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I-TREES: A Context-Aware Framework For Energy-Efficient Tree Health Monitoring In Forest Internet Of Trees (IoTr) Networks

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Abstract

Internet of Trees (IoTr) technology enables a novel approach to real-time remote monitoring, particularly of trees and forest ecosystems. However, existing literature focuses on soil moisture monitoring of trees and lacks the contextual intelligence and adaptive sensing capabilities necessary for smart tree monitoring. This paper proposes a novel layered architecture for IoTr and the I-TREE (IoTr-based Tree Routing for Energy-Efficient Systems) framework for smart sensing and context-driven monitoring. I-TREES integrates embedded IoTr environmental sensors, LPWAN communication, edge processing, and cloud-based reasoning to monitor physiological and ecological stress parameters in vulnerable tree species. The proposed architecture enables selective sensing, where sensors adapt their behaviour based on real-time environmental conditions to reduce energy consumption and avoid redundant transmissions. We evaluate I-TREES using Network Simulator 3 (NS-3) simulations across 700-node deployments under forest-like conditions and compare them with benchmark routing protocols. Results show that I-TREES achieves a superior packet delivery ratio approximately 97%, reduced latency, and lower energy consumption than existing schemes. I-TREES offers a robust solution for sustainable forest ecosystem monitoring and early disease detection by combining scalable sensing with intelligent context awareness.

Introduction

Forest ecosystems, especially those containing vulnerable species, face increasing stress from abiotic and biotic factors (Nawrot-Chorabik et al. 2022). The United Kingdom (UK), several European Union (EU) and North American nations have prioritised early detection and intervention strategies to mitigate tree loss (Brundu et al. 2020; Tomelleri et al. 2022). However, platforms like TreeAlert rely on manual citizen reporting, which can lead to delayed responses and insufficient spatial coverage (Forest Research, UK 2024; Observatree). The rapid development of the Internet of Things (IoT) has revolutionised environmental monitoring with intelligent innovations and real-time data collection (Lesch et al. 2023). By 2030, the global number of IoT devices is projected to reach 500 billion (Systems 2016). One emerging application

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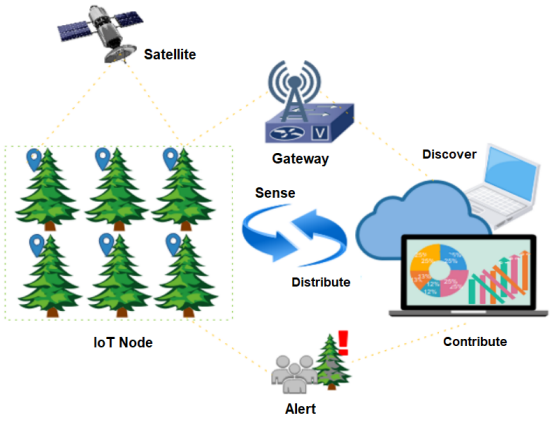


Figure 1: The Internet of Trees (IoTr) System

is the Internet of Trees (IoTr), a specialised subdomain that applies IoT technologies to tree and forest health monitoring (Agrint Sensing Solutions 2025; Dang et al. 2022; Gray 2020; Battistoni et al. 2023; Galle, Nitoslawski, and Pilla 2019). IoTr systems operate autonomously, transmitting data wirelessly to central platforms for analysis and management, thus minimising human intervention (Dang et al. 2022). Figure 1 illustrates an IoTr system consisting of trees nodes capable of sensing and transmitting environmental and biological parameters to generate prompt alerts based on data. Although IoTr shows potential for protecting and managing forest ecosystems, existing literature predominantly focuses on monitoring soil moisture or temperature, lacking contextual understanding for wide-area coverage (Ramzan et al. 2020; Fitzgerald 2016; Dang et al. 2022). This limitation hinders accurate identification or prediction of critical conditions such as drought stress, pest infestation, or disease progression (Ali et al. 2025; Observatree). To address this gap, we propose the I-TREES (IoTr-Based Tree Routing for Energy-Efficient Systems) framework, a layered IoTr architecture designed to monitor trees and forest ecosystems and mitigate threats such as fire outbreaks, drought stress, illegal logging, disease spread, and pest infestation. The framework enables smart sensing and context-driven monitoring, integrating real-time selective sensing and adaptive

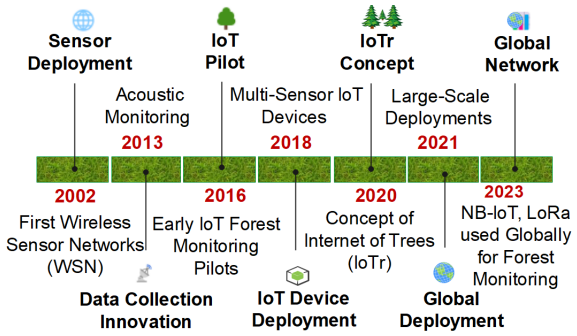


Figure 2: Timeline of Global IoTr Development

decision-making. By dynamically adjusting data transmission based on environmental thresholds and contextual triggers, I-TREES minimises energy consumption while maximising accuracy in anomaly detection. I-TREES leverages Low-Power Wide Area Network (LPWAN) communication, edge-level filtering, and cloud-hosted context reasoning to enhance energy efficiency. We evaluate I-TREES using the Network Simulator 3 (NS-3) in a forest-like environment with 700 IoTr nodes, comparing its performance against six widely used routing and clustering protocols: Low-Energy Adaptive Clustering Hierarchy (LEACH), Power-Efficient Gathering in Sensor Information Systems (PEGASIS), Hierarchical Clustering Algorithm (HCA), Heuristic Clustering and Scheduling Algorithm (H-CSA), Event-Driven Spatio-Temporal Optimisation (ESTO), and K-Means clustering. Results demonstrate that I-TREES consistently outperforms these baselines in key metrics: Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), Throughput, Energy Consumption, Latency, and End-to-End Delay. The rest of the paper is organised as follows: Section 2 presents the literature review. Section 3 outlines the proposed IoTr layered architecture for intelligent tree monitoring. Section 4 introduces the I-TREES framework. Section 5 discusses the simulation setup and evaluation metrics. Section 6 concludes the paper, highlighting its implications for sustainable forest monitoring and identifying opportunities for future work.

Literature Review

Research in forest monitoring has evolved from manual field observations to automated sensing using Wireless Sensor Networks (WSNs) and, more recently, IoTr systems (Fitzgerald 2016; Ramzan et al. 2020; Chau et al. 2023). IoTr technologies have enabled remote and real-time measurement of environmental factors such as soil moisture, humidity, temperature, and air quality. The Great Duck Island deployment in 2000 demonstrated that battery-powered sensor nodes could function in harsh natural environments while wirelessly collecting ecological data (Polastre et al. 2004). Over time, these systems have advanced into large-scale IoTr frameworks employing LPWAN technologies like LoRa (Long Range) and NB-IoT (Narrowband IoT) to enhance connectivity and coverage (Battistoni et al. 2023; Galle, Nitoslawski, and Pilla 2019; Singh et al. 2021; Forestry Research 2025). Figure 2 illustrates this progression. Numerous IoTr initiatives worldwide support forest monitoring, typically deploying environmental sensors to measure humidity, soil conditions, and sap flow to identify tree stress symptoms. These Initiatives include the TreeTalker network, the Ash Dieback E-Nose, IoTree, and Rainforest Guardians (Tomelleri et al. 2022; Forest Research, UK 2024). While these systems focus on real-time environmental data collection, they often lack context-aware decision-making and adaptive sensing mechanisms. Few integrate multi-layered reasoning or dynamically adjust sensing based on environmental triggers. Recent research has started to explore intelligent sensing and AI-based interpretation for forest monitoring. Gabrys et al. (Gabrys 2020) propose integrating automation and inference to support smarter forest governance. Moreover, ML applications, such as anomaly detection in tree health, are being investigated (Tomelleri et al. 2022). However, these approaches often rely on complete data uploads to the cloud, with limited local processing or real-time decision-making. At the protocol level, traditional WSN and IoT protocols like LEACH, PEGASIS, HCA, H-CSA, and K-Means primarily focus on routing efficiency and cluster optimisation without addressing wide area coverage (Kadir, Rosa, and Yulianti 2018; Gantassi, Gouissem, and Othman 2021). While these protocols help reduce energy consumption, they lack context-driven sensing and adaptive communication mechanisms. Platforms like ESTO attempt spatio-temporal optimisation but often fail to provide fine-grained environmental intelligence. Despite advancements in IoTr connectivity and sensor deployment, most systems remain passive, static, and non-adaptive in monitoring trees. The integration of context-aware sensing and intelligent reasoning for early detection of disease or stress remains an underexplored area. This paper addresses this gap by introducing I-TREES, a modular IoTr framework that facilitates selective sensing and context-driven inference for proactive health monitoring in forest ecosystems.

IoTr Layered Architecture

This section proposes a layered I-TREES (Internet of Trees (IoTr) -based Tree Routing for Energy-Efficient Systems) architecture, forming the foundation of the I-TREES framework. The proposed architecture is structured into layered components that work towards supporting specific functions, varying from data collection at the tree level to decision support at the application level. Figure 3 shows the IoTr architecture, comprising physical devices, communications infrastructure, processing components, and cloud intelligence adopting IoT infrastructure. This layered architecture enables independent sensing, communication, computation, and decision-making optimisation. It supports mass deployment, allows for scalability in vast forests, and sustains the efficiency of operations in areas of poor connectivity. This architecture supports the I-TREES ability to make context-based decisions, which can initiate proactive and intelligent responses to tree stress and disease precursors.

Sensing Layer The sensing layer of IoTr architecture is the foundational one that consists of IoTr physical sensor

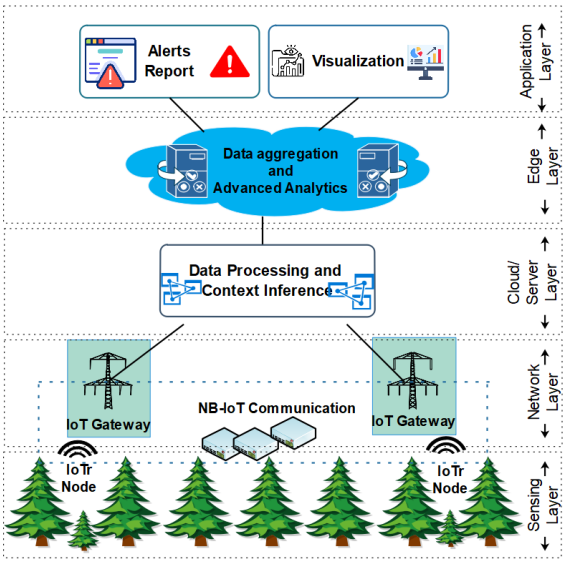


Figure 3: I-TREES System Architecture

nodes deployed in the forest environment on trees, soil, or the surroundings (Ali et al. 2025). The sensing layer uses LPWAN technologies like NB-IoT and LoRa for long-distance communication and low power consumption, making it fit for remote and power-restricted environments of the forest.

Network Layer The network layer enables data transfer from sensor nodes to central processing nodes, where mesh or star topologies (Domínguez-Bolaño et al. 2022) together with LPWAN are utilised. IoT gateways collect local sensor data in clusters and relay it to the cloud infrastructure where pre-processing capabilities such as filtering, deduplication, and compression are provided in some gateways. Edge computing operations are also supported at sites demanding immediate local response, as fire detection or critical limit violation alarms in remote areas.

Edge Layer The edge layer provides initial-stage analysis on the real-time data streams, utilising inbuilt reasoning or light ML models for detection of anomalies and categorisation (Ali et al. 2025; Arshad et al. 2023). It delivers environment-contextual inference at the source by comparing sensor data in real time with known environmental limits. The edge layer enables the dependency on constant upstream data transfer and saves energy and bandwidth. Upon certain conditions, condensed data or trigger events are transmitted to the cloud for in-depth processing and storing.

Cloud Layer The cloud layer organises, indexes, and analyses processed data through high-end cloud data analytics services. Rule-based engines and AI models can be installed to recognise environmental stress factors, derive tree health status, and provide intervention measures (Arshad et al. 2023). The cloud is also the storage centre to support historical analysis and long-term environmental monitoring. The cloud is important for the proposed I-TREES framework, which validates local decision-making and global alerts based on major patterns.

Application Layer The application layer is the system interface with the users, providing real-time dashboards, visualisations, and decision support tools for forest administrators, scientists, or policy-makers. Applications at this level can notify users, monitor environmental trends, and set intervention or threshold levels (Ali et al. 2025). This layer also automates responses based on specified rules and authenticated patterns.

I-TREES Framework for Context-Aware Tree Monitoring

This section presents the proposed I-TREES framework. Figure 4 details the I-TREES framework, which enables context-aware, processing, and intelligent decision-making for tree monitoring.

IoTr Embedded Sensors and Data Collection

The I-TREES framework consists of embedded IoTr sensor nodes deployed on trees or across specific trees in the forest. A sensor density of approximately one per 0.5 hectares is optimal for detailed ecological monitoring. Trees are equipped with 2 to 3 sensors, depending on the monitoring needs and tree species, to detect important information. Sensors are mounted at key locations such as the tree trunk to measure core temperature and moisture content, the tree canopy to monitor leaf wetness and detect airborne pathogens and the tree soil base to record soil moisture and root zone conditions. It will monitor different parameters, including temperature, humidity, soil moisture, leaf wetness, and leaf images. Sensors also communicate with neighbouring trees to form a clustered sensing topology. This allows each sensor to monitor its tree and help infer changes in nearby vegetation by sharing data, which increases spatial awareness. The low-power and long-life sensors act as the foundation for building environmental context across the network. The goal is to detect stress indicators such as prolonged moisture deficiency, leaf lesions, or temperature spikes, which may signify disease onset.

Context-Aware and Selective Activation Sensing

Context-aware is the ability of a system to interpret environmental data in real time and adjust sensing activity accordingly (de Matos et al. 2020). In I-TREES, the sensor nodes do not follow fixed sampling rates. Instead, they monitor environmental trends and adapt their behaviour, reducing sampling during stable periods and increasing it when signs of stress or abnormality are detected, like a gradual drop in humidity combined with increasing leaf wetness, which may indicate disease appearance. In such a case, the node will switch to higher-frequency sampling and flag the event. Selective sensing saves the sensor energy consumption of each node while ensuring relevant, high-priority data collection.

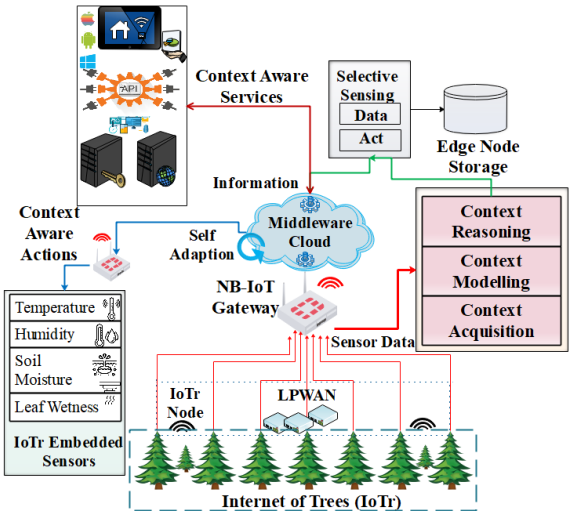


Figure 4: I-TREES framework showing sensor data collection, NB-IoT communication, edge-based selective sensing, context-aware cloud reasoning, and user services.

LPWAN Communication and NB-IoT Integration

Sensor data is transmitted using LPWAN technologies, with NB-IoT preferred for its energy efficiency and long-range capabilities (Mekki et al. 2018). This allows communication even in remote forest settings and through dense canopies. NB-IoT is suitable for connecting large nodes over several kilometres with minimal energy consumption to support long-term deployments without frequent battery replacement (Wang et al. 2019).

Edge Node with Storage and Local Processing

Edge nodes serve as intermediate gateways responsible for initial data processing and storage. They temporarily cache raw data to manage intermittent connectivity, cache raw sensor data and apply filtering, summarisation, or compression to reduce bandwidth use. They also enable basic local decision-making in cases where immediate feedback is needed or connectivity to the cloud is temporarily lost.

Middleware Cloud and Context Reasoning

The core intelligent processing of the I-TREES framework resides in the context-aware cloud-based middleware, which enables multi-stage context reasoning to detect tree health anomalies and environmental stress. The middleware architecture is designed to systematically process, analyse, and reason with heterogeneous data from IoT sensors and external data sources. It consists of four interconnected modules, each responsible for specific aspects of data handling and reasoning (de Matos et al. 2020).

Context Acquisition The Context Acquisition module is the primary interface for gathering data from sensor nodes deployed in the forest environment. It continuously collects multivariate environmental data, gathered through NB-IoT enabled sensors. Additionally, this module is designed to integrate inputs from external sources like meteorological feeds and satellite imagery. These external data streams are dynamically merged with sensor data to create a comprehensive dataset that reflects local and broader environmental conditions.

Context Modelling The Context Modelling structures and organises the acquired data using semantic models. These models are designed to maintain consistency and interoperability between heterogeneous data sources, ensuring that data from different sensor types and external inputs can be seamlessly integrated. Environmental data is organised into structured vectors, each representing a snapshot of current conditions. Context modelling also involves extracting critical features indicative of potential tree stress, such as rapid temperature fluctuations or abnormal moisture patterns. These features serve as inputs to the reasoning module.

Context Reasoning Context reasoning is the most critical layer, where the system applies inference rules and ML algorithms to detect meaningful patterns and infer potential tree health issues. The I-TREES framework incorporates an Isolation Forest–based reasoning layer for anomaly detection (Liu, Ting, and Zhou 2008). The Isolation Forest algorithm partitions multivariate data vectors into random binary trees, where the path length from the root to a leaf indicates the degree of anomaly. The algorithm computes an anomaly score for each sensor vector based on path length, where shorter paths correspond to more isolated and anomalous data points. To enhance detection accuracy, I-TREES can also combine the Isolation Forest with a lightweight supervised classifier at the cloud layer, allowing for contextual refinement based on pre-identified disease patterns.

Context Management The Context Management module acts as the system's knowledge repository. It stores processed data, including detected anomalies and predicted stress conditions, while managing user access and data dissemination. Validated sensor readings and anomaly reports are stored in a structured database for long-term analysis. The system provides authorised users, such as forest managers and environmental scientists, with real-time data, alerts, and visual insights through a cloud dashboard. The module also supports a feedback mechanism where users can label events as false positives or confirm detected anomalies, enhancing the system's learning accuracy over time.

Context Providers and Data Integration I-TREES incorporates context providers that supply external data from meteorological services or satellite imagery, enhancing the system's situational awareness. The acquisition module ensures synchronisation of internal and external data sources to maintain temporal consistency. This integration reduces false positives by correlating abnormal sensor readings with known environmental disturbances.

Context-Aware Services To ensure robustness, I-TREES implements context-aware services that provide stakeholders with actionable insights during extreme environmental conditions.

During heatwaves or sudden humidity drops, nodes activate safe-mode sensing, significantly reducing data transmission to conserve energy. If sensor nodes become nonfunctional due to stress, the system dynamically reconfigures cluster topology to maintain data flow.

Our NS-3 simulations emulated these scenarios by turning off node radios or artificially increasing energy drain, demonstrating adaptive cluster head re-election and data rerouting. The system's cloud dashboard continuously updates stakeholders with visual alerts, indicating stress levels and potential threats. These services are particularly valuable for forest managers and researchers who require real-time, data-driven insights to make proactive conservation decisions.

I-TREES Algorithm: Context-Aware and Adaptive Monitoring The I-TREES algorithm 1 is structured to efficiently monitor tree health by combining context-aware sensing, adaptive cluster head (CH) selection, energy management, and real-time anomaly detection. Sensor nodes deployed across the forest collect data, and mobile nodes may capture images when required. If the deviation from prior readings exceeds a threshold (θ), the system triggers adaptive sensing to increase data collection frequency. Nodes are grouped into clusters, with the most suitable node based on energy, PDR, and quality metrics chosen as the CH using ML techniques. The CH aggregates data from member nodes and forwards it to the base station via NB-IoT communication. Aggregated data is processed at the cloud-based backend, where ML algorithms, such as Isolation Forest, detect anomalies.

If an anomaly is detected, the system triggers an alert, updates the dashboard, and visualises the health status of the monitored area. The algorithm continuously monitors node energy, reducing sensing frequency when energy falls below a set threshold, or switching to low-duty mode when necessary. In node failure, adaptive routing is activated to maintain network connectivity. This algorithm ensures that the I-TREES framework remains energy-efficient, context-aware, and capable of real-time anomaly detection, addressing the core challenges of traditional tree monitoring systems.

Simulation Setup and Evaluation Metrics

The proposed I-TREES framework was evaluated using NS-3 (v3.35) to simulate IoTr deployments in forest ecosystems. The simulation involved 700 IoTr nodes, including sink nodes, randomly deployed in a 3D space of 2000 m × 2000 m × 2000 m. Each node had an initial energy of 100 J and a communication range of 200 m, transmitting CBR traffic at two packets per second, with each packet being 512 bytes. Selective sensing enhanced energy efficiency, activating nodes only when environmental thresholds were exceeded. Mobility was modelled using a random waypoint approach, with speeds ranging from 1 m/s to 25 m/s, simulating environmental dynamics. The simulation ran for 8000 seconds to evaluate network behaviour, energy consumption, and communication stability. Collected logs were exported as CSV files and analysed in MATLAB for performance visualisation. Table 1 provides a summary of the simulation parameters.

Algorithm 1: IoTr-Based Tree Routing for Energy-Efficient Systems (I-TREES)

Input: Sensor Set $S = \{T, H, SM, LW, Img\}$, Deployment Configure $D = (700, 35, 3)$, Energy Budget E, Node Status N_i, Thresholds θ, P_{thresh}
Output: Anomaly Alerts, Performance Logs, Visual Insights

Step 1: Sensor Data Collection
Deploy stationary and mobile sensor nodes across the target forest area.
Periodically collect data from temperature, humidity, soil moisture, and leaf wetness sensors.
if Image data collection required **then**
  Trigger drone to capture images for selected clusters.
end if
Step 2: Clustering and Aggregation
Divide nodes into 35 clusters.
Elect a Cluster Head (CH) for each cluster using ML.
if Node energy $< \epsilon$ **then**
  Trigger CH rotation using reinforcement learning.
end if
CH aggregates and compresses sensor data from member nodes.
Step 3: Communication Phase (NB-IoT)
CH transmits aggregated data to the nearest base station.
Log transmission metrics: latency, energy per hop, and signal strength.
Step 4: Cloud Processing and ML Reasoning
Forward aggregated data to MATLAB-based backend.
Apply ML models for detecting stress or disease using time-series and image features.
if Abnormality score $>$ threshold **then**
  Log an alert.
end if
Step 5: Dashboard and Visual Analytics
Update forest dashboard with Real-time health status, Node health, and Image overlays
Log performance metrics: PDR, PLR, latency, throughput, delay and energy efficiency.
Return: alerts, ML predictions, and simulation statistics.
Step 6: Adaptive Sensing and Energy Optimisation
Monitor residual energy for each node.
if Energy $< P_{thresh}$ **then**
  Reduce sensing frequency and switch to low-duty mode.
end if
Step 7: Failure Handling and Reconfiguration
if Node Failure Detected **then**
  Trigger re-routing to the nearest active node.
  Update network topology dynamically.
end if

I-TREES was benchmarked against six baseline protocols used in WSNs and IoT: LEACH, PEGASIS, HCA, H-CSA, ESTO, and K-Means. These protocols were selected

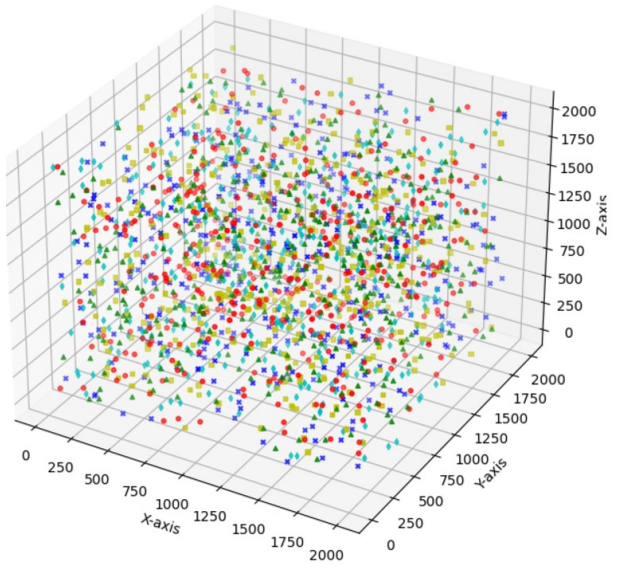


Figure 5: Simulation Scenario

based on their relevance in smart agriculture and forestry. While each protocol employs different clustering and routing strategies, most lack the context-awareness and adaptability required for dynamic forest environments. Performance metrics included PDR, PLR, Throughput, Energy Consumption, Latency, and End-to-End Delay. Table 2 highlights the comparative capabilities of I-TREES and the baseline protocols, focusing on adaptability, clustering strategy, and application suitability. Unlike conventional protocols, I-TREES integrates context-aware logic, selective sensing, and threshold-based activation, allowing it to adjust data collection and transmission based on environmental changes dynamically.

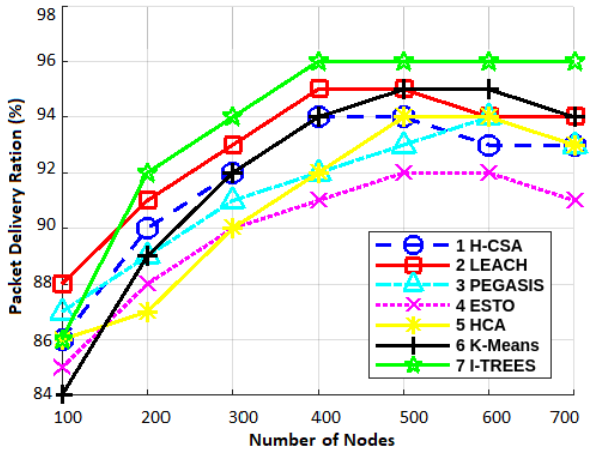


Figure 6: Packet Delivery Ratio (PDR) comparison

Parameter	Value
Network Simulator	NS-3 (v3.35)
Topology Size	2000 m × 2000 m × 2000 m
Initial Node Energy	100 J
Transmission Range	200 m
Bandwidth	2 Mbps
Packet Size	512 bytes
Traffic Type	Constant Bit Rate (CBR)
Transmission Rate	2 packets/sec
Mobility Model	Random Waypoint
Node Speed	1–25 m/s
Simulation Time	8000 seconds
Transmission Energy	0.0005 J
Reception Energy	0.00025 J
Number of Nodes	700 (including sinks)

Table 1: Simulation Parameters for I-TREES Evaluation

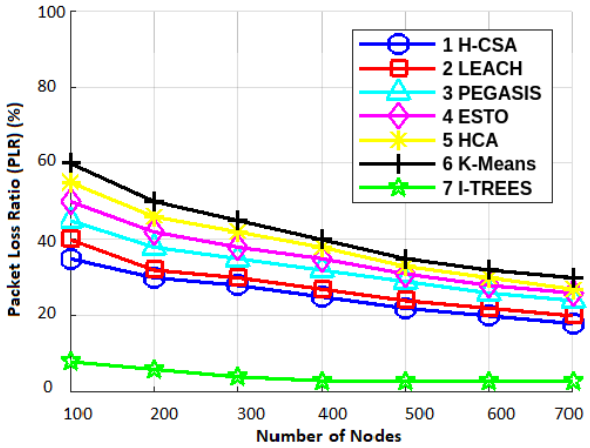


Figure 7: Packet Loss Ratio (PLR) Across Different Routing Schemes

Packet Delivery Ratio (PDR)

PDR measures the ratio of successfully delivered packets to those transmitted (Mnguni et al. 2021). Figure 6 shows I-TREES achieving the highest PDR (96% to 97%) due to its context-aware routing and adaptive data transmission, and fewer packet losses compared to conventional protocols. K-Means follows, benefiting from adaptive clustering, though without environmental filtering. LEACH maintains stable delivery up to a moderate scale but deteriorates beyond 500 nodes. H-CSA remains consistent but lacks predictive sensing. PEGASIS and HCA show performance degradation in dense topologies, while ESTO suffers from congestion under high traffic, recording the lowest PDR.

Packet Loss Ratio (PLR)

PLR reflects the percentage of packets lost during transmission. As seen in Figure 7, I-TREES maintains the lowest

Protocol	Cxt-Aware	Sel. Sens.	Energy Eff.	Cluster. Method	Delay Opt.	Adapt.	App. Suitability
I-TREES	Yes	Yes	Yes	Hierarchical	Yes	High	Smart forestry, early disease detection
LEACH (Raut and Upadhyay 2022)	No	No	Yes	Random	No	Low	Basic WSNs with minimal environmental dynamics
PEGASIS (Raut and Upadhyay 2022)	No	No	Yes	Chain	No	Medium	Suitable for small, linear topologies
HCA (Neamatollahi et al. 2011)	No	No	Yes	Multi-level	Yes	Medium	Scalable networks with hierarchical routing
H-CSA (Liang et al. 2021)	No	Yes	Yes	Heuristic	Yes	High	Delay-sensitive WSN applications
ESTO	Yes	Yes	Yes	None	No	High	Event-driven systems requiring fast response
K-Means (El Khediri et al. 2020)	No	No	Yes	ML-based	No	Medium	Adaptive clustering layouts for changing conditions

Abbreviations: Cxt-Aware: Context-Aware, Sel. Sens.: Selective Sensing, Energy Eff.: Energy Efficient, Cluster. Method: Clustering Method, Delay Opt.: Delay Optimised, Adapt.: Adaptability, App. Suitability: Application Suitability.

Table 2: Feature Comparison of I-TREES with Baseline Protocols

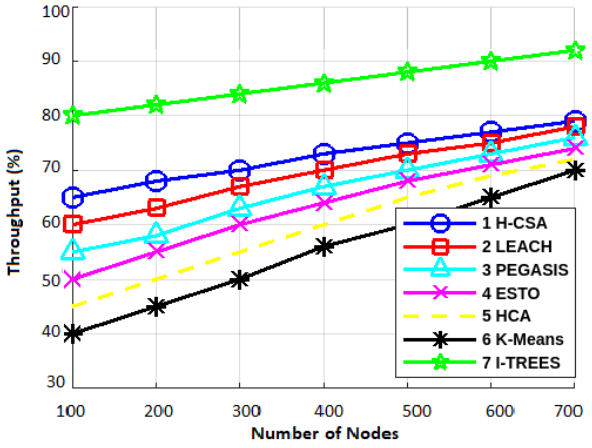


Figure 8: Throughput Comparison Over Simulation Time

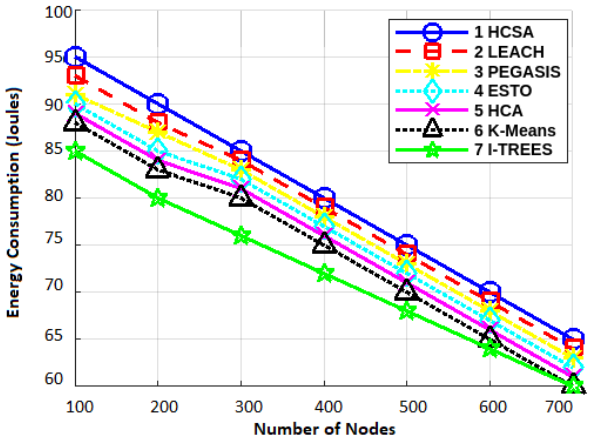


Figure 9: Energy Consumption Comparison

PLR (<4%), supported by selective sensing and load-aware routing. I-TREES maintains a lower PLR than other protocols due to optimised transmission and context-aware adaptive sensing. In contrast, LEACH and PEGASIS experience high loss rates in larger deployments due to static routes and node failure. ESTO exhibits the highest PLR (>10%), affected by limited buffering and congestion control. K-Means and HCA display moderate loss levels, but their lack of environmental awareness leads to inefficient retransmissions under network strain.

Throughput

Throughput indicates the data rate successfully received at the sink (Consortium 2024). Figure 8 illustrates I-TREES achieving the highest and most stable throughput. I-TREES shows higher throughput due to reliable routing and adaptive communication strategies, outperforming other protocols, especially as the number of nodes scales up. -Means performs well initially but fluctuates with scale. EACH and H-CSA show moderate throughput, which is limited by fixed scheduling and a lack of prioritisation. EGASIS underperforms in dense topologies, where its chain-based design becomes a bottleneck. STO and HCA deliver average throughput with minimal adaptability.

Energy Consumption

Energy consumption is a crucial factor in unattended forest deployments. Figure 9 shows I-TREES as the most energy-efficient protocol. It is context-driven activation and threshold-limited sensing that significantly reduces idle

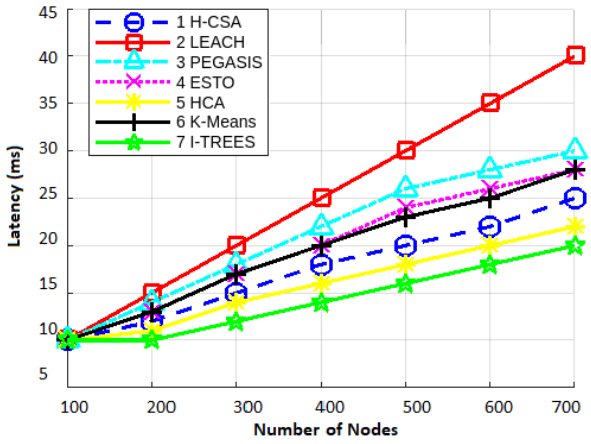


Figure 10: Latency Observed Across Protocols

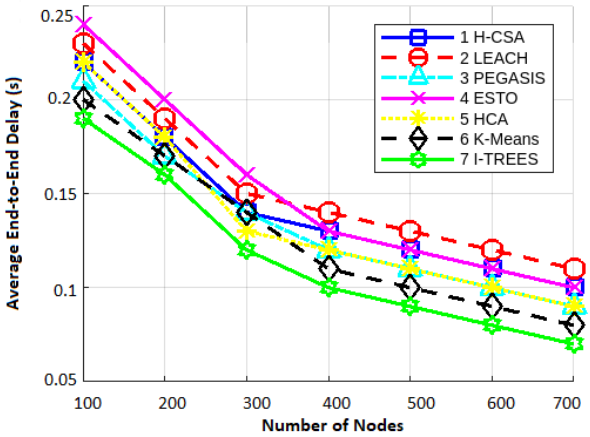


Figure 11: End-to-End Delay Comparison

communication. I-TREES consistently consumes less energy as the number of nodes increases due to energy-aware CH selection and adaptive sensing. H-CSA and LEACH consume more energy due to repetitive transmissions and a lack of adaptive clustering. PEGASIS reduces overall transmissions but burdens nodes near the sink. K-Means and HCA maintain moderate energy use, while ESTO saves energy through event sensing but lacks energy-aware routing decisions, limiting its benefits under dense deployments.

Latency

Latency reflects the time delay from data generation to sink reception. Figure 10 highlights I-TREES with the lowest latency (`<18 ms at 700 nodes`), supported by congestion-aware scheduling and adaptive multi-hop paths. LEACH and PEGASIS display the highest latency due to non-prioritised data flow and serial transmission. ESTO performs moderately, with event-based logic but no dynamic routing. H-CSA and HCA offer reduced latency through cluster-based designs but lack intelligent queue control. K-Means balances latency effectively at mid-scale but degrades under heavy load.

End-to-End Delay

End-to-end delay encompasses the total time from source to sink delivery. Figure 11 shows I-TREES achieving the lowest delay, owing to selective packet triggering, adaptive path selection, and energy-balancing mechanisms. LEACH and PEGASIS lag due to a lack of awareness and transmission bottlenecks. HCA and H-CSA improve performance with structured routing but remain static. ESTO shows efficiency at a moderate scale but fails to adapt under high load. K-Means fluctuates due to dynamic cluster updates without sensing context. As the number of nodes increases, I-TREES shows a lower delay than other protocols due to efficient adaptive routing and energy management.

Conclusion and Future Directions

This paper presents I-TREES, a context-aware, energy-efficient framework for intelligent tree health monitoring within IoTr environments. I-TREES effectively addresses critical challenges in traditional IoT-based forestry systems by integrating selective sensing, adaptive routing, and real-time context reasoning. The framework's layered architecture combines LPWAN communication, edge processing, and cloud-based inference to support responsive and scalable forest monitoring. Simulation results using NS-3 demonstrate that I-TREES significantly outperforms existing protocols, including LEACH, PEGASIS, HCA, H-CSA, ESTO, and K-Means, regarding PDR, energy efficiency, latency, and end-to-end delay. This makes I-TREES a robust solution for proactively monitoring vulnerable tree species, particularly under challenging environmental conditions. Future work will focus on deploying the I-TREES framework in real forest environments, particularly targeting tree species threatened by diseases. We aim to enhance early-stage disease detection by identifying relevant physiological markers through literature and pathology data. The deployment will include context-specific sensors, such as leaf wetness, temperature-humidity probes, and soil monitors, to track physiological changes effectively.

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