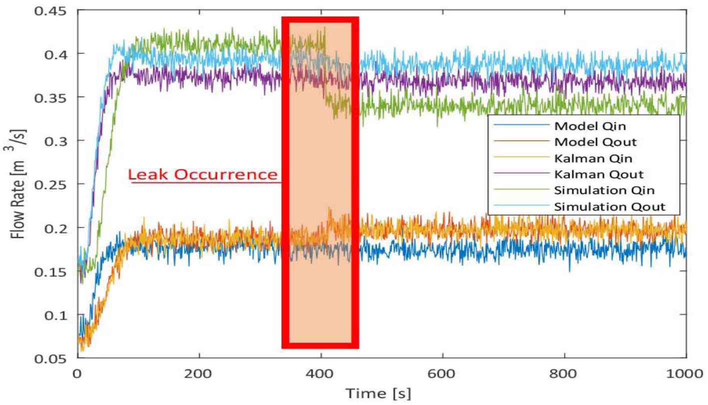


b)

Fig. 7 The pipeline model, the Kalman filter, and the simulation results are contrasted with each other. a) The head pressure (H_{in} -H_{out}) and b) flow rate (Q_{in}-Q_{out}) at the beginning and end of pipeline..

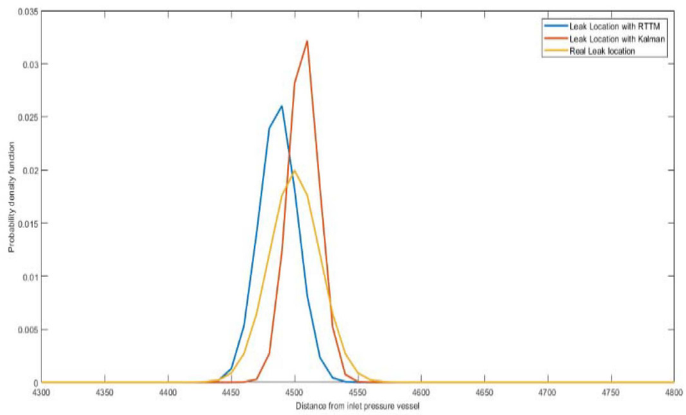


Fig. 8 Comparing real leak location at 4500 meters, RTTM, and Kalman leakage distance estimation methods for leak detection with normal distribution methods.

The performance of RTTM and Kalman Filters varies significantly based on operational conditions. In pipelines with high viscosity and pressure fluctuations, such as oil pipelines, the EKF's ability to compensate for noise and inconsistencies in sensor data offers superior performance compared to RTTM. Similarly, in high-pressure gas pipelines, the Kalman Filter's continuous updates enable it to better handle sudden pressure drops than RTTM. In addition, pipelines with higher flow rates, especially those transporting gas, introduce more noise, which the Kalman Filter is better equipped to manage.

In scenarios with varied environmental conditions, the MRTTM framework, with its integrated EKF, demonstrates higher adaptability and resilience compared to RTTM. RTTM's computational demands and sensitivity to changes in model parameters can hinder its performance in such environments.

On the other hand, real-time connection of data with SCADA and its processing through machine learning enhance leak localization accuracy and robustness, while reducing the likelihood of false alarms through artificial intelligence. This sophisticated approach represents a proactive advancement in pipeline safety, delivering more precise and reliable leak detection systems.

The proposed solution involves a series of steps for detecting and locating leaks in pipelines, drawing from outlined diagnostic procedures and emphasized challenges. Initially, leakage is identified through diagnostic testing that leverages the physical and dynamic characteristics of pipelines. The magnitude of the leakage is then evaluated using the RTTM method and the data collected by the observer. Subsequently, pipeline segments are divided using simulation software, and various leakage scenarios, including large, medium, and small leaks, are examined for each segment. The outcomes of diverse tests under anticipated conditions are systematically classified into classes. The chosen option is then compared to the optimal training algorithm, leading to the creation of LPB.

The MRTTM method, enhanced by the EKF, is employed to achieve the highest accuracy in detecting the location and magnitude of leaks under various dynamic pipeline conditions. Once a leak is detected and the segment in which it is situated is determined, the trained algorithm considers two hypothetical leaks at the beginning and end of the diagnostic pipe section. The actual location of the leak is estimated using the EKF observer, which determines all the rates of pipeline parameters (pressure and flow rate values) as process and measurement noise. The Kalman Filter, specifically the EKF, significantly enhances MRTTM's detection capabilities, particularly in challenging scenarios with high uncertainty and noise. While RTTM struggles in transient conditions, the EKF's ability to continuously update state estimates based on observed measurements provides superior performance. The EKF's robustness to incomplete or noisy data and its integration into MRTTM enable more accurate leak detection by filtering out background noise and adapting to real-time changes. In contrast, RTTM's reliance on computational-intensive hydraulic models and sensitivity to data inconsistencies can lead to delayed leak detection. The EKF's effectiveness in managing transient states, as demonstrated in the manuscript, results in higher detection accuracy and faster response times, especially in challenging operational conditions.

Consequently, all the proposed processes should be seamlessly integrated, and a comprehensive overview of the suggested remedy is presented in Fig. 9. The proposed conceptual real-time framework is divided into three sections: data collection, leak detection, and decision-making. Moreover, in the data collection section, an observer analyzes sensor data in real-time to gather information about the dynamic state of the pipeline. The detection section employs diagnostic methods based on various dynamic conditions of the fluid to identify leaks. Upon detecting a leak, the decision-making phase commences, where the proposed MRTTM is used to estimate the leak's location based on the pipeline's circumstances.

The pipeline concept is illustrated as segments in Fig. 9. Each section is examined under the conditions of a virtual simulation, encompassing three states: low, medium, and high. By considering each state in a systematic manner through predefined classes and applying machine learning, it becomes possible to extract the leakage pattern and, with a high degree of approximation, determine the actual leak.

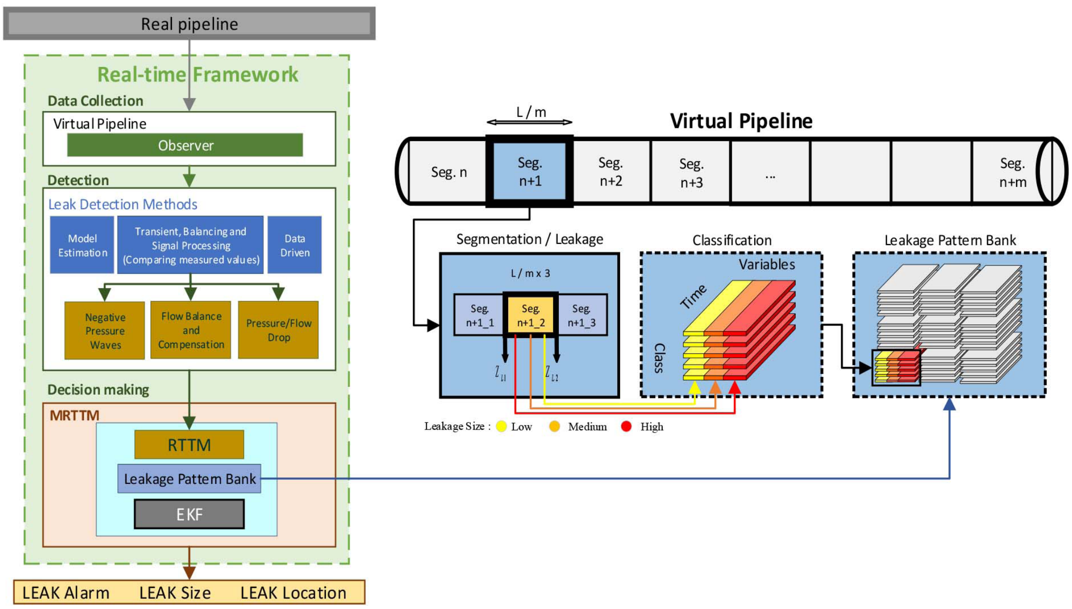


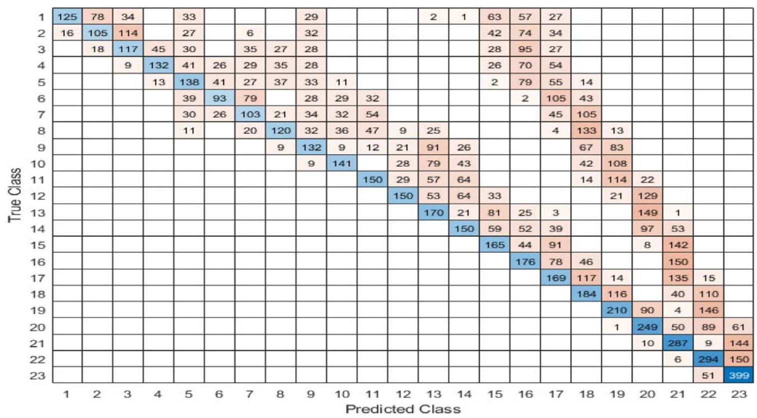
Fig. 9 Concept of MRTTM using Real-time framework and Pipeline Segmentation, Leakage classification and LPB.

While deep learning models, such as CNN and AlexNet, are known for their proficiency in complex classification tasks, this paper focuses on SVM and KNN due to their interpretability, efficiency with moderate-sized datasets, and lower computational demands. Deep learning networks require substantial computational resources and are prone to overfitting on smaller datasets, making simpler models like SVM and KNN more practical. As shown in Table 1, these methods provide a desirable balance between computational cost and prediction accuracy, well-suited for real-time applications where speed and interpretability are crucial. In Table 1, the comparative performance of these classifiers, supporting the choice of KNN and SVM, is illustrated in this study.

This table clearly demonstrates the superior performance of KNN (particularly Fine KNN) in terms of accuracy, speed, and computational efficiency, confirming it as the optimal choice alongside SVM for this paper. The Validation Confusion Matrix diagram, shown in Fig. 10, compares the two KNN and SVM algorithms under the same pipeline conditions. The SVM algorithm has a 93.0% accuracy rate and a 783.19 second training time. The accuracy percentage for the KNN technique is 98.3% and 10.93 seconds are spent on training. As is well knowledge, the KNN approach performs better in terms of training time and accuracy.

Table 1 Performance Comparison of SVM, KNN, and Other Classifiers on a 28,000-sample Dataset.

Classifier	Accuracy (Validation) %	Total Cost (Validation)	Prediction Speed (obs/s)	Training Time (s)
Fine KNN	99.9	10	40,000	8.63
Weighted KNN	99.8	16	38,000	10.59
SVM (Kernel)	99.2	78	590	293.11
Cubic KNN	99.0	105	16,000	9.46
Logistic Regression	98.4	167	490	233.76
Quadratic SVM	98.1	195	2,800	401.28
CNN	97.5	400	2,500	720.55
AlexNet	97.1	520	2,000	950.60
Decision Tree	96.8	350	15,000	18.32
Random Forest	96.3	250	10,000	25.77
Naive Bayes	95.4	300	25,000	12.65



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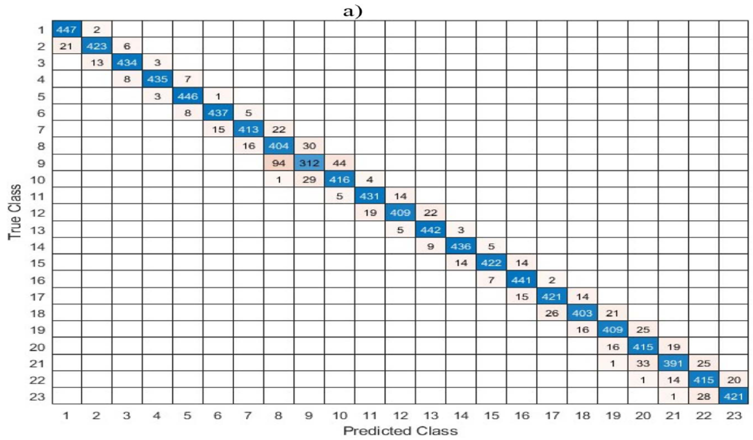


b)

Fig. 10 Validation Confusion Matrix diagram compares the two classifiers a) SVM model and b) KNN model.

While hybridizing SVM, KNN, and EKF increases computational complexity, it improves detection accuracy in complex, nonlinear scenarios. For this paper, the two primary objectives were minimizing detection time for immediate leak response and maximizing precision in leak localization. This is essential for underground pipelines, where precise leak detection and location accuracy translate into reduced repair costs. Moreover, the table below compares the hybrid approach with alternative methods, highlighting detection time, localization time, and accuracy. Furthermore, the machine learning algorithm's ongoing adaptability further ensures that detection speed and accuracy continue to improve with additional training data.

Table 2 reveals that while the hybrid SVM+KNN+EKF method incurs a greater computational burden, it offers significantly improved detection and localization performance compared to conventional methods. While RTTM-based methods are less computationally demanding, the increased accuracy and ongoing machine learning adaptation in our hybrid model provide substantial advantages in complex pipeline environments.

On the other hand, from a practical standpoint, Inductive Automation's implementation of the Ignition platform—which is outfitted with SCADA and HMI—is revolutionary. Moreover, SCADA enables real-time data gathering, control, and monitoring, giving operators the ability to monitor the pipeline network and respond quickly in the event of an issue. Simultaneously, HMI gives operators an intuitive interface via which they can effectively comprehend and use data, enabling quick decision-making in urgent circumstances. The pipeline is divided into several sections, and flow meters and pressure gauge sensors are placed at the beginning and end of each segment. Furthermore, these sensors provide real-time monitoring by sending data via OPC UA to the ignition platform. Concurrently, the program uses OPC UA to interface with algorithm so that it can quickly communicate to the leak detection algorithm and set off an alarm when a leak occurs. Fig. 11 presents a pipeline leak detection management dashboard built on the Ignition platform. This dashboard serves as a centralized hub for monitoring pipeline integrity, enabling operators to proactively identify and respond to potential leaks. By visualizing critical data such as leak location, severity, and historical trends, the dashboard empowers decision-makers to optimize maintenance schedules, reduce downtime, and ensure environmental compliance.

The functioning of the software is demonstrated by the screenshots in Fig. 12 In Fig. 12.a, the hypothetical range is indicated in red, and the moment of a leak is shown in orange within the main area. In Fig. 12.b, details about the leak, including pressure, flow, and location, can be seen by clicking on the orange portion. Similarly, by choosing the red diagnostic section, the leak area is shown on the map, improving the accuracy of leak detection and localization.

Table 2 Quantitative comparison of detection and localization performance for different leak detection methods under the same test conditions.

Method	Detection Time (s)	Localization Time (s)	Detection Accuracy (%)	Leak Localization Accuracy (%)	Computational Load
RTTM	3.2	3.4	89.5	88.7	Low
RTTM + Kalman Filter	2.5	5.9	93.4	91.2	Medium
Kalman + KNN	2.0	4.8	94.1	92.7	Medium
Hybrid (SVM+KNN+EKF)	2.8	7.3	97.2	95.1	High

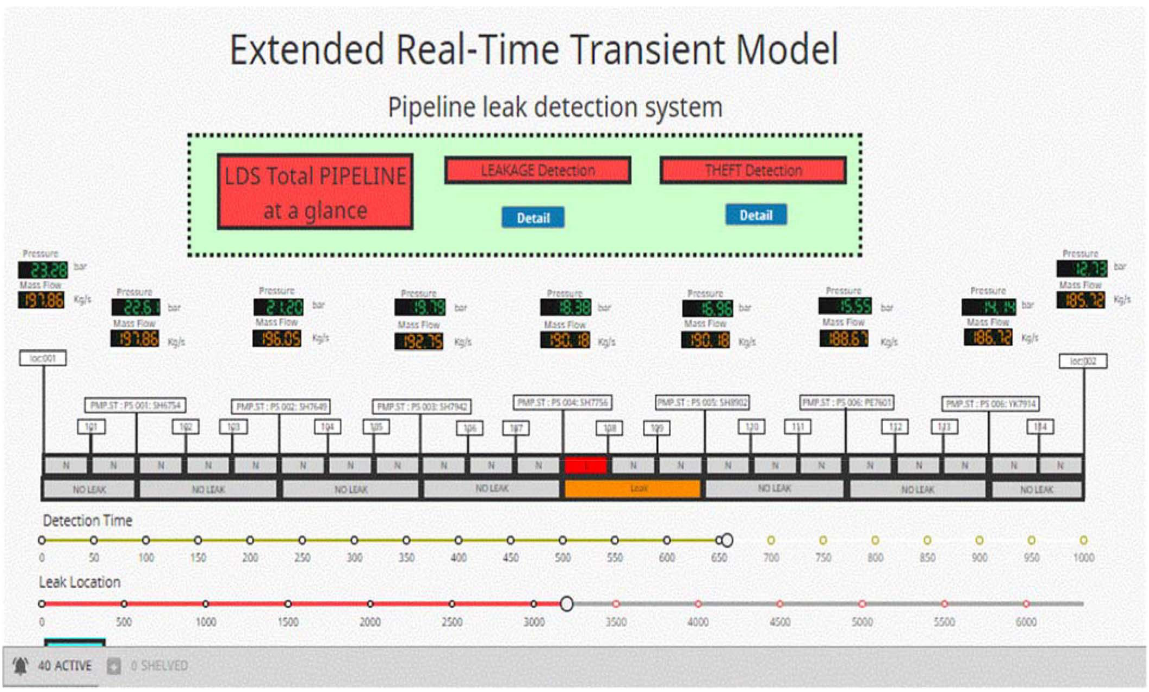
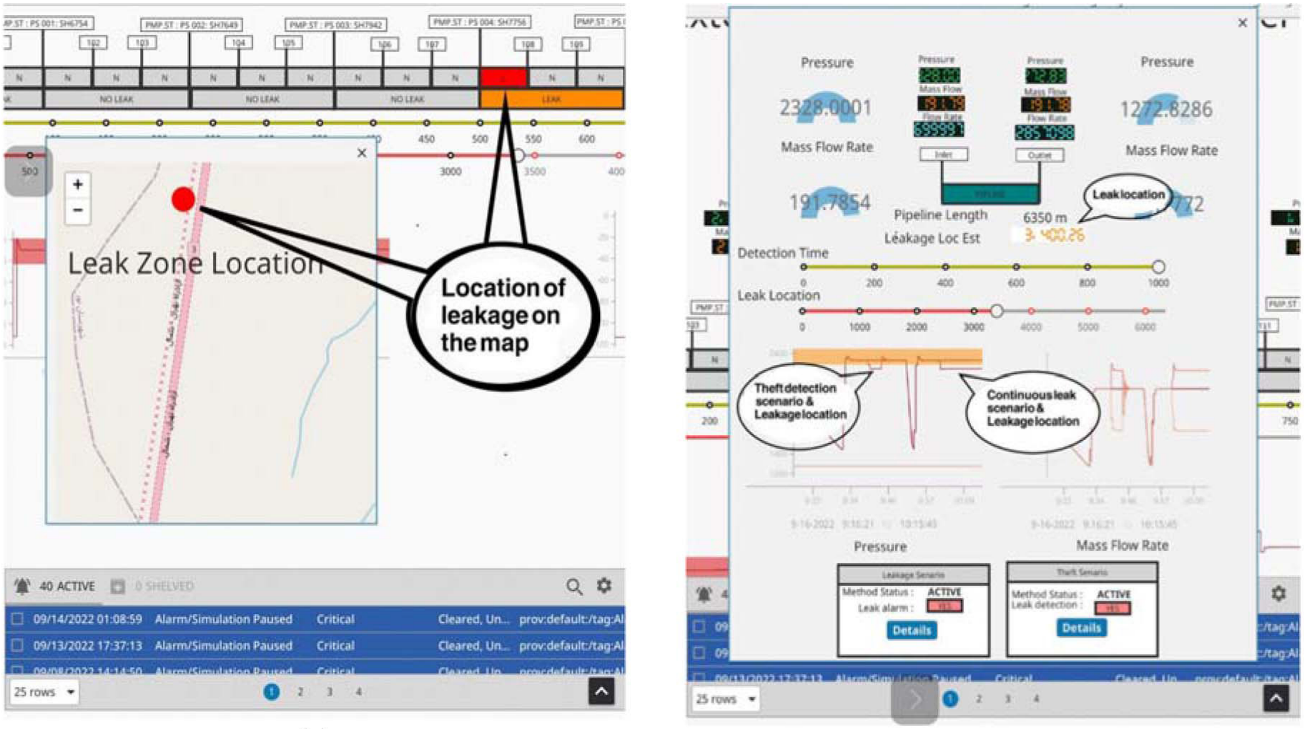


Fig. 11 A view of the pipeline leak detection management dashboard using the Ignition.



(a) (b)

Fig. 12 The provided information offers insights into the fundamental components and functionalities of the pipeline leak detection management. A screenshot of the pipeline management dashboard when a leak occurs. a) Leak alarm pop-up, location of the leak on the map b) Pop-up of the selected segment that has a leak, in which different leakage scenarios can be seen in a time series (leak/theft).

The integrated platform discussed is highly versatile, applicable not only to oil and gas but also to water pipelines. It leverages the advanced capabilities of conceptual DT architecture, enabling comprehensive management across these critical infrastructure networks. One of its key strengths lies in the effective management of resources, allowing access to a wide array of data ranging from precision instrument information to various engineering data like datasheets, CAD models, and maintenance records.

This system's ability to centralize critical information in real-time and promptly adapt to standards and regulations demonstrates its potential to significantly improve safety, enhance regulatory compliance, and optimize operational efficiency within pipeline management. The integration of DT technology serves as a powerful tool in managing and preventing risks, ultimately leading to safer and more resilient pipeline networks across industries.

The quantitative comparison criteria in Table 3 align with established industry benchmarks, including API 1160:2021 [47], ISO 13623:2016 [48], and EN 13702:2014 [49]. These standards outline requirements for pipeline leak detection systems and define minimum performance expectations. The proposed conceptual framework exceeds these benchmarks in terms of accuracy, sensitivity, localization, real-time monitoring, automated response, and cost-effectiveness. Furthermore, Table 4 compares the proposed framework with traditional methods and existing standards, emphasizing its superiority in terms of real-time data acquisition and monitoring, data integration and analytics, predictive maintenance, automated response and control, human-machine interaction, interoperability and scalability, security and cyber resilience, cost-effectiveness, sustainability, and regulatory compliance.

By leveraging advanced technologies such as artificial intelligence, machine learning, and digital twins, the proposed framework offers a significant improvement over traditional leak detection methods. It enables more accurate and timely detection of leaks, reduces operational costs, and minimizes environmental impact.

Table 3 Compares different features of the leak detection system along with standards in traditional and Industry 4.0 moods, highlighting the advantage of the proposed framework.

Feature	Proposed DT-based Leak Detection Framework	Conventional Leak Detection Methods
Accuracy	High detection rate of both small and large leaks, including intermittent or transient leaks	Lower detection rate, especially for small or intermittent leaks
Sensitivity	Can detect leaks at low flow rates	Less sensitive to low flow rates
Localization	Can accurately pinpoint the location of leaks	Less accurate leak localization
Real-time monitoring	Provides continuous real-time monitoring of pipeline conditions	Requires periodic inspections or manual data collection
Automated response	Can automatically initiate corrective actions in response to leaks	Requires manual intervention to detect and respond to leaks
Cost-effectiveness	Can be more cost-effective over time due to reduced maintenance costs and fewer leaks	Can be expensive to implement and maintain

Table 4 Comparison of the leak detection system along with standards in traditional and Industry 4.0 moods, highlighting the advantage of the proposed framework

Feature	Existing Standards	Traditional Methods	Proposed Concept	Advantage
Real-time data acquisition and monitoring	ISO 14224, API 510 [50]	Manually collects data from sensors and input devices.	Continuously monitors pipeline conditions using sensors and data analytics.	Utilizes AAS to manage and organize data from various sources, and RTTM to identify and assess potential leaks.
Data integration and analytics	ISO 27001, IEC 62443-2-4 [51]	Uses separate systems for each data source.	Integrates data from various sources, including sensors, weather data, and maintenance records.	Leverages Apache StreamPipes and Node-RED to integrate data from disparate systems and analyze it in real time.
Predictive maintenance	API 580 [52]	Relies on scheduled maintenance intervals.	Uses historical data and predictive analytics to predict potential leaks and schedule preventive maintenance.	Employs machine learning algorithms, including KNN and SVM, to identify anomalies and predict potential leaks.
Automated response and control	ISO 15926 [53]	Requires manual intervention to isolate leaks.	Automatically takes action to isolate leaks, such as closing valves or reducing flow rates.	Utilizes SimCenter and MATLAB to simulate and model pipeline behavior, enabling automated response to leaks and other anomalies.
Human-machine interaction	ISO 20411, IEC 61508 [54]	Presents complex data in a way that is difficult for operators to understand.	Provides clear and actionable insights to operators, enabling rapid and informed decision-making.	Incorporates Ignition software to create user-friendly dashboards and visualizations, enhancing operator understanding of pipeline status.
Interoperability and scalability	ISO 14224 [55]	Often incompatible with existing systems.	Designed to interoperate with existing systems and infrastructure, ensuring seamless integration and scalability.	Employs open-source technologies and standards to facilitate compatibility with existing systems, enabling integration into existing pipeline networks.
Security and cyber resilience	ISO 27001 [51]	May have vulnerabilities that can be exploited by hackers.	Implements robust security measures to protect sensitive data and prevent unauthorized access or manipulation.	Leverages Apache StreamPipes and Node-RED to secure data transmission and protect against cyberattacks.
Cost-effectiveness	ASME MFC, API RP 580 [56]	Can be expensive to install and maintain traditional leak detection systems.	Minimizes the implementation and operating costs of leak detection systems.	Employs open-source technologies and cloud-based infrastructure to reduce implementation and maintenance costs.
Sustainability	ISO 14001, CDP Water [57]	May have a negative impact on the environment.	Considers environmental impact and incorporates sustainable practices throughout its lifecycle.	Optimizes pipeline operations to reduce energy consumption and emissions, promoting a more sustainable approach to pipeline management.
Regulatory compliance	US EPA SPCC Plan [58], NPDES Permits [59]	May not be compliant with all relevant standards.	Adheres to all relevant safety, environmental, and regulatory standards.	Integrates with SimCenter and MATLAB to model pipeline behavior under various operating conditions, ensuring compliance with safety standards.

Results and Discussion

To delve deeper into the landscape of pipeline management and leak detection the proposed framework is compared with commercially available software options. This detailed evaluation encompassed crucial aspects:

Communication: The effectiveness of communication mechanisms within these software solutions is paramount for real-time data exchange. Examining the communication protocols employed is crucial to assess their impact on system performance.

Orchestration: A comprehensive understanding of how these systems coordinate various components is essential. Investigating orchestration mechanisms that facilitate task coordination and seamless integration is critical.

Data Representation: Scrutinizing data representation provides insights into how information is structured and visualized. Exploring methods employed in presenting pipeline data sheds light on its implications for decision-making.

Analytics and Visualization: Evaluation of analytics capabilities and integrated visualization tools is essential. Robust analytics enhance the ability to derive meaningful insights, while effective visualization aids in interpreting complex data.

Control: Assessing the level of control each software offers in managing pipeline operations is essential for efficient system governance.

Software Architecture: Examining the underlying architecture of each software solution is critical. Architectural design can significantly impact scalability, flexibility, and overall system performance.

Price: Investigating the pricing models of these software solutions is key. Understanding the cost structures, including licensing, maintenance, and additional fees, provides valuable insights.

Leak Detection Method: Delving into the specifics of employed leak detection methods is crucial. Different approaches, such as sensor technologies or data analytics, may offer varying levels of accuracy and efficiency.

Table 5 explains the proposed Framework and other commercial pipeline leak detection software products in terms of evaluation criteria such as communication, orchestration, data representation, analytics, and visualization, control, Software architecture, Price, and Leak detection method.

Table 5 Explaining the proposed Framework and other commercial pipeline leak detection software products in terms of different evaluation Criteria.

Evaluation Criteria	Emerson	Siemens	Krohne	Yokogawa	SSL	DNV	Atmos	Proposed Framework
Communication	OPC UA, BACnet, IEC 61850, Modbus	OPC UA, Modbus	OPC UA, MQTT, Modbus	OPC UA, BACnet, Modbus	OPC UA, MQTT, Modbus	OPC UA, MQTT, Modbus	OPC UA, MQTT, Modbus	OPC UA, MQTT
Orchestration	Kubernetes	Kubernetes	Docker Compose	Docker Compose	Docker Compose	Kubernetes	Kubernetes	StreamPipes, Node-RED, prometheus
Data representation	UAIM, AAS	UAIM	UAIM	UAIM	UAIM	UAIM	UAIM	AASX-FA³ST
Visualization and control	Emerson DeltaV Visualization and Control, Ovation Visualization and Control	Siemens Simatic PCS 7 Visualization and Control, Siemens SCADA Visualization and Control	Krohne MULTICAL Visualization and Control, Krohne Deltapilot Visualization and Control	Yokogawa Centum VP Visualization and Control, Yokogawa Experion PKS Visualization and Control	SSL InTouch Visualization and Control, SSL Wonderware Visualization and Control	DNV GL MarineView Visualization and Control, DNV GL Asset Performance Management Visualization and Control	Atmos Asset Performance Management Visualization and Control, Atmos SCADA Visualization and Control	Ignition Visualization and Control, StreamPipes Visualization and Control
Software architecture	Traditional	Cloud-based	Traditional	Traditional	Traditional	Traditional	Cloud-based	DT
Price	High	High	Medium	Medium	Medium	High	High	Competitive
Leak detection method	CPM, RTTM	CPM, PMM	ERTTM, mass balance, acoustic monitoring	CPM, mass balance	mass balance, acoustic monitoring	CPM, PMM	CPM, acoustic monitoring	MRTTM

Companies that provide leak detection software products offer experience, support, and a proven track record. However, they are expensive, rely on dedicated software, and limited scalability. Moreover, the proposed framework has the potential for higher accuracy, efficiency, and scalability at a lower cost. Furthermore, the proposed framework establishes a robust foundation for future advancements in pipeline management. In addition, by synergizing digital twins with advanced data management and analytics, it offers the potential to achieve unparalleled levels of operational efficiency and reliability. Future research endeavors will center on further refining the framework through the seamless integration of Prometheus, a sophisticated time-series monitoring system, for real-time data collection and analysis.

Employing communication protocols such as OPC UA and MQTT will foster interoperability with a diverse range of industrial devices and systems. Moreover, orchestration platforms like StreamPipes and Node-RED will facilitate the automation of intricate workflows, while AASX-FA³ST will provide a standardized data representation for digital twins. By harmonizing these technologies with advanced visualization and control tools like Ignition and StreamPipes, operators can acquire deeper insights into pipeline performance, optimize maintenance schedules, and make informed decisions grounded in data. However, it is still under development and requires specialized expertise. Organizations seeking a reliable and supported solution may prefer the established companies, while those prioritizing cost-effectiveness and scalability may find the proposed concept more attractive.

Conclusions

The integration of Digital Twins (DTs) and advanced technologies within the proposed conceptual framework marks a significant advancement in pipeline management and leak detection. This comprehensive approach, incorporating AAS, Kalman filters, MRTTM, machine learning algorithms, and cutting-edge visualization tools, aims to enhance operational efficiency, reduce downtime, and optimize overall asset performance. The introduction of the MRTTM concept, utilizing AI to construct a database for detecting leakage patterns, further refines performance accuracy and reduces false alarms.

AAS plays a pivotal role in providing robust data management, forming the foundation for informed decision-making and facilitating proactive pipeline operations management. MRTTM, with its mathematical modeling and continuous evaluation capabilities, precisely identifies potential leak locations. The Kalman filter enhances leak detection accuracy by addressing uncertainties inherent in dynamic pipeline systems. The integration of machine learning algorithms boosts accuracy through the analysis of patterns and anomalies in pipeline data.

The collaborative integration of Apache StreamPipes, Node-RED, SimCenter, and Ignition adds another layer of capabilities to the framework. StreamPipes and Node-RED enable real-time data analytics and automation, facilitating predictive maintenance and rapid response to potential leaks. SimCenter and Ignition provide a robust platform for simulating and visualizing DT models, enabling testing, experimentation, and advanced analysis.

The proposed framework not only addresses current challenges in pipeline management but also sets the stage for an intelligent, interconnected, and sustainable future for pipeline operations. The outlined benefits, including predictive maintenance, early anomaly detection, real-time data integration, and predictive maintenance, underscore the significant potential of this technology in reshaping the landscape of pipeline management. As the industry continues to evolve, ongoing research and development promise even more sophisticated applications, ensuring that pipeline networks become more resilient, responsive, and environmentally sustainable. The adoption of these cutting-edge technologies represents a pivotal moment, steering pipeline management towards a future characterized by innovation, reliability, and environmental stewardship.

Moreover, the proposed framework stands out through a comprehensive comparison with various conventional leak detection methods, standards in traditional and Industry 4.0 contexts, and other commercial pipeline leak detection software products. Ultimatly, this comparative analysis sheds light on the advantages of the proposed framework, showcasing its superiority in terms of different evaluation criteria. Also, the rigorous examination of the proposed solution against existing methods and industry standards highlights its innovation, efficiency, and potential to redefine the standards of pipeline leak detection in both traditional and Industry 4.0 environments.

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