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RESEARCH

Leakage detection in pipeline systems using machine learning

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Abstract
The reliability of pipeline systems as a criterion is of enormous significance in sustainable pipeline operation and the protection of the environment. In their basic form, conventional leak detection techniques are often slow and not sensitive enough to suit many purposes, particularly in the early detection and control of leaks in large distributed systems. In this paper, we examine the application of machine learning—One-Class Support Vector Machine (SVM)—to the existing pipeline leak detection systems. Using both COMSOL Multiphysics for simulation and MATLAB for data analysis, this work proves that machine learning is applicable to improve leakage assessment. Using detailed simulations under various operational conditions, the k coefficients of the One-Class SVM model pinpoint pressure, temperature, and velocity abnormalities that suggest leakage. The results also clearly indicate the model's effectiveness in accurately identifying leak locations in addition to simply identifying their presence, making it a significant improvement over current approaches by increasing response speed while decreasing possible losses and threats to the environment.

Keywords Pipeline leak detection · Machine learning · One-class support vector machine (SVM) · Leakage assessment · COMSOL multiphysics simulation · MATLAB data analysis

Introduction

Pipeline leakage detection plays a critical role in ensuring safe functionality and performance, particularly in fluid transport infrastructure, while also minimizing environmental repercussions. Conventional detection methods, including pressure gauges, flow measurements, and visual inspections, often fall short in sensitivity and timeliness, making them insufficient to prevent significant losses or damages (Momeni & Piratla, 2021). These limitations are particularly evident in large and complex pipeline networks where effective and rapid leak detection is crucial.

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In contrast, Artificial Neural Networks (ANNs) and machine learning algorithms have gained prominence in civil engineering for providing efficient solutions in structural optimization and predictive modeling (Kaveh, 2024; Kaveh & Rahami, 2006). Gradient-based neural networks have proven effective in enhancing computational accuracy and optimizing complex structural designs (Iranmanesh & Kaveh, 1999). Further advancements in machine learning regression models have enabled accurate predictions of ultimate buckling loads in variable-stiffness composite cylinders, ensuring safer and more reliable structural assessments (Kaveh et al., 2021). Additionally, the integration of metaheuristic algorithms with ANNs has significantly enhanced predictive accuracy, as demonstrated in Fiber Reinforced Polymer (FRP) strength estimation (Kaveh & Khavaninzadeh, 2023).

Machine learning technologies are now increasingly applied to pipeline leak detection, offering more sophisticated learning methods, faster response times, and real-time monitoring capabilities. Advanced algorithms analyze large datasets to identify patterns and distinguish between normal operations and potential leak indicators. One-class Support Vector Machines (SVMs) have emerged as a particularly effective method for enhancing pipeline leak detection,

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demonstrating the potential to reduce losses, prevent environmental harm, and optimize operational efficiency. This shift towards AI-driven predictive models marks a significant advancement in infrastructure management and safety.

There is a wealth of literature on using hybrid machine learning, especially the one-class support vector machines, in pipeline leak detection systems. These studies have shown that applying this approach can improve leak detection's reliability, efficiency, and functionality. One-class SVMs, enhanced by data analysis skills, can prosecute and discern oddities and deviations associated with leaks (Coelho et al., 2020; Awolusi et al., 2020; Momeni & Piratla, 2021; Choudhary et al., 2021).

We have employed other more conventional leakage detection methods, such as pressure, flow measurements, and visual observation of pipes. However, these methods do not have high sensitivity and speed for detecting and managing threats resulting from leakage, especially in large and distributed pipeline systems. Although such techniques may be somewhat effective for sensing larger leaks, they may take considerable time to identify small leaks, if any at all, resulting in serious damage or, more importantly, threatening the environment (Cramer et al., 2015). This, particularly in systems where the operating conditions change over time, has highlighted the need for more efficient and accurate leak detection methods.

The new machine learning technologies satisfactorily address these limitations by providing better accuracy of results, faster computation, and online monitoring. Pipeline leak detection systems have incorporated machine learning as a subprocess, utilizing the large data generated from pipeline analysis to identify potential leaks based on specific patterns. Researchers have found neural networks, decision trees, and the One-Class SVM useful, particularly due to their ability to increase diagnostic accuracy over time through training on past data, without the need to recode the algorithm for every possible condition (Xu et al., 2012; Torres et al., 2020).

One-Class SVM is specifically inclined to find 'outliers' in the data, which, regarding pipeline systems, are neat signs of leakage. It can learn from past events, making it capable of diagnostic improvements without resolving to deliberate every contingency imaginable. The use of One-Class SVM in pipeline leak detection has the potential to improve leakage identification accuracy, response time, and efficiency, thereby enhancing the safety and efficiency of transport pipelines (Gao et al., 2021; Wang et al., 2020).

The following paper provides a theoretical and practical review of the use of One-Class Support Vector Machines (SVMs) for pipeline leak detection. We simulate normal flow scenarios and hypothetical leak cases using COMSOL Multiphysics simulation data, which forms the basis for the method's completion. We further analyze the simulation data, which includes pressure, velocity, and temperature of the pipeline at various sections, using MATLAB to extract and normalize the features.

We use a one-class SVM model for leakage detection to identify anomalies. As previously mentioned, the engineered features train and validate the presented model, demonstrating its ability to detect leaks within the developed pipeline system. In the final phase, the authors integrate the model into real-time pipeline monitoring via data streams from the pipeline's sensors. This allows for intelligent and real-time leak detection and isolation with high levels of effectiveness, thereby improving the pipeline system's operating safety and reliability. As this thesis demonstrated, machine learning, albeit specifically One-Class SVM, is a successful approach to identifying and handling pipeline leaks, as well as recommending the most appropriate approach to execute maintenance activities to avoid wastage of resources and time on potential leakages.

Literature review

Overview of traditional leak detection techniques

Pipeline leak detection has in the past been done through other methods, which include physical inspection methods, pressure measurements, flow measurement, and an acoustic emission array. The problem with each of these techniques is that they are generic to pipeline maintenance and monitoring, though they have associated drawbacks in terms of sensitivity, accuracy, response time, and cost of operation (Siebenaler et al., 2014).

Physical inspections

Manual surveying, visual pipeline assessment, and inspection equipment are the traditional methods. These surveys are normally conducted by personnel trained to traverse the pipeline right of way or using tools such as pigs. Pigging is a non-invasive inspection process that involves sending a mechanical device, known as a "pig," into the pipeline to search for signs of corrosion, blockages, cracks, or leaks. This method, however, is productive in that it provides a comprehensive analysis of the pipeline's inter- and extrinsic characteristics, making it recommended (El-Abbasy et al., 2016). Furthermore, conducting physical checks annually or occasionally twice a year implies that leaks may remain undetected for extended periods, posing a risk to both the environment and a company's finances. Furthermore, the application of visual inspection is not feasible for underground pipelines or those whose locations are inaccessible, thereby limiting its applicability.

Blood pressure control and flow measurements

Pressure monitoring is one of the oldest methods, and it has been effectively used in practice for quite some time now. Periodic monitoring of pressure levels in the pipeline enables the detection of existing changes or certain fluctuations that indicate leakage. Similarly, we employ flow rate measurements to assess the fluid flow through the pipeline; specifically, any variation in the flow rates at the pipeline system's inlet or outlet will indicate a leak (Adegboye et al., 2019). However, these techniques are lagging behind due to the fact that they cannot locate small and slow leaks, especially in long and complex pipeline networks. Some external conditions, such as temperature, operating conditions, pipeline geometry, and more, can influence the specific characteristics of these sensors, like pressure and flow, leading to false positive and/or false negative results. Also, it's hard to tell the difference between the signals that mean a leak and the normal output fluctuations because of signal interference from the normal pressure waves that happen when a pipeline is working.

Acoustic emission and machine learning for leak detection

Recent advancements in pipeline leakage diagnosis have therefore focused on combining AE signalling with smart automation through artificial neural networks to enhance the diagnostics of pipeline leakage faults. We use AE sensors to detect the vibrations of sound waves associated with leaks, including breaches as small as a pinhole in the pipeline that cause both burst-type and continuous-type emissions. Various situations require the extraction of statistical characteristics like kurtosis, skewness, mean square, and entropy AE from signals to facilitate leak detection. Ahmad et al. (2023) have employed neural networks, decision trees, random forests, and k-NN classifiers to perform such feature processing, demonstrating good results in leak detection classification accuracy. The combination of machine learning models and AE technology provides a robust way of detecting leakages in pipelines, whether constant or varying pressure, different types of fluids, or leakage sizes.

AE technology, in combination with machine learning, not only serves as a detection tool but also characterizes the leak severity and location. The main advantages include the ability to monitor continuously and in real-time, as well as the enhanced precision due to adaptive thresholds on sliding window approaches even under different operating conditions (Wang & Gao, 2023). It also helps to minimize false positives, which has always been a problem with traditional leak detection systems.

A practical study of artificial neural networks (ANNs) for pipeline leakage

Artificial neural networks (ANNs) have greatly improved pipeline leakage detection because they model and analyze patterns of pipeline operation data. We then apply ANNs to predict unforeseen non-linear correlations between inlet and outlet pressures and flow rates, among other sensitive leak indicators. It also shows that applying more than one generalized linear model and clustering to improve ANNs can increase the sensitivity of leak detection in noisy and unstable operations using the probabilistic approach (Abdulla & Herzallah, 2015).

One major strength of ANNs is their ability to handle high-dimensional data, allowing them to analyze a range of signals with various leak conditions. Recent studies have trained ANNs to distinguish between normal operating conditions and those affected by leaks, achieving very high levels of accuracy. Combining probability distribution in the decision systems of the neural networks has been quite successful in the recent past in alleviating the problems with false alarms, and enhancing the general routines of leak detection.

Support vector machines (SVMs) and one-class SVMs

Again, there is a growing interest in using Support Vector Machines (SVMs) to detect pipeline anomalies by identifying the boundaries that define normal and abnormal data. We design One-Class SVMs for use in scenarios where leaks occur significantly less frequently than in other usage states. Liu and Huang (2023) say that some researchers have shown how one-class SVM can be used with feature normalization and the choice of a kernel to make leak detection systems more sensitive. One-Class SVM finds it easier to spot changes that suggest leaks as it transforms pressure, temperature, and flow velocity data into a high-dimensional space.

Notably, One Class SVMs exhibit exceptional flexibility in adapting to subtle data shifts, thereby empowering our algorithm to pinpoint minute leaks that remain undetectable through other methods. There have been a lot of studies looking at the combination of real-time capabilities with One-Class SVMs for immediate detection and localization of leaks, which can help to prevent major losses for both the environment and the economy (Saleem et al., 2025).

Random forests and majority methods

Pipeline leak detection has utilized random forests and other ensemble methods, particularly due to their ability to handle large and diverse data sets. The 'Random Forest' classifier can be more precise and have lower variance over the classification of leak events than the single decision trees. Recent studies applied these methods to open acoustic emission signals, resulting in fewer false alarms and cases, while simultaneously maintaining the sensitivity to leakage detection (Mishra et al., 2025). This approach has thus been effective in enveloping different operational parameter relationships, providing better leak detection than a one-system approach.

A combination of package data simulation and machine learning

Tools like COMSOL Multiphysics generate simulated data to represent various operational pipeline modes, including leak modes, to overcome this problem. Researchers use these synthetic datasets to train machine learning models in pipeline systems, enabling them to examine and simulate system behavior. A tool like MATLAB can preprocess real simulation data and then feature or normalize it as components like pressure, temperature, and flow velocity for machine learning algorithms (Saleem et al., 2025). The incorporation of high-fidelity simulation data also optimizes both the accuracy of leakage detection models and their adaptability to apply across a broad range of real-world conditions.

The trend in the literature shows that machine learning is an indispensable part of many current pipeline systems for leak detection, such as the methods including AE technology, ANNs, SVMs, and Random Forest. This simulation data improves the training and validation of these models and increases the generalization capabilities when exposed to other pipeline settings. Altogether, the combination of these high-tech tools could change the nature of pipeline monitoring and leak detection significantly.

Methodology

The methodology starts first by modelling and simulating a pipeline system in COMSOL Multiphysics and obtaining a large set of records under different operational conditions of the system, both in normal and leak situations. The simulation data, which includes basic parameters such as pressure, velocity, and temperature in various pipeline segments, serves as the foundation for conducting further analyses. To ensure that all potential operational dynamics are taken into account, it is necessary to collect all possible data about operations.

Feature engineering and data processing

In MATLAB, we postprocess the basic simulation data to design significant features reflective of leakages. This entails extracting statistical parameters such as pressure, temperature fields, and velocity in three directions (X, Y, and Z) from the velocity components U, V, and W, respectively. Another important analysis during this phase is feature scaling, which attempts to bring all features to a common scale in order to give the machine learning model the ability to learn from the data features.

Machine learning model selection

For leak detection and localization, we adopt a one-class support vector machine. The OCSVM was selected because of its superior performance in finding anomalies, especially in cases where leak situations are much smaller than normal operating conditions. It works by computing a decision function for outliers. The OCSVM further categorizes new data to determine if it aligns with the norm set during the training process.

Model training and validation

Similarly, we fine-tune one-class SVM means through multi-processing using the normalised and engineered feature subset, and optimise hyperparameters to ensure the model reacts maximally to any deviations hinting at leaks. Finally, we use a separate segment of simulation data for validation and a highly sensitive check to confirm the model's ability to detect and localize leakage.

Real-time leak detection and localization

We then implement the proposed model in a real-time monitoring system to quickly detect leaks and pinpoint the leaking point within the pipeline system. This system uses pipeline sensors to provide continuous data feed; the assessed One-Class SVM identifies and estimates pipeline anomalies in real-time. In cases where such anomalies indicate leaks, the system can predict their possible locations and degree of leak, which are valuable inputs for quick and concrete rectification measures.

Analysis tools and algorithms

The main technologies used in the primary analysis are MATLAB for data preprocessing and feature design, and COMSOL Multiphysics for creating realistic models of different pipeline states. The core of the machine learning strategy, One-Class SVM, excels in processing data in high-dimensional space and excels in detecting illusions, which are significantly more frequent than typical ones. This makes One-Class SVM a suitable tool for pipeline leak detection.

This method covers a lot of ground throughout the whole process, from collecting data to analyzing it and treating it in real-time for leak detection in pipeline systems, which means it can act quickly if there is a leak (Fig. 1).

The block diagram avoids describing a theoretical and applied approach to pipeline leakage detection based on machine learning. Starting with data acquisition and preparation, the data is simulated via COMSOL multiphysics under both normal flow conditions and/or leak conditions. This information is then subjected to feature engineering and data processing, where, with the aid of MATLAB, pertinent features of leaks such as pressure, temperature, and velocity are obtained.

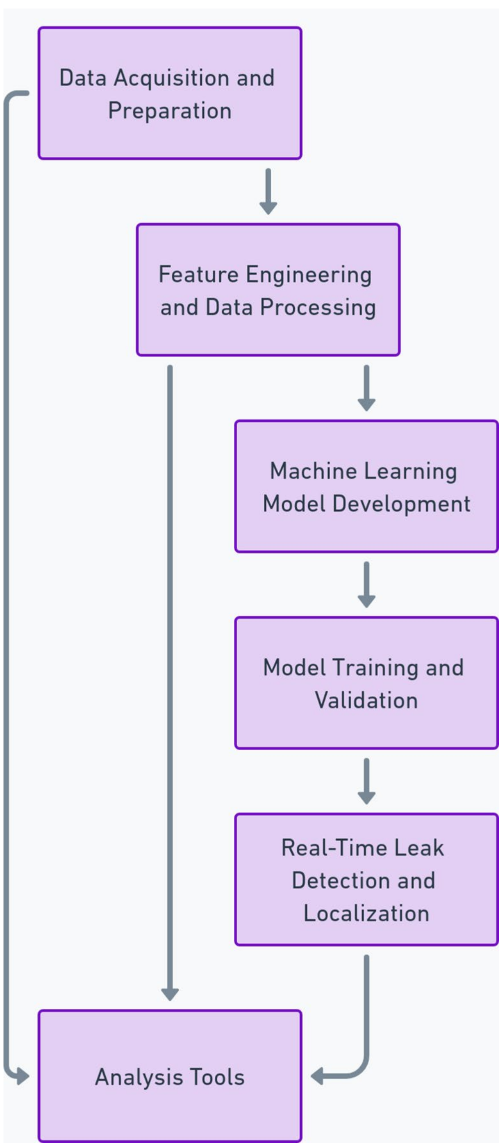

Fig. 1 Block diagram of the proposed methodology

After data processing, the methodology proceeds to the next step known as machine learning model development, where a one-class support vector machine (OCSVM) model is developed to predict anomalies. The model has to go through model training and validation; here, the model is trained and validated by using data from simulation to check the sensitivity and accuracy of the model to detect leaks.

It is then incorporated into the Real-Time Leak Detection and Localisation system, where pipeline conditions can be dynamically monitored with datasets coming from the sensors in real time. MATLAB and COMSOL Multiphysics are used again during the process as analysis tools for processing the data, simulating, and proving the models. Such an approach, as described in this paper, provides a sound and reliable technique for leakage detection in pipeline systems.

Results and discussion

Using machine learning to test how well leakage detection works in pipeline systems means carefully looking at numbers from simulations of the system's performance. These numbers tell us a lot about how well the system works in different situations. This section summarizes the results obtained from using COMSOL Multiphysics simulations, which were then further analyzed using MATLAB. We focus on the One-Class Support Vector Machine (SVM) model for deployment, elucidating its optimal identification and location of leakages in pipelines through the use of pressure, temperature, and velocity data.

Blood pressure measurement and evaluation

The simulation results using COMSOL Multiphysics software showed changes in pressure, which was considered a sign of possible leaks. We detected such pipe anomalies using pressure differentials at various points along the pipeline. The one-class SVM model effectively identified these deviations from normative pressure levels, providing an affirmative answer to the question of leaks' existence and promoting improved precision of localized diagnoses of problematic zones in the pipeline system for the diagnostic process.

The simulation screenshots with COMSOL Multiphysics provided a snapshot overview of pressure and temperature at selected coordinates along the pipeline, as presented in Table 1. (and a particular moment in time) Each row in the table corresponds to a specific point in the pipeline's structure, characterized by spatial coordinates X, Y, and Z. The temperature is Kelvin, and the pressure is Pascals. These

Table 1 Pressure and the temperature data from simulation

X Position (m)	Y Position (m)	Z Position (m)	Temperature (K)	Pressure (Pa)
-1.24	-30.00	79.74	293.15	15.00
-1.55	-30.00	79.36	293.15	26.22
-1.68	-30.00	80.00	293.15	71.61
…	…	…	…	…
1.58	-30.00	79.34	293.15	37.03
1.66	-29.47	79.56	293.15	41.22

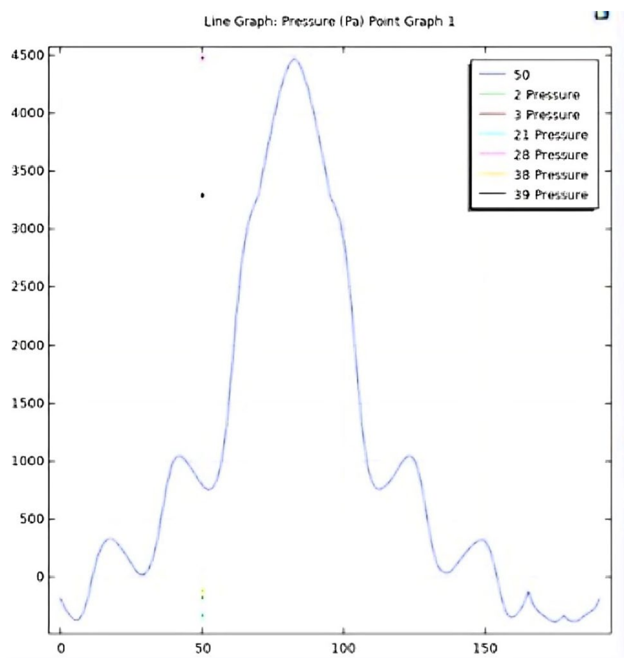

Fig. 2 Line graph of pressure

data points should be included to help determine the possibility of leaks. When combined with temperature readings, the table effectively illustrates the distribution of pressure, enabling the engineering team to pinpoint potential leak locations.

The used graph plots the pressure trends through the x-axis units, rising sharply to about fifty units before progressively dropping. These indicate a zone of high pressure concentration, most likely caused by fluid flow or a reaction in the modelled system. The settings sidebar provides information on selection criteria and parameters used to plot the graph, as well as points to the versatility and ability to analyze results in detail.

It is the pressure plot along a pipe or conduit as shown in the contour plot generated from the COMSOL software in Fig. 2. The plot applies convenient patterns to explain modified pressure levels within the model mentioning the red color for high pressure and blue for low pressure. It helps also to solve some problems related to fluid flow and

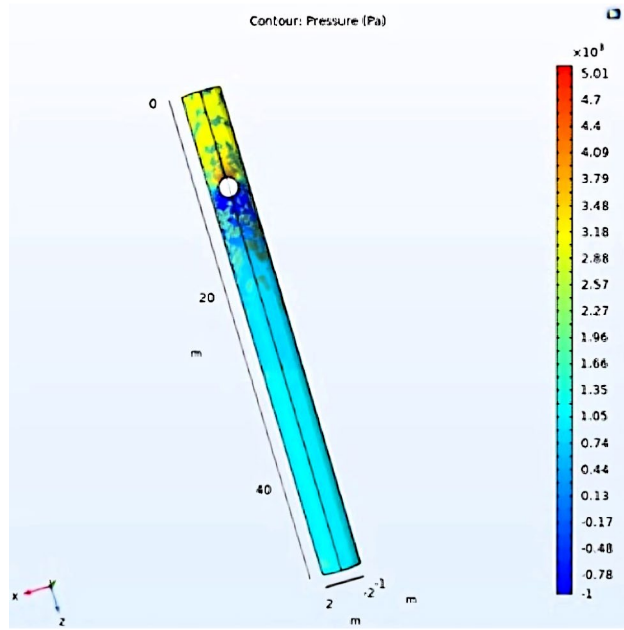

Fig. 3 2D contour plot of pressure

engineering design by visualizing how pressure varies along the length of the system (Fig. 3).

Temperature and velocity monitoring

Additional secondary confirmation possible through extensions of analysis as to temperature and velocity data Digital filtering methods feasible also for such purposes analyzed from the test signals constituting the given temperature and velocity metrics In relation to the given leak incidents the respective extension of the test signal analysis extended also up to temperature and velocity data. To further strengthen the diagnostic capability of the model, temperature anomalies co-related to areas witnessing pressure declines. Also, the time variations of velocity were again considered significant for the identification of the precise leakage points. The detection of these parameters concurrently through one class SVM model helped establishing a reliable leakage detection system increasing the diagnostic efficiency of the overall system (Table 2).

The detailed temperature and velocity distributions across the pipeline, which are presented in Figs. 4 and 5, also reveal features related to leakages of the pipelines.

Model performance and validation

Subsequently, detailed validation of the One-Class SVM model was conducted using datasets generated from the simulations in what is often a pivotal stage to fine-tune the model for accuracy and reliability when applied to different, actual systems. As part of the validation, the model's

Table 2 Velocity and temperature data from extended simulation

X Position (m)	Y Position (m)	Z Position (m)	Temperature (K)	Velocity X (m/s)	Velocity Y (m/s)	Velocity Z (m/s)
3.11	-30.00	105.88	293.15	1.51e-15	2.00	-9.09e-17
4.13	-30.00	106.19	293.15	-1.69e-15	2.00	-8.08e-15
3.68	-28.68	106.45	293.15	-0.023	2.01	-0.110
…	…	…	…	…	…	…
7.34	-28.94	100.97	293.15	-0.042	2.01	-0.075

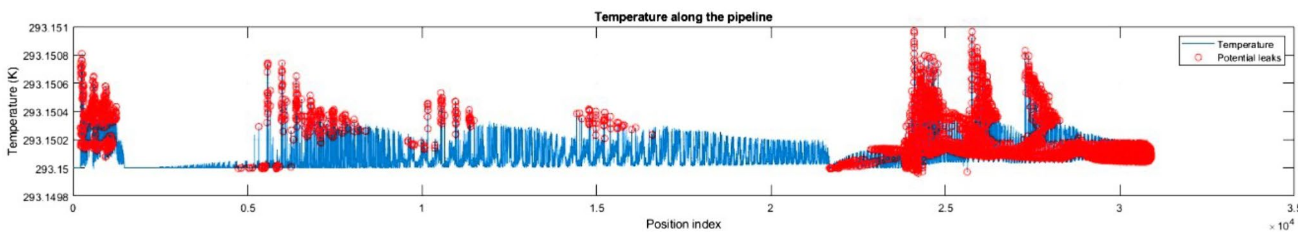

Fig. 4 Temperature along the pipeline

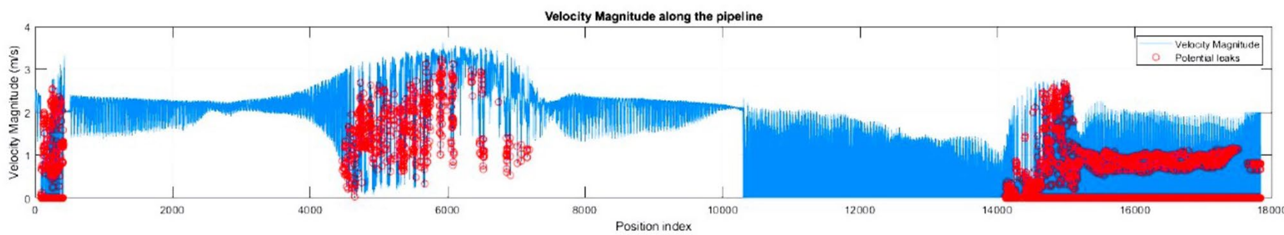

Fig. 5 Velocity along the Pipeline

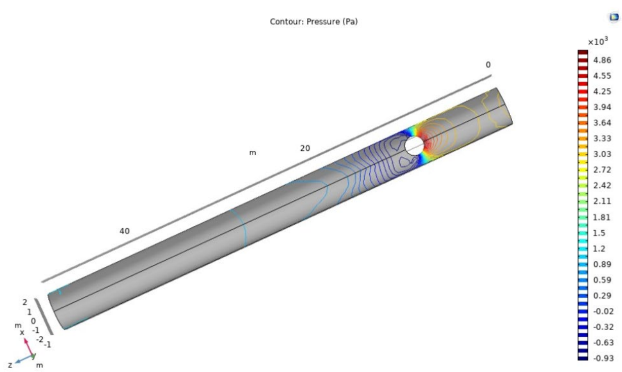

Fig. 6 3D Pressure Visualization

predictions were checked against the created leak scenarios, showing the model's accuracy in leak identification and leakage zone determination. This strong confirmation further supported the model and provided evidence of its potential application in operational pipeline systems.

Figure 6 used pressure gradients colored with separated iso-velocity lines and isotherms to elaborate the flow and structure, providing a three-dimensional view of the pressure distribution around an object in a pipeline.

Real-time studies and diagnostics

Implementation of the One-Class SVM model in a real-time monitoring system was another major milestone in pipeline management. This system utilized continuous data from sensors installed along the pipeline to apply the model, ensuring constant operation integrity and safety. The real-time function enabled prompt identification of leakage sites and significant reduction of potential losses, as well as prompt execution of various maintenance measures.

Maintenance scheduling and its pros and cons

The simulation data led to the development of strategies for predictive maintenance, aimed at preventing potential leak points before major failures. It proved even more useful in preventing more regular and costly interruptions in operational functions and resource management. Following the study, it was confirmed that the benefits of preventing leaks far outweighed the costs of implementing new and advanced technologies for finding them. This showed that the assessment of the pros and cons of incorporating advanced monitoring systems as essential parts of pipeline networks was positive.

The application of complex models, such as the One-Class SVM, has provided a sound approach to identifying, pinpointing, and controlling pipeline leaks. In addition, this approach not only improved the identification of the problem areas but also was a major contributor in preventing pipeline failures through effective maintenance of pipelines and overall cost-effective running of pipelines. The use of several pipelines provided here is suggestive of the potential benefits of the proposed approach for increasing the efficiency and safety of pipeline usage in the long term, and the practical application of this approach for monitoring pipelines and avoiding emergencies is of great importance for future research and development of the technology.

Conclusion

The employment of the One-Class SVM in the area of pipeline leak detection showed a great improvement in the existing means and methodologies of leak identification, as well as presenting a new level of effectiveness and precision to this field. The findings presented in this work confirmed the actual application possibility of the model for the identification and localization of pipeline leakage in real time. Implementation of this model in the existing operating pipeline systems enables constant observation with consequential real-time management, hence boosting the control of pipeline dangers while at the same time strengthening the functionality of the pipeline facilities. Additionally, many industrial systems have benefitted from predictive maintenance strategies based on machine learning analytics, proving that there is a definite commercial advantage to improving leak detection. In summary, the use of such complex models not only improves leak detection work, but also becomes a benchmark for new technological solutions for pipeline management and monitoring of their condition. The approach thus creates an avenue for future advancements in pipeline monitoring with the added benefits of sustainability and reliability of the business of moving fluids.

Author contributions K.B. conceptualized the study and designed the methodology. A.K.B. and M.H.A. conducted the simulations and data analysis using COMSOL Multiphysics and MATLAB. C.D. contributed to model development and validation. K.B. and A.K.B. wrote the main manuscript text, while M.H.A. and C.D. prepared figures and tables. All authors reviewed, edited, and approved the final manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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