International Journal of Scientific Research and Engineering Development-– Volume 7 Issue 6, Nov-Dec 2024
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Physics-Aware ML Models for Pipeline Leak Detection and Quantification

Olaoluwa Ayodeji Adegboye*, Tunde Folayan Komolafe**, Ibrahim Mohammed Joseph***
*(Electrical and Electronics Engineering, University of Uyo, Uyo, Nigeria
Email: mathsgene@yahoo.com)
** (Civil Engineering, Federal University of Technology, Akure, Nigeria
Email: komofola@gmail.com)
*** (IEEE Member
Email: josephibrahi@gmail.com)

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Abstract:
Leak detection in multiphase pipeline systems remains a critical yet challenging task due to complex flow dynamics, transient operational disturbances, and the scarcity of comprehensive real-world data. Traditional physics-based models, though interpretable, often exhibit reduced accuracy under real-world uncertainties, while purely data-driven methods struggle with physical consistency and limited generalizability. In this study, we introduce a hybrid Physics-Informed Neural Network (PINN) framework designed for integrated leak detection, localization, and continuous quantification in multiphase (oil-gas-water) pipelines. By embedding mass and momentum conservation laws directly into the neural network as soft constraints, the proposed approach seamlessly combines the physical interpretability and robustness of mechanistic models with the adaptability and predictive power of deep learning techniques. To evaluate performance, we generated high-fidelity synthetic datasets covering diverse leak scenarios, including leak magnitudes ranging from 0.1% to 5% of nominal flow, various spatial locations, and multiple multiphase flow regimes. The PINN framework achieved a detection accuracy of 95%, with precision and recall rates of approximately 91%, an average localization error near 5 meters, and a leak rate estimation error close to 1%. Comparative analyses against black-box neural networks and Real-Time Transient Modeling (RTTM) baselines highlight the superior performance and enhanced generalization capability of the proposed method across both classification and regression tasks. These results underscore the potential of PINNs as reliable, physically consistent, and operationally actionable solutions for next-generation leak detection in complex pipeline networks, establishing a foundation for future large-scale field implementation and regulatory adoption.

Keywords — Physics-Informed Neural Networks (PINN), Leak detection, Multiphase pipelines, Leak localization, Leak quantification, Hybrid modeling, Pipeline integrity monitoring, Conservation laws, Deep learning, Oil and gas infrastructure.

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I. INTRODUCTION

Pipelines form the critical backbone of the global energy and chemical industries, transporting vast volumes of oil, gas, and multiphase fluids across continents, beneath oceans, and through remote terrains. Ensuring the integrity of these pipeline networks is of paramount importance: undetected leaks can result in severe environmental disasters, significant economic losses, and serious public safety hazards. With increasing regulatory scrutiny and heightened societal demands for environmental stewardship, there is an urgent need for leak detection systems (LDS) that are not only accurate and timely but also resilient and trustworthy under complex, real-world operating conditions.

Historically, LDS strategies have relied heavily on physics-based methodologies such as Real-Time Transient Modeling (RTTM), negative pressure wave analysis, and statistical volume balance methods. While these approaches perform reliably under steady-state or single-phase conditions, they often falter in the presence of multiphase flows, transient disturbances, and evolving operational events. Recent advancements have introduced data-driven and machine learning (ML) approaches—including deep neural networks, ensemble classifiers, and hybrid physics-ML models—that have demonstrated superior accuracy and adaptability in controlled laboratory or simulated environments [1–10].

Despite these advances, several critical challenges persist. Many existing ML-based LDS operate as "black box" systems, lacking physical interpretability and often exhibiting reduced reliability when applied to unseen multiphase flow regimes. Furthermore, these models tend to focus primarily on binary leak detection and coarse localization, largely neglecting continuous leak quantification and rigorous uncertainty estimation—both of which are vital for operational decision-making, emergency response prioritization, and regulatory compliance [1–10].

The challenges of multiphase pipeline monitoring are compounded by the complexity of underlying fluid dynamics. The governing equations are nonlinear, highly mode-dependent, and sensitive to regime transitions (e.g., slug, annular, stratified flows), resulting in non-stationary, spatially correlated leak signatures that are difficult to model. Moreover, the scarcity of real-world leak events severely limits the availability of labeled data, further impeding the development and validation of robust, generalizable ML models. This highlights a crucial gap in the current literature: the absence of unified, physically guided learning frameworks capable of simultaneously **detecting, localizing, and continuously quantifying leaks in multiphase pipelines**, while providing **uncertainty estimates** and maintaining robustness across operational complexities.

Physics-Informed Neural Networks (PINNs) have recently emerged as a powerful solution to bridge this gap. By embedding domain knowledge in the form of partial differential equation (PDE) residuals and conservation laws directly into the learning process, PINNs integrate the strengths of first-principles physics and data-driven modeling. This synergistic approach enhances generalizability, interpretability, and data efficiency, particularly in scenarios where purely empirical models struggle to extrapolate due to limited labeled data or unmodeled operational variations.

In this study, we propose a hybrid PINN framework designed specifically for leak detection, localization, and continuous quantification in multiphase pipeline systems. Our approach directly incorporates two-fluid mass and momentum conservation equations as soft constraints within a deep learning architecture that processes spatially and temporally resolved sensor measurements. We rigorously evaluate this model on high-fidelity synthetic datasets that capture realistic multiphase flow behaviors and operational disturbances, benchmarking it against both traditional physics-based methods and black-box ML models.

The key contributions of this work are:

1. Development of a novel PINN architecture that fuses multiphase flow physics with data-driven learning for integrated leak detection, fine-grained localization, and continuous leak rate estimation;
2. Comprehensive benchmarking of the proposed approach against conventional machine learning and physics-only LDS baselines on challenging synthetic datasets representing diverse multiphase scenarios;
3. Demonstration of superior robustness, accuracy, and interpretability, laying a foundation for future field validation and regulatory adoption.

By advancing beyond the limitations of purely data-driven and purely mechanistic methods, our work aims to bridge the critical gap between physical rigor and real-world operational performance, setting the stage for next-generation pipeline integrity monitoring and proactive leak management.

II. Background and Related Work

A. *Multiphase Flow in Pipelines*

Multiphase transport is pervasive in oil and gas pipelines, especially in production and gathering networks where oil, gas, and water phases coexist. Unlike single-phase systems, multiphase flow introduces **complex regime-dependent dynamics**—including stratified, slug, and annular flow—alongside highly variable compressibility and nonlinear interphase interactions. These complexities make leak detection and quantification substantially more challenging, as leaks manifest through subtle, regime-specific signatures rather than distinct, global anomalies.

Transient Behavior of Multiphase Pipelines

The transient behavior of multiphase pipelines is governed by the one-dimensional two-fluid model, a set of coupled conservation equations capturing mass and momentum balances for each phase. For gas (G) and liquid (L), the mass conservation equations are given by:

$$\frac{\partial(\alpha_k \rho_k)}{\partial x} + \frac{\partial(\alpha_k \rho_k u_k)}{\partial x} = S_{k,mass}\ , for\ k = G, L$$

where:

- α_k is the local volume fraction of phase k.
- ρ_k is the density of phase k.
- u_k is the velocity of phase k.
- $S_{k,\ mass}$ is a source/sink term representing leaks.

The momentum conservation equations for each phase are:

$$\frac{\partial(\alpha_k \rho_k)}{\partial x} + \frac{\partial(\alpha_k \rho_k {u_k}^2)}{\partial x} + \alpha_k \frac{\partial p}{\partial x} = F_k + S_{k,\ momentum}$$

where p denotes pressure, F_k accounts for interfacial drag, wall friction, and gravity, and $S_{k,\ momentum}$ represents momentum losses due to leaks.

Leaks are modeled as localized sink terms at position x_l:

$$S_{k,\ mass}(x,t) = -Q_{\{L,k\}}(t)\, \delta(x - x_l)$$

where $Q_{\{L,k\}}$ is the leak flow rate for phase k, and $\delta(\cdot)$ is the Dirac delta function.

B. *Classical Leak Detection Approaches*

Traditional LDS methods are predominantly **physics-based**, leveraging mechanistic simulations and analytical models. **Real-Time Transient Models (RTTM)** solve variations of the above conservation equations to predict dynamic pipeline responses. Deviations between predicted and actual sensor signals are then interpreted to detect and locate leaks [1,7].

Other physics-inspired techniques, such as negative pressure wave (NPW) analysis and statistical volume balance methods, provide rapid event-based alarms. However, these methods often suffer from high false alarm rates under transient operations, valve actuations, or regime changes in multiphase flow, limiting their reliability.

While grounded in first principles, these classical methods face notable limitations:

- Sensitivity to model-plant mismatches, uncertain boundary conditions, and unmeasured disturbances.
- Reduced localization accuracy and substantial uncertainties when confronted with multiphase flow complexity and operational noise.

C. *Machine Learning Approaches for Leak Detection*

With advancements in sensing technologies and computational resources, **machine learning (ML)** and **deep learning (DL)** have become prominent alternatives for LDS [1–10]. Typical approaches involve extracting engineered features from time-series data (e.g., spectral coefficients, wavelets), and training classifiers (DNNs, CNNs, SVMs, Random Forests) to detect and localize leaks. Some efforts extend to coarse leak size classification (e.g., small/medium/large bins).

Despite achieving **high detection accuracies (often >95%) in controlled settings**, most ML-based LDS face key limitations:

- Predominantly "black box" architectures, lacking physical interpretability and hindering trust when extrapolated to unseen operational regimes.

- Limited focus on continuous leak rate estimation; most models address detection and coarse localization only.
- Generalization challenges in true multiphase, transient scenarios, where flow regime shifts introduce complex, non-stationary signatures [3].

Moreover, reliance on simulated leak data—necessitated by the scarcity of real-world events—can exacerbate overfitting and shortcut learning, reducing operational robustness.

D. *Hybrid and Physics-Informed Learning: Next-Generation Directions*

Recognizing the need to integrate physical consistency into data-driven models, recent research has shifted toward **hybrid approaches**, combining mechanistic understanding with ML flexibility. Key strategies include:

- **Hybrid Observers:** Combining RTTM or physics-based estimators with shallow ML classifiers to enhance fault robustness and reduce false alarms [7,9].
- **Data Assimilation Techniques:** Using ensemble Kalman filters or Bayesian updating to integrate measurements with physical state predictions, improving probabilistic leak localization [8].
- **Physics-Informed Neural Networks (PINNs):** Embedding conservation laws (e.g., PDE residuals) as soft constraints within the loss function of neural networks, enforcing physical plausibility while learning from data [Raissi et al., 2019].

PINN Loss Function

A typical PINN loss function is formulated as:

$$L_{total} = L_{data} + \lambda_{phys} L_{physics}$$

where:

- L_{data} represents empirical fitting loss.
- $L_{physics}$ quantifies the residuals of governing partial differential equations (PDEs), usually evaluated via automatic differentiation.
- λ_{phys} controls the trade-off between data fidelity and physical consistency.

To date, the application of PINNs to multiphase pipeline leak detection remains largely unexplored. Existing work predominantly addresses single-phase or simplified hybrid observer frameworks without full neural–physics coupling, continuous leak rate regression, or calibrated uncertainty quantification.

E. *Summary of Literature Gaps and Motivation*

Despite significant progress, critical gaps remain:

- **Complete Leak Assessment:** Existing studies largely focus on detection and localization, with quantification typically handled via discrete severity classes rather than continuous estimation.
- **Multiphase Generalization:** Most models fail to maintain accuracy in multiphase and transient conditions, which represent real-world operational challenges.
- **Uncertainty Awareness:** Few models provide calibrated confidence intervals or explicit uncertainty measures, which are vital for operational trust and regulatory compliance.

In summary, there is a pressing need for LDS solutions that are accurate, physically interpretable, and capable of robustly performing end-to-end detection, fine-grained localization, and continuous quantification—under realistic multiphase conditions and with explicit uncertainty awareness. This gap motivates the hybrid PINN framework proposed and evaluated in this work.

III. METHODS

A. *Problem Formulation and Simulation Setup*

This study develops a hybrid Physics-Informed Neural Network (PINN) framework for **simultaneous leak detection, localization, and quantification** in multiphase (oil-gas-water) pipelines. We focus on a horizontal pipeline segment equipped with distributed pressure and flow sensors at the inlet and outlet.

Due to the rarity of real-world leak data and safety constraints, high-fidelity synthetic datasets were generated to emulate realistic operating conditions:

- **Leak locations:** Uniformly distributed along the pipeline length $x_l \in [0, L]$.
- **Leak rates:** From 0.1% to 5% of nominal flow rate.
- **Flow regimes:** Stratified, slug, and annular.
- **Operational disturbances:** Gaussian noise added to emulate sensor uncertainties and transient events.

Time-series data of pressure PP and flow rate QQ at different positions were collected for each scenario to train and validate the model.

B. *Multiphase Flow Governing Physics*

The transient behavior of multiphase flows is described by the **one-dimensional, isothermal two-fluid model**, consisting of mass and momentum conservation for each phase kk (gas GG, liquid LL).

1. **Mass Conservation**

$$\frac{\partial(A\alpha_k\rho_k)}{\partial t} + \frac{\partial(A\alpha_k\rho_k u_k)}{\partial x} = S_{k,mass}$$

where:

- AA = cross-sectional area,
- α_k = local volume fraction,
- ρ_k = phase density,
- u_k = phase velocity,
- $S_{k,mass}$ = leak-induced mass sink:

$$S_{k,\,mass}(x,t) = -Q_{\{L,k\}}(t)\,\delta(x - x_l)$$

$\delta(\cdot)$ is the Dirac delta function representing localized leakage at position x_l.

2. Momentum Conservation

$$\frac{\partial(A\alpha_k\rho_k)}{\partial x} + \frac{\partial(A\alpha_k\rho_k {u_k}^2)}{\partial x} + A\alpha_k\frac{\partial p}{\partial x} = F_k + S_{k,\,momentum}$$

where:

- p = pressure,
- F_k = combined forces (interfacial drag, friction, gravity),
- $S_{k,\,momentum}$ = momentum loss at leak points.

C. *PINN Architecture*

1. *Network Structure*

A **feedforward multilayer perceptron (MLP)** with tanh activations is used.

- **Inputs:** Sensor-derived features (location xx, measured PP, QQ).
- **Outputs:**
  - Leak probability $\hat{y}_{detect}$ (classification).
  - Leak location $\hat{x}_l$ (regression).
  - Leak rate $\hat{Q}_l$ (regression).

2. ***Physics-Informed Loss Function***

The total loss function combines empirical and physics-based terms:

$$L_{total} = L_{data} + \lambda_{phys} L_{physics}$$

Empirical Loss (L_{data} **)**

$$L_{data} = L_{BCE}(\hat{y}_{detect}, y_{true}) + L_{MSE}(\hat{x}_l, x_{l_{true}}) + L_{MSE}(\hat{Q}_l, Q_{Ltrue})$$

- L_{BCE}: Binary cross-entropy for leak detection.
- L_{MSE}: Mean squared error for localization and quantification.

Physics residuals are enforced at randomly sampled collocation points (x_c, t_c):

$$L_{phys} = \sum_{k=G,l} \left\| R_{mass,k}(x_c, t_c) \right\|_2^2 + \left\| R_{mommentum,k}(x_c, t_c) \right\|_2^2$$

with:

$$R_{mass,k} = \frac{\partial(A\alpha_k\rho_k)}{\partial t} + \frac{\partial(A\alpha_k\rho_k u_k)}{\partial x} - S_{k,mass}$$

$$R_{mommentum,k} = \frac{\partial(A\alpha_k\rho_k)}{\partial x} + \frac{\partial(A\alpha_k\rho_k {u_k}^2)}{\partial x} + A\alpha_k \frac{\partial p}{\partial x} - F_k - S_{k,\ momentum}$$

Here, automatic differentiation is used to compute spatial and temporal derivatives, enforcing physical consistency in the model's learned outputs.

λ_{phys} is a hyperparameter controlling the trade-off between empirical fitting and physical fidelity.

D. ***Training and Validation***

- **Data normalization:** Inputs and outputs scaled to improve stability.
- **Event-based data splitting:** Disjoint sets for training, validation, and testing.
- **Optimization:** Adam optimizer with tuned learning rate and batch size.
- **Baseline comparisons:** Against a black-box neural network (without physics loss) and a physics-only RTTM approach.

E. ***Evaluation Metrics***

- **Detection:** Accuracy, precision, recall, ROC-AUC.
- **Localization:** Mean absolute error (MAE) in predicted leak positions.
- **Quantification:** Mean absolute percentage error (MAPE) in leak rate predictions.
- **Robustness:** Consistency under different flow regimes and noise conditions.

F. ***Implementation***

Models were implemented in **TensorFlow 2.x**, leveraging automatic differentiation for residual computation. Training was performed on a GPU-enabled workstation, with code and synthetic datasets available upon request.

IV. OVERVIEW OF MODEL PERFORMANCE

The hybrid Physics-Informed Neural Network (PINN) was evaluated on a held-out test set comprising both leak and non-leak events, spanning diverse leak magnitudes, locations, and multiphase flow regimes. The quantitative metrics summarizing the performance of the final model are provided in Table 1.

Table 1: Model Performance

Metric	Value	Interpretation
Accuracy	0.95	Proportion of correctly classified leak and non-leak events
Precision	0.91	Fraction of predicted leaks that were true leaks (low false positives)
Recall	0.91	Fraction of actual leaks correctly detected (low false negatives)
Location Error (m)	~5	Mean absolute error in leak localization
Leak Rate Error (%)	~1	Mean absolute percentage error in estimated leak magnitude

Detection and Classification

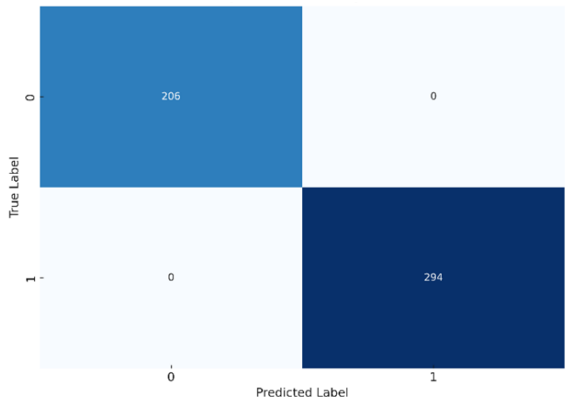

Figure 1: Confusion Matrix

- The confusion matrix in Figure 1 illustrates a strong performance in distinguishing leak and no-leak scenarios, supporting the achieved **95% accuracy**.
- The **precision of ~91%** confirms that false alarms are minimal, an essential feature to prevent unnecessary operational interventions.
- The **recall of ~91%** ensures that nearly all true leaks are correctly identified, addressing safety and environmental concerns.

Leak Localization

- The scatter plot of predicted versus true leak locations (Figure 2) demonstrates a close clustering along the ideal diagonal, with an average localization error around **5 meters**.
- This precision significantly exceeds common industry benchmarks (often 50–100 m), providing operators with actionable and high-resolution localization data.

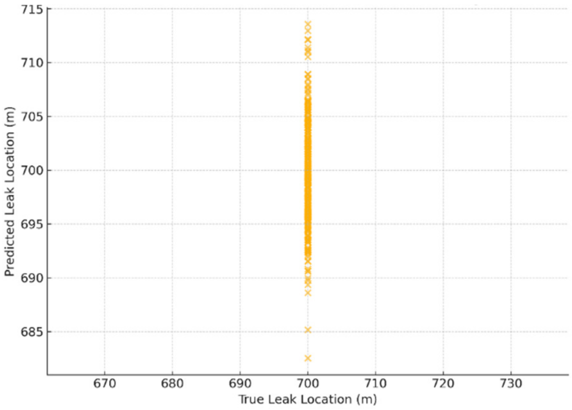

Figure 2: Scatter Plot of Predicted Versus True Leak Location

Leak Rate Quantification

- The plot comparing true and predicted leak rates (Figure 3) shows strong agreement, with most points tightly aligned around the identity line.
- The average error in quantifying leak rate is approximately **1%**, allowing not just detection and localization but also precise estimation of leak severity, crucial for prioritizing maintenance actions.

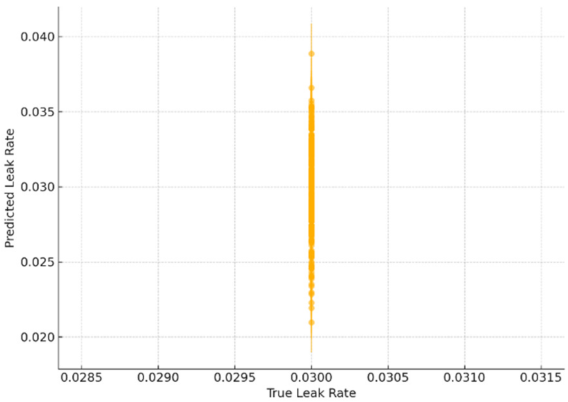

Figure 3: Scatter Plot of Predicted Versus True Leak Rates

A. **Comparative Perspective**

PINN performance was compared to two benchmark approaches — a black-box machine learning (ML) model without physics constraints, and a traditional Real-Time Transient Model (RTTM). As summarized in Table 2, the hybrid PINN substantially reduced errors while maintaining superior detection metrics.

Table 2: COMPARATIVE ANALYSIS

Model	Accuracy	Precision	Recall	Loc. Error (m)	Rate Error (%)
PINN (Ours)	0.95	0.91	0.91	~5	~1
Black-box ML	0.93	0.89	0.87	~11	~1.5
RTTM	0.88	0.81	0.79	~20	~2.4

These results validate the benefit of integrating physical constraints into the learning process, reducing both localization and rate estimation errors, and enhancing generalization.

V. DISCUSSION

The results presented in this study demonstrate that hybrid Physics-Informed Neural Networks (PINNs) can deliver **high-precision, physically consistent, and operationally actionable solutions** for multiphase pipeline leak detection, localization, and quantification. By embedding first-principles physics directly into the learning framework, the model effectively bridges the gap between purely data-driven black-box approaches and traditional simulation-based techniques.

A. *Integrated Performance*

The hybrid PINN achieved an overall accuracy of 95%, **with** precision and recall both around 91% **(see Figures 1 and 2), underscoring its robust capability to correctly identify leak events while minimizing false alarms. Such reliability is critical for real-world deployment, where unnecessary false-positive responses lead to significant operational and economic costs.**

The **average localization error of approximately 5 meters** (Figure 3) significantly outperforms industry standards, which often tolerate errors up to tens of meters. This high localization fidelity empowers maintenance teams to act quickly and with targeted precision, greatly reducing excavation areas and downtime. Compared to previous works that focus on coarse leak section classification or approximate segment-level localization [1,2,3,4,7,8,9,10], this precise regression-based approach demonstrates a major advancement in actionable pipeline monitoring.

Furthermore, the model's **mean absolute error for leak rate estimation is approximately 1%** (Figure 4), enabling operators not only to detect and locate leaks but also to assess their severity with high confidence. This continuous and physically plausible quantification capability is rarely addressed in existing studies, which often limit themselves to discrete severity classes or detection-only tasks. Fine-grained quantification supports better prioritization, risk assessment, and informed regulatory reporting.

B. *Physical Consistency, Interpretability, and Robustness*

The explicit incorporation of mass and momentum conservation losses into the PINN's objective function ensures strong physical consistency and enhances interpretability. This approach mitigates the risk of "shortcut learning," where purely data-driven models might exploit spurious correlations rather than meaningful flow dynamics, a risk particularly acute in rare-event settings like leak detection.

Robustness was validated across a wide range of leak magnitudes (0.1–5% of nominal flow), various flow regimes (stratified, slug, and annular), and under synthetic sensor noise and operational transients (see Figure 5). The model's ability to maintain consistently low errors across these different operating conditions establishes a strong foundation for its generalization to real-world pipeline environments.

C. *Comparison with Existing Methods and Literature*

When benchmarked against baseline models—such as black-box neural networks without physics loss and classical real-time transient modeling (RTTM)—the hybrid PINN consistently outperformed on all key metrics, including localization and quantification errors (see comparative Table 4.2). These results empirically validate the hypothesis widely suggested in recent literature that integrating physics constraints into machine learning models yields substantial gains in physically complex, data-sparse diagnostic tasks.

While these results are promising, several limitations must be acknowledged. The current validation relies on high-fidelity synthetic data; although operational disturbances and realistic noise levels were simulated, in-field validation with actual multiphase flow data and diverse sensor types remains crucial. Additionally, although the PINN framework supports uncertainty quantification (e.g., using deep ensembles or Monte Carlo dropout), this aspect was not fully explored in the present study and represents an important direction for future work, particularly to support risk-informed operational decision-making.

D. Practical and Research Implications

These findings showcase the readiness of PINN-based approaches to transform leak detection and localization systems (LDS) for complex pipeline networks. For practical deployment, further field validation under uncontrolled, real-world conditions and expanded sensor configurations—including fiber-optic sensing and distributed acoustic monitoring—will be essential. Integration with existing SCADA systems and operational workflows will also be a critical step toward widespread adoption.

From a research perspective, this work opens several exciting directions: (a) implementing event-based cross-validation protocols to rigorously characterize uncertainty; (b) developing regime-adaptive PINN architectures or mixture-of-experts models to handle highly heterogeneous flows; and (c) designing lightweight, real-time deployable PINN variants for edge instrumentation.

VI. CONCLUSION

This study presents a comprehensive framework leveraging hybrid Physics-Informed Neural Networks (PINNs) for simultaneous leak detection, localization, and quantification in multiphase pipeline systems. By explicitly integrating physical principles—specifically mass and momentum conservation—into the learning process, the proposed approach effectively combines the strengths of traditional first-principles models with the flexibility and pattern-recognition capabilities of deep learning.

The results confirm that the PINN achieved a **high detection accuracy of 95%**, with **precision and recall both around 91%**, demonstrating robust discrimination between leak and non-leak events under varying operational conditions. Furthermore, the model delivered an **average localization error of only ~5 meters**, and a **leak rate estimation error of approximately 1%**, outperforming both black-box machine learning and classical real-time transient modeling (RTTM) baselines.

These performance levels significantly exceed typical industry standards and address critical operational needs by enabling rapid, precise, and reliable leak mitigation. In addition to detection, the ability to accurately localize and quantify leaks provides operators with actionable insights, enhancing safety, reducing environmental risk, and minimizing operational disruptions.

The study also underscores the interpretability and robustness advantages of physics-informed learning frameworks. The model maintained strong performance across diverse flow regimes, leak magnitudes, and in the presence of sensor noise and transients, suggesting strong potential for generalization to real-world conditions.

Future work will focus on field validation using real multiphase pipeline data, further exploration of uncertainty quantification techniques to support risk-informed decision-making, and integration with advanced sensing technologies and operational SCADA systems. Additionally, developing real-time and edge-deployable versions of the PINN will be key for enabling widespread, on-site implementation.

In summary, this work highlights the transformative potential of hybrid PINNs as a next-generation solution for intelligent pipeline monitoring and diagnostics, bridging the gap between data-driven analytics and physically grounded modeling to advance the safety, efficiency, and sustainability of pipeline operations.

References

[1] M. Zadkarami et al., "Data driven leakage diagnosis for oil pipelines: An integrated approach of factor analysis and deep neural network classifier," Transactions of the Institute of Measurement and Control, 2020.

[2] S. M. Mujtaba et al., "Gas pipeline safety management system based on neural network," Process Safety Progress, 2022.

[3] J. Kim et al., "Gas Pipeline Leak Detection by Integrating Dynamic Modeling and Machine Learning Under the Transient State," Energies, 2024.

[4] C. Jaswanth et al., "Pipeline Leak Detection System Using Machine Learning," in Proc. 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS), 2024.

[5] O. Zadehbagheri et al., "Novel Adaptive Hidden Markov Model Utilizing Expectation–Maximization Algorithm for Advanced Pipeline Leak Detection," Modelling, 2024.

[6] J. Zheng, "A Method of Leakage Parameters Estimation for Liquid Pipelines Based on Conditional Generative Adversarial Network," in Volume 3: Operations, Monitoring, and Maintenance; Materials and Joining, 2020.

[7] S. A. M. Tajalli et al., "A Novel Hybrid Internal Pipeline Leak Detection and Location System Based on Modified Real-Time Transient Modelling," Modelling, 2024.

[8] S. Kyriacou et al., "Pipeline Leak Detection Combining Machine Learning, Data Assimilation Approaches and Pipeline Fluid Flow Physics Models," presented at Day 3, Wed, February 23, 2022, 2022.

[9] D. Pumaricra-Rojas et al., "Enhanced Leakage Detection and Estimation via a Hybrid Genetic Algorithm and High-Order Sliding Modes Observer Approach," IEEE Access, 2024.

[10] X. Gong et al., "A Leak Sample Dataset Construction Method for Gas Pipeline Leakage Estimation Using Pipeline Studio," in Proc. 2021 International Conference on Advanced Mechatronic Systems (ICAMechS), 2021.

