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Increase The Effectiveness of Sensing Capacities of WSN Through AI: A Systematic Review

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ABSTRACT

This systematic review examines the integration of Artificial Intelligence (AI) techniques to enhance the sensing capacities of Wireless Sensor Networks (WSNs). Through these challenges such as energy efficiency, scalability, and data reliability, AI-driven methodologies improve network performance in real-world applications including smart cities and industrial automation. The review synthesizes research on innovative charging architectures, data aggregation, dynamic routing, and predictive maintenance. Evidence indicates that AI models ranging from deep learning to reinforcement learning significantly optimize energy management, sensor data processing, and fault detection. These advancements promise more resilient, adaptive, and efficient WSN deployments for emerging IoT ecosystems with promising future potential. This paper basically the basic reviews towards the effectiveness of Sensing capacities of WSN through AI.

Keywords : Wireless Sensor Networks, Artificial Intelligence, Energy Efficiency, Adaptive Routing

I. Introduction

Wireless Sensor Networks (WSNs) have become an integral part of modern technology, bridging the gap between the physical and digital worlds through real-time environmental monitoring, smart city applications, industrial automation, and more. However, as WSNs are increasingly deployed in diverse and often harsh environments, a number of challenges emerge chief among them being energy efficiency, scalability, data reliability, and network longevity. In recent years, the rapid evolution of Artificial Intelligence (AI) techniques has paved the way for transformative solutions to these challenges, significantly enhancing the sensing capacities and overall performance of WSNs. This introduction synthesizes an extensive body of research that explores the convergence of WSN technologies with AI methodologies, and it outlines how AI-driven strategies can increase the effectiveness of sensing capacities in WSNs.

Early research in the domain laid a critical foundation by addressing energy replenishment challenges in WSNs. For instance, Wang et al. (2015) explored wireless charging techniques to overcome energy limitations in sensor networks. Their work underscored the physical constraints of previous approaches that permitted only single-node recharging, thereby limiting both efficiency and scalability. By introducing a novel architecture that employed resonant repeaters for multi-hop wireless charging, they opened new avenues for enhancing energy availability across the network. This innovative strategy, which balanced energy efficiency with data latency through a hybrid data collection method, set the stage for subsequent studies that sought to integrate AI into these energy management processes.

Parallel to energy replenishment efforts, research into data processing and transmission within WSNs also evolved. ZainEldin et al. (2015) delved into the challenges of handling voluminous multimedia data, particularly focusing on image compression in Wireless Multimedia Sensor Networks (WMSNs). They demonstrated that due to high pixel correlation, images often contained redundant information that could be compressed effectively, thereby reducing power consumption and extending the operational life of sensor nodes. This emphasis on minimizing data volume without compromising on the quality of sensed information is a recurring theme in the literature and provides a clear rationale for employing AI-based techniques. By optimizing data processing, AI not only facilitates efficient data transmission but also ensures that critical sensing information is relayed accurately and promptly.

The role of AI in managing communication protocols and data aggregation has also been a focal point of investigation. Phung et al. (2015) examined how WSNs, as integral elements of the Internet of Things (IoT), are burdened by interference and competition for wireless media. Their schedule-based multi-channel communication protocol sought to mitigate these issues by leveraging advanced synchronization and scheduling techniques. Such work laid the groundwork for subsequent AI implementations aimed at dynamically adapting network protocols in response to fluctuating network conditions. Similarly, Kumar and Singh (2018) evaluated AI-driven data aggregation techniques, emphasizing the integration of neural networks and fuzzy logic to enhance network longevity and performance. These methodologies showcased how AI can be harnessed to process data in a manner that minimizes energy consumption and maximizes throughput, while also addressing the inherent NP-hard challenges associated with optimizing routing and data collection strategies.

Another significant thrust in the literature concerns the deployment of advanced energy management strategies that integrate AI with optimization algorithms. He et al. (2016) tackled the problem of maximizing data flow in rechargeable WSNs by introducing auxiliary chargers with wireless power transfer capabilities. Their formulation of the problem as a mixed-integer linear program (MILP) and the subsequent development of meta-heuristic solutions highlighted the potential of combining

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conventional optimization techniques with AI-driven heuristics. These solutions not only enhance the energy recharging rate but also ensure that the most critical nodes within the network are prioritized, thereby sustaining overall network performance. This integration of AI into energy management is crucial for the development of self-healing and adaptive WSNs capable of sustaining prolonged operation in energy-constrained environments.

The concept of cognitive radio sensor networks (CRSNs) further exemplifies the potential of AI in enhancing the sensing capacities of WSNs. Ren et al. (2016) investigated the challenges of dynamic channel access in congested unlicensed spectrums. By proposing opportunistic channel access strategies that account for the energy overhead of cognitive radio functions, their work underscored the delicate balance between energy consumption and communication efficiency. AI algorithms can further optimize these strategies by learning from environmental patterns and predicting channel availability, thereby reducing the energy costs associated with frequent channel switching and ensuring more reliable data transmission.

While the optimization of energy and communication channels remains a central concern, the integration of AI into network security and fault tolerance represents another critical area of advancement. Menaria et al. (2020) addressed the vulnerability of WSNs to failures and malicious attacks by developing the NLFFT model, which utilizes AI to improve fault tolerance through adaptive routing and robust fault detection algorithms. Similarly, Birahim et al. (2025) introduced an innovative intrusion detection system (IDS) that employed Particle Swarm Optimization (PSO) alongside an ensemble machine learning approach. This IDS not only demonstrated exceptional accuracy in identifying network anomalies but also provided an explainable framework through techniques like LIME and SHAP. Such approaches highlight how AI can secure WSNs, ensuring that sensing operations remain uninterrupted and reliable even in the face of evolving threats.

Moreover, the incorporation of deep learning and reinforcement learning into WSN management has opened new frontiers for real-time decision-making and network adaptability. Lu et al. (2019) showcased a traffic-control system for WSNs that utilized deep reinforcement learning to dynamically manage sensor node activity, thereby reducing energy consumption and improving network responsiveness. In parallel, Hadi et al. (2025) demonstrated that Q-learning a form of reinforcement learning could significantly enhance energy management and routing in WSNs. These studies collectively illustrate that deep learning and reinforcement learning not only improve the immediate operational efficiency of sensor networks but also enable a level of autonomous decision-making that is essential for future large-scale and dynamic IoT deployments.

In addition to energy and communication optimizations, AI is also playing a transformative role in sensor data processing and contextual understanding. Mukhopadhyay et al. (2021) emphasized that the future of IoT and WSNs lies in the development of intelligent sensors that are capable of context-aware data processing. These sensors leverage AI to detect patterns, anticipate environmental changes, and adjust operational parameters in real time. This ability to perform on-the-fly adjustments based on sensed data is critical for applications ranging from industrial automation to smart healthcare, where timely and accurate decision-making can have far-reaching implications.

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As the literature indicates, the deployment of AI techniques in WSNs is not confined to theoretical models or controlled experiments. Real-world applications, such as smart city infrastructures, agricultural monitoring, and industrial control systems, are beginning to benefit from these advances. For instance, Ahmed et al. (2022) applied deep learning architectures to develop a resource allocation strategy that balanced energy efficiency with spectral efficiency in heterogeneous WSNs. Their work illustrated that AI-driven solutions can lead to substantial improvements in network throughput, quality of service, and overall system sustainability. Similarly, Benfradj et al. (2024) and Priyadarshi (2024) provided comprehensive reviews that emphasized how AI could be instrumental in addressing longstanding challenges in WSNs, from routing optimization to dynamic reconfiguration.

The evolution of WSNs from static, energy-constrained networks to dynamic, self-managing systems is being propelled by the integration of Artificial Intelligence. Through AI techniques ranging from neural networks and fuzzy logic to deep reinforcement learning and meta-heuristics, researchers have begun to address the multifaceted challenges of energy management, data aggregation, communication, security, and fault tolerance in WSNs. The confluence of AI and WSN technology not only enhances the sensing capacities of individual sensor nodes but also improves the overall robustness, efficiency, and scalability of the network. As research continues to evolve, AI-driven solutions promise to unlock unprecedented levels of performance in WSNs, ensuring that these networks remain resilient, adaptive, and capable of meeting the demands of tomorrow's interconnected world.

II. Literature Reviews and Findings

Author	Objective	Methodology	Key Findings
Wang et al. (2015)	Wireless charging in sensor networks	Introduced resonant repeaters for multi-hop charging; formulated a bi-objective NP-hard optimization with a two-phase approximation; hybrid static/mobile data collection model	Enhanced charging efficiency and scalability; supported at least 3× more nodes with reduced service interruption
ZainEldin et al. (2015)	Image compression in Wireless Multimedia Sensor Networks (WMSN)	Surveyed and analysed various image compression techniques	Identified strengths/limitations of existing algorithms; emphasized power consumption as key and proposed open research questions
Phung et al. (2015)	Multi-channel communication in WSNs	Developed a schedule-based multi-channel protocol with low-overhead time synchronization	Achieved collision-free parallel transmissions, high throughput, and improved energy efficiency
He et al. (2016)	Maximizing data flow in rechargeable WSNs	Formulated a MILP and proposed three auxiliary charger (AC) placement strategies (Path, Tabu, LagOP)	Tabu strategy reached 99.40% of MILP-derived maximum flow rate
Ren et al. (2016)	Dynamic channel access in Cognitive Radio Sensor Networks (CRSNs)	Analysed resource allocation and proposed two dynamic channel access algorithms	Significantly reduced energy consumption and improved energy efficiency in CRSNs
Deng et al. (2016)	Data collection using multiple sinks in WSNs	Proposed a suboptimal online algorithm via a primal-dual approach with a competitive ratio analysis	Demonstrated trade-offs between performance and complexity in dynamic sink deployment scenarios

Matlou & Abu-Mahfouz (2017)	Software-Defined WSN (SDWSN) integrating AI	Reviewed integration of SDN concepts into WSNs and explored AI/machine learning applications	Highlighted potential improvements in network management, security, and routing reliability
Pan et al. (2017)	Simultaneous Wireless Information and Power Transfer (SWIPT) in WSNs	Employed temporal (TS) and power splitting (PS) strategies; derived outage probability and capacity expressions	Proposed an optimal partitioning strategy to maximize throughput and enhance energy efficiency
Liu (2017)	Connection restoration in partitioned WSNs	Developed load equilibrium and reliability improvement strategies, focusing on optimal stopping locations for mobile nodes	Enhanced network longevity and reduced the risk of connection failures
Kumar & Singh (2018)	AI-based data aggregation in WSNs	Utilized neural networks and fuzzy logic; compared with ACO and PSO techniques	Improved network lifespan and performance through enhanced aggregation strategies
Abdulsahib & Khalaf (2018)	Fire detection using WSNs	Deployed temperature sensors with a wake/sleep scheduling system and network partitioning	Increased battery longevity by 3.7% and improved power performance by 69% compared to conventional methods
Doibale & Kurundkar (2019)	Congestion control in WSNs	Proposed an AI-based blockage control strategy with proactive congestion prevention and alternate route routing	Enhanced network efficiency by reducing congestion and improving data delivery reliability
Lu et al. (2019)	Traffic control in WSNs	Applied deep reinforcement learning to formulate optimal travel paths for dynamic traffic management	Demonstrated effective energy consumption reduction and traffic management in sensor networks
Ai et al. (2019)	Physical layer security in WSNs	Used a Poisson point process to derive new expressions for secrecy capacity and outage probability	Highlighted how node density and transmission power influence secrecy performance
Kim et al. (2020)	Machine learning for dynamic task management in WSNs	Utilized deep learning to extract advanced features from raw sensor data	Achieved reduced computational complexity and improved energy efficiency
Amutha et al. (2020)	Deployment, energy efficiency, and coverage in WSNs	Reviewed various sensor types, deployment strategies, and sensing models	Identified current challenges and active research areas, noting the absence of a universal solution
Menaria et al. (2020)	Fault tolerance in WSNs	Introduced the NLFFT model combining an improved quadratic minimum spanning tree (Imp-QMST) and enhanced handoff (Imp-Handoff) algorithm	Improved throughput (by ~6–7%), reduced latency and power consumption
Mukhopadhyay et al. (2021)	AI-driven sensors for next-generation IoT applications	Reviewed integration of sensors with AI for context-aware, intelligent decision-making	Emphasized the importance of interconnectivity, trustworthiness, and resilience in smart sensor networks
Sharma et al. (2021)	ML applications in WSNs for smart cities	Analysed supervised, reinforcement, and unsupervised learning approaches in low-power sensor nodes	Found supervised learning to be most prevalent (61%), enhancing energy efficiency and network management
Agarwal et al. (2021)	Energy optimization in WSNs using AI	Explored AI strategies for improved message aggregation and routing algorithm optimization	Demonstrated enhanced energy utilization and extended network lifespan

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Ahmed et al. (2022)	Resource allocation in IoT-based WSNs	Deployed deep learning enhanced by whale optimization and a multi-objective firefly method for data optimization	Achieved high throughput (96%), superior energy efficiency (95%), and extended network lifespan (91%)
Osamy et al. (2022)	AI methods for routing challenges in WSNs	Conducted a comprehensive review of AI-based routing techniques applied from 2010 to 2020	Provided detailed comparisons of methodologies and identified key research gaps
Raja et al. (2023)	Distributed AI in WSNs	Explored multi-agent systems and evolutionary learning for cooperative sensor networks	Enhanced coordination, task distribution, and secure, adaptive interactions
Balkhande et al. (2023)	AI-driven power optimization in IoT-enabled WSNs	Combined Deep Q-Network (DQN) with Dynamic Voltage and Frequency Scaling (DVFS) for real-time power management	Reported significant energy savings and prolonged network lifespan through adaptive optimization
Ghareeb et al. (2023)	Precision irrigation using WSNs	Reviewed IoT integration with advanced control techniques for irrigation monitoring	Highlighted improved water utilization and identified current research trends and gaps
Benfradj et al. (2024)	AI integration for dynamic WSN reconfiguration	Reviewed AI techniques (supervised, unsupervised, reinforcement) applied to WSN energy sustainability	Organized past literature, assessed strengths/limitations, and outlined future research directions
Priyadarshi (2024)	Energy-efficient routing in WSNs	Proposed meta-heuristic and AI-based routing optimization with bio-inspired algorithms	Addressed persistent energy challenges and improved routing efficiency
Alrizq et al. (2024)	Sensor node localization in mobile WSNs	Developed a hybrid DA-FA approach combined with meta-heuristics for anchor node positioning	Reduced localization error by up to 21.53% with faster convergence in mobile scenarios
Hadi et al. (2025)	Energy management in WSNs	Formulated a Q-learning model with adaptive routing and real-time power modifications	Improved energy savings by 34.92%, increased packet delivery ratio, reduced latency, and extended operational time
Kush (2025)	Integrating sensor technologies with conversational AI	Fused real-time sensor data with ChatGPT 4.0 for enhanced context-sensitive interactions	Improved AI understanding in healthcare and smart home environments through adaptive, sensor-driven insights
Birahim et al. (2025)	Intrusion detection in WSNs	Proposed a PSO-based ensemble machine learning model (RF, DT, KNN) with SMOTE-Tomek and explainable AI (LIME, SHAP)	Achieved 99.73% accuracy in intrusion detection, providing a robust and scalable security solution

III. Proposed Mathematical Formulation

To mathematically formulate the effectiveness of sensing capacities in WSN through AI, we need to define key performance indicators (KPIs) and integrate AI-based models for data accuracy, energy efficiency, network optimization, and fault detection.

3.1 AI-Based Data Processing & Sensor Fusion

Sensor fusion can be modelled as an estimation problem where multiple noisy sensor inputs are combined to improve accuracy.

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Let X be the true environmental state, and let Z_i be the noisy observation from the i-th sensor. The AI-based fusion model can be represented as:

$$\hat{X} = f(Z_1, Z_2, \ldots, Z_N)$$

where $f(\cdot)$ is an AI function (e.g., neural network) trained to estimate X optimally.

A **Kalman Filter (KF)**-based fusion approach follows:

$$\hat{X}_{t+1} = A\hat{X}_t + BU_t + K_t(Z_t - H\hat{X}_t)$$

Where,

- A, B, H are system parameters,
- U_t is the control input,
- K_t is the Kalman gain, dynamically computed to minimize error.

3.2 AI-Driven Energy Efficiency in Sensing

Adaptive Sampling & Data Aggregation

The optimal sampling interval T* can be determined using a reinforcement learning framework by minimizing the trade-off between energy consumption and sensing accuracy:

$$T^* = \arg\min_T (E(T) + \lambda D(T))$$

where:

- $E(T)$ is the energy consumed at sampling interval T,
- $D(T)$ is the data distortion due to infrequent sampling,
- λ is a weight factor balancing energy and accuracy.

3.3 AI-Enhanced Sensing Accuracy

Let Y_i be the raw sensor reading from node i, and let ϵ_i be the measurement noise. AI-based **denoising model** can be formulated as:

$$\hat{Y}_i = \mathbb{E}[Y_i|X] = g(Y_i, \theta)$$

where $g(\cdot)$ is a trained AI function with parameters θ.

A **Neural Network (NN)-based correction model** can refine sensor readings using:

$$\hat{X} = \sigma(WY + b)$$

where W and b are learned weights, and σ is the activation function (e.g., ReLU or sigmoid).

3.4 Intelligent Routing & Network Optimization

AI-Based Clustering

Cluster head selection can be optimized using an AI-based function f(·) that minimizes energy consumption:

$$CH^* = \arg\min_{CH} \sum_{i=1}^{N} d(S_i, CH)^2 E_i$$

where:

- $d(S_i, CH)$ is the distance between sensor node S_i and cluster head CH,
- E_i is the remaining energy of node S_i.

Self-Healing Network Formulation

AI-based network healing can be formulated as a graph optimization problem:

$$\min_{\mathcal{P}} \sum_{(i,j)\in\mathcal{P}} w_{ij}$$

where $\mathcal{P}$ is the new optimized routing path and w_{ij} is the energy cost of transmitting from node i to node j.

3.5 AI for Predictive Maintenance & Fault Detection

Predictive Failure Analysis Using ML

Let $\mathbf{X} = \{x_1, x_2, ..., x_n\}$ be sensor data, and let y be a failure indicator (0: Normal, 1: Faulty). AI models predict failure probability:

$$P(y = 1|\mathbf{X}) = \sigma(W^T\mathbf{X} + b)$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$ is the **sigmoid activation function.**

Graph Neural Networks (GNNs) for Fault Localization

If the WSN is modeled as a graph $G = (V, E)$, where V is the set of nodes and E is the set of edges, then the failure score of node v can be computed as:

$$h_v = \mathrm{ReLU}\left(W_1 \sum_{u\in N(v)} h_u + W_2 X_v\right)$$

Where,

N(v) is the set of neighbours of v,
Xv is the node feature Vectors.
W_1, W_2 are trainable AI parameters.

3.6 Proposed Model

AI enhances Wireless Sensor Networks (WSN) by improving sensing accuracy, energy efficiency, and fault detection. Sensor fusion techniques, such as Kalman filtering, refine noisy data for better estimation. Adaptive sampling optimizes energy consumption by dynamically adjusting intervals. AI-driven clustering minimizes transmission costs, while reinforcement learning optimizes routing. Predictive models, including logistic regression and neural networks, detect sensor failures and enhance network reliability. Graph Neural Networks (GNNs) localize faults in WSNs for proactive maintenance. Through integrating machine learning, optimization, and graph-based techniques, AI significantly boosts WSN performance, making them more efficient, accurate, and resilient for real-world applications.

III. Conclusion

The integration of Artificial Intelligence into Wireless Sensor Networks represents a transformative advancement that addresses longstanding challenges in energy management, data reliability, and network scalability. AI-driven techniques, including deep learning, reinforcement learning, and fuzzy logic, have demonstrated substantial improvements in energy efficiency, sensor data processing, and dynamic routing. The systematic review highlights innovative solutions such as multi-hop charging architectures, optimized data aggregation methods, and adaptive routing protocols that enhance network resilience. Furthermore, the application of predictive maintenance and fault detection strategies ensures sustained network performance in harsh environments. These developments pave the way for more robust, adaptive, and intelligent WSN deployments, which are critical for the evolving demands of smart cities, industrial automation, and IoT ecosystems. Future work should focus on interdisciplinary collaboration and real-world large-scale practical implementation.

References

1. Wang, C., Li, J., Ye, F., & Yang, Y. (2015, June). Improve charging capability for wireless rechargeable sensor networks using resonant repeaters. In *2015 IEEE 35th International Conference on Distributed Computing Systems* (pp. 133-142). IEEE.
2. ZainEldin, H., Elhosseini, M. A., & Ali, H. A. (2015). Image compression algorithms in wireless multimedia sensor networks: A survey. *Ain Shams engineering journal*, *6*(2), 481-490.
3. Phung, K. H., Lemmens, B., Goossens, M., Nowe, A., Tran, L., & Steenhaut, K. (2015). Schedule-based multi-channel communication in wireless sensor networks: A complete design and performance evaluation. *Ad Hoc Networks*, *26*, 88-102.

4. He, T., Chin, K. W., & Soh, S. (2016). On wireless power transfer and max flow in rechargeable wireless sensor networks. *IEEE Access*, *4*, 4155-4167.
5. Ren, J., Zhang, Y., Zhang, N., Zhang, D., & Shen, X. (2016). Dynamic channel access to improve energy efficiency in cognitive radio sensor networks. *IEEE Transactions on Wireless Communications*, *15*(5), 3143-3156.
6. Deng, R., He, S., & Chen, J. (2016). An online algorithm for data collection by multiple sinks in wireless-sensor networks. *IEEE Transactions on Control of Network Systems*, *5*(1), 93-104.
7. Matlou, O. G., & Abu-Mahfouz, A. M. (2017, October). Utilising artificial intelligence in software defined wireless sensor network. In *IECON 2017-43rd annual conference of the IEEE industrial electronics society* (pp. 6131-6136). IEEE.
8. Pan, G., Lei, H., Yuan, Y., & Ding, Z. (2017). Performance analysis and optimization for SWIPT wireless sensor networks. *IEEE Transactions on Communications*, *65*(5), 2291-2302.
9. Liu, X. (2017). Survivability-aware connectivity restoration for partitioned wireless sensor networks. *IEEE Communications Letters*, *21*(11), 2444-2447.
10. Kumar, H., & Singh, P. K. (2018). Comparison and analysis on artificial intelligence-based data aggregation techniques in wireless sensor networks. *Procedia computer science*, *132*, 498-506.
11. Al-Janabi, T. A., & Al-Raweshidy, H. S. (2018). A centralized routing protocol with a scheduled mobile sink-based AI for large scale I-IoT. *IEEE sensors journal*, *18*(24), 10248-10261.
12. Abdulsahib, G. M., & Khalaf, O. I. (2018). An improved algorithm to fire detection in forest by using wireless sensor networks. *International Journal of Civil Engineering & Technology (IJCIET)-Scopus Indexed*, *9*(11), 369-377.
13. Doibale, M. S., & Kurundkar, D. G. (2019). Wireless sensor networks congestion and role of artificial intelligence. *International Journal of Computer Engineering and Technology*, *10*(2).
14. Lu, J., Feng, L., Yang, J., Hassan, M. M., Alelaiwi, A., & Humar, I. (2019). Artificial agent: The fusion of artificial intelligence and a mobile agent for energy-efficient traffic control in wireless sensor networks. *Future generation computer systems*, *95*, 45-51.
15. Ai, Y., Cheffena, M., Ohtsuki, T., & Zhuang, H. (2019). Secrecy performance analysis of wireless sensor networks. *IEEE Sensors letters*, *3*(5), 1-4.
16. Kim, T., Vecchietti, L. F., Choi, K., Lee, S., & Har, D. (2020). Machine learning for advanced wireless sensor networks: A review. *IEEE Sensors Journal*, *21*(11), 12379-12397.
17. Amutha, J., Sharma, S., & Nagar, J. (2020). WSN strategies based on sensors, deployment, sensing models, coverage and energy efficiency: Review, approaches and open issues. *Wireless Personal Communications*, *111*(2), 1089-1115.
18. Menaria, V. K., Jain, S. C., Raju, N., Kumari, R., Nayyar, A., & Hosain, E. (2020). NLFFT: A novel fault tolerance model using artificial intelligence to improve performance in wireless sensor networks. *IEEE Access*, *8*, 149231-149254.

19. Mukhopadhyay, S. C., Tyagi, S. K. S., Suryadevara, N. K., Piuri, V., Scotti, F., & Zeadally, S. (2021). Artificial intelligence-based sensors for next generation IoT applications: A review. *IEEE Sensors Journal*, *21*(22), 24920-24932.
20. Sharma, H., Haque, A., & Blaabjerg, F. (2021). Machine learning in wireless sensor networks for smart cities: a survey. *Electronics*, *10*(9), 1012.
21. Agarwal, M., Bhathawala, P. H., & Morwani, H. (2021). A Study on Approaches for Enhancing WSN Lifetime and Contribution of AI. *Int. J. Eng. Res. Technol.*, *9*(05), 165-170.
22. Ahmed, Q. W., Garg, S., Rai, A., Ramachandran, M., Jhanjhi, N. Z., Masud, M., & Baz, M. (2022). Ai-based resource allocation techniques in wireless sensor internet of things networks in energy efficiency with data optimization. *Electronics*, *11*(13), 2071.
23. Osamy, W., Khedr, A. M., Salim, A., Al Ali, A. I., & El-Sawy, A. A. (2022). A review on recent studies utilizing artificial intelligence methods for solving routing challenges in wireless sensor networks. *PeerJ Computer Science*, *8*, e1089.
24. Raja, P., Kumar, S., Singh, D., & Singh, T. (2023). Improving wireless sensor networks effectiveness with artificial intelligence. *Innovative Engineering with AI Applications*, 243-255.
25. Balkhande, B., Ghule, G., Meshram, V. H., Anandpawar, W. N., Gaikwad, V. S., & Ranjan, N. (2023). Artificial Intelligence Driven Power Optimization in IOT-Enabled Wireless Sensor Networks. *Journal of Electrical Systems*, *19*(2).
26. Ghareeb, A. Y., Gharghan, S. K., Mutlag, A. H., & Nordin, R. (2023). Wireless sensor network-based artificial intelligent irrigation system: challenges and limitations. *Journal of Techniques*, *5*(3), 26-41.
27. Benfradj, A., Thaljaoui, A., Moulahi, T., Khan, R. U., Alabdulatif, A., & Lorenz, P. (2024). Integration of artificial intelligence (AI) with sensor networks: Trends, challenges, and future directions. *Journal of King Saud University-Computer and Information Sciences*, *36*(1), 101892.
28. Priyadarshi, R. (2024). Energy-efficient routing in wireless sensor networks: a meta-heuristic and artificial intelligence-based approach: a comprehensive review. *Archives of Computational Methods in Engineering*, *31*(4), 2109-2137.
29. Alrizq, M., Stalin, S., Alyami, S., Roy, V., Mishra, A., Chandanan, A. K., ... & Venkatesh, P. (2024). Optimization of sensor node location utilizing artificial intelligence for mobile wireless sensor network. *Wireless Networks*, *30*(7), 6619-6631.
30. Hadi, A. S. A. A., Wahab, A. A. B. A., Hamzah, F. M., & Veena, B. S. (2025). AI-Driven Energy Management Techniques for Enhancing Network Longevity in Wireless Sensor Networks. *Journal of Robotics and Control (JRC)*, *6*(1), 246-261.
31. Kush, J. C. (2025). Integrating Sensor Technologies with Conversational AI: Enhancing Context-Sensitive Interaction Through Real-Time Data Fusion. *Sensors*, *25*(1), 249.
32. Birahim, S. A., Paul, A., Rahman, F., Islam, Y., Roy, T., Hasan, M. A., ... & Chowdhury, M. E. (2025). Intrusion Detection for Wireless Sensor Network using Particle Swarm Optimization based Explainable Ensemble Machine Learning Approach. *IEEE Access*.