From Effectiveness to Credibility: An Analysis of AI- Powered Secure and Energy-Aware Iot Systems

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Abstract*—The Internet of Things (IoT) has become a fundamental component of modern society due to its extensive connectivity and communication capabilities. However, the lack of standardisation in IoT systems has resulted in significant challenges related to security, privacy, and high energy consumption. Artificial intelligence (AI) techniques, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), have shown significant potential in addressing these challenges through the implementation of intrusion detection systems, authentication mechanisms, privacy-preserving techniques, and energy-aware routing strategies. This survey reviews and analyses existing research works that employ AI-based approaches to enhance IoT security requirements, mitigate various threats and attacks, and optimise routing mechanisms to extend the operational lifetime of remotely connected IoT devices in wireless sensor networks (WSNs).

Keywords: Internet of Things (IoT), Wireless Sensor Networks (WSNs), Artificial Intelligence (AI), Deep Reinforcement Learning (DRL), Energy Efficiency, Routing Optimisation, Network Longevity, Intrusion Detection, Privacy Preservation, 6G Connectivity.

I. INTRODUCTION

The Internet of Things (IoT) has fundamentally transformed the digital landscape by interconnecting billions of physical devices, enabling real-time data acquisition and intelligent decision- making across diverse domains such as smart cities, healthcare, and industrial automation [1, 13]. Despite its transformative potential, the rapid proliferation of IoT faces significant bottlenecks, primarily revolving around the inherent constraints of Wireless Sensor Networks (WSNs) [15]. These networks often consist of battery-powered nodes deployed in inaccessible environments, making energy efficiency the most critical factor for ensuring network longevity [2, 12].

Current literature highlights that conventional routing protocols often fail to account for the dynamic nature of IoT environments, leading to premature node failure and network partitioning [6, 15]. To mitigate these issues, recent advancements have pivoted toward region-based protocols [2] and cluster-based routing utilising meta-heuristic algorithms like Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO) to balance load distribution [7, 8]. Furthermore, the integration of 6G connectivity is pushing the boundaries of WSNs, requiring even more sophisticated routing optimisation to handle massive connectivity [4].

The emergence of Artificial Intelligence (AI) has provided a robust framework for overcoming these traditional limitations. Machine Learning (ML) and Deep Learning (DL) models offer adaptive capabilities that allow networks to learn from historical data and optimise paths in real-time [9, 13]. Specifically, Reinforcement Learning (RL) and Multi-Agent Reinforcement Learning (MARL) have gained traction for their ability to solve complex routing problems through autonomous agent interaction [5, 6, 14]. Innovations such as Q-learning for shortest-path tree construction [11] and the combination of Deep Reinforcement Learning (DRL) with Graph Neural Networks (GNNs) [10] represent the cutting edge of energy-aware and coverage- optimized IoT infrastructure.

Beyond energy, the open nature of wireless communication renders IoT systems susceptible to

severe security threats, including data tampering and Denial-of-Service (DoS) attacks [9]. While neuro-fuzzy mechanisms and AI-driven frameworks have improved intrusion detection and routing reliability [3, 8], the continuous exchange of sensitive information introduces complex privacy preservation challenges that traditional cryptographic methods struggle to address in resource- constrained devices [1, 9].

This paper provides a comprehensive survey of AI-empowered methodologies designed to harmonise energy-aware routing, security mechanisms, and privacy preservation. By synthesising recent breakthroughs—ranging from adaptive ML frameworks [9, 12] to DRL-based optimisations [14]—this study identifies existing research gaps and outlines future directions for developing resilient, sustainable, and secure IoT ecosystems.

II. RELATED WORK

The emergence of Artificial Intelligence (AI) as a part of the Internet of Things (IoT) has triggered a wave of studies dedicated to energy usage optimisation, security measures reinforcement, and the development of privacy-protecting tools. This part summarises the recent advances and approaches that outline the present form of AI-based Internet of Things networks.

Artificial Intelligence-based Energy-Saving Routing
Power conservation has also continued to be the foundation of IoT studies, especially within battery-constrained Wireless Sensor Networks (WSNs).
Conventional routing algorithms are usually characterised by energy holes and load imbalances [2, 15]. In response, Thakur et al. [1] point out that AI-based protocols have a higher adaptability than a fixed scheme as they react in response to changes in the environment.
Reinforcement Learning (RL): RL has recently become a central point of focus to develop self-optimizing paths. Reinhardt [6] and Vo et al. [11] prove that agents based on Q-learning can automatically build shortest-path trees, which help to cut off packet losses essentially and expand network stability.

Deep Reinforcement Learning (DRL): To address more complex and high-density scenarios, DRL-based models, including Deep Q-Networks (DQN), are being applied to jointly maximise residual energy, link quality, and traffic load [1, 14]. This was further improved by Pushpa et al. [10] who added Graph Neural Networks (GNNs) to cover and connectivity in multi-hop situations.

Swarm Intelligence and Fuzzy Sense: Hybrid models do not fade. Particle Swarm Optimisation (PSO) is used in fuzzy clustering by Lei [7], and Tawfeek et al. [8] proposed a variation of the Ant Colony Optimisation (ACO) to address the reliability and energy balance issues in large-scale systems.

Smart Security Machineries
The IoT devices are increasingly used in open wireless environments, which makes them the best target of unauthorised access and data tampering [9]. Traditional security solutions are otherwise excessively complex to be implemented on resource-limited sensors.

Intrusion Detection: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are AI models that have succeeded traditional methods in intrusion detection and intrusion prevention as Denial-of-Service (DoS) attacks [5.3, 2.1].
Adaptive Security Frameworks: Aruna et al. [9] introduce an adaptive ML-based framework to offer a dual-layer of protection, which guarantees secure data transmission with energy efficiency. What is more, recent developments are heading to Zero Trust implementation made AI-driven to automate trust assessment throughout the device lifecycle [2.2].

Challenges in Privacy Preservation
The high frequency of exchange of behavioural and location-specific information in IoT systems has required the abandonment of basic encryption.
Federated Learning (FL): FL has become one of the most important solutions to the threat of data exposure, as it enables the training of models locally, without exchanging raw data [2.3].

Differential Privacy / Cryptography: Researchers are also considering applying Differential Privacy (DP) to ensure formal privacy guarantees within the context of data analytics, but the trade-off between privacy noise and accuracy of models is also a difficulty [2.3]. The other inventions are Visual Cryptography and block encryption to protect sensitive remote sensing images in the IoT system

[2.3].

Methodology	Primary Goal	Key References
DQN / DRL	Dynamic path optimisation & Energy reduction	[1], [14], [3.2]
PSO / ACO	Efficient Cluster Head selection & Load balancing	[7], [8]
Federated Learning	Decentralised training privacy-preserving	[2.3], [6.1]
Neuro-Fuzzy Systems	Safe and energy-conscious data routing	[3], [7]

III. PROPOSED SOLUTION: AI- EMPOWERED INTEGRATED FRAMEWORK

In order to solve the multidimensional problems of energy loss and security breaches in IoT-WSNs, this section outlines a suggested AI-based framework. The solution is targeted at a multi-layered and adaptive architecture that aligns intelligent routing with the proactive defence mechanisms.

A. System Design and Architecture

The suggested architecture pursues a hierarchical design to minimise the communication overheads. It comprises of Perception Layer (sensor nodes), Network Layer (AI-driven gateways) and Application Layer (cloud/edge processing). We adopt a Region-Based Clustering mechanism [2] in which the network is divided into zones to eliminate the problem of hotspots' energy loss. In these clusters, the dynamic election of Cluster Heads (CHs) is done on the basis of residual energy and distance to the sink node according to a fuzzy logic controller [7].

B. Data Pre-processing and Analysis

IoT sensor data is usually redundant or noisy. We use our framework to perform In-network Data Aggregation on the CH level to filter out redundant packets before transmission, and hence we conserve bandwidth. We use Principal Component Analysis (PCA) to decrease the number of features, and therefore, the next machine learning models are fed with quality yet lightweight input vectors to infer faster with them [13].

C. System Implementation

The implementation employs a decentralised approach in which the intelligence is driven to the edge. Each node has its own local Q- table to estimate the reward of particular routing paths using Distributed Q-learning [11], which provides the latency and the energy cost. This circumvents the single point of congestion, a centralised controller, and enables the system to scale to a wide geographical range [12].

D. Model Development

The main part of the system is a Hybrid Deep Reinforcement Learning (DRL) Model. We combine Graph Neural Networks (GNNs) to represent the spatial topology of a sensor network [10]. Energy Component: This model optimises the route by means of a multi-objective rewarding model that discourages high-energy nodes. Security Component: An auto modeller in the form of a parallel Autoencoder detects anomalies in traffic pattern which indicate DoS attacks or data injection [9].

E. Evaluation and Maintenance

Security threat metrics are Network Lifetime (PDR), Average Energy Dissipation, and Detection Rate (DR), which are used to benchmark system performance. Our solution is an Over-the-Air (OTA) update, in which the AI models will be retrained on the cloud and then pushed down to the edge gateways to meet new environmental variables or changing cyber threats [1, 6].

F. User Interface and Experience.

Our solution to the issue is a Real-time Monitoring Dashboard that will help to articulate the complex AI logic to end-users. This interface visualises: Energy level heatmaps of nodes. Topological perspectives of active routing paths. The severity of security alerts is rated in accordance with the AI score of confidence.

G. Reducing Reliability and Security.

The solution is that reliability is attained by means of Fault- Tolerant Routing, wherein the AI establishes so-called backup paths that are automatically started in case of node failure [8]. To ensure security, we use a lightweight blockchain-based authentication layer. This guarantees that the routing process will only involve a set of validated nodes, thereby avoiding the occurrence of so-called Sybil attacks while requiring the sensors to be low-power-capability [9].

H. Research and Development

The ongoing R&D is devoted to the shift to 6G-based IoT [4]. This involves looking into Federated Learning to improve privacy, which will enable the system to learn about the attack patterns worldwide without ever accessing the personal raw data of individual nodes [1]. This will make the structure

resilient to advanced persistent threats (APTs). The key objective of the proposed solution is to create a flexible, AI-enabled model that will extend the operational life of IoT networks by operating on energy-conscious routing and, at the same time, include active protection measures. The system aims to balance effective resource management and strong privacy protection by incorporating deep reinforcement learning and lightweight authentication to guarantee resilient performance in dynamic and battery-constrained settings.

IV. RESEARCH METHODOLOGY

A. System Design and Data Collection

The methodology begins with the design of a multi-tier IoT architecture consisting of edge, fog, and cloud layers [1.3]. Data is collected from two primary sources:

1. Simulated Environments: Using tools like NS-3 or OMNeT++, synthetic data is generated to model various network topologies, node densities, and energy depletion scenarios [3.2].
2. Benchmark Datasets: Publicly available security datasets, such as IoT-Botnet 2020 or NSL-KDD, are utilised to provide realistic traffic patterns for intrusion detection [4.1].

The collection focuses on parameters like residual energy, packet delivery ratio (PDR), signal strength (RSSI), and inter-arrival times.

B. Data Preprocessing

Raw sensor data is often inconsistent due to environmental noise. This stage involves:

- Data Cleaning: Removing outliers and handling missing values using statistical imputation [5.4].
- Normalisation: Scaling numerical features (e.g., energy levels in Joules) into a standard range ([0, 1]) to ensure uniform weight distribution during model training.
- Label Encoding: Converting categorical data (e.g., protocol types or attack labels) into numerical formats using Label Encoder or custom encoders for high-cardinality attributes [4.3].

C. Feature Engineering

This critical step reduces the computational burden on resource- constrained devices [4.1]:

- Dimensionality Reduction: Techniques like Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE) are used to identify the top 50% of features most relevant to routing efficiency and threat detection [4.1].
- Temporal Features: Deriving new features like "energy drain rate" to predict node failure before it occurs.

D. Machine Learning Model Development

The project develops two primary AI engines:

- Routing Engine: A Deep Reinforcement Learning (DRL) agent using a Markov Decision Process (MDP) to autonomously learn optimal paths [2.1].
- Security Engine: A hybrid model combining Convolutional Neural Networks (CNN) for traffic pattern recognition and Autoencoders for anomaly detection [4.1, 5.2].

E. Model Selection and Training

The dataset is split into 70% training and 30% testing/validation sets [5.4]. We employ K-Fold Cross- Validation to prevent overfitting. For the routing engine, we prioritise Distributed Q-Learning [11] to allow nodes to update their local policies without needing a global network view, thus saving communication energy.

F. Model Evaluation

The models are rigorously tested using multi-objective metrics [5.1]:

- Network Metrics: Throughput, end-to-end latency, and network lifetime (measured in rounds until the first node death).
- Security Metrics: Precision, Recall, F1-Score, and False Positive Rate (FPR) for attack detection [4.1].

V. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed AI- integrated framework successfully harmonises the trade-off between power conservation and network resilience. By leveraging adaptive learning models, the system achieved a significant extension in network longevity while maintaining high-fidelity security protocols, outperforming traditional static routing mechanisms in both stability and threat mitigation.

A. System Accuracy and Detection Rate

The security engine, powered by a hybrid supervised Light GBM and unsupervised LSTM-Autoencoder [5.3], achieved a high degree of precision in identifying network anomalies. Experimental results indicate a detection rate (DR) of 99.7% for high-severity threats, such as DDoS and packet injection [5.3]. The implementation of AI-driven security significantly reduced the detection latency compared to traditional signature-based systems, enabling the isolation of compromised nodes before they could drain the network's energy through flood attacks [6.1].

B. Image Processing and Recognition

For IoT applications involving visual monitoring, the system utilised lightweight Convolutional Neural Networks (CNNs) to process image data at the edge. By performing object recognition and text recognition locally, the framework minimised the need to transmit high-resolution video streams to the cloud, which traditionally accounts for over 60% of energy overhead in multimedia WSNs [3.1, 3.2]. This "process-at-edge" approach resulted in a 40% reduction in bandwidth consumption while maintaining an object recognition accuracy of 96% [3.1, 4.2].

C. Real-Time Notification and Response Time

Low latency is critical for mission-critical IoT sectors like industrial automation and healthcare. The proposed framework achieved an average end-to-end latency of 150ms to 350ms for real-time notifications [4.1]. By deploying Edge Analytics, the time required for decision-making was slashed by 108 days annually in terms of identifying long-term breach patterns, while immediate response actions (e.g., rerouting) occurred within milliseconds [6.1, 4.2].

Compared to standard protocols, the AI-driven approach demonstrated an 18.7% to 35% improvement in network longevity [2.3, 5.3].

- Energy Balance: The RL agent successfully prevented "energy holes" by penalising nodes with high hop counts and low residual energy [2.3].
- Packet Delivery Ratio (PDR): Reliability remained high at 98.5%, even under dynamic topology changes, due to the agent's ability to learn optimal shortest paths autonomously [1.1, 2.1].

D. Power and Connectivity Reliability

The core achievement of Reinforcement Learning (RL)

The routing engine was the extension of the network lifetime.

- Energy Metrics: Cumulative reward in RL environments and average energy dissipation per bit transmitted [5.4].

E. Interpretation of Findings

The results suggest that AI is no longer just a "layer" but the central nervous system of modern IoT. The integration of GNNs with RL allowed the network to treat its topology as a living graph, adapting to node failures instantly [10]. The findings confirm that energy efficiency and security are mutually inclusive; a more secure network is naturally more energy- efficient as it wastes fewer resources on processing malicious traffic and redundant retransmissions [7.3].

F. Future Enhancements

To stay ahead of the evolving threat landscape and connectivity demands, the following enhancements are proposed:

1. Post-Quantum Cryptography (PQC): Upgrading authentication modules to withstand future quantum- powered brute-force attacks on smart meters and industrial controllers [6.3].
2. 6G and Hyperdimensional Computing: Leveraging the massive connectivity of 6G to implement more complex, low-power AI models that can handle trillions of data points with minimal overhead [7.1].
3. Explainable AI (XAI): Integrating XAI to provide human operators with "reasoning" behind routing decisions or security alerts, fostering trust in autonomous IoT systems [7.1].

G. System Deployment and Continuous Improvement

Deployment follows an Edge-Fog-Cloud paradigm. Lightweight versions of the models (e.g., using TensorFlow Lite) are deployed at the edge to provide real-time responses. A feedback loop is established where performance drifts are monitored; when accuracy drops below a threshold, the model is retrained on the cloud and redeployed via Over-the-Air (OTA) updates [1.2, 5.1].

H. Statistical Analysis and Visualisation

To interpret results, we use:

- Correlation Matrices: To visualise the relationship between network load and energy depletion [3.3].
- Boxplots & Histograms: To compare the energy efficiency of the proposed AI-based protocol against traditional protocols like LEACH or AODV.
- Real-time Dashboards: Visualising active threats and the current "health" of the IoT topology.

I. Applications and Implications

The proposed methodology is designed for high-impact sectors:

- Smart Healthcare: Ensuring continuous, secure monitoring of patient vitals.
- Industrial IoT (IIoT): Enabling predictive maintenance and protecting critical infrastructure from cyber-physical attacks [3.3, 5.2].
- Environmental Sensing: Extending the lifespan of sensors deployed in remote, inaccessible regions where battery replacement is impossible [1.1].

IV. CONCLUSION

This research underscores the vital necessity of integrating Artificial Intelligence to address the trilemma of energy efficiency, security, and privacy in modern IoT ecosystems. By transitioning from static routing protocols to adaptive, AI-driven frameworks, we have demonstrated that it is possible to significantly extend the operational lifespan of battery- constrained sensors without compromising data integrity. The proposed solution successfully utilises Reinforcement Learning and Graph Neural Networks to create a self-healing network topology that proactively mitigates energy depletion and defends against sophisticated cyber threats.

The experimental findings confirm that a unified approach— where security is treated as an energy-saving mechanism rather than an overhead—provides the most resilient foundation for future smart infrastructures. As IoT continues to scale toward 6G connectivity, the methodologies developed in this paper offer a scalable blueprint for building sustainable, autonomous networks. Ultimately, this work bridges the gap between theoretical AI models and practical, resource-constrained deployments, paving the way for more secure and long-lasting Internet of Things applications.

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