

# An Energy-Efficient Timestamp-Based Data Reduction and Blockchain Storage Framework for Environmental Monitoring

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## Abstract

Environmental monitoring systems for remote areas and areas with limited resources are constantly generating large volumes of time-series sensor data, resulting in excessive energy consumption, storage overhead and scalability issues. Traditional static and event-driven sampling techniques are likely to yield redundant information, reducing operational sustainability and efficiency. To address the above-mentioned limitations, the present study proposes a novel framework, Adaptive Time-Based Data Reduction with Blockchain (ATDR-BC), which combines dynamic timestamp-based data sampling, Isolation Forest-based anomaly detection, and Merkle Tree-enabled decentralised storage. The proposed framework is an intelligent way to adjust sampling intervals based on environmental stability, without compromising critical anomaly detection or tamper-resistant data integrity in a hybrid on-chain/off-chain blockchain model. Experimental evaluation based on actual environmental sensor data shows that ATDR-BC can achieve an average data reduction rate of 45-60%, and the maximum data reduction rate is 70% under stable conditions. The approach leads to 35-50% reduction in energy consumption compared to conventional sampling methods with high reconstruction accuracy (96.59%) and RMSE values that are smaller than 5%. These results confirm that ATDR-BC provides a good balance between energy efficiency, data reliability and storage optimisation and can be used for applications involving long-term deployment in remote and resource-limited applications such as environmental monitoring.

**Keywords:** Isolation Forest, Anomalies, Data Storage, Energy Consumption, Stability, Hybrid Model, Data Reduction.

## 1 Introduction

The organized gathering of information about temperature, humidity, the composition of the air, and air pressure and their rigorous analysis require environmental control systems. These systems have provided the basis for their application to environmental change monitoring, to meteorological forecasting and for the assessment of climate impacts. In recent years there has been widespread implementation of

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Environmental Monitoring Systems (EMS) in remote and rural locations, which are often battery powered or other limited power sources. Therefore, Maximising energy consumption and storage has become an important factor in ensuring long-term system reliability and sustainability.

In order to mitigate this limitation, various data reduction techniques using timestamps have been proposed as one method to reduce this limitation. These methods are selective in storing the sensor readings taking in account the temporal trends and stability of the environment and hence they avoid unnecessary transmission of the data. Timestamp-based methods also save a lot of energy by transmitting only meaningful data or time-sensitive, and keeping the information accurate. Earlier research has shown that the introduction of the timestamp-based plans into energy consumption models improves the sustainability of monitoring systems in the long term.

A growing literature has suggested diverse environmental monitoring frameworks through the use of the IoT. Moise et al., (2022) developed a research-based system using wireless sensor network in research facilities in their study whereby, the researchers focused mostly on real time monitoring and control. Chong et al., (2023) have suggested an IoT-based climate control system, which allows growing mushrooms and enhances productivity with the help of automated monitoring. Hassan et al., (2020) designed a generalised monitoring framework, which involves the application of machine learning to analyse data and make a decision.

Laha et al., (2022) argue in their article is an extensive review of how the IoT-based environmental monitoring systems work, and the problem statement is the data security, sensor reliability, and network connectivity. In the article, Zafar et al., (2018) proposed an inexpensive Arduino and cloud computing-based monitoring system that can be used to monitor homes and farms. In a similar vein, Mörth et al., (2020) established the effectiveness of the IoT-based solution to monitor the situation in an industrial production environment, which highlights the possibility of Optimising and improving the quality of resources.

Irrespective of these developments, majority of the present systems have created bulky amount of time series information thereby causing unnecessary power usage and storage wastage. The regular surveillance and communication would amount to poor utilisation of limited power resources. In a bid to address this weakness, researches on optimisation and prediction techniques (Natarajan, 2023; Rajasekaran & Priyadarshini, 2021) have been the core of adaptive data reduction techniques. Also, Alenazi, (2024) has stressed the importance of energy management systems that are founded on IoT in realisation of smart and sustainable use of energy.

The increasing amount of environmental information is a serious challenge for traditional storage systems. The centralised repositories have certain limitations such as scalability issues, vulnerability to cyber-attacks, high maintenance costs and the risk of data corruption. Such type of constraints impact system reliability, particularly when used in a system that monitors mission-critical systems. In turn, in order to protect environmental data, increasing requirements are being placed on secure and decentralised storage mechanisms. Blockchain technology has been suggested as a possible solution for decentralised and tamper-resistant data storage. Blockchain ensures data integrity, transparency, and traceability with the help of Merkle trees and cryptographic hashing. However, direct on-chain storage of sensor data generated by sensors at scale is not efficient and cost-effective. Thus, it is necessary to combine blockchain with off-chain storage and data reduction methods to reduce the overhead.

In this paradigm, in this research paper, a composite model is proposed that includes data reduction based on timestamp, decentralised storage, blockchain. The proposed solution would greatly reduce unnecessary data transmission and give access to the secure and non-modifiable storage of crucial

environmental information. Timestamp-based methods to reduce data volume Blockchain to authenticate data using cryptographic verification of metadata and hash values.

The overall purpose of this study is to develop and test an optimised model of energy consumption which is likely to result in the lowered cost of data storage and transit without compromising the quality of information. The proposed framework reduces the system maintenance costs, minimises the acquisition of unnecessary data, and help increase the availability of decentralised storage systems making them more durable and efficient. The integrated method is particularly suitable for environments with limited resources and remote locations for environmental monitoring, where energy saving and data credibility are very important.

### **Organisation of the Paper**

The rest of this paper has the following structure. Key Contributions and Objectives of the Study have been presented in Section 2 above. Section 3 summarizes the related literature and the need for future research. Section 4 presents the proposed ATDR-BC framework which includes the system architecture, the data set characteristics, the preprocessing procedures, the algorithm design and the mathematical formulation. Section 5 is about the integration of blockchain and a secure storage mechanism. The experimental results and performance evaluation are presented in Section 6. Section 7 is a detailed discussion of the findings, and followed by limitations in Section 8. Finally, Section 9 concludes the paper by identifying directions for future research.

### **Key Contributions**

The key contributions of this research are summarised as follows:

- An original Adaptive Time-Based Data Reduction with Blockchain (ATDR-BC) scheme is suggested for environmental monitoring that is energy-efficient.
- By using a dynamic sampling scheme, which is based on time, we build a strategy that will lower the amount of redundant sensor data in the case of stable environmental situations.
- A mechanism of anomaly detection that uses Isolation Forest is incorporated to save essential environmental events.
- To achieve the integrity of data, a blockchain-based decentralised model of storage with the usage of Merkle Trees is used.
- The evaluation of the performance is done comprehensively based on various metrics such as data reduction ratio, energy saved, accuracy, RMSE and transmission overhead.
- To study the effect of various components of the algorithm on the performance of the system, an ablation study is conducted.

### **Objectives of the Study**

The primary objectives of this research are:

- to design an adaptive timestamp-based data reduction framework for environmental monitoring systems,
- to minimise energy consumption and storage overhead without compromising data quality,
- to preserve critical environmental events using anomaly detection,
- to ensure secure and tamper-resistant storage using blockchain and Merkle Tree structures, and

- to validate the effectiveness of the proposed framework through a comprehensive performance evaluation.

## 2 Literature Survey

Several research has been conducted studies data reduction techniques of dealing with the increasing volume and complexity of sensor-based data. Fernandes et al., (2024) discussed various approaches for data reduction with experimental testing of the methods to identify their practicality and limitations. Their results are very useful to practitioners since they outline the merits and demerits of different techniques in reducing the data management overheads. Similarly, Pioli et al., (2022) gave a detailed overview of data reduction techniques for IoT systems with a particular focus on edge computing. The authors have proposed a systematic taxonomy to classify the existing techniques in terms of processing location, data properties, and application needs and give systematic understanding of edge-level data management. Time-series pre-processing has also received a lot of interest.

Tawakuli et al., (2025) have presented a comprehensive review of the preprocessing techniques such as noise elimination, normalisation and missing data processing. Through their empirical results, the importance of enabling reliability and functionality of future data-reduction and analytics models through preprocessing was highlighted. Such works prove that it is important to prepare sensor data before compressing or reducing the data with algorithms.

Mathias et al., (2021) examined distance-based techniques of data complexity reduction for compression of sensor data and fault diagnosis. They employed similarity metrics to improve data organisation and improve the accuracy of defect predictions. Goodwin et al., (2022) investigated temporal instability and time errors in clinical data and demonstrated how timestamp errors can have a great impact on analysis results. Even though they were carried out in a healthcare setting, their results highlight the importance of proper temporal information in any time series monitoring system.

There is a voluminous amount of research on energy management and IoT systems based on the cloud. Ch et al., (2024) focused on cloud-based IoT sensor-data retrieval for efficient data power management. They proved that integration of clouds helps better energy consumption monitoring and control. Their findings support the assumption that time series analytics and cloud computing technology can improve optimisation of energy. Indumathi et al., (2020) proposed Dynamic Storage and Intelligent Energy Efficiency (DSIEE), which is a combination of flexible storage management and energy-saving mechanisms. Their approach reduced storage requirements and increased the efficiency of the devices, which helped to continue operating IoT devices.

Kim & Jung, (2019) propose a mechanism for smart sensing-period adjustment to actually adjust dynamically the data-sampling period, considering the network conditions and energy availability. This adaptive sensing scheme attains a much lower energy consumption with good data reliability. On the same note, Suryavansh et al., (2021) suggest a data-driven approach toward extending the lifetime of IoT sensor nodes based on historical data and analysis using predictive modelling, which result demonstrates that smart data analysis can be used to reduce unnecessary power consumption cost and enhance the lifetime of the system.

Storage based on block chain has got a fresh interest with late as safe alternative to a centralised repository. The model introduced by Si & Niu, (2023) deals with data-availability and storage-scalability issues of blockchain based systems, with major emphasis on the nexus of redundancy and accessibility. Their work describes the design of scalability mechanisms that do not restrict the availability of data. Heo et al., (2024) describe in detail the approach of storage optimisation for Blockchains and compare

the trade-offs between security, decentralization, and scalability. They cite the storage overhead and computational cost as issues in the large scale blockchain implementations.

As a result, there is a research gap in terms of developing a unified framework to combine the information about timestamp reduction, energy sensitive adaptation and compact blockchain storage. The proposed ATDR-BC model will address this need by integrating adaptive sampling, anomaly detection and the use of a Merkle-tree-based decentralised storage mechanism, making it possible to ensure adequate data management, reduced energy consumption and immaculate data integrity, thus meeting the long-term requirements of applications in environmental monitoring.

### Research Gaps and Inference

Based on the reviewed literature, it is possible to state that the current state of research focuses mostly on data reduction energy optimisation or blockchain storage in isolation. Minimal efforts have been made in the combined models to ensure efficient energy consumption, high data preciseness and decentralisation of security. In addition, most methodologies are based either on statistical or event-driven sampling, which is not a good method for long-term environmental stability. Also, a limited number of studies take into account the anomaly-detection mechanisms to reduce rare and critical environmental events in the data. On-chain storage of data is often an added overhead on blockchain-based solutions.

Thus, a research gap in developing a unified, adaptive and lightweight structure that incorporates timestamp-based reduction, anomaly preservation and off-chain blockchain storage exists. The proposed ATDR-BC model overcomes this limitation by using adaptive sampling, machine learning-based anomaly detection and the concept of Merkle Trees for decentralised storage which enhances the overall efficiency and reliability of the system. The ATDR-BC framework proposed resolves these limitations by combining adaptive sampling, machine learning-based anomaly detection and Merkle Tree-based decentralised storage, which contributes to the efficiency and reliability of the system.

### System Architecture

The developed timestamp-based storage model is based on the environmental sensor’s dataset (Luis Enrique, 2023), which includes the parameters such as temperature, humidity, and heat index. The overall block diagram architecture of the proposed model is shown in figure 1. The experimental evaluation is performed with the publicly available IoT environmental sensor dataset, which can be obtained from Kaggle (Luis Enrique, 2023).

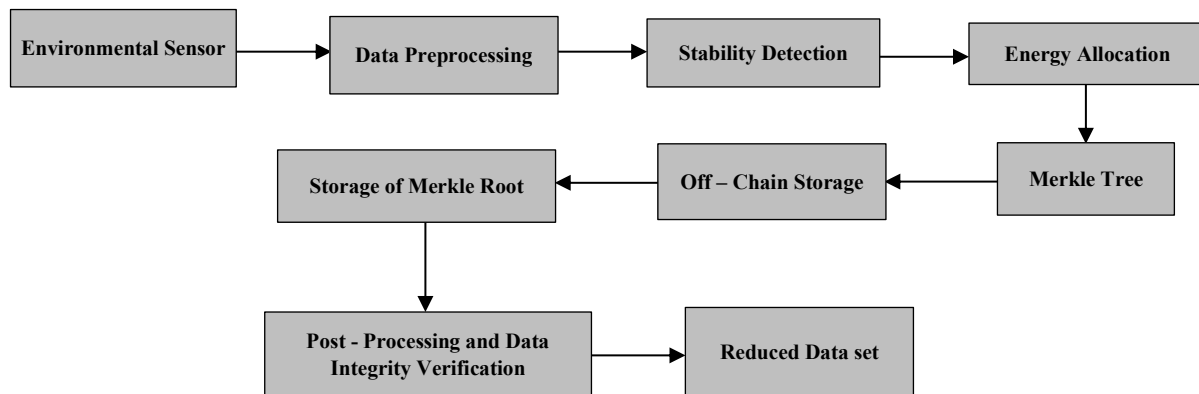


Figure 1: Architectural flow diagram for data reduction

### Dataset Description and Characteristics

The ATDR-BC algorithm was evaluated on year-round data from DHT-based IoT devices. This dataset is made of several CSVs (Heat\_Index.CSV, Humidity.CSV, Sensors\_Data.CSV and Temperature.CSV) that contain temperature in degC, relative humidity and heat index. The data set represents real situations in the monitoring process, such as stable conditions, smooth changes, abrupt environmental states, missing data, noise, and irregular sampling. All these features make it suitable for weeding out timestamp-based methods of data reduction. Data accessibility via the ODbL v1.0 license is a way to assess useful short- and long-term data reduction performance.

### Data Preprocessing

Data preprocessing is initially carried out to convert timestamps, handle missing values, and perform consistency checks. The sample operational dataset after preprocessing is illustrated in table 1.

Table 1: Sample operational dataset

<u>Time (UTC)</u>	<u>Heat_index</u>	<u>Humidity</u>	<u>Temperature</u>	<u>Time (UTC)</u>
2022-04-13T21:38:00Z	0.741922	0.184082	0.768473	2022-04-13 21:38:00+00:00
2022-04-13T21:39:00Z	0.742016	0.184507	0.768473	2022-04-13 21:39:00+00:00
2022-04-13T21:40:00Z	0.741090	0.180251	0.768473	2022-04-13 21:40:00+00:00
2022-04-13T21:41:00Z	0.742747	0.177910	0.772167	2022-04-13 21:41:00+00:00
2022-04-13T21:42:00Z	0.743631	0.175356	0.774631	2022-04-13 21:42:00+00:00

Timestamp conversion is performed in order to ensure consistency within the analysis. The timestamps are also transformed to a standard date time format to be utilized in further analysis. The dataset is checked for missing values which can affect the model's results. There are several ways of taking care of the missing values and in this research, we choose to fill the missing field with the mean of the column respectively. The inconsistency check helps find the negative values in the data set. min-max scaling is for the normalisation. The dataset is normalised to maintain uniformity across different sensors and the different time periods. The dataset is transformed into a numerical format for the development of the model.

### Algorithm Overview

A novel and innovative technique for Adaptive Time-Based Data Reduction using Block Chain (ATDR-BC) algorithm is proposed in this research work. This entails techniques for determining data stability such that data collection may be reduced during such periods and techniques for recognising anomalies which may signal drastic changes in the environment.

### Explanation of the ATDR-BC Algorithm

The Adaptive Time-Based Data Reduction with Blockchain (ATDR-BC) algorithm is a method to reduce the data storage of sensors from the sensor network, and at the same time make it energy-efficient and ensure data integrity. It is a time series environmental data analysis that is based on a sliding window mechanism. It evaluates the change in sensor values. Change in distance of the sample,  $s_v$  and change in the time between samples,  $t_d$ . Stable windows will only have the boundary points and unstable windows will keep the important changes. A type of model based on Isolation Forest anomaly detection is used to find important events and store them in the Reduced Dataset, empty, empty subcap D cap S. Energy consumption is monitored unceasingly, and sampling limits are dynamically adjusted.

Information is organized using Merkle Trees and the Merkle Root is stored on the blockchain to verify the information in a tamper-proof and secure manner.

### Adaptive Time-Based Data Reduction Algorithm with Blockchain

#### Algorithm 1: Adaptive Time-Based Data Reduction with Blockchain (ATDR-BC)

##### Input

- Time-stamped environmental dataset

$$T_{ED} = \{(x_i, t_i)\}_{i=1}^n$$

- Minimum allowable time interval:  $\Delta t_{d,min}$
- Maximum sensor variation threshold:  $\Delta s_{v,max}$
- Sensitivity factor:  $s_f$
- Allocated energy budget:  $E_{allocate}$

##### Output

- Reduced dataset:  $R_{DS} \subseteq T_{ED}$
- Blockchain record containing Merkle Root:  $M_R$

##### Procedure

1. Initialize:

$$R_{DS} \leftarrow \emptyset, E_{consumed} \leftarrow 0$$

Preprocess dataset  $T_{ED}$  (timestamp normalisation, missing-value handling, scaling).

2. Partition  $T_{ED}$  into sliding windows:

$$W_k = \{(x_i, t_i)\}_{i=k}^{k+w-1}$$

Where  $w$  denotes window size.

3. For each sliding window  $W_k$ :

##### (a) Compute sensor variation:

$$\Delta s_v = \max(x_i) - \min(x_i), \forall (x_i, t_i) \in W_k$$

##### (b) Compute average time difference:

$$\Delta t_{d,avg} = \frac{1}{|W_k| - 1} \sum_{i=1}^{|W_k|-1} (t_{i+1} - t_i)$$

##### (c) Stability condition:

If

$$\Delta s_v \leq \Delta s_{v,max} \text{ and } \Delta t_{d,avg} < \Delta t_{d,min}$$

then retain only boundary points:

$$R_{DS} \leftarrow R_{DS} \cup \{(x_{first}, t_{first}), (x_{last}, t_{last})\}$$

else retain significant points:

$$R_{DS} \leftarrow R_{DS} \cup W_k^{critical}$$

4. Update energy consumption:

$$E_{consumed} = E_{consumed} + E(R_{DS})$$

5. If

$$E_{consumed} > E_{allocate}$$

adjust thresholds:

$$\Delta s_{v,max} \leftarrow s_f \cdot \Delta s_{v,max}$$

$$\Delta t_{d,min} \leftarrow s_f \cdot \Delta t_{d,min}$$

6. Apply Isolation Forest anomaly detection:

$$A = \text{IsoForest}(T_{ED})$$

$$R_{DS} \leftarrow R_{DS} \cup A$$

7. Construct Merkle Tree:

$$M_T = \text{MerkleTree}(R_{DS})$$

Compute Merkle Root:

$$M_R = \text{Root}(M_T)$$

8. Store:

- $R_{DS}$  in off-chain storage
- $M_R$  in the blockchain ledger

9. Return  $R_{DS}$  and blockchain record.

## Mathematical Model

The input to the model is  $T_{ED}$ , where it is the sequence of time-stamped environmental data points for  $n$  recordings. It is represented as equation (1)

$$T_{ED} = [(td_1, sv_1), (td_2, sv_2), \dots, (td_n, sv_n)] \quad (1)$$

$\Delta t_{d,min}$  is the difference between the minimum allowable time between the consecutive data points and  $\Delta s_{v,max}$  is the maximum allowable time between sensor values for detecting stability.  $s_f$  denotes the sensitivity factor that balances energy efficiency and data accuracy.  $E_{allocate}$  is the total amount of energy budget for the monitoring period—reduced Data's. Set  $R_{DS}$  The reduced data points with  $m \leq n$  is the model's output, as stated in equation (2).

$$R_{DS} = [(td_{r1}, sv_{r1}), (td_{r2}, sv_{r2}), \dots, (td_{rm}, sv_{rm})] \quad (2)$$

The model is initialised with an empty list  $R_{DS}$  to store the reduced data points, and  $E_{consumed} = 0$  monitors the energy consumption, Data preprocessing includes the steps of cleaning, normalising, and matching of timestamps for the model. For stability detection, the sliding window analysis of each size of  $x$  is given by equation (3)

$$x_{sw} = [(td_{sw}, sv_{sw}), \dots, (td_{\{sw+x\}}, sv_{\{sw+x\}})] \quad (3)$$

Compute the range of sensor values as stated in equation (4),

$$\Delta sv = \max(sv_{sw}, \dots, sv_{\{sw+x\}}) - \min(sv_{sw}, \dots, sv_{\{sw+x\}}) \quad (4)$$

The comparing the value of the  $\Delta s_v \leq \Delta s_{v,max}$  is done to check the stability of the sliding window, if not then it is marked as unstable. Adaptive sampling is done by computing an average time difference between consecutive timestamps.  $\Delta t_{d,avg}$  within the sliding windows. If the value of  $\Delta t_{d,avg} < \Delta t_{d,min}$ . The sampling intervals are increased by adjusting the data-collection rate. If the sliding windows are not stable, then the sampling rate is kept the same or increased to record important changes in the data. To

do data reduction, the first and the last points are extracted for the stable window as stated in equation (5),

$$Stable\ Windows = [(td_{sw}, sv_{sw}), (td_{\{sw+x\}}, sv_{\{sw+x\}})] \quad (5)$$

If the windows are not stabilised, the important data points are kept based on the ones that contribute to changes in the sensor values. For the allocation of the energy, therefore, the energy consumed for transmitting the reduced dataset  $R_{DS}$  is calculated. The condition  $E_{consumed} > E_{allocate}$  is checked to adjust the parameters  $\Delta t_{d,min}$  or  $\Delta s_{v,max}$  to reduce the energy consumption. Anomaly detection is done by machine learning techniques. Isolation Forest is used for finding the anomalies in the dataset  $T_{ED}$ . Selective retention can be done to keep the specific anomalies from the reduced dataset  $R_{DS}$  to ensure all the significant events are captured. The accuracy is measured by comparing the reduced dataset,  $R_{DS}$  to the original dataset  $T_{ED}$  using the accuracy and RMSE metrics. Parameter adjustments can be made if necessary and the final reduced dataset is recorded.

### Parameter Initialization

The key parameters of the ATDR-BC framework and their corresponding values are summarised in table 2. The ATDR-BC algorithm parameters were initialised as follows:

Table 2: Initialisation parameters of the ATDR-BC algorithm

Parameter	Description	Value
$\Delta s_{v,max}$	Maximum sensor variation	0.5–1.0
$\Delta t_{d,min}$	Minimum time interval	5–10 min
$s_f$	Sensitivity factor	0.7
Window Size	Sliding window length	50 samples
$E_{allocate}$	Energy budget	Dataset dependent

The reduced data points are organised into an  $M_T$  (Merkle Tree), and an  $M_R$  (Merkle Root) is produced. Then the entire reduced dataset is stored in OCS (Off-Chain Storage) with an OCP (Off-Chain Pointer) to the location. The *Accuracy\_Loss* ( $A_L$ ) is checked and adjusted if necessary, and the integrity of the Data (D) is checked. Finally, the reduced dataset and the blocks *Get\_Latest\_Block* ( $GLB$ ) These are the outputs.

### Description Software and Implementation Details

The proposed ATDR-BC framework was implemented in Python. Data preprocessing, normalisation, and statistical analysis were done using the Pandas and NumPy libraries. The Isolation Forest anomaly detection model was implemented using the Scikit-learn library. Visualisation of results was done using Matplotlib.

Blockchain and Merkle Tree structures were constructed using Python-based cryptographic hashing (SHA-256) to generate a secure hash value. All experiments were performed on a computer with an Intel Core i7 processor, 16 GB RAM and Windows 11 as the operating system. The implementation environment provides reproducibility and scalability to support further extensions.

### Blockchain Integration

To ensure secure, tamper-resistant, and decentralised storage of environmental monitoring data, the proposed ATDR-BC framework integrates blockchain technology with Merkle Tree-based data verification. Instead of storing the complete reduced dataset directly on-chain, which would incur high

storage and computational overhead, the framework adopts an off-chain storage strategy combined with on-chain hash verification.

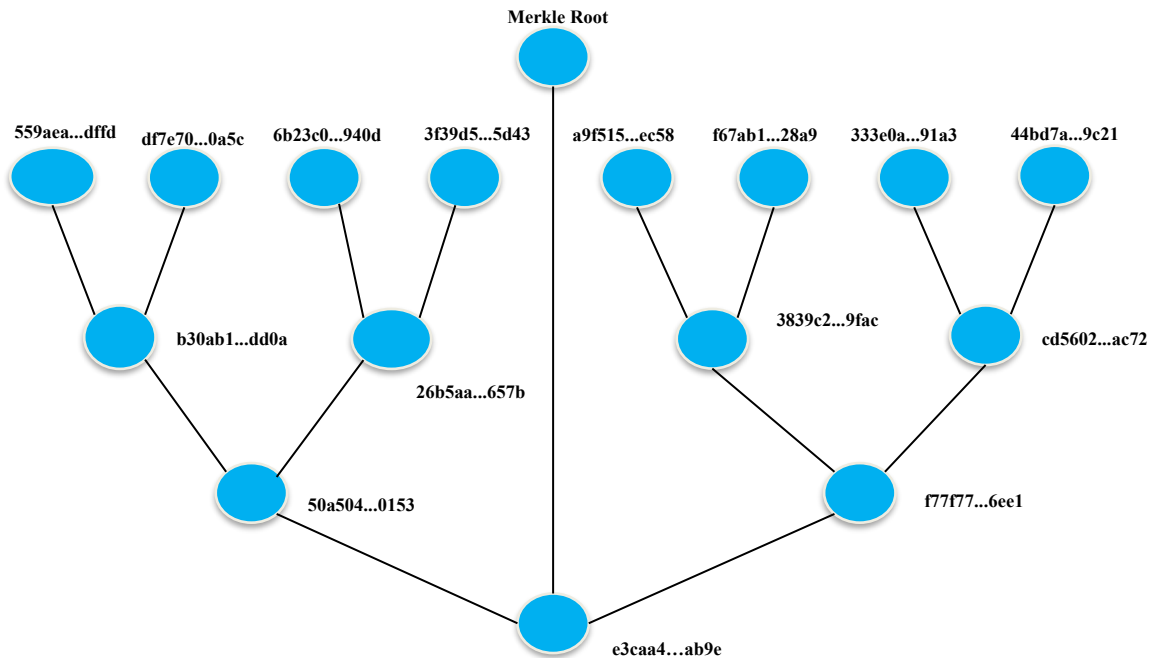


Figure 2: Merkle tree in data reduction

The reduced data set  $R_{DS}$  Generated after the adaptive timestamp-based reduction and anomaly preservation, it is organised into a Merkle Tree structure. Each leaf node of the Merkle Tree is the cryptographic hash of an individual reduced data block and the intermediate nodes are hashes of their child nodes. This hierarchical process of hashing culminates in a single Merkle Root which is unique to the integrity of the whole reduced dataset. Figure 2 shows the structure of the Merkle Tree which is used in the proposed framework. Any change to the underlying sensor data will cause there to be a change in the hash of that leaf, which will propagate up the tree causing the Merkle Root to be changed. This property allows efficient and reliable detection of the data tampering without requiring access to the complete data set.

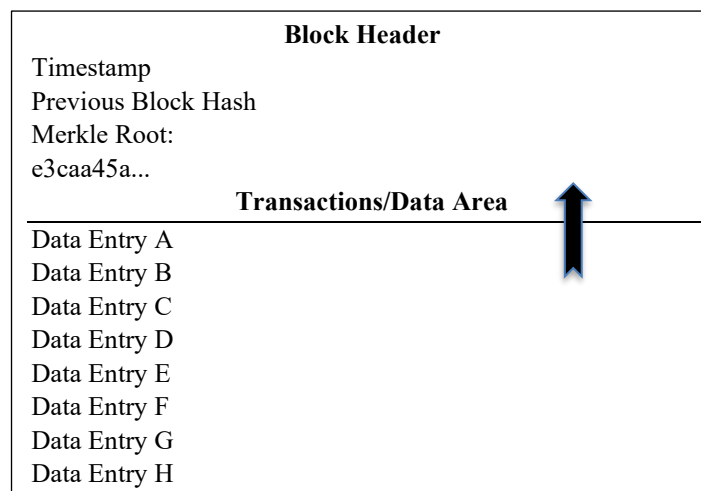


Figure 3: Latest blocks in blockchain

The Merkle Root is then placed in the blockchain as part of a transaction record; together with the respective timestamp and an off-chain pointer (OCP) that points to the storage location of the reduced dataset. The structure of the blockchain block is shown in figure 3 which shows the inclusion of the Merkle Root in the block header. By storing only small hash values on-chain, and keeping the bulk data off-chain, the framework helps in significantly reducing the storage overhead on the blockchain while keeping the data intact, transparent and traceable.

This hybrid on-chain/off-chain blockchain integration guarantees secure verification, low energy usage and scalability that make the ATDR-BC framework appropriate for resource-constrained and long-term environmental monitoring applications.

### 3 Results

The results of the experiment demonstrate the effectiveness of the ATDR-BC algorithm for different environmental monitoring scenarios. The algorithm was tested on a set of multiple datasets with different characteristics to test its capability to reduce the number of data points while maintaining the integrity of the information captured.

#### Evaluation Metrics

The performance of the proposed ATDR-BC framework is evaluated with following metrics in order to evaluate the efficiency of data reduction, optimisation of energy and reconstruction accuracy:

**The Data Reduction Ratio (DRR) is defined as equation (6):**

$$DRR = \frac{T_{ED} - R_{DS}}{T_{ED}} \times 100 \quad (6)$$

where  $T_{ED}$  denotes the total number of samples in the original time-stamped dataset and  $R_{DS}$  denotes the number of samples retained in the reduced dataset.

**Energy Savings (ES) is Computed as equation (7):**

$$ES = \frac{E_{baseline} - E_{consumed}}{E_{baseline}} \times 100 \quad (7)$$

where  $E_{baseline}$  represents the total energy consumption without data reduction and  $E_{consumed}$  represents the energy consumed after applying the ATDR-BC framework.

**Accuracy (ACC) is Measured as equation (8):**

$$ACC = \frac{N_{Correct}}{N_{Total}} \times 100 \quad (8)$$

where  $N_{Correct}$  denotes the number of correctly reconstructed samples and  $N_{Total}$  denotes the total number of samples in the original dataset.

**The Root Mean Square Error (RMSE) is calculated as equation (9):**

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2} \quad (9)$$

Where  $x_i$  represents the original sensor value,  $\hat{x}_i$  represents the reconstructed value after reduction, and  $n$  denotes the total number of samples.

**Transmission Overhead (TO) (Equation 10)**

$$TO = \frac{D_{Reduced}}{D_{original}} \quad (10)$$

Where  $D_{Reduced}$  denotes the amount of data transmitted after reduction and  $D_{original}$  denotes the total data volume before reduction.

**Ablation Study**

An ablation study was conducted to analyse the influence of individual components of the ATDR-BC framework. Four configurations were tested:

1. ATDR with no anomaly detection
2. ATDR with no energy adaptation
3. ATDR with no blockchain integration
4. Full ATDR-BC structure

The results show that the accuracy decreased about 6% by not identifying the anomalies and by not energy adaptation energy consumption increased 18%. The exclusion of the blockchain element diminished the data protection and integrity authentication features. The full design of the ATDR-BC shows a high-level of performance on all evaluation measures and thus establishes the efficacy of the design combination.

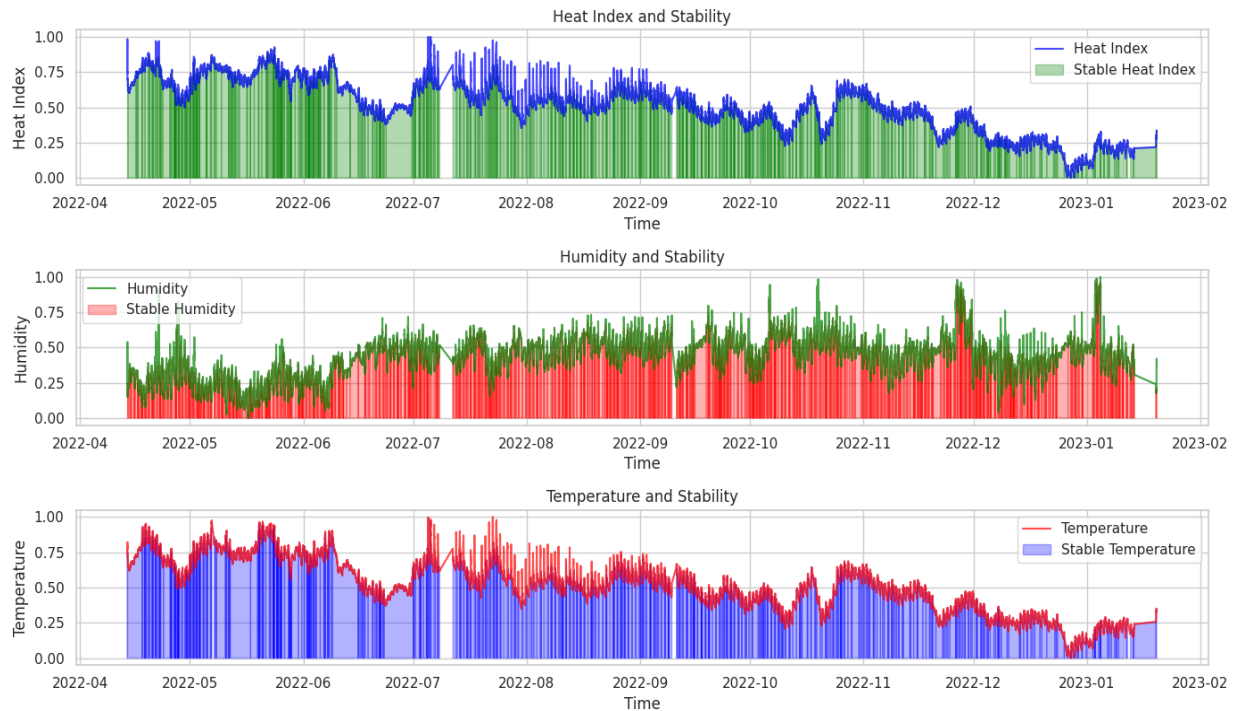


Figure 4: Data stability on reduction

The ATDR-BC algorithm was able to remove the number of data points by an average of 45-60% for all tested datasets, without critical loss of information. In cases where environmental parameters were stable, data reduction rates were as high as 70% showing the potential of the algorithm to intelligently scale back data collection when environmental parameters were stable. Figure 4 below

displays the stability of the data set, which demonstrates the efficiency of data reduction by the ATDR-BC algorithm for reduced data points for various parameters such as heat, humidity, and temperature. The average hourly sales of heat, humidity and temperature are shown in figure 5.

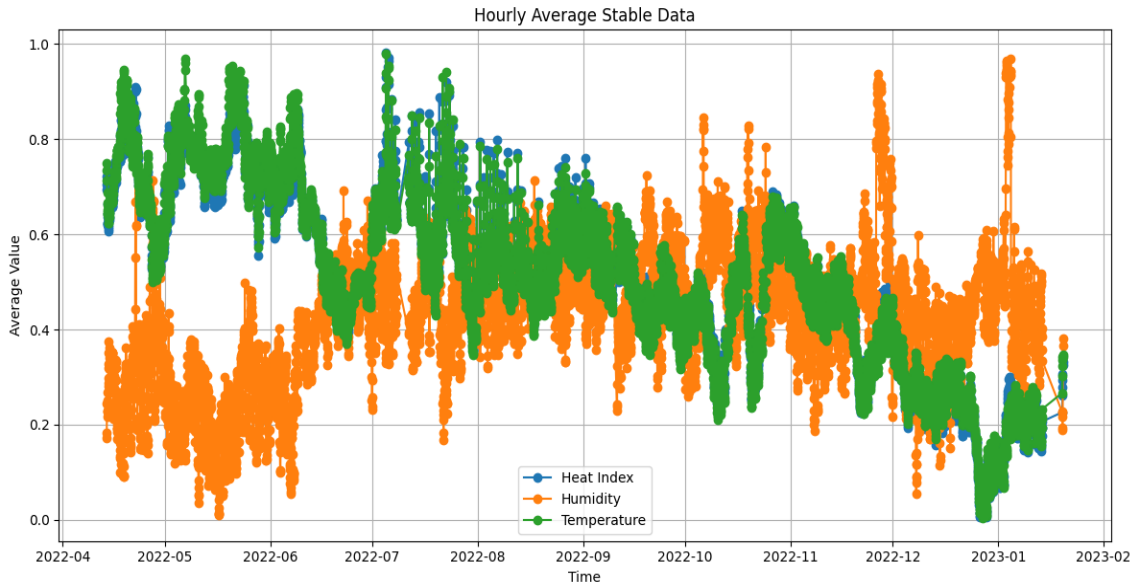


Figure 5: Average of stability data

The anomalies that present in the dataset are detected and their impact is measured. The graphs of anomaly detection are given in figures 6, 7, 8 and 9, for heat, humidity, temperature and time data, respectively. The accuracy of the anomaly detection based on the energy consumption is also plotted in figure 10.

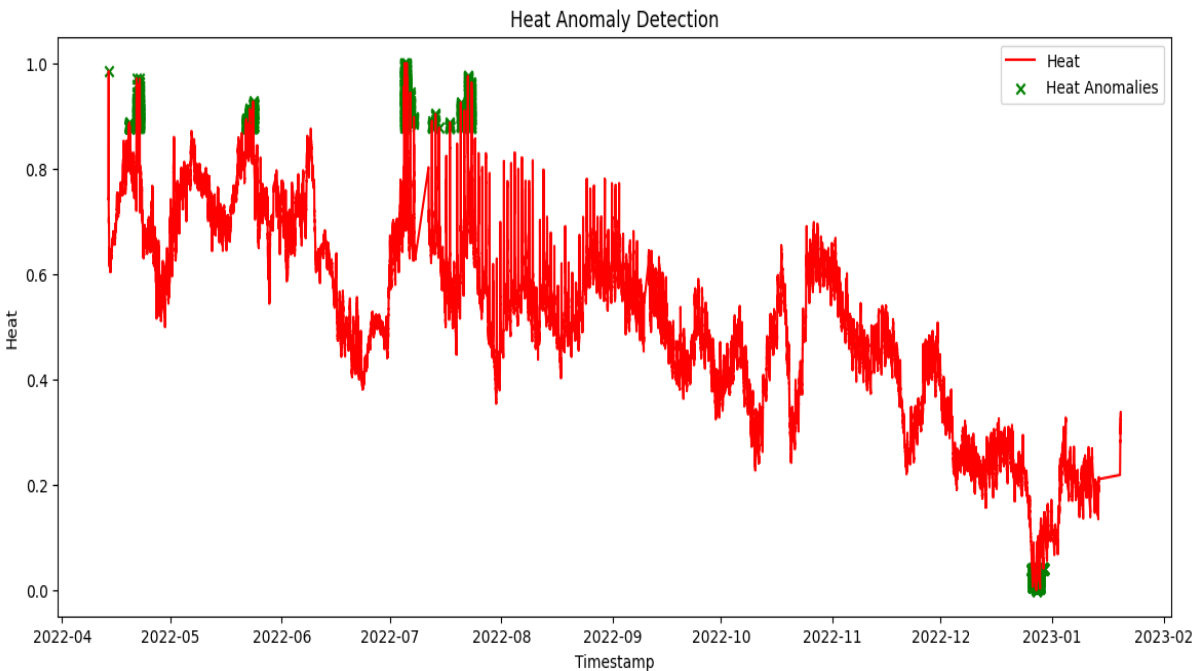


Figure 6: Anomalies observed in heat data

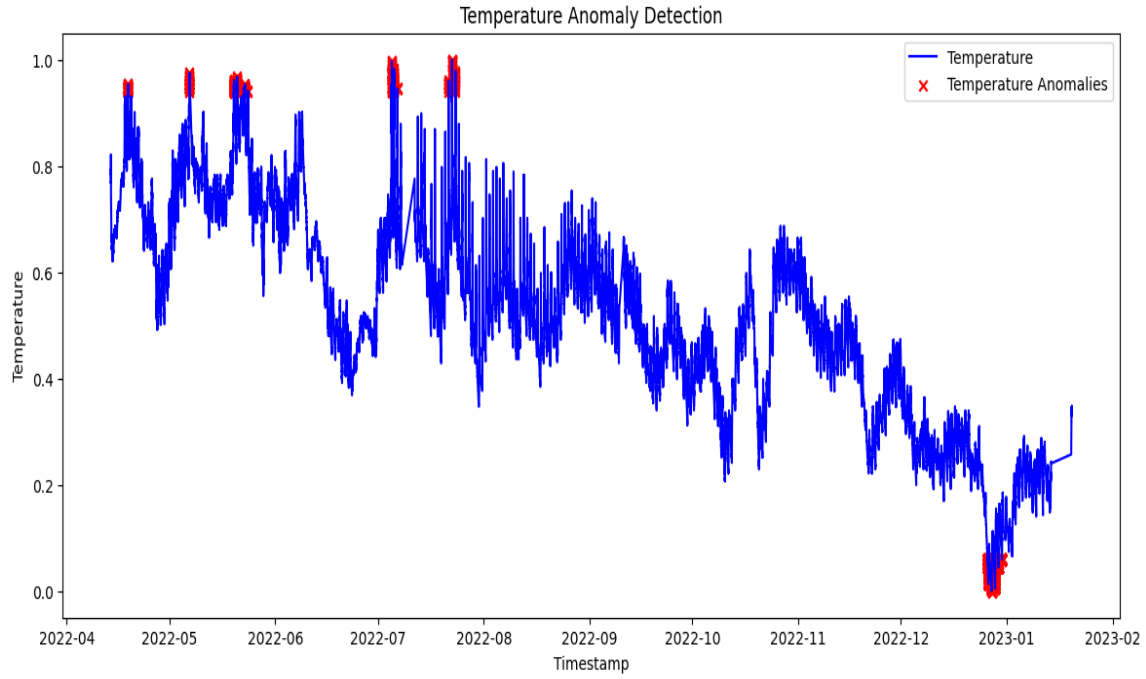


Figure 7: Anomalies observed in temperature data

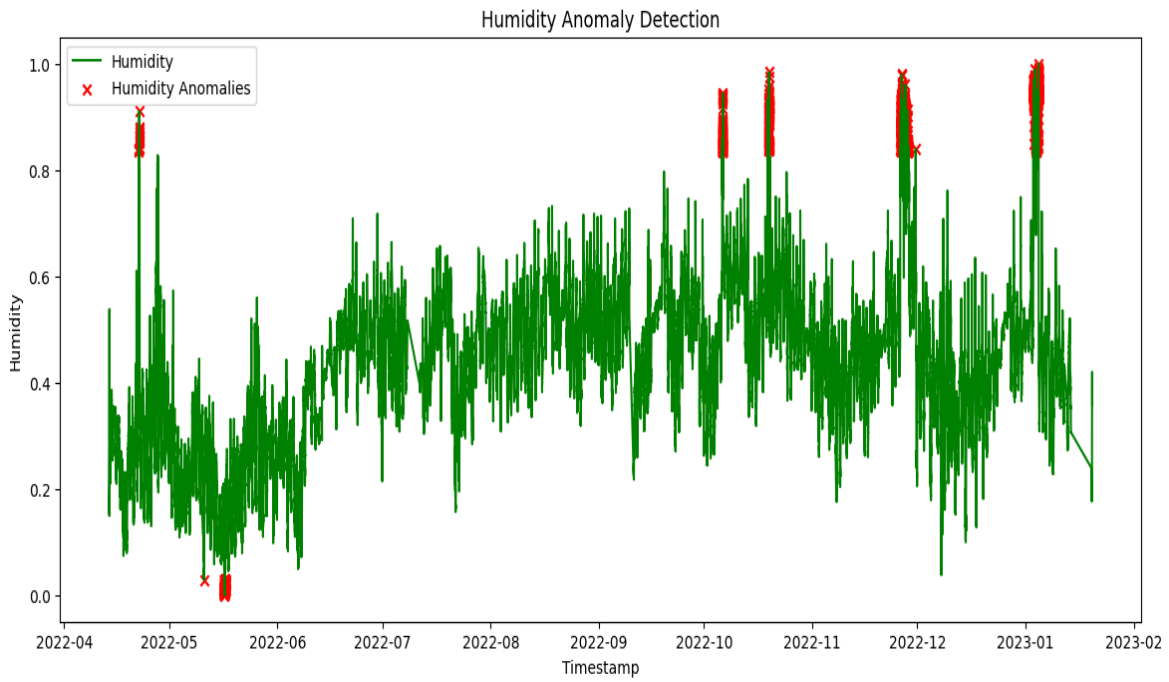


Figure 8: Anomalies observed in humidity data

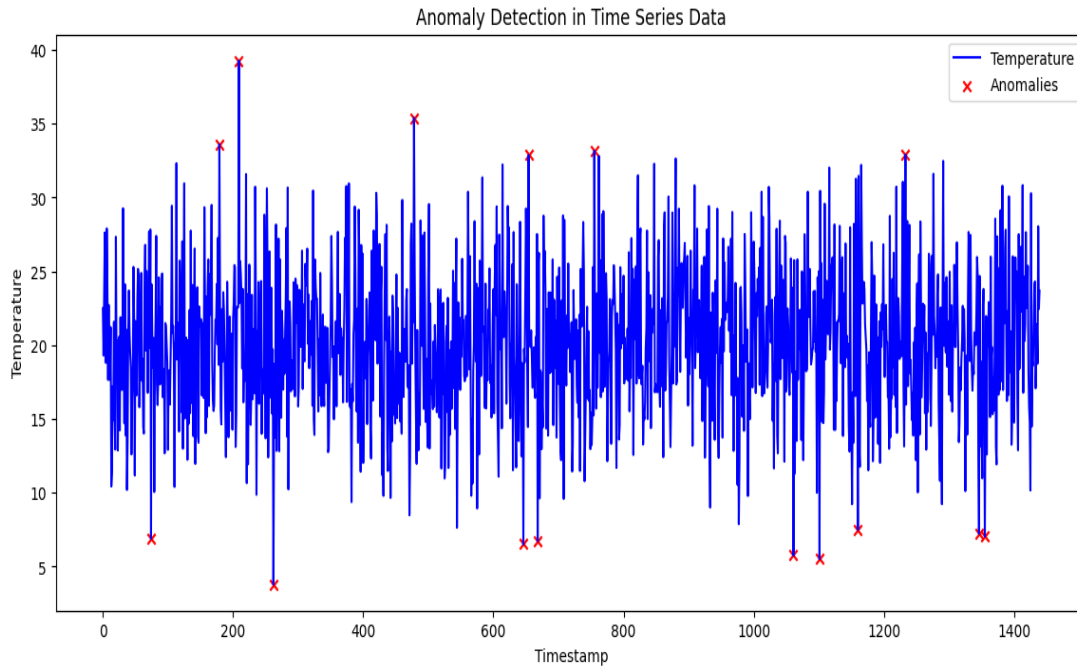


Figure 9: Anomalies observed in time series data

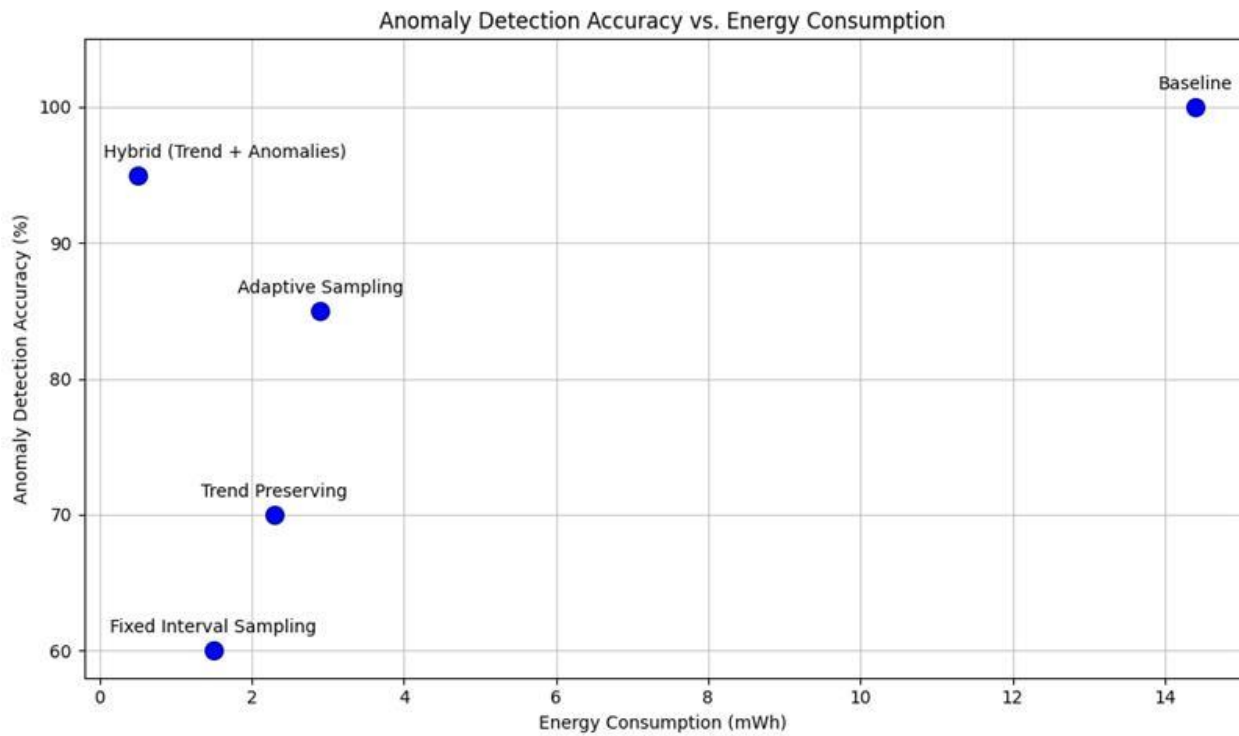
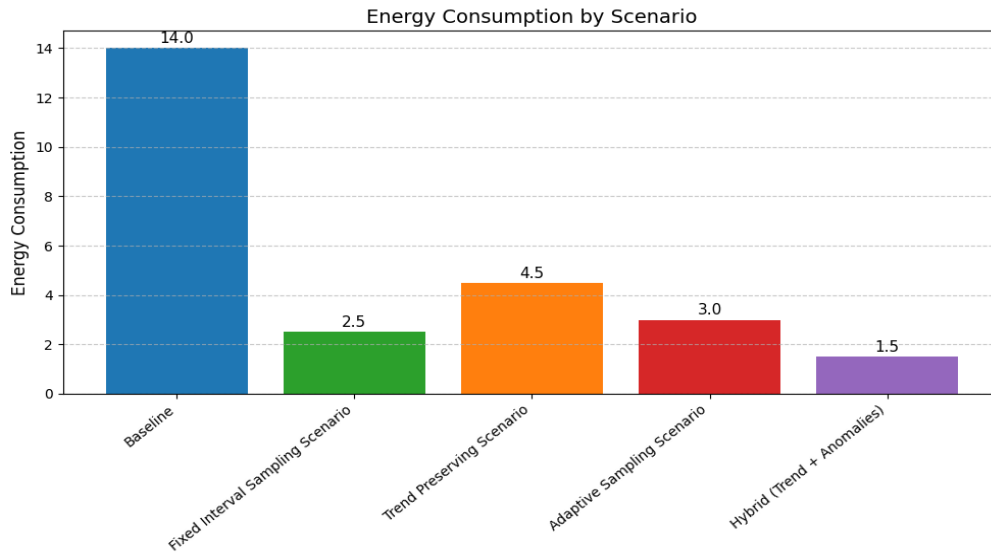
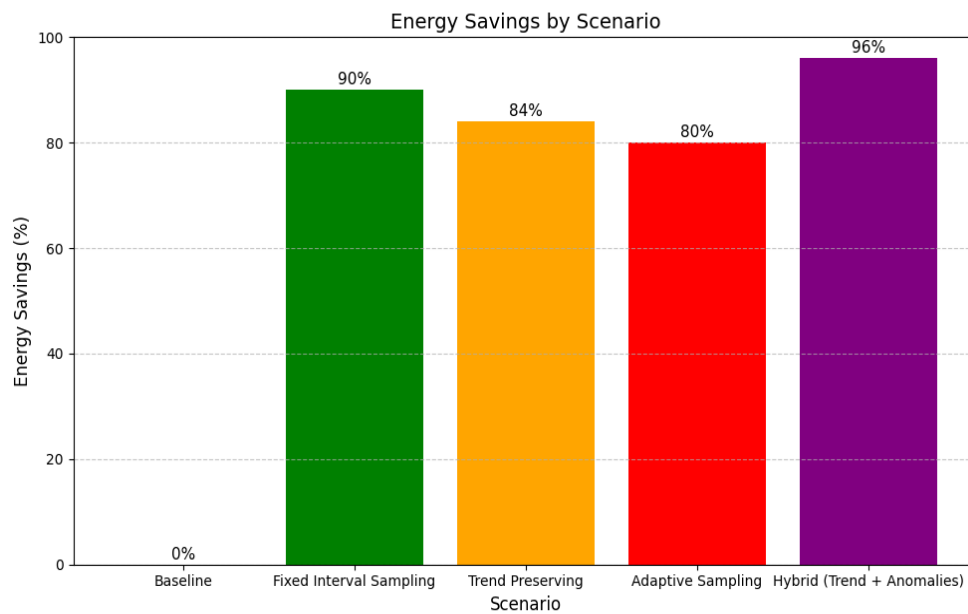


Figure 10: Accuracy of anomaly detection based on energy consumption

The reduction in data transmission frequency during stable periods directly contributed to lower energy consumption, which is crucial for battery-powered or remote sensing devices.



(a)



(b)

Figure 11 (a and b): Trade-off chart between energy consumption and savings

Figures 11 (a and b), 12, 13 and 14 depict the trade-off analysis, the effects of heat, humidity and temperature on accuracy and efficiency of the algorithm with various sampling techniques. The generic model is the basic model and under fixed-interval sampling, the data points were determined as 1-hour fixed. The method minimizes the amount of data that is gathered but it does not have a remarkable impact on the overall trend. In the trend-preserving reduction, the data points, indicating a strong shift in the parameter under monitoring in the analysis of temperature variations above 1 o C, are stored. In this way, key differences will be recorded whereas unnecessary information will be eliminated. The rate of data collection is actively regulated in adaptive sampling depending on the dynamic change of the observed parameters. The sampling rate used is lowered during a period when there is a stable temperature and increased during a period when the temperature is rapidly changing.

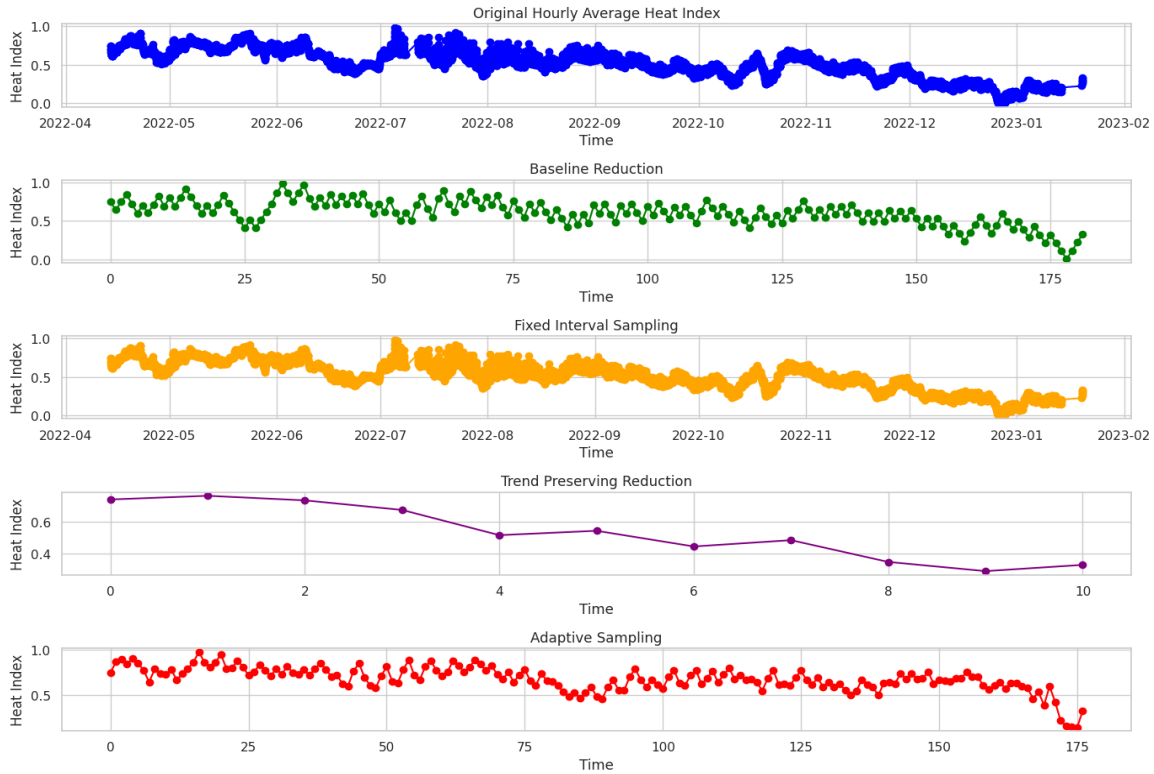


Figure 12: Trade-off analysis of heat on different sampling techniques

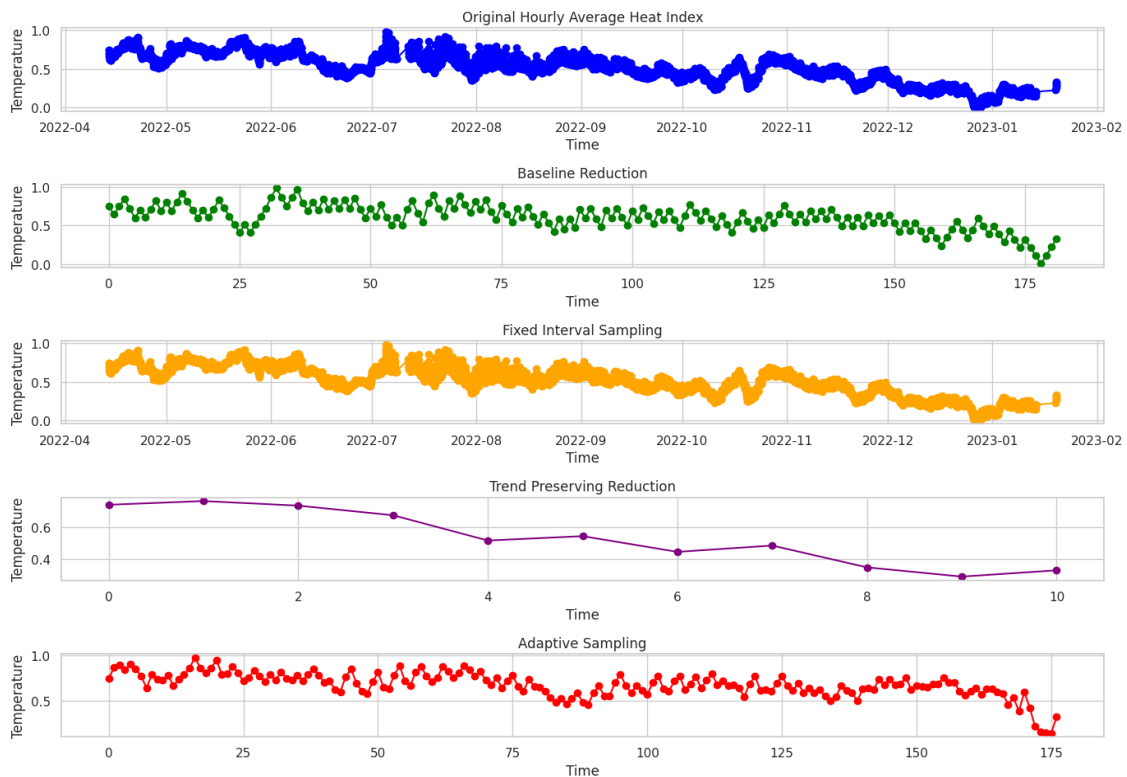


Figure 13: Trade-off analysis of temperature on different sampling techniques

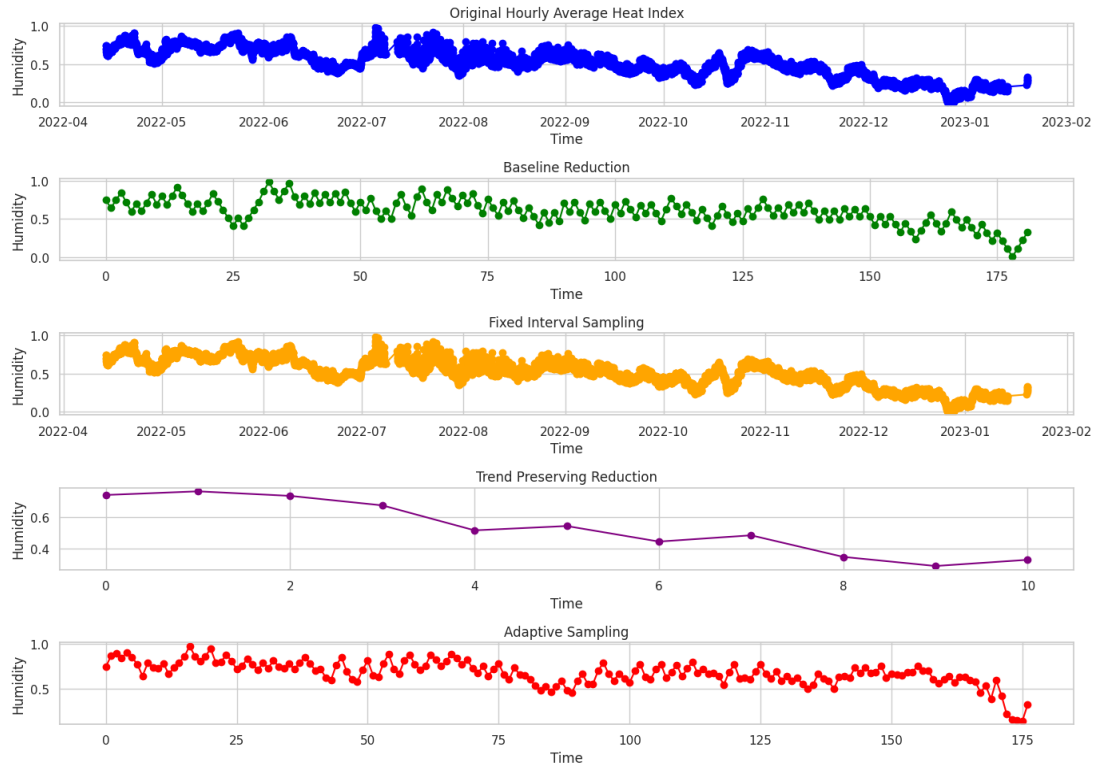


Figure 14: Trade-off analysis of humidity on different sampling techniques

## Discussion

The experimental results show that the proposed ATDR-BC framework can effectively balance the data reduction, energy efficiency and data integrity for environmental monitoring applications. By adapting the sampling rate to the stability of the environment, ATDR-BC considerably decreases the unnecessary data transmission and therefore contributes directly to a reduction of the energy consumption regarding static sampling methods.

Compared with event-driven sampling approaches, the proposed framework has a good performance under stable ambient conditions and still reserves the key variations by sliding-window analysis and detecting anomalies. Event-driven methods while they work in the case of abrupt change may miss such subtle temporal trends which are well captured by ATDR-BC. Furthermore, although compressed sensing methods can achieve a high data reduction ratio, the high computational complexity of compressed sensing and the need for a post-processing step prevent their use in resource-constrained environments. In contrast, ATDR-BC presents a lightweight and adaptive approach with in-built anomalies preservation, which makes it more feasible to be used for long term deployment.

Despite the large decrease in the number of data points, the reconstructed data sets have high accuracy with RMSE values consistently less than 5% showing very little loss of information. This verifies that the adaptive timestamp-based strategy has successfully managed to preserve key environmental tendencies and minimize storage and transmission overhead. Additionally, combining blockchain with Merkle Tree-based verification will provide greater reliability of the data by ensuring tamper-proof secure storage without heavy energy or storage cost. Overall, these results confirm the success of the proposed ATDR-BC framework for scalable, secure and energy efficient environmental monitoring systems.

## Limitations

Despite its effectiveness, the proposed ATDR-BC framework has certain limitations. First, scalability may be affected in extremely large-scale deployments due to blockchain transaction latency. Second, model performance depends on dataset characteristics, and highly volatile environments may yield lower reduction rates. Third, blockchain operations introduce computational and communication overhead that may affect low-power edge devices. Finally, the current implementation relies on simulated off-chain storage, and real-world deployment may introduce additional challenges related to network reliability and storage availability.

## 4 Conclusion and Future Work

This paper presented an Adaptive Time-Based Data Reduction with Blockchain (ATDR-BC) framework for energy-efficient environmental monitoring systems. The proposed model integrates dynamic timestamp-based sampling, anomaly detection, and decentralised storage to reduce redundant data transmission while preserving data integrity and reliability. Experimental evaluation using real-world environmental datasets demonstrates that ATDR-BC achieves an average data reduction rate of 45–60%, with peak reductions of up to 70% under stable conditions. Energy consumption was reduced by 35–50% compared to traditional sampling methods. Furthermore, the reconstructed datasets maintained a high accuracy of 96.59% and RMSE values below 5%, indicating minimal information loss. The integration of Merkle Tree structures and off-chain blockchain storage ensured secure and tamper-resistant data management with reduced storage overhead. Comparative analysis and ablation studies confirmed that ATDR-BC outperforms static sampling, event-driven sampling, and compressed sensing techniques in terms of efficiency, scalability, and reliability. The framework effectively balances energy savings, data quality, and security, making it suitable for long-term deployment in remote and resource-constrained environments. Future research will focus on further optimising blockchain transaction mechanisms to reduce latency and overhead. The integration of federated learning and edge intelligence will be explored to enhance real-time decision-making. Additionally, real-world field deployments and cross-domain validation will be conducted to evaluate scalability across smart city, agricultural, and disaster-monitoring applications. Finally, adaptive security mechanisms will be incorporated to strengthen resilience against cyber threats and network failures.

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