

# Smart Water Security with AI and Blockchain-Enhanced Digital Twins

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**Abstract**—Water distribution systems in rural areas face serious challenges such as a lack of real-time monitoring, vulnerability to cyberattacks, and unreliable data handling. This paper presents an integrated framework that combines LoRaWAN-based data acquisition, a machine learning-driven Intrusion Detection System (IDS), and a blockchain-enabled Digital Twin (BC-DT) platform for secure and transparent water management. The IDS filters anomalous or spoofed data using a Long Short-Term Memory (LSTM) Autoencoder and Isolation Forest before validated data is logged via smart contracts on a private Ethereum blockchain using Proof of Authority (PoA) consensus. The verified data feeds into a real-time DT model supporting leak detection, consumption forecasting, and predictive maintenance. Experimental results demonstrate that the system achieves over 80 transactions per second (TPS) with under 2 seconds of latency while remaining cost-effective and scalable for up to 1,000 smart meters. This work demonstrates a practical and secure architecture for decentralized water infrastructure in under-connected rural environments.

**Index Terms**—Digital Twins, Blockchain, Cybersecurity, Artificial Intelligence, Intrusion Detection System, Water Industry

## I. INTRODUCTION

While remote-sensing techniques have proven valuable for water quality monitoring [1], [2], regarding water distribution, efficient distribution is a significant issue in rural regions, especially where infrastructure is poor and digital monitoring is scarce. Many rural parts of Spain still rely on outdated water distribution systems with manual inspections or partially automated tools, leading to delays in problem detection, inaccurate usage data, and increased risks of human error or data manipulation. Implementing a digital twin (DT) can address these challenges by creating a virtual replica of the water network, enabling operators to detect leaks, predict demand, and optimize maintenance scheduling. However, DT systems also face cybersecurity risks, as data may be altered or falsified before reaching the digital model [3], [4].

DT technology is increasingly central to cyber-physical systems. It provides a real-time virtual representation of physical infrastructures, supporting advanced analysis, forecasting, and anomaly detection [5]–[7]. DTs assist utility operators in identifying leaks, pressure irregularities, and unusual consumption patterns. Despite these advantages, ensuring data

security and trustworthiness within DT-based systems remains a significant challenge, particularly in decentralized settings involving multiple stakeholders.

BC technology offers a novel solution for secure data management within online platforms. It ensures decentralized and tamper-proof information storage and verification through Distributed Ledger Technology (DLT), cryptographic security, and consensus mechanisms [4], [8]. Additionally, smart contracts automate tasks like device registration, real-time billing, and fault detection, thus minimizing reliance on intermediaries and increasing accountability [9], [10].

To address these security concerns, our platform incorporates an Artificial Intelligence (AI)-based IDS that identifies anomalous or suspicious data. Only validated and trusted data are forwarded to the BC, where they are securely and permanently stored. Our method integrates LSTM-based anomaly detection and BC technology, ensuring precise, secure, and transparent water management. Without secure, intelligent prediction, water use remains inefficient and decisions are delayed.

This paper presents an integrated DT system supported by BC technology to enhance water distribution management in rural villages in Spain. Data is collected via long-range, low-power LoRaWAN sensors and securely stored on a private BC network, creating an encrypted foundation for the DT. AI and ML techniques enable predictive analytics and anomaly detection, supporting better decision-making and resource optimization. The integration of BC and DT technologies enhances transparency, scalability, and reliability. This cost-effective solution is suitable for rural communities, water utilities, and governmental entities.

The remainder of this paper is structured as follows: Section II reviews related studies on DT and BC applications in water management. Section III describes the proposed framework, including DT architecture, LoRa-based sensor networks, and the integration of a private BC. Section IV evaluates performance, scalability, and security through real-world tests. Section V discusses key findings, challenges, and implications, and concludes by highlighting the contributions and suggesting future research directions aimed at optimizing BC-based DT solutions.

## II. RELATED WORKS

### A. DT in the Water Industry

Recent studies have highlighted the role of DTs as effective tools for enhancing water distribution systems. DT technologies simulate real-time water network behavior, enabling operators to perform leak detection, forecast water consumption, and improve overall maintenance scheduling [5], [11]. For instance, DT platforms have successfully reduced water losses through predictive analytics, proving valuable for improving efficiency and reducing operational costs [6]. However, existing DT implementations often neglect critical cybersecurity considerations, treating data from IoT sensors as inherently trustworthy, which can expose systems to data spoofing and manipulation risks [3].

### B. Security in Water Distribution Systems

The digitalization of water systems introduces increased cybersecurity threats, particularly where IoT devices and wireless sensor networks (e.g., LoRaWAN) are extensively deployed. Kim et al. [?] revealed multiple vulnerabilities, including weak encryption methods, poor authentication practices, and outdated communication protocols, leaving these systems susceptible to unauthorized access, data falsification, and denial-of-service (DoS) attacks. Traditional cybersecurity frameworks for water infrastructure tend to reactively detect breaches only after data has been compromised or corrupted, lacking real-time predictive detection capabilities [13]. Consequently, an urgent need exists for proactive anomaly detection systems integrated seamlessly within digital water infrastructures to protect against threats before data reaches critical operational layers like DTs.

### C. BC Integration in DT

BC technology has been proposed as a viable solution to improve security, transparency, and immutability in DT applications across multiple sectors. For instance, Mohammed et al. [14] employed Hyperledger Fabric to secure IoT sensor data in smart water management systems, demonstrating enhanced trust and traceability. Similarly, MQTT-based BC solutions have successfully provided tamper-proof logging of sensor readings, reducing risks of data loss and falsification [15]. Despite these advances, existing BC-integrated DT frameworks assume incoming data is valid without verifying it, creating vulnerabilities. Teisserenc et al. [16] addressed some limitations by introducing decentralized DT models with smart contracts for automated decision-making, but lacked robust pre-validation mechanisms to ensure data authenticity. Thus, incorporating anomaly detection before BC data storage is essential to ensure data integrity.

### D. AI and ML in IDS for Critical Infrastructure

To overcome limitations of traditional security approaches, AI and ML techniques have become widely adopted for anomaly detection in critical infrastructure, such as energy grids and water systems. Isolation Forest algorithms have successfully identified statistical anomalies in infrastructure

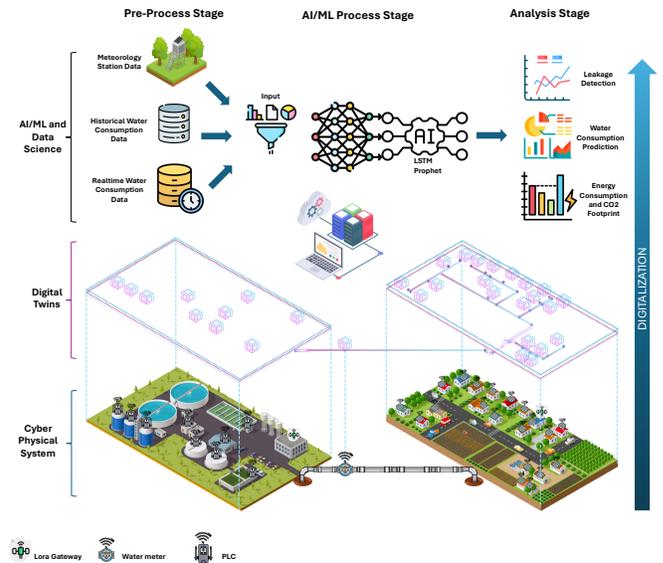


Fig. 1. A Digital Twin Platform in the Water Industry [11]

sensor data, enabling early detection of attacks and faults [8]. Additionally, LSTM Autoencoders have proven effective in detecting temporal anomalies in sequential data, such as abnormal water consumption patterns indicative of leaks or cyberattacks [9], [17]. Nevertheless, existing ML-based IDS solutions are often developed in isolation, lacking integrated deployment within BC-enabled DT frameworks. Furthermore, their evaluation typically occurs under idealized laboratory conditions, without sufficient consideration of intermittent connectivity or rural operational constraints. This research gap motivates the integration of AI-driven IDS within BC and DT ecosystems, specifically addressing rural deployments.

## III. PROPOSED PLATFORM

In this paper, we build on our previous work in the water industry by enhancing the DT system with a stronger focus on security, reliability, and data protection. The DT model proposed in [11] is composed of three main layers (Figure 1): the cyber-physical system (CPS), its digital representation, and an AI-based data analysis and prediction layer. In this updated version, we improve the leak detection process, simplify the identification of data anomalies, and leverage historical data to detect potential cyberattacks and abnormal patterns. To enhance transparency, we integrate a BC system that connects LoRaWAN sensor data to a private Ethereum-based BC. The improved system consists of three key components:

- Leak and unreal detection layer, which processes incoming data and compares it against seasonal trends and long-term average consumption patterns.
- Anomaly and attack detection layer, based on an LSTM model, which prevents out-of-range or incorrect data from being inserted into the BC.

- BC layer, which securely stores validated data from the previous layers on the BC using a dedicated smart contract.

### A. Leakage detection

The first step in ensuring water system integrity involves detecting leaks and unrealistic consumption values based on temporal patterns. The platform uses rule-based logic and thresholding derived from long-term consumption profiles to identify potential leaks, especially during non-usage hours (e.g., 00:00–06:00). The logic assumes that consistent water flow during expected inactivity periods likely indicates leakage. Algorithm 1 summarizes this detection process, which serves as a lightweight filtering mechanism before invoking the AI-based IDS for further validation. Leakage alerts are issued locally and passed to the IDS for anomaly confirmation before BC logging.

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#### Algorithm 1 Leakage Detection and Blockchain Validation

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```

1 Input: LoRaWAN meter data stream  $D$ 
2 Output: Leakage alerts, validated BC records
3 Initialize buffer  $H$ , counters
4 for all  $d \in D$  do
5   Extract hourly data and update  $H$ 
6   Check nighttime (00:00–06:00) consumption
7   Update leakage counter: increment if all  $> 0$ , else reset
8   if counter  $\geq 2$  then
9     Flag leakage; freeze status
10    if next message confirms leakage then
11      Alert consumer
12    end if
13  end if
14  Run IDS on  $d$ 
15  if anomaly detected then
16    Log and reject
17  else
18    Store on BC
19  end if
20 end for

```

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### B. AI-Based IDS for DT

While the BC component guarantees secure and immutable data storage, it does not provide real-time protection against data spoofing, replay attacks, or transaction flooding. To address this, we propose an AI-driven IDS that operates between the data acquisition and BC layers. This IDS employs two complementary models: an LSTM Autoencoder for sequence-based anomaly detection and an Isolation Forest (IF) for statistical outlier detection. Together, they filter out both temporal and point-wise anomalies in water meter data received via LoRaWAN before storing it on the BC.

1) *Design and Threat Model:* The IDS is designed to detect and block:

- *Spoofed data:* Manipulated readings with plausible structure but inconsistent behavior.
- *Replay attacks:* Repetition of legitimate data to flood or mislead the system.
- *Outliers:* Abnormally high consumption, unexpected error codes, or gas usage irregularities.

While smart contracts verify sender identity and enforce structural rules, they cannot detect logical inconsistencies. The

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#### Algorithm 2 Combined LSTM and Isolation Forest IDS

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```

1 Input: Trained LSTM model  $\mathcal{M}$ , trained IF model  $\mathcal{F}$ , thresholds  $\tau, \theta$ 
2 For each meter: maintain buffer  $\mathbf{X}_m$  of size  $N$ 
3 for all incoming event  $e_t$  do
4   Extract feature vector  $\mathbf{x}_t$  and append to  $\mathbf{X}_m$ 
5   Compute IF anomaly score:  $s \leftarrow \mathcal{F}(\mathbf{x}_t)$ 
6   if  $s > \theta$  then
7     Raise anomaly alert (Isolation Forest)
8     Reject record and log the incident
9   else if  $|\mathbf{X}_m| = N$  then
10     $\hat{\mathbf{X}}_m \leftarrow \mathcal{M}.decode(\mathcal{M}.encode(\mathbf{X}_m))$ 
11    Compute reconstruction loss  $\mathcal{L}_{recon}$ 
12    if  $\mathcal{L}_{recon} > \tau$  then
13      Raise anomaly alert (LSTM Autoencoder)
14      Reject record and log incident
15    else
16      Accept and forward to BC
17    end if
18    Remove oldest vector from  $\mathbf{X}_m$ 
19  end if
20 end for

```

---

IDS addresses this gap through both statistical and temporal pattern learning.

2) *Feature Engineering:* The IDS continuously processes incoming real-time data streams from LoRaWAN sensors and BC logs. For each new record, a feature vector is constructed as:

$$\mathbf{x}_t = [\text{WaterUsage}_t, \text{ErrorCode}_t, \text{TxRate}_t, \text{GasUsed}_t] \quad (1)$$

For the LSTM model, a sequence of  $N$  such vectors is maintained per meter:

$$\mathbf{X}_m = \{\mathbf{x}_{t-N+1}, \dots, \mathbf{x}_t\} \quad (2)$$

3) *LSTM Autoencoder Architecture:* The LSTM autoencoder learns to reconstruct sequences of normal behavior. It encodes a sequence into a latent representation and reconstructs it, allowing anomaly detection via reconstruction error:

$$\mathcal{L}_{recon} = \frac{1}{N} \sum_{i=1}^N \|\mathbf{x}_i - \hat{\mathbf{x}}_i\|^2 \quad (3)$$

If  $\mathcal{L}_{recon} > \tau$ , where  $\tau$  is a predefined threshold, the sequence is flagged as anomalous.

4) *Isolation Forest Outlier Detection:* To complement the LSTM, we use an Isolation Forest trained on individual features to detect non-sequential outliers [18]. Given a new observation  $\mathbf{x}_t$ , the IF model returns an anomaly score  $s(\mathbf{x}_t)$  based on how easily the point is isolated in the tree ensemble. An alert is raised if:

$$s(\mathbf{x}_t) > \theta \quad (4)$$

where  $\theta$  is the anomaly threshold determined during training.

5) *Real-Time Detection Algorithm:* The detection process operates in real time using a sliding window buffer and event-based triggers from smart contracts. A record must pass both LSTM-based sequence analysis and IF outlier detection before being accepted.

## Blockchain Platform

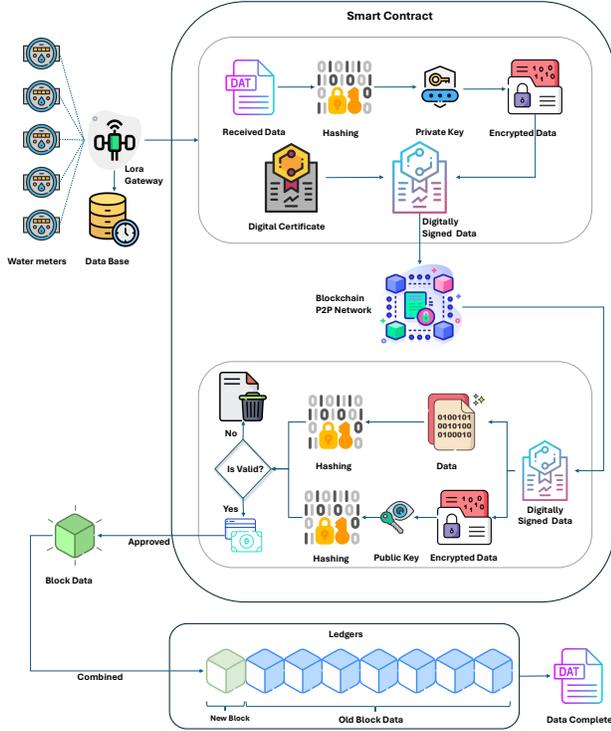


Fig. 2. Proposed Smart contract for DT platform

6) *Integration with Blockchain:* The IDS listens to smart contract events (e.g., *WaterDataLogged*) via Web3 interfaces and buffers incoming records accordingly. Its output dictates whether the data is stored on the BC or discarded. Optional logging of detected anomalies on-chain can improve transparency, support audits, and train future models. The IDS layer is modular and can be deployed alongside any BC network or smart contract design, ensuring seamless integration and compatibility with decentralized infrastructures.

### C. BC

Figure 2 illustrates the smart contract structure used in the proposed platform. This contract handles essential functions such as meter registration, secure logging of consumption data, and automatic transaction processing. Specifically, the contract defines a ‘*WaterData*’ structure that records the timestamp, water usage, error codes, and associated meter IDs. Functions such as *registerMeter()*, *logWaterData()*, and *calculatePayment()* are designed to enforce access control, validate data, and automate billing based on consumption and error codes, as detailed in Algorithm 3.

In parallel, Figure 3 presents the core technologies involved in the BC layer. This includes the use of a private Ethereum network with a PoA consensus model, which ensures fast finality and minimal energy consumption, particularly suitable for edge computing scenarios in rural environments. The integration of DTs with smart contracts enables not only secure

## Algorithm 3 DT and BC Smart Contract

```

1  Contract VillageWaterSystem
2  Struct WaterData: uint256 timestamp, waterUsage, errorCode; string meterId
3  address owner; mapping(string => WaterData[]) waterLogs; string[] registeredMeters
4  Event MeterRegistered, MeterDisabled, WaterDataLogged, PaymentProcessed
5  function ONLY_OWNER
6  Require(msg.sender == owner, "Unauthorized")
7  end function
8  function CONSTRUCTOR VILLAGEWATERSYSTEM
9  owner ← msg.sender
10 end function
11 function REGISTERMETER(string meterId)
12 Require(meterId != empty, "Invalid ID")
13 registeredMeters.push(meterId); Emit MeterRegistered(meterId)
14 end function
15 function DISABLEMETER(string meterId)
16 Require(meterId != empty, "Invalid ID")
17 Remove from registeredMeters; Emit MeterDisabled(meterId)
18 end function
19 function LOGWATERDATA(string id, uint256 u, uint256 e)
20 Require(isMeterRegistered(id), "Unreg.")
21 Require(e < 100, "Invalid err")
22 Store in waterLogs[id]; Emit WaterDataLogged(id, u, e)
23 p ← calculatePayment(u, e); Emit PaymentProcessed(id, p)
24 end function
25 function ISMETERREGISTERED(string id) returns bool
26 Return (id in registeredMeters)
27 end function
28 function CALCULATEPAYMENT(uint256 u, e) returns uint256
29 Return u * 1 ether * ((e > 80) ? 1 : 2)
30 end function
31 function GETWATERLOGS(string id) returns WaterData[]
32 Require(isMeterRegistered(id), "Unreg.")
33 Return waterLogs[id]
34 end function
35 function GETREGISTEREDMETERS returns string[]
36 Return registeredMeters
37 end function
38 function SETBASERATE(uint256 r) onlyOwner
39 Require(r > 0, "Invalid rate")
40 end function

```

## Technologies Platform

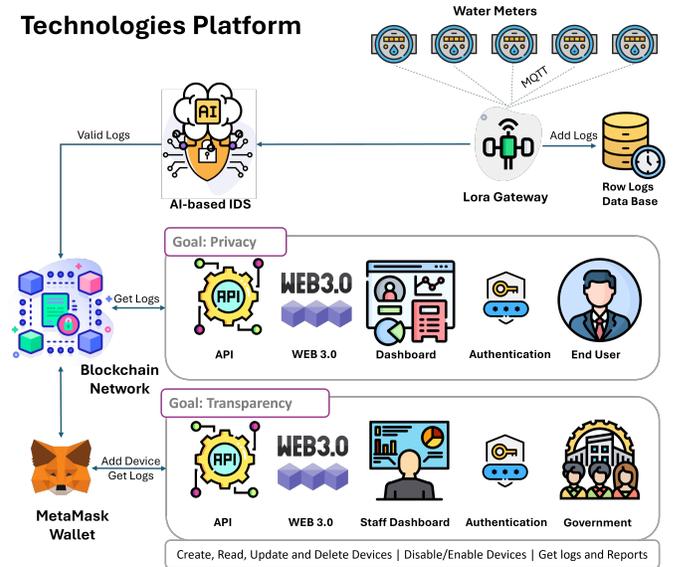


Fig. 3. Technologies in the Platform on the BC side

data storage but also autonomous system behavior, reducing reliance on central servers or human intervention. By combining BC, DT, and AI-driven verification mechanisms, the platform offers a scalable, transparent, and resilient solution for water resource management in under-connected areas.

## IV. EVALUATION

This section presents a practical evaluation of the proposed framework under conditions typical of rural Spanish villages. We assess system-level performance—including throughput, latency, and scalability—as well as security and deployment cost. A private Ethereum blockchain with PoA consensus was

deployed on a dedicated Hetzner server, and a LoRaWAN metering environment was used to emulate real-time consumption data. The evaluation includes analysis of the hardware/software setup, network topology, anomaly detection, tamper resistance, and cost-efficiency.

### A. Leakage Detection Results

To verify the effectiveness of the leakage detection mechanism, we analyzed historical water meter data from 400 devices deployed across rural locations for last three years. The detection algorithm flagged meters with non-zero night consumption over consecutive days, suggesting probable leaks.

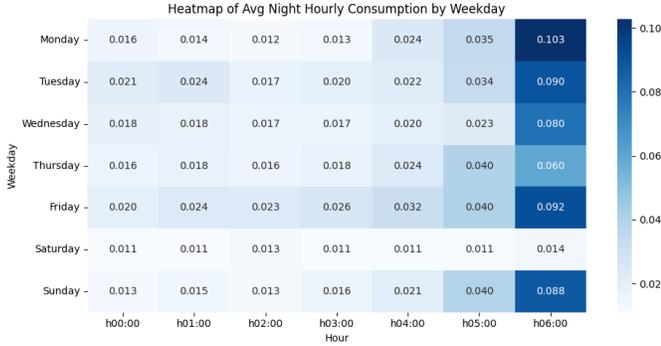


Fig. 4. Night consumption Hitmap for a water meter with leakage

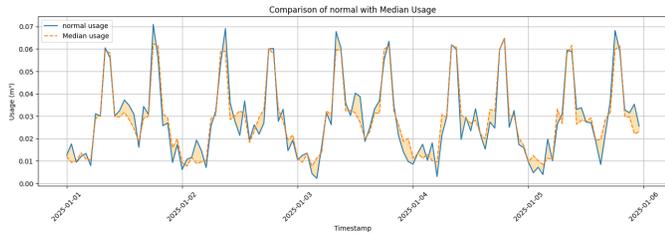


Fig. 5. Comparison Normal and Median usage

Figure 4 shows a heatmap of night-time water consumption (00:00–06:00) for a leaking meter, where consistent activity was detected. Figure 5 compares normal consumption patterns to the median usage, highlighting that anomalies often deviate from expected seasonal or diurnal trends. Additionally, Figure 6 aggregates the night usage across all flagged meters, reinforcing the accuracy of the detection logic.

### B. Anomaly Detection Result via IDS

The system was evaluated using real-world water consumption data injected with synthetic attacks. Figure 7 shows a direct comparison between a normal consumption pattern and an anomalous one. The sample line represents typical usage behavior, while the pattern line reveals injected anomalies, such as abnormal spikes and repeated low-consumption values that mimic night-time leakage or spoofed records.

To further emphasize deviations, Figure 8 plots the detected anomalous consumption values against the meter’s typical

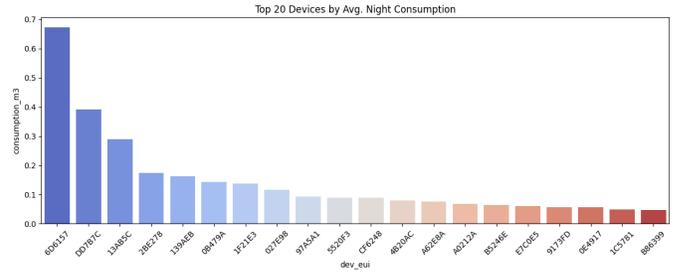


Fig. 6. Leaked meters and their consumption during nights

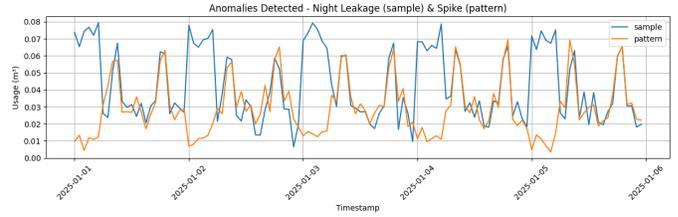


Fig. 7. Anomalies Detected: Comparison of Night Leakage (sample) and Spike Patterns

median usage. The sharp divergence observed during the attack period clearly demonstrates how the IDS identifies data points that deviate significantly from normal patterns while maintaining temporal consistency.

Figure 9 presents a heatmap comparing the IDS performance metrics—Precision, Recall, and F1-Score—for each type of attack. This visual summary is consistent with the quantitative results shown in Table I, highlighting the IDS’s effectiveness across diverse anomaly types.

TABLE I  
ANOMALY DETECTION RESULTS OF THE HYBRID IDS

Attack Type	Injected	Detected	Precision	Recall	F1-Score
Replay Attack	120	112	0.93	0.93	0.93
Spoofed Consumption	100	97	0.91	0.97	0.94
Tampered Error Codes	80	76	0.89	0.95	0.92
Gas Usage Anomalies	70	64	0.91	0.91	0.91
<b>Overall</b>	<b>370</b>	<b>349</b>	<b>0.91</b>	<b>0.94</b>	<b>0.92</b>

### C. Experimental Setup BC

#### • Hardware and Software Configuration:

The proposed framework was deployed on a Hetzner server running a private Ethereum network with a PoA

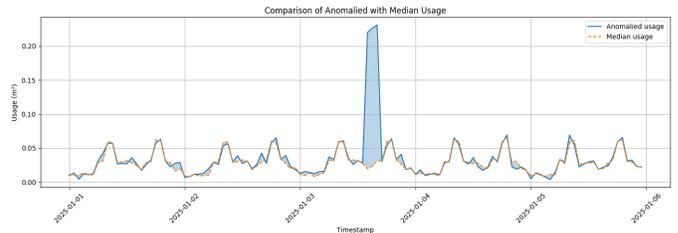


Fig. 8. Detected Anomalies Compared with Median Usage Baseline

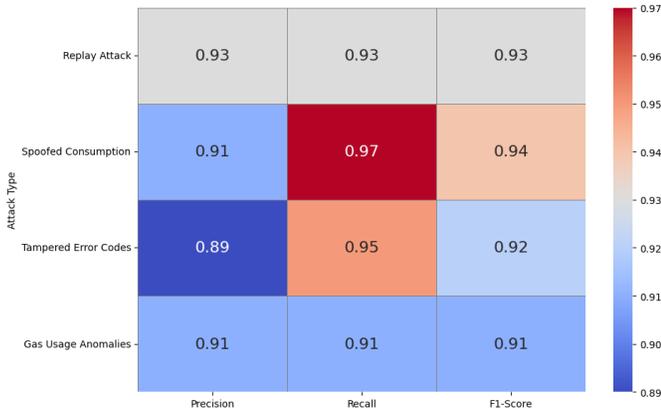


Fig. 9. Heatmap of Precision, Recall, and F1-Score per Attack Type

consensus mechanism. Three validator nodes operated via Docker containers to simulate on-chain validation. Meter data from 400 emulated LoRaWAN devices was batched and submitted in 8-hour intervals. Prometheus and Grafana were used for monitoring. The setup reflects real-world rural conditions, tolerating intermittent connectivity while ensuring secure, scalable, and low-latency operation.

- **Network Topology:**

- *Validator Nodes:* Each validator node runs with a 1-second block interval and a block gas limit of 15 million—settings that enable higher throughput and faster transaction finalization than default Ethereum configurations. We deployed three validator nodes on the same Hetzner dedicated server, each operating in its own Docker container. The nodes communicate over a secure internal network and use static peer discovery to maintain connectivity and validate on-chain transactions.
- *LoRaWAN Gateway:* Meter data is transferred to the BC through a replicated LoRaWAN gateway that aggregates sensor data every 8 hours. It then batches these readings into transactions before submitting them on-chain, ensuring any intermittent connectivity does not result in data loss.

- **Water Metering Scenario:** In our test scenario, we emulate the behavior of 400 water meters installed across multiple rural areas. Each meter is configured to capture the following data at 8-hour intervals:

- Meter ID
- Timestamp
- Water Consumption (in cubic metres)
- Error Code

Each meter transmits its data three times per day to account for potential downtime or connectivity issues. This setup reflects the actual operational conditions in remote Spanish villages, where consistent Internet access cannot always be guaranteed.

#### D. Performance and Scalability

In this section, we present the results of our performance analysis and scalability tests for the proposed BC-based DT framework. We aim to demonstrate that the system can process meter readings efficiently, maintain low transaction latency, and scale to accommodate an increasing number of water meters.

- **Transaction Throughput and Latency:**

To evaluate the performance of the BC network, we focused on two core metrics:

- *TPS's Throughput:* The number of successfully confirmed transactions per second.
- *Transaction Latency (Seconds):* The time interval between the client submitting the transaction and its final confirmation on-chain.

We conducted a series of stress tests by varying the batch sizes (i.e., how many meter readings are grouped into a single on-chain transaction). This approach allowed us to evaluate the system's behavior under different data aggregation strategies—especially relevant for rural deployments where intermittent connectivity may lead to buffered uploads.

The Mean Latency in Table II refers to the time from when a transaction is submitted to its first inclusion in a block. Finality in our PoA setup typically arrives 1–2 blocks after inclusion, corresponding to an additional 2–3 seconds under typical loads.

TABLE II  
TRANSACTION THROUGHPUT AND LATENCY UNDER DIFFERENT BATCHING CONDITIONS

Batch Size	Meters Tested	Throughput (TPS)	Mean Latency (s)	Max Latency (s)
1 reading/tx	400	110	1.2	2.1
5 readings/tx	400	96	1.5	2.4
10 readings/tx	400	89	1.7	2.8
20 readings/tx	400	81	2.1	3.5

*Observations:*

- As the batch size increases, throughput decreases slightly, attributable to larger transaction payloads requiring more on-chain processing time.
- Latency grows proportionally with the batch size. However, even at 20 readings per transaction, the network sustains an average throughput of 81 TPS with a mean latency of around 2 seconds.
- These results indicate that our PoA network can efficiently handle data bursts from hundreds of meters, making it suitable for real-world deployments where large numbers of sensors may periodically transmit readings.

- **Block Finalization:**

Using a PoA consensus mechanism provides faster block finalization times compared to traditional Proof of Work (PoW) networks. Our experiments show that blocks are typically finalized within **2–3 seconds** under the tested workloads. This quick finality has two primary benefits:

- 1) *Timely Data Recording*: Water consumption data are confirmed on-chain almost immediately, enabling near real-time monitoring within the DT environment.
- 2) *Predictive Maintenance*: Rapid confirmation aids anomaly detection algorithms in swiftly identifying irregularities (e.g., leaks or sensor malfunctions), reducing response times and potential water losses.

Such short block finalization intervals are particularly valuable for rural water management, where operators rely on accurate, up-to-date information to schedule maintenance tasks, plan usage patterns, and optimize resources.

- **Scalability with Increasing Meter Count:**

To assess how the system behaves under a growing number of sensors, we conducted additional tests by gradually scaling the number of simulated meters from 100 to 1,000 while holding the transaction batch size at five readings per transaction. Across these tests:

- The network maintained a throughput greater than 85 TPS in all experiments, even as the meter count increased by an order of magnitude.
- System latency showed minimal growth, reinforcing the notion that the PoA-based framework scales well with increased demand.
- These results underscore the system’s potential to extend to larger water distribution networks without significant performance degradation, making it suitable for both small rural communities and larger municipal deployments.

### E. Security and Reliability

Security and reliability are central pillars of any data management solution for critical infrastructure like water distribution. BC’s immutable ledger and PoA-based access controls work together to ensure that the system is tamper-resistant and fault-tolerant. Below, we detail the measures taken to protect against unauthorized modifications and to maintain network reliability.

- **Data Immutability and Tamper Resistance:**

One of the chief advantages of a BC-based solution is the *immutability* of on-chain records. We conducted targeted tests to confirm that malicious attempts to alter data or inject bogus information would be rejected:

- *Direct Database Manipulation*: We tried modifying the raw on-chain data files stored in the local node’s directory. The PoA consensus nodes detected mismatched hashes, invalidating the altered data.
- *Smart Contract Override*: We attempted to call special administrative functions like *logWaterData* and *disableMeter* without proper credentials. These calls were blocked by role-based access controls enforced at the smart contract level.
- *Spurious Node Injection*: We introduced a rogue node with a manipulated ledger history, which the

existing validator nodes refused to add to the network.

Table III summarizes the outcome of these tests:

TABLE III  
TAMPER-RESISTANCE TEST RESULTS

Attempted Attack	Result
Direct on-disk data modification	Rejected (immutable ledger)
Unauthorized smart contract invocation	Rejected (access control)
Rogue validator introduction	Blocked (PoA authority management)

All unauthorized modifications were invalidated by the network’s consensus protocol, confirming that meter data remains tamper-proof once recorded on-chain. This reliability is crucial for building trust among municipalities, local water authorities, and end-users.

- **Access Control and Authentication:**

Access control is enforced via smart contracts. Before a meter can submit data, it must be registered on-chain by an authorized administrator. We tested unauthorized submissions to assess whether the system would correctly reject them:

- *Fake Meter ID*: A transaction with an unregistered meter ID triggered an immediate rejection in the *isMeterRegistered* function.
- *Valid Meter ID, Incorrect Credential*: If the transaction was signed by a private key not recognized by the PoA nodes, the network discarded the transaction before it reached the contract logic.

These findings confirm that the framework effectively prevents unauthorized data entries and ensures only valid meter readings are integrated into the DT environment.

- **Network Reliability in Rural Deployments:**

Rural Spanish villages often face intermittent Internet connectivity. Our solution, therefore, tolerates temporary offline periods without losing data integrity. We simulated a scenario with a 2-hour daily connectivity loss over a week:

- The LoRaWAN gateway buffered the readings until the BC node was reachable.
- Upon reconnection, the pending transactions were submitted in batches.
- No BC reorganization occurred, as the PoA validators incorporated the newly arrived batches without conflict.

This experiment demonstrates the system’s resilience, confirming that brief outages do not compromise the integrity or completeness of stored data. Such robustness is essential for real-world deployments where continuous high-speed Internet is not always available.

### F. Cost Analysis

Although public BCs typically require gas fees for each transaction, our private PoA network could be configured to impose negligible or zero gas costs, significantly reducing financial overhead for municipalities. Our PoA nodes are

hosted on a dedicated Hetzner server, with monthly costs ranging between €20 and €50, depending on the chosen plan. BC maintenance is also cost-effective, as PoA consensus eliminates CPU-intensive mining tasks, and validator nodes have minimal resource requirements beyond basic computation and storage. In terms of network traffic, LoRaWAN-to-BC communications incur only minor data charges, while on-chain transaction fees can be set to near zero, avoiding high per-transaction costs. The system’s scalability ensures that adding additional meters does not significantly increase operational expenses since the same validator nodes can efficiently handle larger data volumes within tested limits. Furthermore, the architecture’s linear scalability ensures that even large-scale deployments remain affordable. Table IV provides an approximate breakdown of costs for a six-month pilot project, excluding expenses related to physical LoRaWAN gateways or sensors, which vary based on specific deployment needs.

TABLE IV  
COST ESTIMATION BREAKDOWN IN A 6-MONTH PILOT

Component	Cost (EUR)	Notes
Server Rental (6 months)	120–300	Depends on hosting plan
Maintenance	~50	Occasional reboots, software updates
Energy	Included	Covered by hosting service
LoRaWAN Gateways	Variable	Based on deployment size and hardware choice
On-chain Gas Fees	Near-zero	PoA network with custom gas price

Overall, this PoA-based BC solution is cost-effective for municipalities of varying sizes, especially when compared to traditional centralized data management systems that may involve higher maintenance and licensing fees.

## V. CONCLUSION

This paper introduced a Blockchain-based Digital Twin (BC-DT) framework that combines a private PoA Ethereum blockchain, LoRaWAN sensors, and a hybrid Intrusion Detection System using LSTM Autoencoder and Isolation Forest to enhance the security and reliability of rural water distribution systems. The proposed system enables real-time anomaly detection, secure data logging via smart contracts, and supports transparent, decentralized monitoring. Evaluation results demonstrated strong performance with over 80 TPS, low latency, tamper resistance, and cost-effective scalability across 1,000 smart meters. The architecture is resilient to intermittent connectivity and adaptable to rural infrastructure constraints. Future work will explore enhancements such as federated learning for decentralized model training, dynamic pricing via smart contracts, and energy-efficient scaling to urban and industrial settings.

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