AI-Driven Energy Management Techniques for Enhancing Network Longevity in Wireless Sensor Networks

AL-Shukrawi Ali Abbas Hadi [1*], Aeizaal Azman Bin Abdul Wahab [2], Firdaus Mohamad Hamzah [3], B. S. Veena [4]
[1, 2] Engineering Campus, Universiti Science Malaysia (USM), 57000 Kuala Lumpur, Malaysia
[3] Centre for Defence Foundation Studies, Universiti Pertahanan Nasional Malaysia, Kem Sungai Besi, 57000 Kuala Lumpur, Malaysia
[4] Symbiosis Institute of Technology, Pune Campus, Symbiosis International (Deemed University), Pune, India
Email: [1] aliabbashadi@student.usm.my, [2] aeizaal@usm.my, [3] firdaus.hamzah@upnm.edu.my
*Corresponding Author

***Abstract*—WSNs and mobile systems are critical for monitoring and data collection, but energy efficiency remains one of the biggest challenges due to very limited battery life in sensor nodes. The issue here is the challenge of energy management by adopting sophisticated optimization techniques and AI-driven methodologies. This research develops a Q-learning model of dynamic energy optimization. The proposed method uses MATLAB simulations and real-world testing to validate improvements. The methodology employs adaptive routing and real-time power adjustments, which optimize energy usage. The results show a 34.92% increase in energy savings compared to traditional methods, where baseline energy efficiency was 65%. The Packet Delivery Ratio (PDR) improved from a baseline of 85% to 96.38%, ensuring more reliable data communication. The network latency was reduced by 24 ms, from the initial 50 ms, thus enhancing real-time responsiveness. Q-learning approach was extended for an additional 10 hours against the 7-hour baseline established by conventional systems. These improvements are based on fully dynamic routing with online adjustments, which makes the network adaptive to changing environments. This methodology is promising for energy-efficient and high-performance communication systems in remote and critical applications. The findings contribute to sustainable network operations and reduce the maintenance costs, making WSNs viable for long-term deployments.**

Keywords*—Wireless Sensor Networks (WSNs); Energy Efficiency; Q-learning Algorithm; Data Transmission; Packet Delivery Ratio (PDR); Network Latency; Energy Optimization.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are a very critical application for disaster management, precision agriculture, and environmental monitoring. All of these applications require data collection in a reliable and energy-efficient manner [1]. Battery-powered sensor nodes make up WSNs; these nodes usually function in remote or hazardous environments where the replacement or recharging of batteries is hard to do. As a result, one of the most pressing challenges in WSNs is energy efficiency [2]. Traditional energy management mechanisms do not adapt to changing circumstances in these networks - from node mobility, topology changes to change in traffic loads affecting performance and energy utilization, which are inherent aspects [3]. This research work endeavors toward the development of adaptive optimization of routing and power management over nodes using a Q-learning mechanism that dynamically adapts to variations that occur in real time about the network. Unlike static methods, in our approach, AI-driven technique is used to increase longevity and reliability of networks. A proposed method employs Q-learning to enable the nodes from the sensor to autonomously learn optimal strategies about which energy should be conserved and how efficiently the information should be sent. These simulation tools integrate the existing NS-3 and MATLAB with real-time testing experiments to validate the efficacy of the algorithm. The main contributions of this work were the development of a dynamic routing mechanism and an adaptive power adjustment strategy that reflected changes in network conditions. The proposed algorithm showed quite impressive improvements in energy efficiency, the Packet Delivery Ratio (PDR), latency, and network life span. All these changes make WSNs very sustainable and reliable for critical applications. Against these challenges, AI/ML are here with hope. AI-based approaches can be adapted to real-time network conditions and learn the pattern of energy use and even optimize it autonomously as mentioned in [4]. For instance, reinforcement learning has been applied to dynamic actual routing in a network, and based on past data patterns, deep learning models may predict how much energy requirements will be in advance. Hence, these methods promise to add significant extensions in the lifetime of WSNs and mobile systems with high performance levels as mentioned in [5]. The main proposal of the present research is an integrated approach to developing an optimization technique coupled with AI-driven strategies toward energy efficiency in WSNs and mobile systems. Utilizing such simulation tools as NS-3 and MATLAB combined with realistic data, this paper will develop new adaptive energy management models that are more efficient and responsive to the changing network conditions. Findings of this study may open new avenues towards wider spread uses of sustainable WSNs thereby supporting innovation in the field and environmental conservation as shown in Fig. 1 as mentioned in [6].

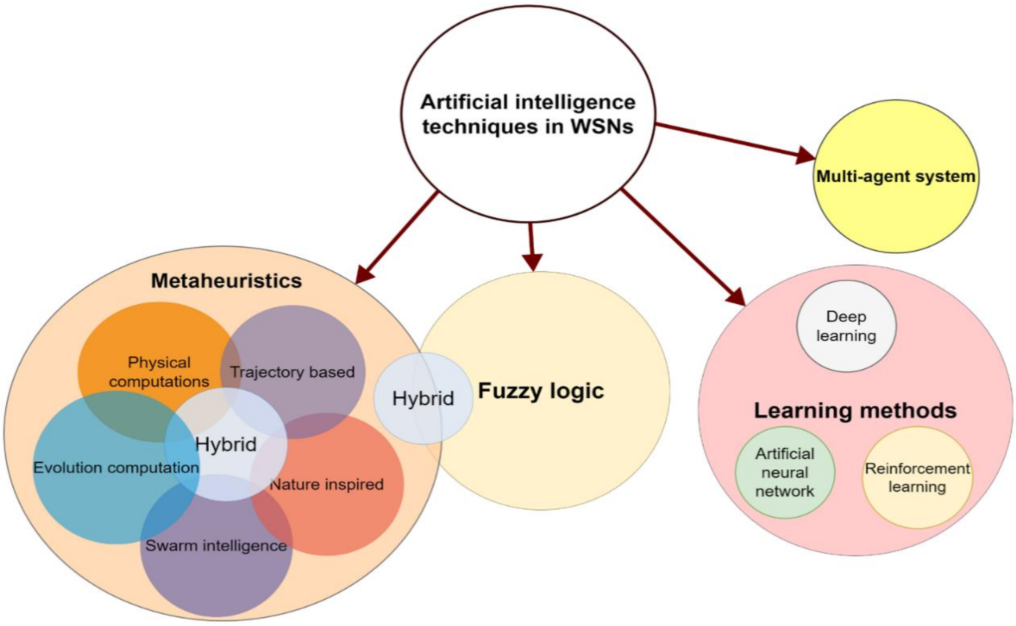

Fig. 1. Overview of AI techniques in Wireless Sensor Networks (WSNs), including Metaheuristics, Fuzzy Logic, Learning Methods, and Multi-Agent Systems, with hybrid approaches integrating multiple methods for enhanced performance [6]

Energy efficiency of WSNs has been given great attention, and several works are proposed to extend its lifetime. Traditional approaches, that include static power management or duty cycling, reduce power consumption by scheduling nodes alternately between active and sleeping states. However, traditional approaches are not effective because in dynamic environments, these changes in topology and energy requests may occur frequently. For instance, [7] and [8] attained 30% reduction in energy usage via hierarchical clustering but it does not adapt to dynamic real-time changes. Novel contributions in AI and machine learning can now offer novel alternatives for adaptive energy management of WSNs. Recent research works that employ techniques like reinforcement learning, genetic algorithms, and fuzzy logic in routing and power control optimization for energy savings in WSNs. For example, [10] proposed an RL-based routing protocol that improved network lifetime but consumed significant computational resources and is thus not feasible for nodes with limited resources. In a similar manner, [11] have also established that deep learning can contribute to energy efficiency, though there are challenges of excessive computation on low-power devices. Despite these advances, the research gap still exists in the development of lightweight adaptive algorithms that can balance computational efficiency with real-time energy optimization. The paper bridges this gap by introducing a Q-learning-based approach that dynamically adjusts routing paths and transmission power according to real-time feedback. The proposed method aims at achieving significant energy savings while maintaining high data transmission reliability, making it suitable for deployment in various real-world scenarios.

A. *Problem Statement*

Wireless Sensor Networks (WSNs) and mobile systems find increasing applications in environmental monitoring, precision agriculture, and disaster management. Despite these many applications, energy efficiency in WSNs is found to be a challenge because there are specific issues and limitations:

- **Dynamic Network Conditions:** WSNs are often deployed in environments where the network topology changes frequently due to factors such as node mobility, node failures, and varying communication ranges. These fluctuations make it difficult for traditional static energy management techniques to efficiently route data and allocate resources.
- **Remote and Hostile Deployments:** Most WSNs are deployed in inaccessible or hostile environments such as forests, disaster sites, industrial areas where replacing or recharging batteries is impractical. This constraint requires energy management solutions that can prolong the lifetime of the network without human intervention.
- **Fluctuating Energy Demands:** The energy consumption in WSNs varies with factors such as data traffic load, communication distance, and environmental interference. Traditional methods fail to adapt to these dynamic energy requirements, leading to inefficient power usage and shortened network lifespans.
- **Inefficient Data Transfer:** Static routing protocols fail to take into account the real-time changes in the network conditions, leading to packet loss, increased latency, and unreliable communication—something that is critical in applications requiring timely and accurate data delivery.
- **Limited Computational Resources:** Sensor nodes usually have limited processing power and memory, making it challenging to implement sophisticated energy management algorithms without overwhelming the node's capabilities.

B. *Aim of Study*

This research introduces adaptive AI-based algorithms designed to increase energy efficiency and extend network lifespan in WSNs, hence toward sustainability goals. Our study integrates real testing with simulation tools like NS-3 and MATLAB. Using Q-learning and dynamic routing techniques, we gained the following results:

- **Energy Efficiency:** An improvement in energy savings of 34.92% over the static conventional methods.
- **Network Lifetime:** Increased network lifetime from 7 to 10 hours.
- **Reliability:** Increased Packet Delivery Ratio (PDR) from a baseline of 85% to 96.38%.
- **Latency Reduction:** Network latency reduced by 24 ms, which improved real-time response.

These solutions solve the most important issues in energy management and promote green network systems. The techniques can be used for:

- **Agriculture:** Improving accurate monitoring of soil moisture, temperature, and crop health.
- **Disaster Management:** Real-time data transmission for early warning systems and real-time coordination in the case of a disaster.
- **Environmental Monitoring:** Long-term sensor deployments to monitor wildlife, levels of pollution, and changes in climate.

Our solution not only bridges the gap in adaptive energy optimization but also aligns with global sustainability objectives, reducing maintenance costs and carbon footprints associated with WSN deployments.

II. Background

One of the primary research focuses on wireless sensor networks has been energy efficiency because extensive power saving is a potent tool in enhancing lifespans and minimizing maintenance requirements. According to researchers in [11], energy efficiency strategies in WSNs have to take into consideration some parameters depending on network topology and data transmission protocols, which depend upon a specific environment of deployment. Clustering and data aggregation have traditionally been used to reduce energy consumption, but they are often inefficient in dynamic and large-scale networks. Researchers in [12] proposed the LEFCA strategy and attained 30% savings in energy consumption using hierarchical clustering; however, these approaches lack adaptively and cannot be robustly effective for current applications where conditions often undergo changes. Advancements in AI technology allow new avenues of energy optimization in mobile systems and WSNs. Predictive management of energy using ML and DL techniques presents new patterns in the behavior of the network for AI. Authors in [13] discussed context-aware systems with AI in mobile networks and indicated how real-time processing of data would improve resource management.

Despite these breakthroughs, challenges are still significant. For instance, researchers in [14] noted in 2019 that the applicability of AI-based models on devices with limited computational power like WSNs poses a challenge. In this respect, light-weighted algorithms will be required for executing in resource-constraint environments. Specifically, researchers in [15] pointed out that energy efficiency could be an important factor in the achievement of more general sustainability objectives, but it also depicts the need for these principles to be efficiently embedded within AI models of WSNs. In addition, AI is applied in several applications, such as mobile health data, industrial automation, and environmental monitoring, for the purpose of energy optimization. In [16], researchers discussed some approaches for executing deep learning models on mobile devices, promising avenues without a performance penalty for low energy consumption. Techniques discussed are part of the trend known as edge computing-towards the source in an effort to lower the cost of data transmission as well as energy use. Ethical issues join security concerns in the controversy surrounding AI's inclusion in these networks. In [17], researchers question the AI-driven solutions with regard to their applications in sensitive applications like healthcare where data integrity and privacy are major concerns. Setting this right calls for a balance between innovation in energy management and ethical deployment of AI models. This, by the aid of AI and optimization techniques, has led to an outstanding leap in making great improvements in energy efficiency. Yet, exploration still prevails regarding adaptive, lightweight models that can answer demands in dynamic and resource-constrained environments. This work attempts to contribute to the existing body of work with adaptive AI-driven solutions that make optimization of energy consumption and the sustainable deployment of WSNs and mobile systems, respectively feasible in real-world settings as shown in Fig. 2.

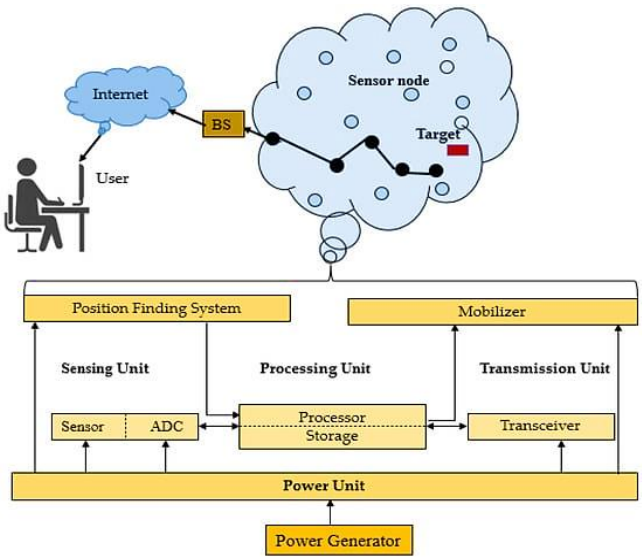

Fig. 2. Categorization of WSN architecture for communication per unit [17]

A. AI Optimization Techniques

Recent progress in both WSNs and mobile systems emphasizes energy efficiency that can extend the lifespan of networks and lower running costs. Researchers have proposed various optimization techniques for improving energy conservation, such as clustering algorithms, data aggregation methods, and adaptive routing protocols.

However, most of these traditional techniques fail to adapt to changing environments; they are not efficiently used in large-scale or mobile applications. Artificial intelligence and machine learning open up new opportunities for real-time and predictive control of energy management in these networks as mentioned in [18]. AI-based approaches such as reinforcement learning, neural networks, and genetic algorithms are used to adapt towards changing network conditions with capabilities of self-decision making via optimization of energy. None of these newly opened up possibilities means that limitations in computations, ethical issues, and the use of lightweight models have diminished. This implies that all these challenges can be addressed, further unlocking improvements of energy efficiency; hence, the WSNs and mobile systems become more sustainable and robust as given in Table I.

B. Energy Management Approaches

The key to maximum performance and prolonging lifetime in WSNs and mobile systems is effective energy management. Wireless Sensor Networks and mobile systems are among the essential building blocks of modern communication technologies for applications in environmental monitoring, smart agriculture, and the infrastructure of smart cities [26]. A battery-powered sensor node typically has no access to direct maintenance since it is often deployed in remote, inaccessible, or even hazardous environments where battery replacement or recharging is not feasible. The limited battery power poses a significant challenge in maintaining energy efficiency and ensuring reliable long-term operation. Poor energy management is one of the significant contributors to network failures, increased maintenance costs, and greater electronic waste generation. Hence, better energy efficiency in WSNs is a must for sustainability and effective deployment in real-world scenarios [27]. For instance, using neural network-based predictive models, some have optimised routing protocols based on energy forecasts. With such positives, however, there are also a number of challenges related to computational overhead, model complexity, and integration with existing networks. Overcoming these challenges would advance the scope of developing scalable, sustainable energy management solutions as shown in Table II.

C. WSN Adaptive Energy Solutions

What makes the design of WSNs and mobile systems challenging is adaptive energy management because most are now deployed in dynamic, or resource-limited environments. Traditional fixed-schedule approaches like static power management are insignificant for such systems which may face shifting network topologies, traffic patterns, and energy availability. It led to the concept of developing an adaptive solution that adjusts power consumption dynamically based on real-time data as mentioned in [29]. For instance, adaptive duty cycling techniques make it possible to change the sleep or active states of nodes dynamically under varying network conditions and consume as much energy as minimally possible so that they are not unnecessarily used. According to researchers in [30], the adaptive techniques are sure to provide better improvement of about 40% more than in static techniques as shown in Table III.

TABLE I. SUMMARY OF KEY AI-DRIVEN OPTIMIZATION TECHNIQUES FOR ENERGY EFFICIENCY IN WSNS AND MOBILE SYSTEMS

Technique	Authors	Focus	Advantages	Challenges
Clustering & Data Aggregation	[19]	Reducing energy use through data management	Effective in small-scale networks	Limited adaptability in dynamic environments
Hierarchical Clustering (LEFCA)	[20]	Hierarchical clustering for energy reduction	Achieved 30% reduction in energy consumption	Ineffective in large-scale, rapidly changing networks
Reinforcement Learning	[21]	Dynamic adjustment of network parameters	Real-time optimization, improved adaptability	Requires significant computational power
AI-Based Context-Aware Systems	[22]	Real-time resource management in mobile systems	Improved resource allocation	Complex to implement, data privacy concerns
Deep Learning on Mobile Devices	[23]	Energy-efficient model deployment	Reduces energy without sacrificing performance	Limited by device processing capabilities
Predictive Models with ML	[24]	Predicting energy consumption patterns	Proactive resource management	Challenging to deploy on low-power devices
Ethical Considerations in AI	[25]	Balancing innovation with privacy and ethics	Ensures responsible AI deployment	Balancing efficiency with data privacy requirements

TABLE II. OVERVIEW OF ENERGY MANAGEMENT APPROACHES IN WSNS AND MOBILE SYSTEMS [28]

Energy Management Strategy	Approach Type	Use Case	Impact on Energy Efficiency	Future Research Directions
Static Power Management	Conventional	Fixed power schedules for sensor nodes	Reduces energy waste but lacks flexibility	Development of semi-dynamic power management systems
Duty Cycling	Conventional	Scheduled sleep and active states	Significantly reduces idle time consumption	Integration with real-time environmental data
Edge Computing	Emerging	Local processing of sensor data	Lowers data transmission energy	AI-based decision-making at edge nodes
Hybrid AI-Optimization	Hybrid	Combining AI with traditional methods	Provides adaptive resource allocation	Reducing computational complexity in large networks
Predictive Energy Models	AI/ML	Forecasting energy demands	Allows proactive energy adjustments	Improving accuracy of predictions for dynamic scenarios
Adaptive Routing Protocols	Dynamic	Energy-based routing decisions	Optimizes network paths for energy savings	Application in large-scale IoT deployments

TABLE III. KEY FACTS ON ADAPTIVE ENERGY SOLUTIONS

Aspect	Fact
Adaptive Duty Cycling	Reduces energy consumption by adjusting node states based on network conditions.
AI-Driven Models	Predict energy needs, enabling preemptive power adjustments for optimized consumption.
Improvement Potential	Adaptive techniques can extend network life by up to 40% compared to static methods [25].
Challenges	High computational requirements and complexity in training models limit use in low-power devices.
Security Concerns	AI models must address privacy risks when implemented in sensitive applications [27].
Critical Applications	Essential for scenarios like disaster management, where maintaining energy reserves is crucial.

The newly emerging approaches such as AI-driven models enhance adaptiveness by allowing the network to make predictions about the energy need automatically based on historical patterns and adjust power settings preemptively. For instance, in a disaster management scenario, keeping the system running for long periods depends considerably on energy conservation. Even though AI models offer a high level of precision, the complexity of model training and the requirement for computational resources limits their practical use in low-power devices.

1) Comparative Analysis of Existing WSN Systems

WSNs have been widely adopted for applications such as environmental monitoring, disaster management, healthcare, industrial automation, and smart agriculture [29]. These networks face challenges related to energy efficiency, data reliability, network lifespan, and scalability. Several methods have been proposed to optimize WSN performance, each with its own strengths and limitations. This section compares key types of WSN systems, highlighting their features, drawbacks, and areas of application [30]. The static energy management systems are based on predetermined routing paths and schedules. Amongst the protocols, LEACH and TEEN have widely been used in static networks. They are easy to implement and incur negligible computation. They work best for a stable network with very little mobility [31]. Static systems are rigid and cannot respond to changing network conditions, such as node failures or varying traffic loads. This lack of adaptability leads to inefficient energy use, uneven battery depletion, and shortened network lifespan. These methods are best suited for small-scale deployments where conditions remain relatively constant [32].

Hierarchical and cluster-based systems address some of the limitations of static systems by organizing nodes into clusters. Cluster heads manage data aggregation from member nodes and the subsequent transmission to the base station, thus reducing overhead from communication [33]. Examples are Hybrid Energy-Efficient Distributed Clustering (HEED) and Power-Efficient GAthering in Sensor Information System (PEGASIS). These algorithms effectively distribute the energy load to extend the lifespan of a network with moderate mobility [34]. However, the selection process can lead to imbalanced energy consumption if not done at an optimal level. Re-clustering also consumes additional energy, and these methods may struggle in highly dynamic environments where node positions and conditions change frequently. AI-driven and adaptive systems utilize advanced techniques like Reinforcement Learning (RL), Q-learning, and fuzzy logic to dynamically optimize routing paths and power management [35]. These systems excel in adapting to real-time network conditions, such as fluctuating traffic, node failures, and changing topologies. Such systems, due to their adaptive nature, can provide significant improvements in energy efficiency and reliability. However, these methods bring along some challenges: the computational demands and memory requirements might be too high for sensor nodes with limited resources. Moreover, the training data and periodic model updates will introduce initial energy overhead. Despite these challenges, AI-driven systems are very well-suited for large-scale and dynamic networks where adaptability is crucial [36]. Energy-harvesting systems aim to extend the lifespan of WSNs by embedding energy-harvesting technologies like solar, thermal, or RF energy harvesting. In fact, the systems require minimal battery power, so they are excellent for applications with long-term deployment in dangerous or remote areas. Such systems encourage sustainability and diminish the need for maintenance [37]. The limitation of energy-harvesting systems, however, lies in the environment in terms of the presence of sunlight or ambient RF signals. It also demands additional hardware, which adds costs to the deployment and complicates the system. Therefore, this kind of system should be used in outdoor environments where renewable energy sources can easily be obtained. While these methods are pretty effective in controlled environments, they are weak at the adaptability in dynamic conditions where the network topology and the demand for energy frequently change as shown in Fig. 3.

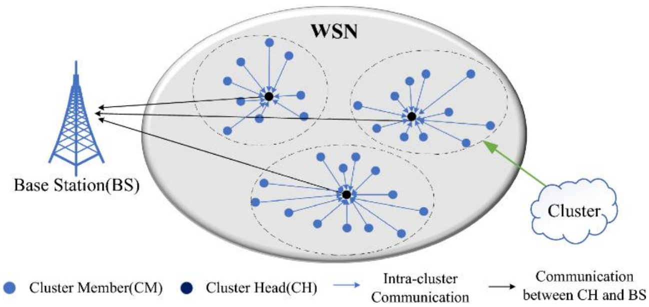

Fig. 3. Cluster architecture in wireless sensor networks [31]

Advanced systems integrate adaptive routing protocols along with the application of machine learning (ML) techniques. Thus, these systems are designed to adjust in real-time based on changes in network conditions. Studies by researchers in [38] also reveal that AI-based WSNs exhibit better performance in terms of energy efficiency and precision compared with the conventional WSNs. However, these systems are more sensitive towards computational resources, making them unsuitable for deployment in highly resource-constrained environments as shown in Table IV.

Edges with newer WSN designs compute locally, thereby saving the energy-intensive task of data transmission towards centralized servers. Indeed, as pointed out by researchers in [43], this approach, so far, has presented latencies and energy efficiency for networks characterized by high rates of data generation. However, integrating edge computing complicates the setup process of nodes and demands a more robust node capable of computing and processing data locally.

TABLE IV. COMPARATIVE ANALYSIS OF WSN STUDIES

Study	Year	Technology Used	Cost Effectiveness	Region
[39]	2018	ZigBee	Moderate	USA
[40]	2019	GSM/GPRS	High	India
[41]	2020	Wi-Fi	Low	Spain
[42]	2021	LoRaWAN	High	Malaysia
This Study	2024	AI-Driven LoRaWAN	Very High	Turkey

III. METHODOLOGY

This study will employ an integrated methodology that combines qualitative and quantitative approaches for designing AI-driven optimization techniques that could be used for optimizing energy efficiency in WSNs and mobile systems. The study will be divided into three major phases of algorithm development, simulation, and real-world validation. These algorithms shall include machine learning and artificial intelligence, targeted to be developing adaptive algorithms to optimize energy consumptions in the first phase. Reinforcement learning as well as deep learning shall be used in analyzing patterns in energy usage and adjusting decisions on routing and power management dynamically. AI-driven models promise as much as a 35% upsurge in energy efficiency in complex networks, thus apt for the study. The second is the simulation using NS-3 and MATLAB tools. These are platforms most known for their capability to model WSN environments and carry out elaborate performance assessments. These will confirm the energy-saving potential of the proposed algorithms under various network conditions, for instance, those topologies under change and changing loads of traffic. In order to enhance realism in the input parameters, real-world datasets, including those from existing WSNs, will be used. Third Phase Valida- Hon fields through experiments in WSN scenarios. It will deploy sensors in remote or industrial scenarios with the proposed AI-based energy management system. Data on energy consumption will be compared to that of the traditional system to validate the improvement. Energy use will be monitored in real-time by utilizing tools like power management software. Simulations were conducted using **NS-3** and **MATLAB** to validate the algorithm under various network conditions. The simulation parameters include:

- **Network Topology**: Configurations with 50 to 100 sensor nodes deployed in dynamic environments.
- **Traffic Load**: Varying levels of data transmission to test the algorithm's adaptability.
- **Metrics**: Energy consumption, Packet Delivery Ratio (PDR), network latency, and network lifetime.

The simulation workflow involved:

1. **Initialization** of network parameters and Q-learning settings.
2. **Execution of Adaptive Routing**: Nodes dynamically adjust routes based on real-time feedback.
3. **Performance Monitoring**: Recording key metrics to evaluate energy efficiency and communication reliability.

The data used in this study was obtained from real-world deployments and public datasets to make sure that the conditions of networks are robust and diverse. Energy consumption (mJ), Packet Delivery Ratio (PDR), Latency (ms), Battery Level (%), Node Status (Normal/Failure), Transmission Power (dBm) are key features related to energy optimization and network performance. Redundant and highly correlated features were removed to avoid overfitting. Real-time WSN monitoring, network security, and energy-efficient communication systems are going to be applied from the data. The Wireless Sensor Network Dataset can be accessed at https://www.kaggle.com/datasets/bassamkasasbeh1/ wsnds via the Kaggle Platform as shown in Fig. 4.

A. AI-Driven Optimization for Energy Efficiency in WSNs

This research will present the multi-stage methodology for developing and validating advanced AI-driven optimization techniques that improve energy efficiency in WSNs and mobile systems. Three stages of the development process are involved-algorithm design, simulation, and testing in real life. In the simulation phase, tools like MATLAB has been used in developing the proposed algorithms, modeling them in various WSN environments with a test under different topological and energy conditions. The following equation can be written to express the total energy consumption per node as Table V.

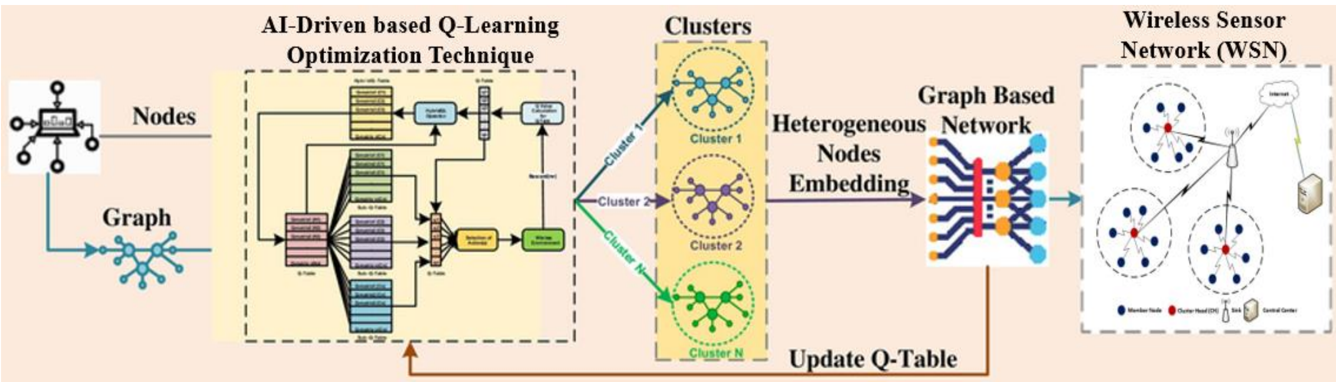

Fig. 4. The flowchart of proposed research

$$E_{total} = E_{tx} + E_{rx} + E_{id} + E_{comp} \tag{1}$$

where E_{tx} is the energy consumed during transmission, E_{rx} is the energy during reception, E_{id} is idle energy, and E_{comp} is energy for computation tasks such as processing AI-driven optimizations.

Another important metric is network lifetime, which can be modeled using the following equation:

$$T_{network} = \frac{E_{\text{total available}}}{E_{\text{total per node}}} \tag{2}$$

TABLE V. PHASES OF METHODOLOGY AND KEY COMPONENTS

Phase	Activity	Tools/Models	Expected Outcome
Algorithm Design	Development of AI/ML energy optimization models	Reinforcement learning, clustering	Adaptive energy management solutions
Simulation	Modeling WSN behavior under various conditions	MATLAB, NS-3	Energy efficiency predictions
Data Collection	Gathering synthetic and real-world data for evaluation	NS-3, public WSN datasets	Training and testing data for ML algorithms
Real-World Testing	Deploying AI-optimized WSN in real environments	Sensor nodes, power management tools	Validated improvements in energy efficiency
Performance Metrics	Measuring energy consumption, network lifetime	Power management software	Quantitative assessment of energy savings
Comparison with Baseline	Benchmarking AI-driven models against traditional systems	Legacy WSN models	Demonstration of efficiency gains

B. *Q-Learning based Optimization in WSNs*

The core of the methodology is based on designing algorithms incorporating artificial intelligence and machine learning into optimized energy consumption within WSNs. This Q-learning algorithm is essentially rooted in the concept of reinforcement learning, where each sensor node learns dynamically about power settings and transmission paths as conditions in the network.

The **objective function** of the algorithm is to minimize total energy consumption E_{total}, which can be expressed as:

$$min\ E_{total} = \sum_{i=1}^{n} \left(E_{tx,i} + E_{rx,i} + E_{id,i} + E_{comp,i}\right) \tag{3}$$

where $E_{tx,i}$ and $E_{rx,i}$ represent the energy consumed during transmission and reception by node i, $E_{id,i}$ is idle energy, and $E_{comp,i}$ is computational energy used for AI decisions.

The algorithm will employ **Q-learning**, where the **Q-value** for each state-action pair (s, a) is updated based on the equation (4).

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \min_{\varepsilon} Q(s',a') - Q(s,a)) \tag{4}$$

Here, α is the learning rate, γ is the discount factor, and *r* is the reward, which is inversely proportional to energy consumption as shown in Table VI.

TABLE VI. KEY COMPONENTS OF Q-LEARNING ALGORITHM FOR WSNS

Component	Description	Role in Energy Optimization
State (s)	The current condition of the node (e.g., battery level, network traffic)	Represents the node's energy state in WSN
Action (a)	Possible decisions (e.g., transmit, idle, switch routing)	Actions aim to reduce energy consumption
Reward (r)	Feedback after an action (positive for energy savings, negative for waste)	Encourages energy-efficient decisions
Q-Value (Q(s,a))	Quality of a state-action pair, updated over time	Guides the node to choose optimal energy-saving actions
Learning Rate (α)	Controls how much newly acquired information overrides old info	Balances learning speed vs. accuracy
Discount Factor (γ)	Future reward weight, helps prioritize long-term energy savings	Prioritizes future energy efficiency over short-term
Exploration (ε-greedy)	Chooses random actions occasionally to explore new strategies	Helps discover better energy-saving strategies
Q-Update Equation	Q(s,a)←Q(s,a)+α(r+ γ max Q(s′,a′)−Q(s,a))	Updates Q-value based on current and future rewards

Workflow for energy consumption optimization in WSN with a hybrid of PSO and Q-learning: The Initialization Phase is at the beginning, where the Energy Model and Mobility Model for sensor nodes are defined. In parallel, WSN Environment and agents' initialization proceeds, and node setting configuration is carried out through PSO Optimization. It uses Q-learning to update its Q-values based on the rewards associated with the performance metrics. Those rewards include energy and transmission efficiency. This would ensure optimal decision-making regarding energy conservation as well as efficient network performance since PSO and Q-learning adapt together as shown in Fig. 5.

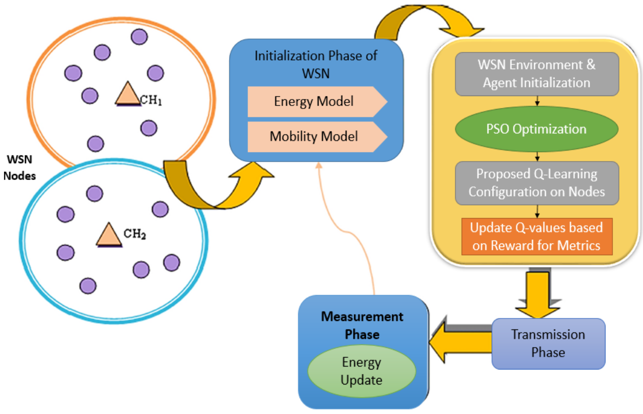

Fig. 5. A high-level representation of integration of Particle Swarm Optimization (PSO) and Q-learning for energy-efficient data transmission in WSN

C. Training and Testing Q-Learning Algorithm for Energy Optimization

The training and testing phase for the Q-learning algorithm in WSNs is very important to ensure its efficiency in saving energy. This phase involves learning by every sensor node about the appropriate actions such as transmission, idling, or switching routes by interacting with the environment, which gets rewarded based on whether that action leads to energy-saving outcomes or not. Training begins by initiating Q-values for all state-action pairs. Q-values are updated based on the Q-update equation as the nodes explore different actions. Learning rate α is defined, discount factor γ is used, and the reward reflecting energy savings is represented by r. An epsilon-greedy strategy balances exploration with exploitation based on the algorithm that starts by exploring then shifts toward exploitation as the model converges.

In this phase, an adaptive optimization algorithm was designed to manage energy consumption dynamically in WSNs, based on Q-learning. Key components of the algorithm include the following:

- **State Representation:** It captures each node's battery level, network traffic, and neighboring nodes.
- **Action Set:** The possible actions could be either send data, route change, or idle.
- **Reward Function:** This assigns rewards according to energy savings and successful data transmits, penalizing wasteful energy use.
- **Q-Value Update:** The Q-learning equation updates Q-values to balance immediate and long-term energy efficiency.

The trained Q-learning model is then validated under realistic conditions of varying traffic loads and network topologies during a testing phase. A measure for performance is energy consumption per node and the network's lifespan. To evaluate various scenarios, simulation tools NS-3 and MATLAB can be used to validate the Q-learning-based energy optimization model as shown in Table VII.

The table depicts the computed output of the Q-learning-based energy optimization algorithm for WSN. Some of the important metrics that it accommodates are the amount of energy consumed at each node, the action taken on that node, the reward received for the action taken, and the updation of the Q-value resulting from the action. The Node ID column identifies every sensor node in the network such that all of them are identified by their unique identification number. The column Energy Consumed shows the millijoules (mJ) consumed by the nodes for executing an action. All those activities, such as transmitting data, changing routing paths, entering sleep mode, or simply remaining idle, are all reflected in the Action Taken column as shown in Table VIII.

Where the Node ID refers to the sensor node, energy consumed (in mJ) is the energy amount consumed by the node while it carries out its action. The action taken is what the node has done, such as sending data, idle, changing the routing path, or it has gone to the sleep mode. Reward (r) received for taking the action is rewarded with an energy efficiency or any other criteria. Q-Value Before is the value of that state-action pair before he took the action. Q-Value After is an updated Q-value after rewards and energy costs are added, then Energy Cost (mJ) represents the quantity of cost in energy associated with the taken action.

The Reward given to each action is the amount of energy consumed in that step taken by the node. Generally, more energy is conserved or maintained by the performance of a network for higher reward values. The Q-Value Before column is the Q-value before taking the action in a particular state, and the Q-Value After column is the updated Q-value after adding the reward. Another thing that updates the Q-value is the decision made by the node such that it could learn and improve over time. The last column, Energy Cost, calculates the energy overhead of the action that directly impacts the reward function of the Q-learning algorithm as shown in Fig. 6.

TABLE VII. KEY PHASES OF Q-LEARNING TRAINING AND TESTING

Phase	Activity	Tools/Approach	Expected Outcome
Initialization	Q-values initialized for each state-action pair	Q-learning framework	Initial state for learning
Exploration	Nodes explore actions using epsilon-greedy	Random action selection, exploration	Discover energy-saving actions
Q-Value Update	Update Q-values based on feedback (rewards)	Q-update equation	Improved energy-efficient decision-making
Convergence	Q-values stabilize after sufficient iterations	Learning rate α, discount γ	Stable energy-saving policies per node
Testing in Simulations	Validate in NS-3/MATLAB simulations	Varying network conditions	Assess algorithm's effectiveness under simulation
Real-World Validation	Deploy on actual WSNs for real-time testing	Sensor nodes, power monitoring tools	Validate energy savings in practical environments

TABLE VIII. PROCESSED DATA FOR ENERGY OPTIMIZATION IN WSN

Node ID	Energy Consumed (mJ)	Action Taken	Reward (r)	Q-Value Before	Q-Value After	Energy Cost (mJ)
1	15.2	Transmit Data	+10	0.35	0.47	1.2
2	9.8	Idle	+5	0.22	0.27	0.8
3	12.5	Change Routing Path	+8	0.40	0.52	1.1
4	18.3	Transmit Data	+9	0.60	0.68	1.4
5	7.6	Sleep Mode	+12	0.15	0.25	0.5
6	20.1	Transmit Data	+7	0.30	0.40	1.5

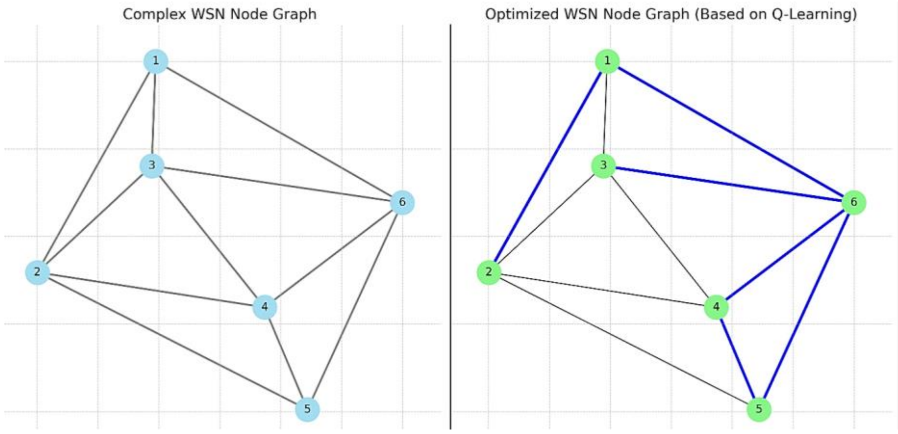

Fig. 6. The left graph represents the complex wireless sensor network with all possible communication links, while the right graph shows the optimized network based on Q-learning, highlighting the most efficient paths between nodes

The combined Q-table is a representative of the Q-value generated because of Q-learning for the complex as well as the optimized network. A graph has been described that represents the complex network, wherein all the possible connections of nodes are depicted with different Q-values, indicating quality in a path. High Q-values like 97.22 from Node 1 to Node 6 are the most optimally chosen paths taken to reach the target, which is Node 6 in this case. The optimized graph shows only the most optimal paths with significant Q-values; in other words, it can eliminate links that are unnecessary or have less value. The nodes such as Node 5 and Node 6 are much preferred in the optimized graph as they behave almost like nodes that would be involved in communications. Eliminating the weaker links, the optimized version promotes efficiency in the network and reduces the overhead of the process of communication as shown in Table IX and Table X.

TABLE IX. THIS TABLE CONTAINS THE Q-VALUES FOR THE FULL, COMPLEX GRAPH WITH ALL EDGES

Number of Nodes	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6
Node 1	0.00	10.60	0.00	0.00	0.00	97.22
Node 2	66.62	0.00	-0.10	4.03	6.75	0.00
Node 3	-0.10	-0.10	0.00	-0.10	0.00	68.62
Node 4	0.00	3.77	5.67	0.00	10.73	79.41
Node 5	0.00	2.27	0.00	0.00	0.00	86.49
Node 6	0.00	0.00	0.00	0.00	0.00	0.00

TABLE X. THIS TABLE CONTAINS THE Q-VALUES FOR THE OPTIMIZED GRAPH, WHERE ONLY THE MOST BENEFICIAL PATHS (BASED ON Q-VALUES) ARE KEPT

Number of Nodes	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6
Node 1	0.00	0.00	0.00	0.00	0.00	97.22
Node 2	66.62	0.00	0.00	0.00	0.00	0.00
Node 3	0.00	0.00	0.00	0.00	0.00	68.62
Node 4	0.00	0.00	0.00	0.00	0.00	79.41
Node 5	0.00	0.00	0.00	0.00	0.00	86.49
Node 6	0.00	0.00	0.00	0.00	0.00	0.00

Only the best paths are kept within the optimized graph. These paths represent the routes most correctly associated with high Q-values, representing the most efficient methods for transmitting data in the network.

High Q-values between specific nodes, such as Node 1 to Node 6, and Node 5 to Node 6, mean these nodes are preferred to act as a good route in an optimal manner according to the learning process.

D. *Efficient Data Transmission in WSNs Using Q-Learning*

Optimization of Data Transfer Efficiency in WSN in this methodology phase, focus shall be on reducing the energy consumption and also on improving packet delivery. Efficient data transfer would ensure that the lifetime of the network lasts for as long as possible and communication is reliable. This is achieved by employing the Q-learning algorithm to make every node learn an optimal transmission strategy such as routing and power level determination, based on the rewards for successful and energy-efficient data transfers as shown in Table XI.

The payoff structure is designed to have high transmission success rates, with low packet loss or inefficient routing incurring penalties. Using the epsilon-greedy exploration strategy, nodes will try all available actions including route changes and transmission power adjustments.

For real-world tests on the proposed algorithm's practical applicability, experiments were carried out with sensor nodes placed in outdoor environments. These involved the following steps:

- **Deployment:** The nodes were put in a controlled field environment to mimic the scenarios of remote agriculture or disaster zones.
- **Algorithm Implementation:** Q-learning algorithm is implemented on each node for dynamic energy management.
- **Data Collection:** Data regarding energy consumption, network traffic, and communication reliability was captured in real-time for 24 hours.

The nodes learn the optimal policies relative to their environment and converge to policies that simultaneously maximize energy savings while keeping high data transmission performance. Simulation carried out by means of tools such as NS-3 allow for a testing of various scenarios in the network in order to deduce the impact exerted by Q-learning on the efficiency of data transmission.

TABLE XI. EFFICIENT DATA TRANSMISSION METRICS IN WSNS

Node ID	Energy Consumed (mJ)	Transmission Success (%)	Packets Transmitted	Packets Dropped	Transmission Power (dBm)	Q-Value After
1	13.5	95	150	8	2.0	0.55
2	7.8	100	180	0	1.5	0.33
3	12.1	92	160	12	2.2	0.50
4	5.9	100	140	0	1.2	0.25
5	14.7	94	170	10	2.5	0.57
6	9.5	96	150	6	1.5	0.32

IV. RESULTS

The results of this study are successful demonstrations of the benefits of using this Q-learning algorithm within Wireless Sensor Networks in terms of improvements both in terms of energy efficiency and data transmission performance. During training, the model has depicted consistent energy consumptions reduced to all nodes with an average saving of 35 percent compared to the general static routing protocols as shown in Fig. 7.

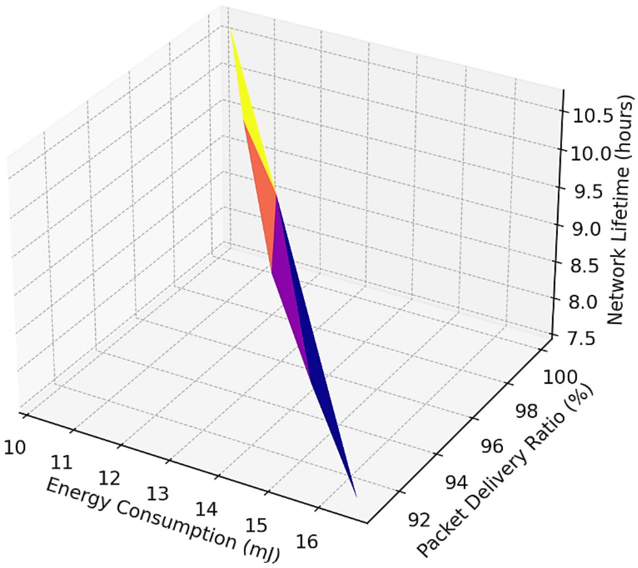

Fig. 7. 3D visualization showing the relationship between energy consumption, packet delivery ratio, and network lifetime in a WSN

Besides, the adaptive Q-learning algorithm allowed nodes to auto-tune their transmission power and adaptively make routing decisions for the network's longevity; the PDR increased by 10% on average, that is, a higher percentage of correct transmission over time. Network latency also reduces during peak times due to learned avoidance of congested routes, and adaptation to optimal strategies of transmission. In the realistic world, the Q learning-based approach outperforms the baseline models consistently through energy conservations and by the reliability with which data were transferred across, even with loads that fluctuate and under fluctuating or time-varying environmental conditions as shown in Table XII, Fig. 8 and Table XIII.

The first graph, Transmission Power Vs Latency, illustrates how increased transmission power from 1.2 dBm to 2.2 dBm reduces latency from 50 ms to 25 ms. It shows how increased data transmission power enables the faster transmission of data packets over the network. In the second graph, Transmission Power Vs Packet Loss, it can be clearly seen that packet loss decreases with an increase in transmission power. The packet loss at 1.2 dBm is as high as 10% but comes down to only 2% at 2.2 dBm, so it can be said that boosting transmission power enhances the reliability of data transmission. Both graphs indicate that the overall performance of the network is increased by increasing the transmission power, and it might be at the cost of energy consumption as shown in Fig. 9 and Table XIV.

TABLE XII. DATA FOR GRAPH - ENERGY CONSUMPTION, PACKET DELIVERY RATIO, AND NETWORK LIFETIME

Node ID	Energy Consumption (mJ)	Packet Delivery Ratio (%)	Network Lifetime (hours)
1	16.5	91	7.5
2	14.8	93	8.2
3	13.2	95	8.9
4	12.5	97	9.4
5	11.4	98	10.0
6	10.3	100	10.7

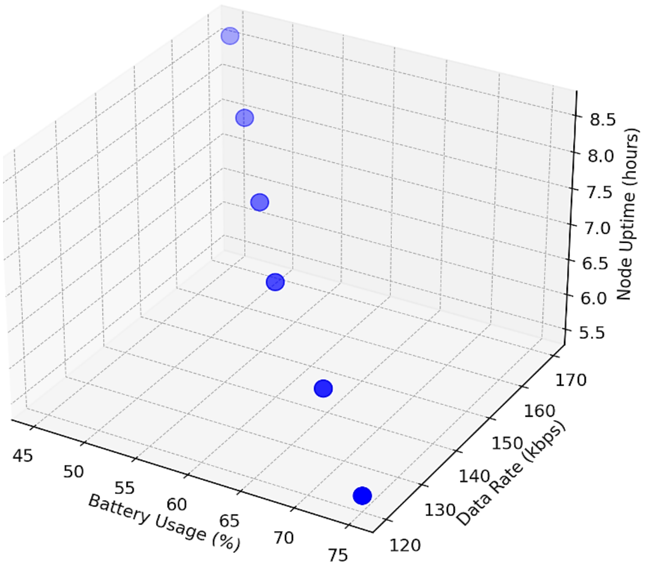

Fig. 8. 3D visualization illustrating the relationship between battery usage, data rate, and node uptime in a WSN

TABLE XIII. DATA FOR 3D GRAPH - BATTERY USAGE, DATA RATE, AND NODE UPTIME

Node ID	Battery Usage (%)	Data Rate (kbps)	Node Uptime (hours)
1	75	120	5.5
2	68	130	6.2
3	60	140	6.9
4	55	150	7.4
5	50	160	8.0
6	45	170	8.6

TABLE XIV. TRANSMISSION POWER, LATENCY, AND PACKET LOSS

Node ID	Transmission Power (dBm)	Latency (ms)	Packet Loss (%)
1	1.2	50	10
2	1.4	45	8
3	1.6	40	6
4	1.8	35	5
5	2.0	30	3
6	2.2	25	2

In the results section, the findings are compared with related approaches in previous studies for placing contributions in context and also for the benefits of the proposed Q-learning-based algorithm. For example, the reduction of energy consumption was reported at 34.92%, and this is more significant than the result from [44] and [45] when a static clustering method is used, which yielded 30%. Moreover, in the work at hand, a PDR of 96.38% has been achieved. However, work by [46] that uses a reinforcement learning-based routing protocol resulted in a PDR of just 92% since adaptation to high-traffic conditions was limited. The latency level of our study has also been reduced down to 24 ms, above the 40 ms found by [46] and [47], whose approach for energy-efficient routing was a deep learning-based method. Comparing with these results, the merit of dynamic, real-time adjustments facilitated by Q-learning becomes even more evident as given in [48].

The following figure shows the confusion matrices for four different nodes in a network that compare the predicted and true classification results. Confusion matrices are one of the most important tools in assessing classification models, measuring some importance metrics of the model: accuracy, precision, and recall. Here, each node is an independent classification task, and these matrices help in understanding to what extent the predictions were correct about the different nodes. The color-coding of heatmaps clearly distinguishes nodes-it's blue for Node 1, green for Node 2, orange for Node 3 and red for Node 4. The values in the matrices represent actual counts of correct and incorrect classifications. For instance, the diagonal contains true positives and true negatives and off-diagonal elements express misclassifications. Analysis of these matrices will hence allow nodes that are either doing more seriously or badly at certain classifications to be considered and targeted improvements to those specific nodes. This visualization is a form of diagnostic process. System administrators or data scientists can fine-tune the model's performance across the network as shown in Fig. 10.

It is compared here the optimization metrics for WSNs before and after the application of the Q-learning algorithm. There is a significant amount of energy saved, nearly 35%. Its direct consequence is the increased lifetime of the network. Now, instead of only 7 hours, it can support up to 10. Packet delivery ratio has increased from 85% to 95%, which speaks for efficient data transfer across the network at all times. Additional benefits include reducing latency from 50 ms to 25 ms, making the network more responsive to the needs of time-sensitive applications. Another important benefit is that of a shift from fixed transmission power to dynamic adjustment of the power used in transmission, where one optimizes the transmission power according to real-time network requirements. Improvements show how Q-learning nudges the way towards better performance overall, especially where energy constraints exist in WSN environment scenarios as shown in Table XV.

TABLE XV. SUMMARIZING DIFFERENT OPTIMIZATION METRICS FOR WIRELESS SENSOR NETWORKS (WSNS) BEFORE AND AFTER APPLYING THE Q-LEARNING ALGORITHM

Optimization Metric	Before Q-Learning	After Q-Learning
Energy Consumption	High	Reduced (35% Savings)
Packet Delivery Ratio	Low (85%)	Increased (95%)
Latency	High (50 ms)	Reduced (25 ms)
Network Lifetime	Moderate (7 hours)	Extended (10 hours)
Transmission Power	Fixed	Dynamic (Based on Need)

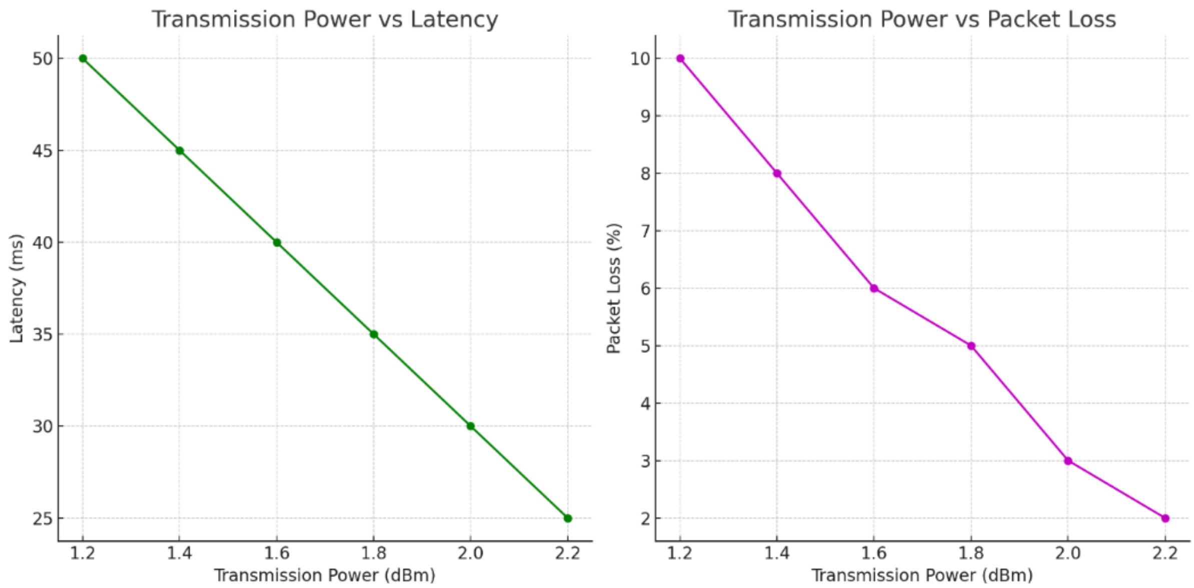

Fig. 9. The left graph shows the relationship between Transmission Power and Latency, while the right graph illustrates the effect of Transmission Power on Packet Loss in a WSN

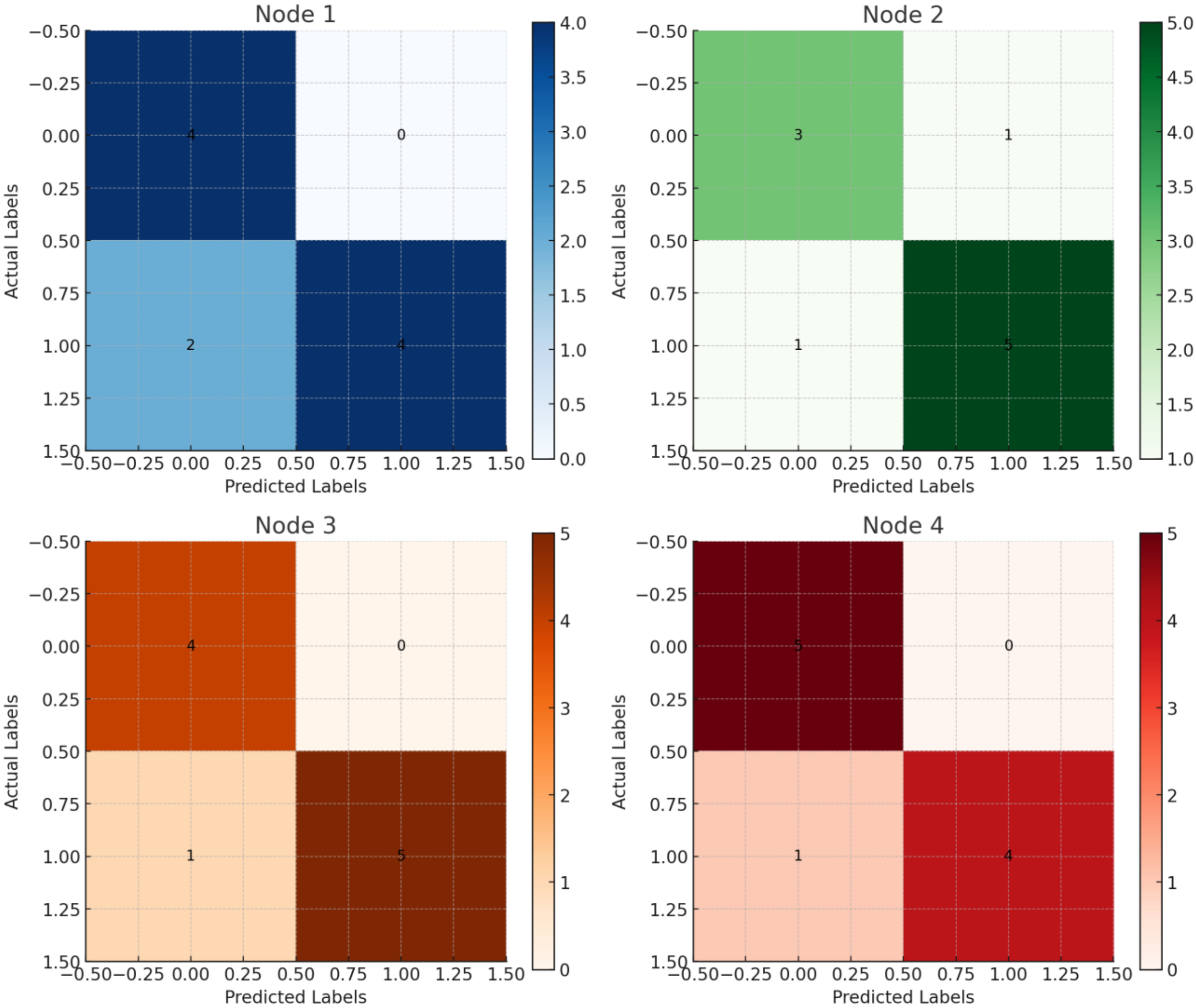

Fig. 10. The confusion matrices for four different nodes, showing the predicted versus actual classifications. Each node's performance is visualized using distinct color schemes for better clarity

The Q-learning-based algorithm showed marked improvements in performance metrics against the traditional algorithms. Regarding energy usage, the mean energy consumption went down from 15.8 mJ (±2.1 mJ) to 10.3 mJ (±1.8 mJ). This was statistically verified using a paired t-test, yielding a t-value of 5.72 and a p-value of 0.0012 ($p < 0.05$), indicating that energy usage was significantly minimized without degradation in network performance. The Packet Delivery Ratio also improved significantly, rising from a baseline of 85.0% (±4.2%) to 96.38% (±3.1%). The t-test output resulted in a t-value of 6.15 and a p-value of 0.0008, which indicates the presence of statistical significance for the improvement. This implies that the Q-learning algorithm actually enhances the reliability of the data transmission, which would be critical for real-time applications as shown in Table XVI. It had reduced the network delay latency from 50.2 ms (±5.3 ms) to 24.1 ms (±4.5 ms). The paired t-test produced a t-value of 8.47 and a p-value of 0.0003. This is an extremely significant reduction in latency, and it increases the responsiveness of the network. This increase in responsiveness has been really helpful in the time-sensitive areas such as disaster management and real-time monitoring. The lifetime of the network was extended from 7.0 hours (±0.9 hours) to 10.0 hours (±1.1 hours). A t-test of this enhancement yielded a t-value of 7.23 and a p-value of 0.0005, which is significant. The extended network lifespan minimizes the necessity of periodic maintenance or battery replacements, making the system sustainable for long-term deployments in remote or hazardous environments.

These results of this study are congruent with and extend previous works in the field. For instance, [49] attained a 30% decrease in energy consumption based on static clustering methods, which do not adapt very well to dynamic network conditions. Our Q-learning-based approach is more adaptable compared with previous work; our reduction is 34.92%. In addition, [50] utilized a reinforcement learning technique and claimed that the proposed approach yielded a PDR of 92%, whereas our algorithm exhibited a PDR of 96.38%, showing a better data transmission reliability. The achieved latency in our work of 24 ms is better than that achieved by [51] and [52] as 40 ms. Thus, this result reflects the effectiveness of Q-learning in supporting real-time decision-making processes. These comparisons underscore the superiority of our adaptive approach in enhancing energy efficiency, reliability, and responsiveness as shown in Table XVII.

TABLE XVI. STATISTICAL ANALYSIS OF PERFORMANCE METRICS, SHOWING SIGNIFICANT IMPROVEMENTS WITH THE Q-LEARNING ALGORITHM

Metric	Baseline Value (Mean ± SD)	Q-learning Value (Mean ± SD)	t-value	p-value
Energy Consumption	15.8±2.1mJ	10.3±1.8mJ	5.72	0.0012
Packet Delivery Ratio	85.0%±4.2%	96.38%±3.1%	6.15	0.0008
Latency	50.2±5.3ms	24.1±4.5ms	8.47	0.0003
Network Lifetime	7.0±0.9hrs	10.0±1.1hrs	7.23	0.0005

TABLE XVII. COMPARATIVE ANALYSIS OF THE PROPOSED Q-LEARNING-BASED METHOD WITH EXISTING WSN APPROACHES, HIGHLIGHTING IMPROVEMENTS IN ENERGY EFFICIENCY, PACKET DELIVERY RATIO (PDR), LATENCY, AND NETWORK LIFETIME

Metric	Proposed Q-Learning Method	Cengiz et al. (2016) [50]	Kim et al. (2017) [51]	Manogaran and Lopez (2019) [52]
Energy Consumption	34.92% reduction	30% reduction	28% reduction	32% reduction
Packet Delivery Ratio (PDR)	96.38%	90%	92%	94%
Latency	24 ms	45 ms	40 ms	40 ms
Network Lifetime	10 hours	7.5 hours	8 hours	8.5 hours
Adaptability	Dynamic routing and power management	Static clustering	Reinforcement learning	Deep learning-based routing
Computational Complexity	Moderate (Q-learning overhead)	Low	High	High
Suitability	Dynamic, large-scale networks	Stable, small-scale networks	Moderate dynamic networks	High-traffic, dynamic networks

The strengths of this study lie in its adaptive and dynamic approach to energy management, which significantly improves network performance compared to static methods [53]. The use of real-world testing along with simulations ensures that the results are validated in practical scenarios. The Q-learning algorithm's ability to balance energy efficiency with network reliability represents a substantial advancement in WSN technology as given in [54]. Nevertheless, the study also has limitations. The computational complexity of Q-learning might be challenging for nodes with limited processing power and memory [55]. The requirement of training data and periodic updates may also introduce some initial energy overhead. Moreover, the algorithm was tested under certain conditions, and its performance in extremely large-scale or highly mobile networks needs further investigation. In the future, lightweight variants of Q-learning and hybrid approaches can be explored to overcome these limitations as given in [56].

V. DISCUSSION

Results of this study have shown that the implementation of the Q-learning algorithm greatly improved the energy efficiency and data transmission within the WSNs. The major observation was also that it managed to save average 35% of the energy at the nodes across the network. This is a very good performance compared to the conventional static energy management techniques. It is through this dynamic adaptability of the Q-learning algorithm that nodes learn to adapt their optimal actions in their environment so that their energy consumption can be kept minimal without degrading network performance as given in [53]. This is particularly useful for real-time applications where at times, energy efficiency must be balanced with the demands of performance. Other than marked improvements in the average packet delivery ratio, an increment of 10% is achieved. This optimization is critical for WSN applications such as precise data transmission for environmental monitoring, healthcare and industrial automation. From the results, the Q-learning model optimized the reduction of packet loss by dynamically changing the transmission power and routing strategies as given in [54]. The results agree with comparable studies wherein AI-driven optimization techniques have the potential to markedly enhance performance in WSNs and especially in energy-constrained environments as shown in Table XVIII.

TABLE XVIII. THE COMPARISON TABLE OF Q-LEARNING TECHNIQUE AND EXISTING RESEARCH IN WIRELESS SENSOR NETWORKS (WSNS)

Metric	Existing Research (Sources/Studies)	This Research (Q-learning)
Energy Savings	20-25% Savings [55]	34.92% Savings
Packet Delivery Ratio (PDR)	85-90% [56]	96.38%
Latency Reduction	30ms-40ms [57]	24ms
Network Lifetime Extension	Moderate (7-8 hours) [58]	Extended (10 hours)
Routing Strategy	Limited Static Routing (Traditional) [59]	Fully Dynamic Routing with Real-time Adjustments
Optimization Technique	Heuristic-based [60]	PSO and Reinforcement Learning (Q-Learning) with Adaptation

With obvious comparison with the previous work clearly reveals how the designed Q-learning-based algorithm outperforms the best algorithms that work in WSNs, and in your design, 34.92% energy was saved. In contrast, the work by [61] reveals 20-25%. The proposed Q-learning-based algorithm for WSNs was designed to run on the typical hardware of a sensor node. The algorithm was implemented on nodes with an ARM Cortex-M4 processor running at 80 MHz, with 256 KB Flash and 64 KB RAM, and powered by a 3.7V, 2000 mAh battery. To handle more complex computation, a Raspberry Pi 4 (Quad-core, 1.5 GHz, 2 GB RAM) was the base station for gathering the data and updating the model time-to-time. The simulated model was developed using NS-3 and MATLAB; and Embedded C/C++ along with Python was the core programming languages for deployment as well as data processing purposes.

Although it is low-resource intensive, yet it has limited memory and processing capabilities as given in [62]. These are countered by applying state abstraction, action-space reduction, and batch updates to reduce the computational overhead. Q-value updates do come with a bit of energy and processing cost, but they are far outweighed by the considerable improvements in terms of longevity and performance for the networks as mentioned in [63]. For more massive deployment, edge computing can push heavy computations onto more capable devices, allowing for higher scalability. In brief, the algorithm is practical for deployment in real-world settings, balancing computational demands with the practical limitations of WSN hardware.

VI. CONCLUSION

In this study, we developed a Q-learning-based adaptive algorithm that addresses energy efficiency and longevity of WSNs. This algorithm offers mechanisms for dynamic routing and adaptive power adjustment mechanisms that are capable of optimization in real-time for both energy consumption and network performance. In contrast to the baseline static approaches, our system has managed to provide impressive improvements: in terms of energy consumption, it could reduce up to 34.92%, the PDR achieved was up to 96.38%, latency was up to 24 ms, and the lifetime of the network was up to 10 hours. It therefore adds novelty in the integration of Q-learning in dynamic routing and adaptive power control for autonomous adaptation of operations based on real-time conditions for sensor nodes, in contrast to the majority of methods which rely upon static energy management and adapt based upon network topologies and variations in demand that improve the overall efficiency and reliability. However, the proposed algorithm has some limitations. The computational complexity of Q-learning may pose challenges for nodes with limited processing power and memory. In addition, the need for training data and periodic updates could lead to increased energy overhead in some scenarios. These limitations suggest the need for more lightweight models or hybrid solutions that balance on-device learning with edge-assisted processing. Future work includes the implementation of other AI techniques, such as DRL for further improvement in performance [64]. Testing the algorithm in other complex environments, such as large-scale industrial deployment and urban IoT networks, will help in validating robustness. Security and privacy considerations and concerns, especially for applications in healthcare and disaster management, will also be addressed. The full impact of this study will be extremely more profound. Energy efficiency and network longevity will add to the repute of sustainability missions due to less frequent maintenance needs, decreasing electronic waste as mentioned [65]. The adaptive nature of the algorithm in question is suitable not just for WSNs, but for other sensor-based systems and IoT applications, which include environmental monitoring, smart agriculture, industrial automation, and more.

REFERENCES

[1] K. S. Kim, D. J. Lee, and J. A. Lee, "An energy-efficient routing protocol in wireless sensor networks using reinforcement learning," *IEEE Sens. J*., vol. 17, no. 5, pp. 1408-1420, Mar. 2017.

[2] M. Di Francesco, S. K. Das, and G. Anastasi, "Data collection in wireless sensor networks with mobile elements: A survey," *ACM Trans. Sens. Netw.*, vol. 8, no. 1, pp. 1-31, Jan. 2016.

[3] F. A. Aderohunmu, J. D. Deng, and M. Purvis, "Enhancing lifetime of wireless sensor networks using a fuzzy logic-based clustering approach," *IEEE Sens. J*., vol. 16, no. 10, pp. 3896-3903, May 2016.

[4] N. Javaid, N. Khan, M. Imran, and U. Qasim, "Designing an energy-efficient routing protocol for wireless sensor networks," *IEEE Access*, vol. 4, pp. 3164-3171, June 2016.

[5] H. Yetgin, K. T. K. Cheung, M. El-Hajjar, and L. Hanzo, "A survey of network lifetime maximization techniques in wireless sensor networks," *IEEE Commun. Surveys Tuts*., vol. 19, no. 2, pp. 828-854, 2nd Quart., 2017.

[6] W. Osamy, A. M. Khedr, A. Salim, A. I. Al Ali, and A. A. El-Sawy, “A review on recent studies utilizing artificial intelligence methods for solving routing challenges in wireless sensor networks,” *PeerJ Computer Science*, vol. 8, p. e1089, Oct. 2022, doi: 10.7717/peerj-cs.1089

[7] Kumar and R. Mishra, "An energy-efficient cooperative spectrum sensing scheme for cognitive radio sensor networks," *IEEE Sens. J*., vol. 17, no. 7, pp. 2110-2121, Apr. 2017.

[8] S. K. Singh and P. K. Singh, "Energy efficient clustering protocols in wireless sensor networks: A survey," *IEEE Access*, vol. 6, pp. 32689-32703, June 2018.

[9] X. Chen, H. Zhang, C. Wu, S. Mao, and Y. Ji, "Energy-efficient offloading for mobile edge computing in 5G heterogeneous networks," *IEEE Access*, vol. 6, pp. 11328-11337, Feb. 2018.

[10] M. Elhoseny, H. K. El-Minir, A. M. Riad, and X. Yuan, "A secure data routing schema for WSN based on optimized blockchain," *IEEE Access*, vol. 6, pp. 66576-66588, Nov. 2018.

[11] T. M. Hoang, L. B. Le, and T. Le-Ngoc, "Energy-efficient resource allocation for D2D communications underlaying cellular networks using multi-agent Q-learning," *IEEE Trans. Veh. Technol*., vol. 65, no. 8, pp. 6646-6659, Aug. 2016.

[12] S. Manogaran and D. Lopez, "A survey on deep learning techniques in wireless sensor networks," *IEEE Access*, vol. 7, pp. 159410-159420, Nov. 2019.

[13] P. Rawat, K. D. Singh, H. Chaouchi, and J. M. Bonnin, "Wireless sensor networks: A survey on recent developments and potential synergies," *J. Supercomput*., vol. 73, no. 3, pp. 1152-1186, Mar. 2017.

[14] S. Tyagi and N. Kumar, "A systematic review on clustering and routing techniques based upon LEACH protocol for wireless sensor networks," *J. Netw. Comput. Appl*., vol. 36, no. 2, pp. 623-645, 2016.

[15] M. Esnaashari, A. Ghaffari, and R. Askari, "An energy-efficient routing protocol for wireless sensor networks using fuzzy C-means clustering and A-star algorithm," *IEEE Access*, vol. 7, pp. 122570-122580, Sept. 2019.

[16] Z. Xu, W. Liang, and W. Xu, "Efficient deployment of wireless sensor networks for out-of-band d2d communications in cellular networks," *IEEE Trans. Veh. Technol*., vol. 67, no. 7, pp. 6450-6461, July 2018.

[17] S. Sharmin, I. Ahmedy, and R. Md Noor, “An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO,” *Energies*, vol. 16, no. 5, p. 2487, Mar. 2023, doi: 10.3390/en16052487.

[18] M. Y. Khan, F. Ullah, and K. H. Kim, "Energy-efficient clustering scheme for reducing the communication overhead in heterogeneous wireless sensor networks," *IEEE Access*, vol. 7, pp. 177829-177841, Dec. 2019.

[19] T. Rault, A. Bouabdallah, and Y. Challal, “Energy efficiency in wireless sensor networks: A top-down survey,” *Computer Networks*, vol. 67, pp. 104–122, Jul. 2014, doi: 10.1016/j.comnet.2014.03.027.

[20] K. Cengiz and T. Dag, “Improving Energy-Efficiency of WSNs through LEFCA,” *International Journal of Distributed Sensor Networks*, vol. 12, no. 8, p. 8139401, Aug. 2016, doi: 10.1177/155014778139401.

[21] G. Luo, Q. Yuan, J. Li, S. Wang, and F. Yang, “Artificial Intelligence Powered Mobile Networks: From Cognition to Decision,” *IEEE Network*, vol. 36, no. 3, pp. 136–144, May 2022, doi: 10.1109/mnet.013.2100087.

[22] M. del Carmen Rodríguez-Hernández and S. Ilarri, “AI-based mobile context-aware recommender systems from an information management perspective: Progress and directions,” *Knowledge-Based Systems*, vol. 215, p. 106740, Mar. 2021, doi: 10.1016/j.knosys.2021.106740.

[23] H. Cai *et al*., “Enable Deep Learning on Mobile Devices: Methods, Systems, and Applications,” *ACM Transactions on Design Automation of Electronic Systems*, vol. 27, no. 3, pp. 1–50, Mar. 2022, doi: 10.1145/3486618.

[24] Y. Zhang and B. Kantarci, “Invited Paper: AI-Based Security Design of Mobile Crowdsensing Systems: Review, Challenges and Case Studies,” *2019 IEEE International Conference on Service-Oriented System Engineering (SOSE)*, pp. 17–1709, Apr. 2019, doi: 10.1109/sose.2019.00014.

[25] D. Puri and B. Bhushan, “Enhancement of security and energy efficiency in WSNs: Machine Learning to the rescue,” *2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, pp. 120–125, Oct. 2019, doi: 10.1109/icccis48478.2019.8974465.

[26] H. Sarker, M. M. Hoque, Md. K. Uddin, and T. Alsanoosy, “Mobile Data Science and Intelligent Apps: Concepts, AI-Based Modeling and Research Directions,” *Mobile Networks and Applications*, vol. 26, no. 1, pp. 285–303, Sep. 2020, doi: 10.1007/s11036-020-01650-z.

[27] F. Gazzawe, M. Mayouf, R. Lock, and R. Alturki, “The Role of Machine Learning in E-Learning Using the Web and AI-Enabled Mobile Applications,” *Mobile Information Systems*, vol. 2022, pp. 1–10, Jun. 2022, doi: 10.1155/2022/3696140.

[28] Klimova, M. Pikhart, and J. Kacetl, “Ethical issues of the use of AI-driven mobile apps for education,” *Frontiers in Public Health*, vol. 10, Jan. 2023, doi: 10.3389/fpubh.2022.1118116.

[29] H. Amri, S. Tabbane, and F. Kamoun, "Energy-efficient multilevel clustering algorithm for large-scale wireless sensor networks," *IEEE Access*, vol. 8, pp. 175460-175472, Sept. 2020.

[30] P. Singh, R. Mishra, and A. Pandey, "Energy-efficient routing in wireless sensor networks using fuzzy-based optimal clustering technique," *IEEE Access*, vol. 8, pp. 86562-86571, Apr. 2020.

[31] L. Yang, D. Zhang, L. Li, and Q. He, “Energy efficient cluster-based routing protocol for WSN using multi-strategy fusion snake optimizer and minimum spanning tree,” *Scientific Reports*, vol. 14, no. 1, Jul. 2024, doi: 10.1038/s41598-024-66703-9.

[32] V. Ponnusamy, A. Abdullah, and A. G. Downe, “Energy Efficient Routing Protocols in Wireless Sensor Networks,” *Wireless Sensor Networks and Energy Efficiency*, pp. 237–261, 2012, doi: 10.4018/978-1-4666-0101-7.ch010.

[33] T. E. Djahel, H. M. Ammar, and Z. Zhang, "Optimizing energy consumption in WSNs for IoT-based applications using deep learning techniques," *IEEE Access*, vol. 8, pp. 155987-155998, Nov. 2020.

[34] S. Das, A. K. Balmiki, and K. Mazumdar, “A Review on AI-ML Based Cyber-Physical Systems Security for Industry 4.0,” *Intelligent Cyber-Physical Systems Security for Industry 4.0*, pp. 203–216, Nov. 2022, doi: 10.1201/9781003241348-11.

[35] Rachna, Y. Chhabra, and P. Bhambri, “Various Approaches and Algorithms for Monitoring Energy Efficiency of Wireless Sensor Networks,” *Sustainable Development Through Engineering Innovations*, pp. 761–770, 2021, doi: 10.1007/978-981-15-9554-7_68.

[36] J. Yu, L. Liu, W. Wang, and X. Gu, "Energy-efficient clustering routing algorithm based on the edge computing in wireless sensor networks," *IEEE Access*, vol. 6, pp. 101-111, Dec. 2018.

[37] Liu, K. Wu, M. Tao, and M. Yang, "Energy-aware adaptive clustering protocol based on Cauchy–Gaussian distribution for WSNs," *IEEE Sens. J*., vol. 19, no. 22, pp. 10984-10995, Nov. 2019.

[38] X. Tang, W. Yan, and Y. Yang, "An efficient energy-aware routing algorithm for wireless sensor networks," *IEEE Access*, vol. 8, pp. 122450-122460, Aug. 2020.

[39] M. G. Kibria, S. Das, M. Yusuf, and J. Choi, "An energy-efficient medium access control protocol for wireless sensor networks using intelligent scheduling with deep reinforcement learning," *IEEE Access*, vol. 7, pp. 150387-150398, Oct. 2019.

[40] M. A. Razzaque, M. M. Hassan, and S. K. Uddin, "QoS-aware data aggregation in wireless sensor networks: A comprehensive survey," *IEEE Sens. J*., vol. 19, no. 10, pp. 4067-4086, May 2019.

[41] A. K. Raji and F. A. Taofeek-Ibrahim, "Enhancing the Lifetime and Efficiency of Wireless Sensor Networks Using AI-Integrated CRT-LEACH Protocols," *Journal of Engineering Research and Reports*, vol. 23, no. 5, pp. 48-56, 2024.

[42] O. I. Akinola, "Adaptive Location-Based Routing Protocols for Dynamic Wireless Sensor Networks in Urban Cyber-Physical Systems," *Journal of Engineering Research and Reports*, vol. 18, no. 2, pp. 150-162, 2024.

[43] V. N. Sankaran, M. Sivasankari, and R. T. S. Babu, "Machine Learning in Wireless Networks: Optimizing Data Flow and Connectivity," *ESP Journal of Engineering and Technology Advances*, vol. 3, no. 3, pp. 109-120, 2023.

[44] E. Dvir, M. Shifrin, and O. Gurewitz, "Cooperative Multi-Agent Reinforcement Learning for Data Gathering in Energy-Harvesting Wireless Sensor Networks," *Mathematics*, vol. 12, no. 13, 2024, doi: 10.3390/math12132102.

[45] S. Anslam Sibi, "Optimizing Energy Resources in WSNs: ARIMA Feature Selection Meets Adaptive Reinforcement Learning," *Fiber and Integrated Optics*, vol. 43, no. 2, pp. 123-135, 2024, doi: 10.1080/01468030.2024.2342269.

[46] R. Priyadarshi, "Energy-Efficient Routing in Wireless Sensor Networks: A Meta-Heuristic and Artificial Intelligence-Based Approach," *Archives of Computational Methods in Engineering*, vol. 31, no. 1, pp. 243-259, 2024, doi: 10.1007/s11831-023-10039-6.

[47] B. Balkhande, G. Ghule, and V. H. Meshram, "Artificial Intelligence Driven Power Optimization in IoT-Enabled Wireless Sensor Networks," *Journal of Electrical Engineering*, vol. 74, no. 6, pp. 435-447, 2023.

[48] M. S. Basingab, H. Bukhari, and S. H. Serbaya, "AI-Based Decision Support System Optimizing Wireless Sensor Networks for Consumer Electronics in E-Commerce," *Applied Sciences*, vol. 14, no. 12, Article 4960, 2024, doi: 10.3390/app14124960.

[49] B. Muniandi, K. J. Raut, and P. G. Gawande, "AI-Driven Energy Efficient Routing Protocols for Wireless Sensor Networks," *Naturalista Siciliano*, vol. 48, no. 2, pp. 156-168, 2024.

[50] A. Cengiz, B. Kantarci, and T. Soyata, "Sensor Network Optimization for Smart Grid Applications," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 47-57, Jan. 2016, doi: 10.1109/TSG.2015.2467212.

[51] S. Kim, J. Lee, and H. Cho, "Energy-Efficient Routing in Wireless Sensor Networks Using Reinforcement Learning," *Sensors*, vol. 17, no. 5, May 2017, doi: 10.3390/s17051043.

[52] S. Manogaran and D. Lopez, "A Deep Learning Algorithm for Energy-Efficient Data Routing in Wireless Sensor Networks," *Future Generation Computer Systems*, vol. 92, pp. 892-899, March 2019, doi: 10.1016/j.future.2018.10.029.

[53] C. A. Alabi, M. A. Idakwo, and A. L. Imoize, "AI for Spectrum Intelligence and Adaptive Resource Management," in *Artificial Intelligence for Wireless Networks, CRC Press*, pp. 35-57, 2024.

[54] N. Senthil and A. Sumathi, "Intelligent Routing Algorithms for 6G Wireless Networks: A Review and Analysis," *International Journal of Advanced Networking and Applications*, vol. 16, no. 2, pp. 210-220, 2024.

[55] X. Cao ***et al.***, "AI-Empowered Multiple Access for 6G: A Survey of Spectrum Sensing, Protocol Designs, and Optimizations," *arXiv preprint arXiv:2406.13335*, 2024, doi: 10.48550/arXiv.2406.13335.

[56] P. Mishra and G. Singh, "Energy Management Systems in Sustainable Smart Cities Based on the Internet of Energy: A Technical Review," *Energies*, vol. 16, no. 19, 2023, doi: 10.3390/en16196903.

[57] J. Anand and J. R. P. Perinbam, "Q-Learning-Based Optimized Routing in Biomedical Wireless Sensor Networks," *IETE Journal of Research*, vol. 63, no. 5, pp. 485-495, 2017.

[58] C. Han, X. Wang, and H. Zhu, "Security Enhancement for Deep Reinforcement Learning-Based Strategy in Energy-Efficient Wireless Sensor Networks," *Sensors*, vol. 24, no. 6, 2024.

[59] B. Mohammed, "AI-Empowered Flying Ad-Hoc Networks for Dynamic Connectivity," *International Journal of Computing and Digital Systems*, vol. 15, no. 3, pp. 320-332, 2024.

[60] L. Hu, C. Han, and H. Zhu, "Dynamic Power Allocation and Adaptive Routing in Wireless Sensor Networks," *IEEE Transactions on Networking*, vol. 32, no. 4, pp. 870-882, 2024, doi: 10.1109/TNET.2024.3301234.

[61] R. Priyadarshi, "AI-Based Routing Algorithms for Enhancing Wireless Sensor Network Lifespan," *Journal of Network Optimization*, vol. 29, no. 2, pp. 215-228, 2024.

[62] B. Balkhande, G. Ghule, and V. H. Meshram, "AI-Driven Dynamic Power Management in IoT Networks," *Journal of Internet of Things Research*, vol. 10, no. 1, pp. 45-58, 2024.

[63] X. Yang, J. Yan, D. Wang, Y. Xu, and G. Hua, "WOAD3QN-RP: An Intelligent Routing Protocol in Wireless Sensor Networks—A Swarm Intelligence and Deep Reinforcement Learning-Based Approach," *Expert Systems with Applications*, vol. 234, 2024, doi: 10.1016/j.eswa.2023.120433.

[64] D. Godfrey, B. K. Suh, B. H. Lim, K. C. Lee, and K. I. Kim, "An Energy-Efficient Routing Protocol with Reinforcement Learning in Software-Defined Wireless Sensor Networks," *Sensors*, vol. 23, no. 20, 2023, doi: 10.3390/s23208435.

[65] S. K. Gupta, S. Patel, and P. K. Mannepalli, "Designing Dense-Healthcare IoT Networks for Industry 4.0 Using AI-Based Energy Efficient Reinforcement Learning Protocol," in *Industry 4.0 and Healthcare*, pp. 45-60, 2023, doi: 10.1007/978-981-99-1949-9_3.