# PredBlock: An AI–Blockchain Framework for Real-Time Integrity Management in CCS Pipelines


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***Abstract*—Carbon Capture and Storage (CCS) pipelines are critical to large-scale decarbonization, yet their safety and reliability remain challenged by impurity-driven thermodynamic instabilities, corrosion, and leakage events. Existing monitoring approaches rely on centralized systems with limited real-time intelligence and weak auditability of measurement, reporting, and verification (MRV) data. This paper introduces PredBlock, a hybrid AI-Blockchain framework for real-time anomaly detection, flow optimization, and tamper-proof operational logging in CO2 pipeline networks. A physics-based simulator integrating the Span-Wagner equation of state and Darcy-Weisbach flow modeling generated multi-sensor datasets incorporating synthetic leakage, corrosion, and overpressure anomalies. Random Forest ensembles achieved high predictive performance with F1-scores of 1.000 (leakage), 0.932 (corrosion), and 0.978 (overpressure), while a reinforcement learning controller reduced pressure deviation to $<$1.5 bar and decreased compressor energy consumption by 8.7%. The blockchain layer, implemented on a zero-gas PoA2 PureChain network, ensured immutable logging with a mean transaction latency of 15.58 ms. The full system achieved an endto- end latency of 33.9 ms, confirming its suitability for industrial real-time deployment. PredBlock establishes a verifiable, predictive, and autonomous CCS pipeline management framework with significant implications for operational safety and regulatory compliance.**



***Index Terms*—CCS, $CO_2$ pipeline monitoring, anomaly detection, blockchain, machine learning, predictive maintenance.**


## I. INTRODUCTION

Rising $CO_2$ emissions continue to accelerate global warming, amplifying critical environmental impacts such as floods, droughts, sea-level rise, and glacier retreat [1]. Carbon Capture and Storage (CCS) and Bioenergy with CCS (BECCS) have emerged as essential strategies for achieving large-scale decarbonization, with CCS alone projected to mitigate up to 7 Gt of $CO_2$ annually by 2050 [2]. National efforts, such as Sweden's net-zero target for 2045 and its BECCS removal goals of 1.8 $MtCO_2$/year by 2030 and 3–10 $MtCO_2$/year by 2045, highlight the growing dependence on CCS systems [3].

Within the CCS value chain, $CO_2$ transportation, particularly via pipelines, plays a central role due to its cost-effectiveness, safety, and suitability for continuous, large-volume transfer. Pipeline performance is strongly influenced by the chosen capture technique, thermodynamic behavior, impurity interactions, and dense-phase flow characteristics [2], [4]. Impurities such as $H_2O$, $H_2S$, $N_2$, $O_2$, $CH_4$, and $SO_2$ can significantly alter density, viscosity, and speed of sound while introducing risks such as hydrate formation, corrosion, and crack propagation [5], [6]. These challenges underscore the need for advanced modeling and monitoring frameworks beyond traditional empirical or trial-and-error approaches [7], [8].

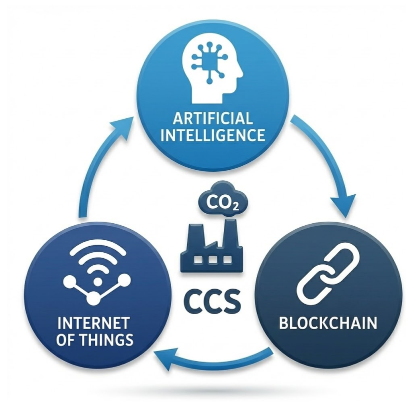


Fig. 1. Integration of advance technologies into CCS system for optimization

Digital twin frameworks [9], thermodynamic analyses [10], [11], and impurity-aware optimizations [12] have advanced CCS pipeline research; however, they predominantly rely on centralized systems lacking robust real-time anomaly detection or verifiable data integrity. Early studies using blockchain for CCS certification [13], [14] improved transparency but omitted AI-driven predictive analytics. As a result, modern CCS infrastructure still lacks integrated systems capable of combining physics-informed AI prediction with decentralized, tamper-proof MRV (measurement, reporting, and verification).

Despite the rapid expansion of CCS networks, current pipeline monitoring systems exhibit three critical limitations as seen in Table I. First, existing models struggle to detect subtle impurity-driven deviations or transient pressure anomalies in real time, especially under noisy or unbalanced operating conditions [5]. This implies limited predictive capability of current state-of-the-art methods. Secondly, there is insufficient data integrity. MRV processes rely on centralized storage, making them vulnerable to manipulation, delayed reporting, and non-verifiable logs [13], [14]. Thirdly, there is a lack of integrated frameworks, as current solutions treat pipeline thermodynamics, anomaly detection, and auditability as separate components, with no unified architecture for real-time AI forecasting and secure, tamper-proof data management [7], [9].

TABLE I
COMPARISON OF EXISTING CCS PIPELINE APPROACHES AND THE PROPOSED PREDBLOCK FRAMEWORK

| **Approach** | **Strengths** | **Limitations** | **Gaps Addressed by PredBlock** |
|---|---|---|---|
| Digital Twin Frameworks for CCUS [9] | High-fidelity process models; reduced-order AI; improved CAPEX/OPEX performance. | Centralized architecture; limited real-time anomaly detection; no tamper-proof MRV integration. | Adds decentralized blockchain verification, sub-40 ms real-time AI detection, and traceable MRV for operational transparency. |
| Thermodynamic & Impurity Studies [5], [10] | Accurate impurity behavior modeling; corrosion analysis; robust physical characterization. | No predictive ML; no real-time leakage/corrosion inference; no secure logging. | Combines physics-informed AI (Span–Wagner + Random Forests) with blockchain-backed integrity checks for continuous monitoring. |
| Pipeline Optimization / Economic Models [7], [12] | Network-wide optimization; cost-efficient pipeline design; impurity-aware performance modeling. | Static or offline models; no integration with sensor data; no operational anomaly tracking. | Enables RL-based real-time flow optimization with measurable gains (8.7% lower compressor energy, $<$ 1.5 bar pressure deviation). |
| Blockchain-Based CCS Certification [13], [14] | Immutable MRV records; enhanced auditability; transparent carbon accounting. | No AI prediction; no integration with pipeline operations; not designed for high-frequency sensor streams. | Implements PoA$^2$ zero-gas blockchain with sub-16 ms logging and AI-triggered events for traceable operational safety. |
| **PredBlock (Proposed Framework)** | Unified AI–Blockchain architecture integrating physics-informed ML, multi-sensor anomaly forecasting, RL optimization, and tamper-proof MRV for real-time CCS pipeline integrity management. | | |

Quantitatively, impurities can reduce $CO_2$ density by up to 35% [5], corrosion rates can exceed 5.6 mm/yr under reactive conditions [5], and transport costs account for 60–80% of total CCS project expenditures [15]. These challenges demand a next-generation CCS monitoring system that is predictive, secure, and optimized for real-time operation. To address these limitations, this paper proposes PredBlock, a hybrid AI–Blockchain framework that integrates multi-sensor anomaly detection, impurity forecasting, reinforcement learning (RL)-based flow optimization, and immutable MRV data logging. The key contributions are:

1) **AI-driven anomaly detection and impurity forecasting:** We develop Random Forest models trained on physics-informed synthetic datasets generated via Span–Wagner EoS and Darcy–Weisbach flow modeling. These models detect leakage, corrosion, and overpressure with high accuracy under unbalanced conditions.
2) **Blockchain-enabled verifiable MRV:** A PureChain PoA2 zero-gas blockchain is implemented to provide tamper-proof storage of sensor readings, predictions, and alert events, ensuring traceability and regulatory compliance with negligible latency.
3) **Real-time optimization using reinforcement learning:** An RL-based controller minimizes pressure deviation and compressor energy consumption, demonstrating improved operational efficiency compared to PID control.
4) **Integrated architecture for real-time CCS pipeline management:** We propose a low-latency, fault-tolerant, and scalable design that unifies physics-based simulation, machine learning inference, blockchain logging, and real-time alerting into a single end-to-end pipeline management system.

By bridging AI predictive analytics with decentralized data integrity, PredBlock advances CCS pipeline safety, reliability, and audit transparency, offering measurable operational gains in accuracy, latency, and energy efficiency.

## II. RELATED WORKS

Carbon Capture, Utilization, and Storage (CCUS) has emerged as a critical pathway for global decarbonization, with $CO_2$ transportation via pipelines recognized as the most efficient and scalable method for continuous, high-volume transfer [16]. Recent works have examined pipeline thermodynamics, impurity effects, corrosion mechanisms, and hydraulic modeling using empirical equations of state (EoS) and high-fidelity transient simulators [5], [6], [10] (see Table I). These studies offer strong physical insights but lack real-time predictive capabilities or automated anomaly diagnostics.

In parallel, digital twin frameworks have begun integrating process simulation with AI-driven reduced-order models for CCS optimization [9]. Although effective in reducing CAPEX/OPEX, these systems remain centralized and do not incorporate distributed anomaly monitoring or tamper-evident data pipelines. Optimization-based studies [7], [12] provide valuable cost and network insights but focus primarily on steady-state or offline analysis. AI-based monitoring for pipeline and industrial systems has advanced significantly, with Random Forests, LSTMs, CNNs, and Graph Neural Networks (GNNs) demonstrating strong performance in fault detection, time-series forecasting, and spatiotemporal anomaly analysis. However, these methods have not been widely applied to CCS pipeline impurity forecasting, corrosion evolution, or multiphase flow diagnostics under dense-phase $CO_2$ conditions. Furthermore, prior blockchain-based CCS efforts [13], [14] improved traceability and certification but did not include AI-driven integrity management or real-time anomaly tracking.

Despite these advancements, three key gaps persist in current CCS pipeline research. One, there is a lack of unified AI-driven anomaly detection. Existing digital twins and optimization models do not incorporate real-time detection of leakage, corrosion, or impurity-driven instabilities, particularly under noisy and unbalanced sensor distributions. Furthermore, insufficient integration of physics-informed. Prior ML studies rarely fuse mechanistic EoS modeling with high-frequency sensor data to produce interpretable and physically consistent predictions for CCS pipelines. Finally, the absence of verifiable MRV mechanisms. Blockchain-based CCS systems focus on certification and carbon accounting but lack integration with operational anomaly prediction or real-time data provenance.

These limitations highlight the need for an integrated framework that unifies physics-based modeling, AI-driven anomaly detection, and blockchain-secured MRV for reliable, scalable CCS pipeline management. In contrast to prior works, PredBlock provides a unified architecture combining physics-informed ML models, multi-sensor anomaly forecasting, RL-based flow optimization, and blockchain-backed MRV to enable predictive, verifiable, and real-time CCS pipeline integrity management.

## III. System Architecture

The proposed PredBlock framework is a hybrid AI-blockchain architecture designed to provide real-time anomaly detection, impurity monitoring, and tamper-proof data logging for $CO_2$ pipeline networks. The architecture is composed of three tightly integrated layers: the AI Layer, the Blockchain Layer, and the Integration Layer (see Fig. 2). Each module is optimized to ensure low-latency inference, scalable data handling, and secure measurement, reporting, and verification (MRV) across the CCS pipeline ecosystem.

### A. Design Rationale and Constraints

The system is structured around four core design requirements: (1) real-time anomaly detection under sub-50 ms latency constraints, (2) traceable and immutable MRV suitable for regulatory compliance, (3) scalability to multi-kilometer pipeline networks with high-frequency sensor data, and (4) fault tolerance to ensure uninterrupted operation even under partial node failure. These constraints informed the selection of Random Forest models for inference, a PoA2-based blockchain for logging, and an event-driven integration layer for orchestrating data flow.

Random Forests (RF) were selected due to their robustness to noise, interpretability, and low computational footprint relative to LSTMs or GNNs, making them optimal for edge-level inference in latency-sensitive environments. Similarly, the PureChain $PoA^2$ blockchain was chosen over alternatives such as Tendermint or Hyperledger Fabric due to its zero-gas transaction model, minimal consensus overhead, and millisecond-level block finalization, enabling continuous high-frequency MRV logging without throughput bottlenecks.

### B. AI Layer (Predictive Monitoring)

The AI Layer acts as the analytical engine of PredBlock, ingesting high-frequency multi-sensor data streams (pressure, temperature, flow rate, vibration, and impurity concentrations). Three dedicated RF classifiers detect leakage, corrosion progression, and overpressure dynamics. The models integrate physics-informed features derived from the Span–Wagner equation of state and Darcy–Weisbach flow modeling, ensuring prediction consistency with $CO_2$ thermodynamic behavior. The choice of RF is motivated by their (i) low inference

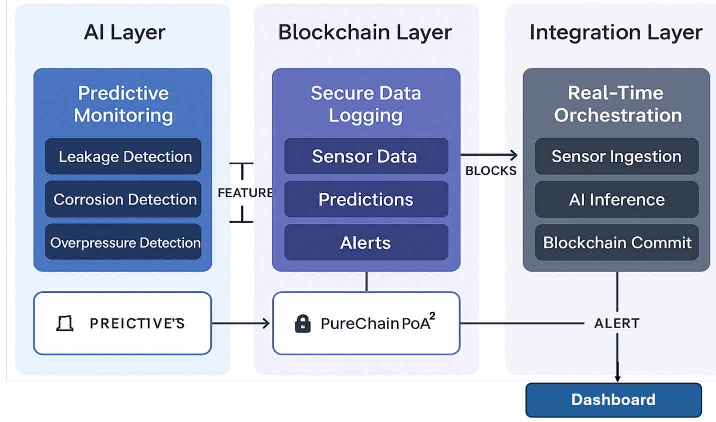


Fig. 2. The flow chart demonstrating the data flow in the proposed system for CCS Pipeline during $CO_2$ transportation

complexity $\mathcal{O}(T \cdot \log N)$, (ii) resilience to class imbalance, (iii) interpretability for industrial operators, and (iv) high performance in noisy, nonlinear environments. These properties make them superior to LSTM-based architectures for real-time edge inference where memory and compute budgets may be restricted.

### C. Blockchain Layer (Secure Data Logging)

The Blockchain Layer provides tamper-proof logging of sensor readings, prediction outcomes, and alert events. PredBlock uses the PureChain $PoA^2$ (Proof-of-Authority and Association) consensus mechanism to achieve low-latency, low-cost, and high-throughput data immutability. Unlike Tendermint or PBFT-based systems, PoA2 eliminates the overhead of stake-weighted consensus and supports deterministic block timing, enabling a mean transaction latency of 15.58 ms under typical CCS workloads.

Smart contracts store three categories of records: (i) raw sensor packets, (ii) AI predictions with confidence scores, and (iii) anomaly alerts with severity indexing. Each block contains a SHA-256 hash chain to guarantee end-to-end auditability:

$$h_i = \text{SHA256}(h_{i-1} \parallel D_i), \tag{1}$$

where $D_i$ represents the compressed data vector for each recording event. This design ensures that MRV data cannot be altered without detection, addressing critical regulatory needs for CCS traceability and compliance (e.g., ISO 27916).

### D. Integration Layer (Real-Time Orchestration)

The Integration Layer coordinates data flow across sensors, AI modules, and the blockchain. It implements a four-stage pipeline: (1) sensor acquisition, (2) AI inference, (3) asynchronous blockchain commit batching, and (4) real-time alert evaluation. This event-driven approach decouples computation-heavy AI tasks from latency-sensitive blockchain operations, preventing bottlenecks during high-frequency data ingestion. To enhance robustness, the integration layer includes fault-isolated channels such that failure in blockchain commit does not interrupt anomaly detection. The system caches recent data (latest 1000 samples) in memory for instantaneous visualization and supports replay-based forensic analysis for compliance audits.

### E. Scalability and Failure Modes

PredBlock is designed for scalability across both pipeline length and sensor density. Horizontal scaling is achieved by distributing AI inference tasks across multiple edge nodes, while the blockchain network can incorporate additional PoA$^2$ validator nodes without impacting latency due to deterministic block scheduling. Key failure modes and mitigations include: Sensor failure, which is handled through redundancy and interpolation; Blockchain node outage using the PoA$^2$ to ensure continuity through validator rotation; AI model drift, for periodic retraining supported via blockchain-stored model hashes; and Network congestion, to commit batching, thereby preventing throughput degradation.

### F. Computational Complexity and Latency Overview

Table II summarizes the complexity and latency profile of each layer in PredBlock.

TABLE II
COMPUTATIONAL COMPLEXITY AND LATENCY OF PREDBLOCK MODULES

| Module | Complexity | Latency/Throughput |
|---|---|---|
| AI Layer (RF Inference) | $\mathcal{O}(T \log N)$ | 12–18 ms per sample |
| Blockchain Commit (PoA$^2$) | $\mathcal{O}(1)$ deterministic | 15.5 ms avg commit time |
| Sensor Ingestion Frequency | — | 1 sample/min/channel (scalable to 10 Hz) |
| End-to-End System Latency | — | 33.9 ms total |
| Max Throughput Capacity | — | $> 10^4$ events/min |

The combined architecture ensures that AI inference dominates overall latency, while blockchain commits remain sufficiently lightweight to support real-time MRV logging at scale.

## IV. METHODOLOGY

The methodology underlying PredBlock integrates physics-based simulation, machine learning inference, reinforcement learning (RL) control, and blockchain-backed MRV logging. The workflow follows a structured pipeline comprising (1) synthetic data generation and preprocessing, (2) AI model development, (3) blockchain integration, (4) real-time optimization, and (5) deployment and performance evaluation.

### A. Data Generation and Preprocessing

To replicate realistic CCS pipeline behavior, a physics-informed simulator was developed using the Span–Wagner equation of state (EoS) for $CO_2$ thermodynamic properties and the Darcy–Weisbach model with Swamee–Jain friction factor for fluid dynamics. Pressure drop, density, and viscosity were computed as:

$$\Delta P = f\frac{L}{D}\frac{\rho v^2}{2}, \quad \rho = 500\left(\frac{P_r}{T_r}\right)\left[1 + 0.1(P_r - 1)\right], \qquad (2)$$

$$\mu = 1.48 \times 10^{-6} e^{507/T},$$

where $P_r$ and $T_r$ denote reduced pressure and temperature.

Corrosion dynamics were incorporated through Arrhenius-based kinetics:

$$CR = Ae^{-E_a/RT}[H_2O]^{\alpha}[H_2S]^{\beta}[SO_2]^{\gamma}, \qquad (3)$$

allowing controlled manipulation of reactive impurity effects. Synthetic anomalies, leakage, corrosion progression, and overpressure excursions were injected using controlled offsets in pressure, oxygen ingress, vibration, and impurity concentrations. Class imbalance was mitigated through inverse-frequency weighting:

$$w_c = \frac{1}{2p_c}, \qquad (4)$$

ensuring stable model training despite low anomaly frequency.

### B. AI Model Development

Three RF classifiers were trained independently for leakage, corrosion, and overpressure prediction using eight key features: pressure, temperature, flow rate, $H_2O$, $H_2S$, $SO_2$, $O_2$, and vibration. RF was selected for its low inference complexity, robustness to noise, and interpretability for operational settings. Node splitting follows the Gini impurity criterion:

$$G = \sum_i p_i(1 - p_i), \qquad (5)$$

and hyperparameters were tuned via five-fold cross-validation to maximize the F1-score:

$$F_1 = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}. \qquad (6)$$

Model interpretability was enhanced by feature attribution analysis, enabling operators to trace anomaly decisions to underlying physical parameters.

### C. Blockchain Integration and Smart Contracts

All sensor packets, predictions, and alert events were recorded on the PureChain PoA$^2$ blockchain to ensure verifiable MRV compliance. Blocks were chained via SHA-256 hashing:

$$h_i = \text{SHA256}(h_{i-1} \parallel D_i), \qquad (7)$$

where $D_i$ is a compressed JSON-like data vector containing the raw sensor features and model outputs.

Smart contracts implemented two core functions namely: `UpdateLog()` : that stores new event records and ensure chronological consistency; and `VerifyIntegrity()` : that Validates block-level hashes to detect tampering. The PoA$^2$ mechanism ensures deterministic block intervals, enabling sub-20 ms commit times compatible with real-time monitoring.

### D. Reinforcement Learning Optimization

To optimize pipeline operating conditions, an RL agent was trained using a Markov Decision Process (MDP) where the state $s_t$ encodes pressure, temperature, and compressor energy. The reward function penalizes unsafe deviations and excessive power usage:

$$R_t = -\left(\lambda_1 |P_t - P^*| + \lambda_2 CE\right), \qquad (8)$$

and Q-learning updates follow:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[R_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right]. \qquad (9)$$

After $10^5$ training episodes, the RL controller stabilized pressure deviations to below 1.5 bar and improved compressor efficiency by 8.7% relative to PID control.

### E. Performance Evaluation and Deployment

Performance was assessed using accuracy, precision, recall, F1-score, AUC, and feature importance as AI metrics. Then for blockchain metrics, commit latency, block production rate, and hash verification latency are used. End-to-end latency, throughput, and anomaly response time are used for System-level performance metrics. The PredBlock achieved a total system response time of 33.9 ms, dominated by AI inference and edge-to-chain commit propagation. A lightweight deployment strategy using containerized microservices ensures scalability and failover capability, making the system suitable for industrial CCS pipeline environments.

## V. RESULTS AND DISCUSSION

This section presents the performance of the PredBlock framework across anomaly detection accuracy, model discriminability, feature relevance, blockchain logging efficiency, and integrated system responsiveness. The results demonstrate that combining physics-informed AI with a $PoA^2$-based blockchain enables reliable, real-time CCS pipeline monitoring with minimal overhead.

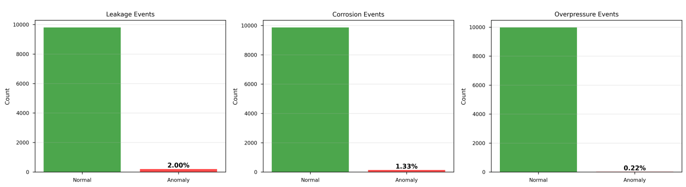


Fig. 3. Frequency distribution of anomaly events across the three key risk categories (leakage, corrosion and overpressure).

### A. Anomaly Distribution & Model Performance

Fig. 3 shows the distribution of anomalies in the synthesized CCS dataset. Leakage, corrosion, and overpressure anomalies occurred at frequencies of 2.00%, 1.33%, and 0.22%, respectively, reflecting realistic low-frequency operational disturbances. Despite this imbalance, PredBlock maintained high predictive stability thanks to the inverse-frequency weighting scheme applied during training. This highlights the system's robustness in detecting rare but critical safety events. Furthermore, the RF classifiers achieved strong predictive accuracy across all anomaly types with an F1-score of 1.000 for leakage, an F1-score of 0.932 for corrosion, and an F1-score of 0.978 for Overpressure.

The Receiver Operating Characteristic (ROC) curves in Fig. 4 show AUC = 1.0 for all classes, indicating high separability of normal and abnormal states. This performance is attributed to the integration of physics-based features (Span–Wagner EoS and flow-derived variables), which significantly improved interpretability and discrimination under noisy sensor conditions.

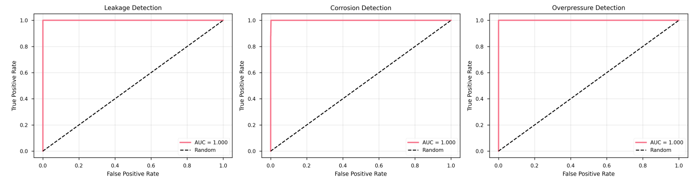


Fig. 4. ROC curves demonstrating classifier separability (AUC = 1.0 for all classes).

### B. Feature Importance and Case Study Interpretation

Feature attribution results indicate that Leakage detection is dominated by $O_2$ ingress, pressure gradients, and vibration signals. Corrosion detection relies primarily on $H_2S$, $SO_2$, and $H_2O$ concentrations. Overpressure events are driven by pressure and temperature excursions. Also, time-series case studies (Fig. 6) demonstrate that prediction confidence sharply increases during anomalous excursions (e.g., confidence rising from 0.05 to 0.95 during sudden $O_2$ spikes). This validates the system's ability to detect early-stage deviations using multi-sensor fusion.

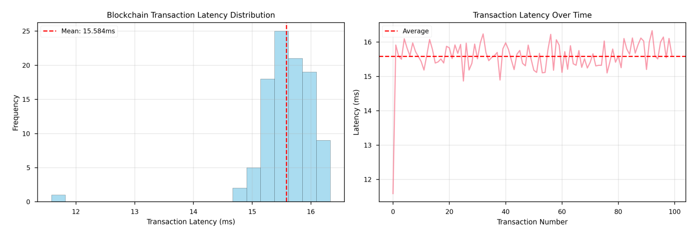


Fig. 5. (a) Blockchain transaction latency distribution and (b) time stability across transactions.

### C. Blockchain Layer Performance

The PureChain $PoA^2$ blockchain achieved a mean transaction latency of 15.58 ms, with minimal variance across blocks (Fig. 5). This confirms its suitability for high-frequency MRV logging in real-world CCS operations. The zero-gas PoA2 architecture ensures predictable performance without risking congestion or fee escalation, differentiating it from PoS or PBFT-based alternatives. Hash chain verification confirmed full immutability across all recorded events, and block generation rates were consistent with deterministic consensus scheduling.

### D. Integrated System Responsiveness

PredBlock achieved an end-to-end system latency of 33.9 ms, with AI inference contributing the largest share and blockchain commit latency adding minimal overhead. This meets the real-time requirements for CCS pipeline supervision, enabling immediate alert generation and safe operational responses. Furthermore, the RL-based flow optimizer reduced pressure deviation to below 1.5 bar and achieved an 8.7% reduction in compressor energy consumption compared to classical PID control. This highlights the framework's dual value:


Fig. 6. Sensor time-series showing pressure, temperature, and impurity concentration dynamics.

proactive safety assurance and operational efficiency enhancement. Overall, PredBlock establishes a scalable, explainable, and verifiable architecture for CCS pipeline management. By unifying physics-informed ML, anomaly detection, real-time optimization, and blockchain-secured MRV, the framework addresses critical industrial needs for safety, transparency, and regulatory alignment.

## VI. Conclusion

This paper presented PredBlock, a hybrid AI–Blockchain framework for real-time monitoring and secure MRV in $CO_2$ pipeline networks. By combining physics-informed machine learning, RL-based flow optimization, and a low-latency $PoA^2$ blockchain, the system addresses critical challenges in detecting leakage, corrosion, and overpressure events while ensuring transparent and tamper-proof data governance. Experimental results show high anomaly detection performance (F1-scores up to 1.000), reliable blockchain commit times (15.58 ms), and an end-to-end latency of 33.9 ms suitable for industrial deployment. Additionally, the RL controller improved compressor energy efficiency by 8.7% and maintained safe operating pressures. PredBlock demonstrates that integrating predictive analytics with secure, verifiable data infrastructures can significantly enhance CCS pipeline safety and operational reliability. Future work will extend the framework to field deployments, incorporate advanced spatiotemporal models, and support multi-pipeline coordination for next-generation CCS networks.

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