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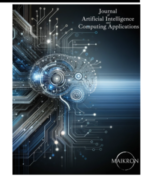

Review article

Machine learning in wireless sensor network applications: a short narrative review

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ABSTRACT

This review explores the applications of Machine Learning in Wireless Sensor Networks, emphasizing its impact on various aspects such as routing, security, energy efficiency, speed, and quality. Its purpose is to bring attention to the most significant aspects and commonly employed applications of Machine Learning in Wireless Sensor networks for new and future research endeavors. The implications involved in obtaining 10 selected from 340 articles were the identification of specific articles, the screeening filtered by titles and abstracts and the Eligibility of the evaluated articles.The result of ten selected articles delve into the use of ML techniques, particularly Reinforcement Learning, with Q-learning being a prominent algorithm and so highlights the significance of ML in optimizing Wireless Sensor Networks performance, enhancing energy efficiency, and addressing specific challenges like wildfire detection and agricultural monitoring, systems that requires rapid response with low power consumption. Despite rigorous article selection, potential biases and criteria applicability limitations are acknowledged. Recommendations include further exploration of AI integration in practical applications, sophisticated approaches for energy optimization and security, and addressing emerging challenges in wireless sensor networks.

Keywords: wireless sensor networks, machine learning, deep learning

1. Introduction

Advancements in wireless technologies have been a major driver of modern human progress, enabling rapid, long-distance, and instantaneous communication. Among these technologies, the Internet of Things (IoT) stands out, integrating various devices and systems for seamless data exchange. At the core of many IoT systems are wireless sensor networks (WSNs), which play a crucial role in gathering and transmitting environmental data for real-time analysis.

WSNs are fundamental in applications such as battlefield surveillance, smart living environments, real-time environmental monitoring, and traffic optimization. By connecting numerous sensor nodes wirelessly, WSNs can measure various physical parameters precisely. However, efficient management of WSNs poses significant challenges, including issues related to routing, security, and, most critically, energy efficiency. Despite their design for low energy consumption [1], relying on batteries for WSNs with a large number of nodes is unsustainable due to the need for periodic replacement and the ecological risks associated with battery disposal [2].

Addressing energy efficiency is a priority, especially when utilizing renewable energy sources that may not provide a continuous power supply. Therefore, optimizing the energy consumption of WSNs is crucial, and this is where artificial intelligence (AI) and, more specif-

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ically, machine learning (ML) methods, can be highly beneficial. ML techniques can enhance WSN performance by reducing energy usage and minimizing human intervention [3]. Additionally, in the context of data security, the increasing complexity of WSNs has highlighted vulnerabilities such as weak authentication, insecure network services, and poor encryption practices [4]. The lack of common standards balancing power consumption and security exacerbates these issues, leaving WSNs susceptible to attacks, especially in the communication layer [5].

The purpose of this review is to analyze the application of ML methods in WSNs, focusing on their role in enhancing energy efficiency and addressing security challenges. By examining the current state of research and anticipating future trends, this review aims to provide a comprehensive orientation of ongoing ML work in the context of WSNs.

This article is structured as follows: Section 2 outlines the inclusion and exclusion criteria used for selecting relevant studies, while Section 3 presents the main findings in terms of the different prevailing themes from the review of the selected articles. Section 4 discusses specific applications and benefits of ML in WSNs, highlighting deep learning (DL) techniques and their impact. Finally, Section 5 provides concluding remarks, summarizing the implications of ML in WSNs and projecting future challenges and research directions.

2. Methodology

The methodology of this review outlines a systematic approach aimed at identifying, selecting, and analyzing relevant literature on the applications of ML in WSNs. To ensure a comprehensive and high-quality selection of studies, a rigorous search strategy was implemented using defined inclusion and exclusion criteria. The process involved multiple stages, including initial identification of records, a thorough screening of titles and abstracts, an in-depth eligibility assessment based on quality metrics, and a final selection of the most impactful articles.

A total of 340 records were initially identified using Google Scholar with the search term intitle:"machine learning" AND intitle:"wireless sensor networks", covering publications from 2014 to the present. Following a preliminary review of the titles and abstracts, 43 articles were selected for an initial screening based on their relevance to the review topic, leaving 297 articles for a more detailed eligibility assessment.

During the eligibility phase, the full text of the remaining 297 articles was carefully examined. Of these, 67 articles were excluded as they addressed topics outside the scope of machine learning applications in wireless sensor networks. An additional 150 articles were removed because they were not indexed in the Journal Citation Reports (JCR), which was used as a quality filter to ensure the selection of impactful studies. Among the JCR-indexed articles, 55 were further excluded for not being classified within the top quartile (Q1), as the review prioritized high-impact research. Finally, 15 articles were excluded for failing to meet the threshold of an average citation rate of at least 1.5 citations per year.

The final selection consisted of 10 high-impact articles that provide a focused and comprehensive overview of ML applications in WSNs. This short narrative review includes a small number of studies, intentionally chosen to capture only the most impactful and influential works in the field. While this approach offers a concise yet in-depth analysis, it also introduces certain limitations. A broader, more exhaustive review could potentially include a wider range of studies, capturing additional insights and emerging trends that may have been omitted here. Nevertheless, the selection process ensured that the included articles represent significant contributions to the domain. This process, along with the stages of identification, screening, and eligibility assessment, is summarized in Figure 1. The complete list of the 10 selected articles is presented in Table 1.

3. Thematic Overview

The reviewed articles cover various applications of ML algorithms in WSNs, particularly those offering significant benefits tailored to specific objectives within the context of Industry 4.0. The use of ML techniques emerges as a strategic solution to key challenges in WSNs, including smart farming, routing, security, energy conservation, scheduling, localization, node clustering, data aggregation, fault detection, and real-time data integrity. DL techniques, integrated into automated networks, have shown promise, as highlighted in the work by [6]. These techniques are well-suited for handling dynamic, real-world scenarios through effective learning processes, reducing the need for frequent manual adjustments. This thematic overview summarizes and critically analyzes the contributions of ML algorithms to WSNs, identifying gaps and contradictions while maintaining a clear connection to the research objective stated in the Introduction.

In smart agriculture, ML techniques play a pivotal role in analyzing data collected by WSNs to identify various agricultural issues [8]. This application demonstrates the practical use of ML algorithms in addressing challenges within the agricultural domain. The integration of these technologies represents a progressive shift towards more advanced and sophisticated approaches for tackling agricultural concerns. By critically examining the literature, including the seminal work of [8], we highlight the current applications of ML in smart agriculture and identify areas for further exploration and improvement. This thematic analysis aligns with the research question presented in the Introduction, emphasizing the contemporary relevance and potential future developments of ML algorithms in the agricultural context.

The application of ML techniques in WSNs offers several advantages, including reduced computational complexity, improved feasibility in identifying optimal solutions, maximized resource utilization, extended net-

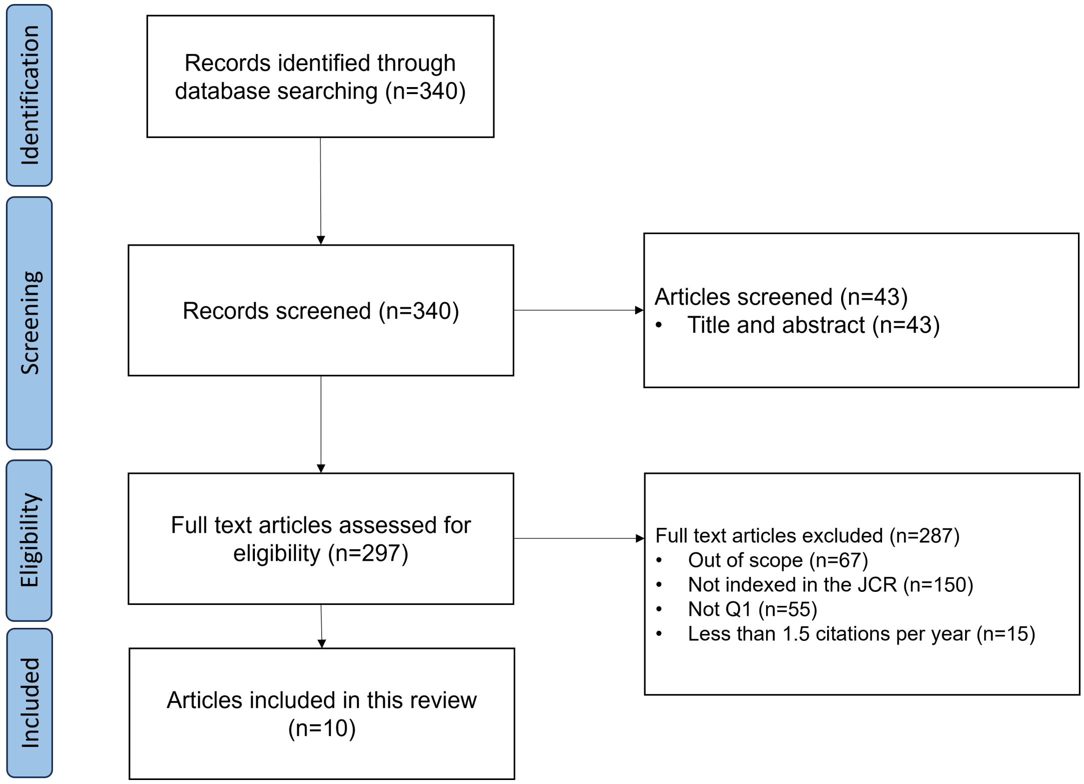

Figure 1. Diagram illustrating the systematic process of identifying, screening, and selecting relevant studies for this review on machine learning applications in wireless sensor networks. The diagram outlines each stage of the methodology, including the initial search, assessment of eligibility based on defined criteria, and the final inclusion of 10 high-impact articles.

work lifespan, and significant gains in energy efficiency [9]. A critical examination of the literature highlights the substantial contributions of ML to the field of WSNs, particularly in enhancing overall efficiency and extending the useful life of the networks.

Energy management is a crucial area where traditional methods, such as optimal routing protocols, node failure detection, and WSN topology construction, have been widely recognized for their utility. However, these methods have limited effectiveness in significantly reducing energy consumption. To overcome these limitations, advanced techniques like ML, metaheuristics, and Q-learning have been explored in the context of WSNs [7, 15].

The integration of IoT in WSNs has advanced significantly with the development of various smart devices. However, devices that are not connected to a conventional electrical grid face limitations in operating time. To address this, AI techniques, particularly reinforcement learning (RL), have been applied for energy optimization, providing enhanced control over battery charge levels and extending the operational lifespan of these devices [13]. The application of RL methods in WSNs also includes the identification of energy-efficient data transmission paths, which is essential for maintaining network efficiency. Additionally, RL techniques contribute to data security by mitigating risks associated with compromised nodes and potential data theft [12].

A practical application of DL is in combating forest fires, catastrophic events that cause significant economic, ecological, and environmental damage worldwide. Existing detection methods, such as satellite image processing systems, optical sensors, and digital cameras, often prove ineffective. In response, integrating WSNs with low-energy DL models has been proposed. By monitoring multiple sensor nodes measuring parameters like temperature, humidity, light intensity, and CO_2 levels, this approach stands out as a promising solution, enhancing detection efficiency and enabling rapid response to minimize potential damage [14].

Communication overloads in WSNs pose a significant challenge, as they can quickly deplete node energy and reduce network lifetime, thereby affecting the quality of service. To mitigate these issues, the Q-learning technique has been implemented. This RL approach involves two stages: (1) reward-dependent cluster head selection and (2) double-constraint path selection. By improving the efficiency of cluster head and route selection, Q-learning reduces uneven energy consumption and helps extend the network's lifetime [11].

Resilience in WSNs is another major challenge, re-

Table 1. The final list of articles used in this review, including information for title, journal, year of publication and citation.

Title	Journal	Year	Citation
Wireless sensor networks in agriculture through machine learning: A survey	Computers and Electronics in Agriculture	2022	[6]
A New Energy Prediction Algorithm for Energy-Harvesting Wireless Sensor Networks With Q-Learning	IEEE Access	2016	[7]
Machine Learning in Wireless Sensor Networks: Algorithms, Strategies, and Applications	EEE Communications Surveys	2014	[8]
Machine Learning for Advanced Wireless Sensor Networks: A Review	IEEE Sensors Journal	2020	[9]
Resilient Routing Mechanism for Wireless Sensor Networks With Deep Learning Link Reliability Prediction	IEEE Access	2020	[10]
Optimizing the network energy of cloud assisted internet of things by using the adaptive neural learning approach in wireless sensor networks	Computers in Industry	2019	[11]
A Trusted Routing Scheme Using Blockchain and Reinforcement Learning for Wireless Sensor Networks	Sensors	2019	[12]
Reinforcement and deep reinforcement learning for wireless Internet of Things: A survey	Computer Communications	2019	[13]
Early Forest Fire Detection System using Wireless Sensor Network and Deep Learning	International Journal of Advanced Computer Science and Applications	2020	[14]
Machine Learning-Based Energy-Saving Framework for Environmental States-Adaptive Wireless Sensor Network	IEEE Access	2020	[15]

quiring the network to efficiently recover and adapt to changes in topology, such as node failures or attacks, especially when information about network links is incomplete. To address this issue, the Weighted Laplacian Deep Convolutional Neural Network (WL-DCNN) has been proposed. This DL model, combined with a predictive routing mechanism, optimizes data transmission and prolongs the network's useful life [10].

The thematic overview has highlighted several key areas where ML techniques have been effectively applied to enhance the performance of WSNs. From energy management and communication optimization to resilience and real-time applications, the integration of ML models, particularly DL and RL, shows great promise in addressing the inherent challenges of WSNs. This analysis provides a solid foundation for the subsequent discussion, where the implications and future directions of these advancements will be explored in greater detail.

4. Discussion

In WSNs, the speed and efficiency of data transmission are crucial considerations [14]. However, this efficiency must also account for security measures to protect the integrity of the transmitted data [5]. Balancing these factors becomes more complex when incorporating low-energy consumption nodes, which impose significant demands on both hardware and software, while still being constrained by energy limitations [12, 13]. This delicate balance between transmission efficiency, security, and power management poses a substantial challenge in the design and operation of WSNs, underscoring the need for innovative solutions that effectively address these competing requirements.

The variation in the findings of the reviewed studies was critically analyzed through a comprehensive comparison of the issues addressed in the selected articles. This analysis revealed common challenges consistently identified across multiple studies, including route optimization [13], energy-aware routing [8], energy saving [7, 15], security [10], speed [14], performance [12], quality of service [11], and programming complexity [9]. The goal of the review was to provide a detailed understanding of these variations and to identify patterns or consistencies in how the studies addressed key challenges within the scope of the selected articles.

To identify the most effective learning techniques for specific problems in WSNs, the findings of each applied method were interpreted within their respective contexts and evaluated based on their results. In WSN applications, these techniques have been utilized for continuous monitoring in agricultural fields [6], forest fire detection [14], and other scenarios. These techniques help improve routine processes and enable continuous monitoring, often replacing humans in tasks that may pose safety risks. However, to fully harness the potential of AI in WSNs, a large volume of data samples is required, which in turn demands significant time and resources [9].

RL has emerged as a key tool for energy optimization in WSNs, with Q-learning being identified as the preferred algorithm due to its simplicity and low computational complexity. Despite these advantages, the algorithm's impact on network performance has been significant, leading to notable improvements in transmission routes and the overall efficiency of WSN batteries, as demonstrated in studies such as [12, 13]. The Q-learning-based solar energy prediction (QL-SEP) algorithm is one notable approach that has shown promise in optimizing energy use in WSNs [7, 9, 11, 13, 15].

The Q-learning algorithm, a key component of RL, stands out as an essential tool in the field of ML. Its adaptive nature enables it to learn directly from interactions with the environment, making it applicable to a wide range of real-world problems. The algorithm's success has been demonstrated in practical applications, often outperforming human performance in various tests, highlighting its relevance and effectiveness in solving complex, dynamic problems. This RL approach is a valuable asset for addressing challenges that require optimized decision-making over time [9].

While RL techniques have shown promise in energy optimization, DL methods offer complementary advantages, particularly in event prediction and security applications. DL has proven effective for energy-aware routing in WSNs and has also been employed to address security issues [9, 10, 11, 12, 13]. Additionally, DL methods have been utilized in real-time event prediction tasks, providing valuable solutions for applications such as forest fire detection and continuous monitoring [14, 9, 11, 13].

However, it is essential to critically consider certain limitations in this review process. The thoroughness of the search strategy and the applicability of the inclusion and exclusion criteria may affect the representativeness of the selected studies. Additionally, attention should be given to the methodology used for assessing study quality and ensuring consistency in the application of criteria among reviewers. Although the review aims for transparency, the generalization of results and the temporal relevance of the information are important aspects to consider. Acknowledging these limitations is crucial for accurately interpreting the findings and identifying areas for future improvements in similar research endeavors.

The findings from the selected articles demonstrate a strong alignment with previous research, particularly in highlighting the importance of ML for optimizing the performance of WSNs and improving energy efficiency [9, 12, 13]. These results are consistent with earlier studies that emphasize the relevance of ML in the field of WSNs [12, 7]. Overall, the integration of ML techniques has proven effective in addressing core challenges such as energy management, data security, and resilience in WSNs. This synthesis of findings underscores the transformative potential of ML techniques in the ongoing development of WSNs, reinforcing their role as foundational components of smart, interconnected systems and paving the way for future research directions in this rapidly evolving field.

5. Conclusion

This review highlights the effective use of ML techniques in optimizing the performance of WSNs, with particular emphasis on RL and the widespread adoption of Q-learning as a prominent algorithm [9, 12, 13]. The findings demonstrate the significant impact of ML in enhancing energy efficiency and addressing critical challenges, such as wildfire detection [14] and agricultural monitoring [6], both of which require rapid response with low power consumption.

The review identified diverse applications of ML across key areas of WSNs, including routing, security, energy conservation, speed, and quality of service. It also explored the contributions of different ML algorithms, noting the importance of DL for energy-aware routing and improving WSN security. These insights underscore the transformative role of ML in advancing WSN capabilities and addressing complex, real-world challenges.

Despite the rigorous selection process, the review acknowledges certain limitations related to the applicability of inclusion and exclusion criteria and the potential for selection biases. Maintaining transparency in the methodology and ensuring consistency in evaluating study quality are crucial for accurately interpreting the findings and guiding future research efforts.

Further exploration is recommended in integrating AI into practical WSN applications, developing more sophisticated approaches for energy optimization and security, and tackling emerging challenges. The findings from this review serve as a valuable reference for future research, encouraging the pursuit of innovative and sustainable solutions in WSNs. By expanding the scope of literature searches to include not only Q1 but also high-quality Q2 articles, future studies can capture a broader range of emerging trends and insights, helping to guide new research initiatives and foster continued innovation.

This review demonstrates the substantial potential of ML techniques in driving the evolution and continuous improvement of WSNs within today's rapidly advancing technological landscape. The integration of ML into WSNs offers promising opportunities for enhanced efficiency, resilience, and intelligence, paving the way for more adaptive and capable networks in the future.

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