Original Article

Energy-Efficient Framework for IoT based Smart Agriculture

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Abstract - Internet of Things enabled Wireless Sensor Network (IoT-WSN) uses low-powered devices that are capable enough to transmit the data over a very long range. This type of network may be utilized to automate the farming process, and it can also be deployed to monitor the environmental parameters continuously. In IoT-WSN, multiple layers are engaged, and energy consumption fluctuates based on the operations executed at each layer. This disproportionate usage can diminish overall network performance and result in the premature depletion of essential resources. It is necessary to optimise the energy consumption over the network to support long-term network operations. This paper presents an energy-efficient framework designed to improve performance in IoT networks. The framework is evaluated using multiple IoT protocols, including Long Range Wide Area Network (LoRaWAN), SigFox, IPv6 over Low-power Wireless Personal Area Networks (SixLoWPAN), and Low-Rate Wireless Personal Area Network (LR-WPAN), under scalable sensor density. Experimental analysis demonstrates that the proposed methodology significantly extends network longevity, particularly within the frameworks of LoRaWAN and LR-WPAN. Compared to existing solutions, including the Hybrid Trust Aware Algorithm (HTWA) and the Improved Smart Energy-Based Routing Protocol (ISEBRP), the proposed configuration LoRaWAN-EF achieves superior results marked by heightened throughput, augmented residual energy, and reduced delay. thereby demonstrating that the proposed cross-layer framework offers a robust and scalable solution for energy-constrained IoT-WSN-based smart agriculture.

Keywords - Energy-Efficiency, Smart agriculture, Reliable communication, LoRAWAN, SigFox, Sixlowpan, LR-WPAN.

1. Introduction

IoT networks can be effectively used in agriculture to monitor and analyse various parameters concerning soil quality, crop growth, irrigation, and livestock management through the integration of sensors, actuators, and intelligent devices. Long-range data transmission in these networks requires substantial resources, including energy, bandwidth, and dedicated spectrum, which may result in increased overhead and reduced network efficiency if not properly managed. The quality of IoT communication may deteriorate due to many factors, including environmental obstacles such as buildings, foliage, or water surfaces, the need for scalable coverage, and the variability of network operations. Furthermore, resource utilisation in IoT networks can fluctuate significantly because of these constraints, directly affecting the energy efficiency and overall system performance [1-5].

- Protocol Behaviour: IoT-WSN may use different protocols to enable end-to-end point communication. Each protocol is designed to follow some sort of rules and configurations to perform dedicated network operations. Energy consumption may vary depending on the nature and duration of the specific operation, and it is necessary to optimise the routing protocol's behaviour to maintain higher network performance [6-8].

- Operations at layers: IoT-WSN consists of different layers, i.e., application layer, network layer, physical layer, MAC layer, perception layer, etc. Each layer is configured to perform dedicated operations, which may consume different resources as per their requirements. It is essential to optimise layer-wise operations to reduce overall resource consumption [9-15].

- Cross-Layer Dependencies: Sometimes, it is necessary to exchange data between different layers, and it may also increase the resource consumption. Excessive cross-layer operations must be avoided [16].

- Signal Propagation Medium: IoT-WSN may be deployed over the surface or underwater. In each case, resource consumption may vary. IoT devices may be configured to adapt different propagation models to minimise resource utilisation [17].

- Compatibility: IoT-WSNs frequently incorporate a variety of devices and software platforms, which causes compatibility issues during data transmission.

Furthermore, differences in individual device energy consumption ratings can lead to uneven power depletion, which results in varying device lifespans and the potential for network partitioning. Using compatible hardware and software components can significantly reduce these issues while improving overall network stability [18, 19].

- Network Dynamics: In the case of mobile IoT systems, the devices can leave or join the network at any point in time; therefore, for this, more resources are required for reliable transmission [20].
- Payload: The sensors may be configured to produce data either randomly or periodically, as per the requirements of the application. The consumption of resources may vary due to the dynamic payload [21].
- Dependencies on Third-Party Services: IoT-WSNs are designed to operate over different platforms, i.e., cloud/edge/fog computing, etc., using internet services. This dependence could lead to higher resource usage and increased operational costs.

The factors discussed above still present major challenges for the performance of IoT-WSN, especially concerning scalability, reliability, fault tolerance, and Quality of Service (QoS). It becomes increasingly clear that energy efficiency in IoT-WSN–based smart agriculture depends on the combined behaviour of protocols, device heterogeneity, network dynamics, and multi-layer interactions. As modern smart-agriculture deployments scale to cover larger and more diverse environments, unmanaged resource utilisation can lead to rapid energy depletion, reduced network lifespan, and impaired service quality.

1.1. Research Contribution

This paper addresses the discussed critical gaps by proposing an energy-efficient cross-layer framework for IoT-WSN systems in smart agriculture. The primary contributions of this research are presented below.

- Cross-Layer Energy Optimisation Framework: To reduce energy inefficiencies caused by uncoordinated cross-layer operations, this framework integrates coordinated operations across the application, network, MAC, and physical layer.
- Adaptive State Management and Energy Harvesting: The framework introduces a dynamic sensor state transition mechanism (Tx → Rx → idle → sleep → harvesting) that helps in minimising energy leakage while extending the network lifetime under high-density deployments.
- Comprehensive Protocol Evaluation: The framework validates itself with the standard industry IoT protocols (LoRaWAN, SigFox, 6LoWPAN, and LR-WPAN) under scalable network sizes (100–300 nodes), showing consistent improvements under various parameters such as delay, throughput, residual energy, etc.
- Scalability and Performance Validation: The framework validates the robustness at realistic agricultural scales by

maintaining Quality of Service across all performance metrics.

These contributions collectively emphasise the importance of an intelligent, adaptive, and flexible framework that reduces overhead while maintaining reliable communication. The structure of this paper is organized as follows: starting with Section 1, which provides a comprehensive overview of the energy efficiency challenges in IoT-based smart agriculture, identifying the critical problem of uncoordinated energy consumption across different network layers and protocols in wireless sensor networks. It presents the motivation behind developing an integrated and energy-efficient framework, the framework outlines the key contributions of the research, and highlights the necessity for holistic optimisation strategies to sustain long-term agricultural IoT deployments under scalability constraints. After that, Section 2 presents a comprehensive literature survey on IoT-enabled smart agriculture, with emphasis on communication protocols, energy-efficient routing, irrigation management, soil and crop monitoring, pest and disease detection, and AI/ML-based optimisation techniques. It also includes a research gap and analysis, helping researchers to understand the problem statement better. Then, Section 3 details the proposed energy-efficient framework for IoT-WSNs, describing its cross-layer design, state management strategy, and integration of energy harvesting. Later, Section 4 explains the simulation setup, experimental parameters, and performance metrics, followed by an extensive performance analysis of LoRaWAN, SigFox, SixLoWPAN, and LR-WPAN using the proposed framework, along with a comparative evaluation against existing energy-efficient schemes. Finally, Section 5 concludes the paper by summarising the key findings and discussing the limitations of the current work along with potential future research directions in heterogeneous environments.

2. Literature Survey

The integration of the Internet of Things into agricultural systems has transformed traditional farming into precision farming or smart agriculture. Smart agriculture uses networked sensors and actuators to enable real-time monitoring, automated control across the field area of agriculture or in diverse farming operations, and, lastly, data-driven decision-making. Recent studies on IoT-enabled smart agriculture have focused on various aspects, including communication protocols, irrigation management, soil and crop monitoring, pest and disease detection, storage solutions, and the integration of AI/ML (Artificial Intelligence/Machine Learning) for optimisation. A review of recent IoT-enabled smart agriculture studies shows that a significant portion of existing research focuses directly on improving energy efficiency, prolonging network lifetime, and enabling low-power sensing and communication in different farming processes.

In the domain of communication technologies, researchers [22-28] emphasise reducing transmission overhead, optimising routing pathways, and employing lightweight protocols such as LoRaWAN and SigFox to minimise energy use while maintaining scalability. These studies consistently highlight that protocol selection, adaptive power regulation, edge computing, and intelligent routing significantly influence the overall energy footprint of smart agriculture networks. Energy-efficient irrigation has also attracted substantial attention. Solutions proposed by authors [29-31] demonstrate that automated irrigation based on soil and environmental parameters can considerably reduce both water and energy waste. Renewable-energy-powered systems, such as the solar and hybrid irrigation methods introduced by researchers [32-34], further show the importance of harnessing sustainable energy sources to enable long-term autonomous operation.

Additionally, machine-learning-based irrigation decision systems, such as the regression models by the author [35], contribute to energy-efficient water allocation and smart scheduling. In soil and crop monitoring, energy conservation is achieved through low-power sensing, energy-harvesting mechanisms, and intelligent control strategies. Studies [36-38] show that soil sensors optimised for minimal energy use, combined with fuzzy-logic decision-making and harvesting techniques, can significantly extend sensor lifespan and maintain reliable environmental monitoring. Similar trends are observed in pest and disease monitoring, where lightweight deep learning models and UAV-assisted sensing proposed by the author [39, 40] improve detection accuracy while maintaining low computational and operational costs. Environment-aware IoT systems, such as the one proposed in [41], further illustrate the role of optimised sensing and communication in reducing energy consumption during environmental monitoring. Energy efficiency is also addressed in the post-harvest and supply-chain context. Low-energy BLE-based storage monitoring is introduced in [42], and efficient aerial soil moisture measurements are presented

in [43], showcasing how IoT systems can reduce resource waste and operational overhead while ensuring data reliability. Finally, optimisation and AI-centric studies, including works by authors [44, 45], reveal that bio-inspired optimisation, clustering strategies, and predictive machine-learning models can significantly reduce routing energy, enhance network adaptability, and optimise overall IoT system performance.

From the above literature, it is clear that existing research has made substantial progress in improving individual aspects of energy efficiency, monitoring, irrigation, and optimisation. However, most studies focus on specific layers, particularly on application-oriented or protocol-dependent solutions, resulting in fragmented energy management. Only a few work efforts focus on coordinated cross-layer optimisation that jointly considers sensing, communication, routing, state management, and energy harvesting. Moreover, scalability analysis under dense sensor deployments and heterogeneous protocol environments remains insufficiently explored. These limitations clearly indicate the need for an integrated, adaptive, and cross-layer-aware energy optimisation framework capable of sustaining Quality of Service while ensuring long-term network stability in large-scale smart agriculture IoT systems. This research is motivated by these identified gaps and aims to address them through a cross-layer-aware optimisation framework.

3. Energy Efficient Framework for IoT-WSN

In the case of IoT-WSN, various network operations are managed by different layers, and energy consumption may vary at each layer. These layers can exchange data with each other using cross-layer communication. It is necessary to optimise operations at the layer level to reduce overall energy consumption. In the case of smart farming, IoT networks perform long-term network operations, and energy harvesting support is essential to extend the network lifespan. In this paper, an energy-efficient framework is presented in Figure 1.
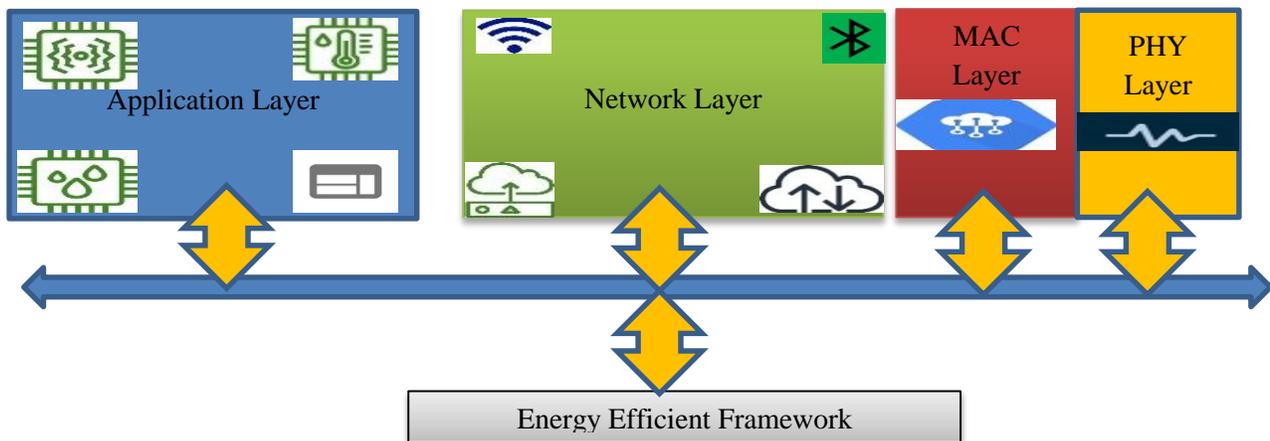

Fig. 1 Overview of an energy-efficient framework for cross-layer communication

The proposed energy-efficient framework for IoT-WSN can manage the operations at various layers and can also regulate the packet transmission. Table 1 lists the parameters used in the proposed scheme.

Table 1. Parameters description used for proposed scheme

Variables for IoT networks	Variables for different states	Variables for energy	Variables for data/payload/packet generation
S_n Sensor	tx transmission state	Iel, energy at the initial level	Si Sampling Interval
GW Gateway	rx reception state	Vlt voltage	Ps Packet Size
BS Base station	sp sleep state	CVlt Current voltage	Cdl Current Data load
IoT-WSN IoT Wireless Sensor Network	idl idle state	E_Tx energy required for packet transmission	Cdl = Si* Ps
		E_Rx energy required for packet receiving	Pl Payload
		E_Idl_ energy spent during Idle state	Pl= Cdl /2
		E_Sp energy spent during the Sleep state	Pg packet generation
		B_dp Battery depletion Status	ai current interval can be used for tx, rx, idl, and sp state as: ai_tx, ai_rx, ai_idl, ai_sp
		Cdpr current depletion rate	TH threshold value for operations
		Re residual energy	

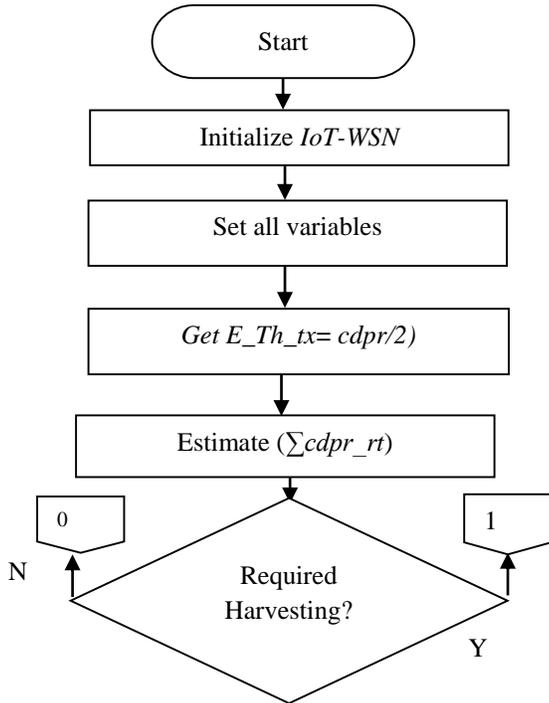The proposed scheme uses different steps, as shown in the Figure 2 below:

Fig. 2 Energy framework for IoT-WSN

Step 1: At the initial stage, IoT-WSN is initialised using IoT sensors and gateways. Set the initial state for $\sum S_n$ =IDLE.

Step 2 (a): Sensors join the intermediate gateway as members and Set state =tx:

$$\sum GWn \in \{Si, Sj, Sk, , ...\ Sn\}\ Where\ GWi \cap GWn = \emptyset \tag{1}$$

and initiate the current duty cycle for data collection.
Set $\sum S_{n->}$ tx=TRUE for transmission. Data is collected by $\sum S_n$ and finally, it is forwarded to *BS* through $\sum GW_n$.

Step 2 (b): In case sensors do not have enough energy to start the transmission, then, as per the Figure 2, energy harvesting operation is initiated to retain the energy level of the entire network for reliable packet transmission as discussed in Figure 3.

To extend the network's life span, it is necessary to integrate the energy harvesting support with sensors.

First of all, the minimum energy requirement is estimated as per the given equation: With the minimum energy level eMn, initial energy level Iel, minimum energy k required to transfer p packets over distance d, and it can be defined as eMn = k * d, and the total number of packets to be transferred:

$$\sum p \leq Iel/(eMn * d) \tag{2}$$

It is also reflected in ai_tx and $\sum Dpr\_tx$, as discussed in step 3.
To retain the efficient level of residual energy, the requirements of the energy harvesting can be estimated as per the given equation, Bcr, which is the time taken by the battery for charging or discharging at time t.
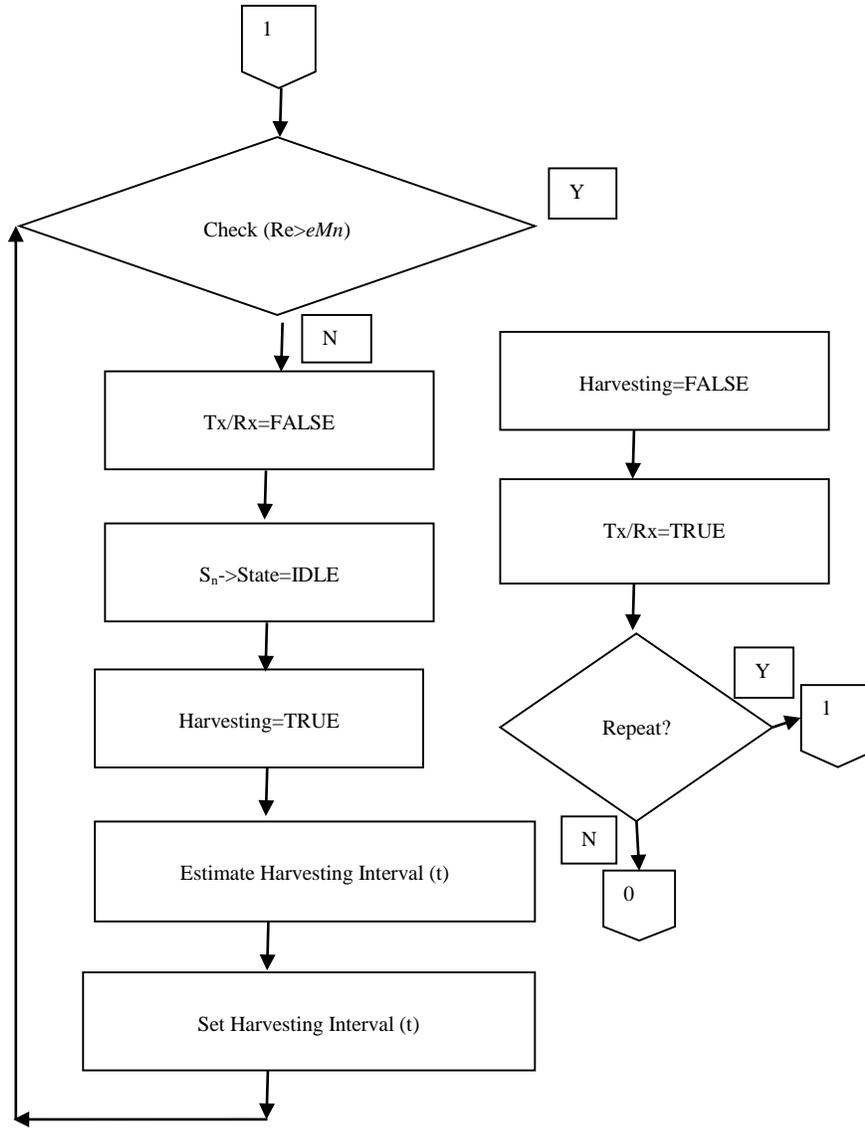
$$\sum t = interval/Bcr \tag{3}$$

Fig. 3 Energy harvesting operation

If one interval =60 minutes and Bcr =30, then 60/30=2

Minutes are required for charge/discharge.

Set Sn->tx=FALSE

Set Sn->state=IDLE

Set Sn->state=HARVESTING= TRUE

Set Sn->state=HARVESTING_Interval ($\sum$t)

After expiry of the harvesting interval, as per step 9, if the sensor fulfils the constraints of minimum energy that is required for tx, its state is updated as:

Set Sn->state=HARVESTING= FALSE
Set Sn->tx=TRUE

This step can be repeated, as required.

Step 3: Energy is consumed during the network operations, so estimate the battery depletion rate Dpr for tx, rx, idl, and sp states as per the equation below:

$$Dpr\_tx = ai\_tx * E\_Tx * CVlt \tag{4}$$

$$Dpr\_rx = ai\_rx * E\_Rx * CVlt \tag{5}$$

$$Dpr\_Idl = ai\_idl * E\_Idl * CVlt \tag{6}$$

$$Dpr_{sp} = ai_{sp} * E_{sp} * CVl \tag{7}$$

Finally, the total battery depletion rate is estimated as:

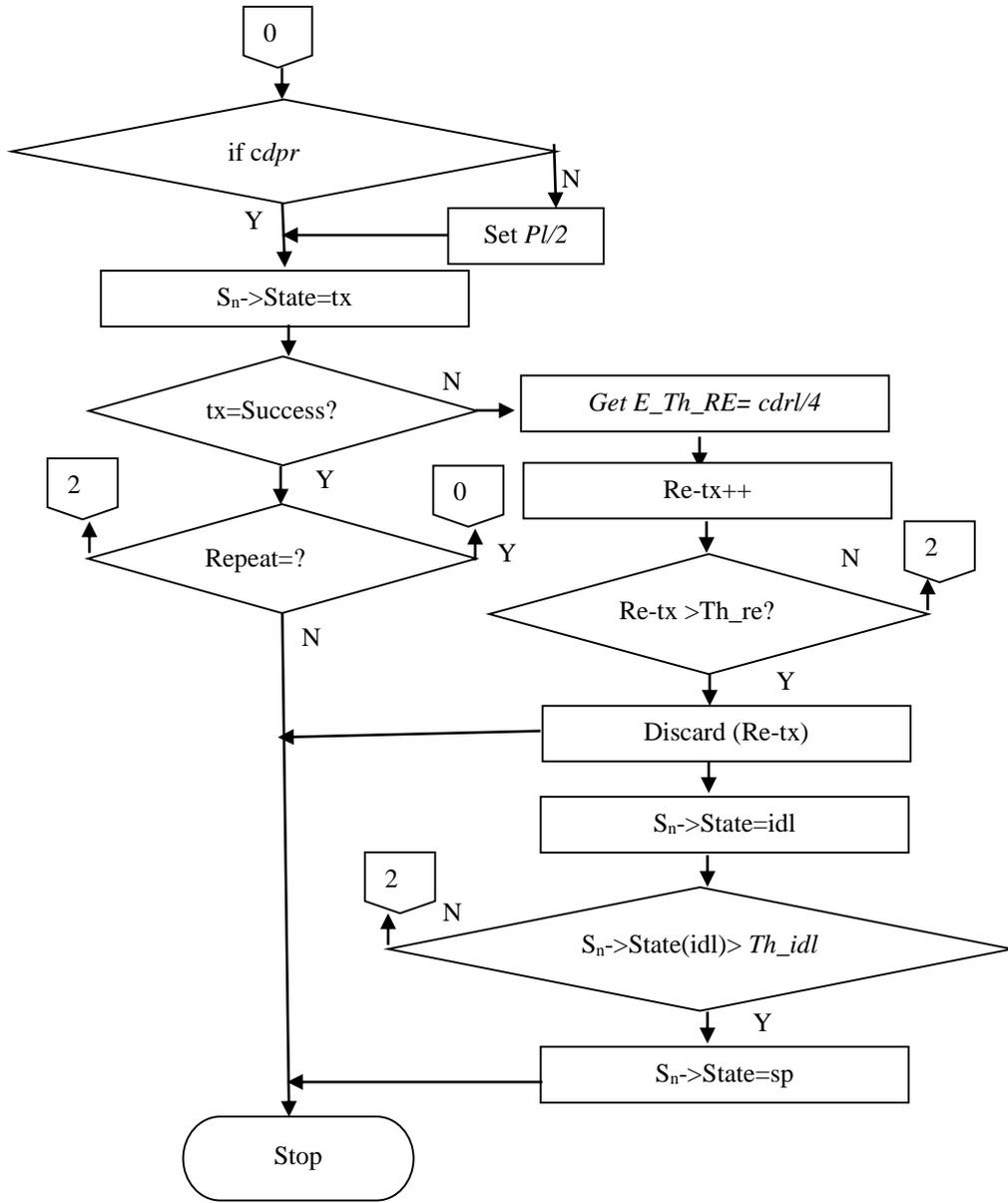$$\sum cdpr\_rt = \sum Dpr\_tx + \sum Dpr\_rx + \sum Dpr\_Idl + \sum Dpr\_sp \tag{8}$$

Fig. 4 Battery depletion rate estimation

Figure 4 illustrates the systematic calculation of battery depletion rates across all operational states of IoT sensors within the energy-efficient framework.

Step 4: For normal transmission, calculate the threshold energy to allow transmission as per the equation:

$$E\_Th\_tx = cdpr/2 \qquad (9)$$

Step 5: In case of packet retransmission, threshold energy is estimated as per the equation:

$$E\_Th\_RE = cdrl/4 \qquad (10)$$

Step 6: Packet transmission is initiated. If *cdpr* is less than the *E_Th_tx,* otherwise reduce the *Pl* as per the equation:

$$cdpr <= E\_Th\_tx \text{ then } S_n\text{->State=tx else } Pl/2$$

Step 7: In case of packet retransmission, *TH* is estimated as discussed in the above step 5. It is initiated as per the following equation:

$$\text{if } cdpr >= E\_Th\_re \text{ then } S_n\text{->State=re\_Tx}$$

Step 8: Packet retransmission is discarded after multiple failure attempts.

The energy-efficient framework manages or controls operations across the protocol stack by coordinated interactions among four critical layers, each performing specific functions to optimise energy consumption and ensure reliable communication and transmission.

At the application layer, packet generation and state management are controlled based on sensing activity; the network layer is for managing routing and multi-hop forwarding decisions; the MAC layer is used to control channel access and manages collision-induced backoff intervals; and the physical layer governs low-level state transitions, including SLEEP, IDLE, and energy harvesting modes.

This cross-layer coordination makes sure that energy-aware decisions are made holistically across the network stack, as detailed below. These layers are discussed in the following sections.

3.1. Application Layer

This layer collects the data from sensors that are responsible for sensing the field data. The collected data is then forwarded to the gateway using the routing layer. For packet transmission, the current state is changed to tx. Packets are generated and forwarded to the gateway, and in case of failure, packets are retransmitted. Figure 5 shows that if the sensor is sensing the data from the coverage area, only then are packets generated and forwarded to the gateway. If the sensor is not engaged in the sensing process, then after some interval, its state is updated to the IDLE state, in order to preserve its residual energy.

If (Sense==TRUE) Set Pg=TRUE

If (Sense==FALSE) Set Pg =FALSE

If (Pg) then Set S_n->tx=TRUE else Set S_n->tx=FALSE
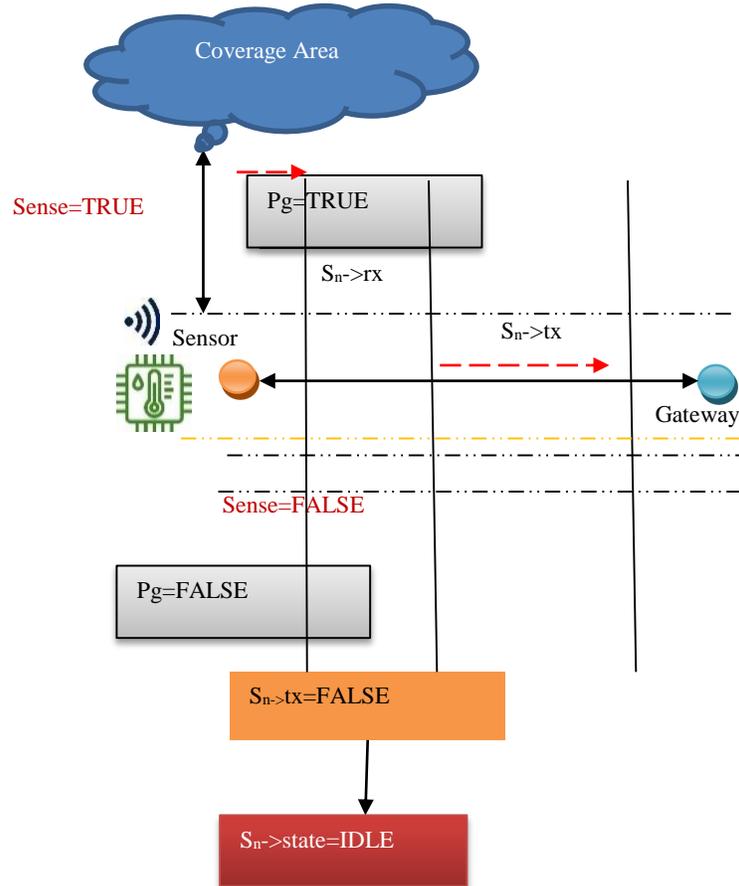

Fig. 5 Packet generation and forwarding

3.2. Network Layer

It performs routing and forwards the data from the source (sensors/gateway) to the end receiver (base station). It may use single or multi-hop packet forwarding strategies. If Pg, *tx, and rx are all initiated, only then is packet routing* performed.

Figure 6 shows that the duty cycle is initiated by the gateway for its members. During this interval, members can forward their data to the gateway that is responsible for forwarding it to the base station further.
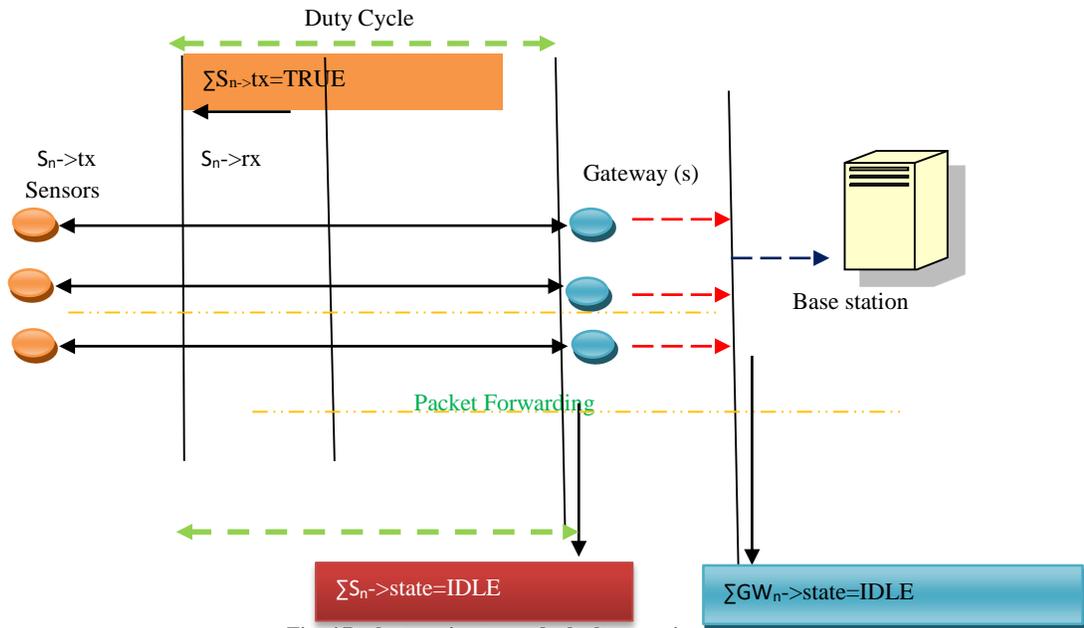
$\sum S_{n}\text{->}tx=TRUE$

$S_{n}\text{->}tx$
Sensors

$S_{n}\text{->}rx$

Gateway (s)

Base station

Packet Forwarding

$\sum S_{n}\text{->}state=IDLE$

$\sum GW_{n}\text{->}state=IDLE$

Fig. 6 Packet routing towards the base station

3.3. MAC Layer

It controls the access to the shared channel. Multiple sensors can transmit the packets simultaneously, which may cause a collision on the channel. Due to a collision, packet drop/retransmission or delay may occur. In case of a collision, the current state is changed, and sensors may retry transmission after an interval, called the backoff interval, estimated by the MAC layer, as shown in Figure 7.
If (S_{n}->collision ==TRUE)

Set S_{n}->tx=FALSE
Set S_{n}->state=IDLE

3.4. PHY Layer

It performs low-level operations between sensors and gateways. It also facilitates communication between the lower and upper layers. If the sensor is IDLE for a long interval, then Set S_{n}->state=SLEEP, in order to preserve the energy.

Duty Cycle

$S_{n}\text{->}tx$

Normal

Sensor

Collision=TRUE

Gateway

$\sum S_{n}\text{->}tx$

$\sum GW_{n\text{->}}Backoff=TRUE$

$\sum S_{n\text{->}}tx=FALSE$
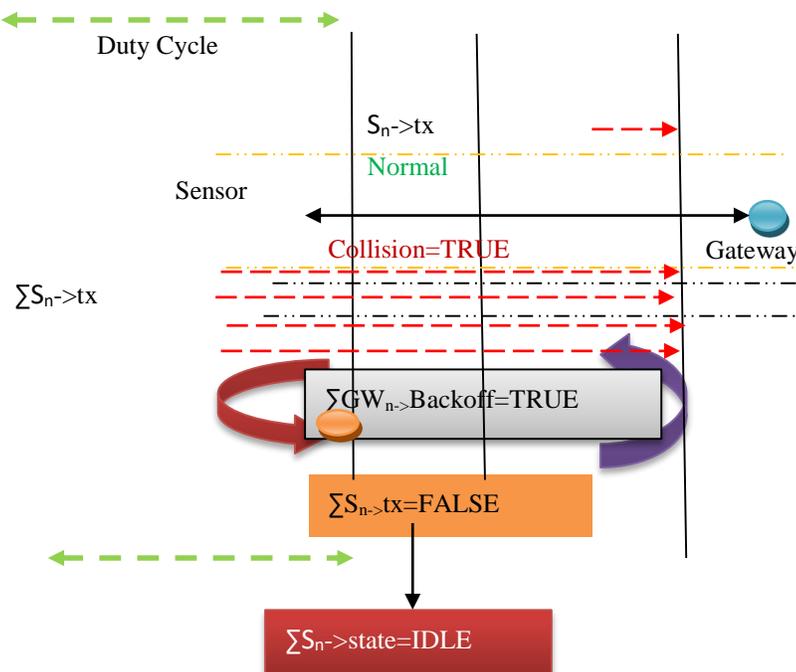
$\sum S_{n}\text{->}state=IDLE$

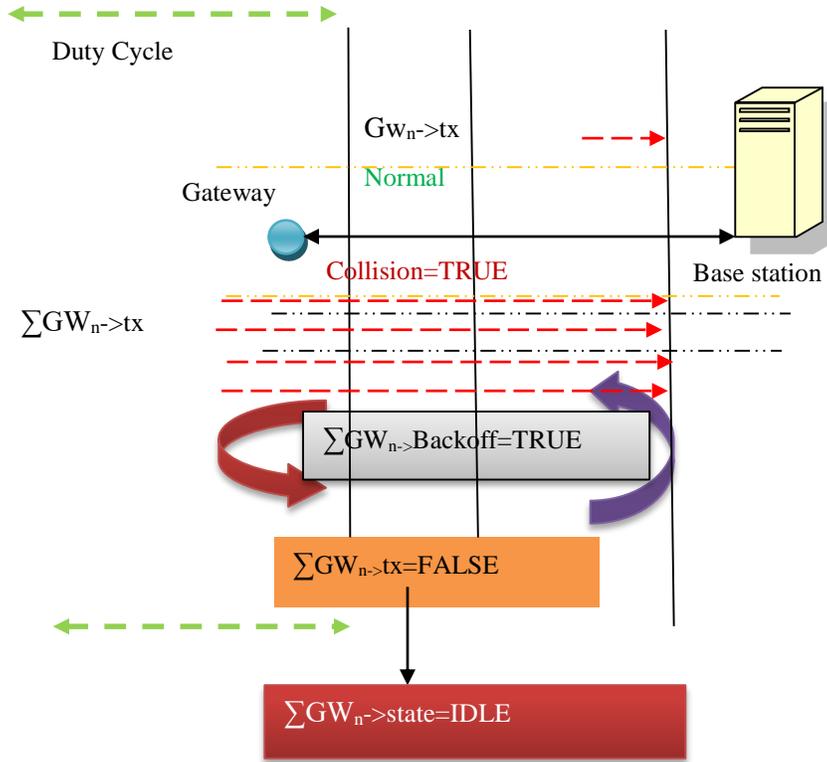**Fig. 7 MAC layer constraints for sensor(s)**

Fig. 8 MAC layer constraints for gateway(s)

Figure 8 shows that after completion of the current duty cycle, the gateway forwards data to the base station. A collision may occur if multiple gateways try to forward the data at the same interval. In this scenario, the MAC layer estimates the backoff interval for the gateway(s) in order to halt the simultaneous packet transmission. During this interval, the gateway cannot initiate the transmission, nor can a new duty cycle be initialised. If the gateway cannot access the channel for a long interval, its current state is updated to IDLE to preserve residual energy.

4. Simulation Setup

The following Table 2 shows the simulation environment set up used for experiments:

Table 2. Parameters used for the experiment

Parameters	Description
Simulation Tool	Network Simulator version 3 (NS-3)
IoT Protocols	LoRAWAN, SigFox, Sixlowpan, LRWPAN
Sensor Density	100-300
Initial Energy	7J
Receiving and Transmission Power	10w
Simulation Interval	600s
Platform	Linux

4.1. Comparison of Average Harvested Energy

The individual energy harvesting profiles for each protocol across varying sensor densities demonstrate protocol-specific and density-dependent variations in harvesting patterns. To provide a comprehensive comparative analysis, this section aggregates these protocol-specific outcomes and examines the normalised average harvested energy levels across all IoT protocols under scalable sensor densities.
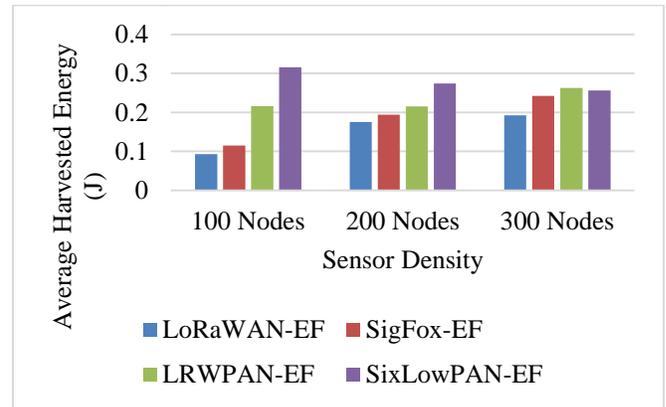

Fig. 9 Average harvested energy

Figure 9 shows the comparison of average harvested energy under the constraints of sensor density variations (100-300) using different IoT protocols (i.e., LoRaWAN-EF, SigFox-EF, LRWPAN-EF, SixLowPAN-EF). It can be analysed that in the case of 100 sensors, it is higher for SixLowPAN-EF (0.31572745), followed by LRWPAN-EF

(0.21645117), whereas it is at a moderate level for SigFox-EF (0.115251), and it is minimal for LoRaWAN-EF (0.093211047). In the case of 200 sensors, it is higher for SixLowPAN-EF (0.273611571), followed by LRWPAN-EF (0.21504392), whereas it is at a moderate level for SigFox-EF (0.194034), and it is minimal for LoRaWAN-EF (0.17501352). In the case of 300 sensors, it is higher for both SixLowPAN-EF (0.256188623) and LRWPAN-EF (0.26282839), whereas it is slightly less for SigFox-EF (0.242228), and it is minimal for LoRaWAN-EF (0.192128381).

Analysis shows that there is a lot of variation in the energy harvesting level. Excessive transmission consumes a lot of energy, thus triggering the energy harvesting. After regaining a sufficient level of residual energy, sensors reattempt transmission, which causes the energy depletion. This process is repeated till the end of the simulation.

4.2. Performance Analysis of Different Protocols using the Proposed Scheme

To comprehensively understand the effectiveness of the energy-efficient framework, in this section, the authors present a detailed performance analysis across four widely adopted IoT protocols—LoRaWAN, SigFox, LR-WPAN, and SixLoWPAN—under scalable sensor densities ranging from 100 to 300 nodes. The analysis examines three key performance metrics: network throughput, residual energy retention, and end-to-end delay, comparing baseline protocol performance against its Energy-efficient Framework (EF) counterparts. The proposed framework combines the cross-layer optimisation, adaptive state management, and energy harvesting support to dynamically regulate packet transmission, manage collision-induced overhead, and preserve residual energy by using smart intelligence state switching mechanisms. The following subsections elaborate on each performance metric, demonstrating how the EF variants consistently outperform their baseline counterparts and existing energy-efficient schemes through protocol-specific optimisations.
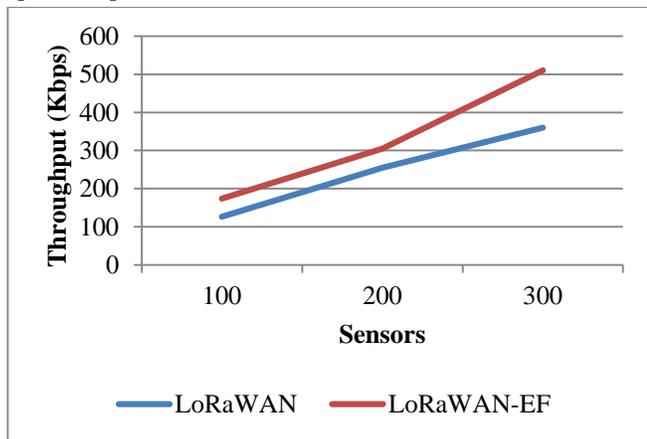

Fig. 10 Throughput-LoRAWAN and LoRAWAN-EF

Figure 10 shows the comparison of the throughput of LoRAWAN and LoRAWAN-EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 126Kbps for LoRAWAN and 174Kbps for LoRAWAN-EF. With 200 sensors, it is 255Kbps for LoRAWAN and 305Kbps for LoRAWAN-EF, and with 300 sensors, it is 360Kbps for LoRAWAN and 510Kbps for LoRAWAN-EF. It can be observed that with minimal sensors, both delivered average throughput, and it is slightly increasing with 200 sensors.

With the highest sensor density, it reaches up to its peak value, and it is higher for LoRAWAN-EF as compared to LoRAWAN. The framework dynamically adjusts Packet size (Ps) in response to energy constraints, ensuring continuous data flow even under resource scarcity. The integration of energy harvesting support (Step 2b) allows sensors to replenish energy reserves during idle periods, maintaining higher active node counts and sustaining throughput as density increases.

The random state switching capability($sp/Idl/tx/rx$) enables sensors to conserve energy when not sensing, allocating more resources to actual data transmission during active cycles, thereby increasing throughput.
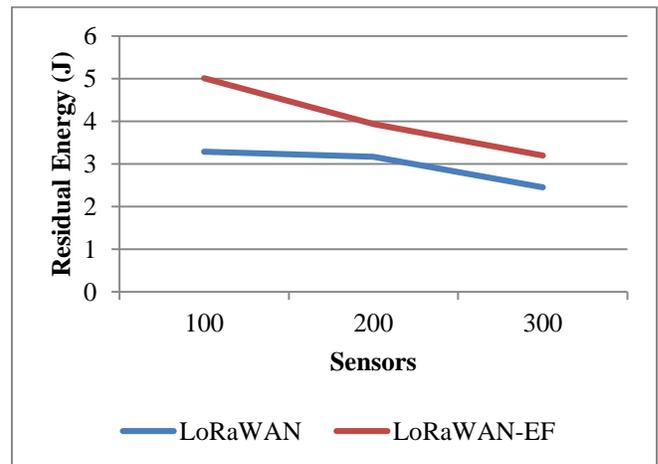

Fig. 11 Residual energy-LoRAWAN and LoRAWAN-EF

Figure 11 shows the comparison of residual energy of LoRAWAN and LoRAWAN-EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 3.2912J for LoRAWAN and 5.0117J for LoRAWAN-EF. With 200 sensors, it is 3.1714J for LoRAWAN and 3.94123J for LoRAWAN-EF, and with 300 sensors, it is 2.4526J for LoRAWAN and 3.20107J for LoRAWAN-EF.

The Continuous battery depletion rate estimation (Step 3) enables proactive harvesting decisions, while state management prevents energy leakage, ensuring net-positive residual energy retention despite increased throughput demands.
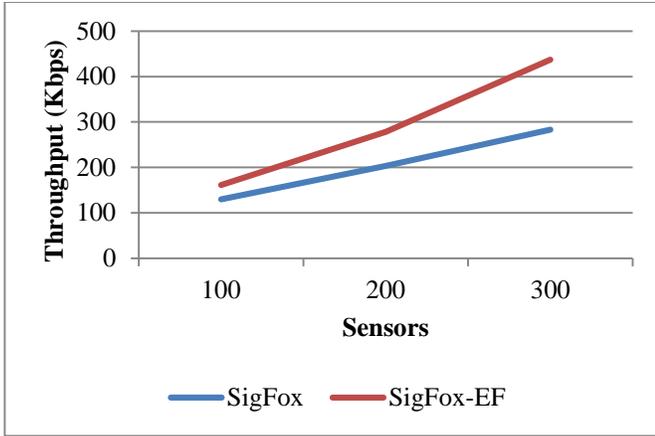
Fig. 12 Throughput-SigFox and SigFox –EF

Figure 12 shows the comparison of the throughput of SigFox and SigFox –EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 129.72973Kbps for SigFox and 161.04Kbps for SigFox -EF. With 200 sensors, it is 202.816901Kbps for SigFox and 278.52Kbps for SigFox-EF, and with 300 sensors, it is 284.050633Kbps for SigFox and 437.124829Kbps for SigFox-EF. Energy-harvesting support maintains a higher active node density, enabling the EF variant to sustain superior throughput across all scalability levels, while the baseline SigFox suffers from increasing packet loss.
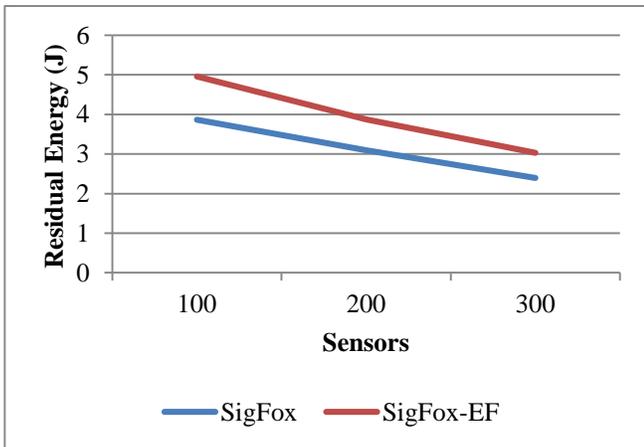

Fig. 13 Residual energy- SigFox and SigFox -EF

Figure 13 shows the comparison of residual energy of SigFox and SigFox-EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 5.52178J for SigFox and 4.95475J for SigFox -EF. With 200 sensors, it is 4.02862J for SigFox and 3.87669J for SigFox-EF, and with 300 sensors, it is 2.83552J for SigFox and 3.02504J for SigFox-EF. Analysis indicates that there is a sharp decline in residual energy level for the SigFox and SigFox-EF with respect to sensor density. However, SigFox-EF consumed the excessive energy resources and delivered a higher throughput as compared to SigFox. It indicates that SigFox is not capable enough to switch the sensors' states randomly, thus causing

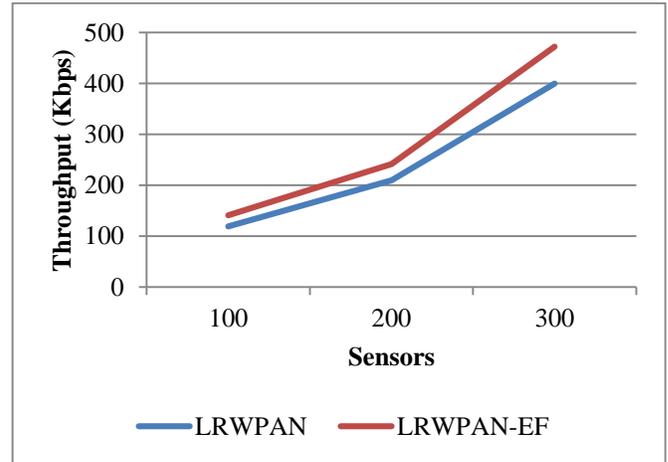excessive energy consumption, but it tried to deliver the average throughput.

Fig. 14 Throughput- LRWPAN and LRWPAN–EF

Figure 14 shows the comparison of the throughput of LRWPAN and LRWPAN–EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 119.54Kbps for LRWPAN and 141.02Kbps for LRWPAN - EF.

With 200 sensors, it is 209.81Kbps for LRWPAN and 241.58Kbps for LRWPAN -EF, and with 300 sensors, it is 399.84Kbps for LRWPAN and 472.14Kbps for LRWPAN - EF.
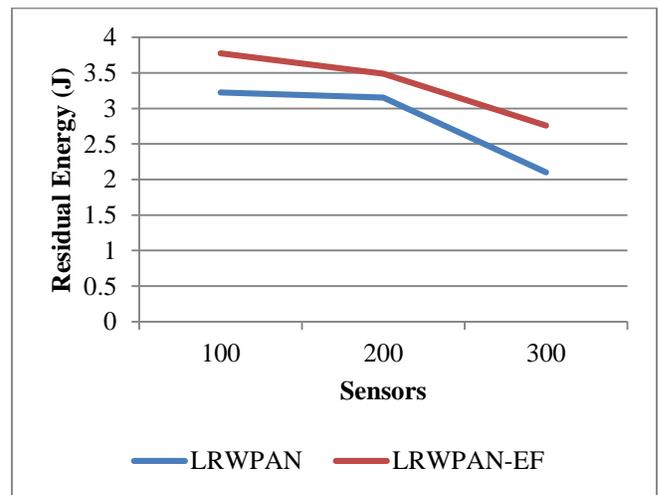

Fig. 15 Residual energy- LRWPAN and LRWPAN–EF

Figure 15 shows the comparison of residual energy of LRWPAN and LRWPAN-EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 5.52178J for LRWPAN and 4.95475J for LRWPAN -EF. With 200 sensors, it is 4.02862J for LRWPAN and 3.87669J for LRWPAN-EF, and with 300 sensors, it is 2.83552J for LRWPAN and 3.02504J for LRWPAN-EF.
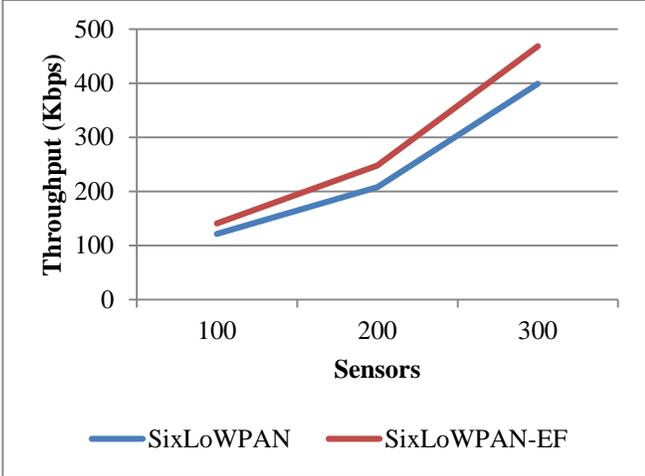
Fig. 16 Throughput- SixLoWPAN and SixLoWPAN–EF

SixLoWPAN and 3.41897J for SixLoWPAN-EF, and with 300 sensors, it is 1.98565J for SixLoWPAN and 2.59855J for SixLoWPAN-EF.

Analysis indicates that the residual energy level varied for the SixLoWPAN and SixLoWPAN–EF with respect to sensor density. As the sensor density increases, more sensors initiate transmission and thus may trigger random sensor states switching (Slp/Idl/rx/tx). Finally, it results in higher throughput at the cost of higher energy consumption, thus reducing the overall residual energy level.

Figure 16 shows the comparison of the throughput of SixLoWPAN and SixLoWPAN–EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 121.34Kbps for SixLoWPAN and 140.78Kbps for SixLoWPAN -EF. With 200 sensors, it is 207.91Kbps for SixLoWPAN and 247.9Kbps for SixLoWPAN-EF, and with 300 sensors, it is 399.2Kbps for SixLoWPAN and 468.39Kbps for SixLoWPAN-EF. Figure 17 shows the comparison of residual energy of SixLoWPAN and SixLoWPAN -EF under the constraints of scalable sensor density. In the case of 100 sensors, it is 2.92835J for SixLoWPAN and 3.87398J for SixLoWPAN-EF. With 200 sensors, it is 2.35697J for
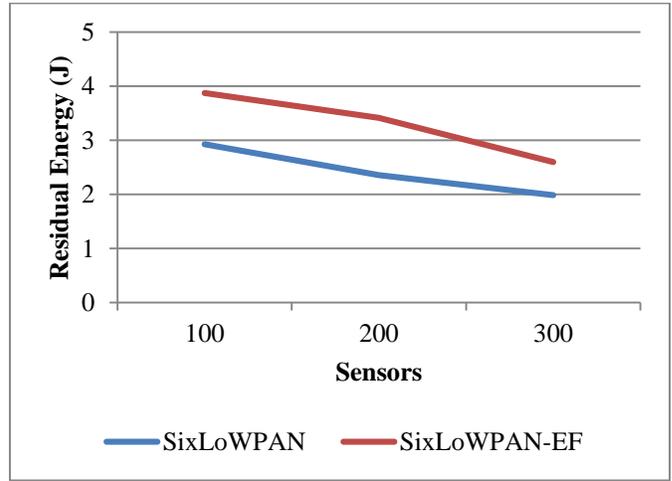

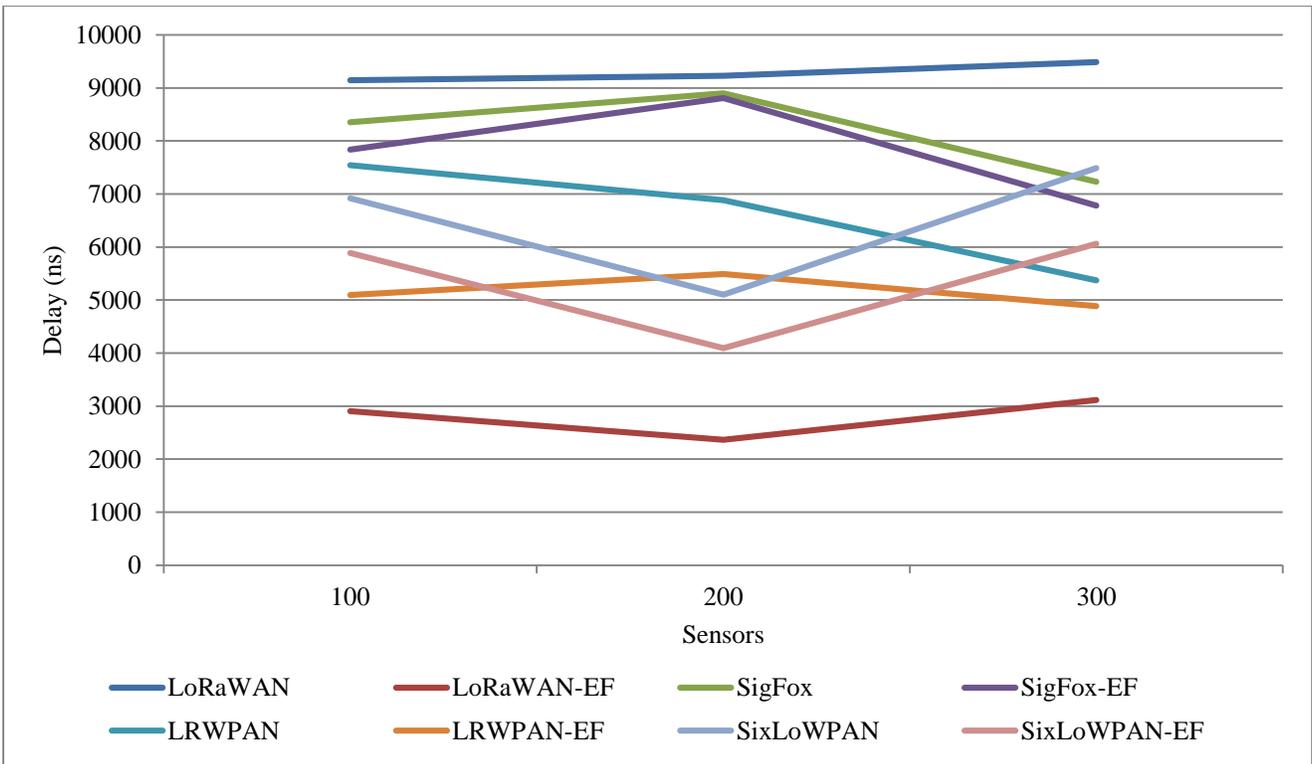**Fig. 17 Residual energy- SixLoWPAN and SixLoWPAN–EF**

Fig. 18 Comparison-delay

Figure 18 shows the comparison of delay for LoRAWAN-EF, SigFox-EF, LRWPAN-EF, SixLowPAN-EF, etc. It can be observed that LoRAWAN and SigFox both have the highest delay as compared to LRWPAN and SixLowPAN under the constraints of scalability. Results show that the proposed scheme optimises the delay factor for all above IoT protocols at a significant level, i.e., without using the proposed scheme, with 100 sensors, it is 9148ns for LoRaWAN, 8354ns for SigFox, 7543ns for LRWPAN, and 6918ns for SixLoWPAN. In the case of 200 sensors, it is 9232ns for LoRaWAN, 8901ns for SigFox, 6885ns for LRWPAN, and 5102ns for SixLoWPAN. In the case of 300 sensors, it is 9488ns for LoRaWAN, 7230ns for SigFox, 5369ns for LRWPAN, and 7490ns for SixLoWPAN. Using the proposed scheme, with 100 sensors, it is 2906ns for LoRaWAN-EF, 7838ns for SigFox-EF, 5094ns for LRWPAN-EF, and 5885ns for SixLoWPAN-EF. In the case of 200 sensors, it is 2366ns for LoRaWAN-EF, 8807ns for SigFox-EF, 5490ns for LRWPAN-EF, and 4095ns for SixLoWPAN-EF. In the case of 300 sensors, it is 3113ns for LoRaWAN-EF, 6784ns for SigFox-EF, 4885ns for LRWPAN-EF, and 6063ns for SixLoWPAN-EF.

Analysis indicates that sensor density directly affects the delay for all IoT protocols, and the proposed scheme reduces the delay for these protocols. It can be observed that with minimal sensor density, it is at the lowest level due to less routing overhead and minimal state switching, and there are more variations in its value due to higher routing load and random state switching with respect to IoT protocols.

4.3. Comparative Analysis of Proposed Energy Framework with Existing Energy–Efficient Schemes

The proposed energy-efficient framework builds on existing methods and is designed to compare with the existing schemes, such as the Hybrid Trust Aware Algorithm (HTWA) and the Improved Smart Energy-Based Routing Protocol

(ISEBRP), particularly in terms of network throughput, residual energy, and communication delay.

- Hybrid Trust-Aware Algorithm: In this, the authors use a combination of optimization techniques and trust evaluation to route data in order to select cluster heads. The approach used here is to prioritize reliable nodes to reduce packet loss and improve network stability. While the approach improves network lifetime and throughput, it adds computational overhead, and it is limited to a single protocol without cross-layer energy coordination [45].
- Improved Smart Energy-Based Routing Protocol: Authors in this paper focus on energy-efficiency communication in IoT sensor networks by optimizing cluster head selection using residual energy and link quality indicators such as RSSI.
- SNR, and LQI. The work provided is able to improve the network lifetime and reliability, but it mainly focuses on the two layers, which are the MAC and network layers [46].

When compared to these existing schemes, the proposed energy-efficient cross-layer framework provides a better and more flexible solution. While ISEBRP is limited to the single-layer optimaztion and HTWA, on the other hand, increases overhead due to trust and optimization processing, the proposed framework uses the power of enabling coordination across all four layers to reduce energy and to improve the overall energy utilization. This results in higher residual energy, lower communication delay, and improved throughput. A detailed comparison of these parameters with these schemes is presented in the subsequent section using dedicated graphical analysis. Moreover, the proposed framework supports better scalability and adaptability under various communication conditions and network densities, making the framework more suitable for real-world IoT deployments.
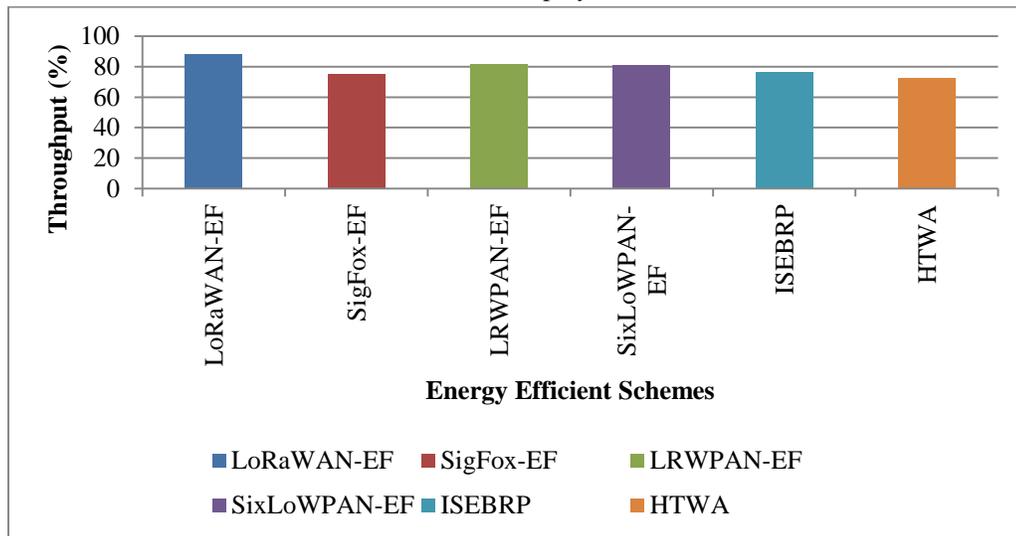

Fig. 19 Comparison-throughput-energy efficient schemes

Figure 19 shows that the proposed framework results in a higher throughput for LoRAWAN-EF, LR-WPAN-EF, and SixLoWPAN-EF than the HTWA and ISEBRP schemes, while SigFox-EF still maintains an acceptable rate. This is due to the fact that the proposed framework gains results from integrated cross-layer control. In the proposed framework, the packet size and retransmission are regularly tuned according to the current status of the battery depletion rate. Keeping in mind the harvesting state transitions, i.e., (tx/rx/Idle, Sleep), which helps in keeping the sensors ready for forwarding data without rapidly draining their energy. On the other hand, in comparison to HTWA, which only concentrates on optimization-driven, trust-aware cluster-head and route selection, ISEBRP focuses on cluster head selection with link quality-based routing and harvesting; neither coordinates application, MAC, routing, and PHY states jointly, which limits the achievable throughput, particularly under dense deployments.
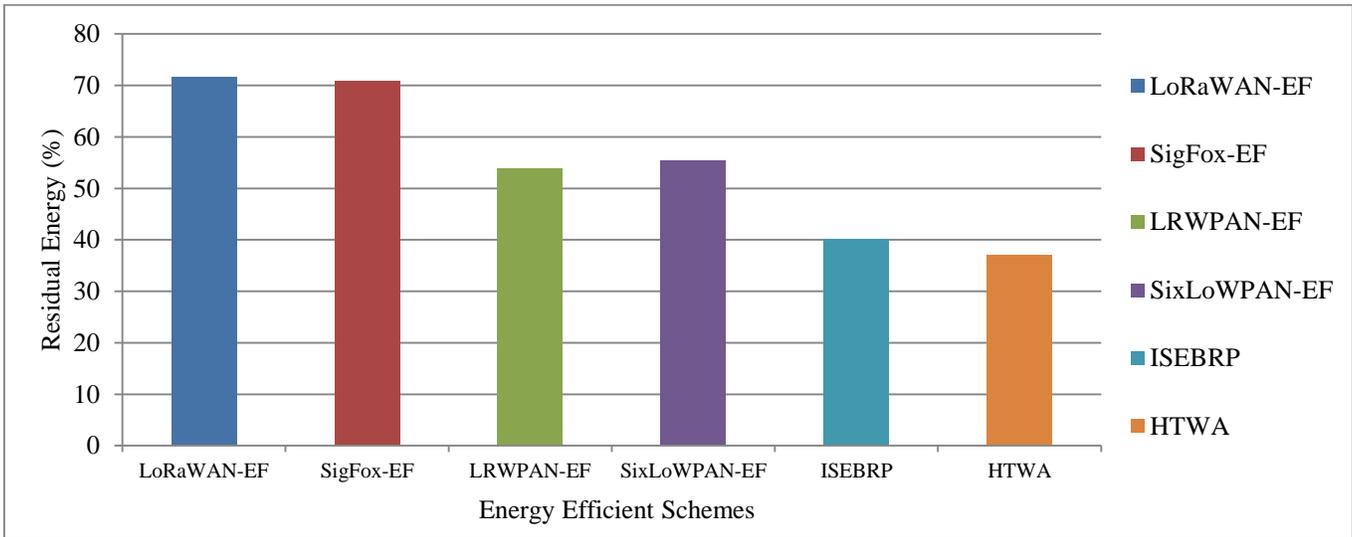

Fig. 20 Comparison-Residual-Energy

Figure 20 shows the comparison of residual energy for the different energy-efficient schemes. It can be analysed that the proposed energy-efficient framework has efficiently retained the energy level of the different IoT protocols (i.e., LoRAWAN-EF, SigFox-EF, LRWPAN-EF, SixLowPAN-EF) as compared to the ISEBRP and HTWA. It shows that it is highest for LoRAWAN-EF and SigFox-EF as compared to SixLowPAN-EF. It is average for LRWPAN-EF, in contrast to ISEBRP and HTWA. This is achieved by continuous depletion rate estimation and harvesting triggers that avoid unnecessary transmission and keep the nodes from depleting their batteries prematurely. In Contrast to HTWA and ISEBRP, which focus mainly on the routing mechanism and clustering, they lose more energy in dense deployment environments.
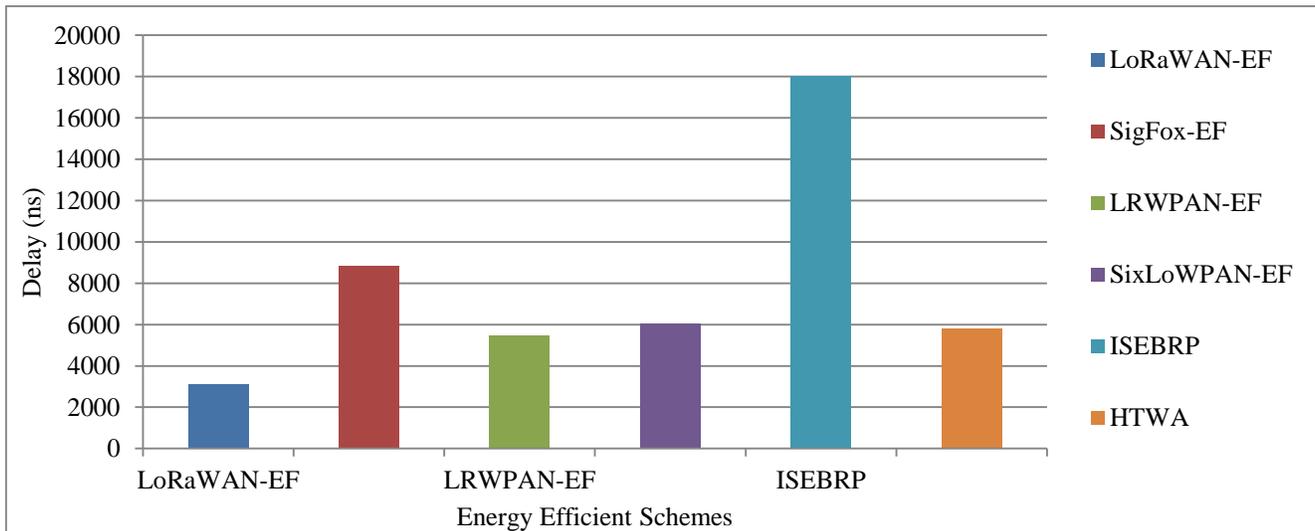

Fig. 21 Comparison-Delay-Energy efficient schemes

Figure 21 shows the comparison of the delay for the different energy-efficient schemes. The proposed LoRaWAN-EF configuration achieves the lowest delay (3113 ns), while LR-WPAN-EF and SixLoWPAN-EF exhibit moderate delay, and SigFox-EF remains within an acceptable range. The delay is consistently lower than HTWA, and it is drastically lower than ISEBRP, which reaches up to 18000 ns due to longer multi-hop paths and repeated CH re-selection and retransmissions under heavy load.n the proposed framework, energy-aware MAC backoff, bounded retransmission based on depletion thresholds, and proactive harvesting maintain a stable forwarding set and avoid persistent collision or congestion phases, which collectively minimise end-to-end delay even in dense IoT-WSN scenarios.

5. Conclusion

In this paper, an energy framework for smart agriculture is presented to optimise the operations at different layers, i.e. at the application layer, it manages the sense and packet generation operations, at the MAC layer, it controls the device behaviour during collision state, at the routing layer, it enables the data forwarding only if packets have been produced by the application layer. At the PHY layer, it managed the device-level state, i.e., SLEEP, IDLE, TX/RX, HARVESTING, etc. Its performance is compared using different IoT routing protocols, i.e., LoRAWAN, SigFox, Sixlowpan, LRWPAN, etc., under the constraints of scalable sensor density (100-300). Results illustrate that throughput increased with respect to sensor density variations for all protocols. LoRAWAN-EF has a higher throughput, followed by LRWPAN-EF. It is average SixLoWPAN-EF, and it is minimal for SigFox-EF. Scalability affected the residual energy level, thus also increasing the energy harvesting level to support the reliable transmission. With minimal sensors (100), all protocols retained a significant level of residual energy, thus reducing the overall energy harvesting. With medium sensor density (200), the network consumed more resources for transmission, thus consumed more energy, and it also triggered the energy harvesting. In the case of peak sensor density (300), the network could not retain a sufficient energy level, thus also increasing the dependency on energy harvesting. It can also be observed that protocol behaviour may degrade the overall network performance, and it may also increase the resource consumption. So it can be stated that (except SigFox), the proposed scheme is compatible with these protocols and retains the performance. Performance of the proposed scheme was also compared with existing schemes, i.e, HTWA and ISEBRP, which confirms that it outperforms in terms of higher network performance, optimal delay, and residual energy. Finally, it can be concluded that LoRAWAN-EF delivered the highest throughput while retaining the optimal level of residual energy along with minimal delay, and it also required the minimal energy harvesting support as compared to other IoT protocols under the constraints of scalability.

The scope of the current research work is to introduce an energy framework for IoT network-based smart farming. There are a few limitations of the proposed scheme. For experiments, four different IoT protocols (i.e., LoRAWAN, SigFox, Sixlowpan, LRWPAN) were used, and their performance was analysed. Farming can be done over different landscapes (i.e., rural/urban/hills/underwater), and in each case, energy consumption and harvesting requirements may vary. It may also affect the network performance. There is also a need to analyse its performance in a heterogeneous environment. For energy harvesting, solar power-based ambient energy resource was used, and there is a need to compare its performance with the different ambient energy resources (Wind/thermal/and mechanical). Mobile ad hoc networks and unmanned aerial vehicles can both be deployed to monitor the farming processes. In the future, the proposed framework will be integrated with these resource-constrained networks (where energy consumption is a major issue), and its performance will also be analysed under the above-discussed constraints. Also, the proposed scheme can be analysed against other IoT protocols as well.

Declaration
Ethics Approval

On behalf of all authors, they confirm that the submitted manuscript is original, has not been published previously, is not under consideration by any other journal, and that all results are presented truthfully and without fabrication. The submitted work is original and has not been published elsewhere in any form or language.

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