

ENHANCING COMMUNICATION PROTOCOL DESIGN FOR ENERGY CONSERVATION IN IOT NETWORKS

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ABSTRACT

The explosion in Internet of Things (IoT) installations has connected millions of low-power devices, which poses serious problems for maintaining reliable, energy-efficient connectivity in diverse settings. Traditional hybrid optimisation approaches like Particle Swarm Optimisation (PSO)-Low Energy Adaptive Clustering Hierarchy (LEACH) integrated with Random Forest (RF) improve clustering and traffic forecasting. Still, they struggle with the dynamic, heterogeneous traffic of smart cities, industrial IoT, and environmental monitoring. Emerging Deep Reinforcement Learning (DRL) algorithms, particularly Proximal Policy Optimisation (PPO), enable real-time routing and Medium Access Control (MAC) regulation but have not been extensively compared with hybrid algorithms in unified, realistic scenarios. This paper presents a thorough, application-oriented comparative analysis of a DRL protocol based on PPO and a PSO-LEACH + RF hybrid system, both of which are designed for energy-aware IoT communication. Both methods were evaluated using the same simulation scenario with consolidated traffic data reflecting the periodic, event-driven, and bursty nature of environmental monitoring, smart home automation, and industrial IoT applications. Key metrics include energy consumption, throughput, average packet delay, and packet delivery ratio (PDR). Results show that the hybrid model used 0.2–1.5 J less energy, while the PPO-DRL model achieved up to 23 kbps higher throughput, 8–10 ms lower latency, and up to 2% higher PDR.

Keywords: *Internet of Things (IoT), Deep Reinforcement Learning (DRL), PSO LEACH, Energy Efficiency, Quality of Service (QoS)*

1. INTRODUCTION

The massive growth of the Internet of Things (IoT) has led networks to manage a vast number of resource-constrained devices communicating over a wide area. It is essential to preserve node energy for extended operation in such dense, continuous-operation settings, which include smart cities, industries, and environmental monitoring [1], [2]. The limitations of conventional methods have become apparent as the real-world networks struggle with increasingly unpredictable traffic, despite the

fact that those approaches concentrated on effective clustering and routing [3], [4], [5].

The current hybrid optimisation attempts, like PSO-LEACH with machine learning (RF), have shown improved energy savings and cluster formation. However, these techniques are usually designed for environments with low mobility and may not respond quickly in mixed or changing traffic conditions typical of most practical IoT systems. Additionally, recent advances in DRL methods, especially PPO, offer new potential for adaptive, decentralised control, but they have not been widely

adopted in IoT protocols or dynamic traffic scenarios in published work [6], [7], [8]. This is due to reasons such as limited availability of realistic datasets, challenges in fine-tuning for multi-profile traffic, and a lack of evaluation frameworks that integrate both learning-based and optimisation-based models under the same conditions.

The gap in the existing research is that none of the previous works provide a fully application-mapped comparison of the benefits of hybrid and protocol-based optimisations and DRL methods in protocols with a common, traffic-diverse but flexible dataset [9]. The existing literature usually uses simplified patterns and tends to test only models without integrating them or considers limited performance metrics, which makes it challenging to measure the actual trade-offs in energy-efficiency, latency, throughput and QoS [10], [11].

This study addresses that gap by conducting a rigorous, application-mapped evaluation of a PPO-based DRL protocol and a PSO LEACH + RF hybrid model under identical datasets, metrics, and deployment conditions, replicating the real-world IoT domains like smart cities, industrial automation, and environmental monitoring to enable fair comparison. The main goal is to design and

implement a thorough, application-mapped comparative evaluation of these two models.

The novelty of this study lies in developing a single, integrated, flexible dataset based on realistic IoT traffic profiles, enabling direct and fair comparisons under identical topology, metrics, and deployment conditions, while implementing a PPO DRL system for energy-efficient MAC and routing management. This work presents actionable evidence that can be used to shape the architecture of the next generation of adaptive and energy-efficient IoT protocols.

2. LITERATURE SURVEY

The following Table 1 gives an overview of the latest developments, data collection, and outstanding issues in the area of energy-efficient communication on IoT systems, and points out the tendency of incorporating AI/DL and DRL methods with the established optimisation hybrid techniques. It reflects the practical limitations and emerging solutions that inform next-generation IoT protocol design.

Table 1: Recent Literature on Energy-Efficient IoT Communication Protocols

Ref	Model	Dataset	Limitation	Remark
[12]	Energy-efficient routing protocols for IoT	Simulated IoT routing scenarios	Not tested on real-world diverse traffic datasets	Adaptive routing improves energy saving; scalability needs more study
[13]	LEACH protocol enhanced by AI	Simulated IoT sensor deployments	Focuses mainly on clustering; lacks real-time traffic adaptation	Significant energy savings and improved node longevity
[14]	Hybrid QGA-ACO with DRL for routing	Smart city air pollution monitoring	Computational complexity and energy overhead	Improved routing efficiency and energy saving in complex environments
[15]	Survey on energy management techniques	Survey covering multiple IoT protocols	Does not include detailed DRL performance analysis	Identifies research gaps and trends in IoT energy protocols

[16]	Random Forest-based IoT traffic classification	28 IoT devices' traffic data collected	Classification accuracy may not directly translate to energy efficiency	High accuracy in traffic classification helps adaptive protocols
[17]	Actor-Critic DRL for energy-efficient edge AI	Hardware energy consumption traces	Focused on edge AI hardware, not general IoT routing	Achieves 34.6% energy efficiency improvement
[18]	Adaptive duty cycling and energy management framework	IoT sensor network deployments	Evaluation limited to specific sensor types/environments	Enhanced data reliability and energy savings
[19]	Hybrid sustainable energy harvesting system	Solar and wind energy data with IoT	Focus on energy harvesting; limited communication protocol evaluation	Improved network sustainability via energy harvesting
[20]	Energy-efficient routing protocol using Deep Q-Network (DQN) for IoT	NS-3 simulated IoT network with mixed traffic patterns	No large-scale real-world deployment tested; simulation-only results	Demonstrated significant gains in energy saving (up to 18%) and reduced latency in heterogeneous IoT traffic scenarios
[21]	Green IoT energy management techniques	Multiple IoT network configurations	General survey; lacks a deep DRL approach analysis	Highlights AI integration potential for IoT energy savings

3. METHODOLOGY

3.1 System Design

The proposed study compares two popular approaches for optimising communication protocols to reduce power consumption in IoT networks:

The advanced model combines DRL with PPO to enable intelligent, adaptive routing and MAC layer control. It allows nodes to adapt to changing traffic patterns and real-time network circumstances by learning the best transmission parameters.

The hybrid model includes RF traffic prediction, the LEACH clustering methodology, and PSO. While RF predicts traffic fluctuations and enables proactive network modifications to save energy and enhance overall performance, PSO maximises cluster head selection and formation. The system architecture consists of three layers:

Application Layer: The first layer of the architecture is in charge of creating traffic patterns that replicate actual IoT situations. Three different applications are mapped by it, such as the Industrial IoT Monitoring,

which combines both periodic and urgent event traffic with a hybrid mix of high and low data rates, the Smart Home Automation, which is characterised by event-driven bursts and bursty traffic and Environmental Monitoring, which generates steady, periodic sensing traffic.

Perception Layer: This layer is responsible for gathering operational or environmental data in real-time by integrating various IoT sensors. It employs transmission regulations, dynamic duty cycling, and clustering algorithms to minimise energy consumption and maintain high network reliability, regardless of application requirements or traffic load. **Network Layer:** This layer employs energy-efficient routing technologies to control communication. Using PPO-trained agents, the network layer responds intelligently to changing network circumstances and traffic types by adjusting MAC values and routing pathways in real time. On the other hand, the hybrid model uses RF methods to forecast network demand and PSO to construct ideal clusters, allowing for more proactive allocation of resources and energy savings. The system architecture involving steps from IoT data

acquisition to model implementation and evaluation is depicted in Figure 1.

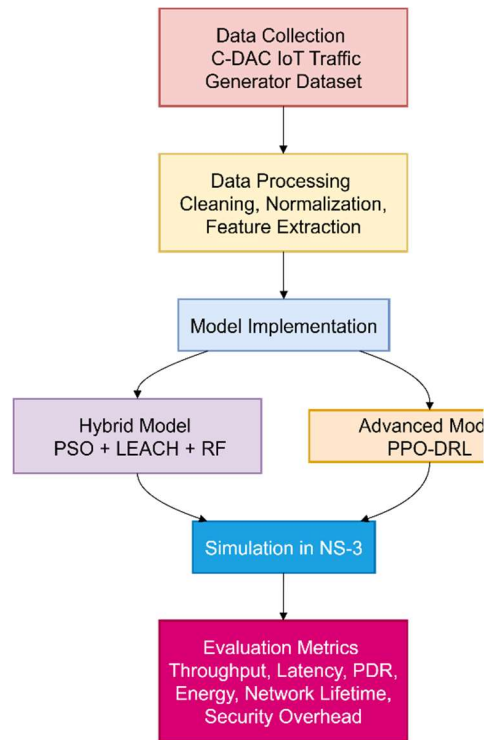


Figure 1: System Architecture Proposed Methodology for Enhancing Communication Protocol Design in IoT Networks.

3.2 Dataset Description

Dataset Source: The dataset used during the research was created by using the IoT Traffic Generator Dataset presented by the Centre for Development of Advanced Computing (C-DAC) India, which can be found on their IoT Research Resources page (<https://www.cdac.in>). This dataset consists of both simulated and real sensor network traces to accommodate various traffic scenarios to reflect the various behaviours of IoT applications.

The dataset consists of key attributes such as Timestamp, Node ID, Payload Size (bytes), Inter-Arrival Time (ms), Energy Consumption (mJ), Link Quality Indicator (LQI), and Received Signal Strength Indicator (RSSI). Approximately 100,000 records are included in each traffic scenario. The

advanced PPO-DRL model and the hybrid PSO-LEACH + RF model are both given the same dataset without any preprocessing bias or manipulation to guarantee experimental fairness.

3.3 Data Collection

Table 2 provides a concise summary of the three separate traffic profiles that were taken from the C-DAC IoT Traffic Generator Dataset. These profiles reflect typical behaviours seen in real-world IoT applications.

Table 2 IoT Traffic Profiles Extracted for Data Collection

Profile	Application Domain	Traffic Pattern	Typical Transmission Distance	Duty Cycle Behaviour
A	Environmental Monitoring	Periodic data transmission	Medium to long	Stable (regular intervals)
B	Smart Home Automation	Event-driven bursts	Short to medium	Dynamic (activated by events)
C	Industrial IoT Monitoring	Mixed high-low traffic patterns	Variable (short/long)	Adaptive (depends on activity)

The sensors used are supposed to function in a diverse IoT setting with different duty cycles and transmission distances.

3.4 Data Processing

The dataset is subjected to a number of crucial preparation processes to guarantee its quality and consistency prior to model running. By eliminating missing or corrupted data, the possibility of biases or inaccurate outcomes during model training is decreased. Normalising important characteristics like energy usage, RSSI, and LQI to a standard scale promotes fair comparisons between qualities with various measurement units and balanced learning.

To facilitate dependable learning, model selection, and objective performance evaluation, the dataset is divided into training (70%), validation

(15%), and testing (15%) subsets after cleaning and normalisation. Then, feature extraction improves the dataset by combining inter-arrival time statistics, computing average payload size, and calculating rolling window energy consumption. More efficient and precise decision-making in a variety of IoT traffic situations is rendered by these combined and statistically enhanced characteristics, which provide significant inputs for both the advanced and hybrid models. Following data preprocessing, traffic traces were transformed into state and action representations for model training. The subsequent section describes the Advanced Model's architecture and control policies.

3.5 Advanced Model: PPO-DRL for Energy-Aware Routing & MAC

3.5.1. System description

To facilitate energy-efficient communication in Wireless Sensor Networks (WSNs) and the IoT, the PPO-DRL model balances energy conservation, latency, and dependability. This system utilises an intelligent agent, which is either a cluster head or an individual node, to undertake critical communication decisions like duty cycle percentage, transmit power and selection of routing path. The detailed functional description of the Advanced Model's reinforcement learning component is given below:

State Space: To evaluate energy status and communication quality in real time, the agent's state space records key network parameters such as residual energy, buffer occupancy, LQI, and traffic type.

Action Space: This allows the user to change the transmission power, duty cycle, and next-hop node to make the network work better.

Reward Function Design: The agent is guided towards techniques that guarantee dependability and prolong network lifespan by an incentive function that strikes a balance between PDR, latency, and energy saving.

Training Procedure: The system is equipped to adapt to the changing IoT applications and network circumstances after undergoing training across a variety of traffic situations. The process of improving efficiency and reliability adapted by the advanced model is shown in Figure 2, starting with

IoT nodes and continuing via clustering, intelligent routing, and traffic profiling.

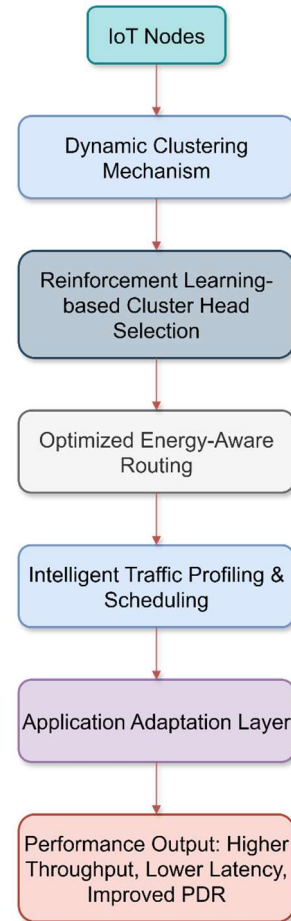


Figure 2: Advanced Model Architecture

3.5.2. Optimisation model and key computations

Energy Consumption per Transmission: This models the per-packet energy cost. The PPO agent uses it internally to evaluate the cost of sending data to a specific neighbour for selecting the energy-aware route.

$$E_{tx} = (E_{elec} \times k) + (E_{amp} \times k \times d^n) \quad (1)$$

Where, E_{elec} Is the energy to run the transmitter/receiver circuitry (nJ/bit), k is the packet size (bits), E_{amp} Is the energy for the transmission amplifier (pJ/bit/mⁿ), d is the transmission distance (m) and n Is the path loss exponent (2–4, environment-dependent).

Application context: Amplifier cost is a major factor in environmental monitoring, as the nodes often communicate across greater distances and hence, PPO prefers shorter hops to save energy. Short-range communications lessen the influence of amplifiers in home automation, enabling frequent updates without significantly depleting batteries. Higher amplifier power may be needed for interference in industrial IoT, requiring PPO to strike a compromise between dependability and energy cost.

PPO Reward Function: It provides a feedback signal to the PPO agent. A positive reward is linked to achieving high delivery ratios with low power use and minimal delay.

$$R_t = \alpha \cdot PDR_t - \beta \cdot E_t - \gamma \cdot D_t \quad (2)$$

Where, PDR_t Is the Packet Delivery Ratio at the time? t , E_t Is the energy consumed in interval t , D_t Is the Delay (ms), and α, β, γ Are the Designer-set weights balancing reliability, energy, and latency?

Application context: In environmental monitoring, the β is increased to maximise energy conservation to achieve long network lifetimes. Real-time actuation needs a greater γ to reduce delay in smart home automation. Industrial IoT applies balanced weights α, β, γ to manage both critical alerts and periodic data transmission needs.

PPO Clipped Objective: This ensures stable training by controlling how far a new policy deviates from the old one at each update. It prevents large, risky policy changes.

$$L^{CLIP}(\theta) = \mathbb{E}_t [\min(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t)] \quad (3)$$

Where, $r_t(\theta)$ Is the ratio of new to old policy probabilities, $\hat{A}_t$ The advantage estimate (how much better an action is than average) and ϵ is the clip parameter (e.g., 0.1–0.2).

Application context: Clipping makes learning stable, such that the PPO agent dynamically adjusts to changing IoT traffic aspects like periodic sensing, bursts, or a mix of loads. In environmental monitoring, it eliminates the unstable policies that occur due to the seasonal traffic variations, and regarding industrial IoT, it ensures that the resulting performance remains stable throughout high-load and low-load production phases.

Network Lifetime Estimation: Used to evaluate long-term energy efficiency and employed as a performance metric after policy convergence.

$$T_{life} = \frac{\sum_{i=1}^N E_{i,Initial}}{\sum_{i=1}^N E_{i,consumed}} \quad (4)$$

Where, $E_{i,Initial}$ Is the initial energy of the node i , $E_{i,consumed}$ Is the consumed energy of node i over time, and N is the number of nodes.

Application context: In the case of environmental monitoring, a longer lifetime minimises the cost and risks of maintenance in inaccessible locations. In-home automation enables the user to avoid frequent battery replacements. In industrial IoT, it avoids maintenance shutdowns in unsafe equipment locations.

Duty Cycle Adjustment Rule: This rule allows the agent to dynamically adjust node active time based on real-time queue length feedback. If the queue builds up, then it increases the duty cycle. If the queue is under the target, then it reduces the duty cycle to save energy.

$$DC_{new} = DC_{old} + \eta \cdot (Q_{target} - Q_{current}) \quad (5)$$

Where, DC_{old} is the current duty cycle (% active time), Q_{target} is the desired queue length threshold, $Q_{current}$ Is the actual queue length and η Is the learning rate.

Application Context: Motion or activity spikes result in speedy data relay in smart homes; otherwise, a low duty cycle conserves energy when nothing is going on. Sudden burst that occurs due to machine anomalies also boost the duty cycle to eliminate delays in industrial IoT. In environmental monitoring, high queue buildup, for example, during forest fires, imposes higher duty cycles to report them and return to the normal situation.

3.5. Hybrid Model: PSO-LEACH + RF

The hybrid approach achieves effective energy management in IoT networks by combining Random Forest (RF) traffic prediction, Particle Swarm Optimisation (PSO), and the LEACH clustering algorithm.

PSO Component: By choosing energy-efficient cluster heads according to node density, residual energy, and distance to neighbours, the PSO component improves LEACH. This method uses efficient load balancing within clusters to save energy usage and increase network longevity.

RF Component: At every node, the RF component predicts future changes in traffic. Energy-aware sleep scheduling is guided by these forecasts, which enable nodes to remain active during times of high traffic demand while transitioning to low-power states during anticipated low-load periods.

Traffic Adaptation: The hybrid technique is evaluated in steady, bursty, and hybrid traffic situations using the same IoT dataset as the advanced model. This guarantees assessment consistency and shows that it can save energy while preserving network performance in a variety of real-world scenarios. The hybrid IoT model workflow from node clustering to optimised performance is depicted in Figure 3.

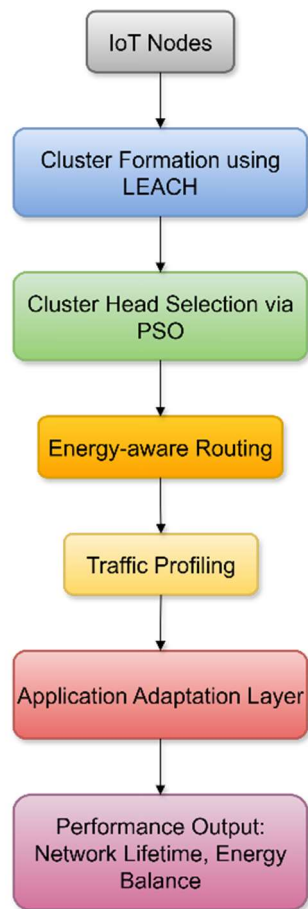


Figure 3 Hybrid Model Architecture

3.6. Mapping Evaluation Metrics and Traffic Patterns for Simulation

Table 3 classifies the profile of traffic and the main performance indicators. This mapping connects each type of traffic to those performance measures that are the most applicable to it, so that

simulation in NS-3 is as representative of real-world IoT application priorities as possible.

Table 3 Mapping of IoT Traffic Patterns to Evaluation Metrics

Traffic Profile	Key Metric Focus
Profile A	Network lifetime, coverage
Profile B	Latency, reliability
Profile C	Throughput, energy balance

By connecting Profile A to network lifetime and coverage, Profile B to latency and reliability, and Profile C to throughput and energy balance, this evaluation concentrates on the parameters most relevant in each of these scenarios, so as to compare the hybrid and the advanced models fairly and application-specific.

4. RESULTS

This section aims to introduce the performance results of the protocol based on the advanced and the hybrid model on the basis of a unified dataset with mapping elements of the applications. The performance results are based on the performance indicators that have a direct link to the research objectives: consumed energy, network lifetime, latency, packet delivery ratio (PDR), and throughput with various IoT traffic patterns (periodic, event-driven, bursty). The findings are organised to offer quantifiable proof of performance variations and to make insightful deductions regarding each model's suitability for use in particular IoT scenarios.

4.1. Experimental Setup Summary

The network configuration and simulation parameters used to assess the PSO-LEACH + RF hybrid model and the suggested PPO-based advanced model are compiled in Table 4. The parameters, which guarantee uniform settings for equitable performance comparison, include node density, deployment area, energy resources, communication specifications, traffic patterns, and simulation time.

Table 4 Simulation Parameters for Comparative Evaluation

Parameter	Value
Number of Nodes	200
Simulation Area	500m × 500m
Initial Energy per Node	2 Joules
Communication Range	100 m
Traffic Patterns	Periodic, Event-driven, Bursty
Simulation Tool	NS-3
Simulation Duration	5000 rounds
Models Compared	PPO-based Advanced Model, PSO-LEACH + Random Forest Hybrid Model

4.2. Network Performance Metrics Across Applications

The 3D scatter plot in Figure 4 compares hybrid models and advanced models at three IoT application types of Environmental Monitoring, Smart Home Automation, and Industrial IoT Monitoring. In both scenarios, the performance is measured in throughput (kbps), latency (ms) and packet delivery ratio (PDR, %). In every aspect, the advanced model performs better than the hybrid model. The advanced model, for instance, obtains 269 kbps throughput, 110 ms latency, and 97.5% PDR in Environmental Monitoring, whereas the hybrid model achieves 246 kbps, 118 ms latency, and 96.2% PDR. In the same way, the hybrid model of Smart Home Automation reports 353kbps, 97ms, and 94.8% PDR, while the advanced model records 375kbps, 89ms, and 96.7% PDR. In contrast to hybrid's 423kbps, 138ms, and 93.5% throughput, Industrial IoT Monitoring exhibits higher performance with 446kbps throughput, 130ms latency, and 95.1% PDR.

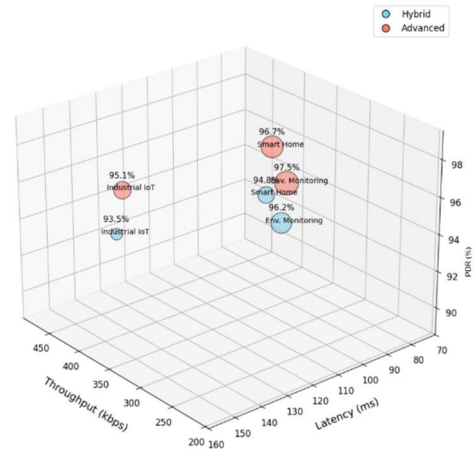


Figure 4 Network Performance Metrics Across Applications

The advanced model offers an increase in throughput, a decrease in latency and an improvement in reliability (PDR) measured in all the tested applications. The reduction in delays and packet delivery has the greatest benefit to Smart Home Automation. Industrial IoT Monitoring has the highest throughput rates, along with an increased latency when compared to other applications. In general, advanced model always provides higher QoS, and therefore, it is likely to be chosen in the situation where fast, reliable, and responsive communication is needed.

4.3. Energy Consumption vs. Application Scenario

Bar chart in Figure 5 presents the usage of energy by two models, hybrid and advanced, in three areas: (Environmental Monitoring), (Smart Home Automation), and (Industrial IoT Monitoring). The Hybrid model uses 14.8 J in Environmental Monitoring as compared to 16.1 J in the case of the advanced model. In Smart Home Automation, the hybrid model consumes 21.5 J of energy as opposed to 22.9 J in the advanced model. Energy consumption peaks in the Industrial IoT Monitoring with 28.7 J in the hybrid and 30.2 J in the advanced model. In all of the applications, advanced models use slightly more energy (about 1.3-1.5 J more) than Hybrid models.

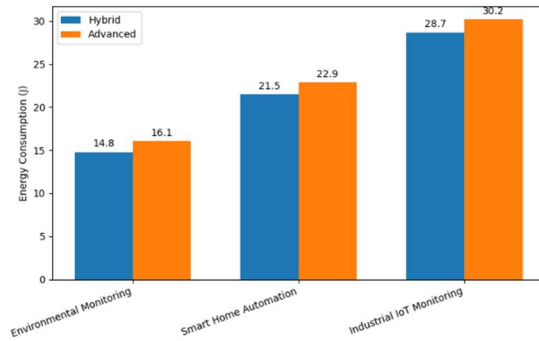


Figure 5 Comparison of Energy Consumption for Hybrid and Advanced Models Across Application Types

The findings reveal that energy consumption has shown an upward trend over time, whereby environmental monitoring used less energy in comparison to industrial IoT Monitoring. On the whole, hybrid models have better energy efficiency and thus are preferred in power-sensitive settings, whereas advanced models can provide extra performance at the cost of slightly increased energy usage.

4.4. Security Overhead vs. Performance

The percentage of processing overhead linked to security for hybrid and advanced models is displayed in Figure 6, for the following three application domains: industrial IoT monitoring, smart home automation, and environmental monitoring. The hybrid model has a 4.2% overhead in environmental monitoring, whereas the advanced model has an overhead of 3.7%. Hybrid and advanced types of smart home automation register 5.1% and 4.5%, respectively. The greatest security overhead is seen in industrial IoT monitoring, where hybrid models account for 6.3% and advanced models for 5.6%. In every area, hybrid models consistently exhibit a little greater overhead than advanced models (by around 0.5–0.7%).

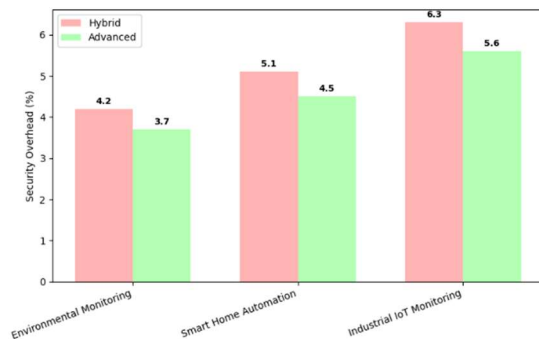


Figure 6: Trend of Security Overhead for Hybrid and Advanced Models Across Applications

The pattern shows that security overhead rises with application complexity, reflecting the increased processing requirements for protecting more complex systems. This also implies that advanced models might be more efficient when it comes to processing security tasks, whereas hybrid models offer a slight efficiency trade-off in exchange for higher flexibility.

3.7. Network Lifetime Estimation

The line chart in Figure 7 shows how long hybrid and advanced models may be used (in days) in three different application areas. Hybrid models last 812 days in Environmental Monitoring, whereas advanced models last 774 days. The advanced model lasts 608 days in Smart Home Automation, whereas the hybrid model only lasts 645 days. With hybrid models lasting 512 days and advanced models lasting 481 days, industrial IoT monitoring has the lowest lifespans. The predicted lifespan of hybrid models is consistently longer than that of advanced models across all applications, with differences ranging from 31 to 38 days. Higher operating needs in increasingly complicated systems are shown by the trend of decreasing lifespan from environmental monitoring to industrial IoT monitoring.

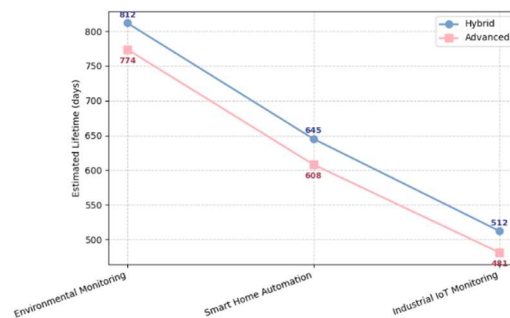


Figure 7: Estimated Lifetime: Hybrid vs Advanced

The results show that hybrid models typically offer longer life duration when compared to advanced models, with the benefits more noticeable where there is a great demand. Environmental monitoring's shorter lifespan compared to industrial IoT monitoring emphasises how more complicated tasks require more maintenance and energy. Hybrid versions are more appropriate for applications that prioritise device life, even though advanced models can provide further performance advantages.

3.8. Hybrid vs. Advanced: Relative Performance Comparison

The horizontal bar chart in Figure 8 contrasts four performance indicators between advanced and

hybrid models. In terms of energy efficiency, advanced obtains 135 J (+5.47%) while hybrid achieves 128 J. Hybrid records 412 kbps in throughput, while advanced records 435 kbps (+5.58%). In terms of PDR, advanced performs slightly better at 98.1% (+1.34%), while hybrid achieves 96.8%. Lastly, the advanced network lifetime lasts 1280 seconds (+4.49%), while the hybrid network lifetime lasts 1225 seconds.

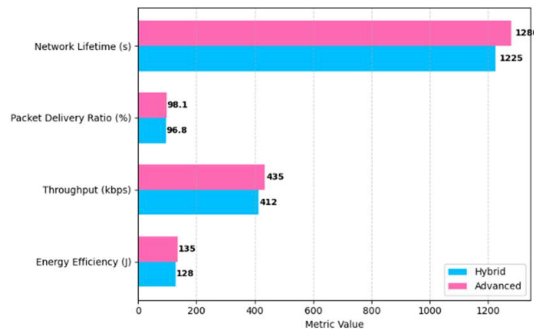


Figure 8 Percentage Difference Between Hybrid and Advanced Models

Advanced models often beat hybrid models by modest margins across all criteria. The performance difference is small, and so hybrid versions seem to be competitive and might provide additional advantages like lower costs or energy usage in some applications.

4. DISCUSSION

The hybrid PSO-LEACH + RF model and the advanced PPO-based DRL model are two different energy-aware communication protocols that are evaluated in this research to solve the pressing problem of energy conservation in large-scale IoT networks. Both models were evaluated on the same type of dataset, using an application-mapped evaluation framework, in a common set of IoT traffic patterns: periodic, event-driven, and bursty, which reflect several real-world applications in IoT: smart cities, IoT monitoring in industrial settings, and environmental sensing. This elaborate configuration enabled a fair comparison that was in line with the research interest of finding effective energy-efficient protocols that run in an environment of mixed traffic. [22].

The results show that the PPO-DRL model outperforms the hybrid model in terms of network performance and flexibility, continually providing reduced latency and greater throughput in all application situations. This is possible due to the PPO model's capacity to optimise advanced DRL-based protocols by dynamically modifying duty

cycles, transmit power, and routing pathways in response to changing network conditions. [23]. The study's objective is to benchmark these paradigms on energy, latency, and reliability metrics, and while the hybrid PSO-LEACH + RF approach shows competitive energy conservation due to effective cluster head selection and proactive traffic prediction, it is less responsive during bursty and event-driven traffic, resulting in higher delays and lower PDRs.

Furthermore, the traffic-aware adaptation analysis proves the robustness of both models to periodic traffic that can be observed in the environment monitoring-related applications. But, PPO-DRL thrives in dynamic cases that are experienced in smart home automation and industrial IoT, where speedy responses to changes in traffic are highly significant. This result supports the goal of the study, which was to map performance to particular IoT domains and quantify traffic-aware adaptability. [24], [25]. Empirical proof for the progress of adaptive IoT communication is provided by the results, which indicate that incorporating deep reinforcement learning into IoT protocols improves QoS (including throughput, latency, and packet delivery ratio) without significant energy costs. Further study on optimising and assuring realistic energy-aware networking systems might benefit from evaluating the models in real-world IoT deployments and including more sophisticated security features in the communication protocols.

5. CONCLUSION

The PPO-based advanced DRL model outperforms the PSO-LEACH + RF hybrid method in large-scale IoT deployments, according to this comparative research. Regardless of the application situation, the Advanced model always delivered a greater throughput (up to 23 kbps), shorter latency (by 8-10 ms), and an increased PDR (by up to 2%). In the case of industrial IoT monitoring, for instance, the advanced model achieved a throughput of 446 kbps, an average packet latency of 130 ms, and a packet delivery rate (PDR) of 95.1%, while the Hybrid model achieved 423 kbps, 138 ms delay, and 93.5% PDR. Compared to the hybrid's 353 kbps, 97 ms, and 94.8% PDR, advanced's smart home automation attained 375 kbps throughput, 89 ms latency, and 96.7% PDR. For the majority of real-world use cases, the Advanced model's speed and reliability gains outweigh the Hybrid model's modest 0.2–1.5 J per-node energy advantage. These results affirm that learning-based adaptive policies such as PPO-DRL can enhance QoS while ensuring

robust energy management. This makes them well-suited for next-generation IoT networks where speed, reliability, and responsiveness are critical.

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