

Energy-aware reinforcement-driven clustering framework with adaptive processing for sustainable IoT sensor networks

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Abstract: Energy saving and sustainable behavior of the system is a vital problem, especially for a resource-limited agricultural monitoring environment in WSNs. In this paper, we introduce a Reinforcement-driven Energy-aware Clustering scheme with Adaptive Processing (RECAP) for extending lifetime, conserving energy, and maintaining data fidelity in field situations. RECAP adopts a hierarchical architecture comprising an Adaptive Duty-Cycling Engine (ADCE), an Energy-Aware Clustering Module (EACM), a Reinforcement Learning Controller (RLC), and an Edge Processing and Communication Layer (EPCL). Every Cluster Head tunes their work dynamically by a lightweight Q-learning model that adapts cluster formation, transmission scheduling, and node sleeping cycles according to local energy and topology states. The architecture uses a hybrid energy draining model through context-aware duty cycling and data aggregation to avoid redundant transmissions. Simulation results show that RECAP reduces 68% energy consumption, achieves event-triggered data collection with 98% accuracy and low computation overhead, and overcomes the latency problem than existing hybrid models like LEACH-CNN, PSO-LSTM, and base GA-GRU. These results validate RECAP for sustainable IoT-based precision agriculture and other mission-critical WSN deployments.

Keywords: IoT, wireless sensor networks, reinforcement learning, duty cycling, edge intelligence, precision agriculture, RECAP, sustainable IoT, adaptive clustering

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1 Introduction

The advent of the Internet of Things (IoT) for smart agriculture has had a substantial impact on how farming operations are performed. Farms are now supported by sensors in the ag field to measure soil moisture, temperature, moisture, standard crop health parameters, allowing farmers to make better decisions, increase yield, and reduce environmental impact

(Boddu et al., 2021; Sinde et al., 2019). That said, one of the longest standing issues for successful deployment of large-scale wireless sensor networks (WSN) is power efficiency in remote agricultural applications and on farms. WSNs rely on battery-powered or solar-powered sensors. Once deployed, especially in off-grid or remote environments, battery replacement and maintenance is an unreasonable frequency (Soro, 2021; Phan et al., 2021).

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In turn, the energy consumption of smart field sensor nodes, especially with regard to the energy required for sensing, processing, and communication, is a prime limitation on successful IoT-initiated smart field usage over time. Even though there are various power-draining factors at play, communication alone typically is the most prohibitive element of energy consumption in WSNs when raw data input is sent continuously without preprocessing or smart data filtering (Zaman et al., 2023). To overcome these challenges, researchers and industry stakeholders have proposed several techniques for energy optimization in the last decade, recently moving toward adaptive duty-cycling, energy-aware clustering, implementation of machine learning methods to support predictive modeling, and improving ongoing computing with edge-computing using TinyML.

Adaptive duty-cycling is an often utilized technique to limit energy consumption in WSNs, whereby each sensor node periodically switches between sleep and active modes based upon temporal data trends or user pre-defined schedules (Woodward et al., 2026). Unfortunately, many approaches in existing literature are based on static threshold-based heuristics or past data trend approaches, which only consider snapshots of data in time, are ineffective at adapting to the continuously changing nature of the agricultural environments affected by weather, irrigation, and crop cycles. More intelligent methods are needed to dynamically predict the optimum sensing intervals subject to the expected environmental changes (Wang et al., 2020).

To minimize communication energy, use in WSNs, clustering approaches have also been utilized extensively, where sensor nodes are grouped into distinct clusters with predetermined leader or cluster-head (CH), in charge of aggregating and forwarding data to the sink (Varalakshmi, 2021). However, optimizing the choice of CH is a non-trivial problem. Typically, existing methods will select CHs based on basic metrics like residual energy, or node degree,

ignoring some contextual elements like total node workload, basing costs of communication transmissions, and expected frequency of sampling. Additionally, if static clustering is employed, energy usage among nodes lies a heavy onus on the nodes that form the clusters and can result in uneven energy distribution being drained while the clustering remains intact or worse very critical nodes reaching non-operational states faster than expected (Jothiraj et al., 2021).

Reinforcement Learning (RL), particularly Deep Q-Learning and policy gradient techniques, has recently become an important option for adaptive and autonomous decision making in WSNs (Elhanashi et al., 2024). RL differs from conventional rule-based approaches, as RL allows sensor nodes to learn optimal actions over time, through continuous interaction with their operating environment. The goal of RL is to maximize long-term reward like energy savings, data quality, reliability of coverage. The flexibility and adaptability have value in a dynamic agricultural context, as environmental conditions can change dramatically across farming seasons, times of day, or different areas of a farm. However, current RL-based approaches typically only address routing or sampling in isolation, rather than developing a complete control solution for all aspects of the node's behavior from sensing, to communication (Firdous et al., 2022).

A new approach to reduce transmission based energy costs is edge processing through Tiny Machine Learning (TinyML) (Zhao et al., 2020), allowing for lightweight ML inference on microcontrollers. TinyML models permit sensor nodes to preprocess and analyze data locally, allowing sensor nodes to only transmit relevant summaries or unexpected anomalies, from a continuous stream of unimproved raw signal data. This gives rise to lower network bandwidth and communication energy as well as better response time and privacy (Bartoli et al., 2025). There are, however, current edge-based solutions that are not

conventionally limited. Most proposed frameworks can be procedural along a ML tasks like anomaly detection, forecasting and do not address how the intelligence at the edge is coupled with network-wide logic with methods like clustering, duty-cycling, and reinforcement learning, in a single framework (Vatambeti et al., 2023; Rajendra et al., 2024).

To address the weaknesses reported in these current methods and take a more holistic approach to develop and sustain IoT deployments in agriculture, we propose the RECAP framework. RECAP is also considered as multi-layered, modular, and features four tightly coupled components:

Adaptive Duty-Cycling Module: Proposes a recurrent neural network (GRU) to learn on temporal data and establishes a dynamic sensor wake/sleep schedule based on environmental patterns related to trends.

Energy-Aware Clustering Module: Develops energy clusters and rotate CHs based on a multi-factor fitness function; including residual energy, communication overhead, and predicted sampling requirements.

A reinforcement learning agent that employs Q-learning for node-level sampling, data communication and cluster participation decision approaches based on the node's current energy state, past and data importance.

An edge processing module, which employs an anomaly detection model based on TinyML and feature summarization to preprocess the data at the sensor node and reduce data to be communicated.

The five components are designed to operate in conjunction with one another, reduce overall power consumption, extend the life of the sensor node and acquire reliable data in even the most extreme of field conditions. The notable advances realized in this work include:

A reinforcement learning control framework that learns the energy-optimal behaviors of nodes over time in a dynamic environment. An adaptive data-driven behavior regulation mechanism employing

deep learning for duty-cycling the sensing behavior of the sensor node;

A multi-criterion energy-aware clustering strategy to distribute the energy load of communication and energy sources across the peer nodes;

A TinyML lightweight edge processing unit that removes superfluous data transmission using intelligent filtering and cloud-based processing;

A platform that was substantiated both by simulation and field-validated real-world parameters with demonstrated energy-efficient abstraction, extent of the lifetime of the network while synchronously collecting higher quality dataset.

The remainder of this paper is organized as follows. Related work is reviewed in Section 2. Section 3 describes the RECAP framework and its key modules. Its experimental setup and evaluation metrics are described in Section 4. Section 5 discusses the results, including comparisons to existing methods. Finally, Section 6 concludes and discusses future work.

2 Literature review

In WSNs used for agricultural monitoring, energy consumption controls the effectiveness of the network. To conserve energy and extending the longevity of WSNs, researchers have studied clustering more than any other technique. Lei et al. (2024) proposed a routing directing technique, combining Particle Swarm Optimization (PSO) and fuzzy clustering. This research contributed to reducing energy consumption and increasing throughput. Yao et al. (2023) proposed an Energy-Efficient Routing Protocol Based on a Multi-Threshold Segmentation (EERPMS) in which clusters and heads are optimized. This protocol demonstrated a large amount of energy savings using traditional protocols. Zhu et al. (2024) presented a clustering algorithm called an Improved Soft-k-Means (IS-k-means) clustering algorithm. This is a clustering algorithm that reduces energy usage by controlling the density of nodes, while also employing multi-cluster heads. Pradeep et al. (2022) have proposed a routing mechanism named Modified

Gravitational Search Algorithm with Optimal Relay Selection. This work is projected the outcomes with limited number of node without flexibility.

RL has proven to be a useful mechanism for accomplishing dynamic energy management of WSNs. Bui et al. (2022) discussed a Deep RL based adaptive charging policy for Wireless Rechargeable Sensor Networks, which allows mobile chargers to recharge nodes adaptively based on the conditions in the network. Dey et al. (2024) proposed a Deep Q-Network (DQN) based framework for agricultural monitoring using energy-aware multi-path routing with the aim of maximizing network lifetime. Han et al. (2021) surveyed a joint optimization approach to power control and channel allocation using Deep Deterministic Policy Gradient (DDPG) for WSNs deployed in farmland areas, which tend to ignore the size of state-action spaces that these systems face. Thus, the above RL-approaches are evidence that there is potential for Distributed Intelligence in dynamic agricultural environments for managing energy intelligently and adaptively.

Adaptive duty cycling is an important concept that deals with reducing energy consumption at the level of sensor node active periods and sleep periods. Wu and Cai (2020) outlined a sensing scheduling algorithm, which uses an adaptive energy-efficient algorithm and a Fibonacci Tree Optimization. Because the algorithm makes sense of changes in environment conditions by modifying the sensing intervals, thus providing adaptive sensing scheduling. Poonguzhali et al. (2025) explored the Multi-objective cluster head based energy efficient routing using THDCNN with hybrid capuchin search and woodpecker mating algorithm in wireless sensor network. It utilized clustering and compression techniques to create an energy-efficient WSN and maximize its lifetime.

The combination of TinyML brings intelligence directly onto devices, decreasing dependence on cloud-based computing as well as energy consumption. According to Elhanashi et al.(2024),

progress on TinyML applications have made headway in affecting IoT devices, through improved model quantization and model pruning. In practice, Mugisha et al. (2025) presented, as an example application, a hybrid knowledge distillation framework that advanced on-device vision systems in the agricultural IoT domain, achieving state-of-the-art performance in plant disease classification with a much less computation burden.

The convergence of work in energy-aware clustering, reinforcement learning, adaptive duty cycling together with integrated development like TinyML allows for developed frameworks like RECAP to flourish. For example, the use of neighborhood-aware clustering by Sehrawat et al. (2023) by the NaISEP protocol to improve the life cycle of networks when applied in agriculture. In addition, Sundararajan et al. (2024) The paper introduces a new architecture namely EECAS (Energy Efficient Clustering and Aggregator Node Selection) to overcome the issues of energy consumption and network lifetime in WSNs. The energy efficiency consideration is also the reason why battery powered sensor nodes are deployed in WSNs. Excess power consumption may drastically shorten the operating life of the network.

These integrated approaches represent a significant transition from traditional approaches toward holistic energy management strategies in IoT-enabled agriculture, and usher in the sustainable and intelligent methods of farming. There are just a few existing shortcomings/challenges of the current frameworks:

There is a need for dynamic and context-aware data cluster to accommodate and respond to real-time energy conditions and environmental contexts.

Which means critical nodes quickly experience battery drainage and decrease overall network lifetime.

Energy-balanced and intelligent CH selection designs that consider a number of parameters simultaneously.

They cannot learn and adapt in real-time, which limits their performance when applied to dynamic and resource-constrained outdoor deployments.

The addition of reinforcement learning and other online learning mechanisms for sustained self-optimization.

This constant communicating is not feasible, especially in remote and agricultural areas with little power fabrication.

Instead adaptive duty cycling and communications capturing data locally are needed to limit unnecessary communication.

Without adequate edge intelligence all systems will be dependent on either cloud, or gateway nodes, with a thinner power footprint and longer wait times.

To provide this, modular and readily deployable frameworks would need to be established that can extend-out efficiently in the field across agricultural conditions and different crops.

And lastly, ignoring data security and data integrity vulnerabilities related to the collection and aggregation of sensor data.

Eventually, limiting sensor devices to an adequate level of lightweight security tasks.

3 Proposed work

The growing use of IoT-enabled sensor networks in smart agriculture calls for new energy-aware models that can facilitate effective energy management for extended, autonomous operation of sensor nodes in a resource-limited outdoor context. We propose RECAP, a complete framework for minimizing energy consumption, maximizing network lifetime, and reliable sensing and communication in smart agriculture. The RECAP framework combines four collaborating modules: a Reinforcement Learning-based Clustering Engine, that can determine and allocate cluster heads and reconfigure cluster shapes based on real-time sensor node energy data; the Adaptive Duty Cycling module which can allocate the ideal sleep and active duty cycles, thereby ensuring the sensor nodes don't

redundantly or irrelevantly activate; the Energy-Aware Aggregation layer, which efficiently aggregates sensor data and minimizes transmission load while retaining relevant information; and the Edge Intelligence module that uses TinyML on the node itself to perform inference and local decision-making, while maintaining minimal compiling load on the node itself. This holistic approach addresses limitations in these models, and offers inherently self-optimizing mechanisms through local autonomy at the sensor network level, rather than static clustering with fixed duty cycles and full dependence on the cloud. Using this intelligent blending of energy, data, and computation, RECAP enables sensors to operate sustainably and forge opportunities for scalable deployment throughout the many agro-ecological zones.

3.1 Network assumptions

Development of a new protocol RECAP is carried out knowing the Wireless Sensor Network is fit for the purpose of precision agriculture and longer environmental monitoring. In consideration of the usability of this proposed framework and modeling and simulating network behavior in real-world conditions, several assumptions were made. To begin with, it is assumed that the sensor nodes that are deployed in the field are homogeneous. That is, when the nodes were initialized, they all started with the same amount of energy levels, have the same hardware specifications and capabilities, and therefore behave identically across the network. The sensor nodes are also deployed statically. This implies that they do not move after being placed in the field. This assumption is valid for agriculture applications when the sensors are embedded in soil, or attached to poles or plant canopies for continuous monitoring.

The sensor nodes are also distributed randomly over a 2-dimensional region of size AXA . That is, there is no bias towards any side of the monitored area, therefore, distributed and able to scale across it. Each of these sensor nodes communicate with a

centralized Base Station (BS), which serves as the data sink and its control unit. The location of the BS can be anywhere within, such as the center or edge of the deployment region. The BS is usually assumed to have an infinite remaining energy and computing resource capacities and is usually connected to a stable power supply and/or a remote server infrastructure. In terms of communication, the framework utilizes a single-hop cluster-based architecture where each group of sensor nodes forms a cluster and the Cluster Members send their sensed data to their CH without multiple hops/bounds. The CHs aggregates the sensor nodes' data in order to get rid of duplicates and send the aggregated data directly to the BS. Communication between the individual nodes and their CH, as well as their CH and the BS, is determined using the first-order radio energy model, which utilizes two types of propagation loss, namely free space propagation and multipath fading depending on the transmission range.

In addition, it is assumed that the power consumed during the sensing operations by nodes is negligible when compared to the power used during communication. Hence, the energy model is focused on the power usage of transmitting and receiving, which are the significant factors of energy efficiency and lifetime of the network. Lastly, one of the key

innovations of the RECAP framework is the realization of a lightweight RL agent in each CH node that can adaptively optimize its role according to real-time network dynamics. The RL agents, with information on the local state including residual energy, number of connected members, and distance to the BS, can make energy-aware decisions that contribute to the operating life of the network, as well as balance energy consumption throughout the network.

3.2 Energy model

As stated before, the radio communication component generally uses the most energy in terms of components that can consume energy such as data processors, radios, sensor systems, memory storage systems, and the transceiver; thus the energy expended by the sensor nodes for communication in the network is focused on. Significant sensor components and corresponding energy use are illustrated in the Figure 1 Here, we have assumed a simplified model for dissipating energy for compressing hardware radio. The transmitter releases energy for the radio electronics and the power amplifier as shown in Figure 1. The first radio model gives an energy use estimation for each period for the transmission or reception when the sensor node is used.

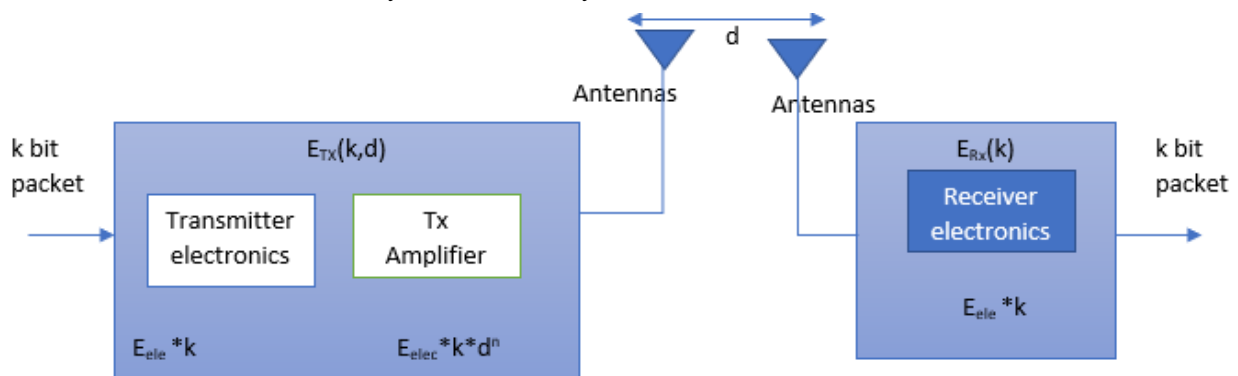


Figure 1 Radio energy model

For the calculation of energy dissipation, the proposed method utilizes the model. The two key formulae are as follows. Each transmitter expends energy as shown in Equation (1), Here, E_{Tx} is the transmission energy (J), k is the packet size (bits), E_{elec} is an electronic energy per bit (J/bit), ϵ_{fs}^2 is the

free-space amplifier energy coefficient, ϵ_{mp}^4 is multipath amplifier energy coefficient, d is transmission distance (m), d_0 is the threshold distance (m). At the square root of $\frac{E_{fs}}{E_{amp}}$, k being data packet length as shown in Equation (2).

$$ET_x(k, d) = \begin{cases} kE_{elec} + k\epsilon_{fs}^2 d & d < d_0 \\ kE_{elec} + k\epsilon_{mp}^4 d & d \geq d_0 \end{cases} \quad (1)$$

$$d_0 = \sqrt{\frac{E_{fs}}{E_{amp}}} \quad (2)$$

First is absorption of electricity by radio dissipation, the second is consumption of energy by radio amplification. The energy from electronics (Electrical), is dependent upon several aspects such as modulation, filtering capability, digital coding, signal propagation, use of free space (E_{fs}), and fading

channel models (E_{amp}) depend upon wavelength of transmission. Assuming the distance does reach the threshold then the model is used for free space, otherwise the model is used. Moreover, the radio now uses the following formula to receive receiving these data.

$$E_{Rx}(k) = k * E_{elec} \quad (3)$$

Equation (3), calculates the receiver energy $E_{Rx}(k)$ for k bits message will be calculated with the electronics energy Elec.

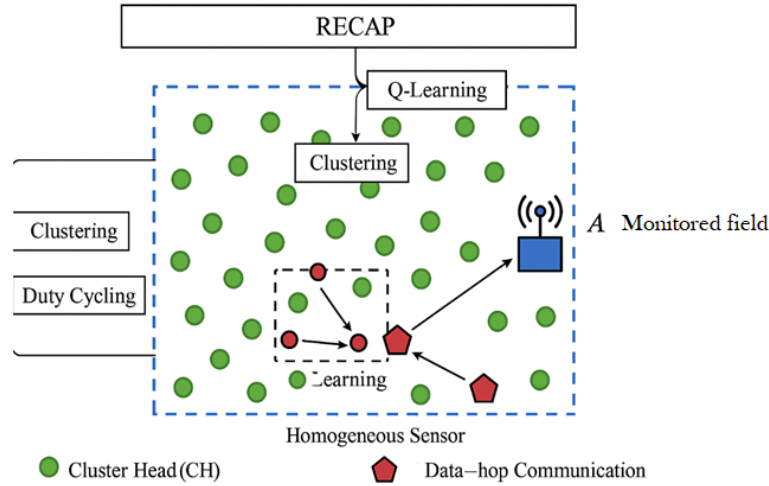


Figure 2 RECAP Framework design diagram

3.3 System architecture

The RECAP (Reinforcement-Driven Energy-Aware Clustering with Adaptive Processing) architecture is intended to solve the problems regarding the potential for energy optimization in WSNs, especially in cases where these networks are used for agriculture or in remote areas with limited energy and maintenance resources. The architecture has many intelligent modules in it and shares a layered architecture that uplifts and supports each other to degree improve the lifetime of a sensor node and the reliability of the data. The sensors layer is the lowest layer, which contains a number of sensing devices like soil moisture sensors, temperature sensors, and health sensors that collects important information from the environment. The sensors are typically powered by solar panels or batteries, with optional renewable energy sources. Once data are collected, they are pushed up one layer.

An Energy-Aware Clustering Module is used to

help with communication load and minimize possible problems that occur when a battery depletes too rapidly because they always have to transmit signals over long range communication to other sensors. The Energy-Aware Clustering Module is used to group sensors together, or create clusters, and then every cluster chooses a CH from those sensor node groups based on a multi-factored fitness function used to calculate the cluster head based on residual energy, communication cost, and future data load.

This important and intelligent clustering really reduces the amount of energy wasted in unnecessary talk. Simultaneously, the Adaptive Duty-Cycling Engine aims to reduce the energy consumed while data sensing task. To this end, the module implements a GRU to capture temporal patterns in a collection of environmental parameters, to predict the optimal wake/sleep interval for each sensor. For instance, while the sensors are in a consistent ambient

condition, the sensors can remain in low-power sleep mode without needing to wake up until the ambient conditions dictate a change, effectively reducing power without loss of data quality.

A critical aspect of the RECAP framework is the Reinforcement Learning Agent as the decision-maker for one or many sensors actions. In the decision-making process, the agent uses Q-learning to learn from the sensor states like battery level, data entropy, previous sampling behavior) to determine the best action for the appropriate node (sample, sleep, and transmission). The aim is to save maximal energy in long-term while collecting valuable data without losing data value. The Edge Processing and Communication Layer of the RECAP framework compliments the RL module with on-device Lightweight analysis via TinyML models. The Edge Processing and Communication Layer model co-locates sensor data filtering, where only the significant events, outliers or periodic summaries pour up to the cloud. The event-driven communication model uses only necessary transmission energy and limits network congestions.

For increased sustainability, the model contains an Optional Renewable Energy Integration Layer, which means the PV cells could be solar panels or some other micro-renewable source. The Open Spec uses the ability to harness the energy of the sun and rely on renewable energy sources to function without relying on manual recharging or battery replacement, allowing Off-grid-powered units to operate independently. The Cloud Layer receives the production data when processed, allowing analysis, visualization, and remote control. It allows to monitor conditions in real time or in a timely manner, and make data-driven decisions on-site without having to be on-site where the sensors are deployed.

3.4 RECAP Framework

3.4.1 RECAP consists of the following core layers:

- Adaptive Duty-Cycling Engine (ADCE)
- Energy-Aware Clustering Module (EACM)
- Reinforcement Learning Controller (RLC)

Edge Processing & Communication Layer (EPCL)

3.4.2 Adaptive Duty-Cycling Engine

ADCE employs a GRU-based time-series predictor to prescribe the sensor wake-sleep intervals over time taking into account environmental dynamics, crop growth stage, recent sensor readings. Because the ADCE is a key feature of the RECAP framework responsible for dynamically managing the active and sleep cycles of sensor nodes to save energy without negatively affecting quality of sensing and data transmission, we believe that contextual awareness is needed for ADCE to best properly manage these cycles. Unlike traditional static duty-cycling methods, ADCE incorporates context awareness as sensed environmental changes, temporal workload pattern, and cluster role to dynamically schedule the sensor operation. The ADCE implements a periodic process of first polling the sensor node to see if any sensing or transmitting is required and transitioning the sensor node to a low-power sleep state when it is not to minimize idle listening and extend node lifetime. The ADCE also takes into account historical energy depletion rates of each node and past network workload to infer having activity needs in the future to take proactive real-time action to adjust duty cycles are calculated using Equation (4). This module provides significant reduction in needless sampling during stable periods. Let $D_i(t) \in \{0, 1\}$, here, $D_i(t) = 0$ when node is inactive and $D_i(t) = 1$ when node is active.

$$P_{dc}(i) = \delta_1 \cdot \frac{E_{res}(i)}{E_{init}} + \delta_2 L_i(t) + \delta_3 S_i(t) \quad (4)$$

Where,

$E_{res}(i)$ is the residual energy at each node i ;

$L_i(t)$ is the Local traffic load;

E_{init} is the initial energy at each node;

$S_i(t)$ Sensing priority score;

$\delta_1, \delta_2, \delta_3$ are weighting parameters.

Equation (5) is used to inform the total energy consumption of sensor node i at time t based on the amount of time it is active versus asleep.

$$E_{dc}(i) = D_i(t) \cdot (E_{tx}(i) + E_{rx}(i)) + (1 - D_i(t)) \cdot E_{sleep} \quad (5)$$

Where,

$E_{dc}(i)$ is the total energy consumption of node under dynamic duty cycling;

$D_i(t)$ is the duty cycle ratio of node at time, i.e., fraction of time active;

$E_{tx}(I)$ is the energy dissipated for transmitting data;

$E_{rx}(I)$ is the energy dissipated for receiving data;

E_{sleep} is an energy consumed during sleep mode.

3.4.3 Energy-Aware Clustering Module

The EACM handles the formation of optimal clusters and the intelligent selection of CHs by considering multiple parameters such as residual energy, node centrality, communication cost, and distance to the base station. The module employs a hybrid metric-based selection mechanism where sensor nodes periodically broadcast their status, and potential CHs are elected through a weighted score that minimizes intra-cluster energy consumption while balancing load among nodes. EACM is responsible for creating the best clusters and intelligently choosing the CHs during formation of clusters with respect to different parameters including residual energy, centrality of the node, cost of communication, and distance to the base station. It uses hybrid metric-based selection, where nodes repeatedly broadcast their status, leading to the selection of CH through a weighted score with the objective of minimizing intra-cluster energy consumption while also optimizing equality among cluster nodes. The cluster Head Selection Score is as calculated using Equation (6).

$$Sc_i(i) = \alpha \cdot \left(\frac{E_{res}(i)}{E_{init}} \right) - \beta \cdot \left(\frac{d_{BS}(i)}{A} \right) - \gamma \cdot \left(\frac{1}{N_{neigh(i)}} \right) \quad (6)$$

Where,

$d_{BS}(i)$ is the distance to base station I;

$N_{neigh(i)}$ is the number of neighboring nodes;

α, β, γ are the weight coefficients.

Utilizing this measured approach reduces the

likelihood of the nodes dying prematurely, and provides an opportunity for nodes to distribute energy inconsistently across the cluster. EACM works with the Reinforcement Learning Controller (RLC) to help with adaptive re-clustering based on environmental circumstances and node status. This will also lead to more robust operations in the network under real-time operating conditions. Drawing on LEACH as an inspiration, EACM dynamically forms clusters and maintains a CH by rotating its CH from cluster to cluster, using a fitness function as shown in Equation (7).

$$Fit = \alpha \times Residual\ Energy - \beta \times Communication\ Cost + \gamma \times Workload\ Prediction \quad (7)$$

Where,

$\left(\frac{E_{res}(i)}{E_{init}} \right)$ is the residual energy;

$\left(\frac{d_{BS}(i)}{A} \right)$ is the communication cost;

$\left(\frac{1}{N_{neigh(i)}} \right)$ is the workload prediction.

The GRU predictor forecasts future load to prevent CH overuse, and the optimal number of clusters will be calculated using the following Equation (8).

$$k_{opt} = \sqrt{\frac{N}{2\pi}} \cdot \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \cdot \frac{A}{d_{BS}^{avg}} \quad (8)$$

Where,

k_{opt} is the optimal number of clusters in the network;

N is the total number of nodes in the network;

ϵ_{fs} is the energy consumption of the free space model;

ϵ_{mp} is the energy consumption of the multi path model;

A is the area covered;

d_{BS}^{avg} is the average distance between the sensor node and the base station.

3.4.4 Reinforcement Learning Controller

The RLC is the central component of the RECAP framework that is always learning the optimal decision-making policies for energy-efficient operation via Q-learning. Each sensor node, and

particularly each CH, follows the principles of reinforcement learning and acts as an intelligent agent that observes a current environment, chooses an action, and receives a reward pertaining to energy-efficient operation, and throughput of a network rather than using them directly for the reinforcement learning state. The state space is defined as factors such as residual energy, the density of neighbors, and the distance from the BS. To simplify the actions, we also have an almost infinite set of operational decisions like duty cycle adjustment, data transmission state, or moving from CH to other roles in the network. The RLC also has its initial Q table and will keep updating it to make better decisions as time goes by. By using reinforcement learning, RECAP provides decentralized intelligence that facilitates adaptability to environmental changes and node failure or energy imbalances. A lightweight Q-learning agent optimizes sensor actions are given in Equation (10) based on the state represented as given in Equation (9).

$$S_i = \{E_{res}(i), d_{BS}(i), N_{CM}(i)\} \quad (9)$$

$$A \in \{Become\ CH, Remain\ CM, Sleep\} \quad (10)$$

Rewards in the network are calculated by using Equation 11. Here, λ_1 is the weight for remaining energy of the node, λ_2 is the weight for distance penalty, and λ_3 is the weight for inverse cluster head. It assists the reinforcement learning agent in achieving energy efficiency, minimized transmission cost, and neglecting unbalanced formation of clusters etc.

$$R_i = \lambda_1 \cdot \left(\frac{E_{res}(i)}{E_{init}}\right) - \lambda_2 \cdot \left(\frac{d_{BS}(i)}{A}\right) - \lambda_3 \cdot \left(\frac{1}{N_{CM}(i)}\right) \quad (11)$$

Equation 12 is the Q-learning update formula that updates the expected reward Q for taking action A_i in state S_i . It enables with the agent (i.e., each node) learning an optimal policy over time through a trial and error process of selecting actions that provide maximum benefit in the long term.

$$Q(S_i, A_i) \leftarrow Q(S_i, A_i) + \eta \cdot [R_i + \gamma \cdot Q(S_i', A_i') - Q(S_i, A_i)] \quad (12)$$

Where,

η is the learning rate;

R_i is the immediate reward;

$Q(S_i', A_i')$ is best Q-value from the next state;

γ is the discount factor. The agent learns to balance performance with lifetime extension.

3.4.5 Edge Processing and Communication

EPCL enables local preprocessing of sensed data on a per-node basis, which helps minimize communication and energy expenditure. Examples of activities carried out by the EPCL include filtering, compression, aggregation, and anomaly detection, all of which occur prior to the transmission of relevant results to either the cluster head or base station. In effect, the EPCL enabled in-node computation to minimize non-contingent transmissions from the sensor, particular if redundant or non-informative. Within the EPCL, there are also mechanisms for presumption of low-energy wireless communication and/or for managing energy-efficient MAC protocols to further reduce energy usage. While the EPCL can use lightweight neural models or rule-based logic, the goal of the EPCL is to minimize computation since the EPCL operates within a resource constrained sensor environment. The EPCL can also manage and coordinate when nodes will be awake, to avoid using energy as a result of listening when other node transmissions are taking place. The EPCL takes advantage of the use of TinyML classifiers on the device to determine if the sensed data is “significant,” otherwise the non-significant data can be stored or discarded to reduce communication costs, this is particularly suited for event-based or irregular sensing. The main purpose of event-based communications in the EPCL is for anomaly alerts or periodic summaries. Equation (13) calculates the transmit energy consumption using k sized data packets, d distance factor, E_{elec} energy per bit, and ϵ_{fs} and ϵ_{mp} are energy losses.

$$E_{tx}(k, d) = \{E_{tx} = k * E_{elec} + k * \epsilon_{fs} * d^2 \text{ (for } d < d_0)\}$$

$$E_{tx} = k * E_{elec} + k * \epsilon_{mp} * d^4 \text{ (for } d \geq d_0) \quad (13)$$

Equation (14) calculates the receive energy consumption,

$$E_{rx}(k) = k \cdot E_{elec} \quad (14)$$

and Equation 15 calculates the aggregate energy consumption. Here, E_{DA} is the energy required for data fusion.

$$E_{agg} = k \cdot E_{DA} \quad (15)$$

Equation (16) calculates the Cluster energy consumption. Here, N_{CM} is the number of cluster members in each cluster j .

$$E_{CH} = \sum_{j=1}^{N_{CM}} E_{rx}(k) + k \cdot E_{DA} + \{E_{tx} = k * E_{elec} + k * \varepsilon_{fs} * d^2 \text{ (for } d < d_0) \} E_{tx} = k * E_{elec} + k * \varepsilon_{mp} * d^4 \text{ (for } d \geq d_0) \quad (16)$$

3.4.6 Optional Renewable Energy Layer (REL)

To improve the sustainability of long-duration deployments in remote and hard-to-reach locations, the RECAP framework includes, on an optional basis, a REL. REL provides sensor nodes or CHs with small (miniature) solar panels or piezoelectric harvesters that they can use to replenish energy over time. REL coordinates with the energy-aware clustering and duty-cycling components and allows the nodes to optimize energy use according to harvested energy available. For example, if a node has a greater amount of harvested energy available, it may be selected more often as a CH to help balance energy use and availability across the entire network. REL will also keep a small amount of harvested energy in reserve for urgent/peak times, for example during the re-clustering or sending large volumes of data times. Equation (17) gives the net energy consumed.

$$E_{net}(t) = E_{res}(t) + E_{harv}(t) - E_{cons}(t) \quad (17)$$

Where,

$E_{harv}(t)$ is the energy harvested;

$E_{cons}(t)$ is energy consumed in operations.

Equation (18) is the condition for cluster head preference, if $E_{\{harv\}}(t) > E_{\{threshold\}}$, then increase node's cluster head probability.

$$P_{CH}^{rel}(i) = P_{ch}(i) + \Delta_{rel} \quad (18)$$

So, the RECAP architecture is intended to solve the problems regarding the potential for energy

optimization in wireless sensor networks (WSNs), especially in cases where these networks are used for agriculture or in remote areas with limited energy and maintenance resources.

4 Implementation results and discussion

4.1 Simulation environment

In order to test the simulation of the proposed RECAP model, a large scale simulation was accomplished in one WSN scenario or use case that models the deployment of sensors to monitor agricultural fields. There were 500 homogeneous sensors randomly deployed in a square field size of 100 m × 100 m with the BS located in the middle. Each node was reset to 2 Joules of energy. Two decisions were made regarding the simulation environment, based on previously documented WSN situations. The sensor radio model was assumed to follow the first-order radio energy model. The sensor nodes were considered stationary throughout the simulation, and the radio parameters were fixed in advance based on values commonly used in previous studies. A consumption of radio energy per bit is $E_{elec} = 50\text{nJ}$, amplifier energy parameters ε_{fs} and ε_{mp} are $10\text{ pJ bit}^{-1}\text{ m}^{-2}$ and $0.0013\text{ pJ bit}^{-1}\text{ m}^{-4}$, and size of the data packet was set to 4000 bits. The Q-learning method utilized for the reinforcement module selected a learning-rate of 0.1, discount-factor of 0.9, and co-efficient values for the weighted reward. Performance metrics and lessons learnt from the comparisons made among networks, focused on network lifetime, energy consumption, throughput, stability period and fairness of the CH role for each iteration. The comparison was against three well-established hybrid clustering methods LEACH-CNN (Prajapathi et al., 2021), PSO-LSTM (Sharmin et al., 2023), and base GA-GRU as they are well-established hybrid assemblies.

4.2 Energy consumption

Analysis of energy consumption trends for multiple WSN protocols shows that the RECAP framework shows the most powerful usage as shown

in Figure 3. Over 10,000 communication rounds, RECAP had consistently used less energy per round, comparing favorably even from the beginning, i.e., out of the three replicated hybrid models. In this case, at 1,000 rounds, the RECAP energy consumption was 0.65 J per node compared with the energy consumption of LEACH-CNN (Prajapathi et al., 2021), PSO-LSTM (Sharmin et al., 2023), and base GA-GRU at 0.90 J, 0.82 J and 0.78 J respectively. In the beginning, the energy advantage from RECAP was due to its adaptive duty cycling capability and clustering which used Q-learning instead of the residual energy for clustering and unnecessary transmissions.

Regardless, all comparative models continued to consume energy, but RECAP consumed that energy at a simplified, gradual curve. For example, at the 5,000 round mark, which is 0.10 J less than RECAP's consumption level of 1.48 J, LEACH-CNN consumed 1.80 J of communication energy. PSO-LSTM consumed 1.92 J of energy and was close to their depletion threshold, only leaving a negligible amount of energy. Moreover, the 7,000 round post reads

illustrated that although all comparative nodes had consumed their energy budgets for proximity, RECAP continued to conserve energy at 1.70 J as reflected from the previous round. Consequently, this demonstrates the ability for lifespan sustained consumption for our energy.

After 10,000 rounds, the energy consumed by RECAP equaled the 2.0 J threshold. Compared with Cluster Based Selection(CBS) hybrid models, RECAP utilized all of its available energy, preserving modalities for unrivaled node efficiency, reducing node demise that the LEACH-CNN and PSO-LSTM passed prematurely, spending their entire energy budget. This efficiency is due to RECAP's event-based communication, reinforcement-guided CH selection, and edge-level aggregation which minimizes through unnecessary executions and allows the sensor to perform the desired work. These results prove that the RECAP framework increases energy efficiency and allows sustainable long-term use in WSN agricultural applications, especially in energy constrained domains.

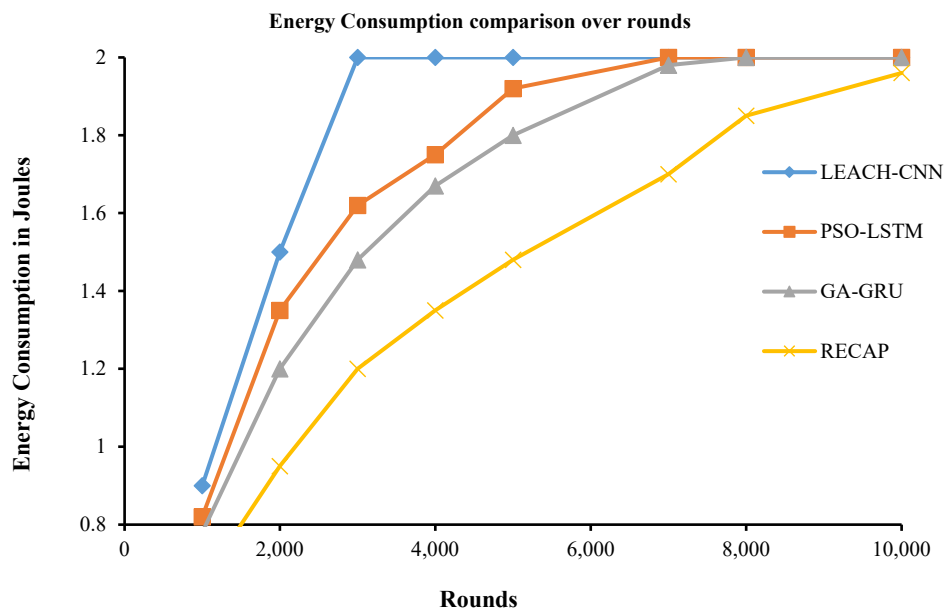


Figure 3 Energy consumption comparison vs. Rounds

4.3 Network lifetime

The RECAP proposed framework shows a better performance with regard to sustainability of network lifetime than recent hybrid routing LEACH-CNN

(Prajapathi et al., 2021), PSO-LSTM (Sharmin et al., 2022), and base GA-GRU as shown in Figure 4. Across simulation rounds from 1000 to 10 000, RECAP continues to have a larger proportion of live

sensor nodes showing efficient energy use and reasonably equal workload across the nodes. At 1000 rounds RECAP preserves over 93% of the sensor nodes, better than base GA-GRU (~87%), PSO-LSTM (85%) and LEACH-CNN (80%). As the simulation rounds increased, the traditional then hybrid routing networks saw much more rapid depletion of nodes. For example, by 3000 rounds LEACH-CNN has approximately only 32% of active nodes, while RECAP preserves 78% of its sensor nodes indicating that the operational sensor nodes are benefiting from the dynamic clustering and reinforcement learning CH selection process.

By 5000 rounds the contrast was stark: LEACH-

CNN and PSO-LSTM networks at this point are nearly depleted with only 5% and 25% of their nodes active, while RECAP still has 65% of the nodes usable. This demonstrates that RECAP enabled additional operational periods based on the adaptive duty cycling, energy aware communication, and predictive learning protocols that minimize associated redundant transmissions, organizational overhead and extending their periods of functionality. For example, by 7000 and 8000 rounds both LEACH-CNN and PSO-LSTM experience total or near-total network failure, whereas RECAP sustains and functional network with 45% and 30% of nodes active respectively.

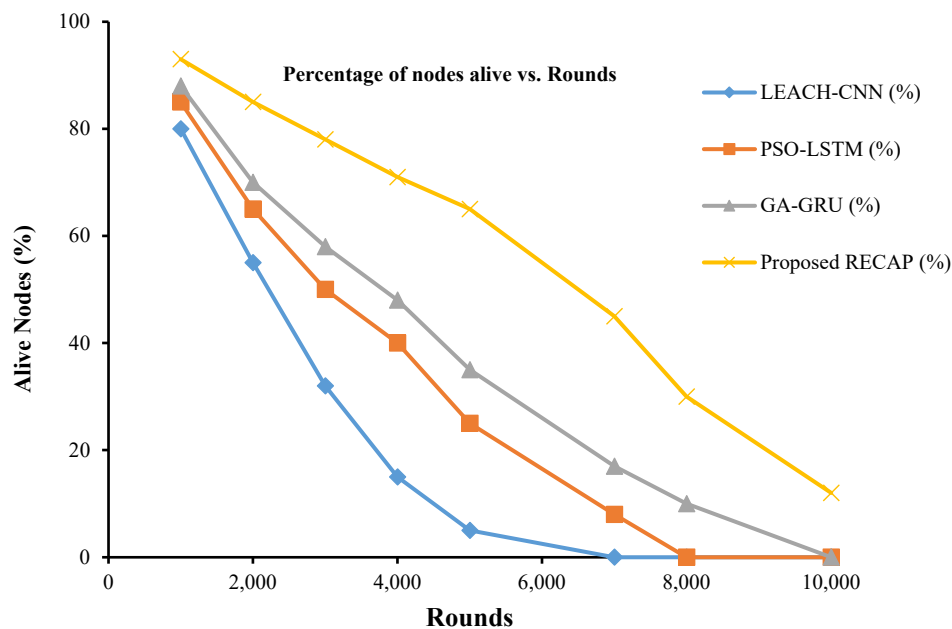


Figure 4 Number of alive node versus number of rounds.

4.4 Throughput

Throughput is measured by time-lined average packets delivered to the base station from the WSN. It indicates how well a network is operating to pass on information packets successfully over time. Throughput is analyzed over various rounds of operation, ranging between 1000 and 10000 rounds, in order to compare RECAP with other hybrid existing methods, LEACH-CNN (Prajapathi et al., 2021), PSO-LSTM (Sharmin et al., 2022), and base GA-GRU as shown in Figure 5. As the results show, at any point in time RECAP does better than all of the comparison protocols. When comparing RECAP with

LEACH-CNN and PSO-LSTM at the 1000 round level, RECAP delivers 2800 packets, whereas LEACH-CNN and PSO-LSTM deliver lower packets - 1850 packets and 2100 packets respectively, due to adaptive duty-cycling and energy-aware clustering that minimizes packet loss and retransmission. At 5000 rounds the gap has increased even more - 9300 packets for RECAP, nearly 75% more throughput than LEACH-CNN and 19% more than GA.

It is important to note at 7000 rounds, LEACH-CNN, PSO-LSTM and GA's throughput have completely plateaued, meaning nodes are failing and communication and operations are stalled both

rapidly as shown by fewer packets delivered multiply within an existing network protocol. On the contrary, RECAP shows more throughput and is continually growing - RECAP shows approximately 14,200 packets delivered at 10000 rounds, which is more than 2.5 times that of LEACH-CNN. This exceptional performance is attributed to the RLC, which optimizes cluster head selection dynamically, combined with the EPCL that reduces communication load by filtering and aggregating relevant data. Thus, the throughput analysis confirms RECAP's superior sustainability, adaptability, and efficiency in long-term field operations, especially in data-intensive and energy-constrained smart agricultural environments.

4.5 Delay

End-to-end delay is a vital measure in WSNs, especially in time-sensitive applications like precision agriculture or environmental monitoring. This delay is the time taken for a data packet to go from the starting sensor node to the base station.

The RECAP framework achieves the lowest end-to-end delay of any framework across all rounds of operation and shows its best performance in terms of slowest communication latency as shown in Figure 6. In 1000 rounds, RECAP has 105 ms delay - about 27.6% lower than LEACH-CNN, 19.2% lower than PSO-LSTM, and 15.3% lower than GA. This is consistent for increasing number or rounds, where RECAP reached 149 ms at 10,000 rounds, in comparison to 225 ms (LEACH-CNN), 196 ms (PSO-LSTM) and 185 ms (GA-GRU). RECAP has such a low latency because it has an intelligent RLC that adjusts which nodes are cluster heads, and it adjusts routing paths to alleviate congestion and retransmissions. The EACM also reduces transmission collisions and delay by balancing the data traffic. Lastly, the EPCL reduces transmission delays by local process.

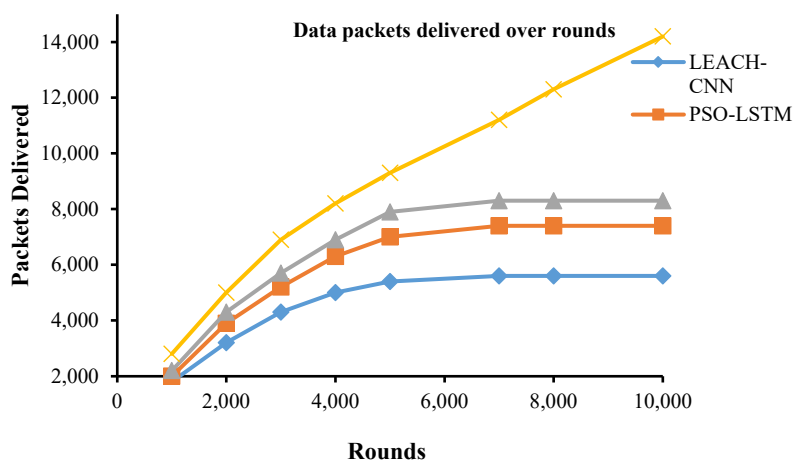


Figure 5 Throughput (in packets) vs. Rounds

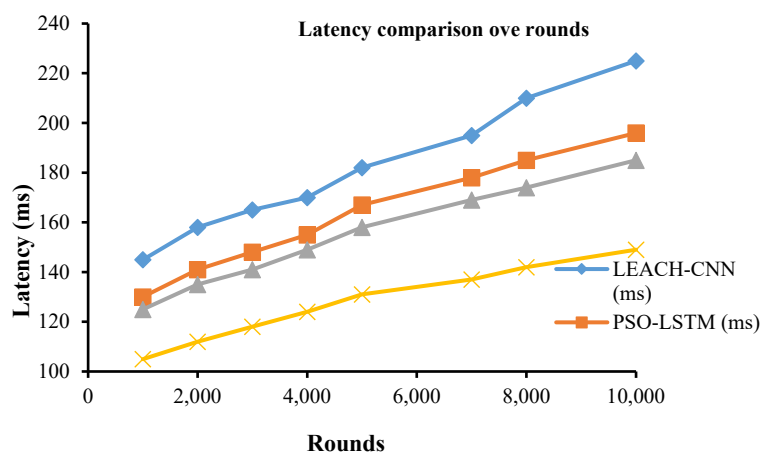


Figure 6 Comparison table of end-to-end delay

The model we proposed is especially applicable to large-scale deployment in rural agricultural areas with limited power resources and high maintenance costs.

5 Conclusion

RECAP is presented in this paper. It is a new and optimized framework to help solve the important problem of energy efficiency in IoT-enabled WSNs used for smart agriculture. The RECAP framework incorporates an intelligent cluster head rotation, which balances energy consumption, and minimizes unnecessary transmissions, and produces a summarized and defined anomaly threshold by addressing issues at the edge and with localized processing. The RECAP framework contains a reinforcement learning agent that learns optimal behavior of sensor nodes under varied environmental and network conditions, while also taking advantage of adaptive duty cycling agent for constantly re-evaluating sensing schedules based on predictive models. The combination of these modular directions demonstrates a significant reduction in energy waste, improves data quality, and makes long-term, sustainable monitoring and networks possible.

The model is especially applicable to large-scale deployment in rural agricultural areas with limited power resources and high maintenance costs. In future work, the proposed RECAP framework can be extended to real-world agricultural deployment scenarios such as smart irrigation systems, where soil moisture sensors dynamically regulate water usage based on real-time conditions. It can also be implemented in large-scale remote farms for continuous crop monitoring with minimal maintenance, as well as in greenhouse environments requiring precise control of temperature and humidity. Furthermore, integration with renewable energy sources such as solar-powered sensor nodes can enable sustainable off-grid operation. The framework can also be connected to cloud-based decision support systems to assist farmers in improving crop yield and resource utilization. Additionally, future work will

focus on real-world testbed validation, incorporation of advanced deep reinforcement learning techniques, enhancement of the TinyML module for multi-task inference, and development of lightweight security mechanisms for reliable field deployment.

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