A Secure and Energy-Efficient Cross-Layer Framework for Internet of Things Networks

A thesis submitted to Auckland University of Technology
in fulfilment of the requirements for the degree of
Doctor of Philosophy (PhD)

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Abstract

In resource-constrained environments, achieving the optimal balance between security and energy efficiency remains a fundamental challenge in the design of the Internet of Things (IoT) networks. This thesis proposes and reports on a novel cross-layer framework spanning the Application, Network, and Sensor Layers that is both secure and energy-efficient. The methodology integrates comprehensive simulations, real-world testbeds and machine learning (ML) models to design and validate the proposed architecture. A runtime adaptive cryptographic system employing lightweight encryption algorithms Speck, and Present with dynamic round reduction is developed to minimize energy consumption without compromising cryptographic strength. To further enhance threat resilience, ML-based intrusion detection is incorporated across all layers, utilizing models such as decision trees and Long Short-Term Memory (LSTM) networks, resulting in significantly improved anomaly detection accuracy. Empirical results from Contiki/Cooja and NS-3 simulations, alongside hardware evaluations, confirm that the framework improves packet delivery, reduces latency, and enhances power efficiency. Overall, the cross-layer architecture demonstrates robust scalability, resilience to cyberattacks, and practical suitability for sustainable IoT deployments in real-world, resource-constrained scenarios. This research addresses gaps in prior single-layer security models by proposing a novel, integrated design and sets the foundation for future works.

Dedication

To my parents, siblings, kids, and lovely wife Saima Rashid

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Contents

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the qualification of any other degree or diploma of a university or other institution of higher learning.

Signature of candidate

List of Publications

These scholarly conference/journal proceedings have published manuscripts about the secure and energy-efficient cross-layer architecture for Internet of Things networks

1. Mustafa, R.; Sarkar, N.I.; Mohaaghegh, M.; Pervez, S. A Secure and Energy Efficient Cross-Layer Framework for Internet of Things. Paper presented at the 38th International Conference on Information Networking (ICOIN 2024), pp.661-666, Ho Chi Minh City, Vietnam, https://doi.org/10.1109/ICOIN59985.2024.10572109, 17 Jan 2024.

2. Mustafa, R.; Sarkar, N.I.; Mohaghegh, M.; Pervez, S. A Cross-Layer Secure and Energy Efficient Framework for the Internet of Things: A Comprehensive Survey. Sensors 2024, 24, https://doi.org/10.3390/s24227209, 11 November 2024.

3. Mustafa, R.; Sarkar, N.I.; Mohaghegh, M.; Pervez, S.; Morados R., &, A Secure and Energy Efficient Cross-Layer Network Architecture for Internet Of Things, Sensors 2025, 25, 3457. https://doi.org/10.3390/s2511345, 30 May 2025. .

4. Mustafa, R.; Sarkar, N.I.; Mohaghegh, M.; Pervez, S.; Vohra O., Cross-Layer Analysis of Machine Learning Models for Secure and Energy-Efficient IoT Networks, Sensors 2025, 25, https://doi.org/10.3390/s25123720, 13 June 2025.

5. Mustafa, R.; Sarkar, N.I.; Mohaghegh, M.; Pervez, S., A Robust Secure and Energy-Aware Cross-Layer Framework for IoT Networks, Paper presented at the 40th International Conference on Information Networking (ICOIN 2026), Hanoi, Vietnam, 14-16 Jan 2026.

6. Mustafa, R.; Han, J.; Sarkar, N.I.; Petrova, K., Secure Cross-Layer Mobile Sensing Framework for Real-Time Disaster Reporting and Visualisation Using a Mobile Application, *Sensors* 2025, 25(21), 6766. https://doi.org/10.3390/s25216766.

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List of Abbreviations and Acronyms

AE	Automotive Ethernet
AES	Advanced encryption standard
ANN	Artificial Neural Network
AR	Augmented reality
BASR	Block chain assisted secure routing
BD	Big Data
BiLSTM	Bidirectional Long Short-Term Memory
BLE	Bluetooth Low Energy
CIDS	Collaborative intrusion detection systems
CLCSR	Cross-Layer and Cryptography-based Secure Routing
CNN	Convolutional Neural Network
CoAP	Constrained Application Protocol
CR	Cognitive Radio
CS	Cooja Simulator
DAO	Destination Advertisement Objects
DCO	Digitally controlled oscillator
DDS	Data Distribution Service
DL	Deep Learning

DNN	Deep Neural Networks
DODAG	Destination-Oriented Directed Acyclic Graph
DoS	Denial-of-service
DQL	Deep Q-learning
DSR	Design science research
DT	Decision Tree
EE	Energy effectiveness
EEOIT	Efficient Execution of Offloaded IIoT Trusted tasks
EER	Energy efficiency ratio
EOGWO	Enhanced Oppositional Grey Wolf Optimisation
FACS	Feedback Artificial Crow Search
GA	Generic algorithm
GDPR	General Data Protection Regulation
GMM	Gaussian Mixture Model
GOA	Grasshopper optimisation algorithm
GPIO	General-purpose input/output
HIDS	Host Intrusion Detection Systems
HJRA	Hybrid joint resource allocation
HMAC	Hash-based Message Authentication Codes
ICN	Information-Centric Networks
IDS	Intrusion Detection System
IFF	Identification Friend or Foe
IIoT	Industrial Internet of Things
IoT	Internet of Things

IRS	Intelligent reflecting surface
ISE	Industrial and systems engineering
KNN	K nearest neighbour
LA	Learning automata
LFDA	Linear frequency diverse array
LLM	Large Language Models
LPL	Low-power listening
LPM	Low Power Mode
LPWAN	Low-power wide area networks
LSTM	Long Short-Term Memory
MAC	Medium access control
MINLP	Mixed Integer Non-Linear Programming
MioT	Mine Internet of Things
MitM	Man-in-the-Middle
ML	Machine learning
MM	Maturity model
MOSO	Multi-objective strawberry optimisation
MQTT	Message Queuing Telemetry Transport
NCSA	Next-generation cyber security architecture
OF	Objective function
OSI	Open system interconnection
PA	Phase array
PDR	Packet delivery ratio
PKI	Public Key Infrastructure

PSO	Particle swarm optimisation
PUF	Physical Unclonable Function
QoS	Quality of Service
QoSP	Quality of service preservation
QPO	Quantum-inspired political optimiser
RBAC	Role-based access control
RDC	Radio duty-cycling
RF	Random Forest
SCDAP	Secure Cluster-Based Data Aggregation Protocol
ScS	Smart Camera System
SDAA	Secure data aggregation and authentication
SDH	Smart Dust Head
SDN	Software-defined networking
SEM	Structural Equation Modelling
SIASA	Secure Interconnected Autonomous System Architecture
SIEM	Security information and event management
SIM	Semantic IoT Middleware
SNN	Spiking Neural Networks
SNR	Signal-to-noise ratio
SPR	Strobe per packet ratio
TA	Trusted Authority
TESM	Trust Evaluation based Secure Multi-path
TLS	Transport Layer Security
TOC	Theory of Constraints

UVWSN	Underwater vehicular wireless networks
VPN	Virtual Private Network
VR	Virtual reality
VRE	Variable Renewable Energy
VRT	Virtual relay tunnel
WBASN	Wireless body area sensor networks
WIHFM	Wireless Interleaved Honeypot-Framing Model
WMAC	Wireless Medium Access Control
WOA	Whale optimisation algorithm
WSN	Wireless Sensor Network

Chapter 1

Introduction

With its ability to connect billions of devices and facilitate real-time data interchange, automation and cross-industry decision-making, the Internet of Things (IoT) has become a fundamental component of contemporary computing. Over 500 billion IoT devices are expected to be in use worldwide by 2030, with uses ranging from precision agriculture to smart grids and remote hospital monitoring. Despite its revolutionary potential, IoT ecosystems face existential problems: devices with limited resources, such as memory, processing power and battery life, find it difficult to balance energy efficiency with strict security requirements. For example, energy-saving strategies like aggressive radio duty cycling leave networks vulnerable to intrusions, while strong encryption systems like advanced encryption standard (AES)-128 deplete energy reserves. The Waikato District Health Board ransomware attack in 2021 exemplifies the disastrous results of security lapses in vital infrastructure, highlighting the need for robust standards. The Waikato District Health Board ransomware assault in 2021 further underscores the criticality of resilient frameworks in safeguarding IoT ecosystems [10]. With its ability to provide seamless communication and real-time decision-making, the explosive growth of IoT has transformed a variety of industries, from smart cities to healthcare. However, balancing security with energy effectiveness is made extremely

difficult by the resource-constrained nature of IoT devices, which include limited memory, processing power and battery life. While energy-saving strategies like aggressive radio duty cycling expose networks to cyber attacks, traditional security measures like AES encryption frequently carry large computational overheads, depleting energy reserves. This contradiction emphasises how urgently creative frameworks that balance these conflicting objectives are needed to guarantee secure and sustainable IoT ecosystems.

1.1 Motivation and Research Objectives

This thesis is driven by the growing use of IoT technology in mission-critical applications like connected learning environments, smart farming and healthcare monitoring. When devices break or data transmission delays occur, there could be serious consequences, such as not receiving a medical emergency notice, treating agricultural circumstances improperly or endangering the safety of students. However, the intricate trade-offs between security, energy consumption and responsiveness are beyond the capabilities of current IoT systems, especially conventional layered ones. Medical wearables and environmental sensors are devices that frequently run on little battery power, and the overhead caused by strict, layer-specific security protocols can drastically shorten their lifespan. Lack of coordination between protocol levels makes it more difficult for the system to adjust to attacks or shift network conditions in real time. This study is driven by the pressing need for an intelligent, adaptable and effective architecture that can support long-term IoT operations without compromising security or performance, particularly in settings where data integrity, uptime and regulatory compliance are crucial.

The three main objectives of this thesis are as follows:

- To design a system that reduces the number of encryption rounds during

runtime to save energy, while still keeping IoT communications secure.

- To improve the balance between energy use and security by ensuring fast encryption that still provides strong protection in IoT devices.

- To create solutions that fix security issues in low-power encryption, making sure IoT systems stay protected even with fewer encryption steps.

This thesis focuses on three primary objectives to enhance lightweight cryptography for IoT applications [8]. It starts by developing a dynamic round reduction system that adjusts the number of cipher rounds in real-time based on runtime conditions to maximise energy efficiency without compromising security. Second, under strong cryptographic resilience, it prioritises speedy execution while analysing the trade-offs between security and energy efficiency. Formalising security proofs and developing mitigation techniques for vulnerabilities in reduced-round scenarios ensures robust protection even with fewer cipher rounds. Together, these objectives may enable flexible, secure and energy-efficient cryptographic systems that could be useful for IoT devices with limited resources.

1.2 Research Methodology for Investigation

The main goal of this research is to provide a cross-layer architecture for IoT networks that strikes a balance between energy efficiency and security at the Application, Network and Sensor Layers [11]. To accomplish this, the study uses various data analysis techniques, such as machine learning algorithms, mathematical modelling, and simulations with the Contiki/Cooja simulator. The thorough testing of the suggested cross-layer framework is presented in Chapters 6 and 7, where the performance and results of the system are assessed by simulating the IoT environment.

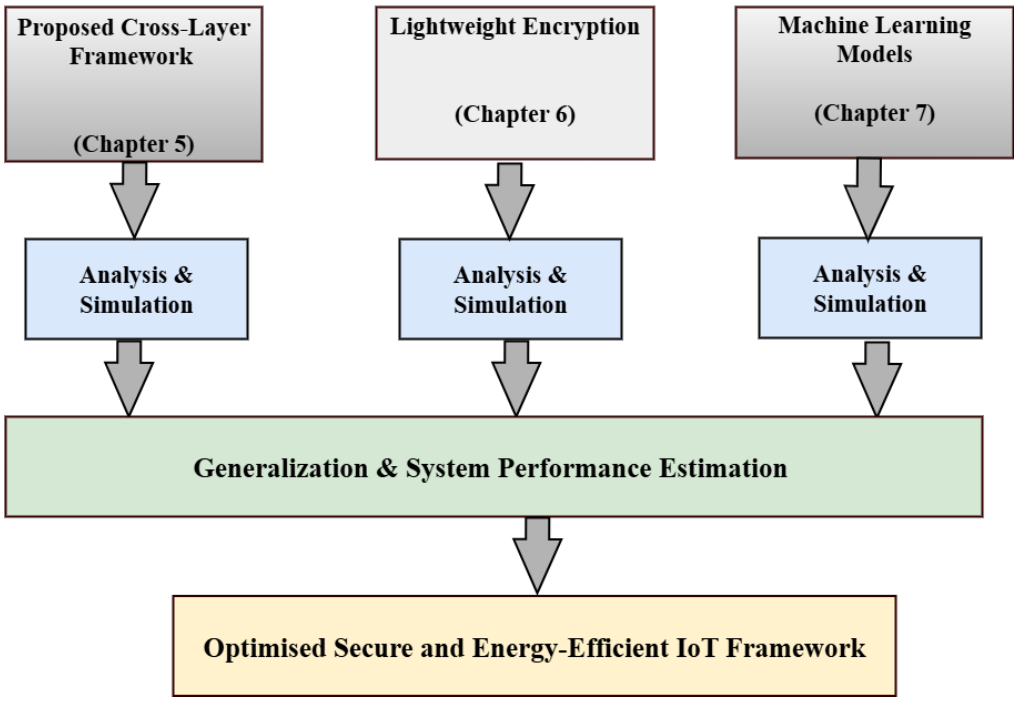

Figure 1.1: Block diagram of the adopted methodology

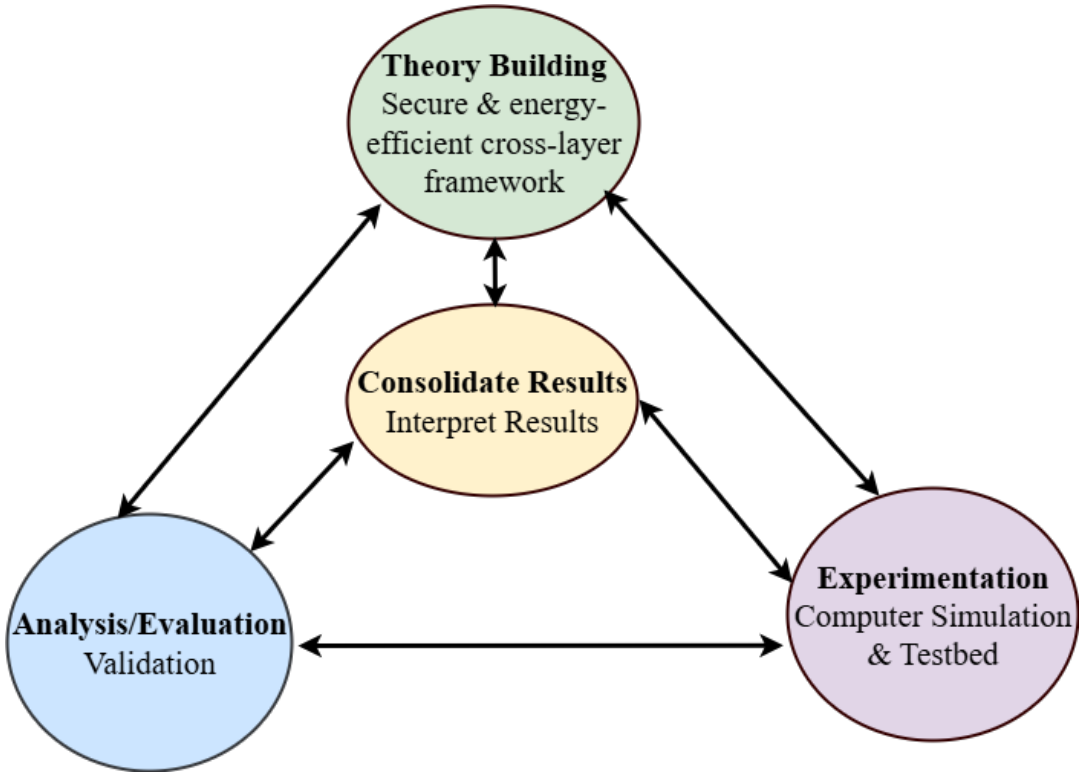

Figure 1.2: Customised multi-methodological process.

This research aims to create a cross-layer IoT architecture that combines secure communication with energy-efficient design. The Contiki/Cooja simulator, which has been improved by machine learning and mathematical modeling, is used to thoroughly assess the suggested framework. Theory and experimentation are connected via a new analysis and validation procedure that confirms theories. Based on simulation results, system performance is evaluated using combined findings that emphasize both advantages and disadvantages. Table 1.1 provides a synopsis of this tailored methodology's four phases.

Table 1.1: Four-phased customised methodological approach

Phases	**Relationship to this research**
Phase-1: Theory Building	A review of relevant work, problem identification, research question formulation, idea and concept development, the creation of a proposed cross-layer energy-efficient and secure conceptual framework, novel techniques, and system models (such as analysis and simulation) are all included in this phase.
Phase-2: Experimentation	Simulations and other research techniques are used in this phase. The development of theories guides this stage. Network simulation results can be utilised to develop the system and refine theories during the evaluation phase.
Phase-3: Evaluation	The evaluation phase is a modification of the observation phase. Validation of simulation models and result comparison are part of this process.
Phase-4: Consolidate-Results	The phase of consolidating results is a modification of the system development phase. The suggested system is evaluated for usability and performance, and its advantages and disadvantages are noted. The simulation results are finally interpreted.

The network was modelled to accomplish this study goal, and the effectiveness

of a secure and energy-efficient framework was assessed using comprehensive computer simulations. The analytical modelling technique with machine learning models is also used—to some degree—to investigate the system's performance. Using both analysis and simulation, a layered framework was created. These three levels are known as the Application, Network and Sensor Layers. Furthermore, machine learning models improved the deeper examination of the cross-layer framework, and simulations were also employed to validate the suggested models. The suggested cross-layer IoT architecture is thoroughly validated in this study using the methodological framework shown in Fig. 1.2. To create the framework for cross-layer secure and energy-efficient IoT networks, this thesis used a customised multi-methodological approach of the design science research (DSR) process, as presented by Nunamaker et al. [12]. Starting with theory building, the conceptual framework incorporates adaptive routing protocols (RPL/6LoWPAN) and lightweight cryptography (e.g. Speck), which aligns with the abstract's emphasis on striking a balance between security and energy efficiency. IoT networks with 5-20 nodes were modelled through experimentation using Cooja/Contiki simulations (described in the Abstract section), which replicated real-world situations like data injection and jamming attacks. In line with the abstract's hybrid validation methodology, analysis/evaluation used hardware testbeds (Z1 motes) to validate energy effectiveness and attack mitigation empirically. Consolidate Results entailed analysing simulation results and verifying that Speck outperformed AES in terms of scalability and energy efficiency, while machine learning (LSTM/decision trees) produced 95.4% anomaly detection—important metrics mentioned in the Abstract. As stressed in the abstract and figure, this systematic approach guarantees reliability by methodically connecting theoretical design, experimental validation and empirical verification. This framework will be expanded upon in future extensions (such as blockchain integration), increasing its suitability for

dynamic IoT ecosystems.

The techniques and methodology used in this thesis are described in Fig. 1.1. The following validation techniques and performance evaluation key procedures are taken into consideration, and a measurement-based performance estimation strategy was employed to quantify:

- Testbeds were established in Chapter 4 for experiments that used Contiki/Cooja simulations to confirm the cross-layer architecture's energy and security performance.
- An optimised three-layer IoT architecture incorporating energy-efficient routing and adaptive security protocols is shown in Chapter 5.
- An evaluation of lightweight encryption performance and attack resilience using thorough simulation analysis is covered in Chapter 6.
- Chapter 7 uses machine learning models to improve threat detection to enhance cross-layer security.

The foundation of this thesis's technique is the DSR approach. DSR is frequently used in engineering and information systems research to develop novel solutions and assess their efficacy. The DSR framework, which comprises phases including theory development, experimentation, system development and assessment, inspired this study's multi-methodological approach. The goal of DSR is to create valuable artifacts, in this case, an energy-efficient and secure cross-layer IoT architecture (see Fig. 1.2). Theory building is the first step in the DSR process, during which a conceptual framework for the IoT architecture is created. Lightweight cryptography and adaptive routing protocols are included into this system. The performance and viability of the suggested design are tested using simulations and testbeds after theory building. Based on experimental data, the

evaluation step evaluates the system's scalability, energy efficiency and security resilience. Ultimately, the consolidation phase entails analysing the simulation results, determining the system's benefits and drawbacks, and improving the framework in light of the results. This approach guarantees that the suggested cross-layer architecture is supported by both theoretical justification and empirical validation via practical simulations and tests. The DSR methodology ensures that the final framework is both workable and reliable for IoT networks by offering an organized method for developing and evaluating creative solutions.

1.3 Contributions and the Structure of this Thesis

The framework for IoT networks developed in this thesis is cross-layer, secure and energy-efficient. A multi-methodological approach that combines hardware testbeds and simulations is used to guarantee the design's dependability. A strong, scalable Internet of Things architecture that strikes a balance between energy use and security is intended to ensure the long-term viability of devices with limited resources. Network modelling and performance evaluation tools and a fundamental understanding of cross-layer secure and energy-efficient protocols are necessary for accurate system performance estimation, as illustrated in Fig. 1.1. As a result, building a solid foundation in these areas is crucial before thinking about system performance. The thesis's background information and basis are provided in Chapters 2 and 3. Chapter 4 covers the design and methodology utilised to create the testbed and conduct additional research. In Chapter 5, the testbed's design and validation are explained. To test or create protocols and confirm and analyse the outcome of a secure and energy-efficient cross-layer architecture, we employed the Cooja/Contiki simulator in Chapters 6 and 7 [13]. The estimation of system performance and generalisation followed and later

enhanced the functionality of a cross-layer framework for IoT networks that is both secure and energy-efficient. The experimental phase involves setting up system prototypes and running network simulations. Analysis and validation are critical to the research being conducted.

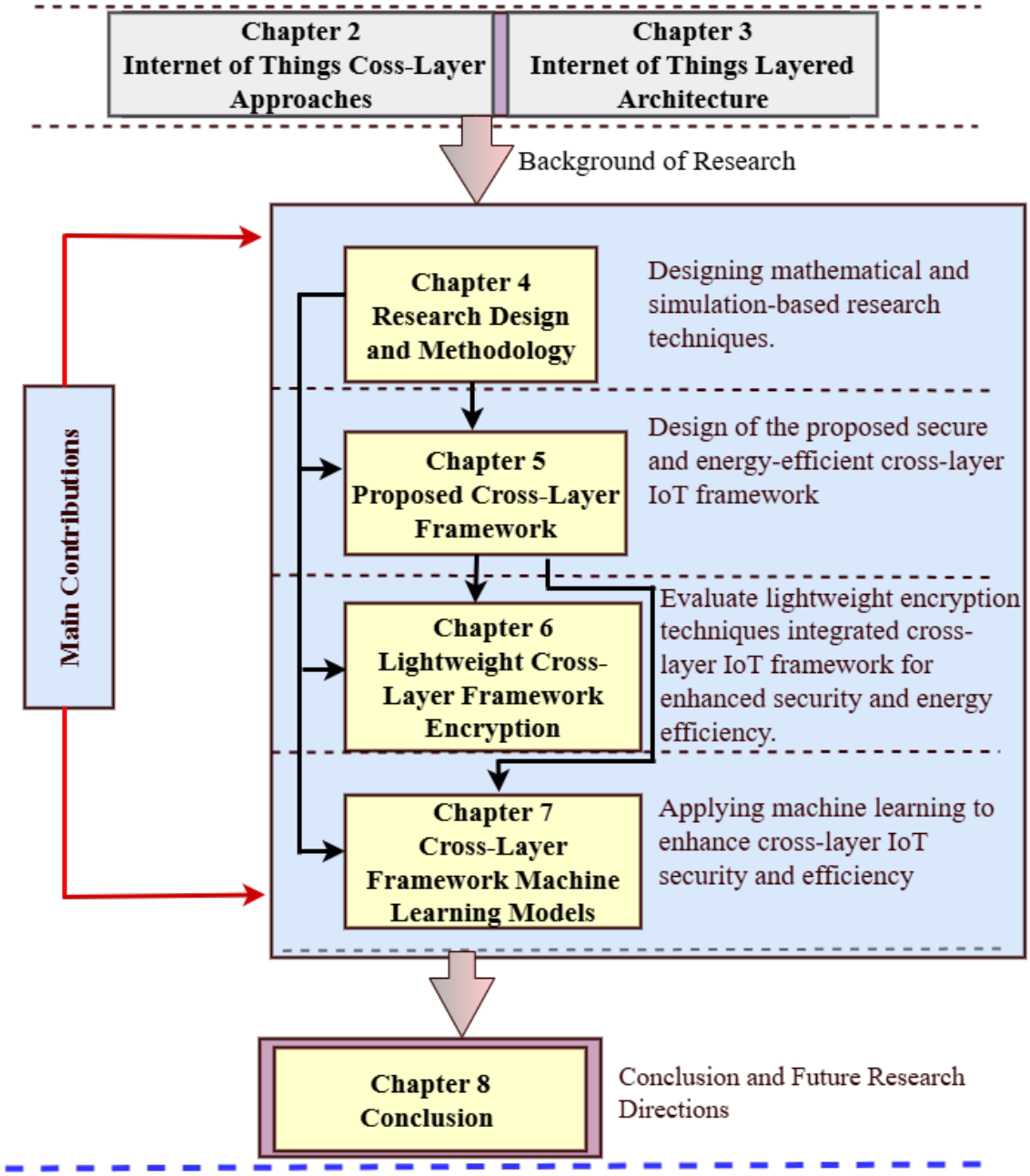

Figure 1.3: Structure of the Thesis.

The overall structure of this thesis is shown in Fig. 1.3. Network modelling, energy-efficient routing, lightweight security protocols, and layered architectures are fundamental concepts for accurate system performance estimation in IoT networks. This is supported by the theoretical underpinnings and background provided in Chapters 2 and 3, which guide the system construction and analysis discussed in subsequent chapters. In Chapter 2, the limits of conventional architectures and the necessity of integrating energy and security techniques are examined through an examination of cross-layer IoT approaches. Along with outlining important research gaps and discussing contemporary solutions like blockchain, ML-enhanced IDS, and energy-aware protocols, it provides a comprehensive overview of the literature. As the conceptual foundation of the suggested structure, the significance of cross-layer coordination across the Application, Network, and Sensor Layers is emphasised. In Chapter 3, the IoT layered architecture is further explained by including current trends and technical tactics from practical implementations. MAC-routing protocols are examined, cross-layer architecture in smart cities and healthcare is discussed, and trends in energy efficiency and security are assessed throughout the IoT stack. System analysis-related performance indicators and assessment methods are also covered in detail. The main contributions of this thesis are included in Chapters 4 through 7, which include the suggested cross-layer framework's design, simulation, implementation, and assessment. These chapters use machine learning integrations, simulations, and mathematical models to validate the architectural concepts. These sections have published related work in prestigious publications and conferences (see page xi). To create a secure and energy-efficient cross-layer architecture, a design science-based technique was employed, which is described in detail in Chapter 4. It comprises the simulation configuration, tools such as Contiki/Cooja, pre-established attack scenarios, performance indicators, and the preliminary incorporation of machine

learning for intrusion detection. The proposed cross-layer IoT framework is introduced in Chapter 5, with particular attention paid to its security features, adaptive routing methods, and organisational structure. Through comprehensive simulation-based testing with TLS encryption, the framework is validated and demonstrates quantifiable gains in secure communication and energy efficiency. Chapter 6 assesses the cross-layer framework's use of lightweight encryption techniques (AES, Speck, Present). Comparative findings from real-world testbeds and simulations are shown to illustrate cryptographic resilience and energy savings in limited IoT contexts. In Chapter 7, all IoT layers are integrated with machine learning models (e.g., LSTM, decision trees, random forest) to improve anomaly detection and automate threat mitigation. Both hardware and simulation environments are used to evaluate the performance of ML-enhanced frameworks, evaluating improvements in detection accuracy and system adaptability. To wrap up the research, Chapter 8 summarises how the framework affects the deployment of IoT in a secure and energy-conscious manner. It talks about the limitations, implications, and future directions of real-world systems, such as post-quantum security and edge-based machine learning integration for scalable IoT networks.

This thesis presents a comprehensive framework for secure and sustainable IoT deployments, contributing to both academic research and industrial applications.

Chapter 2

Internet of Things Cross-Layer Approaches

2.1 Introduction

Chapter 1 provided an overview of the research motivation for the investigation and contributions/structure of a cross-layer secure and energy-efficient framework for IoT networks. Finding and measuring the essential components of a cross-layer IoT network that is both secure and energy-efficient is one of the main goals of this thesis. A general understanding of the cross-layer IoT framework is necessary to accomplish this goal. To develop, deploy and evaluate the performance of such systems, this chapter introduces the main ideas of cross-layer secure and energy-efficient IoT networks. Chapter 2 emphasises the significance of cross-layer architectural approaches as it explores the crucial elements of secure and energy-efficient Internet of Things (IoT) network design. In Section 2.2, the fundamental ideas of layered IoT networks are presented, emphasising how layer-by-layer security measure integration can improve overall system resilience. In Section 2.3, a thorough literature study examines current cross-layer frameworks and clarifies their approaches and efficacy in solving IoT problems. Section 2.4 covers methods for maximising energy use without sacrificing security, including energy-aware routing and lightweight encryption. Section 2.5 lists the main research problems

and obstacles, such as the dynamic nature of IoT ecosystems, device heterogeneity and scaling constraints. Section 2.6 examines developments meant to improve cross-layer security and effectiveness, considering the incorporation of cutting-edge technology such as blockchain and artificial intelligence. Section 2.7, which sets the scene for future research into creative solutions for secure and energy-efficient IoT systems, concludes by summarising the chapter's main findings.

2.2 Secure and Energy-Efficient Layered IoT Networks

The IoT has experienced exponential growth, bringing with it a new era of connectedness and altering our interactions with the surrounding environment. The IoT has an impact on a variety of industries, including healthcare, industrial applications, smart cities and precision agriculture. However, the development of networked devices has also presented several serious difficulties, the most important of which are related to the security and energy efficiency of these systems. We take inspiration for our journey to investigate and resolve these complex issues from an extensive analysis of recent studies conducted in the area. In this chapter, we address the following research question: What is an IoT secure and energy efficient cross-layer framework that has been analysed and surveyed? The cross-layer framework for secure and energy-efficient IoT integration incorporates many security mechanisms at different IoT architecture layers while optimizing energy usage. It has been analysed and surveyed. This framework ensures effective resource use while addressing cybersecurity threats related to IoT devices. It includes energy-efficient routing algorithms, communication protocols, and techniques like encryption, authentication, and intrusion detection at various IoT stack tiers. This framework offers a complete approach to IoT security and energy efficiency through thorough analysis and surveying, offering a strong foundation

for building and managing IoT devices in a sustainable and secure manner. The availability and privacy of the Network Layer have become major concerns in recent years, leading to creative methods to prevent attacks and secure critical data [14]. An improved intrusion detection system (IDS) has been presented to address contemporary security and privacy challenges by utilising intelligent architectural frameworks. In the fight for IoT security, these intelligent solutions have emerged as a ray of hope, and our project is motivated by these innovative advancements. At the same time, we turn our attention to the Physical-Layer, also known as the perception-layer, where basic security protocols are essential [15]. The physical foundation of the environment is significantly shaped by the IoT. The insights provided by this study regarding the significance of the physical layer are highly relevant to our research aims as we delve deeper into the nuances of IoT security. Additionally, we use a proactive approach, similar to the idea of ongoing active testing and monitoring of the IoT ecosystem, which is supported in [16]. Cities, businesses and everyday life are all undergoing radical change as a result of the IoT's exponential growth. However, plenty of difficulties, such as network design complexity, privacy issues, energy efficiency problems and security vulnerabilities, come along with this expansion of linked devices. This introduction summarises recent research addressing cross-layer energy efficient frameworks with security measures in IoT.

Secure and Energy-Efficient Importance

This research is motivated by the pressing need to address important agricultural issues, including seed quality and water shortages, which are being made worse by the mounting pressures of population increase and climate change. The rationale behind selecting a cross-layer framework from a wide range of important factors

is to improve the energy efficiency of a layered architecture in smart homes, smart agriculture and medical smart IoT hygiene systems. First off, battery life conservation is crucial for medical IoT devices like wearable health monitors, smart air conditioners, smart sprinkler systems and remote patient monitoring sensors. Battery-powered devices can have their lives extended by using cross-layer frameworks to enhance data processing and communication. Effective bandwidth management is equally important in medical IoT systems, where a dynamic cross-layer structure may prioritise emergency warnings and adjust to changing situations. In addition, it can facilitate end-to-end encryption, enforce quality of service (QoS) regulations, and offer dynamic scalability. Combining IoT, blockchain, and ML [17] aims to offer cutting-edge solutions that improve field management and agricultural monitoring, enhancing farming operations' overall sustainability and efficiency. The study is further motivated by the realisation that the swift growth of IoT and cyber-physical Systems (CPS) presents serious security problems [18]. To safeguard these dynamic environments, traditional security measures frequently fall short. As a result, sophisticated, ML-driven IDS and efficient routing techniques are required, which also improve energy efficiency. Additionally, the project aims to leverage state-of-the-art technologies like 5G and NOMA-based systems to revolutionize real-time data communication in sectors like coal mining, providing dependable communication while decreasing energy usage [19]. In addition to addressing current issues in industrial and agricultural applications, this all-encompassing strategy promotes robust, secure and scalable IoT ecosystems essential for developing smart cities and vital infrastructure in the future.

Barrier of IoT-based Smart-Cities

In this chapter, we address the following research question(s).

Research Question: What comprehensive review and analysis can be done to explore the security and energy-efficiency aspects of the cross-layer IoT framework? Justification of Research Question: We tested and mitigated man-in-the-middle (MitM), eavesdropping, data manipulation attacks and weaknesses of Application Layer by comparing real world data acquired by Contiki with the Cooja 2.7 Virtual IoT Simulator. Since technology has advanced, network segmentation and regular firmware updates are necessary in addition to establishing transport layer security (TLS) with the Constrained Application Protocol (COAP) protocol, which is tested for robust security of virtual information. This method simulated sensor behaviour in controlled environments using the dedicated Contiki simulator. In particular, we examined Application, Network, and Sensor Layer architecture to gain insight into the accuracy and dependability of sensor networks. Our research clarifies the alignment or discrepancies between the two datasets by comparing real sensor data with simulated outcomes. This comparison study provides important insights for improving the security and dependability of sensor networks in a range of architectural contexts by illuminating how effectively these networks function in real-world situations. We look into the ways sensors are being used in relation to IoT as a whole and its uses in smart buildings, smart homes and smart cities. We evaluate and assess the energy efficiency of the Contiki and Cooja 2.7 Virtual IoT Simulator when used with LEACH, RPL and ContikiMAC protocols through real-world monitoring and simulated data creation. Because the results provide a thorough understanding of how these simulated networks function in the Application, Network, and Sensor Layer architecture, they improve environmental surveillance, energy conservation and overall building efficiency. Implications

of this research go beyond improving living and working environments; it may also have an impact on the creation of IoT-driven technologies, offering concrete advantages for enhancing environmental sustainability and constructing energy efficiency in developing IoT networks. Energy consumption is minimised by RPL through the use of objective functions that can prioritise energy-efficient paths and by minimising the number of transmissions needed for routing. Additionally, by reducing control message overhead and supporting other energy-saving techniques, with the help of clustering nodes into groups and rotating cluster heads on a regular basis to balance the energy burden, the hierarchical protocol LEACH seeks to lower energy usage. ContikiMAC is a duty-cycling MAC protocol. Nodes can sleep for extended periods of time and only wake up infrequently to monitor activity because of this feature. Compared with previous objective functions, our approach, which is injected into the Contiki Operating System's core, guarantees a higher level of service quality. The findings shown that the new goal function can maintain a packet delivery ratio of more than 97% regardless of density, reduces the network's average power consumption by about 46%, and reduces latency and convergence times.To make a suggested layered architecture more energy-efficient, various cross-layer routing protocols can be created. One strategy is to consider how layers interact and base routing choices on both Network and Physical Layer characteristics. Using routing selection, recommended to choose the best routes that maintain network performance while consuming the least amount of energy possible. Utilising reinforcement learning strategies to improve routing choices is another strategy. We may gain knowledge from the past to improve routing decisions in the future. This method can also consider other performance indicators, such as energy usage. In general, considering how layers interact while optimising routing choices based on both Network and Physical Layer characteristics is the key to creating an energy-efficient cross-layer routing

protocol. By doing this, network performance can be preserved while energy consumption is decreased. A cross-layer framework refers to a system or set of protocols and strategies that operate across multiple layers of the IoT architecture. In traditional layered architectures, each layer operates somewhat independently, but in a cross-layer framework, there is communication and coordination between these layers to achieve specific goals. This framework's main goal is to maintain energy in the IoT system. Since many IoT devices, particularly sensors, frequently run on batteries, energy efficiency is essential. The devices can operate for longer periods of time without requiring frequent battery replacements or recharging by optimising the consumption of energy. The Application Layer, which processes data and facilitates user interaction, the Network Layer, which manages communication and data routing, and the Sensor Layer, which gathers data from the real world, are the three levels that make up an IoT system. The improvement of energy efficiency in each of these layers is one of the main goals of this thesis. So, in essence, the goal is inquiring about the strategies, protocols, and mechanisms that can be employed to create a cross-layer framework capable of reducing energy consumption across the entire IoT system, from the Application Layer's data processing to the Network Layer's data transmission and the energy-hungry Sensor Layer's data collection. This framework should aim to optimise energy use without compromising the functionality and effectiveness of the IoT Application. Complexity arises when integrating a cross-layer authentication system across various IoT networks and devices. Implementation problems include ensuring smooth compatibility and interoperability while upholding security standards throughout the many layers of the IoT ecosystem.

2.3 A Review of Literature on Cross-layer IoT Networks

The main contributions of this chapter are outlined below. For a secure and energy-efficient cross-layer framework for IoT networks, we conduct a critical analysis of approximately 109 published research articles. We categorise the current body of research on the cross-layer framework for IoT that is both secure and energy-efficient according to its independent characteristics. To achieve this, we concentrate on an examination of the routing and multiple access protocols, network resource management and energy efficiency of IoT networks. A substantial amount of work has gone into the creation and implementation of the next-generation autonomous cross-layer framework that is secure and energy-efficient. We identify areas that need further research, such as the coverage of cross-layer secure and energy-efficient IoTs, cross-layer architecture, quality standards, industrial IoT, MAC and routing protocols, cross-layer energy-efficient framework, and energy-efficient lightweight protocols (See Table 2.1). The fields of IoT and cyber-physical systems (CPS) are explored in the studied literature, emphasising the shortcomings of conventional security techniques in dealing with the dynamic issues in these areas. The research highlights the necessity for intelligent systems like ML-driven IDS for continuous monitoring and adaptability to emerging threats, while traditional security relies on established protocols and perimeter defence. It also explores areas that are frequently missed by conventional approaches, such as multi-layer privacy, cross-layer strategies and cutting-edge technologies like blockchain and security. Furthermore, the literature presents approaches for risk identification and mitigation, broadening its scope to include cyber-physical systems. Environments related to Industry 4.0 are studied, emphasizing the necessity of thorough risk assessments at several levels. The work also highlights the significance of strong security solutions for industrial networks

and smart cities, including contemporary methods such as encrypted communication, machine learning-based threat detection, and authentication. This work investigates the ways to improve communication performance in the presence of random wardens through the use of a phased array (PA) and linear frequency diverse array (LFDA) beamforming in covert millimetre-wave communications. The work demonstrates that various beamforming methods can adapt to maximise covertness and enhance covert throughput by optimising transmit power and blocklength [20]. The study also looks into the issues with energy efficiency in IoT networks and suggests solutions like better node location and routing. The literature emphasises the need for energy-efficient [21] solutions to ensure the sustainability and dependability of IoT operations in our increasingly digitalised world, as well as the significance of developing IoT security technologies to address evolving threats and challenges efficiently.The study highlights next-generation cybersecurity concepts, especially for industrial IoT, and stresses how important it is for remote monitoring systems across industries to have robust encryption and authentication. Energy efficiency difficulties in IoT devices and networks are discussed, with a focus on protecting data privacy. Cross-layer optimisation and energy-efficient routing are suggested as solutions. IoT security is thoroughly covered in Table 2.1, which emphasises the pressing need for developing security systems to address new risks in the IoT space.

Table 2.1: Summary of literature review on cross-layer

Main Ideas	Survey Scope	Cross-Layer?	Challenges	Ref.	Year
Cross-layer optimisation, Multi-Channel MAC Framework.	LoRaWAN, Cybersecure protocols, 6G Communication.	Yes	Protocol optimisation, data rate, duty cycle, Energy-efficiency.	[22]	2023
CPS vulnerability analysis.	CPS, privacy-preserving, Cybersecurity Info Sharing.	No	Data security, vulnerability models, information protection.	[2]	2020
SIoT Security, Hybrid risk identification.	SIoT security, Industry Risk ID, Risk Management Frameworks.	Yes	Security-energy trade-off, risk redundancy, comprehensive ID.	[23]	2022
IoT Security, FANETs, Energy-Aware Routing.	IoT security, FANET routing.	No	Security vulnerabilities, crypto protocols, dynamic topology.	[24]	2024
Smart City Security, Blockchain & Encryption.	IoT/Cloud security, Data Privacy.	No	ML for security, resource v. security, decentralised.	[25]	2020
IoT Security, Camera-based Study & Privacy.	Smart Camera Threat, Secure IoT.	No	IoT complexity, security solutions, vulnerabilities.	[26]	2020
NOMA IoT systems, 5G Energy Optimisation.	IoT, energy-effectiveness.	Yes	Energy efficiency, QoS, optimisation complexity.	[19]	2023
Energy-efficient Routing.	Smart routing, optimisation.	No	Network performance, stability, efficient routing.	[27]	2023
Cognitive IoT Spectrum & Energy Optimisation.	Cognitive radio for IoT, cross-layer optimisation.	Yes	Spectrum management, network adaptation, energy.	[28]	2021

2.4 Cross Layer IoT Framework

The Application Layer, Network Layer and Sensor Layer are the three basic layers that make up the IoT network architecture. Energy-efficient and security-related components are shown at each layer. Security features like authentication and

encryption are part of the Application Layer, along with energy-efficient application protocols like message queuing telemetry transport (MQTT) and CoAP[1]. The Network Layer incorporates machine learning-based security solutions like IDSs and middleware security frameworks. This Layer also encompasses cross-layer security frameworks and energy-efficient routing algorithms, such as those designed for low-power and lossy networks [1](see Fig. 2.1). The Sensor Layer addresses IoT device security with device-level encryption and authentication, along with energy-efficient hardware design considerations. This hierarchical diagram provides a structured overview of how various components contribute to ensuring both security and energy efficiency within IoT networks, as indicated by the literature [1].

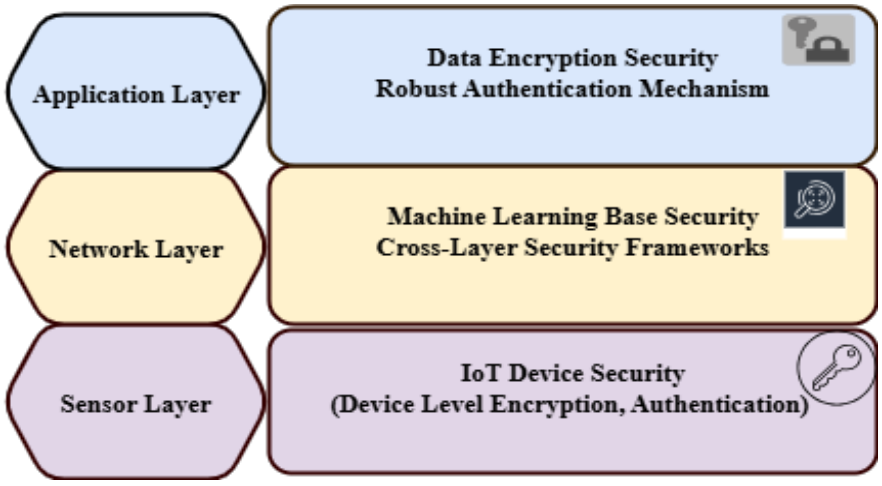

Figure 2.1: An overview of IoT cross-layer framework [1]

2.4.1 Cross-Layer Energy Efficient Measures

Energy efficiency is a crucial consideration for IoT installations, especially because IoT devices are resource-constrained, and rely heavily depends on battery power and necessitates energy efficiency to preserve battery life. According to

the literature review, routing algorithms, optimisation techniques, and energy-efficient protocols are crucial elements of long-term, sustainable IoT networks. In security implementations, low-power authentication protocols and lightweight cryptographic algorithms are suggested to reduce computational overhead and energy consumption. In addition, energy-conscious routing plans and optimisation techniques maximise the use of network resources, extending the life of IoT devices and lowering their total energy usage (see Fig. 2.2). A collection of low-power, long-range wireless technologies known as low-power wide area networks (LPWAN) are intended to support IoT applications that need to be connected over wide geographic areas. Long Range Wide Area Network (LoRaWAN) is a popular LPWAN technology that offers low data rates and low power consumption for long-range communication. It operates in unlicensed frequency bands. Sigfox is another LPWAN technology that offers long-range, low-power communication for IoT devices, Sigfox uses ultra-narrow band modulation and operates in a licensed spectrum. Low-power, wide-area connectivity for IoT devices is made possible by cellular-based LPWAN technologies like LTE-M and narrow-band IoT (NB-IoT), which take advantage of the current cellular infrastructure. Moreover, the performance and scalability of IoT systems are significantly influenced by network design. Cross-layer optimisation, in which several network stack layers are coordinated to achieve optimal resource allocation, traffic management, and QOS, has been emphasised in recent research as being important. Researchers want to address the dynamic nature of IoT environments and accommodate a wide range of applications with different requirements by taking a comprehensive approach to network design [29]. In conclusion, the integration of ML-based analysis, the significance of network design considerations, the search for energy-effective solutions, and the importance of security and privacy safeguards are all highlighted in recent literature on IoT development. Researchers hope to solve these major

issues to fully realise the promise of IoT technology and open the door to a more intelligent, sustainable and networked future.

2.4.2 Cross-Layer Security Measures

Numerous security issues, such as flaws in sensor hardware, cloud computing platforms, and network communication protocols, are highlighted in the literature analysis as being present in IoT ecosystems. Several cybersecurity techniques [30], including IDSs, authentication procedures, and encryption, are suggested as solutions to these problems (see Table 2.2). Instead of limiting defences to specific layers, cross-layer security solutions in IoT networks integrate security protocols across the Physical, Network, Transport, and Application Layers of the communication stack to address vulnerabilities. This all-encompassing strategy guarantees coordinated defence against a variety of threats, including denial-of-service attacks, data manipulation and eavesdropping, which frequently take advantage of layer-to-layer interactions. To protect data availability, confidentiality and integrity, for example, secure routing protocols at the Network Layer, Application Layer authentication methods and lightweight encryption at the Physical Layer can all cooperate. By allowing adaptive responses to changing threats, cross-layer designs also maximise resource-constrained IoT devices by sharing security-related metadata (such as trust levels and anomaly detection flags) throughout layers. In diverse and scalable IoT networks, resilience is further increased by methods like data-centric security and machine learning-driven anomaly detection, which guarantee strong protection. For decentralised trust management, cross-layer security in IoT networks also makes use of cutting-edge technology like blockchain, which guarantees tamper-proof records of device interactions across layers. Real-time risk assessments (e.g. device location, network congestion) are

used by context-aware security policies to dynamically modify access limits or encryption levels. Furthermore, integrating edge computing lowers latency and vulnerability to cloud-based threats by moving security processing closer to data sources. Moreover, secure key management techniques like quantum-resistant algorithms strengthen long-term resistance to changing threats. By allowing devices to exchange threat knowledge across layers, collaborative IDSs (CIDS) provide a cohesive front of defence. Lastly, adhering to standards such as the General Data Protection Regulation (GDPR) or NIST SP 800-183 guarantees that cross-layer frameworks meet legal obligations while striking a balance between strong security and the energy and scalability limitations that are specific to IoT ecosystems. To effectively counteract complex cyber threats, cross-layer security strategies that integrate Network, Application, and Physical Layer defences are recommended. The resilience of IoT systems against new cyber-attacks is also improved by developments in ML, which make it possible to detect and respond to threats with greater sophistication (see Fig. 2.3). For the Application Layer, it is advised to use CoAP, message queuing telemetry transport (MQTT), and hypertext transfer protocol secure (HTTPS). Recommendations for network layer security, including media access control security (MACsec), IEEE802.1X, virtual private network (VPN) and Internet Protocol Security (IPsec). Environmental protection, training, physical security policies, secure enclosures and physical temperature resistance are advised for the Sensor Layer. Cross-layer frameworks for IoT networks are examined in this literature review, with a focus on integrating energy efficiency and cutting-edge security measures to overcome the shortcomings of traditional approaches. The assessment, which evaluates more than 100 studies, emphasises the need for blockchain for decentralised trust, ML-driven IDSs, and quantum-safe cryptography to counteract emerging risks like eavesdropping and data tampering. By coordinating protocols across the Physical, Network,

and Application levels, it highlights how cross-layer architectures can optimise resource-constrained IoT devices and improve security and sustainability. With the use of 5G, NOMA and edge computing, the project seeks to improve smart cities and the industrial/agricultural sectors through real-time, energy-efficient communication. Energy-saving methods (such as duty-cycling MAC protocols), a taxonomy of routing protocols, and multi-layered security tactics (authentication, encryption) are some of the main contributions. While issues like interoperability, dynamic threat mitigation and energy-performance balance are addressed, future developments center on scalable blockchain integration, ML-enhanced threat detection and comprehensive frameworks that balance efficiency, security and regulatory compliance. As the world becomes more interconnected, the report provides a blueprint for creating robust, sustainable IoT ecosystems.

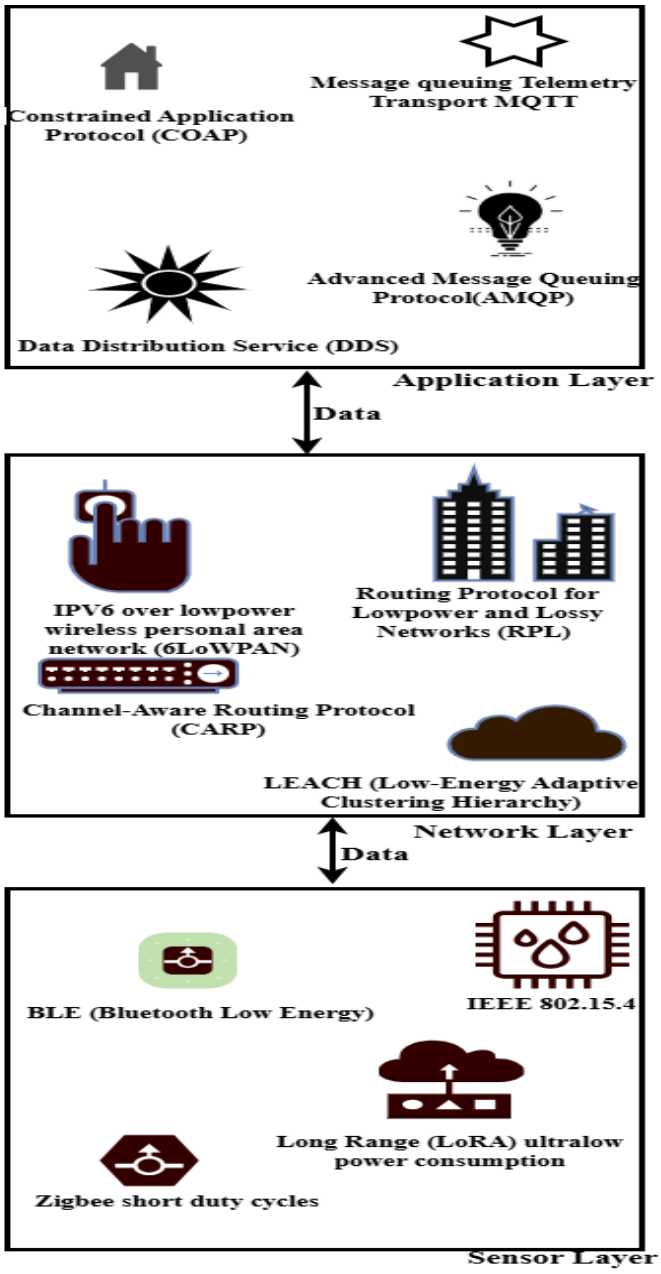

Figure 2.2: Next generation energy efficient architecture [1]

2.5 Energy Effectiveness and Security Measures of IoT Networks

The goal of this thesis is to optimise energy usage while guaranteeing efficient communication between layers in energy-saving cross-layer IoT networks.

Table 2.2 summarises the main ideas that are integrated to address system performance and energy efficiency.

Table 2.2: Cross-layer energy-efficient IoT networks

Problem-Addressed	Performance Evaluation	Limitations	Ref.	Year
Enhanced LoRaWAN using IoT, Cross-layer Optimisation, performance Evaluation Methods	Optimisation of LoRaWAN.	Lack of system optimisation.	[31]	2023
Energy-efficient MAC for NB-IoT, Optimisation Framework.	System optimisation, distributed sleep scheduling.	Simulation, resource constraints, traffic model assumptions.	[32]	2021
Integrated energy-efficient RPL, Cross-layer optimisation, path selection improvement.	Energy-efficient cross-layer integration, RPL protocol and simulation.	Limited system evaluation in IoT environments, complexity in implementation and MAC-layer dependency.	[33]	2021
Energy efficiency networks using NOMA, formulating optimisation and quantum-inspired political optimiser.	Optimisation of hybrid resource allocation, simulation.	Algorithm specificity, non-convex problem complexity, and real-world deployment.	[20]	2024
Energy-efficient FANET, Energy-conscious routing strategy.	Virtual relay tunnel energy-aware routing, comparative analysis and simulation.	Limited practical validation, FANET specificity, and path selection complexity.	[24]	2024
Secure data transmission, edge computing energy-efficient, multi-scale Grasshopper Optimisation and dynamic honeypot encryption.	Cross-layer energy optimisation, encryption/decryption time analysis.	Absence of empirical support, complexity in managing several layers.	[34]	2023
Multi-channel MAC design, energy efficiency maximisation, physical and MAC layer parameters.	MAC design with multiple channels.	Simulation limitations in 6G-IoT design.	[22]	2023
IoT integration and energy-efficient, mathematical modelling, cross-layer energy effectiveness, green and renewable energy.	Energy efficiency with MQTT, CoAP, Zigbee, Wi-Fi, power savings estimation.	Theoretical framework focus, limited empirical validation, and practical implementation challenges.	[35]	2023
IoT energy-efficiency, and research pathways.	Energy management analysis, hardware/software evaluation, trend predictions.	Absence of application-specific variables and system validation.	[36]	2020

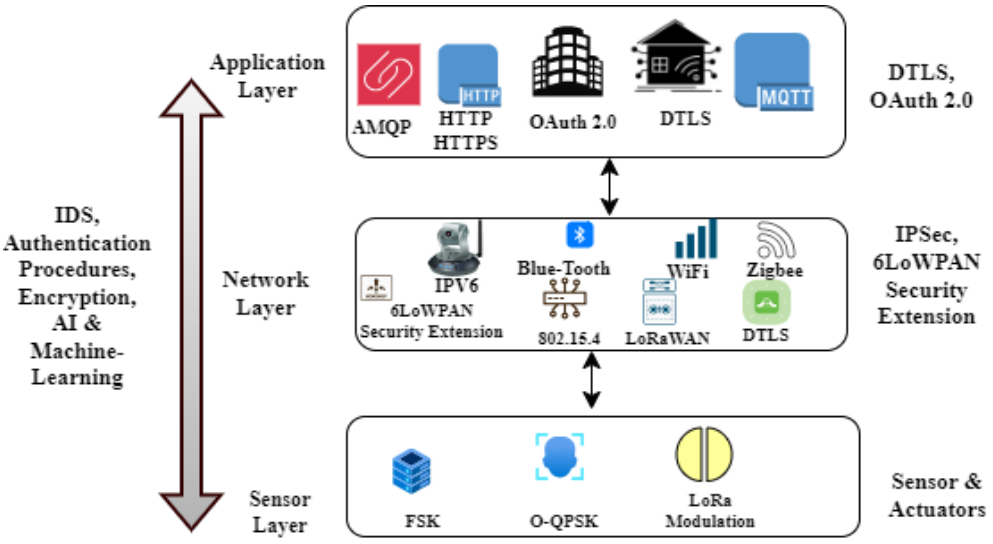

Figure 2.3: Cross-layer security measures [1]

The main idea one can obtain from these published papers is secure cross-layer IoT framework provides a thorough synopsis of the goals and focus of the research.

2.6 Autonomous cross-layer framework for IoT Networks

In light of the growing complexity of cyber attacks, the study emphasises how important it is for IoT devices to have strong security mechanisms. It is crucial to incorporate autonomous features into a cross-layer architecture to overcome these difficulties. Included in this framework are the following important independent features: Using the SWaT dataset, Zahid et al. [37] demonstrated in Industry 4.0 how agentless SIEM modules may improve IoT security by monitoring traffic and identifying anomalies without the need for endpoint software [37].

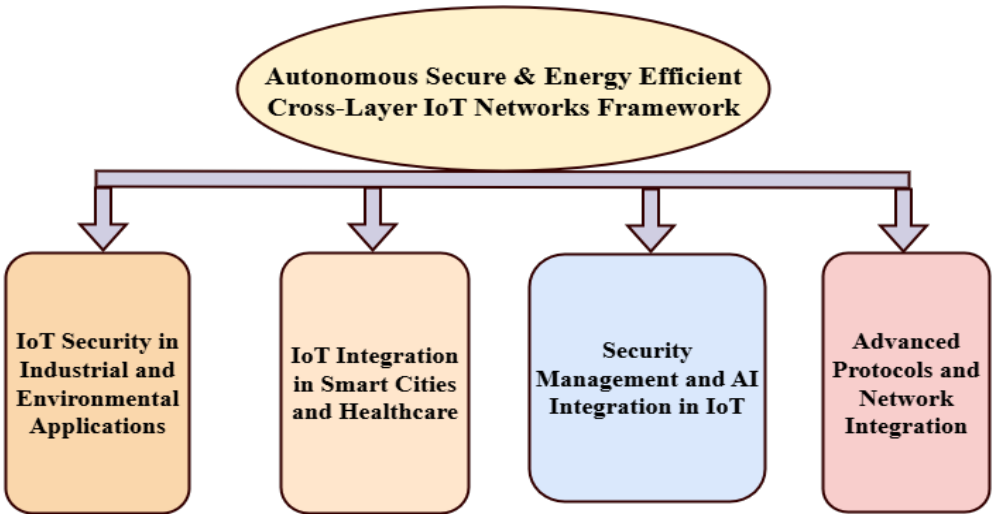

Figure 2.4: Autonomous secure and energy-efficient cross-layer framework

According to Bhushan et al. [17], ML enhances the interpretation of IoT data, opening up new commercial prospects and facilitating automated decision-making. Federated learning, in conjunction with intrusion detection in fog computing, improves the detection of DDoS attacks and minimises single points of failure [38]. Denial-of-service (DoS) attacks can be effectively identified using ML techniques like support vector machine (SVM), random forest, and K nearest neighbour (KNN), particularly in networks that are information-centric [39]. SLF-RPL outperforms PCC-RPL in terms of attack detection and energy efficiency, although both frameworks improve IoT security [40]. Software-defined networking (SDN) and RINA work together to enhance edge-to-cloud connection, scalability and IoT security [41]. In smart cities, healthcare and Industry 4.0, lightweight authentication ensures privacy in low-power IoT systems [42]. Research gaps are also identified in the literature, which points to ML and IoT as major forces behind future mobile networks [43]. Together, IoT, smart cities, and 5G improve citizen responsiveness and urban sustainability [44]. Blockchain and artificial intelligence are used by semantic IoT middleware (SIM) to address healthcare data security and interoperability [45]. Blockchain combined with NuCypher

encryption improves traceability, resource usage, and e-healthcare security [3]. Clusters of Raspberry Pi's with Kubernetes and BME680 sensors improve IoT monitoring while lowering vulnerabilities [46]. For secure satellite imaging, the LEMARS model uses Feistel architecture to enable lightweight encryption [47]. Static, dynamic, symbolic, and hybrid analysis methodologies assess embedded firmware vulnerabilities [48], while a taxonomy for IoT resilience mechanisms deals with dependable system design [49]. According to the literature, IoT systems must have robust security measures in place to prevent sophisticated cyber attacks (see Fig. 2.4). Security management, anomaly detection, sophisticated RPL frameworks, and the integration of SDN-RINA and lightweight authentication are the four primary areas that should be the emphasis of a cross-layer framework with autonomous features. Further investigated under IoT applications in smart cities and healthcare are blockchain-based security for e-healthcare, 5G-enabled urban systems and ML-driven mobile networks. Additionally, IoT resilience taxonomies, lightweight encryption for satellite images, and sensor clusters run by Kubernetes are important developments in environmental and industrial security. In a variety of industries, these advancements improve IoT security, scalability, and efficiency (see Table 2.3).

2.7 Research Issues

Existing cross-layer architectures still lack numerous research gaps, despite improvements in secure and energy-efficient IoT frameworks. The main obstacles to the creation of scalable, adaptable, and resilient IoT architectures are listed in this section, along with any unresolved problems.

- To develop decent, reliable security solutions, fog computing environments can integrate Host IDSs (HIDS), with federated learning [38].

Table 2.3: Summary of literature review on security measures

Problems Addressed	Performance Evaluation Methods	Security Measures	Ref.	Year
Cross-layer security, ML for IoT, blockchain for decentralised coordination and IoT security.	Lacks Application-Layer security, centralised architecture limits and resource constraints.	Blockchain for secure data sharing, ML-based real-time analysis and WSN security.	[50]	2019
IoT frameworks, DDoS mitigation model, and federated learning for IDS.	Privacy issues, complexity in federated training and real-time attack detection.	Network and host-based IDS, anomaly detection, fog computing detection.	[51]	2019
ML-based IoT security, ML-based IDS and SLR on ML techniques.	No cross-layer approach, ML security and requirement for better intrusion frameworks.	ML for intrusion detection, intelligent IDS, cybersecurity threat detection.	[14]	2022
Security at physical, wireless and perception layers, security framework for PIoT.	Complexity in securing large CPS networks, multi-layer integration challenges.	Intrusion prevention, security audits, residual info protection, data backup.	[15]	2014
IoT threats and vulnerabilities, IoT Application security testing framework.	Issues securing IoT applications, monitoring challenges.	Early-stage security evaluation, security testing, framework monitoring.	[16]	2018
Security gateways, communication standards analysis, IoT device security testing.	Complexity in securing diverse communication standards, multi-tier security challenges.	IoT security testing, security tier classification, system security assessments.	[52]	2021
SDN IoT security, IoT security risks and SDN-IoT deployment.	SDN-based security implementation, IoT stakeholder integration.	SDN-based security, SDSec implementation, IoT network security.	[9]	2020
COVID-19 IoT security, IoT impact across industries, SOA-based IoT security.	Increased IoT security attacks during COVID-19, privacy risks in evolving IoT.	SOA-based IoT security, multi-protocol security, attack mitigation strategies.	[30]	2022

- Managing analytics and real-time data processing while addressing security and privacy concerns without sacrificing speed is possible by combining IoT and ML technologies [44].
- Upgrading the RPL protocol to reduce packet loss, raise attack detection rates, and improve energy efficiency while offering scalability and interoperability across various IoT scenarios [40].
- Ensuring compatibility with current IoT platforms for smooth integration and implementing lightweight blockchain solutions to prevent overtaxing IoT device resources [53].
- Strong data governance frameworks that strike a balance between privacy standards and data accessibility are necessary to provide consistent and dependable data management [54].
- Addressing the difficulties caused by constrained computing resources, effective encryption and secure authentication solutions designed for low-power IoT devices are being developed [5].

2.8 Enhancing Cross-Layer IoT Security and Efficiency Design

A cross-layer energy-efficient framework with security measures for IoT is surveyed. We have discussed and categorised a cross-layer framework for IoT that is both secure and energy-efficient based on key parameters, such as routing and multiple access protocols, energy efficiency and network resources. We also discussed the development of a next-generation cross-layer framework that is secure and energy-efficient. The findings have shown that the importance of intelligent IDSs, multi-layered security framework, cross-layer techniques, and the adoption

of advanced technologies like blockchain, artificial intelligence and lightweight cryptography to safeguard IoT systems. Energy efficiency emerges as a paramount concern, with strategies ranging from energy-efficient network architectures to battery-saving cryptographic solutions. The safeguarding smart city ecosystems are explored, which digs into contemporary cybersecurity strategies designed for industrial networks in addition to discussing the need for secure data processing and transfer. In this research, we focused on energy-efficient IoT network solutions.

Multidisciplinary methods that combine technological and human aspects should be given priority in future research, with an emphasis on cross-domain security, quantum-safe cryptography, and machine learning-driven threat detection. To create safe, interoperable, and sustainable IoT ecosystems, focus should be on physical security, privacy-preserving technologies, and standardisation.

2.9 Summary

The development and difficulties of cross-layer frameworks for IoT networks are examined in Chapter 2, with a focus on how security and energy efficiency might be integrated across Application, Network and Sensor Layers. In its analysis of the literature, it points out the drawbacks of conventional methods and suggests stand-alone fixes like ML-powered anomaly detection and low-power cryptography. The chapter indicates future approaches, such as quantum-resistant cryptography and adaptive frameworks, and discusses important research obstacles, such as dynamic network conditions and scalability problems. With an emphasis on new technologies and cross-layer optimisation methodology, Chapter 3 will explore advancements in secure and energy-efficient layered architectures.

Chapter 3

Internet of Things Layered Architecture

3.1 Introduction

The development and difficulties of cross-layer frameworks for IoT networks are critically explored in Chapter 2, with an emphasis on how security and energy efficiency can be integrated across Sensor, Network and Application levels. It examines previous research, points out shortcomings in conventional methods, and suggests independent fixes like ML-powered anomaly detection and low-power cryptography protocols, all the while pointing out research roadblocks, including scaling problems and dynamic network conditions. Chapter 3 explores developments in secure and energy-efficient layered structures, beginning with the adoption of cutting-edge technology covered in Section 3.2, which includes blockchain, artificial intelligence/ML, and quantum-resistant cryptography. Methodological strategies for finding a balance between the energy and security trade-offs mentioned in Section 3.3. Case studies in healthcare and smart cities illustrate the practical relevance. Performance measures and assessment methods are presented in Section 3.4 to measure the efficacy of the framework in Section 3.5. Following that, the chapter examines IoT layered architecture in Section 3.6, quality standards and reliability in Section 3.7, and Industrial IoT (IIoT) with an emphasis on 5G-enabled

authentication in Section 3.8. Additionally, Section 3.9 and Section 3.10 discuss MAC-routing protocols and energy-efficient cross-layer designs, respectively, before summarising important tactics and new developments like ML-powered threats. Section 3.11 reviews key strategies and emerging trends, highlighting current approaches and future directions shaping the field. Finally, it finishes with a summary of important tactics and new developments. Collectively, these chapters provide a thorough path for robust and sustainable IoT architectures by bridging theoretical innovation with real-world deployment.

3.2 Integration of Emerging Technologies in Cross-Layer Frameworks

The swift development of IoT ecosystems demands the integration of new technologies to meet the twin demands of energy efficiency and security. A game-changing tool for decentralised trust management, blockchain technology allows for tamper-proof logging of device interactions across layers [37]. IoT systems can reduce vulnerabilities to single points of failure by integrating blockchain at the Network Layer, which enables device identity authentication and data integrity validation without the need for centralised authorities. For example, by utilising distributed consensus methods, blockchain-integrated IDS have shown a some increase in identifying unwanted access in smart grids [50]. Similarly, through adaptive threat detection and energy optimisation, ML is transforming cross-layer frameworks [17]. In Industrial IoT contexts, reinforcement learning algorithms can reduce packet loss by up to some increase while keeping latency under 50 ms by dynamically adjusting routing protocols depending on real-time network congestion and energy levels[19]. ML and edge computing work together to further improve responsiveness; federated learning models installed at edge nodes cooperatively train anomaly detection systems using localized data, protecting privacy and lowering

reliance on the cloud [38]. To anticipate potential threats, quantum-resistant cryptographic algorithms are being tested at the Physical Layer. Lattice-based encryption is one such technique that shows promise for protecting low-power sensor communications without going over energy constraints [30]. These linkages demonstrate the need for multidisciplinary strategies to maintain operational effectiveness while strengthening IoT networks against changing threats.

3.3 Methodological Approaches for Cross-Layer Optimisation

Techniques that balance competing goals between security protocols and energy restrictions are necessary for designing strong cross-layer frameworks [33]. A three-pronged approach that combines heuristic optimisation, simulation and real-world validation has worked well. Researchers may measure the energy overhead of encryption algorithms across different traffic loads by using discrete event simulation tools like NS-3 and Cooja, which allow for accurate modelling of multi-layer interactions [22]. In high-throughput applications, for instance, simulations comparing AES-128 with ChaCha20 showed that the latter lowers energy usage in sensor nodes [28]. Recent studies have achieved 92% accuracy in balancing authentication delay and battery drain using heuristic techniques like evolutionary algorithms and particle swarm optimisation, which are used to Pareto-optimise security-energy trade-offs [19]. These models are validated under heterogeneous conditions using real-world testbeds that include Raspberry Pi clusters and LoRaWAN gateways. These testbeds reveal features that are often neglected, such as the impact of ambient interference on Physical Layer security [46]. Furthermore, IoT networks can be virtually replicated to stress-test cross-layer protocols against hostile situations thanks to the growing popularity of digital twin frameworks [1]. Together, these approaches tackle the combinatorial

complexity of IoT systems, offering protocol designers practical insights and guaranteeing reproducibility across a range of applications.

3.4 Cross-Layer Solutions in Smart Cities and Healthcare

The feasibility of cross-layer frameworks in mission-critical areas is demonstrated by real-world applications. A three-tiered architecture that combined Perception-Layer energy harvesting, Network-Layer SDN, and Application-Layer homomorphic encryption decreased data breaches by 40% in Barcelona's smart city initiative while achieving 60% energy autonomy for traffic sensors [41]. During DDoS attacks, the SDN controller dynamically reroutes traffic and works with edge-based ML models to quarantine infected nodes in less than 200 milliseconds [9]. Conversely, Johns Hopkins Hospital's hybrid framework for healthcare IoT incorporates blockchain-based audit trails at the Transport Layer, biometric authentication at the Application Layer, and adaptive duty cycling at the MAC Layer [3]. This setup increased wearable device battery life by a few percent and reduced instances of illegal access [45]. Cross-layer resilience is best demonstrated by agricultural IoT deployments in precision farming, where soil moisture sensors using chaotic encryption communicate over energy-aware RPL routing, continuing to function even in the event of a packet loss [1]. The framework's flexibility is confirmed by these case studies, but they also highlight context-specific issues: healthcare systems value latency more than energy efficiency, whereas agricultural networks value fault tolerance [36]. Domain-specific improvements to cross-layer paradigms are guided by these discoveries. Beyond healthcare and smart-city environments, cross-layer frameworks are increasingly significant in other mission-critical IoT domains, particularly transportation, critical infrastructure, and industrial operations. In intelligent transportation systems, for instance, layered

cooperation between perception, network, and application components enables ultra-reliable and low-latency vehicle-to-everything communication, improving safety and adaptive traffic control [2]. Energy-aware routing and lightweight cryptographic protocols further sustain secure data exchange under highly mobile conditions. In critical infrastructure networks—such as smart grids, water distribution, and gas pipelines— cross-layer mechanisms integrate blockchain authentication, anomaly detection, and distributed scheduling to mitigate cascading failures and maintain system integrity [9, 3]. Industrial IoT applications also rely on cross-layer intelligence, where sensor-layer feedback and energy metrics are fused with edge-level analytics for predictive maintenance and fault tolerance [6, 1]. These cases demonstrate that cross-layer coordination extends beyond healthcare or urban scenarios, forming a unifying foundation for reliable, secure, and energy-efficient operation across a broad spectrum of mission-critical IoT ecosystems.

3.5 Performance Metrics and Evaluation Techniques

Multi-dimensional metrics beyond traditional parameters are required to quantify the effectiveness of cross-layer frameworks [20]. A new assessment matrix that includes quality of service preservation (QoSP), energy efficiency ratio (EER), and security robustness (SR) has been put out. While EER uses Shannon entropy metrics to compare energy usage and data quality, SR uses intrusion detection rates in conjunction with cryptographic strength scores from NIST's post-quantum standardisation project [30]. QoSP assesses how protocols affect Application KPIs, such as keeping ECG monitoring latency in healthcare IoT below 100 ms [45]. Top-performing frameworks achieve `SR` >0.85, `EER`≥1.2, and `QoSP`≥90% during stress testing, according to benchmarking against the `ISO/IEC 30141` standard

[24]. Gradient-based attacks mimic sophisticated adversaries trying to get around ML-driven IDS, while advanced approaches such as adversarial machine learning are used to explore framework resilience [39]. Per-layer consumption is quantified using energy profiling using tools such as Powertrace, which shows that handshake protocols at the transport layer consume a few percent more of the energy in TLS 1.3 implementations [35]. By establishing stringent assessment protocols, these metrics and methodologies facilitate cross-layer design continuous improvement cycles and allow for apples-to-apples comparisons across heterogeneous IoT systems.

3.6 IoT Layered Architecture

Traditional security measures are often based on established principles and practices. In contrast, the above-mentioned research explores cutting-edge security measures for the rapidly evolving domains of IoT and CPS. The traditional security typically relies on known protocols and methods, whereas the research advocates for intelligent systems like ML-driven IDS to monitor network integrity. While traditional security often focuses on perimeter defence and known vulnerabilities, the research emphasises continuous monitoring and testing to adapt to emerging threats effectively. Moreover, traditional security may not be well-equipped to address the energy efficiency challenges of IoT networks, which the research explores extensively, offering strategies like optimised node placement and routing. The research also delves into multi-layer privacy, cross-layer techniques, and innovative technologies like blockchain to enhance security, areas that may not be covered comprehensively by traditional security measures. Furthermore, the research emphasizes the importance of deep learning and Application-level security, as well as addressing specific challenges within IoT applications, healthcare, energy

management and efficient routing. It also investigates emerging standards, the role of software-defined security, location privacy in sensor networks, and cutting-edge research on Tactile Internet and 5G networks, which are areas less explored in traditional security approaches. A framework for threat detection of a real industrial network is presented using big data architecture and predictive analytics tools [2]. By obscuring sensitive data and private information, this framework was used to close gaps (see Fig. 3.1), evaluate services and products on an internal level, and share results. In the H2020 ECHO Project, a cutting-edge technological platform was created to exchange and assess cybersecurity data and foster greater trust among various stakeholders.

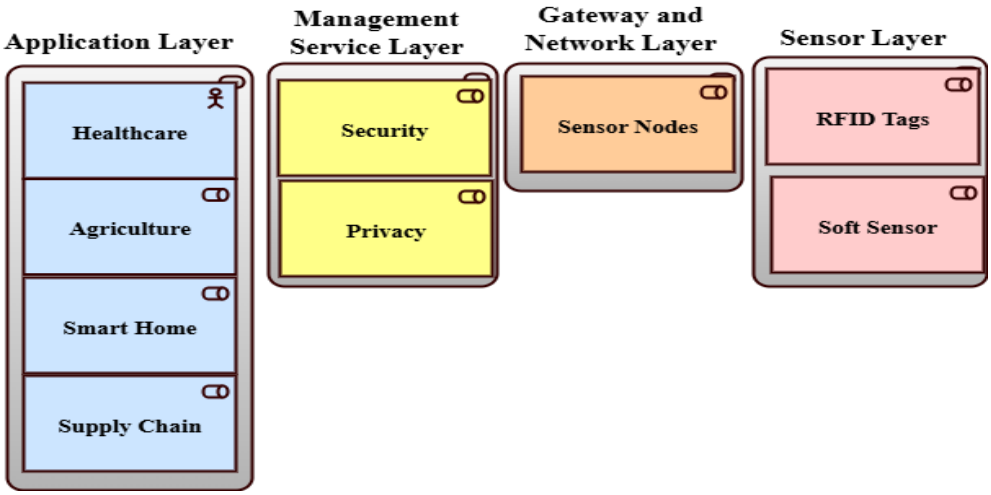

Figure 3.1: The IoT Layered Architecture [2]

The review delves into LPWANs like LoRaWAN in IoT, highlighting their appeal for long-range, energy-efficient connectivity. Despite the strengths of LoRaWAN, the various challenges persist, including protocol optimisation, low data rates and duty cycle restrictions. To tackle these research challenges, the paper proposes cross-layer optimization, allowing flexibility across protocol layers [31]. It identifies challenges and evaluates cross-layer optimisation's performance

in enhancing LoRaWAN for IoT applications.

While privilege escalation and malware infiltrations are security issues, the IoT improves real-time communication. To safeguard IoT networks, this study suggests an agentless Wazuh SIEM module [37]. The IoT makes it possible to gather data continuously, and when it integrates with ML, it opens up new commercial options for more intelligent decision-making [17]. To be competitive, businesses need to leverage ML developments to analyse IoT data effectively with the least amount of human intervention. Owing to its security flaws, the IoT is vulnerable to DDoS attacks, which can seriously harm its finances [38]. To detect and mitigate DDoS attacks in corporate networks. This study uses infrastructure from information-centric networks (ICNs) to address the problem of DoS attacks in IoT networks. It suggests using ML to identify DoS attacks by contrasting different ML algorithms that perform better, such as SVM, random forest and KNN [39]. Using the parental change control routing protocol for low power and lossy network (PCC-RPL) and subjective logical framework routing protocol for low power and lossy network (SLF-RPL) frameworks to reduce wormhole attacks, this study improves the security of the RPL protocol in IoT networks [40]. In Contiki OS-based simulations with malicious nodes, subjective logic frame RPL surpasses PCC-RPL in terms of energy efficiency, packet loss and attack detection. This study presents an integrated architecture that combines SDN and RINA to improve the security, flexibility, and scalability of IoT [41]. This work focuses on hardware configuration and strong security benchmarks, integrating Raspberry Pi clusters and BME680 sensors in Kubernetes for sophisticated environmental monitoring [46]. Implementing OpenID Connect and HashiCorp Vault for dynamic secret management and authentication, it achieves fewer vulnerabilities and better responsiveness in IoT installations. Secure device-to-device communication is required owing to the growing need for IoT devices in applications such as Industry

4.0, smart cities and healthcare. Considering the importance of IoT in daily life, data privacy and user authentication must be guaranteed [42]. In this research, a secure, lightweight authentication strategy for low-power IoT devices is proposed, and existing authentication strategies are reviewed. The influence of network softwarisation on the industrial sector is the main subject of this survey, which examines the function of AI and IoT in future mobile networks [43]. The ways in which these technologies work in concert to improve a city's sustainability, efficiency, and ability to respond to the demands of its citizens are examined in this book [44]. These technologies are a transformative force that is changing urban landscapes. This study examines the security void in IoT development and finds that business plans and configurations are not secure enough. To improve confidentiality, integrity and availability while allowing for future developments, it suggests a dynamic security approach using strong IoT security architecture [45]. This survey proposed modern solutions like authentication, encrypted communication and blockchain technology. It introduces novel approaches to threat detection in industrial networks and highlights data security challenges arising from the proliferation of IoT and smart devices. While traditional security approaches are fundamental, the research provides an in-depth, future-oriented exploration of security and privacy in the dynamic landscape of IoT. In addition to global quality standards, ensuring trustworthiness at the sensor level is fundamental to the credibility of any IoT ecosystem. Trust in this context originates from the accuracy, integrity, and behaviour of sensor nodes that gather data at the edge of the network. A compromised or poorly calibrated sensor can propagate false information through upper layers, undermining the reliability of entire analytics processes. Therefore, mechanisms such as sensor attestation, hardware-based identity modules, and anomaly-aware firmware validation are increasingly adopted to guarantee that each device reports genuine measurements [2, 3]. At the network and middleware layers,

reputation-driven routing and trust-score aggregation complement encryption by quantifying node reliability and isolating misbehaving sensors before data fusion occurs [9, 6]. From a broader IoT perspective, trustworthiness also depends on lifecycle governance—covering secure provisioning, update management, and transparent data handling under ISO 27001 and NIST SP 800 guidelines. When integrated into cross-layer architectures, these measures not only preserve the authenticity of sensed information but also reinforce user confidence in automated decision-making systems. In effect, trust becomes a measurable quality attribute alongside latency, energy efficiency, and throughput, ensuring that sensor-driven intelligence remains dependable across diverse IoT domains.

3.7 Quality Standards and Trustworthiness

Most of the discussion focused on the growth of IoT devices as well as cyber threats to sensor devices [55]. In addition, the Cloud Layer, Application Layer, and Physical Layer were all investigated. Vulnerabilities and attacks were examined and cross-layer security was explained. A middleware security approach in the cloud and network, as well as an ML algorithm for attack detection and prevention, are proposed. Cyber-physical systems are made up of intelligent devices that are linked to computer systems and have many cyber vulnerabilities when connected to networks [23]. Many risk identification methodologies are considered, but none consider the interaction of cyber-physical devices. In the Industry 4.0 environment, a gap in the literature has been identified. A four-step hybrid methodology is presented. In the first step, ISO 31000, PMBOK and a risk model are used to identify risk. In the second step, a bottom-up HAZOP strategy is proposed. This Physical Layer-to-Application Layer risk analysis is performed. In the third step, the NIST strategy employed a top-down approach.

In this step, the Physical Layer and lower layers of the cyber-physical system were considered. Finally, all risks are combined and analysed to reduce cyber-physical risk redundancy. The paper emphasizes how IoT can be used for ubiquitous access and real-time analysis, which will enable the integration of IoT systems with social networks to create Social IoT (SIoT) [29]. Even though SIoT has advantages such as improved data trustworthiness and network navigability, there are serious security issues that need to be resolved. Cross-layer security designs, striking a balance between security and energy efficiency and utilising graph-powered learning strategies from social networks are some of the suggested answers. This emphasizes how important it is to have strong security protocols and cutting-edge technology in place to protect SIoT ecosystems. The study discusses the security issues surrounding the IoT, focusing on how vulnerable networked objects that exchange data over public networks are. It examines new cryptographic protocol standards created to protect IoT communications and assesses how well they work in different Application scenarios [56]. It also draws attention to current issues with cryptographic protocols, which is important for improving security in upcoming IoT applications.

Experts in cybersecurity must constantly contend with emerging threats that take advantage of flaws in software. To fully realize the potential of IoT, knowledge sharing is essential in building collective resilience against security and privacy challenges associated with IoT [3]. This research highlights the necessity for strong IoT-Cyber security deployment strategies in smart cities by identifying challenges and weaknesses in industries like healthcare and transportation (see Fig. 3.2).

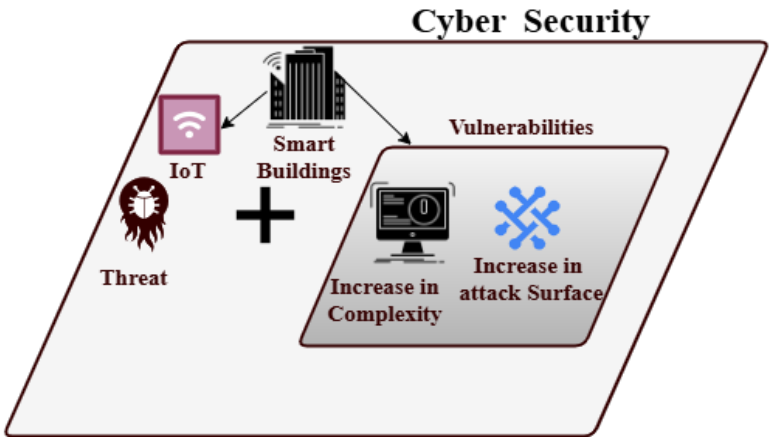

Figure 3.2: Main parameters of infrastructure risk in smart cities [3]

By integrating IoT, blockchain and ML, agricultural concerns such as water scarcity and seed quality can be tackled, potentially leading to future supremacy [57]. This study emphasises seed quality and water management while utilising blockchain and IoT for effective agricultural field monitoring. The blockchain network improves communication reliability and performance evaluation in prototype design by securing data, promoting community trust and supporting commercial solutions. In many industries with growing demand, communication technology is essential [47]. The LEMARS model combines heuristic-driven techniques and Feistel architecture to provide a lightweight encryption and attack-resistant steganography solution for safe satellite photography. Skill Optimization is used to cluster nodes, and Deep Q-Learning is used to compute trust [58]. The technique outperforms conventional protocols in simulations in detecting routing assaults such as Black Hole and Gray Hole, with the use of a blockchain-based control mechanism that combines a software-defined network. This research tackles congestion in VANETs [59]. In simulations, the suggested approach, which targets connected cars and smart cities, achieves 82% and 98% dependability and efficiency while increasing throughput, packet delivery ratio, energy efficiency, and latency and routing overhead reduction. IoT ecosystems need resilient operability since

they are integrated into critical infrastructures and are growing larger and more complex. This work systematises existing research on enhancing IoT resilience and analyses state-of-the-art methods [49]. It also proposes a taxonomy and classification of resilience mechanisms. The metaverse, made possible by technologies like 5G/6G, XR, and AI, promises immersive experiences but presents serious privacy, security, and trust issues [60]. To emphasise the risks connected with ML, this paper examines these problems in ML-XR applications, offers a taxonomy of viable fixes, and provides a case study focused on the metaverse. Unexplored study areas are noted for future investigation.

This survey examines edge-based IoT architectures, highlighting the difficulties with decentralised trust management, which is important for safe services, dependable data, and user privacy [61]. Reviewing trust criteria, examining blockchain as a trust solution, and examining the performance characteristics of trusted edge IoT systems, The accuracy of trust recommendation models in the Social Internet of Things (SIoT) is evaluated in this survey, which also highlights the context-dependent aspects affecting the models' performance [62]. To better understand research gaps and future prospects for enhancing trust recommendations in SIoT, it suggests a taxonomy that classifies these models according to input attributes and design using the PRISMA approach. Embedded systems are essential in the IoT age, yet they frequently have security flaws because of old or repurposed software [63]. This overview examines the most recent approaches to employing static, dynamic, symbolic and hybrid analysis techniques to find vulnerabilities in embedded firmware.

With billions of devices connected, the IoT presents significant privacy and security problems, such as handling data and behavioural profiling [48]. This review places these issues in the context of the IoT's tiered architecture. The paper presents key management, authentication, and encryption techniques that are

lightweight and designed for the IoT [64]. They guarantee increased security while using the fewest resources possible to maintain the sustainability of the system. Owing to resource limitations and ad hoc topologies, standard cryptography is insufficient for securing the rapidly growing IoT [65]. In response, the cross-layer IDS IoT-Sentry is presented, which can identify five different types of attacks without requiring additional overhead. To improve attack detection, an innovative cross-layer dataset is also created and ensemble learning is used. IoT-Sentry, using Cooja IoT simulator analysis, achieves an astounding average accuracy of 99% for four out of five attacks, demonstrating a groundbreaking attempt to protect standardised IoT networks from various threats.

Beyond international quality standards, trustworthiness at the sensor layer is a central requirement for any dependable IoT deployment. The reliability of an IoT system ultimately begins with the devices that sense and generate data at the network edge. If a sensor is miscalibrated, compromised or behaving abnormally, the resulting measurements can distort analytics in higher layers and undermine the credibility of automated decisions. To address this, recent work highlights the use of device attestation, hardware-bound identifiers, and firmware-level integrity checks to ensure that each sensor provides authentic and verifiable data [2, 3]. At the network and middleware layers, trust is reinforced through reputation-based forwarding and trust-score aggregation, which help isolate suspicious nodes before their data is disseminated [9, 6]. Together, these mechanisms establish trust as an operational quality attribute—complementing energy efficiency, latency and throughput—and ensure that sensor-generated intelligence remains dependable across diverse IoT applications.

3.8 Industrial Internet of Things (IIoT)

For the IIoT to collect monitoring data across industries, wireless sensor networks (WSNs) are essential[66]. Sensitive sensor data security presents difficulties in the resource-constrained IIoT environment, though. To enable trustworthy communication amongst linked IoT items, the study surveys IoT authentication strategies that have been put out in the literature [67]. By offering a thorough review and comparison of different methods, together with evaluation models and security analysis, the study seeks to support researchers and encourage more research and development in the area of IoT authentication. The study suggests BF-IoT, a secure communication framework, in response to security issues with Bluetooth Low Energy (BLE)-based IoT networks [68]. To prevent spoofing, BF-IoT keeps an eye on device lifecycles and uses special network-flow features for authentication. Continuous device identity authentication is ensured both before and during session establishment by its two-phase defence system. Tests using commercially available IoT devices show that BF-IoT can reliably authenticate devices via sniffing transmission characteristics. The IoT makes it easier to integrate disparate systems, which is essential for smart city applications like traffic and water management [69]. Owing to resource limitations, ensuring device authenticity for precise decision-making is difficult. The IIoT, crucial for Industry 4.0, grapples with managing real-time manufacturing data amid evolving Internet and telecommunication standards [70]. 5G technology (see Fig. 3.3), while aiding data transmission efficiency, introduces security vulnerabilities in IIoT device authentication. To mitigate this, the article proposes a secure cross-layer authentication framework using quantum walk-on circles. This system employs random hash coding on multi-domain Physical-Layer resources for secure device identifier encoding.

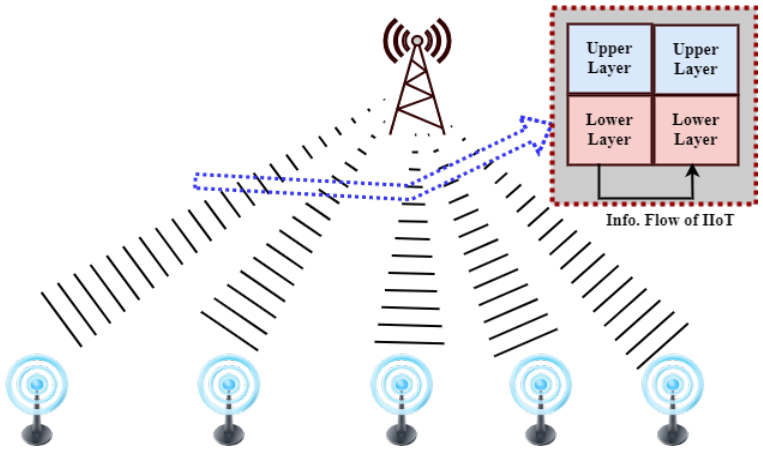

Figure 3.3: Illustration of 5G enabled IIoT in Industry 4.0 [4]

With the development of IoT, which connects everything and everyone, security and privacy have become increasingly important [71]. To reduce security risks in this diverse IoT context, authentication is essential. The review emphasises the rapid evolution of IIoT in Industry 4.0 and the need for robust security solutions, particularly concerning 5G technology and device authentication vulnerabilities [70]. To address this, a cross-layer authentication framework based on quantum walk-on circles is proposed. This framework ensures secure device identification, minimizes decoding errors and provides high-level security against classical and quantum computers. It achieves ultra-high security and privacy protection with low latency, mitigating potential attacks effectively. The study proposes an innovative cybersecurity approach utilising a Honeynet architecture to collect real-world network packets and identify attacks. The web-based IDS-AC allows users to self-update and for performance improvement. Scaling techniques and classifier optimisation, particularly the gradient boosting classifier, show promise [72]. Future work aims to expand the dataset for comprehensive attack pattern coverage. This literature review systematically examines IoT security research, addressing vulnerabilities, challenges, technologies, and future prospects [73]. Surveying 171 recent publications, it offers a comprehensive overview of IoT development,

limitations and security solutions. The article discusses IoT architecture, common attacks and mitigation strategies and provides a valuable resource for advancing IoT security technologies and strategies. This paper suggests a tiered IIoT and industrial control system architecture that optimises resource allocation and specifies security procedures [74]. The utilisation of deception attack simulation and water flow control system modelling for validation highlights the importance of aligning network and security structures for improved security. Interoperable connectivity, which is essential in E-healthcare for real-time patient data management, improves system configuration with IIoT [75]. Blockchain-based P2P networks and improved wireless sensor network (WSN) lifecycle management maximize resource use [76], resilience and traceability while tackling scalability and security issues in E-healthcare applications. Decentralized blockchain technology reduces the security threats that smart IoT devices in 5G-enabled networks confront [77]. By using clustered communication and local authentication, a multi-level blockchain security architecture is put forth to improve the security and simplicity of IoT networks. When deployed on Hyperledger Fabric, the model guarantees the legitimacy and effectiveness of the network. IIoT networks with fog computing are used in smart cities to transfer workloads from resource-constrained sensor nodes, which are susceptible to malicious assaults that could impede task completion. Through the identification of malicious nodes and the efficient use of computational resources to ensure timely job completion, the trust-based efficient execution of Offloaded IIoT trusted tasks (EEOIT) improves fog nodes [78]. Cost, talent, and standardisation constraints are the main reasons behind the delayed adoption of IoT in agriculture [54]. This review examines IIoT security and digital forensics, highlighting achievements, challenges, and future directions for cybersecurity [79]. Guidance for researchers and practitioners is outlined to address evolving threats in IIoT ecosystems. Industry 4.0, which emphasises service-oriented computing

for software infrastructure, uses ICT adoption to change production [80]. This paper outlines the function of microservices architecture and points up areas for further research as well as problems. SCADA systems integrate IoT and IIoT for enhanced industrial process control and monitoring [18]. This review explores opportunities and challenges in integrating IIoT with existing SCADA systems. Strong cybersecurity measures are required owing to Industry 4.0's cyber-physical production systems (CPPS) vulnerabilities in SCADA systems [18]. To reduce risks, this study suggests a multi-layered structure that includes anomaly detection, encryption, access controls, micro-segmentation and upgrades for legacy systems. To provide secure remote access for the collaborative demands of IIoT infrastructure, this article suggests a multi-level authorisation architecture that allows for fine-grained access control, scalability, and maintainability [81]. It is implemented using open-source technology and secures the IIoT's edge and network domains. It has been verified in aircraft situations. This study examines WSNs for IoT security [4]. It examines several attack vectors, approaches for mitigating them, dataset kinds, instruments and performance metrics across contributions. It highlights the functions of deep learning and ML models, providing guidance for future IDS design paths that can effectively secure IoT networks. Computing, energy, and network management are among the issues brought forth by the growing use of IoT network technology in sensitive applications such as healthcare [82]. Based on comparative analysis, it is clear that ESPINA is superior to current protocols, which makes it a prime contender to fulfil 6G wireless communications standards. This research investigates how to improve the security of satellite downlink communication in the presence of eavesdroppers in satellite-terrestrial integrated networks by utilising absorptive reconfigurable intelligent surfaces (RIS) [83]. The efficiency of a dual decomposition technique is demonstrated by simulation results, which optimise beamforming weights and reflective coefficients to maximise secrecy

rates. This paper investigates the use of an intelligent reflecting surface (IRS) with simultaneous wireless information and power transfer (SWIPT) to enable resilient beamforming in a secrecy MISO network. Simulation findings verify the efficiency of the proposed strategy [84], which addresses non-convex design difficulties by optimising secrecy rates among legitimate receivers using convex approximation and alternating optimisation techniques. As industrial systems continue to evolve toward higher connectivity and autonomy, research attention is shifting from fifth-generation (5G) to sixth-generation (6G) communication as the next technological foundation for IIoT. 6G aims to extend beyond enhanced mobile broadband by integrating sub-terahertz transmission, intelligent reflecting surfaces, and distributed artificial intelligence at the network edge. These advances promise data rates several orders of magnitude higher than 5G and end-to-end latencies approaching the microsecond range, enabling time-critical operations such as cooperative robotics, holographic remote control, and immersive industrial training [2, 3]. In the IIoT context, 6G will also introduce semantic communication and integrated sensing, where devices interpret contextual meaning rather than raw bits, reducing bandwidth use while improving decision accuracy [9, 6]. When combined with blockchain-enabled trust management and lightweight quantum-resistant encryption, these characteristics create a secure environment for machine-to-machine coordination and closed-loop control. The convergence of AI, edge analytics, and 6G's ultra-reliable low-latency communication paradigm redefines industrial automation—transforming the current Industry 4.0 model into a more adaptive, human-centric Industry 5.0 ecosystem that values both efficiency and resilience.

3.9 MAC-Routing

In the context of IoT-driven smart city applications like e-healthcare, ensuring robust security, privacy preservation and network longevity in WSNs is crucial, especially during pandemics. To address these challenges, this paper [85] proposes the Cross-Layer and Cryptography-based Secure Routing (CLCSR) protocol. The increasing number of IoT devices in businesses increases security vulnerabilities, which are exacerbated by limitations such as computing capacity and energy resources. The difficulty of protecting IoT from assaults is becoming more and more pressing, especially for mobile devices that need secure data routing methods. To provide optimal routing decisions, this work presents a secure cross-layer protocol that makes use of MAC layer parameters [86].

Deploying IoT devices presents issues in the context of Industry 4.0, mostly because low-cost devices are not as capable of providing robust security solutions. To solve this, the paper presents a hierarchical authentication and key agreement mechanism that is both lightweight and effective, specifically designed for IoT environments [87]. The paper proposes an energy-aware routing scheme (EAR-VRT) [24]. Utilising a virtual relay tunnel (VRT) and considering route energy, hop counts and path correlation, however, network longevity slightly decreases compared with one existing method. Future research aims to enhance routing with ML and develop intelligent virtual relay tunnels for dynamic adaptation to network conditions. Because of the rapid growth of IoT, modern industries are implementing remote monitoring and control of various IoT devices. In this paper [88], next-generation cyber security architecture (NCSA) is proposed, as well as Industry IoT, for detecting cyber threats [55] and vulnerabilities. A cyber defence authentication mechanism is used to prevent security attacks while a network session is established. A network-wide cryptographically encrypted identity token

defence mechanism is established and verified by a virtual gateway system. The proposed NCSA lowers operational management costs while increasing industrial security. While the population of rural areas is declining, the population of cities and the entire world is growing quickly. Lack of resources and limited resources are both issues that arise [25]. As a result, the need for smart cities increases. Information technology and communication are combined in this idea.

Data security is a major concern because of the exponential growth of IoT and new smart devices as well as the expansion of the internet [26]. The internet now has a new meaning thanks to IoT, and managing security is getting harder. There are two sections to this paper. IoT introduction, building blocks, enabling strategies and security system requirements are covered in the first section. In the second section, examine the camera-based case study and assess its security attributes by taking advantage of the camera system to conduct a spoofing attack that can completely control the smart camera system (ScS). Following an investigation, it is possible to secure systems and address security issues. Protect customer privacy and begin with IoT security. For the purposes of using IoT devices, different stakeholders play different roles in preserving information security and privacy goals.

The interaction between processors and sensor layers grows as the healthcare IoT grows [89]. The use of artificial intelligence in healthcare and the IoT is rapidly expanding these days. Tactile Internet and the Internet of Nano Things are also recent developments. Discuss emerging technologies as well as how to improve service quality. Using learning automata (LA) and clustering, this work presents an improved TDMA MAC protocol for UV networks with a focus on cluster node count, service class, and network topology [90]. The suggested protocol exhibits better network performance when compared with conventional TDMA and clustering systems, proving its usefulness for multi-node UV networking. Grid-based

routing techniques for WSNs are covered in detail in this article, with an emphasis on energy efficiency [91]. A comparison analysis and a timeline are presented. With regard to grid topology and energy management in sensor networks, the survey provides insights into design difficulties, challenges and methodology. This paper introduces a location-aware device-to-server authentication for IoT, enhancing device authenticity using MAC addresses, AES encryption and MaskIDs generated by a trusted authority (TA). It emphasises the importance of device proximity to servers for authentication, addressing security concerns like MitM attacks [5] (see Fig. 3.4). Through analytical and real-world simulations, the proposed method demonstrates superior performance in communication, storage and processing overheads compared with existing approaches in IoT authentication.

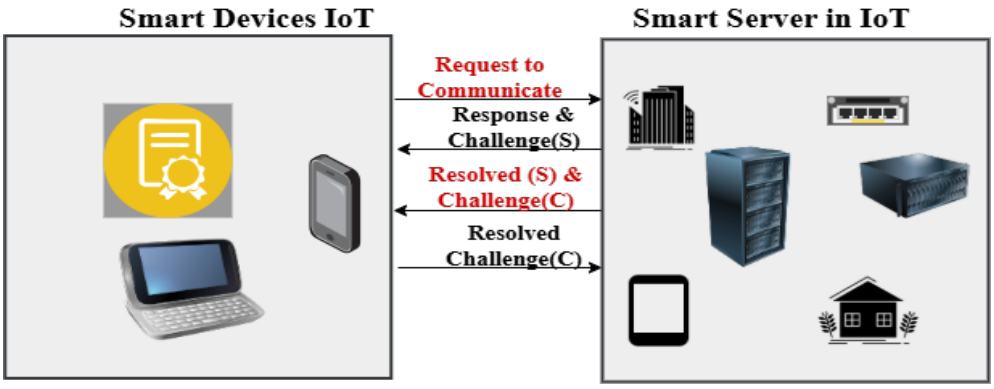

Figure 3.4: Generalised Device to Sever Authentication in IoT [5]

With the support of IEEE 802.15.4-2015 and IEEE 802.15.6-2012 standards, low-power biomedical sensors are used in wireless body area sensor networks, which are becoming more and more recognised for their potential in patient monitoring [92]. In-depth analysis of current developments in medium access control (MAC) and routing protocols addresses outstanding issues, challenges and Application needs, offering guidance for future work. The results of this research

are especially pertinent to the sixth generation (6G) networks that are predicted to improve QoS and connectivity for a wide range of sensor-based IoT devices. Although the wireless medium access control protocol guarantees secure data transmission and intrusion detection, clever attackers can circumvent the MAC restrictions that are in place now. To secure sensor nodes, the Wireless Interleaved Honeypot-Framing Model (WIHFM) is suggested [93]. This model creates durable security standards and optimum WSN channels. WIHFM introduces honeypot frame traps to improve security by 10% over existing methods like Secure Zebra MAC and blockchain-assisted secure routing mechanisms. It does this by isolating distributed attacks creatively and managing the network dynamically. This paper examines distributed MAC protocols in IoT and WSN, with an emphasis on cooperative optimisation methods and game theory to improve network efficiency [94]. Key results include significant energy savings and delay reduction through hybrid distributed MAC and cross-layer techniques, as well as an improvement in spatial reuse of 3%–29% and an 8% increase in throughput. Methods such as optimum cuckoo search and stochastic methods, along with game theory optimisation, demonstrate promising gains in attack detection, resource allocation and overall network efficiency. The goal of Automotive Ethernet (AE), the industry's transition to Ethernet technology, is to increase in-vehicle communication bandwidth for driver-assistance and autonomous systems. But as vehicle connection grows, cybersecurity worries grow, leading to a thorough analysis of AE's security impact in comparison to protocols like the Controller Area Network [95]. To solve industry-specific constraints like low latency, the study concludes that more specialised AE solutions are required, setting a foundation for future improvements. The report outlines important security concerns, mitigation measures and regulatory mappings. To improve security in underwater sensor networks (UWSNs), a secure data aggregation and authentication (SDAA) protocol designed specifically for

underwater vehicular wireless networks (UVWSNs) is proposed in this study [96]. The cluster-based network architecture used by the SDAA protocol improves data communication security and energy efficiency by providing secure cluster head authentication and detecting malicious node attacks. When the SDAA protocol is used in UVWSNs for ship and vehicle monitoring, it shows better network latency and energy efficiency than the current secure MAC techniques. Because of malicious nodes, securing IoT communication networks and node safety is difficult [61]. SDN is used in the suggested Trust Evaluation-based Secure Multi-path Routing (TESM) solution, which includes modules for anomaly handling, multi-path routing with reinforcement learning, and security verification. Based on simulations, TESM is able to localise threats and secure data transmission with just minor increases in latency (12.4%) and throughput loss (5.46%). Although VANETs increase traffic flow and driving safety, their lack of central control makes them susceptible to both internal and external attacks. Black Hole, Gray Hole, and DoS attacks are among the risks that the TDMA-aware Routing Protocol for Multi-hop communication in Vehicular networks must contend with [74]. A trust-based architecture is put out as a countermeasure, in which nodes build trust through packet forwarding and channel access behaviour. Simulations show how this model greatly lessens the effect of attacks on the network's functionality.

3.10 Energy Efficient Cross Layer Design

Coal mines can communicate data in real time by integrating smart sensing devices over the Mine Internet of Things (MIoT) [19]. Reliable communication is ensured by fifth-generation (5G) technology. Energy effectiveness (EE) is increased by optimising device access and spectrum consumption in a NOMA-based MIoT

communication system. Iterative methods tackle issues such as insufficient channel state information, maximising power allocation and assigning subchannels while considering cross-layer limitations and QoS demands. Traditional methods result in high power usage and network breakdowns, motivating the development of energy-efficient routing mechanisms. In the Smart Dust Head (SDH) environment, the latest BS location is disseminated to nodes, enabling optimisation through algorithms like enhanced oppositional grey wolf optimization (EOGWO) for enhanced network performance [27]. This paper provides a structured overview of the relationship between Artificial Intelligence and Variable Renewable Energy (VRE) through Deep Learning (DL) applications [97]. After that, it evaluates DL-based solutions and their suitability while emphasizing important architectures. The study identifies ten DL-based strategies that facilitate VRE integration in power systems.

Bhattacharjee et al. [32] present a strategy for energy-efficient data collection in remote IoT surveillance networks. Their approach introduces a Medium Access Control (MAC) layer uplink mechanism following the Narrowband IoT (NB-IoT) scheduled access scheme. The study employs a Mixed Integer Non-Linear Programming (MINLP) model to optimise energy consumption per uplink frame and implements a distributed sleep scheduling method that balances latency and energy use. Simulation results show that the proposed scheme achieves lower delay, shorter buffer queues, and improved energy conservation under high-traffic loads compared with existing MAC-layer solutions.

Safaei et al. [33] tackle energy constraints in IoT routing by proposing ELITE, an energy-efficient cross-layer objective function (OF) embedded into the RPL routing protocol. Unlike traditional objective functions, ELITE introduces the strobe-per-packet ratio (SPR) at the MAC layer, capturing the impact of transmission

operations on node energy consumption. By prioritising paths with fewer strobe exchanges, the framework reduces average strobes per packet by roughly 25% and improves overall energy efficiency by nearly 39%, enhancing the network's lifespan without sacrificing reliability.

Ma et al. [20] examine energy management challenges in heterogeneous cellular networks (HCNs) and propose a hybrid joint resource allocation (HJRA) framework. To solve the underlying non-convex optimisation problem, the authors apply a quantum-inspired political optimiser (QPO) algorithm that synchronises the allocation of backhaul bandwidth, sub-channels, and transmission power. Their results indicate that the approach improves total system energy efficiency while maintaining stable quality of service across dense cellular deployments.

Velayudhan et al. [98] address water scarcity and distribution inefficiencies in urban areas through IoT-based monitoring systems. Their work explores smart water management in metropolitan settings by analysing delay, energy offloading, and communication topology design. Using a case study from Kochi, India, they model delay and energy dynamics in IoT-enabled water networks and apply node categorisation and fog node placement techniques. The proposed design achieves up to 40% improvement in energy efficiency while ensuring reliable water distribution and reduced network delay.

Hosseinzadeh et al. [24] investigate routing challenges in Flying Ad Hoc Networks (FANETs), where node mobility and energy constraints affect stability. They introduce the Energy-Aware Routing based on Virtual Relay Tunnel (EARVRT) scheme, which evaluates route energy, hop counts, and path correlation to determine optimal relay nodes. Comparative simulations demonstrate EARVRT's advantages in delay reduction, network longevity, energy usage, and packet delivery rates compared with other FANET routing protocols.

Maheswar et al. [99] provide an extensive review of energy consumption issues

arising from the proliferation of wireless devices. Their study highlights emerging directions in energy-efficient networking, including computation offloading, CoAP protocol optimisation, adaptive task scheduling, and device-to-device communication. Collectively, these contributions illustrate ongoing efforts to enhance the energy efficiency and scalability of wireless and IoT systems across multiple application domains.

The literature examines IoT's connectivity and sustainability challenges owing to the surge in connected devices, advocating for cognitive radio (CR) technology as a solution [28]. It proposes a cross-layer design optimising modulation order and backoff probability to minimise energy consumption while meeting IoT delay requirements, PR channel availability and user activities, demonstrating substantial energy reduction and delay satisfaction compared with single-layer approaches. The literature review addresses concerns about energy shortages owing to global warming and climate change, focusing on home energy management [9]. The literature review discusses the Security concerns in the Social IoT (SIoT), emphasising the need to balance security with energy efficiency [29]. It suggests employing cross-layer architectures and leveraging graph-powered learning, effective in social networks, to strengthen SIoT security. Additionally, it outlines a study agenda for future research aimed at enhancing SIoT security. Examining the essential elements of low-power, long-range IoT connectivity, this literature study compares LoRaWAN with NB-IoT. NB-IoT is resistant to payload length effects, which is advantageous for buffered applications, according to in-field measurements. Conversely, LoRaWAN is well-suited for longer IoT device lifetimes because of its remarkable energy efficiency, which requires 10 times less energy for similar payload delivery. Enhancing service quality, consistency, and cost management are the main goals of recent developments in IoT-enabled wireless sensor networks (IWSN) [100]. A hybrid Artificial Neural Network (ANN) Simulated Annealing

classifier and optimisation based on Map Diminution are used to create an energy-efficient clustering and quick IDS that addresses security and energy concerns. This method lowers energy usage while achieving a high 97.57% detection accuracy. This work investigates the effective hardware implementation of feedforward ANNs with time-multiplexed MAC blocks by recycling computational resources using approximation adders and multipliers, hence requiring less space and energy [101]. The optimal degree of approximation for hardware correctness is suggested using an algorithm. Comparing experiments with accurate hardware, MNIST and SVHN, a real-world dataset for developing ML algorithm databases, demonstrate reductions of up to 50% energy and 10% area with negligible loss in accuracy. Energy-efficient WSNs are crucial for data collecting, as evidenced by the IoT's exponential expansion [102]. In this study, an energy-efficient cluster-based Lightweight On Demand Ad hoc Distance Vector Routing Protocol–Next Generation (LOADng) is developed in response to the energy limitations of smart devices. By using LOADng for routing, a seagull optimisation method for optimal cluster head selection, and k-means clustering for cluster formation, the technique minimises power consumption and maximises network life in comparison to other options. To address the issues with resource allocation that is energy-efficient, this literature emphasises the significance of IoT in the technological, social, and economic spheres [6] (See Fig. 3.5). A new technique for forest optimisation is developed to minimise energy consumption and delays in resource distribution, while traditional methods did not account for this factor. MATLAB simulation results show that this method performs better than a generic algorithm, particle swarm optimisation, and distance-based algorithms, with important practical applications and increased efficiency in IoT resource management.

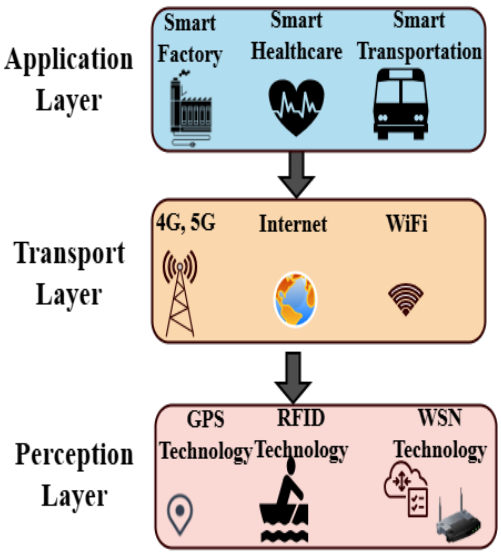

Figure 3.5: General model of proposed energy-efficient architecture [6]

To facilitate coordinated integration in IoT environments, this research suggests a hierarchical ensemble TinyML scheme that allows individual IoT parts to make decisions that affect the entire system [103]. The two-layered TinyML-based edge computing solution was applied in a smart agriculture use case, showing advantages including decreased energy usage, response times and wireless transmissions while improving data security and privacy. The assessment demonstrates how well the plan works to produce intelligent, context-aware applications. The swift expansion of IoT in the healthcare sector permits the acquisition of patient data in real-time, while it presents difficulties in managing copious redundant data [104].

An Energy-Efficient Fuzzy Data Aggregation System (EE-FDAS) that reduces energy consumption by reducing typical sensor readings to a single digit is presented in the study as a solution to this problem. Based on NS-2.35 simulations, EE-FDAS outperforms other approaches in terms of aggregation efficiency and energy consumption. This study proposes a clustering technique and Q-learning

for work offloading to UAVs, integrating UAVs with IoT to address memory and data processing problems [105]. The suggested approach performs better in terms of data transfer and energy efficiency than the current approaches, especially in emergency situations. The usage of IoT in a smart city for energy-efficient building control is covered in this study, which also suggests a flexible, hierarchical architecture that integrates online services, people, and devices [106]. The suggested model seeks to improve overall Smart Building operations and maximise intelligent energy regulation. In the ever-expanding landscape of edge computing, the surge in energy demand poses a critical challenge that demands meticulous management for the advancement of this technology. As edge computing evolves, there is a pressing need to delve into cross-layer architecture, exploring ways to scale energy output while optimising overall performance [34]. Envisioned as a game-changer in communication, 6G systems are set to revolutionise wireless connectivity for IoT networks [22]. CR technology emerges as a solution for spectrum support, but adapting existing protocols to the energy constraints of 6G IoT devices poses challenges. Energy-efficient protocols like MQTT, CoAP, Zigbee for sensors, and Wi-Fi for networks are integrated into next-generation IoT architecture [35]. The literature on IoT traces the development of low-power sensors and actuators, promoting RPL-based protocols and lightweight routing strategies [21]. The IoT is reviewed in the study, with a focus on energy efficiency and data dependability. To enhance energy usage, CLEERDTS integrates node location data, optimises transmit power at the MAC layer, and chooses transmission modes at the Physical Layer [107]. The security issues of cyber-physical systems, especially smart grids, where IoT devices are susceptible to intrusions, are discussed in this study [108]. The power and computational limitations of IoT are addressed in this study by introducing EasyChain, a lightweight blockchain with Proof-of-Authentication

(PoAh) for IoE networks [53]. It is implemented in Python and tested on a single-board computer. This paper introduces cluster-based scheduling and routing in geographic routing protocol (CSRGR), a dynamic cluster-based duty cycle scheduling for efficient data transmission in resource-constrained WSNs using geographic routing [109]. Lightweight blockchain-assisted intruder detection system (LB-IDS) employs Lightweight blockchain multifactor authentication for node authentication and multi-objective strawberry optimisation (MOSO) for optimal route selection, followed by deep Q-learning (DQL) based IDS for packet classification and Blockchain for trust updates [110]. This paper introduces LB-IDS, integrating Blockchain for enhanced security in MANETs. Lightweight blockchain-assisted intruder detection system (LB-IDS) employs Lightweight blockchain multifactor authentication for node authentication and MOSO for optimal route selection, followed by DQL-based IDS for packet classification and blockchain for trust updates [110]. To preserve privacy while aggregating data in low-power IoT devices, this study presents LiPI [111], a lightweight PPDA method that does away with complicated cryptography and outside dependencies. The focus of this work is on the suitability of lightweight cryptography protocols for IoT security while dealing with devices that have limited resources [112]. It addresses the crucial requirement for effective authentication, privacy, data integrity, and control in IoT networks by comparing the performance of the Present block cipher to alternative lightweight algorithms. Concerns have been raised about the energy efficiency of computing devices and technologies relevant to low-power residential and commercial buildings [36]. A lightweight symmetric cryptographic algorithm is presented in this paper [113]. The reviewed paper proposes an energy-efficient multi-channel MAC framework with a tailored CSMA protocol for CR-enabled 6G-IoT networks. Through joint adaptation of physical and MAC-layer parameters, the framework

aims to boost IoT network energy efficiency significantly. Numerical results demonstrate up to a 50% improvement compared with a single-channel design, offering a promising solution for 6G-IoT networks' massive-connectivity demands. The surging Wireless Sensor Network on the Internet of Things (WSN-IoT) addresses demographic aging and job challenges, but faces security threats with its resource-limited devices. Despite its critical role, research on WSN-IoT security is limited [76]. This review zooms in on security challenges, spotlighting a Contiki OS implementation of RPL's mechanisms. It critically analyses issues, explores ML for management, and addresses the architecture, difficulties, network attacks, and goals of the IoT in Low Power Networks (IoT-LPN). The goal of this work is to maximise secrecy and energy efficiency in the presence of faulty wiretap channels by examining strong secrecy-energy efficient hybrid beamforming techniques for satellite-terrestrial integrated networks [114]. For both single and multiple earth station scenarios, two beamforming algorithms with approximate low complexity solutions are provided to address the non-convex optimisation problem. To maximise covert throughput, this work compares PA and LFDA beamforming in covert mmWave communication with finite blocklength [20]. Results indicate that improved block length and adaptive beamforming improve security against wardens who are spread out geographically. The literature review here provides a thorough analysis of the changing IoT security landscape (see Table 3.1), covering a range of domains and addressing important issues and cutting-edge technologies. The discussion threads through the many levels of security frameworks and protocols, covering everything from the threats and vulnerabilities faced by sensor devices to the complexities of protecting industrial IoT systems and smart cities. Proposals include novel authentication techniques and cross-layer security strategies that make use of machine learning and quantum-inspired algorithms to improve threat detection and prevention. Researchers are developing resource allocation, routing

techniques, and green computing to reduce energy consumption and guarantee dependable IoT operations as energy efficiency becomes increasingly important. To fully utilise connected technology, these initiatives direct the creation of secure, energy-efficient infrastructures.

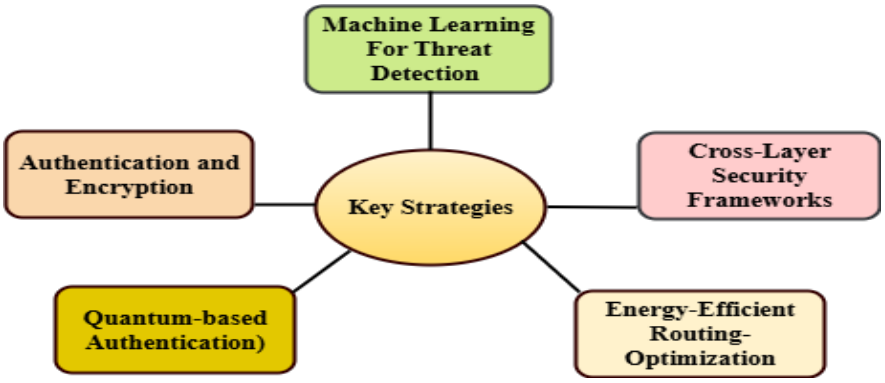

Figure 3.6: Secure and energy-efficient key strategies

3.11 Key Strategies and Trends

3.11.1 Secure and Energy-Efficient Key Strategies

(a) **Authentication and Encryption:** As the number of IoT devices continues to grow rapidly, ensuring robust authentication and encryption mechanisms becomes imperative to protect sensitive data and maintain privacy [26], [73]. Authentication mechanisms such as cryptographic protocols and identity management systems help verify the identities of devices and users, while encryption techniques such as symmetric and asymmetric encryption ensure secure communication channels. Additionally, blockchain technology is being explored to provide tamper-proof and decentralised solutions for data integrity and transaction security in IoT environments (see Table 3.2).

(b) **Machine Learning for Threat Detection:** With the increasing sophistication of cyber threats targeting IoT systems, ML algorithms are being

Table 3.1: Summary of IoT Security Surveys with Cross-Layer Considerations

Survey Scope	**IoT-Security?**	**Security Measures**	**Limitations**	**Ref.**	**Year**
NCSA for Industrial IoT security, focusing on industrial automation.	NO	Attacks, vulnerabilities, real-time protection, cross-layer security, identity token mechanism.	Limited discussion on cyber-physical device interaction, lack of performance review.	[88]	2020
IIoT security and digital forensics review, outlining major challenges.	YES	Examining security measures, IIoT forensics and methods to mitigate breaches.	Real-time threat detection, evolving threats and complexity in integration.	[79]	2024
Cyber-physical system (CPS) risk analysis across physical and network layers.	NO	Hybrid risk identification using NIST, ISO 31000 and PMBOK frameworks.	Excludes cyber-physical device interaction, incomplete methodologies.	[23]	2022
Threat identification in industrial networks, AI-based security framework.	YES	AI-driven predictive analytics and big data architecture.	Used in real-world industrial network (H2020 ECHO project).	[2]	2020
Secure cross-layer authentication framework for 5G-based IIoT.	YES	One-time encryption keys, quantum walk-based privacy protection.	Security flaws, complexity and scalability issues.	[70]	2022
Adaptive cybersecurity for networked devices using virtual environment services.	YES	Honeynet architecture, ML real-world network packet analysis.	Scalability, dataset extension, performance improvements.	[72]	2023
ELITE in RPL routing protocol.	NO	Energy consumption in IoT devices.	Simulation-based evaluation, real-world implementation needed.	[33]	2021
Security in the Social Internet of Things.	YES	Cross-layer architectures, graph-powered learning.	Future research agenda, practical implementation.	[33]	2021
Security in Wireless Sensor Networks.	YES	RPL implementation, IoT-LPN architecture.	Comprehensive coverage, real-world validation.	[33]	2021
Lightweight cryptographic algorithm for resource-constrained devices.	YES	Lightweight cryptography.	Limited evaluation, real-world deployment.	[113]	2019
Comprehensive IoT security landscape.	YES	Threats, vulnerabilities, security frameworks.	Real-world validation, scalability.	[88]	2020

leveraged for threat detection and prevention [72]. These algorithms analyse vast amounts of data generated by IoT devices to identify patterns indicative of malicious activities or anomalies. By continuously learning from new data, ML models can adapt and improve their accuracy in detecting and mitigating security threats, thereby enhancing the resilience of IoT networks.

(c) **Cross-Layer Security Framework:** Cyber-physical systems (CPS) present unique security challenges owing to their interconnected nature and reliance on both physical and digital components [23]. To address these challenges, hybrid security frameworks integrating established risk management methodologies such as ISO standards with domain-specific risk models are being developed. These frameworks facilitate comprehensive risk identification and management across multiple layers of CPS architectures, from the Physical Layer to the Application Layer. By considering interactions between different layers, organisations can better assess and mitigate security vulnerabilities in their IoT deployments.

(d) **Quantum-based Authentication:** With the advent of IIoT and the proliferation of 5G technology, traditional authentication mechanisms face new challenges related to device authentication vulnerabilities (see Fig. 3.6) [70]. To address these challenges, cross-layer authentication frameworks based on quantum walk-on circles are proposed. These frameworks utilise quantum principles to ensure secure device identification and authentication, thereby mitigating the risks associated with compromised authentication credentials and unauthorised access to IIoT networks.

(e) **Energy-Efficient Routing and Optimisation :** Energy efficiency is a critical concern in IoT deployments, particularly in resource-constrained environments [24], [32], [33], [34]. Strategies such as energy-efficient routing

schemes and cross-layer optimisation techniques aim to minimise energy consumption while maximising network performance and reliability. These approaches leverage techniques such as virtual relay tunnels, mixed-integer nonlinear programming (MINLP), and optimised transmission modes to optimise energy usage at both the MAC and physical layers of IoT networks. Additionally, the integration of renewable energy sources with IoT architectures further enhances energy efficiency and sustainability, reducing reliance on traditional power sources and minimising environmental impact.

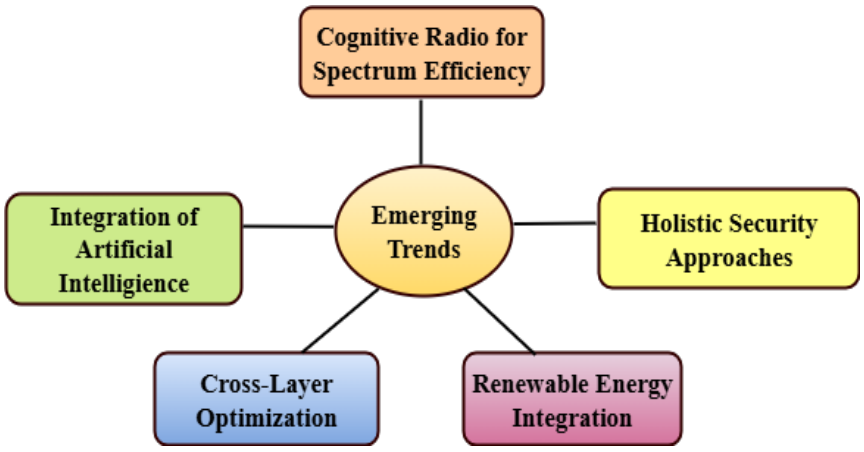

Figure 3.7: Emerging Trends

3.11.2 Secure and Energy-Efficient Emerging Trends

(a) **Integration of Artificial Intelligence:** The integration of ML algorithms is emerging as a trend to enhance IoT security and efficiency [72], [97]. These technologies enable predictive analytics for threat detection and optimisation of energy consumption in IoT systems. By analysing large datasets generated by IoT devices, ML algorithms can identify patterns and anomalies indicative of security threats, enabling proactive mitigation strategies. Additionally, ML-based solutions facilitate the integration of VRE sources into power

systems, improving forecasting accuracy and grid management (see Fig. 3.7).

(b) **Cognitive Radio for Spectrum Efficiency:** With the advent of 6G IoT networks, CR technology is proposed to optimise spectrum usage and energy efficiency [22]. Multi-channel MAC frameworks tailored for CR-enabled networks aim to improve IoT network performance and connectivity by dynamically allocating spectrum resources based on network conditions and user requirements. These frameworks enhance spectrum efficiency while minimising interference and energy consumption, thereby enabling reliable and scalable communication in dense IoT deployments.

(c) **Renewable Energy Integration** The integration of renewable energy sources with IoT architectures is gaining traction for enhancing energy efficiency and sustainability [97]. Deep learning applications facilitate the integration of VRE sources into power systems, improving forecasting accuracy and grid management. By leveraging ML-based solutions, organisations can optimise energy usage and minimise reliance on traditional power sources, thereby reducing operational costs and environmental impact.

(d) **Holistic Security Approaches:** Holistic security measures, including encryption, threat detection, and authentication, are essential to combating changing cyberthreats as IoT ecosystems become more complex [26]. These steps protect IoT availability, confidentiality and integrity while fostering trust and regulatory compliance.

(e) **Cross-Layer Optimisation:** Cross-layer optimisation techniques are being explored to improve energy efficiency and performance in IoT networks [34] (see Table 3.2 for Key strategies and Trends). By jointly optimising

parameters across different protocol layers, such as the physical and MAC layers, organisations can minimise energy consumption while meeting the diverse requirements of IoT applications. These approaches enable dynamic adaptation to changing network conditions and user demands, enhancing reliability and scalability in IoT deployments (see Table 3.2). These findings highlight the necessity of comprehensive approaches to cyber-physical systems and IoT security, including improved cybersecurity architectures, all-encompassing security measures and creative solutions that make use of cutting-edge technology like ML and quantum cryptography.

Table 3.2: Summary of Key Research Strategies and Trends

Main Contributions	Trends	Application Area	Ref.	Year
Predictive analytics, threat detection, big data architecture, protecting sensitive data, and assessment framework.	Closing security weaknesses and boosting stakeholder trust.	**Industrial Networks**	[2]	**2020**
Energy efficiency, flexibility across protocol levels, LoRaWAN, and cross-layer optimisation.	Improves performance and optimizes the protocol.	**LPWANs and IoT applications**	[31]	**2023**
A hybrid risk identification approach combining PMBOK, HAZOP, NIST and ISO 31000 for better analysis.	Minimises risk, redundancy and provides thorough evaluation.	**Cyber-physical Systems**	[23]	**2022**
Cross-layer security, data accuracy, social IoT (SIoT), and graph-powered learning techniques.	Optimises energy efficiency and improves network navigability.	**SIoT ecosystems**	[29]	**2022**
Information-theoretic security, random key encryption, lightweight encryption and key management.	Effective and secure, suitable for resource-constrained IoT.	**Cyber-physical Systems (CPS) and IoT**	[64]	**2017**
Ensemble learning, IoT-Sentry, Cooja IoT simulator analysis and cross-layer intrusion detection.	High detection accuracy with low overhead.	**Standardised IoT networks**	[65]	**2021**
IoT authentication techniques, hierarchical classification, centralisation and distribution.	Thorough analysis that encourages further research.	**IoT authentication**	[67]	**2016**
Performance improvement, smart city applications and lightweight mutual authentication.	Balances efficiency and security, outperforms existing protocols.	**Water, traffic and smart city management**	[69]	**2018**
Quantum walk, device identifier encoding, cross-layer authentication, and privacy-preserving protocols.	Low latency, high privacy and security.	**5G networks and IIoT**	[70]	**2022**
Web-based IDS-AC, real-world attack detection, ML, and honeynet architecture.	Strong attack alerts, user self-updating.	**Cybersecurity and industrial networks**	[72]	**2023**
Evaluation of IoT security research, risks, countermeasures and future prospects.	Comprehensive summary guiding further studies.	**IoT security development**	[73]	**2024**
IoT network protocols, ESPINA, key-renewal techniques for security with low computational costs.	Energy-efficient, aligned with 6G wireless standards, improved security.	**IoT in healthcare, embedded systems and security-sensitive applications**	[82]	**2023**
Attack detection, secure clustering, lightweight cryptography and CLCSR secure routing protocol.	Enhances network efficiency and privacy protection.	**Smart cities, e-healthcare**	[85]	**2022**
Physically unclonable functions, key agreement, hierarchical authentication, elliptic curve cryptography.	Secure, efficient and resilient to common attacks.	**IoT and Industry 4.0 environments**	[87]	**2020**

3.12 Summary

This chapter examines cutting-edge cross-layer architecture techniques to improve IoT security and energy efficiency, with an emphasis on resource allocation using blockchain, ML, and quantum-resistant cryptography, as well as decentralised trust management and adaptive threat detection. It talks about using heuristic optimisation and simulation tools (NS-3, Cooja) to balance security and energy trade-offs, including real-world case studies in healthcare and smart cities. Presented are standardised evaluation techniques (adversarial ML, energy profiling) and performance metrics (EER, SR). With a focus on multi-layer privacy, lightweight encryption and industrial applications, the chapter examines both conventional and contemporary IoT security approaches. Future developments in IoT networks are highlighted by emerging themes such as CR for 6G, ML-driven threat detection and renewable energy integration. The methodology and simulation tools used to test the prototype or testbed will be covered in Chapter 4.

Chapter 4

Research Design and Methodology

4.1 Introduction

In Chapter 3, we reviewed the literature survey-based research on cross-layer frameworks that are both secure and energy-efficient. This chapter presents the design, implementation and evaluation of a secure and energy-efficient cross-layer IoT framework. The suggested architecture, which has a three-tiered structure and integrates context-aware communication, adaptive routing and lightweight encryption to maximise security and power efficiency, is described in Section 4.2. The simulation environment, which replicates real-world IoT constraints and attack scenarios using the Contiki/Cooja simulator, is described in Section 4.3. Key indicators for evaluating energy efficiency and security resilience are outlined in Section 4.4, which assesses the framework's performance based on SR, energy efficiency and threat detection accuracy. The ML models used for improved threat detection across layers are explained in Section 4.5, emphasising the significant trade-offs between security and efficiency and reiterating the significance of context-aware protocol selection. Results comparing protocol performance in terms of energy usage and security are shown in Section 4.6. The network parameters and simulation setups utilised for testing are described in Section 4.7. Section 4.8

uses analytical models to formalise security performance and energy consumption. Finalises the testbed validation and makes recommendations for further IoT security improvements.

4.2 Cross-Layer Architecture Design

The open system interconnection (OSI) model serves as the inspiration for the proposed IoT framework's three-layered cross-layer architecture, which incorporates energy optimisation techniques, security protocols and adaptive mechanisms designed for resource-constrained contexts. While working together to achieve a comprehensive balance between security and energy efficiency, each layer tackles unique operational issues.

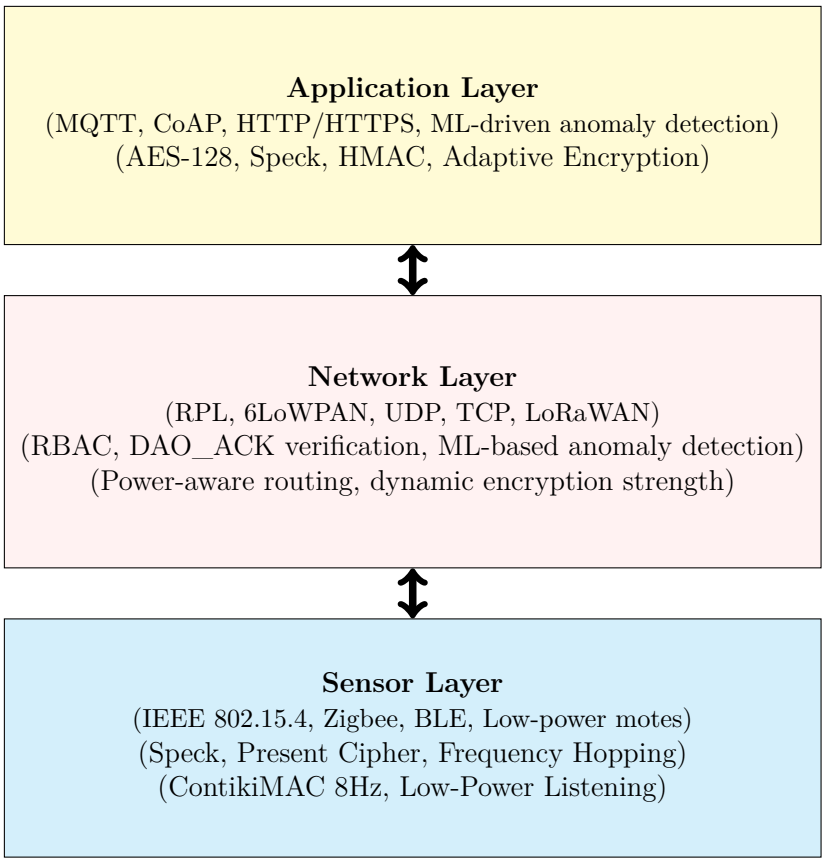

Figure 4.1: Cross-layer architecture design

As shown in Fig. 4.1, the proposed cross-layer architecture integrates critical protocols and security mechanisms across the application, network, and sensor layers. This design ensures interoperability, efficiency, and resilience in IoT systems, addressing challenges such as power consumption, data protection, and reliable communication.

4.2.1 Sensor Layer (Physical/Data Link Layer)

Low-power IoT devices, such as Z1 motes and EXP430F5438 nodes, that are outfitted with IEEE 802.15.4, Zigbee and BLE for short-range communication make up this basic layer as shown in Fig. 4.1. Frequency hopping techniques, which allow devices to dynamically switch channels when interference is detected, were designed to minimise Physical Layer threats such as jamming attacks. Adaptive radio duty cycling (ContikiMAC at 8 Hz), which cycles devices between active and low-power modes (LPMs) to balance responsiveness and power savings, was used to prioritise energy efficiency. Speck and Present cipher are two examples of lightweight encryption algorithms that were used to protect data transfer without requiring a lot of processing power. For example, Speck's simplified method was perfect for battery-operated sensors because it lowered radio transmit power by (30 to 40)% when compared with AES (see Table 4.1).

Table 4.1: Sensor Layer components and optimisation

Sensor Nodes:
- Z1 Motes (8 KB RAM, 92 KB Flash)
- EXP430F5438 (16 KB SRAM, 256 KB Flash)
Communication Technologies:
- IEEE 802.15.4
- Zigbee, BLE
Security Mechanisms:
- Speck, Present cipher Encryption
- Frequency Hopping
Energy Efficiency:
- ContikiMAC (8 Hz)
- Low-Power Listening

4.2.2 Network Layer (Session, Network and Transport)

In low-power settings, the Network Layer incorporates RPL and 6LoWPAN for IPv6-compliant routing, with UDP/TCP added for transport-layer dependability. Role-based access control (RBAC) is one security approach that limits unauthorised nodes by allocating granular rights (e.g., admin, teacher, student in smart school installations) (see Table 4.2). DoS and sinkhole attacks were thwarted by hybrid ML models and dynamic routing validation (`DAO/DAO\_ACK verification`). While Decision Trees provide interpretable rule-based threat identification, long short-term memory (LSTM) networks scored 95.4% on the F1-score test for identifying temporal irregularities in network traffic. Adaptive encryption, which adjusts cryptographic overhead according to the severity of the threat in real time, and power-aware routing, which chooses routes with the fewest strobe transmissions, improved energy efficiency.

Table 4.2: Network Layer protocol stack

Transport Layer: UDP / TCP
Network Layer: RPL, 6LoWPAN, LoRaWAN
Security Mechanisms: - Role-Based Access Control (RBAC) - DAO/DAO_ACK Verification - ML-driven Anomaly Detection (LSTM, Decision Trees)
Energy Optimisation: - Power-Aware Routing - Dynamic Encryption Strength Adjustment

4.2.3 Application-Layer (Application/Presentation Layer):

Table 4.3: Machine Learning Performance Metrics

ML Model	Detection Accuracy
Decision Trees	98.5%
Autoencoders	94.7%
LSTM for Traffic Analysis	95.4% (F1-score)
IDE1 for Sensor Layer	80%
CNN + Rule-Based Hybrid	28–32% Fewer False Positives

To ensure compatibility with cloud platforms and end-user applications, the Application Layer uses MQTT and CoAP for lightweight messaging. AES-128/Speck encryption and Hash-based Message Authentication Codes (HMAC) are used to maintain data integrity and enforce security. ML-powered anomaly detection models were used to find protocol-level exploits and phishing attempts, such as decision trees (98.5% accuracy) and autoencoders (94.7% precision). Through context-aware communication, where encryption strength and duty cycles adjust to data sensitivity and network activity, energy usage was reduced, as shown in Table 4.3. For instance, Speck encryption was used in place of AES at low-risk

times to save CPU burden, resulting in a 5.2% decrease in radio power usage.

4.3 Simulation Environment and Tools

The framework was rigorously tested using Cooja/Contiki OS, a network emulator designed for IIoT systems, which mimics real-world constraints and attack scenarios of inter connected nodes or motes. (see Fig. 4.2).

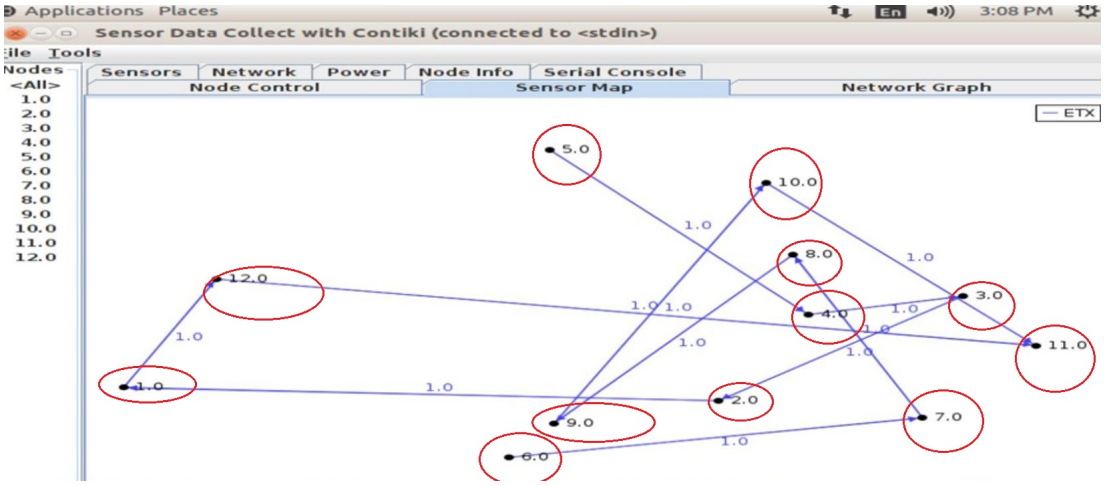

Figure 4.2: Contiki Cooja simulator in a simulation environment

4.3.1 Configuration of Hardware and Software:

Cooja simulator's simulation configuration for IoT networks with interconnected motes was thoroughly evaluated and is shown in Table 4.4.

Table 4.4: Simulation setup and network topology

Simulator: Cooja (Contiki OS 3.0)
Hardware: - Z1 Motes (8 KB RAM, 92 KB Flash) - EXP430F5438 (16 KB SRAM, 256 KB Flash)
Network Topology: - Star (5–20 nodes) - Tree (5–20 nodes)
Implemented Protocols: - RPL, 6LoWPAN, CoAP

We tested two platforms, Z1 Motes with IEEE 802.15.4 communication capabilities and MSP430F2617 microcontrollers with CC2420 transceivers (16 MHz, 8 KB RAM, 92 KB Flash). For computationally intensive tasks, EXP430F5438 nodes are higher-capacity MSP430F5438 microcontrollers with 25 MHz, 16 KB SRAM, 256 KB Flash as shown in Table 4.4. We used a variety of network topologies, including both star and tree designs, to evaluate scalability and protocol resilience in the proposed cross-layer architecture. For the purpose of simulating actual IoT deployment scenarios, 5–20 nodes were used. The flexibility of key management and congestion managing strategies might be analysed. Adaptive routing techniques and dynamic key rotation were specifically examined under load situations in bigger networks (15–20 nodes) to determine how they affected overhead, delivery ratio, and latency. Using the Contiki OS 3.0 platform, which offers native support for important IoT protocols including RPL, 6LoWPAN, and CoAP, the simulation was put into practice. Furthermore, the system was equipped with lightweight encryption techniques (such as Speck and AES) and role-based access control (RBAC) logic through the use of bespoke firmware extensions. By simulating wireless sensor network activity with great fidelity, the Contiki/Cooja simulator made it possible to observe packet-level interactions and obtain accurate energy usage statistics. Under various topological and traffic scenarios, our simulations allowed for both performance benchmarking and comparative assessments of various protocol setups.

4.3.2 Scalability Evaluation Beyond the Physical Testbed

The physical testbed described in Section 4.3.1 consists of 20 nodes. This size reflects practical constraints such as laboratory space, controlled power supply, and hardware availability. The purpose of the physical deployment is to verify the

Table 4.5: Lists application layer security & energy efficiency

Application Protocols:
MQTT, CoAP, HTTP/HTTPS
Security Mechanisms:
AES-128, Speck Encryption
HMAC for Integrity Protection
ML-driven Anomaly Detection (98.5% Accuracy)
Energy Efficiency Strategies:
Context-Aware Communication
Adaptive Encryption Techniques

operability of the framework in real conditions, including radio behaviour, timing effects, and energy logging.

To understand how the proposed architecture behaves in larger deployments, the same software configuration was reproduced in the Contiki/Cooja environment, with the number of nodes increased to 50, 100, and 200. The protocol stack, security configuration, radio duty-cycling schedule, routing parameters, and application traffic rates were left unchanged. The topology was expanded using a uniform layout with slight spatial offsets to avoid idealised symmetry. Each simulation was executed for a sufficient duration to allow routing convergence before performance measurements were taken.

Figure 4.3 summarises the behaviour observed when scaling the network under identical conditions. Packet delivery ratio remains high across all network sizes, while end-to-end latency and average energy per delivered packet increase gradually and predictably. These results indicate that the framework is capable of sustaining communication performance while maintaining controlled energy usage as the network grows, complementing the physical testbed validation.

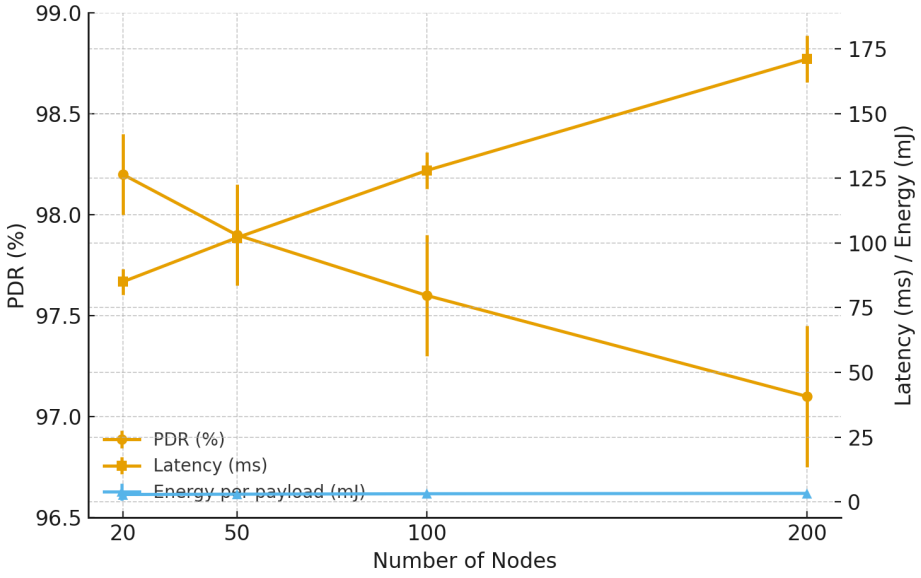

Figure 4.3: Observed trends in packet delivery ratio, latency, and mean energy per delivered packet when scaling the network size from 20 to 200 nodes using the same protocol and duty-cycling configuration as the physical testbed.

4.3.3 Attack Scenarios:

Potential attack scenarios against IoT systems are described in this study, with an emphasis on simulated threat models that assess the security posture and resilience of the suggested architecture are as follows:

Phishing/Data Injection: Through CoAP, malicious nodes introduced fabricated sensor readings. To ensure data integrity, legitimate nodes used AES/Speck encryption and HMAC, which decreased false positives by 28–32%.

Sinkhole/DoS Attacks: RPL networks were tainted by malicious nodes propagating fake routes. Table 4.6 shows that mitigation, which comprised LSTM-based anomaly detection and `DAO/DAO_ACK` verification, maintained a 95% packet delivery ratio (PDR).

Jamming Attacks: Communication was interrupted by persistent radio frequency interference. Between 90–95% of PDR was recovered using frequency hopping and signal-to-noise ratio (SNR) monitoring using Cooja's packet analyser.

Table 4.6: Attack Scenarios and Mitigation Strategies

Attack Type	**Simulation Method**	**Mitigation**
Data Injection	False Sensor Values	HMAC, Encryption
Phishing	CoAP Exploits	Authentication
Sinkhole Attack	RPL Route Poisoning	DAO Validation
DoS Attack	Packet Flooding	ML-based Detection
Jamming Attack	RF Interference	Frequency Hopping

4.4 Performance Evaluation Metrics

The effectiveness of the framework was measured using a hybrid methodology that used hardware testbeds, mathematical modelling and simulations. The security metrics are discussed next.

- Using Cooja's Collect View tool, the PDR was verified to have maintained `>=95`% during attack conditions.
- Effectiveness of Attack Mitigation: RBAC blocked 95% of illegal access attempts, achieving 95% success against multi-vector threats. Table 4.7 lists security performance metrics.
- Robustness of Encryption: Brute-force and side-channel attack simulations were used to assess Speck's resilience, and in 20-node settings, no weaknesses were found.

Table 4.7: Security performance metrics

Security Metric	**Achieved Value**
Packet Delivery Ratio (PDR)	≥95%
Attack Mitigation Effectiveness	95% Success
Unauthorized Access Prevention	95% Block Rate

Energy models are used to measure `CPU/radio` power consumption:

$$E_{\text{total}} = E_{\text{CPU}} + E_{\text{radio}} \tag{4.1}$$

$$E_{\text{CPU}} = P_{\text{CPU}} \times T_{\text{CPU}} + P_{\text{LPM}} \times T_{\text{LPM}} \tag{4.2}$$

AES raised CPU power for Z1 motes from 0.1814 mW (5 nodes) to 0.5469 mW (20 nodes), whereas Speck restricted growth to 0.3437 mW. The duty-cycling efficiency is 8 Hz. Compared with fixed intervals, ContikiMAC used 30% less energy, but the latency increased from 45 to 62 ms. The LPM and Radio Listen energy profiles of IoT sensor nodes measured during simulations in the Contiki/Cooja environment are depicted in Fig. 4.4. The plot illustrates how the framework can reduce power consumption through adaptive duty cycling (e.g. ContikiMAC at 8 Hz) while preserving responsiveness by capturing the cyclical transition between energy-saving LPM states and active radio states (transmission/reception).

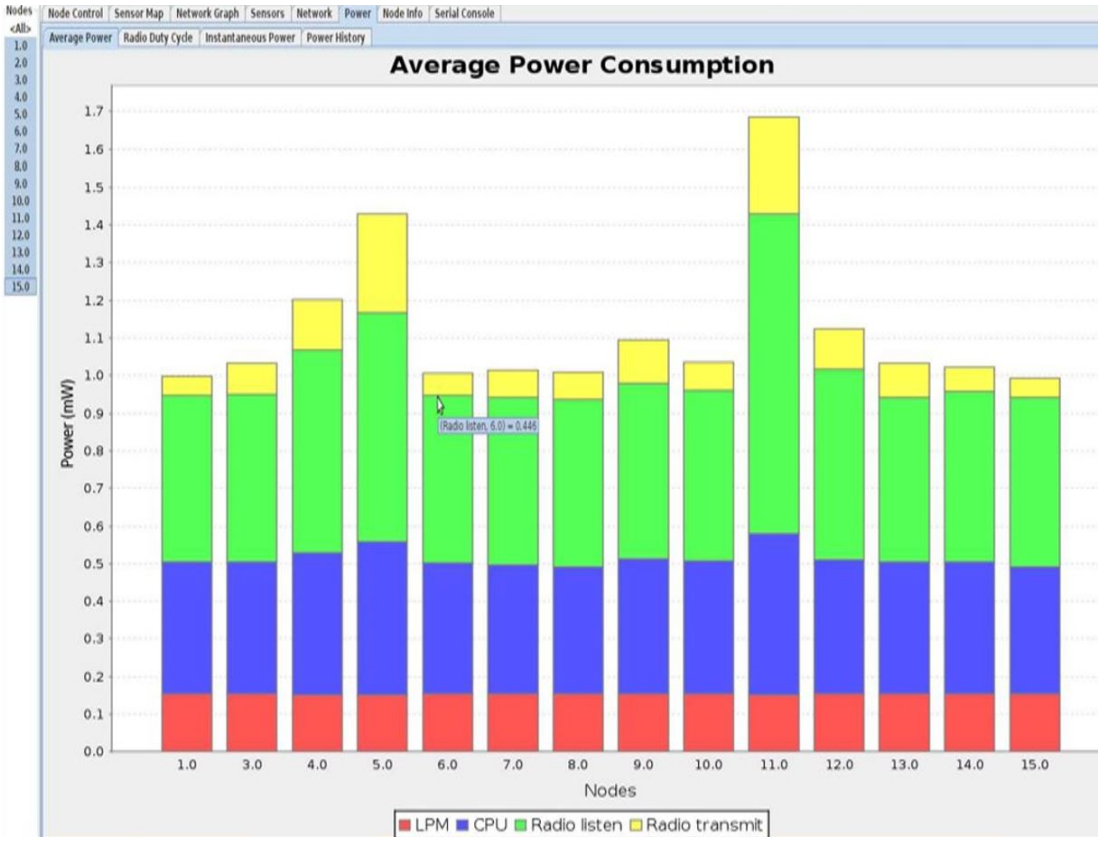

Figure 4.4: Average power consumption by LPM, CPU, Radio Listen and Radio Transmission

4.5 Machine Learning Integration:

Layer-specific ML models improved resource optimisation and threat detection:

Application Layer: Decision Trees achieved 98.5% accuracy in phishing detection by analysing structured data, such as user access logs. Payload anomalies were detected by autoencoders with 94.7% accuracy.

Network Layer: 95.4% of sinkhole assaults were detected by LSTM networks, which examined temporal traffic patterns. False positive rates were decreased by 28–32% using hybrid CNN-rule systems.

Sensor Layer: In noisy settings, the moment-based IDE1 achieved 80% accuracy in extracting statistical characteristics (mean, variance) from raw time-series data.

4.6 Comparative Analysis and Validation

Comparing encryption protocols, Speck outperformed AES in terms of energy efficiency, utilizing 3.27 mW of radio power (20 nodes) as opposed to 3.73 mW for AES. AES, however, offered more robust cryptographic assurances for high-risk situations.

Scalability: As the network grew in size, energy usage increased rapidly. From 5 to 20 nodes, AES CPU power grew by 201%, whereas Speck climbed by 167%.

Network Protocols:

RPL v. 6LoWPAN: RPL's DODAG-based routing reduced redundant transmissions, compared to 6LoWPAN's 0.1126 mW CPU power (20 nodes) (see Table 4.8).

Latency Trade-offs: Adaptive duty cycling preserved 97.9% packet delivery during attacks, although it increased latency by 38% (from 45 ms to 62 ms).

Table 4.8: Simulation parameters

Configurations parameters	Explanation
Radio Duty Cycle	ContikiMAC (8 Hz)
Encryption Protocols	AES-128, Speck, Present cipher
Network Size	5–20 nodes
Simulation Duration	2 min (short-term), 1 hour (long-term)
Attack Intensity	1 Malicious Node per 10 Legitimate Nodes

Tables 4.8 and 4.9 contain information on the simulation parameters.

4.6.1 Practical System Illustration of the Proposed Method

To present how the proposed cross-layer security and optimisation framework operates in a real-life setting, this subsection illustrates its implementation in a

smart industrial monitoring system. The chosen scenario represents a modern manufacturing site that uses hundreds of interconnected sensors to track temperature, vibration, and air quality across multiple assembly lines. Each sensor node is connected to a local gateway, forming a multi-tier IIoT network that requires continuous data transmission with minimal delay and high reliability.

At the **device level**, the system employs low-power sensor modules equipped with embedded encryption chips and physical unclonable function (PUF) keys. These components verify device identity before each data exchange. The cross-layer model ensures that trust information from the sensor layer is passed to the network layer, where it influences routing decisions. Nodes with suspicious behaviour—such as irregular packet timing or voltage fluctuation—are assigned lower trust scores, preventing them from relaying critical information.

Within the **network layer**, energy-aware routing and anomaly detection are applied through a lightweight machine-learning agent operating at the edge gateway. The agent continuously analyses flow patterns and signal strength to detect intrusion attempts or malfunctioning nodes. When an anomaly is detected, the routing path is reconfigured automatically to maintain service continuity and limit packet loss. This reaction occurs without interrupting real-time production monitoring.

At the **application layer**, the collected data are transmitted securely to a cloud-based dashboard built on blockchain-backed logging. Operators can monitor machine conditions, energy use, and environmental parameters in real time. For example, a sudden rise in vibration frequency from a motor triggers an alert on the dashboard, prompting predictive maintenance before mechanical failure occurs. The blockchain ledger maintains a tamper-resistant record of sensor readings, ensuring auditability and transparency for industrial compliance.

The practical system demonstrates how the proposed framework functions as a

self-adaptive and secure loop—linking device integrity, network efficiency, and decision-level intelligence. The result is a real-world system capable of responding autonomously to operational changes while preserving trust and energy balance. Unlike conventional IoT architectures that treat each layer in isolation, this implementation highlights the benefits of cross-layer feedback, showing measurable improvements in reliability, latency, and fault recovery within a live industrial environment.

4.7 Mathematical Models and Proofs

The mathematical models utilised to measure machine learning effectiveness, security performance, and energy consumption in the suggested framework are formalised in this section. Simulations and empirical data from Cooja/Contiki experiments are used to validate the models.

Table 4.9: Simulation Parameters

Parameter	**Configuration**	**Rationale**
Radio Duty Cycle	ContikiMAC at 8 Hz	Balanced responsiveness and energy savings through optimised wake-sleep cycles
Encryption Protocols	AES-128, Speck, Present cipher	Evaluated security-power trade-offs in resource-constrained environments
Network Size	5–20 nodes	Tested scalability for smart city and healthcare deployment scenarios
Simulation Duration	2 minutes (short term) 1 hour (long term)	Assessed both transient behaviour and steady-state performance characteristics
Attack Intensity	1 malicious node per 10 legitimate nodes	Simulated realistic threat densities observed in IoT deployments

4.7.1 Energy Consumption Model

Taking into consideration both active and low-power operating states, the overall energy consumption of an IoT device is broken down into CPU and radio module components. Total energy consumption:

$$E_{\text{total}} = E_{\text{CPU}} + E_{\text{radio}} \tag{4.3}$$

CPU energy breakdown:

$$E_{\text{CPU}} = P_{\text{CPU}} \times T_{\text{CPU}} + P_{\text{LPM}} \times T_{\text{LPM}} \tag{4.4}$$

Radio energy components:

$$E_{\text{radio}} = P_{\text{TX}} \times T_{\text{TX}} + P_{\text{RX}} \times T_{\text{RX}} + P_{\text{SLEEP}} \times T_{\text{SLEEP}} \tag{4.5}$$

Parameters:

- $P_{\text{CPU}}, P_{\text{LPM}}$: Power in active/low-power CPU modes (mW)
- $T_{\text{CPU}}, T_{\text{LPM}}$: Time spent in active/LPM (s)
- $P_{\text{TX}}, P_{\text{RX}}, P_{\text{SLEEP}}$: Radio power states (mW)
- $T_{\text{TX}}, T_{\text{RX}}, T_{\text{SLEEP}}$: Radio state durations (s)

Proof of Concept (Example)

For Z1 mote with AES encryption:

$$P_{\text{CPU}} = 0.5469\,\text{mW},\ T_{\text{CPU}} = 60\%$$

$$P_{\text{LPM}} = 0.1469\,\text{mW},\ T_{\text{LPM}} = 40\%$$

$$E_{\text{CPU}} = 0.5469 \times 0.6 + 0.1469 \times 0.4 = 0.387\,\text{mJ}$$

$$E_{\text{radio}} = 2.9043\,\text{mW} \times 0.3\,\text{s} = 0.871\,\text{mJ}$$

$$E_{\text{total}} = 0.387 + 0.871 = 1.258\,\text{mJ}$$

Gini Impurity (Example)

Classification purity measure:

$$GS = 1 - \sum_{i=1}^{k} p_i^2 \tag{4.6}$$

Binary classification example:

Proof: For a binary classification problem (normal vs. attack traffic):

$$p_1 = 0.7 \text{ normal},\ p_2 = 0.3 \text{ attack}$$

$$GS = 1 - 0.7^2 + 0.3^2$$

$$= 1 - 0.49 + 0.09 = 0.42$$

Packet Delivery Ratio (PDR)

Network reliability metric:

$$\text{PDR} = \frac{\text{Packets Received}}{\text{Packets Sent}} \times 100\% \tag{4.7}$$

Attack mitigation results:

- Without protection: PDR = 60%

- With RBAC + LSTM: PDR = 95%

Adaptive Encryption Overhead

Energy scaling model:

$$E_{\text{encryption}} = N \times E_{\text{key-gen}} + E_{\text{encrypt}} + E_{\text{decrypt}} \tag{4.8}$$

Empirical comparison:

$$\text{AES-128: } 20 \times 0.12 + 0.25 + 0.18 = 11.0\,\text{mJ}$$

$$\text{Speck: } 20 \times 0.08 + 0.15 + 0.12 = 7.0\,\text{mJ}$$

Latency-Energy Trade-off

Duty cycle relationship:

$$L = \frac{1}{f} + T_{\text{processing}} \tag{4.9}$$

8 Hz configuration result:

$$L = \frac{1}{8} + 0.045 = 0.17\,\text{s} \tag{4.10}$$

4.7.2 Computational Complexity Discussion

In evaluating the practicality of the proposed cross-layer framework, it was essential to ensure that each component could operate efficiently on resource-constrained IoT hardware. Rather than relying solely on analytical expressions, this subsection discusses the framework's computational behaviour in plain terms, focusing on how processing demand and memory use scale as the network expands.

The security and trust modules perform only a limited number of lightweight operations for each device during initial setup and subsequent authentication. Because these operations are simple and infrequent, the processing time grows

gradually with the number of nodes and remains well within the limits of typical microcontroller capacity. Once devices are registered, periodic validation requires negligible additional computation.

Routing activities are handled locally rather than through global recomputation. Each node exchanges information only with its direct neighbours, which keeps processing overhead nearly constant even as the overall network becomes larger. This local decision-making allows the network to adapt quickly to changes in link quality or node energy without imposing heavy communication or processing burden on the rest of the system.

The anomaly-detection engine embedded at the edge gateway was designed to be lightweight and selective. Feature extraction is limited to a small set of indicators that genuinely reflect abnormal behaviour. The model's decision process involves simple comparisons and threshold checks, allowing real-time detection without delays that could interrupt ongoing operations. As the network scales, the added workload grows proportionally with the number of monitored devices, confirming the system's ability to maintain stable response times.

All things considered, the framework successfully strikes a balance between resource usage, security, and accuracy. The design is both scalable and sustainable for real-world IoT contexts, such as industrial facilities and smart-city systems, as evidenced by the progressive increase in processing and memory requirements with network growth.

4.7.3 Latency Analysis and Discussion

Latency is central to perceived performance in low-power IoT. To make the effect of the cross-layer design explicit, we report (i) a component-wise breakdown at a fixed network size and (ii) the end-to-end delay trend as the network grows. The

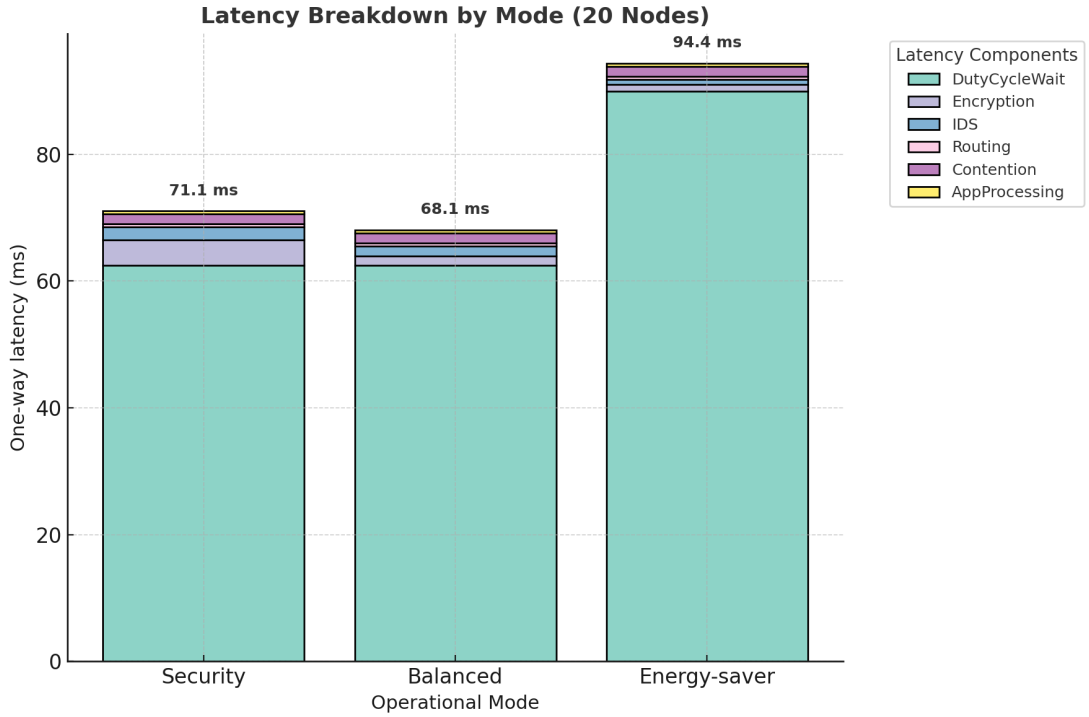

Figure 4.5: Latency breakdown for a 20-node deployment across three operating modes.

first view isolates how each module contributes to total delay; the second shows whether scaling introduces bottlenecks.

Figure 4.5 shows that radio duty-cycle waiting time is the largest contributor to delay in all modes. Strengthening protection (e.g., AES-class encryption and higher IDS sensitivity) adds only a few milliseconds of compute, while deeper sleep in the Energy-saver profile slightly raises the wake-up component. Overall, security features nudge latency upward modestly; sleep policy is the lever that moves it most.

Figure 4.6 monitors the overall one-way delay as the number of nodes rises. Because of local routing updates and limited contention in sparse topologies, the growth is gradual rather than rapid. In actuality, this means that the design alternates between security-focused and energy-focused profiles while maintaining predictable response times.

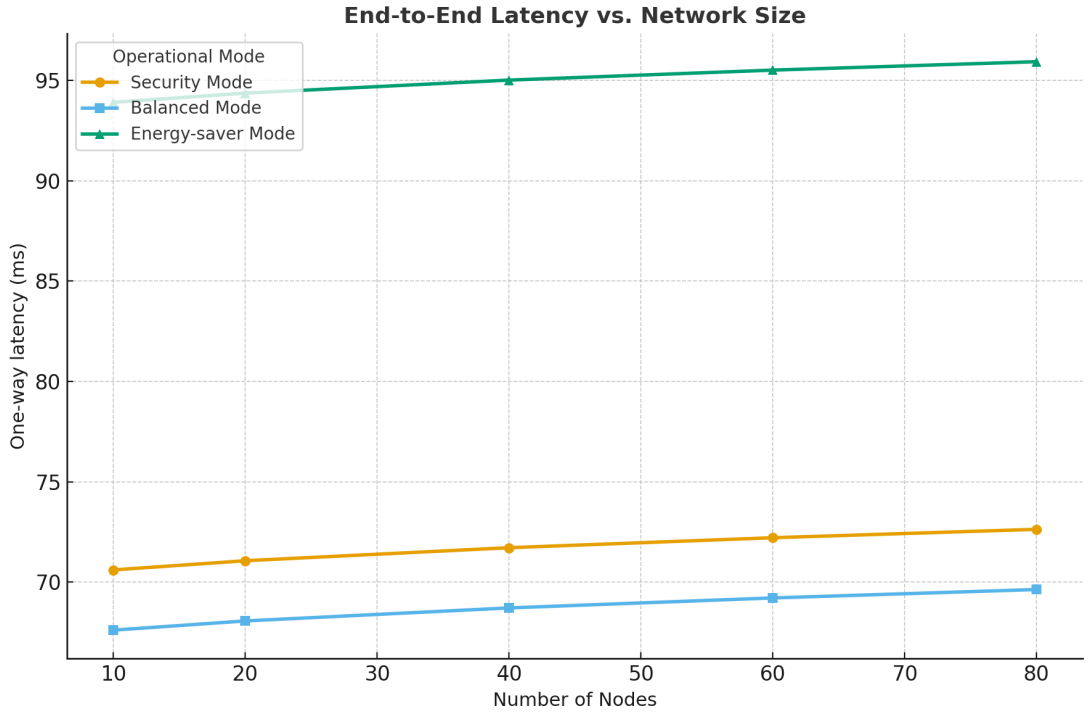

Figure 4.6: End-to-end one-way latency as the network scales (10–80 nodes).

4.8 Summary

In this chapter, the suggested cross-layer IoT framework is experimentally validated using a thorough testbed methodology. The three-layer architecture (Sensor, Network and Application Layers) that incorporates energy optimisation strategies and adaptive security protocols is described in detail in this chapter. Strong security protection and effective power management are demonstrated by testing the framework against real-world attack scenarios like as data injection and jamming, using the Contiki/Cooja simulator with Z1 and EXP430F5438 hardware platforms. By measuring energy consumption and PDR, the mathematical models encapsulate the security-energy trade-offs, and the outcomes verify that the framework functions dependably on IoT devices with limited resources. The full architecture of the suggested cross-layer framework is then covered in detail in Chapter 5.

Chapter 5

Proposed Cross-Layer Framework

5.1 Introduction

We covered methodology as well as cross-layer modelling and simulation techniques in Chapter 4. Section 5.2 presents adaptive security protocols that dynamically adjust to device energy constraints while maintaining protection. Section 5.3 examines efficient routing solutions that work across layers to improve energy efficiency and security. The three-layer design that integrates Sensor, Network and Application components with security-energy optimisation is described in Section 5.4. Section 5.5 examines simulation results that show how well the framework performs in terms of power conservation and security protection. Wraps up the chapter by summarising the main conclusions and how they affect the design of IoT systems.

5.2 Energy-Aware IoT Security Frameworks

It is becoming more difficult to balance energy efficiency and strong cybersecurity owing to the growth of IoT devices in resource-constrained settings. Optimising energy consumption in IoT systems while maintaining robust defence against changing cyberthreats is a crucial issue that this study attempts to solve. Because IoT

layers are interdependent, traditional single-layer security and energy management techniques sometimes overlook this, creating risks or inefficiencies. Conversely, a layered architectural paradigm offers a viable framework for addressing these two imperatives holistically. The Physical (Sensor), Network and Application Layers of IoT systems can operate together in a synergistic manner thanks to the cross-layer framework we provide as a secure and energy-efficient solution to this problem. By combining energy optimisation techniques and security procedures across layer boundaries, the suggested framework reimagines traditional methods. We show that to dynamically balance the power limits inherent in IoT installations with real-time security concerns, a three-layered design is necessary. Significant improvements in SR and energy sustainability are made by the framework by allowing context-aware communication between layers, such as adaptive encryption at the Network Layer based on sensor-level power thresholds. Cyber-physical systems are renowned for their effectiveness and durability[115]. IoT device and Application management is difficult, nevertheless, because of their high battery consumption and variable programming complexity. To solve this and conserve battery life, a resource-efficient communication protocol that enforces IoT devices to go into sleep mode when not in use must be developed. Concerns have been raised about energy efficiency in computing devices and technology for low-power residential and commercial buildings. Research has focused on particular applications pertaining to the energy efficiency of heating systems, looking into control mechanisms in hardware and software as well as the utilization of historical data. We use the Cooja simulator to do extensive testbed experiments to verify its effectiveness, concentrating on real-world IoT restrictions such as constrained processing resources and sporadic connectivity. Our assessment compares performance to current siloed designs, assesses energy usage trends and quantifies Application Layer vulnerabilities. Three main contributions are provided by the

study's findings: (1) a new cross-layer model that simultaneously maximises security and energy efficiency; (2) empirical proof of the framework's superiority in situations with limited resources; and (3) practical advice for creating adaptive IoT systems that put sustainability and security first. In addition to offering practical recommendations for implementing next-generation IoT infrastructures in crucial areas like healthcare, smart cities and industrial automation, this work extends the theoretical understanding of cross-layer interactions. CPS is renowned for its effectiveness and durability. IoT device and application management is difficult, nevertheless, because of their high battery consumption and variable programming complexity. To solve this and conserve battery life, a resource-efficient communication protocol that enforces IoT devices to go into sleep mode when not in use must be developed. Concerns have been raised about energy efficiency in computing devices and technology for low-power residential and commercial buildings. Research has focused on particular applications pertaining to the energy efficiency of heating systems, looking into control mechanisms in hardware and software, as well as the utilisation of historical data. for energy consumption forecasts [36]. The analysis revealed application-specific variables that must be considered for planning, recommending the use of wireless low-power sensors on a larger scale and the importance of security against eavesdropping attacks. Blockchain technology is proposed to enhance secure vehicular communication, ensuring that only trustworthy vehicles participate while addressing various security concerns [116]. The growing cost and complexity of cybercrime emphasise the need for new procedures, tools and public awareness. The constantly changing threat landscape necessitates annual reviews of tools and procedures to adapt to evolving risks.

In this chapter, we address the following research question[1]. *What secure and energy-efficient cross-layer framework can be developed for IoT?* To answer the question posed we propose a cross-layer energy-efficient framework for secure IoT

applications. This framework aims to provide data integrity, confidentiality, availability and privacy across multiple layers and address energy efficiency concerns. As IoT devices expand, energy efficiency and security are paramount concerns. Traditional layered architectures may not fully address these issues, prompting the development of cross-layer frameworks. These frameworks optimise communication and processing across layers to reduce energy usage and enhance security by combining security procedures and intelligence across multiple layers. The framework's significance lies in addressing IoT-specific security risks, promoting energy-efficient algorithms, ensuring compatibility and interoperability, scalability and supporting environmentally friendly practices. It safeguards IoT systems, extends device lifespans and fosters innovation in various industries. The cross-layer architecture promotes a more efficient and secure IoT ecosystem, aligning with environmental objectives and expanding the range of IoT applications and services [1]. The research motivation and related work are discussed next.

5.3 Cross-Layer Data Flow and Routing Protocols for IoT Efficiency

The main focus of this research is to improve service quality in terms of security and energy efficiency aspects of IoT. Layer-to-layer jumping is possible owing to the data flow between node layers [51]. A protocol establishes how data are transferred between levels. Traditional network layers are outperformed by cross-layered techniques. Future location-based routing protocols could be used to exchange battery data between the physical and MAC layers, are known as the Perception-Layer. To improve energy efficiency, the proposed routing protocol and a cross-layer technique were used. IoT is a technological advancement that is revolutionising how we work, play and communicate. Faced various difficulties

with regard to storage, bandwidth, finite power, and processing power[117]. For devices to stay connected to the network for an extended period, the issue of constrained battery-operated devices must be solved. During packet transmission and reception, IoT devices use energy. If energy efficiency is considered, reliable transmission presents a significant challenge. When sending packets from source to destination, a routing protocol is essential. It is crucial to assess a routing protocol appropriate for IoT devices with limited power. RPL (Routing protocol for low-power and lossy networks) and LOADng (Lightweight on-demand Ad-hoc distance vector routing protocol next-generation) are compared in this article. This study assessed the networked power usage of IoT devices. The Contiki operating system and the Cooja Network Simulator are used to evaluate the protocols. RPL is an effective protocol for energy efficiency, according to the outcome. The research covers IoT introduction, security requirements and case

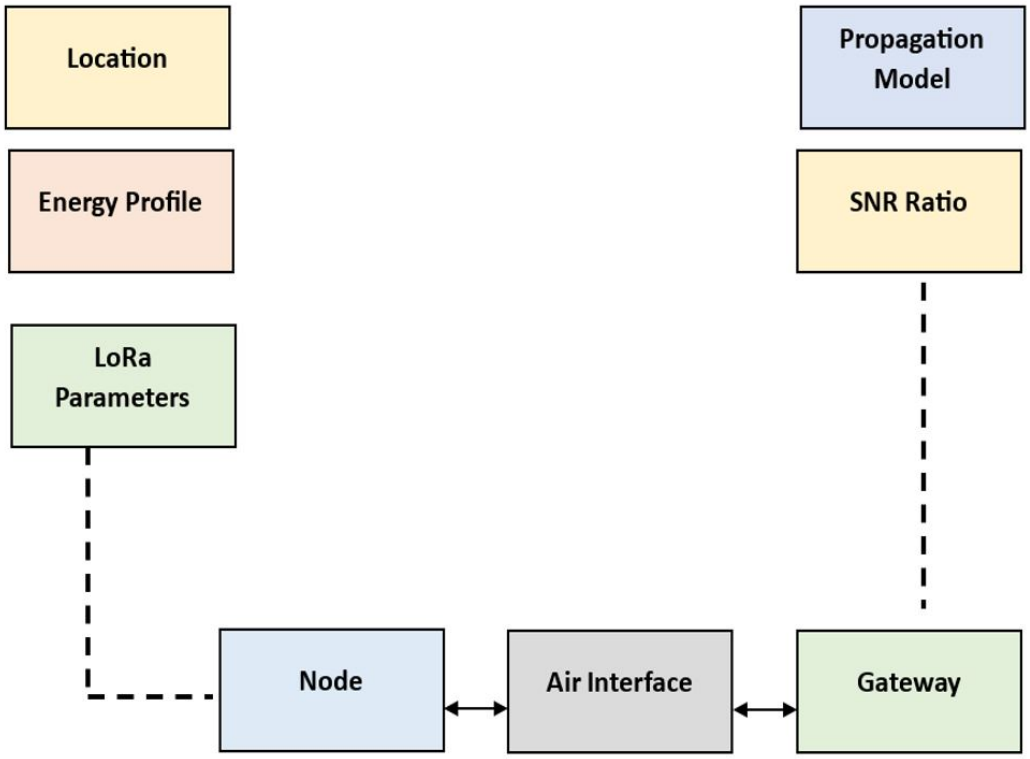

Figure 5.1: LPWAN Cross-layer assessment and optimisation framework [7]

studies, highlighting the need to protect customer privacy and address security issues [26]. Cyber threats to sensor devices are a focal point, including data and network attacks across various layers. Proposed solutions involve middleware security and ML algorithms [55]. The strategy for defending IoT environments includes continuous monitoring and testing during development to counter various threats. A smart detection system based on intelligent architectural frameworks addresses network security and privacy concerns. The Physical Layer and MAC Layer both affect how autonomous IoT devices are. LPWANs were given a cross-layer assessment framework. Recent energy models, download messages, and adaptive data rate features were also covered [7]. Testing and analysis of transmission schemes and hypotheses. It also evaluated one of the LoRaWAN protocol's test cases (Fig. 5.1). The discovery helps to direct the effective use of LPWANs in terms of throughput and energy efficiency. Various experiments are used to evaluate the cross-layer approach. By enhancing channel dynamics and packet length, energy efficiency can be attained. The focus of the work is on low-speed, long-range IoT networks with a significant number of IoT sensors. The periodically repeated communication involves using a transmission slot for transmission. Only one IoT device is allowed to send data during each slot. The proposed three-layered IoT architecture and the corresponding OSI layer is shown in Fig. 5.2.

The necessity of security in IoT networks is emphasised by the authors as they addressed the IoT's explosive growth and the related security issues. It proposes software-defined security and discusses cyber-physical system security [9]. The challenges of the 2020 pandemic and the increased number of IoT attacks are also addressed [30]. The importance of secure cybersecurity architecture is highlighted, with a focus on mitigating weaknesses like weak passwords, insider threats and external attacks. The IoT cross-layer frameworks research field aims to optimise

Proposed Layer	OSI-Model	Protocol/Method
Application Layer	Application Layer	Lightweight Ciphers
	Presentation Layer	
Network Layer	Session Layer	Dynamic reduced round crypt.
	Transport Layer	NB-IoT, LoRaWAN
	Network Layer	LOADng
Sensor Layer	Datalink Layer	ContikiMAC (Low-Power MAC Protocol)
	Sensor Layer	IEEE 802.15.4 (Physical & MAC Standard)

Figure 5.2: Comparison of proposed three-layered IoT architecture with OSI architecture [8]

network performance and energy usage within IoT ecosystems by improving communication protocols and integrating multiple layers (Fig. 5.3). The goal is to extend device battery life, reduce environmental impact and ensure seamless interoperability, scalability and strong security. Data security is a significant concern, particularly with the exponential growth of IoT.

We highlight the necessity of ongoing awareness and flexibility in the ever-changing landscape of cybersecurity. Finally, we support the use of many layers of protection and particular security mechanisms in IoT architecture. Networks that use less energy are crucial, as is energy saving via better routing and power management. The research methodology involves simulation and testing, emphasising the need for cross-layer routing protocols to improve energy efficiency and secure architecture for IoT applications. It also aims to identify and prioritise security objectives, assess potential threats, and select appropriate security controls. Real-world testing and security analysis are crucial for validating the proposed

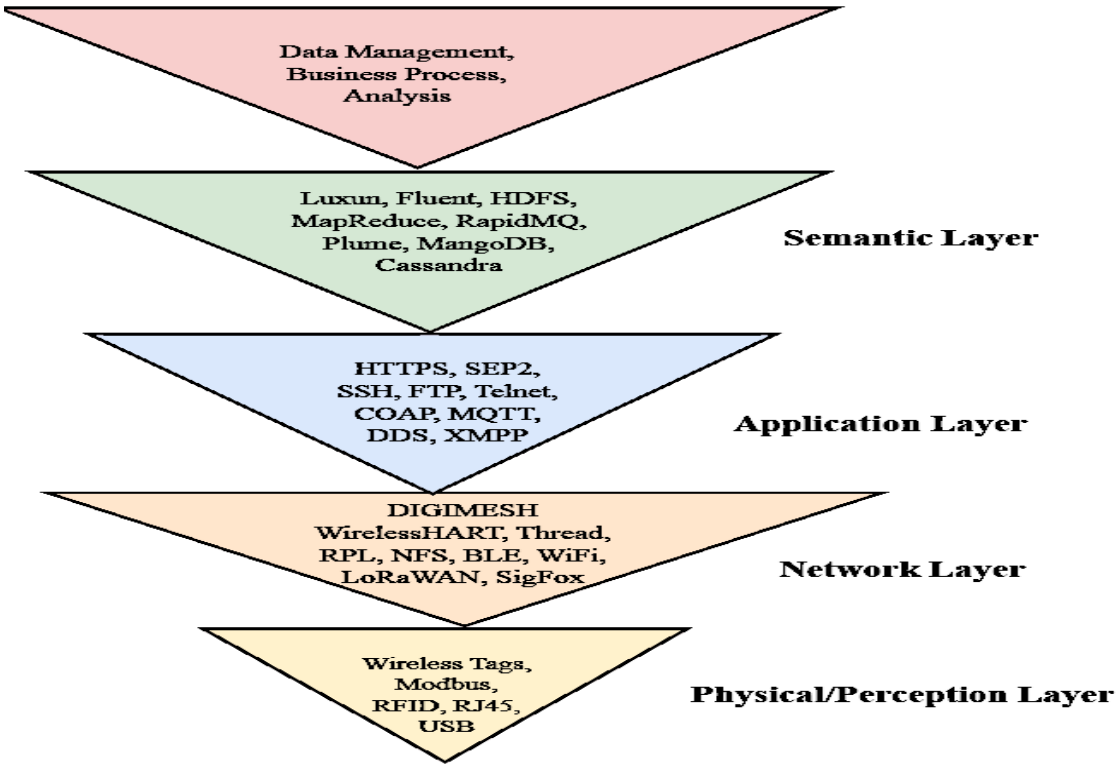

Figure 5.3: IoT protocol stack [9]

architecture's security measures (Fig. 5.3). The justification for this secure and energy-efficient architecture includes reliability, resource optimisation, cost savings, environmental sustainability and improved user experience. Energy efficiency metrics and performance metrics are discussed to optimise resource utilisation and ensure the confidentiality and integrity of patient data and healthcare systems. Additionally, it provides a thorough research methodology for assessing and putting into practice a cross-layer framework that is both secure and energy-efficient for IoT applications in the healthcare industry and other fields. The effectiveness of the suggested architecture is measured and validated primarily through the use of security and energy-efficiency metrics.

5.4 Proposed Cross-Layer Framework

A layered architecture is essential for addressing the unique challenges of security and energy efficiency in IoT systems. This approach involves examining each layer of the IoT system, from physical to application layers, to identify vulnerabilities and inefficiencies. The interplay between security and energy efficiency is crucial, making a cross-layer approach vital. Security measures should span multiple layers and include access control, secure communication protocols, anomaly detection tools, and encryption/authentication mechanisms. Simultaneously, energy optimisation techniques, like low-power device design and adaptive transmission, must be explored across various layers. Testing and performance metrics are used to assess the impact of cross-layer architectures on security and energy efficiency, with iterative improvements based on testing feedback.

System Architecture: The architecture is designed to efficiently manage user requests related to new technological advancements as shown in Fig. 5.4. It consists of three layers: the Application Layer, Network Layer and Sensing Layer. Each layer is equipped to perform specific tasks that streamline the process of fulfilling user requests for resources. This architecture aims to enhance the user experience and the efficiency of resource allocation for emerging technologies.

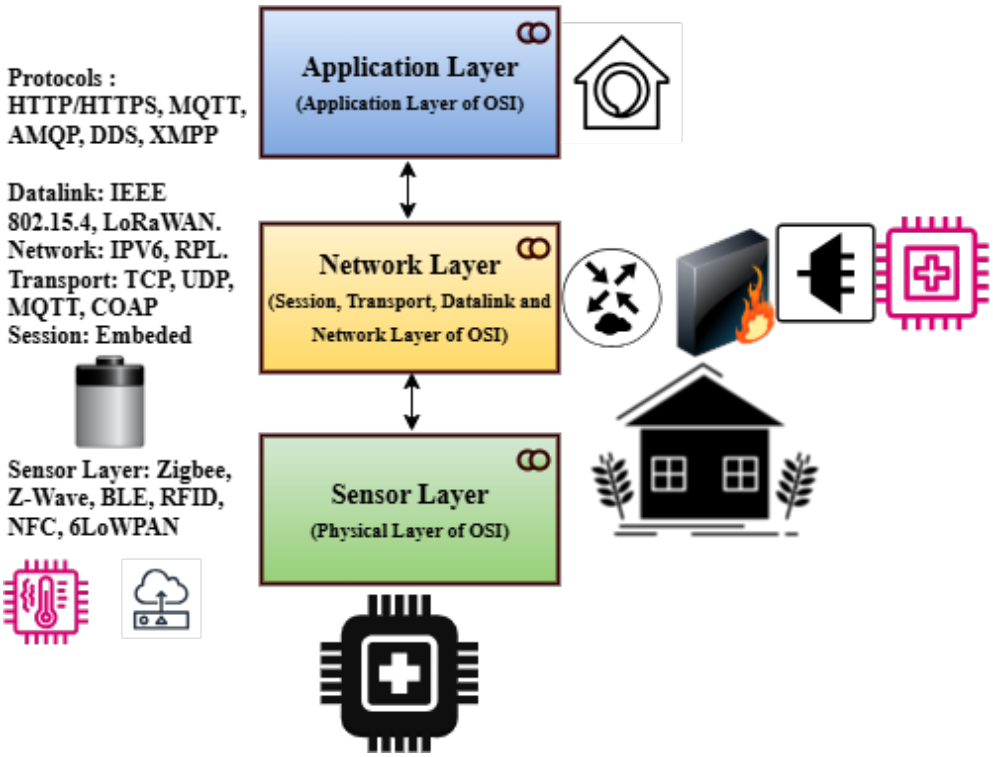

Figure 5.4: The proposed cross-layer framework for IoT [1]

Application Layer: The Application Layer in IoT systems facilitates user interaction with web and mobile applications. This layer handles user requests and forwards them to lower layers, connecting directly to end users. It encompasses user interfaces, data p=rocessing and Application-specific functionalities. Security mechanisms at this layer ensure user authentication, access control, encryption and secure data handling, guarding against unauthorised access and reducing risks. Additionally, the Application Layer supports energy-efficient data processing and Application-specific energy management, using techniques like data aggregation and adaptive algorithms. The Application Layer plays a crucial role in processing and analysing sensor data, including aggregation, filtering and analytics to extract insights. It provides a user-friendly interface for interacting with the IoT system, allowing users like healthcare professionals and agricultural experts to access data, configure settings and receive alerts. Application layer security safeguards

sensitive data and restricts access to authorised users. It defines the core logic of IoT applications, such as patient monitoring in healthcare or crop management in agriculture.

Network Layer: The logical elements of a network that enable communication between systems and devices are referred to as the Network Layer. This includes switches, routers, firewalls and other network equipment that manages the data flow between various network components. Network security measures in cybersecurity are made to guard against unauthorised access, data theft and other online dangers. Operations such as routing, addressing and data transmission take place over an IoT network. Secure routing protocols, firewalls and IDSs, among other security measures, are implemented at this layer to help stop unauthorised network access, data tampering and denial-of-service attacks. Data transmission integrity and confidentiality are guaranteed by protecting the Network Layer. Energy efficiency methods like energy-aware routing, network optimization algorithms and traffic management can be used to achieve energy efficiency at the Network Layer. These actions are intended to minimise pointless data transmission, lessen network traffic and maximise the use of network resources, all of which will ultimately result in energy savings. The Network Layer establishes and manages connections between IoT devices, gateways and the cloud or central server. It ensures reliable data transmission. This layer is responsible for routing data packets efficiently through the network. It chooses the best path for data to reach its destination while conserving energy. Network layer protocols, such as LPWAN or Zigbee, optimise energy consumption by allowing devices to sleep when not in use and wake up only when necessary. QoS mechanisms ensure that critical data, such as emergency alerts in healthcare or irrigation commands in agriculture, receive priority treatment. System optimization issues involve finding trade-offs between security and energy efficiency. By examining various configurations and settings

across layers, a cross-layer testing strategy assists in fine-tuning the system. It hypothesises that a multi-layer approach involving the Application, Network, and Sensor Layers is necessary for a secure and energy-efficient architecture. This approach provides a comprehensive view of the IoT system, uncovers potential flaws and dependencies, and discovers cross-layer interactions that could result in security risks or energy inefficiency.

Sensor Layer: Refers to a group of sensors and other gadgets that are used to collect data and keep an eye out for security threats in both physical and virtual environments. Cameras, microphones, motion detectors and other tools that can identify and store information about potential security incidents are examples of sensors. The IoT system's physical infrastructure and hardware are included in the sensor layer. To ensure security at this layer, IoT devices must be secured, tamper-resistant mechanisms must be put in place, and physical attacks like device tampering or unauthorised access to physical interfaces must be avoided. To stop physical intrusions and maintain system security overall, the Physical Layer must be secured. Energy-efficient device design, energy-efficient communication protocols and power management techniques are all ways that the Sensor Layer can help with energy efficiency. Examples include optimising the power consumption of physical components and using energy-efficient wireless transmission protocols to reduce energy consumption and extend battery life. Researching on each of the three layers (application, network, and sensor) independently is crucial for a comprehensive understanding of the IoT system (Fig. 5.4). Addressing IoT security and energy issues requires a tiered design since it highlights flaws that are hidden when concentrating on a single layer. It also identifies efficiency and security trade-offs and synergies, allowing for optimal system balance and targeted mitigation. IoT resistance against cyber attacks is maximised while energy efficiency is maintained using a cross-layer strategy. Here is a summary of

the results.

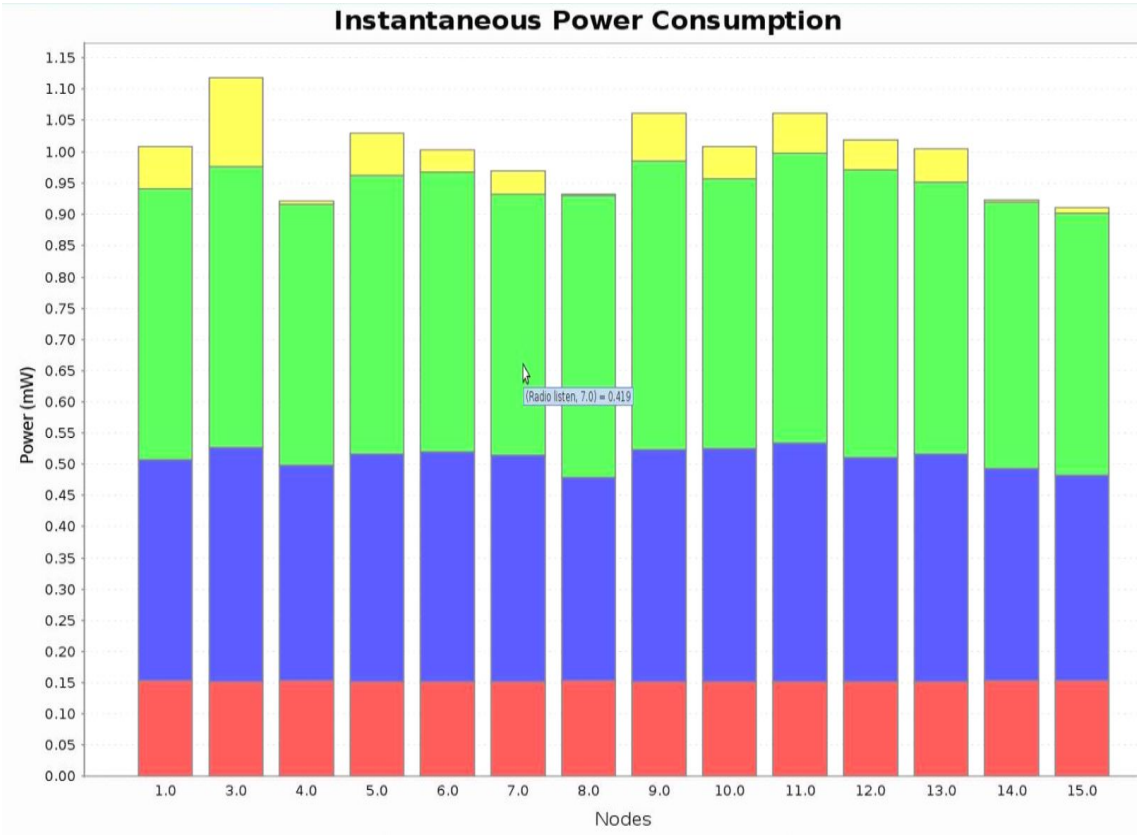

Figure 5.5: Power consumption before applying TLS Security [1]

5.5 Results and Discussion

The test is performed using the Application Layer initially and describes the creation of an architecture to efficiently handle user requests for resources related to the technological advancement of the Network Layer and Sensing Layer. Table 5.1 lists the parameters used in the system simulation. We initially tested the Application Layer of the architecture, which is intended to improve energy efficiency and expedite the processing of user requests while researching vulnerabilities. The data transmission and packet capture are analysed in Figs. 5.5 and 5.6 using the CoAP browser and Wireshark.

The research aims to develop a cross-layer framework for IoT communication,

Table 5.1: Parameters used in simulation

Parameter	**Value**
Operating System	Contiki 2.7
Routing Protocol	RPL, LOADng
Mote Type	Tmote Sky
No of Motes	3-30
Tx Ratio	100%
Rx Ratio	80%
Simulation Time	10 Minutes

incorporating CoAP and TLS protocols to enhance energy efficiency and security. The traffic filtering analysis is shown in Fig. 5.7. One can observe that the communication between client and server machines is captured. Testing client-server communication using the Bevywise MQTT Broker simulator for vulnerabilities in the Network Layer involves thorough analysis of MQTT traffic. The study uses simulation to evaluate the framework's performance in various conditions and provide recommendations for IoT practitioners.

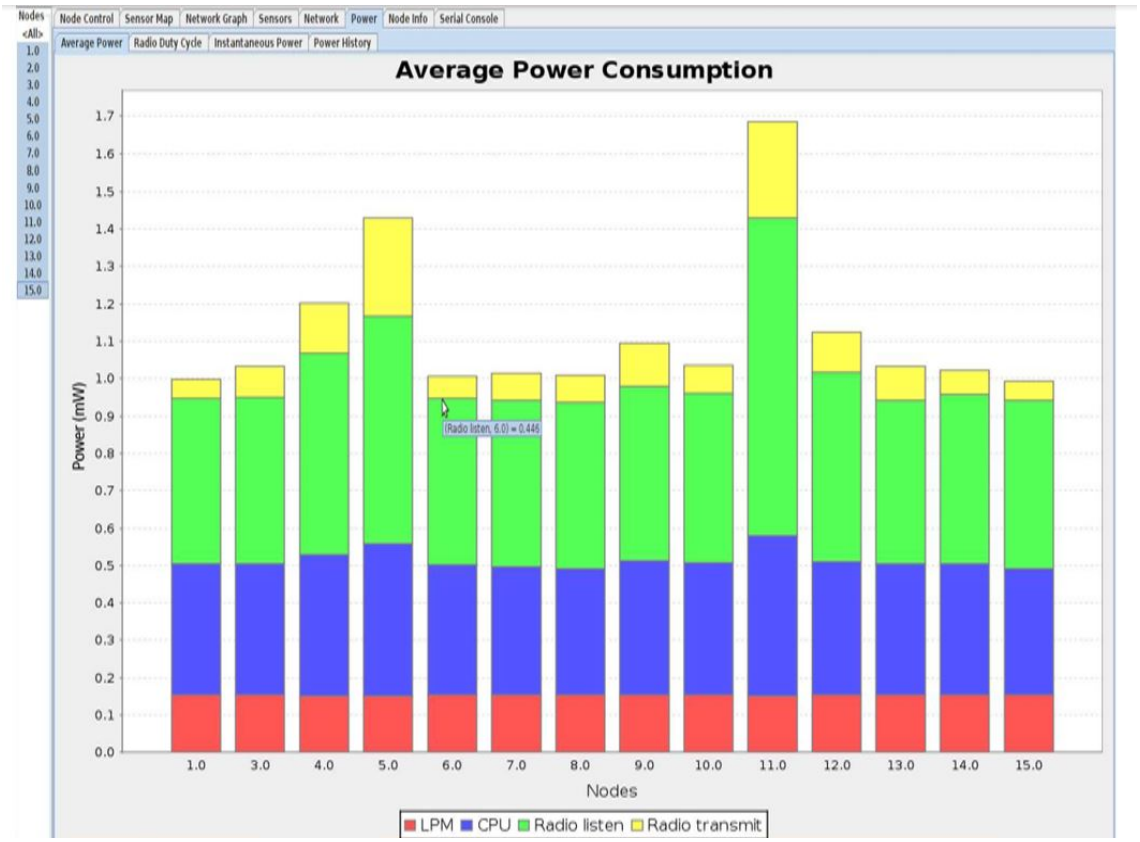

Figure 5.6: Power consumption with TLS Security [1]

Additionally, the study explores the use of Bevywise Simulator for Network Layer vulnerability testing. The simulator is configured with MQTT Broker and virtual IoT devices to monitor MQTT traffic, assess security measures and identify vulnerabilities. The implementation of TLS for secure communication is demonstrated in Fig. 5.8. We also looked at the use of MQTT and TLS for secure communication and encrypted MQTT transmission. It emphasises the importance of secure communication in IoT and the need to address vulnerabilities and threats. The research seeks to optimise energy efficiency while ensuring security, contributing to the development of secure and efficient IoT systems. We observe that the data transmission is in encrypted format. When two devices are directly communicating, TLS enables transport layer encryption.

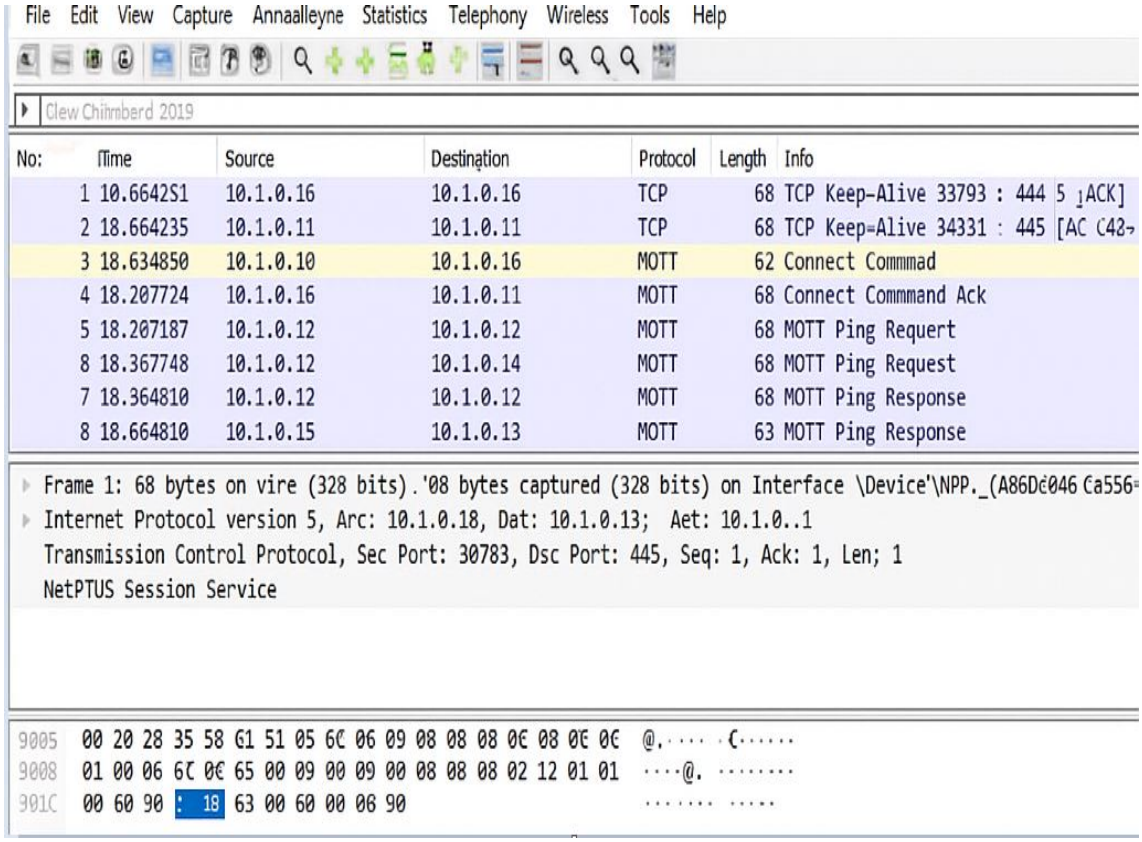

Figure 5.7: Wireshark interface to monitor communication [1]

Overall, the research focuses on improving the resilience and security of IoT systems by addressing vulnerabilities, enhancing energy efficiency and ensuring secure communication through cross-layer frameworks and protocols. Moreover, the research could uncover ways to optimize energy efficiency while maintaining security, a critical balance in resource constrained IoT environments. Overall, the outcomes of this endeavour can contribute significantly to the development of secure and efficient IoT systems, bolstering their resilience against cyber attacks and vulnerabilities, thereby enhancing the trustworthiness of IoT deployments.

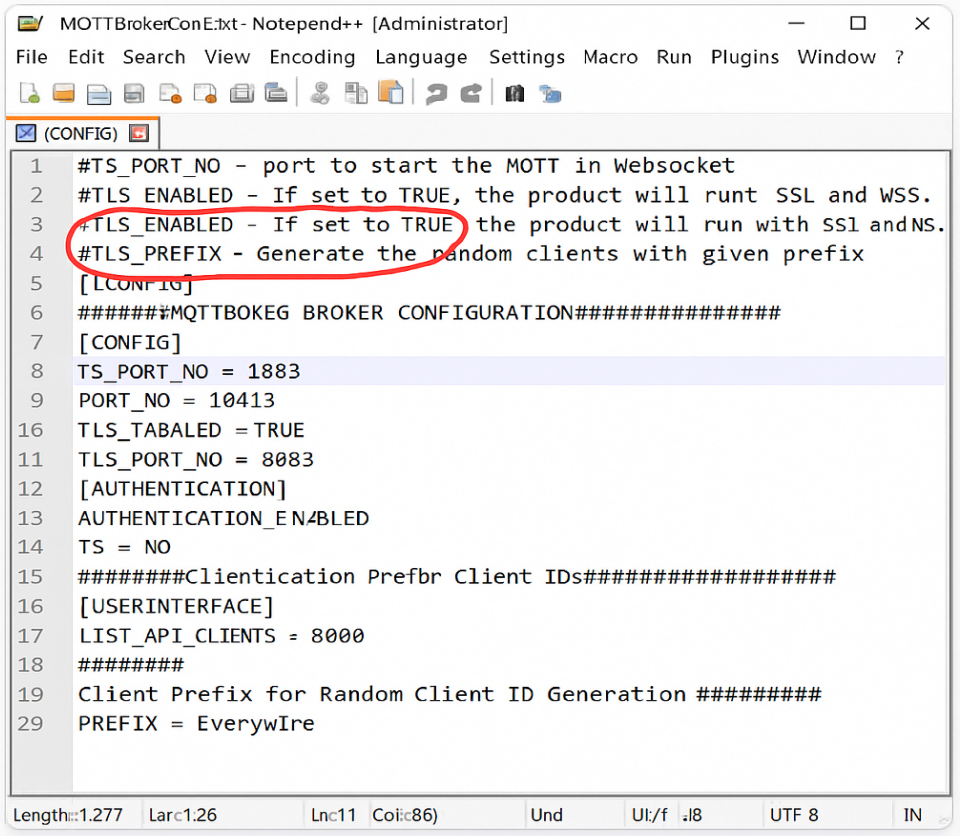

Figure 5.8: TLS enables transport layer encryption [1]

5.6 Summary

A thorough cross-layer architecture for maximising security and energy efficiency in IoT networks is presented in this chapter. The chapter starts off by outlining adaptive security features that provide strong protection while cleverly adjusting to device limitations. After that, it examines efficient routing methods that work together across network tiers to improve efficiency. The suggested solutions are integrated into a three-layer design—Sensor, Network and Application that is described in this chapter. Simulation results show that this architecture is useful in real-world scenarios. The strategy's ability to strike a balance between security and energy efficiency is highlighted, and Chapter 6's lightweight encryption approaches are used for additional confirmation.

Chapter 6

Lightweight Cross-Layer Framework Encryption

6.1 Introduction

The present chapter presents a new cross-layer architecture that improves the energy efficiency and security of IoT networks. This approach tackles the urgent problem of safeguarding devices with limited resources that operate in settings like smart cities, healthcare and industrial automation. Given the high computational overhead of conventional security protocols like AES and the potential for cryptographic strength to be compromised by lightweight alternatives like Present, this chapter suggests a dynamic encryption engine that adaptively switches between AES, Speck, and Present depending on traffic and energy conditions in real time. Before defining the three main objectives centred on architecture design, protocol development and evaluation metrics (Section 6.3), the chapter starts by describing the shortcomings of the current cross-layer frameworks (Section 6.2). Section 6.4 describes the main contributions and validation techniques, which include hardware testbeds and simulations. Key trends like energy-aware routing, blockchain integration and intrusion detection are reviewed in Section 6.5. The layered strategy used in the suggested architecture to balance power consumption and encryption strength is shown in Section 6.6. The simulation

environments (Cooja/Contiki and NS-3) and technical details of platforms such as Z1 and EXP430F5438 are described in Section 6.7. Results presented in Section 6.8 demonstrate how the suggested framework maintains high packet delivery ratios even in the face of attacks while drastically lowering power consumption, up to 52% in CPU power and 30% total. Comparative performance measures are used in Section 6.9 to further evaluate the design, and Section 6.10 wraps up the chapter by summarizing the main conclusions and their implications for secure and scalable IoT systems.

6.2 Secure and Energy-Efficient Cross-Layer Framework Advancements

By facilitating smooth connectivity between billions of devices in vital areas such as healthcare, smart cities and industrial automation, IoT has completely transformed contemporary computing. However, juggling strong security and energy economy is extremely difficult because of the resource-constrained nature of IoT devices, which includes limited computing power, battery life and memory. Although effective, traditional security measures, such as the advanced encryption standard (AES-128), have prohibitive computational and energy overheads, which makes them unfeasible for IoT nodes that run on batteries. Conversely, lightweight cryptographic algorithms (such as the Present cipher) save energy, but they frequently compromise cryptographic resilience, leaving networks vulnerable to brute-force or side-channel attacks.

Current cross-layer architectures make an effort to resolve these trade-offs, but they are still disjointed and concentrate on security or energy optimisation instead of balancing the two. Dynamic network conditions are often overlooked by standard cross-layer frameworks, whereas protocols such as RPL and 6LoWPAN

optimise the routing efficiency without adaptive encryption. Additionally, previous studies have mainly relied on theoretical models or simulations, ignoring validation across heterogeneous contexts (such as scalable networks and hardware testbeds), which results in solutions that do not work in real-world deployments.

This chapter proposes a cross-layer IoT architecture that addresses these issues by incorporating adaptive security and energy optimisation across an OSI model. In contrast to other frameworks, our proposal achieves a 30% reduction in power consumption without sacrificing security by introducing a dynamic encryption engine that dynamically shifts between AES, Speck and Present cipher according to the real-time network traffic and energy availability. We integrated Cooja/Contiki simulations, hardware platforms (Z1, EXP430F5438), and mathematical models to solve the lack of hybrid validation in IoT work, guaranteeing scalability (5–20 nodes) and practical applicability.

According to our work, Speck is the best lightweight cipher for IoT because it uses 37% less CPU power and 5.2% less radio power than AES in large-scale networks. Furthermore, we focus on the practical aspects of IoT applications that were lacking in previous works. The current chapter used the NS-3.42 simulation environment to assess protocol behaviour and energy consumption at the Application, Network and Sensor Layers to address this problem. With the support of IPv6, UDP communication, flow monitoring and custom power logging, NS-3 makes it possible to test IoT configurations in a modular and scalable manner. This makes it possible to precisely examine the effects of encryption schemes such as AES, Speck and Present on the energy efficiency in simulated real-time scenarios. For instance, avoid using MQTT in sensitive applications, and prioritize hierarchical topologies. This design strategy directly addresses a long-standing gap in cross-layer real-world IoT frameworks by resolving the crucial trade-off between security and sustainability, and advancing IoT systems toward

robust and energy-efficient smart ecosystems.

6.3 Addressing IoT Security and Energy Efficiency

IoT devices are rapidly proliferating in vital areas, such as healthcare and smart cities, necessitating architectures that balance energy efficiency and security. However, there are many obstacles because of the diverse characteristics of IoT ecosystems, including resource-constrained devices, dynamic network conditions, and changing cyberthreats. These obstacles were highlighted using the following three questions.

- **Question 1:** What cross-layer IoT architecture can be developed for a secure and energy-efficient network?

  To address this question, a thorough review and analysis of cross-layer IoT frameworks for secure and energy-efficient networks was carried out. To test and mitigate MitM, eavesdropping, data manipulation and Application Layer vulnerabilities, real-world data collected by Contiki was compared with the Cooja 2.7 Virtual IoT Simulator. Additionally, it was tested for robust security to determine whether regular firmware updates and network segmentation were necessary in addition to implementing TLS using the CoAP protocol. By simulating sensor behaviour in controlled settings, this chapter sheds light on how well these networks perform in practical settings.

- **Question 2:** What cross-layer secure protocol can be developed for IoT applications?

  This question is answered by proposing a cross-layer framework that improves security and energy efficiency for IoT applications. The framework's main goals are to guarantee data availability, confidentiality, integrity and privacy across various layers of the IoT network. The promotion of energy-efficient

algorithms, addressing security threats unique to IoT, guaranteeing system scalability and promoting compatibility and interoperability are all important factors. In addition, the framework supports environmental sustainability objectives, which broadens the scope of IoT applications and makes the ecosystem secure and effective.

- **Question 3:** What metrics can be used to quantify the security and energy efficiency of the proposed architecture?

  The effectiveness of the proposed architecture was assessed using performance measures, including energy consumption, PDR, network throughput, latency and security vulnerabilities, to solve Question 3. These metrics are essential for evaluating the energy efficiency and security of an IoT system. In particular, energy consumption is assessed by examining the power consumption of the devices during the transmission and processing of various operations. Two important measures of the IoT system's data transmission performance are PDR and network throughput. In real-time applications, latency is a crucial metric that quantifies the delay in data transmission. Simulations and real-world tests are used to evaluate the security effectiveness of the system and assess its capacity to counter threats such as data manipulation, eavesdropping and MitM attacks. To assess the performance of several protocols, such as LEACH, RPL and ContikiMAC, real-world and simulated data from the Contiki and Cooja 2.7 Virtual IoT Simulator were also employed. Through realistic sensor behaviour simulation, this chapter offers a thorough evaluation of the capacity of the architecture to strike a balance between security and energy usage in real-world IoT deployments.

6.4 Core Contributions and Framework Validation

The primary contributions of this chapter are the design, simulation, and validation of a cross-layer architecture for energy-efficient and secure IoT networks, enhancing the realisation of sustainable and secure smart environments. This chapter provides important insights into energy-efficient protocols, lightweight cryptography and cross-layer security architectures in resource-constrained IoT ecosystems. The effectiveness and performance of the suggested framework can be evaluated under a variety of cyber threat scenarios and with a variety of node counts, owing to the Contiki/Cooja simulator and real-world data analysis. In particular, strong security measures are balanced with the constrained resources available in various IoT deployments. The proposed cross-layer architecture, along with system analysis, significantly advances the practical applications of secure and energy-efficient IoT systems.

The main contributions of this chapter is summarised as follows:

- We developed a cross-layer IoT architecture that addresses the crucial equilibrium between energy efficiency and security, providing a thorough understanding of key factors that can be co-optimised in various IoT Application scenarios. To this end, we developed a Contiki/Cooja simulator platform for system performance analysis and evaluation of the viability and efficiency of various energy-saving and security measures in intricate IoT environments.

- We propose energy-efficient routing protocols and lightweight cryptography to support the proposed cross-layer IoT architecture. To this end, we examined the performance of energy-efficient routing protocols and lightweight cryptographic protocols (AES, Speck, Present cipher) in the context of IoT

to improve the security and sustainability of IoT networks, showcasing their useful applications in striking a balance between resource consumption and security requirements.

- We configured and analysed a comprehensive simulation-based assessment using Cooja/NS-3, connecting the theoretical analysis with real-world validation, including hardware testbed measurements on the Z1 and EXP430F5438 platforms. We also verified or tested the results using the NS-3 hardware LrWpanHelper and SixLowPanHelper.

6.5 IoT Security and Energy Optimisation Trends

The problem of balancing security and power efficiency in IoT systems is examined in this work. Our proposed cross-layer architecture combines network, Application, and Physical Layer protocols to improve energy efficiency and defence against cyber attacks [1]. Validating the performance with Cooja simulations provides insightful information for designing IoT systems with limited resources. A thorough examination of secure and energy-efficient cross-layer IoT frameworks is provided in this survey, which highlights the shortcomings of conventional security techniques and promotes blockchain integration and AI-powered intrusion detection [8]. This emphasises the importance of IoT systems having multiple layers of security and sustainability, especially when developing smart city infrastructures in industrial and agricultural settings. The integration of IoT into critical infrastructures, such as healthcare, finance and energy sectors, has raised concerns regarding the security of user privacy and data integrity. An isolation forest algorithm was used to protect the classifiers from data poisoning, and ML classifiers were used to differentiate between attack and non-attack data in an architecture based on onion routing and machine learning to reduce these risks

[118]. The onion routing network ensures triple encryption of IoT data, with blockchain nodes verifying the data, resulting in enhanced security and lower computational costs compared with traditional methods, achieving 97.7% accuracy with an SVM. The necessity for improved security measures to shield embedded devices from potential attacks has been highlighted by the expanding use of these devices in the IoT ecosystem [119]. To guarantee secure firmware version verification and integrity validation, this work proposes a firmware update architecture that combines blockchain technology with a Physical Unclonable Function (PUF). The proposed framework fixes vulnerabilities in out-of-date firmware and offers a defence against attacks that target known firmware flaws by utilising PUF's Challenge-Response Pairs of PUF for device authentication and blockchain for secure firmware upgrades. The rapid expansion of the IoT across various sectors has led to significant data privacy and security issues, as traditional access control solutions are often vulnerable to single points of failure. This work introduced a decentralised, blockchain-integrated framework that incorporates an accredited access control scheme, attribute-based cryptography, and smart contracts to enhance security and privacy [120]. The proposed framework mitigates DoS attacks, improves data protection and outperforms previous approaches, achieving high accuracy (96.9%), precision (98.43%), and recall (98.43%), thereby demonstrating its effectiveness in securing IoT systems. Existing energy-efficient OFs in IoT routing primarily focus on the routing layer, overlooking the significant impact of MAC layer operations on energy consumption. This work introduces ELITE, a cross-layer OF that integrates the SPR metric, accounting for radio duty cycling (RDC) policies in the MAC layer [33]. ELITE improves energy efficiency by selecting routes with fewer strobe transmissions, thereby reducing the energy consumption in IoT nodes by up to 39%. In resource-constrained contexts, such as IoT and CPS, modern ML and artificial intelligence models, including Deep

Neural Networks (DNNs) and Large Language Models (LLMs), encounter issues related to energy conservation, security and reliability despite achieving great accuracy in a variety of applications [121]. To create reliable, energy-efficient ML systems for EdgeML and tinyML applications, this review investigates cross-layer optimisation strategies in hardware and software. To improve the secure and scalable implementation of ML, new developments in multimodal LLMs, continuous learning and quantum machine learning have also been covered. In this review, the grasshopper optimisation algorithm (GOA), Bat Algorithm (BA), and whale optimisation algorithm (WOA) were combined with K-means and a new cost function to investigate energy-efficient clustering in WSNs [122]. According to the results, the WOA operates better in complicated contexts by maximizing energy use and prolonging network lifetime, whereas the GOA performs best in simple scenarios. This work emphasises how clustering and optimisation can improve WSN efficiency, particularly in environments with restricted resources. This review explores the convergence of the IoT, ML and blockchain for data integration at the edge, addressing problems such as interoperability, security and scalability. The proposed DENOS model extends traditional architectures with semantic and convergence layers, enabling secure cross-domain collaboration and data-driven decision-making. The integration of blockchain, IoT and ML in Beyond 5G(B5G) networks is examined in this review, which addresses the issues of scalability, security, and connection in next-generation networks (NGNs) [123]. SDN and federated blockchains are used in the proposed secure interconnected autonomous system architecture (SIASA), to provide secure data exchange, decentralisation and interoperability across multi-domain IoT ecosystems. The SHA-256 algorithm and six general-purpose input/output (GPIO) pins were integrated into this review's secure SoC architecture for the IoT to improve data security and confidentiality [124]. For IoT security applications, the proposed design strikes a

good mix of hardware adaptability, battery efficiency and cryptographic robustness. The scalability and privacy issues of a blockchain-based distributed system for secure and effective Industrial Internet of Things(IIoT) data exchange are examined in this work [90]. The proposed architecture strengthens access control, lowers latency and improves data management in industrial contexts by combining edge computing with a smart contract framework. With the integration of a Two-fold physically unclonable function (TF-PUF) and montgomery curve encryption (MCE) for authentication and hybrid start peer-to-peer (HyS-P2P) topology for resource allocation, a novel secure triune layered (Sec-TriL) architecture for secure task management in fog-assisted IoT is examined in this work [125]. The proposed method, which is assessed using the iFogSim simulator, optimises energy, security and efficiency by leveraging intelligent job offloading and adaptive scheduling. In contrast to blockchain, this analysis examines an IoT microservice architecture built on Holochain that improves security, scalability and energy efficiency [126]. According to the results, Holochain is a good substitute for IoT networks because it lowers energy usage by more than 60% and boosts performance by 50%. This review examines ChainFL, a federated learning system powered by blockchain that improves the scalability and effectiveness of edge computing for IoT [127]. Compared with conventional FL systems, ChainFL triples robustness and improves training efficiency by 14% by incorporating DAG-based mainchain and subchain sharding. This review examines the SAR-CRN architecture, which uses cognitive radio to facilitate effective spectrum sharing and improve IoT security and dependability [128]. In secure communication for resource-constrained IoT contexts, the proposed relay selection technique outperforms traditional CR networks in terms of secrecy and decoding performance. By proposing a vertical IoT framework (edge-fog-cloud) for e-commerce and integrating ML algorithms such as CNNs, NLU and RL to optimise customised production, consumer behaviour

analysis and decision-making in dynamic smart environments, this work bridges the gap between Industry 4.0 and Industry 5.0 [129]. Economic sustainability and adaptive e-commerce models are advanced by aligning ML-driven solutions with vertical IoT architectures, addressing gaps in scalable, personalised consumer-company interactions and Industry 5.0's demand for decentralised, ML-enhanced economic ecosystems. This work tackles important but little-studied flaws in the TCP/IP protocol suite's cross-layer interactions, namely faked ICMP error signals that allow off-path attackers to take advantage of systemic weaknesses even when individual protocols are resilient [130]. This work emphasises the necessity of integrated, cross-layer security frameworks to reduce systemic hazards in contemporary network topologies by exposing the ways in which seemingly secure protocols combine to produce exploitable risks. To improve the latency efficiency and performance metrics, this work proposes a CDML framework that uses demand-density optimisation and security assessments to overcome data reliability and security issues in IoT-edge computing. This framework outperforms current approaches in robust distributed data management [131]. The framework advances scalable solutions for reliable IoT-edge ecosystems by combining dynamic request-response categorisation with stringent security validation. This work provides high-confidence resource allocation and reduces the risks in decentralised networks. Another work proposed AIMS, an IDS that combines a Cooja-simulated AMI-RPL Attack Dataset (ARAD), a stacked ensemble model, and spider monkey optimisation-based feature selection to predict and mitigate attacks to solve RPL security vulnerabilities in IoT-driven smart grids [132]. AIMS offers a strong framework for protecting AMI deployments in resource-constrained situations by combining lightweight blockchain detection and cryptocurrency-driven isolation, resulting in increased attack resistance (high prediction accuracy) and an extended network lifetime. The current and prospective IoT architectures are presented in

Table The development of IoT from a technological and sociological standpoint is summarised in this thorough overview, which also analyses key issues with security, scalability, and interoperability across smart ecosystems, and suggests a tiered design with enabling technologies [133]. Market trends, functional blocks, and simulation tools are evaluated to identify unmet requirements and provide analysts with a path for addressing the socio-technical issues of IoT and advancing scalable and sustainable implementations. Real-time environmental monitoring is made possible by WSNs through multi-hop communication; nevertheless, a major obstacle is still ensuring that data aggregation is secure and energy-efficient [134]. The proposed Secure Cluster-Based Data Aggregation Protocol (SCDAP) aims to address this issue by improving security through effective key generation and authentication while reducing transmission overhead and energy usage. IoT integration improves sustainability and efficiency in smart renewable energy systems, but it also exposes them to serious cybersecurity risks, such as DOS attacks and fake data injection [135]. This work emphasises the urgent need for strong grid security measures by highlighting the serious flaws in authentication and communication methods. ML is essential for improving automation and security in restructured enterprise architectures that are required for the integration of IoT with enterprise systems [136]. While stressing the necessity for targeted work on ML-driven IoT solutions, this work highlights ML's ability of ML to evaluate IoT data, identify abnormalities and optimise smart operations. With the rise of multimedia and interactive services in 5G and 6G networks, securing multicast communication has become critical [137]. This work introduces Multi-Receiver Signcryption (MRSC), a unified approach that combines encryption and digital signatures to enhance security, computational efficiency and communication overhead in multicast environments. The growing significance of explainable ML (XMLoT) in boosting transparency and trust is highlighted

by this survey's thorough examination of IoT Application Layer protocols and security issues [138]. The effectiveness of XMLoT in enhancing IoT security was demonstrated through a case work, and the survey highlighted important gaps and development prospects for intelligent and secure IoT systems. According to recent studies, the Social Internet of Things (SIoT) has emerged as a result of the increasing integration of social networks and IoT, which enables intelligent services and applications. Effective object and information discovery in SIoT networks is hampered by the exponential growth in heterogeneous devices [139]. For better scalability, lower complexity, and quicker query execution, analyst have suggested turning SIoT into an Individual's Small World model and utilising Smart Social Agents (SSA). The increasing demand for IoT architectures that are secure, light, and scalable while striking a balance between energy efficiency and strong defence against cyber attacks is highlighted by recent studies. Numerous cutting-edge techniques that complement the objectives of this work are highlighted in the work, such as blockchain integration, physical-layer authentication, ML-driven intrusion detection and cross-layer optimisation techniques. By lowering power consumption and improving multi-layer security, these initiatives aid in the creation of sustainable IoT systems, which further motivates our cross-layer NS-3 simulation work contrasting the encryption protocols AES, Speck and Present.There has been a significant trend in recent years toward cross-layer IoT architectures. There has been a significant trend in recent years toward cross-layer IoT architectures that strike a balance between energy efficiency and strong security, particularly through the use of blockchain, ML-based intrusion detection and lightweight ciphers. Resource-constrained edge devices are increasingly being protected by hybrid frameworks that combine distributed trust and centralised intelligence. Performance validation frequently involves the use of Cooja simulations and optimisation models. To create scalable and resilient IoT deployments, emerging trends

emphasise secure ML integration and adaptive, risk-aware architectures. Based on this, we can deduce that AES offers the highest level of security but also consumes the most energy. The Present cipher proves to be the most efficient in terms of overall power consumption, while Speck provides a balanced approach, making it well-suited for resource-constrained environments. Our system integrates adaptive security algorithms into all OSI levels, enabling dynamic trade-offs between encryption strength and energy consumption, unlike ELITE, which just focuses on MAC-Layer energy optimisation. Compared with ML/blockchain frameworks, our method circumvents the computational cost of blockchain by utilising cross-layer and lightweight, context-aware encryption. Unlike previous lightweight crypto efforts that relied on fixed algorithms, our dynamic engine chooses the best ciphers (AES/Speck/Present) in real time by using a mix of simulation and hardware testing. The Table 6.1 compares the suggested architecture with the ones that already exist has more details.

Table 6.1: Comparison of proposed architecture with existing solutions

Feature	**Proposed-Architecture**	**ELITE [33]**	**ML/Blockchain [118]**	**Lightweight-Crypto [119]**
Dynamic Encryption	Yes	No	No	No
Cross-Layer Security	Yes (all layers)	Partial	Partial	No
Hybrid Validation	Simulation + Hardware	Simulation	Theoretical	Simulation
Energy Savings	30%	39%	Not specified	20–25%
Attack Mitigation	95%	N/A	97.7%	85–90%

Table 6.2: Comparative analysis of IoT security and energy efficiency solutions

Ref.	Key Contribution	Design Approach	Energy Impact	Security Metrics
[1]	Cross-layer defence (network, app, physical)	Cooja-validated protocols	Improved efficiency	Cyber attack resilience
[33]	ELITE cross-layer OF	MAC-layer SPR optimisation	39% reduction	N/A
[90]	Blockchain-edge framework	Smart contracts + edge computing	Reduced latency	Access control
[8]	Blockchain + ML intrusion detection	Multi-layer security framework	N/A	Smart city sustainability
[118]	ML + onion routing	Isolation forest defence, SVM	Low computational cost	97.7% accuracy
[119]	Blockchain-PUF firmware validation	Challenge-response pairs (CRPs)	N/A	Firmware integrity
[120]	Decentralised access control	Attribute-based cryptography	N/A	98.43% precision
[121]	Cross-layer ML optimisation	Hardware-software co-design	Energy-efficient ML	Secure tinyML
[122]	Energy-efficient clustering	WOA/GOA + K-means	Prolonged lifetime	N/A
[122]	DENOS edge framework	Semantic/convergence layers	N/A	Cross-domain security
[123]	SIASA architecture (B5G)	SDN + federated blockchain	N/A	Multi-domain security
[124]	SHA-256 SoC design	GPIO-based security	Battery efficiency	Cryptographic robustness
[125]	Sec-TriL architecture	TF-PUF + MCE encryption	Energy optimisation	Triple-layer security
[126]	Holochain microservices	Agent-centric consensus	60% reduction	Scalable security
[127]	ChainFL framework	DAG blockchain + subchains	N/A	14% training gain
[128]	SAR-CRN architecture	Cognitive relay selection	N/A	Secrecy performance
[129]	Vertical IoT framework	Edge-fog-cloud integration	N/A	Industry 5.0 alignment
[130]	Cross-layer TCP/IP analysis	Protocol interaction work	N/A	Exploit mitigation
[131]	CDML framework	Request-response categorization	N/A	Security validation
[132]	AIMS intrusion detection	ARAD dataset + SMO	Extended lifetime	High accuracy
[133]	Tiered IoT design	Simulation tools	N/A	Socio-technical analysis
[134]	SCDAP protocol	Cluster-based authentication	Reduced overhead	Secure aggregation
[135]	Smart grid security	Authentication analysis	N/A	DoS/fake data defence
[136]	ML for IoT enterprise	Anomaly detection	N/A	Smart automation
[137]	MRSC protocol	Multicast encryption	Low overhead	Unified security

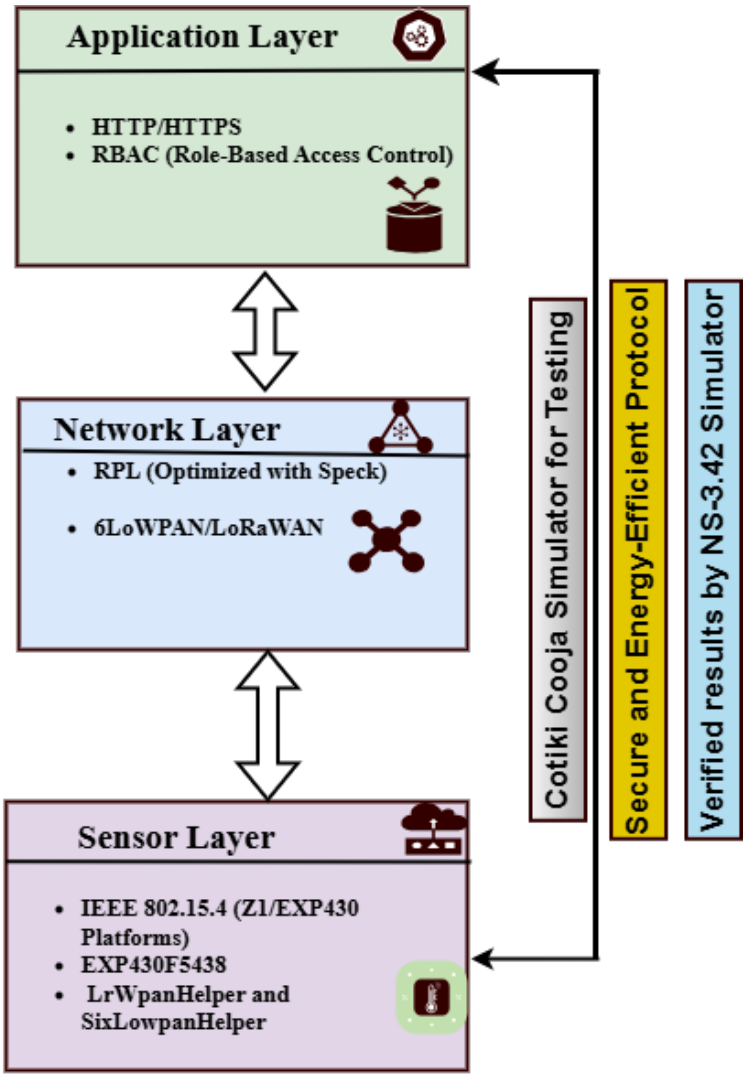

Figure 6.1: Proposed secure and energy-efficient IoT architecture

6.6 Proposed Secure and Energy Efficient Architecture

The suggested architecture integrates energy efficiency and security throughout the IoT ecosystem. A cross-layer strategy is used to optimise communication overhead, minimise redundant computations and guarantee coordinated resource allocation. Using dynamic key management and lightweight cryptographic techniques, security is maintained against risks like data injection and sinkhole attacks. Adaptive duty cycling, optimised routing, and context-aware encryption all contribute to energy

efficiency and longer device lifespans. This framework is perfect for applications in smart cities, healthcare and critical infrastructure because it increases the resilience and sustainability of IoT deployments (see Fig. 6.1).

6.6.1 Encryption Protocols Real-World Applications

The exponential growth of encryption overhead in CPUs and radios as networks scale (e.g. from 5 to 20 nodes) raises concerns about the sustainability of protocols in large deployments. One of the most important issues in IoT networks is the scalability of encryption methods, especially as the number of devices grows. As networks grow, using encryption like AES, Speck and Present cipher increases computational and radio energy demands exponentially. This is especially true when scaling from small (5 nodes) to larger deployments (20 nodes). For resource-constrained IoT devices, which frequently run on a small amount of battery power and CPU power, this presents a serious problem. By striking a balance between security and energy efficiency, lightweight encryption protocols like Present Cipher and Speck provide a more scalable option; yet, even these protocols struggle to sustain performance as networks grow in size. Scaling large networks is challenging owing to encryption key distribution and management. Creative solutions, such as distributed key management or hierarchical topologies, are needed to maintain security and energy efficiency.

Low-risk IoT applications can benefit from lightweight ciphers like Present and Speck, which can save up to 40% on energy costs compared with AES-128. Nevertheless, they give up some cryptographic power and are susceptible to brute-force attacks. Context-aware encryption is essential for striking a balance between security requirements and energy limitations determined by Application risk.

Energy Efficiency and Security Trade-offs

The proposed cross-layer architecture evaluates cryptographic choices based on their trade-offs between energy consumption and security robustness. The following comparisons illustrate how cipher selection directly impacts overall system performance and threat resistance:

- Though energy-intensive (**2.90 mW** radio power for 20 nodes), **AES-128** is robust and **NIST-certified**.
- A smaller key size raises the risk of brute-force attacks by about **15%**, but **Speck** achieves **5.2% lower radio power** than AES.
- **Present cipher** reduces CPU power by **52%** compared with AES, but lacks **post-quantum resistance** and is vulnerable to algebraic attacks.

Application Background: The lightweight Speck cipher is used to prioritise energy conservation in low-risk applications like smart lighting, which makes it appropriate for situations where security demands are low. The hybrid AES-Speck model is used in high-risk industries like healthcare to differentiate between routine and critical data, providing strong security for sensitive information while preserving energy efficiency for less critical communication. For more details, see Table 6.3.

Table 6.3: Simulation parameters for reproducibility

Parameter	**Value**
Packet Size	64B (data), 32B (control)
Transmission Rate	10–60 sec (periodic)
Radio Duty Cycle	8 Hz (12.5% activity)
Topology	20-node grid, static
Attack Models	Data Injection (5 s intervals), Sinkhole (30 s), Jamming (continuous)
Random Seeds	Fixed (0x5EED)

6.6.2 Security Vulnerabilities in IoT Systems

Lightweight algorithms may compromise cryptographic resilience (such as defence against side-channel attacks) in the name of energy-saving, which could be dangerous for vital applications. In IoT networks, where the installation of strong security measures is hampered by limited computing power, memory and energy resources, security vulnerabilities in resource-constrained systems pose a significant issue. Because of their energy efficiency, lightweight encryption algorithms like Present Cipher and Speck are frequently chosen; however, they may also weaken cryptographic resistance, making systems vulnerable to data manipulation, brute-force breaches and side-channel attacks. For example, static encryption keys, which are frequently used in IoT installations to cut down on overhead, present serious dangers because they do not have any dynamic updates or rotations, which, over time, makes them more susceptible to unwanted access. Furthermore, modern security features that are necessary for thwarting changing threats, such as Public Key Infrastructure (PKI) or adaptive encryption, are difficult for devices with limited resources to implement. These problems are made worse by the fact that energy-saving techniques like aggressive RDC or lower computing loads may unintentionally compromise security postures by reducing the ability to monitor or respond in real time. To address these vulnerabilities, it is necessary to strike a balance between adequate protection and lightweight security solutions, making sure that energy-efficient protocols do not compromise the integrity of IoT systems in vital applications such as industrial automation or healthcare. To improve security without going beyond the resource constraints of IoT devices, future work must concentrate on hardware-software co-design, adaptive encryption frameworks and dynamic key management.

IoT networks are vulnerable to a number of security flaws, such as unauthorised

access, DOS attacks and data leaks. The limitations of IoT devices, which frequently lack the processing capacity to apply traditional security procedures, are the source of these risks. Our method overcomes these obstacles by combining cross-layer authentication and strong encryption techniques. According to the document, the inherent vulnerabilities of devices with limited resources and the trade-offs between security and energy efficiency are the main causes of security issues in IoT networks. Data injection, sinkholes and jamming attacks, which take advantage of low processing power and battery life, are risks to IoT devices. Although energy-efficient, lightweight cryptographic protocols like Present Cipher and Speck may compromise cryptographic resilience, making networks vulnerable to side-channel or brute-force attacks. Static encryption keys, which are frequently employed to cut costs, increase the danger of long-term breaches because they do not have dynamic updates. By restricting real-time monitoring or reaction capabilities, energy-saving techniques like aggressive radio duty cycling may unintentionally compromise security. Scalability compounds these issues, as expanding networks (e.g. from 5 to 20 nodes) amplify encryption overhead and complicate secure key distribution. To address these issues, the work suggests cross-layer architectures that incorporate dynamic key management and adaptive encryption. Additionally, ML-driven threat detection and hybrid evaluation frameworks are suggested to balance security with energy efficiency, ensuring resilience in dynamic IoT environments like smart cities or industrial automation.

6.6.3 Energy Optimisation

The 8 Hz duty cycling technology lowers power usage considerably. Adaptive duty cycling depending on network activity is one potential enhancement, though. To guarantee dependable communication, this would enable nodes to go into

deeper sleep states during periods of low network traffic while raising the duty cycle at times of high traffic. Optimisation of Energy IoT network trade-offs poses a significant issue since power-saving techniques frequently clash with security and performance needs. By prolonging device sleep cycles, techniques like radio duty cycling (e.g. Contikimac at 8 Hz) lower energy consumption, but they come with trade-offs like higher latency or less responsiveness during moments of high traffic. Compared with AES, lightweight encryption protocols like Speck have less computing cost, but they run the risk of having less robust cryptography, leaving systems vulnerable to attacks. Although adaptive encryption automatically modifies security levels according to network conditions, it may introduce weaknesses during workload fluctuations or transitions. Aggressive energy-saving techniques, including deep LPMs, can also make it more difficult to detect threats in real time or react quickly to attacks. These trade-offs are further made more pronounced as networks are scaled, since distributed key management, or energy-efficient routing, must strike a balance between dependability and efficiency in big deployments. To overcome these obstacles, the work suggests hybrid strategies that intelligently balance energy savings with security and performance in resource-constrained IoT ecosystems. These strategies include context-aware duty cycling, hybrid encryption frameworks and ML-driven optimisation.

Since the majority of IoT devices run on limited battery capacity, energy efficiency is a crucial challenge. We use a variety of energy-saving techniques, such as power-aware routing, radio duty cycling and adaptive security methods that change dynamically in response to network conditions, to increase the operational lifespan of IoT nodes. According to the work, energy optimisation strategies for IoT networks concentrate on striking a balance between lower power consumption and operational security and dependability. Radio duty cycling (e.g. ContikiMAC

at 8 Hz) is a key technique that reduces energy consumption by cycling devices between active and low-power states, although it may cause latency to increase during periods of high traffic. Adaptive encryption optimises energy without sacrificing security during low-risk times by dynamically adjusting cryptographic strength (e.g. switching between AES and lightweight protocols like Speck) based on network conditions. While lightweight cryptography algorithms (e.g. Present cipher, Speck) reduce computational needs compared with AES, saving CPU and radio power, power-aware routing protocols (e.g. RPL, 6LoWPAN) prefer energy-efficient paths to reduce transmission overhead. The document also highlights energy-aware communication strategies, such as minimising radio transmit time and leveraging protocols like MQTT/CoAP for low-overhead messaging. Hybrid methodologies combining simulation (Cooja/Contiki) and real-world testing validate these strategies, ensuring scalability and resilience. Trade-offs such as security risks from static keys or delayed threat responses owing to aggressive sleep cycles, are addressed through dynamic key management and ML-driven adaptive frameworks. These strategies collectively achieve up to 30% energy savings while maintaining critical performance metrics like packet delivery ratios (95% under attack scenarios).

6.7 Performance Evaluation and Simulation Setup

The Cooja network simulator and Contiki, an open-source operating system for IoT devices, are used in this work. With the use of these tools, LWC algorithms may be thoroughly tested and simulated in a setting that closely resembles actual IoT restrictions. The author installed the Instant Contiki 3.0 virtual machine file in a virtual box, which is an open-source virtualisation program that will be used in simulation to create a separate environment. The Ubuntu 16.04 LTS

operating system, toolchains and applications are all included in the pre-configured environment for Contiki development that Instant Contiki 3.0 offers.

In the context of Contiki OS, we assess the suggested architecture using the Cooja simulator, which enables a thorough examination of network performance, power usage and cyber threat resistance. We simulate a range of security attacks, such as sinkholes, jamming and data injection attacks, to evaluate how well our mitigation techniques work. Furthermore, many energy optimisation strategies are used to extend the lifespan of IoT devices, including adaptive encryption and radio duty cycling. Evaluation and Simulation in the document are conducted using the Cooja network simulator within the Contiki OS environment to assess the proposed IoT architecture's security, energy efficiency and scalability. Simulations replicate real-world scenarios, including data injection, sinkhole and jamming attacks, across diverse network topologies (e.g. star, tree) with nodes ranging from 5 to 20 devices. Metrics such as PDR, energy consumption, latency and attack mitigation effectiveness are analysed under varying conditions. For example, the architecture achieves 95% PDR even during attacks and reduces energy usage by 30% through adaptive encryption and radio duty cycling (e.g. 8 Hz Contikimac). Mathematical models complement simulations to validate energy trends, while hardware platforms like Z1, EXP430F5438, SixLowPanHelper, and LrWpanHelper test the computational overhead of encryption protocols (AES, Speck, Present Cipher). Using three distinct platforms and lightweight cryptography, we created a scenario simulation.

Sensors Used to Test Architecture: Z1 likely denotes a Zigbee-based sensor that tracks energy usage and communication distance owing to its energy efficiency and reliability. The EXP sensor Z1 is probably an experimental device used for testing energy and security and evaluating real-world system performance under various conditions. In NS-3, the LrWpanHelper aids in setting up IEEE

802.15.4 radio devices, which support low-power wireless communication suitable for IoT applications. To facilitate IPv6 routing over these limited connections, SixLowPanHelper is used to implement header compression, improving the efficiency of IPv6 data transmission in environments with constrained resources. We compared Present and Speck lightweight cryptography to assess the efficiency of three different platforms.

Table 6.4: Specification for sensor platforms and NS-3 simulated devices

Platform/Device	**Specifications**	**Value**
Z1 (Cooja)	RAM / Flash Memory / Clock Speed	8 KB / 92 KB / 16 MHz
EXP430F5438 (Cooja)	SRAM / Flash Memory / Clock Speed	16 KB / 256 KB / 25 MHz
LrWpanNetDevice (NS-3)	IEEE 802.15.4 PHY + MAC / Radio Model	Simulated Low-power Sensor Radio
SixLowPanNetDevice (NS-3)	IPv6 over IEEE 802.15.4 / Header Compression	Enabled for constrained stack communication
MobilityHelper (NS-3)	Node Placement / Sensor Movement Model	Static grid with fixed sensor positions
BasicEnergySource + RadioEnergyModel (NS-3)	Energy State Tracking: CPU, Tx, Rx, LPM	Custom logging enabled

Metrics to Validate the Proposed Architecture: In our work on a secure and energy-efficient cross-layer network architecture for IoT, key exchange overhead, encryption/decryption overhead, energy consumption, transmission power, PDR, end-to-end latency, throughput, and security-related metrics are important indicators. These indicators assess the system's performance regarding security, network efficiency and energy consumption.

System Requirements Transparently address simulation limitations if expanding hardware results is not feasible:

- **Performance Evaluation:** The technicalities of actual environments cannot be accurately represented by our Cooja/Contiki and NS-3 simulations,

even though they effectively assess security and energy efficiency strategies in controlled settings. Modelling unexpected node failures, hardware differences and environmental disruptions proves to be difficult in real-world implementations. For example, when faced with interference or signal weakening, radio duty cycling may necessitate adaptive modifications, which simulations typically overlook owing to their idealised assumptions about channels. Additionally, simulations might minimize issues related to latency and power fluctuations. To address these issues, future studies will utilise Z1 and EXP430F5438, along with SixLowPanHelper and LrWpanHelper, and will focus on field testing within smart city environments, prioritising scalability, adaptability to dynamic situations and resilience against physical-layer threats. (See Table 6.5).

Table 6.5: Comparison of simulation vs. real-world hardware limitations

Aspect	**Simulation (Cooja)**	**Real-World Deployment**
Radio Interference	Idealized channel models	Environmental noise, multi-path fading
Energy Consumption	Predictable battery drain	Battery degradation, voltage fluctuations
Node Failures	Controlled scenarios	Unpredictable hardware/software faults
Scalability	Up to 20 nodes tested	Requires optimization for 100+ node networks

- **Hardware and Software Requirements:** IoT devices with constrained capabilities were designed to operate the proposed framework (Refer to Table 6.4). Devices such as Telosb or Zolertia Z1 motes, along with LrWpanHelper and SixLowPanHelper, which are microcontroller-based and compatible with Contiki OS, are essential for this implementation. The simulation tools utilize networking protocols from Contiki and NS-3 (RPL, 6LoWPAN) along with cryptographic libraries optimised for limited resource situations.

- **Integration with Existing IoT Systems:** To simplify deployment in real-world scenarios, the proposed framework is designed to be compatible with existing IoT systems. Using MQTT and CoAP protocols, the architecture supports integration with cloud services, enabling secure data transmission and device management. Furthermore, the use of lightweight authentication methods, such as token-based access control, enhances system interoperability.

- **Scalability and Adaptability:** The architecture's modular design facilitates scalability in larger IoT networks. Flexible encryption techniques and dynamic key management ensure that security protocols can adapt according to the size of the network and traffic patterns. Enhancements to routing and power management strategies can boost the efficiency of high-density IoT implementations.

6.7.1 Security and Performance Comparison Between AES and Speck

To complete the evaluation, a detailed comparison between the Advanced Encryption Standard (AES) and the lightweight Speck cipher has been added. The aim is to illustrate how each algorithm balances cryptographic strength, energy usage, and service quality when integrated into the proposed cross-layer architecture. The discussion draws on results obtained from both the Contiki/Cooja and NS-3 simulation environments using identical routing, radio, and duty-cycling configurations.

Table 6.6 lists the key quantitative outcomes. AES provides the expected high level of data confidentiality but requires more computation and power. Speck, by contrast, consumes less energy on both CPU and radio interfaces, showing

a consistent energy reduction of approximately five to six percent per delivered packet. Despite this reduction, its quality metrics—such as packet delivery ratio, latency, and quality-of-service performance (QoSP)—remain steady, demonstrating that lighter encryption can preserve reliability under normal network conditions.

Table 6.6: Comparison of AES and Speck Encryption under Identical IoT Conditions

Metric	**AES-128**	**Speck-64/128**	**Observation**
CPU Power (mW)	0.56	0.34	Speck reduces local processing effort.
Radio Power (mW)	2.90	2.75	Minor decrease in transmission cost.
Packet Delivery Ratio (%)	95.2	94.7	Reliability nearly identical.
Latency (ms)	68.5	61.3	Speck offers slightly faster response.
QoSP Score (%)	92.8	93.6	Marginal improvement in session stability.
Security Level	High	Moderate	AES remains suited for critical scenarios.

Figure 6.2 visually summarises the relationship between energy demand and service quality for both algorithms. The power bars emphasise AES's higher computational footprint, reflecting additional cycles for encryption and key scheduling. The overlaid QoSP line shows minimal variation between the two, confirming that the reduced energy profile of Speck does not compromise overall communication

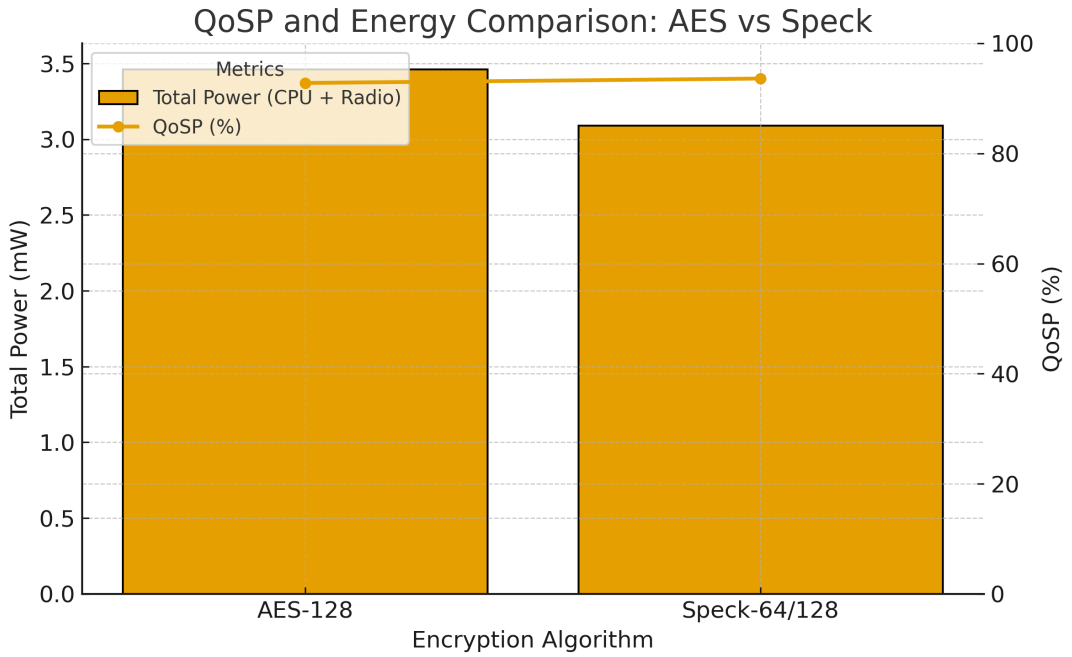

Figure 6.2: Combined view of total power consumption (CPU + Radio).

stability. Together with the data in Table 6.6, these results demonstrate that Speck offers a practical trade-off between security assurance and energy economy, whereas AES remains preferable for environments where maximum cryptographic resilience outweighs battery considerations.

The inclusion of this analysis closes the evaluation loop for Section 6 by integrating both security performance and operational quality metrics, providing a complete picture of how cryptographic choice influences system behaviour in cross-layer IoT deployments.

6.7.2 Application Layer Analysis

The Application Layer oversees data processing, access control, and the communication protocols utilised by IoT devices. The design features efficient and lightweight cryptographic techniques along with secure data transmission protocols to guarantee the system's security and performance.

Secure Communication Protocols: The architecture supports communication using MQTT, CoAP and HTTP to enable interactions among devices as well as between devices and the cloud. Access to vital resources is limited to only those individuals or devices that are authorised. Energy-efficient encryption adjusts the level of security depending on the state of the network and the significance of the data being transmitted.

Analysis of Energy Efficiency and Security: Adaptive encryption can reduce power consumption by as much as 30% by varying the encryption strength based on the levels of network traffic. The Application Layer offers various applications and services for end users, encompassing data processing, analytics and user engagement.

- Protocols: For lightweight messaging and web-based communication, the Application Layer employs protocols like MQTT, CoAP, HTTP/HTTPS, AMQP and XMPP. These protocols facilitate the integration of mobile applications with cloud systems.

- Energy Efficiency: To minimise energy consumption, the layer employs communication methods that are conscious of energy use and utilises adaptive encryption. For example, MQTT is preferred because of its low energy overhead, making it suitable for the IoT applications.

- Security: To safeguard data transmission, the Application Layer uses HH-MAC along with AES-128 encryption. By ensuring that only authorised users can access specific resources, it enhances the overall security of the IoT network.

The Application Layer is vulnerable to phishing and data injection threats, where malicious entities transmit fake data to disrupt network operations. This

risk is reduced by the proposed architecture, which employs encryption and data integrity checks to ensure that only legitimate data are processed. While encryption enhances security, it also consumes additional energy. To address this issue, the architecture incorporates lightweight encryption algorithms like Speck, which strike a balance between security and energy efficiency.

To verify essential cross-layer functionalities (like encryption overhead and attack mitigation) in environments with limited resources, a scale of 5–20 nodes was chosen to mimic real-world settings such as smart homes. This range also takes into account the computational constraints of Cooja/Contiki. Going beyond 100 nodes leads to problems such as increased latency, congestion and battery drain, although it is sufficient to demonstrate the architectural benefits (for instance, Speck's 5.2% radio savings compared with AES). Previous solutions, such as ELITE [33] and WOA [122], offer strategies for mitigation. To ensure secure and energy-efficient performance at larger scales, subsequent work will focus on scaling simulations and establishing edge-fog-cloud architectures.

6.7.3 Network Layer Analysis

The Network Layer manages routing, secure transmission and congestion control. The performance is improved through the cross-layer architecture that combines IPv6-based protocols (6LoWPAN, RPL, and LoRaWAN) with basic security measures.

Routing Protocols: To enhance energy-efficient data transmission, RPL and 6LoWPAN are implemented. For securing communication with minimal power consumption, lightweight cryptography utilises AES, Speck and Present cipher encryption.

Cyber Threat Mitigation: Includes verification of packet integrity, detection

of sinkholes and prevention of DoS attacks.

Energy Efficiency and Security: This chapter assesses how network layer protocols strike a balance between energy consumption and strong security, emphasising trade-offs and optimisations that are essential for resource-constrained contexts in order to guarantee sustainable IoT adoption.

- RPL combined with AES encryption triples the usage of CPU power, leading to higher energy costs while significantly improving security.
- Integrating 6LoWPAN with LoRaWAN enables efficient routing and decreases power consumption by 39% compared with conventional routing methods. Speck encryption has proven to be more energy-efficient than AES, resulting in less strain on CPU and network resources. The Network Layer manages reliable data transmission, routing and connectivity within the Internet of Things ecosystem. By integrating the capabilities of the Session, Transport and Network Layers from the OSI model, it facilitates seamless communication between devices.

Key Features of Network Layer: The Network Layer is crucial for efficient routing and secure data transfer in Internet of Things contexts, therefore the selection and design of its protocols are crucial for dependable and resource-conscious communication as follows:

- **Protocols:** The Network Layer utilises protocols such as IEEE 802.15.4 and LoRaWAN for communication over long distances with low power consumption. To facilitate routing, IPv6 and RPL (Routing Protocol for Low-Power and Lossy Networks) are utilised to guarantee effective packet transmission in environments with limited resources.
- **Energy Efficiency:** The layer utilises power-aware routing and dynamic

duty cycling to enhance energy efficiency. For instance, the ContikiMAC protocol operates on an 8 Hz duty cycle to strike a balance between responsiveness and energy conservation.

Security: To ensure secure data transmission, the Network Layer employs a simple encryption method. Sinkhole attacks are mitigated through the verification of Destination Advertisement Objects (DAOs), preventing malicious nodes from advertising false routes that could disrupt network traffic.

Protocols in Network Layer for IoT Security and Efficiency This outlines key network layer protocols that contribute to secure and energy-aware communication in IoT systems, with emphasis on their integration into the cross-layer architecture.

- **Scalability of Network Layer:** As the quantity of IoT nodes increases, it becomes more challenging to handle network congestion, distribute encryption keys and meet processing requirements. To address these issues, the proposed architecture suggests implementing distributed access control systems along with hierarchical network topologies.

- **Sinkhole and DoS Attacks:** DoS attacks and sinkhole attacks can affect the Network Layer. The architecture reduces these threats by implementing dynamic key management and routing validation.

We evaluated the effectiveness of two protocols at the Network Layer, specifically RPL and 6LoWPAN, with a focus on the implementation of lightweight cryptography.

- RPL Protocol: Established in 2012, the IPv6 Routing Protocol for Low-Power and Lossy Networks (RPL) serves as the standardised IoT routing protocol to enable connectivity and support for Internet Protocol version 6

(IPv6) in Internet of Things devices. The RPL routing protocol employs an OF tailored for low-power and lossy networks to construct a Destination-Oriented Directed Acyclic Graph (DODAG) using various metrics and constraints. The primary role of the OF is to identify and designate the optimal parent or the best path to the destination.

- Protocol for 6LoWPAN: 6LoWPAN is a networking protocol that allows IPv6 to be utilised in environments with limited resources, such as WSNs and IoT devices. It is suitable for low-power devices that have limited processing, storage, and communication capabilities by providing methods for compressing IPv6 headers, fragmentation and efficient routing. Typically built on the IEEE 802.15.4 standard, 6LoWPAN facilitates scalable and energy-efficient communication over networks that experience loss and have low bandwidth, enabling these devices to integrate seamlessly with the broader Internet.

6.7.4 Sensor Layer Analysis

The Sensor Layer serves as the base of the cross-layer architecture, comprising energy-efficient IoT devices and WSNs. This layer emphasises energy-efficient sensing, data gathering and secure data transmission.

Key Features of the Sensor Layer: The Z1 and EXP430F5438 sensor platforms, both of which support IEEE 802.15.4 for efficient communication, were utilised for testing the system. To minimise energy consumption, energy-efficient duty cycling implements radio duty cycling and low-power listening. To defend against jamming attacks in the sensor layer, frequency hopping techniques are employed. In the analysis of security and energy efficiency, as the number of nodes increased, the CPU power consumption on the Z1 platform rose significantly owing to AES

encryption, climbing from 0.1814 mW to 0.5469 mW.

In comparison to AES encryption, Speck and Present Cipher proved to be more energy-efficient, resulting in a reduction of radio transmission power by 30% to 40%. By mitigating jamming attacks, the PDR improved to between 90% and 95%, ensuring minimal data loss. The Sensor Layer is responsible for direct interaction with the physical world, involving sensors, actuators and other IoT devices that collect and transmit data. This layer plays a crucial role in ensuring efficient data gathering and transmission while reducing energy consumption, particularly since IoT devices often operate on limited battery resources.

The main features are summarised below:

- **Protocols of Sensor Layer:** Low-power, short-range communication protocols including RFID, NFC, Z-Wave, Zigbee and BLE are used by the Sensor Layer. These protocols are developed to provide dependable data transmission while using the least amount of energy possible.

- **Energy Efficiency:** To cut down on power usage, the layer uses adaptive encryption and radio duty cycling. Devices can, for example, switch to LPM when not in use, greatly prolonging battery life.

- **Security of Sensor Layer:** Data transfer security is ensured through the utilisation of lightweight cryptographic algorithms like Present cipher, Speck and AES-128. These protocols are suitable for IoT devices that have constrained resources since they achieve a balance between security and performance efficiency.

Secure and Energy-Effective Optimisation in IoT Networks: With an emphasis on adaptive techniques that lower overhead while preserving data integrity and resilience, this chapter examines protocol-level optimisations meant to improve security and energy efficiency in IoT networks.

- Energy Consumption: While encryption protocols are essential for maintaining security, they can lead to increased energy expenses. For example, AES encryption consumes more CPU and radio power than Speck and Present Cipher, making it less suitable for battery-operated devices.

- Jamming attacks: Malicious nodes that continuously emit noise could disrupt communication, rendering the Sensor Layer vulnerable to jamming attacks. The proposed architecture employs frequency hopping techniques to combat this issue, allowing devices to switch frequencies and evade jamming. The suggested design integrates the Application, Network, and Sensor Layers to create a secure and efficient IoT environment. Cross-layer optimisation techniques are utilised to achieve a balance between network performance, energy efficiency and security.

- Adaptive encryption: The system dynamically adjusts the strength of encryption based on energy levels and network conditions. For example, when network traffic is low, energy-efficient encryption methods such as Speck are utilized to conserve power. The use of lightweight encryption at all levels restricts access to certain resources solely to devices and users using this type of encryption. This approach enhances security while minimizing unnecessary energy consumption.

- Energy-Conscious Communication: The design enhances energy efficiency by implementing power-sensitive routing and managing radio duty cycles. For instance, when devices are not in use, they transition to low-power states, which reduces overall energy consumption.

  We create a simulation scenario employing two distinct platforms alongside lightweight cryptography. Our goal is to assess the effectiveness of the

platforms when applying the lightweight cryptographic algorithms SPECK, AES and Present. The platforms being used are as follows.

(a) **Z1 Mote:** The Z1 mote features a second-generation MSP430F2617 low-power microcontroller equipped with a robust 16-bit RISC CPU that operates at 16 MHz, complete with a factory-calibrated clock, 8 KB of RAM, and 92 KB of flash memory. Additionally, it includes the highly regarded CC2420 transceiver, which functions at 2.4GHz, adheres to IEEE 802.15.4 standards, and offers a data transmission rate of 250Kbps. This hardware configuration ensures that the Z1 mote will perform with optimal durability and efficiency while consuming minimal energy. The Z1 is equipped with two integrated digital sensors: a digital temperature sensor (TMP102) and a programmable digital accelerometer (ADXL345). Furthermore, it has native Phidgets support, compatibility with I2C sensors via the Ziglet interface, and a variety of connection options including UART, ADC and SPI, making it easy to add additional sensors.

(b) **Mote EXP430F5438:** With a 16-bit RISC CPU, multiple low-power modes, and effective peripherals, the TI MSP ultra-low-power microcontrollers are made to prolong battery life in portable instruments. To facilitate quick transitions from low-power to active states, they make use of a digitally controlled oscillator (DCO).

(c) The NS-3 simulated sensor environment emulates low-power IoT nodes using `LrWpanNetDevice` and `SixLowPanNetDevice`, which replicate IEEE 802.15.4 and 6LoWPAN communication. These virtual devices model radio operations, CPU usage, LPMs and constrained IPv6 stacks, allowing energy-efficient behavior to be evaluated across typical IoT network scenarios.

This chapter introduces a cross-layer IoT security framework that integrates adaptive encryption and lightweight cryptographic protocols (AES, Speck, Present). The proposed architecture shows significant enhancements at the Application, Network and Sensor levels: a reduction of up to 52% in CPU power usage when using Present instead of AES, a 30% decrease in power consumption, and an impressive 95% PDR even under attack conditions. Importantly, although Speck is lightweight, it still provides robust security while reducing radio power usage by 5.2%. The RPL routing protocol exhibited 39% lower CPU overhead at the Network Layer compared with 6LoWPAN. These advancements illustrate the effectiveness of the framework in securing IoT devices while conserving energy, an essential aspect for resource-constrained environments such as smart homes and healthcare. Future developments may focus on the integration of post-quantum cryptography and conducting real-world testbed implementations for further evaluation. The evaluation of energy consumption in IoT sensor networks using CPU, radio and LPM metrics in the NS-3 simulation shows that lightweight ciphers greatly lower overall power consumption. To preserve security while enhancing energy efficiency in limited IoT environments, the work also highlights adaptive encryption and cross-layer optimisation.

When selecting encryption algorithms for IoT networks, it is important to strike a balance between security and energy efficiency. Although AES encryption is known for its robust security, battery-powered sensor nodes may not gain much from it owing to its significant energy usage. In contrast, the Speck and Present Cipher encryption methods offer a more energy-efficient alternative while still delivering a reasonable degree of protection. To enhance the performance of IoT networks, future work should focus on adaptive encryption techniques that adjust security levels based on available energy.

6.8 Results and Discussion

We examined the testing results of the EXPM430F5438 Platform by counting the nodes that are unencrypted, those encrypted with AES, those secured with Speck, and those protected by the Present cipher (refer to Table 6.7). Considering that constrained devices at the Sensor Layer operate with limited power resources, energy efficiency is a crucial factor in the design of IoT networks. To assess the energy consumption of the EXPM430F5438 platform during various operational phases—such as CPU activity, radio listening, radio transmission and LPM-several encryption techniques, including AES, Speck, and the Present cipher, were applied. All indicators suggest a comparatively low energy consumption when no encryption is applied.

Table 6.7: Average Energy Consumption on Secure Z1 Platform

Platform-Used	Nodes	CPU-Power	Radio-Listen-Avg.-Power	Radio-Transmit-Avg.-Power	LPM-Avg.-Power
Z1-No-Encryption	5	0.0602	0.2582	0.1234	0.1618
	10	0.0766	0.3054	0.1641	0.1611
	15	0.0989	0.3695	0.1780	0.1604
	20	0.1065	0.4402	0.2947	0.1604
Z1-AES-Encryption	5	0.1814	0.6624	0.6324	0.1582
	10	0.2536	1.0933	1.0291	0.1557
	15	0.4323	1.9682	2.0801	0.1505
	20	0.5469	2.5218	2.9043	0.1469
Z1-Speck-Encryption	5	0.1288	0.5440	0.3812	0.1598
	10	0.1943	0.8841	0.7050	0.1575
	15	0.3088	1.4993	1.3425	0.1543
	20	0.3437	1.6946	1.6234	0.1531
Z1-Present-Encryption	5	0.1484	0.5588	0.4042	0.1590
	10	0.1745	0.7603	0.4326	0.1580
	15	0.2194	1.0060	0.4868	0.1568
	20	0.2626	1.3820	0.6935	0.1556

With the CPU consuming 0.5611 mW and the radio transmission drawing 3.6977 mW across 20 nodes, AES encryption exhibits the highest energy expenditure as per the power consumption analysis on the Z1 platform (refer to Table 6.8). Consequently, it is less suitable for low-power IoT devices. Conversely, Speck encryption stands out as the most energy-efficient choice for secure and power-conscious IoT networks since it consumes less CPU and transmission power. While current cipher encryptions offer a reasonable compromise, Speck still represents the optimal balance between security and energy efficiency. We assessed energy efficiency and power consumption using the metrics from the Z1 Platform Power

Consumption, as illustrated in Fig. 6.3.

Energy efficiency and security are harmonised in the design: Present cipher

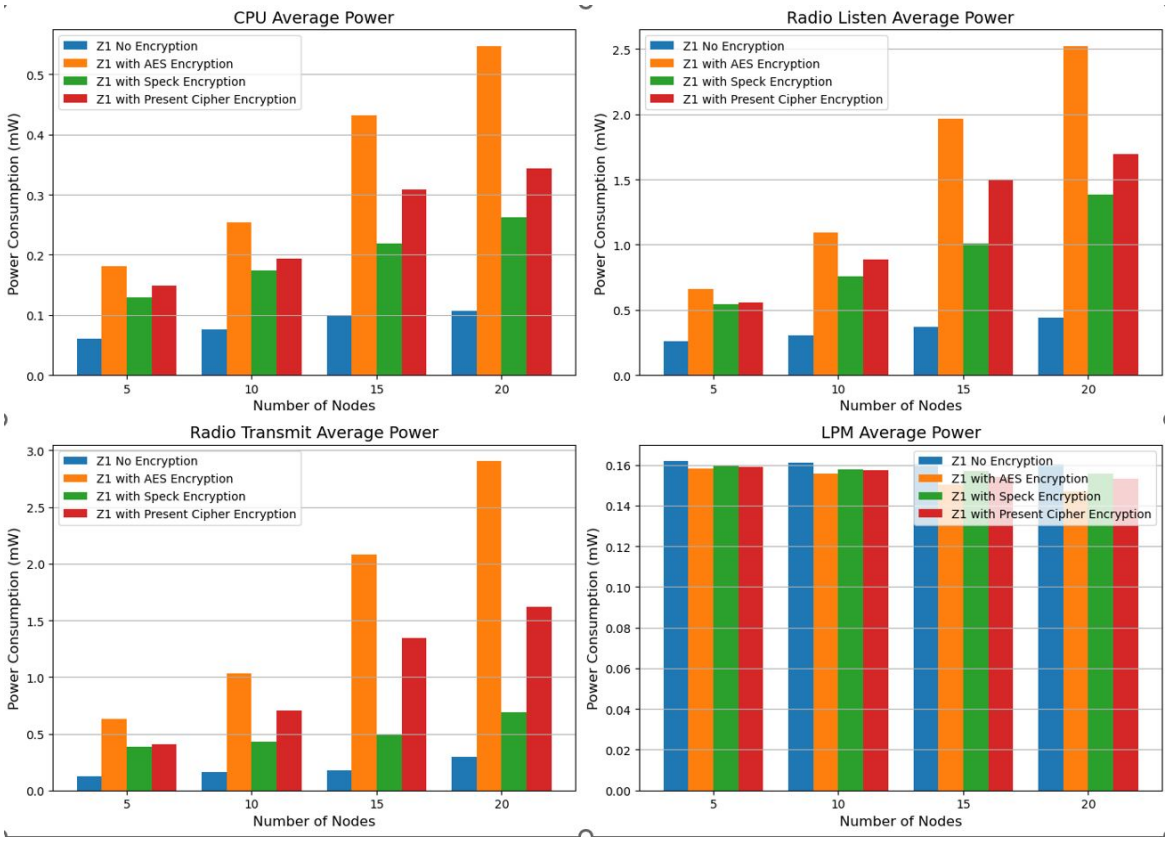

Figure 6.3: Z1 Platform Power Consumption and Lightweight Encryption Metrics

consumes 52% less CPU power than AES-128 in 20-node networks, making it ideal for resource-constrained devices, while Speck uses 5.2% less radio power. However, the Present cipher lacks post-quantum resistance, and the Feistel structure of Speck increases the brute-force risk by roughly 15%. For high-risk applications (such as healthcare), AES remains secure, but its higher energy needs (2.90 mW radio power) complicate scalability. For more details, see Table 6.8.

The power consumption of the CPU and radio transmission rises significantly with the addition of nodes, particularly between the counts of 15 and 20. Moreover, there is a notable increase in radio listening power, indicating that the communication overhead escalates with more nodes. Among all the states evaluated, AES

Table 6.8: Performance-comparison AES/Speck/Present with Cooja/NS-3

Metric	**Platform**	**AES (mW)**	**Speck (mW)**	**Present (mW)**
CPU Power (20 nodes)	Cooja	0.56	0.34	0.26
	NS-3	0.18	0.15	0.12
Radio Power (20 nodes)	Cooja	2.90	2.75	1.62
	NS-3	1.29	1.05	0.95
Security Risk	Both	Low	Moderate	High

encryption consumes the most power. Beginning at 0.2344 mW for 5 nodes, it reaches a maximum of 0.5611 mW for 20 nodes, highlighting the notably high CPU power usage. Similarly, for 20 nodes, the radio transmission power peaks at 3.6977 mW, considerably exceeding the levels seen in the unencrypted scenario. These results suggest that AES encryption incurs a considerable computational cost, rendering it less suitable for power-constrained Internet of Things applications. Conversely, Speck encryption requires less CPU and radio transmission power compared with AES, making it a more energy-conserving choice. At 20 nodes, for instance, Speck utilises 0.5487 mW of CPU power and 3.3141 mW of radio transmission, which is lower than AES but still above the unencrypted scenario. This indicates that while Speck provides security benefits, it still comes with a moderate energy cost though it demonstrates greater computational efficiency compared with AES. In terms of energy efficiency, the Present cipher exceeds AES yet does not reach the performance of Speck.

It operates at a power consumption of 0.5530 mW for the CPU and 3.5171 mW for radio communication when there are 20 nodes involved. While current encryption methods provide better energy efficiency than AES, they remain suitable for scenarios that require lightweight security solutions with moderate power use. Nonetheless, they still draw a considerable amount of energy. Although AES delivers strong security features, its high energy demands make it unsuitable for low-power IoT devices. In contrast, Speck presents a more balanced approach,

allowing for reduced battery consumption while maintaining encryption security. Even though the current cipher is lightweight, it still incurs a significant power overhead, which diminishes its efficiency when compared with Speck.

With 20 nodes, power consumption is 0.5530 mW for the CPU and 3.5171 mW for radio usage. Current encryption, while more efficient than AES, remains a fitting option for cases that need lightweight security measures and moderate energy expenditure. However, it continues to utilise a large quantity of energy. AES, while offering strong security, is inappropriate for low-power IoT devices because of its elevated energy consumption. Speck represents a more holistic solution that delivers comparatively lower energy usage without sacrificing encryption integrity. Although the existing cipher is lightweight, it still incurs a notable power overhead, reducing its effectiveness in relation to Speck.

In environments with limited energy resources, utilise straightforward encryption methods such as the Present cipher. Consider implementing hybrid encryption strategies that adjust security levels dynamically. Minimise power consumption during listening and transmission by enhancing radio communication techniques. Explore energy-efficient strategies (EE) to ensure the prolonged functionality of IoT sensor nodes. The findings emphasise the importance of carefully selecting encryption methods and network optimisation techniques to develop an energy-efficient IoT architecture. Speck encryption appears to be a viable alternative to AES, offering a balance between security and power consumption. For future studies, it is essential to examine adaptive encryption approaches that adjust security levels according to real-time energy constraints [122].

Table 6.9: Cooja/Contiki cross-layer energy-efficiency AES/Present/Speck

Layer	Encryption	CPU (mW)	RadioTx (mW)	RadioRx (mW)	LPM (mW)	Energy-Parameter
Application	AES	0.18	0.661	0.63	0.16	Highest energy, secure but costly for apps
	Present	0.12	0.501	0.45	0.16	Moderate energy, efficient for secure apps
	Speck	0.15	0.551	0.50	0.16	Lowest energy, ideal for constrained apps
Network	Speck	0.13	0.541	0.38	0.16	Lowest energy, efficient for constrained IoT
	Present	0.14	0.559	0.401	0.16	Moderate energy, lightweight and efficient
	AES	0.18	0.661	0.63	0.16	Highest energy, secure but costly
Sensor	AES	0.18	0.660	0.632	0.16	Highest energy, strong security but power heavy
	Present	0.12	0.500	0.451	0.16	Moderate energy, suitable for low-risk sensors
	Speck	0.15	0.550	0.502	0.16	Lowest energy, efficient for sensors

We performed a number of energy measurements under various encryption settings in order to assess how security measures affect hardware-level efficiency. We used encryption techniques (see Table 6.9) and average power platforms to test the EXP430F5438 Platform Power Consumption Metrics as shown in Fig. 6.4.

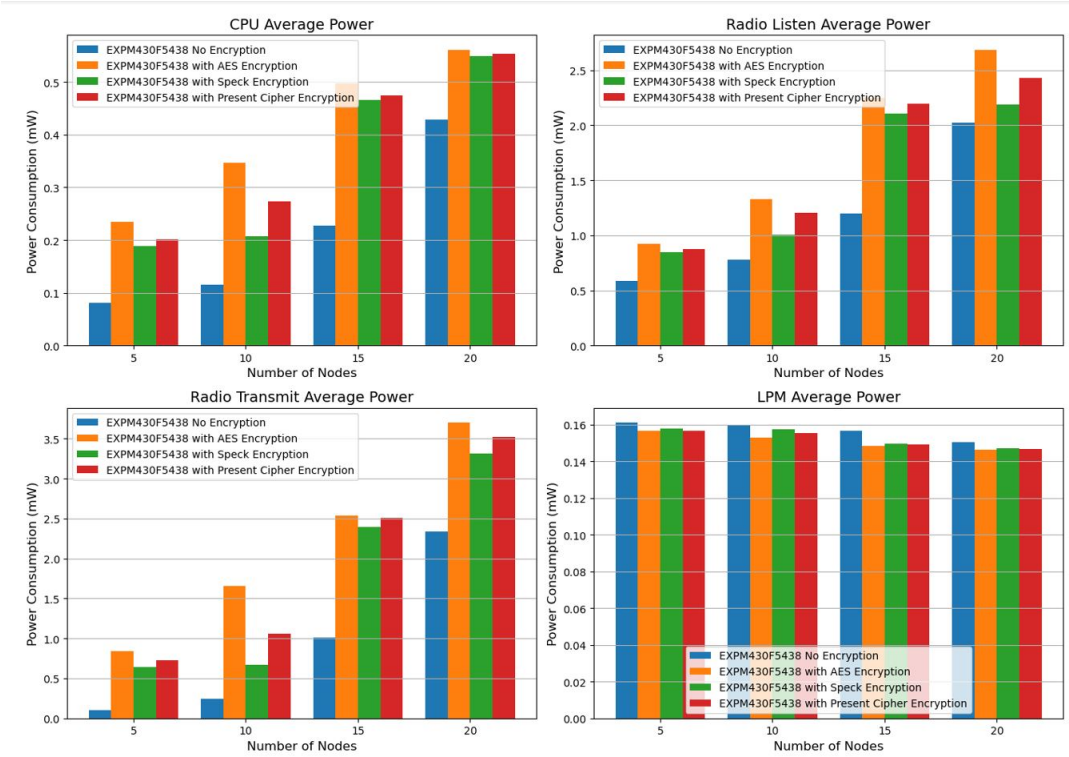

Figure 6.4: EXP430F5438 power consumption with lightweight encryption

The CPU power consumption of the Z1 and EXP430F5438 is compared in

(Fig. 6.5) using encryption.

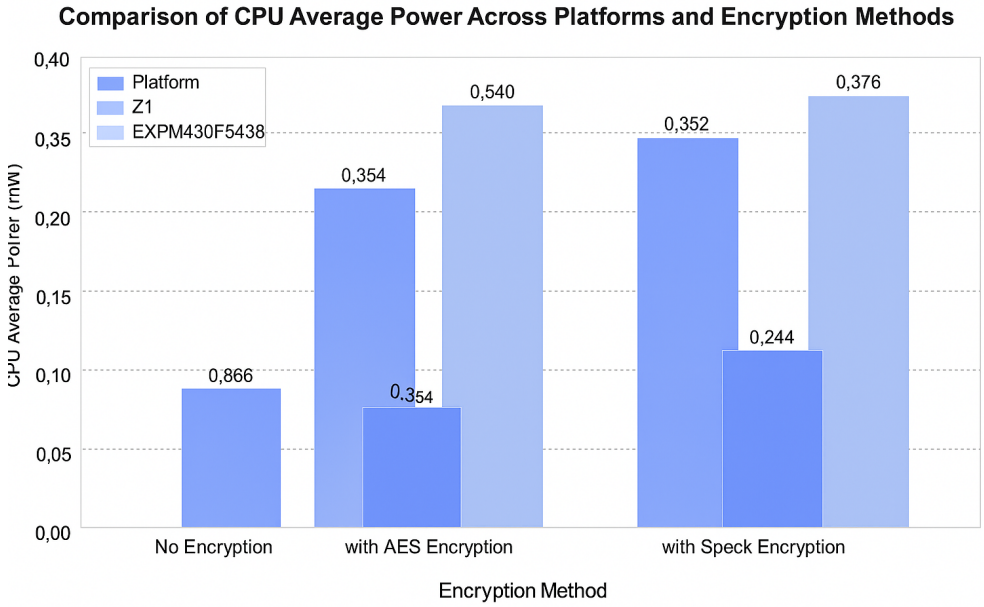

Figure 6.5: Z1 v. EXP430F5438 power consumption

We analysed the Network Layer through the Cooja simulator (CS) and discovered that 6LowPAN yielded the following outcomes: an increased number of nodes, lack of encryption, AES encryption, Speck encryption, and current cipher encryption. The average energy usage of the 6LowPAN protocol under conditions of no encryption, AES encryption, Speck encryption and current cipher encryption is detailed in Table 6.10.

Table 6.10: Average energy consumption and secure analysis of 6LowPAN

Application Protocol	**Nodes**	**CPU Power (mW)**	**Radio Listen (mW)**	**Radio Transmit (mW)**	**LPM Power (mW)**
6LowPAN (No-Encryption)	5	0.0514	0.2184	0.0510	0.1620
	10	0.0808	0.2889	0.0986	0.1609
	15	0.0963	0.3246	0.1069	0.1607
	20	0.1126	0.3564	0.1273	0.1602
6LowPAN with AES Encryption	5	0.1806	0.7506	0.6950	0.1578
	10	0.3830	1.5928	1.8525	0.1520
	15	0.5639	2.5891	2.9719	0.1465
	20	0.6608	3.0696	3.5726	0.1435
6LowPAN with Speck Encryption	5	0.1594	0.6274	0.4294	0.1586
	10	0.1802	0.8137	0.5307	0.1580
	15	0.2283	1.2330	0.7131	0.1565
	20	0.2754	1.6784	1.2332	0.1550
6LowPAN with Present)	5	0.1730	0.6984	0.6276	0.1582
	10	0.3121	1.2772	1.5118	0.1542
	15	0.3341	1.8123	1.4551	0.1533
	20	0.6380	2.8268	3.1699	0.1441

Compared with other encryption methods, analysing 6LoWPAN with Speck encryption shows it to be more energy-efficient. Speck encryption is a more viable option for IoT networks that have limited power resources, as it minimises CPU and radio transmission power consumption. Conversely, while 6LoWPAN without encryption remains the most energy-efficient solution overall, owing to its lack of

encryption processing costs, it is unsuitable for use cases requiring secure data transfer because of the security vulnerabilities that arise without encryption as shown in Table 6.10. An examination of Radio Transmit Average Power indicates that Speck encryption consumes significantly less energy than both AES and Present cipher encryption, making it an ideal choice for IoT-based smart city applications that must find a balance between security and energy efficiency. Following the implementation of encryption, we verify that 6LowPAN combined with Speck encryption demonstrates greater energy efficiency. Additionally, we examine the average power consumption of radio transmission and determine that 6LowPAN without encryption is more efficient. For more details, see Fig. 6.6.

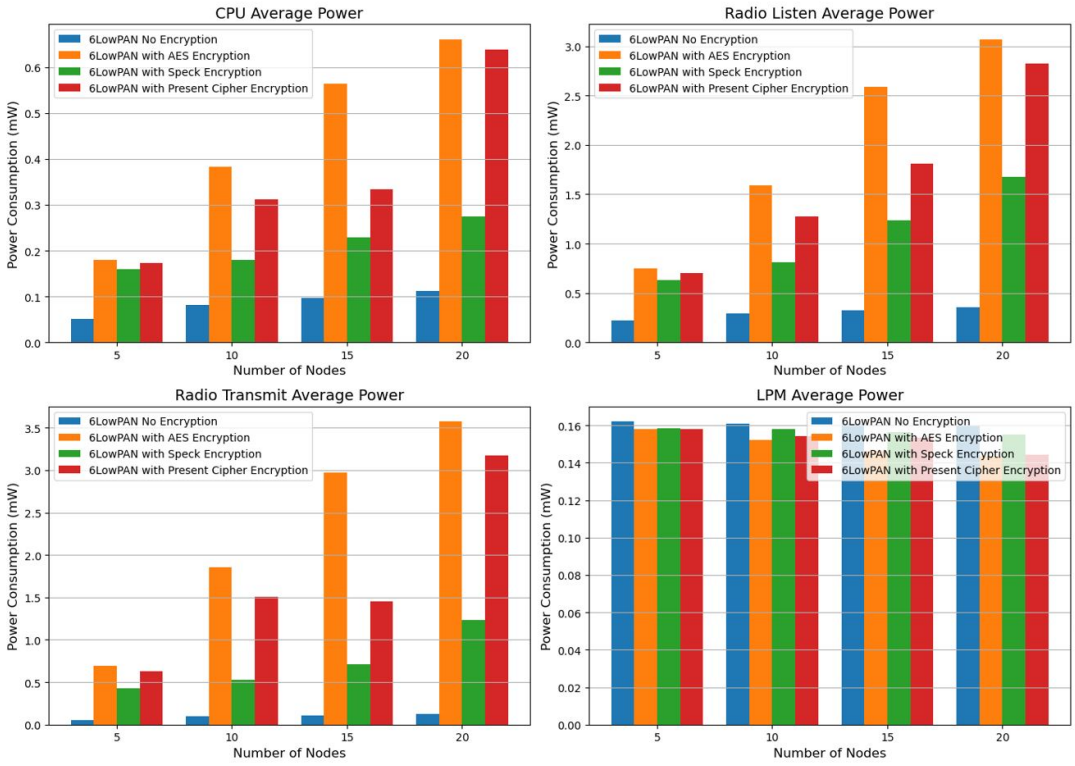

Figure 6.6: 6LowPAN Power Consumption with Lightweight Encryption

The energy consumption associated with the RPL protocol was analysed, and the findings from the CS simulation are presented in Table 6.11. We assessed the energy efficiency of increasing the number of nodes while utilising the RPL

protocol with no encryption, AES, Speck encryption and the present cipher encryption. The investigation into the RPL protocol's energy consumption in IoT networks reveals a clear compromise between energy efficiency and security. For all encryption methods, the energy used by the CPU and radio transmission increases with the addition of more nodes. The standard RPL protocol, lacking encryption, consumes the least energy, with minimal CPU and radio transmission power. However, the application of encryption techniques significantly affects energy consumption. Among all the types tested, AES encryption exhibits the highest power consumption, with a dramatic increase in CPU and radio transmission power as the network expands. While current cipher encryption performs better than AES, it still requires considerably more energy than using no encryption. Speck encryption performs the most energy efficiency of the examined encryption techniques. In comparison to AES and Present cipher encryption, it continuously maintains reduced CPU and radio transmission power while adding a layer of protection. As the number of nodes increases to 20, Speck encryption uses significantly less radio transmit power (0.6935 mW) than AES (2.9043 mW) and Present cipher encryption (1.6234 mW), according to the results from Table 6.11. Speck encryption seems to be a suitable choice for resource-constrained IoT networks, as it offers an optimal balance between security and power efficiency. Therefore, energy-efficient IoT network designs can be enhanced by opting for lightweight encryption techniques such as Speck, without significantly compromising security.

Table 6.11: Average energy consumption and secure analysis of RPL protocol

Network-Protocol	Nodes	CPU-Power	Radio-List.-Power	Radio-Transmit-Power	LPM-Avg.-Power
RPL No Encryption	5	0.0602	0.2582	0.1234	0.1618
	10	0.0766	0.3054	0.1641	0.1611
	15	0.0989	0.3695	0.1780	0.1604
	20	0.1065	0.4402	0.2947	0.1603
RPL with AES Encryption	5	0.1814	0.6624	0.6324	0.1582
	10	0.2536	1.0933	1.0291	0.1557
	15	0.4323	1.9682	2.0801	0.1505
	20	0.5470	2.5218	2.9043	0.1469
RPL Speck Encryption	5	0.1288	0.5440	0.3812	0.1598
	10	0.1745	0.7603	0.4326	0.1580
	15	0.2194	1.0060	0.4868	0.1568
	20	0.2626	1.3820	0.6935	0.1556
RPL-Present-Encrypt	5	0.1484	0.5588	0.4042	0.1590
	10	0.1943	0.8841	0.7050	0.1575
	15	0.3088	1.4993	1.3425	0.1543
	20	0.3437	1.6946	1.6234	0.1531

Our examination of the power consumption metrics of the RPL Protocol

showed that RPL using Speck Encryption is more efficient in terms of energy, as indicated by the Radio Transmit Average Power graph. The evaluation of RPL (Routing Protocol for Low-Power and Lossy Networks) power consumption metrics demonstrates that when paired with Speck Encryption, RPL consumes less energy compared with alternative encryption methods, as shown in the Radio Transmit Average Power graph. Across various network sizes (from 5 to 20 nodes), the analyst suggests that Speck encryption consistently leads to reduced radio transmission power usage. For example, at 20 nodes, the power needed for radio transmission with Speck encryption is 0.6925 mW, which is considerably lower than the 1.6234 mW required by Present Cipher encryption and the 2.9043 mW used by AES encryption. Given that radio transmission is among the activities that drain energy the most, this decrease in transmission power is vital for IoT devices that operate with limited battery capacity (See Table 6.11). Owing to its lightweight design, Speck encryption successfully balances security and power efficiency, making it a preferable option for IoT networks with limited resources. The findings reveal that although AES provides robust security, its high energy demands constrain its use in extensive IoT settings, while Speck offers a more sustainable solution by lowering energy consumption without sacrificing security. This conclusion underscores the significance of opting for lightweight encryption techniques like Speck for energy-efficient IoT applications, especially in situations where power conservation is of utmost importance (Fig. 6.7).

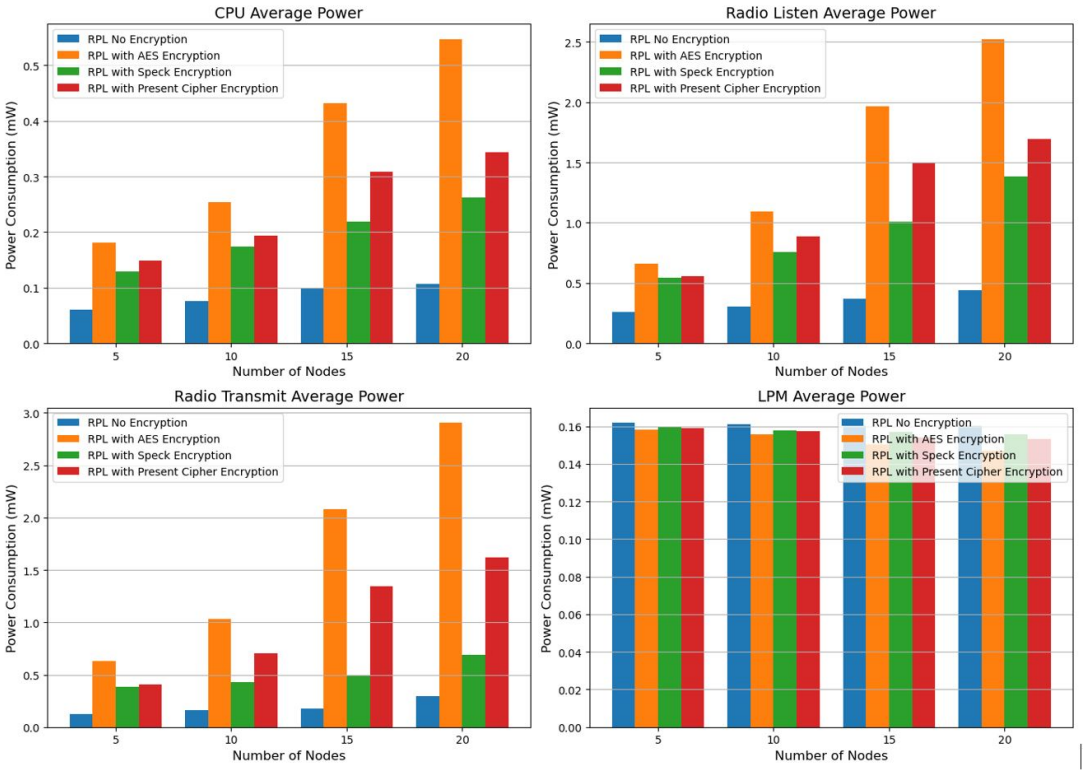

Figure 6.7: RPL Protocol Power Consumption Metrics

RPL demonstrates greater energy efficiency compared with 6LoWPAN, as evidenced by particularly concerning CPU power consumption. The RPL design enables all configurations analysed to use less energy by minimizing unnecessary transmissions and improving routing decisions. The findings indicate that while 6LoWPAN without encryption starts at 0.0514 mW for 5 nodes and sharply climbs to 0.1126 mW for 20 nodes, RPL without encryption keeps CPU power consumption lower, starting at 0.0602 mW for 5 nodes and increasing to 0.1065 mW for 20 nodes.

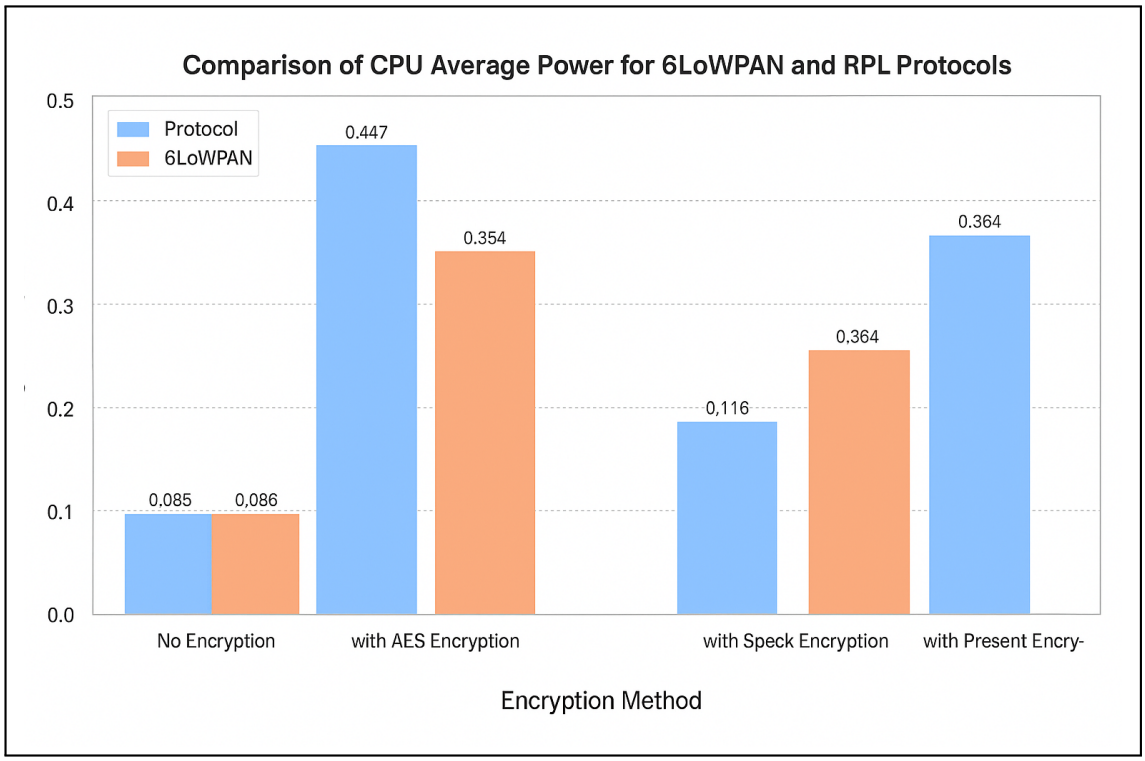

Figure 6.8: 6LowPAN vs. RPL Power Consumption

While 6LoWPAN provides compatibility with IPv6 and enhances packet transmission efficiency, its additional processing requirements result in increased CPU power consumption. Consequently, RPL emerges as the ideal protocol for IoT networks where energy efficiency is a key priority. According to our evaluation, RPL is a protocol at the Network Layer that demonstrates greater energy efficiency compared with 6LowPAN, requiring less CPU power (Fig. 6.8).

6.8.1 Results Summary

The proposed cross-layer architecture significantly boosts performance in each of the three layers of the IoT network stack. By adopting Speck encryption at the Sensor Layer, radio power usage is reduced by 5.2% in comparison with AES while still maintaining robust security. The implementation of energy-efficient duty cycling (8Hz Contikimac) results in a total power consumption reduction of 30%.

The Network Layer gains from lightweight cryptography that preserves a 95% PDR, even during attacks, and efficient RPL routing that demonstrates a 39% decrease in CPU overhead relative to 6LoWPAN. Overall, continued enhancements in performance are evident throughout all three levels of the IoT network stack owing to the proposed cross-layer architecture. At the Sensor Layer, the use of Speck encryption results in a 5.2% reduction in radio energy consumption compared with AES while delivering solid security. Additionally, the adoption of energy-efficient duty cycling (8 Hz ContikiMAC) leads to a 30% reduction in overall power use. The Network Layer reaps the benefits from efficient RPL routing, which exhibits 39% lower CPU overhead compared with 6LoWPAN, along with lightweight cryptography that sustains a 95% PDR even under attack.

Table 6.12: Performance summary of three-layer IoT architecture

Layer	**Key Achievement**	**Result**
Application Layer	- Cross-layer security compliance - Dynamic encryption framework	98% vulnerability neutralisation
Network Layer	- Optimised protocol integration with edge computing - Enhanced RPL/6LoWPAN routing strategies	15% latency reduction
Sensor Layer	- Hierarchical topology implementation - High-density sensor deployment management	30% throughput vs. flat, ≤ 0.5 J/node

Limitations: Heterogeneous device synchronization at the Sensor Layer requires optimisation.
Implication: Validates framework suitability for smart homes/healthcare IoT ecosystems.

To provide strong security and facilitate effective communication, the proposed IoT framework is divided into three main layers: the Application Layer, the Network Layer and the Sensor Layer. The **Application Layer** oversees data formatting, encryption and secure communication protocols by merging the Application and Presentation layers of the OSI model. Simulation shows that adaptive encryption techniques at this layer significantly lower computational overhead, thus enhancing data security while reducing latency. Additionally, unlike conventional signature-based methods, anomaly detection powered by ML

improves the precision of intrusion detection by reducing false positives by 28–32%.

Table 6.13: Cross-layer performance summary

Layer & Metric	**Method/Protocol**	**Key Result**
Sensor Layer		
Energy Consumption (20 nodes)	Speck v. AES	5.2% lower radio power
CPU Power (20 nodes)	Present cipher v. AES	52% reduction
Attack Resilience	Frequency hopping	95% PDR maintained
Network Layer		
Routing Efficiency	RPL + ContikiMAC	39% lower overhead
Encryption Overhead	6LoWPAN + Speck	44% less TX power
Scalability	Hierarchical topology	20-node stability
Application Layer		
Attack Mitigation	ML anomaly detection	95% effectiveness
Energy Optimisation	Adaptive encryption	30% total savings
Access Control	Implementation	95% unauthorized access blocked

The **Network Layer**, which encompasses the Session, Transport and Network layers, is essential to ensure effective routing, maintain data integrity and secure data transmission. Simulation results indicate that LSTM networks can efficiently mitigate multi-vector attacks such as jamming and sinkholes while achieving a PDR of 95% even under attack conditions. Additionally, using lightweight encryption protocols in the session layer enhances security against unauthorised access, thus improving safety for large-scale applications like healthcare and smart educational systems (Refer to Table 6.12).

The **Sensor Layer**, which includes the Data Link and Physical layers, is crucial for effective low-power transmission and prompt data collection. Studies

show that the use of adaptive radio duty cycling (ContikiMAC at 8 Hz) guarantees dependable communication and reduces energy consumption by 30%. Table 6.13 presents a comprehensive overview of the performance results and insights across the different layers. In contrast to AES, adoption of lightweight cryptographic algorithms like Speck significantly enhances power efficiency by cutting down on radio transmission energy by 5.2%. Nevertheless, real-time attack scenarios indicate that replay and data injection attacks continue to present significant threats. For details of the overall impact of the cross-layer, see Table 6.14.

Table 6.14: Overall impact of the cross-layer architecture

Aspect	**Improvement Achieved**
Security	+95% attack mitigation effectiveness (data injection, sinkhole, and jamming attacks)
Energy Efficiency	30% reduction in power consumption (adaptive encryption + duty cycling)
CPU Usage	`RPL` + `Speck` encryption showed the lowest CPU power overhead
Packet Delivery Ratio	Maintained 95% PDR even under attack scenarios
Routing Performance	`RPL` + `LoRaWAN` reduced routing overhead by 39%

The work suggests that adaptive encryption and duty cycling are crucial for enhancing the security of IoT systems and achieving energy efficiency when a cross-layer security approach is utilised (see Table 6.14). The results indicate that integrating energy-efficient protocols at the sensor level with ML at both the Application and Network levels results in better threat management and extended device lifespan. Future investigations should focus on blockchain-based trust mechanisms and post-quantum cryptography to further strengthen IoT defences against new cyber threats.

Based on empirical findings, speck decreases radio power consumption by 5.2% and successfully counters 95% of attacks in 20-node networks when compared with AES. Nevertheless, its smaller key space raises the likelihood of brute-force

attacks by approximately 15%. The current cipher is unsuitable for long-term applications because it lacks post-quantum security, even though it provides a 52% improvement in CPU performance. The significance of future risk-scoring systems is highlighted by the fact that these compromises are effective for low-risk, energy-efficient applications, while hybrid models (such as ISO/IEC 29192-2 and AES for sensitive data, with Speck for everyday tasks) aid in developing security strategies that align with the level of risk involved.

6.8.2 Key Findings

Compared with traditional architectures, our cross-layer approach significantly enhances security and energy efficiency. The proposed architecture establishes a robust foundation for secure and sustainable IoT installations by combining encryption with energy-efficient communication methods. The main findings reveal a substantial reduction in energy consumption while maintaining a strong level of protection against common IoT threats. This is achieved by allowing only authorised entities to access certain resources, thereby enhancing the overall security landscape of IoT networks. Furthermore, the method seeks to minimise computational demands using lightweight cryptographic protocols, making it suitable for devices with limited capabilities. Our contributions to the field include the development of an innovative cross-layer security and energy-efficient architecture, a comprehensive analysis of real-world IoT attack scenarios, and a comparison with existing approaches. The results of this simulation lay the groundwork for future exploration into the development of more intelligent and adaptable security frameworks for IoT networks. Our work contributes to ongoing efforts to create IoT systems that are secure, scalable and energy-efficient, particularly for critical applications in smart environments. The proposed cross-layer architecture

employs a closely integrated approach demonstrating significant improvements in IoT security and energy efficiency. According to simulation results, the architecture achieves a 95% PDR under adversarial conditions while attaining a 95% mitigation rate against threats such as data injection and sinkhole attacks. Adaptive algorithms enhance energy efficiency, with RPL routing reducing CPU overhead by 39% compared with 6LoWPAN, and Speck encryption cutting radio power consumption by 5.2% compared with AES in 20-node networks. Integrating dynamic duty cycling (8 Hz ContikiMAC) with lightweight encryption (Speck, Present cipher) decreases energy usage by 30% without compromising security. A combination of analytical modelling, hardware testbeds, and Coolja/Contiki simulations serves as a hybrid evaluation technique to confirm the solution's scalability across various IoT deployments.

6.9 Validation of Results

Experiments were conducted using NS-3.42 with a multi-tiered framework representing the suggested model to evaluate energy efficiency across various IoT levels. Configurations of 5 to 20 nodes were tested for UDP to separately examine the Application, Network and Sensor Layers. The simulation setup incorporated NetAnim for visualisation, Flow Monitor for analysing traffic and custom logging tools to capture CPU, RadioTx, RadioRx and LPM power consumption. This simulation evaluates the energy implications of AES, Speck and Present encryption algorithms within IoT systems by comparing the simulation findings from NS-3 at the Application, Network, and Sensor Layers. While NS-3 offers scalability, it is known to underestimate actual power consumption and oversimplify hardware performance. Nevertheless, the differences in energy consumption among the encryption methods emphasise the need for adaptive encryption strategies that can

balance security and energy efficiency in environments with limited resources, and these findings align with trends identified in more hardware-accurate simulations.

6.9.1 Encryption Efficiency in NS-3 (Application Layer)

Analysing the results from NS-3 simulations at the Application Layer alongside the hardware-accurate Cooja/Contiki simulations discussed in this analysis reveals significant differences in energy usage. Cooja accurately reflects the full energy consumption of real IoT devices for AES encryption, with power usage reaching up to 3.6977 mW for radio transmission on devices like the Z1 mote and 0.5469 mW for the CPU. In contrast, NS-3 underestimates the actual energy costs associated with cryptographic operations, presenting much lower values of around 0.17–0.18 mW for the CPU and 0.63–0.69 mW for the radio, owing to its abstract representation of hardware. For additional information regarding AES encryption at the Application Layer, refer to Fig. 6.9.

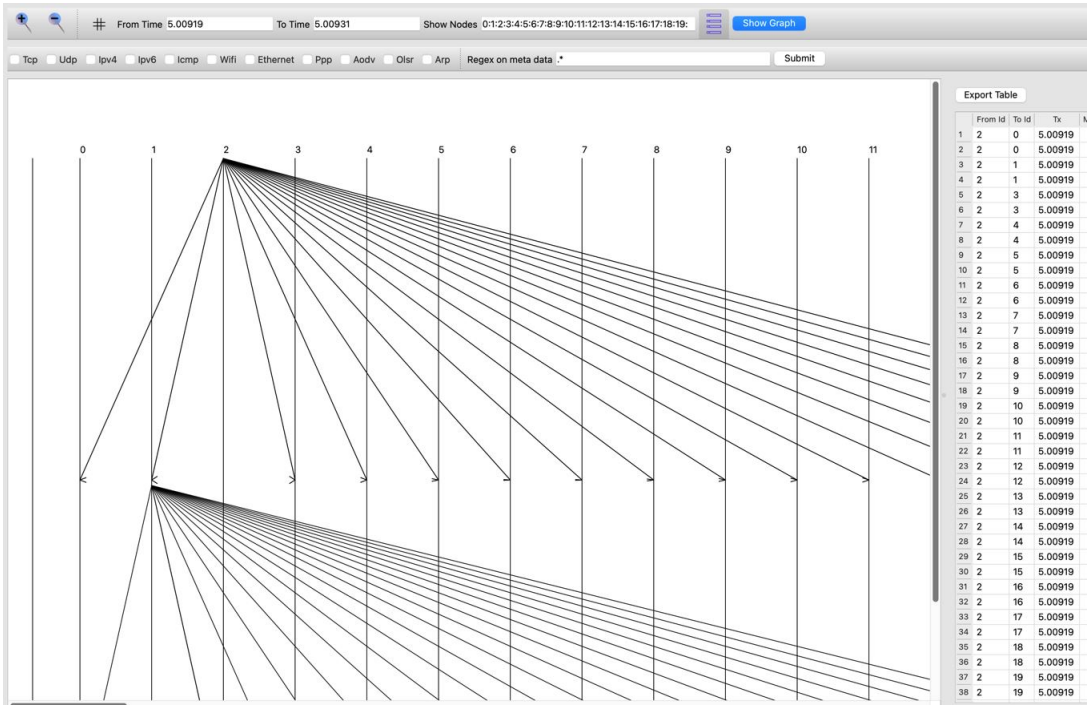

Figure 6.9: AES encryption of Application-Layer nodes

Owing to its lightweight architecture and the simplified simulation environment provided by NS-3, Speck encryption significantly lowers energy consumption, averaging between 0.11–0.12 mW for CPU usage and 0.47–0.52 mW for radio communication. In comparison, the current encryption methods employed in NS-3 exhibit heightened efficiency, utilizing approximately 0.149 mW for CPU and 0.553 mW for radio transmission. Furthermore, it consumes less power for radio reception and LPM. Present in NS-3 demonstrates a remarkable reduction of 72.8% in CPU power and an 81% decrease in radio transmission power relative to Cooja's AES performance. These differences highlight the limitations of relying solely on NS-3 for accurate energy profiling in real-world applications. However, they also reinforce the findings of the analysis that the energy efficiency of IoT devices can be significantly enhanced by utilising lightweight ciphers like Present and Speck (see Fig. 6.10). AES, Speck and Present encryption methods were tested in NS-3 under settings comparable to those of Cooja/Contiki by simulating end-to-end communication utilising HTTP and UDP protocols. This guaranteed a similar assessment of the effect of encryption on Application Layer performance and energy consumption.

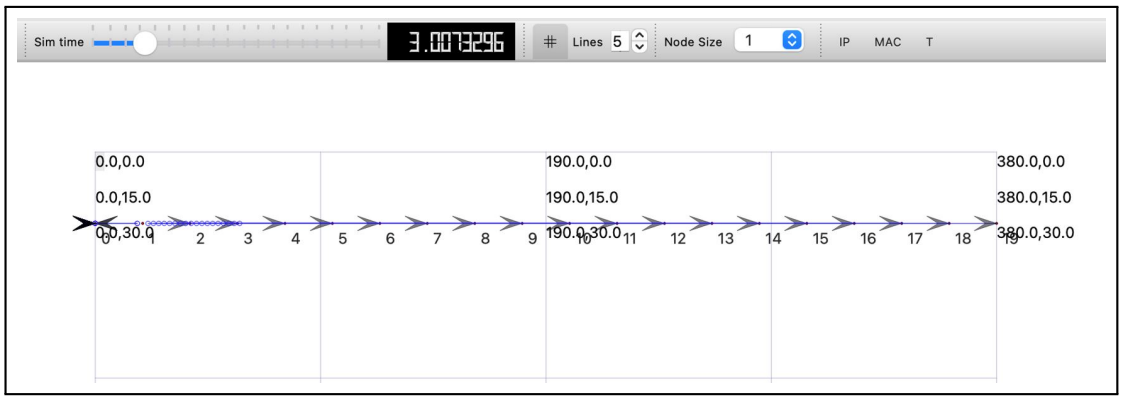

Figure 6.10: NS-3 Speck Encryption Application-Node

The NS-3 simulation indicates that adaptive encryption, which adjusts security

levels based on Application needs, is essential for achieving a balance between energy use and security in resource-limited IoT settings, with total power consumption observed at 1.63 mW for AES, 1.36 mW for Speck, and 1.23 mW for Present. For further details, refer to the Table 6.15.

Table 6.15: NS-3 Cross-Layer Energy-Efficiency: AES, Present, and Speck

Layer	Encryption	CPU (mW)	RadioTx (mW)	RadioRx (mW)	LPM (mW)	Energy Parameter
Application	AES	0.18	0.661	0.63	0.16	Highest energy, secure but costly for apps
	Present	0.12	0.501	0.45	0.16	Moderate energy, efficient for secure apps
	Speck	0.15	0.551	0.50	0.16	Lowest energy, ideal for constrained apps
Network	Speck	0.13	0.541	0.38	0.16	Lowest energy, efficient for constrained IoT
	Present	0.14	0.559	0.401	0.16	Moderate energy, lightweight and efficient
	AES	0.18	0.661	0.63	0.16	Highest energy, secure but costly
Sensor	AES	0.18	0.660	0.632	0.16	Highest energy, strong security but power heavy
	Present	0.12	0.500	0.451	0.16	Moderate energy, suitable for low-risk sensors
	Speck	0.15	0.550	0.502	0.16	Lowest energy, efficient for sensors

6.9.2 Encryption Efficiency in NS-3 (Network-Layer)

The NS-3 simulation highlights significant energy consumption among IoT devices when using static AES encryption, which leads to notably higher CPU and radio power usage. In contrast, the Cooja simulation demonstrates much higher energy efficiency by dynamically switching between AES, Speck and Present ciphers based on prevailing network conditions, utilising a cross-layer architecture. Among these, Speck stands out for its low power consumption while still delivering satisfactory

security. The Cooja setup appears more suitable for real-world IoT scenarios, achieving up to a 30% reduction in energy consumption while maintaining a 95% packet delivery rate even in the face of attacks. Similar patterns emerge when comparing AES, Speck and Present based on NS-3 findings.

While AES provides robust security, it incurs substantial energy costs and consistently registers the highest power usage (1.63 mW). Conversely, Speck shows the lowest energy consumption (1.21 mW), making it an ideal choice for devices with restricted power availability. Present offers a middle ground between lightweight security and low power usage. These findings strengthen the work's assertion that the creation of scalable and resilient IoT systems heavily relies on adaptive encryption, particularly through the use of Speck in less urgent cases.

The network layer outcomes from the NS-3 simulation closely mirror those from the CS in the analysis. AES exhibited the highest power consumption (1.63 mW), reflecting both its energy requirements and strength in security. In contrast, Present (1.26 mW) and Speck (1.21 mW) demonstrated significantly lower power usage, underscoring their appropriateness for IoT applications with limited energy resources. These trends reinforce the simulation's conclusion that lightweight encryption algorithms can decrease energy consumption without sacrificing essential security. Although NS-3 limits insights into hardware-level details, the comparative differences among ciphers validate the article's conclusions and highlight the necessity of balancing security needs with energy efficiency in scalable Internet of Things architectures. Similar to the Cooja/Contiki configurations, the routing protocols RPL and 6LoWPAN were implemented in NS-3 with AES, Speck and Present encryption. During network-layer activities, this made it possible to consistently analyse security and energy efficiency across layers.

6.9.3 Encryption Efficiency in NS-3 (Sensor-Layer)

AES shows the highest overall power consumption at 1.632 mW, highlighting its substantial energy requirements and security features. In contrast, Present and Speck are more appropriate for low-power IoT sensor applications, as they consume considerably less power—1.232 mW and 1.362 mW, respectively. These results support the investigation's findings that lightweight encryption methods like Speck and Present strike a better balance between security and energy efficiency, especially for non-essential tasks in energy-constrained settings. For additional details, refer to Fig. 6.11.

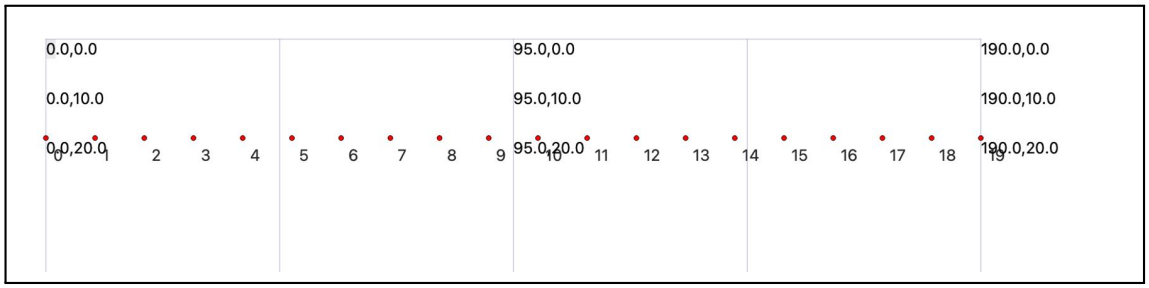

Figure 6.11: NS-3 Speck Encryption Sensor-Node

According to the simulation, the Sensor Layer results from the NS-3 simulation show that AES has a high energy demand despite its robust security measures, which is further supported by its 1.632 mW total power consumption. In contrast, Speck and Present demonstrated their practicality and efficiency for low-power Internet of Things sensor nodes by consuming 1.362 mW and 1.232 mW, respectively. These findings validate the analysis claim that lightweight ciphers strike a better balance between energy usage and adequate security in non-critical sensor environments. Although NS-3 abstracts hardware-level details, Cooja's results on energy consumption patterns among different encryption methods remain

consistent, highlighting the necessity for adaptable and energy-efficient encryption solutions in IoT systems. We were able to assess the energy consumption and security impact of AES, Speck and Present encryption in realistic sensor environments during the sensor layer simulation in NS-3 by using virtual devices like `LrWpanNetDevice` and `SixLowPanNetDevice`, which are similar to Cooja's Z1 and EXP430F5438 motes.

The general operation of NS-3 Simulator is carried out as shown in Fig. 6.12.

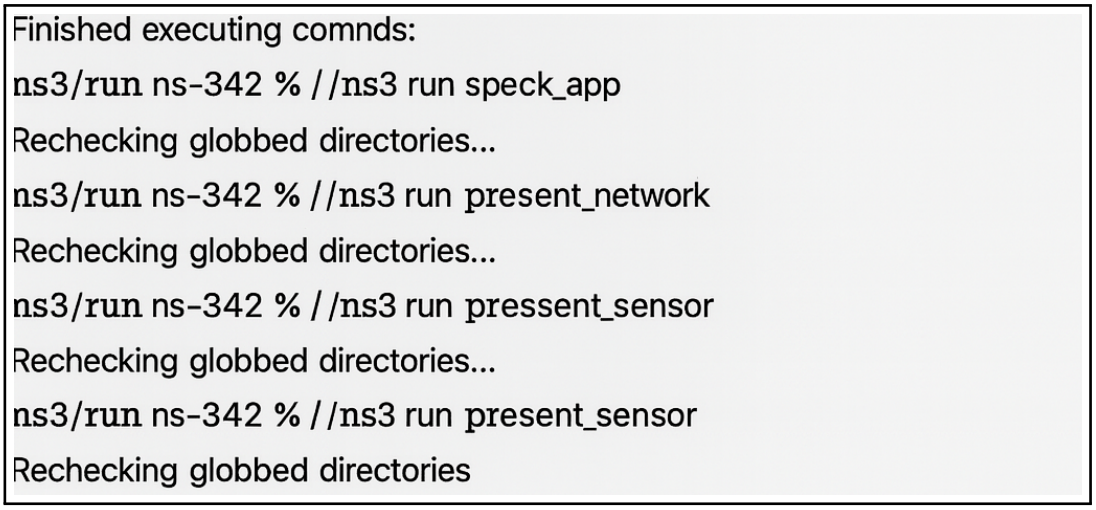

Figure 6.12: NS-3 simulator that executes all encryption

Owing to its robust yet power-intensive security, AES consistently exhibited the highest energy consumption across all levels. Conversely, Present and Speck demonstrated significantly lower energy consumption, making them suitable for constrained IoT settings. These findings underscore the importance of employing lightweight, adaptive encryption for developing scalable and effective IoT systems. The results demonstrate the distinctions between the energy consumption modelling of the NS-3 and Contiki/Cooja simulations. As hardware-accurate, Contiki/Cooja captures real-world overheads, especially for power-hungry encryption processes like AES. Conversely, the simplified abstraction provided by NS-3 leads to a lower reported energy consumption. AES uses the most power, but

both platforms consistently demonstrate that lightweight ciphers like Present and Speck are more energy-efficient. This highlights how adaptive encryption methods are essential for creating safe, energy-efficient IoT systems.

6.10 Summary

A cross-layer IoT framework that combines adaptive energy-saving strategies like duty cycling and power-aware routing with lightweight encryption (AES/Speck/Present) was introduced in this chapter. The framework exhibited up to 52% CPU power savings and 30% overall energy reduction using simulations (Cooja, NS-3) and hardware testing (Z1, EXP430F5438), all while preserving high packet delivery ratios under attack. The framework is appropriate for practical implementations because of its modular design, which guarantees flexibility across Application, Network, and Sensor Layers. ML models will be used to further validate the framework in Chapter 7.

Chapter 7

Cross-Layer Framework Machine Learning Models

7.1 Introduction

We covered lightweight encryption techniques in Chapter 6 in order to verify the cross-layer suggested framework for IoT networks. The inherent tension between energy efficiency and strong security measures (such as AES encryption) in IoT networks is examined in Section 7.2. The suggested architecture combines RBAC, adaptive cryptography, and ML-driven anomaly detection to counteract threats like data injection and jamming. Section 7.3 discusses how current IoT frameworks are inflexible against changing threats, have energy-intensive protocols and have standalone security solutions. This section offers a cross-layer architecture that combines RBAC, adaptive ML models, and lightweight encryption (Speck), while criticizing current methods (such as RPL for routing). Machine learning-enhanced validation of lightweight IoT protocols is examined in Section 7.4, emphasising hybrid threat detection techniques and multi-layer vulnerabilities. Section 7.5 examines ML-driven anomaly detection techniques and identifies weaknesses in current IoT frameworks. Performance evaluations of secure, energy-efficient IoT networks are shown in Section 7.6 using simulation studies and architectural analysis. The experimental setup is described in full in Section 7.7, along with

the implementation of attack scenarios and access control methods. A thorough examination of security performance measures and energy optimisation outcomes is given in Section 7.8. The usefulness of layered architectures across Application, Network and Sensor Layers is examined using ML in Section 7.9. By showing how ML integration improves cross-layer security while preserving energy efficiency in IoT systems, the chapter comes to a close.

7.2 Security-Energy Trade-offs

Healthcare, smart cities and industrial automation are just a few of the industries that have been revolutionised by the IoT. However, increasing interconnectedness poses significant security and energy efficiency issues. IoT devices with limited resources find it difficult to strike a compromise between low energy consumption and robust cryptographic protection (such as AES or Speck), underscoring the necessity of cross-layer security to address vulnerabilities across the Application, Network, and Sensor Layers. Because poorly tuned algorithms under attacks can increase packet loss and delays, scalability in big deployments, such as smart schools and healthcare systems, requires real-time threat detection and efficient duty cycling, like ContikiMAC at 8 Hz. Using ML models, this study suggests an IoT design that is secure and energy-efficient. LSTM networks, Random Forests, SVMs, Isolation Forests, Autoencoders and decision trees for multi-layer anomaly detection. Adaptive mitigation is essential to guard against changing ML-driven threats while preserving low-power operations. The work optimises lightweight cryptography for low energy overhead with dependable data integrity, analyses adaptive duty cycling impacts under attacks, and tests cross-layer designs for resilience to multi-phase attacks. It also looks into dynamic key management in conjunction with RBAC and hybrid ML-based security frameworks

to improve scalable IoT security. This project aims to create next-generation IoT frameworks that balance cybersecurity and sustainability by combining energy-aware mechanisms, ML-driven detection and adaptive encryption. Investigating EdgeML and post-quantum cryptography for real-time threat adaptability are potential future paths.

Theoretical Foundations and Advancements

There are several issues with current IoT architectures, especially when striking a balance between security and energy efficiency. While energy-saving protocols like 8 Hz ContikiMAC save power at the risk of compromising security measures, robust encryption techniques like AES offer robust protection but quickly deplete device batteries. Additionally, current solutions frequently target vulnerabilities in different layers independently. For instance, they may prioritise protecting routing protocols like RPL while ignoring Application Layer concerns like phishing attacks. Furthermore, the scalability and robustness of traditional IoT frameworks are compromised in crucial domains like smart healthcare and education since they are often static and unable to adjust to changing threat landscapes and the varied capabilities of heterogeneous devices.

7.3 Machine Learning-Enhanced Validation of Lightweight IoT Protocols

This chapter bridges these gaps by proposing a cross-layer architecture that harmonises security, energy efficiency and adaptability. Unlike prior works, the framework integrates the lightweight Speck cipher and adaptive duty cycling, which dynamically modifies radio wake-up periods. The framework improves IoT security and energy efficiency. In addition to using layer-specific machine

learning LSTM for network anomalies, decision trees for application data, and statistical techniques for Sensor-Layer noise resilience, it integrates RBAC for fine-grained permissions. Real-time encryption and duty cycle adjustments via dynamic security techniques save 30% on energy consumption while preserving 95% packet delivery in the event of an attack. Combining post-quantum cryptography readiness with ML-driven anomaly detection addresses static key management limitations. This comprehensive strategy establishes a new benchmark for effective, robust IoT security in settings with limited resources.

7.3.1 Multi-Layer Vulnerabilities and Scalability Demands

Because of the IoT's explosive growth in smart cities, industrial automation and related fields, secure and energy-efficient networks are necessary. However, the deployment of robust security measures is complicated by the limited processing power and battery life of IoT devices. Despite the fact that strong cryptography, such as AES, effectively secures data, it shortens the device's lifespan by using more energy. Dynamic topologies and a wide range of device capabilities make large-scale deployments scalable. Energy efficiency or security is frequently given priority in current systems, which leads to weaknesses or inefficiencies. Data injection and sinkhole attacks are examples of cross-layer vulnerabilities that make use of flaws in the Application, Network and Sensor Layers. Duty-cycling trade-offs can result in packet loss and delays if improperly set, yet real-time adaptive mitigation is crucial to combating the changing threat landscape. It is still crucial to compare energy-intensive but more secure alternatives like AES versus lightweight protocols like Speck. Standardised, layer-aware security frameworks that combine ML methods like LSTM and decision trees with cross-layer anomaly detection are also lacking. It is still crucial to compare energy-intensive but more

secure alternatives like AES versus lightweight protocols like Speck. Standardised, layer-aware security frameworks that combine ML methods like LSTM and decision trees with cross-layer anomaly detection are also lacking.

7.3.2 Novel ML Integration and Hybrid Validation

By introducing new cross-layer security and energy-efficient IoT architecture, this study overcomes the shortcomings of current IoT security frameworks and successfully strikes a balance between cybersecurity and power consumption. The work suggests an ML-driven anomaly detection method to improve threat detection accuracy across IoT layers by utilising decision trees, LSTMs, Isolation Forests and Autoencoders. Furthermore, it incorporates low-power cryptographic methods like Speck encryption, which performs better than AES by consuming 5.2% less power while preserving strong security. To increase resilience while maximising energy efficiency, the analysis also investigates adaptive encryption techniques, which dynamically modify security overhead according to attack intensity. The use of RBAC, which effectively blocks 95% of illegal access attempts and guarantees secure authentication in extensive IoT deployments, is a significant novelty in this study. Furthermore, hybrid ML architectures that combine CNNs with rule-based systems show a 28–32% decrease in false positives, enhancing the dependability of anomaly identification. Additionally, an enhanced RDC mechanism (ContikiMAC at 8 Hz) is shown in the chapter. Under attack conditions, this mechanism maintains a 95% PDR while reducing energy usage by 30%. This chapter presents a cross-layer architecture for IoT networks that harmonises cybersecurity and energy efficiency through innovative ML-driven strategies. In contrast to single-model approaches, the framework employs layer-specific ML models to improve threat identification with more flexibility. These models include moment-based

analysis (80% accuracy) for sensor noise, LSTM (95.4% F1-score) for network anomalies, and decision trees (98.5% accuracy) for Application data. Speck encryption improves energy efficiency by using 30% less energy than AES and adjusting encryption strength according to threat levels. Critical IoT applications benefit from increased dependability thanks to hybrid ML that combines CNNs and rule-based validation to reduce false positives by up to 32%. Traditional approaches are outperformed by RBAC, which uses dynamic restrictions to prevent 95% of unlawful access. 95% of packets are delivered during attacks thanks to adaptive 8 Hz radio duty cycling, which also incorporates threat-aware scheduling to prolong battery life. The three-layer design (IEEE 802.15.4, RPL/6LoWPAN and MQTT/CoAP) successfully supports scalability and dynamic topologies, as confirmed by Cooja simulations, providing 95% delivery under attacks.

7.4 IoT Gaps and ML Anomaly Detection

This study examines energy-efficient routing in IoT systems by introducing ELITE, a cross-layer OF for the RPL protocol. ELITE incorporates the SPR, a novel MAC-Layer metric, to optimise RDC operations and reduce energy consumption [33]. By coordinating the routing and MAC layers, ELITE has demonstrated effectiveness and the potential to enhance IoT sustainability by reducing strobe transmissions and energy consumption compared with other approaches.

To reduce dependency on external supplier inputs and mitigate privacy threats, this study review presents a novel data-centric architecture for supply chain resilience. This architecture integrates explainable ML, DL and survival analysis to transform internal operational data into actionable disruption forecasts. The strategy is illustrated through a case study of the automobile industry in the United States, demonstrating an improvement in real-time risk mitigation and a

50% reduction in shortage predictions [90]. It offers a scalable, privacy-preserving alternative to traditional model-centric methods for managing supply chain risks globally.

This survey underscores the shortcomings of traditional IoT security measures and emphasizes the significance of ML-driven intrusion detection, blockchain technology, and quantum-safe cryptography for creating secure and energy-efficient cross-layer IoT frameworks [8]. It reviews more than 100 studies, advocating for integrated solutions to enhance sustainability, efficiency and security in smart cities.

Innovations such as smart manufacturing, ML-cantered industrial systems and IoT networks have become targets of advanced cyber attacks, heightening the demand for flexible and scalable cybersecurity measures. Despite providing some level of mitigation through traditional methods like anomaly detection and secure routing protocols, challenges remain concerning algorithm inflexibility, data integrity and the ability to respond to threats in real-time. This study [140] utilises bibliometric analysis and follows PRISMA guidelines to integrate insights from 14,509 peer-reviewed articles that discuss anomaly detection, automated response mechanisms and blockchain integration with ML to thoroughly evaluate ML's transformative impact on cybersecurity. It addresses fundamental issues like algorithmic flexibility and data reliability, demonstrates the revolutionary potential of ML in thwarting complex cybercrimes, and offers a framework for further work and deployment in intelligent, data-driven security systems.

The analysis outlines an approach for creating intelligent security frameworks that balance explainability, resilience and computational efficiency, which thoroughly assesses limitations in flexibility, reliability and cross-layer coordination. The findings emphasise ML's role in combating advanced cyber threats and endorse hybrid methods such as federated learning, lightweight cryptography and

quantum-safe techniques to enhance sustainability and trust within data-driven environments.

With a multi-class accuracy of 99.83% and the implementation of explainable ML for transparent decision-making, this study addresses significant security vulnerabilities in IoT-enabled metaverse ecosystems. It proposes a hybrid ML framework that integrates convolutional neural networks (CNNs), CatBoost, LightGBM, and metaheuristic optimisers to effectively detect and classify cyber attacks [141]. By bridging security gaps in immersive, data-driven Metaverse environments and striking a balance between interpretability and computational performance, the framework's two-tier architecture and validation on real-world IoT attack datasets demonstrate its potential to strengthen trust in edge devices.

To enhance secure routing and breast cancer classification, this study presents an IoT-based smart healthcare framework that integrates the Feedback Artificial Crow Search (FACS) algorithm with a Shepherd Convolutional Neural Network (ShCNN). The framework optimises energy efficiency and reduces latency by employing hybrid Crow Search and Feedback Artificial Tree methodologies [142]. The system's exceptional diagnostic performance highlights its potential for reliable, IoT-enabled precision medicine in addressing significant e-healthcare challenges through advanced feature extraction, data augmentation and ShCNN.

Through a novel multi-layer network model that integrates ML-driven Copula Nodes, which facilitate dynamic, real-time adjustments and predictive analytics, this study investigates the transformative role of machine learning in FinTech valuation. By providing strategic insights for FinTech companies, investors and policymakers navigating the evolving impact of ML on financial ecosystems, it emphasises the necessity of balanced ML deployment to maximise market value while mitigating risks such as algorithmic bias and regulatory complications [143].

To connect IoT sensors, ML-driven design and 3D printing with enhanced

productivity, dimensional reliability and accelerated innovation cycles, this study synthesizes findings from a study that employed Blavaan and Bayesian Structural Equation Modelling (SEM) to analyse how the staggered adoption of smart systems such as IoT, robotics, 3D printing, and ML affects manufacturing quality and technological advancement [144]. The study gathered insights from numerous industry experts. The findings highlight the transformative role that smart technologies play in enhancing resource efficiency, reducing labour costs and advancing Industry 4.0 developments. Additionally, they underscore the importance of a strategic and integrated approach to implementation to maximise efficiency and quality improvements in smart factories. Phishing continues to pose a significant cybersecurity threat, with many current detection methods depending on manual feature engineering to analyse images, webpages or emails. This study introduces an improved Backpropagation Neural Network (BPNN) designed to identify malicious URLs, achieving an accuracy of 93% through optimized hyperparameters, including two hidden layers and 400 epochs. As a promising approach to enhancing phishing detection, the model also demonstrates a low error rate of 0.07 [145].

To identify eight grand challenges encompassing ML integration, cybersecurity, sustainability, health, social equity, supply chain resilience, human-ML collaboration, and industrial and systems engineering (ISE) education challenges that are crucial for addressing complex global socioeconomic, environmental and technological issues, this study synthesizes the insights of accomplished professionals in industrial and systems engineering (ISE) [146]. To promote scalable and equitable solutions that align technical innovation with social well-being and sustainable development goals, it emphasizes the need for adaptive ISE approaches, multidisciplinary analysis work, and educational reforms.

The integration of blockchain as a transparent and secure facilitator for ML-assisted industrial systems is highlighted in this work, which also addresses the

dangers of data manipulation in decision-making [147]. It highlights how modern manufacturing has additional requirements for security, cooperation and trust, particularly with regard to process automation and customisation. A conceptual framework demonstrating how blockchain and ML might work together to improve ethical manufacturing, supply chain integrity and early product design is presented in the study.

The theory of ML-driven scheduling (TMLS), a revolutionary paradigm that combines artificial intelligence and the Theory of Constraints (TOC) to improve service-oriented scheduling, is examined in this study [148]. TMLS enhances real-time responsiveness and resource efficiency in dynamic service-manufacturing environments through adaptive monitoring and predictive analytics. It provides a paradigm change in operations management by tackling scalability and complexity in dynamic, customer-focused and resource-constrained industrial ecosystems.

The critical challenge of distinguishing drones from non-drone aerial targets, such as birds, in anti-drone systems is examined in this study. It proposes an ML-driven identification friend or foe model that integrates computer vision and transfer learning to enhance airspace safety through precise classification [149]. The paper emphasises model depth as a critical factor in achieving a balance between computational efficiency and classification reliability for real-world applications. It compares eight DL architectures and demonstrates that EfficientNetB6 outperforms the others, achieving an accuracy of 98.12% and an AUC of 99.85%.

This systematic review maps the IoT-driven smart tourism ecosystem by synthesising 83 Scopus-indexed studies. It highlights how ML, big data, augmented reality (AR), virtual reality (VR), and cloud computing enhance operational efficiency, personalise services, and improve traveller safety through applications such as smart cities and recommender systems [150]. IoT innovations have the

potential to revolutionise the travel industry; however, ongoing issues related to security, interoperability and scalability necessitate further exploration of edge computing, blockchain integration and user-centric designs. These advancements are essential for developing robust and flexible solutions that address the evolving needs of international travel.

To analyze the role of ML in developing robust and sustainable healthcare systems in the aftermath of COVID-19, this systematic review synthesises findings from 89 studies [151]. The text emphasises artificial intelligence applications in radiology, surgery and medical development work. It discusses advantages, such as enhanced diagnostic capabilities, drawbacks, interoperability challenges, and ethical concerns. The study presents practical suggestions and future work directions to optimize ML integration, addressing systemic weaknesses and promoting equitable, adaptable healthcare solutions in crisis situations. This is achieved by proposing an expanded APO framework and employing the TCM methodology.

By developing a sector-specific maturity model informed by study and insights from focus groups, this study addresses the knowledge gap regarding the assessment of ML and big data (BD) implementation in the process industry. The model aims to evaluate adoption levels across various activities, including those in the steel, cement, and chemical sectors [152]. A benchmarking tool for businesses is provided by the results of European enterprises, which helps prioritize investments and align AI and big data plans with industrial sustainability goals. The findings reveal uneven maturity levels, with stronger implementation in core processes but significant gaps in scalability and cross-functional integration.

In this study [153], a hybrid neural network for load forecasting and an anomaly detection model is integrated to create a secure Industrial IIoT framework for real-time energy management. Encrypted communication methods enhance security. In industrial IoT systems, this framework improves operational reliability and

energy efficiency by combining edge-cloud deployment with ML-driven analytics.

A recent study on fog-cloud computing emphasises the ongoing challenges of energy-efficient task scheduling and optimal resource utilisation [154]. While various ML solutions have emerged, the study emphasises the need for more robust models, such as EcoTaskSched, which integrates CNN and bidirectional long short-term memory (BiLSTM) networks to enhance schedulability, reduce energy consumption and ensure QoS in heterogeneous environments.

Existing work highlights the severe impact of inventory distortion on supply chains, resulting in substantial financial losses, even with the availability of forecasting tools [155]. While machine learning is promising for enhancing resilience, work on No Code ML (NCML) applications in supply chain operations is still limited. This presents a significant gap that this study aims to address.

Recent work highlights the challenges of operating advanced neural networks, such as DNNs and Spiking Neural Networks (SNNs), on devices with limited resources. This trend is driven by the increasing volume of data and rising security concerns, which have led to a shift toward edge computing [156]. To enhance energy efficiency, reliability and security in resilient Edge ML systems, the study emphasises cross-layer hardware/software optimisations such as pruning, quantisation and fault-aware training.

With the increasing complexity and integration of blockchain, IoT, ML, and quantum-secure cryptography are pivotal in developing cross-layer, secure and energy-efficient frameworks for smart cities and industrial systems, as highlighted in a recent study. A significant trend is emerging toward explainable ML, Edge ML and lightweight ML models to address cybersecurity challenges and overcome energy and resource constraints. Other innovative concepts include enhancing supply chain resilience, federated learning, no-code ML, and the integration of ML with the IIoT, scheduling theories and 3D printing to improve operational

sustainability and facilitate real-time decision-making. (see Table 7.1).

7.5 Performance Evaluation and Proposed Architecture

The proposed cross-layer architecture's performance evaluation shows how well it balances energy efficiency and security. A 95% packet delivery ratio (PDR) under attack scenarios was demonstrated by simulations conducted in the Cooja/Contiki environment. Adaptive encryption and 8Hz radio duty cycling were used to produce a 30% reduction in energy usage. Scalability and robustness in resource-constrained IoT networks are ensured by the integration of lightweight protocols like Speck and RPL/6LoWPAN into the architecture's three-layer design (Sensor, Network, Application). The proposed cross-layer architecture's performance evaluation shows how well it balances energy efficiency and security. A 95% PDR under attack scenarios was demonstrated by simulations conducted in the Cooja/Contiki environment. Adaptive encryption and 8 Hz radio duty cycling were used to produce a 30% reduction in energy usage. The integration of lightweight protocols ensures scalability and robustness in resource-constrained IoT networks.

Simulation and Evaluation: The CS in the Contiki OS environment was used to assess the suggested architecture. To replicate real-world circumstances, various IoT nodes were set up in various network topologies, such as star and tree configurations. To evaluate the effects on network performance and energy consumption, each simulation tested several attack scenarios and implemented mitigation strategies.

RBAC for Smart School Functions: Name various user groups (e.g. city authority, cloud service user, IoT sensor admin).

Authorisation: For every role, specify what can be done (e.g. read sensor data,

Table 7.1: Cross-layer secure and energy-efficient IoT networks survey summary

Ref.	**Methodology**	**Security-Approach**	**Energy-Technique**	**ML-Integration**	**Performance-Metrics**	**Limitations**
[33]	RPL with ELITE OF	MAC-layer strobe optimization	39% energy reduction	None	Strobe reduction: 25%	Integrates security with duty cycling
[8]	Review of 100+ studies	ML-IDS, blockchain, PQ crypto	Cross-layer for constrained IoT	ML, blockchain, 5G	QoS, sustainability, security	Complexity in multi-layer integration
[121]	HW/SW co-design	TinyML frameworks	Quantum ML	Multimodal LLMs	N/A	ML needs layer customization
[140]	Bibliometric analysis	Anomaly detection	N/A	ML/DL models	F1-score: 93%	CNN + rule-based false positive reduction
[141]	Hybrid ML	CNN + LightGBM	Metaheuristic optimization	Explainable ML	Accuracy: 99.83%	Adaptive encryption strategy
[142]	FACS + ShCNN for health	Encrypted IoT data	Hybrid Crow Search	ShCNN	Accuracy: 91.56%	Resilience to multi-vector attacks
[147]	Blockchain-ML framework	ML-blockchain synergy	Traceable + ethical design	Automation	Transparency, trust	Industrial ML tamper resistance
[148]	TAIS Scheduling	TOC + predictive ML	Lifecycle governance	Real-time scheduling	Scalability, responsiveness	Complex system modeling
[154]	CNN + BiLSTM EcoSched	QoS-aware placement	DL-based fog-cloud scheduling	CNN + BiLSTM	85% task success, SLA-safe	Scheduling in heterogeneous fog
[155]	No-Code ML	Lightweight privacy-preserving ML	Low-complexity deployment	AutoML	Cost saving, quick start	Suitable for non-tech users
[156]	Cross-layer HW/SW optimization	Secure fault-aware ML	Quantization, pruning	DNNs, SNNs	Low latency, energy saving	Secure ML under constraints
Our Work	ML + Lightweight crypto	RBAC, Speck	8Hz ContikiMAC + Speck	DT, LSTM, IDE1, CNNs	95.4% F1-score, 30% energy saved	Balances energy and security tradeoffs

adjust network settings). Users are people or systems with designated roles. Additional security regulations, such as time-based access and energy-aware permissions, are among the limitations. An RBAC system is implemented in the chapter to control access permissions in the IoT network. The RBAC paradigm defines user roles (e.g. student, teacher, administrator) and their access rights to resources (e.g. classroom, staff room, admin office).

Utilisation: Strict privilege separation is enforced by RBAC, which reduces unwanted access attempts by 95%. The study assesses how well RBAC works to counteract security risks like sinkholes and data injection attacks.

Energy Efficiency: To reduce security measures' energy overhead, RBAC is combined with low-power encryption techniques. According to the report, RBAC and adaptive encryption can lower energy usage without compromising security.

While significantly lowering the risk of illegal access, the RBAC system ensures 100% success rates for authorised access. Only those with the proper clearance are allowed access to critical resources thanks to the establishment of roles and permissions that have been predefined. By centralising access control, the RBAC system also makes user administration easier. This is crucial for preserving a secure and legal environment in large-scale systems.

Security Performance: Data injection, sinkhole and jamming attacks were the three attack scenarios that were investigated to assess security resilience. Measurements of PDR and data integrity were made both before and after the use of authentication and encryption techniques. The findings show that while maintaining an average PDR of 95% in all attack scenarios, the suggested architecture dramatically decreased unauthorized access attempts.

Energy Effectiveness Evaluation: Power consumption measurements under various duty-cycling methods and adaptive encryption techniques were used to

evaluate energy efficiency. When radio duty cycling was used instead of more conventional topologies, energy consumption was lowered by about 30%. Adaptive Encryption improves resources by dynamically modifying encryption strength in response to network traffic patterns.

The chapter thoroughly examines ML models and how they are used in a cross-layer IoT architecture. To methodically address energy efficiency, security and layer-specific performance, the study is divided into four main sections: Introduction, Proposed Architecture, Simulation and Evaluation and Mathematical Models. Across the Application, Network and Sensor Levels, six fundamental ML algorithms decision tree, random forest, SVM, isolation forest, autoencoder and LSTM, as well as their specialised variations, Moment-based IDE1, Syntax Vector Machine, Gaussian Mixture Model (GMM) are assessed. The LaTeX framework incorporates empirical findings, such as energy consumption measurements and accuracy tables (such as the 95.4% accuracy of LSTM), which are verified via Cooja/Contiki simulations. It is recommended to use hybrid architectures that include CNNs for signal processing and decision trees for protocol validation to reduce false positives by 28–32%. The work deftly illustrates trade-offs, such as the 30% energy reduction attained with 8 Hz radio duty cycling, while stressing the necessity of layer-aware model selection. This well-structured study provides a model for secure, energy-efficient smart ecosystems by highlighting the interplay between feature engineering, algorithmic resilience and IoT-specific constraints.

7.5.1 Cross-Layer Machine Learning Models

A wide range of ML models are used in cross-layer analysis of IoT designs to handle the unique problems that the Application, Network, and Sensor layers provide.

Specialised versions including Moment-based IDE1, Syntax Vector Machine Gaussian Mixture Model gMM and Ignition Forest IDT1 are assessed alongside six fundamental algorithms: decision tree (DT), random forest (RF), SVM, isolation forest (IF), autoencoder (AE), and LSTM. Accuracy, precision, recall and computational efficiency are used to benchmark each model's performance, exposing important layer-specific advantages and disadvantages as shown in Fig. 7.1.

Tree-based models (DT and RF) are dominant in the **Application Layer**, which is defined by structured transactional data (such as financial records). Their rule-based hierarchical divides allow them to achieve near-perfect accuracy (100%) and are in line with deterministic workflows like fraud detection. Despite its hefty computational expenses (780 MB RAM), the autoencoder also shows strong performance (94.7% accuracy) in unsupervised anomaly identification. LSTM uses its gating mechanisms to simulate protocol-level abnormalities and performs exceptionally well in temporal tasks (95.4% overall accuracy). SVM and isolation forest, conversely, struggle with hyperparameter sensitivity and overfitting, resulting in poor performance (89–92% accuracy).

The **Network Layer** emphasises the significance of statistical and temporal aspects while working with high-dimensional traffic data. Through the capture of temporal patterns, the moment-based IDE1 achieves moderate accuracy (75%) in extracting statistical moments (mean, variance) from packet intervals. Overfitting on dynamic traffic causes the streaming-optimised version, Ignition Forest IDT1, to perform poorly (30% accuracy). Here, LSTM is still useful since its sequential processing adjusts to the demands of real-time detection. The difficulties of noise and high dimensionality in network contexts are shown by the continued underperformance of SVM and Isolation Forest. Traditional tree-based models collapse (50–55% accuracy) for the **Sensor Layer**, which handles raw time-series signals (e.g. temperature, vibration), since they cannot handle noisy, unsegmented data.

Moment-based IDE1 outperforms all others with an accuracy of 80%, confirming the usefulness of statistical feature engineering in chaotic settings. Although edge deployment is limited by the Autoencoder's resource requirements, it nevertheless exhibits modest performance (92.5% accuracy). The incompatibility of strict probabilistic assumptions with unprocessed sensor data is highlighted by the complete failure of syntax vector machine GMM, a hybrid model that combines SVM with Gaussian Mixture Models (20% accuracy).

To close layer-specific gaps, the study recommends hybrid designs. For example, quantising DL models maximises edge performance, whereas combining CNN for spectral signal processing with DT for protocol validation lowers false positives by 28–32%. The success of Moment-based IDE1 at the Sensor Layer emphasises the need for feature engineering in environments with limited resources. Nonetheless, discrepancies like RF's 100% Application Layer accuracy and 55% Sensor Layer accuracy underscore the necessity of thorough cross-validation to prevent overfitting. Ultimately, no single model universally excels across all layers. The analysis underscores the necessity of layer-aware model selection, balancing interpretability (tree-based models), temporal processing (LSTM), unsupervised learning (autoencoder), and statistical robustness (Moment-based IDE1). Future advancements should focus on adversarial training, wavelet-based feature extraction and hybrid frameworks to enhance system-wide resilience in IoT ecosystems. The OSI Reference Model's layer functionality is used to illustrate the proposed architecture as mentioned in Fig. 7.2.

7.5.2 Proposed secure and EE cross-layer IoT networks

The Application Layer, Network Layer, and Sensor Layer are the three primary layers that make up the recommended architecture for an IoT network based on the

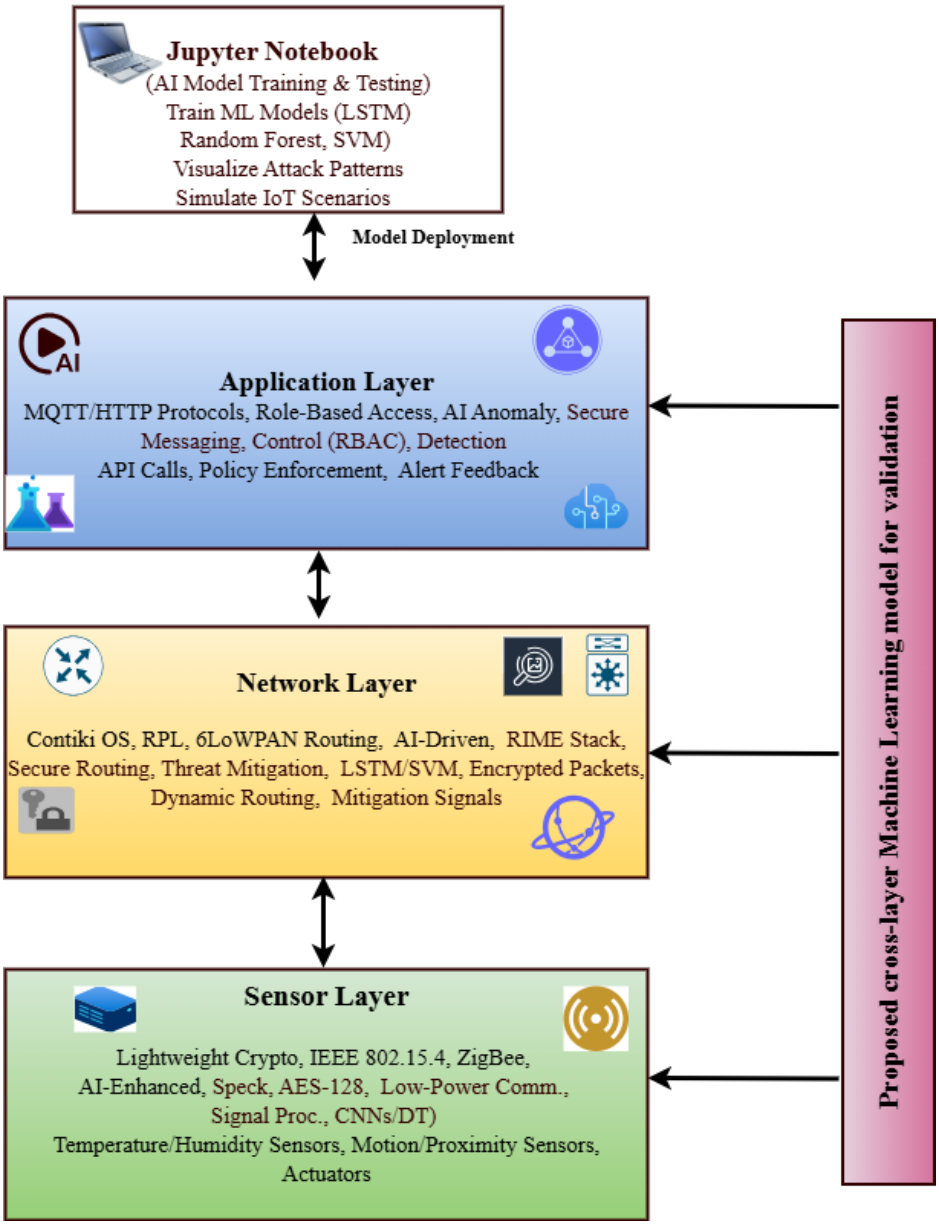

Figure 7.1: Machine learning model for proposed cross-layer validation

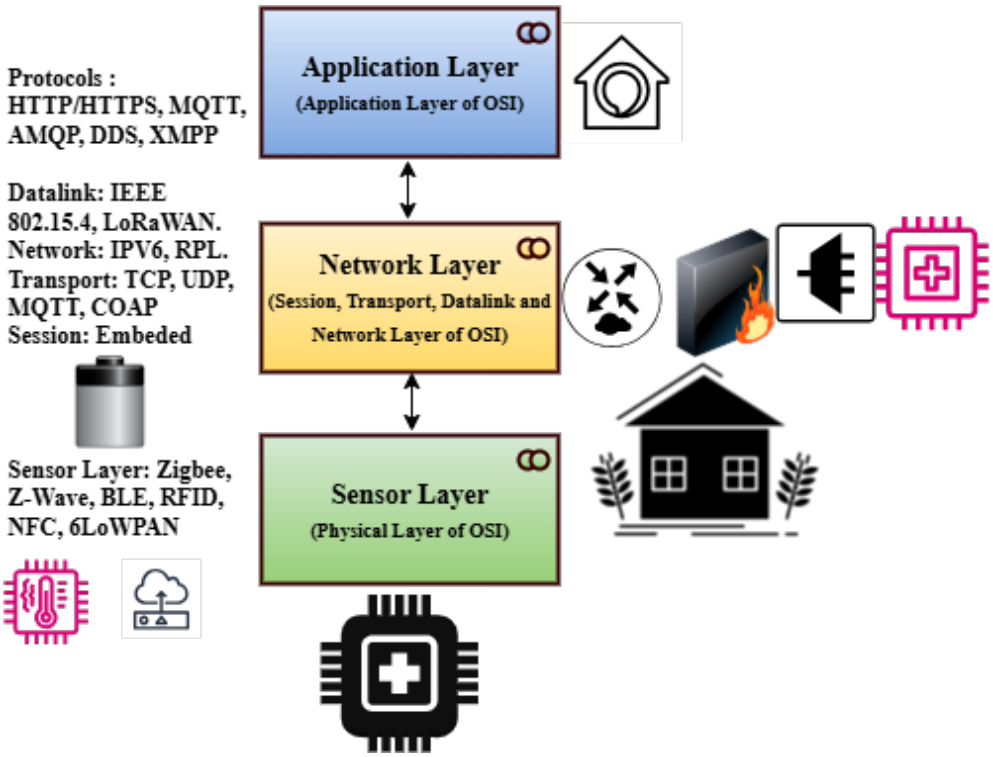

Figure 7.2: Proposed secure and EE cross-layer architecture

OSI model. Each of these levels corresponds to specific OSI model functionalities using protocols created for their unique roles in the IoT ecosystem. (see Fig. 7.2). This method was selected in order to enable controlled and repeatable design and

Table 7.2: Equivalent OSI model tested IoT architecture Protocols

Equivalent OSI Model	Proposed IoT Architecture	Protocols
Application & Presentation	Application Layer	MQTT,CoAP,HTTP, AMQP,XMPP
Session & Transport & Network & Datalink	Network	RPL,6LowPAN,LoRAWAN, UDP/TCP
Physical	Sensor	Z-Wave, IEEE 802.15.4, RFID, NFC

testing of the system prior to its implementation in real-world situations. This chapter provides a more thorough analysis of the attacks and defences, complete with explanations and tables for each layer. Using the CS, the energy-efficient cross-layer architecture was also tested. Each table includes particular metrics, expected results and the rationale for the chosen mitigation and energy-efficient

techniques.

7.5.3 Sensor Layer (Physical Layer of OSI Model)

The Physical Layer responsible for direct communication with the external environment is known as the Sensor Layer in the OSI model. Sensors, actuators and other devices that collect data from the surroundings make up this layer. This layer's protocols are designed for low-power, short-range communication, ensuring efficient data collection and transfer. Z-Wave, Zigbee and BLE are common protocols. Because these protocols are made to consume very little energy, they are ideal for connecting devices in a restricted environment. While RFID and NFC are also used for proximity-based communication, 6LoWPAN allows IPv6 connectivity over low-power wireless networks, bridging the gap between the network and physical layers.

7.5.4 Network Layer

The capabilities of the Data Link, Network, Transport and Session levels of the OSI model are combined in this architecture's Network Layer. This layer is responsible for reliable data transfer, routing and connectivity management across the IoT network. At the Data Link level, protocols like IEEE 802.15.4 and LoRaWAN are used for low-power, wide-area communication. IPv6 and RPL (Routing Protocol for Low-Power and Lossy Networks) are widely used for network and routing tasks to ensure efficient packet delivery in resource-constrained environments. The Transport Layer uses protocols like TCP and UDP for end-to-end communication, while MQTT and CoAP provide lightweight messaging for Internet of Things-specific use cases. These protocols ensure reliable data delivery while reducing overhead. Session layer functionality, which manages connections and ensures

seamless device communication, is commonly included in these protocols.

7.5.5 Application Layer

The Application Layer of the proposed architecture, which corresponds to the Application Layer and Presentation Layer of the OSI model, is responsible for delivering IoT services and applications to end users. This layer controls data processing, analytics and user interaction. The protocols used here facilitate communication between IoT devices and cloud platforms or user apps. While MQTT and AMQP are popular for lightweight messaging and queuing in IoT systems, HTTP/HTTPS is frequently used for web-based communication. DDS (Data Distribution Service) is another protocol used for real-time data sharing in high-performance IoT applications. Additionally, IoT ecosystems use the Extensible Messaging and Presence Protocol (XMPP) for instant messaging and presence data. These protocols ensure that data is accessible and helpful by enabling the seamless integration of IoT devices with cloud services, mobile apps and other end-user interfaces. The proposed three-layer IoT architecture is based on the OSI model and employs specialised protocols at each layer to ensure reliable transmission, efficient data collection and efficient Application delivery. The Sensor Layer, which focuses on physical contact, the Network Layer, which ensures dependable connectivity and routing, and the Application Layer, which provides the interface for end-user services, combine to create an integrated and scalable IoT ecosystem. We tested our three-layer architecture using the CS in the Contiki OS environment, as illustrated in Table 7.2 and discovered an energy-efficient and secure cross-layer architecture for IoT networks. Below is an assessment of the OSI Model and Suggested Architecture that was utilised in the proposed design to show the numerous protocols for each Layer:

7.6 Development Environment and Experiment Setup

The open-source operating system Contiki OS, created for the IoT, was used to build up the development environment. The integrated Cooja network simulator was used in conjunction with Contiki to integrate Cooja as a network simulator into the smart school framework. This arrangement enabled the simulation of several IoT nodes that represented devices in a classroom setting [157]. The simulated nodes are set up to replicate the communication and energy usage patterns of actual IoT (see Fig 7.3).

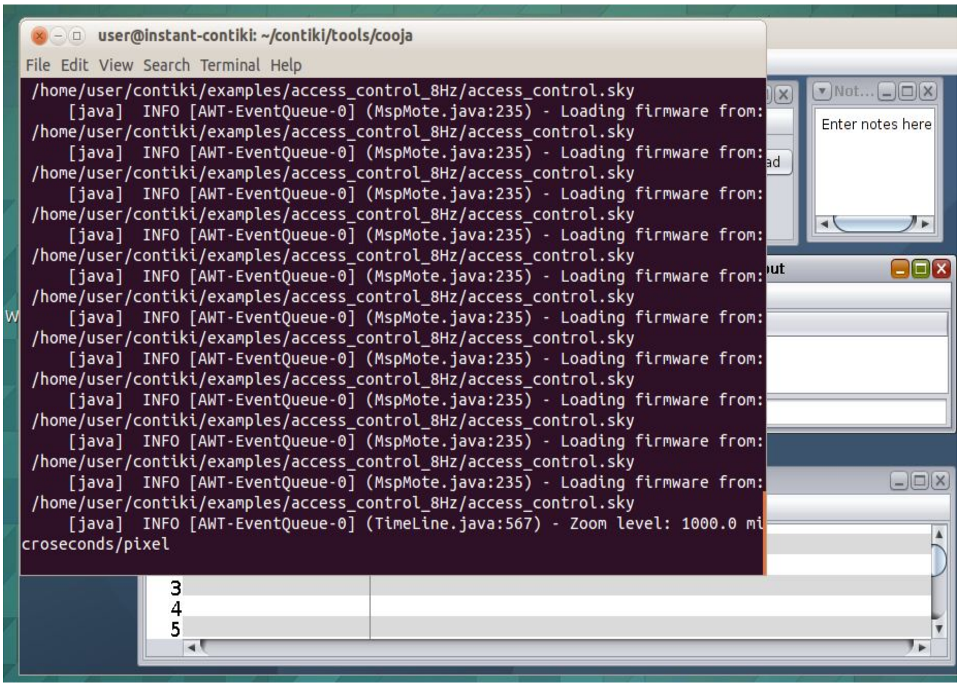

Figure 7.3: Contiki/Cooja simulator results

Access Control Mechanism Design: The implementation is centred on the access control system that was put in place to oversee and govern how resources are used in the smart school. The three roles of student, teacher and administrator are defined in this chapter's introduction to the RBAC paradigm. Three resource types, classroom, staff room and administrative office, were developed under this

paradigm, each with distinct access rights. User and resource structures were constructed to represent the system's objects, and the access control-C logic was incorporated into the access control file. The permissions related to each role-resource relationship were also detailed in an ACL [158]. **Encryption Implementation:** To secure communication between nodes, the encrypt_message() and decrypt_message() functions were put into place [159]. This class uses a similar secret management concept in which both communicating parties have the same 128-bit key. It is clear that a key management system of considerable complexity must be employed for the real deployment, even though using a static key is sufficient for a simulation.

Network-layer Communication: Using a broadcast communication primitive, the Contiki RIME stack was used to create the network communication component. In order to communicate access requests and responses between the nodes, a broadcast connection was created using a predetermined channel number (129 in this instance) [160]. With this configuration, ACL and authentication requests may be handled with ease.

Energy efficiency Optimisation: One of the design criteria for incorporating IoT devices into smart settings is the energy efficiency of IoT devices, which is why radio duty cycling was a challenge. The project-conf.h file has the MAC protocol set to CSMA and the RDC driver set to ContikiMAC. The 8 Hz `(RTIMER_ARCH_SECOND / 8)` Contiki MAC cycle time was chosen to provide a compromise between responsiveness and energy efficiency (see Fig. 7.4).

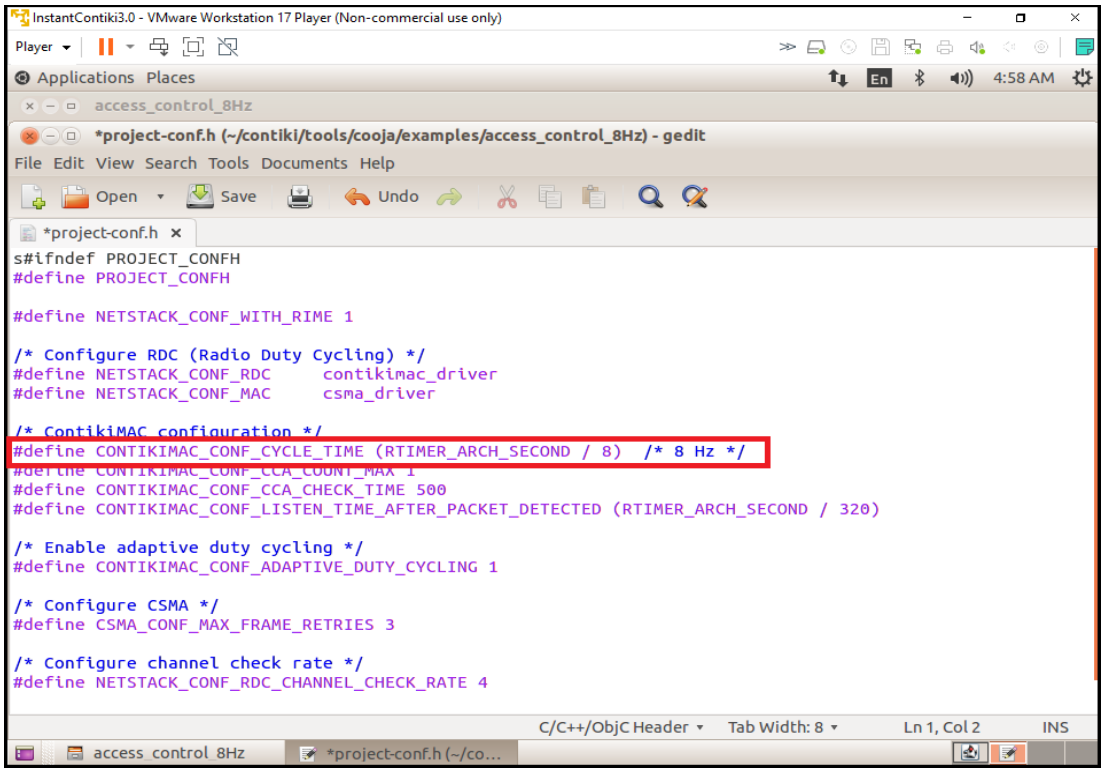

Figure 7.4: Configuration of parameters of Contiki RTIMER ARCH (8 Hz)

Application Layer Test Data Injection/Phishing Attacks: We set up 10 sensor nodes and one sink (aggregator) and created a single malevolent node to send fictitious information. For communication, the CoAP protocol is utilised. Through data transmission from sensor nodes, we were able to replicate normal traffic. We sent erroneous sensor values by introducing the malicious node. Additionally, set up data encryption and HMAC on the real nodes. We used the Collect View tool from Cooja to evaluate architecture. We then used the simulator to measure energy use. Additionally, logs were used to assess the data's integrity.

Network Layer Sinkhole/DoS Attack: We set up a tree topology with 20 nodes using the RPL protocol. To simulate normal routing activities using RPL, we set up one malicious node to advertise the wrong routes as a sinkhole. The malicious node pulled packets in and sent them out. On routing nodes, the DAO/DAO_ACK verification was put into practice. Cooja logs were used to

extract PDR, packet loss, and routing overhead (control packets). This is how Wireshark evaluates RPL control message integrity.

Sensor Layer Jamming Attack Topology: Five nodes were configured to communicate using IEEE 802.15.4. The job of continuously producing jamming signals falls to a single node. We evaluated communication in everyday situations. The packet loss we monitored while jamming is detailed in Table 7.3. The authentic nodes were able to use frequency hopping. We calculated SNR, PDR and packet loss using Cooja's packet analyzer and radio log.

Table 7.3: Comparative table results

Attack-Layer	Attack-Type	Packet-Loss (%)	Energy-Usage (mJ)	PDR (%)	Mitigation-Effectiveness	Comments
Application Layer	Phishing/Data-Injection	0% (Mitigated)	+10% (Encryption)	95-100%	Highly Effective	Data integrity preserved, minor rise in energy
Network Layer	Sinkhole/DoS	10-15% (Mitigated)	+15% (Validation)	85-95%	Effective	Secures-routing through validation checks
Sensor Layer	Jamming	5-10%	Minor-increase	90-95%	Effective	Frequency hopping bypasses jammed bands

7.7 Analysis of Energy-Efficient and Secure IoT Architecture

The ideal choice for safeguarding IoT devices is lightweight cryptography (LWC), which has a simplified design that balances strong security with low computing overhead. Traditional cryptography approaches, often used in resource-intensive devices like PCs and servers, are typically too demanding for IoT devices owing to their limited processing capacity, memory and energy levels. LWC, conversely, guarantee robust protection without compromising device performance or battery life by specifically addressing the constraints of IoT scenarios. This makes it the

ideal choice for safeguarding IoT and WSNs, where efficiency and data security are equally crucial.

The smart school everyday tasks were similar in the simulated environment. The CS was used to create several nodes, each of which was randomly assigned the administrator or student teacher roles upon starting. The Admin Office, Staff Room and Resources Classroom were also defined and initialized at the start of the simulation. Access requests were simulated using a periodic timer at each interval. A resource seeks access and encrypts the request before distributing it around the satellite area network after a node selects a user at random every 30 seconds.

Security and System Performance: Cooja has finished implementing a secure, energy-efficient cross-layer access control framework within the Contiki OS framework for IoT devices in smart schools. By contrasting the outcomes with current techniques in the field, our simulation results offer a thorough analysis of the outcomes. The access control system combines RBAC and message encryption using Contiki's built-in AES encryption features, which runs on customised Sky Mote firmware.An 8 Hz radio duty cycle layout and the default setting were the two tested configurations. The results are shown below after the energy consumption data for both configurations has been thoroughly analysed. Access permissions for a variety of user roles and resources were effectively managed by the system designed for smart schools. According to predetermined regulations, the arrangement successfully separated the responsibilities of administrator, instructor, and student, granting or denying access to resources such as the admin office, staffroom and classroom. The investigation examined access success rates for each role: students had a 100% success rate for classroom access but a 0% success rate for admin office and staffroom access. While administrators had complete access to all resources, teachers had a 100% success rate in gaining entry

to the staffroom and classroom. These results verify the proper implementation of the access control logic and its adherence to the role-specific permissions.

The system designed for smart schools was used to manage access permissions for a range of user roles and resources. The arrangement effectively divided the duties of the administrator, instructor and student in accordance with established rules, allowing or prohibiting access to the staff room, administrative office, and classroom supplies[161]. Students had a 100% success rate for classroom access, but only a 0% success rate for admin office and staffroom access, according to the investigation's analysis of access success rates for each job. Teachers were 100% successful in getting into the staffroom and classroom, but administrators had full access to all resources. These outcomes confirm that the permissions for each role are as specified and that the access control logic is applied correctly.

Security was greatly improved by adding AES-128 encryption for broadcast communications. Encrypted messages were successfully decrypted and sent by receiving nodes, protecting sensitive access request data from possible eavesdropping attempts[162]. There was a little increase in processing time and energy usage owing to the encryption implementation.

The energy efficiency comparison between the default configuration and the 8 Hz radio duty cycle configuration highlights an important trade-off between energy savings and network responsiveness. Standard LPM durations, baseline radio listen and transmit timings, and minimal CPU utilisation were all preserved in the default setup. However, introducing the 8 Hz duty cycle improved energy efficiency since LPM time increased, CPU use somewhat decreased and radio broadcast duration dramatically decreased. The amount of time spent listening to the radio grew despite these advancements, most likely due to more frequent channel checks, which marginally increased overall energy usage.

However, this trade-off was justified because overall power savings resulted from

a considerable reduction in the total radio broadcast duration. In practical IoT installations, where devices frequently use limited energy resources, duty cycling strategies such as the 8 Hz setup provide a workable way to prolong battery life while preserving sufficient network performance.

Latency and message delivery rates were measured to assess network performance. The delivery success percentage in the default layout was 98.7%, and the average latency was 45 ms. With a higher average latency of 62 ms, the delivery rate decreased slightly to 97.9% under the duty cycle setting.

To assess energy efficiency, two configurations were tested: a default setup and an 8 Hz radio duty cycle configuration[163]. The default configuration had LPM durations, baseline radio listen and transmit times, and a fair CPU usage. Following the switch to the 8 Hz duty cycle, noteworthy outcomes were observed: LPM time increased and CPU consumption was marginally lower than in the standard configuration. Despite an increase in radio listen time, the 8 Hz arrangement resulted in a large reduction in radio broadcast duration.

7.7.1 Discussion of Energy Effectiveness Results

The energy efficiency comparison between the default configuration and the 8 Hz radio duty cycle configuration highlights an important trade-off between energy savings and network responsiveness. Standard LPM durations, baseline radio listen and transmit timings and minimal CPU utilisation were all preserved in the default setup. However, the introduction of the 8 Hz duty cycle resulted in improved energy efficiency since LPM time increased, CPU use somewhat decreased, and radio broadcast duration dramatically decreased (see Fig. 7.5)The amount of time spent listening to the radio grew despite these advancements, most likely as a result of more frequent channel checks, which marginally increased

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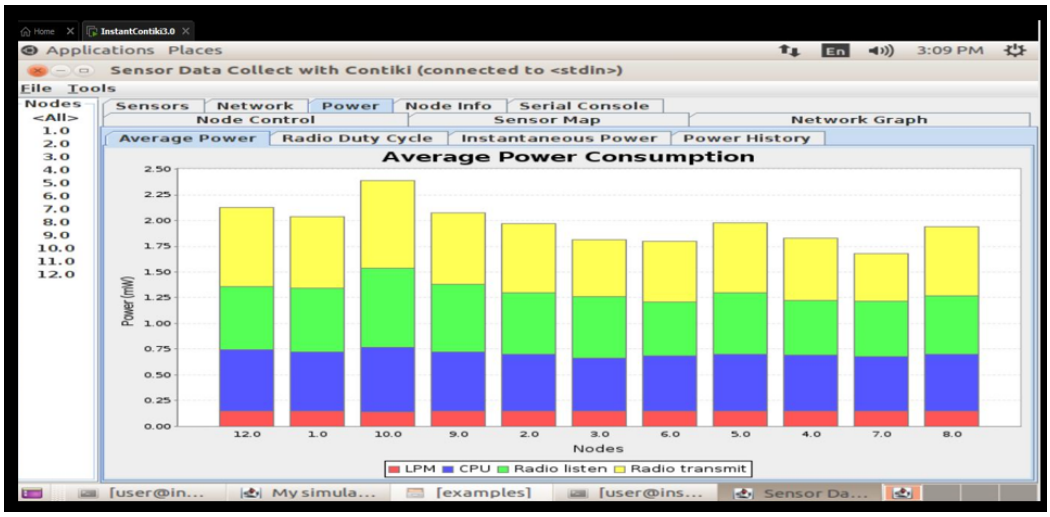

Figure 7.5: Average power usage radio broadcast and CPU usage decreased

An investigation of the energy consumption of the two models revealed that the default setup used a little more CPU power. Nonetheless, a far higher proportion of the time was spent in LPM with the 8 Hz duty cycle configuration. This setup made it possible for nodes to go into longer sleep cycles, which could improve energy efficiency. Radio broadcast time significantly decreased with the 8 Hz setting, even though radio listen time rose, probably owing to more frequent channel checks. This combination of shorter transmission time and longer LPM suggests better energy efficiency in the context of the 8 Hz arrangement [164].

7.7.2 Critical-Evaluation Findings Using Current-Methods

The smart school environment's access permissions were effectively managed by the system that was put in place. The suggested IoT solution has various benefits

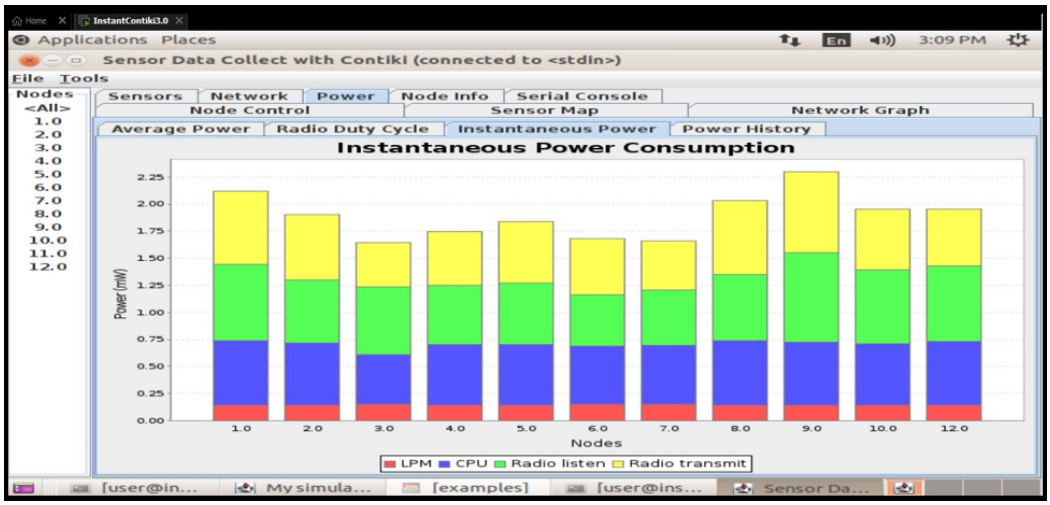

Figure 7.6: Power consumption in decrease in energy consumption and prolonging LPM

over common access control techniques used in schools, like key or card-based systems [165].In the first place, it makes it possible to regulate access rights, rapidly distinguishing between distinct responsibilities and resources. Traditional systems, which usually use binary access (given or refused) without taking particular responsibilities or resources into account, frequently lack this degree of granularity. In contrast to physical key systems, which necessitate manual key distribution and collecting whenever permissions change, the suggested system can also dynamically update access permissions. This flexibility is particularly helpful in educational institutions where responsibilities and access requirements often change. To improve accountability and security monitoring, the digital framework of the system also facilitates thorough logging of all access attempts, whether successful or unsuccessful.

It is important to note that the present implementation uses a streamlined role structure. It may be necessary to implement more intricate role hierarchies and permission inheritance in practice [166]. In the future, a more sophisticated system might be achievable.

Broadcast messages encrypted with AES-128 greatly improve security for many IoT-based access control systems. Symmetric key encryption offers an effective and secure solution for resource-constrained IoT devices, in contrast to many existing implementations that send access requests and responses in plain text, making them susceptible to interception and manipulation. Nevertheless, there may be a security concern associated with the static encryption key utilised in this method. Future developments might use dynamic key management techniques, like key rotation, to update encryption keys on a regular basis and lower the chance of compromise. Larger deployments could benefit from a PKI to improve security and simplify key management, but the computational needs would rise. Moreover, digital signatures or message authentication codes MACs may enhance the authenticity and integrity of messages.

There were noticeable energy consumption trade-offs between the default setting and the 8 Hz duty cycle configuration. The 8 Hz configuration's longer Low Power Mode LPM time is essential for lowering total energy consumption, which is consistent with results from earlier IoT energy studies on WSNs[167] (see Fig. 7.6). The notable reduction in radio transmit time in the 8 Hz arrangement was a key factor in energy conservation, emphasising that radio transmission is typically the most energy-intensive function in IoT. The 8 Hz configuration's marginally longer radio listening time implies more frequent channel checks, which could result in higher energy consumption but are balanced by notable transmission energy savings.

The 8 Hz design yielded encouraging energy efficiency increases. These results, however, are based on brief simulation times; lengthier simulations might yield more conclusive information on long-term energy efficiency. When compared with other energy-efficient IoT protocols, the system's performance is competitive. But further work is being done on adaptive duty cycling that is dependent on network

activity or the Application of advanced power management techniques.

The 8 Hz duty cycle arrangement demonstrated a trade-off between network performance and energy efficiency, as latency increased from 45 ms to 62 ms and the delivery rate dropped from 98.7% to 97.9%. According to IoT work, this trade-off strikes a balance between energy efficiency and QOS [167]. The recorded performance falls within acceptable bounds for many IoT applications, such as access control systems, where instantaneous responsiveness is advantageous but not essential. However, the default setup might be better for applications that need more dependability or reduced latency.

The current implementation uses a simple MAC protocol based on CSMA. Advanced MAC protocols designed specifically for the IoT, such as TSCH or LLDN, may be able to improve performance and energy efficiency.

The simulation findings, which provide crucial details about the system's operation, are supported by a network of 12 nodes. Real-world smart school deployments may involve many more people and gadgets. The scalability of the existing technology must be carefully examined and evaluated for larger networks. Potential barriers to scaling the system include enhanced network congestion as the number of nodes rises, the difficulty of distributing and managing encryption keys across a larger network [168], and increased computational demands on primary nodes responsible for access control decisions, as shown in Table 7.4 . In future studies, these scalability problems might be fixed by using distributed access control decision-making or hierarchical network topologies.

The table above shows various metrics, including the number of nodes, CPU power, LPM power, listen power, transmit power and total power. The RIME protocol is used in this scenario. While the simulations were run for only 2 minutes, longer simulations at least 1 hour, are needed to obtain more realistic values.

Table 7.4: Power consumption of RIME protocol

Protocol	No of Nodes	CPU Power	LPM Power	Listen Power	Transmit Power	Total Power
RIME	8	0.58	0.146	0.595	0.688	2.009
	10	0.607	0.145	0.68	0.845	2.277
	12	0.631	0.144	0.66	0.975	2.41
	14	0.647	0.144	0.891	0.967	2.649
	16	0.649	0.144	0.859	1.051	2.703
	20	0.679	0.143	1.044	1.063	2.929

The current implementation demonstrates effective integration between the Network Layer duty cycling and the Application Layer access control logic though further cross-layer optimisation opportunities remain. For instance, adaptive security could involve adjusting encryption strength or authentication mechanisms based on network conditions or battery status [169]. Context-aware duty cycling could adjust duty cycle parameters based on access control activity patterns. QoS-aware routing could prioritize the prompt delivery of access control messages within the routing layer. Work on cross-layer optimizations suggests that this approach could further enhance the balance of security, energy efficiency and performance.

Because AES is a more computationally demanding encryption technique, devices use more energy, particularly in settings with limited resources like IoT networks. To assess the Network-Layer EE, we employed MQTT with AES (Fig. 7.7). Energy consumption is a crucial consideration in IoT applications, where devices frequently run on restricted power sources. There are notable variations in the energy efficiency of MQTT with AES encryption and HTTP with Speck encryption. Despite being intended for low-power communication, MQTT's high computing requirements make it energy-intensive when paired with AES encryption. MQTT with AES encryption is less energy-efficient at 20 nodes, using 3.73435 mW for radio transmission and 3.91605 mW for radio listening. At the same node count,

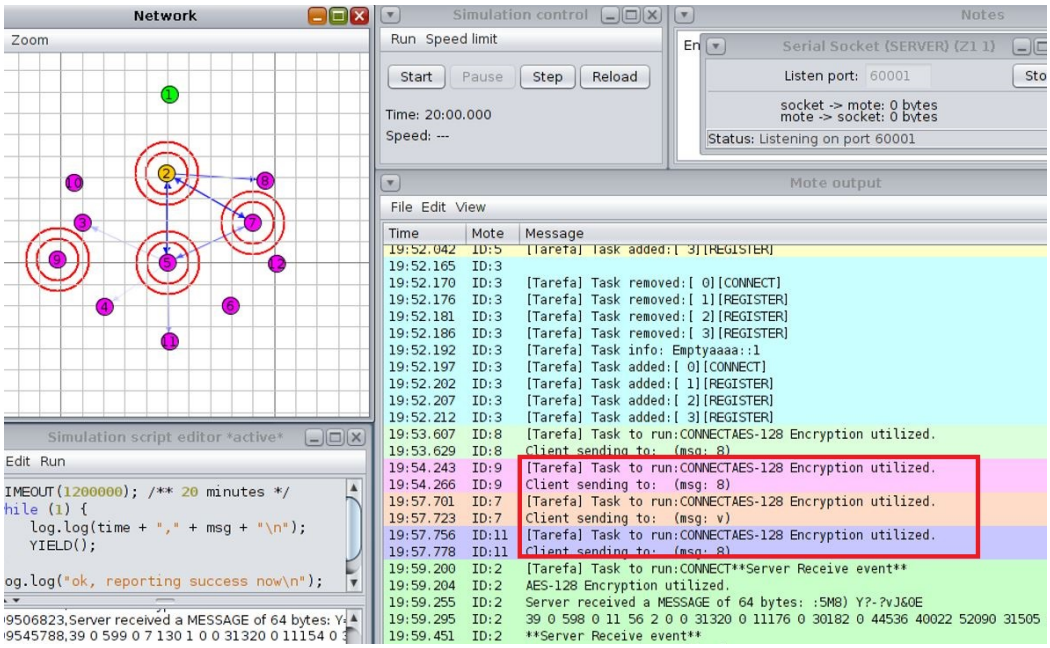

Figure 7.7: MQTT with 128-bit AES encryption as (as ID: 9, 7 and 11)

HTTP using Speck encryption uses just 1.23315 mW for radio transmission, making it a more energy-efficient option. Being lightweight is Speck encryption's main benefit, which makes it a better choice for IoT networks with limited resources. Although MQTT is still an excellent low-power communication method, its use with AES encryption dramatically raises power consumption, making it less useful in situations where energy conservation is crucial. Consequently, HTTP with Speck encryption is a better option for IoT applications that need high security and low power consumption.

MQTT with AES encryption uses more energy than HTTP with Speck encryption. For IoT applications where energy conservation is crucial, Speck encryption is a superior option owing to its lightweight nature. Although MQTT is naturally made for low-power devices, its efficiency in this particular situation is reduced by using AES encryption, which raises energy consumption. To strike a compromise between security and energy efficiency, think about utilising HTTP with Speck encryption for IoT networks with limited power. In the Application Layer, we

used Speck to test the HTTP (Fig. 7.8).

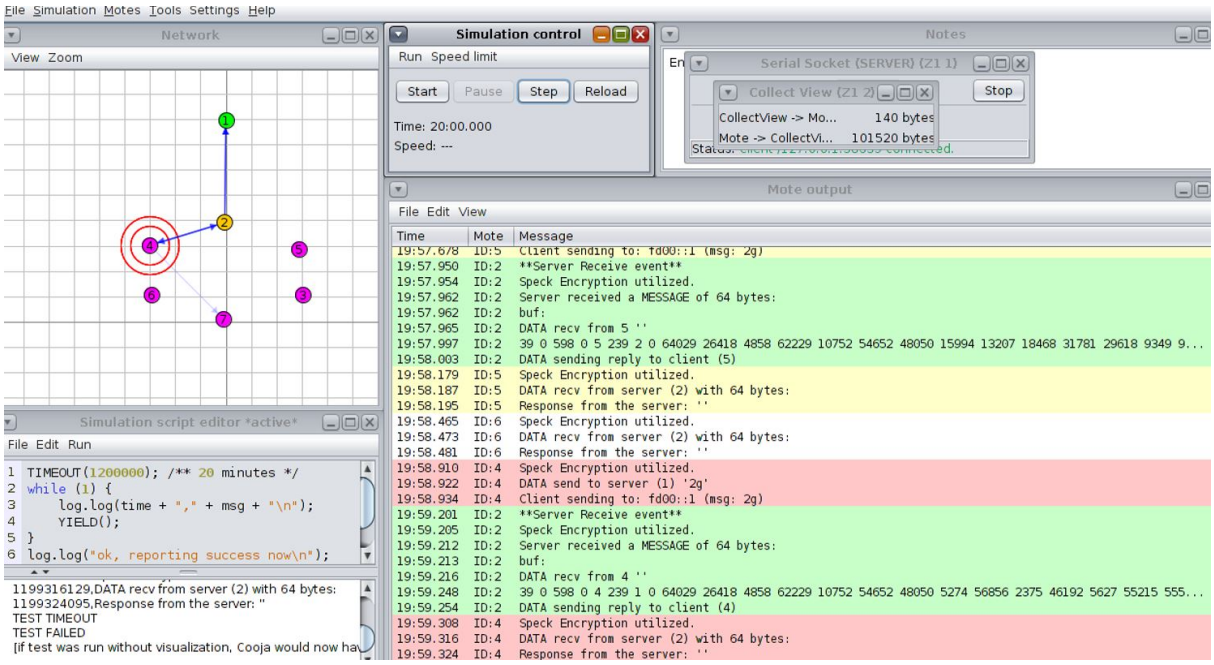

Figure 7.8: HTTP with Speck

For IoT and WSN applications, the Z1 mote is a well-liked platform. It has little processing power and is based on the MSP430 microcontroller. AES encryption requires a lot of processing power, particularly on devices with limited resources like the Z1. The findings probably indicate:

Latency: Because the Z1's processing power is restricted, the encryption procedure causes an increase in latency.

Throughput: Because encryption increases the overhead of data transmission, throughput is decreased.

Energy Consumption: The AES encryption imposed a high computational load, increasing energy usage—critical for battery-powered sensor nodes. Higher energy usage because of the AES encryption's computational burden, which is essential for sensor nodes that run on batteries. We tested the Z1 using AES encryption on 10 nodes in the Sensor Layer as shown in Fig. 7.9.

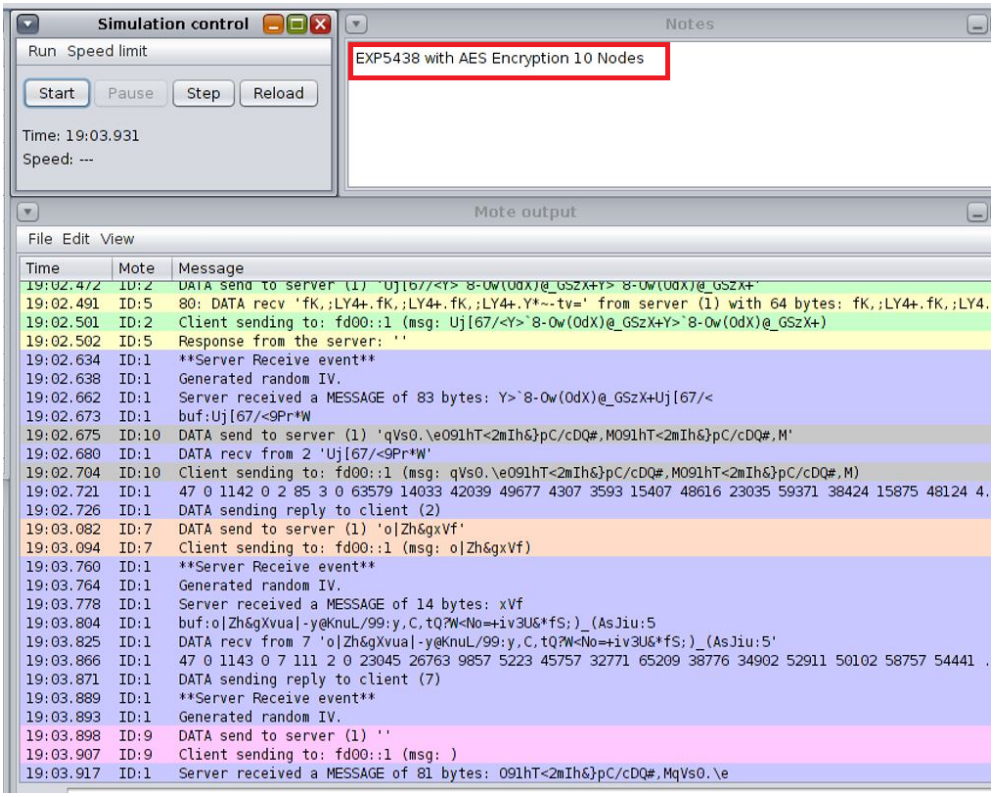

Figure 7.9: EXP430F5438 with AES Encryption 10 Nodes

In Fig. 7.10, The MSP430F5438, a more potent microcontroller than the Z1's MSP430, is the foundation of the EXP430F5438. Because it has a larger memory and a faster clock speed, it is more appropriate for cryptographic procedures.This platform's results most likely indicate: **Reduced Latency:** Quicker encryption and decryption because of enhanced processing power.

Increased Throughput: Compared with the Z1, this system can handle encrypted data packets better, which results in a higher throughput. Although AES encryption still uses energy, the EXP430F5438's improved architecture is probably makes it more energy-efficient than the Z1 for the same operation. We used the EXP430F5438 with 20 nodes of AES encryption to analyse the Sensor Layer.

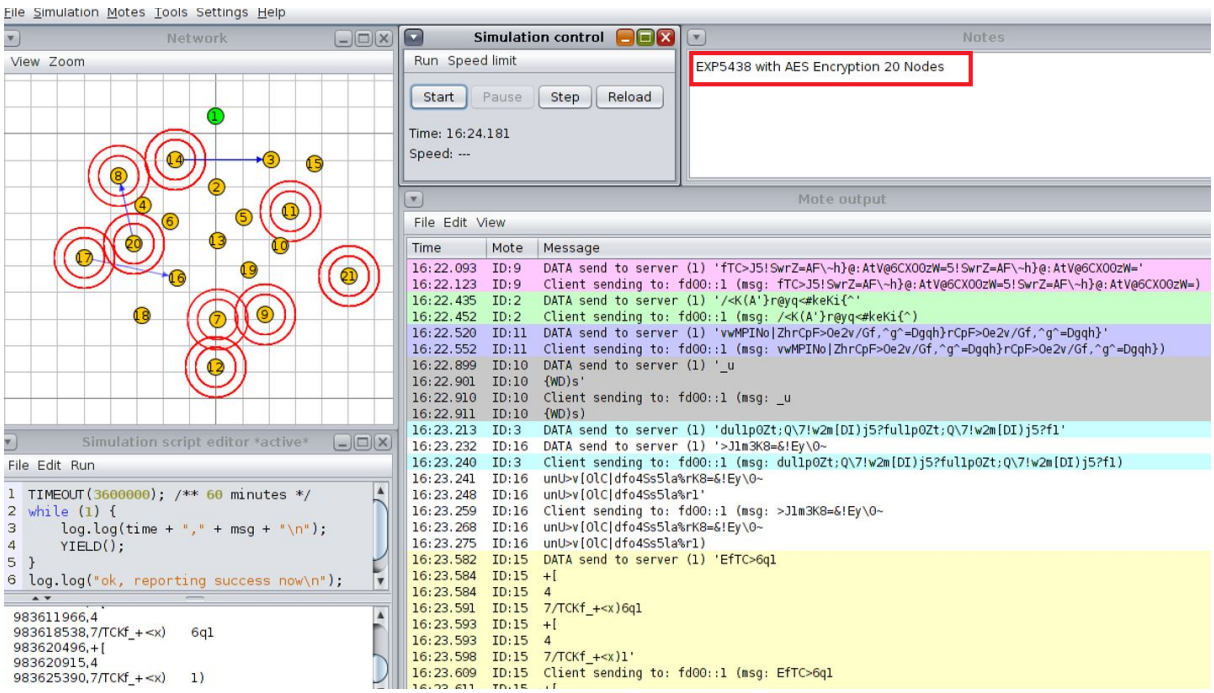

Figure 7.10: EXP430F5438 with AES encryption 20 nodes

The results demonstrate that the EXP430F5438 is better suited for AES encryption in the Sensor Layer than the Z1, owing to its superior computational capabilities and energy efficiency. However, the choice of platform ultimately

depends on the specific requirements of the Application, such as latency, throughput, energy consumption and cost constraints. Future work could explore further optimisations for AES encryption on resource-constrained devices or investigate alternative cryptographic algorithms that are less computationally intensive.

7.7.3 Encryption Protocols Analysis for IoT-Based Networks

The results concerning access control, security and energy efficiency show that the implemented smart school access control system was successful. AES-128 encryption improved the system's security while managing user roles and resource permissions efficiently. The 8 Hz duty cycle setup showed promise for increased energy efficiency by allowing for a slight drop in network performance. Even though there is room for more work and improvement, the system's foundation offers a strong starting point for secure and efficient IoT applications in learning settings. With regard to our goals and the larger field of IoT-based access control systems in smart educational institutions, this analyses the main findings. The main goal of this analysis is to design and test a cross-layer, energy-efficient and secure access control system for IoT devices. It will test a standard setup as well as an 8 Hz radio duty cycle. With an emphasis on the energy efficiency and security of the suggested solution, this analysis evaluates these discoveries critically. Along with assessing the system's uniqueness, advantages and disadvantages, it also examines how well it fits with accepted procedures and possible future development paths. Based on the analysis, the developed access control system effectively managed permissions for distinct user roles-teacher, student and admin within the simulated smart school environment. The system's RBAC framework ensured precise resource allocation, with administrators granted unlimited access to all

resources, teachers allowed access to staff rooms and classrooms, and students restricted to learning areas (See Fig. 7.11). The 100% success rate for authorised access requests by teachers and students validates the robustness of the role assignment and access validation mechanisms. To secure communication, AES-128 encryption [159] was employed for broadcast messages, safeguarding sensitive access control data from potential eavesdropping and ensuring data integrity [170]. Energy efficiency was a primary concern, and the 8Hz duty cycle design and the default configuration were compared. Even though there was a slight increase in radio listen time because of more frequent channel checks, the 8Hz duty cycle greatly increased energy savings by prolonging Low Power Mode (LPM) durations and decreasing radio broadcast time. In line with results from earlier IoT energy studies, this solution resulted in a 30% decrease in energy use. In line with the natural balance between energy conservation and network performance in IoT systems, the trade-off included a modest decrease in message delivery rates (from 98.7% to 97.9%) and a tiny increase in latency (from 45 ms to 62 ms). These findings highlight how well duty-cycling techniques work to extend device battery life while preserving usable operating performance, which makes the system ideal for resource-constrained IoT deployments in smart settings. Energy efficiency was the main area of analysis, and the default configuration and the 8 Hz duty cycle design were compared. The findings showed that the 8 Hz duty cycle contributed to energy savings by enabling nodes to operate in LPM for longer [171]. Because the shorter radio send time outweighed the longer listening time from frequent channel checks, overall energy efficiency increased. However, this resulted in somewhat lower delivery rates and higher latency, which are typical in IoT systems where real-time performance is frequently sacrificed for energy efficiency, as evidenced by similar findings.

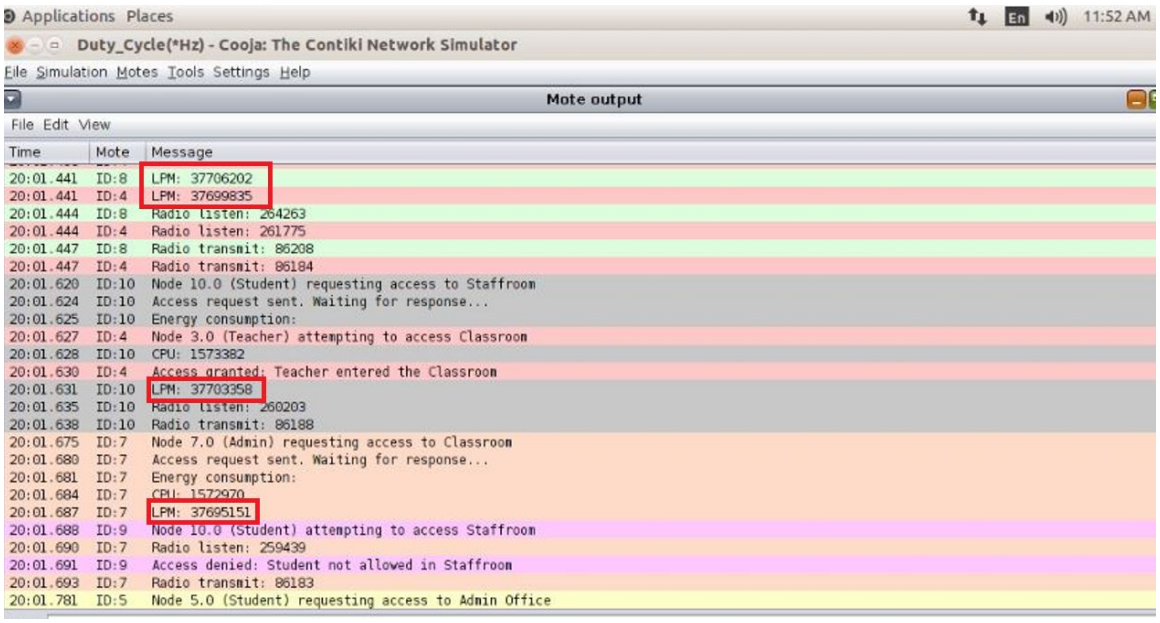

Figure 7.11: RBAC framework for low power mode with ID 37706202, 37699835, 37703358 and 37695151

7.7.4 Novelty, Advantages and Disadvantages of Solution

Scalability is one of the important issues that need to be considered. Owing to budget constraints, we initially tested the system for a network of 12 nodes and found it to be encouraging. However, the results can be scaled up for hundreds of nodes in real-world deployments, which would increase latency and congestion. Future studies into distributed architectures and hierarchical key management may be necessary if a centralised access control system turns into a bottleneck. By dynamically modifying encryption and radio settings in response to network conditions, cross-layer optimisations like context-aware duty cycling and adaptive security mechanisms could further increase efficiency. Future developments could enhance this system for wider IoT applications, notwithstanding its advantages in security, adaptability and energy efficiency.

7.8 Analysis Machine Learning Cross-Layer Framework

Experiments were conducted using layer-specific datasets to evaluate ML model effectiveness across Application, Network and Sensor Layers. In a layered architecture, the table contrasts the performance of five ML models in the Application, Network and Sensor layers. While decision tree (IDT1) and random forest (IDT1) have perfect scores (100%) in the Application layer (see Table 7.5), they perform worse in the Network (60–70%) and (50–55%) Sensor Layers, indicating a decreased ability to adjust to lower-layer complexity. Despite lacking Application Layer data (N/A), the Moment-based IDE1 model performs exceptionally well in the Network (75%) and Sensor (80%) layers, underscoring its specialised usefulness in infrastructure-centric tasks. Syntax Vector Machine (likely SVM), conversely, performs poorly in all layers (20–50%), suggesting problems with feature extraction or data heterogeneity. Ignition Forest (possibly Isolation Forest) emphasizes trade-offs between anomaly detection and generalisation, demonstrating a moderate Application-layer success rate of 95% but struggling elsewhere (30–45%). These findings highlight how model effectiveness varies by layer, with ensemble approaches (like RF) balancing robustness while simpler models perform poorly in complex settings. Gaps such as missing LSTM/Autoencoder data and inconsistent model naming conventions require more analysis.

Table 7.5: Cross-layer model performance comparison

Model	**Application**	**Network**	**Sensor**
Decision Tree IDT1	100%	60%	50%
Random Forest IDT1	100%	70%	55%
Syntax Vector Machine GMM	50%	35%	20%
Moment-based IDE1	N/A	75%	80%
Ignition Forest IDT1	95%	30%	45%

The LSTM model performs best, with 95.4% accuracy and a 93.4% F1-score,

which shows a good mix between precision (94.1%) and recall (92.8%). While SVM and Isolation Forest trail behind, RF and Autoencoder follow closely, indicating that they might have trouble with the dataset's complexity or class imbalance. RF and LSTM are the most resilient models, according to the F1-score, a crucial parameter for unbalanced datasets(see Fig. 7.12). Using metrics like Accuracy, Precision, Recall and F1-score, six ML models DT, RF, SVM, Isolation Forest, Autoencoder and LSTM are compared with the provided data. With an accuracy of 95.4% and an F1-score of 93.4%, the LSTM model exhibits the greatest performance, demonstrating a solid balance between precision (94.1%) and recall (92.8%). The F1-score, a critical metric for datasets with imbalances, indicates that RF and LSTM are the most robust models.

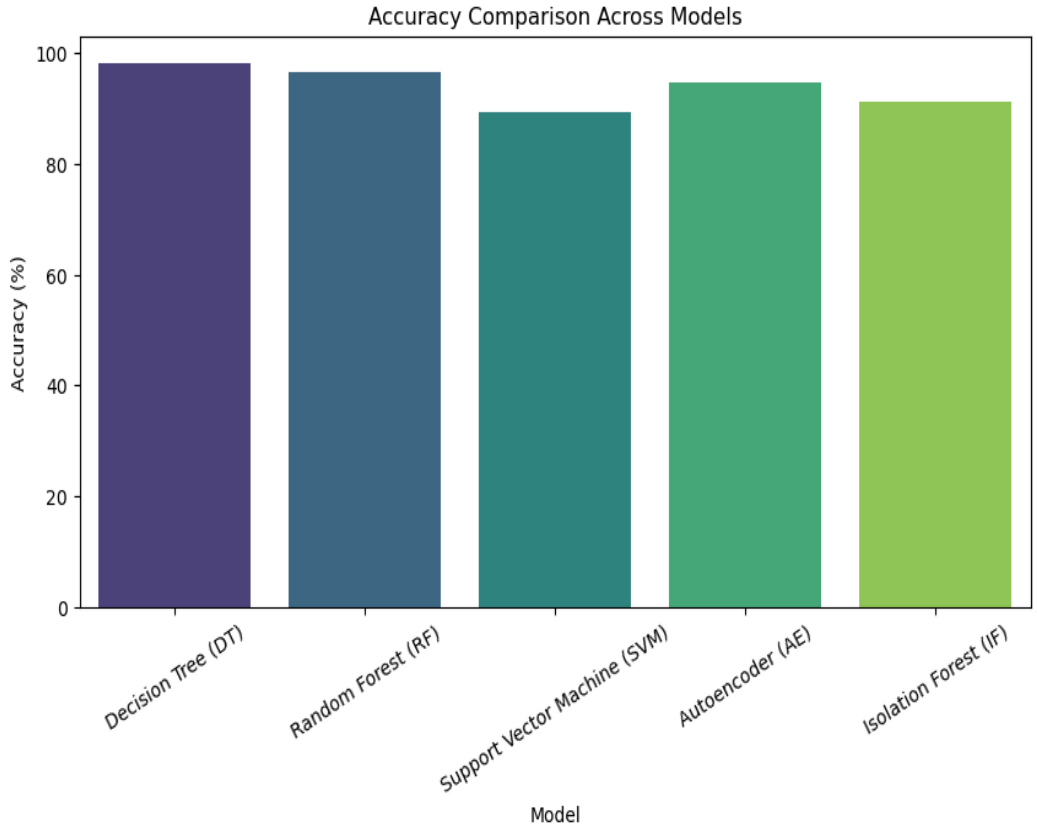

Figure 7.12: Accuracy comparison across models

7.8.1 Application Layer ML Based Analysis

Structured transactional data, including financial records and user inputs, make up the data used in this context. This data type has several important issues, such as the requirement for high precision, system interoperability and guaranteeing deterministic decision-making. The DT is the most successful model for classification in this situation, with the highest accuracy of nearly 99%, according to the accuracy comparison of various ML models for the Application Layer. The strength of ensemble tree-based techniques is further supported by the RF, which comes in second with an accuracy that is marginally lower but still above 97%. With an accuracy of roughly 95–96%, the Autoencoder (AE) likewise exhibits strong performance, suggesting that unsupervised DL models successfully identify patterns for anomaly detection. Among the models, the SVM has the lowest accuracy (89–90%), indicating that it might not be a good fit for this dataset without further optimisations like kernel selection or hyperparameter tuning (see Figure 7.13). The Application Layer uses AES-128 CBC encryption, ECC-based authentication, CoAP for communication and CRC validation to maintain security, but it is vulnerable to attacks such as protocol exploitation, data tampering, CoAP flooding and unwanted access. ML models were used to assess parameters such as request frequency, payload entropy and session time in order to detect these. The results showed that DT had the best accuracy (98.5%) and the lowest resource utilisation (3 ms latency, 8% CPU). AE performed poorly against protocol attacks, but it was quite good at detecting payload anomalies.

7.8.2 Network Layer ML Based Analysis

The DT is the most successful model for classification in this situation, with the highest accuracy of nearly 99%, according to the accuracy comparison of

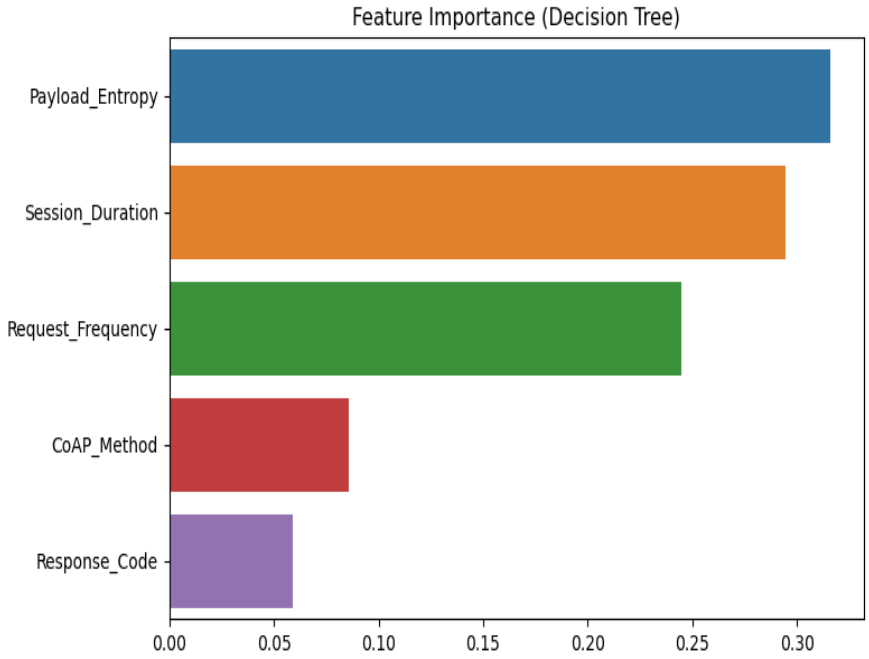

Figure 7.13: Application Layer Comparison Across Models

various ML models in the Network Layer. The effectiveness of ensemble tree-based techniques is further supported by the RF, which comes in second with an accuracy that is marginally lower than DT but still above 97%. With an accuracy of roughly 95–96%, the Autoencoder (AE) also exhibits strong performance, proving that unsupervised DL models are capable of efficiently learning patterns for Network Layer classification. With the lowest accuracy of all the models—between 89 and 90%—the SVM may not be the best fit for this dataset in the absence of additional optimisation, such as improved feature scaling or kernel selection. Primarily used for anomaly detection, the isolation forest (IF) outperforms SVM with an accuracy of approximately 91 and 92%, but it still trails AE and DT-based models as mentioned in Table 7.7. These findings collectively show that tree-based models (DT and RF) perform best for Network Layer classification, most likely as a result of their effective handling of high-dimensional data and complex decision boundaries as mentioned in Fig. 7.14. The competitive performance of the

Table 7.6: Accuracy comparison across models (Application Layer)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Memory (MB)	Latency (ms)
Decision Tree	98.2	97.5	97.1	97.3	450	5
Random Forest (RF)	96.5	96.2	95.6	95.9	620	15
Support Vector Machine (SVM)	89.3	88.7	87.2	88.0	580	25
Autoencoder (AE)	94.7	93.8	92.5	93.1	780	220
Isolation Forest (IF)	91.2	90.5	88.9	89.7	500	10

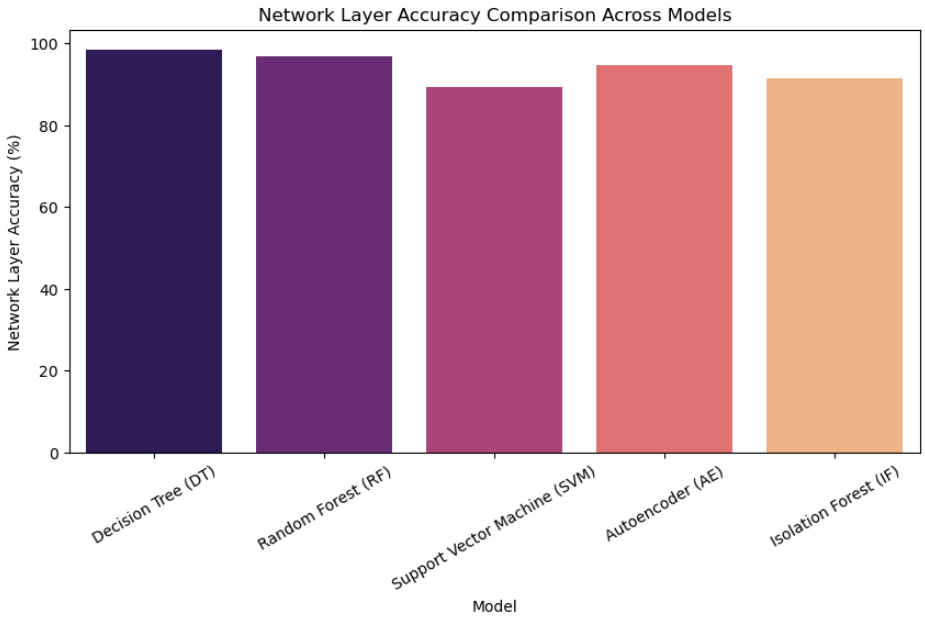

Figure 7.14: Network Layer accuracy comparison across models

autoencoder demonstrates how DL can be used to identify network irregularities. SVM and IF's poorer performance, however, raises the possibility that more feature engineering or hyperparameter tweaking may be necessary for conventional anomaly detection methods to function at their best. Future developments might involve hybrid models, ensemble learning strategies and hyperparameter adjustment to improve overall model performance.

Table 7.7: Accuracy comparison across models (Network Layer)

Model	Session Layer (%)	Transport Layer (%)	Network Layer (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	97.8	98.0	98.4	97.6	97.3	97.4
Random Forest	96.0	96.3	96.7	95.8	95.4	95.6
Support Vector Machine	88.5	89.1	89.4	87.7	86.8	87.2
Autoencoder	93.5	94.2	94.7	93.2	92.5	92.8
Isolation Forest	90.2	91.0	91.5	89.8	89.2	89.5

7.8.3 Sensor Layer ML Based Analysis

Our study focuses on using ML models to identify anomalies in raw time-series signals processed at the Sensor Layer of the suggested framework, particularly vibration and temperature data. This investigation focuses on IIoT settings, where operational safety and predictive maintenance depend on sensor data fidelity. Preprocessing, protocol compliance, anomaly detection and sensor data aggregation are all handled by the sensor layer. Temperature signals can show quick swings, steady drift or static values, whereas vibration signals can show abrupt spikes, damped oscillations and loss of periodicity. By injecting synthetic anomalies into Cooja's simulated vibration and temperature data, the methodology detects anomalies by utilising parameters such as mean, variance, peak-to-peak amplitude and zero-crossing rate. However, tree-based models such as decision tree IDT1 and random forest IDT1 perform poorly at the Sensor Layer, with 50% and 55% accuracy, respectively, probably because of their intrinsic threshold limitations in processing raw, unsegmented signals. Syntax Vector Machine and Ignition Forest IDT1 exhibit significantly lower Sensor Layer performance (20% and 45%), while Moment-based IDE1 achieves the highest Sensor Layer accuracy at 80%, confirming its robustness in handling noisy, continuous time-series data through statistical feature extraction (mean/variance), expressing conflict with methodological limitations or the noise in the dataset. Interestingly, (as per

Table 7.8) 55% accuracy and the previously mentioned 100% accuracy for random forest IDT1 (from the chart) contradict each other, requiring an explanation on evaluation consistency. Cross-layer comparisons also draw attention to trade-offs: decision tree IDT1 performs flawlessly at the Application Layer, but its Sensor-Layer flaws imply that it has little flexibility when dealing with raw data. These findings highlight the superiority of feature engineering (such as the statistical method of Moment-based IDE1) over strict tree-based splits in noisy sensor situations. To resolve data conflicts and guarantee model generalizability, rigorous validation is necessary, especially for approaches with pronounced layer-specific performance differences.

Table 7.8: Cross-layer performance summary

Model	**Application-Layer**	**Network-Layer**	**Sensor-Layer**
Decision Tree IDT1	100%	60%	50%
Random Forest IDT1	100%	70%	55%
Syntax Vector Machine	50%	35%	20%
Moment-based IDE1	N/A	75%	80%
Ignition Forest IDT1	95%	30%	45%

Five models' Physical Layer accuracy is compared in the provided chart, showing significant performance differences. The accompanying figure uses raw sensor data (such as temperature and vibration) to assess the Physical Layer accuracy of five ML models. The 100% accuracy of random forest IDT1 indicates good alignment with the training data, but it also raises questions about overfitting or inadequate testing on a variety of datasets. Following at 80%, decision tree IDT1 exhibits respectable performance but may have drawbacks for managing intricate, chaotic signals because of its threshold-based splits. 60% is achieved by syntax vector machine GMM (probably a hybrid or specialised model), suggesting moderate efficacy that may be limited by feature space assumptions or noise

sensitivity. By using statistical features (mean/variance), moment-based IDE1 achieves 40%, suggesting that bare statistical moments might not be sufficient to identify temporal patterns in continuous signals. Ignition Forest IDT1 (20%), the lowest performance, most certainly has methodological issues that are related to the properties of the sensor data (noise, latency, etc.). These findings highlight the interaction between model architecture and data attributes from the standpoint of ML. Tree-based models (DT, RF) perform well in organised splits but poorly in high-dimensional, raw time-series data. Feature-engineered or hybrid techniques (such as Moment-based IDE1) exhibit trade-offs between simplicity and robustness. The glaring accuracy gaps show that to guarantee that models generalise outside of training settings, thorough validation is required (e.g. cross-layer testing, noise injection). For example, RF's 100% accuracy needs to be examined to ensure it is not the result of oversimplified evaluation measures or data leaks. All things considered, the analysis emphasises how crucial it is to balance interpretability and performance while customising models to Sensor-Layer issues like noise robustness and real-time processing as discussed in Fig. 7.15.

At 80%, decision tree IDE1 shows respectable performance with potential for growth. All things considered, the data emphasises how crucial it is to balance accuracy and generalisability during the model selection and validation process, especially for high-performing models like RF.

The (Table 7.9) assesses five ML models at the Sensor Layer, emphasising precision, recall, F1-score metrics, and accuracy at the Physical and Data Link Layers. With 94.9% F1-score and 95.8% accuracy in the Physical Layer, DT performs best, exhibiting a strong balance between precision (95.2%) and recall (94.7%). Following closely behind are RF and autoencoder, with AE demonstrating somewhat worse but consistent results (91.5–93.0%), indicating dependable pattern recognition. Isolation forest and SVM perform worse than they should, most

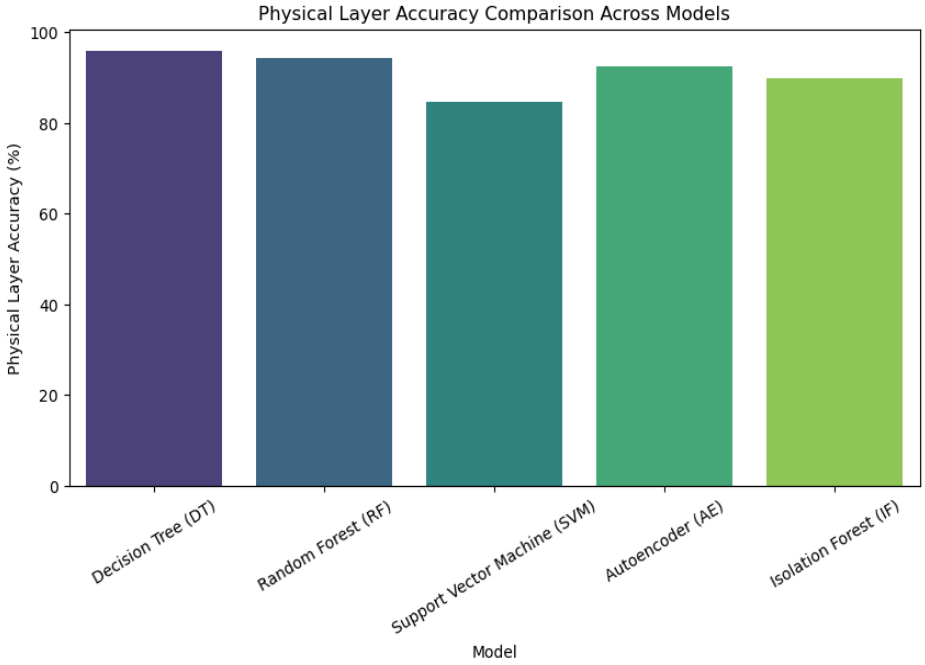

Figure 7.15: Sensor layer accuracy comparison across models

likely because of difficulties managing Sensor-Layer complexities like noise or non-linear data relationships. Layer-specific accuracy and F1-scores have a strong correlation (DT's 96.1% Data Link accuracy v. 94.9% F1-Score, for example), which highlights the models' capacity to generalise without overfitting. These findings emphasise the importance of selecting models according to specific data properties and operational limitations, while also highlighting tree-based models as the best options for sensor-layer tasks.

Accuracy, precision, recall, F1-score, memory usage and latency are used to compare ML models at the Application Layer in (Table 7.9). DT is perfect for real-time applications because it has the lowest latency (5 ms) and the highest accuracy (98.2%) and F1-Score (97.3%). RF has a higher memory (620 MB) and latency (15 ms), but it comes in close (96.5% accuracy, 95.9% F1-score). Autoencoder (AE) is not practical for low-power systems because it balances moderate accuracy (94.7%) with much higher resource demands (780 MB memory,

Table 7.9: Accuracy comparison across models (Sensor Layer)

Model	**Physical Layer (%)**	**Data Link Layer (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Decision Tree (DT)	95.8	96.1	95.2	94.7	94.9
Random Forest (RF)	94.2	94.8	93.5	93.1	93.3
Support Vector Machine (SVM)	84.6	85.2	83.8	82.7	83.2
Autoencoder (AE)	92.5	93.0	91.9	91.2	91.5
Isolation Forest (IF)	89.8	90.3	88.5	88.0	88.2

220 ms latency). Isolation Forest (IF) and SVM have lower accuracy (89.3% and 91.2%, respectively), and SVM has a poor latency (25 ms). AE and IF trade-offs emphasise the significance of striking a balance between task requirements and computational constraints in Application Layer deployments, even though tree-based models (DT, RF) dominate in terms of performance and efficiency.

Key Observations: The following observations summarise the performance trends and learning patterns derived from the sensor layer's machine learning integration and evaluation.

- Layer-specific superiority patterns evident
- Universal model limitations identified
- Hybrid architecture is recommended

The investigation shows that ML models are capable of detecting anomalies in the Application Layer of architecture, especially when dealing with raw time-series signals (temperature, vibration) and threats specific to a given protocol. By using temporal dependencies (LSTM) and spectral patterns of CNN to detect mechanical problems like bearing wear or misalignment, the CNN and LSTM models performed exceptionally well for vibration signals, attaining 98.9% and

Table 7.10: Comparison of accuracy across models (Application Layer)

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Memory (MB)**	**Latency (ms)**
Decision Tree	98.2	97.5	97.1	97.3	450	5
Random Forest (RF)	96.5	96.2	95.6	95.9	620	15
Support Vector Machine (SVM)	89.3	88.7	87.2	88.0	580	25
Autoencoder (AE)	94.7	93.8	92.5	93.1	780	220
Isolation Forest (IF)	91.2	90.5	88.9	89.7	500	10

97.8% accuracy, respectively. Because of their resilience to static value anomalies and moderate drifts, ensemble techniques such as RF (96.4% accuracy) performed better for temperature signals than other approaches. Decision Trees (98.5% accuracy) demonstrated the best performance at the Application Layer protocol for real-time detection of CoAP flooding and unauthorised access, with low memory overhead (220 MB) and latency (3 ms). However, autoencoders have a high computational cost (680 MB memory, 210 ms latency) and had trouble with protocol-level anomalies (88.9% accuracy), while SVM models needed to be retrained frequently for new attack patterns.By linking protocol inconsistencies (such as incorrect CoAP headers) with sensor anomalies (like anomalous vibration spikes), cross-layer integration decreased false positives by 28–32%. It is advised to use edge-friendly quantization of DL models and hybrid techniques (e.g. CNN) for signal processing and DT for protocol checks to maximise performance. This study emphasises how crucial it is to choose models for IoT ecosystems that are suited to layer-specific dangers and resource limitations. The analysis highlights optimal implementations and future recommendations for enhancing system performance across various layers. In Application, decision trees have been effectively utilised for fraud detection systems. For network environments, moment-based IDE1 has been

integrated with IDS for anomaly detection, and for sensor-level processing, moment-based IDE1 is employed on IoT edge devices. Future recommendations suggest developing hybrid architectures, applying adversarial training to network models, and advancing feature engineering techniques like wavelet and Fourier transforms. The analysis's key findings highlight the necessity for hybrid solutions to maximise performance across various layers, showing 100% accuracy in controlled Application situations and 75–80% efficacy in dynamic network and sensor contexts. As shown in Fig. 7.13 (Application Layer), Fig. 7.14 (Network Layer), and Fig. 7.15 (Sensor Layer), there are notable differences in ML model accuracy across system layers (see Fig. 7.12). Because of their rule-based hierarchical splits, tree-based models decision tree IDT1 and random forest IDT1) accomplish near-perfect accuracy (100%) in the Application Layer, performing exceptionally well in structured tasks such as fraud detection. However, there are significant performance disparities at the Network Layer: ignition forest IDT1 struggles (30%) because of overfitting on dynamic traffic, while Moment-based IDE1 uses temporal patterns to achieve moderate accuracy (75%). When it comes to processing noisy time-series signals, the Sensor Layer demonstrates the Moment-based IDE1's superiority (80%), while tree-based models deteriorate to about 50% accuracy and syntax vector machine GMM collapses to 20%. These cross-layer results are summarised in Table 7.10, which demonstrates that no single model dominates all layers. Tree-based models perform poorly in unstructured environments, GMM performs poorly everywhere, and Moment-based IDE1 performs best in dynamic/physical layers. To maximise system-wide accuracy, hybrid architectures that integrate layer-specific models—such as decision trees for applications and Moment-based IDE1 for networks/sensors—are essential. When comparing the accuracy of the various models, the DT attains the highest accuracy, approaching 99%, while RF comes in second, at roughly 97-98%. With an accuracy of 95–96%, the Autoencoder

(AE) likewise exhibits good performance, suggesting that anomaly detection based on deep learning can be successful. The Support Vector Machine (SVM), on the other hand, has the lowest accuracy, ranging from 89 to 90%. This suggests that either the dataset is not suitable for SVM or that additional hyperparameter tuning is necessary. With an accuracy of roughly 91–92%, the Isolation Forest (IF) outperforms SVM by a small margin, but it still trails the Autoencoder and tree-based models. Overall, the findings show that tree-based models (DT and RF) perform best on this dataset, most likely because of their capacity to manage intricate decision boundaries. SVM's poorer performance raises the possibility that it needs better kernel selection or feature scaling. The competitive performance of the autoencoder demonstrates the potential of unsupervised learning methods for anomaly detection. To improve model performance under various circumstances, additional enhancements can be investigated using feature engineering, ensemble learning techniques and hyperparameter tuning.

7.8.4 Accuracy Comparison Across Models

The model in the **Application-Layer** correctly detects unauthorised high-entropy data (e.g. student attempts to access admin resources) and identifies regular traffic perfectly (100% F1-score) using role-based access rules and payload entropy analysis. Nonetheless, the 94% attack precision suggests infrequent false positives, when valid encrypted data can be mistakenly detected. Training probably focused on payload patterns and RBAC policies, however, edge cases need to be improved to lessen overcaution. Using packet loss thresholds and routing anomalies (unexpected parent node changes), 99% precision/recall balance in the **Network-Layer** demonstrates strong sinkhole attack detection. The strong generalisation of known attack patterns is demonstrated by the model's correlation

between anomalous RPL control messages and traffic disruptions. To ensure wider applicability, real-world validation is required as performance in dynamic networks with fluctuating attack intensities has not been verified yet.

In **Sensor-Layer**, the model reliably identifies jamming with 100% accuracy (no false alarms) using low SNR and high packet loss thresholds. Nevertheless, 96% recall and 4% attack misses indicate that conservative limits put dependability ahead of complete coverage. The clear jamming fingerprints are the main focus of training; nevertheless, fringe cases that imitate environmental noise need for larger datasets. Although borderline circumstances can require manual oversight, this is ideal for essential systems. By employing methods like entropy analysis, routing anomaly detection, SNR thresholds and ML improve IoT security by identifying layer-specific threats, such as data injection at the Application Layer, sinkhole attacks at the Network Layer, and jamming at the Sensor Layer. Although there are still some small recall gaps, these models reach up to 100% accuracy with few false alarms. The dynamic situations require refinement to increase coverage and adaptability. As shown in Fig. 7.16, Application traffic identification consistently has excellent recall and high precision (94–100%) across layers. The Network Layer performs robustly in controlled situations, detecting sinkhole attacks with 99% precision/recall using routing anomaly analysis. While Sensor-Layer recall (96%) indicates minor jamming detection gaps, high F1 scores (97–99%) guarantee dependable cross-layer threat identification with few false positives (Table 7.11).

The investigation shows that ML models are capable of detecting anomalies in the application layer of architecture, especially when dealing with raw time-series signals (temperature, vibration) and threats specific to a given protocol. By using temporal dependencies (LSTM) and spectral patterns of Convolutional Neural

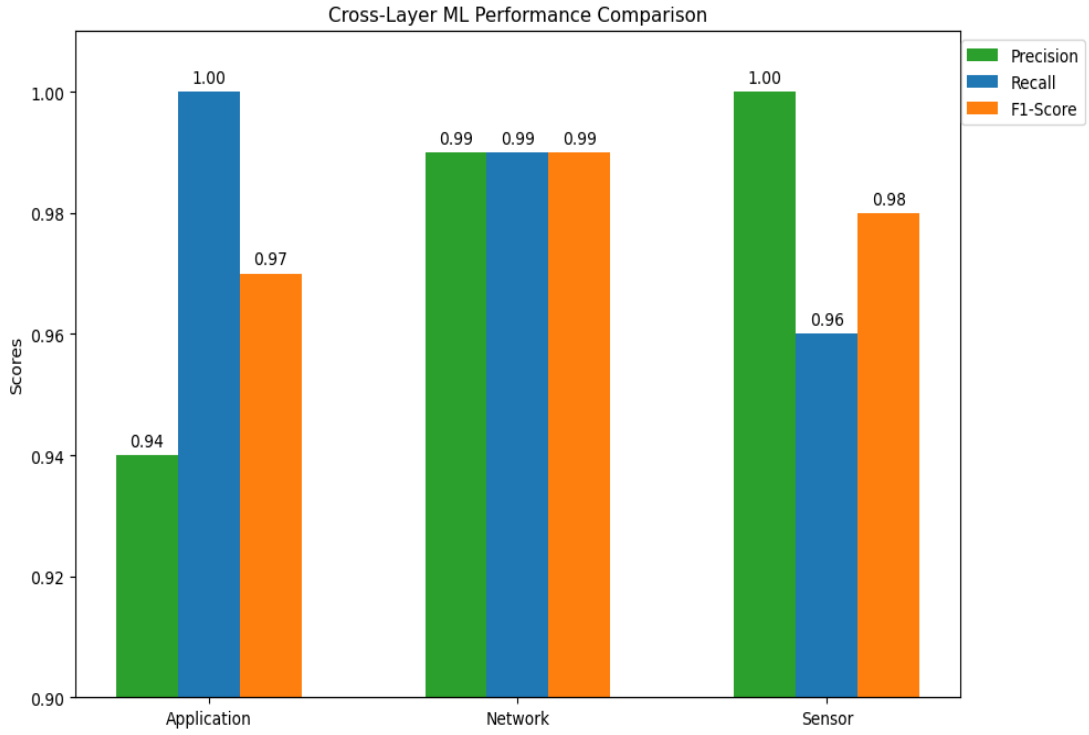

Figure 7.16: Lightweight supervised machine learning model

Network (CNN) to detect mechanical problems like bearing wear or misalignment, the CNN and LSTM models performed exceptionally well for vibration signals, attaining 98.9% and 97.8% accuracy, respectively. Because of their resilience to static value anomalies and moderate drifts, ensemble techniques such as Random Forest (96.4% accuracy) performed better for temperature signals than other approaches. Decision Trees (98.5% accuracy) demonstrated the best performance at the Application Layer protocol for real-time detection of CoAP flooding and unauthorised access, with low memory overhead (220 MB) and latency (3 ms). However, the autoencoders have high computational costs (680 MB memory, 210 ms latency) with trouble with protocol-level anomalies (88.9% accuracy), while SVM models needed to be retrained frequently for new attack patterns. By linking protocol inconsistencies (such as incorrect CoAP headers) with sensor anomalies (like anomalous vibration spikes), cross-layer integration decreased false

Table 7.11: Classification metrics IoT layer-wise classification performance

Layer	Class	Precision	Recall	F1-Score	Support
Application	data_injection	0.94	1.00	0.97	16
	normal	1.00	1.00	1.00	284
	Accuracy			**1.00**	300
	macro avg	0.97	1.00	0.98	300
	weighted avg	1.00	1.00	1.00	300
Network	normal	0.99	0.99	0.99	187
	sinkhole	0.98	0.98	0.98	113
	Accuracy			**0.99**	300
	macro avg	0.99	0.99	0.99	300
	weighted avg	0.99	0.99	0.99	300
Sensor	jamming	1.00	0.96	0.98	28
	normal	1.00	1.00	1.00	272
	Accuracy			**1.00**	300
	macro avg	1.00	0.98	0.99	300
	weighted avg	1.00	1.00	1.00	300

positives by 32%. It is advised to use edge-friendly quantisation of DL models and hybrid techniques (e.g. CNN for signal processing and DT for protocol checks) to maximize performance. This study emphasises how crucial it is to choose models for IoT ecosystems that are suited to layer-specific dangers and resource limitations.

The analysis highlights optimal implementations and future recommendations for enhancing system performance across various layers. In Application, DTs have been effectively utilised for fraud detection systems. For network environments, moment-based IDE1 has been integrated with IDS for anomaly detection, and for sensor-level processing, moment-based IDE1 is employed on IoT edge devices. Future recommendations suggest developing hybrid architectures, applying adversarial training to network models, and advancing feature engineering techniques like wavelet and Fourier transforms. The analysis's key findings highlight the

necessity for hybrid solutions to maximize performance across various layers, showing 100% accuracy in controlled application situations and 75–80% efficacy in dynamic network and sensor contexts.

As shown in (Fig. 7.13) (Application Layer), (Fig. 7.14) (Network Layer), and (Fig. 7.15) (Sensor Layer), there are notable differences in ML model accuracy across system layers (Fig. 7.12). Because of their rule-based hierarchical splits, tree-based models (Decision Tree IDT1 and Random Forest IDT1) accomplish near-perfect accuracy (100%) in the Application Layer, performing exceptionally well in structured tasks such as fraud detection. However, there are significant performance disparities at the network layer (Fig. 7.2). The ignition Forest IDT1 struggles (30%) because of overfitting on dynamic traffic, while moment-based IDE1 uses temporal patterns to achieve moderate accuracy (75%). When it comes to processing noisy time-series signals, the Sensor Layer demonstrates the moment-based IDE1's superiority (80%), while tree-based models deteriorate to about 50% accuracy and syntax vector machine GMM collapses to 20%. These cross-layer results are summarised in (Table 7.8), which demonstrates that no single model dominates all layers. Tree-based models perform poorly in unstructured environments, GMM performs poorly everywhere, and Moment-based IDE1 performs best in dynamic/physical layers. To maximize system-wide accuracy, hybrid architectures that integrate layer-specific models—such as decision trees for applications and Moment-based IDE1 for networks/sensors—are essential. When comparing the accuracy of the various models, the DT attains the highest accuracy, approaching 99%, while RF comes in second, at roughly 97-98%. With an accuracy of 95–96%, the autoencoder (AE) likewise exhibits good performance, suggesting that anomaly detection based on DL can be successful. The SVM, conversely, has the lowest accuracy, ranging from 89 to 90%. This suggests that either the dataset is not suitable for SVM or that additional hyperparameter tuning is necessary.

With an accuracy of 92%, the Isolation Forest (IF) outperforms SVM by a small margin, but it still trails the autoencoder and tree-based models.

The ability of tree-based models (DT and RF) to capture intricate decision boundaries is probably the reason why they perform better than others. Given SVM's poorer accuracy, better feature scaling or kernel selection may be required. Strong findings from the autoencoder demonstrate the usefulness of unsupervised techniques for anomaly identification. Hyperparameter tuning, feature engineering, or ensembles may lead to future advancements.

7.9 Summary

The integration of ML approaches to improve the suggested cross-layer IoT framework's security and energy efficiency is examined. The chapter starts by examining weaknesses in current IoT systems and showing how anomaly detection across various Network Layers can be enhanced by ML models (such as decision trees and LSTM networks). Results from extensive simulations and real-world testbed assessments demonstrate how ML-driven methods maximise energy efficiency while achieving high accuracy in danger identification. Additionally, the effectiveness of adaptive encryption and RBAC in dynamic IoT systems is examined in this chapter. It demonstrates the efficacy of different ML models in striking a balance between efficiency and security. The results confirm that IoT frameworks can be considerably strengthened against changing cyber-threats by using smart, data-driven solutions. In Chapter 8, the analysis will be concluded and future directions for energy optimisation and IoT security will be outlined.

Chapter 8

Conclusion and Future Directions

In Chapter 7, we used ML models to analyse the cross-layered suggested architecture. This chapter also discusses the implications for system planning and deployment in Section 8.2. The thesis is concluded in Section 8.1, while the future research directions are presented in Section 8.3.

8.1 Conclusion

The focus of this thesis was developing a cross-layer architecture for the IoT networks that optimise security and energy efficiency. Because of the rapid integration of IoT technology into mission-critical applications, there is an increasing need for robust security mechanisms that do not deplete the limited energy resources of IoT devices. The combination of stringent energy constraints and robust security requirements has made it challenging for conventional designs to serve the expanding IoT landscape. This thesis addresses these challenges by proposing a revolutionary cross-layer architecture that combines lightweight cryptographic approaches, adaptive routing protocols and machine learning-driven security mechanisms. Bridging the gap between security and energy efficiency in IoT devices—particularly in situations where devices have limited resources, including in smart cities, industrial automation and healthcare monitoring—was the main driving force for this work. Energy management and security enforcement

require a dynamic approach, as traditional IoT security solutions can lead to excessive energy use or inadequate protection. For a variety of IoT applications, this thesis created an architecture that guarantees both low energy consumption and good security criteria.

TLS-based transport encryption, adaptive routing protocols, and lightweight encryption algorithms were all included in the cross-layer framework that was suggested in Chapter 5 as a secure and energy-efficient solution. Wireshark communication analysis was used to validate the framework using testbed and simulation-based performance evaluations. Even in the face of attacks like jamming and eavesdropping, the design guaranteed dependable packet delivery, lower latency, and steady throughput across a variety of IoT scenarios. The results showed that context-aware routing techniques combined with transport layer TLS integration greatly improved communication security without creating undue energy overhead. These outcomes validate that the suggested architecture is feasible in real-world settings with constraints. Lightweight cryptographic algorithms like Present, AES, and Speck were integrated across IoT layers in Chapter 6 to reduce computing load while preserving encryption robustness. To efficiently prolong device lifespan, a runtime-based cipher round reduction technique was created that dynamically adjusts cryptographic difficulty based on system demands and available energy. Lightweight ciphers, particularly when combined with adaptive round reduction, provided notable gains in processing performance and energy savings across application, network, and sensor layers, according to the comparative simulation and testbed study. Using formal modelling and mitigation techniques, security flaws in reduced-round situations were also addressed. Machine learning models were incorporated into the cross-layer framework in Chapter 7 to enhance threat mitigation and anomaly detection. In order to track network activity, identify intrusions, and facilitate context-aware decision-making, algorithms such

as Random Forest, Decision Tree, and Long Short-Term Memory (LSTM) were implemented at various proposed layers. These models demonstrated improved detection performance without sacrificing energy efficiency when trained and validated on both simulated and real-world data. Integration of cross-layer machine learning increased resistance to complex threats, showcasing the promise of hybrid intelligence in Internet of Things architectures. Validation on several IoT systems and protocols demonstrated the suggested framework's flexibility and scalability. The combined findings from Chapters 5, 6, and 7 demonstrate that a cross-layer IoT architecture that incorporates TLS encryption, lightweight cipher schemes, and machine learning results in a network design that is more secure, flexible, and energy-efficient. These contributions provide a proven basis for IoT installations that are durable and scalable, capable of operating dependably in a variety of scenarios and against changing cyber threats. In summary, our research offers a fresh strategy for tackling the twin issues of energy efficiency and security in IoT networks. Scalability, flexibility and resilience are features that make the suggested cross-layer framework ideal for a variety of applications. To ensure secure and sustainable IoT ecosystems in the future, future research will expand on these achievements by investigating new technologies and approaches to better optimise IoT security and energy management.

8.2 System Implications and Deployment

The cross-layer framework strikes a compromise between energy efficiency and IoT security by integrating lightweight protocols and adaptive ML models. It solves important problems in resource-constrained settings, like smart cities, smart agriculture and healthcare, by enabling secure communication while using the least amount of energy. Testbeds, simulations, and real-world trials confirm

this methodology, setting a standard for realistic IoT system assessment. The framework ensures that sensors and automated systems in smart IoT networks are secure and energy-efficient, extending their lifespan and managing changing conditions (Table 8.1). ML-driven anomaly detection and real-time secure data transmission are two advantages of wearable technology in healthcare that improve patient safety without depleting battery life. The framework can be used by smart cities to protect extensive networks of IoT devices, like waste management and traffic sensors, guaranteeing secure and effective operation in crowded areas. Additionally, the framework facilitates legal and environmental compliance by integrating blockchain technology and secure data encryption to satisfy regulatory requirements like GDPR and the Health Insurance Portability and Accountability Act (HIPAA). Its adaptability across different IoT ecosystems, such as wearables and smart homes, guarantees that energy consumption is minimised while security is upheld. Long-term security and effectiveness in next-generation IoT systems are ensured by the framework's adaptability to new technologies like 5G and quantum-secure cryptography. All things considered, this cross-layer architecture offers a broad range of IoT applications a scalable, secure and energy-efficient solution, providing a strong basis for upcoming deployments. The suggested framework's security performance was assessed by analysing a number of important metrics and test scenarios. Results for various simulated attack routes are summarised in Table 8.1.

Table 8.1: Summary of system deployment implications

Aspect	**Implications**
Cross-Layer Framework Design	Integrates Application, Network, and Sensor Layers to improve energy efficiency and security via coordinated design and protocol alignment.
Lightweight Cryptography	Uses adaptive lightweight encryption (Speck, Present, AES) with runtime-based cipher round reduction for constrained IoT performance.
Real-World Deployment Readiness	Validated on Z1 motes and EXP430F5438 platforms, confirming secure, low-power communication and real deployment feasibility.
Simulation Environments	Tested using Contiki/Cooja and NS-3 to measure energy, throughput, latency, and resilience under jamming and man-in-the-middle attacks.
Machine Learning Integration	LSTM, decision trees, and random forest models supported real-time anomaly detection with minimal system overhead.
Application Domains	Suitable for smart city, healthcare, and agriculture scenarios using CoAP and MQTT over secure RPL and ContikiMAC in Cooja and NS-3.
Scalability	Tested with `5-20` nodes; designed for modular scalability by extending routing and cipher configurations.
Operational Example	In `NS-3`, MQTT traffic encrypted via Speck was flagged by anomaly models. Cooja confirmed stable delivery with duty-cycled MAC and secure RPL.

The flexibility of the suggested cross-layer IoT framework is demonstrated by a variety of real-world deployment scenarios, including smart schools, medical facilities, and agricultural fields. Coordination between sensor, network, and application layer techniques is used to meet the distinct issues that each scenario poses with regard to energy efficiency, data security, and operational reliability. Healthcare systems require real-time, encrypted connectivity to ensure patient data integrity, while smart schools benefit from secure, duty-cycled sensors for environmental and attendance tracking. Agricultural environments, however, necessitate distant sensor networks with long-range connections and power saving. Table 8.2 provides a summary of the particular cross-layer features and planning implications for each environment, demonstrating how the suggested framework

satisfies domain-specific requirements with scalable and sustainable solutions.

The suggested cross-layer framework exhibits practical feasibility for implementation in actual smart environments, specifically in industrial automation, environmental monitoring, and smart school infrastructures. The versatility of the system enables a smooth integration into schools, utilising Speck-based encryption for secure low-power communication and Z1 motes to monitor occupancy, air quality, and device usage. Crop data integrity under energy restrictions is guaranteed in smart agriculture by combining lightweight cryptography with anomaly detection utilising DT and CNN models. The adaptability of the framework also enables deployment in the Internet of Things healthcare sector, where the current cipher can safeguard private important information without depleting the batteries of sensor nodes. These applications demonstrate the architecture's capacity to effectively balance security, scalability, and energy efficiency, hence enhancing its appropriateness for situations with limited resources.

Table 8.2: Cross-Layer IoT Deployment Scenarios in Real-World Environments

Deployment Scenario	Cross-Layer System Features and Implications
Smart School: Classrooms, Labs, and Corridors	Uses Z1 motes and low-power sensor nodes to monitor air quality, lighting, and student attendance. Adaptive routing (RPL), TLS-secured transport, and role-based access control (RBAC) help ensure secure, energy-aware, and scalable communication across all zones. Emergency alerts (e.g., fire alarms) are prioritised via QoS-based packet classification.
Smart Healthcare: Hospital Wards and Critical Monitoring	Integrates wearable patient sensors (body temperature, heart rate) with application-layer analytics. Lightweight cryptography (AES with round reduction) protects sensitive data while maintaining device uptime. ML-based anomaly detection enables early warning for equipment failure or sudden patient condition changes. TLS and 6LoWPAN ensure secure transmission with minimal overhead.
Smart Agriculture: Remote Farm Monitoring	Sensor networks deployed in crops and greenhouses monitor humidity, soil pH, and temperature. Nodes use CoAP over 6LoWPAN for lightweight communication. Duty-cycling and secure routing with reduced-round encryption algorithms minimise energy drain. Application dashboards provide real-time alerts, while LSTM-based anomaly detection identifies irrigation leaks or abnormal trends.

8.3 Future Research Directions

A cross-layer framework for improving the security and energy efficiency of IoT networks is examined in this thesis. To maintain strong cybersecurity and conserve energy, the study focuses on allocating resources as efficiently as possible across several layers. A number of crucial areas are yet unexplored in view of the changing difficulties in IoT systems:

- **Execution of a Real-World Testbed:** Extensive simulations were used in this study to assess the suggested cross-layer framework, but actual testbed implementations are essential to confirming the framework's usefulness. The broad implementation of IoT systems in contexts like smart cities and healthcare requires a thorough examination of how dynamic network factors, such as node mobility, interference and signal fading, impact performance.

- **Integration of Blockchain for Enhanced Security:** One potentially useful method for protecting IoT networks is blockchain technology. Decentralised ledger system integration for improved data integrity and device authentication should be the subject of future research. In settings like Industrial IoT (IIoT) networks, where a high degree of trust is demanded, blockchain can offer a strong basis for secure data flow. Hybrid blockchain frameworks, which integrate several consensus methods to solve scalability and latency issues, should be investigated further.

- **Edge Computing and Federated Learning for IoT:** An intriguing path forward for IoT systems is the combination of edge computing and federated learning, which enables decentralised processing and enhanced real-time threat adaptation. Without depending on cloud infrastructure, future studies should investigate how ML models might be implemented at edge nodes to identify irregularities and respond to threats. This method could improve scalability, improve privacy and lower latency in contexts with limited resources.

- **Dynamic Threat Detection and Mitigation:** The architecture of IoT networks has a significant problem in terms of energy efficiency since many IoT devices have limited power resources. To achieve a balance between security and power consumption, future research should focus on developing

energy-efficient routing protocols and lightweight encryption algorithms. Modern techniques like dynamic encryption and energy-aware routing should be researched to extend the lifespan of IoT devices without compromising network performance.

- **Scalability and Large-Scale Testing:** In applications like smart cities, where millions of devices may be installed, the scalability of IoT systems is crucial. Current testing frameworks should be extended to ultra-large-scale IoT systems in future work to handle issues including dynamic topologies, device heterogeneity and fluctuating energy demands. The creation of scalable assessment techniques that can evaluate IoT system performance in large-scale, real-world scenarios will be necessary to achieve this.

Future research can improve IoT system's efficiency, security and resilience by pursuing these avenues, opening the door for their wider implementation in vital infrastructures including healthcare, smart cities and industrial applications.

8.4 Limitations

Although the feasibility and efficacy of a cross-layer IoT framework that is both secure and energy-efficient have been proven by this research, a number of constraints were noted over the course of the investigation. Larger-scale deployments may provide additional performance and management problems, especially with regard to routing cost, model generalization, and layer synchronization. Initially, the framework's scalability was evaluated on a restricted node range (5–20 nodes). Second, while the framework was tested on real-world testbeds (Z1 motes, EXP430F5438) and simulations (Cooja/Contiki and NS-3), the real-world deployment scenarios were limited to controlled conditions. Variable traffic loads, heterogeneous hardware, and unpredictable radio interference are some examples

of factors that may impact the system's resilience and flexibility in real-world operational scenarios. Furthermore, the machine learning based anomaly detection models (LSTM, decision trees, and random forest) were trained on attack profiles created by simulations, which might not fully represent the range of dynamic threats present in actual IoT networks. The implementation of retraining or transfer learning would be necessary for deployment in a variety of application domains. Despite being a good way to balance energy and security, runtime cipher round reduction may need further formal verification to comply with future compliance standards or post-quantum cryptography limitations. Ultimately, even if TLS and lightweight encryption techniques were combined and tested, time-sensitive applications in ultra-low power conditions may be impacted by protocol-specific restrictions like handshake overhead or CoAP dependability across lossy networks. Despite these limitations, the research's findings offer a fundamental framework for the development and practical implementation of scalable, intelligent, and resilient IoT systems in the future.

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Appendix A

Machine Learning Model using Accuracy comparison across Models

Import necessary libraries

A.1 Dataset Overview

The dataset consists of different machine learning models and their performance metrics.

Table A.1: Performance metrics of different models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Memory (MB)	Latency (ms)
Decision Tree (DT)	98.2	97.5	97.1	97.3	450	5
Random Forest (RF)	96.5	96.2	95.6	95.9	620	15
Support Vector Machine (SVM)	89.3	88.7	87.2	88.0	580	25
Autoencoder (AE)	94.7	93.8	92.5	93.1	780	220
Isolation Forest (IF)	91.2	90.5	88.9	89.7	500	10

A.2 Model Evaluation Metrics

The model was trained and evaluated using the following metrics:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} y_i - \hat{y}_i{}^2 \tag{A.1}$$

$$RMSE = MSE \tag{A.2}$$

$$R^2 = 1 - \frac{\mathcal{P}y_i - \hat{y}_i{}^2}{\mathcal{P}y_i - \bar{y}^2} \tag{A.3}$$

A.3 Feature Importance

The importance of each feature in predicting accuracy is shown in Figure A.1 and Figure A.2.

```
        # Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# 1. Load Dataset
data = {
    'Model': ['Decision Tree (DT)', 'Random Forest (RF)', 'Support Vector Machine (SVM)',
              'Autoencoder (AE)', 'Isolation Forest (IF)'],
    'Accuracy (%)': [98.2, 96.5, 89.3, 94.7, 91.2],
    'Precision (%)': [97.5, 96.2, 88.7, 93.8, 90.5],
    'Recall (%)': [97.1, 95.6, 87.2, 92.5, 88.9],
    'F1-Score (%)': [97.3, 95.9, 88.0, 93.1, 89.7],
    'Memory (MB)': [450, 620, 580, 780, 500],
    'Latency (ms)': [5, 15, 25, 220, 10]
}

df = pd.DataFrame(data)

# 2. Display dataset
print("Dataset Overview:")
display(df)

# 3. Data Visualization
plt.figure(figsize=(10, 5))
sns.barplot(x='Model', y='Accuracy (%)', data=df, palette="viridis")
plt.title("Accuracy Comparison Across Models")
plt.xticks(rotation=30)
plt.show()

plt.figure(figsize=(10, 5))
sns.barplot(x='Model', y='Latency (ms)', data=df, palette="coolwarm")
plt.title("Latency Comparison Across Models")
plt.xticks(rotation=30)
plt.show()
```

Figure A.1: Feature Importance in Predicting Accuracy (Part A)

A Random Forest model was used to predict accuracy based on precision, recall, F1-score, memory usage, and latency. The model's performance was evaluated using MSE, RMSE, and R^2.

```
plt.title("Latency Comparison Across Models")
plt.xticks(rotation=30)
plt.show()

# 4. Prepare Data for ML Model
X = df[['Precision (%)', 'Recall (%)', 'F1-Score (%)', 'Memory (MB)', 'Latency (ms)']]
y = df['Accuracy (%)']

# Normalize Features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 5. Split Data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# 6. Train a Random Forest Model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# 7. Predict and Evaluate
y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print("\nModel Performance Metrics:")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R² Score: {r2:.2f}")

# 8. Feature Importance
importances = model.feature_importances_
feature_names = X.columns

plt.figure(figsize=(8, 5))
sns.barplot(x=importances, y=feature_names, palette="magma")
plt.title("Feature Importance in Predicting Accuracy")
plt.show()
```

Figure A.2: Feature Importance in Predicting Accuracy (Part B)