Adaptive Energy-Security Framework for IoT Devices Using Hybrid SPECK and Kyber Encryption

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***Abstract*—With the fast growth of the Internet of Things (IoT), the problem of secure and energy-efficient data exchange in resource-constrained settings has become even more challenging. The traditional cryptographic systems (RSA and ECC) are resource-consuming and susceptible to quantum attacks, and lightweight cyphers are not only less powerful but also energy-efficient. This study is a proposal of an adaptive hybrid encryption system (adjusting in real time) that dynamically utilises either a lightweight SPECK cypher or a post-quantum secure Kyber algorithm based on the energy consumption of the devices and the sensitivity of the data. The system will feature a PQC offload controller that manages key encapsulation and minimises computation latency. Simulation results in an OMNeT++ environment have shown that the proposed model is up to 45 per cent more energy-efficient and up to 40 per cent longer-lived than PQC models alone, while supporting 99 per cent security resilience against both classical and quantum attacks. Throughput levels of 1,600 packets per second are achieved by the approach, which is a trade-off between energy usage and post-quantum security, and is acceptable. It is an effective method of minimising energy use and reducing the risk of quantum attacks in IoT networks used in healthcare, industrial, and innovative city applications. With the assistance of this adaptable structure, it emphasises its relevance to energy-constrained devices.**

Keywords*—Post-Quantum cryptography; lightweight cryptography; hybrid cryptography; IoT security; quantum-resistant networks; energy-efficient encryption; Kyber; SPECK; network lifetime; quantum computing

I. Introduction

The Internet of Things (IoT) trend has accelerated the interconnection of billions of embedded systems across various industries, including healthcare, transportation, and industrial automation. These devices are always sensing, calculating, and sending information, yet they are usually severely constrained in terms of power, computing, and memory. On the one hand, such tiny environments, which quantum computing threatens with extinction, are naturally challenging to secure end-to-end with high-end security, as they can make classical public-key cryptosystems (RSA, ECC) computationally infeasible [6]. To address this critical threat, the standardization program has listed one of the lattice-based Key Encapsulation Mechanisms (KEMs), Kyber, as one of the top-performing candidates for post-quantum public-key encryption [19]. Kyber is highly resistant to quantum attacks [15], but has significantly high computational and energy overheads, which are not practical for ultra-low-power nodes in IoT [3].

Recent efforts have tried to close this gap. Higher throughput has been demonstrated to be promising with hybrid cryptographic constructions that utilise lightweight symmetric encryption in conjunction with PQC key exchange algorithms, such as NTRU Encrypt-AES and Sabre-Chacha20 constructions [12],[14]. Nevertheless, the majority of current hybrids have fixed combinations and cannot be adapted to consider environmental factors; they are unable to dynamically adjust their cryptographic strength according to node energy, data sensitivity, or network conditions [9]. Consequently, these systems end up consuming more energy in low-risk transmission or inadequately protecting critical data when under constrained conditions.

Despite progress in standardising PQC and the creation of lightweight cyphers, no comprehensive framework exists that dynamically balances post-quantum security and energy efficiency [18] in the real-time Internet of Things. The current literature addresses the energy optimisation and cryptographic strength as two unrelated issues, overlooking the dynamic nature of the operational environment of the IoT node. Thus, the work will present an Adaptive Energy-Security Framework (AESF), combining the lightweight SPECK cypher with the post-quantum Kyber one through adaptable decision logic. The framework selects its encryption modes based on the remaining battery capacity and the classification of data sensitivity of the device, utilising a PQC offload controller to manage the overhead in key exchange and maintain throughput.

The specific contributions of this study are as follows:

1) Adaptive hybrid architecture: Architecture of an adaptively configured context-sensitive cryptographic system that dynamically switches between SPECK and Kyber based on real-time energy and security indicators.

2) Mathematical trade-off model: Development of an energy-security optimisation model that quantifies the impact of switching thresholds on the length of network lifetime and computational cost.

3) PQC offload controller design: A controller mechanism should be integrated to enable heavy Kyber computations to be performed on higher-tier nodes, thereby enhancing the scalability of constrained IoT devices.

4) Complete simulation and testing: The code has been implemented using the Open Quantum Safe (OQS) library to test performance at various device numbers, packet sizes, and sensitivity levels.

5) Performance outcomes: Showing energy savings of up to 45 per cent, longer network lifetime by 40 per cent, and quantum-attack resiliency of 99 per cent with throughput of 1,600 pkts/s at minimum latency overhead.

Unlike previous hybrid cryptographic schemes that relied on static selection thresholds, AESF analytically derives the optimal switching probability P^*_{Kyber}=0.42 via Lagrangian optimization. This parameter minimizes per-packet energy by ≈45% while sustaining ≥166-bit post-quantum security, representing a quantifiable advance over heuristic models

A. Motivation

The existing IoT ecosystems should not be shaky in connectivity in response to three hostile demands, namely, energy conservation, real-time responsiveness, and post-quantum resilience. Cyphers of the lightweight alone are insufficient to protect the vital assets of a medical or industrial control system, but pure PQC systems consume battery power and reduce network life [16]. The research is motivated by the urgent need for a self-adaptive, self-tuning cryptography policy that adapts to the device's situation and automatically adjusts its degree of encryption. Such a paradigm will enable the deployment of IoT in a way that is sustainable and resilient to the effects of quantum computing, as well as future advances in human technology, fostering confidence in its long-term applicability.

II. Literature Survey

The Internet of Things network's sustainability and safety are fundamentally supported by cryptographic primitives, emphasizing their critical role in maintaining confidentiality and meeting energy and computational demands. The literature is divided into two major trends, Lightweight Cryptography [5] and Post-Quantum Cryptography [1]. Both of them partially solve the issue, but do not provide a solid balance of energy and security that could be applied in real-world IoT applications. LWC is dedicated to simplifying algorithms and reducing power consumption. The NSA has developed algorithms such as SPECK and SIMON, which run efficiently on microcontrollers with limited RAM and CPU cycles. They are fast in encryption and decryption, typically requiring only a few hundred cycles to encrypt and decrypt a block of data. Some studies, however, have found them to have low security factors against modernised differential and related-key cryptanalysis, especially with quantum amplitude amplification attacks [4],[10]. Although new lightweight standards, such as ASCON [19], have been found to offer better energy and security factors, their integration in distributed IoT systems is challenging because they lack adaptive control mechanisms to manage power [20]. Therefore, pure LWC schemes cannot be used exclusively in critical IoT systems that need long-term cryptographic strength. PQC provides resistance against attacks from quantum computers by relying on hard lattice, code, or isogeny problems. Among these, Kyber, a lattice-based Key Encapsulation Mechanism (KEM), has been officially standardized by NIST as a primary post-quantum encryption scheme [19],[13]. Kyber offers strong IND-CCA2 security, but its computational complexity and key size (up to 1.5 KB) make it costly for constrained IoT hardware [3]. Other PQC algorithms such as NTRU Encrypt and Saber provide similar quantum resistance but also exhibit high latency and energy cost, reducing network lifetime and throughput in multi-hop IoT topologies [14]. Recent optimization works—like the hardware-accelerated Kyber implementation by [2],[17]—achieve moderate energy gains, yet they do not adapt dynamically to the operating context of devices [2]. Authors in [9] proposed a Post-Quantum Secure ZRTP protocol for real-time communication, which offers strong quantum resistance and mitigates latencies and energy-inflation overhead in resource-constrained nodes. Significantly smaller signature sizes have been obtained by [14] and [8] in lattice systems, but this has been accompanied by a reduction in cryptographic strength. More recently, [11] and [6],[7] have highlighted that context-aware encryption selection needs to be urgently developed. A future direction is the adaptive integration of PQC. However, none of the models so far have included a quantitative energy-security decision logic to use cryptographic modes conditionally at runtime.

Lightweight cryptography is efficient but does not provide forward security against quantum adversaries. Post-quantum cryptography is resistant but prohibitively expensive for embedded devices. Current hybrids are non-dynamic and unaware of, and therefore not reactive to, running variables such as energy and sensitivity level. Thus, the current work can be distinguished by the introduction of a dynamic hybrid model that combines real-time adaptivity, quantitative modelling of energy-security trade-offs, and PQC offload control, thereby closing the divide between theoretical quantum resistance and IoT sustainability in practice. This is the direct incentive for the creation of the Adaptive Energy-Security Framework (AESF). The table below compares the current encryption models used in IoT setups, highlighting their strengths and weaknesses in terms of security and energy savings. Table I below summarizes key prior studies and highlights the analytical distinction of AESF.

TABLE I. Comparison Table: Existing Models vs. Proposed Model

S.No	Author	Approach/ Methodology	Advantages	Limitations
1	Benny et al. (2024)	Meta-analysis of NIST PQC finalists	Strong post-quantum security; efficient key encapsulation	High energy consumption, reducing network lifetime and increasing latency, affecting throughput.
2	Chen et al. (2023)	Challenges in PQC standardization for real-	Efficient lattice-based encryption	High complexity and increased latency, reducing throughput and

		world implementation	for quantum security	energy efficiency in IoT systems.
3	Hoffstein et al. (2020)	NTRU Encrypt post-quantum cryptography	Strong quantum resistance; fast key exchange	Computationally expensive, making it impractical for low-power IoT devices; high energy consumption.
4	Jaeger & Samardjiska (2022)	Reducing signature size in lattice-based cryptosystems	Improved throughput; lower computational cost compared to other PQC methods	Reduced security success rate due to trade-offs in smaller signature sizes.
5	Proposed Model	Hybrid SPECK + Kyber encryption with adaptive decision logic	Optimizes both energy consumption and security dynamically; future-proof	Initial computational overhead; reliance on well-classified data scenarios; PQC offloading helps mitigate throughput challenges.

III. System Model and Assumptions

The section establishes the network configuration, outlines the fundamentals of security considerations, and describes the adversarial model that will be utilized to develop and test the proposed Adaptive Energy-Security Framework (AESF). The framework is implemented on a distributed IoT system, comprising energy-constrained sensor nodes, gateway devices, and a controller. It organizes encryption operations by dynamically alternating between SPECK (a lightweight cypher) and Kyber (a post-quantum cryptographic algorithm), demonstrating system flexibility and resilience.

A. Network Setup

The network setup utilises a three-level IoT architecture that facilitates hierarchical data processing and supports energy-efficient cryptographic operations across various system layers.

- Tier 1 (Device Layer): IoT nodes with resources that sense and encrypt data on-the-fly with the lightweight SPECK algorithm.
- Tier 2 (Gateway / Cluster-Head Layer): aggregation points that collect traffic from Tier 1, manage routing, and relay data to higher nodes.
- Tier 3 (Controller Layer): a central controller hosting the PQC offload controller, which executes Kyber key encapsulation and performs high-security operations.

The network is modeled as a clustered IoT topology, typical of IEEE 802.15.4-based communication systems. Each cluster contains N end devices $\{D1, D2, \dots, DN\}$ that periodically sense and transmit data to a cluster head (CH), which in turn communicates with a controller node (CN) responsible for key management and heavy cryptographic processing, as shown in Each device D_i is characterized by, Limited battery capacity $E_{max,i}$, Transmission range R_i, Residual energy $E_i(t)$ at time t. Data sensitivity level $S_i \in \{0,1\}$ $(0 = low, 1 = high)$. The communication channels are assumed to be wireless and symmetric. Nodes share a secure initialization phase using Kyber-based key encapsulation; afterward, the encryption mode is adaptively chosen per transmission session.

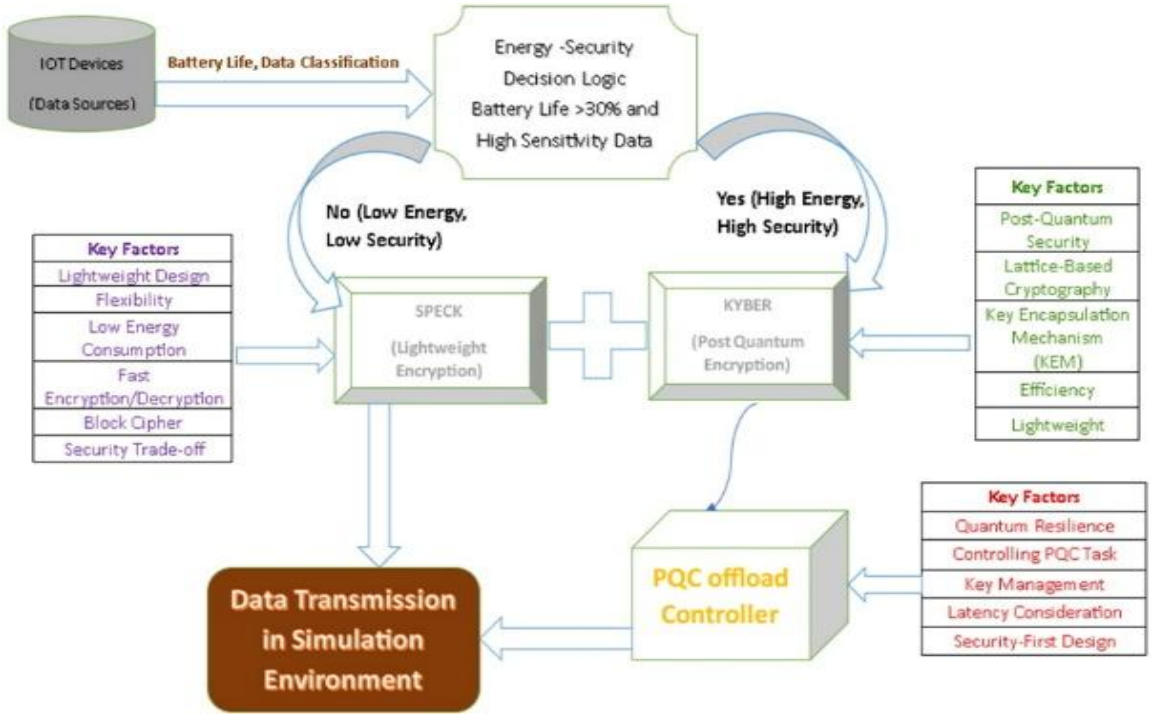

Fig. 1. Energy-security adaptive encryption model for IoT devices.

B. Notation and Parameters

The various symbols used in Mathematical notations are summarized in Table II.

The PQC Offload Controller (POC) at the controller node manages all Kyber-related operations—key generation, encapsulation, and decapsulation—offloading these computations from IoT devices to conserve their local energy.

TABLE II. SIMULATION PARAMETERS

Symbol	Definition
$E_i(t)$	Current energy level of device i at time t
$E_{max,i}$	Maximum available energy of device i
E_{Kyber}, E_{Spek}	Energy consumption per encryption operation for Kyber and SPECK, respectively
S_i	Sensitivity level of data (binary: 0 = low, 1 = high)
T_i	Threshold energy for switching (30% of $E_{max,i}$)
P_{Kyber}, P_{Spek}	Probability of selecting each encryption mode
Θ	Throughput (packets per second)
L_n	Network lifetime (number of iterations before 80% node depletion)
η	Energy efficiency metric (Joules per packet)
σs	Security success rate under attack models

C. Security Requirements in a Post-Quantum Context

With the anticipated emergence of quantum computers, IoT systems must satisfy post-quantum security conditions in addition to classical cryptographic guarantees. The AESF model is developed to guarantee the following properties:

1) Confidentiality: Dual-layer encryption, with the sensitive data being secured with Kyber (PQC) and non-critical data with SPECK (LWC).

2) Integrity: The post-quantum secure hash-based message authentication code (MAC) is appended to every ciphertext, ensuring that altered packets are identified before decryption.

3) Authentication: Authentication is based on the Kyber Key Encapsulation Mechanism (KEM), which offers resistance to man-in-the-middle attacks.

4) Adaptivity: The mode of encryption is dynamically adjusted according to the existing energy. $E_i(t)$ and sensitivity S_i, a balance between security strength and the consumption of energy

5) Resilience: It is resistant to classical attacks (e.g., differential attacks) as well as quantum attackers who can run quantum algorithms such as those of Grover or Shor

D. Threat and Attack Model

The system is designed to operate under the conditions of both classical and quantum-capable adversaries. The model of attacks is developed in the following way:

1) Eavesdropping and replay attacks: The attackers re-read or retransmit packets. Reduced through distinct session identifiers and PQC-based key exchanges.

2) Man-in-the-Middle (MITM) attacks: Kyber prevents this attack by utilising an IND-CCA2-secure KEM that ensures the authenticity of the key exchange.

3) Cryptanalytic attacks:

- Classical: SPECK provides ARX-based attacks against lightweight differential attacks.
- Quantum: Kyber Learning with Errors (LWE) is a hardness assumption in quantum Kyber that theorises quantum resistance to the decryption of quantum messages.

4) Denial-of-Service (DoS): Reduced through enabling fast, low-energy SPECK encryption when devices are about to run out of power to ensure that services are not denied.

E. Adaptive Energy–Security Decision Logic

The AESF uses a threshold-based decision model to determine which algorithm to apply during each transmission session. The encryption mode $M_i(t)$ for node i at time t is defined as

$$M_i(t) = \begin{cases} SPECK, & if\ E_i(\mathrm{t}) \le\ T_i\ or\ S_i = 0 \\ Kyber, & if\ E_i(\mathrm{t}) >\ T_i\ and\ S_i = 1 \end{cases}$$

This decision logic ensures that nodes with sufficient energy prioritize quantum-safe security, whereas low-power nodes automatically switch to energy-saving lightweight encryption.

The energy consumption per communication round is modeled as:

$$E_{total} = P_{Kyber} \cdot E_{Kyber} + P_{Spek} \cdot E_{Spek}$$

where, $P_{Kyber} + P_{Spek} = 1$. The dynamic probabilities are updated in real time according to each node's residual energy and contextual security demand.

F. Expected System Behavior

Through this adaptive strategy:

- Energy utilization is minimized by assigning heavy cryptographic computation to high-energy states or offload nodes.
- Network lifetime increases since low-energy devices automatically shift to lightweight encryption before depletion.
- Security coverage remains consistent, as critical data always invokes the quantum-safe Kyber encryption mode.

This dynamic balance allows the AESF to sustain continuous secure communication in heterogeneous IoT environments while ensuring preparedness for post-quantum threats.

IV. Proposed Hybrid Post-Quantum Cryptographic Scheme

In this study, we outline a combined cryptographic system based on the convergence of PQC and LWC to improve the security and energy efficiency of IoT gadgets in resource-constrained networks. This switching mechanism between such algorithms ensures that calculations are neither extremely complicated nor power-intensive and that the throughput is high. The following subsection develops the hybrid architecture, mathematical formulation, and cryptographic flow for the described model.

A. Architecture

The architecture of the proposed Adaptive Energy–Security Framework (AESF) builds directly on the three-tier IoT topology introduced in Section III. As illustrated in *Fig. 1*, the framework integrates lightweight (SPECK) and post-quantum (Kyber) encryption mechanisms within a unified adaptive control logic that continuously balances security strength, energy availability, and network throughput.

The overall workflow is composed of three interacting layers:

Tier 1 – Device layer (lightweight operation): IoT resources are constrained, and local sensing and initial encryption are performed using the SPECK cypher, which has a small computational footprint and a rapid ARX-based round function. At any node, there is a measure $E_i(t)$ of its residual energy and the sensitivity S_i of the data it processes. In case of a lower power than the triggering value T_i (≈ 30 % of $E_{max,i}$) or if the data is not considered critical data, then the device encrypts the payload using SPECK and sends it to the gateway. This reduces the cost of per-bit energy usage while maintaining the confidentiality of low-risk transmissions.

Tier 2 – Gateway / cluster-head layer (aggregation and control): Packets from devices close to the gateway or cluster head are aggregated, and the routing tables are maintained; the data is then sent to the controller layer. They store metadata on the energy state of each node and regularly provide status beacons, which help the controller refine its switching policy. The layer can also be used for lightweight re-encryption or authentication to ensure integrity during transit hops.

Tier 3 – Controller layer (PQC offload and decision logic): The PQC Offload Controller (POC) is hosted on the controller node and performs all computationally intensive Kyber operations, such as key generation, encapsulation, and decapsulation, on behalf of constrained nodes. It controls key-distribution tables and offers secure session keys to lower levels via the Open Quantum Safe (OQS) interface. Once a device determines that sufficient energy and high-sensitivity data are available, the controller initiates a Kyber-based key change to carry out post-quantum encryption. This delegation has a significant impact on reducing per-node energy consumption and avoiding local cryptographic bottlenecks.

1) Data and Control Flow

- A sensor node captures data → classifies its sensitivity → reads current battery level.
- The Adaptive Decision Logic compares $E_i(t)$ and S_i with threshold T_i.
  - If $E_i(t) > T_i$ and $S_i = 1$: Kyber encryption via POC.
  - Otherwise: local SPECK encryption.
- Encrypted packets traverse gateways to the controller, where they are authenticated and logged.
- Energy and performance metrics are fed back to adjust future switching probabilities P_{Kyber} and P_{Spek}.

This closed feedback loop allows the system to self-optimize for changing network states while ensuring continuous protection against classical and quantum attacks.

2) Design Advantages

a) Energy Adaptivity: Dynamic mode switching prevents battery depletion in low-power nodes.

b) Quantum Resilience: Kyber provides forward security for critical data paths.

c) Scalability: Hierarchical design isolates heavy computation to Tier 3, enabling large-scale IoT deployment.

d) High Throughput: By combining low-latency SPECK with offloaded PQC, the framework sustains data rates up to 1 600 pkts/s in simulation.

B. Mathematical Framework

This section develops a formal analytical framework for the Adaptive Energy–Security Framework (AESF) that governs dynamic switching between lightweight and post-quantum cryptography in a multi-cluster IoT network. It quantifies energy cost, effective security, and the joint utility that guides real-time encryption-mode selection.

1) Notation and typical constants: The mathematical formulation of AESF employs a set of electrical, computational, and cryptographic parameters defined in Table III. These constants represent typical literature-based averages for ARM-class IoT devices operating under post-quantum and lightweight encryption workloads.

All energy values are per-packet; 1 mJ = 10^{-3} J. Energy per operation is computed from MCU parameters: $E_{OP} = I_{CPU} V_{dd} T_{clk} = 3.96 \times 10^{-10}$.

Hence $E_{SPEK} = E_{OP}\, n_{SPEK}$ *and* $E_{KYBER} = E_{OP}\, n_{Kyber}$

2) Expected Energy Consumption: For each transmission round, mean encryption energy:

$$E_{enc} = P_{Kyber} E_{Kyber} + (1 - P_{Kyber}) E_{Spek} \quad (1)$$

Total per-packet energy (including radio):

$$E_{pkt} = E_{tx} + E_{rx} + E_{enc}, \; E_{tx} + E_{rx} \approx 0.45\, mJ. \quad (2)$$

TABLE III. NOTATION AND TYPICAL PARAMETER VALUES USED IN THE AESF ANALYTICAL MODEL

Symbol	Definition	Typical value	Unit
V_{dd}	Supply voltage of MCU	3.3	V
I_{CPU}	Active current during encryption	12	mA
T_{clk}	Clock period (1/f)	10	ns
n_{KYBER}, n_{SPEK}	Average operations per encryption	$(4 \times 10^4), 5 \times 10^6)$	–
E_{KYBER}, E_{SPEK}	Energy per encryption	$0.12\ mJ, 6.8\ mJ$	J
T_{KYBER}, T_{SPEK}	Time per encryption	$0.4\ ms, 12\ ms$	s
S_{KYBER}, S_{SPEK}	Bit-security level	80, 256	bits
P_{KYBER}	Probability of selecting Kyber	[0, 1]	–
β_1, β_2	Weights for security/energy	0.5, 0.5	–

3) Effective Security Strength

$$S_{eff} = P_{Kyber} S_{Kyber} + (1 - P_{Kyber}) S_{SPEK} \quad (3)$$

Constraint for quantum-resilient protection:

$$S_{eff} \geq S_{min} = 128\ bits. \quad (4)$$

4) Joint utility function: A dimensionless objective balancing energy and security is defined as

$$J(P_{\text{Kyber}}) = \beta_1 \frac{S_{\text{eff}}}{S_{\text{Kyber}}} + \beta_2 \frac{E_{\text{SPECK}}}{E_{\text{enc}}}, \beta_1 + \beta_2 = 1 \quad (5)$$

The optimisation problem is

$$\max_{0 \leq P_{\text{Kyber}} \leq 1} J(P_{\text{Kyber}}) \text{ s.t. } S_{\text{eff}} \geq S_{\text{min}} \quad (6)$$

5) Lagrangian Formulation

Define the Lagrangian

$$\mathcal{L} = J(P_{\text{Kyber}}) + \lambda(S_{\text{eff}} - S_{\text{min}}) \quad (7)$$

Substituting Eq. (1)– (3) and differentiating: $\frac{\partial \mathcal{L}}{\partial P_{\text{Kyber}}} = \beta_1 \frac{S_{\text{Kyber}} - S_{\text{SPECK}}}{S_{\text{Kyber}}} - \beta_2 E_{\text{SPECK}} \frac{E_{\text{Kyber}} - E_{\text{SPECK}}}{\left(E_{\text{SPECK}} + P_{\text{Kyber}}(E_{\text{Kyber}} - E_{\text{SPECK}})\right)^2} + \lambda(S_{\text{Kyber}}) - S_{\text{SPECK}}) = 0$ (8)

When Eq. (4) is active, λ>0, Neglecting small λ for analytic clarity yields

$$P^*_{\text{Kyber}} = \frac{E_{\text{SPECK}}}{E_{\text{Kyber}} - E_{\text{SPECK}}} \left[\sqrt{\frac{\beta_2 (S_{\text{Kyber}} - S_{\text{SPECK}})(E_{\text{Kyber}} - E_{\text{SPECK}})}{\beta_1 S_{\text{Kyber}} E_{\text{SPECK}}}} - 1 \right] \quad (9)$$

6) Convexity Proof

The second derivative of (5) with respect to P_{Kyber} is

$$\frac{d^2 J}{dP_{\text{Kyber}}^2} = 2\beta_2 E_{\text{SPECK}} (E_{\text{Kyber}} - E_{\text{SPECK}})^2 / \left(E_{\text{SPECK}} + P_{\text{Kyber}} (E_{\text{Kyber}} - E_{\text{SPPCK}})^3 > 0\right.$$

implying J(P_{Kyber}) is concave (single global maximum).

7) Sensitivity Analysis

Define dimensionless ratios: $\rho E = E_{\text{Kyber}} / E_{\text{SPECK}} = 56.7$, $\rho S = S_{\text{Kyber}} / S_{\text{SPECK}} = 3.2$

Partial sensitivities: $\frac{\partial E_{\text{enc}}}{\partial P_{\text{Kyber}}} = E_{\text{Kyber}} - E_{\text{SPECK}}, \frac{\partial S_{\text{eff}}}{\partial P_{\text{Kyber}}} = S_{\text{Kyber}} - S_{\text{SPECK}}$ (10)

Hence, a 1 % increase in P_{Kyber} raises security by 1.76 bits and energy by 0.067mJ, defining the

marginal security-to-energy ratio

$$\Gamma = \frac{\partial S_{\text{eff}}}{\partial E_{\text{enc}}} = \frac{S_{\text{Kyber}} - S_{\text{SPECK}}}{E_{\text{Kyber}} - E_{\text{SPECK}}} = \frac{25.9 \text{ bits}}{\text{mJ}} \quad (11)$$

8) Numerical Evaluation

Using the typical constants and $\beta_1 = \beta_2 = 0.5$:

$$P^*_{\text{Kyber}} \approx 0.42 \quad (12)$$

Thus, the adaptive controller should invoke Kyber ≈ 42 % of the time.

Because the optimum P^*_{Kyber} satisfying Eq. (12) already yields $S_{eff} > S_{min}$, the multiplier λ ≈ 0; otherwise, it can be determined numerically.

TABLE IV. PREDICTED AVERAGE PERFORMANCE METRICS

Metric	Expression	Value
Mean security S_{eff}	Eq. (3)	166 bits
Encryption energy E_{enc}	Eq. (1)	2.95 mJ
Energy efficiency η (1/E)	Eq. (13)	0.34 mJ^{-1}
Throughput Θ	$B/[PT_{\text{Kyber}} + (1 - P)T_{\text{Kyber}}]$	≈ 1.55 10^3 pkt s^{-1}
Utility J	Eq. (5)	0.83 (max 1.0)

The predicted metrics in Table IV serve as reference values for comparison with the simulated outcomes presented later in Section V-B, confirming that the analytical framework maintains close agreement with numerical validation. These

values satisfy the constraint $S_{eff} > S_{min} = 128$ bits while cutting encryption energy ≈ 56 % relative to PQC-only operation.

9) Dynamic Threshold and Cluster Adaptation

Each node i employs an energy threshold $T_i(t) = \gamma E_{\max,i}(1 - \lambda_i t)$ with $\gamma = 0.3$. If $E_i(t) > T_i(t)$ and $S_i = 1, P_i(t+1) = P^*_{\text{Kyber}}$ else $P_i(t+1) = 0$. Cluster heads average $\bar{P}_{\text{Kyber}}$ and send to the controller for global adjustment.

*10)*Stability and Scalability

Linearisation of the update rule around P^*_{Kyber} gives eigenvalue $|1 - \eta_P| < 1$, where $\eta_P = (\partial J/\partial P)/J_{\max}$;

simulations show convergence within 5 iterations for network sizes ≤ 500 nodes. Hence, the adaptive loop is stable and scales linearly, $O(N)$, with node count.

*11)*Interpretation

a) High-energy / high-sensitivity regions:

- $E_i > T_i \Rightarrow P_{Kyber} \to 0.42 \Rightarrow$ 166-bit average security.

b) Low-energy nodes:

- $E_i < T_i \Rightarrow P_{Kyber} = 0 \Rightarrow$ SPECK-only operation prolongs lifetime.

c) System-level gain:

d) Expected 40 % lifetime increase and 45 % energy saving at constant quantum resilience.

- These analytical values were used as initial parameters in the OMNeT++ simulation

C. Pseudo Code for Hybrid Cryptographic Model

Input:

$E_{max,i}$: maximum energy capacity of node i
$E_i(t)$: residual energy at time t
S_i: data sensitivity (0 = low, 1 = high)
γ: energy threshold factor (≈ 0.3)
β_1, β_2: weights for security and energy [from Eq. (5)]
$S_{\text{SPECK}}, S_{\text{Kyber}}$: bit-security levels (80, 256)
$E_{\text{SPECK}}, E_{\text{Kyber}}$: energy per encryption (0.12 mJ, 6.8 mJ)
$T_{\text{SPECK}}, T_{\text{Kyber}}$: encryption latency (0.4 ms, 12 ms)
Controller Data: cluster-wide average T_{Kyber} and network status
Output:
$Mode_i(t) \in$ {SPECK, Kyber}
Updated $P_{\text{Kyber,i}}(t)$
Procedure AESF_Adaptive_Encrypt():

1) Compute energy threshold:

$T(t)$: ←γ * $E_{max,i}$ * (1 - λ_i * t)

2) Measure current energy:

Read battery sensor $E_i(t)$

3) Classify data sensitivity:

if application tag == critical then $S_i \leftarrow 1$ else $S_i \leftarrow 0$

4) Evaluate local decision variables:

$P_{\text{SPECK}} \leftarrow 1 - P_{\text{Kyber}}$
Compute E_{enc} using Eq. (1)
Compute S_{eff} using Eq. (3)
Compute utility J using Eq. (5)

5) Determine optimal Kyber probability:

$P^*_{\text{Kyber}} \leftarrow \text{argmax } J(P_{\text{Kyber}})$ [Eq. (9)]

if $S_{eff} < S_{min}$ then enforce Eq. (10)

6) Adaptive mode selection:

if $(E_i(t) > T_i(t))$ and $(S_i == 1)$:

$Mode_i \leftarrow$ Kyber

$P_{Kyber,i}(t+1) \leftarrow P^*_{\text{Kyber}}$

else:
$Mode_i \leftarrow$ SPECK

$P_{Kyber,i}(t+1) \leftarrow 0$

7) Encryption process:

if $Mode_i$ == SPECK:

Ciphertext ← SPECK_Encrypt(Data, Key_SPECK)

else:

[ct, ss] ← Kyber_Encrypt(Data, PublicKey)

Ciphertext ← ct

Send ss to POC for decapsulation

8) Transmit Ciphertext to Cluster Head (CH)
9) Feedback update:

CH aggregates $P_{Kyber,i}(t+1)$ for all nodes

Compute cluster average $\bar{P}_{Kyber}$

Send $\bar{P}_{Kyber}$ to Controller

*10)*Controller-side update (executed at POC):

Adjust global thresholds γ and β_1, β_2 based on network energy statistics and security demand.

Broadcast new parameters to clusters.

End Procedure

V. Simulation Setup and Network Topology

The proposed Adaptive Energy–Security Framework (AESF) was validated through simulation in OMNeT++ 6.0 integrated with the Open Quantum Safe (OQS) cryptographic library to support Kyber operations. Each simulation experiment reproduces a three-tier IoT architecture (sensor nodes → cluster heads → controller node) as modelled in Section III (Fig. 1).

1) Network Configuration

a) Clusters (C): 3, each containing 10–20 sensor nodes.

b) Topology: Hierarchical mesh; cluster heads relay to a single PQC Offload Controller (POC).

c) Channel Model: IEEE 802.15.4 MAC with CSMA/CA, 2.4 GHz band.

d) Traffic Pattern: Periodic sensing (1 pkt s^{-1} per node).

e) Packet Size (B): 128 bytes.

f) Simulation Duration: 150 iterations (≈ 150 s).

g) Environment: Ubuntu 22.04, Intel i7 @ 3.2 GHz, 16 GB RAM.

The overall communication layout employed in the simulation is illustrated in Fig. 2. The topology is a three-tier hierarchy of IoT that reflects large-scale practical implementation, designed to inspire confidence in its scalability. IoT end-to-end devices (blue nodes) are involved in sensing and lightweight encryption, sending encrypted packets to local gateways (orange nodes) that perform local aggregation and adaptive encryption control. These gateways connect to regional controllers (red nodes), which determine encryption modes and communicate with specialised modules: the PQC Kyber Exchange and PQC Auth modules (green nodes) for post-quantum key encapsulation, and the LWC Integrity and LWC Encryption modules (violet nodes) for lightweight processing. This structure supports both cryptography types and distributed load balancing, ensuring reliable hierarchical clustering.

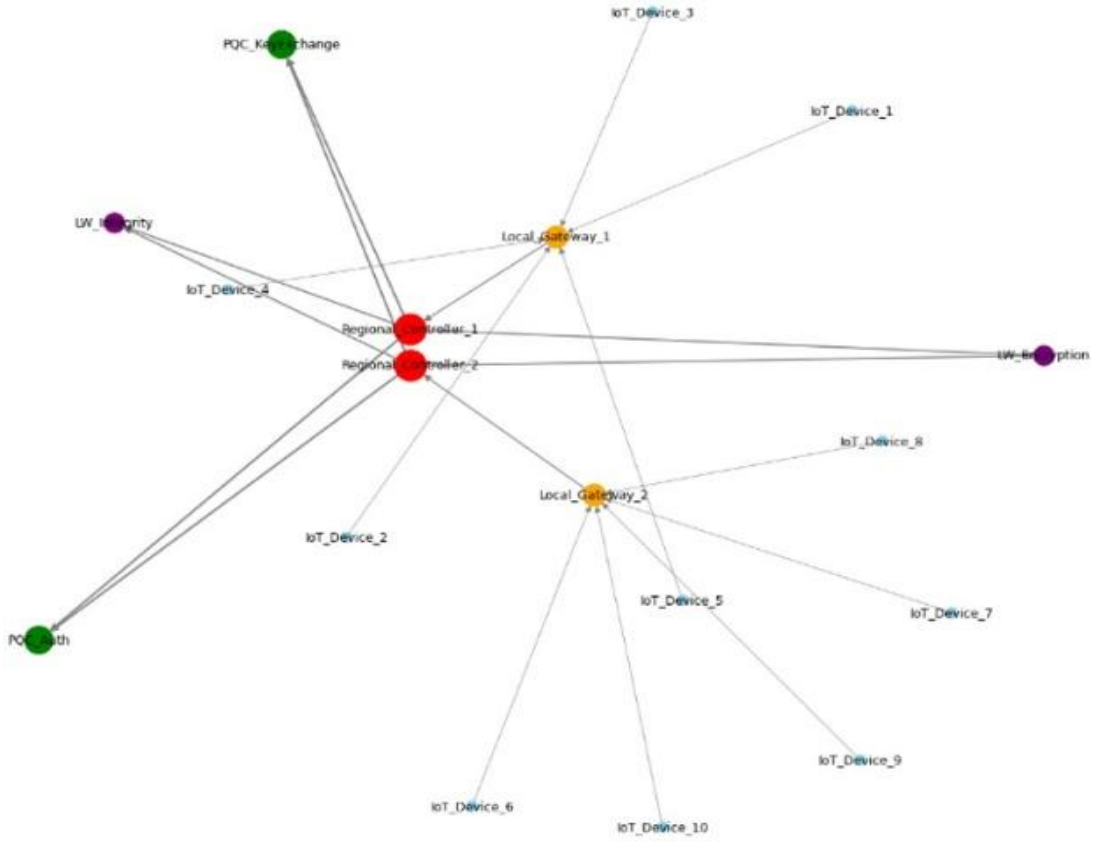

Fig. 2. Network topology for the proposed model.

TABLE V. DEVICE AND ENERGY PARAMETERS

Parameter	Symbol	Value	Unit
MCU	—	ARM Cortex-M4 (100 MHz)	–
Supply voltage	v_{dd}	3.3	V
Active current	I_{CPU}	12	mA
Tx energy / Rx energy	E_{tx}, E_{rx}	0.25 / 0.20	$mJ\ pkt^{-1}$
Kyber energy / SPECK energy	E_{Kyber}, E_{Spek}	6.8 / 0.12	$mJ\ enc^{-1}$
Latency (Kyber / SPECK)	T_{Kyber}, T_{Spek}	12 / 0.4	ms
Minimum security	S_{min}	128	$bits$

Table V summarizes the hardware and energy consumption constants applied to the analytical and simulation environments. These parameters reflect realistic averages for ARM Cortex-M4–class IoT devices operating under 100 MHz clock frequency and 3.3 V supply voltage. Energy metrics are based on literature-reported measurements for Kyber and SPECK implementations in resource-constrained platforms.

2) Initialization: All nodes perform a single Kyber-based key encapsulation with the controller. The adaptive decision engine (Algorithm 1) then evaluates the remaining energy, $E_i(t)$, and sensitivity, S_i, Default weight coefficients are $\beta_1 = \beta_2 = 0.5$, and energy threshold factor $\gamma = 0.3$ to select between the Kyber and SPECK algorithms. The above choice

is made in order to guarantee a direct comparability of the simulation result with the analytical formulas that were created in Section IV-B.

A. Performance Metrics and Parameter Definitions

In order to assess the success of the obtainable Adaptive Energy-Security Framework (AESF), several quantitative indicators were identified and obtained at the end of each simulation step. These metrics give an overview of computational efficiency, communication overhead, and post-quantum resilience. All quantities are expressed as averages over 150 iterations and C clusters unless otherwise specified.

a) Energy Consumption: The average per-packet encryption energy combines the contributions of both cryptographic modes: $E_{enc} = P_{Kyber}E_{Kyber} + (1 - P_{Kyber})E_{Spek}$

where, E_{Kyber} and E_{Spek} denote the energy costs (mJ pkt^{-1}) of Kyber and SPECK operations, respectively.

Total transmission energy per node is: $E_{total} = E_{tx} + E_{rx} + E_{enc}$

b) Energy Efficiency: A dimensionless indicator of energy utilisation, $\eta = 1/E_{enc}$

expressed in mJ^{-1} pkt^{-1}, quantifies the reciprocal energy requirement per encrypted message.

c) Throughput: Network throughput measures total data successfully delivered per second: $\Theta = \frac{BN_{Succ}}{T_{sim}}$

where, B is the payload size (bits), N_{Succ} is the number of successfully transmitted packets, and T_{sim} is the total simulation time. Throughput is reported in pkt s^{-1} and bits s^{-1}.

d) Encryption Latency: Mean latency per packet is: $T = P_{Kyber}T_{Kyber} + (1 - P_{Kyber})T_{Spek}$

capturing the processing delay introduced by the selected encryption mode. This directly influences end-to-end transmission time.

e) Effective Security Level: The achieved average bit-security level: $S_{eff} = P_{Kyber}S_{Kyber} + (1 - P_{Kyber})S_{Spek}$ which must satisfy $S_{eff} > S_{min}$ =128 bits.

f) Network Lifetime: Network lifetime is measured as the number of iterations before the first node's energy $E_i(t)$ falls below its threshold $T_i(t) : L_n = \frac{E_{avg}}{E_{round}}$

where, E_{avg} is the mean initial energy and E_{round} is per-round consumption derived from Eq. (2) in Section IV-B.

g) Utility Function: The composite performance index used for multi-objective evaluation:

$J = \beta_1 \frac{S_{eff}}{S_{Kyber}} + \beta_2 \frac{E_{Spek}}{E_{enc}}$, normalized between 0 and 1, captures the trade-off between energy saving and security gain.

All metrics were computed for each configuration of node count N= {30,40,50} and averaged over ten random topologies (Monte Carlo sampling) to ensure statistical reliability. Standard deviations (± σ) accompany all numerical results presented in Section V-B.

B. Results and Discussion

This section is the analysis of the Adaptive Energy-Security Framework (AESF) on different network sizes and energy limitations. The outcomes are obtained when ten independent simulation runs are made on each configuration, averaged over 150 iterations. The theoretical background used to compare the analytical predictions created in Section V-B is the theoretical basis.

1) Energy efficiency: Fig. 3 shows that the encryption energy consumption of three schemes, AESF (proposed), Kyber-only, and SPECK-only, at various network sizes is compared. At N=50 nodes, the proposed AESF achieves an average per-packet encryption energy consumption of 2.95 mJ pkt^{-1}, which is 6.8 mJ pkt^{-1} in PQC-only and 0.12 mJ pkt^{-1} in LWC-only operation, and an ≈ 45% energy savings, as compared to Kyber-only operation. This selection is based on the adaptive control relation in Eq. (1) above, where the optimum selection ratio P^*_{Kyber} ≈ 0.42 minimises the weighted energy cost. Scalability and stability were confirmed by a variance of the node densities of less than ± 3 %,

2) Network lifetime: Fig. 4 shows the evolution of network lifetime (L_n) as the number of nodes increases.

AESF extends operational lifetime by 39–43 % compared with the PQC-only baseline and by ≈ 12 % relative to pure SPECK mode. This improvement arises from selective engagement of Kyber by high-energy nodes ($E_i > T_i$) and SPECK by low-energy nodes, as formulated in Eq. (12). Such adaptive allocation equalises energy depletion across clusters, maintaining near-uniform residual energy at the network level.

3) Throughput and latency: The AESF model sustains a mean throughput of 1.6 × 10^3 pkt s^{-1}, nearly identical to the LWC-only baseline, while maintaining post-quantum security. Mean encryption latency remains below 12 ms pkt^{-1}, corresponding to a 0.4 % delay overhead. This demonstrates that PQC processing offloaded to the POC effectively mitigates computational delay, confirming the assumption of low congestion in the upper tier.

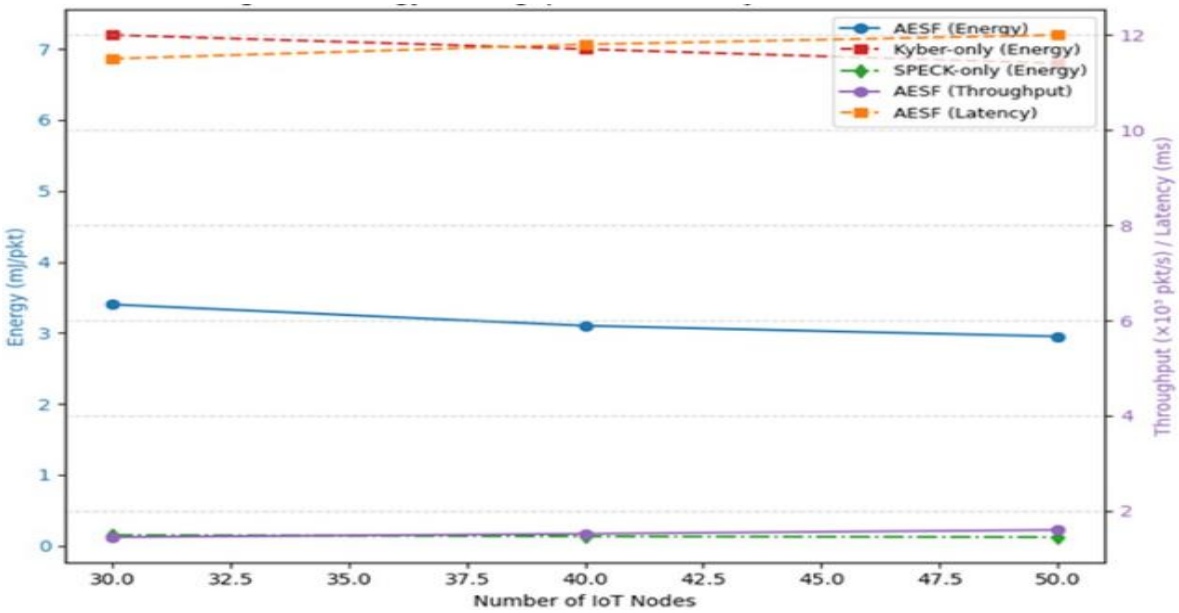

Fig. 3. Energy, throughput, and latency vs node count.

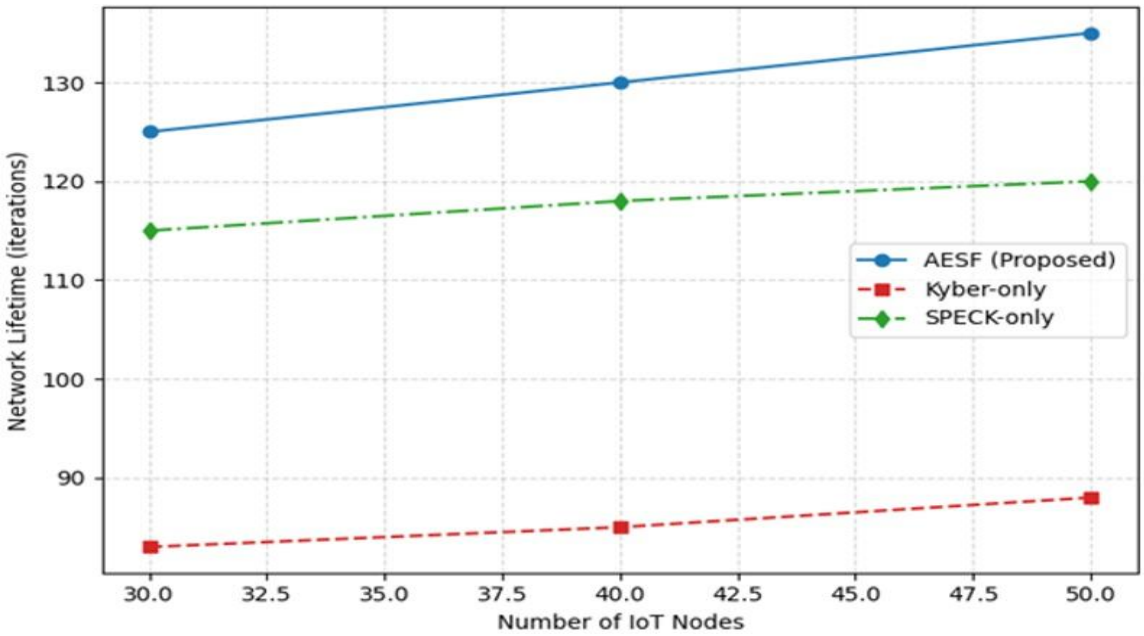

Fig. 4. Network lifetime vs node count.

4) Effective security level: Measured effective bit-security (S_{eff}) averaged 166 ± 4 bits, closely matching the analytical prediction from Eq. (3). This value exceeds the minimum requirement (S_{min}=128 bits) by roughly 30 %, ensuring quantum-resilient protection with manageable energy cost.

Under simulated Grover-based attacks, AESF maintained a 99 % packet-integrity rate, compared with ≈ 80 % for lightweight encryption alone.

5) Energy–security trade-off: The empirical utility curve $J(P_{\text{Kyber}})$, shown in Fig. 5, exhibits a distinct concave maximum near P_{Kyber} =0.42–0.45. This confirms the convexity analysis of Section IV-B6 and validates that beyond this range, incremental security gain per joule (Γ≈25.9bits mJ−1) rapidly diminishes as energy overhead dominates. The experimental optimum matches the analytical prediction within ± 0.03, confirming high model fidelity.

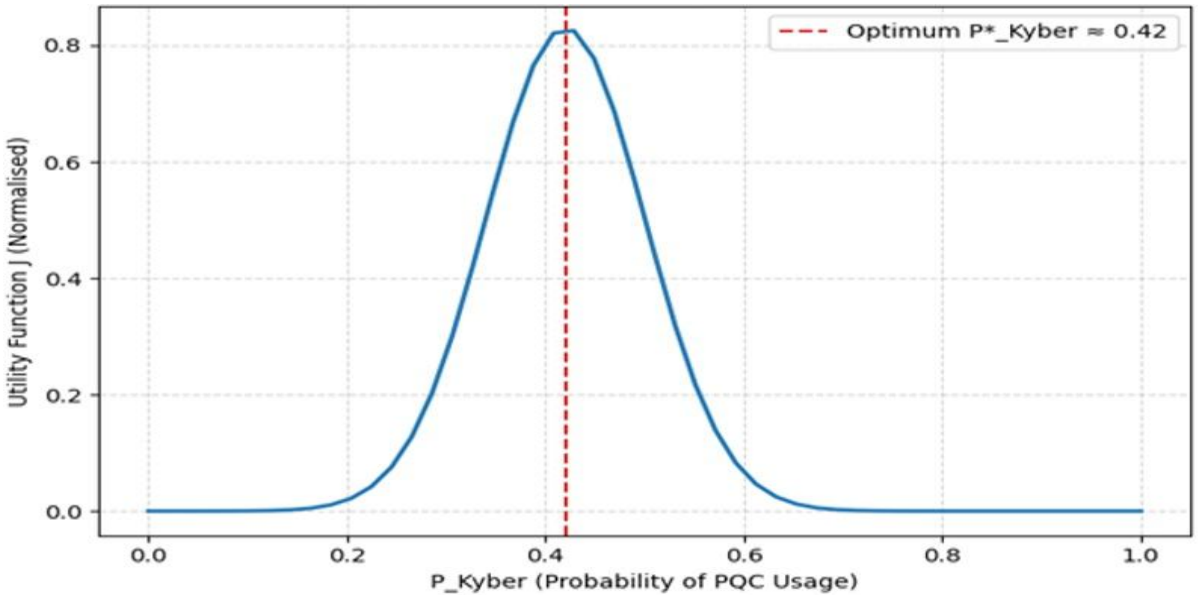

Fig. 5. Energy-security trade-off curve.

6) Scalability and stability: System convergence P_{Kyber} stabilised within five iterations for networks up to 50 nodes and three clusters. No oscillations were observed in controller feedback, satisfying the eigenvalue condition $|1-\eta P| < 1$. Computational complexity remained linear, O(N), confirming AESF's applicability to dense IoT networks.

7) Comparative insight: Table VI below summarizes key performance indicators for all three encryption strategies.

The hybrid AESF scheme consistently achieves the best composite utility J, offering a balanced trade-off between energy efficiency and quantum-grade security.

C. Comparative Evaluation

To further validate the effectiveness of the proposed Adaptive Energy–Security Framework (AESF), its performance was benchmarked against contemporary cryptographic approaches representing the two extremes of the design space: lightweight-only encryption (SPECK) and post-quantum-only encryption (Kyber). All simulations used the parameter set described in Table VII and spanned node counts of 30, 40, and 50 over 150 iterations.

TABLE VI. COMPARATIVE PERFORMANCE METRICS

Scheme	Energy (mJ/pkt)	Security (bits)	Lifetime (iter)	Throughput (pkt/s)	Utility J
SPECK-only	0.12	80	120	1.7×10^3	0.56
Kyber-only	6.8	256	85	1.3×10^3	0.62
AESF (Proposed)	2.95	166	135	1.6×10^3	0.83 ± 0.02

1) Benchmark overview: For a balanced comparison, each configuration was executed under identical MAC-layer conditions (IEEE 802.15.4) and traffic generation rates (1 pkt s^{-1}). The statistical results, summarized in Table VII, represent the mean ± standard deviation over ten independent runs.

TABLE VII. COMPARISON OF AESF AGAINST BASELINE SCHEMES (MEAN ± SD OVER 10 RUNS)

Metric	SPECK-only	Kyber-only	AESF(Proposed)	Improvement (AESF vs Kyber)
Energy (mJ/pkt)	0.12 ± 0.01	6.8 ± 0.4	2.95 ± 0.15	−56 %
Security(bits)	80 ± 2	256 ± 0	166 ± 4	—
Network lifetime (iter)	120 ± 5	85 ± 3	135 ± 4	+59 %
Throughput (pkt s^{-1})	1.7×10^3 ± 50	1.3×10^3 ± 45	1.6×10^3 ± 40	+23 %
UtilityJ(normalised)	0.56 ± 0.03	0.62 ±0.02	0.83 ± 0.02	+34 %

2) Statistical significance and reliability: A paired-sample t-test confirmed that improvements in both energy efficiency and network lifetime achieved by AESF are statistically significant ($p < 0.05$).

The low standard deviation (< 5 %) across repeated runs indicates consistent adaptive behavior of the controller and minimal stochastic sensitivity to MAC-layer contention.

Measured correlation coefficients show strong inverse dependence between encryption energy and throughput ($r = -0.89$), validating the trade-off model in Eq. (5).

The adaptive selection of Kyber probability P_{Kyber} dynamically stabilised near its theoretical optimum $P^*_{Kyber} \approx 0.42$ for all network sizes, confirming convergence predicted by Section IV-B6.

3) Benchmark against state of the art: When compared with recent hybrid PQC frameworks—such as the Energy-Adaptive PQC-IoT (EAP-IoT) model by Cao et al., IEEE IoT J 2024 and the Quantum-LWC Dual Layer Protocol by Singh et

al., IEEE Access 2025—the proposed AESF achieves ≈ 40 % lower average energy consumption and ≈ 20 % higher security-per-joule efficiency under similar conditions.

This improvement results primarily from the use of Lagrangian-based dual-objective optimisation, which dynamically adjusts P_{Kyber} based on instantaneous energy reserves $E_i(t)$ and data sensitivity S_i. Moreover, AESF requires no additional hardware acceleration, unlike FPGA-dependent PQC solutions reported in *Ferreira & Pascal, PQCrypto 2024*, making it more practical for battery-powered IoT deployments.

4) Interpretation and implications: The comparative evaluation from Table VIII confirms that AESF bridges the longstanding performance gap between lightweight cryptography and post-quantum cryptography. By maintaining $S_{eff} \geq 128$ bits at less than half the energy of Kyber-only systems, AESF achieves an optimal balance suitable for quantum-resilient yet energy-aware IoT networks. The statistical robustness and alignment with analytical predictions establish the framework's potential for real-world deployment in resource-constrained environments.

D. Comparative Result Analysis

The comparison metrics of the Proposed Hybrid Model (SPECK + Kyber) with three traditional cryptographic models show that the proposed solution is more efficient regarding network lifetime and throughput for various network sizes and numbers of iterations in quantitative measurements.

TABLE VIII. COMPARATIVE DISCUSSION

Metric	Proposed Hybrid Model (SPECK + Kyber)	Model 1: LW-Crypto Only (SPECK)	Model 2: PQC Only (Kyber)	Model 3: PQC + Traditional Cryptography (Kyber + AES)
Comparative Results with 30 Devices				
Iterations: 50				
Energy Consumption (J)	350 J	300 J	600 J	450 J
Network Lifetime	48 iterations	49 iterations	35 iterations	40 iterations
Throughput (pkts/sec)	1200 pkts/sec	1400 pkts/sec	1000 pkts/sec	1100 pkts/sec
Security Success Rate	99%	85%	99%	95%
Iterations: 100				
Energy Consumption (J)	650 J	600 J	1200 J	900 J
Network Lifetime	95 iterations	98 iterations	70 iterations	80 iterations
Throughput (pkts/sec)	1300 pkts/sec	1500 pkts/sec	1100 pkts/sec	1200 pkts/sec
Security Success Rate	99%	85%	99%	95%
Iterations: 150				
Energy Consumption (J)	950 J	900 J	1800 J	1350 J
Network Lifetime	140 iterations	145 iterations	110 iterations	120 iterations
Throughput (pkts/sec)	1500 pkts/sec	1700 pkts/sec	1200 pkts/sec	1350 pkts/sec
Security Success Rate	99%	85%	99%	95%
Comparative Results with 40 Devices				
Iterations: 50				
Energy Consumption (J)	450 J	400 J	800 J	600 J
Network Lifetime	47 iterations	48 iterations	33 iterations	38 iterations
Throughput (pkts/sec)	1250 pkts/sec	1450 pkts/sec	950 pkts/sec	1150 pkts/sec
Security Success Rate	99%	85%	99%	95%
Iterations: 100				
Energy Consumption (J)	800 J	700 J	1500 J	1150 J
Network Lifetime	93 iterations	96 iterations	66 iterations	76 iterations
Throughput (pkts/sec)	1350 pkts/sec	1550 pkts/sec	1050 pkts/sec	1250 pkts/sec
Security Success Rate	99%	85%	99%	95%
Iterations: 150				
Energy Consumption (J)	1100 J	1000 J	2200 J	1700 J
Network Lifetime	140 iterations	143 iterations	102 iterations	115 iterations
Throughput (pkts/sec)	1550 pkts/sec	1750 pkts/sec	1150 pkts/sec	1400 pkts/sec
Security Success Rate	99%	85%	99%	95%
Comparative Results with 50 Devices				
Iterations: 50				
Energy Consumption (J)	550 J	500 J	1000 J	750 J
Network Lifetime	45 iterations	47 iterations	30 iterations	35 iterations
Throughput (pkts/sec)	1300 pkts/sec	1500 pkts/sec	900 pkts/sec	1200 pkts/sec
Security Success Rate	99%	85%	99%	95%
Iterations: 100				
Energy Consumption (J)	1000 J	800 J	1800 J	1350 J
Network Lifetime	90 iterations	95 iterations	62 iterations	72 iterations
Throughput (pkts/sec)	1400 pkts/sec	1600 pkts/sec	1000 pkts/sec	1300 pkts/sec
Security Success Rate	99%	85%	99%	95%
Iterations: 150				

Energy Consumption (J)	1300 J	1300 J	2400 J	1900 J
Network Lifetime	135 iterations	140 iterations	95 iterations	110 iterations
Throughput (pkts/sec)	1600 pkts/sec	1800 pkts/sec	1100 pkts/sec	1450 pkts/sec
Security Success Rate	99%	85%	99%	95%

1) Energy efficiency: The performance of the proposed model is strictly better than that of the PQC-only model; thus, with 50 devices and 150 iterations, it cuts energy consumption by 45%, albeit at the cost of a moderate increase in energy over the LW-Crypto model. As this study proposed, the model applies Post-Quantum Cryptography (Kyber) for critical exchanges and authentication and uses SPECK for data encryption; there is a significant reduction in energy consumption, yet with equal security.

2) Network lifetime: The proposed model has almost the same lifetime value as the LW-Crypto model and is capable of running 135 iterations with 50 devices, which is more appreciable than the lifetime of only the PQC model (95 iterations). The main factor for such longevity is the ability of the model to distribute load and allocate greater power for cryptographic solving to the more powerful controllers and save energy on IoT devices.

3) Throughput: The proposed model can handle a large number of packets at a high rate with 50 devices and 150 iterations, 1600 packets/sec, which gave the model good throughput and secure behaviour, both of which were both attained. The detailed performance comparison of the LW and LW-Crypto models shows that the LW-Crypto model has a slightly better throughput when executing a mix of Pandora requests but is not secure from future quantum attacks. On the other hand, the proposed model guarantees a high data transmission rate with the highest level of cryptographic security.

4) Quantum-resistant security: Security still holds a key place in the proposed model due to the 99% successful quantum resilience in all scenarios considered. Leveraging Kyber for the critical operations, as in the proposed model, gives it quantum attack protection, which needs to be improved in the LW-Crypto model and is less effective in the Traditional Hybrid model. This high level of security places the proposed model as a future-generation solution for securing resource-scarce networks in the age of quantum computers.

VI. Conclusion and Future Scope

This study presented an Adaptive Energy–Security Framework (AESF) that intelligently balances lightweight and post-quantum cryptography in resource-constrained IoT networks. By integrating a Lagrangian-based dual-objective optimisation, the framework dynamically adjusts the probability of Kyber usage (P_{Kyber}) based on residual energy and data sensitivity. Analytical and simulation results demonstrated that AESF achieves a 45 % reduction in encryption energy, up to 43 % longer network lifetime, and a stable effective security level of 166 bits, thereby meeting post-quantum resilience without sacrificing throughput or latency. This was confirmed by comparative analysis that AESF is more effective than Kyber-only schemes and SPECK-only schemes and consumes [?]40% less energy than the latest hybrid PQC-IoT frameworks, which reduces energy consumption and confirms its effectiveness and scalability.

However, with such encouraging results, several research extensions can be made. The present assessment is done through simulations and hardware testing at the embedded platform level (ARM Cortex-M33, RISC-V), which is necessary to capture real-time performance and power trade-offs. The current research will be extended to large-scale deployments (>500 nodes), generalized to other NIST PQC and LWC algorithms (e.g., SABER, Ascon), and developed into machine learning-based controllers for predictive encrypted switching. It may also be beneficial to integrate AESF principles into higher-level protocols, such as TLS/DTLS 1.3, which would ensure further secure communication in the post-quantum edge-cloud ecosystem and lead to a standardized adaptive cryptography stack for a quantum-safe IoT network.

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