Grenze International Journal of Engineering and Technology, January Issue

Energy Efficient Wireless Sensor Network with Machine Learning

Divya Singh
Department of Electronics and Communication, GLA University, Mathura
Email: divya.singh@gla.ac.in

***Abstract*— Wireless Sensor Networks (WSNs) face critical challenges in energy efficiency due to the limited power resources of sensor nodes. This paper presents a comprehensive analysis of how machine learning (ML) techniques can be leveraged to significantly reduce energy consumption and extend the operational lifetime of WSNs. Key strategies include feature selection through Recursive Feature Elimination (RFE), knowledge-based optimization models, multi-level energy-saving frameworks, and adaptive clustering and routing protocols. The paper also highlights the role of reinforcement learning and predictive models in dynamically managing network behavior to minimize redundant transmissions and enhance reliability. Performance metrics such as energy savings, latency reduction, network lifetime, and communication efficiency are evaluated across various ML-integrated approaches. Comparative analysis demonstrates that predictive models achieve up to 92.68% transmission suppression, clustering methods yield a 48.85% improvement in energy efficiency, and routing optimizations extend network stability by over 31%. The findings underscore the transformative potential of ML in creating intelligent, adaptive, and energy-efficient WSNs, laying the groundwork for future smart city and IoT applications.**

***Index Terms*— Wireless Sensor network, Machine Learning, Energy Efficiency and Reinforcement Learning.**

I. INTRODUCTION

Energy efficiency in wireless sensor networks (WSNs) is a critical challenge due to the inherent limitations of sensor nodes, which frequently run on limited power from batteries. This constraint necessitates the consideration of energy-efficient techniques to extend the networks lifetime [1]. Machine learning has emerged as a powerful solution to address these energy challenges across multiple aspects of WSN operation.

II. KEY APPROACHES AND TECHNIQUES

A. Feature Selection and Optimization

Machine learning approaches utilize sophisticated feature selection methods to optimize energy consumption. An integrated approach has been presented to improve the energy efficiency of Wireless Sensor IoT Networks (WSINs) by using modern machine learning algorithms with stochastic optimization. Recursive Feature Elimination (RFE) is utilized for the feature selection thus optimizing the input features for various machine learning models.

Grenze ID: 01.GIJET.12.1.7

Research shows that RFE-driven feature selection has significant effects on model performance and that Random Forest is effective at reaching higher accuracy [1].

B. Knowledge-based Learning Models

Industrial applications have benefited from enhanced energy optimization models. Machine Learning techniques have been used to create an enhanced energy optimization model for Industrial WSNs. This model utilizes knowledge-based learning to identify and optimize the energy consumption of the nodes, allowing Industrial WSNs to consume the least amount of energy for the given tasks. These models demonstrate impressive results, with 64.72% transmission energy consumption, 35.28% transmission energy saving, 67.27% received energy consumption, 32.73% received energy storage [2].

C. Multi-level Energy Saving Frameworks

Advanced frameworks implement multi-phase energy saving strategies. An energy-saving framework for Wireless Sensor Networks (WSN) using machine learning techniques and meta-heuristics according to environmental states has been proposed. First, network-level energy saving, called N1-energy saving, is achieved by finding the minimum sensor nodes needed to ensure the performance of the WSN. Second, energy savings of the WSNs by manipulating the sampling rate and the transmission interval of the sensor nodes to achieve node-level energy saving, which is referred to as N2-energy saving [3].

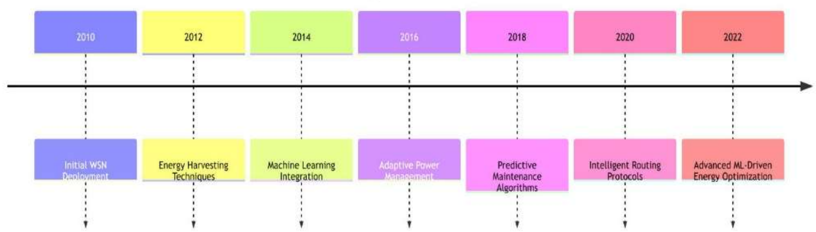

Figure 1: Time line picture of energy efficient wireless sensor network

III. MACHINE LEARNING ALGORITHMS AND APPLICATIONS

A. Clustering and Routing Optimization

Machine learning significantly improves clustering algorithms for WSNs. The k-means clustering algorithm, which comes under the unsupervised machine learning method, is incorporated with the LEACH algorithm and has shown better results. This paper proposes the modified k-means algorithm with LEACH protocol for optimizing the Wireless Sensor Network. The results show 48.85% efficiency compared to the existing protocol [4].

B. Reinforcement Learning Applications

Reinforcement learning offers dynamic optimization capabilities. One of the most important topics in field wireless sensor networks is development approaches to improve network lifetime. This algorithm based on reinforcement learning energy management network. seeks optimize policies maximize long-term reward received by each node, using learning, which a machine approach [5].

C. Predictive Models for Data Collection

Machine learning enables predictive approaches to reduce redundant data transmission. Data prediction algorithms in WSNs have become crucial for reducing redundant data transmission and extending the network's longevity. Redundancy can be decreased using proper machine learning (ML) techniques while the data aggregation process operates. Advanced models like The Dual Graph Convolutional Network (DGCN) is an analytical method that predicts future trends using time series data [6] achieve remarkable results with transmission suppression rate of 92.

III. PERFORMANCE IMPROVEMENTS AND RESULTS

A. Energy Consumption Reduction

Modern ML-based protocols demonstrate significant energy savings. The system integrates adaptive duty cycling, context-aware routing, and machine learning, considerably boosting energy efficiency, lowering latency, and increasing overall reliability. The average energy consumption is reduced from 173 to 108 units/joule, the average latency is reduced from 37 to 21.7 milliseconds, and the average reliability is increased from 85% to 90.3% [7].

B. Network Lifetime Extension

Machine learning approaches significantly extend network lifetime. Multi-hop Low Energy Adaptive Clustering Hierarchy (MHLEACH) protocol is proposed. MHLEACH protocol enhances the routing process through a multi-hop cluster-based approach by utilizing an optimization Ant Colony algorithm to efficiently determine the optimal shortest path to the base station. It extended the stability period of the network by approximately %31.3 compared to the original LEACH [8].

C. Adaptive Environmental Response

ML enables environmental adaptation for energy efficiency. Energy efficiency is achieved through techniques such as duty cycling, low-power communication modes, and dynamic sleep scheduling, which collectively reduce energy consumption and extend battery life. Adaptability is ensured by opportunistic and topology-aware routing strategies that dynamically adjust to real-time network conditions [9]. From the above comprehensive analysis, the following issues were identified and listed in table.1

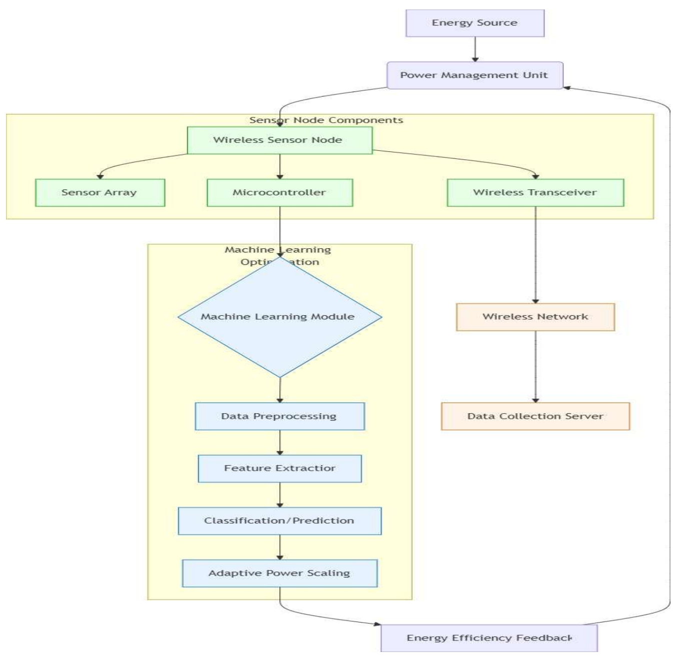

Figure 2: Flow diagram of energy efficient wireless sensor network

TABLE I: COMPREHENSIVE ANALYSIS

Paper Title	Authors	Year	ML Technique	Primary Approach	Key Performance Metrics	Energy Savings	Network Lifetime
AI-Based Wireless Sensor IoT Networks for Energy-Efficient Consumer Electronics Using Stochastic Optimization [1]	Fahad Masood et al.	2024	Recursive Feature Elimination (RFE) with Random Forest [1]	Integrated approach using modern ML algorithms with stochastic optimization [1]	RFE-driven feature selection shows significant effects on model performance with Random Forest achieving higher accuracy [1]	Not specified	Not specified

An Enhanced Energy Optimization Model for Industrial WSNs Using Machine Learning [2]	A. Bagwari et al.	2023	Knowledge-based learning to identify and optimize energy consumption [2]	Enhanced energy optimization model for Industrial WSNs [2]	90.44% prevalence threshold, 90.33% critical success index, 93.93% Delta-P, 90.06% MCC and 92.17% FMI rates [2]	35.28% transmission energy saving, 32.73% received energy storage, 47.84% idle-mode energy storage, 33.69% sleep-mode energy storage [2]	Not specified
Machine Learning-Based Energy-Saving Framework for Environmental States-Adaptive WSN [3]	Jaewoong Kang et al.	2020	Hybrid filter-wrapper feature selection with Simulated Annealing [3]	Two-phase energy savings using ML techniques and meta-heuristics [3]	Effective sensor node selection with minimal performance loss while maintaining QoS through optimal sampling rate and transmission interval [3]	N1-energy saving (network-level) and N2-energy saving (node-level) [3]	Not specified
Energy-Efficient Communication Protocols for 6G Wireless Sensor Network [4]	K. Leela Ranganayagi et al.	2024	Machine learning with adaptive duty cycling and context-aware routing [4]	Novel communication protocol for 6G-enabled WSNs integrating ML [4]	Average latency reduced from 37 to 21.7 ms, reliability increased from 85% to 90. [4]3%	Energy consumption reduced from 173 to 108 units/joule [4]	Not specified
Optimization of LEACH Protocol in WSN Using Machine Learning [5]	S. Ramesh et al.	2022	K-means clustering (unsupervised ML) with modified LEACH [5]	Modified k-means algorithm with LEACH protocol using weight-based cluster head selection [5]	48.85% efficiency compared to existing protocol with more successful data transfer [5]	48.85% efficiency improvement [5]	Optimistically balanced network in terms of energy [5]
A Robust and Energy Efficient Opportunistic Routing Protocol Design over WSN [6]	S. Shifani et al.	2024	Machine learning for smarter decision-making processes [6]	Duty cycling, low-power communication modes, dynamic sleep scheduling with opportunistic routing [6]	Packet delivery ratios: 95% with error detection, 97% with error correction, 99% with route redundancy [6]	Techniques collectively reduce energy consumption and extend battery life [6]	Extended battery life
A Prediction Model Based Energy Efficient Data Collection for WSNs [7]	Balakumar D, Rangaraj J	2023	Extreme Learning Machine (ELM) with Dual Graph Convolutional Network (DGCN) [7]	Adaptive Seagull Optimization Algorithm (ASOA) for cluster head selection [7]	Transmission suppression rate of 92.68%, difference of 22.33%, 16.69%, and 12.54% compared to existing methods [7]	92.68% transmission suppression rate [7]	Extending network's longevity through reduced redundant data transmission [7]
RLBEEP: Reinforcement-Learning-Based Energy Efficient Control and Routing Protocol [8]	Ali Forghani Elah Abadi et al.	2022	Reinforcement learning for energy management network to maximize long-term reward [8]	Three approaches: route optimization, sleep scheduling, and data transmission control [8]	Method significantly outperforms previous reported methods in terms of lifespan [8]	Not specified	Significantly improved network lifetime [8]

Machine Learning-Based Energy Optimization Routing Protocol For WSNs [9]	Amhmed Bhih	2024	Ant Colony optimization algorithm for optimal shortest path determination [9]	Multi-hop Low Energy Adaptive Clustering Hierarchy (MHLEACH) protocol [9]	Extended stability period by approximately 31.3% compared to original LEACH [9]	Not specified	31.3% improvement in network stability period [9]

TABLE II: KEY PERFORMANCE INDICATORS COMPARISON

Metric	Best Performance	Paper
Energy Savings	92.68% transmission suppression [7]	Prediction Model Based Data Collection
Efficiency Improvement	48.85% efficiency gain [5]	LEACH Protocol Optimization
Network Lifetime	31.3% stability period extension [9]	MHLEACH Protocol
Reliability	99% packet delivery with route redundancy [6]	Opportunistic Routing Protocol
Latency Reduction	37 to 21.7 ms (41.4% reduction) [4]	6G Communication Protocols

This comparison reveals that machine learning approaches significantly enhance energy efficiency in WSNs, with predictive models achieving the highest energy savings and clustering-based approaches providing substantial efficiency improvements.

IV. FUTURE DIRECTIONS AND APPLICATIONS

The field is evolving toward more sophisticated applications. Machine Learning techniques as optimization methods for WSN-IoT nodes (Network of sensors) that are used in Smart City initiatives have been proposed. The algorithms used varied in context of type as shown by results suggesting supervised learning (61%) for smart city applications, unsupervised learning (12%), and reinforcement learning (27%) [10]. Research indicates that techniques can quickly adapt environmental changes integrate multiple factors for decisions, which provides new ideas intelligent energy-efficient [11] solutions, overcoming the limitations of traditional green routing algorithms that usually have problems poor flexibility, single consideration factor, reliance on accurate mathematical models.

The integration of machine learning with wireless sensor networks represents a paradigm shift toward intelligent, adaptive, and highly energy-efficient systems that can significantly extend network lifetime while maintaining or improving performance metrics across various applications.

III. CONCLUSIONS

Machine learning has emerged as a pivotal technology for addressing energy efficiency in Wireless Sensor Networks by enabling intelligent decision-making and dynamic system adaptation. This study has illustrated how ML techniques—ranging from feature optimization and reinforcement learning to predictive analytics and hybrid protocols—enhance energy conservation and extend network longevity. Performance evaluations across multiple research efforts reveal notable advancements: predictive data collection methods yield the highest energy savings, modified clustering protocols significantly improve operational efficiency, and adaptive routing strategies extend network lifespan. As the demand for sustainable and scalable sensor networks grows, especially in the context of smart cities and industrial IoT, the integration of ML will be instrumental in overcoming the limitations of traditional energy management schemes. Future research should continue exploring hybrid models and context-aware learning to further optimize performance in diverse environmental and application-specific scenarios.

REFERENCES

[1] Masood, Fahad, Khan, Muhammad Abbas, Alshehri, Mohammed S., Ghaban, Wad, Saeed, Faisal, Albarakati, Hussain Mobarak, and Alkhayyat, A.. 2024. "AI-Based Wireless Sensor IoT Networks for Energy-Efficient Consumer Electronics Using Stochastic Optimization". IEEE transactions on consumer electronics. https://doi.org/10.1109/TCE.2024.3416035

[2] Bagwari, A., Logeshwaran, J., Usha, K., Raju, K., Alsharif, Mohammed H., Uthansakul, P., and Uthansakul, M.. NaN. "An Enhanced Energy Optimization Model for Industrial Wireless Sensor Networks Using Machine Learning". IEEE Access. https://doi.org/10.1109/ACCESS.2023.3311854

[3] Kang, Jaewoong, Kim, Jongmo, Kim, Minhwan, and Sohn, Mye M.. NaN. "Machine Learning-Based Energy-Saving Framework for Environmental States-Adaptive Wireless Sensor Network". IEEE Access. https://doi.org/10.1109/ACCESS.2020.2986507

[4] Ramesh, S., Rajalakshmi, R., Dwivedi, J., Selvakanmani, S., Pant, B., Kumar, N. Bharath, and Demssie, Zelalem Fissiha. 2022. "Optimization of Leach Protocol in Wireless Sensor Network Using Machine Learning". Computational Intelligence and Neuroscience. https://doi.org/10.1155/2022/5393251

[5] Abadi, Ali Forghani Elah, Asghari, Seyyed Amir, Marvasti, Mohammadreza Binesh, Abaei, Golnoush, Nabavi, Morteza, and Savaria, Yvon. 2022. "RLBEEP: Reinforcement-Learning-Based Energy Efficient Control and Routing Protocol for Wireless Sensor Networks". Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/access.2022.3167058

[6] D, Balakumar and J, Rangaraj. 2023. "A Prediction Model Based Energy Efficient Data Collection for Wireless Sensor Networks". Journal of Machine and Computing. https://doi.org/10.53759/7669/jmc202303031

[7] Ranganayagi, K.Leela, Aravind, T., Kumar, S. P., Ramya, S., Lingaraja, D., and Dinesh, G.. 2024. "Energy-Efficient Communication Protocols for 6G Wireless Sensor Network". None. https://doi.org/10.1109/ICNWC60771.2024.10537356

[8] Bhih, Amhmed. 2024. "Machine Learning-Based Energy Optimization Routing Protocol For Wireless Sensor Networks". None. https://doi.org/10.1109/MI-STA61267.2024.10599684

[9] Shifani, S., S.Maheswari, Mary, A. A., Metilda, M., Rajkumar, G., and Sutha, Muppudathi. 2024. "A Robust and Energy Efficient Opportunistic Routing Protocol Design over Wireless Sensor Network to Enhance Communication Performance". None. https://doi.org/10.1109/GCCIT63234.2024.10862723

[10] N, Basavaraj G, Kumar, J. V. R., Jayareka, K. S., Sivakumar, T. B., Balaji, Raja Rajeswari, and Abinaya, A. B.. 2024. "Machine Learning in Smart Cities: Survey of Wireless Sensor Network Applications". None. https://doi.org/10.1109/I3CEET61722.2024.10993915

[11] Ding, Qianao, Zhu, Rongbo, Liu, Hao, and Ma, Maode. 2021. "An Overview of Machine Learning-Based Energy-Efficient Routing Algorithms in Wireless Sensor Networks". Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/electronics10131539