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Enhancing energy efficiency in wireless mesh networks through time-synchronized sleep scheduling and low-power hardware

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ABSTRACT

Energy efficiency remains a critical challenge in wireless mesh networks (WMNs), particularly for internet of things (IoT) deployments with battery-powered nodes and multihop communication. This paper proposes a time-synchronized sleep scheduling framework that integrates a lightweight regression-based time synchronization model with low-power hardware to reduce energy consumption in long range (LoRa)-based WMNs. The proposed mechanism aligns local node clocks with a global reference using slope and offset correction, enabling synchronized active and sleep states across nodes. This coordination significantly reduces idle listening and unnecessary radio-on time. The proposed approach is validated through real-world experiments on a multihop LoRa mesh testbed with up to three hops. Results show a substantial improvement in energy efficiency, reducing cumulative energy consumption from 125.31 mWh to 28.18 mWh over 10 hours (77.5% reduction). The sleep-mode current is reduced to 0.01 mA, demonstrating effective duty cycling. Furthermore, the approach maintains stable routing, bounded latency, and high packet delivery ratio (PDR). These findings confirm that accurate time synchronization is a key enabler for energy-efficient and reliable multihop communication, providing a practical solution to extend the operational lifetime of IoT-based WMNs.

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1. INTRODUCTION

Wireless mesh networks (WMNs) have become a key enabling technology for internet of things (IoT) applications due to their self-organizing capability, multi-hop communication, and robustness against single-node failure. Each node in a WMN not only transmits its own data but also forwards packets from other nodes, enabling wide-area connectivity without relying on fixed infrastructure. These characteristics make WMNs highly suitable for large-scale deployments such as smart agriculture, environmental monitoring, industrial systems, and public infrastructure surveillance, especially in remote or infrastructure-limited environments [1]–[4].

However, ensuring energy efficiency remains a fundamental challenge in WMNs, particularly when nodes are powered by batteries that are difficult to recharge or replace [5]–[8]. To maintain network connectivity, nodes generally remain active for long periods, which leads to high power consumption, increased idle listening, and rapid battery depletion. Failure of one or more nodes may disrupt routing paths, reduce data delivery reliability, and shorten overall network lifetime [4], [9], [10]. Therefore, developing an effective energy management strategy is essential to prolong operational duration while maintaining stable communication performance.

Previous research has attempted to address energy consumption from both hardware and software perspectives. Hardware-based approaches commonly focus on adopting low-power communication modules and energy-efficient sensor components, while software-based studies emphasize optimization at the routing, scheduling, and protocol levels to minimize unnecessary communication overhead [11]–[14]. Although these approaches have demonstrated promising results, most of them treat hardware optimization and communication strategies as separate problems, without integrating their potential in a unified framework. Several representative studies addressing WMN energy efficiency are summarized in Table 1.

Table 1. Summary of previous studies on energy efficiency in WMNs

Author and year	Research gap	Method	Novelty
Del-Valle-Soto *et al.* (2020) [11]	Lack of real-world comparison between protocols and sleep algorithms	Simulation and real-world experiments	Comprehensive comparison of Zigbee/wireless fidelity (WiFi) protocols
Trotta *et al.* (2020) [12]	Wireless relay (WR) synchronization and unmanned aerial vehicle (UAV)-wireless ground station (WGS) efficiency not yet optimal	UAV path heuristics with objective modular network testbed in C++ (OMNeT++)	Integration of WR and UAV path optimization based on value of sensing
Suresh *et al.* (2022) [13]	No adaptive energy-based sleep scheduling	Simulation of dynamic algorithm	Combination of residual energy and flow rate
Zou (2023) [14]	Limited self-sustaining energy for wireless sensors	Piezoelectric harvester and fast fourier transform (FFT)	Cantilever design optimization for self-powered energy
This Study (2025)	No integration of low-power hardware and precise time synchronization in real networks	Time-based sleep scheduling and experiments on a real testbed	Combination of energy-efficient hardware and time-synchronized algorithm in WMNs based on direct experimentation

As shown in Table 1, existing research demonstrates substantial progress in reducing energy consumption through individual optimization strategies. However, two important limitations remain evident. First, many studies do not explicitly address accurate time synchronization among nodes, even though synchronization is a key enabler for coordinated sleep–wake scheduling [15]–[17]. Without precise synchronization, nodes tend to operate asynchronously, leading to unnecessary wake periods and inefficient energy usage. Second, a significant portion of prior work relies primarily on simulations or analytical models, with limited experimental validation in real multihop environments, particularly for long range (LoRa)-based WMNs. As a result, the practical impact of synchronization accuracy on energy efficiency under realistic deployment conditions is still insufficiently explored [18]–[20].

To further clarify these limitations and to position the contribution of this study, Table 2 presents a structured comparison between the key limitations identified in previous research and the corresponding contributions offered by the proposed approach. Based on the synthesis presented in Table 2, it is evident that most prior studies focus on optimizing either hardware components or communication protocols in isolation, with limited attention to precise time synchronization and coordinated sleep scheduling in real-world multihop networks. Moreover, experimental evaluations on practical LoRa mesh deployments remain scarce, limiting the generalizability of simulation-based findings.

Table 2. Limitations of previous studies and contributions of this study

Limitations of previous studies	Contributions of this study
Optimization in previous studies is generally separated between hardware and software aspects	Integrates low-power hardware with a time-synchronized sleep scheduling algorithm
Lack of attention to accurate time synchronization among nodes	Implements precise time synchronization to enable collective and efficient sleep–wake scheduling
Energy efficiency evaluations are mostly based only on simulations with static models	Conducts direct implementation and testing on a real platform (testbed)
Limited representation of real-world challenges in the evaluation process	Provides a more representative evaluation of energy efficiency and network performance in actual conditions

To address these gaps, this study proposes an integrated energy-efficient framework for LoRa-based WMNs that combines a regression-based time synchronization model with coordinated sleep scheduling using low-power hardware. The proposed approach aligns local node clocks with a global reference through slope and offset correction, enabling nodes to enter synchronized active and sleep states collectively. Unlike many existing works, this research emphasizes real-world experimental validation using a multihop LoRa mesh testbed. The main contributions of this study can be summarized as: (i) development of a lightweight regression-based time synchronization model suitable for multihop LoRa mesh networks; (ii) integration of synchronization accuracy with coordinated sleep scheduling using low-power hardware; and (iii) experimental validation on a real testbed demonstrating significant improvements in energy efficiency compared to conventional unsynchronized operation.

2. METHOD

This study adopts an experimental research methodology to evaluate the effectiveness of time-synchronized sleep scheduling for improving energy efficiency in LoRa-based WMNs [21]–[23]. The proposed approach integrates low-power hardware design with a regression-based time synchronization model and coordinated sleep scheduling, and it is validated through real-world experiments on a multihop LoRa mesh testbed. Figure 1 presents the overall workflow of the proposed methodology, illustrating the sequential stages from system design to experimental evaluation.

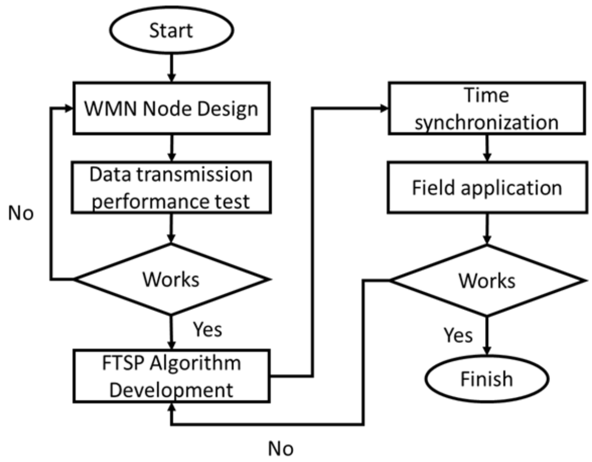


Figure 1. Flowchart of WMN system development and time synchronization

2.1. System architecture and hardware design

The proposed system architecture is designed to support energy-efficient operation in a LoRa-based WMN through coordinated communication and time-aware power management among distributed nodes. The network adopts a multihop mesh topology consisting of multiple low-power sensor nodes and a single cluster head (CH) that serves as the global time (GT) reference and data aggregation point [24]–[26]. Each sensor node is built using an ATmega328 microcontroller integrated with an SX1276 LoRa transceiver operating in the 915 MHz ISM band [27], [28]. The microcontroller manages packet handling, time synchronization, and sleep scheduling, while the LoRa transceiver provides long-range, low-power wireless communication suitable for IoT applications. LoRa technology is selected due to its low energy consumption, robustness in non-line-of-sight environments, and suitability for multihop communication.

The CH periodically broadcasts synchronization packets containing timestamp information to establish a GT reference for the network. Sensor nodes receive these messages either directly or via intermediate nodes depending on their hop distance, enabling consistent time alignment across multiple hops without additional synchronization hardware [2], [29], [30]. All nodes are powered by a 3 V battery supply to represent energy-constrained IoT deployment conditions and operate predominantly in deep sleep mode, activating the microcontroller and radio only during scheduled communication intervals. The hardware supports multiple operating states sleep, run, transmit (Tx), receive (Rx), and idle allowing fine-grained power control throughout the communication cycle. Figure 2 illustrates the overall LoRa-based WMN architecture, including the multihop topology, the roles of the CH and sensor nodes, and the flow of synchronization and data packets, which form the basis for implementing the regression-based time synchronization model and coordinated sleep scheduling algorithm described in the subsequent sections.

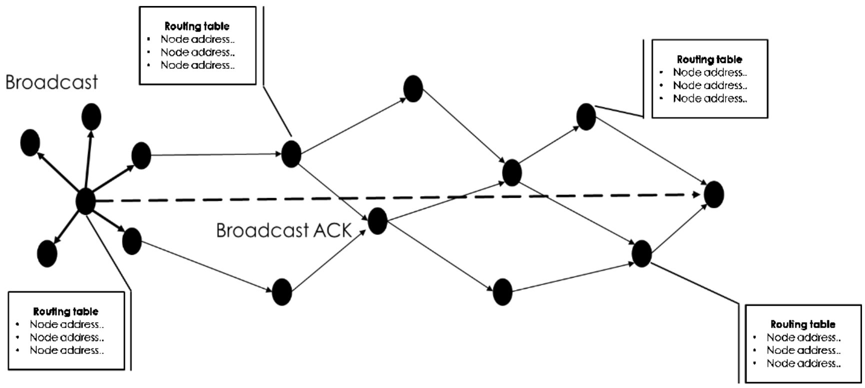


Figure 2. Architecture of the proposed LoRa-based WMN and routing mechanism.

2.2. Synchronization model

Accurate time synchronization is a fundamental requirement for enabling coordinated operations in multihop WMNs, particularly for sleep scheduling mechanisms that depend on simultaneous transitions between active and sleep states [17], [31]. In practical deployments, each node maintains an independent local clock that is subject to drift and offset caused by hardware imperfections, temperature variations, and oscillator instability; without synchronization, these discrepancies accumulate over time and prevent coordinated operation. In the proposed system, a regression-based time synchronization model is used to align each node's local time (LT) with the GT reference provided by the CH, which periodically broadcasts synchronization packets containing timestamp information. Sensor nodes receive these messages either directly or via intermediate hops and record paired global and local timestamps to perform time alignment [15], [32].

To correct clock drift and offset, the relationship between the GT and the LT of a node is modeled using linear regression. Let GT_i denote the GT timestamp received from the CH and LT_i denote the corresponding LT recorded by a sensor node at the $i-th$ synchronization event. The relationship between global and LT can be expressed as:

$$GT_i = a \,.\, LT_i + b \quad (1)$$

where, a is the slope correction factor representing the relative clock drift between the global and local clocks, and b is the offset correction factor representing the initial time difference between the clocks.

The parameters a and b are estimated using linear regression based on multiple pairs of (GT_i, LT_i) are estimated using linear regression based on multiple pairs of (LT_s)can be computed as:

$$LT_s = a \,.\, LT + b \quad (2)$$

This correction allows each node to align its local clock with the global reference time while minimizing the need for frequent synchronization messages, which is particularly important for low-power LoRa-based networks.

Compared to conventional time synchronization protocols such as flooding time synchronization protocol (FTSP) [19], reference broadcast synchronization (RBS) [33], [34], and timing-sync protocol for sensor networks (TPSN) [35], [36], the proposed regression-based approach provides a lightweight solution suited for low-data-rate and energy-constrained environments. Unlike FTSP and TPSN, which rely on frequent message exchanges and hierarchical synchronization, and RBS, which requires reference broadcasts among neighboring nodes, the proposed model reduces communication overhead by applying regression-based clock correction with sparse synchronization updates. This makes it particularly suitable for multihop LoRa mesh networks where minimizing transmission activity is critical for energy efficiency. The model produces a corrected LT_s that closely follows the GT reference across different hop counts and serves as the foundation for the coordinated sleep scheduling algorithm. By ensuring a consistent time reference among all nodes, the approach enables simultaneous sleep–wake transitions and eliminates idle listening caused by unsynchronized operation.

2.3. Sleep scheduling algorithm

After obtaining a synchronized LT reference through the regression-based model in section 2.2, the proposed system applies a coordinated sleep scheduling algorithm to reduce unnecessary energy consumption. The main objective of this algorithm is to minimize idle listening and prolonged active states by allowing nodes to enter sleep mode simultaneously while maintaining reliable multihop communication. Each operational cycle is divided into two intervals: an active period and a sleep period [12], [37], [38]. During the active period, nodes perform sensing, packet transmission, packet reception, and synchronization updates if required. During the sleep period, both the microcontroller and the radio module are switched to low-power mode. Let T_c denote the total cycle duration, T_a the active period, and $T_s$the sleep period. Their relationship is defined as:

$$T_c = T_a + T_s \quad (3)$$

The duty cycle D, which represents the fraction of time a node remains active, is given by:

$$D = \frac{T_a}{T_c} \quad (4)$$

Using the synchronized LT_s, all nodes schedule their sleep–wake transitions at the same GT instants. This temporal alignment ensures that neighboring nodes are active simultaneously during communication windows and inactive during idle periods. As a result, idle listening is reduced and packet forwarding across multiple hops becomes more energy efficient.

2.4. Experimental setup and performance metrics

To validate the proposed framework, real-world experiments were conducted using a multihop LoRa-based WMN. The objective is to evaluate the impact of time synchronization and coordinated sleep scheduling on energy consumption, current draw, and synchronization accuracy under practical operating conditions [39]. The experimental network consists of up to eight sensor nodes and one CH arranged in a multihop topology with a maximum of three hops. Each node is built using an ATmega328 microcontroller and an SX1276 LoRa transceiver. The spreading factor is set to SF = 8, while other LoRa parameters are configured according to the implemented system. All nodes are powered by a 3 V battery supply. The CH acts as the GT reference and data aggregation point. Two operating modes are compared: (i) an unsynchronized mode, in which nodes remain active without coordinated sleep scheduling, and (ii) the proposed synchronized mode, which applies the regression-based time synchronization model and the coordinated sleep scheduling algorithm described in sections 2.2 and 2.3.

The total energy consumption E is computed as:

$$E = V \cdot \int_0^T I(t)dt \quad (5)$$

where $V$is the supply voltage, $I(t)$ is the instantaneous current, and T is the observation duration. The average current consumption $\bar{I}$ is defined as:

$$\bar{I} = \frac{1}{T}\int_0^T I(t)dt \quad (6)$$

Current measurements are obtained using a digital multimeter, and each experiment is repeated multiple times under identical conditions. To evaluate synchronization performance, the synchronization error is defined as:

$$e_i = \left|GT_i - LT_{s,i}\right| \quad (7)$$

where GT_idenotes the GT reference and $LT_{s,i}$ epresents the corrected LT at the $i-th$ synchronization event. The average synchronization error and its variation across different hop counts are used to assess the robustness of the proposed synchronization mechanism.

3. RESULTS AND DISCUSSION

This section presents the results of the development of low-power WMN nodes, the performance testing of the mesh network, the time synchronization process, and the implementation of sleep scheduling in the WMN. Each result obtained is then analyzed to address the research objectives, assess the effectiveness of the developed method, and identify the contributions and limitations arising from this approach.

3.1. Node-level power characteristics and energy profile

This subsection evaluates the power consumption characteristics of the proposed LoRa mesh node under different operating modes. The objective is to validate the low-power hardware design described in section 2.1 and to establish a baseline for analyzing the impact of time-synchronized sleep scheduling in later subsections. Figure 3 shows the physical implementation of the proposed WMN node, which consists of a microcontroller unit, a LoRa transceiver, and a battery-powered supply module. This compact and modular design enables flexible deployment in multihop mesh scenarios while maintaining low hardware complexity.

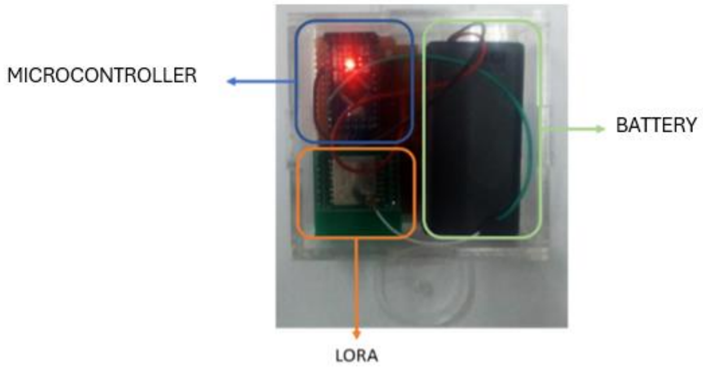


Figure 3. WMN node

Figure 4 illustrates the current consumption profile of the WMN node over a single transmission cycle, including sleep mode, Tx mode, Rx mode, and idle mode. The results reveal a significant variation in current draw across different operational states. The highest current consumption occurs during transmission, followed by reception, while the sleep mode exhibits the lowest power usage.

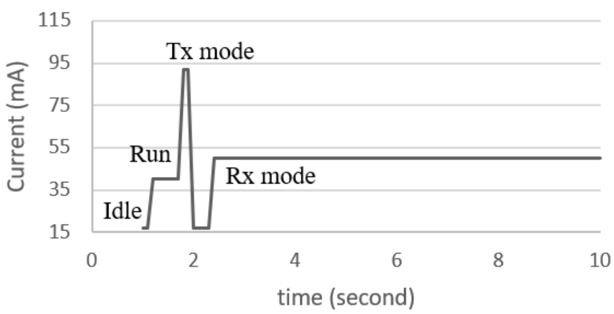


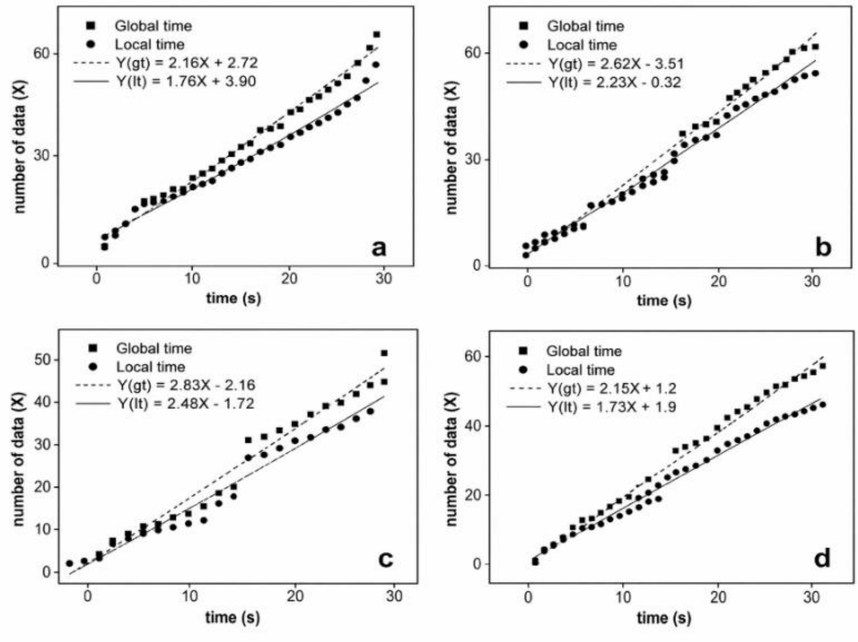
Figure 4. Measurement of WMN node power consumption in each mode within one data transmission cycle

This behavior confirms that the radio module dominates the overall power consumption, particularly during active communication periods [5], [27], [40]. Consequently, reducing the duration of radio-on time becomes a critical strategy for extending node lifetime. These observations justify the use of coordinated sleep scheduling, as described in section 2.3, which aims to minimize the time spent in high-power states.

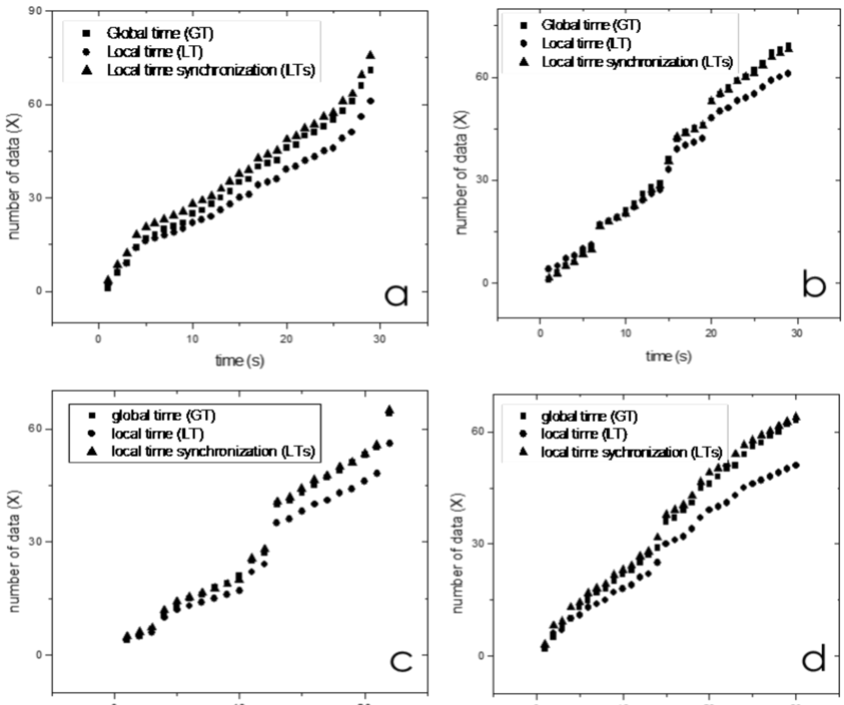
Furthermore, the presence of a distinct low-power sleep mode demonstrates that the hardware platform is capable of supporting aggressive duty cycling. Without such a capability, any software-based energy-saving strategy would be ineffective. Therefore, these results validate the hardware-level feasibility of the proposed framework and motivate the integration of time-synchronized scheduling mechanisms. In the next subsections, this baseline power profile is used to quantify how synchronization accuracy and coordinated sleep scheduling translate into measurable energy savings at the network level.

3.2. Synchronization accuracy and performance of time-synchronized sleep scheduling

This subsection evaluates the performance of the proposed regression-based time synchronization model and its role in enabling coordinated sleep scheduling in a multihop LoRa mesh network. Accurate synchronization is essential in multihop environments, where clock drift accumulates across hops and may disrupt coordinated sleep–wake transitions and energy-efficient duty cycling. To examine drift behavior, the relationship between the GT broadcast by the CH and the LT recorded by each node is analyzed. Figure 5 presents the synchronization behavior before and after regression-based correction.



(a)



(b)

Figure 5. Time alignment before and after regression correction: (a) raw GT–LT drift and (b) corrected LTs

As shown in Figure 5(a), LT exhibits a linear deviation from GT that increases over time and hop distance. This confirms the presence of clock drift caused by oscillator instability and hardware imperfections. The magnitude of this deviation becomes more pronounced as hop count increases, indicating cumulative timing errors in multihop communication. Without correction, such drift would lead to time misalignment and disrupt coordinated node operation. To quantitatively model this behavior, the GT–LT relationship is approximated using linear regression. The resulting trendline equations for each hop distance are summarized in Table 3.

Table 3. Trendline equations between GT and LT for each hop distance

Hop	Trendline equations of GT	Trendline equations of LT
0	$Y(gt) = 2.16X + 2.72$	$Y(lt) = 1.76X + 3.90$
1	$Y(gt) = 2.62X - 3.51$	$Y(lt) = 2.23X - 0.32$
2	$Y(gt) = 2.83X - 2.16$	$Y(lt) = 2.46X - 1.72$
3	$Y(gt) = 2.15X + 1.20$	$Y(lt) = 1.73X + 1.90$

Based on Table 3, the slope of each regression line represents clock skew, while the intercept corresponds to time offset. The variation of these parameters across hop distances indicates that each node experiences distinct drift characteristics and therefore requires hop-specific correction factors. The slope and offset correction factors are computed using:

$$M_{lt}.a = M_{gt} \text{ or } a = \frac{M_{gt}}{M_{lt}} \quad (8)$$

$$O_{lt} - b = O_{gt} \text{ or } b = O_{lt} - O_{gt} \quad (9)$$

- a is the slope correction factor for the LT
- b is the offset correction factor for the LT
- M_{gt} is the slope of the GT
- M_{lt} is the slope of the LT
- O_{gt} is the offset value of the GT
- O_{lt} is the offset value of the LT

The (8) and (9) are used to rescale the local clock and shift its offset so that it aligns with the global reference. By applying these correction factors, the unsynchronized LT is transformed into the synchronized LT_s. The calculated values of the correction factors a and b for each hop distance are summarized in Table 4.

Table 4. Slope and offset correction factors for each hop distance

Hop	M_{gt}	M_{lt}	a	O_{gt}	O_{lt}	b
0	2.16	1.76	1.23	2.72	3.90	1.18
1	2.62	2.23	1.18	−3.51	−0.32	3.19
2	2.83	2.46	1.15	−2.16	−1.72	0.44
3	2.15	1.73	1.24	1.20	1.90	0.70

Table 4 shows that the correction factors increase with hop count, confirming that nodes farther from the CH experience larger timing deviations that must be compensated accordingly. After applying these correction factors, the local clocks are transformed into synchronized LT_s. As illustrated in Figure 5(b), the corrected LT_s closely follows GT across all hop distances, indicating that both clock skew and offset are effectively compensated even in multihop scenarios.

This synchronization accuracy forms the foundation for coordinated sleep scheduling. By using LT_s as a common temporal reference, nodes align their active and sleep periods within predefined communication windows. The impact of synchronization on node behavior is illustrated in Figure 6.

Figure 6 shows longer sleep intervals and shorter, well-defined active periods compared to unsynchronized operation, where nodes remain active longer to avoid packet loss. This confirms that accurate synchronization enables aggressive duty cycling without compromising communication reliability.

The cumulative impact on long-term energy consumption is shown in Figure 7. Figure 7 indicates that cumulative energy consumption in synchronized mode increases at a significantly slower rate than in normal operation. The difference in slopes confirms sustained energy savings over time rather than a temporary improvement. Overall, these results establish a clear causal relationship between synchronization accuracy and energy efficiency [16], [35], [41]. The proposed regression-based synchronization model enables stable time alignment in a multihop LoRa mesh network, allowing coordinated sleep scheduling to reduce idle listening and radio-on time, thereby achieving measurable long-term energy savings.

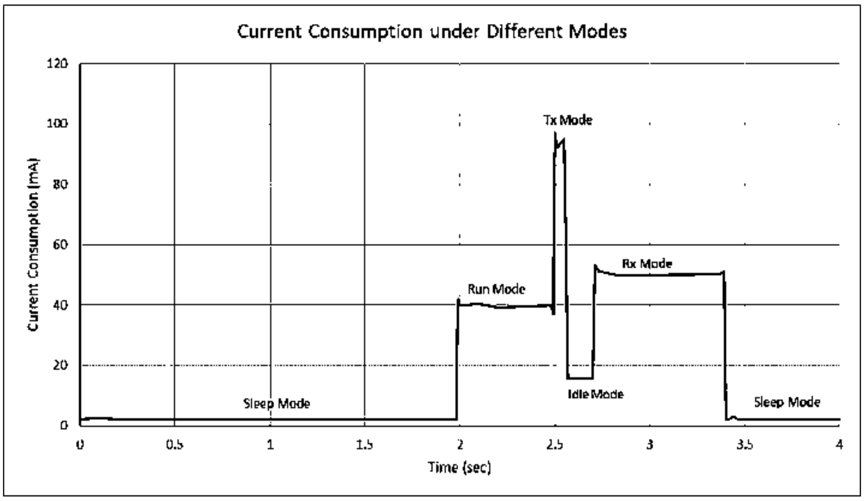


Figure 6. Current consumption profile of a sensor node under time-synchronized sleep scheduling

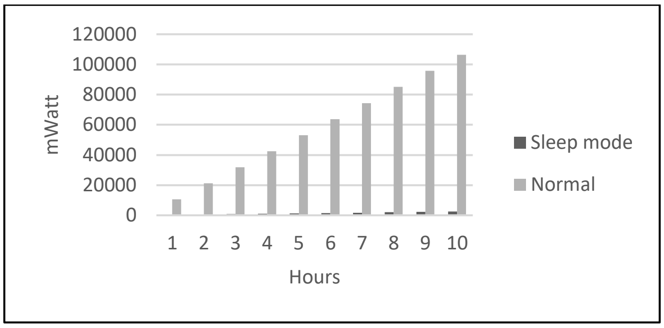


Figure 7. Comparison of cumulative energy consumption between normal operation and synchronized sleep scheduling mode over 10 hours

3.3. Multihop mesh network performance under coordinated sleep scheduling

This subsection evaluates the impact of the proposed time-synchronized sleep scheduling mechanism on the operational performance of the LoRa-based multihop mesh network. While section 3.2 demonstrated that accurate synchronization enables energy-efficient duty cycling, it is equally important to verify that these energy savings do not compromise essential network functions such as routing stability, latency behavior, and communication reliability.

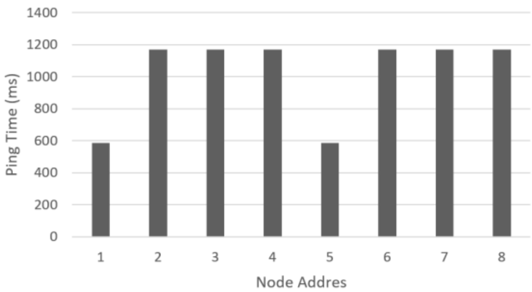
The experimental deployment was conducted in an urban residential area in Bandung to represent a practical IoT scenario where nodes are spatially distributed and rely on intermediate relays for multihop communication. The routing behavior, latency characteristics, and packet delivery performance under synchronized operation are summarized in Figure 8.

Figure 8(a) illustrates the routing behavior of the mesh network based on measured ping paths. Packets are forwarded through intermediate relay nodes following the shortest-delay paths, indicating that synchronized sleep scheduling does not interfere with route selection or forwarding mechanisms. The observed routing patterns remain stable under coordinated duty cycling.

Figure 8(b) presents the average ping time as a function of hop count, measured from 0 to 3 hops. As expected, latency increases monotonically with hop distance due to additional forwarding delays introduced at each relay node. However, this increase is deterministic and bounded, with no abrupt spikes or irregular fluctuations. This behavior confirms that synchronized sleep scheduling maintains stable multihop forwarding without introducing unpredictable delays or network instability.

Figure 8(c) shows the packet delivery ratio (PDR) across different hop distances after synchronization is applied. The PDR remains consistently high, with only slight degradation at higher hop counts due to cumulative wireless losses. Importantly, the high delivery ratios indicate that reduced active time does not compromise communication reliability. Coordinated sleep scheduling allows nodes to operate with aggressive duty cycling while preserving dependable packet forwarding.

Collectively, these results demonstrate that the proposed synchronization-aware sleep scheduling mechanism achieves energy efficiency without sacrificing fundamental mesh network performance. The deterministic latency growth, stable routing behavior, and sustained high PDR confirm that coordinated sleep–wake cycles maintain reliable connectivity while minimizing unnecessary radio activity. Although the current evaluation is limited to a moderate network size and up to three hops, the findings provide strong evidence that synchronization-based duty cycling is a practical and effective strategy for energy-efficient and reliable multihop LoRa mesh communication.



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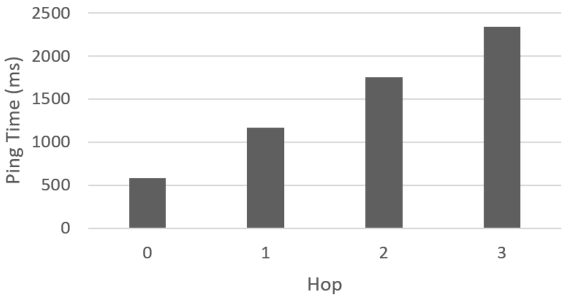

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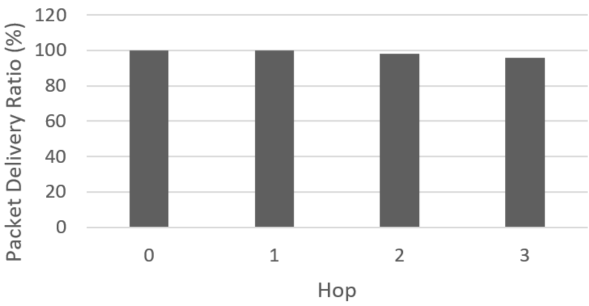

(c)

Figure 8. Network performance under synchronized scheduling: (a) routing behavior, (b) latency vs hop count, and (c) PDR vs hop count

4. CONCLUSION

This study proposes a time-synchronized sleep scheduling framework to improve energy efficiency in LoRa-based WMNs. By integrating a lightweight regression-based synchronization model with coordinated sleep–wake scheduling and low-power hardware, the proposed system enables substantial energy savings while preserving essential network functionalities. Experimental results show that the synchronized LT closely follows global reference with minimal error, even across multiple hops. This accurate alignment enables deterministic duty cycling, significantly reducing idle listening and radio-on duration. As a result, cumulative energy consumption is reduced by 77.5% over a 10-hour period, with the sleep current reaching as low as 0.01 mA. Beyond node-level efficiency, the proposed approach maintains stable multihop communication. Packet forwarding remains reliable, latency increases in a bounded and predictable manner, and PDRs remain high. These findings demonstrate that synchronization-aware scheduling does not compromise mesh network performance. Unlike most existing studies, this work provides real-world experimental validation without relying on external timing infrastructure. Although the current evaluation is limited to small-scale networks with up to three hops, the results confirm the feasibility of the proposed framework for energy-constrained IoT deployments. Future work will focus on larger-scale evaluations and adaptive scheduling mechanisms. Overall, this research highlights time synchronization as a key enabler of both energy efficiency and reliability in multihop LoRa mesh networks.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Solihin	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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