SINERGI Vol. 30, No. 3, October 2026: 765-792
http://publikasi.mercubuana.ac.id/index.php/sinergi
http://doi.org/10.22441/sinergi.2026.3.007

Detection methods for asphalt and wax deposition in crude oil pipelines: a systematic review

Hamdani Wahab[1], Asral Asral[2], Awaludin Martin[2]*
[1]Department of Sustainable Engineering, Faculty of Engineering, Universitas Riau, Indonesia
[2]Department of Mechanical Engineering, Faculty of Engineering, Universitas Riau, Indonesia

Abstract
Crude oil with high pour point oil (HPPO) characteristics exhibits elevated viscosity at low temperatures, promoting the deposition of wax and asphaltenes along pipeline walls. These deposits restrict flow and can lead to partial or complete blockages, posing serious challenges to flow assurance, operational safety, and environmental sustainability. Despite extensive studies on deposition mechanisms, blockage detection methods remain fragmented, with no universally reliable or integrated solution. This study presents a systematic review combined with a bibliometric analysis of Scopus-indexed publications to map research evolution, trends, and technological advancements in blockage detection methods for crude oil pipelines. Bibliometric network mapping is applied to identify dominant research clusters and emerging themes. The review evaluates key detection techniques, including pressure wave analysis, gamma-ray inspection, computational fluid dynamics (CFD), and machine learning approaches. Reported results indicate that pressure wave methods achieve detection accuracies of around 5% with prediction errors up to 35%, while gamma-ray techniques show errors of approximately 5% with maximum deviations of 0.59 cm. CFD models effectively represent flow and deposition behavior but are limited in quantifying blockage size. Machine learning approaches demonstrate improved performance, with accuracies ranging from 80.67% to 89.96%, although their robustness depends on data quality and generalizability. The analysis highlights critical gaps, including limited accuracy under varying conditions, lack of methodological integration, and reliance on single-technique approaches that fail to capture the multi-physics nature of blockage formation. The novelty of this study lies in its integrated bibliometric–systematic synthesis linking detection performance, methodological limitations, and research trends, while proposing a hybrid framework combining physical sensing, numerical modeling, and artificial intelligence. This work provides a comprehensive reference and strategic direction for developing next-generation pipeline blockage detection systems.

This is an open access article under the CC BY-SA license

Keywords:
Heavy Crude Oil;
Pipe Blockage;
Pipeline blockage;
Viscosity Characteristic;

Article History:
Received: September 4, 2025
Revised: March 7, 2026
Accepted: April 4, 2026
Published: October 2, 2026

Corresponding Author:
Awaludin Martin
Department of Mechanical Engineering, Faculty of Engineering, Universitas Riau, Indonesia
Email:
awaludinmartin@eng.unri.ac.id

INTRODUCTION

The upstream oil and gas industry is one of the supporting sectors of the global economy, and this industrial production operation facility has been operating for several decades [1]. Due to the large demand for petroleum, daily production must remain stable by making risk mitigation efforts, analyzing obstacles that disrupt operations, and making efforts to prevent disruption of facilities and equipment that could reduce world oil production [2].

The oil and gas industry production process starts with oil production wells, which are a mixture of several fluids and solids that are then sent through the production distribution pipe to the collecting station for further separation between crude oil, water, gas, and other sediments. The crude oil flows through the distribution pipe to the final receiving station [3], [4].

The majority of oil well fields produce crude oil with almost the same type of characteristics, namely oil with an API Gravity viscosity of 30-47, where oil with this API range will have a tendency to congeal when the temperature is below its Pour Point value [5].

The process of sending heavy and extra heavy crude oil through the pipeline system is a very important production process because it is related to the final chain of a crude oil production operation. If a delivery failure occurs, it will affect the process chain below [6].

To flow heavy and extra heavy oil through the piping system, it can be diluted with other substances, formed as an oil-in-water emulsion, increased and/or maintained the oil's temperature, and lowered the crude oil's pour point, which is generally a combination of two or more alternative solutions [7].

Maldonado et al. [8] said that there are several chemical structures in the complex mixture of hydrocarbons that form crude oil, namely naphtha, paraffin, aromatics, isoparaffin, asphalt, as well as sulfur, nitrogen, and oxygen compounds. This mixture of chemical structures is classified based on polarity and solubility, resulting in the physical property of viscosity, which is related to the shear rate where the relationship is that the higher the viscosity, the greater the flow resistance so that the fluid's shear rate to move is smaller [9].

Crude oil produced from oil wells throughout the world has different content characteristics. The composition of the compounds it contains varies greatly depending on its origin or geographical location, but the flow characteristics are almost the same. In general, the composition of crude oil is differentiated as shown in Table 1. The elemental composition of crude oil is 84.5% carbon, 13% hydrogen, 1–3% sulfur, and less than 1% each of nitrogen, oxygen, metals, and salts [10].

Crude oil based on API gravity is classified according to specific gravity and viscosity, namely extra heavy (API gravity below 10 °API or greater than 1000 kg/m³), heavy (API gravity from 22.3 °API to 10 °API or 920 kg/m³ to 1000 kg/m³), medium (API gravity from 31.1 °API to 22.3 °API or 870 kg/m³ to 920 kg/m³) and light (API gravity greater than 31.1 °API or less than 870 kg/m³) where specific gravity is measured according to American Petroleum Institute standards in API degrees, a low API value indicates a higher specific gravity of crude oil while viscosity which is the resistance of crude oil to flow is measured in centipoise (cP) where for fluids with high viscosity it has a large centipoise number [12].

In addition to the issue of asphaltene deposition, wax deposition may also occur in crude oil pipeline networks containing paraffin wax. This compound exhibits a characteristic turbidity point known as the Wax Appearance Temperature (WAT). When the temperature of crude oil containing paraffin wax falls below the WAT (typically between 14.2 °C and 37.83 °C), wax crystals begin to form and adhere to the pipe walls [13].

To gain a better understanding of wax deposition behavior, Wang et al. [14] conducted research by carrying out modeling involving the disciplines of thermodynamics, heat transfer, mass transfer, crystal growth, and fluid dynamics so that accurate predictions can be obtained as a reference for the piping system design process and maintenance strategies that must be carried out to ensure the avoidance of large amounts of asphalt and paraffin deposits which will cause pipe flow blockages in the superficial velocity range of the experimental gas/liquid phase (Vsl = 1.1, 1.3 m/s, Vsg = 8.3-8.4, 9.39.6 m/s), the thickness of the two-phase oil-gas wax deposition tends to increase as the Vsg value increases. Heavy and extra-heavy oil contains asphalt and wax, so it has a high viscosity, making it difficult to flow through distribution pipes under normal conditions. Thus, it will become an obstacle in the process of sending crude oil through the pipe system [15].

Table 1. Physicochemical properties [11]

Properties	**Typical Range**
Specific gravity	*0.80-0.95*
Calorific value	*42-47 MJ/Kg*
Sulfur content	*0.05-5 wt%*
Flashpoint or ignition point	*38-120 °C*
Viscosity	*1-1000 cP*
Moisture and sediment content	*0.1-1%*
Specific heat and coefficient of expansion coefficient of thermal expansion	*1.7-2.5 kJ/Kg.K* *(6-10) x 10^{-4} °C*

It requires large amounts of energy, such as heating or viscosity-reducing chemical products, to circulate this heavy and extra-heavy oil. If the flow of heavy and extra-heavy oil is not managed properly. This phenomenon may induce the deposition of asphaltenes and wax on the pipe walls, which can lead to significant fouling and flow obstruction in the pipeline [16].

The efforts to reduce the viscosity that have been mentioned are only so that fluid can flow through the piping system where gradually asphalt and wax will form deposits on the pipe walls (Figure 1) with a long pipe stretch consisting of many interconnected segments it will be very difficult to detect the position of the accumulation of asphalt and wax deposits on the pipe walls so that in an instant there will be an increase in pressure in the upstream position and a large pressure drop in the downstream position [17].

An increase in pressure in the upstream position causes the operational pressure to be greater than the maximum allowable working pressure, causing leaks in the [17]. Apart from causing environmental pollution due to oil spills, it also requires high costs to identify blockage points and appropriate handling methods [18].

A pipeline leak, suspected to be caused by increased pressure within the pipeline, occurred in 2023-2024 on the Poole Port oil pipeline in Dorset, England, where up to 200 barrels of petroleum hydrocarbons leaked and contaminated the waters of Poole Port, ultimately leading to extensive recovery and cleanup operations and an incident declaration by local authorities [19]. A year earlier, in 2022, a Nord Stream pipeline leak occurred in the Baltic Sea, where an estimated 778 million cubic meters of methane gas leaked and spilled into the sea, damaging the ecology and marine environment across Russia and Western Europe [20]. This also occurred in Indonesia, where there were 117 pipeline leaks in 2020, 20 in 2021, and an oil spill in 2022 caused by a pipeline leak of 27.12 barrels [21].

The root cause of blockages in crude oil and gas pipes comes from paraffin wax and asphalt deposits, where an incorrect diagnosis will result in an inappropriate and ineffective handling strategy, which will result in the volume of deposits becoming larger and handling costs increasing significantly [22].

Wax deposition is caused by molecular diffusion at high temperatures and fluxes. Where this has a significant impact on the operational efficiency of the piping system because the deposit will increase the surface roughness as a cause of large pressure drops in turbulent flow and reduce the cross-sectional area of the pipe so that throughput occurs in a limited pressure system. It can be explained that in normal fluid flow, Bernoulli's law equation applies where frictionless flow does not lose energy, fluid pressure is constant, kinetic energy and potential energy remain constant along the flow line [23], as shown in Figure 2.

The blockage of the pipe diameter begins with the adhesion of material deposits on the pipe wall, which gradually causes a narrowing of the pipe cross-section (Figure 3). Finally, under certain conditions, the pipe hole through which this fluid passes becomes closed or blocked [24].

When there is a build-up of deposit material on the pipe wall, there will be a narrowing of the pipe cross-sectional diameter ($A_1 > A_2$), which will cause an increase in fluid velocity ($V_1 < V_2$), and there will also be a pressure drop at the downstream position ($P_1 > P_2$) [24].


Figure 1. Wax deposit in a 24-inch pipe

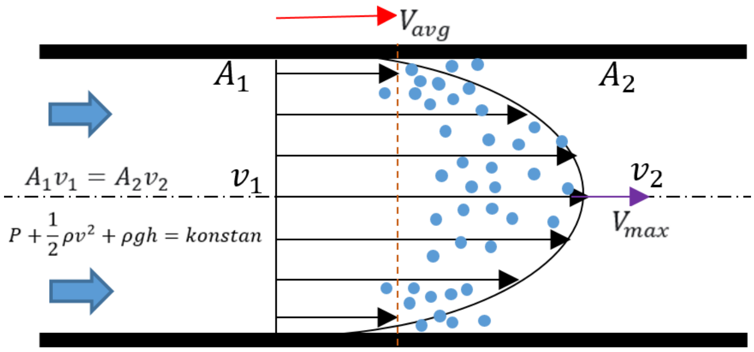

Figure 2. Normal flow conditions of the pipe according to Bernoulli's law [24]

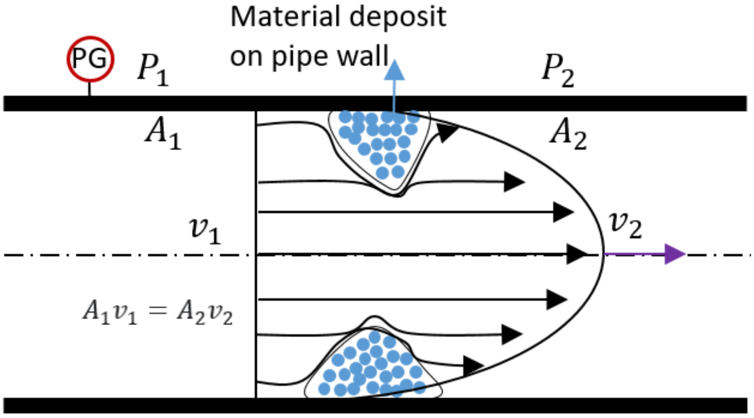

Figure 3. Start of formation of deposits on pipe walls [24]

Deposits adhering to the pipe wall will reduce the diameter of the pipe cross-section flow. At one point, this pipe diameter hole will suddenly close (totally blocked) without knowing the position, amount, and area of the blockage. The closure of this fluid flow will cause an increase in pumping pressure at the upstream position, which will be greater than the maximum allowable working pressure, causing the weakest part of the pipe or the smallest thickness to be penetrated by its working pressure, resulting in leakage (Figure 4) [24].

This leakage will disrupt the production of oil and gas flowing through the pipeline network, work accidents and of course will become an environmental, safety and health issue that will have regional and national impacts so that it is considered necessary to be able to use flow operating parameters such as changes in pressure, temperature, and flow shape for the method of immediately detecting blockages before leaks occur [26].

The methods that have been studied provide various ways with varying levels of effectiveness to find blockage points caused by wax and asphalting, which are influenced by the complexity of the composition and condition of the pipe, so a multidisciplinary or multifaceted approach is needed.

Integration of several methods using acoustic equipment and experimental simulation offers new hope with an easier strategic approach [22].

However, the effectiveness of the method depends on environmental conditions, fluid characteristics, and piping system configuration, so ongoing research is needed so that the level of accuracy and effectiveness of the method for determining blockage points can help for proper handling to overcome the blockage that occurs.

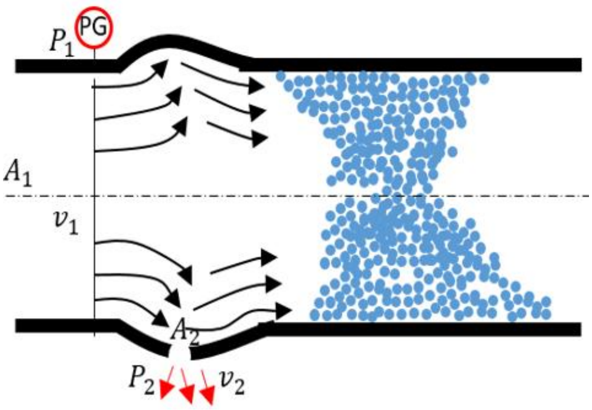

Figure 4. Upstream Pressure increases causing the pipe to burst [25]

In addition, economic feasibility and technical ease of application and implementation can be achieved on complex and difficult pipe networks.

Piping system engineers employ various methods and technologies, each possessing unique characteristics and differing degrees of technical complexity. The level of success is determined by the accuracy of the data and the suitability of the method used. Mathematical methods known today include calculation methods, computational simulations, special equipment for vibration analysis, acoustic techniques, gamma rays, X-rays, and others [27]. The methods that have been researched and developed can be well documented (see Table 2) so that the phenomenon of blockage in pipes can be studied in more detail with many numerical parameters until the most appropriate, cheap, easy, and effective method is found.

The method used to detect and identify blockages in the piping system will involve a series of combinations of traditional and sophisticated methods. Each method has advantages and limitations in its application, so it is expected that the combination of methods used can complement each other and cover the shortcomings.

Table 2. Comparison of research methods for identifying blockages in crude oil pipelines

Method	**Principle**	**Data Type**	**Detection Capability**	**Advantages**	**Reported Performance**	**Limitations**
Pressure Wave / Pressure Transient [21, 22, 23, 24, 32, 33, 34]	Detects reflection and attenuation of pressure waves caused by anomalies in the pipeline	Pressure signals	Estimation of blockage location and extent	Non-invasive, suitable for long pipelines	Accuracy ≈ 5%, prediction error up to 35%	Sensitive to noise, boundary condition uncertainty
Acoustic Wave Propagation (AWP) [25, 26, 27, 28, 29, 40]	Uses sound wave propagation characteristics to identify flow disturbances	Acoustic signals	Detects blockage presence and approximate location	Real-time monitoring, non-destructive	Moderate detection accuracy	Interference from turbulence and environmental noise
Gamma-Ray Transmission [30][31]	Measures density variation caused by deposits in the pipe	Radiation intensity	Deposit thickness measurement	High sensitivity and accuracy	Error ≈ 5%, maximum deviation 0.59 cm	Expensive equipment, radiation safety concerns
Computational Fluid Dynamics (CFD) [43, 44, 45, 46]	Numerical simulation of flow, heat transfer, and deposition processes	Flow and thermal parameters	Predicts deposition behavior	Useful for understanding blockage mechanisms	Good qualitative prediction of deposition	Limitations in accurately determining the precise location of the blockage
Intelligent Network Models Sensors [40, 47, 48, 49, 50]	Detect strain and pressure changes through wavelength shifts	Optical wavelength signal	Real-time blockage monitoring	High sensitivity and distributed sensing capability	RMSE ≈ 0.845	High installation cost
Machine Learning Models [28, 51, 52, 53, 54, 55, 56, 57, 58, 59]	Data-driven prediction using pressure, flow, and sensor datasets	Sensor datasets	Blockage prediction and classification	Handles complex nonlinear relationships	Accuracy 80.67% – 89.96%	Requires large training datasets

In addition, it is necessary to consider the economy and impact of the method used on the handling that will be carried out so as not to harm the company in terms of finance, loss of production, and environmental damage. To identify existing research gaps and evaluate current methodological developments, a comparative analysis of the most recent and widely investigated methods was conducted, as summarized in the following section.

The comparison presented in Table 2 highlights the diversity of approaches used for pipeline blockage detection and evaluates the performance of several reported methods. Pressure-based approaches, such as the pressure wave method, are widely applied due to their non-invasive characteristics and suitability for long-distance pipeline systems. However, these methods often experience relatively high prediction errors, primarily due to signal noise and complex boundary conditions.

Gamma-ray transmission techniques offer higher sensitivity in detecting deposits within pipelines. Nevertheless, their practical implementation is limited by the high cost of specialized equipment and concerns related to radiation safety. Numerical approaches, such as Computational Fluid Dynamics (CFD) simulations, provide a cost-effective means of analyzing the mechanisms of wax and asphaltene deposition. Despite their usefulness in understanding flow and deposition behavior, these models remain limited in accurately identifying the precise location of blockages in real pipeline systems.

In recent years, data-driven approaches, including machine learning and intelligent network models, have demonstrated promising detection performance when integrated with advanced sensing technologies. These methods have shown the potential to significantly improve detection accuracy, achieving reported accuracy levels of up to 89.96%. However, their effectiveness depends largely on the availability of large datasets and robust training processes, and their implementation may still encounter practical constraints under real operational conditions.

Overall, these findings suggest that no single method can provide optimal performance across all aspects of pipeline blockage detection. This highlights the need for the development of hybrid approaches that integrate physical sensing techniques, numerical modeling, and artificial intelligence methods to enhance detection accuracy and reliability.

Based on the research that has been carried out in accordance with Table 2 above, an appropriate framework for effective action, prevention and detection methods has been developed, which is broadly depicted in Figure 5.

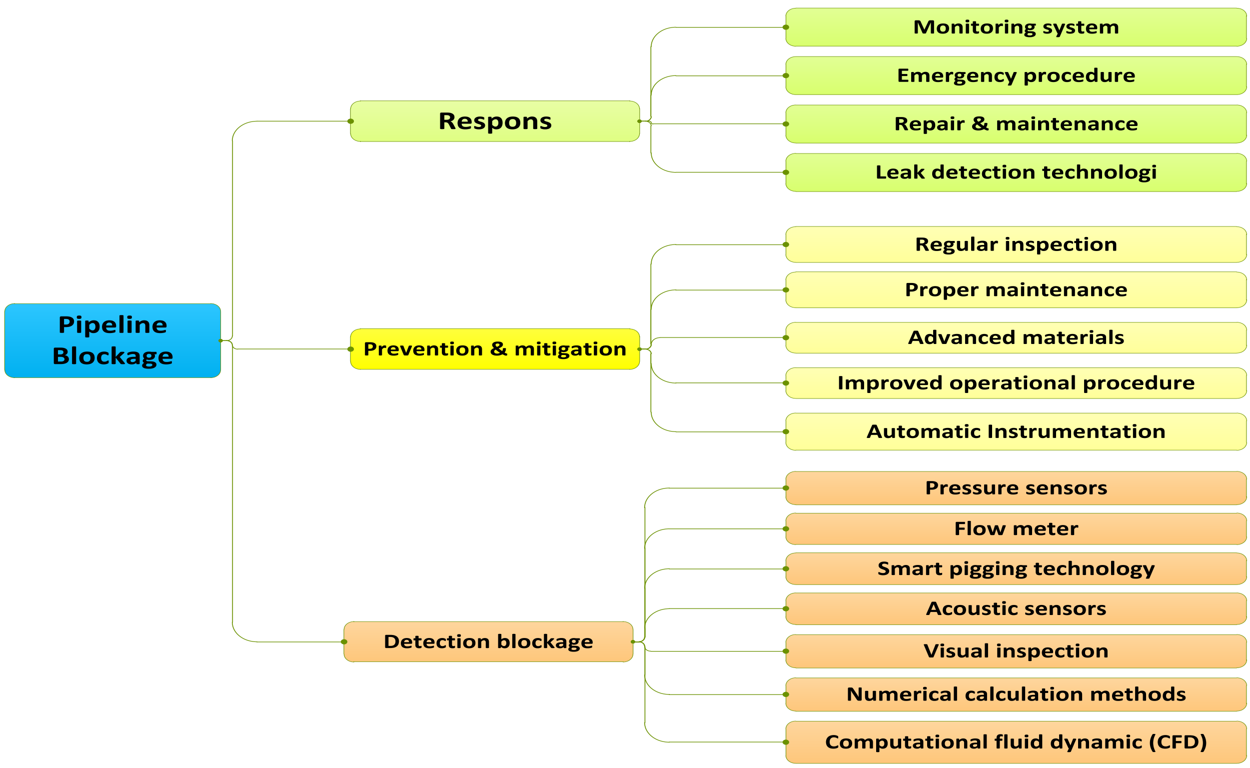

Figure 5. Mind map of causes, effects, mitigation and solutions to pipe blockages [60][61]

Based on research, it is known that pipe blockage is caused by mechanical failure, corrosion, damage to valves and accessories, natural disasters, operational errors, the presence of solid materials, and paraffinic wax and asphalt deposits. The damage caused by this blockage has consequences for environmental damage, oil prices, financial losses, disruption of oil and gas supply, safety hazards, political disruptions, and, of course, the company's reputation.

The high risk of blockage incidents in this pipeline necessitates a real-time monitoring system to ensure timely detection and operational intervention, emergency procedures, maintenance and repairs, and using the latest technology to detect leaks where regular inspections are carried out. Proper maintenance methods, appropriate materials, improving operational procedures, and using automatic instrumentation systems are also required.

In general, there are several tools used to detect the point of blockage in the pipe, namely by using pressure sensors, flow meters, smart pigging, acoustic sensors, and visual inspection, where all measurement results using this equipment can be developed to be more accurate with numerical calculation methods combined with computational fluid dynamics.

A variety of methods and technologies are employed by pipeline engineers, each with distinct characteristics and different levels of implementation complexity. The level of accuracy by the accuracy of the data and the suitability of the methods used. The methods currently known include mathematical calculation methods, computational simulations, special equipment for vibration analysis, acoustic techniques, gamma rays, X-rays, and others. Various approaches used in previous studies with different levels of accuracy and operating conditions, then a research diagram can be described that can be combined and validated with other methods according to the following flow diagram.

Figure 6 shows that, in general, determining the blockage in the pipe can be done with special equipment to take field operation data such as vibration, sound, pulse, pressure, and temperature, which is then used in the numerical calculation equation. Laboratory experiments validate numerical calculations. This means that the methods used can be combined and validated with each other so that the level of accuracy and percentage of error can be found so that accurate results are obtained and can then be simulated in the form of computational fluid dynamics.

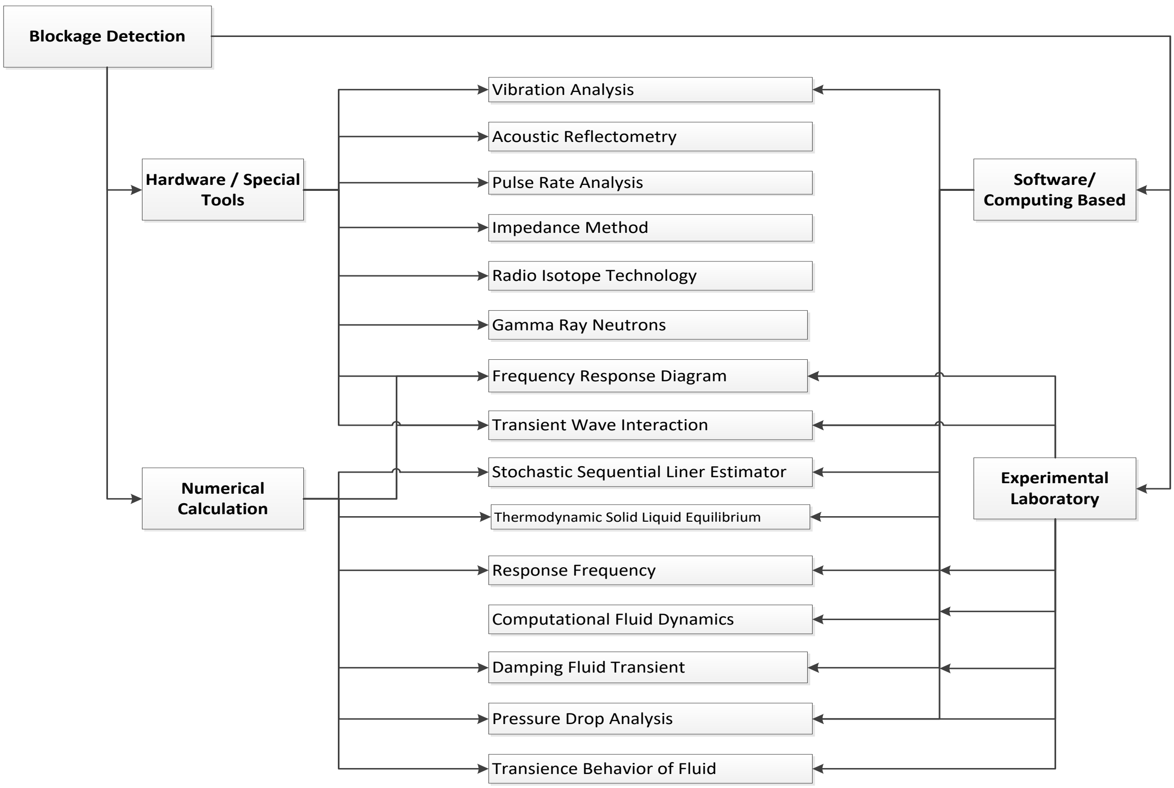

Figure 6. Flowchart of studied methods for determining blockages [27, 28, 41, 62, 63, 64]

In the section "Discussion of Several Previous Methods for Blockage Detection," we provide an overview of commonly employed techniques for detecting blockages. These methods were identified through a literature search in the Scopus database and subsequently filtered to include studies published within the past five years. A bibliometric network map of relevant publications on pipeline blockage detection methods was previously generated using the *VosViewer* application.

This article reviews those studies and emphasizes the current state of the art, existing knowledge gaps, and potential avenues for further development in several approaches, including pressure wave reflection analysis, mathematical and numerical modeling, gamma-ray transmission, computational fluid dynamics (CFD), and machine learning techniques utilizing pressure data and neural networks.

The concluding section of the subchapter "Comparison of Current Methods, State of the Art, Knowledge Gaps, and Development Possibilities" elaborates on the novel contributions proposed by each research approach to the identification of oil pipeline blockages. The perspectives and conceptual developments discussed herein are anticipated to advance the current methodologies of blockage detection and provide a solid foundation for future scholarly investigations.

METHODS

Methodology Strategy

This study employs a systematic literature review combined with bibliometric analysis to examine the development of detection methods for crude oil pipeline blockages. The overall framework consists of data collection, screening, analysis, and synthesis. Relevant publications were retrieved from the Scopus database using a Boolean search strategy with the keyword "pipeline blockage". The initial search yielded 1,858 documents. Scopus was selected due to its comprehensive coverage of high-quality peer-reviewed literature.

A multi-stage screening process was conducted to ensure the relevance of the selected studies. First, filtering based on publication stage and title reduced the dataset to 453 articles. Subsequently, further screening was performed using publication year, abstracts, and keywords focusing on "pipeline blockage detection". This step resulted in 44 eligible articles published between 1996 and 2025. Only studies directly related to detection techniques were included for in-depth analysis.

Bibliometric analysis was conducted using *VOSviewer* to map the knowledge structure and research trends. Co-occurrence and network visualization techniques were applied to identify dominant clusters, relationships among studies, and emerging themes in blockage detection methods. The results provide a spatial representation of the research landscape.

A mind mapping approach was used to classify the selected studies into key themes, including causes, consequences, prevention, mitigation, and detection of pipeline blockages. Furthermore, a comparative analysis was performed to evaluate various detection methods in terms of accuracy, applicability, advantages, and limitations. This step also explored the potential of integrating multiple techniques to improve detection performance.

The findings from bibliometric and qualitative analyses were synthesized to identify research gaps and technological challenges. Based on this synthesis, a conceptual framework is proposed, emphasizing the integration of physical sensing, numerical modeling, and data-driven approaches to enhance blockage detection in crude oil pipelines.

Figure 7 illustrates the overall research framework, with the nomenclature provided to support the analysis presented in Table 3.

The nomenclature in Table 3 is a naming system, and units used in pipeline blockage research so that the identification process is easier and more consistent with the terms, avoids ambiguity, reduces the possibility of misunderstanding this pipeline blockage research, and makes it easy to classify in various research methods.

Bibliometric Search Results

The results of the bibliometric search from the Scopus database found 14 articles (Table 4) with more specific keywords regarding the method of identifying blocking points in the pipeline, where the results can then be described in the form of network visualization or bibliometric network maps using the VOSviewer application, which is free software used to visualize bibliometric networks, making it easier to find relationships between literature, visualize publication data, identify gap trends and research contributions.

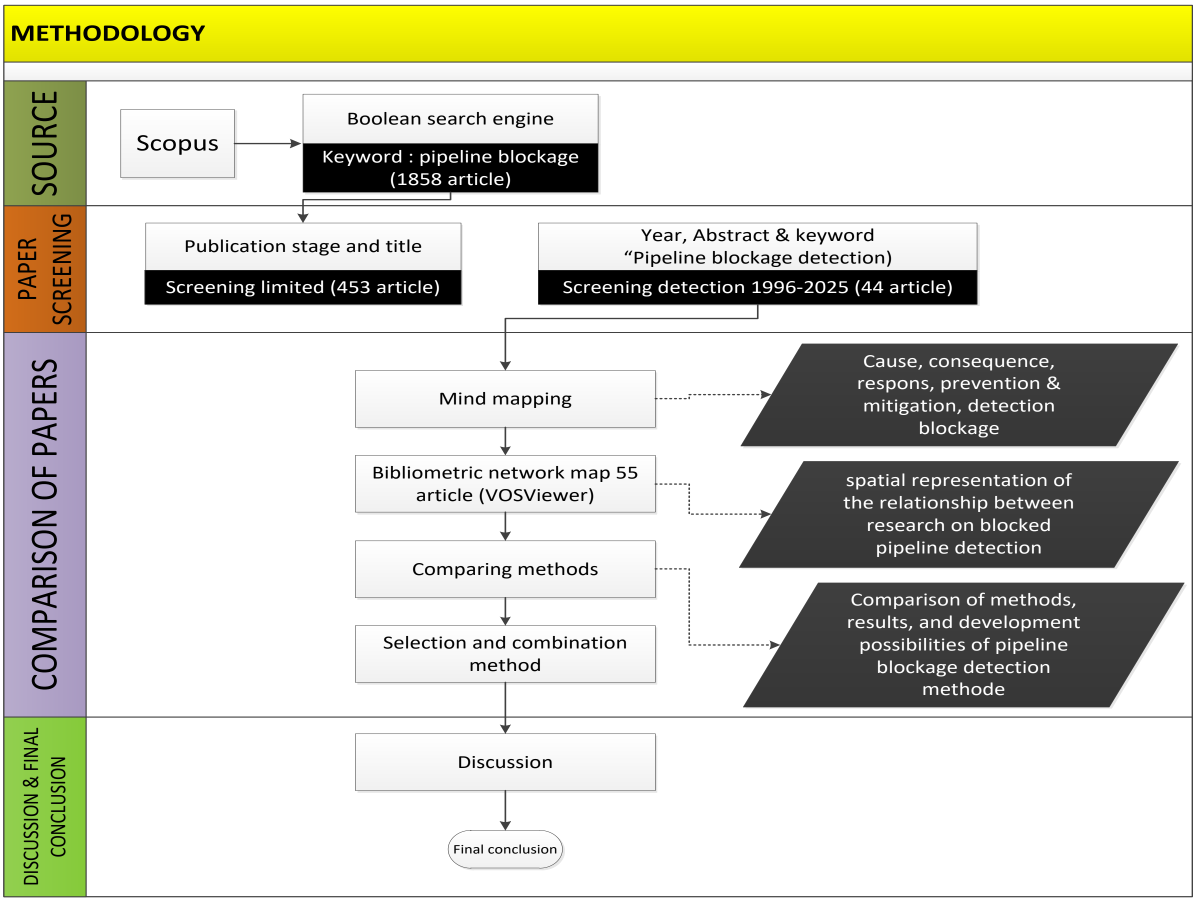

Figure 7. Research framework

Table 3. Pipeline blockage nomenclatures

Symbol	Note
HPPO	High Pour Point Oil
API	American Petroleum Institute standards
PPV	Pour Point value
cP	Centipoise
WAT	Wax Appearance Temperature
ΔH_B	Head loss across blockage
MeV	Mega-electron volt
FFT	Fast Fourier Transform
RMS	Root Mean Square
FRD	Frequency response diagram
CFD	Computational Fluid Dynamics

Figure 8 is a bibliometric diagram showing the evolution of research on pipeline blockages, allowing for the identification of changes in insightful ideas for further development. This bibliometric analysis was conducted using VOSviewer to explore the intellectual structure and research trends in crude oil pipeline blockage detection. The keyword co-occurrence network reveals distinct thematic clusters and a clear evolution of research focus from conventional monitoring approaches to advanced predictive modeling. From this bibliometric map, it is concluded that several methods are highly sought after and still have room for further research and development.

From Figure 8, which is a bibliometric network map created using VOSViewer. The bibliometric network reveals a clear structural transition from sensor-based monitoring (e.g., IoT and flow sensors) to advanced data-driven modeling approaches. The neural network model emerges as a central node, indicating its critical role in bridging real time data acquisition and predictive analytics. Furthermore, the right cluster highlights the growing integration of machine learning techniques, such as support vector machines and optimization algorithms, with experimental and flow modeling data. This suggests a paradigm shift toward hybrid and intelligent detection systems.

Table 4. Bibliometric search results from the Scopus database

No	Title	Reference
1	Blockage detection techniques for natural gas pipelines: A review.	[27]
2	Experimental Investigation of Gas Transmission Pipeline Blockage Detection Based on Dynamic Pressure Method.	[30]
3	Research on Method for Detecting Pipeline Blockages Based on Fluid Oscillation Theory.	[65]
4	Partial Blockage Detection in Pipelines by Modified Reconstructive Method of Characteristics Technique.	[64]
5	Visual detection method of metal mine filling pipeline blockage based on ERT.	[66]
6	Development of a Hydrate Kinetics-Based Digital Twin for Blockage Detection and Production Optimization.	[67]
7	Assessment of the acoustic reflectometry technique to detect pipe blockages.	[68]
8	Blockage Detection in Gas Pipelines to Prevent Failure of Transmission Line.	[69]
9	Machine learning approach for blockage detection and localization using pressure transients.	[28]
10	Experimental platform for blockage detection and investigation using propagation of pressure pulse waves in a pipeline.	[29]
11	Simulation and detection of blockage in a pipe under mean fluid flow using acoustic wave propagation technique.	[70]
12	Fluid-Structure Interaction in Transient-Based Extended Defect Detection of Pipe Walls.	[71]
13	Experimental verification of the accuracy and robustness of Area Reconstruction Method for Pressurized Water Pipe System.	[72]
14	Pipe network blockage detection by frequency response and genetic algorithm technique.	[73]

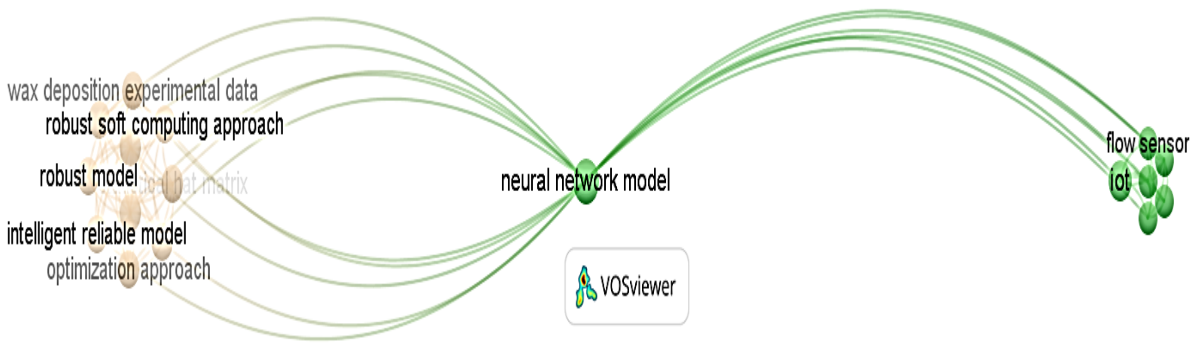

Figure 8. Bibliometric network map for specific articles on detection methods.

Figure 9 is a bibliometric visualization of VOSViewer that maps the relationship of keywords in scientific article documents that have been collected from the Scopus database. The bibliometric network highlights a clear evolution in modeling approaches for pipeline blockage studies. Early research is dominated by physics-based and numerical methods, as indicated by clusters involving numerical calculation, full models, and model performance evaluation.

The network visualization identifies three major clusters. The first cluster is associated with sensor-based monitoring and data acquisition, characterized by keywords such as flow sensor and IoT. This cluster reflects research focusing on real-time detection and field instrumentation, emphasizing data collection from pipeline systems.

The second cluster centers on computational intelligence and data-driven methods, where neural network model emerges as a dominant node. Its central position indicates a pivotal role in connecting raw data acquisition with advanced analytical techniques. This cluster also includes methods such as support vector machines, optimization approaches, and statistical models, highlighting the increasing adoption of artificial intelligence in blockage detection.

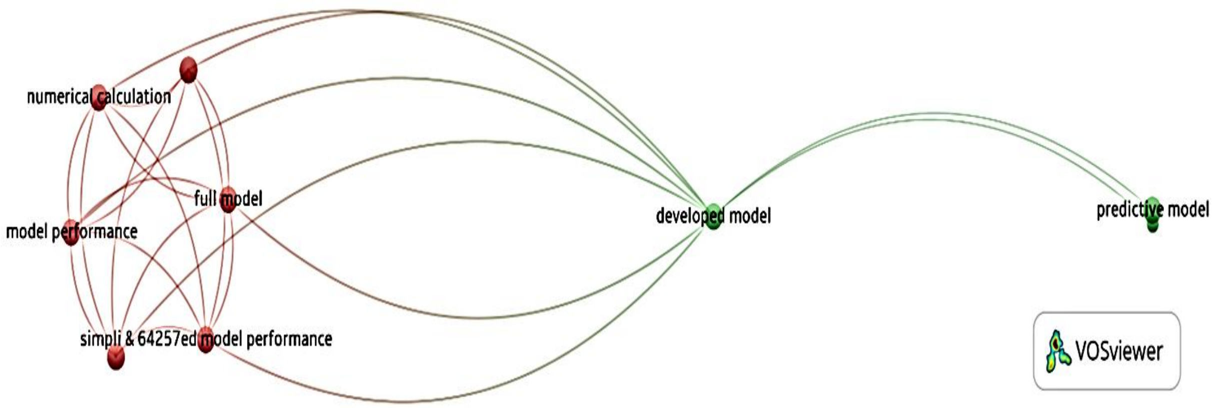

Figure 9. Bibliometric network map based on keywords for specific articles

The third cluster represents modeling and simulation approaches, including numerical calculation, full model, simplified model, and model performance. These studies primarily focus on physics-based and mechanistic modeling to understand flow behavior and deposition phenomena. The presence of the developed model node indicates ongoing efforts to improve or hybridize existing models.

The network structure demonstrates a clear transition in research paradigms. Early studies were dominated by numerical and physics-based models aimed at understanding blockage mechanisms. Over time, research has shifted toward predictive and data-driven approaches, as indicated by the emergence of predictive model and machine learning techniques. The neural network model acts as a bridging node, signifying the integration of sensor data with predictive analytics.

This evolution suggests a movement from deterministic modeling toward intelligent systems capable of real-time prediction and decision-making. Additionally, the growing linkage between experimental data (e.g., wax deposition) and computational methods highlights the increasing importance of hybrid approaches.

Overall, this analysis suggests that future research should focus on developing integrated, multi-scale, data-driven detection systems to improve the accuracy, robustness, and real-time applicability of crude oil pipeline blockage detection. Research methods can be combined and integrated, and utilizing data will create a more practical, cost-effective, and accurate method.

Table 5 displays the results of filtering research methods that have been carried out, classified based on the ranking with the highest number of citations in the last 10 years, to be reviewed and discussed in more detail in further studies.

Furthermore, the research search results in Table 4 are specifically for blockage detection research methods according to Table 5, which shows numerical research methods that utilize pressure, oscillatory flow, acoustic waves, frequency response, genetic algorithms, and hydraulic transient analysis plus other methods studied using vibration methods, thermodynamics, and computational fluid dynamics.

From Table 5 above, it is known that the majority of pipe blockage studies with numerical analysis use pressure theory, fluid oscillation flow, acoustic waves, frequency response, genetic algorithms, and hydraulic transient analysis, vibration analysis model, thermodynamic model and computational fluid dynamic.

Research on pressure theory has been developed using several methods, namely the Dynamic Pressure Method or Pressure Transients (pressure oscillations). The frequency signal method is developed using acoustic reflectometry or acoustic wave propagation.

DISCUSSION OF SEVERAL PREVIOUS METHODS FOR BLOCKAGE DETECTION

Fluid Transient Damping Method

The fluid transient damping method is the development of a linear analytical solution that is applied to find blockage points in piping systems. Based on linear analysis, it is known that the fluid friction factors in transient flow and blockage flow are exponential, and each is a harmonic component (Figure 10).

This figure shows a control volume model for a pipe segment of length Δx containing a blockage point. This section analyzes the distribution of pressures and forces acting on deposits adhering to the pipe wall.

Table 5. Research on blockage detection by numerical study

No	Title	Quantity
1	Dynamic Pressure Method or Pressure transients (pressure oscillations)	14
2	Fluid Oscillation Theory (damping of fluid transients).	2
3	Acoustic reflectometry technique or acoustic wave propagation technique.	6
4	Frequency response (transient frequency)	9
5	Genetic algorithms.	2
6	Hydraulic transient analysis	1
7	Vibration analysis.	1
8	Thermodynamic model	1
9	Ultrasonic torque waves	1
10	Gamma-ray	1
11	Computational fluid dynamic.	1

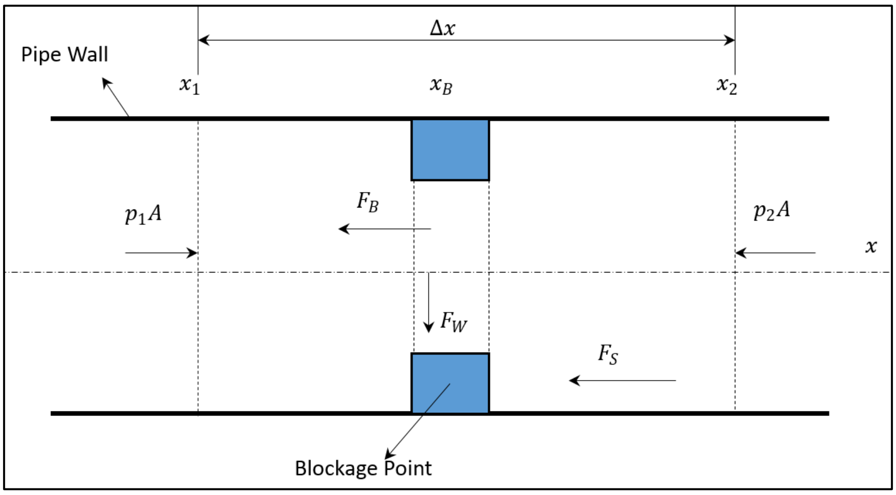

Figure 10. Blocking point diagram and parameter [71]

Geometrically, a pipe segment is bounded by two axial positions: x_1 and x_2 with length Δx, while x_b indicates the location of the blockage within the segment. Fluid flows along the *x-axis* from the upstream side to the downstream side. Reduced flow due to a blockage depends on the extent and location of the blockage.

From the schematic illustrated in Figure 10, the governing equation describing the unsteady flow in a pipeline with a blockage can be derived and expressed as follows. [74].

$$\frac{\partial H}{\partial x} + \frac{1}{gA}\frac{\partial Q}{\partial t} + \frac{Q}{gA^2}\frac{\partial Q}{\partial x} + \frac{fQ^2}{2DgA^2} - \Delta H_B \delta(x - x_B) = 0 \quad (1)$$

$$\frac{\partial H}{\partial t} + \frac{Q}{A}\frac{\partial H}{\partial x} + \frac{a^2}{gA}\frac{\partial Q}{\partial x} = 0 \quad (2)$$

$$\Delta H_B = \frac{K_B Q^2}{2gA^2} \quad (3)$$

Where x denoted the distance along the pipe (meters), t the time (hours), H the piezometric height (meters), Q the flow rate in pipe (m/hours), D the pipe diameter (mm), g the acceleration due to gravity (m/s^2), A the pipe cross-sectional area (m^2), a the wave speed in fluid (m/s), x_B the blockage location, $\delta(x - x_B)$ the Dirac Delta Function, ΔH_B the head loss across blockage, and K_B the head loss coefficient of blockage and as an indicator of blockage size.

If the K_B and flow rate are known, then the diameter of the blockage in the pipe cross-section can be estimated. Transients in a pipe experiencing a blockage are a series of harmonic components that exponentially correspond to the Fourier components so that the attenuation rate parameter of the harmonic components indicates the presence of a blockage. They are significantly different from each other so that in some components, the level of attenuation is greater than the friction factor, where, based on this Fourier component, it is concluded that the attenuation due to blockages is a function of the size of the blockage and the location of the blockage.

From research conducted by Brunone et al., 2023 [62] it was found that transient flow in pipes can be used to detect and find blockages with an area of 20% of the cross-sectional area of the pipe, where it can be concluded that this transient calculation method is easy to apply but cannot be applied to complex and long pipe network systems. Furthermore, the experimental results demonstrate that accurate blockage detection requires sufficiently high flow rates to achieve optimal performance, as blockage locations along a pipeline may generate different transient signatures.

Gamma Ray Neutron Method

One method for finding blocking points in pipe networks is to use gamma rays and hydrogen neutrons to capture images of deposition in pipe networks.

This method begins by shooting thermal neutrons at the part of the pipe where deposition is suspected. When the thermal neutrons that have been irradiated through the pipe encounter deposition of wax containing hydrogen and carbon, this hydrogen will then capture most of the thermal neutrons and quickly produce $2.223\ MeV$ gamma rays. This hydrogen is the target of analysis because when neutrons are rotated around the pipe, there will be a change in the intensity of the gamma rays emitted back by the hydrogen due to differences in the thickness of the hydrogen content in the wax layer attached to the inside of the pipe wall [41].

The neutron release circuit of the $5\ \mu g$ $252Cf$ isotope, with the scintillation detector used being $LaBr_3$:Ce, which is protected by tin measuring $10 \times 10 \times 10\ cm^3$, which is located on the outer surface of the pipe [42].

From research carried out by Hei et al. in 2016 [75] using a $252\ Cf$ neutron source and a $LaBr_3$ detector by measuring the height of the hydrogen peak from scanning gamma-ray images, it was concluded that this method could be applied to images of wax deposition in pipe networks without requiring specific accumulation information in the scanned pipe flow (Figure 11). However, further research is needed to measure the thickness of the deposits formed with certainty. This method is less effective for checking deposits in long pipe networks with large diameters and connected to many branches

Vibration Analysis Method

Fluid flowing through a pipe with a certain flow speed and pressure at a cross-sectional area that is getting smaller due to a blockage will have the potential to increase the vibrations produced by the pipe walls.

Figure 12 below shows a schematic of the research conducted using a round carbon steel pipe with a length of 1000 mm and a diameter of 30 mm. This figure illustrates the configuration of a vibration monitoring system used to detect flow obstructions in a pipeline. In this system, multiple accelerometer sensors are installed along the surface of the pipe and connected to a data acquisition system to record vibration signals generated during fluid flow. Three accelerometer sensors, labeled A, B, and C, are positioned at different locations along the pipeline.

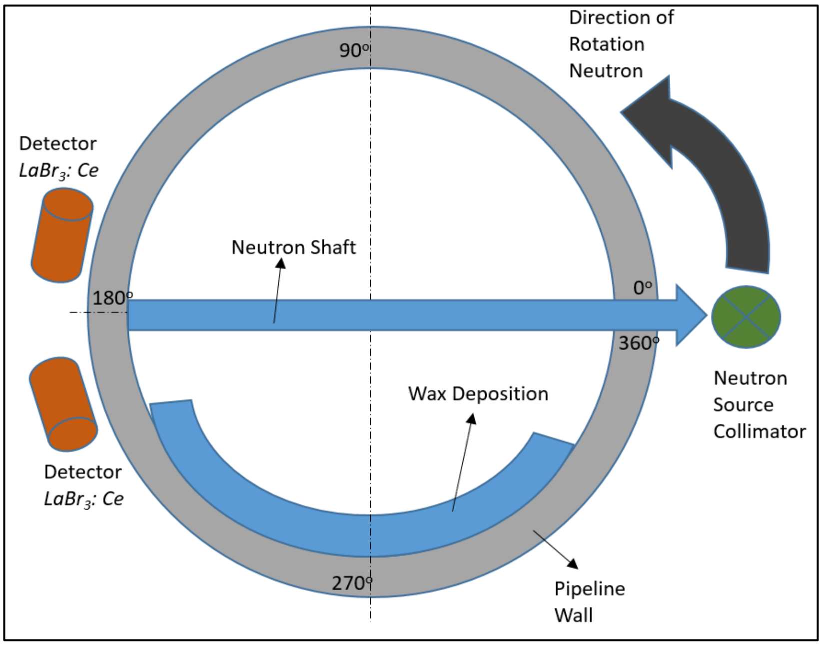

Figure 11. Neutron sensing schematic [41]

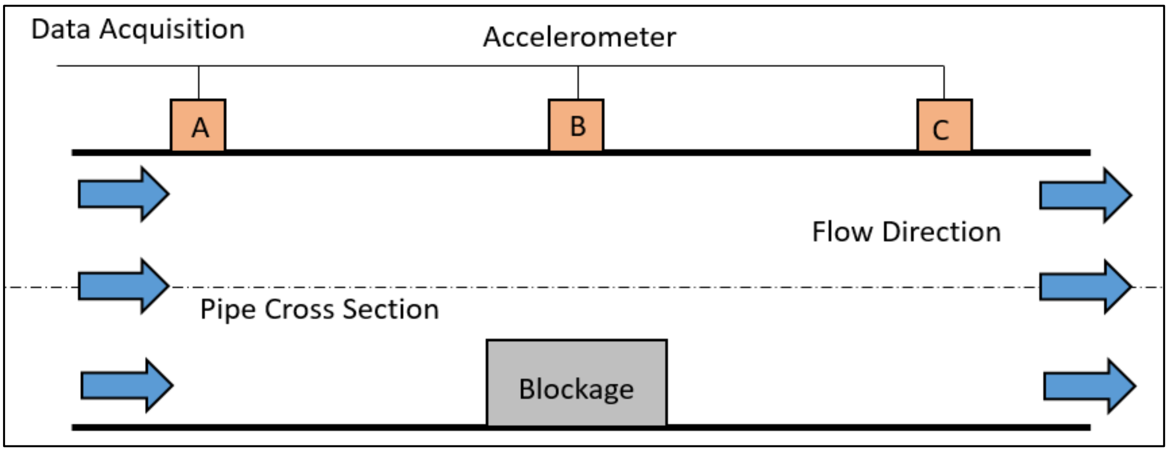

Figure 12. Schematic of vibration analysis [77]

These sensors measure the vibration acceleration generated by the interaction between the flowing fluid and the pipe structure. The recorded vibration signals are subsequently transmitted to the data acquisition system for further processing and analysis. The material was installed in the center of the pipe to simulate blockage at 4 points with different thicknesses, namely 5 mm, 10 mm, 15 mm, and 20 mm. The arrows in the figure indicate the direction of fluid flow within the pipeline, while the central part of the figure illustrates the pipe cross-section, highlighting the presence of a blockage inside the pipe. Such blockages may consist of wax deposits, asphaltene accumulation, or solid particles that adhere to the pipe walls and consequently reduce the effective flow cross-sectional area.

The presence of a blockage alters the flow characteristics, including increased turbulence, pressure fluctuations, and changes in the vibration behavior of the pipe structure. These changes can be detected by the accelerometer sensors as variations in the measured vibration signals at each monitoring location. By comparing the vibration signals recorded by sensors A, B, and C, the location of the blockage can be identified based on differences in signal amplitude and frequency characteristics observed along the pipeline.

The results of research conducted by Ding et al. in 2025 [76] concluded that fluid flow passing through a cross-section that has decreased due to a blockage will cause the fluid velocity to increase, pressure to decrease, and vibrations through it to be greater.

The experimental results indicate that the vibration signals detected by the accelerometer are influenced by the size of the blockage and the placement of the accelerometer. The detected signals are characterized by their signal patterns, frequency, and vibration amplitude. Observations were conducted based on the patterns and parameters of the vibration signals in m/s^2 units using the Fast Fourier Transform (FFT) and Root Mean Square (RMS) tools [13]

This vibration analysis method is less effective for pipeline networks that are long, have large diameters, and contain multiple branches. Further research is required to investigate the vibration characteristics of fluid flow involving crude oil, wax, paraffin, and asphaltene deposition media.

Frequency Response Numerical Method

The numerical frequency response method is a development of the fluid transient method, which is used to find blockage points non-invasively or non-destructively [74].

This method is a modification of the fluid transient method, which utilizes transient wave changes to describe the internal conditions of the pipe (Figure 13). The schematic illustrates a pipeline system used to analyze the effect of blockages on fluid flow behavior. The pipeline connects two reservoirs located at positions *(n_1)* and *(n_6)*, which represent the upstream and downstream boundary conditions of the system. The pipeline is divided into two main sections: Section A *((n_1)–(n_2))*, representing the upstream flow region under normal conditions, and Section B *((n_3)–(n_4))*, representing the downstream region influenced by flow disturbances. The process initially begins by sending a transient amplitude into the pipe and then measuring the pressure variations for analysis [31].

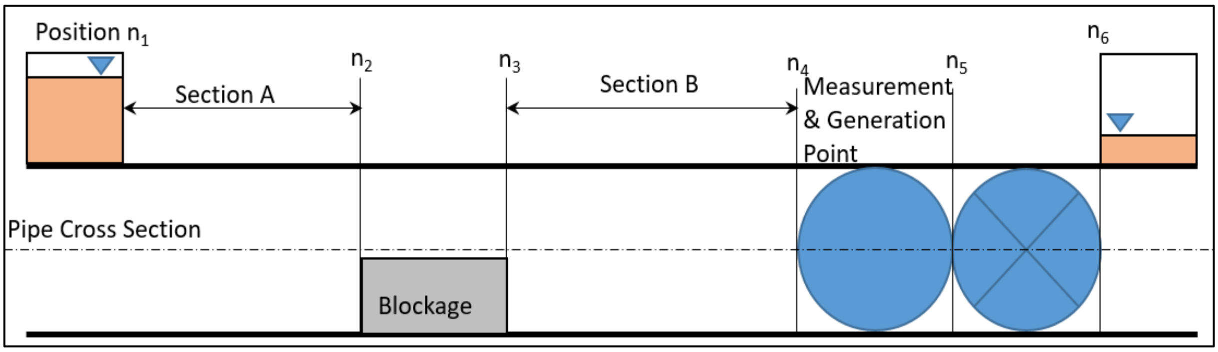

Figure 13. Frequency Response Method Diagram [73]

The location of the dimensionless blockage, x_b^*, can be defined as follows:

$$x_b^* = \frac{L_A}{L_A + L_B} \tag{4}$$

To determine the size of the block, it can be expressed in dimensionless form as follows:

$$I_B^* = \frac{I_B}{B} \tag{5}$$

Where L_A denoted the Length of pipe section A (meters), and L_B the Length of pipe section B (meters) and I_B^* the size of the block.

To obtain predictions at arbitrary locations, a transfer matrix formulation is employed under the assumption of linear conditions in an unsteady pipe system. The matrices are multiplied sequentially according to their locations, starting from the downstream end, to generate a transfer matrix representing the entire pipeline system. This matrix is then combined with known boundary conditions, such as discharge and head disturbances.

Research using the frequency response diagram (FRD) method carried out by Zhang et al in 2024 [39] produced an oscillation pattern at the top of the FRD, which, using analytical expressions from the derivative of the unsteady flow equation and the Fourier transform with frequency, phase and amplitude parameters, can be concluded to be able to detect the location of the blockage but there are slight differences regarding the size of the obstruction. This method assumes that blockages occur uniformly with parallel holes when, in fact, blockages occur randomly, and their physical properties are distorted with non-uniform geometry distributed along the pipe. For two blockage points, this method only detects one blockage location, and for blockages near the system boundary, the frequency is close to zero.

Based on these findings, further research can be undertaken to develop frequency-domain analysis methods for detecting large blockage locations and blockages occurring near system boundaries.

Temperature Analysis Method

This research model utilizes changes in temperature where one of the factors causing blockages in crude oil pipes is the loss of temperature, which causes asphalt, wax, and paraffin to increase in viscosity and stick to the pipe walls, which will gradually form deposits as insulating material in the pipe [8]

This research method uses the energy transfer equation, which states that heat moves from high temperature to low temperature [13].

Research conducted by Kiyingi et al. in 2025 [78] carried out manual temperature measurements on the pipe walls in each pipe zone (Figure 14). The figure illustrates a cylindrical obstruction located inside a pipeline and its influence on the surrounding flow field using cylindrical coordinates *((r,z))*. The axial direction *(z)* represents the flow direction along the pipe, while *(r)* denotes the radial direction from the pipe centerline. The obstruction has a length of ΔL and is positioned within a pipe segment of total length *(L)*. The presence of this obstruction alters the local flow characteristics and generates disturbances in the stress or flux components within the pipe. The terms $\Phi zz/_z$ represent the axial flux component along the *(z)-direction*, evaluated at *(z=L)* and $(z = L + \Delta L)$, while (Φrz) denotes the radial–axial interaction component occurring near the pipe wall. Then, based on the point where the temperature was lowest, they recalculated the heat transfer from the pipe walls to the fluid flowing inside, taking data collection time when the environmental temperature was highest.

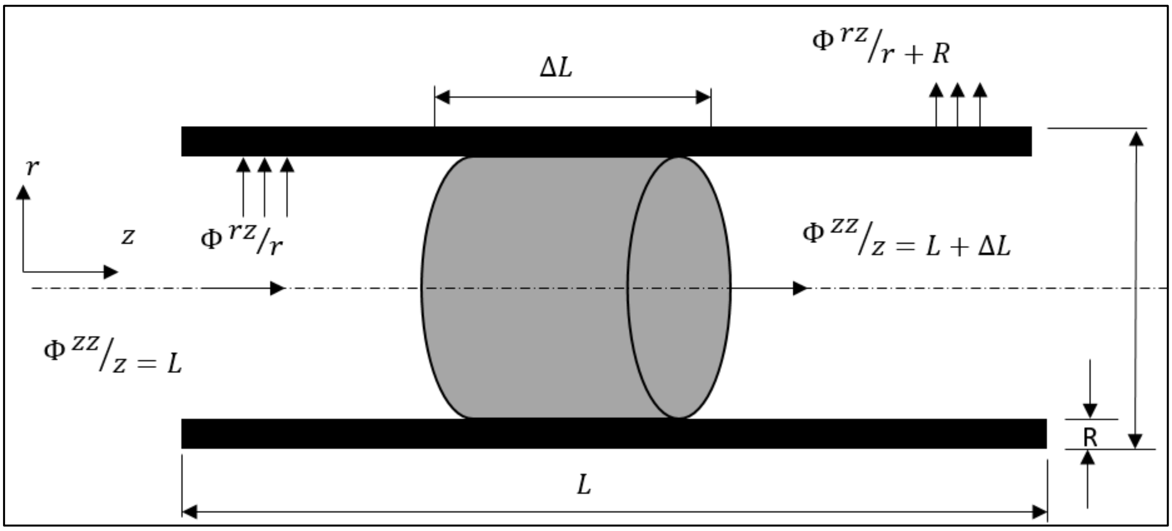

Figure 14. Temperature Transfer Model Diagram [78]

This research concludes that temperature can be used as a parameter that influences the formation of blockages. This method cannot be used on pipes that are below ground level or pipes for which temperature data cannot be taken and is not effective for pipes with long stretches and large diameters.

Computational Fluid Dynamics (CFD) Method

This approach for identifying blockage locations in piping systems employs computational fluid dynamics (CFD) simulations under steady-flow conditions to assess the effects of blockage diameter, length, and location, with pressure drop and blockage characteristics serving as the primary parameters.

One of the tools used for this simulation method is the ANSYS Workbench Design Modeler and Mesh Module to create progressive mesh pyramid cell geometries and 350,000-440,000 mesh meshes with orthogonal grid quality [63].

Figure 15 is a basic schematic diagram that will be used to draw the geometry and mesh where, based on the CFD simulation results, it can be seen that the pipe flow rate is the same as a function of the square root of the pressure drop where when the fluid pressure increases there will be a decrease in pressure at the point where the block occurs so that more fluid is compressed in the pipe due to the cessation of flow. In contrast, the flow rate will decrease in proportion to the reduction in the flow area, or other words, the flow rate will be lower compared to the increase in the block size, where the length of insulation on the pipe also affects the pressure drop along the center line [43].

The CFD simulation results were validated with a laboratory-scale experimental model. The pressure drop deviation was obtained, and the laboratory experimental model was greater than the CFD simulation by 2% -22%. This is because the ideal blockage shape and pipe diameter in the CFD are slightly different from the actual blockage shape. In connection with these deviations, this CFD method can still be developed in further research so that deviations can be avoided.

Another drawback is that the best computer specifications are needed to carry out meshing and iteration on long, large-diameter industrial-scale pipe networks. Therefore, it is necessary to find the right method so that meshing and iteration can still be carried out with moderate computer specifications.

Comparison of Current Methods, State of the Art, Knowledge Gaps and Development Possibilities

The aforementioned research provides a fundamental foundation that integrates approaches from physics, chemistry, and mathematical modeling. These methodologies have been further developed and combined by contemporary researchers to achieve more accurate and reliable results, particularly when addressing complex pipelines, multiphase fluid flow, and other unresolved limitation. The performance of each study should be evaluated using quantitative parameters that measure its accuracy and effectiveness such as the percentage accuracy in identifying blockage locations, the number, extent, and thickness of blockages, and the degree of complexity of pipe branching. Such evaluation is essential to ensure that the developed models and methods can be effectively implemented in future industrial applications.

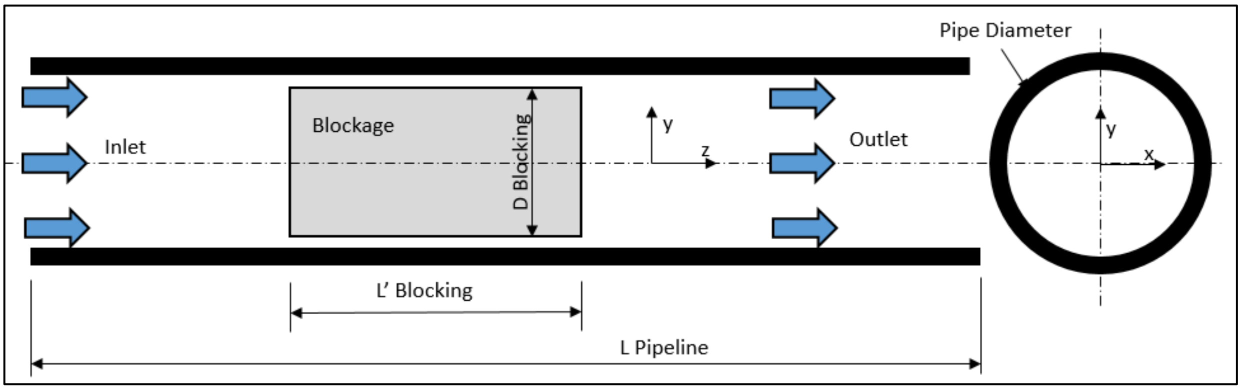

Figure 15. Computational Fluid Dynamic method diagram for blockage points [63]

Transient pressure-based detection methods represent a recent advance in research, utilizing acoustic or pressure waves generated and reflected at points of discontinuity, such as blockages, valves, and joints. The location and intensity of these discontinuities can be determined by analyzing the time-of-flight and amplitude ratio of the reflected signals. This approach is based on classical mathematical models, including linear acoustic theory and water hammer theory for low-compressibility flows, the one-dimensional wave equation, and the speed of sound equation used to estimate density and bulk modulus. Furthermore, the impedance mismatch principle is used to quantify wave reflections, while the Method of Characteristics (MOC) is applied to solve the nonlinear conservation equations governing mass and momentum under transient flow conditions.

Recent research on transient pressure methods increasingly employs numerical and computational approaches, such as finite-difference, finite-volume, and Method of Characteristics (MOC) schemes, to address time-domain analyses. High-order and shock-capturing schemes are also utilized to handle nonlinear effects associated with strong transients. Furthermore, combined two-dimensional and three-dimensional Computational Fluid Dynamics (2D/3D CFD) simulations are applied to model flow separation around deposits, while one-dimensional transient models are used for long-domain or multi-scale coupling analyses. To acquire real-time data, inverse problems are solved using probabilistic Bayesian approaches in conjunction with various sensor types including discrete pressure sensors, acoustic sensors, degradation sensors, and temperature sensors. Additionally, hybrid physics-based wave propagation models integrated with data-driven techniques and optimized sensor network configurations enable accurate monitoring of operational variations in multiphase flow systems.

Current research on transient pressure methods still exhibits several gaps and limitations. Most existing studies rely on the assumption of linear wave propagation and homogeneous single-phase fluids, indicating the need for further development to extend applicability to crude oil, which exhibits nonlinear behavior (viscoelasticity and strong attenuation), multiphase characteristics, and temperature dependence. Noise-handling algorithms such as those addressing ambient noise, pump-induced transients, and overlapping multiple reflections are typically derived from laboratory simulations, which often fail to accurately represent real field conditions. As a result, uncertainties in wave velocity can significantly affect the calculation of arrival times, while the sensors employed are frequently modeled under idealized conditions without optimization regarding their number or placement. Another major limitation of current research lies in the lack of reflection modeling in multiphase flows and complex geometries, including gas pockets, emulsions, fittings, bends, diameter variations, and branching. Furthermore, quantitative validation data for both field and experimental applications remain limited, and uncertainty analyses are rarely reported, despite the use of computationally intensive and costly optimization models.

To address the aforementioned limitations, several recommendations are proposed to enhance the modeling framework. These include incorporating frequency-dependent attenuation, wall viscoelasticity, and multiphase effects into one-dimensional (1D) wave modeling, as well as introducing an empirical attenuation dispersion model. Numerical computations can be further improved by integrating the Method of Characteristics (MOC) with finite-volume schemes, following sensitivity calibration against sound velocity parameters at various fluid densities and boundary reflection coefficients. Data quality and model validation can be strengthened by conducting experiments under multiple operating scenarios and disturbances such as synthetic noise and by recording statistical data to quantify localization errors, which can subsequently serve as parameters in Computational Fluid Dynamics (CFD) simulations. Sensor placement should be optimized through sensor placement optimization techniques (e.g., maximizing Fisher Information) to ensure proper spatial identification. Furthermore, the use of hybrid solutions that combine physics-based forward models with data-driven approaches is recommended, alongside the adoption of evaluation metrics such as Mean Absolute Error (MAE, in meters), Root Mean Square Error (RMSE), median error, and the percentage of predictions within a specified tolerance range (e.g., ±5 m).

Another method that has recently attracted significant research interest is Gamma-Ray Transmission (GRT), a non-invasive technique used to measure the intensity of gamma radiation penetrating fluids or products within pipelines. By analyzing the reduction in radiation intensity, this method is particularly effective for detecting local density variations caused by deposit formation. The technique is based on the Beer–Lambert attenuation principle, in which the measured attenuation depends on gamma-ray energy, material composition, path length, and geometric configuration. Measurement accuracy can be enhanced through various configurations, including single-beam transmission for simple profiles and multi-angle detector arrays for cross-sectional assessments. Additionally, the use of external gamma densitometers combined with Monte Carlo simulations has been shown to improve both spatial resolution and deposit quantification accuracy.

The application of Gamma-Ray Transmission (GRT) techniques in crude oil pipeline systems still faces several technical constraints. One major limitation is the sensitivity to thin deposits, which is constrained by the trade-off between spatial resolution and permissible radiation dose. Variations in material composition such as the presence of water, oil, wax, or sand can introduce bias if the attenuation coefficients are not properly calibrated. Moreover, many existing studies remain confined to laboratory environments or rely solely on Monte Carlo simulations, lacking long-term field validation. Operational safety concerns and regulatory considerations associated with the use of radioactive sources are also seldom quantified or systematically evaluated. To advance this technique toward industrial implementation, further research is required that integrates multi-energy or multi-angle data acquisition, probabilistic or uncertainty quantification (UQ)-based inversion methods, sensor fusion strategies, and extensive field validation campaigns.

Recent studies employing Computational Fluid Dynamics (CFD) for blockage simulations have integrated flow analysis, heat transfer, and precipitation mechanisms to predict the formation and evolution of deposits. These approaches typically involve the use of Reynolds-Averaged Navier–Stokes (RANS) simulations to characterize macroscopic flow behavior, Volume of Fluid (VOF) or Eulerian methods to capture multiphase interactions, and simplified kinetic models to represent wax or asphaltene precipitation. High-fidelity models, such as Large Eddy Simulation (LES), are capable of resolving local flow fluctuations that influence particle transport and detachment processes. However, due to the significant computational cost associated with these models, researchers often rely on simplified representations for simulations over full pipe-length domains. To address this limitation, data-driven approaches and reduced-order modeling techniques have been increasingly adopted to optimize CFD analyses, reducing computational expenses while preserving predictive accuracy.

Although CFD-based numerical studies have advanced considerably, several research gaps remain that hinder their effective application to industrial-scale pipeline blockage conditions. Quantitative experimental validation of deposit rates and profiles remains limited, and precipitation kinetics as well as rheological parameters are often adopted directly from the literature without calibration for specific crude oils. Furthermore, the complex interactions among multiphase flow behavior, emulsions, and chemical reactions have not yet been comprehensively modeled. Computational scalability also constrains the ability to perform continuous simulations over realistic pipeline domains. Therefore, to enhance predictive accuracy and facilitate industrial adoption, future research should focus on experimental calibration, uncertainty quantification (UQ), the development of mechanistic erosion–adhesion models, and the implementation of surrogate modeling techniques for operational applications.

Machine learning approaches based on pressure transients have emerged as a highly active area of research, as they integrate advanced signal processing techniques with data acquired from multiple sensors. Recent developments in this field have combined traditional signal processing methods with modern machine learning algorithms to enhance detection accuracy and efficiency. Feature-based approaches typically utilize time-domain, frequency-domain, and wavelet-derived features, which are then applied to supervised learning models such as Random Forest, Support Vector Machines (SVM), and XGBoost for classification and detection tasks. The adoption of deep learning architectures such as one-dimensional Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM) networks, and hybrid CNN–LSTM models has further enabled end-to-end processing of raw transient pressure signals, allowing real-time blockage detection and localization. Although high performance has been achieved in controlled laboratory settings, existing studies still encounter difficulties in generalizing to field conditions due to domain shifts, imbalanced blockage cases, and variations in sensor configurations. Moreover, critical operational aspects, including uncertainty quantification, model interpretability for engineering practitioners, and inference latency in real-time applications, remain underexplored in the existing literature.

Although machine learning methods have demonstrated substantial progress in the rapid detection and localization of blockages, several limitations persist. Most existing studies have been validated only on limited simulation or laboratory datasets and have not been extensively tested under noisy and heterogeneous field conditions. Issues such as class imbalance and the rarity of blockage events are frequently overlooked, leading to an increased risk of false negatives and false positives. Furthermore, the absence of uncertainty quantification and model explainability constrains industrial adoption, as technical personnel require both confidence levels and interpretable reasoning to support informed operational decision-making. Research assessing the influence of sensor network design and sensor placement optimization on localization accuracy also remains scarce. To mitigate these constraints, future studies should integrate multi-source data, simulation-to-reality (sim-to-real) transfer techniques, uncertainty quantification (UQ), and experimental design strategies for optimal sensor deployment.

One of the most recent yet relatively limited areas of research involves the application of Cascade Forward Neural Networks (CFNN) and Generalized Regression Neural Networks (GRNN). Conventional studies on wax deposition prediction and modeling have primarily relied on physics-based thermodynamic and data-driven approaches. In such physical models, paraffin precipitation is typically predicted through calculations of solid–liquid equilibrium and compositional distribution; however, these methods often depend on parameters that are difficult to measure and costly to obtain. To address these existing limitations, neural network–based approaches such as Multilayer Perceptrons (MLP), Radial Basis Function (RBF) networks, and their variants, including GRNN and CFNN, have been adopted. These methods offer the advantage of capturing complex nonlinear relationships directly from experimental or field data without requiring detailed knowledge of the underlying physical mechanisms. Despite their potential, current research still exhibits several limitations, including the use of narrow datasets, insufficient validation rigor, limited benchmarking against established baselines, and a lack of uncertainty analysis and model interpretability.

Currently, Cascade Forward Neural Network (CFNN) and Generalized Regression Neural Network (GRNN) methods are widely applied for nonlinear regression using laboratory-scale datasets. However, several limitations and critical research gaps remain. Reported accuracy metrics are often based on limited datasets, and consequently, the generalizability of these models to real field conditions has not been adequately demonstrated. Moreover, the lack of comparative studies with other state-of-the-art algorithms such as XGBoost or Gaussian Process Regression—renders claims of superior performance less convincing. Sensitivity analyses and uncertainty quantification are also rarely performed, despite their importance for operational decision-making (e.g., pigging schedule optimization). In addition, limited reproducibility due to unavailable code and data constrains independent verification and benchmarking by other researchers. To address these issues, future work should emphasize rigorous validation protocols, interpretability assessment, uncertainty quantification, and field-scale demonstrations. Integrating physics-based models for feature derivation with robust machine learning frameworks, alongside enforcing transparency and reproducibility practices, will accelerate progress and enhance the reliability of CFNN- and GRNN-based predictive modeling.

The results of current research models can be systematically compared to guide future researchers in identifying promising directions for further investigation. Based on the comparison of the basic methods in Table 2, the comparative analysis can contribute to the development and improvement of sustainable blockage detection methodologies in crude oil pipelines (Table 6).

.

Table 6. Current state of the art, knowledge gaps, possible developments & proposed novelties

No	Methods	State of the Art	Knowledge Gaps	Development Possibilities
1	Pressure wave reflection analysis, mathematical numerical calculations [29, 55, 65, 13, 28, 29, 31, 80, 81, 82, 83, 84, 85, 86, 32]	The latest research model of 1-D wave propagation uses acoustic equations, Characteristic Method (finite-volume numerical scheme) for transient amplitude, time-of-flight and reflection analysis combined with CFD.	The assumptions of linearity and homogeneous fluid are not valid for multiphase crude oil; the effects of dispersion and frequency-dependent attenuation tend to be neglected, leading to estimation bias.	Future research should use damping/dispersion models and inversion methods that quantify uncertainty, optimizing sensor placement to evaluate performance under real operational conditions.
2	Gamma ray transmission techniques for crude oil pipelines [41, 42, 87]	Recent research utilizes the Beer-Lambert attenuation principle, single to multi-angle source–detector configurations, combining Monte Carlo and light tomography techniques to improve the resolution of deposits.	Less sensitive to thin deposits depending on radiation dose, biased results due to variations in material composition (water/oil/wax/sand), still limited to laboratory settings (Monte Carlo simulation) without field validation, does not discuss regulations related to radioactive sources (transport, storage, safety).	Future studies need to combine multi-energy or multi-angle acquisition, probabilistic-based inversion (UQ), sensor fusion, and field validation campaigns.
3	Computational fluid dynamic. [38, 39, 40, 64, 73, 74, 44, 47, 90]	Recent research integrates CFD with data-driven & reduced order modeling methods to lower computational costs while maintaining predictability.	Lack of validation data, parameters using literature data without calibration, the complexity of multiphase flows has not been modeled, and there are limitations in computational scale.	Further research should conduct experimental calibration, UQ, mechanistic erosion-adhesion models, and the development of surrogate models.
4	Machine learning approach using pressure transients [27, 44, 46, 47, 75, 76, 77]	Recent research combines traditional signal processing techniques with modern machine learning methods with feature-based approaches.	Research evaluating the impact of sensor network design and sensor location optimization on localization accuracy is very limited.	Future research needs to combine multi-source data, sim-to-real techniques, UQ, and experimental design for sensor placement.
5	Cascade forward neural networks and generalized regression [49, 92, 93, 94, 95, 96]	Recent research models complex non-linear relationships from experimental/field data without detailed knowledge of the physical mechanisms.	Limited datasets result in less accuracy for field application and have not yet been proven.	Future research should conduct more rigorous validation, interpretability analysis, UQ, and demonstration on field data.

Each blockage detection method offers distinct advantages and unique opportunities for further refinement and development. Consequently, considerations of cost and time efficiency should remain central in determining the suitability and scalability of each approach for industrial applications. Moving forward, it is imperative for future researchers to adopt a more integrative and interdisciplinary perspective combining physics-based modeling, computational intelligence, and experimental validation to overcome current limitations and enhance predictive reliability. By advancing research in this direction, the longstanding phenomenon of crude oil pipeline blockages can be addressed more effectively, thereby fostering innovation that enhances industrial operations, improves economic efficiency, and promotes environmental sustainability.

A novel approach is proposed to integrate PWR method with a numerical model based on 1D and 2D fluid acoustic transient wave equations. This model measures the travel time of reflected waves and the characteristics of pressure transients, followed by numerical verification using finite volume or finite difference methods to simulate pressure wave propagation. Notably, most existing studies on the PWR method have relied primarily on direct signal analysis without incorporating mathematical to validate the pressure phenomena. The integration numerical modeling represents a significant advancement toward more comprehensive blockage detection.

Building upon this concept of combining experimental and computational techniques, a similar innovation is proposed for the gamma-ray transmission method. Traditionally, research on this method has been largely experimental; however, the present approach employs numerical simulations using Monte Carlo and finite element radiation transport techniques. Through this integration, the method can generate baseline datasets for real-time simulations of various blockage levels. These simulations, when combined with N_{al}(Tl) or HPGe detectors and machine learning–based pattern recognition, provide a foundation for developing a more robust and adaptive blockage detection framework.

Extending the application of numerical modeling to fluid dynamics, another novel framework is introduced to address limitations in current CFD studies, which predominantly assume Newtonian fluids such as water. In contrast, the proposed CFD model focuses on predicting non-Newtonian flow behavior of crude oil under blockage conditions. This three-dimensional transient numerical model incorporates key physical aspects, including fluid rheology (shear thinning), temperature effects, and viscosity variations described by the Power-Law or Herschel–Bulkley models. The ultimate objective of this approach is to develop a real-time predictive tool that can be integrated into early-warning systems of pipeline monitoring.

To complement these physics-based approaches, an intelligent data-driven strategy is also proposed through the integration of machine learning (ML) with pressure transient analysis. Unlike prior studies that typically rely on steady state data (mean pressure), the proposed deep learning approach leverages transient features such as pressure decay rate, peak reflection amplitude, and time lag to directly learn from waveform patterns without manual feature extraction. This integration not only accelerates the diagnostic process but also improves detection accuracy. By employing a multi-class classification scheme, the system is expected to identify the type of deposit material and quantify the extent of blockage based on pressure signals, thereby enabling multi-level detection, comprehensive risk assessment, and more accurate maintenance planning.

Together, these interconnected approaches spanning physical modeling, numerical simulation, and intelligent data analysis highlight a cohesive research direction aimed at developing an integrated and adaptive pipeline blockage detection system. Such synergy between traditional methods and modern computational intelligence offers promising potential for advancing the state of the art in pipeline monitoring and maintenance.

CONCLUSION

This study presents a systematic review combined with bibliometric analysis to elucidate the knowledge structure and research trends in crude oil pipeline blockage detection caused by wax and asphaltene deposition. The findings reveal a clear evolution of the field from conventional experimental and physics-based approaches toward data-driven and intelligent detection systems. Bibliometric mapping identifies three dominant and increasingly interconnected domains sensor based monitoring, mechanistic modeling, and machine learning indicating a progressive shift toward methodological convergence. The analysis demonstrates that existing approaches ranging from experimental techniques to numerical modeling and machine learning offer complementary strengths but remain individually insufficient to achieve consistent accuracy and reliability under diverse operational conditions. Experimental methods such as pressure wave and gamma-ray techniques provide relatively low measurement errors (~5%), yet are highly sensitive to blockage geometry and sensor configuration. Physics-based models, particularly CFD, effectively capture flow dynamics but lack precision in blockage localization and quantification. In contrast, data-driven approaches, including machine learning and neural networks, exhibit superior predictive performance (up to ~90% accuracy), although their robustness is constrained by data dependency and limited generalizability. A key scientific insight emerging from this work is that pipeline blockage detection constitutes a multi-physics and multi-scale problem, requiring the integration of heterogeneous data sources and modeling paradigms. Accordingly, this study establishes a generalized framework that emphasizes the synergistic integration of physical sensing, mechanistic modeling, and artificial intelligence, supported by uncertainty quantification and optimized sensor placement. This integrative approach represents the primary contribution of this work and provides a pathway toward more accurate and adaptive detection systems. From a practical perspective, the findings suggest that industry applications should move beyond single-method implementations toward hybrid detection architectures. Specifically, the integration of real-time sensor data (e.g., IoT-based flow monitoring) with predictive machine learning models and physics-based simulations can significantly enhance detection accuracy and early warning capabilities. Additionally, incorporating uncertainty quantification can improve decision-making reliability under variable field conditions. The optimization of sensor placement and the use of multi-source data fusion are also critical to reducing detection errors and improving system robustness.

ACKNOWLEDGMENT

This research received no external funding. The authors thank the Energy Conversion Laboratory, Department of Mechanical Engineering, Universitas Riau, for its valuable technical support and expertise. The views expressed are solely those of the authors.

REFERENCES

[1] Y. Yang, Z. Liu, H. B. Saydaliev, and S. Iqbal, “Economic impact of crude oil supply disruption on social welfare losses and strategic petroleum reserves,” *Resources Policy*, vol. 77, p. 102689, Aug. 2022, doi: 10.1016/j.resourpol.2022.102689.

[2] Y. Mahmood, T. Afrin, Y. Huang, and N. Yodo, “Sustainable Development for Oil and Gas Infrastructure from Risk, Reliability, and Resilience Perspectives,” *Sustainability*, vol. 15, no. 6, p. 4953, Mar. 2023, doi: 10.3390/su15064953.

[3] Awaludin Martin and Hamdani Wahab, “Energy and Thermo-Economic Analysis of Crude Oil Gathering Station and Hydrocarbon Transport,” *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, vol. 97, no. 2, pp. 146–156, Aug. 2022, doi: 10.37934/arfmts.97.2.146156.

[4] P. I. Murungi and A. A. Sulaimon, “Petroleum sludge treatment and disposal techniques: a review,” *Environmental Science and Pollution Research*, vol. 29, no. 27, pp. 40358–40372, Jun. 2022, doi: 10.1007/s11356-022-19614-z.

[5] V. H. Cauduro, K. O. Alessio, A. O. Gomes, E. M. M. Flores, E. I. Muller, and F. A. Duarte, “A simple, fast and green method for API gravity, density, sulfur and nitrogen determination in crude oil by ATR-FTIR,” *Microchemical Journal*, vol. 200, p. 110348, May 2024, doi: 10.1016/j.microc.2024.110348.

[6] M. Shao *et al.*, “A review and perspective on viscosity reduction development technologies for heavy oil,” *Petroleum Science and Technology*, pp. 1–17, doi: 10.1080/10916466.2025.2465835.

[7] S. Rushd, H. Ferroudji, H. Yousuf, T. W. Walker, A. Basu, and T. K. Sen, “Applications of drag reducers for the pipeline transportation of heavy crude oils: A critical review and future research directions,” *The Canadian Journal of Chemical Engineering*, vol. 102, no. 1, pp. 438–458, Jan. 2024, doi: 10.1002/cjce.25023.

[8] M. Lam-Maldonado, Y. G. Aranda-Jiménez, E. Arvizu-Sanchez, J. A. Melo-Banda, N. P. Díaz-Zavala, J. F. Pérez-Sánchez, E. J. Suarez-Dominguez, “Extra heavy crude oil viscosity and surface tension behavior using a flow enhancer and water at different temperatures conditions,” *Heliyon*, vol. 9, no. 2, p. e12120, Feb. 2023, doi: 10.1016/j.heliyon.2022.e12120.

[9] E. Colleoni, V. G. Samaras, C. Canciani, P. Guida, A. Frassoldati, T. Faravelli, W. L. Roberts, “On the relation between solubility, chemical structure and pyrolysis of complex hydrocarbon mixtures: Experimental campaign and model,” *Journal of Analytical and Applied Pyrolysis*, vol. 186, p. 106959, Mar. 2025, doi: 10.1016/j.jaap.2025.106959.

[10] K. Z. Alzarieni, Y. Zhang, E. Niyonsaba, K. E. Wehde, C. T. Johnston, G. Kilaz, H. I. Kenttämaa, “Determination of the Chemical Compositions of Condensate-like Oils with Different API Gravities by Using the Distillation, Precipitation, Fractionation Mass Spectrometry (DPF MS) Method,” *Energy Fuels*, vol. 35, no. 10, pp. 8646–8656, May 2021, doi: 10.1021/acs.energyfuels.0c04286.

[11] E. H. de Paulo *et al.*, “Variable Selection Methods Applied In Htgc Data To Determine Physicochemical Properties Of Crude Oils,” *Revista Ifes Ciência*, 2024, [Online]. Available: https://api.semanticscholar.org/CorpusID:269320663

[12] E. V. Barros, P. R. Filgueiras, V. Lacerda, R. P. Rodgers, and W. Romão, “Characterization of naphthenic acids in crude oil samples – A literature review,” *Fuel*, vol. 319, p. 123775, Jul. 2022, doi: 10.1016/j.fuel.2022.123775.

[13] A. S. Shalygin, I. V. Kozhevnikov, E. V. Morozov, and O. N. Martyanov, “Features of Wax Appearance Temperature Determination of Waxy Crude Oil Using Attenuated Total Reflection Fourier Transform Infrared Spectroscopy Under Ambient and High Pressure,” *Applied Spectroscopy*, vol. 78, no. 3, pp. 277–288, Mar. 2024, doi: 10.1177/00037028231218714.

[14] Y. Wang, Q. Wang, Y. Zhang, Q. Yue, and X. Zhang, “Optimization of subsea production facilities layout based on cluster manifold system considering seabed topography,” *Ocean Engineering*, vol. 291, p. 116575, Jan. 2024, doi: 10.1016/j.oceaneng.2023.116575.

[15] F. Souas, A. Safri, and A. Benmounah, “A review on the rheology of heavy crude oil for pipeline transportation,” *Petroleum Research*, vol. 6, no. 2, pp. 116–136, Jun. 2021, doi: 10.1016/j.ptlrs.2020.11.001.

[16] R. K. Ratnakar, S. Pandian, H. Mary, and H. Choksi, “Flow assurance methods for transporting heavy and waxy crude oils via pipelines without chemical additive intervention,” *Petroleum Research*, vol. 10, no. 1, pp. 204–215, Mar. 2025, doi: 10.1016/j.ptlrs.2024.07.005.

[17] Q. Zhuang, H. Li, Y. Bao, G. Liu, and D. Liu, “Research on the prediction model of wax deposition thickness of waxy crude oil in pipeline transportation,” *Petroleum Science and Technology*, vol. 42, no. 7, pp. 869–885, Apr. 2024, doi: 10.1080/10916466.2022.2149801.

[18] A. M. Sousa, T. P. Ribeiro, M. J. Pereira, and H. A. Matos, “Review of the Economic and Environmental Impacts of Producing Waxy Crude Oils,” *Energies*, vol. 16, no. 1, p. 120, Dec. 2022, doi: 10.3390/en16010120.

[19] A. Taylor, *Dorset’s Black Gold: A History of Dorset’s Oil Industry*. Amberley Publishing Limited, 2021.

[20] K. Poursanidis, J. Sharanik, and C. Hadjistassou, “World’s largest natural gas leak from nord stream pipeline estimated at 478,000 tonnes,” *iScience*, vol. 27, no. 1, p. 108772, Jan. 2024, doi: 10.1016/j.isci.2023.108772.

[21] Directorate General of Oil and Gas, Oil and Gas Safety Atlas Vol. 4: Towards Net Zero Emissions while Maintaining Oil and Gas Safety, Special Edition., vol. Vol 4. in 1, no. Ministry of Energy and Mineral Resources, vol. Vol 4. Jakarta: Directorate of Oil and Gas Engineering and Environment, 2022. [Online]. Available: www.migas.esdm.go.id.

[22] A. Vatandoost, B. Tohidi, M. Hoopanah, M. K. Meybodi, H. Mozaffar, and E. Joonaki, “Challenges in Accurate Detection of the Main Cause of Blockage: Case Studies,” presented at the Abu Dhabi International Petroleum Exhibition and Conference, Nov. 2024, p. D021S045R005. doi: 10.2118/222132-MS.

[23] P. A. Hasnizam, I. Taib, S. N. K. Fadillah, Z. H. Zainol, A. M. T. Ariffin, and R. Abdurrahman, “Investigate How the Height Difference Affects the Flow Rate by Use Siphon System,” vol. 4, no. 1, 2025, doi: 10.37934/sjotfe.4.1.2534.

[24] M. R. Elkatory *et al.*, “Mitigation and Remediation Technologies of Waxy Crude Oils’ Deposition within Transportation Pipelines: A Review,” *Polymers*, vol. 14, no. 16, p. 3231, Aug. 2022, doi: 10.3390/polym14163231.

[25] Z. Huang *et al.*, “Research and application of oil pipeline leakage monitoring technology,” in *International Conference on Computer Graphics, Artificial Intelligence, and Data Processing (ICCAID 2024)*, X. Xu and A. B. Mohd Zain, Eds., Nanchang, China: SPIE, Apr. 2025, p. 82. doi: 10.1117/12.3061416.

[26] Q. Zhuang, H. Li, Y. Bao, G. Liu, and D. Liu, “Research on the prediction model of wax deposition thickness of waxy crude oil in pipeline transportation,” *Petroleum Science and Technology*, vol. 42, no. 7, pp. 869–885, Apr. 2024, doi: 10.1080/10916466.2022.2149801.

[27] C. Li, Y. Zhang, W. Jia, X. Hu, S. Song, and F. Yang, "Blockage detection techniques for natural gas pipelines: A review," *Gas Science and Engineering*, vol. 122, p. 205187, Feb. 2024, doi: 10.1016/j.jgsce.2023.205187.

[28] S. Gurav, P. Kumar, G. Ramshankar, P. K. Mohapatra, and B. Srinivasan, "Machine Learning Approach for Blockage Detection and Localization using Pressure Transients," in *2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON)*, Greater Noida, India: IEEE, Oct. 2020, pp. 189–193. doi: 10.1109/GUCON48875.2020.9231242.

[29] J. Chu *et al.*, "Experimental Platform For Blockage Detection And Investigation Using Propagation Of Pressure Pulse Waves In A Pipeline," *Measurement*, vol. 160, p. 107877, Aug. 2020, doi: 10.1016/j.measurement.2020.107877.

[30] K. Yan, D. Xu, Q. Wang, J. Chu, S. Zhu, and J. Zhao, "Experimental Investigation of Gas Transmission Pipeline Blockage Detection Based on Dynamic Pressure Method," *Energies*, vol. 16, no. 15, p. 5620, Jul. 2023, doi: 10.3390/en16155620.

[31] J. Liu, H. Tang, and S. Li, "Reduced order model based on sound pressure frequency response function for modal parameter estimation," *Ships and Offshore Structures*, pp. 1–10, Apr. 2025, doi: 10.1080/17445302.2025.2486202.

[32] B. Yang, D. Tang, W. Yuan, X. Zhao, and L. Fu, "Experimental study on pressure drop and ice blockage characteristics of ice slurry flow in big-diameter pipes," *International Journal of Refrigeration*, vol. 169, pp. 214–225, Jan. 2025, doi: 10.1016/j.ijrefrig.2024.10.016.

[33] H. Liang *et al.*, "Experimental research on the reflection and response characteristics of pressure pulse waves for different gas pipeline blockage materials," *Energy Science & Engineering*, vol. 12, no. 6, pp. 2505–2518, Jun. 2024, doi: 10.1002/ese3.1759.

[34] H. Liang *et al.*, "Experimental research on the reflection and response characteristics of pressure pulse waves for different gas pipeline blockage materials," *Energy Sci. Eng.*, vol. 12, no. 6, pp. 2505–2518, 2024, doi: 10.1002/ese3.1759.

[35] D.-G. Lee, J.-S. Lim, Y.-J. Kim, N.-S. Woo, S.-M. Han, and J. Ha, "Monitoring and Detection of Paraffin Wax Deposition Process Based on Ultrasonic Analysis," *Journal of Nanoscience and Nanotechnology*, vol. 20, no. 1, pp. 168–176, Jan. 2020, doi: 10.1166/jnn.2020.17282.

[36] A. Akbari, Y. Kazemzadeh, D. A. Martyushev, and F. Cortes, "Using ultrasonic and microwave to prevent and reduce wax deposition in oil production," *Petroleum*, vol. 10, no. 4, pp. 584–593, Dec. 2024, doi: 10.1016/j.petlm.2024.09.002.

[37] F. You and B. Chen, "Research on Rapid Detection Method of Pipe Blockage Based on The Transient Flow Method," *International Journal of Fluid Machinery and Systems*, vol. 16, no. 4, pp. 308–319, Dec. 2023, doi: 10.5293/IJFMS.2023.16.4.308.

[38] Y. Fu and B. Chen, "Locating Blockage and Leak in Piping Systems Based on Valve Stroking," *Journal of Pipeline Systems Engineering and Practice*, vol. 15, no. 1, p. 04023049, Feb. 2024, doi: 10.1061/JPSEA2.PSENG-1519.

[39] C. Zhang *et al.*, "Feasibility of using the frequency-domain electromagnetic method to detect pipeline blockages: Experimental study," *Geophysics*, vol. 89, no. 4, pp. E141–E150, May 2024, doi: 10.1190/geo2022-0668.1.

[40] S. R. Tatiparthi *et al.*, "Real-Time detection of sewer water levels and blockages using UHF-RFID sensors," *Water Research*, vol. 278, p. 123380, Jun. 2025, doi: 10.1016/j.watres.2025.123380.

[41] Z. Chen *et al.*, "Oil Scale Profile Detection in Oil Pipeline Based on Improved Gamma-Ray Scanning Transmission Method," *Nuclear Science and Engineering*, vol. 196, no. 10, pp. 1255–1265, Oct. 2022, doi: 10.1080/00295639.2022.2072660.

[42] M. Askari, A. Taheri, M. Mojtahedzadeh Larijani, A. Movafeghi, and H. Faripour, "A gamma-ray tomography system to determine wax deposition distribution in oil pipelines," *Review of Scientific Instruments*, vol. 90, no. 7, p. 075103, Jul. 2019, doi: 10.1063/1.5095859.

[43] N. M. C. Martins, D. I. C. Covas, S. Meniconi, C. Capponi, and B. Brunone, "Hydrodynamics of laminar pipe flow through an extended partial blockage by CFD," *Journal of Hydroinformatics*, vol. 25, no. 6, pp. 2268–2280, Nov. 2023, doi: 10.2166/hydro.2023.042.

[44] M. Colombo and M. Fairweather, "Prediction of bubbly flow and flow regime development in a horizontal air-water pipe flow with a morphology-adaptive multifluid CFD model," *International Journal of Multiphase Flow*, vol.

184, p. 105112, Mar. 2025, doi: 10.1016/j.ijmultiphaseflow.2024.105112.

[45] J. Wang *et al.*, “A CFD Study of the Unsteady Leakage and Dispersion of Natural Gas Pipelines Containing High-H2S in Mountainous Terrain,” *Process Safety and Environmental Protection*, p. 106981, Mar. 2025, doi: 10.1016/j.psep.2025.106981.

[46] X. Zhou, D. Li, D. Yi, Y. Geng, and X. Li, “Research on liquid pipeline blockage based on quasi-distributed FBG,” in *Fourth International Computational Imaging Conference (CITA 2024)*, X. Shao, Ed., Xiamen, China: SPIE, Feb. 2025, p. 36. doi: 10.1117/12.3055462.

[47] X. Zhou, D. Li, D. Yi, Y. Geng, and X. Li, “Research on liquid pipeline blockage based on quasi-distributed FBG,” in *Fourth International Computational Imaging Conference (CITA 2024)*, X. Shao, Ed., Xiamen, China: SPIE, Feb. 2025, p. 36. doi: 10.1117/12.3055462.

[48] N. Acevedo, S. Radji, M. Saidoun, F. Tort, and J.-L. Daridon, “Chemical additive effect on asphaltenes destabilization and deposition studied using quartz crystal resonator (QCR) sensor: From atmospheric pressure titration to isothermal depressurization of non-diluted crude oil,” *Geoenergy Science and Engineering*, vol. 237, p. 212812, Jun. 2024, doi: 10.1016/j.geoen.2024.212812.

[49] H. Woldesellasse and S. Tesfamariam, “Risk assessment of gas pipeline using an integrated Bayesian belief network and GIS : Using Bayesian neural networks for external pitting corrosion modelling,” *The Canadian Journal of Chemical Engineering*, vol. 103, no. 1, pp. 98–109, Jan. 2025, doi: 10.1002/cjce.25393.

[50] U. Dao, S. Adumene, Z. Sajid, M. Yazdi, and R. Islam, “A Bayesian network-based susceptibility assessment model for oil and gas pipelines suffering under-deposit corrosion,” *Can J Chem Eng*, vol. 103, no. 1, pp. 126–136, Jan. 2025, doi: 10.1002/cjce.25234.

[51] A. M. Al-Sabaeei, H. Alhussian, S. J. Abdulkadir, and A. Jagadeesh, “Prediction of oil and gas pipeline failures through machine learning approaches: A systematic review,” *Energy Reports*, vol. 10, pp. 1313–1338, Nov. 2023, doi: 10.1016/j.egyr.2023.08.009.

[52] L. Wu, Z. Feng, G. Huang, Y. Li, and X. Zhu, “Pipeline Blockage Detection Based on Sparse Characterization Classification Enhanced by VMD,” in *2019 IEEE 8th Data Driven Control and Learning Systems Conference (DDCLS)*, May 2019, pp. 814–819. doi: 10.1109/DDCLS.2019.8909060.

[53] M. Nait Amar, A. Jahanbani Ghahfarokhi, and C. Shang Wui Ng, “Predicting wax deposition using robust machine learning techniques,” *Petroleum*, vol. 8, no. 2, pp. 167–173, Jun. 2022, doi: 10.1016/j.petlm.2021.07.005.

[54] E. B. Priyanka, S. Thangavel, X.-Z. Gao, and N. S. Sivakumar, “Digital twin for oil pipeline risk estimation using prognostic and machine learning techniques,” *Journal of Industrial Information Integration*, vol. 26, p. 100272, Mar. 2022, doi: 10.1016/j.jii.2021.100272.

[55] J. Chen *et al.*, “Application of machine learning to leakage detection of fluid pipelines in recent years: A review and prospect,” *Measurement*, vol. 248, p. 116857, May 2025, doi: 10.1016/j.measurement.2025.116857.

[56] J. Sun *et al.*, “Investigation on flow characteristics of highly viscous oil-water core-annular flow in horizontal pipes based on machine learning,” *International Journal of Multiphase Flow*, vol. 189, p. 105265, Aug. 2025, doi: 10.1016/j.ijmultiphaseflow.2025.105265.

[57] J. Kim *et al.*, “Real-time monitoring of CO2 transport pipelines using deep learning,” *Process Safety and Environmental Protection*, vol. 181, pp. 480–492, Jan. 2024, doi: 10.1016/j.psep.2023.11.024.

[58] E. B. Priyanka, S. Thangavel, P. H. Prasad, and R. Mohanasundaram, “IoT fusion based model predictive pid control approach for oil pipeline infrastructure,” *International Journal of Critical Infrastructure Protection*, vol. 35, p. 100485, Dec. 2021, doi: 10.1016/j.ijcip.2021.100485.

[59] C. Stewart, B. Ayaz, N. Fough, and R. Prabhu, “Towards the underwater internet of things for subsea oil and gas monitoring,” *Internet of Things*, vol. 30, p. 101510, Mar. 2025, doi: 10.1016/j.iot.2025.101510.

[60] N. A. Barton, S. H. Hallett, S. R. Jude, and T. H. Tran, “Predicting the risk of pipe failure using gradient boosted decision trees and weighted risk analysis,” *Npj Clean Water*, vol. 5, no. 1, p. 22, 2022, doi: 10.1038/s41545-022-00165-2.

[61] A. Aljaroudi, F. Khan, A. Akinturk, M. Haddara, and P. Thodi, “Risk assessment of offshore crude oil pipeline failure,” *Journal of Loss Prevention in the Process Industries*, vol. 37, pp. 101–109, Sep. 2015, doi: 10.1016/j.jlp.2015.07.004.

[62] B. Brunone, F. Maietta, C. Capponi, H.-F. Duan, and S. Meniconi, "Detection of Partial Blockages in Pressurized Pipes by Transient Tests: A Review of the Physical Experiments," *Fluids*, vol. 8, no. 1, p. 19, Jan. 2023, doi: 10.3390/fluids8010019.

[63] L. Yang, H. Fu, H. Liang, Y. Wang, G. Han, and K. Ling, "Detection of pipeline blockage using lab experiment and computational fluid dynamic simulation," *Journal of Petroleum Science and Engineering*, vol. 183, p. 106421, Dec. 2019, doi: 10.1016/j.petrol.2019.106421.

[64] P. Kumar and P. K. Mohapatra, "Partial Blockage Detection in Pipelines by Modified Reconstructive Method of Characteristics Technique," *Journal of Hydraulic Engineering*, vol. 148, no. 4, p. 04022003, Apr. 2022, doi: 10.1061/(ASCE)HY.1943-7900.0001971.

[65] K. Wu, Y. Feng, and Y. Xu, "Research on Method for Detecting Pipeline Blockages Based on Fluid Oscillation Theory," *Energies*, vol. 15, no. 15, p. 5373, Jul. 2022, doi: 10.3390/en15155373.

[66] P. Wang, J. Li, Y. Li, L. Liu, X. Qin, and B. Zhang, "Visual detection method of metal mine filling pipeline blockage based on ERT," *Journal of Central South University*, vol. 53, no. 2, pp. 643–652, 2022, doi: 10.11817/j.issn.1672-7207.2022.02.027.

[67] P. Dhoorjaty, I. Wold, and D. Penmetsa, "Development of a Hydrate Kinetics-Based Digital Twin for Blockage Detection and Production Optimization," in *Day 4 Thu, May 05, 2022*, Houston, Texas, USA: Offshore Technology Conference, Apr. 2022, p. D041S046R004. doi: 10.4043/32102-MS.

[68] P. C. C. Monteiro, L. L. Da Silva Monteiro, T. A. Netto, and J. L. A. Vidal, "Assessment of the Acoustic Reflectometry Technique to Detect Pipe Blockages," *Journal of Offshore Mechanics and Arctic Engineering*, vol. 143, no. 5, p. 051801, Oct. 2021, doi: 10.1115/1.4049064.

[69] V. Pratap, S. Rajendran, R. K. Agrawal, S. S. Indimath, B. P. Reddy, and S. Balamurugan, "Blockage Detection in Gas Pipelines to Prevent Failure of Transmission Line," *Journal of Pipeline Systems Engineering and Practice*, vol. 12, no. 3, p. 04021031, Aug. 2021, doi: 10.1061/(ASCE)PS.1949-1204.0000568.

[70] M. Abdullahi and S. O. Oyadiji, "Simulation and detection of blockage in a pipe under mean fluid flow using acoustic wave propagation technique," *Journal Structural Control and Health Monitoring*, vol. 27, no. 4, Apr. 2020, doi: 10.1002/stc.2449.

[71] R. Zanganeh, E. Jabbari, A. Tijsseling, and A. Keramat, "Fluid-Structure Interaction in Transient-Based Extended Defect Detection of Pipe Walls," *Journal of Hydraulic Engineering*, vol. 146, no. 4, p. 04020015, Apr. 2020, doi: 10.1061/(ASCE)HY.1943-7900.0001693.

[72] F. Zouari, M. Louati, S. Meniconi, E. Blåsten, M. S. Ghidaoui, and B. Brunone, "Experimental verification of the accuracy and robustness of Area Reconstruction Method for Pressurized Water Pipe System," *Journal of Hydraulic Engineering*, vol. 146, no. 3, p. 04020004, Mar. 2020, doi: 10.1061/(ASCE)HY.1943-7900.0001674.

[73] H. Yao, D. Li, Y. Li, B. Yang, and Y. Meng, "Blockage detection in pipelines based on linear frequency modulated acoustic reflection method," *Journal Developments in the Built Environment*, vol. 23, p. 100723, Oct. 2025, doi: 10.1016/j.dibe.2025.100723.

[74] T.-C. Che, H.-F. Duan, and P. J. Lee, "Transient wave-based methods for anomaly detection in fluid pipes: A review," *Journal of Mechanical Systems and Signal Processing*, vol. 160, p. 107874, Nov. 2021, doi: 10.1016/j.ymssp.2021.107874.

[75] D. Hei *et al.*, "Design of a setup for 252Cf neutron source for storage and analysis purpose," *Nuclear Instruments and Methods in Physics Research Section B: Beam Interactions with Materials and Atoms*, vol. 386, pp. 1–3, Nov. 2016, doi: 10.1016/j.nimb.2016.09.003.

[76] L. Ding, Y. Fu, X. Li, and J. Ran, "Review of vibration induced by gas-liquid two-phase flow inside pipes," *Ocean Engineering*, vol. 316, p. 120006, Jan. 2025, doi: 10.1016/j.oceaneng.2024.120006.

[77] Y. Yu, A. Krynkin, and K. V. Horoshenkov, "Modal coupling analysis of the acoustic wave scattering from blockage in a pipe," *Journal of Sound and Vibration*, vol. 588, p. 118522, Oct. 2024, doi: 10.1016/j.jsv.2024.118522.

[78] W. Kiyingi, J. Guo, R. Xiong, S. Zhang, and C. Gao, "A potentially fast approach for detecting wax appearance temperature and quantification in crude oils using optical back scattering analysis," *Journal of Colloids and Surfaces A: Physicochemical and Engineering Aspects*, vol. 713, p. 136517, May 2025, doi: 10.1016/j.colsurfa.2025.136517.

[79] A. Keramat and R. Zanganeh, "Statistical performance analysis of transient-based

extended blockage detection in a water supply pipeline," *Journal of Water Supply: Research and Technology-Aqua*, vol. 68, no. 5, pp. 346–357, Aug. 2019, doi: 10.2166/aqua.2019.014.

[80] M. Al-Tofan, M. Elkholy, S. Khilqa, J. Caicedo, and M. H. Chaudhry, "Use of Lower Harmonics of Pressure Oscillations for Blockage Detection in Liquid Pipelines," *Journal of Hydraulic Engineering*, vol. 145, no. 3, p. 04018090, Mar. 2019, doi: 10.1061/(ASCE)HY.1943-7900.0001568.

[81] N. Adeleke, M. T. Ityokumbul, and M. Adewumi, "Blockage Detection and Characterization in Natural Gas Pipelines by Transient Pressure-Wave Reflection Analysis," *SPE Journal*, vol. 18, no. 02, pp. 355–365, Apr. 2013, doi: 10.2118/160926-PA.

[82] B. Chen, J. Bi, Q.-H. Kang, and X.-Z. Wang, "Performance Analysis of Transient Pressure Wave Method for Detecting Partial Blockage of CO2 Pipeline," in *Proceedings of the 2022 International Petroleum and Petrochemical Technology Conference*, Springer Nature, 2023, pp. 427–440. doi: 10.1007/978-981-99-2649-7_40.

[83] J. Chu *et al.*, "Experimental investigation on blockage predictions in gas pipelines using the pressure pulse wave method," *Energy*, vol. 230, p. 120897, Sep. 2021, doi: 10.1016/j.energy.2021.120897.

[84] H. Liang *et al.*, "Experimental research on the reflection and response characteristics of pressure pulse waves for different gas pipeline blockage materials," *Energy Science & Engineering*, vol. 12, no. 6, pp. 2505–2518, Jun. 2024, doi: 10.1002/ese3.1759.

[85] V. De Almeida, E. Serris, A. Cameirão, J.-M. Herri, E. Abadie, and P. Glénat, "Monitoring gas hydrates under multiphase flow in a high pressure flow loop by means of an acoustic emission technology," *Journal of Natural Gas Science and Engineering*, vol. 97, p. 104338, Jan. 2022, doi: 10.1016/j.jngse.2021.104338.

[86] A. Santoso, F. D. Wijaya, N. A. Setiawan, and J. Waluyo, "Comparison of data mining algorithms for pressure prediction of crude oil pipeline to identify congeal," *E3S Web of Conferences*, vol. 325, p. 02002, 2021, doi: 10.1051/e3sconf/202132502002.

[87] N. M. Leite, C. A. B. D. O. Lira, and A. G. Rodriguez, "Computational analysis for wax detection in deepwater pipelines using nuclear techniques," *Braz. J. Rad. Sci.*, vol. 11, no. 1A (Suppl.), pp. 1–20, Jul. 2023, doi: 10.15392/2319-0612.2023.2193.

[88] E. I. Jassim, M. A. Abdi, and Y. Muzychka, "A CFD-Based Model to Locate Flow-Restriction Induced Hydrate Deposition in Pipelines," in *All Days*, Houston, Texas, USA: Offshore Technology Conference, May 2008, p. OTC-19190-MS. doi: 10.4043/19190-MS.

[89] S. P. Veluri, C. J. Roy, and E. A. Luke, "Comprehensive code verification techniques for finite volume CFD codes," *Computers & Fluids*, vol. 70, pp. 59–72, Nov. 2012, doi: 10.1016/j.compfluid.2012.04.028.

[90] J. Wang *et al.*, "A CFD Study of the Unsteady Leakage and Dispersion of Natural Gas Pipelines Containing High-H2S in Mountainous Terrain," *Process Safety and Environmental Protection*, p. 106981, Mar. 2025, doi: 10.1016/j.psep.2025.106981.

[91] M. Nait Amar, A. Jahanbani Ghahfarokhi, and C. Shang Wui Ng, "Predicting wax deposition using robust machine learning techniques," *Petroleum*, vol. 8, no. 2, pp. 167–173, Jun. 2022, doi: 10.1016/j.petlm.2021.07.005.

[92] B. Amiri-Ramsheh, R. Zabihi, and A. Hemmati-Sarapardeh, "Modeling wax deposition of crude oils using cascade forward and generalized regression neural networks: Application to crude oil production," *Geoenergy Science and Engineering*, vol. 224, p. 211613, May 2023, doi: 10.1016/j.geoen.2023.211613.

[93] M. Duarte, V. Coch, J. Dias, S. Botelho, N. Duarte, and P. Drews, "Thermographic Non-Invasive Inspection Modelling of Fertilizer Pipelines Using Neural Networks," in *Proc. - SIBGRAPI Conf. Graph., Patterns Images, SIBGRAPI*, Institute of Electrical and Electronics Engineers Inc., 2020, pp. 280–286. doi: 10.1109/SIBGRAPI51738.2020.00045.

[94] Z. Chen, N. Wang, W. Jin, and D. Li, "Prediction Model of Wax Deposition Rate in Waxy Crude Oil Pipelines by Elman Neural Network Based on Improved Reptile Search Algorithm," *Journal of Energy Engineering*, vol. 121, no. 4, pp. 1007–1026, 2024, doi: 10.32604/ee.2023.045270.

[95] A. Khaksar Manshad, S. Ashoori, M. Khaksar Manshad, and P. Omidvar, "The Prediction of Wax Precipitation by Neural Network and Genetic Algorithm and Comparison With a Multisolid Model in Crude Oil Systems," *Petroleum Science and Technology*, vol. 30, no. 13, pp. 1369–1378,

Apr. 2012, doi: 10.1080/10916466.2010.499403.
[96] A. Oladiipo, A. Bankole, and E. Taiwo, "Artificial Neural Network Modeling of Viscosity and Wax Deposition Potential of Nigerian Crude Oil and Gas Condensates," in *Nigeria Annual International Conference and Exhibition*, Abuja, Nigeria: Nigeria Annual International Conference and Exhibition, Aug. 2009, p. SPE-128600-MS. doi: 10.2118/128600-MS.